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Stochastic planning of electric vehicle charging station integrated with photovoltaic and battery systems

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Abstract: Charging stations not only provide charging service to electric vehicles (EVs), but also integrate distributed energy sources. This integration requires an appropriate planning to achieve the future sustainable distribution network. Real EV charging demand is stochastic and affected by many uncertainties, which pose challenges to the planning of a charging station. This paper presents a stochastic planning model of the EV charging station with PV, battery and transformer, mainly considering the uncertainties from charging demand and PV power generation. Firstly, a comprehensive EV charging demand model is established through reflecting the coupling among the EV stochastic charging behavior, charger specifications and EV charging assignment model. Then, the planning model is formulated to minimize the total cost of the charging station, where the uncertainties arising from EV charging are addressed in various constraints. Using this model, the optimal sizing of the charging station is determined, together with the associated optimal operation strategy. Finally, the effectiveness of the proposed model is validated by multiple case studies.

1 Introduction

Electric vehicles (EVs) are now being widely considered to be a promising solution for energy saving and emission reduction in the transportation sector, and they interact with the power grid via EV charging stations [1, 2]. However, the potential mass penetration of EVs places a heavy burden on current power system and may require to expand the thermal plant capacity to accommodate the growing charging demand. Renewable energy sources and energy storage devices could be deployed in today's power grid to reduce the dependence on fossil fuel and promote sustainable charging stations. Appropriate planning of charging stations is important for the widespread use of EVs and environmentally friendly power grid.

Recently, there have been many literatures on the planning and operation of a charging station. These studies proposed different planning models. For instance, Ref. [3] considered various types of charging facilities in an urban area in its planning model to reduce the social cost of the entire charging system. Ref. [4] established a two-objective collective planning model to describe the coupling of EV charging infrastructure and power distribution network. The purpose was to not only minimize the charging station investment cost and energy loss but also to maximize the captured traffic flow by the charging station. Ref. [5] presented a state-of-charge (SOC) characterisation based hierarchical planning to address the tradeoff among the number of EV charging stations, charging demands, and economic profit.

At the same time, the aforementioned work only took the power grid as a single energy source in the charging station network, without involving distributed renewable energy and energy storage devices. It is worth noting that this straightforward energy network configuration may not be sustainable considering a huge energy demand from EVs in future. The introduction of renewable energy and energy storage devices inevitably complicates the system configuration and the charging station planning problem. In Ref. [6], the planning of the charging station was investigated based on given power dispatch strategy. The coupling between the current and subsequent schedules and the coupling between energy management and planning were not addressed, which may lead to sub-optimal solutions. In Ref. [7], a bi-level planning for an islanded microgrid with compress air energy storage was proposed to determine the optimal capacities of each component based on an existing energy demand curve. Ref. [8], with a fixed EV usage pattern and deterministic solar irradiation, developed a Levelized Energy Storage (LES)-sizing method in a PV-aided EV charging station to minimize the system daily cost. Meanwhile, in real scenarios, the EV charging profile is not deterministic. It is affected by many factors, start charging time, start charging SOC, EV battery capacity, etc [9–12]. Ref. [9] took the initial charging SOC and the arrival time into account. These two factors were represented by probabilistic functions in the proposed model. And stochastic EV arrival and charging time were considered in [10]. Ref. [11] modeled the stochastic EV charging factors to obtain charging demand, and then optimized the size of energy storage system. The number of charger and EV charging assignment were not addressed. Ref. [12] discussed the charging demand optimization, which involves the EV start charging time and initial charging SOC. Ref. [13] also included the above two stochastic variables in the EV charging demand profile, in which the on-board battery capacities and renewable energy sources were not reflected.

Although the aforementioned literatures introduced the stochastic factors into their developed models, further improvements are still needed and important. Major stochastic EV charging behavior factors have not been synergetically included in a unified framework, which might not truly reflect the practical charging demands. The number of EVs has been usually assumed to be fixed, but it contradicts with the actual scenarios. In addition, the constraints of the number of chargers and EV charging assignment have been seldom discussed, especially with the other stochastic charging factors. The limited number of available chargers is an important factor that significantly impacts the serving capacity of a charging station and thus the EV charging demands. Besides, it is practically expected that sizes of energy storage, PV panels, and transformers should be optimized together during the charging station planning, instead of being separately discussed.

Based on the above review of the existing work, a comprehensive stochastic planning model of the EV charging station is proposed and developed. The main contributions of this paper are summarized as follows:

1.The planning of the charging station considers two major sources of uncertainties in EV charging demands and intermittent PV power generation. Especially, the start charging time, initial charging SOC, battery capacity, and number of charging EVs are fully reflected when establishing the charging demand model.
2.The impact of limited number of chargers and their rated charging powers are investigated and demonstrated.
3.The capacities of PV panel, battery energy storage, and transformer are optimized at the same time to achieve an economic solution.
4.With the following relaxation of constraints, the proposed planning problem of the EV charging station is formulated as a convex programming problem and thus can be efficiently solved.

Based on the above discussions, this paper is organized as follows. Stochastic EV charging model and PV power generation model are separately established in Section 2 and 3. Then, stochastic planning model is developed in Section 4, and multiple case studies are provided in Section 5. Finally, conclusions are drawn in Section 6.

