Techno-Science Research Journal V13 (2) (2025) P 60-67

Content list available at ITC

Techno-Science Research Journal

Journal Homepage: http://techno-srj.itc.edu.kh/

Techno-Science Research Journal

Prediction on Load model for future load profile of Electric Vehicle charging demand in Phnom Penh

Songchhay Pet*, Bunthern Kim, Monyvathna Chheng

Research and Innovation Center, Institute of Technology of Cambodia, Russian Federation Blvd., P.O. Box 86, Phnom Penh, Cambodia

Received: 06 September 2024; Revised: 01 October 2024; Accepted: 09 October 2024; Available online: 31 August 2025

Abstract: The widespread adoption of Electric vehicles (EVs) is largely attributed to their eco-friendly and cost-effective attributes. As the number of EVs charging on electrical distribution systems is expected to rise, it is essential to consider the potential effects on the infrastructure, including generation capacity, transformer overloading levels, line congestion, and load profiles, with the impact of EV charging on load profiles being the most pressing concern, Consequently, developing accurate models and predicts of EV charging demand is crucial. This paper presents a methodology for analyzing the load demand of load profiles due to EV battery charging. A comparative study is carried out by simulating three EV charging scenarios, uncontrolled charging, controlled off-peak charging, and smart charging. The proposed method considers the initial state of charge and start time of EV battery charging. Results show that a 10% market penetration of EVs in the studied system would result in increase in peak demand by up to 17.3% for an uncontrolled charging scenario is a worst-case to the system and may cause congestion issues to the local network. A controlled off-peak charging scenario can shift the EV charging load to an off-peak time; therefore, the EV can be introduced to a new peak or near-peak in early off-peak time. Smart charging method which optimizes the start time of EV charging is the most beneficial charging method to distribution network operators and EV users.

Index Terms: electric vehicles, load model, electrical distribution system, battery charging.

1. INTRODUCTION

The effort to roll out EVs is a new phenomenon as the world races to reduce greenhouse gas emissions from the transport sector to help tackle the climate crisis. That is why it is not so popular in developing countries like Cambodia, where many people are accustomed to driving vehicles that run on fuel or gasoline.

Multiple studies have shown that automobile exhaust emissions are responsible for most urban air pollution [1]. It is worth noting that PM2.5 is particularly problematic, and according to statistics, automobile exhaust emissions account for a substantial 31.1% of local PM2.5 emissions, making them the largest contributor [2]. By 2018, China's reliance on imported crude oil had grown to 70.9% and is projected to rise even higher to approximately 75% by 2030, which could have significant implications for China's energy security [3].

With so many EVs being connected to power systems to charge their batteries, the charging demand can significantly increase the peak demand on the utility distribution system. Although it is desired that EV battery charging loads can be contained during system off-peak hours without affecting peak demand, the charging behaviors of various EV users have an element of randomness.

Several studies have already been carried out to predict the overall effect of EVs on power systems. MJ Rutherford, V Yousefzadeh, et al [4] investigated the impact of EV battery chargers on the distribution transformer life expectancy. The results show that power management of the EV battery charging profile can help manage the loss of life of the distribution transformer. However, the dynamics of large-scale EVs in urban road networks will concurrently affect the integration of transportation systems and power grids, necessitating a coordinated approach to their management [5]. The interaction between resident trip rules, urban road network structure, and

*Corresponding author: Songchhay Pet

E-mail: chhaysong23@gmail.com; Tel: +855-10 306 620

charging facility distribution has significant implications for vehicle driving distribution and charging decision-making. In contrast, the characteristics of vehicle batteries, driving paths taken, and energy supply modes have substantial consequences on the traffic network's unobstructed degree and power grid operation state [6], [7]. Therefore, in the study in Asia [8], a large amount of EV plug-in grid will cause overload, voltage deviation issues, harmonic distortion, etc, which affect the regular operation of the power grid and may cause congestion in the entire power grid. Preeti Khasa *et al* [9] developed a Simulink model for synchronized charging and discharging of EVs to the distribution grid and for V2G and G2V applications, with this work, charging of vehicles will be faster due to the discharging of EV batteries to the grid, and the charging price will be reduced. Hence, oversimplifications were adopted in the EV battery charging characteristics work by modeling the charging load as a piecewise constant function.

The research aims to quantify the influence of the introduction of electric vehicles on the power system load profile, taking into account real-world factors such as EV battery charging characteristics, user behavior, and actual power system operation data of:

The EV charging load profile with the inclusion of time, size, and the shape of the load curve

The EV charging load model

The EV charging scenarios.

The remainder of the paper is organized as follows: In section 2, the Modeling fo EV charging demand is described. In section 3, we study system the effects of EV charging scenarios on two seasonal load profiles. In section 4, the Datasets have been inserted into the three scenarios as result. Finally, section 5 concludes this paper with a summary of our findings.

2. ELECTRIC VEHICLE CHARGING DEMAND MODEL

As the transportation carrier, the distribution of travel rules of EVs directly affects the driving decision and charging requirement. Accordingly, it is significant to utilize the existing data to mine the trip rule of urban residents in modeling reasonably and predicting EV charging demand.

