2017 Twelfth International Conference on Ecological Vehicles and Renewable Energies (EVER)

Placement of EV Charging Stations Integrated with PV Generation and Battery Storage

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***Abstract*— This paper introduces an optimal way to configure a grid-connected charging station for electric vehicles (EVs), in which the photovoltaic (PV) generation and local battery storage are integrated. The proposed method aims at generating the optimum combination of EV chargers, PV panels and local batteries, while considering: 1) EV mobility and uncertainties (PV generation, electricity price, etc.); 2) the impact on the grid; and 3) stochastic charging demand from EVs. The Erlang-loss system and the stochastic programming are adopted to model the EV mobility and uncertainties. Besides, the attribute sets as well as the clustering-based scenario generation method are proposed to generate necessary scenarios for stochastic programming. Finally, numerical experiments are conducted to validate the effectiveness of the proposed approach and show the impact of different factors on the final placement scheme.**

Keywords*—electric vehicle; photovoltaic generation; battery storage; charging station placement.

I. INTRODUCTION

As an environmentally friendly transportation technology, EVs are offering promising potentials for improving the power system reliability and flexibility [1-3]. The EV market has been growing in a fast pace [4], and thus leading to a pressing need of charging stations, especially due to the limited energy capacity of EV batteries. Since the rapid growth of the renewable generation has already created difficulties in the power system operation, the integration of large numbers of charging stations may further burden the power grid if not planned appropriately.

Fortunately, the controllability of the EV charging station can more or less compensate for the negative impact caused by the variability of the renewable generation. Therefore, the coordination among them, with the help of the local battery storage, can benefit the power system operation [5]. One of the easiest way to enable this collaboration is to establish a charging station integrated with renewable generation and local battery storage.

A few studies have been found referencing charging station planning [6-12], in which the optimal sizing and siting of charging stations, from the system operators' points of view, is discussed. Those approaches do not pay much attention to the detailed configuration of a single charging station or the integration of the renewable generation. References [13-19] present the optimal design of the charging station with battery storage: [13, 14] provide some general information on the design requirement and schemes for the charging station; battery size is optimized in [15] for a renewable-powered charging station; minimization of the impact on the grid is the main focus of [16]; [17, 18] focus on optimizing the battery size and charger size, respectively, with the modeling of EV mobility through queuing theory; simulation based method for the optimal design of the charging station is adopted in [19]. References [20, 21] show the optimal combination of the wind and PV generation for a stand-alone charging station. However, neither EV mobility nor uncertainties are considered in most of the aforementioned works. Moreover, those works mainly aim at optimizing just one or a few components, not the entire system solution.

This paper proposes a placement planning scheme to co-optimize all the components including EV chargers, PV panels as well as local battery storage in a single charging station, with the consideration of their collaboration, as shown in Fig.1. Different from the previous studies, the impacts on the grid, EV mobility, and uncertainties of the EV charging needs are taken into account in this co-optimization problem. The attribute sets as well as the clustering-based scenario generation method are proposed to create scenarios for stochastic programming, which is adopted to model uncertainties.

The rest of the paper is organized as follows: Section II introduces the Erlang-loss system and the modeling of the EV mobility; Section III presents the placement scheme to calculate the optimal combination of EV chargers, PV panels and battery cells; The linearization process and the scenario generation for the proposed model are discussed in Section IV; Numerical experiments are conducted in Section V and the results under different scenarios are listed to show how the placement planning scheme gets

This publication was made possible by NPRP 8-241-2-095 award from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors.

