Traffic-Constrained Multiobjective Planning of Electric-Vehicle Charging Stations

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***Abstract*—Smart-grid development calls for effective solutions, such as electric vehicles (EVs), to meet the energy and environmental challenges. To facilitate large-scale EV applications, optimal locating and sizing of charging stations in smart grids have become essential. This paper proposes a multiobjective EV charging station planning method which can ensure charging service while reducing power losses and voltage deviations of distribution systems. A battery capacity-constrained EV flow capturing location model is proposed to maximize the EV traffic flow that can be charged given a candidate construction plan of EV charging stations. The data-envelopment analysis method is employed to obtain the final optimal solution. Subsequently, the well-established cross-entropy method is utilized to solve the planning problem. The simulation results have demonstrated the effectiveness of the proposed method based on a case study consisting of a 33-node distribution system and a 25-node traffic network system.**

***Index Terms*—Charging station, cross-entropy, data-envelopment analysis, distribution systems, electric vehicle (EV), locating and sizing, traffic flow.**

I. INTRODUCTION

IN RECENT years, the climate change has aroused international awareness about the negative impacts of using fossil fuels. Development of electrical vehicles (EV) industry is regarded as an important measure to reduce the carbon emissions. With the development of power electronics and battery technology, the EV ownership number gained a rapid growth given governmental supports and incentives like tax reductions. Particularly in China, ambitious plans have been made to take the lead of future EV implementation in the world [1].

At the initial stage, barriers to successful deployment of EVs at large scale exist in various aspects. Among others, lack of sufficient charging infrastructure is the most critical one. Generally, EV charging infrastructure can be of different types including mainly battery swapping station and fast charging station. It is widely believed that fast charging stations have the potential to be widely used [2], and consequently more and more attentions have been paid to the optimal planning of them in the past few years [3]–[7]. A dynamic traffic network method is used to build a model with a time constraint to obtain the optimal location and size of EV charging stations in [3], in which the investment and charging costs are to be minimized. In [4], a two-step method considering environmental factors and service radius is presented to identify the candidate EV charging stations. The resultant multiobjective function considering investment and operation costs, as well as the network losses, is solved by the interior point algorithm. In [5], the feasibility of optimally utilizing the potential of the Ontario's grid for charging plug-in hybrid EVs (PHEVs) is analyzed for off-peak load periods by employing a simplified zonal model of the Ontario's electric transmission network and a zonal pattern of base-load generation capacities for the years from 2009 to 2025.

In [6], an environmentally and economically sustainable integration of PHEVs into a power system is addressed under a robust optimization-based planning methodological framework taking the constraints of both power systems and transport sectors into account. In [7], a smart load management approach for coordinating multiple plug-in EVs chargers in distribution systems is proposed, with the objectives of shaving peak demands, improving voltage profiles and minimizing network losses.

Research on EV charging station planning is still in the early stage. There are still many influential factors that should be incorporated in planning charging stations. These include the EV owner's driving behavior, the topologies of distribution system and the traffic network, and the economics and security issues of power systems. These factors have only been partially addressed in most existing publications. In this work, the power distribution and traffic network topologies and the EV owner's driving behavior are taken into account and a new multiobjective charging station planning method is formulated. Because of its robustness and fast convergence, the cross-entropy method is utilized to solve the multiobjective planning model and obtain the Pareto planning solutions. A novel data-envelopment method is then used to make the final planning decision among the Pareto solutions to determine the optimal charging station location and its size simultaneously. The effectiveness of the proposed method has been demonstrated through a case study based on a test system consisting of a 33-node distribution system and a 25-node traffic network system.

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II. Multiobjective Planning Model

The aim of the optimal planning problem of EV charging stations is to determine the locations and capacities of new charging stations to be built with a defined objective function, subject to associated constraints. In the present work, it is assumed that the EV charging station planning is managed by one single entity, whose main interest is to fulfill the charging needs subject to the behaviour in which the EVs are driven and to the battery capacities. Considerations are also given to minimize the distribution network losses due to EV charging power flows and to the efficiency and reliability of both the traffic and power networks. Thus, the main objective of the EV charging station planning problem in this paper has two components. One component is to minimize the power losses and node voltage deviations in the distribution network and the other is to maximize the utilization of charging stations described by the total EV traffic flows according to EV traveling routes in the traffic network. The planning objectives and their constraints will be described in detail below.

A. Maximization of Charging Service Ability

Mathematically, the optimal planning of EV charging stations is a typical facility locating and sizing problem. In traffic and logistic research, well-established methods such as the location theory have been developed that allow analysts and decision-makers to explore trade-offs among different objectives and to analyze the impacts of constraints on the decision-making of facility locations and capacities [8]. In the classical location theory, the demand for service is assumed to occur at fixed locations within a traffic network. This process is generally termed as node-based demand. Consumers like drivers residing at other nodes of the traffic network need to travel to facility locations to obtain service, e.g. to fully charge EVs as in the present work. Given the node-based demand assumption, the main purpose of location planning in the network is to maximally serve the demand at these nodes. Classically, this can be mathematically formulated as follows [25]:

$$\text{Maximize :} \quad \sum_i d_i Z_i \tag{1}$$

$$\text{subject to :} \quad Z_i \leq \sum_j c_{ij} X_j \quad \forall i \tag{2}$$

$$\sum_j X_j = R \tag{3}$$

where

d_i	demand at node i;
R	number of facilities to locate;
$Z_i = 1$	if node i is covered, 0 otherwise;
$c_{ij} = 1$	if candidate site j covers demands at node i, 0 otherwise;
$X_j = 1$	if facility locates at candidate site j, 0 otherwise.