A. Electric vehicle composition by users

Figure 1 shows a statistical analysis of the proportion of various car user groups within the Cambodian car market, according to the Ministry of Public Works and Transport, covering 31 years from 1990 to 2021 and comprising approximately 920,000 registered vehicles. Around 49% of cars are privately owned and used for commuting, and 21% are service transportation owned and used for business, a other trip 30% [15]. This paper assumes that the same characteristics of car user groups hold for EV owners in Cambodia.

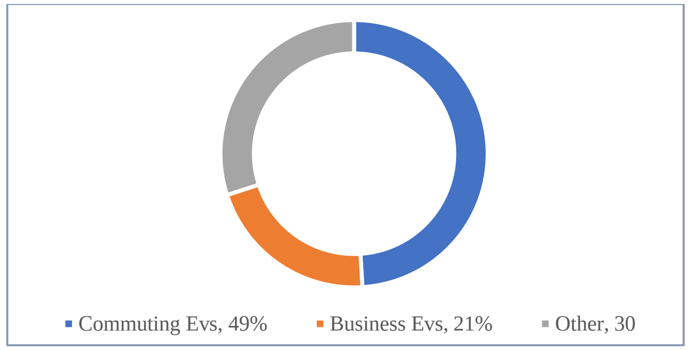

Fig.1. Proportion of various car user groups

B. Composition of electric vehicle battery types

In the United States, the US Advanced Battery Consortium (USABC) has played a key role in driving the development of advanced batteries for electric vehicles (EVs) and hybrid electric vehicles (HEVs). Focusing on cobalt, nickel-metal hydride (NiMH), and lithium-ion batteries, USABC's efforts have sought to improve battery performance and efficiency. The advantages of these technologies, including their high-performance capacity, reliability, safety features, and cost-effectiveness, have led to their widespread adoption in both EVs and HEVs. In recognition of the rapid progress being made in EV battery technology research, we have made sure to account for the latest developments. This paper assumes that EV batteries consist of 60% lithium-ion batteries, 30% cobalt batteries, and 10% NiMH batteries [10], Most of today's EVs and HEVs use lithium-ion batteries, which are the rechargeable batteries used in electric vehicles with higher energy density.

C. Electric vehicle charging start time

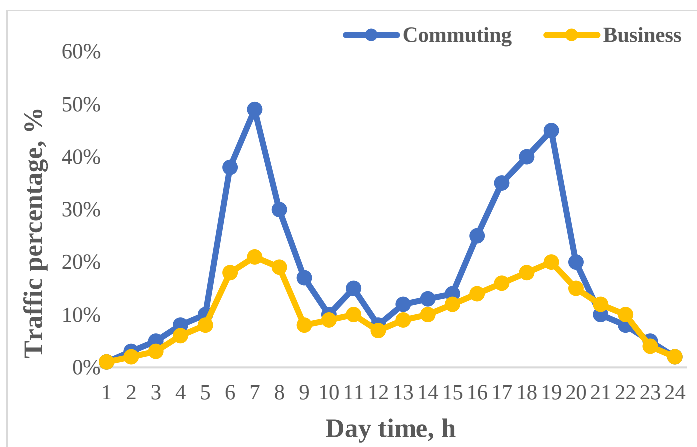

Fig.2. Commuting and business trips distribution

The start time of battery charging, determined by the purpose of the use of the EVs and by the tariff structure, has an element of randomness. Figure 4 illustrates the daily traffic flow in Phnom Penh, showing the proportion of vehicles used for commuting and business purposes by time of day. Notably, two distinct peaks emerge, corresponding to the morning (06:00 am-08:00 am) and evening (16:00-18:00) hours [14]. The type of trip purpose will dictate when Electric vehicles (EVs) become available for recharging. Furthermore, the analysis will be provided in the proceeding section of the paper, i.e., the probability density function of recharging start time: f1(t), f2(t).

D. State of Charge (SOC) of EV batteries before charging

The amount of electrical power required to support EV charging depends on various stochastic variables, including the time of day charging occurs and the battery's starting charge level at that time. Vehicles are assumed to recharge at distinction amperage rates, influenced by their initial battery state of charge. Therefore, the distribution of initial SOC Eini can be considered to have a probability density function h(E), where E is the SOC, and its value varies from fully discharged to fully charged capacity of the battery.

Initial State of Charge before charging (Eini): To model the power demand of electric vehicle battery charging over time, we need to analyze the statistical distribution of vehicle state-of-charge levels during a recharge cycle. This is based on general knowledge about travel patterns of private and company vehicles [15]. probability distribution of daily distance driven is developed in this paper. Figure 3 shows for private vehicle travel. It is found in general, the distribution of lognormal type, with zero probability of occurrence of all negative distance, and a "tail" extending to infinity for positive distance. where d is the daily distance in kilometers (km) driven by a vehicle.