2 Stochastic modeling of EV charging demand

Fig. 1 shows the configuration of the PV and battery integrated EV charging station. The PV, battery and transformer are the main energy sources and charging station interacts with EVs through chargers. In the system, there exist two aspects of uncertainties: intermittent PV power generation and random EV charging demand, which directly affect the size optimization of the charging station. Therefore, it is necessary to model them firstly. As the charging service provider, the EV charging station will serve a large amount of EVs every day. Thus, corresponding EV charging demand certainly has a great impact on the planing of the charging station. In addition, the reality is the charging demand in each day are different, thus the fixed constant charging demand profile is not suitable for the planning of the charging station. In order to build a stochastic charging demand model, EV charging behavior related factors including EVs start charging time, energy required for charging, initial charging SOC, daily number of EVs are all modeled in the following. As explained above, the charging demand of charging station is actually the combined result of both EVs charging and specification of chargers, therefore, the final stochastic EV charging demand model is obtained by accommodating them.

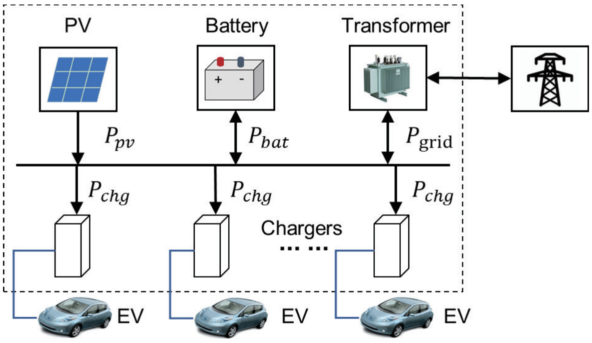


Fig. 1: *The configuration of EV charging station*

2.1 Stochastic EV charging behavior

In this study, three stochastic variables are considered for modeling the EV charging behavior: start charging time, start charging SOC and daily served number of EVs. And following assumptions are made:

1.EV drivers charge their EVs immediately when they arrive at the charging station;
2.The SOC of the batteries of EVs are assumed to be charged to 0.8.

Such a charging end condition is acceptable because the main purpose of the public charging station is to satisfy the EV charging in short time while people much prefer full charging at home over night. Since EV charging behavior is highly random, the useful method of modeling uncertainty variable is using statistics and probability method [11]. Lognormal distribution is suitable for modeling the distribution of the start charging SOC of the EV battery [9], which is defined by the average ($\mu_{soc_{ini}}$) and standard deviation ($\sigma_{soc_{ini}}$) of the logarithm of the SOC variable. Here assume that the start charging SOC of EV varies from 0.2 to 0.5. Fig. 2 shows the simulated lognormal distribution of SOC.

$$f(SOC_{ini}) = \frac{1}{soc_{ini}\sigma_{soc_{ini}}\sqrt{2\pi}} e^{-\frac{(\ln SOC_{ini}-\mu_{soc_{ini}})^2}{2\sigma^2_{soc_{ini}}}}, \quad (1)$$

Another stochastic variable is the EV start charging time which depends on when the drivers arrive at the charging station, and in the study assume that the EV is charged immediately upon arrival. In addition, the start charging time is associated with drivers' travel pattern. Ref. [11, 12] show a charging load profile that mainly concentrates in the period from 6 am to 22 pm, in which there are two peaks at around 8 am and 6pm. Respect this characteristic, the EV starting charging time is modeled by following, and the effect of different travel pattern on the optimal sizing will be discussed in Section 5.

$$f(t_{ini}) = \begin{cases} \frac{1}{\sigma_{t_{ini}}\sqrt{2\pi}} e^{-\frac{(t_{ini}-\mu_{t_{ini}})^2}{2\sigma_t^2}}, & \mu_{t_{ini}} = 8 \text{ am}, \\ & 6 \text{ am} \le t_{ini} \le 11 \text{ am} \\ \frac{1}{\sigma_{t_{ini}}\sqrt{2\pi}} e^{-\frac{(t_{ini}-\mu_{t_{ini}})^2}{2\sigma_t^2}}, & \mu_{t_{ini}} = 6 \text{ pm}, \\ & 2 \text{ pm} \le t_{ini} \le 10 \text{ pm} \end{cases} \quad (2)$$

where t_{ini} is the start charging time, $\mu_{t_{ini}}$ and $\sigma_{t_{ini}}$ are the average arrival time and the standard variance, and the setting of such parameters refers to [14].

The EV battery capacities on the market are various and depend on vehicle type. According to Ref. [15] and market product surveys, most EVs have battery capacities ranging from 30 kWh to 80 kWh. In this study, the arrival EV battery capacities are randomly distributed according to the assumed Gaussian distribution as follows:

$$f(c) = \frac{1}{\sigma_c\sqrt{2\pi}} e^{-\frac{(c-\mu_c)^2}{2\sigma_c^2}}. \quad (3)$$

where c denotes the battery capacity, and μ_c and σ_c are average and standard deviation of the EV battery capacity, respectively.

Moreover, the number of EVs that are charged daily at the charging station n is also not constant. In this study, it is determined by a Gaussian distribution (μ_n and σ_n) shown as follows. The average number μ_n and σ_n are 80 and 10, respectively, which refers to Ref. [10, 11].

$$f(n) = \frac{1}{\sigma_n\sqrt{2\pi}} e^{-\frac{(n-\mu_n)^2}{2\sigma_n^2}}. \quad (4)$$

Based on above-mentioned probabilistic models, Fig. 2 shows an example for the above mentioned random quantities for 90 EVs .