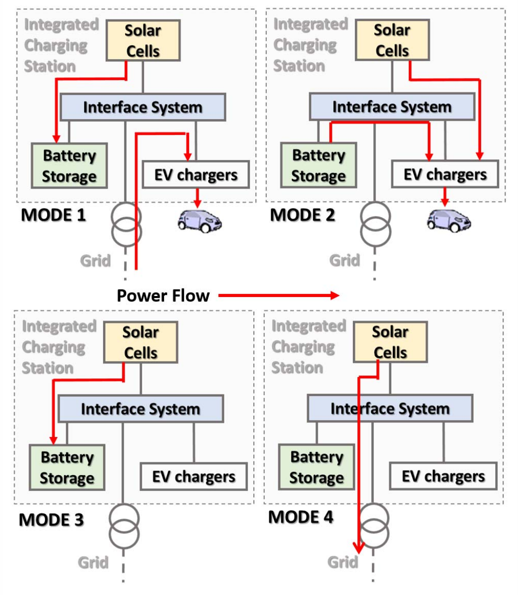

Fig. 1: Illustration on the collaboration among different elements.

affected by different factors; Finally, Section VI lists the contributions of this paper.

II. EV MOBILITY MODELING

The mobility of EVs in a charging station can be modeled through an *M/M/n/n* Queue (Erlang-loss system), by assuming EVs' arrivals are in Poisson processes and their charging times are exponentially distributed. The new customer will be lost if all of the n EV chargers are busy. According to [22], two of the most important measures, which will also be adopted in the planning process, are: 1) the probability of the charging station being full (denoted as P_{block}), as shown in (1); and 2) the mean number of customers (denoted as $\overline{M}$) in the charging station, as modeled in (2).

$$P_{block}(\lambda,\mu,N)=\left[(\lambda/\mu)^N/N!\right]^{-1}\times\left[\sum_{t=0}^{N}(\lambda/\mu)^t/t!\right] \tag{1}$$

$$\overline{M}(\lambda,\mu,N)=(\lambda/\mu)\times\left[1-P_{block}(\lambda,\mu,N)\right] \tag{2}$$

Where λ is EV arriving rate, μ is EV charging rate, and N is the total number of chargers in the charging station.

III. CHARGING STATION PLACEMENT PLANNING SCHEME

The placement scheme aims at minimizing the total cost, through the optimal combination of the numbers of EV chargers, PV panels and battery cells. Stochastic optimization is adopted in order to consider different uncertainties.

A. *Objective Function*

The total cost of the charging station consists of the capital cost, which includes the initial investment cost G_{in} and the maintenance cost G_m, and the operation cost G_{op}, as presented in (3), (4) and (5) respectively. The total objective function is shown in (6).

$$G_{in}=\left(N_{pv}C_{pv\_in}+N_{bs}C_{bs\_in}+N_{ch}C_{ch\_in}\right)\times\frac{r(1+r)^{L_p}}{(1+r)^{L_p}-1} \tag{3}$$

$$G_m=N_{pv}C_{pv\_m}+N_{bs}C_{bs\_m}+N_{ch}C_{ch\_m} \tag{4}$$

$$G_{op,i}^j=\begin{bmatrix}-R_{E,i}^j p_{e,i}^j+C_{Bdis}p_{Bdis,i}^j+C_{EVdis}p_{EVdis,i}^j-R_{EVch,i}^j p_{EVch,i}^j\\+\varepsilon_B\left(p_{Bdis,i}^j+p_{Bch,i}^j\right)+\varepsilon_{EV}\left(p_{EVdis,i}^j+p_{EVch,i}^j\right)\end{bmatrix} \tag{5}$$

$$obj=\min\left[G_{in}+G_m+\sum_{j\in\{S\}}P_{rob}^j\sum_{i=1}^{T}G_{op,i}^j\right] \tag{6}$$

Where N_{pv}, N_{bs}, and N_{ch} are the numbers of the battery cells, the PV panels and the EV chargers; C_{pv_in}, C_{bs_in}, and C_{ch_in} are the unit investment cost of the PV panel, battery and EV charger respectively; L_p is the project lifetime; r is the interest rate; C_{pv_m}, C_{bs_m}, and C_{ch_m} are unit maintenance cost of the PV panel, battery and EV charger respectively; R_E is energy price; p_e is the energy exchange between the charging station and the grid; C_{Bdis}, C_{EVdis} are the discharging cost of battery and EV respectively; p_{Bdis}, p_{Bch}, p_{EVdis}, p_{EVch} are battery/EV dis-charging/charging power respectively; ε_{EV}, ε_B are unit cost of battery degradation for EV/fixed battery respectively; R_{EVch} is EV charging price; $\{S\}$ is the uncertainty set to consider different scenarios regarding to uncertainties; P^j_{rob} is the probability of the j^{th} scenario; T is number of time durations.

