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Optimal Sizing and Placement of Multiple Photovoltaics Considering Electric Vehicles Charging Stations

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Abstract— Due to the fluctuated generation of Photovoltaic (PV) and stochastic charging and discharging schemes of electric vehicles (EVs), risky operational issues are observed in the medium-voltage distribution systems. Expected issues are excessive energy losses, voltage drop and voltage rise, and disruptions of operational boundaries in power distribution systems. To tackle these issues, we propose an optimization planning model in this paper for optimally allocate PV to accommodate EV charging stations in distribution systems. The proposed planning approach has the ability to determine the best PV locations and sizes to reduce the electrical energy losses in the distribution system, considering voltage and power flow boundaries. Consequently, the allocation problem of PV is created as a double-layer optimization model, which is solved by the gravitational search algorithm. To indicate the effectiveness of the proposed allocation approach of PV, different simulations are performed in the IEEE 69-bus distribution system. The computed results demonstrate that the proposed planning approach can optimally allocate multiple PV units while satisfying the EV charging requirements.

Keywords—Distribution systems, Energy losses, photovoltaic, planning problem, electric vehicles.

I. INTRODUCTION

As the demand for electrical energy increases, the utilization of renewable energy sources (RES) in electrical networks has curiously enlarged worldwide. Among various RES types, photovoltaic (PV) is the most preferable distributed generation to be integrated into distribution systems near load centers. Besides, electric vehicles (EVs) charging stations are widely deployed recently [1], [2]. These stations are connected to the distribution systems to provide the EVs batteries charging requirements. If not managed and allocated properly, PV units and EVs charging stations can have various impacts on the distribution systems such as line thermal overload, voltage deviation, and power quality issues [7]–[9]. On the other hand, if managed properly, they can provide various significant benefits to distribution systems, including regulating voltage levels, increasing the reliability of the electricity supply, enhancing the power quality, and reducing the power losses [3]–[6]. Further, the charging stations of EVs along with their charging strategies can have substantial influences on the selected sizes and locations of multiple PV units in distribution systems.

Several approaches in the previous research works have aimed to determine the optimal planning of PV units in distribution networks considering different technical and economic aspects. In [10], a planning approach for PV and two other RES types has been proposed based on load and generation probabilistic models where the objective has been selected to be energy loss minimization. In [11], [12], novel analytical expressions have been formulated for the ideal planning of RES in distribution systems. Typically, the benefits of these analytical expressions are that they can provide an accurate solution with a very small computational time. Analytical expressions have also been introduced in [13] to optimize the location and the size for one PV unit for reducing losses. To reduce costs and emissions, a multi-objective based planning model has been developed in [14] for the optimal allocation of RES in distribution systems. Other PV planning approaches have utilized advanced metaheuristic optimization algorithms due to their flexibility and efficiency. Many methods have been developed in [15] – [17] to maximize the RES hosting capacity in distribution networks. Common examples of these metaheuristic-based approaches for PV planning involve gravitational search-based approach [18], genetic-based approach [19], Grey wolf based approach [20], simulated annealing based approach [21], tabu search-based approach [22], and ant colony optimization based approach [23]. In [24], a novel machine learning-based method has been introduced to optimally size PV units in electrical distribution systems. Diverse approaches have been presented in [25], [26] for grid optimization with PV units. The option for the oversizing of the utility-owned interfacing inverter of PV has been proposed in [20] for voltage rise prevention in electrical distribution networks. To highlight the impacts of EVs on the PV integration, the authors of [27] have studied various potentials to RES considering different charging schemes of EVs.