2.2 Charger specification and EV charging assignment model

Different from stochastic EV charging behavior, the configuration of the charger can affect charging demand in indirect way from two aspects: the number of chargers and the equipped charging level. In terms of the charging level, the higher charging level can shorten the charging duration while increasing the charging load in the charging station. According to the current EV charging standards SAE J1772 and IEC 62196, EV charging power level can be basically classified into 3 types: 1) AC level 1 at peak power 3.7 kW, 2) AC level 2 at 3.7-22 kW, 3) AC level 3 at 22-43.5 kW, and DC level 3 at maximum

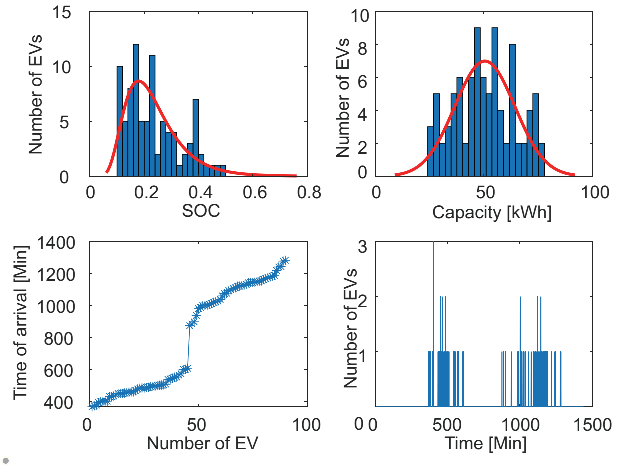


Fig. 2: *EV charging behavior random quantities simulation*

200 kW. Generally, level 1 is used for EV onboard charger which normally takes 7-9 h to fully charge the EV, while level 3 requires a specific charger usually deployed in the public charging station [16]. Considering the main function of the charging station is to provide rapid recharging service for coming EVs, here the chargers of level 3 are used in this study. Referring to [17], the charging process of the battery can be simplified to constant power charging from SOC at 0.3 to SOC at 0.8.

Since the number of chargers in the charging station is finite, when a large amount of EVs come to the charging station for charging, if the number of upcoming EVs is greater than the number of unoccupied chargers, this situation will certainly result in some EVs fail to charge. Therefore, a mechanism needs to be devised to determine which EV is assigned to which charger and which EV will be rejected. To solve the problem, a charging assignment model for the arriving EV is established. In the assignment model, all arrival EVs are sorted and tagged in order. In this control mechanism, each time the arriving EV will access the available charger according to the given charger sorting number until an unoccupied charger is found. EVs may leave or queue if no empty charger. Fig. 3 shows the charging assignment model.

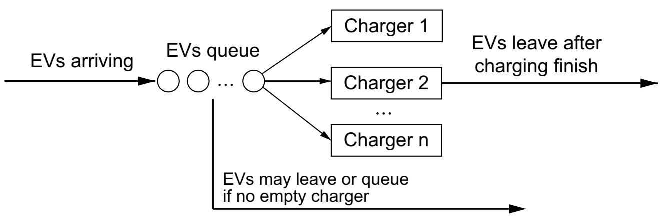


Fig. 3: *EV charging assignment model*

On the one hand, more number of chargers and higher charging power rating can capture more arrival EVs and bring more benefit. On the other hand, this could consequently increase the charging load and raise the investment cost of charging station. Recognizing that the number of chargers and charging level are closely coupled with the charging demand, multiple candidate sets of different charging level (22 kW and 40 kW) and different number of chargers (5, 10, 15, 20 and 25) are summarized and listed in the charger options Table 1. Obviously, for each candidate charger option, there would be a corresponding stochastic charging demand profile which will be obtained in the following section.

2.3 Final EV charging demand

Once the relevant random quantities: start charging SOC, start charging time, EV battery capacity, number of arriving EVs, and charging station configuration: the number of chargers, charger power and the

Table 1 Candidate charger options

Power	Number of chargers 5	10	15	20	25
22 kW	P22N5	P22N10	P22N15	P22N20	P22N25
40 kW	P40N5	P40N10	P40N15	P40N20	P40N25

EV charging assignment model, are all completely determined, then the total charging demand of the charging station P_l at each time instant k can be estimated as following,

$$P_l(k) = \sum_{n_{chg}} P_{chg}(k), \tag{5}$$

where n_{chg} is the number of charger and $P_{chg,c}$ represents the charging power of the cth charger.

Charging load reflects the EV stochastic charging behavior. To obtain the stochastic property of the EV charging demand load arising from the coupling of the multiple factors mentioned above, Monte Carlo simulation (MCS) can be applied to repeat sampling from the assumed probability distributions of these related random quantities. N_m is the sample times in the MCS. Note that since the stochastic nature of the charging behavior, the charging demand load at same time t at different simulation time are consequently different. In order to represent the stochastic property of the charging demand, the generated charging demand load $P_l(k)$ in N_m times can be characterized by the Gaussian distribution:

$$P_l(k) \sim N(\overline{P}_l(k), \sigma^2_{P_l}(k)), \tag{6}$$

where $\overline{P}_l(k)$ is the average value of charging load and $\sigma_{P_l}(k)$ is the standard deviation at time k, which can be calculated as following:

$$\begin{cases} \overline{P}_l(k) = \frac{1}{N_m} \sum\limits_{n_m=1}^{N_m} P_l^{n_m}(k) \\ \sigma_{P_l}(k) = \left(\frac{1}{N_m} \sum\limits_{n_m=1}^{N_m} (P_l^{n_m}(k) - \overline{P}_{l,m}(k))^2\right)^{\frac{1}{2}} \end{cases} \tag{7}$$

For example, given 15 chargers and 22kW charging level, the charging behavior related uncertainty quantities are randomly sampled from their respective possibility distributions, as mentioned above. Through one time MCS, Fig. 4 shows an example of charging demand at the charging station with the time interval of 1 min. Then the average charging demand within each hour can be calculated.

