PSO-based Siting and Sizing of Electric Vehicle Charging Stations

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Abstract. With the rapid growth of the number of electric vehicles, the optimization of charging network is imminent. In this paper, a screening method for the siting and sizing of electric vehicle charging station is developed to minimize the total cost including capital investment on stations, EV charging stations’ operation cost and maintenance cost. Driving distance of electric vehicles and service radius of stations are taken into account to pick out the optimal sites of EV charging stations. A mathematical model with electric physical constraints is designed to distribute appropriate capacities for each EV charging station to prevent the negative effects on the power grid and the PSO optimization algorithm is applied to obtain the optimal sizing parameters. Finally, the IEEE 123-bus test feeder case study is used to confirm the validity of the proposed method and increase the economic benefits.

1. Introduction
In recent years, the rapid development of battery technology promotes the popularization of electric vehicles (electric vehicle, EV) in the whole world. The number of EVs has risen steadily year by year. Under this background, the optimal planning of electric vehicle charging stations becomes one of the most important issue worthy of study.

Up to now, EV charging station siting and sizing problem has been formulated as different optimal program models with different constraints or cost functions. Paper [1], introduces a method to deal with the tradeoff between reducing the number of required charging stations versus providing more charging spots and waiting spaces. Paper [2] compares the results of three different location-allocation models for EV charging station siting problem, including the set covering model, the maximal covering location model and the p-median model. In addition, most existing researches focus on charging infrastructure planning with a single decision entity, but in [3], the infrastructure system is shaped by collective actions of multiple decision entities to support business-driven EV charging infrastructure investment planning problem.

In this paper, the objective function consists of infrastructure investment on station and network, operation and maintenance cost. In addition, various physical constraints for charging stations are taken into consideration to prevent the negative effects on the power grid.

The remaining of this paper is organized as follows. A mathematic model is employed to get the optimal capacities for the selected EV charging station sites in Section 2. The PSO algorithm is introduced to solve the problem in Section 3. In Section 4, a case released to validate the method, followed by Section 5 that concludes this paper.
2. Optimization Model

2.1. Objective Function

According to the service radius of the charging station, the feasible sites of charging stations are firstly selected from the list of raw site candidates. Then the presented model takes into account the total cost of EV charging stations in the planning period. For example, the objective function consists of capital investment on stations and lines, operation and maintenance cost of stations, which can be given as:

\[
\min f = \sum_{k=1}^{N} \sum_{i=1}^{T} C_{ci}^s + C_{ci}^r + C_{ci}^{mu} \frac{(1 + \alpha)^{T - n}}{(1 + \alpha)^{T}}
\]

(1)

where \( N \) denotes the number of EV charging stations concerned in this case. And \( T \) depicts the duration of the planning period whose unit is year. \( \alpha \) is a conversion rate to transform the future cost to the present value because of currency appreciation or depreciation. Moreover \( C_{ci}^s \), \( C_{ci}^r \) and \( C_{ci}^{mu} \) correspond to infrastructure investment, Operation and maintenance cost of the EV charging station \( k \) in the planning period. We will show more detailed information about the cost function in the next part.

2.2. Economic Model

The first part of the economic model is the investment cost for the charging station \( k \), which can be defined as:

\[
C_{ci}^s = \alpha_{ci}^s W_{cap}^s + \alpha_{ci}^r W_{cap}^r + \alpha_{ci}^{mu} W_{cap}^{mu} + \alpha_{ci}^b W_{cap}^b
\]

(2)

where \( \alpha_{ci}^s \), \( \alpha_{ci}^r \) and \( \alpha_{ci}^{mu} \) are the per-unit capacity investment cost of charging station \( k \). \( \alpha_{ci}^b \) is the per square meter land utilization price of charging station \( k \), which covers \( A_{ci} \) square meters area.