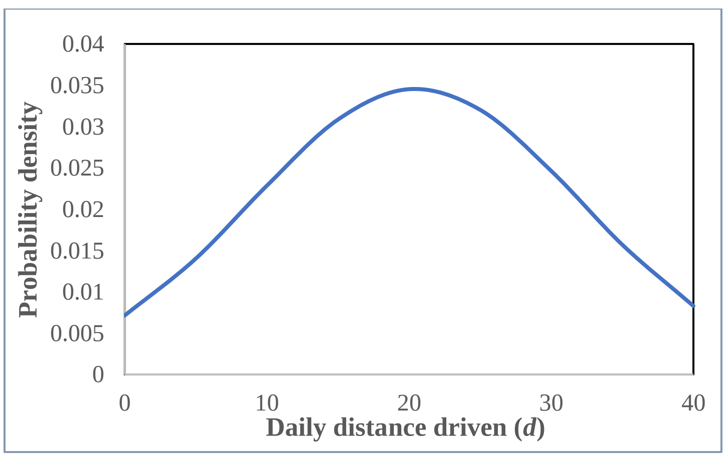

Fig. 3. Probability density of daily distance driven for private vehicle travel.

The probability density function for vehicle travel concerning distance demonstrated by Fig. 3 can be using the equation:

$$g(d;\mu;\sigma) = \frac{1}{d\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln d-\mu)^2}{2\sigma^2};\, d>0} \quad (1)$$

where d is the daily distance driven by a vehicle, μ is the mean, and σ is the standard deviation of the probability function.

According to the JICA transportation survey data [15], for private vehicles, the mean of the distribution is 20.5 km and the standard deviation is 11.5 km. In contrast, the mean daily mileage for business vehicles is 30.5 km and the standard deviation is 17.3 km.

populations, specifically those EV owners who use their vehicles for commute and those who use them for business purposes. The privately owned EVs used for commuting charging behaviors can be divided into two categories, every five-day charging and every one-week charging. In the case of business EVs, every five days recharging is assumed to be necessary. Given the average daily travel distance, the SOC at the beginning of a recharge cycle (residual battery capacity) can be estimated using (2), assuming that the SOC of an EV drops linearly with the distance of travel:

$$E_{ini} = \left(1 - \frac{d_d}{d_R}\right) x100\% \quad (2)$$

Where Eini represents the initial SOC of an EV battery, d is the daily distance traveled by a vehicle, which is a stochastic variable subjected to a lognormal distribution, α is the number of days that the EV has traveled since the last charge, dR is the maximum range that EV can travel. 465 km is the typical range value for the lithium-ion (LFP) battery-powered BYD Han EV and 405 km is the typical range value for the lithium-ion (CATL) battery-powered Toyota bZ4X [12], [13]. Fig. 4 shows the probability distribution of the initial battery state of charge after five days and one-week travel for privately owned and business-owned EVs. Separately, this is plotted from the probability density function h for the initial battery SOC given by equation (3), which is derived from equation (1) and (2):

$$h(E;\mu;\sigma) = \frac{1}{\frac{d_R}{\propto}(1-E)^2\pi\sigma^2} * e^{-\frac{[\ln(1-E)-\left(\mu-\ln\left(\frac{d_R}{\propto}\right)\right)]^2}{2\sigma^2}};\ 0<E<1. \quad (3)$$

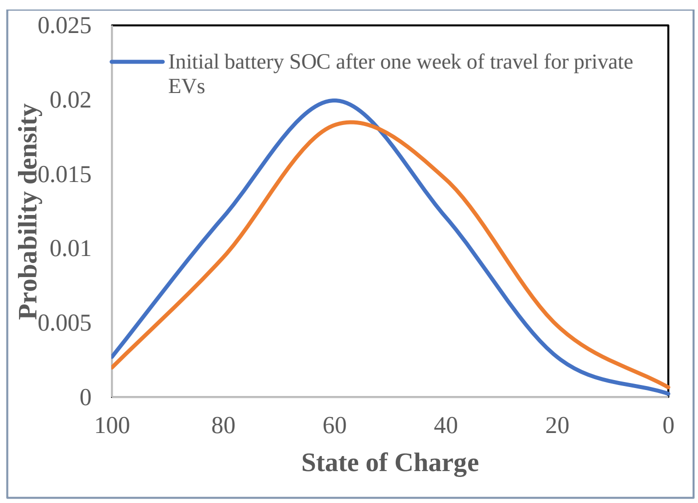

Fig. 4. Probability density function of the initial battery SOC for lithium-ion (CATL) based on Toyota bZ4X

This model considers the effect of the interval in the number of days between the recharge of an EV battery and the initial SOC. The initial SOC has a mean of 50% for private vehicles after five days of travel, 30% after one week, and 25% for business vehicles after five days of travel.

E. Electric vehicle battery charging characteristics

The leading contenders in the electric vehicle (EV) battery market have been cobalt, lithium-ion, and Nickel Metal Hydride (NiMH), which offer a unique combination of attributes, including high performance, reliability, long lifespan, and cost-effectiveness [10]. This paper uses two types of EVs –the BYD Han EV and the Toyota bZ4X –based on lithium-ion phosphate (LFP) and Contemporary Amperex Technology Co., Limited (CATL) lithium-ion batteries [11]. respectively, have been chosen as examples to examine the influence of battery charging load on the distribution system load profile, the widespread availability of data, and their prominent market share, these two EV batteries are suitable examples for this analysis. Figures 5 and 6 show the power demand and associated battery state of charge profile for the two battery types, correspondingly [12], [13]. The two types of batteries have the same capacity, despite differences in the duration of their charging processes and charging characteristics, i.e., the lithium-ion (LFP) based on BYD Han EV has a nominal capacity of 84.5 kWh whereas the lithium-ion (CATL) Toyota bZ4X has 71.4 kWh when fully charged from a fully discharged state.

