

Article

Predicting and Managing EV Charging Demand on Electrical Grids: A Simulation-Based Approach

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Abstract: Electric vehicles (EVs) are becoming increasingly popular, and it is important for utilities to understand their charging characteristics to accurately estimate the demand on the electrical grid. In this work, we developed simulation models for different EV charging scenarios in the home sector. We used them to predict maximum demand based on the increasing penetration of EV consumers. We comprehensively reviewed the literature on EV charging technologies, battery capacity, charging situations, and the impact of EV loads. Our results suggest a method for visualizing the impact of EV charging loads by considering factors such as state of charge, arrival time, charging duration, rate of charge, maximum charging power, and involvement rate. This method can be used to model load profiles and determine the number of chargers needed to meet EV user demand. We also explored the use of a time-of-use (TOU) tariff as a demand response strategy, which encourages EV owners to charge their vehicles off-peak in order to avoid higher demand charges. Our simulation results show the effects of various charging conditions on load profiles and indicate that the current TOU price strategy can accommodate a 20% growth in EV consumers, while the alternative TOU price strategy can handle up to a 30% penetration level.



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1. Introduction

The adoption of electric vehicles (EVs) is increasing rapidly due to factors such as global air pollution, the cost of fuel, and the decreasing cost of EV components. EVs are important for reducing greenhouse gas emissions and noise pollution, and many countries are implementing policies to encourage their adoption. Automakers are also facing increasing public pressure and regulatory scrutiny to shift towards renewable energy vehicles. The growth of the EV industry is expected to surpass that of internal combustion engines in the coming years. In Thailand, the increasing number of EVs on the road could help to reduce levels of ultra-fine particulate matter (PM 2.5) emitted from traditional gasoline-powered vehicles in cities such as Bangkok. While 100,000 EVs were registered in Thailand in 2020, the government has set a goal of having 750,000 out of 2.5 million vehicles (representing 30%) by 2030 [1]. This goal will require Thai authorities to ramp up their efforts to promote EVs and carefully assess the impacts of technological advancements.

The widespread use of EVs will have significant impacts on the design and operation of the electric power system, as these vehicles require high-capacity batteries and large electric loads for charging. To keep up with the rapid adoption of EVs, the energy distribution network infrastructure may need to be updated. Research on EV integration has focused on understanding the impact of EV loads on distribution networks. Previous studies [2,3] have examined the EV charging process, battery capacity, and effects on the distribution system. Others, e.g., [4,5], have analyzed the impact of uncontrolled EV charging on daily load profile data and demonstrated how coordinated charging can improve the load profile.

Many publications [2,6–10] have shown how EV charging affects the load pattern. EVs act as active loads that increase the demand on the grid while charging and act as generators while in regeneration mode. In order to address the impact of EV loads, maintain frequency stability, and account for reactive power in the distribution system, real-time vehicle-to-grid (V2G) control solutions have been developed [11–15]. Charging time control has been proposed as a way to shift peak consumption to periods of low demand [2,16–18].

The main aim of this work is to evaluate the effect of EV load demand on the distribution system of the Provincial Electricity Authority (PEA) in Thailand [19]. This research focuses specifically on the impact of residential EV load on the PEA system. The second objective of this work is to suggest methods for mitigating the impact of residential EV load on the PEA distribution system.

The novelty of this work lies in the development of simulation models for different EV charging scenarios in the home sector and the comprehensive review of literature on EV charging technologies, battery capacity, charging situations, and the impact of EV loads. A new method for visualizing the impact of EV charging loads by considering factors such as state of charge, arrival time, charging duration, rate of charge, maximum charging power, and involvement rate is proposed. In addition, this study explores the use of a time-of-use (TOU) tariff as a demand response strategy to manage EV charging demand on the electrical grid. The simulation results provide insights into the effects of various charging conditions on load profiles and indicate the capacity of current and alternative TOU price strategies to accommodate increasing EV consumers. Overall, the paper contributes to the field of EV charging management by providing new insights and strategies for managing the impact of EV charging on the electrical grid.

This article is organized as follows. Section 2 presents a review of the relevant literature. In Section 3, we describe the research methodology. Section 4 presents the results and discussion. Finally, in Section 5, we provide our conclusion.

2. Literature Review

In this literature review, we will explore various aspects of EV charging technology, battery capacity, EV charging scenarios, and the impact of EVs on the electrical grid. We will also discuss the electricity tariff used by PEA in Thailand and its impact on EV charging behavior. By understanding these factors, we can better predict the demand for EV charging and develop strategies to mitigate its impact on the electrical grid.

2.1. Electric Vehicle Charging Technology

The automotive industry is undergoing a significant shift as EV technology becomes more widely accepted. EVs are more environmentally friendly and cleaner than gasoline or diesel vehicles because they emit no pollutants and have higher energy efficiency due to their reliance on electricity rather than fuel combustion [20,21]. Governments around the world are promoting EVs as greener alternatives to internal combustion engine (ICE) vehicles, which are believed to be a major contributor to air pollution [22]. In order to gain a larger market share, EV manufacturers are focusing on making their vehicles more affordable by increasing their range and improving efficiency. However, there are several challenges to the adoption of EVs, including the availability of charging infrastructure, government regulations, and energy security. As the number of EVs on the road increases, it will be necessary to develop charging platforms and associated infrastructure for EV charging at both private and public stations.

The development of cost-effective, practical, and safe charging infrastructure is crucial for the success of EVs in the market. While there are many different EV charging technologies available, there is no consensus on the best infrastructure to support them. There are various relevant EV charging standards from organizations such as the International Standards Organization (ISO), the International Electromechanical Commission (IEC), the American National Standards Institute (ANSI), Deutsches Institut für Normung e. V. (DIN),

and the Japan Electric Vehicle Association Standards (JEVS). This has resulted in a wide range of charging devices with varying levels of voltage and current [23–26].

There are two EV charging infrastructure categories: conductive charging infrastructure and non-conductive charging infrastructure. Conductive charging involves the use of physical cables to transfer electricity to the EV, while non-conductive charging uses wireless technology, such as inductive or capacitive power transfer. In inductive charging, a magnetic field is used to transmit electricity between coils, while in capacitive charging, an electrical field is formed in the space between two capacitors. Non-conductive charging has the advantage of convenience, as it allows EVs to be charged while parked or waiting at traffic lights; it can also be implemented on the surface of roads for charging while driving. However, conductive charging is still more widely used and is generally more effective than non-conductive charging [27–30].

According to the IEC 61851-1 standard [31], there are four methods for conductively charging EVs:

- Mode 1: Slow charging using a household-style AC outlet. This method involves connecting the EV charger to a regular socket outlet in the home, along with an overload and earth leakage protection circuit breaker. Charging is limited to a maximum of 16 A in this mode, without communication.
- Mode 2: Slow charging using a special cable. This cable has built-in safety features to prevent electric shock, and the current cannot exceed 32 A. Mode 2 charging is currently the most commonly used method for EV charging.
- Mode 3: Slow or fast charging using a dedicated charging station with a special EV socket outlet with permanently installed control and protection functions.
- Mode 4: Fast charging using a direct-current (DC) external charger.

There are three main connection scenarios covered by the IEC standard:

1. The cable and plug are fixed to the EV and detachable from the charging station (often referred to as electric vehicle supply equipment (EVSE)).
2. A detachable cable at both ends connects the EV to an AC source.
3. The wire and connector are permanently connected to the EVSE.

Table 1 provides further details on these charging modes and connection scenarios.

Currently, there are three types of EV technologies available on the market: hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) or all-electric vehicles. HEVs do not require external charging equipment as they have a hybrid power system that combines a traditional internal combustion engine with an electric motor. On the other hand, BEVs rely solely on an electric power source and must be charged using external charging equipment. PHEVs have both an internal combustion engine and an electric power source, but they can also be charged externally and have a longer all-electric range compared to HEVs.

Table 1. EV charging level IEC 61851-1.