The objective function (1) is to be maximized for the number of covered demands. Constraint (2) states that demand at node i cannot be covered unless at least one of the facility sites that cover node i is selected, which is usually decided by the distance between a demand node and the candidate facilities. Constraint (3) states that R facilities are to be located.

The model described in (1)–(3) associates a demand level with each demand node and finds the facility locations to maximize the number of covered nodal demands. Thus the model considers the network geographical information and the nodal demand differences. However, in the model, the demands are regarded as static and fixed at each node, which may not be true for the case of EV charging.

Due to EVs' mobility, the charging demand served by a charging station is time varying and depends on a variety of factors such as the behaviors of individual EV drivers, local traffic conditions, the charging power and total capacity of EV battery storage as well as its status of charge. As such, the static nodal demand oriented modeling in the classical location theory cannot reflect the complexities involved in the EV charging demands. Therefore it is inappropriate for the charging station planning problem. In modeling EV charging demands, the focus is to fulfill the traveling needs of the EV drivers, which are complex because of the large number of EVs and diversified traveling patterns. The modeling should also consider the situations that EV drivers may prefer to charge their cars on the way during a trip, rather than perform a dedicated travel to procure charging services alone. Thus, it may be more realistic to model the EV charging demands as the traffic flows inside the traffic network. This consideration should be accommodated by the planned charging stations, subject to other considerations such as the EV storage capacity and travelling distance. EV drivers usually prefer to travel on the route with the shortest distance between the origin and the destination, and this route can be identified by the well-developed Dijkstra or Floyd algorithms [27]. If a charging station is located along the pre-determined travel route, then the EV drivers may choose to obtain charging service there. Under the above premises, we define the *EV traffic flows* as the number of EVs which travel along the lines or *edges* connecting the different nodes along a pre-determined travel route.

Consequently, the main purpose of location planning can be regarded as to select available facilities to best fulfill the flow-based charging demand, rather than to simply serve the demand at nodes as in the classical location theory. A significant feature of the proposed traffic flow-based planning model is that the traffic network topology and driving patterns can be well addressed for the travelling and charging convenience. Moreover, because the travelling behavior of EVs is well considered, special planning scenarios such as traffic jam or even traffic emergency control can be included in the future work.

Based on the above considerations, the optimal charging station planning is essentially an *EV flow-based maximal covering* problem that locates charging stations to maximize the EV flow to be captured by a charging station anywhere along the route of EV traffic flow. Thus the objective function is to maximize the total EV traffic flows that can be charged by the planned stations

$$\text{Maximize :} \quad F_1 = \sum_{q \in Q} f_q y_q \tag{4}$$

$$\text{subject to :} \quad \sum_{h \in H} b_{qh} v_h \geq y_q \quad \forall q \in Q \tag{5}$$

$$a_{hk}U_{ik} \geq v_h \quad \forall h \in H; \quad U_{ik} \in U \tag{6}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{m} U_{ik} = M \tag{7}$$

$$\sum_{k=1}^{m} U_{ik} \leq 1 \tag{8}$$

where

f_q	EV traffic flow on route q;
U	set of all potential EV charging station locations;
h	index of candidate construction plan of EV charging stations;
H	set of all potential EV charging station plans;
$y_q = 1$	if all EVs of f_q can be charged, 0 otherwise;
$b_{qh} = 1$	if the plan h can fulfill the charging need of f_q, 0 otherwise;
$v_h = 1$	if all EV charging station in h are available for charging services, 0 otherwise;
$a_{hk} = 1$	if EV charging station k is in h, 0 otherwise;
$U_{ik} = 1$	if an EV charging station is located at node i, 0 otherwise. Subscript k denotes the options of charging station capacity;
q	the shortest route between O and D;
Q	set of all routes;
m	the total number of EV charging station capacity options;
N	the total number of nodes in the traffic network;
M	the number of EV charging stations to be constructed.

Constraint (5) requires at least one eligible candidate plan h available for EVs on route q to be charged. The eligible plans may consist of one or several EV charging stations that can charge the EVs on their traveling route. Constraint (6) holds v_h to 0 unless all EV charging stations in h available for services without violations of e.g. charging capacity limits. Constraint (7) requires exactly M EV charging stations to be built according to the investment cap. Constraint (8) indicates that only one charging station of a certain capacity can be built at a node.

Irrational placement of EV charging stations with respect to the traffic network will lead to extra driving distance potentially exceeding EVs' driving capability. Thus, the limit of EV's battery capacity will also have significant influences on the resultant optimal locations of charging stations. In view of this, the traffic network and vehicle driving patterns, as well as the EV battery capacity, should be included in making a proper construction plan of EV charging stations. For EV development, the limited battery storage is the key issue which can affect the planning results. A single station may not be enough for charging purpose in a route from an origin node O to a destination node D and return. It is because EVs have a finite energy capacity S_{max}. For example, for an EV with an energy consumption of 0.25 kWh/km, the driving range (l_{max}) is 50 km only, which can just fulfill the need of one way trip from node O to D as shown in Fig. 1. Given different EV battery capacities, planning of charging stations for the case in Fig. 1 should consider a number of cases described below.

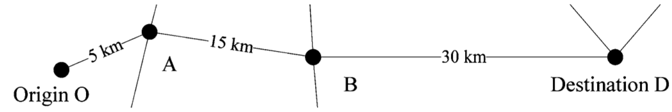

Fig. 1. Example round-route flow for an origin-destination pair.