Note that the investment cost needs to be converted and allocated into the unit planning period, say 1 year [23]; and the battery degradation cost is modeled through the coefficients ε_{EV} and ε_B [24].

B. *Power Balance Requirement*

The power among EV chargers, local battery storage, PV generation as well as the power grid should be balanced all the time, as modeled in (7), where P_{solar} is the PV generation of a unit PV panel. It becomes an inequality considering the PV generation can be curtailed if needed.

$$0\le-\begin{pmatrix}p_{Bdis,i}^j-p_{Bch,i}^j+p_{EVdis,i}^j\\-p_{EVch,i}^j-p_{e,i}^j\end{pmatrix}\le N_{pv}P_{solar,i}^j,\quad i\in T,\ j\in S \tag{7}$$

C. *Local Battery Dynamics Modeling*

The dynamics of the local battery are modeled in (8) – (10). Equation (8) models the relationship between the (dis)charging power and the SOC of local batteries; (9) gives the limitation of the total SOC of each moment; (10) sets the requirement of battery's SOC at some points of time.

$$E_{B,i-1}^{j}-E_{B,i}^{j}=\left(\frac{1}{\eta_B^{+}}p_{Bdis,i}^{j}-\eta_B^{-}p_{Bch,i}^{j}\right),\quad i\in T,\ j\in S \tag{8}$$

where $E_{B0}^{j}=N_{bs}u_{bs}E_{B0\_p}^{j}$

$$N_{bs}u_{bs}E_{Bup}^{\min}\le E_{B,i}^{j}\le N_{bs}u_{bs}E_{Bup}^{\max},\quad i\in T,\ j\in S \tag{9}$$

$$E_B^j\Big|_{i=t_k}\ge E_{B0p}^{j}N_{bs}u_{bs},\quad t_k\in\{T_k\},\ j\in S \tag{10}$$

Where E_B is the total SOC of local battery storage; η_B^{+}, η_B^{-} are the discharging and charging efficiency of local battery; E^j_{B0} is the initial SOC of the local battery storage under scenario j, which should be related to the number of battery cells; u_{bs} is the unit energy capacity of a battery cell; $E^j_{B0\_p}$ is the initial energy percentage of the local battery storage under scenario j; $E_{Bup}^{\min}$, $E_{Bup}^{\max}$ are the minimum and maximum SOC percentage of the local battery storage; $\{T_k\}$ is a set to collect the time steps when the SOC of the local battery storage needs to be regulated.

D. EV Battery Dynamics Modeling

Equations (11) – (14) model the dynamics within EV batteries. Equation (11) models the relationship between the (dis)charging power and SOC of EV batteries; (12) models the energy need from all EVs during periods of time. Different from the local battery, EVs are moving, and therefore it is hard to set the limitation on their total SOC at each moment. However, it is possible to model the difference between two successive SOCs, as shown in (13). Equation (14) shows that the aggregated EV power cannot be both positive and negative at the same time, which is in a quadratic form. EVs' mobility is considered in (12) and (13), where $P^j_{block,i}(\lambda_i^j,\mu_i^j,N_{ch})$ and $\overline{M_i^j}(\lambda_i^j,\mu_i^j,N_{ch})$ are calculated through (1) and (2).

