IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 3, 2018, accepted May 28, 2018, date of publication June 4, 2018, date of current version July 19, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2843810

Optimal Allocation Model for EV Charging Stations Coordinating Investor and User Benefits

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This work was supported in part by the National Natural Science Foundation of China under Grant 51377111, in part by the Fundamental Research Funds for the Central Universities of China under Grant YJ201654, in part by the New Century Higher Education Teaching Reform Project of Sichuan University under Grant SCU8007, in part by the Innovation and Entrepreneurship Research Project of Sichuan University under Grant SCUCXCY1736, in part by the National Key Research and Development Program of China under Grants 2017YFE0112600 and 2018YFB0905200, and in part by the Open Research Subject of Key Laboratory of Sichuan Power Electronics Energy-Saving Technology and Devices under Grant szjj2017-052.

ABSTRACT Deploying charging stations (CSs) catering to the demand from electric vehicles plays an important role in modernizing energy infrastructures. In this paper, a bi-level optimal allocation model for allocating fast CSs is proposed aiming to maximize the CS investor benefit (upper layer sub-problem) by optimally allocating CSs with the coordinated determination of the expected efficiency of charging service supply (lower layer sub-problem). The efficiency is formulated as a charging performance index in terms of user satisfaction degree, which mathematically couples the upper level and lower level sub-problems. The proposed nonlinear bi-level model is reduced to a single-layer optimization model under the Karush–Kuhn–Tucker optimality conditions. An improved dynamic differential evolution algorithm with an adaptive update strategy is proposed to solve this single-layer optimization model. The proposed method is validated using a realistic case. The test results show that the proposed methodology is able to co-ordinate both objectives of interest, i.e., allocating CSs network with the maximized benefits and optimizing the fast charging service efficiency at the same time.

INDEX TERMS EV charging station, optimal allocation model, user satisfaction degree, bi-level programming.

I. INTRODUCTION

In the recent decades, under the pressure of both energy crisis and environmental pollution [1], many countries have reached a consensus to enhance the renewable energy exploitation and utilization [2]. The electric vehicle (EV), as a sustainable participant in the transportation system, is being significantly developed to pursue the energy modernization [3], [4]. In the foreseeable future, the large-scale utilization of EVs can largely reduce the fossil fuels usage and particulate emission [5]. The emerging mature of the EV industry requires the commercialized charging service, which motivates the increasing importance on the optimal design of charging networks [6]. However, the business models of the charging station (CS) operation vary in terms of the social environment and the economic structure, which can be generally categorized into the following three types: i) government regulated service, offering non-profit charging service for the public usage; ii) market-oriented service, featured by the existence of independent companies pursuing financial benefits through their investment on CSs; iii) individual-owned service, referred as the self-used charging pile. In many countries, the charging service is now available in their commercialized market, stimulating investors to seek for the business opportunity. These CS investors usually have profit ambitions, which might result in disordered allocation of charging resources without necessary coordination. That may also cause unnecessary redundant charging infrastructure investment and pose extra pressure on the limited space of cities as well as the power supply system.

In addition, the convenience of using the charging infrastructure significantly affects the people's motivation to purchase EVs [7], which has been quantified by using the expectation of charging service efficiency. The charging service efficiency is usually defined as the charging-related time consumed by EV users, including traveling, queuing, and charging time. The appropriate CSs allocation plays a major role in providing convenient service for EV drivers, which would no doubt promote the EV penetration [8]. On the contrary, insufficient or unreasonable planning may either throttle the growth of the EV industry or result in a waste of resources.

The modeling of the EV charging load and its associated typical profile is the first step to address the optimal location and sizing problem of CSs [9]. There have been extensive efforts in the literature investigating the modeling and prediction of the EV charging load [5]. For example, the measured consumption data are used in [10] to model the EV demand by estimating the parameters in a pre-designed model. The charging behavior for a number of commonly used EV batteries is analyzed in [11] and [12], providing a stochastically formulated analytical method to characterize the stochastic nature involved in the battery charging. Besides, the probability density function, which offers a statistical measure for the occurrence of a specific charging status, was adopted to describe the daily travel distance for various types of EVs considering uncertainties by using a Monte Carlo based method [13], [14]. To predict the daily charging load, Arias *et al.* [15] presented a time-spatial forecast model based on EV battery information and the traffic flow data acquired by monitoring the transportation network. However, realistic data of EV charging behaviors are shortage at present. Thus, probability modeling [16] or other feasible methods [1], should be adopted to simulation the EV charging modeling.