The total capacity of charging devices equals to the sum of capacity of every charger in stations. So \( W_{cap}^s \) is formulated as[4]:

\[
W_{cap}^s = p_s \sum_{i=1}^{n} W_{cap}_{i,j} = p_s \sum_{i=1}^{n} \frac{E_{ci,i,j}^{active}}{\eta_{ci,j} \cos \phi_{ci,j} \eta_{ci,j}}
\]

(3)

where \( n_i \) is the number of charging devices in charging station \( k \). \( E_{ci,j}^{active} \) is the output active power of charging device \( i \). \( \eta_{ci,j} \) is the charging efficiency of the charging device \( i \). \( \cos \phi_{ci,j} \) is the power factor of charging devices. And \( p_s \) is the user-defined constant which denotes the simultaneity coefficient of charging devices in charging station \( k \).

At charging station \( k \), the sum of all transformers’ capacities \( W_{cap}^r \) could be derived from \( W_{cap}^s \), which is calculated as:

\[
W_{cap}^r = \frac{W_{cap}^s + W_{cap}^{mu}}{W_{cap}^{max}}
\]

(4)

where \( W_{cap}^{max} \) is the maximal load rate that charging station \( k \) can bear every day. And \( W_{cap}^{mu} \) is the total capacities of other devices excluding charging devices and transformers in charging station \( k \).

The secondary part of the economic model is the operation cost \( C_{ci}^o \) of charging station \( k \), which consists of charging cost \( c_{ci} \) of EVs, electricity fee cost of electric charging devices \( c_f \), electrical filter and compensator cost including active power and reactive power \( c_r \), and human resource cost \( c_h \). Operation cost could be calculated as:
\[ C_{ch}^p = C_{ch} + C_{ed} + C_{hr} \]  \hspace{1cm} (5)

Then, the charging cost \( C_{ch} \) and the electricity fee cost of electric devices \( C_{ed} \) could be defined as (6-7) respectively:

\[ C_{ch} = c_{ep} P_{max}^e t_{ed} \]  \hspace{1cm} (6)

\[ C_{ed} = c_{ep} P_{max}^e t_{ed} \]  \hspace{1cm} (7)

where \( c_{ep} \) is the electricity price when EV charging station \( k \) purchases active power from the power grid. \( P_{max}^e \) and \( P_{max}^e \) are the rated power of charging devices and the maximal active power consumed by electric devices. And electric devices are designed to assist charging devices. \( t_{ed} \) is the total utilization hours of charging devices in a whole year at the EV charging station \( k \). Similarly, \( t_{ed} \) is annual average utilization hours of electric devices.

To guarantee electrical energy quality, there are always electrical filter and compensator equipment at EV charging stations. So, the relevant cost \( C_{fc} \) is formulated as:

\[ C_{fc} = \sum_{i=1}^{n} \rho_{fc}^{cap} \theta_{harmonic} \omega_{cap} \]  \hspace{1cm} (8)

where \( \omega_{fc}^{cap} \) is the cost on per-unit capacity when it requires power filter and compensator equipment. \( \kappa \) is an overall compensation factor in the cost \( C_{fc} \) for charging station \( k \). \( \rho_{fc}^{cap} \) is the reliability coefficient of the charging device \( i \) in charging station \( k \). \( \theta_{harmonic} \) is the harmonic current containing rate of charging device \( i \) when AC power is supplying.

The adjustment coefficient for electricity price is proposed which aims to balance loads at different nodes and to avoid peak loads. \( c_{ep} \) could be adjusted with the following equation:

\[ C_{ep} = C_{ep}^{ave} \]  \hspace{1cm} (9)

where \( C_{ep}^{ave} \) is the standard electricity price given by network grid, and \( \omega_{ave}^{load} \) is average load rate of charging station \( k \) per day.

The third part of the economic model is maintenance cost \( C_{ma} \) whose components are very similar with those in investment cost \( C_{in} \). The cost equation could be defined as:

\[ C_{ma} = \omega_{ma}^{cap} W_{cap}^{ct} + \omega_{ma}^{ct} W_{cap}^{tr} + \omega_{ma}^{ct} W_{cap}^{od} \]  \hspace{1cm} (10)

where \( \omega_{ma}^{cap} \), \( \omega_{ma}^{ct} \), \( \omega_{ma}^{ct} \) are the maintenance cost on per-unit capacity of the transformers, charging devices and other devices in charging station \( k \) respectively.