Connection Mode	Connection Phase	Current	Power	Type of Charge
Mode 1	1 phase	16 A	3.7 kW	Slow charging
	3 phase	16 A	11.0 kW	
Mode 2	1 phase	32 A	7.4 kW	Slow charging with an in-cable protection
	3 phase	32 A	22.0 kW	
Mode 3	1 phase	32 A	14.5 kW	Slow or fast charging
	3 phase	62 A	43.5 kW	
Mode 4	1 phase	400 A	200 kW	DC fast charging with an external charger

2.2. Battery Capacity

Battery performance is a key factor in the adoption of EVs. Larger battery EVs are expected to have longer ranges, requiring fewer charges and reducing the frequency of charging. Electric vehicle batteries offer a good power-to-weight ratio, and lighter batteries are preferred to reduce the weight of the EV and improve efficiency. However, the capacity of the battery also affects how much electricity is needed to charge it. Energy recovery technology is also used in EV batteries, allowing the electric motor to act as a generator when braking or coasting, which helps to increase the range of the vehicle. The initial cost of an EV is significantly influenced by the battery capacity, and using batteries with lower capacity can reduce operating costs and emissions. However, utilities must also consider the impact of uncontrolled EV deployment on the stability of the grid. The charging capacity and schedule of EVs can have significant impacts on the distribution system, depending on the level of EV penetration [13,18,32–34].

In recent years, the EV market has rapidly altered. It appears that battery capacity is increasing. The standard battery capacities of today's popular EV vehicles are 54 kWh for the 2021 Tesla Model 3 [35], 44.5 kWh for the 2020 MG ZS EV [36], and 63 kWh for the 2023 Nissan ARIYA [37]. New automobile models that can be used as long-distance vehicles are being released, such as the 2021 Volkswagen ID.4 and 2021 Tesla Model S, which have corresponding energy capacities of 77 and 100 kWh [38]. The summary of EV battery capacities is indicated in Table 2.

Table 2. Popular commercially available EV battery capacity.

EV Model	Manufacturer	Model Year	Battery Capacity (kWh)
Leaf S	Nissan	2019	40
Leaf SL Plus		2019	62
ARIYA		2023	63, 87
ZS EV Excite	MG	2020	44.5
e	Honda	2020	35.5
Ioniq	Hyundai	2020	38.3
i3s	BMW	2020	42.2
Model 3	Tesla	2021	54
Model X		2021	100
Model Y		2021	74
Model S	Volkswagen	2021	100
ID.3		2021	58
ID.4		2021	77
Bolt EV LT	Chevrolet	2021	66
Mustang Mach-E	Ford	2021	75.7

2.3. EVs Charging Scenarios

The scenarios of EV charging were disclosed by a number of past studies on residential clients. Various EV penetration scenarios are considered. Residential networks, such as unregulated, time-controlled, unidirectional, and bidirectional V2G, are used for EV charging activities.

The uncontrolled or “dumb” charging approach allows EV owners to freely charge their vehicles without any restrictions. However, it means that the EV battery is recharged when the owner arrives home, which can lead to unexpectedly high demand or overloading the grid. If there is no active control over EV charging rates, all EVs are expected to start charging at the highest possible rate at the beginning of the charging interval. Such uncontrolled charging can significantly impact the distribution network, particularly during peak load hours or when many EVs return home at the same time. One way to address this issue is to encourage off-peak charging through TOU pricing or dual tariffs (peak and off-peak rates). Off-peak charging occurs at night when there is a low demand for electricity, and most consumption is from baseload sources. In the short term, off-peak charging can increase the available generation and transmission capacity and create a more

efficient baseload generation infrastructure [39–42]. It also encourages EV owners to accept a waiting period before charging in exchange for lower tariff charges. Considering the variety in the SOC and EV charging start times is important. The unpredictability of the SOC and charging start times and assigning them with certain values to obtain definite results are helpful for us to comprehend the optimal charging model [43–46].

The charging time of an electric vehicle depends on the SOC of the battery. When the SOC is high, it takes less time to charge the vehicle. When the battery is charging, the current remains constant, known as the “constant current mode”, while the voltage gradually increases until it reaches the rated voltage. After that, a constant voltage charge, or the “constant voltage mode”, is applied until the battery is fully charged, as shown in Figure 1 [15].

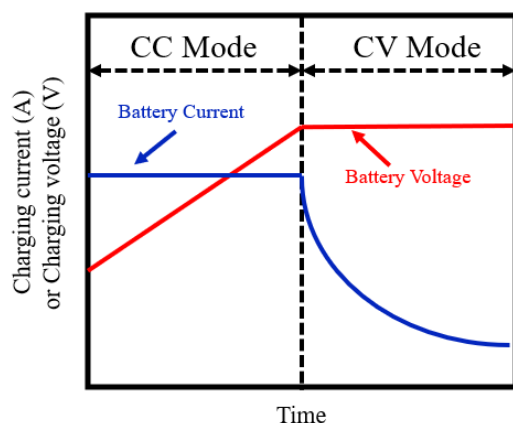


Figure 1. Typical profile of EV battery charging.

2.4. PEA Electricity Tariff

PEA is a state-owned organization in Thailand that is responsible for supplying electricity to support functions in the public and private sectors. PEA serves over 20 million customers in 74 provinces, with the exception of Bangkok, Nonthaburi, and Samutprakarn provinces, covering an area of over 500,000 square kilometers. PEA’s operations include high and low-voltage power plants, distribution systems, power transmission systems, and distribution transformers. PEA determines electricity rates based on the purchasing, maintenance, and use of electrical equipment, including energy meters. However, the Energy Regulatory Commission (ERC) regulates Thailand’s energy rate structure. PEA divides its customers into different categories, such as households, small businesses, medium-sized businesses, large businesses, specific types of businesses, non-profit organizations, and customers who need free electricity or only need it occasionally, according to electricity tariffs [47].

Residential electricity bills in Thailand typically consist of three components: the base rate, float time (ft), and value-added tax (VAT). There are two types of base tariffs for residential customers, i.e., the TOU tariff and the progressive rate. Under the progressive rate, customers pay higher prices as they use more electricity. There are two main categories of electricity usage for residential customers, i.e., consumption of up to 150 kWh per month and more than 150 kWh per month. PEA customers can also opt for a TOU tariff, which has different rates depending on the amount of electricity used. The TOU tariff has two pricing categories: on-peak time, from 9 a.m. to 10 p.m., Monday through Friday, and off-peak time, from 10 p.m. to 9 a.m., Monday through Friday. On Saturdays, Sundays, and national holidays, the pricing is considered off-peak, as shown in Table 3. The TOU tariff is designed to help customers reduce their electricity costs by encouraging them to use their loads at times of lower demand instead of during peak demand periods.

Table 3. PEA TOU tariff.

TOU Tariff	Duration Time	Days
On-peak time	9:00 a.m.–9:59 p.m.	Monday to Friday
Off-peak time	10:00 p.m.–8:59 a.m.	Monday to Friday
	0:00 a.m.–11:59 p.m.	Saturday, Sunday, and national holidays

2.5. Related Work

As EV adoption increases, managing EV charging load has become a critical issue due to the potential impact on the power grid. The variability in EV charging patterns can cause power grid instability and peak demand, particularly during peak hours, making it a significant challenge for utility companies. To address this challenge, various studies have proposed methods to estimate and forecast EV charging loads, which can aid in planning and developing EV infrastructure.

Forecasting the electricity demand for electric vehicles by investigating consumer charging habits is one way to manage the EV charging load. Based on consumer preferences for EVs, charging hours, and the types of electric vehicle supply equipment, this method predicts changes in the power charging demand (EVSE). The study by Moon et al. [48] stresses the significance of taking into account user preferences and the types of EVSE while building EV infrastructure. Using data-driven techniques to estimate EV charging demand is another strategy. For instance, Xing et al. [49] present a forecasting model for EV charging demand based on a data-driven technique that analyzes EV charging demand using real-world traffic data and incorporates the characteristics of space-time transfer of charging load in urban functional areas. Additionally, Castro et al. [50] suggest utilizing the logistic growth approach to estimate projected values for energy consumption and power demand in EV fast charging stations. The suggested concepts were put into practice in a concept facility in Campinas, Brazil, which had two 50 kW DC fast chargers.

Lastly, to increase forecasting accuracy for both non-spike and spike wholesale market prices, Sarikprueck et al. [51] suggest a hybrid technique. The work reduces high error spike magnitude estimates using support vector classification, regression, and three clustering algorithms. These techniques can help manage the load on EV charging stations and offer suggestions for designing and building EV infrastructure.