$$E_{EV,i-1}^{j}-E_{EV,i}^{j}=\left(\frac{1}{\eta_{EV}^{+}}p_{EVdis,i}^{j}-\eta_{EV}^{-}p_{EVch,i}^{j}\right),\quad i\in T,\ j\in S \tag{11}$$

$$E_{EV}^{j}\Big|_{i=t_p}\ge\overline{D_{EV}}\sum_{i=t_{p-1}+1}^{t_p}\left\{\lambda_i^j\left[1-P_{block,i}^{j}\left(\lambda_i^j,\mu_i^j,N_{ch}\right)\right]\right\}+E_{EV0},\quad t_p\in\{T_p\},\ j\in S \tag{12}$$

$$\begin{aligned}-\left(1-\delta_{EV,i}^{j}\right)\cdot\overline{B_{CEV}}\cdot\overline{M_i^j}\left(\lambda_i^j,\mu_i^j,N_{ch}\right)&\le E_{EV,i-1}^{j}-E_{EV,i}^{j}\\&\le\delta_{EV,i}^{j}\cdot\overline{B_{CEV}}\cdot\overline{M_i^j}\left(\lambda_i^j,\mu_i^j,N_{ch}\right),\quad i\in T,\ j\in S\end{aligned} \tag{13}$$

$$p_{EVdis,i}^{j}\times p_{EVch,i}^{j}=0,\quad i\in T,\ j\in S \tag{14}$$

Where $E^j_{EV,i}$ is the energy that is provided to EVs; η_{EV}^{+}, η_{EV}^{-} are (dis)charging efficiency of EV (chargers); $\overline{D_{EV}}$ is the average energy need of a single EV; $\delta^j_{EV,i}$ is the utilization factor of EV battery; $\overline{B_{CEV}}$ is the average battery capacity of a single EV; $\{T_p\}$ is a set to collect the time steps when energy provided to EVs needs to be regulated.

E. Impact on the Grid

In this planning problem, we decide to restrict the impact of the charging station on the grid through limiting its power scale, as presented in (14).

$$p_{\min}\le p_{e,i}^{j}\le p_{\max},\quad i\in T,\ j\in S \tag{14}$$

Where $p_{\min}$, $p_{\max}$ are the minimum and maximum power exchange between the charging station and the power grid.

The selection of $p_{\min}$ and $p_{\max}$ mainly depends on: 1) the capacity of the feeder that is connected to the charging station; 2) the limitation on the voltage amplitude of the bus where the charging station is located. The relationship between the exchanging power of the charging station and the voltage on the bus can be approximated through (15), where the matrix $\mathbf{\Lambda}$ is calculated through (16) [25].

$$V_i=V_i^0+\begin{bmatrix}\left(Z_{i2}-Z_{i1}\frac{Z_{12}}{Z_{11}}\right)\\\left(Z_{i3}-Z_{i1}\frac{Z_{13}}{Z_{11}}\right)\\\vdots\\\left(Z_{im}-Z_{i1}\frac{Z_{1m}}{Z_{11}}\right)\end{bmatrix}^{\mathrm{T}}\times\mathbf{\Lambda}^{-1}\times\begin{bmatrix}\left(Z_{21}\frac{Z_{1i}}{Z_{11}}-Z_{2i}\right)\\\left(Z_{31}\frac{Z_{1i}}{Z_{11}}-Z_{3i}\right)\\\vdots\\\left(Z_{21}\frac{Z_{1i}}{Z_{11}}-Z_{2i}\right)\end{bmatrix}\times\frac{p_e}{V_i^*}+\left(Z_{ii}-Z_{i1}\frac{Z_{1i}}{Z_{11}}\right)\times\frac{p_e}{V_i^*} \tag{15}$$

$$\mathbf{\Lambda}=\begin{bmatrix}\left(Z_{22}-Z_{21}\frac{Z_{12}}{Z_{11}}\right)&\left(Z_{23}-Z_{21}\frac{Z_{13}}{Z_{11}}\right)&\cdots&\left(Z_{2m}-Z_{21}\frac{Z_{1m}}{Z_{11}}\right)\\\left(Z_{32}-Z_{31}\frac{Z_{12}}{Z_{11}}\right)&\left(Z_{33}-Z_{31}\frac{Z_{13}}{Z_{11}}\right)&\cdots&\left(Z_{3m}-Z_{31}\frac{Z_{1m}}{Z_{11}}\right)\\\vdots&\vdots&\ddots&\vdots\\\left(Z_{m2}-Z_{m1}\frac{Z_{12}}{Z_{11}}\right)&\left(Z_{m3}-Z_{m1}\frac{Z_{13}}{Z_{11}}\right)&\cdots&\left(Z_{mm}-Z_{m1}\frac{Z_{1m}}{Z_{11}}\right)\end{bmatrix} \tag{16}$$

Where V_i^0 is the original voltage without introducing the charging station; Z_{ij} is the element of the impedance matrix of the system with n buses ($n\ge m$); and bus 1 is selected as the slack bus while buses 2 to m are all the PV buses.