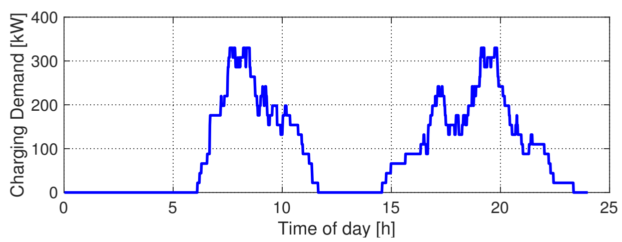
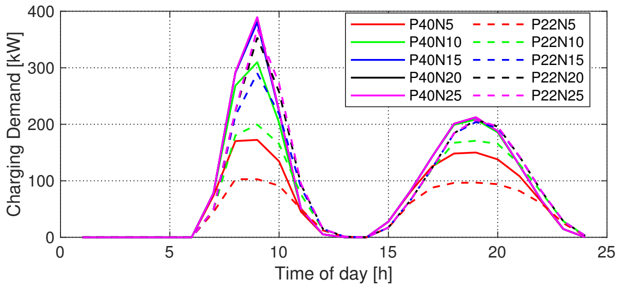
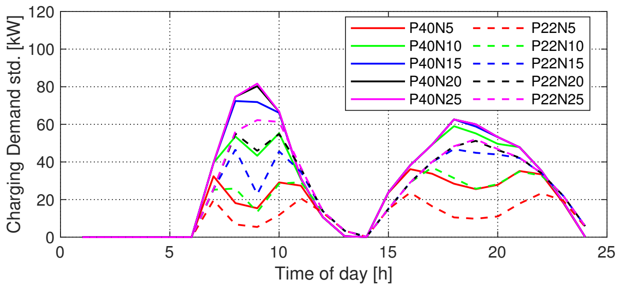


Fig. 4: *An example of charging demand with 1 min time interval for charging station with P22N15.*

After performing multiple times of MCS, the generated charging demand data is processed and the uncertain characterisation is captured by the Gaussian distribution with $(\overline{P}_l(k), \sigma^2_{P_l}(k))$ according to (7). Fig. 5 shows the values of the above two parameters for each candidate charger option at each hour of one day, and the values change over time. As shown in the figure, with a less number of chargers, the charging demand is lower. With more chargers, the charging demand increases because more EVs can be captured by the charging station. As the number and rated charging powers of chargers grow, the charging demand does not proportionally increase, but the associated investment cost of chargers does. Besides, a larger charging demand means higher revenue from serving EVs. But it requires a higher power supply capacity. Therefore, a tradeoff exists when determining an optimal charger option in Table 1.



(a)



(b)

Fig. 5: *Charging demand characterization at each hour under each candidate charger option. (a) $\overline{P}_l(k)$. (b) $\sigma_{P_l}(k)$.*

3 Stochastic modeling of PV generation power

The PV output power P_{pv} can be evaluated by the following equation [18]:

$$P_{pv} = G_i A_{pv} \eta_{pv} \Big(1 - c_T * (T_{env} - T_{STC})\Big), \tag{8}$$

where G_i is the global solar irradiance, A_{pv} is the installed PV panels surface, η is the conversion efficiency of the PV panels, c_T denotes the temperature coefficient of the PV panels, T_{env} and T_{STC} are the environmental temperature and standard test condition (STC) temperature, respectively. The technical parameters of a PV panel used in this study are listed in Table 2.

Table 2 PV panel parameters

Parameter	value	Parameter	value
Length	1650 mm	Width	990 mm
Conversion efficiency	15.3%	Maximum Power	250 W
Temperature coefficient	0.0045		

Based on the above mentioned PV panel parameters and annual data of solar irradiance and temperature [19], the output power of the PV panel can be estimated and shown in Fig. 6. Overall it can be seen that the PV output power is intermittent and varies with the time of day and a specific season. As shown in Fig. 7, four typical power profiles are used here to represent the uncertain PV power output in the four seasons (spring: Mar.–May, summer: Jun.–Aug., Autumn: Sep.–Nov., Winter: Dec., Jan.–Feb.) of a year [19]. In the following sections, the set of the typical PV power profiles is represented by symbol $\mathcal{Y}$, and each profile is indexed by $y \in \mathcal{Y}$ ($|\mathcal{Y}|$=4, $y = 1, ..., 4$).

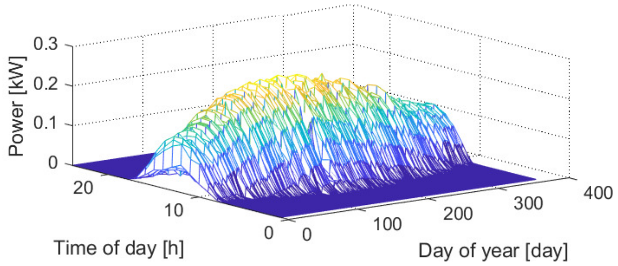


Fig. 6: *Annualized PV power generation for the specific PV panel*

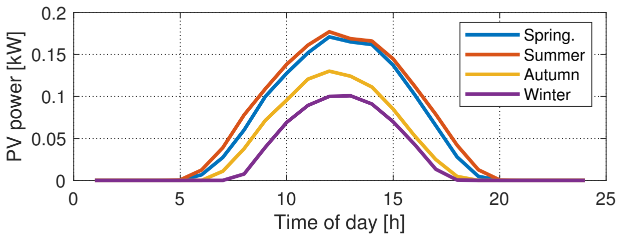


Fig. 7: *Typical daily PV power generation of four seasons for the specific PV panel.*