In addition to forecasting, managing the EV charging load can also involve implementing optimized charging models that consider TOU pricing and SOC curves. In response to TOU pricing in a regulated market, Cao et al. [43] provide an intelligent way to limit EV charging loads. If the peak and valley periods are properly divided, the optimum charging pattern can lower expenses and flatten the load curve. In a different study, Goh et al. [52] suggest an orderly charging strategy based on the EV's optimal time-of-use pricing (OTOUP) demand response, which can lower peak–valley discrepancies, increase operational voltages, and lower charging costs.

To provide stability and regulation to the system operator, Sharma and Jain [53] propose coordinated and distributed charging rates for EVs over the connection hours (SO). The study demonstrates how integrated scheduling with price-based demand response (PBDR) can encourage EVs to charge at off-peak times and make use of their adaptability for load balancing and peak reduction. Understanding, identifying, and mitigating the effects of household EV charging on distribution system voltages were the goals of Dubey and Santoso [2]. Their study offered workable alternatives, including infrastructure modifications and indirectly controlled charging with TOU pricing to reduce the effects of EVs on load. In addition, the paper considered using smart charging algorithms to directly regulate EV charging rates and beginning times.

Overall, the studies discussed in this literature review highlight the importance of managing EV charging loads to maintain power grid stability and reduce peak demand. The methods proposed in these studies can aid in estimating and forecasting EV charging loads

and developing effective EV infrastructure. Furthermore, implementing smart charging algorithms and using renewable energy sources, such as PV solar and storage systems, can help optimize energy consumption and power demand in EV charging stations [50]. As the adoption of EVs continues to grow, the need for effective EV charging load management strategies will become increasingly critical to ensure the stability and reliability of the power grid.

3. Research Methodology

According to the literature, it is important to have access to detailed PEA load profile data, including data on EV loads and charging conditions, in order to fully understand the impacts of EV charging on the PEA distribution system. The data can be used to analyze and evaluate the peak load demand for different charging scenarios. It is also important to consider the impact of uncontrolled fees and TOU price policies on peak demand. The research process for this analysis consists of four steps: selection of data, simulation, analysis, and evaluation of EV charging states, as shown in Figure 2.

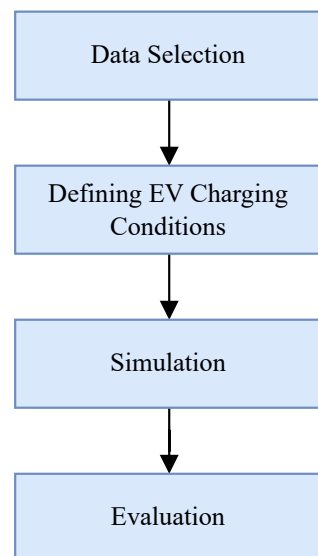


Figure 2. Research process.

3.1. Data Selection

The data used in this work were obtained from the Power Economy Division of the PEA and are available on the PEA website [19]. The data are organized by PEA office location, customer type, e.g., residential, small business, specific business service, month, and year. To select the data for this study, the following criteria were used: PEA office is the “Overview” (all PEA district areas), the customer type is “Overview” (all customers except temporary service and others), the month is December, and the year is 2020. The data, which are available in the form of downloadable files on the website, include power demand (kW) information at 15 min intervals for peak days, workdays, Saturdays, Sundays, and holidays for December 2020. The peak day load profile was used in the simulations for this study. The PEA’s electricity sales report for December 2020 also provides detailed information on the number of electricity consumers in each category, as shown in Table 4. To estimate the number of EV users, the number of residential consumers who use more than 150 kWh per month was used as the baseline, with 10–30% of these consumers assumed to be EV users. Based on this assumption, a simple proportional equation was used to calculate the number of EV users.

Table 4. Number of PEA electricity users.

Types of Electricity Users	Number of Users (Unit: Person)		Increasing (%)
	2019 December	2020 December	
Residences (≤ 150 kWh)	9,992,167	9,821,425	−1.71
Residences (> 150 kWh)	7,824,239	8,487,467	8.48
Small-sized businesses	1,665,138	1,681,395	0.98
Medium-sized businesses	80,928	82,605	2.07
Large-sized businesses	7043	7351	4.37
Specific type of businesses	14,152	13,688	−3.28
Non-profit organization	1076	1063	−1.21
Water pumping for agriculture	5879	5871	−0.14
Electricity for temporary use	352,046	371,422	5.50
Electricity back-up	95	98	3.16
Interruptible power distribution	4	4	0.00
Free of charge electricity	251,098	262,327	0.17

3.2. Defining EV Charging Condition

In order to create an accurate simulation, it is important to consider several key variables, including the number of EV users, EV charging time, charging start time, and SOC. The number of EV users can be calculated based on a ratio of residential electricity consumers, which we focus on in the range of 10–30% in this study based on the projections of the Thai government [1]. EV charging times may vary depending on the initial SOC, S_i , or portion of remaining energy in the battery, and the charging start time may be influenced by different charging scenarios, e.g., uncontrolled or TOU price policy. The distribution of S_i can be assumed to follow a uniform distribution. However, the assumption of the normal distribution of S_i is also provided in this work for comparison purposes. It is important to ensure that all of these variables are properly accounted for in the simulation in order to produce reliable results.

The probability density function for uniform distribution is

$$f(x) = \frac{1}{b - a}, \quad (1)$$

where x is the random variable, a is the lower bound of the distribution, and b is the upper bound of the distribution [54]. This distribution describes a scenario where all outcomes are (equally) likely within a fixed range from a to b , but the probability of outcomes outside this range is zero. For comparison, we also use the normal distribution for S_i . The probability density function for normal distribution is given by

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right), \quad (2)$$

where μ is the mean or expected value of the distribution and σ is the standard deviation, which describes the spread of the distribution [54].

3.3. Simulation

The Monte Carlo simulation is a statistical method that is widely used to model and analyze complex systems, particularly in the field of EV charging [55,56]. In this study, the simulation was implemented using MATLAB, a numerical computing software, with a sampling rate of 15 min due to the recording data rate. The primary objective of the simulation was to assess the effects of different EV charging scenarios on contemporary electrical loads, with the model of EV charging influenced by various factors, such as battery capacity, charger rating power, charging time, and the number of phases. The simulation results revealed that a planned TOU pricing strategy could increase the efficiency of the distribution system. Moreover, the power range for single-phase, 230 V charging was

between 3.3 kW (16 A) and 7.4 kW (32 A), while the power range for the three-phase, 380 V charging was between 11 kW (16 A) and 22 kW (32 A) according to modes 1 or 2 of the IEC61851-1 standard. Overall, the Monte Carlo simulation employed in this study is a useful tool for evaluating the impacts of different EV charging scenarios on the power grid and can assist in the development of efficient EV infrastructure.

For this investigation, it was assumed that all vehicles were charged using the slow charging mode, which typically requires 3.3 kW (16 A) of power and takes 4 h or less to fully charge a battery with a capacity of 24 kWh at a SOC of 50%. During the charging process, the charging profiles maintain a constant current until the voltage of the battery cell reaches a predetermined level. Various charging time models have been proposed depending on interesting dimensions [2,49,55,57]. To estimate the full charge time, T_{ch} , with 100% charging efficiency for a slow charging mode on a single phase, we can accomplish this by using the model from [52]. The charging time model becomes

$$T_{ch} = (1 - S_i) \frac{E_m}{P_{ch}}, \quad (3)$$

where T_{ch} is the time needed to fully charge the battery (hours), E_m is the maximum battery capacity (kWh), and P_{ch} is the charging power (kW).

Figure 3 shows sample charge profiles for a 24 kWh EV battery, where S_i of the battery is 50% and 75%, respectively. In addition, the effect of the charging start time, T_s , is also presented in this simulation, where T_s is 1:00 and 1:30 h. The charging capacity of the EV charger is 3.3 kW. The y-axis represents the power demand of charge, and the x-axis is charging time in hours. The SOC of the battery affects the charging time of the EV. We can see that a higher S_i will result in a shorter charging time while the T_s shifts the charging profile. In this work, the distribution of S_i is assumed to be either uniform or normal as described previously. For the uniform distribution, we assume that the battery level is consistently randomized between 25% and 75% as shown in the histograms in Figure 4. The histogram is an estimate of the probability density function, where the height of each bar represents the relative number of observations. The total area of all the bars is no more than 1 [58]. On the other hand, for the normal distribution, μ and σ are set at 50% and 15%, respectively, as shown in the histograms in Figure 5. The normal distribution can provide values outside of the SOC range, i.e., less than 0% and more than 100%. If this case occurs, the provided values will be neglected.