The corresponding $p_{\min\_V}$ and $p_{\max\_V}$ can be calculated by limiting the amplitude of the voltage after the relationship between the voltage and the power is obtained. Therefore, $p_{\min}$, $p_{\max}$ can be determined through (17) and (18), where $p_{\max\_C}$ is the feeder capacity.

$$p_{\min}=\max\left(p_{\min\_V},-p_{\max\_C}\right) \tag{17}$$

$$p_{\max}=\min\left(p_{\max\_V},p_{\max\_C}\right) \tag{18}$$

F. Capacity Limitation Modeling

The numbers of PV panels, EV chargers and battery cells are also restrained by the available spaces for each other, as modeled in (19) – (21).

$$0 \le N_{pv} \le \lfloor S_{pv}/S_{pv,u} \rfloor \alpha_{pv} \tag{19}$$

$$0 \le N_{bs} \le \lfloor S_{bs}/S_{bs,u} \rfloor \tag{20}$$

$$0 \le N_{ch} \le \lfloor S_{ch}/S_{ch,u} \rfloor \tag{21}$$

Where $\lfloor x \rfloor = \max\{n \in Z | n \le x\}$; S_{pv}, S_{bs} and S_{ch} are the available areas to install PV panels, battery cells and EV chargers; $S_{pv,u}$, $S_{bs,u}$ and $S_{ch,u}$ are the sizes of a single PV panel, battery cell and EV charger; α_{pv} is the coefficient to consider the possible shadow area in the given region.

G. Charging/Discharging Modeling

The (dis)charging limits of both EVs as well as local batteries are modeled through (22) – (27). Note that the limitation on EV (dis)charging is also related to the number of EVs in the system in addition to the total power capacity of all EV chargers to be installed in the charging station.

$$0 \le p^j_{EVdis,i} \le p^{\max}_{ch,dis\_u} \cdot \overline{M}^j_i \left(\lambda^j_i, \mu^j_i, N_{ch}\right), \quad i \in T, j \in S \tag{22}$$

$$0 \le p^j_{EVch,i} \le p^{\max}_{ch,ch\_u} \cdot \overline{M}^j_i \left(\lambda^j_i, \mu^j_i, N_{ch}\right), \quad i \in T, j \in S \tag{23}$$

$$0 \le p^j_{EVdis,i} \le N_{ch} p^{\max}_{ch,dis\_u}, \quad i \in T, j \in S \tag{24}$$

$$0 \le p^j_{EVch,i} \le N_{ch} p^{\max}_{ch,ch\_u}, \quad i \in T, j \in S \tag{25}$$

$$0 \le p^j_{Bdis,i} \le N_{bs} p^{\max}_{B,dis\_u}, \quad i \in T, j \in S \tag{26}$$

$$0 \le p^j_{Bch,i} \le N_{bs} p^{\max}_{B,ch\_u}, \quad i \in T, j \in S \tag{27}$$

IV. LINEARIZATION AND SCENARIO GENERATION

A. Model Linearization

The optimization model proposed above is nonlinear, and its nonlinearity lies in: 1) the involvement of non-linear functions $P^j_{block,i}(\lambda^j_i,\mu^j_i,N_{ch})$ and $\overline{M}^j_i(\lambda^j_i,\mu^j_i,N_{ch})$; and 2) the quadratic form of constraint (14).