4 Stochastic planning model of charging station

From the perspective of the charging station owner, the planning of the charging station aims to minimize the economic cost, which requires calculation of the investment costs of the charging station, operation cost, and subtracting the revenue from the serving charging of EVs. The investment costs include the total cost of PV, battery, transformer, and chargers, which are measured according to their sizing. Among them, chargers and transformers are rarely discussed in literatures. Operation cost primarily includes electricity purchasing cost from the main grid, which is related to the operation of the charging station. Therefore, the objective function of the planning of the charging station is to minimize the daily cost of the charging station formulated as follows:

$$\begin{aligned} \min \sum_{y \in \mathcal{Y}} \Big(& c_s s + c_b b + c_{ts} ts + c_{chg} n_{chg} P_{chg} \\ & + \sum_{k=0}^{N} c_g(k) P_g^+(k) + \sum_{k=0}^{N} c_{g,fb}(k) P_g^-(k) \\ & - \sum_{k=0}^{N} c_{ev}(k) P_l(k) \Big), \end{aligned} \tag{9}$$

where c_s, c_b, c_{ts} and c_{chg} represent the unit cost of PV panels in USD/(kW·day), the unit cost of battery in USD/(kWh·day), the unit cost of transformer in USD/(kW·day), the charger cost in USD/(kW·day), respectively. $c_g(k)$ represents the electricity price purchasing from the grid, and $c_{g,fb}(k)$ represents the electricity price that charging station sells to the grid. Index k is the time slot index for the time of day from 0 to $N = 23$, namely one day is divided into 24 time slots. c_{ev} represents the charging price for EV. In addition, the electric power exchange with power grid is P_g which is composed of P_g^+ (charging station buys electricity from the grid) and P_g^- (charging station sells electricity to the grid). Variables s, b, ts are PV size, battery size and transformer size, respectively. P_l is the charging demand load of EVs, P_{chg} is the equipped charging power of the charger, and n_{chg} is the number of chargers to be installed in the charging station.

In the charging station, power balance should be always guaranteed at any time expressed by:

$$P_{pv}(k) + P_{bat}(k) + P_g(k) = P_l(k), \tag{10}$$

where $P_{pv}(k)$, $P_{bat}(k)$ and $P_g(k)$ are the generation power of PV, the discharging or charging power of battery, and the grid power, respectively.

The battery energy dynamics can be determined by the following model:

$$E_{bat}(k+1) = E_{bat}(k) - (P_{bat}(k) + \eta|P_{bat}(k)|)\Delta t, \quad (11)$$

where $E_{bat}(k)$ is the battery energy level, the battery power $P_{bat}(k)$ value can be either negative (i.e. charging) or positive (i.e. discharging), and η is the lost efficiency of battery, which is very small since lithium-ion battery is characterised by high efficiency. Furthermore, a terminal constraint is added

$$E_{bat,0} = E_{bat,N+1}, \quad (12)$$

which ensures that the energy level of battery at the end of the day is equal to the beginning energy level. Such a terminal constraint in essence guarantees that the operation during this day does not influence the operation of subsequent day. In addition, the battery power $P_{bat}(k)$ and stored energy $E_{bat}(k)$ are limited by the following inequality constraints

$$E_{bat,min} \leq E_{bat}(k) \leq E_{bat,max}, \quad (13)$$

$$P_{bat,min} \leq P_{bat}(k) \leq P_{bat,max}, \quad (14)$$

where $E_{bat,min}$ and $E_{bat,max}$ are the minimum and maximum limits of the stored energy. They are 10% and 90% of the full battery energy capacity (i.e., the optimized battery size b), respectively,

$$E_{bat,min} = 0.1b, \; E_{bat,max} = 0.9b. \quad (15)$$

$P_{bat,min}$ and $P_{bat,max}$ are the permitted charging and discharging power limits, which again relate to the battery size b,

$$P_{bat,min} = -rb, \; P_{bat,max} = rb, \quad (16)$$

where coefficient r represents the maximum allowable C-rate. It depends on battery specifications and needs of a specific application, i.e., a user-defined parameter. Since the batteries deployed at the charging stations are mainly energy type batteries, a smaller C-rate is generally preferred, such as ± 0.5C in this paper.

The grid power cannot exceed the permitted power limits $P_{g,min}$ and $P_{g,max}$ (i.e., the optimized transformer size ts) of the transformer:

$$-ts \leq P_g(k) \leq ts, \quad (17)$$

In addition, the design variables: PV size s, battery size b and transformer size ts are subject to following bounds:

$$s_{min} \leq s \leq s_{max}, \quad (18)$$

$$b_{min} \leq b \leq b_{max}, \quad (19)$$

$$ts_{min} \leq ts \leq ts_{max}, \quad (20)$$

However, it should be noted that in (10), the charging demand load P_l and the PV power generation P_{pv} are random variables. Therefore, the optimization problem becomes to optimize the component sizes while scheduling the system operation power flow under uncertainties. The random PV power generation is represented by the four seasonal typical profiles. Once the charging demand is determined by (6), then the right inequality of constraint (17), namely the upper bound, can be converted into the follow chance constraint:

$$\Pr\Big(P_l(k) \leq P_{bat}(k) + ts + P_{pv}(k)\Big) \geq \alpha, \quad (21)$$

where α is a constant parameter meaning confidence level or reliability. The higher the α value, the higher the reliability that the system can guarantee. Then the normal cumulative distribution function can be obtained by converting the chance constraint shown as follows:

$$\Phi\Big(\frac{-\overline{P_l}(k) + P_{pv}(k) + P_{bat}(k) + ts}{\sigma_{P_l}(k)}\Big) \geq \alpha. \quad (22)$$

Then the upper bound constraint can be rewritten as:

$$\sigma_{P_l}(k) \leq \frac{1}{\Phi^{-1}(\alpha)}\Big(P_{pv}(k) + P_{bat}(k) - \overline{P}_l(k) + ts\Big). \quad (23)$$

And the lower bound constraint is rearranged as:

$$\sigma_{P_l}(k) \leq \frac{1}{\Phi^{-1}(\alpha)}\Big(- P_{pv}(k) - P_{bat}(k) + \overline{P}_l(k) + ts\Big). \quad (24)$$

By far, all of the constraints have been convex except for the non-affine equality constraint (11), which is also nonlinear due to the existence of the absolute function. In order to solve the problem efficiently, (11) is relaxed to become convex without qualitatively altering the original problem as follows [20],

$$E_{bat}(k+1) \leq E_{bat}(k) - (P_{bat}(k) + \eta|P_{bat}(k)|)\Delta t. \quad (25)$$

The advantage of convex problem is that it can guarantee the solution of the problem is existing and unique. By far, the original sizing optimization problem has been transformed into a nonlinear convex programming problem. Then convex optimization solving software can be used to efficiently solve the problem, comparing other heuristic methods used in [13, 21].