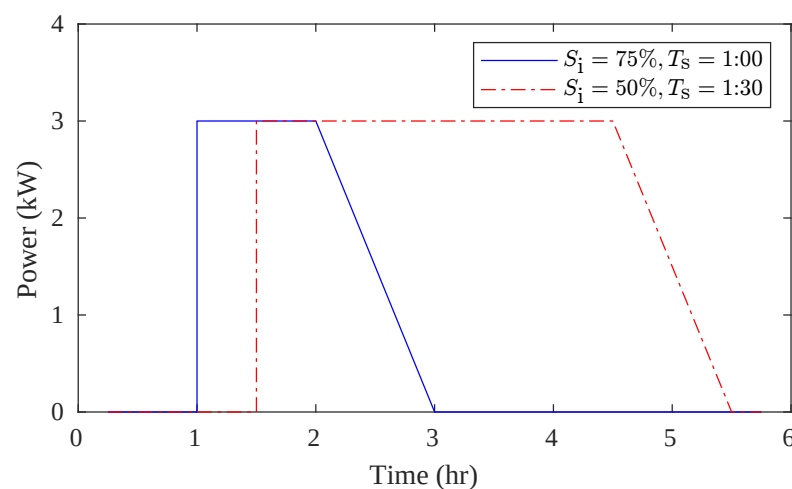


Figure 3. Examples of the charging profiles of EV batteries with different S_i and T_s .

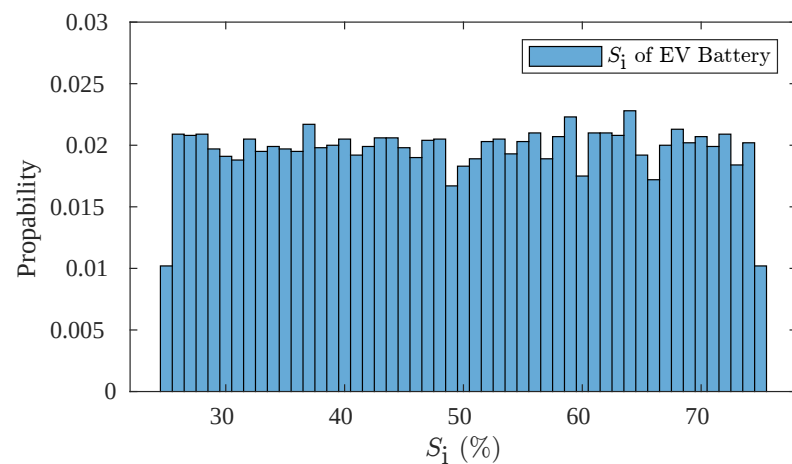


Figure 4. Distribution of the initial SOC, S_i , where the uniform distribution is considered.

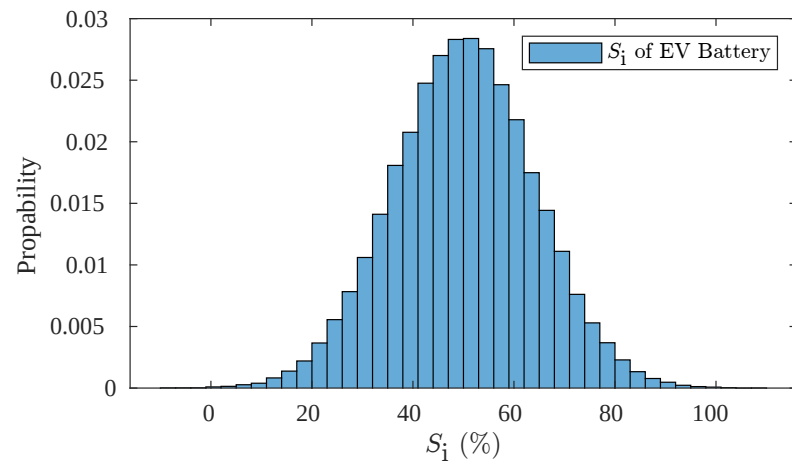


Figure 5. Distribution of the initial SOC, S_i , where the normal distribution is considered.

3.4. Evaluation

This work compares traditional uncontrolled charging with TOU pricing schemes to minimize the negative impacts and improve the power system. The analysis compares the peak load demand in each scenario to evaluate the impact. The aim is to examine the feasibility of generating and distributing electricity to sustain the peak load increase caused by the demand for EV charging at various penetration levels.

The evaluation criteria for this study include the PEA customer load, the number of EV users, TOU schemes, T_s , and S_i . The PEA TOU tariff policy offers reduced pricing between 10 p.m. and 9 a.m. the following day. To demonstrate the effect of this policy, we created various scenarios of TOU schemes by varying the beginning periods of TOU, T_b , such as between 10:00 p.m. and 11:00 p.m., while the end periods of TOU were fixed at 9:00 a.m. T_b represents the different TOU schemes used in the study.

EV users who prefer lower charging costs have to start charging their vehicles at T_b . However, not all users will involve the TOU tariff policy. Therefore, the rate of involvement, R_i , is introduced, which is defined as the ratio of EVs that have adopted the TOU tariff policy to the total number of EVs, i.e.,

$$R_i = \frac{n_{ad}}{N_t}, \quad (4)$$

where n_{ad} is the number of EVs that adopt the TOU tariff policy and N_t is the total number of EVs. In this study, R_i is evaluated under different conditions.

4. Results and Discussions

The impact of residential EV charging on the PEA distribution system is assessed by utilizing the PEA's load curve demand distribution system, with variations in various factors as described in the previous section. Both uncontrolled charging and TOU pricing scenarios will be considered in the simulation. By examining these factors, it will be possible to gain insights into the effects of EV charging on the PEA distribution system and develop strategies for optimizing the utilization of the power system.

4.1. PEA Customer Load

The load profile data of the PEA is used in this work to evaluate the consumption behavior of electricity users. The PEA has classified electricity users into different sectors. The PEA offers electricity at various pricing tariffs, including a residential tariff for households and other dwellings with single energy meters, divided into two categories, i.e., for consumers who use up to 150 kWh per month and those who use more. The load profile data, which are collected at 15-min intervals, are utilized to simulate the daily load demand of customers.

In December 2020, 8,487,467 residential consumers used more than 150 kWh per month out of 20,734,717 PEA customers; the load profiles for 'Peakday', 'Workday', 'Saturday', 'Sunday', and 'Holiday' are shown in Figure 6. The load profile for the Peakday represents the peak demand day. The load profile for Workday is the average of the load profiles for weekdays in the given month. The load profiles for Saturday and Sunday are the averages of the load profiles for those respective days in December 2020. Finally, the load profile for Holiday is the average load profile on holidays in December 2020. We can see that the maximum daily load profile data demand was 17.47 GW at 06:45 a.m., and the Peakday has the highest load profiles. Our study utilizes the Peakday as the scenario representing the highest customer load demand for the PEA. However, the exact date of the Peakday is not provided in the data. Therefore, we assume the first day of December 2020 as the Peakday for demonstration purposes. From Figure 6, the x-axis presents the time from midnight on 1 December 2020 to midnight on 2 December 2020. This timeline was chosen for the simulation to focus specifically on the overnight charging of EVs.

