Optimal Sizing of A PV Based Electric Vehicle Charging Station Under Uncertainties

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***Abstract*—This paper studies a photovoltaic (PV) based electric vehicle charging station. It consists of multiple energy components: PV panel, battery and transformer. There exist uncertainties inside the system: stochastic charging behavior of electric vehicles (EVs) and intermittent nature of PV power generation, which present challenges to the design of entire system components. In this paper, the EV charging demand model is firstly developed. Then, the optimal components sizing problem of the charging station is formulated to minimize the entire system economic cost. In the problem formulation, the introduced uncertainties are included and converted into the reliability to guarantee. Then, the optimal size for each component is obtained. Results show that equipping PV panel facilitates the charging station to achieve lower economic cost than that of without PV panel.**

***Index Terms*—charging station, electric vehicle, optimal sizing, uncertainties.**

I. Introduction

Nowadays electric vehicles (EVs) are receiving increasing attention from academia and industry due to zero emissions and increasing driving range [1]. However, as the number of electric vehicles increases, it is necessary to establish charging infrastructure to meet the growing charging requirements. In order to meet more charging needs, building more thermal power plants, which will consume more fossil fuels, is unsustainable and harmful to the environment. Recently, renewable energy development and energy storage systems have made great progress and attracted great attention [2]. Therefore, charging station that integrates renewable energy, energy storage and grid-connected devices are beneficial to reduce the grid burden. However, as a result, charging station contains many random factors (such as the random charging behavior of electric vehicles and the uncertainty of renewable energy source), and leads to complex structure, which together challenge the energy management and design of charging station.

Previous studies analyze different types of electric vehicle charging station (EVCS), and they focus on the operation of charging station. A game theory based EVs charing strategy was proposed in [3], where the charging station can dynamically adjust the electricity price to affect the charging power of the EV group. However, renewable energy source was not included in this studied charging station. A PV-grid based workplace charging station was studied in [4], and in the two energy source system it scheduled EVs charging to maximize the use of solar energy as well as reduce the impact on the power grid. Due to the intermittency of PV power generation, battery is introduced in [5] to constitute a PV-battery-grid based charging station, where a decentralized energy management strategy was applied.

In addition to energy management, it is important to design a suitable charging station size that is designed not only to meet the EVs charging needs but also to minimize the economic cost of construction and operation of the charging station. [6] studied a charging station that included two types of power supplies (flywheel energy storage and grid-connected systems). This purpose of the paper is to obtain the optimal energy storage (flywheel) size. To obtain the charging demand profile, PHEV characteristics and the PHEV daily mileage probabilistic property were considered. However, there is no renewable energy resource in the charging station, and the optimization of grid side was not considered. In [7], a more complex charging station was studied, which included three energy sources: PV, battery and grid. To address the optimal battery size problem, it used a typical PV power generation profile, fixed charging SOC range, EV type, and optimal EV charging profile. However, PV power generation varies randomly and depends on temperature and irradiance. And large-scale EV charging will bring different amounts of uncertainty in charging behavior, such as starting charging SOC, EV battery capacity, starting charging time, and departure time.

Therefore, the two mentioned types of uncertainties must be carefully considered in the charging station design. To evaluate the impact of charging demand uncertainty on the charging station, [8] directly utilized the collected charging station load data. Therefore, the method is accurate, however data collection work is expensive and susceptible to specific charging stations. In addition, a variety of probability distributions can be used to characterize random variables. Literature [6] used the survey results of NHTS traditional car daily mileage probability distribution to estimate the daily mileage of EV, and calculated the expected demand for charging as an optimized input, which was also adopted by [9]. However, the average method does not take the variation around the the average into account.

In order to avoid the above problems, this study adopted a modeling method based on probability distribution for charging demand and PV power generation. However, the difference from the above literature is that after the Monte Carlo simulation is used to obtain the distribution result of the charging demand, in addition to the average value of the charging demand, the variance information is also obtained. And in the subsequent capacity optimization, the uncertainty information is converted into reliability processing by the power supplier and the demand side. Also, please note that the charging demand depends not only on the EVs themselves. As a charging service provider, charging station configurations such as the number of charging stations and charging power levels also have an impact, which will also be discussed in this study. And the capacity of PV, battery and transformer are also considered for optimization in the design of the charging station, and the above paper only focuses on the optimization of battery capacity. With the proposed method, the optimal charging station size and the corresponding energy management strategy can be obtained.