As stated above, various procedures have been introduced for the optimal PV allocation in electrical distribution systems. However, most of these works ignore the EVs when formulating the planning model of PV, and so missing an important representation of the PV charging stations. To cover this research gap, an optimization model is proposed in

this paper to allocate PV units in electrical distribution systems interconnected to charging stations of EVs considering the uncertainties. The proposed method can decide on the optimal sizes and locations of the PV components considering diverse operational constraints for minimizing energy losses. For reaching this goal, the planning paradigm is established as a double-layer optimization model where this model is accurately solved by the gravitational search algorithm. To evidence the usefulness of the proposed PV allocation approach, various simulation results are accomplished on the 69-bus test distribution system. The obtained results reveal that the suggested PV allocation model fulfills the EV charging requirements and optimally allocates PVs in distribution systems.

The rest of this paper is ordered as follows. Section II describes the accurate formulations of the suggested PV allocation model. The PV modeling procedure and the solution procedure of the planning model are defined in Sections III and IV, respectively. The simulation results and conclusions are given in Sections V and VI, respectively.

II. PROPOSED METHOD

The main objective of the presented approach is to optimally plan the PV systems in distribution systems considering the EV effects. The objective function has been chosen to be the energy loss minimizing in the distribution system. The probability distribution functions (pdf) of the demand load and solar radiation have been divided into multi-states and integrated with the optimization model. In every state, the losses are computed and weighted according to their occurrence probability in the planning period. The objective function is mathematically given as:

$$\text{Min } OF = \sum_{t=1}^{N_t} \sum_{g=1}^{N_s} E_{\text{loss},g}^t \times \text{prob}_{\text{com}}^t(\chi_g) \quad , \quad (1)$$

were,

$$E_{\text{loss},s}^t = P_{\text{loss},s}^t \times \Delta T, \quad \forall g, T \quad , \quad (2)$$

subject to:

$$\chi(g,1)P_{PV,i}^t - \chi(g,2)P_{d,i}^t \pm P_{CS,i,g}^t - V_{i,g}^t \sum_{j=1}^{NB} V_{j,g}^t \left[\begin{array}{l} G_{ij} \cos \delta_{ij,g}^t \\ + B_{ij} \sin \delta_{ij,g}^t \end{array} \right] = 0, \quad \forall i, g, t \quad , \quad (3)$$

$$\chi(g,2)Q_{d,i}^t - V_{i,g}^t \sum_{j=1}^{NB} V_{j,g}^t \left[\begin{array}{l} G_{ij} \sin \delta_{ij,g}^t \\ + B_{ij} \cos \delta_{ij,g}^t \end{array} \right] = 0, \quad \forall i, g, t \quad , \quad (4)$$

$$P_{cs,i,g}^{\min,t} \leq P_{CS,i,g}^t \leq P_{cs,i,g}^{\max,t}, \quad \forall i \in \phi_b, g, t \quad , \quad (5)$$

$$P_{PV,i}^{\min} \leq P_{PV,i}^t \leq P_{PV,i}^{\max}, \quad \forall i \in \phi_b \quad , \quad (6)$$

$$V^{\min} \leq V_{i,g}^t \leq V^{\max}, \quad \forall i \in \phi_b, g, t \quad , \quad (7)$$

$$0 \leq I_{ij,g}^t \leq I_{ij}^{\max} \quad , \quad (8)$$

$$SOC_{n,d,g} \geq SOC_{n,\min,g} \quad , \quad (9)$$

where, $E_{\text{loss},g}^t$ represents the energy losses in the lines;

$\text{prob}_{\text{com}}^t(\chi_g)$ represents the joint probability of the solar radiation and demand power of state g at time instant t which is given in [18]; $P_{\text{loss},g}^t$ represents the active power losses of the lines; N_t represents the number of the time instants; N_s represents the number of the states in the time instant; χ represents a two columns matrix includes the possible amalgamations of solar radiation and load demand states; G_{ij} , denotes the conductance of line ij ; B_{ij} denotes the susceptance of line ij ; $V_{i,g}^t$ represents the voltage magnitude at node i for state g of time instant t ; $P_{cs,i,g}^{\min,t}$ is the minimum limit of the charging station power at bus i ; $P_{cs,i,g}^{\max,t}$ is the maximum limit of the charging station power at bus i ; $P_{PV,i}^{\min}$ represents the minimum PV generation at bus i ; $P_{PV,i}^{\max}$ represents the maximum PV generation at bus i ; $V^{\min}$ represents the minimum limit of the voltage; $V^{\max}$ represents the maximum limit of the voltage; $I_{ij,g}^t$ represents the current of the line ij ; $I_{ij,g}^{\max}$ represents the maximum permitted current of the line ij ; NB denotes the number of buses; ϕ_b is the PV and charging station set of buses; $\text{SOC}_{n,d,g}$ denotes the state of charge (SOC) of an EV at parting time; $\text{SOC}_{n,\min,g}$ denotes the minimum limit of the SOC that has been preset by the owner.