In order to determine the load demand due to EVs, it is crucial to evaluate at any instant "t" in time the charging demand by an individual EV. To facilitate numerical calculations, the power demand P during the battery charging process is discretized with its discrite values Pi taken in half-minutely intervals from the curves shown in Figures 5 and 6. The corresponding power levels of charging load is therefore expressed as:

$$P_i = \frac{P((i-1)\Delta t + P(i\Delta t)}{2}, i \text{ as an index } = 1,2,3, \dots n_c \quad (4)$$

where nc is the number of half-minutely intervals in the battery charging profile, i.e., nc is 11 half-minute intervals for the lithium-ion (CALT) battery, as it takes 74 minutes for this type of battery to be fully charged from a fully discharged state, and nc = 10 for the lithium-ion (LFP) type.

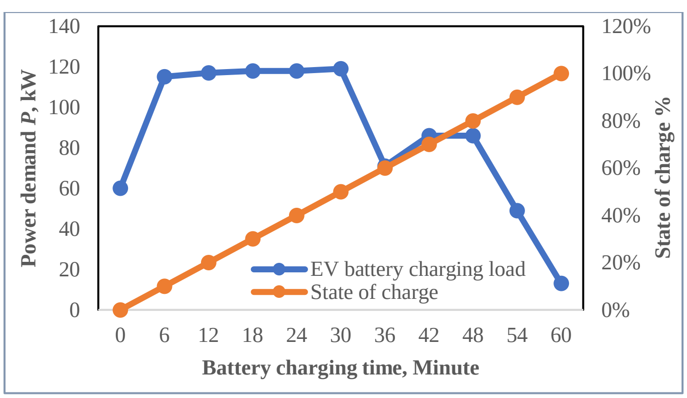

Fig. 5. Charging profile of the BYD Han EV battery (lithium-ion LFP)

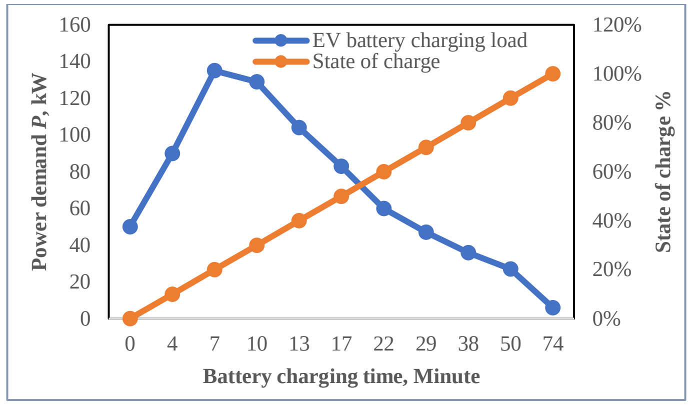

Fig. 6. Charging profile of the Toyota bZ4X battery (lithium-ion CATL)

In order to determine the load demand due to EVs, it is crucial to evaluate at any instant "t" in time the charging demand by an individual EV. To facilitate numerical calculations, the power demand P during the battery charging process is discretized with its discrite values Pi taken in half-minutely intervals from the curves shown in Figures 5 and 6. The corresponding power levels of charging load is therefore expressed as:

$$P_i = \frac{P((i-1)\Delta t + P(i\Delta t)}{2}, i \text{ as an index } = 1,2,3, \dots n_c \quad (4)$$

where nc is the number of half-minutely intervals in the battery charging profile, i.e., nc is 11 half-minute intervals for the lithium-ion (CALT) battery, as it takes 74 minutes for this type of battery to be fully charged from a fully discharged state, and nc = 10 for the lithium-ion (LFP) type.

The probability of a battery charging load operating at power level Pi at time instant t can be represented as Φ(Pi,t), where Φ is the probability density function, 1≤ t ≤ 24. If the EV battery starts recharging at time instant k (k ≤ t), then the charging load at time instant k is $P_{i-(t-k)}$s, assuming as initial battery SOC $E_{i-(t-k)}$. Assuming that the charging start time and battery initial SOC are two independent variables, the probability of a battery starting charging at the time instant k (k ≤ t, 1 ≤ k ≤ 24) and operating at power level Pi at time instant t can be mathematically expressed as:

$$\Phi(Pi, t) = \sum_{k=1}^{t} f(k)\ h\ (E_{i-(t-k)}) \quad (5)$$

where f(k) is the probability of charging started at time instant k (k ≤ t), while h($E_{i-(t-k)}$) is the probability of an initial battery SOC being at power level $P_{i-(t-k)}$. From (5), the expected value (mean) μ(P) and standard deviation σ(P) at any time instant t can be calculated, equation (6) shows the mathematical expectation of the charging load at time instant t for an individual battery:

$$\mu(P) = \sum_{i=1}^{n_c} P_i \Phi(P_i, t) \quad (6)$$

3. STUDIED SYSTEM

In this paper, we study the system load profile during one year, and consider the various start times for charging EV batteries of the three charging scenarios.