II. Uncertainties modelling

The configuration of the PV-battery-grid based EV charging station is shown in Fig. 1. The EV charging power can be supplied by a transformer, a mounted PV panel and a battery, and the charging station can export electricity to the grid. Charging station and EVs interact and restrict each other by chargers. Inside the system, uncertainties come from PV power generation and EV charging behavior, which are also the input of sizing optimization of the charging station. Therefore, it is necessary to model them first.

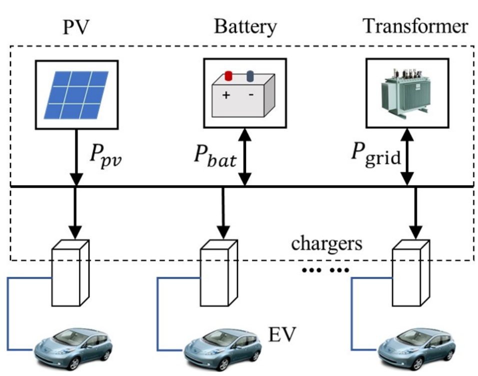

Fig. 1. Architecture of charging station.

A. Charging demand modeling

The EV charging demand profile has a great impact on the operation and size of the charging station. In order to optimize the size of each component of the charging station, it is necessary to establish and analyze a charging demand model. Since the actual charging demand is not deterministic, the fixed constant charging demand profile cannot be directly applied to the energy management and the calculation of the optimal size of the charging station. To model the stochastic charging demand, EV charging behavior (EV start charging time, energy required for charging, initial charging SOC, daily charging EV number) and charging station configuration (charging rate, charging station) charging station number) are considered in detail.

In addition, previous studies do not consider the aspect of chargers and assume that the charging station can satisfy all incoming EV charging demand without rejection, but in reality, the number of chargers in charging station is finite. When the number of arrival EVs is greater than the number of chargers, there will be EVs to be rejected. Therefore, the charging demand load of the charging station is a comprehensive result of the EVs and the chargers, and it is necessary to consider them in the model.

1) EV charging behavior: Since EV charging behavior is highly random, a common method of establishing correlation uncertainty is to use statistics and probability theory. Some papers based on NHTS survey data to establish a probability distribution model based on the daily use of vehicles [6]. In addition, in [10], the number of PHEVs in a given hour in the charging station and the uncertainty of the initial SOC of the PHEV battery are simulated using a normal distribution function. Similarly, this paper models the relevant EV charging random variables according to the probability distribution model. First, it is assumed that in this study the start charging SOC of EV ranges from 0.2 to 0.5, and it obeys a Gaussian distribution, which can be expressed as follows:

$$f(SOC_{ini}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(SOC_{ini}-\mu)^2}{2\sigma^2}}, \tag{1}$$

where mean value μ =0.35 and standard variance $\sigma = 0.075$, and the setting method refers to [11].

Second, you need to determine the start charging time of the EV. The EV start charging time is related to the time the driver arrives at the charging station, and it is assumed that the driver is charged immediately upon arrival. Here, EVCS is supposed to be open during the day to provide charging services to the public, as people usually drive to the workplace during the day and go home in the afternoon. The start charging time can then be modeled as a Gaussian distribution shown as follows:

$$f(t_{ini}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t_{ini}-\mu_t)^2}{2\sigma_t^2}}. \tag{2}$$

This distribution is defined by two parameters: the average arrival time μ_t and the standard variance σ_t.