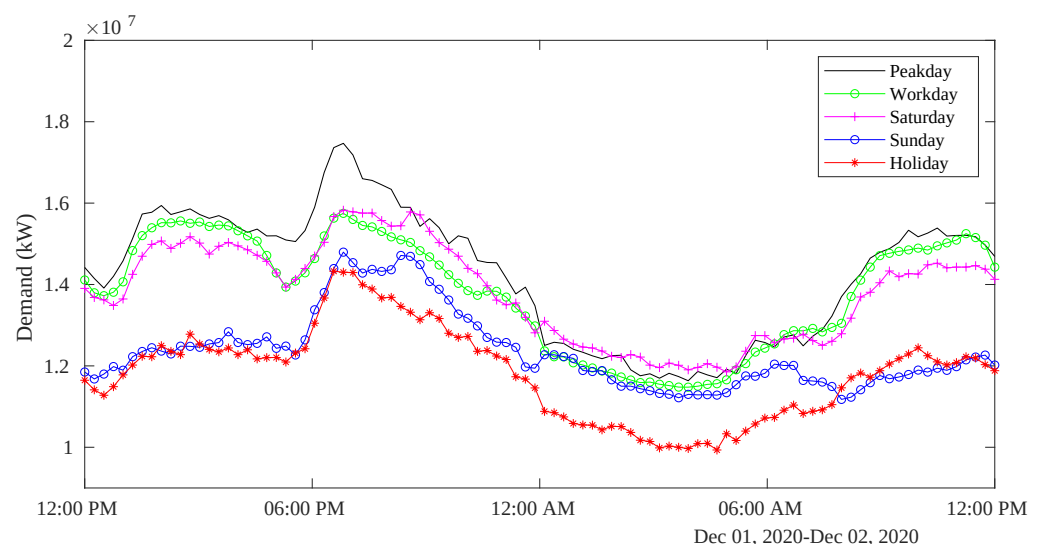


Figure 6. The PEA customer load demand in December 2020.

4.2. EV Charging Start Time

In the uncontrolled charging scenario, EVs are charged as soon as the user arrives home and plugs in the charger. The charging process will start immediately upon connection to the charger. It is assumed that EVs will arrive home after working hours and will use a slow charging profile to connect to the power grid, as shown in Figure 3.

The distribution of the arrival time of EV users in this study is considered to be a normal distribution with μ at 7:00 p.m. and σ of 2 h. It is also assumed that each EV can be charged once per day. Due to this assumption, we can obtain the charging start time, T_s , as shown in Figure 7. We can see that the vast majority of EV users (95%) arrived home between 3:00 p.m. and 11:00 p.m. With the aid of the EV charging system, all vehicles are completely charged before the end of the charging period.

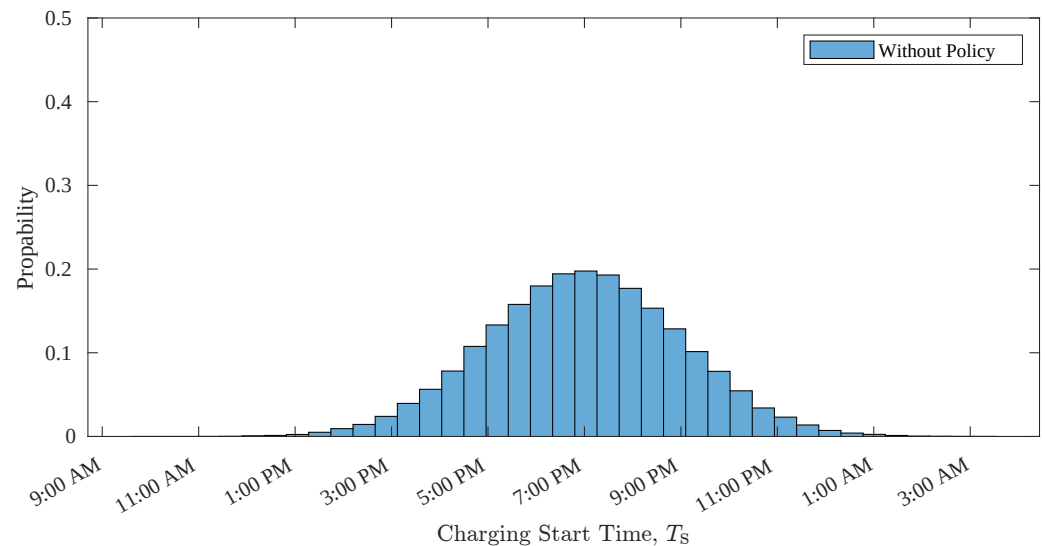


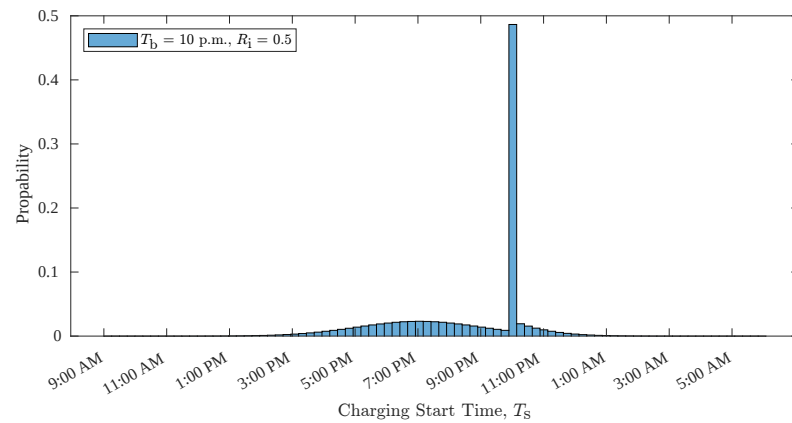
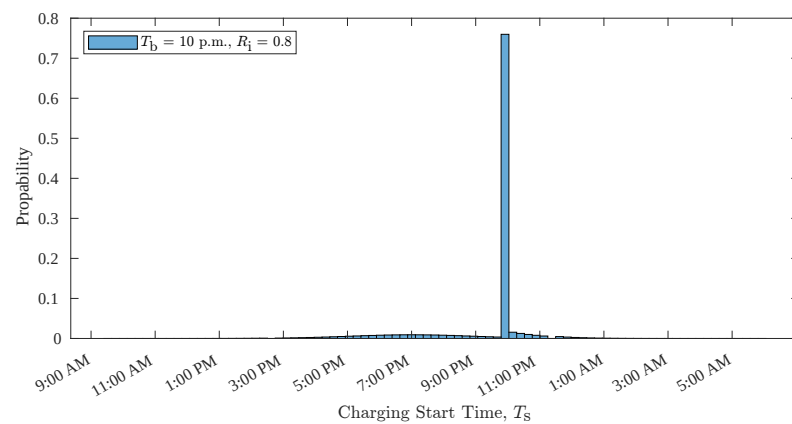
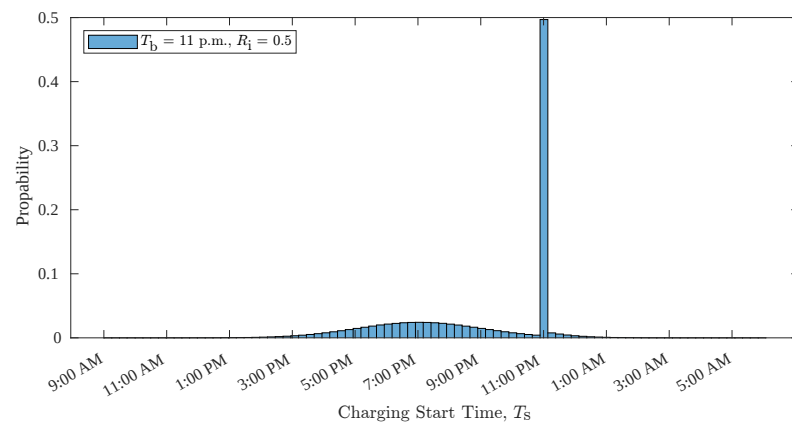
Figure 7. The distribution of the uncontrolled charging starting time, T_s .

In this study, the impact of varying T_b and R_i on the load demand was investigated under the TOU strategy, which aims to encourage EV owners to charge their vehicles during off-peak hours when electricity is cheaper. While T_b is a controlled parameter in practice, R_i is an uncontrolled parameter. However, both parameters can be controlled in computer simulations. Histograms of the charging start times for EVs under different assumptions, including $T_b = 10$ p.m. with $R_i = 0.5$, $T_b = 10$ p.m. with $R_i = 0.8$, and $T_b = 11$ p.m. with $R_i = 0.5$, are shown in Figure 8a–c, respectively. These figures illustrate that the distribution of the start times can be approximated as a normal distribution, adding an impulse at T_b . We can see that the impulses occur at T_b , and the height of the impulses depends on the value of R_i .

The computer simulation is used to demonstrate each charging strategy and its effects on the power system. The simulation uses data from the load profile to create several EV charging scenarios in order to analyze the impact on the power system. These scenarios represent real-world charging situations in the time domain.