The location and sizing of EV CSs could be determined once the charging load features are obtained, which is modeled essentially as an optimization problem. Many efforts have been devoted to solving this problem. Khalkhali *et al.* [17] introduced a two-stage approach to determine the optimal location and capacity for the plug-in hybrid EV CSs. A two-step screening approach combining the determination of the geographical information-based service radius and the allocation of CSs was proposed in [18]. A modified primal-dual interior point algorithm was used to solve the above problem. Considering the operational features of the public transportation system, two scenarios associated with the battery size limitation were discussed in [19], which were used to establish an optimal placement optimization problem for electric bus systems. A novel framework was presented in [20] using rapid-charging and battery swapping modes considering the life cycle cost. However, majority of the existing approaches using a single-level programing model merely consider the allocation cost. In addition, the user satisfaction degree is also usually ignored in the literature, which, in fact, is a vital driving force in promoting the EV industry, since the EV charging behavior significantly impacts business income of CS such that the user experience should be considered in the CS allocation problem.

In this paper, the independent investor is regarded as the main body of the charging station investment. A bi-level CS allocation optimization model is formulated for the market-oriented business model to maximize the investment benefits while at the same time guaranteeing the EV user satisfaction degree (USFD) for fast charging service. This model couples the benefits of the investor and the EV users through iterations involving variables from both the upper- and lower-levels, providing an effective solution to optimally deploy the charging service infrastructure while facilitating the most efficient charging selection.

The rest of the paper is organized as follows. Section II introduces the generic model of the EV charging load. Section III presents the bi-level optimization model. In Section IV, an equivalent single-layer model is derived for the proposed bi-level optimization problem, and the final model is solved by an improved dynamic differential evolution algorithm. Numerical studies are performed in Section V to validate the methodology. The conclusion is drawn in Section VI.

II. GENERIC MODELING OF EV CHARGING LOAD

A. PROBABILITY DISTRIBUTION OF DAILY TRAVEL DISTANCE

The daily travel distance of an EV depends upon the user's traveling purpose and driving habits. According to the statistical and fitting study of national household travel survey [16], the probability density function (PDF) and the cumulative distribution function (CDF) are used to fit the numerical features of vehicles driving [7], [21].

The daily travel distance of an EV is assumed to follow the law of logarithmic normal PDF

$$f_d(d) = \frac{1}{d\sigma_d\sqrt{2\pi}} \exp\left(-\frac{(\ln d - \mu_d)^2}{2\sigma_d^2}\right) \tag{1}$$

where d is the daily travel distance of a vehicle, whose PDF is $f_d(d)$; μ_d and σ_d are respectively the mean value and the standard deviation.

B. PROBABILITY DISTRIBUTION OF START TIME OF CHARGING

The start time of EV charging is another important parameter characterizing the EVs' behavior. Based on the existing statistical analysis [9], the PDF and CDF of charging start time is assumed to have the following form:

$$f_s(t_s) = \begin{cases} \dfrac{1}{\sigma_s\sqrt{2\pi}} \exp\left(-\dfrac{(t_s-\mu_s)^2}{2\sigma_s^2}\right) \mu_s \\ \qquad\qquad -12 < t_s \le 24 \\ \dfrac{1}{\sigma_s\sqrt{2\pi}} \exp\left(-\dfrac{(t_s+24-\mu_s)^2}{2\sigma_s^2}\right) 0 \\ \qquad\qquad < t_s \le \mu_s - 12 \end{cases} \tag{2}$$

where $f_s(t_s)$ is the PDF of the charging start time t_s; μ_s and σ_s are respectively the mean value and the standard deviation.