5 Case studies and analysis

This section presents the optimal sizing results solved by the proposed model and analyzes the impact of different parameters on the results. Since the charging demand profile relies on a specific number of chargers and charger rated power, each of the candidate charger options listed in Table 1 is applied and compared to finally determine an optimal charger option with the lowest total cost. Section 2 explains the uncertainties of the charging demand profile for each candidate charger option [see Fig. 5]. The uncertainties of PV power generation also have been addressed in section 3 which are shown in Fig. 7. Those uncertainties results are then utilized in the following case studies. Based on the results of charging demand and PV power generation, the optimal size of each component can be solved using the proposed stochastic planning model. Technical parameters used in the simulation calculation are summarized in the Table. 3. The

Table 3 Parameters in simulation [11, 20, 22–24]

Parameter	Value	Parameter	Value
PV cost	2025 USD/kW	Battery cost	900 USD/kWh
Transformer cost	788 USD/kW	Charger cost	500 USD/kW
Battery size	0-1000 kWh	PV size	0-500 kW
Transformer size bounds	0-500 kW	PV design life	20 Years
Battery design life	10 Years	Transformer design life	20 Years
Charger design life	10 Years	α	0.9

PG&E dynamic electricity tariff $c_g(k)$ is used in the study, including peak periods, shoulder and off-peak periods [20]. For the charging station, the operation power flow can be divided into three directions: the charging station sells electricity to the EVs at price $c_{ev}(k)$, the charging station buys electricity from the grid at price $c_g(k)$, and the charging station sells electricity to the grid at price $c_{g,fb}(k)$. The relationship between the three prices are set as follows: the $c_{ev}(k)$ is generally greater than $c_g(k)$, and $c_g(k)$ is much larger than $c_{g,fb}(k)$. Such setting $c_{g,fb}$ is lower can promote the charging station to use the local energy resources to charge EVs instead of selling it to the grid. Fig. 8 shows the specific information of the three prices.

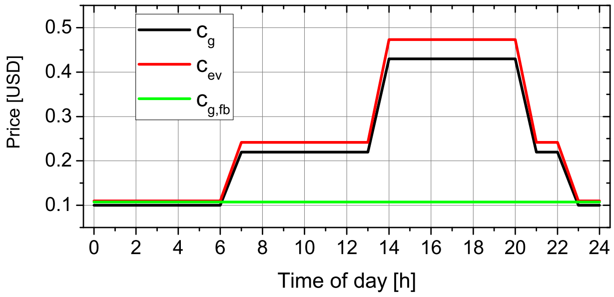


Fig. 8: *Hourly prices of electricity for the charging station*

The optimal cost results for each candidate charger option listed in Table 1 are shown in Fig. 9. It clearly shows that the charger option

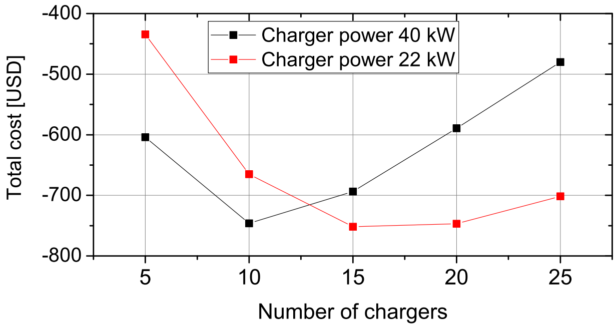


Fig. 9: *Optimal cost comparison in the charging station for different charger options.*

(number of chargers and charger power level) has a large impact on the economic cost. For the charger power with 40 kW, the most economical number of installing chargers is 10. For the charger power with 22 kW, the most economical number of chargers is 15. And more or less than that optimal number could result in larger cost. The optimal sizes of each energy device in each candidate option are summarized in Table. 4. As shown, as the number of chargers increases, the optimal size of each device has almost the same trend: firstly it rapidly increases, and then gradually slows down or remains constant, which means that this increase is nonlinear. Comparing the resulted total cost for the two charging configuration, the most economical configuration for the charging station is: 15 chargers with charging power 22 kW, PV size 394.75 kW, battery 907 kWh, and transformer 125 kW. This optimal case is named as Case 1 which will be compared with other cases in the following case study discussion. The optimal results indicate:

Table 4 Optimal size of each component in different charger options

Device	Charger options				
	P22N5	P22N10	P22N15	P22N20	P22N25
PV(kW)	215.5	343.75	394.75	447	461.5
Battery(kWh)	489	813	907	890	883
Transformer(kW)	90	121	125	125	125
Device	P40N5	P40N10	P40N15	P40N20	P40N25
PV(kW)	301	409	453	452.25	452.25
Battery(kWh)	724	922	909	910	910
Transformer(kW)	106	129	128	128	128

1.The appropriate size selection of energy component can achieve remarkable cost saving for the planning of EV charging station;
2.The number of chargers and the charging level have a great impact on the objective function. More or less than the number of chargers will increase the system cost dramatically and the charging level can also affect the outcome, which is not explicitly discussed in other studies.