The EV battery capacities on the market are various. According to [12] and market product survey, most battery capacities range from 16 kWh to 80 kWh. Therefore, the arriving EV battery capacity is randomly distributed, according to the Gaussian distribution (μ_c and σ_c) as follows:

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

Similarly, the number of EVs that are charged every day is also random, so it is also modeled as a Gaussian distribution (μ_n and σ_n):

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

2) Charging Station Configuration: Configuration of charging station will affect the charging demand in two ways: the number of chargers and the charging power. In the case where many EVs come to the charging station for charging but the number of chargers is finite, if the number of upcoming EVs is greater than the number of unoccupied chargers, this will definitely cause some EVs to be rejected. Therefore, a mechanism needs to be devised to determine which EV will be rejected. To solve the problem, a queueing model for arriving at the EV is established. In the queuing model, all EVs are sorted and labeled in order, and if the number of EVs present at the same time is greater than the number of available chargers, the EVs that follow will automatically leave and go to the next charging station. In this algorithm, the arriving EV will access the available charger at each time according to the given charger serial number until it finds an empty charger. Otherwise, this EV will be rejected. Regarding the charging power, since the charging rate is determined by the charging power of the charger, the higher charging power can shorten the charging period while increasing the charging load. According to the charging standard SAE J1772, three current charging levels are currently used for electric vehicles. Class 1 works at 120 VAC, 1.4 kW, Class 2 operates at 208 or 240 VAC, 7.2 kW, and Class 3 operates at 200 to 450 VDC, with maximum 200 kW. EVs are usually equipped with an onboard level 1 charger, and level 2 and level 3 chargers are usually equipped at the charging station.

Once the relevant random number: start charging SOC, start charging time, EV battery capacity, number of arriving EVs, and charging station configuration: the number of chargers and the charge level are all fully determined, then the EVCS total charge demand load at each moment can be calculated by:

$$P_{evcs}(k) = \sum_{c=1}^{m} P_{charger,c}(t), \tag{5}$$

where k represents the time instant, c represents the cth charger, P_{evcs} is the total charging demand load of EVCS, and $P_{charger,c}$ represents the charging power of the cth charger.

To show the effect of the proposed charging demand modeling method, it is assumed that one EVCS is equipped with four chargers with a charging power of 40 kW, and the daily charging demand of the EVCS generated by a random simulation is shown in Fig.2. Then Monte Carlo simulation can be applied to repeat the sampling from the probability distributions of these related random variables to obtain the distribution of charging demand.

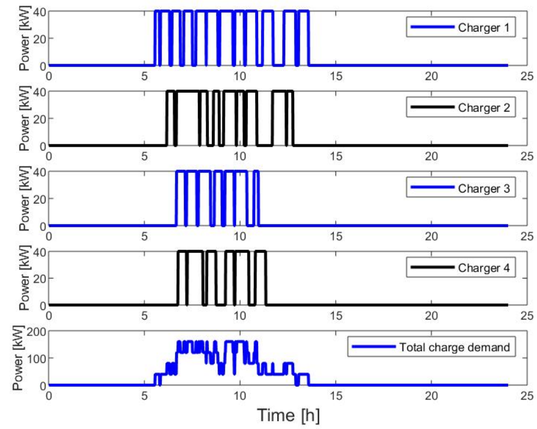

Fig. 2. One year power generation profile of a PV unit

B. PV power generation

The output power generation of the PV panels can be evaluated by the following equation [13]:

$$P_{pv} = G_i A_{pv} \eta_{pv}, \tag{6}$$

where G_i is the global solar irradiance, A_{pv} is the installed PV surface, and η is the conversion efficiency of the PV system. The area of the PV unit used in this study is 1.46 m^2, and the conversion efficiency is 17%. The output power under the clear-sky model is shown in Fig.3. Overall it can be seen the PV output power is uncertain, which is related to the season and the time of day. In summer, the power generation is the highest, and the power generation time is longer than other time periods.

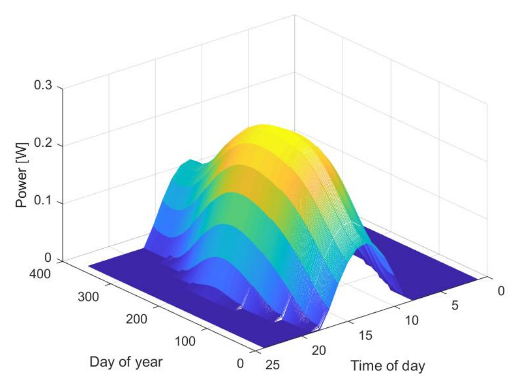

Fig. 3. One year power generation profile of a PV unit.