C. CHARGING TIME

It is assumed that the average kWh consumption per 100 kilometers of EV driving and power output of the charger are constant. The charging time duration can be derived as:

$$T^{\mathrm{CHA}} = \frac{d \cdot w_{100}}{100 \cdot P^{\mathrm{CHA}}} \tag{3}$$

where T^{CHA} is the charging time of an EV, w_{100} is the average energy consumption for 100 kilometers, P^{CHA} is the active power output of the EV charger. It should note that although EV battery follows constant current and constant voltage (CCCV) scheme when the fast charger works, from planning point of view, it is reasonable to assume that CSs, with sufficient voltage regulation ability, provide constant power charging [22] aiming to simplify large-scale EV capacity estimation and enable long-term load balance analysis in planning issues.

D. STEPS OF CHARGING DEMAND FORECAST

Let one minute be the sampling time interval, so a whole day can be discretized into 1440 time points. The steps for generating the charging load profile are summarized as follows:

1). Parameter setup, including μ_d, σ_d, μ_s, σ_s, w_{100} and P^{CHA}.

2). Monte Carlo simulation, generating the enough samples for d and t_s.

3). Calculation of the end time of charging, according to the start time generated in step 2) and the charging duration calculated by (3).

4). For each sampling time interval, the number of EVs in charging status can be determined, which is used to calculate total charging power in the region by using (4).

$$P_t = P^{\mathrm{CHA}} N_t \tag{4}$$

where P_t is the total active power at time t. N_t is the number of EVs in charging status at time t.

III. BI-LEVEL OPTIMAL ALLOCATION MODEL

The bi-level model in [23] is adopted in this paper for optimally allocating CSs, which includes an upper-level (UL) optimization and a lower-level (LL) optimization. The detailed formulation is summarized below.

A. UL OPTIMIZATION MODEL

The UL optimization model aims to maximize the investor benefits. Intuitively speaking, deploying CSs as many as possible could probably achieve a higher service efficiency, which is able to attract more users and gain the higher profit. But the investment cost is unacceptable in that case.

In general, an investor needs to comprehensively consider the overall conditions such as population and traffic to properly site CSs. In this paper, the binary variable x_i denotes the choice of selecting candidate location i as CS place. If a CS is sited at i, $x_i = 1$, and vice versa.

$$x_i = \begin{cases} 1, & \text{if an EVCS is placed at } i \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

To take service efficiency into consideration when siting CSs, the objective function of the UL model is formulated.

$$\max C^{\mathrm{VAL}} = C^{\mathrm{BEN}} - C^{\mathrm{OPE}} - C^{\mathrm{RET}} - C^{\mathrm{TIM}} \tag{6}$$

$$\begin{cases} C^{\mathrm{BEN}} = 365 \cdot \sum_{i=1}^{N} \sum_{t=1}^{24} x_i P_{i,t} \left(c_{i,t}^{\mathrm{SEL}} - c_{i,t}^{\mathrm{PUR}} \right) \\ C^{\mathrm{OPE}} = \sum_{i=1}^{N} x_i [\left(A_i S_i + c^{\mathrm{PRI}} n_i + c^{\mathrm{COE}} n_i^2 \right) \\ \qquad \dfrac{r_0 (1+r_0)^{\tau}}{(1+r_0)^{\tau} - 1} + f_{\mathrm{CS}}(n_i)] \\ C^{\mathrm{RET}} = \sum_{i=1}^{N} x_i c_{ia}^{\mathrm{LIN}} l_{ia} \dfrac{r_0 (1+r_0)^{\pi}}{(1+r_0)^{\pi} - 1} \\ C^{\mathrm{TIM}} = 365 \cdot \sum_{i=1}^{N} \sum_{j=1}^{M} y_{ij} t_{ij} c^{\mathrm{CMS}} \end{cases} \tag{7}$$