Case 1) For $\mathrm{S_{max}} < 7.5$ kWh and $\mathrm{l_{max}} < 30$ km, no candidate plan can be formed to charge the EV on a round trip along the route.

Case 2) For 7.5 kWh $\leq \mathrm{S_{max}} < 15$ kWh and 30 km $\leq \mathrm{l_{max}} < 60$ km, more than 1 charging stations are required to serve for a round trip along the route.

Case 3) For 15 kWh $\leq \mathrm{S_{max}} < 22.5$ kWh and 60 km $\leq \mathrm{l_{max}} < 90$ km and if only one charging station is allowed to charge an EV for the round trip, then it can only be located at node B.

Case 4) For 22.5 kWh $\leq \mathrm{S_{max}} < 25$ kWh and 90 km $\leq \mathrm{l_{max}} < 100$ km, the charging station can either be located at A or B for charging for the round trip along the route.

In our planning study, it is assumed an EV starts at the origin with an SOC (State Of Charge) m% out of the maximum capacity S_{max}, unless a charging station is located at the origin, in which case, it starts with full charge. EVs then move to the next node along the pre-determined route given enough energy. If EVs reach a node with a charging station, EVs can then be fully charged. If EVs reach a node without charging stations, the electric energy consumed for driving from present node (F) to the next (T) $(E_{F,T})$ in the previous route section will be deducted from the remaining stored energy (S). If there is not enough energy left to reach the next node, the charging station plan cannot charge EVs along this route. If EVs can move from the origin to the destination and back to the origin without running out of energy, the route is considered chargeable by the planned charging stations. Based on above analyses, the EV energy constraint check logic for every route is illustrated in Fig. 2.

With this procedure repeated for every possible travel routes of EVs, it can be determined whether the traffic flow on a specific route could be sufficiently charged (whether the $y_q = 1$) or not.

B. *Minimization of Total Power Loss and Voltage Deviation*

When new EV charging stations are connected to a distribution system, the power flow pattern will change, so as the transmission loss. The transmission loss is minimized by minimizing the objective function F_2 below in equation set (9). The EV charging may also cause nodal voltage deviations. These deviations are minimized by minimizing objective function F_3 in (9) below.

Minimize :

$$F_2 = P_{\text{Loss}}\left(U_{ik}P_{Si}^{k}, U_{ik}Q_{Si}^{k}\right)$$
$$F_3 = \sum_{i=1}^{N_d} \frac{|V_i - V_0|}{V_0} \tag{9}$$

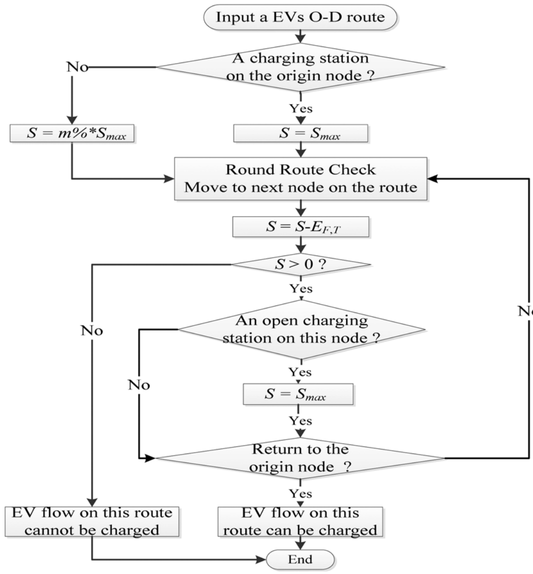

Fig. 2. Flow chart of EV round-route energy constraints check.

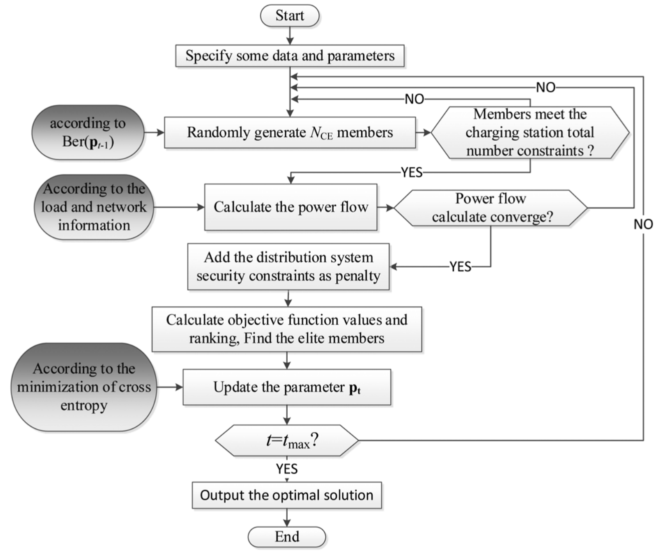

Fig. 3. Flowchart of the CE method.