By replacing (14) with (28) to (31), we can transform the quadratic constraint into linear forms, where $x^j_{EVdis,i}$ and $x^j_{EVch,i}$ indicate the status of EV discharging and charging.

$$0 \le p^j_{EVdis,i} \le n_{\max\_charger} p^{\max}_{ch,dis\_u} x^j_{EVdis,i}, \quad i \in T, j \in S \tag{28}$$

$$0 \le p^j_{EVch,i} \le n_{\max\_charger} p^{\max}_{ch,ch\_u} x^j_{EVch,i}, \quad i \in T, j \in S \tag{29}$$

$$x^j_{EVdis,i} + x^j_{EVch,i} \le 1, \quad i \in T, j \in S \tag{30}$$

$$x^j_{EVdis,i}, x^j_{EVch,i} = 0 \text{ or } 1, \quad i \in T, j \in S \tag{31}$$

Meanwhile, (32) to (34) can be added to linearize the functions $P^j_{block,i}(\lambda^j_i,\mu^j_i,N_{ch})$ and $\overline{M}^j_i(\lambda^j_i,\mu^j_i,N_{ch})$, where N_{max} is the maximum number of chargers that can be installed, and $n_{ch,k} = 1, 2, \ldots, N_{max}$.

$$N_{ch} = \sum_{k=1}^{N_{\max}} \omega_k n_{ch,k} \tag{32}$$

$$P^j_{bl,i}\left(\lambda^j_i, \mu^j_i, N_{ch}\right) = \sum_{k=1}^{n+1} \omega_k P^j_{bl,i}\left(\lambda^j_i, \mu^j_i, n_{ch,k}\right) \tag{33}$$

$$\omega_1 + \omega_2 + \ldots \omega_{N_{\max}} = 1, \ \omega_k = 0 \text{ or } 1 \tag{34}$$

B. Scenario Generation

The scenario set $\{S\}$ and the corresponding probabilities are of vital importance for uncertainty modeling in the stochastic programming. A clustering-based scenario generation method is proposed to extract different scenarios from large amounts of historical data. Meanwhile, the attribute sets are proposed to maintain some of the key characteristics of the uncertainties (e.g., variability, peak value, and seasonal variation), which are more important to the planning decision.

The selection and establishment of the attribute sets are to characterize the data within a period of time, i.e. a day, a week, a month, etc. The problem presented is in a planning scale which usually involves huge volumes of data and computation. Here, in order to enable high computation performance, typical days are generated through the scenario generation to calculate the operation cost. Therefore the objective function in (6) can be modified into (35), where n_{period} is the number of days in the scheduling period. TABLE I lists the attribute sets to characterize the patterns such as variation, seasonal change and shifting, etc. of different uncertainties (This can be easily extended to model the typical week, month or year by simply modifying the attribute sets.), where E (·), σ(·), max (·) denote the mean value, standard deviation and the maximum value of the data respectively. For the electricity price, EV arriving rate and charging rate, the data are divided into multiple groups according to different time periods to show the shifting effect of the pattern due to different seasons, holiday, etc., and therefore, E(·), σ(·), max (·) are calculated for different groups of data accordingly.

$$obj = \min\left[G_{in} + G_m + n_{period} \times \sum_{j \in \{S\}} P^j_{rob} \sum_{i=1}^{T} G^j_{op,i}\right] \tag{35}$$

Then k-means clustering technique is utilized to partition the historical data of each factor into several groups. Those scenarios whose attribute sets are closest to or exactly at the K-centers of the clustering result are selected as the typical scenarios. The corresponding

TABLE I: ATTRIBUTE SETS FOR DIFFERENT STOCHASTIC FACTORS

Stochastic factor	*Attribute set*
PV generation	{ E (·), σ(·), max (·)}
Electricity price	{ E1 (·), σ_1(·), max1 (·), E2 (·), σ_2(·), max2 (·) … Ep (·), σ_p(·), maxp (·)}
EV arriving rate	{ E1 (·), σ_1(·), E2 (·), σ_2(·), … Ep (·), σ_p(·)}
EV charging rate	{ E1 (·), σ_1(·), E2 (·), σ_2(·), … Ep (·), σ_p(·)}

probabilities are calculated according to the frequency of the data within the clustering sets. Assume that those stochastic factors are independent of each other, considering the charging station as a price taker, the final scenarios and probabilities for the stochastic optimization are generated by the permutation and combination of the typical scenarios and the corresponding probabilities of different factors.