where C^{BEN} is the annual operation benefit by CS, C^{OPE} is the annual operation cost of CS, C^{RET} denotes the power line reconstruction cost from CS to the nearest bus from the power grid, C^{TIM} is the charging time-consuming cost, N is the number of candidate locations for the CS, $P_{i,t}$ is the and $c_{i,t}^{\mathrm{PUR}}$ are respectively the charging price and electricity purchasing price of the i-th CS in t-th hour, A_i is the fixed cost of the i-th CS (i.e. land acquisition and construction costs), S_i is the area of the i-th CS, n_i is the number of chargers installed in the i-th CS, c^{PRI} denotes the investment factor associated with the unit price of chargers, c^{COE} is the equivalent investment factor related to the number of chargers, r_0 is discount rate, τrepresents the depreciation period of CS, $f_{\mathrm{CS}}(n_i)$ is the annual operating cost of the CS, which is a function of chargers, cLIN ia is the unit power line reconstruction cost from i-th CS to bus a, l_{ia} is the length of the line from i-th CS to bus a, π is the depreciation period of line, M is the number of charging users, y_{ij} is the binary variable that the j-th user selected the i-th CS, t_{ij} is the expected charging time of j-th charge user from demand point to i-th CS, including travel time and waiting time, c^{CMS} is the cost per unit time.

The UL objective function is subject to the following constraints:

1) Power flow constraint

$$\begin{cases} P_{ga}(t) - P_{La}(t) = V_a(t) \sum_{b=1}^{N_T} V_b(t) \left(G_{ab} \cos \theta_{ab}(t) \right. \\ \qquad \left. + B_{ab} \sin \theta_{ab}(t) \right) \\ Q_{ga}(t) - Q_{La}(t) = V_a(t) \sum_{b=1}^{N_T} V_b(t) \left(G_{ab} \sin \theta_{ab}(t) \right. \\ \qquad \left. - B_{ij} \cos \theta_{ab}(t) \right) \end{cases} \tag{8}$$

2) Bus voltage constraint:

$$V_a^{\min} \le V_a(t) \le V_a^{\max} \tag{9}$$

where, $V_a^{\min}$ and $V_a^{\max}$ are the upper and lower limits of the voltage at bus a.

3) Branch transmission power constraint:

$$|P_{ab}(t)| \le P_{ab}^{\max} \tag{10}$$

where, $P_{ab}^{\max}$ indicates branch transmission power limit.

4) The power constraint of the integration bus for the CS:

$$x_i \sum_{c=1}^{n_i} P_{ic}^{\text{CHA}} + \eta \cdot \max\left\{P_a^{\text{LOA}}(t)\right\} \le P_a^{\max} \tag{11}$$

where, P_{ic}^{CHA} indicates the real-time charging power of the c-th charger in the CS i, $P_a^{\max}$ is the maximum power that can be connected to the bus a, η is the simultaneous rate between the charging demand and the conventional load.

5) Investment constraints can be expressed as:

$$C^{\text{OPE}} + C^{\text{LIN}} \le C^{\text{BUG}} \tag{12}$$

where, C^{BUG} is the investment budget.

B. LL OPTIMIZATION MODEL

The LL optimization model is used to guarantee a satisfactory EV charging service, which is characterized by maximizing the total USFD. The USFD is a quantified indicator describing the satisfaction level of a cluster of EV users when using the charging service. The Cumulative Prospect Theory (CPT) proposed in [24] is adopted in this paper to introduce the value awareness of users to paradigm of decision procedure. The following shows the CPT-based value function $v(x)$ to represent the USFD of EV users.

$$v(x) = \begin{cases} x^{\alpha}, & x \ge 0 \\ \lambda(-x)^{\beta}, & x < 0 \end{cases} \tag{13}$$

where x denotes the gains or losses, α and β are the exponent parameters which show that the value function is concave for gains and convex for losses. And the ranges of these two parameters are both in [0, 1]. λ means the risk aversion degree of people, a larger value of λ expresses a higher risk-averse level of people.

In (14), we define the USFD as the piecewise satisfaction value of EV users according to the time assumption tolerance during the charging period.

$$T(t_{ij}) = \begin{cases} \left[-(t_{ij} - u_{ij,\max})\right]^{\alpha}, & t_{ij} \le u_{ij,\max} \\ -\lambda\left(t_{ij} - u_{ij.\max}\right)^{\beta}, & t_{ij} > u_{ij,\max} \end{cases} \tag{14}$$

where $u_{ij,\max}$ is a threshold of time assumption tolerance which implies the maximal acceptable waiting time of EV. If $t_{ij} > u_{ij,\max}$, satisfaction degree $T(t_{ij})$ is negative, representing that the users are unsatisfied with the charging service. The principle of determining the value of α and β can be derived from [24].