subject to

$$P_{\mathrm{SUB}} = P_{\mathrm{Loss}} + \sum_{i=1}^{N_d-1} P_{Di} + \sum_{i=1}^{N_d-1}\sum_{k=1}^{m} U_{\mathrm{ik}} P_{Si}^k \quad (10)$$

$$\begin{cases} -P_{Di} - U_{ik}P_{Si}^k = V_i \sum_{j=1}^{N_d} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \\ -Q_{Di} - U_{ik}Q_{Si}^k = V_i \sum_{j=1}^{N_d} V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) \end{cases}$$

$$\forall i \in [1, N_d] \quad (11)$$

$$P_l \le P_l^{\max}\ \forall l \in L \quad (12)$$

$$V_{i,\min} \le V_i \le V_{i,\max}\ \forall i \in [1, N_d] \quad (13)$$

$$\sum_{i=1}^{N_d-1}\sum_{k=1}^{m} U_{ik}P_{Si}^k - W_{min} \ge 0 \quad (14)$$

where

$P_{Si}^k\ Q_{Si}^k$	active and reactive power of EV charging station at node i. Subscript k denotes the options of charging station capacity;
N_d	total node number of distribution network;
V_0	nominal voltage;
V_i	voltage of node i;
P_{Di}	load on node i without EV charging station charging
P_{Load}	total load of the distribution network;
P_{SUB}	inject power to the distribution system from upstream network;
P_{Loss}	total power loss of the distribution network;
$U_{ik} = 1$	if an EV charging station is located at node i, 0 otherwise. Subscript k denotes the options of charging station capacity;
m	total number of EV charging station capacity options;
$G_{ij}\ B_{ij}$	conductance/susceptance between node i and node j;
θ_{ij}	voltage angle difference between node i and node j;
$P_l\ P_l^{\max}$	active power flow/active power upper limit in branch l;
L	set of distribution system branches;
$\mathrm{V}_{i,\min}\mathrm{V}_{i,\max}$	lower/upper voltage limit at node i;
$W_{\min}$	minimum charging power demand.

Equation (10) is the power flow balance constraint at the charging station, and (11) is the power flow equations for the whole distribution system. (12) and (13) address the power and voltage limits for lines and nodes. (14) indicates that the total charging station charging power should not be less than the total minimum charging power demand of all EVs.

III. Implementation of the CE-DEA Method

The EV charging station planning problem in this paper is a three-objective optimization problem. The Pareto solutions of the multiobjective optimization problem can be obtained by simply applying different weighting coefficients [26], and then transforming the problem into a single objective problem through the sum weighted approach:

$$\min F = \min[\alpha_1 F_1 + \alpha_2 F_2 + \alpha_3 F_3] \quad (15)$$

where α_1, α_2 and α_3 are the weighting coefficients of the three objectives, respectively. Since the objectives can be of different orders of magnitude, normalizing these objectives is needed. There are different ways for normalization [17], and in this work an advanced normalization method [30] is employed which requires solving the optimization problem with each individual objective beforehand to find the extreme values $F_{k,min}(x)$ and $F_{k,max}(x)$ ($k = 1, 2, 3$) which will then be used for normalization: $F_{k,norm}(x) = (F_k(x) - F_{k,min}(x))/(F_{k,max}(x) -$

$F_{k,min}(x))$, where $F_{k,norm}(x)$ is the normalized function. This method is employed in our case study.

The solution to the multiobjective problem is not unique and a subjective selection has to be made to reflect the preference by the decision maker. Therefore a novel objective approach to make the final decision based on a data-envelopment method is adopted in this paper. The optimization model of (15) is then solved using the cross-entropy (CE) method due to its simplicity and high efficiency.

A. CE Algorithm for Optimization

The CE method originated from the field of rare event simulation, where very small probabilities need to be accurately estimated [20]. The CE method can be applied to static and noisy combinatorial optimization problems and is therefore suitable to solve the developed optimization model because of its fast convergence, robustness and insensitivity to the starting points.

To minimize some "performance" function $J(\boldsymbol{x})$ over all states $\boldsymbol{x}$ in some set χ, denote the minimum by $\gamma_{\min}$, then

$$S(\boldsymbol{x}^*) = \gamma_{\min} = \min_{x \in \chi} J(\boldsymbol{x}). \tag{16}$$

To proceed with CE, a deterministic problem is firstly randomized by defining a family of probability distribution functions (PDFs) $\{f(\boldsymbol{x};\boldsymbol{v}), \boldsymbol{v} \in \boldsymbol{V}\}$ on the set χ, parameterized by a real-valued parameter (vector) $\mathbf{v}$. Next, for a certain $\boldsymbol{u} \in V$, (16) is associated with the estimation of

$$l(\gamma) = P_{\boldsymbol{u}}\left(J(\boldsymbol{X}) \leq \gamma\right) = E_{\boldsymbol{u}} I_{\{J(\boldsymbol{X}) \leq \gamma\}} \tag{17}$$

where γ is an adaptively updating parameter. $P_{\boldsymbol{u}}$ is the probability measure under which the random state $\boldsymbol{X}$ has a PDF of $f(\boldsymbol{x};\boldsymbol{u})$, and $E_{\boldsymbol{u}} I_{\{J(\boldsymbol{X}) \leq \gamma\}}$ means that the expectation of the random vector $\boldsymbol{X}$ is taken with respect to the measure (PDF) $f(\boldsymbol{x};\boldsymbol{u})$. $I_{\{J(\boldsymbol{X}) \leq \gamma\}}$ is an indicator random variable and $I_{\{J(\boldsymbol{X}) \leq \gamma\}} = 1$ if $J(\boldsymbol{X}) \leq \gamma$ is true and $I_{\{J(\boldsymbol{X}) \leq \gamma\}} = 0$ otherwise.