V. NUMERICAL EXPERIMENTS

Assume that a charging station is planned to be established, with available areas for the installation of PV panels (S_{pv} =1888 Sq. feet). The limitations on the maximum number of local battery cells and EV chargers are assumed to be L_{bs}=105 and L_{ch}=20, respectively. The SolarWorld Sunmodule SW 320 PV panel with 320W peak power is selected as the default solar unit. The fixed battery storage is assumed to be Hoppecke6OPzS 600 (maximum capacity 1200 Wh per cell), and more detailed information can be referred to Table I of [23]. Besides, the EV charger is assumed to be a level 2 charger with maximum charging power of 7.2kW per charger. The goal of the placement is to find the best combination of the numbers of such equipment to be installed. Therefore, the limitation on the maximum power capacity of PV generation and EV chargers would be $P^{max}_{pv\_total}$=0.17MW and $P^{max}_{ch\_total}$=0.144 MW; the limitation on the maximum energy capacity of batteries is $E^{max}_{b\_total}$=0.126MWh. ($P^{max}_{pv\_total}$ is selected to be a little bit higher than $P^{max}_{ch\_total}$ since PV) generation cannot always operate at its maximum output. The selection of $E^{max}_{b\_total}$ is based on [26]) Hourly energy price data of 2015 is obtained through [27], and hourly solar irradiance data (the PV generation is closely related to the solar irradiance) in the year 2010 are collected from the California Irrigation Management Information System (CIMIS) [28]. The clustering result of the solar data is shown in Fig. 2.

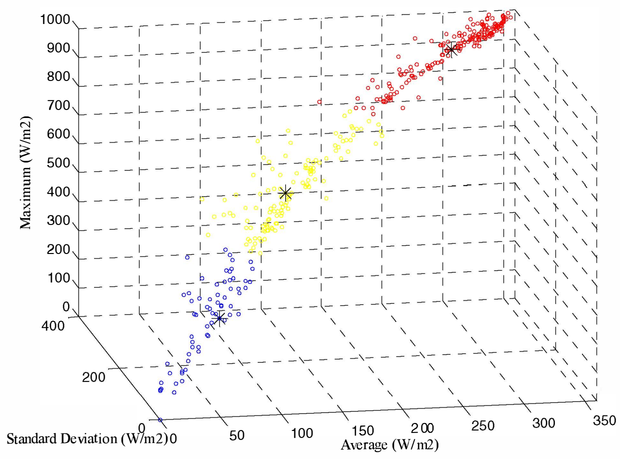

Fig. 2: Clustering result of the solar data.

As shown in Fig. 2, the solar data are clustered into 3 groups by the k-means clustering technique. The samples denoted in black star are selected to be the typical scenarios with probabilities 0.1808 (blue), 0.4819 (red) and 0.3342 (yellow) respectively. The similar procedures are also applied to the other stochastic factors.

After obtaining the final scenarios, the proposed placement scheme is conducted under different cases, and the results are illustrated in Fig. 3.

To further show the impact of different placement schemes on the power grid, the minimum variation to the power grid that can be achieved in some of the above cases is listed in TABLE II.

From Fig.3 and TABLE II, one can observe that: 1) local batteries are very important to limiting the impact on the grid (case 3 to 5); 2) the impact on the grid depends not only on the battery and PV installed, but also on the number of chargers (TABLE II); 3) the number of chargers is mainly affected by: a) the limitation of the impact on the grid (case 1 to 5), b) the available spaces for local battery and PV panels (case 6 & 7), and c) the arriving rate of EVs (case 8 & 9, note that the battery and PV limitations in these two cases are relaxed a little bit to accommodate the highly increasing charging demand); and 4) the potential benefit can be elevated if the limitation on the grid impact is relaxed (case 1-5 & 10) or EV arriving rate is increased (case 8 & 9). Although the benefit