III. Components size optimization

From the point of view of the charging station owner, the planning of the charging station needs to consider the minimization of the economic costs including investment costs and operation costs. In this study, the charging station is composed of multiple energy sources, so the investment cost should be fully considered in relation to solar panel size, battery storage size and transformer size. The operation costs primarily include electricity purchase costs from the main grid, which relates to the energy management strategy. Therefore, the optimal sizing problem combined with optimal economic energy management strategy can be formulated as follows:

$$\min c_s \cdot s + c_b \cdot b + c_{ts} \cdot ts + \sum_{k=1}^{N} c_g(k) \cdot P_G(k), \quad (7)$$

where c_s represents the unit cost of solar panel in USD/kW, c_b denotes the unit cost of battery in USD/kWh, c_{ts} means the unit cost of solar panel in USD/kW, $c_g(k)$ represents the electricity tariff at time instant k, and $G(k)$, s, b, ts are optimization variables and their meaning are electric power at time instant k, PV panel size, battery size and transform size, respectively.

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

$$s \cdot P_{pv}(k) + P_{bat}(k) + P_g(k) = P_l(k), \quad (8)$$

where $P_{pv}(k)$,$P_{bat}(k)$,$P_g(k)$ and $P_{l,k}$ are the generation power of PV panels, the the power from battery, the electric power from main grid, and the charging demand load from EVs at time instant k, respectively.

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

$$E_{bat}(k+1) = E_{bat}(k) - (P_{bat}(k) + \eta|P_{bat}(k)|)\Delta t, \quad (9)$$

$$E_{bat,0} = E_{bat,ini}, \quad (10)$$

where $E_{bat}(k)$ indicates the battery energy state at time k and $E_{bat,ini}$ is the initial energy. Battery power $P_{bat}(k)$ value can be either negative (charging) or positive (namely discharging). η is the lost efficiency of battery, which is assumed constant since lithium-ion battery is characterised by high efficiency. In addition, the battery power $P_{bat}(k)$ and $E_{bat}(k)$ are limited by the following inequality constraints

$$E_{bat,min} \leq E_{bat}(k) \leq E_{bat,max}, \quad (11)$$

$$P_{bat,min} \leq P_{bat}(k) \leq P_{bat,max}, \quad (12)$$

where $E_{bat,min}$ and $E_{bat,max}$ are the minimum and maximum energy levels, here we separately set the limits by 20% and 95% of the nominal energy and this range is beneficial for battery to maintain stable voltage. $P_{bat,min}$ and $P_{bat,max}$ are the permitted maximum charging power and maximum discharge power.

The grid power cannot exceed the maximum power of transformer:

$$P_{g,min} \leq P_g(k) \leq P_{g,max}, \quad (13)$$

where $P_{g,min}$ and $P_{g,max}$ are the maximum allowable export power and maximum import power. In this study, the charging station is allowed to provide power to the main grid.

In addition, the design variables: PV panel size, battery size and transformer size are subject to:

$$s_{min} \leq s \leq s_{max}, \quad (14)$$

$$b_{min} \leq b \leq b_{max}, \quad (15)$$

$$ts_{min} \leq ts \leq ts_{max}. \quad (16)$$

For the objective function (7) of the optimization problem, the optimization variables s, b and ts are limited to integer, then the problem becomes a mixed integer linear programming problem (MILP).

However, in Equ. (8), the charge demand load P_l and the PV power generation P_{pv} are uncertain quantities. Therefore, the optimization problem becomes to optimize the component size while scheduling the system power flow under uncertainty. Based on the proposed charging demand modeling method of EVCS, and using Monte Carlo simulation to simulate a certain number of times, after the statistical probability analysis, the generated charging demand load $P_l(k)$ can be expressed by a Gaussian distribution:

$$P_l \sim N(\overline{P}_l(k), \sigma^2_{P_l}(k)), \quad (17)$$

where $\overline{P}_l(k)$ is the mean value of charging demand load and $\sigma^2_{P_l}(k)$ is the variance.

For example, if the finite number of chargers is 20 and the charging power of charger is Level 2. And the mentioned uncertainty quantities are sampled from their specified distributions. The charging end condition is when the SOC of each EV reaches 95%. After 200 Monte Carlo simulations, it means that there are 200 data points at each time instant, and then their distribution is described by a Gaussian distribution with ($\overline{P}_l(k)$,$\sigma^2_{P_l}(k)$). Those parameter value at each time instant are shown in Fig. 4 (a).