The CE method solves the problem described by (17) efficiently by adaptively updating the PDF parameter $\boldsymbol{v}$ through minimizing the cross entropy or the variance of $l(\gamma)$, resulting in a set of degenerated PDFs $f(\boldsymbol{x};\boldsymbol{v_1}), f(\boldsymbol{x};\boldsymbol{v_2}), f(\boldsymbol{x};\boldsymbol{v_3})$, which will quickly converge to the global optimal PDF $f^*(\boldsymbol{x};\boldsymbol{v}^*)$. Thus the CE method is comprised of the following two steps:

1) *Generate a set of candidate solutions according to a predefined pdf*;
2) *Update the parameters of this pdf by using the elite solutions to steer the search towards the global optimal in subsequent iterations.*

Only a few parameters such as the size of the population (N_{CE}) and the percentage of elite solutions ρ need to be predefined and most key parameters are adaptively updated in the iterative process.

In this case, let $\mathbf{x}$ be the vector of binary decision variables x_{ik} represents whether or not a candidate charging station are placed on node i. At each iteration, the PDF for $\mathbf{x}$ is Bernoulli function with success probability vector $\mathbf{p}$, thus $\mathbf{x} \in \mathrm{B}(\mathbf{p})$.

The CE method is implemented for solving the aforementioned optimization model in the following steps:

Step 1) The input of the CE method include: a. system and load data; b. population size N_{CE} for CE method; c. initial parameter $\boldsymbol{u} = \mathbf{p_1}$; d. maximum iteration time $t = t_{\max}$.

Step 2) Set the iteration counter $t = 1$;

Step 3) Generate the population $\boldsymbol{X}_1, \ldots, \boldsymbol{X}_{\mathrm{NCE}}$ (candidate planning schemes) randomly using distributions $\mathrm{Ber}(\mathbf{p}_{t-1})$, Every population member $\boldsymbol{X}$ has n_{CE} population member components, and each component represents whether a charging station is located at a candidate node. Furthermore, each population member $\boldsymbol{X}$ is constrained by the maximal total number of stations;

Step 4) Carry out the power flow calculation for each population member and check the power flow calculation's convergence and whether the distribution system security constraints have been met. If the power flow does not converge or constraints are not met, $t = t + 1$ and return to Step 3);

Step 5) Calculate the objective function for all population members according to (15) and rank them. The performance parameter γ in (17) is the worst solution of the $N_{\mathrm{elite}} = \rho N_{\mathrm{CE}}$ best elites.

Step 6) Update the parameters:

$$p_{ik,t} = \frac{\sum_1^{N_{CE}} I_{\{J(\boldsymbol{X}) \leq \gamma\}} X_{ik}}{N_{elite}}. \tag{18}$$

Step 7) Repeat Steps 3)–6) until a pre-specified stopping criterion is satisfied.

B. DEA-Based Method for Final Decision-Making

The data-envelopment analysis (DEA) method, a multidimensional measurement method incorporating multiple input and output variables, is a data-oriented method for the final decision making. It was developed to assist decision makers in comparing the performance of a group of candidate solutions, termed as decision-making units (DMUs), and selecting the best one [18]. The determination of final decision based on the DEA method can reflect more objective and comprehensive physical significance, and has been successfully applied in our previous work [9].

DEA can measure the relative efficiency of peer DMUs with multiple inputs and outputs [19]. Suppose there are n DMUs, each DMU has m $\mathrm{inputs}(x)$ and produce s $\mathrm{outputs}(y)$. The best solution of the efficiency of the k^{th} DMU is obtained by:

$$\text{Maximize}: \quad E_k = \sum_{r=1}^{s} u_r y_{rk} \Big/ \sum_{i=1}^{m} v_i x_{ik}, \ (k = 1, 2, \ldots, n) \tag{19}$$

$$\text{subject to}: \quad \begin{aligned} &\sum_{i=1}^{m} v_i x_{ik} = 1 \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \ j = 1, 2, \ldots, n, \ j \neq k \\ &u_r, v_i \geq \varepsilon > 0, \ r = 1, 2, \ldots, s, \ i = 1, 2, \ldots, m \end{aligned} \tag{20}$$

where E_k is the efficiency index of the k^{th} DMU, s is the number of $\mathrm{outputs}(y)$, m is the number of $\mathrm{inputs}(x)$, x_{ik} and

y_{rk} are the i^{th} input and the r^{th} output of the k^{th} DMU, v_i and u_r are parameters relative to x_{ik} and y_{rk}, respectively, which can be determined by the solution of this problem.

Candidates with $E_k \geq 1$ are valid candidate solutions for the specific weight coefficient. The best candidate has the highest E_k. A candidate with E_k less than 1 has at least one solution better than itself (akin to dominance).

In this paper, DEA is utilized to make the final decision, that is, to find the best planning result from Pareto solutions. In this case, n optimization solutions with different specific weight coefficients, are considered to be n DMUs. The DMUs can be represented in the form of inputs and outputs. The objectives to be maximized (n normalized F_1 with different specific weight coefficients) are considered as outputs, while the objectives to be minimized (n normalized F_2 and F_3 with different specific weight coefficients) are considered as inputs.

The procedure of the proposed methodology is given in the following:

1) Initially, independent optimization of each objective is performed before multiobjective optimization;
2) For each DMU, the weight coefficients are randomly generated by a uniformly distributed function in [0,1] and the sum of the three weight coefficients is 1;
3) Find out the optimal solution of (15) with different weight coefficients using the CE method. The optimal value of objective F is denoted as min(F);
4) With the solutions in 3)given different weight coefficients, the values of each objective F_1, F_2, F_3 can be determined;
5) Taking the minimized solutions from 1–4 as the inputs of the DMUs and the maximized solutions as the outputs of the DMUs, evaluate the efficiency of kth DMUs by the DEA method;
6) Rank the DEA efficient E_k to find the best solution (best weight coefficient);
7) Get the final optimal solutions with the best weight coefficient found in 6.