2.3. Optimization Electric Physical Constraints

The optimization constraints are modeled by inequalities and equalities. In order to eliminate this negative effect caused by a surging amount of EVs that are charged at one charging station in a short time, some inequality constraints should be obeyed during selecting optimal EV charging station sites. The following inequalities are to ensure the stability of electrical power system [5]. And these constraints are modeled respectively:

\[ W_{cap}^{tr} \leq W_{cap}^{max} \]  \hspace{1cm} (11)

\[ \omega_{ reactive}^{ max} \leq \omega_{ reactive}^{ max} \]  \hspace{1cm} (12)
\[
\sum_{k=1}^{N_c} E_{c_k}^{\text{active}} = \sum_{k=1}^{N_c} \sum_{j=1}^{N_n} E_{c_k,j}^{\text{active}} \leq E_{c_k}^{\text{active, max}}
\]  
(13)

\[
\eta_{\text{load}_j}^{\text{max}} \leq \eta_{\text{load}_j}
\]  
(14)

\[
F_{\text{min}} \leq \frac{E_{c_k}^{\text{active}} + E_{c_k}^{\text{reactive}}}{\sqrt{(E_{c_k}^{\text{active}} + E_{c_k}^{\text{reactive}})^2 + (E_{c_k}^{\text{reactive}} + E_{c_k}^{\text{reactive}})^2}}
\]  
(15)

where \( k \) represents the index of EV charging station with \( k=1,2,\ldots,N_c \). And all those constraints (11-15), are in term of charging station \( k \). In addition, they are maximal transformer capacity limit, minimal and maximal reactive power for compensation limits, the permitted maximal charging power limits, the upper daily average load rate limits, and the minimal load power factor limits.

But beyond that, there are some constraints for feeders between nodes in the network. The voltage offset limits at each bus and the permitted maximal current limit are given as follows:

\[
V_j^{\text{min}} \leq V_j \leq V_j^{\text{max}}
\]  
(16)

\[
|I_j| \leq I_j^{\text{max}}
\]  
(17)

where \( l \) and \( j \) are indicators, which is used to indicate the serial number of different node in the network. And \( V_j \) is the voltage of the bus \( j \) with \( j=1,2,\ldots,N \). Where \( N \) is the number of nodes in the network. Similarly, \( l=1,2,\ldots,N \), and \( I_j \) is the current in the feeder between the \( l \)th node and the \( j \)th node.

3. General Structure of PSO

In this section, the optimal siting and sizing of electric vehicle charging stations have been determined by using optimization method. Once all the constraints have been described, the optimization algorithm should be selected and carried out, even some of the constraints are nonlinear equations similar to neural networks [6-9]. PSO is an emerging population-based and meta-heuristic algorithm that simulates birds flocking to promising position to achieve in a multi-dimensional space [10]. In this paper, we define that the size of population is 100 as and the termination criterion is 100. The iteration is terminated if the PSO algorithm reaches the pre-defined maximum number of iteration.

Finally, for the sake of using PSO to solve the optimization problem, the algorithm implementation steps are as follows:

Step 1: Generate initial swarm randomly.

Step 2: Measure the fitness of each particle in the population.

Step 3: Calculate the velocity of each particle.

Step 4: Change the position of each particle.

Step 5: Evaluate objective functions, update best previous experience achieved \( X_{p}^{\text{best}} \) and best experience of entire swarm \( X_{g}^{\text{best}} \).

Step 6: Stop algorithm if termination reaches the maximum predetermined number. Otherwise return to step 3.