A. Example system

In this paper, The Electrical Du Cambodia (EDC) will conduct an in-depth study to examine the effects of EV battery charging on the Phnom Penh power grid's load profile. Figure 7 shows the seasonal load profile in Phnom Penh which has a greater load demand during the summer, while a much lower load during the rainy season. EVs will be considered for a greater proportion of the total load in the rainy than in the summer. Moreover, EV charging load will result in greater peak demand in summer and may exceed the line capacity under some circumstances, for instance, uncontrolled charging load during peak load time.

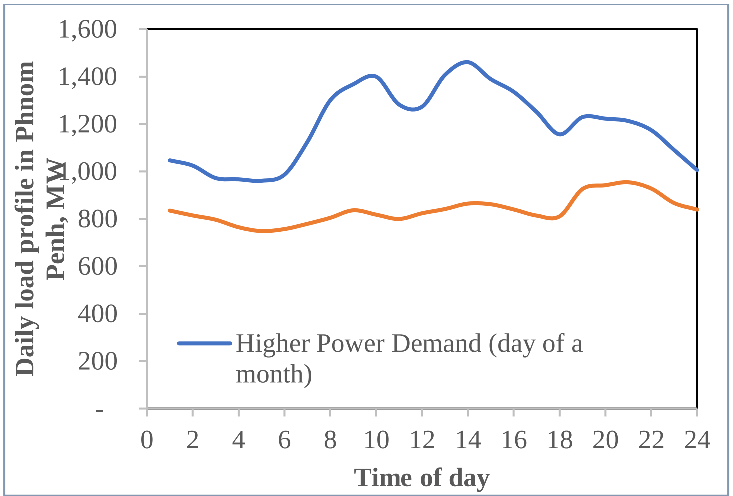

Fig. 7. Load profile in Phnom Penh

Only the impacts of EV charging load on the summer load profile are studied. It was ascertained that to base the electricity demand on the day of the month over the summer could be misleading so the highest working day of the year 5th June 2024 was selected. Selecting the power demand for a particular day can be justified because the charging scenario model is not an average value, but rather a possible scenario that can help determine the maximum level of EV penetration that can be integrated into the grid during peak periods.

In this paper, the total vehicle number and base load demand at present level (2024) is assumed as basis for consideration of the impact of EV charging load for the studied system. The vehicle number of the sample system is also assumed to be proportional (0.01%) to that of the Phnom Penh city, i.e., there are 2,968 cars in the sample system (there are 920,000 registered cars in the Phnom Penh city at present).

B. Scenarios

A set of charging scenarios is proposed, taking into account various start times for charging EV batteries. It is anticipated that the electricity tariff structure will have a significant impact on EV charging habits. According to the Electricity Authority of Cambodia (EAC) [16], table 1 shows the electricity tariff, Riel per kWh, and the fixed electricity rate purchased during the year was fixed as 610 Riels/kWh, in Phnom Penh city.

Category of Consumer	Electricity Tariff, Riels/kWh	Condition
Domestic in Phnom Penh and Takmao Town of Kandal Province	610	All kWh if monthly consumption ≤ 50 kWh
	720	All kWh if monthly consumption ≤ 200 kWh
	820	All kWh if monthly consumption > 200 kWh

Table 1. Tariff of EDC for Phnom Penh city

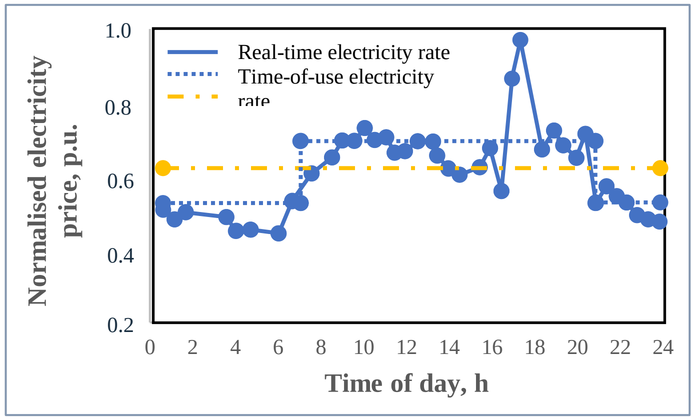

Fig. 8. Electricity tariff structure

In this paper, three types of typical electricity tariff structure are given consideration: fixed electricity rate, time-of-use electricity rate, and real-time electricity rate. The fixed electricity rate refers to the tariff in which energy charge per kWh remains constant regardless of the time of use. Time-of-use electricity price divides the tariff into two main blocks: off-peak and on-peak price. The real-time price, i.e., the electricity rate per kWh varies by time of day and month of year as shown in Figure 8, is based on the wholesale price in the U.K. in winter in 2008 [17]. These ignore any capital recovery or standing charge element to the tariff structure.