IV. Case Studies

A. Test System

For case studies, a test system consisting of an 11 kV 33-node distribution system and a 25-node traffic network is used. The test system is shown in Fig. 4. In the test system, the traffic nodes 1–25 geographically overlap with the distribution system nodes 1–25. Node 26 in the distribution system is connected to the grid supply point (GSP). Details of the 25-node traffic system are given in Table I. The 33-node distribution system is from [29] but the nodes are renumbered so as to correspond with the traffic node numbers.

For a practical system, the traffic flows can be measured via different methods [22], [23]. In our case studies, the traffic flow data is artificially generated by the gravity spatial interaction model [21] to reflect a realistic flow structure as follows:

$$f_q = W_O * W_D / (d_q * 1.5) \tag{21}$$

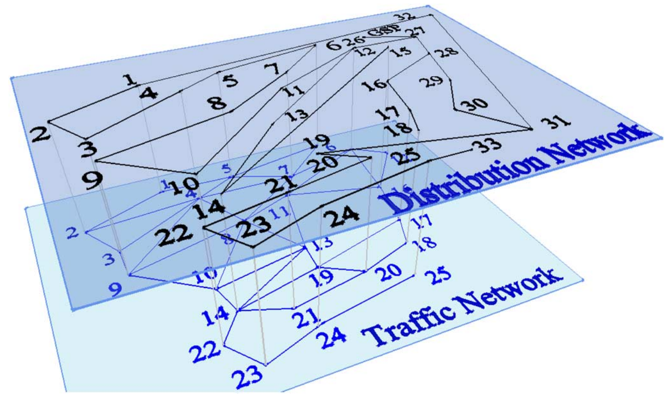

Fig. 4. Test system with 33-node distribution system and a 25-node traffic network. (Gray links: indicate the geographic overlapping of the nodes in the distribution network and nodes in the traffic network).

TABLE I
System and Weight Parameters for the 25-Node Traffic System

Line parameters			Weight on from-node	Line parameters			Weight on from-node
F	T	l/km	w	F	T	l/km	w
1	2	40	0.54	11	13	30	0.05
1	5	50	0.54	11	16	70	0.05
2	3	30	0.80	11	12	20	0.05
2	4	40	0.80	12	15	40	0.54
3	4	40	0.27	12	16	40	0.54
3	9	40	0.27	13	14	70	0.05
4	9	70	0.27	13	19	40	0.05
4	8	50	0.27	14	19	70	0.54
4	7	50	0.27	14	21	20	0.54
4	5	30	0.27	14	22	40	0.54
5	6	50	0.27	15	16	40	0.27
5	7	50	0.27	16	17	40	0.27
6	7	30	0.07	17	18	30	0.27
7	8	30	0.05	17	19	30	0.27
7	11	80	0.05	18	20	30	1.07
7	12	90	0.05	19	20	30	0.80
8	9	60	0.54	20	21	20	0.27
8	10	60	0.54	21	14	20	0.27
8	11	70	0.54	21	20	20	0.27
8	13	70	0.54	22	23	30	0.54
9	10	60	0.27	23	24	30	0.05
10	13	60	0.54	24	25	80	1.34
10	14	30	0.54	25	24	80	0.05

where d_q is the shortest route distance between O and D, and W_O or W_D is the weight of nodes. The distances between various nodes and weights of nodes are listed in Table I. The weight physically presents the ability of the node to attract the traffic flow, i.e. the node with a super market or residential area may attract more traffic flow and has a larger weight than a common node.

For EVs, it is assumed that there are 400 EVs in the system, and the probability that an EV is in charging state is 10%. EV's charging power is set to be 10 kW and the charging rate is set to be 90%. The EV battery has a maximum capacity of 30 kWh and the consumption rate is 0.25 kWh/km. When starting a route, EVs are assumed to have 50% SOC at the original nodes.

It is assumed that the minimum EV charging power demand $W_{\min}$ within the test system is set to be 0.8 MW. The candidate charging stations have charging power rating options of

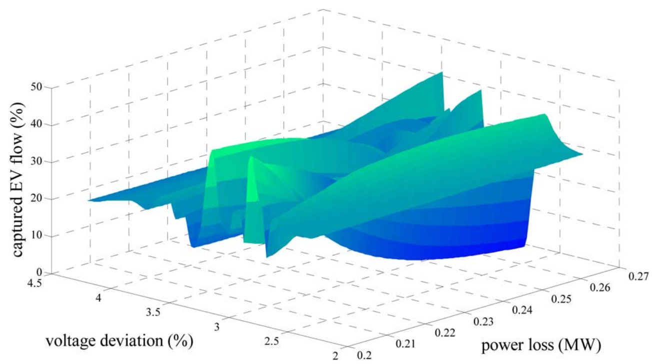

Fig. 5. Pareto surface of the multiobjective optimization.