4.3. Uncontrolled Charging Scenario

In this simulation, four levels of EV penetration were studied, including 10%, 20%, 30%, and 100% of the PEA's residential customers. The first scenario was an uncontrolled charging experiment, where EV customers do not have the advantage of avoiding charging during times of high load demands. A distribution model of the charging start time was created by randomly assigning the charging start time, assuming that the distribution follows a normal distribution as given in Section 4.2.

(a) $T_b = 10$ p.m. with $R_i = 0.5$ (b) $T_b = 10$ p.m. with $R_i = 0.8$ (c) $T_b = 11$ p.m. with $R_i = 0.5$ **Figure 8.** Distributions of the charging start time, T_s , at various values of T_b and R_i .

It is clear from the results shown in Figure 9 that uncontrolled charging of electric vehicles can significantly increase the peak load demand on the power distribution system. The peak load demand increased by 5.8%, 11.7%, 17.5%, and 74.4% when the EV penetration levels were 10%, 20%, 30%, and 100%, respectively. These significant increases in peak load demand can strain the capacity of the PEA's distribution feeders and highlight the need for a comprehensive strategy and incentives to encourage EV charging during off-peak times. For an uncontrolled charging scenario with the normal distribution of the SOC, the results showed that the peak load demand of the electrical distribution system increased by 5.8%, 11.5%, 17.3%, and 70.0% when the EV penetration levels were 10%, 20%, 30%, and 100%, respectively, as shown in Figure 10.

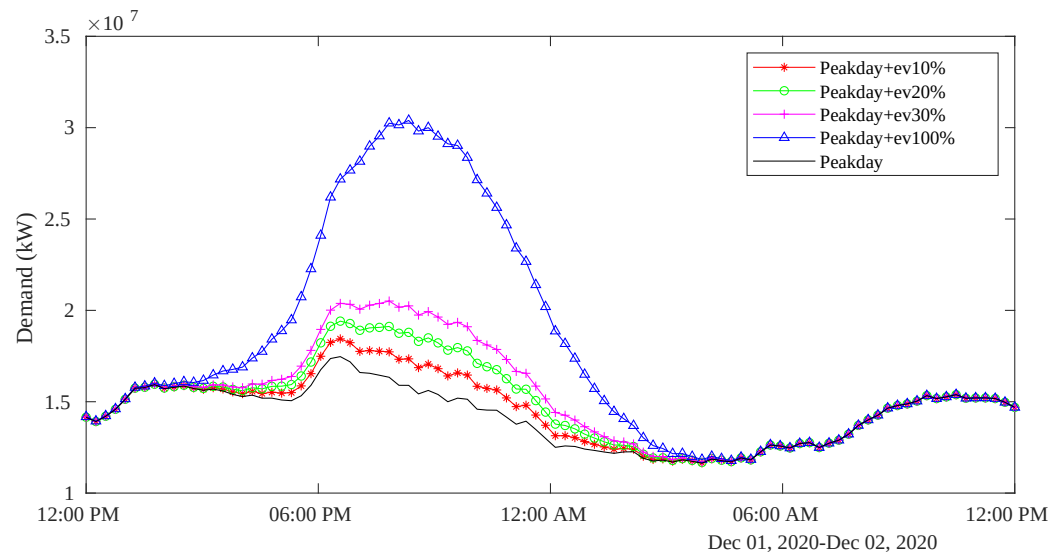


Figure 9. Load demand of the PEA when various levels of EV penetration are applied and uniform distribution of S_i is considered.

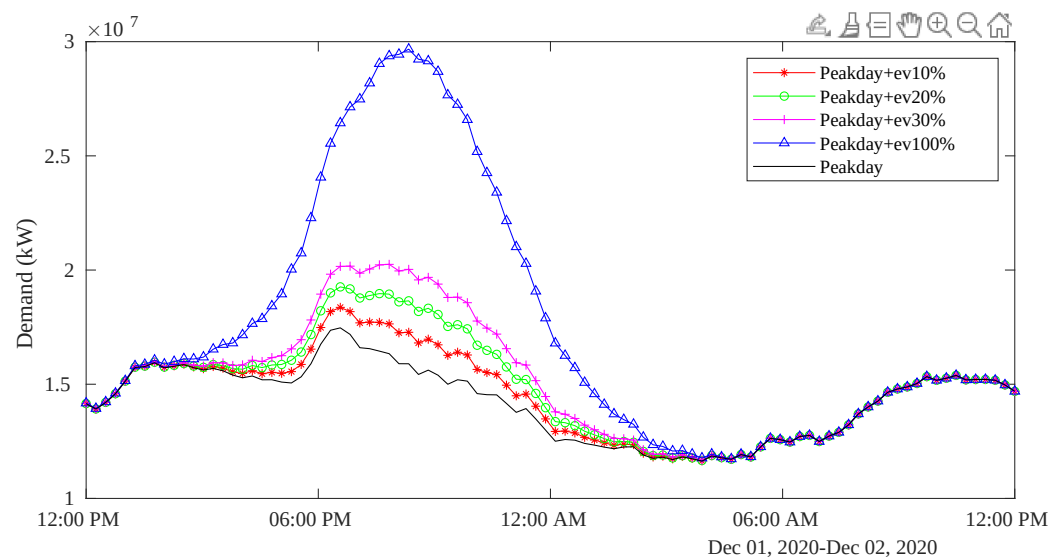


Figure 10. Load demand of the PEA when various levels of EV penetration are applied and normal distribution of S_i is considered.

4.4. TOU Price Charging Scenario

According to PEA's TOU tariff policy, the reduced pricing lasts from 10:00 p.m. to 9:00 a.m. Therefore, EV users who are willing to wait for lower costs and accept an adjustable fixed start delay can begin charging their electric vehicles at 10:00 p.m. in this simulation. It is assumed that 50% of EV owners will switch to a more affordable charging schedule, with half of those EV owners starting to charge at 10:00 p.m. immediately, as shown in Figure 8a. Charging demand simulations are conducted for EV loads at 10%, 20%, and 30% penetration. The 100% penetration is eliminated because the result of low-level penetration is addressed. Including the 100% penetration will reduce the detail of the low-level penetration result when plotting in the same graph. The results show that the TOU pricing strategy can prevent EV charging during peak hours. For the uniform distribution of SOC, the peak load demand of the electrical distribution system increased by 2.4%, 4.8%, and 15.23% when the EV penetration levels were 10%, 20%, and 30%, respectively, as shown in Figure 11. For the normal distribution of SOC, the peak load demand of the electrical

distribution system increased by 2.5%, 5.1%, and 11.9% when the EV penetration levels were 10%, 20%, and 30%, respectively, as shown in Figure 12.

The usual peak is 17.47 GW at 6:45 p.m. However, a second peak of the TOU schemes can occur at 10:45 p.m. in both the uniform and normal distribution of the SOC conditions, as shown in Figures 11 and 12. From the uncontrolled charging and TOU scheme results, the effect of uniform and normal distributions of S_i is insignificant. Therefore, the following simulation will use only uniform distributions of S_i .

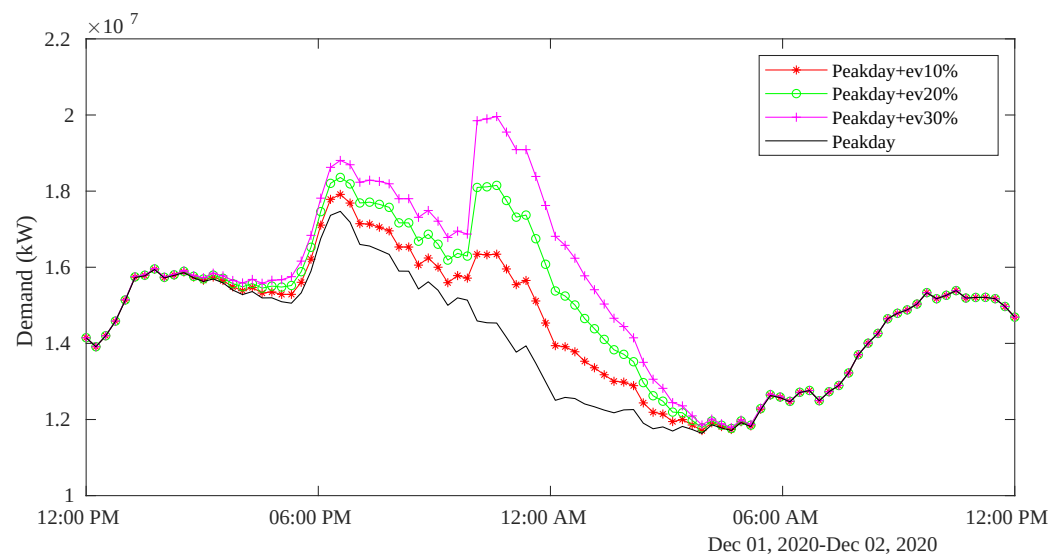


Figure 11. Load demand of the PEA when the TOU pricing policy is applied with $T_b = 10:00$ p.m. and uniform distribution of S_i .