Uncontrolled charging

In the uncontrolled charging scenario, a 10% penetration rate of EVs was considered. To account for the variability in plug-in times, which is caused by factors like departure and arrival times, road conditions, and other factors, three groups of charging would occur. Business vehicles would likely start charging earlier, assuming they would be recharged at the workplace. Nevertheless, some business vehicles may need to charge later due to the diver working extended hours or being stuck in traffic returning to the workplace. Business vehicles would recharge at 5 pm, 5: 30 pm, and 6 pm. Private vehicles would also recharge in the three groups from 5:30 pm, 6 pm, and 6:30 pm. In this worst-case scenario, EVs are not motivated to avoid peak-time charging, so a fixed electricity tariff is implemented, consequently, a uniform probability density function f1 (t) of recharging start time is employed, shown in (7):

$$f_1(t) = \begin{cases} 1.00, & t = 18 \\ 0, & t = any\ other\ time \end{cases} \quad (1 \leq t \leq 24). \qquad (7)$$

The total charging power load at instant t can be calculated using (7) incorporating the appropriate battery charging profile and initial battery SOC probability density function as presented as (3).

Controlled off-peak charging

In this scenario, a peak-off-peak electricity pricing scheme is implemented to influence EV charging patterns, by providing a lower rate for charging during off-peak hours, which incentivizes EV owners to charge their vehicles at these times. In this paper, the off-peak time is defined as from 9 pm to 6 am, and peak load time is defined as 7 am to 8 pm. This scenario assumes that Electrical Du Cambodia (EDC) has adopted to lower electricity prices in the off-peak times, to identify the moment when battery charging should be initiated. Therefore, it is assumed that both private and business vehicles would recharge in the three times categories at 9 pm, 9:30 pm, and 10 pm. Private EVs are assumed to charge at, while business EVs are assumed to charge at the workplace. A uniform discrete distribution f2 (t) for EV off-peak charging is employed in order to consider the effect of Time-of-use (TOU) electricity rate on battery recharging start time. Since EV batteries should be fully charged at the end of the off-peak load time, the charging start time can be expressed as:

$$f_1(t) = \begin{cases} 0.33, & t = 21, 22, 23 \\ 0, & t = any\ other\ time \end{cases} \quad (1 \leq t \leq 24). \qquad (8)$$

The total charging power load, at instant t, in this scenario can be calculated based on the distribution of recharge start time, as defined by (8) and the distribution of battery initial SOC defined by (3).

Smart charging

In this scenario, it is assumed that a real-time electricity tariff structure applies to optimize EV charging behaviors. The distribution of the battery recharging start time is determined by traffic data and real-time electricity rate data. by comparing the reciprocal of the product of distribution of the vehicle's traffic pattern and the real-time electricity rates shown in Figure 2 and Figure 8, respectively, it can be found that the resultant distribution of charging start time is intervals from 11 pm to 1 am. Since EVs should be fully charged before 7 am for commuting, lithium-ion batteries require charging from the fully discharged to the fully charged period of roughly nine hours from a wall connector charger (level 1). it is assumed that EVs are charged from 10 pm, 10:30 pm, and 11 pm, by an initial SOC of more or less 10%. A distribution is therefore employed to depict the probability density function of battery recharging start time.

The probability density function can be obtained by:

$$f(x; \mu; \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/(2\sigma^2)} \qquad (9)$$

where μ is the mean, indicating the location of maximum probability density, σ is the standard deviation, and x is the total EV battery charged be $x_1, x_2, \ldots x_n$ at $t = 1, 2 \ldots t_n$, individually, then $\sum_{t=1}^{n} x_t = 100\%$. Let the total battery charging load be $y_1, y_2, \ldots y_n$ at $t = 1, 2 \ldots t_n$, individually. Assume the system demand excluding the EV battery charging load is $P_{L1}, P_{L2}, \ldots P_{Ln}$ at $t = 1, 2 \ldots t_n$, individually. After adding the charging load of EV batteries, the modified load will change to, $P_{L1} + y_1, P_{L2} + y_2, \ldots P_{Ln} + y_n$. The mathematical modeling of smart charging therefore becomes an optimization problem of which the aim is to minimize the charging cost, as expressed in (10):

$$\min \left(\sum_{t=1}^{n} c_t \cdot y_t\right) \qquad (10)$$

with constraint of $x_1 + x_2 + \cdots x_n = 100\%, 0 < x_t < 1$

where ct is the real-time electricity rate, in USD/kWh, xt is the percentage of total EV charged and yt represents the battery charging load at time instant t, individually. yt is a function of xt and the battery charging characteristics. Due to the linearity of the objective function, equality constraints, and inequality constraints, the optimization of smart charging in (10) is a typical linear programming problem.

4. RESULTS AND DISCUSSION

To consider future changes to electricity tariffs and the regulation of EV load, three EV charging scenarios have been developed in this paper: uncontrolled charging, controlled off-peak, and smart charging. we assumed that to use the normalized electricity price per unit of electricity tariff structure as an example.

Uncontrolled charging

Figure 9 shows the load profile in summer with EV battery charging loads for every five days of charging and every one week of charging, individually.