TABLE II
SIMULATION AND DEA EVALUATION RESULTS

DMUs				Inputs		Outputs	DEA
index	α_1	α_2	α_3	power loss MW	voltage deviation	EV flow captured	E_k
1	0.614	0.135	0.251	0.2068	2.719%	32.25%	1.0077
2	0.083	0.404	0.513	0.2168	2.853%	34.02%	1.0053
3	0.156	0.661	0.183	0.2122	2.803%	32.47%	0.9860
4	0.570	0.229	0.201	0.2637	3.164%	36.46%	0.9664
5	0.781	0.110	0.109	0.2131	2.674%	30.51%	0.9569
6	0.070	0.524	0.406	0.2226	2.883%	32.45%	0.9442
7	0.582	0.014	0.404	0.2226	2.897%	32.45%	0.8987

0.1, 0.2, 0.3, and 0.4 MW, respectively. The charging station number and capacity in the system should be similar to the situation for planning gasoline stations. Considering the total EVs in the test system and the experience of gasoline station planning [24], the maximum station number is set to be 4 according to the investment cap. All EV charging stations are available for charging service.

The implemented CE method includes the following parameters: the number of the population member components $n_{\mathrm{CE}} = 25{*}4$, population size $N_{\mathrm{CE}} = 35$, percentage of elite population member $\rho = 0.1$, elite population number $N^{\mathrm{elite}} = \rho * N_{\mathrm{CE}} = 4$, specified maximum allowed iteration time $t_{\max} = 1000$. The probability density function $f(\boldsymbol{x}; \boldsymbol{u})$ is specified to be a Bernoulli distribution function, and the initial probability of building an EV charging station at each node in the 25-node traffic network is set to be 0.04.

B. Final Decision Making by DEA

The optimization results form the Pareto surface as shown in Fig. 5. In the DEA-based approach (19), (20), the objective to be maximized is considered as output y, while objectives to be minimized are considered to as inputs x. Accordingly, the three objectives for the charging planning can be treated as a case with two inputs and single output. The idea is to maximize the efficiency of each optimization problem under different weight coefficients, specifically in this case, to minimize power loss and voltage deviation and maximize the EV flow that can be captured for charging. The DEA efficient E_k of different candidate solutions is calculated and the best 7 results are presented in Table II.

TABLE III
COMPARISON OF SIMULATION RESULTS IN THE 33-NODE DISTRIBUTION SYSTEM

Compared item	CE	PSO
Best objective value	0.8121	0.8177
Worst objective value	0.8354	0.8415
Average objective value	0.8230	0.8247
Average execution time (sec)	900.13	949.02

It is observed that 2 groups of candidate solutions can achieve $E_k \geq 1$, indicating the best optimization efficiencies among all others are resulted. The most efficient cases are those better candidate solutions than the remaining cases in terms of the relatively better convergence of the EV flow, and relatively lower network loss and nodal voltage deviations. For example, comparing the best case $(\mathrm{index} = 1)$ to the case with smaller E_k $(\mathrm{index} = 7)$, the former has a lower power loss (0.2068 versus 0.2226), a smaller voltage deviation (2.719% versus 2.897%), but a slightly smaller captured EV flow (32.25% versus 32.45%). The DEA is able to further distinguish between the two best cases and revealed that the case with index 1 is the most efficient one with lower power loss and voltage deviation. However, the best case captures slightly less EV flow (32.25% versus 34.02%). This indicates that none of the best solutions could have an overwhelming superiority.

C. Effectiveness of the Proposed Method

To verify the effectiveness and efficiency of the proposed optimization approach, the proposed planning model has been solved using both the CE and particle swarm optimization (PSO) methods [28] using Matlab 2010b on a 2.13 GHz PC computer. The parameters for the PSO algorithm are given as follows:

The variable number $n_{\mathrm{PSO}} = 25{*}4$, population size $N_{\mathrm{PSO}} = 35$, maximum iteration time $t_{\max} = 1000$, initial weight factor $w_{\mathrm{start}} = 0.9$, final weight factor $w_{\mathrm{end}} = 0.4$, acceleration constant $\mathrm{c}_1 = \mathrm{c}_2 = 2$.

One candidate solution with $\alpha_1 = \alpha_2 = \alpha_3 = 0.3333$ is taken as an example to demonstrate the superiority of the proposed method. Owing to the randomness in the proposed CE and PSO method, these algorithms are executed 50 times when applied to the test system. Table III shows the best, the worst and the average objective values and the average computational time, where statistically the CE method generates better solution than the PSO method. The average and best values by the CE method are smaller than the results by the PSO. The average execution time by CE is also 5% less than that by PSO. Fig. 6 compares the convergence speed of the two methods, where it is clearly shown the CE method converges to high-quality solutions at an earlier iteration (within about 30 iterations) than the PSO does. Therefore, it can be concluded that the proposed CE-based approach outperforms the PSO-based approach, both in the quality of the obtained solution and in the speed of computation convergence.

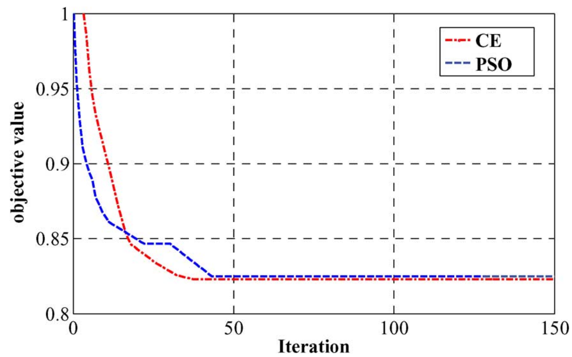

Fig. 6. Convergence characteristics of CE and PSO for the 33-node system.