There is no doubt that EV drivers will select the most appropriate charging station according to the current location and battery state. The binary variable y_{ij} represents whether the user j selects the charging station i.

$$y_{ij} = \begin{cases} 1, \text{ if user } j \text{ selected charging station } i \\ 0, \text{ otherwise.} \end{cases} \tag{15}$$

The LL optimization ensures the optimal decision made by the EV drivers, whose objective function is to maximize the total USFD of the charging selection.

$$\max T^{\text{SAT}} = \sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij} T(t_{ij}) P_j^{\text{UER}} \tag{16}$$

where, P_j^{UER} is the charging demand of the j-th charging user.

The following constraints are considered:

$$\sum_{i=1}^{N} y_{ij} = 1 \tag{17}$$

$$y_{ij} - x_i \le 0 \tag{18}$$

$$\sum_{j=1}^{M} y_{ij} P_j^{\text{UER}} \le P_i^{\max} \tag{19}$$

where, $P_I^{\max}$ is the maximum charging power of CS i; equation (17) guarantees that one user can only charge the EV at one CS at one time; equation (18) guarantees that user j can choose CS i only if it exists; equation (19) shows that the total charging power of the user who selects the i-th CS cannot exceed its maximum capacity.

The framework of the proposed bi-level optimal allocation model is summarized in Fig.1.

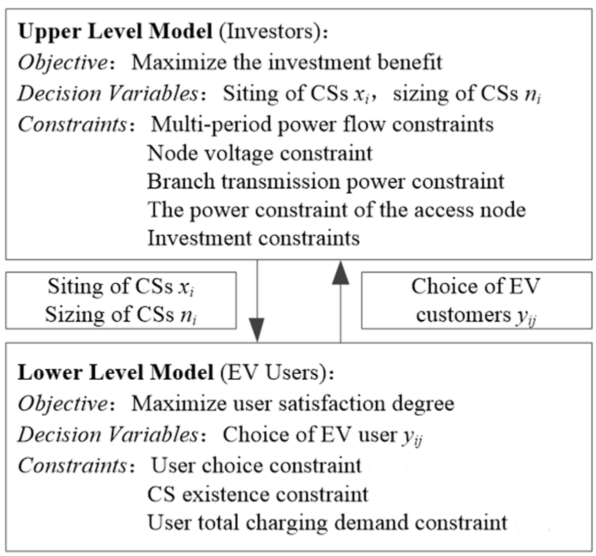

FIGURE 1. Framework of the bi-level allocation model for EV CSs.

IV. SOLUTION ALGORITHM

Bi-level programming is difficult to solve since it is *NP*-hard and non-convex, which as a result causes a highly-intensive computation burden [25]. A number of methodologies have been proposed in the literature. For example, extreme point method, branch and bound method, penalty function method and intelligent search method [26]. Similar to the branch and bound method, thanks to the convexity of the LL model in this paper, the original bi-level optimization model could be mathematically transformed to a single-layer model by replacing the LL model with the set of equations that define its Karush-Kuhn-Tucker (KKT) optimality conditions [27]. To solve such single-layer model, an improved Dynamic Differential Evolution (IDDE) algorithm is proposed which combines the advantages of two update strategies, i.e. DE/rand/1/bin and DE/best/1/bin. The proposed algorithm has both global and local search abilities.

A. LL MATHEMATICAL MODEL

Given the decision variable x_i of the UL problem, the Lagrange function of the LL optimization model shown in Eq. (16) $\sim$ Eq. (19) can be formulated.

$$L = \sum_{i=1}^{N}\sum_{m=1}^{M} y_{ij}T\left(t_{ij}\right)P_j^{\mathrm{USR}} - \rho_1\left(\sum_{i=1}^{N} y_{ij}-1\right) - \rho_2\left(y_{ij}-x_i\right) - \rho_3\left(\sum_{j=1}^{M} y_{ij}P_j^{\mathrm{USR}} - P_i^{\max}\right) \quad (20)$$

where ρ_1, ρ_2 and ρ_3 are the Lagrange multipliers of equality constraints and inequality constraints, respectively.