The SOC of the EV is updated according to:

$$SOC_{n,g}^t = SOC_{n,g}^{t-1} + \eta_{ch,n} P_{ch,n,g}^t \Delta t X - \frac{1}{\eta_{dc,n}} P_{dc,n,g}^t \Delta t Y \quad , \quad (10)$$

The charging and discharging powers of the EV are represented as a percentage of the total power of the charging station. They depend on the capacity (C_n) of the battery, current SOC, and the lingering time before the paring (T_n). Hence, the charging power ($P_{ch,n,g}^t$) of the n^{th} EV n can be calculated as by:

$$P_{ch,n,g}^t = \frac{(1/T_n)(C_n - SOC_{n,g}^t \times C_n)}{\sum_{j=1}^m (1/T)_j (C_j - SOC_{j,g}^t \times C_j)} \times P_{CS,g}^t \quad , \quad (11)$$

While the discharging power ($P_{dc,n,g}^t$) is computed based on:

$$P_{dc,n,g}^t = \frac{T_n (SOC_{n,g}^t \times C_n)}{\sum_{j=1}^m T_j (SOC_{j,g}^t \times C_j)} \times P_{CS,g}^t \quad , \quad (12)$$

where X and Y are belonging to the range $\{0,1\}$, and $X.Y = 0$ in which the EV is not allowed to charge and discharge at the same time; η_{ch} and η_{dc} represent the charging and discharging efficiencies, respectively.

In this work, the arrival time and the initial SOC of the EVs are modeled using a normal probability distribution functions [28]. Hence, the daily pdf of the arrival time can be given as follows:

$$f_n^t(T_A) = \frac{1}{\sigma_{T_A}^t \sqrt{2\pi}} \times \exp \left[-\frac{(T_A - \mu_{T_A}^t)^2}{2(\sigma_{T_A}^t)^2} \right], \quad (13)$$

Similarly, the SOC of the EV can be described as follows:

$$f_n^t(SOC) = \frac{1}{\sigma_{SOC}^t \sqrt{2\pi}} \times \exp \left[-\frac{(SOC - \mu_{SOC}^t)^2}{2(\sigma_{SOC}^t)^2} \right] \quad (14)$$

III. MODELING OF LOAD DEMAND AND SOLAR RADIATION

Due to the uncertainty of the load in the system, a normal pdf is used to model its distribution as follows [29]:

$$f_n^t(l) = \frac{1}{\sigma_l^t \sqrt{2\pi}} \times \exp \left[-\frac{(l - \mu_l^t)^2}{2(\sigma_l^t)^2} \right] \quad (15)$$

On the other hand, to model the uncertainty of the solar radiation, a Beta pdf is employed for this purpose as follows [10], [30]:

$$f_b^t(R) = \begin{cases} \frac{\Gamma(\alpha^t + \beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} \times (R^t)^{(\alpha^t-1)} \times (1-R^t)^{(\beta^t-1)}, & 0 \leq R^t \leq 1, \alpha^t, \beta^t \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

where α^t and β^t represent the shape parameters of Beta pdf; Γ represents the gamma function.