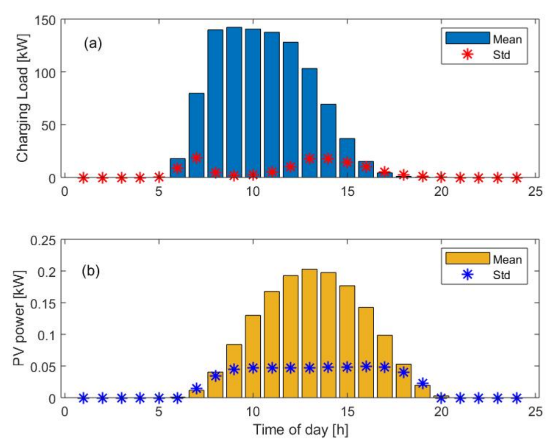

Fig. 4. Gaussian distribution parameter at each time instant: (a) Charging demand, (b) PV power.

Likewise, the PV module power generation data can also be treated as:

$$P_{pv} \sim N(\overline{P}_{pv}(k), \sigma^2_{pv}(k)), \quad (18)$$

where $\overline{P}_{pv}(k)$ is the mean value of PV generation power and $\sigma^2_{P_l}(k)$ is the variance. The calculated parameter is shown as Fig. 4 (b).

Once the uncertainties are determined, then the right inequality of constraint (13), namely the upper bound, can be converted into chance constraint:

$$\Pr(P_l(k) - s \cdot P_{pv}(k) \leq P_{bat}(k) + P_{g,max}) \geq \alpha, \quad (19)$$

where α is a constant parameter meaning reliability. The higher the α value, the higher the reliability that the system can guarantee.

The normal CDF can be obtained by converting the chance constraint shown as follows:

$$\Phi(\frac{-\overline{P_l}(k) + s \cdot \overline{P_{pv}}(k) + P_{bat}(k) + P_{g,max}}{\sigma^2_{P_l}(k) + s^2\sigma^2_{P_{pv}}(k)}) \geq \alpha. \quad (20)$$

Then the upper bound constraint can be rewritten as:

$$\sqrt{\sigma^2_{P_{pv}}(k) \cdot s^2 + \sigma^2_{P_l}(k)} \leq \frac{1}{\Phi^{-1}(\alpha)}(s \cdot P_{pv}(k) + P_{bat}(k) - P_l(k) + P_{g,max}). \quad (21)$$

And the lower bound constraint is rearranged as:

$$\sqrt{\sigma^2_{P_{pv}}(k) \cdot s^2 + \sigma^2_{P_l}(k)} \leq \frac{1}{\Phi^{-1}(\alpha)}(-s \cdot P_{pv}(k) - P_{bat}(k) + P_l(k) + P_{g,max}). \quad (22)$$

Because the two above inequalities form a second order cone constraints, the original size optimization problem is transformed into a second order cone program problem, which actually is convex. So convex optimization tool can be used to solve it and the advantage of convex problem is the solution of the problem can be guaranteed to be existence and unique.

IV. Results and Analysis

This section will present the optimal size results of the three components through the proposed method, and analyze the effects of different parameters on the results.

Technical parameters used in the simulation are summarized in the Table. I.

TABLE I
TECHNICAL PARAMETERS USED IN THE SIMULATION.

Parameter	Value	Unit
PV cost	500	USD/kW
Battery cost	400	USD/kWh
Transformer cost	1000	USD/kW
PV design life	10	Year
Battery design life	5	Year
Transformer design life	10	Year
Battery module energy	200	kWh
Battery module permitted power	200	kW
Reliability coefficient	0.9	NAN
PV size range	0-1200	Unit
Battery size range	0-4	Module
Battery SOC range	0.1-0.9	NAN
Transformer size range	0-200	kW

Using the uncertainties' simulation results as shown in Fig.4 and incorporate them into the optimization method, the optimal components size can be solved. The optimal results of the sizes of those components are: 3 battery modules (600 kWh), 1200 PV units (300kW) and the transformer with 200 kW, respectively. Meanwhile, the optimization results can provide the optimal system power flow shown in Fig. 5. A time of use electricity tariff is used in the simulation, which includes the peak hour, middle peak hour and off-peak hour periods. It can be found that when the charging station charges EVs from 5 am, at this early stage, since the PV power generation amount is less than the charging demand, the PV, the battery and the main power grid together provide charging power for the EV. As PV power generation increases, the battery absorbs additional PV power generation, while the remaining power is fed back to the grid. During the peak hours from 3 pm to 8 pm, the charging station releases energy from the battery to arbitrage. The battery is then recharged to the initial SOC at the end of the day. Through a day's operation, the optimal cumulative cost is -0.012 USD, which means that the charging station can even make a profit according to this energy management strategy.