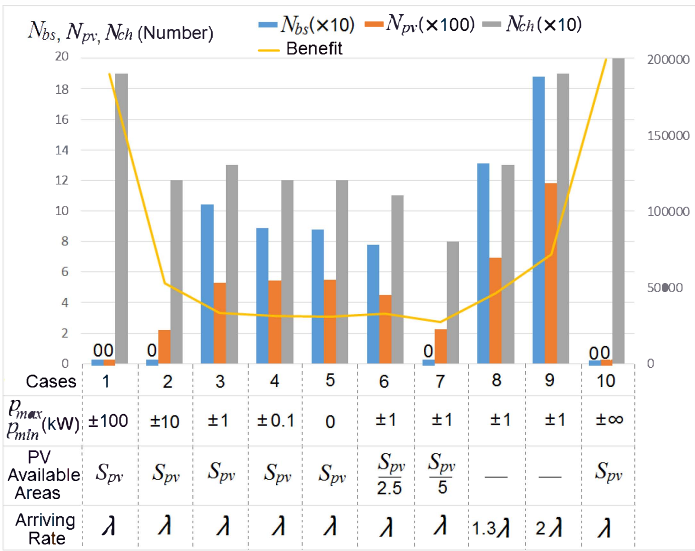

Fig. 3: Placement results under different cases.

TABLE II: MINIMUM VARIATION ACHIEVED UNDER DIFFERENT CASES

Case No.	1	2	3	4	5	10
Minimum variation to the grid (kW)	10	1	0	0	0	10

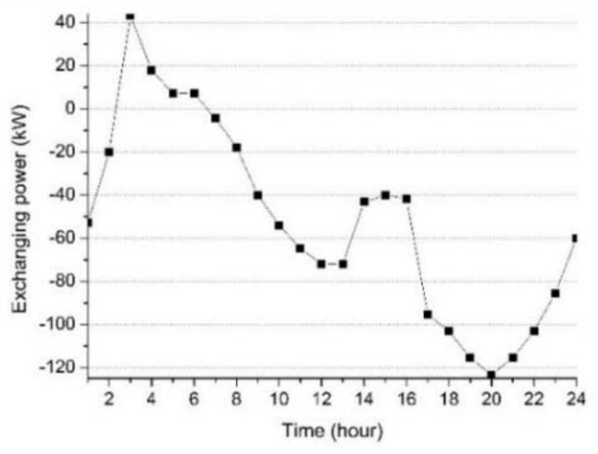

Fig. 4: Exchanging power in a day in case 10.

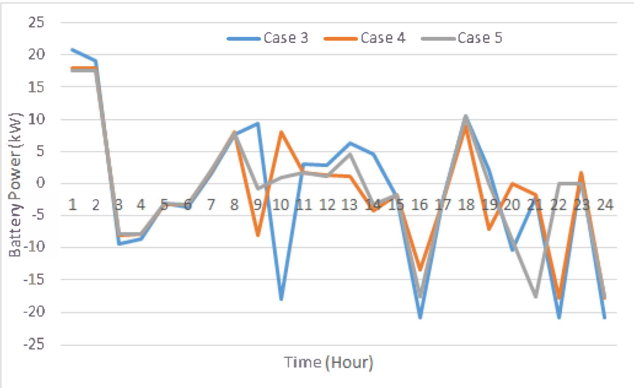

Fig. 5: Illustration on the power of local batteries.

becomes the highest when there is no limitation on the grid impact (case 10), the exchanging power p_e between the grid and the charging station becomes quite variant, as shown in Fig. 4. The power of local battery cells within one day in cases 3 to 5 are illustrated in Fig. 5. It can be observed that the power from battery cells becomes more variant when the limitation of the grid impact becomes stricter.

VI. Conclusion

The contributions of this work are summarized as follows:

- A placement planning scheme with stochastic optimization is proposed for a grid-connected charging station to find an optimal combination of PV panels, local battery cells as well as EV chargers to minimize the total cost, with EV mobility, uncertainties and impact on the power grid taken into account;
- Clustering based scenario creation method and attribute sets are proposed to model the uncertainties;
- Numerical experiment is conducted to validate the proposed placement scheme as well as to evaluate the impact of different factors on the final optimal placement scheme.

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