For Case 1, the optimal charging station operation power flow is obtained associated with the optimal sizing as shown in Fig. 10.

Due to the four different typical PV power profiles, the charging station presents different operation strategies. For typical profiles of spring, summer and autumn, the PV power is relatively sufficient . The battery is charged between 0 am to 6 am by the main grid. However, it is worth noting that the battery is not fully charged (e.g. the SOC is approximate 0.42 at 7 am in Fig. 10(a)). This is because that the battery need keep a low SOC level in order to prepare for storing the excess PV power at noon. At that time, the battery is charged to its maximum energy level, and thus is ready to meet the most of charging demand in the evening. During the whole day, the working period of transformer is quite short. It concentrates at the off-peak time, which helps save the operation cost. In contrast, for the winter profile in Fig. 10(d) which has the least PV power, the battery is charged to the full SOC level before 7 am. And much more electricity has to be purchased under this profile, comparing with the results under the other three profiles. Ultimately, at the end of each day, the energy management strategy respects the formulated constraint to guarantee the battery SOC to be as same as its beginning SOC level of a day.

5.1 *Comparison with deterministic model*

In the charging station planning model, there are two sources of uncertainties being considered, the charging load and PV power generation. We define the Case 2 as a deterministic model. In this model, only the hourly average profile is used, and the deviations from the average are not reflected. Thus it is relatively ideal because uncertainties are inevitable in real scenarios. Since the charging load and PV power generation are also fixed, the chance constraints, (23) and (24), in the original problem are eliminated. In Case 2, the four typical PV power profiles are averaged at each time point to produce a 24-hour profile. Applying the same charger option, i.e., P22N15 in Case 1, the calculated sizes of the components in Case 2 are listed in Table 5. Comparing the results of Case 1 and Case 2 particularly show that the battery size is increased in Case 2, while the sizes of PV and transformer are decreased in the same case. This indicates that the uncertainties certainly impact the results of the charging station planning. Although the total cost of the ideal Case 2 is lower, the stochastic model is still beneficial because it is closer to practical situations.

5.2 *Impact of renewable energy source*

Ref. [11, 25] studied the economic benefits of deploying energy storage systems in charging station, but their studied systems lack renewable energy resources. In this study, to show the benefits from integrating renewable energy resource, the solved optimization results of the charging station without installing PV are shown as Case 3. According to the optimal design results, lacking of PV generation power, less amount of battery capacity is used but larger size of transformer is preferred. Compared with Case 1, this case purchases bulk of electricity from the grid which results in higher operation cost. Thus, if PV could be installed, then PV and battery can provide power together during the EV charging period, and larger battery size can be used to store PV power and then be released at next charging period, which could finally reduce the total cost. Therefore, from the perspective of the whole system daily cost, it proves the excellent economy of introducing renewable energy into the design of the charging station.

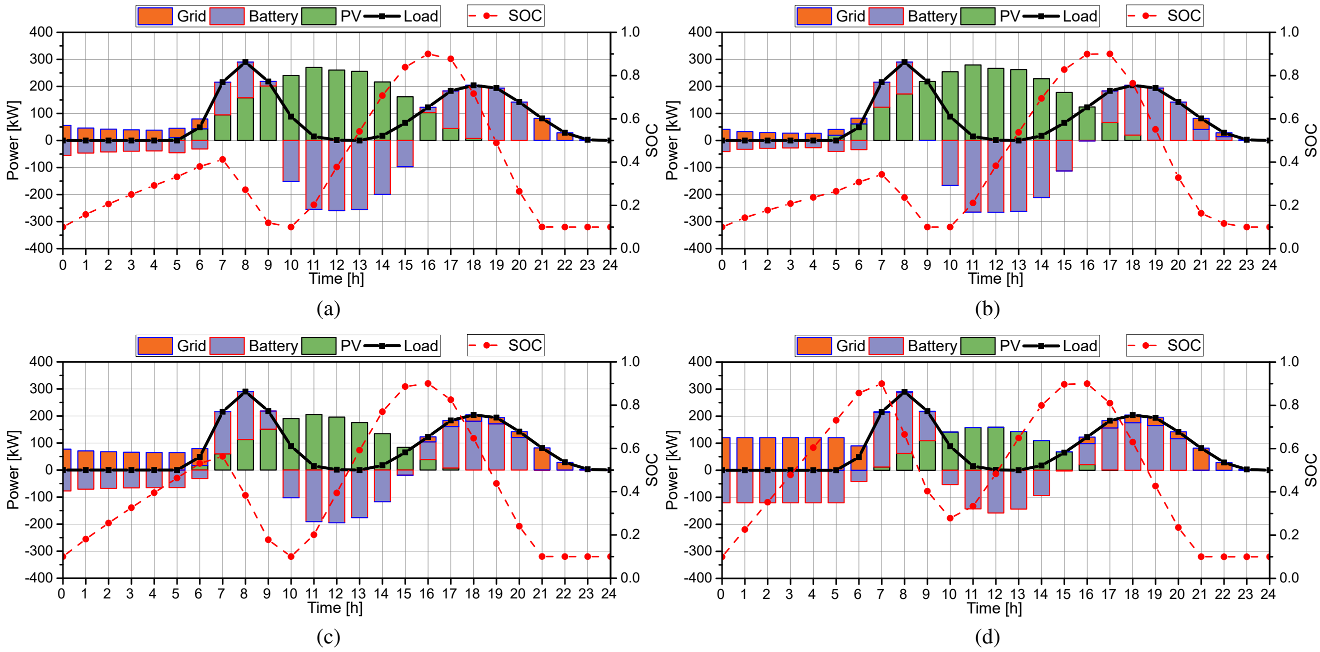


Fig. 10: *Power flow of the charging station with P22N15. (a) Typical spring PV power profile. (b) Typical summer PV power profile. (c) Typical autumn PV power profile. (d) Typical winter PV power profile.*