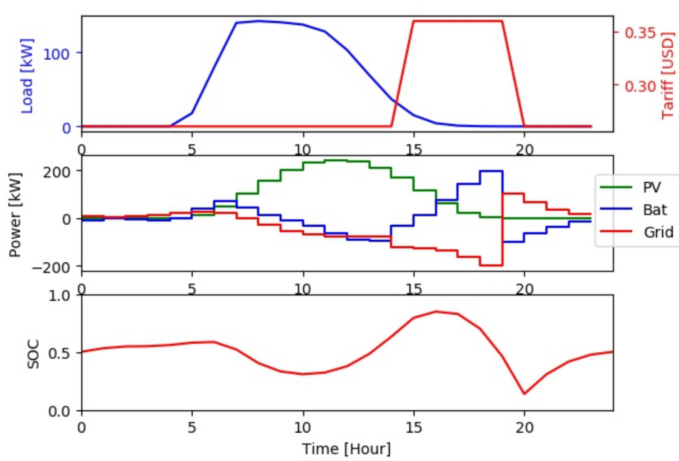

Fig. 5. Power flow in the charging station.

Some studies have focused on the economic benefits of deploying energy storage systems, and most of their systems do not involve renewable generators. The component size optimization results for charging stations without PV power generation are: 4 battery modules (800 kWh) and 200 kW transformers. Its optimal power flow is shown in Fig. 6. However, the optimal cost is 238.43 USD, which is much higher than the results including PV systems. It demonstrates the significance of taking all of components into account in the design of the charging station.

V. Conclusion

In this paper the optimal components' sizing of an electric vehicle charging station is solved, which consists of the PV

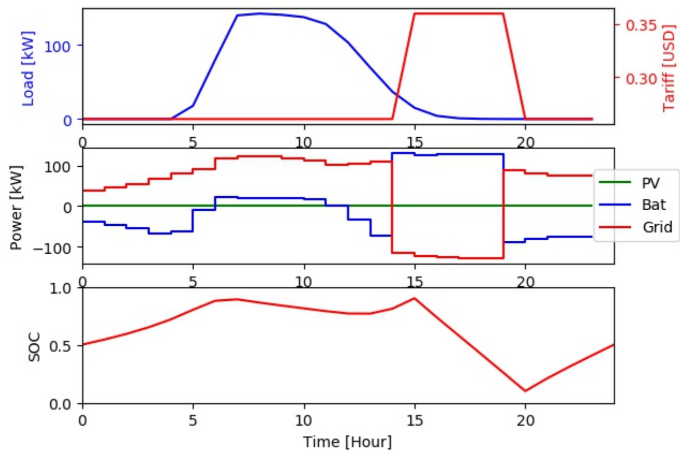

Fig. 6. Power flow in the charging station without PV system.

array, the battery, and the transformer. Considering the size of charging station can be greatly affected by the EV charging demand, the EV charging demand model is established before formulating the optimization problem. To address the problem that the charging demand is not deterministic, several related uncertain quantities are involved: EV starting charging time, start charging SOC, EV battery capacity and the number of arriving EVs, which are modeled according to their assumed probability distribution function. The charging demand stochastic is obtained through Monte Carlo simulation. Then, the sizing optimization problem is formulated to minimize the investment cost and operation cost, and the uncertainties are included in the problem. The solved results show a preference for large PV array and transformer size. While for the case that does not equipped with PV array, the final system cost is higher than that of including PV system, which indicates equipping the PV array can effectively reduce the cost of the charging station.

In the future work, the number of chargers will also be considered to optimize, and the impacts of other parameters such as different electricity tariff, charging pattern, and different component costs, will be deeply studied.

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