After generating the Beta pdf, the PV output power corresponding to each state s can be computed by:

$$P_{PV_s} = N \times \frac{V_{MPP} \times I_{MPP}}{V_{OC} \times I_{SC}} \times V_{cell_s} \times I_{cell_s} \quad (18)$$

in which

$$T_{cell_s} = T_A + R_{avs} \left(\frac{N_{OT} - 20}{0.8} \right) \quad (19)$$

$$I_{cell_s} = R_{avs} (I_{SC} + K_i (T_{cell_s} - 25)) \quad (20)$$

$$V_{cell_s} = V_{OC} - K_v T_{cell_s} \quad (21)$$

in which V_{MPP} represents the voltage maximum power point; I_{MPP} represents the maximum power point current; V_{OC} represents the open-circuit voltage; I_{SC} represents the short circuit current; V_{cell_s} represents the cell voltage; I_{cell_s} represents the cell current; PV modules number is represented by N ; T_{cell_s} represents the cell temperature; T_A represents the ambient temperature; R_{avs} represents the average solar radiation; N_{OT} represents the cell nominal temperature; K_i represents the temperature coefficient of the current; K_v represents the temperature coefficient of the voltage.

IV. SOLUTION PROCESS

In this section, the solution practice of the planning method is described for the optimal allocation of PV systems in the distribution systems considering the effects of the EVs. For this purpose, the planning problem is developed as a double-layer optimization model. This model is solved using a gravitational search algorithm (GSA) [18]. The first step in the solution process is the input data reading such as the

historical data of solar radiation and load demand. Based on these data, the probabilities can be generated. Furthermore, the system constraints are demarcated. The whole planning problem is divided into the main problem and sub-problem. The main problem is solved in the outer layer, and the sub-problem is solved in the inner layer.

The outer layer, the main problem, suggests the optimal location and capacities of PV systems. Hence, optimal EV charging and optimal EV discharging must be considered. The optimal scheduling of the EVs is solved in the inner layer, which is the sub-problem of the optimization problem. Hence, the inner layer outputs are the probabilistic optimal EV charging power and EV discharging power. For determining the objective for each state in the inner layer, a power flow program is used.

The suggested capacities and locations of the PV systems in the outer layer are utilized by the inner layer to determine the energy losses in the distribution system and the optimal charging and discharging powers of the EVs. For every iteration of the outer layer, the inner layer is performed many times for the suggested capacities and locations of the PV systems. Further, for every iteration of the inner layer, the load flow is performed many times for calculating the optimal EV charging power and EV discharging power and the objective function. The collection of the objective functions is used as an objective function for the outer layer. This procedure is recurrent until the concurrence of the outer layer.

V. RESULTS AND DISCUSSIONS

A. Description of the Test System

The proposed method is tested on the IEEE 69-bus radial distribution test system as shown in Fig. 1. This system is widely used in the literature for the allocation of RES. The 69-bus system includes 69 bus and 68 lines with the total active and reactive load demand of, respectively, 3082.1 kW and 2694.6 kVAR. The data of this system are taken from [31]. The distribution system accommodates 4 charging stations of EVs. These charging stations are connected to nodes 33, 36, 52, and 65 as illustrated in Fig. 1. Sixty EVs can be accommodated by each charging station. The daily distribution of the EVs depends on their arrival time to the station and can be determined using (13). The expected initial SOC of the EV can be determined using (14).

In this paper, we have used the Tesla Model S batteries with 85 kWh capacity[32]. Once the EV arrives at the charging station, it parks for 12 hours till the next parting time. To guarantee that each EV battery has enough SOC at parting time, the constraint given in (9) is considered during V2G technology (discharging to the grid). The maximum charging

Fig. 1. One line drawing of the IEEE 69-bus distribution system.

and discharging rates are 20% of the battery capacity [18], [20]. For demonstrating the efficacy of the presented approach, it has been performed for allocating three PV systems in the distribution system. The historical data of three years for the solar radiation and load are used for generating their probability. A day (24 hours) throughout the three years is used to represent them. The simulation results have been conducted using MATLAB.