Table 5 Results of optimal sizing in different cases

	Case 1 Base case	Case 2 Determined PV&load	Case 3 Without PV	Case 4 Lower electricity price	Case 5 Fixed electricity price	Case 6 New charging pattern	Case 7 20% increase of PV cost	Case 8 20% increase of battery cost	Case 9 20% increase of transformer cost	Case 10 20% increase of charger cost
PV(kW)	394.75	346	0	1.75	389.75	500	382.5	396.25	394.75	394.75
Battery(kWh)	907	986	534	0	504	368	913	834	907	907
Transformer(kW)	125	81	155	320	144	118	125	125	125	125
PV cost (USD)	438.01	383.92	0	1.94	432.46	554.79	509.3	439.67	438.01	438.01
Battery cost (USD)	894.58	972.49	526.68	0	497.1	362.96	900.49	987.09	894.58	894.58
Transformer cost (USD)	53.97	34.97	66.93	138.17	62.18	50.95	53.97	53.97	64.77	53.97
Charger cost (USD)	180.82	180.82	180.82	180.82	180.82	180.82	180.82	180.82	180.82	216.99
Operation cost (USD)	-2319.23	-2406.78	-726.16	-72.37	-1311.77	-2435.47	-2310.57	-2242.97	-2319.23	-2319.23
Energy selling to Grid (kWh)	0	0	0	-3.87	-30.79	0	0	0	0	0
Total cost (USD)	-751.85	-834.57	48.28	248.56	-139.21	-1285.95	-665.98	-581.41	-741.06	-715.69

5.3 Comparison with different type of electricity tariff

Since different cities have different electricity tariffs, in order to study the impact of the electricity tariff type on the design of charging station, another two electricity tariffs used in [20] are introduced, as shown in Fig. 11. From the figure, it can be seen that the Austin tariff is lower than PG&E, and the other is a customized fixed electricity tariff. The optimal components sizes and daily costs of the two selected electricity tariffs are defined as Case 4 and 5 shown in Table 5.

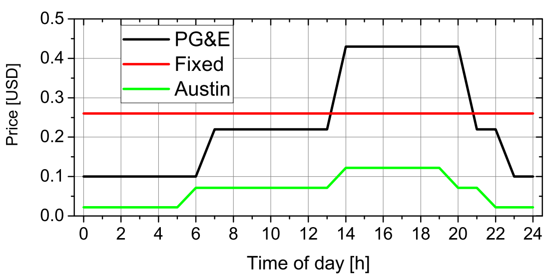


Fig. 11: *Three types of electricity tariff*

Case 4: Among the three different tariffs, it has the maximum transformer capacity, whose capacity is more two times larger than that of Case 1, and the highest operation cost, while the capacity of PV and battery are very less. It can be inferred that since the electricity price of Case 4 is relatively cheap, it is the most economic way to take the grid as the primary energy source. Therefore, the local electricity tariff factor should be seriously considered in the design of charging station

Case 5: The results show the daily cost resulting from fixed price type is in the middle between Case 1 and 4. The PV and battery are beneficial for the charging station resulting in that more PV and battery capacity are needed while transformer capacity is reduced correspondingly.

5.4 Impact of charging demand pattern

Since the optimization results of the charging station are based on the charging demand model, a completely different charging behavior pattern will result in completely different results. The previously generated charging demand based on the charging station has two charging peaks in one day: the peak appears in the morning and in the afternoon. Here one stochastic factor, the start charging time, is changed in this case and other factors remains unchanged, which could generate a new different charging pattern. It is assumed that the charging demand is mainly concentrated between 6 am to 10 pm, and the single charging peak appears around 1pm, which can be described through following probability expression

$$f(t_{ini}) = \frac{1}{\sigma_{t_{ini}}\sqrt{2\pi}} e^{-\frac{(t_{ini}-\mu_{t_{ini}})^2}{2\sigma_{t_{ini}}^2}}. \quad (26)$$

This case is defined as Case 6 in which other conditions and parameters are unchanged. The obtained results are listed in Table 5. In this case more PV are utilized while the size of battery and transformer are decreasing, as well as the least total cost. Such results stem from the shape of charging demand is in line with the PV power profile.

5.5 *Sensitivity of components cost*

The cost of components is another key factor affecting optimization results. Before conducting the sensitivity analysis of component costs, the unit costs value used in Case 1 are firstly considered as the base values. Then, the unit cost of one single component is increased to 120% of its base cost, while the cost of other components remains at the base value. Case 7, 8, 9 and 10 show the results on changing the unit costs of PV, battery, transformer and charger. It can be found that once the costs of PV and battery are increasing their corresponding design sizes are decreased. Comparing the total cost results, it can be found the most sensitive variable is the battery cost, which causes the maximum incremental cost, while the total cost is the least sensitive to the cost of transformer.

6 Conclusion

This paper studied the planing of charging station mainly considering the system uncertainties from the stochastic EV charging demand and PV power generation. Particularly, the charging demand establishment considered many EV charging behavior, charger configuration, and charging assignment model, which made the modeled charging demand of charging station more realistic. A stochastic planning model for EV charging station was then proposed to optimize the component sizes by minimizing the capital cost and simultaneously optimize the operation power flow, which tackled the uncertainties into the technical constraints and objective function. The effectiveness of the proposed model was validated by the case study. The optimal charger option, i.e., the number of chargers and charging level, and the size of PV, battery and transformer were found. A set of case studies for comparison were conducted to examine the major sensitive parameters affecting the charging station planning.

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