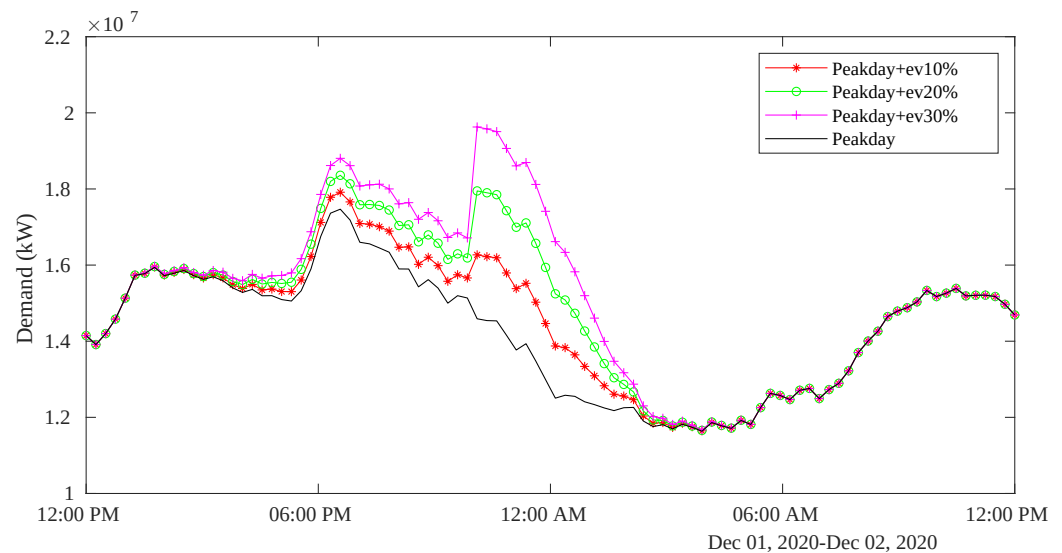


Figure 12. Load demand of the PEA when the TOU pricing policy is applied with $T_b = 10:00$ p.m. and normal distribution of S_i .

Next, the effect of the involvement rate, R_i , is demonstrated. The simulation is done by varying the R_i from 0.2–0.8 where $T_b = 10:00$ p.m., the EV penetration level is 20%, and the distribution of S_i is uniform. The results are shown in Figure 13. We can see that when the R_i increases, the first peak at 6:45 p.m. decreases while the second peak at 10:00 p.m. increases. The peak load demand of the electrical distribution system increased by 7.9%, 6.5%, 5.8%, and 8.5% when the R_i were 0.2, 0.4, 0.6, and 0.8, respectively.

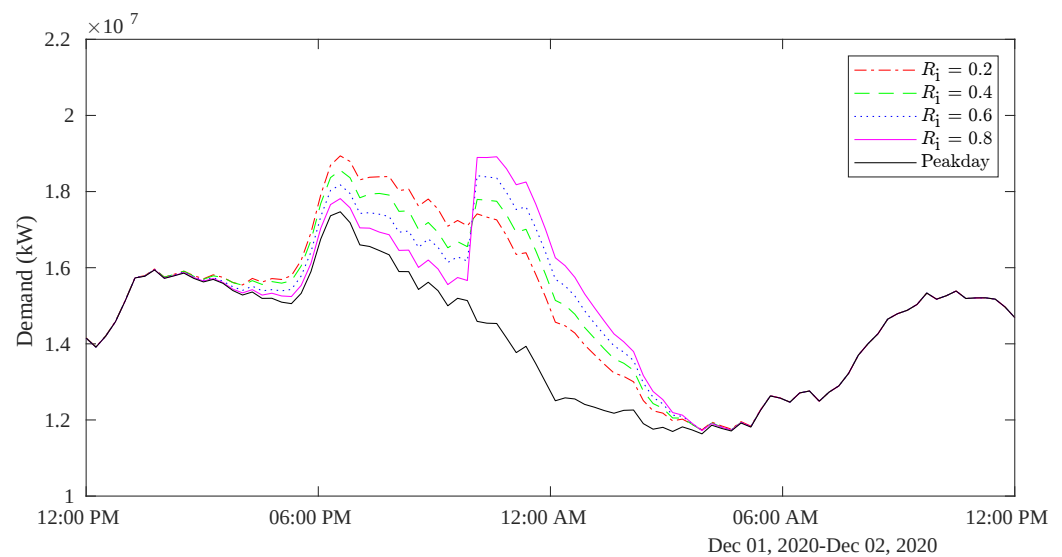


Figure 13. Load demand of the PEA under different levels of R_i when the TOU pricing policy is applied with $T_b = 10:00$ p.m., 20% penetration, and uniform distribution of S_i .

The last simulation is about the variation of T_b . Each variation of T_b results in the changing of the TOU tariff policy where T_b varies from 9.00 p.m. to 12.00 a.m. where the R_i is 0.5, and the EV penetration level is 20% on the uniform distribution of S_i . The simulation results in Figure 14 show that when the T_b is shifting, the second peak of load demands is shifting and decreasing. The maximum peak load demand of the electrical distribution system increases by 8.4%, 5.6%, 5.5%, and 5.5% when the T_b are 9:00 p.m., 10:00 p.m., 11:00 p.m., and 12:00 a.m., respectively. We can see that for $T_b = 9:00$ p.m., the maximum peak occurs at 9:00, while for $T_b = 10:00$ p.m., 11:00 p.m., and 12:00 a.m., the maximum peak occurs at 6:45 p.m.

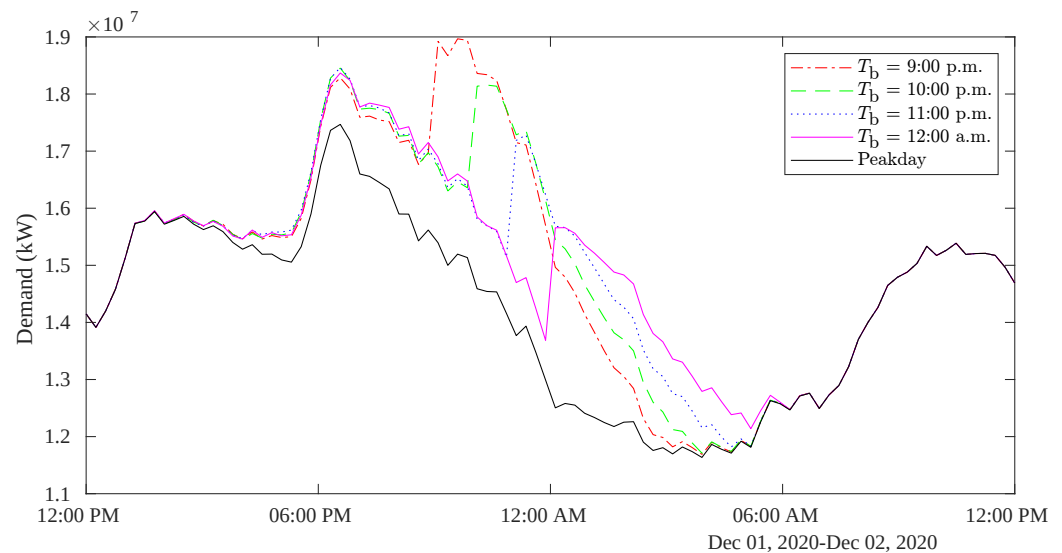


Figure 14. Load demand of the PEA under different T_b when the TOU pricing policy is applied with $R_i = 0.5$, 20% penetration, and uniform distribution of S_i .