4. Study Results

The IEEE 123-bus test feeder case released by IEEE PES Distribution System Analysis Subcommittee [11] is studied in this section. As for electric vehicle model, the HFF6112GK50 EV bus is taken as an instance to validate the proposed method in this paper [12]. And relevant parameters are listed in table 1 and table 2. In addition, other data for line lengths of test feeder and original loads at different nodes are provided by the IEEE 123-bus test feeder case.
During the process of selection for optimal sites, urban geospatial information is taken into consideration and some EV charging station candidate sites are picked out from original data. Meanwhile these sites should be away from central business districts and transportation hubs in city as far as possible, and they should be located near residential districts and other load centers.

Then the reasonable driving distance is calculated according to the known parameters, so that service radius of EV charging stations should be shorter than this driving distance, that is to say, 
\[ r_s \leq 7.22 \text{km} \]. At the same time, the actual distance between two adjacent stations is restricted between 7.22km and 14.44km, or rather to say, 
\[ 7.22 \leq d_s \leq 14.44 \]. Finally, EV charging station sites are determined from the candidate spots with these two aforementioned constraints.

And an optimization model considering total cost of these EV charging stations and physical network constraints is employed to obtain the optimal capacities distribution among these stations. With the model described in section III, optimal locations and capacities of EV charging station are illustrated in table 2.

As the PSO algorithm is a heuristic algorithm that may not reach the same and best solution even after running the same problem many times. Each case has been run more than twenty times with different initial populations and all solutions have good convergence properties. We could get a good and reasonable EV charging stations’ optimal locations and capacities distribution for these stations. In this case, the total cost mentioned in section III is about 1.31 million dollars.

Table 1. Known parameters for optimization model.

| Parameter | Value | Unit     | Parameter | Value | Unit     |
|-----------|-------|----------|-----------|-------|----------|
| \( P_{\text{eng}} \) | 124   | kW       | \( c_{\text{eng}} \) | 95.63 | dollar/m2|
| \( \eta_{\text{eng}} \) | 90%   | -        | \( p_k \) | 0.8   | -        |
| \( v_{\text{ave}} \) | 40    | km/h     | \( \eta_{\text{cs-1}} \) | 90%   | -        |
| \( V_{\text{ret}} \) | 384   | V        | \( \cos \phi_{\text{cs-1}} \) | 0.95  | -        |
| \( W_{\text{cap}} \) | 255   | Ah       | \( C_{\text{upper}} \) | 16476.41 | dollar   |
| \( C_{\text{upper}} \) | 50%   | -        | \( c_{\text{upper}} \) | 10.16 | dollar/kVA|
| \( C_{\text{lower}} \) | 30%   | -        | \( k \) | 0.61  | -        |
| \( \eta_{\text{cap}} \) | 1.27  | -        | \( \kappa_{\text{cap}} \) | 1.05  | -        |
| \( T \) | 3     | year     | \( \theta_{\text{cap}} \) | 3%    | -        |
| \( \alpha \) | 12%   | -        | \( \gamma_{\text{cap}} \) | 0.06  | dollar/kWh |
| \( c_{\text{in-cd}} \) | 34.71 | dollar/kVA | \( c_{\text{out-cd}} \) | 8.92  | dollar/kVA |
| \( c_{\text{in-cd}} \) | 40.84 | dollar/kVA | \( c_{\text{out-cd}} \) | 11.92 | dollar/kVA |
| \( c_{\text{in-cd}} \) | 30.94 | dollar/kVA | \( c_{\text{out-cd}} \) | 5.21  | dollar/kVA |

Table 2. Optimal locations and capacities.

| Optimal Sites | Optimal Capacities |
|---------------|--------------------|
| Value | Unit |
| 1 | 300 | kVA |
| 16 | 200 | kVA |
| 39 | 80 | kVA |
| 67 | 80 | kVA |
| 89 | 100 | kVA |
| 107 | 120 | kVA |
5. Conclusion
In this paper, an optimization model is identified to distribute capacities for these EV charging stations. Especially, the total cost of these stations is regarded as the optimal objective, and some critical electric physical constraints are taken into consideration which will minimize the side effect caused by peak loads of charging. In future, coordination between multiple stations with multiple storages shared within communities will be marked in our calendar.

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