It can be observed that on the studied summer day, the electricity demand peaked at 1,390 MW at 3 pm and reduced to 1,336 MW at 4 pm. At 5 pm the original demand was 1,251 MW but due to the business vehicles beginning recharging, it reached 1,376 MW and decreased to 1,272 MW at 6 pm and did not reduce to below 1,300 MW until 8:30 pm when the original demand was reduced to 1,223 MW. Results in Figure 9 show that every five days of charging of EVs results in an increase of 17.3% on the summer peak load, while every one week charging results in an increase of 9% in the peak load. Results also show that charging every one week requires a longer time than charging every five days.

Results show that with 10% EV penetrations, there will be a daily peak increase in power demand of 17.3%, for the scenario of uncontrolled charging. Such a significant increase in peak electricity demand will significantly impact the distribution feeder with respect to capacity limit. This suggests the need to devise and provide proper incentives to achieve distributed charging load during off-peak times, even at low levels of EV penetration.

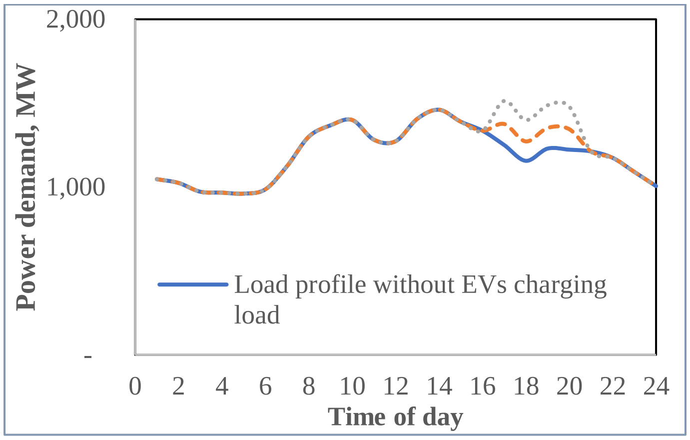

Fig. 9. Load profile with EVs battery charging load (uncontrolled charging)

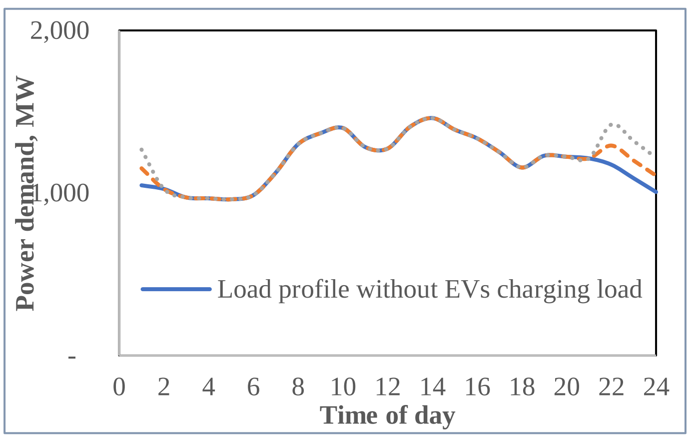

Fig. 10. Load profile with battery charging load (Controlled off-peak charging)

Controlled off-peak charging

It appears from Figures 10 that in this scenario (Controlled off-peak) where the uniform distribution of EV's battery charging start time, during the first three hours of off-peak period, as discussed earlier is assumed, the addition of charging load comfortably absorbed by the whole system without an increase to peak demand. The addition appears to improve the load factor since it helps to fill up some portions of the off-peak valley. However, under this scenario (time-of-use electricity rate), there is a significant increase in system load between 9 pm and midnight. Compared to Figures 9 (Uncontrolled charging), the results shown in Figures 10 indicate that the EV charging load does not form a new peak load, since the EV charging loads will be distributed over the off-peak time.

Smart charging

The purpose of smart charging is to minimize the electricity price of battery charging of EVs (10), under the real-time electricity structure Figure 8. It can be observed from Figure 11 that Smart charging can provide the most efficient usage of energy and does not form a new peak load. Results show that at the intervals from 11 pm to 1 am, the proportion of EVs starting charging has its largest value. From the electric utility operation aspect, the potential of EV smart charging to fill in the valley in the load curve will result in more electricity sales during the off-peak load time for nearly the same system capacity. Smart charging therefore implies more effective utilization of all equipment in the system.

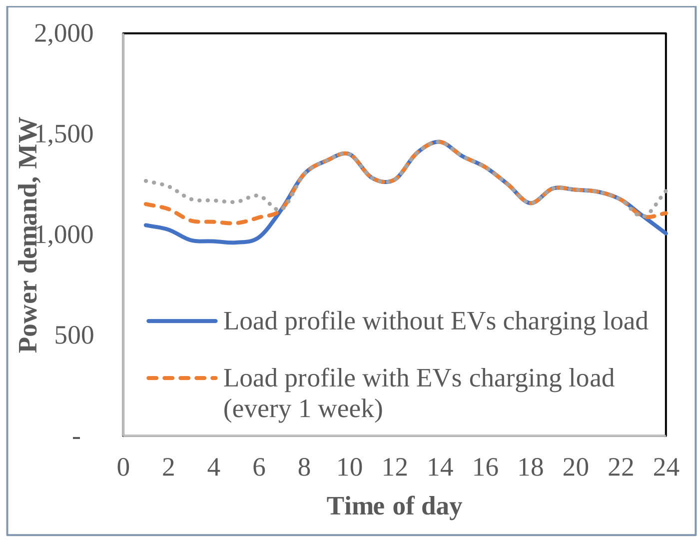

Fig. 11. Load profile with battery charging load (Smart charging)

5. CONCLUSIONS AND DISCUSSION

This paper develops a methodology to determine a distribution system's EV battery charging load. Three scenarios were simulated: uncontrolled charging, controlled off-peak charging, and smart charging. The proposed method in this paper considered for the initial state-of-charge and the stochastic in batteries charging start time. The paper comes to the following conclusions.