Table 5 compares the peak load demands of various scenarios. These results are gathered from the previous simulation, including uncontrolled charging and TOU pricing policy schemes with $T_b = 9:00$ p.m., 10:00 p.m., 11:00 p.m., and 12:00 a.m. The EV penetration level varies from 10–30%. We can see that by increasing the EV penetration level, there is a need to shift the T_b to later. We can control the peak load of the 20% penetration of the EV to be similar to the peak load of the 30% penetration of the EV by shifting the T_b . However, these peaks load higher than those without EV charging, by about 5%.

Table 5. Load demand of the PEA under different scenarios when $R_i = 0.5$ and uniform distribution of S_i .

Penetration of EV (%)	Peak Load (GW)				
	Uncontrolled	$T_b = 9:00$ p.m.	$T_b = 10:00$ p.m.	$T_b = 11:00$ p.m.	$T_b = 12:00$ a.m.
10	18.43	17.89	17.93	17.99	17.96
20	19.40	18.80	18.39	18.52	18.44
30	20.53	20.59	20.00	19.06	18.93

4.5. Discussions and Limitations

In this simulation, we investigated the impact of EV charging on the power distribution system of the PEA by studying various levels of EV penetration, ranging from 10% to 100% of the PEA's residential customers. We compared two SOC models, normal and uniform distributions, and found no significant difference, leading us to use the uniform distribution for this study.

We compared the uncontrolled charging of four TOU pricing schemes that incentivize EV charging during off-peak hours by offering reduced pricing during specific periods. The simulation results show that uncontrolled EV charging can increase the peak load demand on the power distribution system by 5.8%, 11.5%, 17.3%, and 70.0% for 10%, 20%, 30%, and 100% EV penetration levels, respectively. These increases in peak load demand can strain the capacity of the PEA's distribution feeders, highlighting the need for a comprehensive strategy and encouraging EV charging during off-peak times.

To address this issue, we implemented four TOU pricing schemes with different TOU starting times, T_b , at 9:00 p.m., 10:00 p.m., 11:00 p.m., and 12:00 a.m. The simulation results reveal that a higher penetration requires a later shifting of T_b . For example, when the penetration is at 10%, the TOU scheme with $T_b = 9:00$ p.m. can be used; when the penetration is at 30%, the TOU scheme with a T_b at midnight is preferred. The TOU schemes prevented an increase in the peak demand on the electrical system, with an extraction of approximately 5% of the peak demand necessary to maintain electricity demand during electric vehicle (EV) charging.

The involvement rate, R_i , was also considered in this study, and results showed that when the R_i increased, the first peak at 6.45 p.m. decreased, while the second peak at 10.00 p.m. increased. Furthermore, the effect of shifting the TOU pricing policy time, T_b , was analyzed. When T_b shifted, the second peak of load demands shifted and decreased. The maximum peak load demand of the electrical distribution system increased by 8.4%, 5.6%, 5.5%, and 5.5% when T_b shifted from 9:00 p.m. to 12:00 a.m., respectively.

Overall, these results suggest that a combination of TOU pricing policies and incentives to encourage EV owners to charge during off-peak times can help alleviate the strain on the power distribution system caused by uncontrolled charging of EVs. Additionally, considering the involvement rate of EV owners in charging during off-peak times and shifting the TOU pricing policy time can further optimize the use of the power distribution system. Future research should investigate additional strategies and incentives to encourage EV owners to charge during off-peak times and explore the potential benefits of implementing these strategies on a larger scale.

The simulation in this study is based on several assumptions, including a normal distribution of the charging start time and a uniform distribution of S_i of the EV battery.

Moreover, this study only addresses the peak day and does not consider seasonal variations in EV charging demand. Other factors, such as long weekends or special events that increase the demand for EVs, may directly impact electricity demand. These factors were not considered in this study.

Further research could explore the sensitivity of the results to variations in these assumptions. Additionally, it would be valuable to study the impacts of different TOU pricing schemes with various reduced pricing periods and examine the potential for dynamic pricing strategies to optimize the charging of EVs and mitigate their impact on the power distribution system.

4.6. Managing EV Charging Demand Implications

To manage the impact of electric vehicle EV charging on the power distribution system, several strategies can be implemented. One effective approach is to encourage EV charging during off-peak hours through TOU pricing policies. This provides incentives for EV owners to charge their vehicles when electricity demand is low, thereby reducing the strain on the power distribution system during peak demand periods. Additionally, the implementation of smart charging systems can assist in managing EV charging by enabling better coordination between the charging of multiple vehicles, reducing the likelihood of overloading the power distribution system [59]. This can be achieved through the use of advanced algorithms that prioritize charging based on factors such as vehicle battery levels, charging speed, and electricity demand on the grid.

The results of this research demonstrate that uncontrolled charging of electric vehicles can significantly increase the peak load demand on the power distribution system. This increase in peak load demand can strain the capacity of the electrical distribution system, especially when the EV penetration level is high. On the other hand, a TOU pricing strategy can prevent EV charging during peak hours and encourage EV owners to charge their vehicles during off-peak times.

The implications of this research for managing EV charging demands are clear. To reduce the peak load demand on the electrical distribution system, it is essential to develop and implement comprehensive strategies and incentives to encourage EV owners to charge their vehicles during off-peak times. These strategies could include the implementation of TOU pricing policies, which offer lower rates during off-peak times and higher rates during peak times.

Moreover, the findings of this research highlight that the involvement rate of EV owners in TOU pricing schemes can significantly impact the peak load demand on the electrical distribution system. Therefore, it is critical to increase the involvement rate of EV owners in TOU pricing schemes to achieve a more significant reduction in the peak load demand. One solution to enhance the involvement rate of EV owners in TOU pricing schemes is to educate and raise awareness about the benefits of charging during off-peak hours. This can be accomplished through marketing campaigns and targeted outreach to EV owners, emphasizing the potential cost savings and environmental benefits of charging during off-peak hours. Additionally, offering incentives such as discounts or rebates for EV owners who participate in TOU pricing schemes can also help increase involvement rates. Finally, providing easy-to-use tools and technologies, such as mobile apps or online platforms that enable EV owners to easily monitor and manage their charging schedules, can also help increase involvement.

In addition, as the EV penetration level increases, the shifting of T_b is required to manage the peak load demand on the electrical distribution system. However, shifting T_b to later times may decrease the involvement rate of EV owners in TOU pricing schemes due to the inconvenience of late-charging times. A potential solution to this issue is to implement programmable charging times, which allows EV owners to set their preferred charging times in advance. This can help overcome the inconvenience of late-charging times and increase the involvement rate in TOU pricing schemes. By encouraging more EV owners to participate in TOU pricing schemes, the peak load demand on the electrical distribution

system can be reduced, thus improving the reliability and stability of the system while supporting the growth of EV adoption.

In conclusion, this research provides valuable insights into the impacts of uncontrolled EV charging and TOU pricing policies on the peak load demand of the electrical distribution system. The findings suggest that effective management of EV charging demand is essential to ensure the reliability and stability of the electrical distribution system while supporting the growth of EV adoption.

5. Conclusions

This study investigated the impact of electric vehicle (EV) charging on the power distribution system of the Provincial Electricity Authority (PEA) in Thailand. The study used load profile data obtained from the PEA's website from December 2020 and simulated various levels of EV penetration, ranging from 0% to 100% of the PEA's residential customers, using both uncontrolled charging and four TOU pricing schemes. The simulation results show that uncontrolled charging could significantly increase the peak load demand on the distribution system, with an increase of up to 74.4% for a 100% EV penetration level. However, the TOU pricing strategy can prevent EV charging during peak hours, with a peak load demand increase of up to 15.23% for a 30% EV penetration level when the starting TOU is at 9 a.m. With the late starting TOU at midnight, a peak load mean can be reduced to 5% for a 30% EV penetration. The involvement rate also affects the peak load demand, increasing from 5% to 8.1% when the involvement rate increases from 0.5 to 0.8. It is important to note that the simulation was based on certain assumptions, and further research could explore the sensitivity of the results to variations in these assumptions. Nonetheless, this study highlights the need for a comprehensive strategy and incentives to encourage EV charging during off-peak hours to mitigate the potential strain on the power distribution system. Overall, this study provides valuable insights for policymakers and utility companies in developing effective strategies for integrating electric vehicles into the power system and promoting sustainable transportation.

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