On the basis of KKT optimality conditions of the LL optimization model, its equality constraints are listed as:

$$\frac{\partial L}{\partial y_{ij}} = \sum_{i=1}^{N}\sum_{m=1}^{M} T\left(t_{ij}\right)P_j^{\mathrm{UER}} + \rho_1+\rho_2+\rho_3 P_j^{\mathrm{UER}} = 0 \quad (21)$$

$$\rho_1, \rho_2, \rho_3 \geq 0 \quad (22)$$

$$\rho_1\left(\sum_{i=1}^{N} y_{ij}-1\right) = 0 \quad (23)$$

$$\rho_2\left(y_{ij}-x_i\right) = 0 \quad (24)$$

$$\rho_3\left(\sum_{j=1}^{M} y_{ij}P_j^{\mathrm{USR}} - P_i^{\max}\right) = 0 \quad (25)$$

According to the above equivalent transformation, the bi-level model is mathematically decoupled into a single-level optimization model. To sum up, the objective function of the single-level optimization model is given in (6), including constraints in (8)-(12) and (20)-(25).

B. IMPROVED DYNAMIC DIFFERENTIAL EVOLUTION ALGORITHM

DE (Differential Evolution) is a highly efficient generation evolution-based stochastic algorithm for solving optimization model. However, the highly nonlinear model, inappropriate generation update and incorrect parameter configuration might cause problems, e.g. convergence failure and premature. To overcome these drawbacks, the dynamic differential evolution (DDE) was proposed in [28], providing a dynamic update mechanism for the generation evolution. Note that there exist two update mechanisms, i.e. DE/rand/1/bin and DE/best/1/bin [29]. The first one is characterized by its robust global search ability and relatively low-efficient convergence due to the random choice of individuals, while the second one selects the best individual in the current generation, improving the computing performance but encountering the risk of local optimum.

Based on the advantages of DE/rand/1/bin and DE/best/1/bin, we improve the mutation in the DDE method by introducing a piecewise threshold κ to determine the generation update mode. In this way, a trade-off between the convergence and the global optimum can be achieved. The procedure of IDDE is detailed as follows.

1) INITIALIZATION OPERATION

Randomly generate NP D-dimensional real vectors $Z_i(t)$ in the D-dimensional real space $S \subset R^D$, where each vector represents an individual, expressed as:

$$Z_i\left(t\right) = \left\{z_{i1}\left(t\right), z_{i2}\left(t\right), \cdots z_{iD}\left(t\right)\right\} \quad \forall i = 1, 2, \cdots, NP \quad (26)$$

where, t is the evolutionary generation, $z_{iD}(t)$ represents the i-th individual of the t-th population in the D-dimensional space.

Hence, the initial population vector $P(t)$ can be expressed as:

$$P\left(t\right) = \left\{Z_1\left(t\right), \cdots, Z_i\left(t\right), \cdots Z_{NP}\left(t\right)\right\} \quad (27)$$

2) MUTATION OPERATION

Randomly generate three vectors $Z_a(t)$, $Z_b(t)$ and $Z_c(t)$ in the current population different from vector $Z_i(t)$, where $i = 1, 2, \ldots, NP$. It should be noted that $i \neq a \neq b \neq c$. Then the differential vector formed by any two vectors in these three is scaled by the scaling factor F and added to the third vector, in this way the mutation individual of $Z_i(t)$ can be obtained, expressed as:

$$V_i\left(t\right) = Z_a\left(t\right) + F\cdot\left[Z_b\left(t\right) - Z_c\left(t\right)\right] \quad \forall a, b, c = 1, 2, \cdots, NP \quad (28)$$

where $V_i(t)$ represents the mutation individual of $Z_i(t)$ and there are NP mutation individuals.