A 10% market EV penetration in the studied system would result in every interval 5-day peak increase in power demand of 17.3%, for the scenario of uncontrolled charging is the worst case in terms of peak power demand. Other scenarios are less challenging: controlled off-peak, for example, increases electricity consumption throughout the night but has no impact on the daily peak load.

The distribution of start time for EV battery charging has a significant impact on the overall power consumption for charging. The optimized Smart charging method, which adjusts the timing and number of batteries charging at each interval is the most significant advantages to both EV customers and the distribution network operator. Despite the potential benefits of charging EVs during peak hours, it will also introduce a new peak or near-peak load on the power system. Furthermore, charging EVs during the early off-peak period may also bring about a new peak or near-peak demand, which would require careful consideration and planning to mitigate any negative impacts.

To ensure a comprehensive assessment of the impacts of EV battery charging on the feeder load profile, it is necessary to divide the overall load into three categories: industrial, commercial, and residential, as this enables to identification of potential overloading of individual feeders. The significant loading impact on the local system might be masked if an overall load profile is adopted.

REFERENCES

[1] J. Du, M. Ouyang, and J. Chen, "Prospects for Chinese electric vehicle technologies in 2016_2020: Ambition and rationality," Energy, vol. 120, pp. 584_596, Feb. 2017.

[2] L. Liu, K.Wang, S.Wang, R. Zhang, and X. Tang, "Assessing energy consumption, CO2 and pollutant emissions and health benefits from China's transport sector through 2050," Energy Policy, vol. 116, pp. 382_396, May 2018.

[3] R.-J. Huang et al., "High secondary aerosol contribution to particulate pollution during haze events in China," Nature, vol. 514, no. 7521, pp. 218_222, 2014.

[4] MJ Rutherford, V Yousefzadeh, "The impact of electric vehicle battery charging on distribution transformers", 2011 – ieeexplore.ieee.org

[5] M. D. Galus, R. A. Waraich, F. Noembrini, K. Steurs, G. Georges, K. Boulouchos, K. W. Axhausen, and G. Andersson, "Integrating power systems, transport systems, and vehicle technology for electric mobility impact assessment and ef_cient control," IEEE Trans. Smart Grid, vol. 3, no. 2, pp. 934_949, Jun. 2012.

[6] M. Muratori, "Impact of uncoordinated plug-in electric vehicle charging on residential power demand," Nature Energy, vol. 3, no. 3, pp. 193_201, 2018.

[7] X. Cheng, X. Hu, and L. Yang, "Electri_ed vehicles and the smart grid: The ITS perspective," IEEE Trans. Intell. Transp. Syst., vol. 15, no. 4, pp. 1388_1404, Aug. 2014.

[8] Y Jin, KA Agyeman, S Han, "Grid impact analysis of electric vehicles charging with different load profiles", - … and Expo, Asia-Pacific (ITEC Asia …, 2019 - ieeexplore.ieee.org

[9] P Khasa, DK Jain, "Simultaneous charging and discharging integrating EV for V2G and G2V", - 2016 7th India International Conference …, 2016 - ieeexplore.ieee.org

[10] "Trends in batteries – Global EV Outlook 2023 - Analysis", International Energy Agency (IEA). [Online]. Available: http://www.iea.org/reports/trends-in-batteries. [Accessed: btween Jan and March, 2023].

[11] X Chen, W Shen, TT Vo, Z Cao, "An overview of lithium-ion batteries for electric vehicles". – 2012 10th international …, 2012 – ieeexplore.ieee.org

[12] "BYD Han charging curve & performance", [Online]. Available: http://www.evkx.net/model/byd/han/chargingcurve. [Accessed: Sep 29, 2024].

[13] "Toyota bX4X AWD charging curve & performance", [Online]. Available: http://www.evkx.net/model/toyota/bz4x/chargingcurve. [Accessed: Sep 29, 2024].

[14] "The study on the transport master plan of the Phnom Penh", Japan International Cooperation Agency (JICA). [Online]. Available: http://openjicareport.jica.go.jp. [Accessed: 2015].

[15] "Data Collection Survey on Urban Transport in Phnom Penh", Japan International Cooperation Agency (JICA). [Online]. Available: http://openjicareport.jica.go.jp. [Accessed: Feb 3, 2023].

[16] "Report on power sector of the Kingdom of Cambodia 2016", Electricity Authority of Cambodia (EAC) . [Online]. Available: http://data.opendevelopmentcambodia.net. [Accessed: Jan 30, 2017].

[17] "APX Power UK Daily Settlement Prices", ukpx. [Online]. Available: http://www.ukpx.co.uk [Accessed: Jan. 20