TABLE IV
PLANNING RESULTS

Case number	Optimal Sites	Optimal Charging Power Rating (MW)	Power Loss (MW)	Voltage Deviation (%)	Travel Flow Captured (%)
1	12	0.1	0.1953	2.493%	24.93%
	13	0.2			
	14	0.4			
	16	0.1			
2	8	0.2	0.2575	3.251%	45.83%
	14	0.1			
	18	0.2			
	23	0.3			
3	14	0.1	0.2068	2.719%	32.25%
	15	0.1			
	18	0.4			
	23	0.2			
4	2	0.1	0.1926	2.491%	53.27%
	19	0.1			
	22	0.2			
	20	0.4			

D. Effect of Different Optimization Objectives

To further demonstrate the performance of the proposed method, 3 cases are studied.

1) Case 1: To obtain a minimum power loss and voltage deviation solution, only distribution power system factors (Objectives F_2 and F_3) are considered.
2) Case 2: To obtain a maximum captured traffic flow solution, only traffic system factor (Objective F_1) is considered.
3) Case 3: Combining Cases 1 and 2 to obtain a "hybrid planning solution", both distribution power system and traffic system situations (Objectives F_2, F_3 and F_1) are considered.

Results of optimal siting and sizing of EV charging stations for Cases 1, 2, and 3 are given in Table IV. It can be seen from Table IV that the power loss and voltage deviation in Case 1 are less than Case 2 and Case 3 as expected. However, because the traffic network is ignored, 4 charging stations (at nodes 12, 13, 14, and 16) are placed geographically close to one another. This may cause inconveniences for EV drivers in other parts of the system. As a result, the travel flow captured is reduced greatly to 24.93%. Turning to Case 2, it focuses on the traffic system alone and improves the drivers' charging convenience because of its geography-based problem formulation. In this case, the power loss increases to 0.2575 MW and the voltage deviation increases to 3.251%.

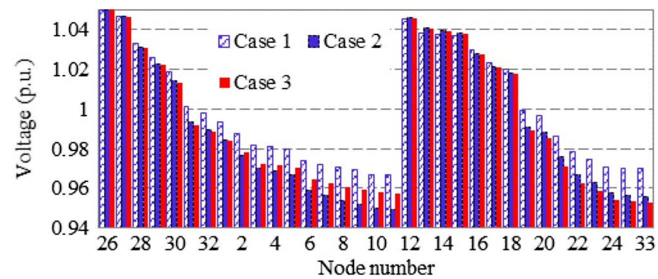

Fig. 7. Nodal voltage profiles of different study cases.

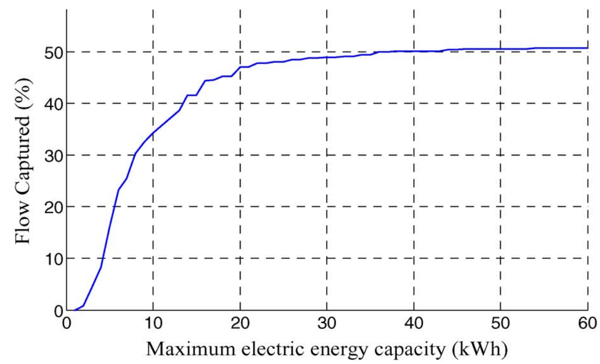

Fig. 8. Traffic flow captured by charging stations against different EV battery capacities.

Case 3 takes both the distribution system and traffic network into the problem formulation. From Table IV, only a slight decrement is observed in the captured traffic flow, but the power loss and voltage deviation have been reduced greatly when compared with Case 2 and only slightly higher than that in Case 1. Fig. 7 shows the profiles of the voltage magnitudes in all cases. Improved voltage profiles are observed for Cases 1 and 3. This indicates a rational tradeoff has been achieved among the different concerns that the power system and the traffic network have.

E. Effect of Battery Energy Storage Capabilities

The influence of EV energy storage is also investigated. Fig. 8 shows a study of the traffic flows captured in relation to the different EV battery capacities. It can be found that when the capacity is less than 20 kWh, it can affect significantly the traffic flow captured. However, when the battery storage exceeds 40 kWh, it will no longer give significant impacts to the captured EV traffic flow. This is not unreasonable as larger battery storage will enable EV drivers to enjoy a longer driving distance without frequent stopovers at charging stations.

Case 4 in Table IV shows the planning results without battery capacity limits taken into account. The power losses and voltage deviations are lowered and more traffic flows are captured. The comparison between Case 4 and Case 3 clearly indicates that the EV battery capacity will have a prominent influence on the charging station planning. The effects of EV battery capacity should therefore be taken into account carefully by the planning decision makers. Specifically, the increase of EV battery capacity will benefit the power system as well as the traffic system.

V. Conclusion

Rapid deployment of EVs could impose significant challenges to the secure and economic operation of a power system concerned. Optimal charging station planning must facilitate EV development by offering sufficient charging conveniences while minimizing any negative impacts to the power systems such as the power losses and voltage deviations introduced by the EV charging flows. To this end, a new multiobjective EV charging station planning model has been developed in this paper to address the various concerns from both the traffic system and power system perspectives. A DEA method has been utilized to determine the best candidate solution in the multiobjective formulation. The cross-entropy algorithm has been employed to solve the optimization problem because of its efficiency and simplicity. Based on the proposed method, optimal EV charging station sizing and locating can be achieved to minimize the power losses and voltage deviations as well as the EV travelling distances. The case studies indicate that the proposed method have successfully attained reasonable construction plans of EV charging stations, while improving the operation economy and the voltage profiles of the power system.

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