In this paper, combing the advantages of DE/rand/1/bin and DE/best/1/bin, a new update strategy is proposed as follows: Firstly, set the minimum probability $p_{\min}$ and the maximum probability $p_{\max}$ for choosing update strategy DE/rand/1/bin, set the current evolution generation t and the maximum evolution generation T and calculate the selection threshold κ according to (29); Secondly, randomly produce a uniformly distributed random number n_{RA} in [0,1]; Thirdly, compare the random number n_{RA} with the threshold κ: if $n_{\mathrm{RA}} < \kappa$, use the formula of DE/rand/1/bin strategy, otherwise, use the formula of DE/best/1/bin strategy, as shown in (30).

$$\kappa = \left(p_{\max} - p_{\min}\right)\cdot\sin\left(\frac{\left(T-t\right)\pi}{2T}\right) + p_{\min} \quad (29)$$

$$V_i(t) = \begin{cases} Z_a^{RE}(t) + F_{RE} \cdot \left[Z_b^{RE}(t) - Z_c^{RE}(t)\right], & n_{RA} < \kappa \\ Z_a^{BE}(t) + F_{BE} \cdot \left[Z_b^{BE}(t) - Z_c^{BE}(t)\right], & n_{RA} \geq \kappa \end{cases} \tag{30}$$

where, $Z_a^{RE}(t)$, $Z_b^{RE}(t)$ and $Z_c^{RE}(t)$ are three random vectors (individuals) generated by the strategy of DE/rand/1/bin. Similarly, $Z_a^{BE}(t)$, $Z_b^{BE}(t)$ and $Z_c^{BE}(t)$ are three random vectors (individuals) generated by DE/best/1/bin. These six vectors differ from $Z_i(t)$. F_{RE} and F_{BE} represent the scale factors of two predefined update strategy respectively. It also can be seen from (29) that the defined selection threshold can help improve the mutation operation. When t is quite small at the beginning, κ is approximately equals to p_{max}, which is good for finding the potential globally optimal point due to the mutation mechanism of the proposed DE/rand/1/bin algorithm. On the other hand, with the increase of t, κ gets close to p_{min}, which could improve the ability of local searching and algorithm convergence.

3) CROSSOVER OPERATION

In order to have diverse population, the current individual $Z_i(t)$ is crossed with the corresponding variant individual $V_i(t)$ to generate the test individuals $W_i(t) = [w_{i1}(t), w_{i2}(t), \ldots, w_{iD}(t)]$, expressed as:

$$w_{ij}(t) = \begin{cases} v_{ij}(t), & n_{RA} \leq p_R \\ z_{ij}(t), & n_{RA} > p_R \end{cases} \quad \forall j = 1, 2, \cdots, D \tag{31}$$

where, p_R is the crossover probability, denoted p_{RR} and p_{RB} respectively under DE/rand/1/bin and DE/best/1/bin.

4) SELECTION OPERATION

In order to maintain the size of the offspring population, the test individual $W_i(t)$ generated by the mutation and crossover will compete with the target individual $Z_i(t)$ to determine who will enter the next generation of population. In this paper, the choice is made according to maximize the fitness function, i.e. the formula (6), then the selection can be expressed as:

$$Z_i(t+1) = \begin{cases} W_i(t), & f[W_i(t)] \geq f[Z_i(t)] \\ Z_i(t), & f[W_i(t)] < f[Z_i(t)] \end{cases} \tag{32}$$

As can be seen from the above formula, only when the fitness of the test individual is greater than the target individual, the target individual will be replaced by the test individual in the next generation. Therefore, the fitness value will always be improved over generations.

C. STEPS OF SOLUTION ALGORITHM

The procedures of the solution algorithm for the bi-level optimization are as follows:

1) Transform the bi-level optimization model into a single-layer optimization model by the KKT method with the objective function and associated constraints.

2) Set up the parameters of IDDE algorithm, including population size NP, differential variance vector scaling factor F_{RE} and F_{BE}, crossover probability p_{RR} and p_{RB}, initialize each individual within the constraint range of each variable, set the current iteration counter $t = 0$ and set the maximum iteration number.

3) Calculate the fitness value of each individual according to (6) and find the corresponding optimal fitness value f_{best} and the optimal individual Z_{best}.

4) Determine whether the evolutionary generation reaches a predetermined maximum evolutionary generation. If so, terminate the evolution and output the final result; otherwise, proceed to step 5).