B. Case Studies and Analysis

Here, the proposed approach has been performed for allocating three PV systems and compared with the reference case and traditional case. The different cases (i.e., base case, traditional case, and proposed approach) can be discussed as follow:

Case 1: this is the reference case where the distribution system does not have any RES, while the EVs start their charging once they reach to the station.

Case 2: this is the traditional case in which the PV systems are optimally allocated without considering the EV effects.

Case 3: in this case, the PV systems are optimally allocated considering the effect of EVs (proposed approach).

The simulation results of the different cases of the planning problem are described in Table I, and Fig. 2. The results show that the yearly energy loss is substantially decreased when the PV systems are optimally allocated in the

TABLE I. RESULTS OF DIFFERENT CASE STUDIES

Case study	Location	Size (MW)	Energy loss (MWh)	Reduction of Energy loss (%)
Case 1	-	-	1772	0.0
Case 2	49	1.00	1023	42.0
	51	1.23		
	61	2.21		
Case 3	19	0.61	891	50.0
	61	1.30		
	62	0.96

Fig. 2. Active power losses of distribution system by applying the different cases.

Fig. 3. Hourly percentage of power loss reduction by applying Case 2

distribution system (Case 2 and Case 3) compared to the reference case (Case 1). Nevertheless, the loss reduction of the energy of Case 3 is greater than that of Case 2. In other words, the loss reduction of the energy by applying Case 3 is 50%, while it is 42% in the case of Case 2. This shows that considering the effect of EVs in the allocation problem has an obvious effect on decreasing the yearly energy losses. The optimal PV capacities and locations are changeable based on the applied case. For instance, by applying Case 2, the optimal locations are buses 49, 51, and 61 with capacities of 1 MW, 1.23 MW, and 2.21 MW, respectively. Furthermore, the optimal locations when Case 3 is applied are buses 19, 61, and 62 with capacities of 0.61 MW, 1.30 MW, and 0.96 MW, respectively.

The resulted power loss in the distribution system by applying Case 2 and Case 3 is shown in Fig. 3. This figure shows the superiority of the presented approach (Case 3) over the traditional approach (Case 2) on reducing the hourly power losses of the distribution system. It is worth mentioning that, thanks to enabling the V2G technology of the EVs, the proposed approach can reduce the power losses in the distribution systems even at night-time where there is no PV power to be injected into the distribution system.

Fig. 4 shows the SOC of EVs at the charging stations connected to bus 33 and bus 36 in the case of the proposed approach (Case 3). Not that the EVs that reach to station at the ending of the prior day are taken into account in which they must remain for charging at the start of the studied day. The figure demonstrates that the EV state of charge can rise in the case of charging, and it declines in the case of discharging. The charging and discharging of the EVs is decided by the optimizer for minimizing the total losses in the distribution system. Moreover, the figure shows that the SOC of any EV at parting time is sufficient for regular driving.

These results prove that the considering of EVs in the optimization problem for optimal allocating of PV systems can significantly increase the loss reduction of the energy in the system. Regarding the SOC of EVs at bus 56 and bus 65,

Fig. 4. SOC of EVs of Case 3, at charging stations connected to the distribution system. a) charging station connected to bus 33, b) charging station connected to bus 36.

they follow the same trend as Fig. 4. Therefore, they have not been drawn to avoid results repetition. Generally, at parting time, all EVs will have SOC as preset by their owners.

VI. CONCLUSIONS

This paper proposes a new planning model to optimally allocate PV units in distribution systems while considering the EV charging stations. Specifically, the proposed approach can accurately decide the optimal PV sizes and locations to minimize the losses in the system. To consider both PV and EVs, the planning problem has been established as a double-layer optimization model solved by the GSA. Various case studies on the IEEE 69-bus radial distribution system are presented to prove the usefulness of the proposed allocation approach. The results illustrate that the proposed PV planning approach can significantly reduce the power losses while meeting the EV charging requirements and the operative constraints of the electrical distribution system under study.

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