5) Randomly select three individuals in the population different from individual $Z_i(t)$, and perform the mutation operation according to (29)-(30) to generate the mutation individual $V_i(t)$.

6) Perform the crossover operation on objective individual Z_i(t) and mutation individual $V_i(t)$ to generate the test individual Z_i(t) according to (31).

7) Calculate the fitness value of the test individual $W_i(t)$ according to (6), compare to the fitness value of the target individual $Z_i(t)$, and perform the selection operation according to (32) to generate the $t+1$ new generation of individual $Z_i(t+1)$.

8) Let $t = t + 1$ and return to step 3).

V. CASE STUDY

A. CASE DESCRIPTION

In this paper, the optimal CS allocation is demonstrated in a local area of a city in western China. The distribution system includes two 110 kV substations and 57 buses. The total load in the planning area is 102.24 MW, the number of vehicles is estimated to be 100,000, the proportion of EVs is estimated as 10%, and the total charge load is 9.38 MW. There are 10 CS candidates shown in Figure 2 with green icons. The capacity of the transformer in CS is 630 kVA, the ratio is 10/0.4, the power factor is 0.9, and the efficiency is 90%. The power of a single charger is 30 kW and the charging efficiency is 90%. In this way, a single set of charging equipment can be configured with 15 chargers and covers an area of 400 m^2. The parameters related to the distribution and transportation network, as well as those of the model and algorithm can be found in https://github.com/eexxyy/EVCS/blob/master/Appendix.pdf.

B. OPTIMAL PLANNING OF CSs

The optimal planning results of the EV CS obtained by the proposed model and IDDE algorithm are depicted in Table 1, which shows that both the total investment income of investor and USFD will change accordingly when the location and capacity of CS changes. In terms of the total investment income, plan #1 is better than plan #2, mainly caused by the increased number of charging stations in the plan #2 resulting in the increased construction and operation cost. Besides, there are a certain distance between the charging stations S-5, S-10 and distribution network bus, hence, and the cost of line

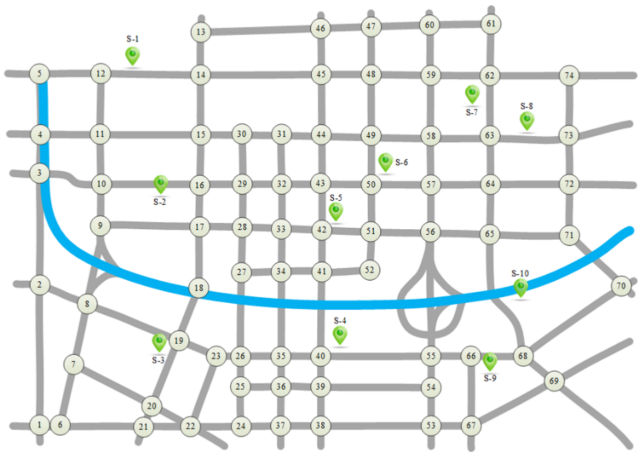

FIGURE 2. Ten candidate sites for CSs.

TABLE 1. Optimal planning results of the CSs.

Plans	1	2
Sites (set)	S-1(4)、S-3(6) S-7(6)、S-9(5)	S-1(4)、S-3(5) S-5(4)、S-8(5)、S-10(5)
Total income (10^4 CNY)	748.36	665.92
Construction costs (10^4 CNY)	2106.94	2343.71
Line reconstruction cost (10^4 CNY)	194.16	254.52
User time-consuming cost (10^4 CNY)	164.83	128.64
USFD	493	587

reconstruction cost increases. Overall, the net investment revenue of plan #2 is less than that of plan #1 by about 11.02%.

However, plan #2 is better than plan #1 in terms of user satisfaction, since four charging stations in plan #1 are all distributed in the boundary of the focused area, and EV users located in the center area need to spend more travel time to charge their vehicles. On the other hand, in plan #2, there is a CS S-5 located in the center area. In this way, EV users located in the center area can charge their vehicles at S-5 with less travel time. Therefore, the USFD can be improved about 19.07% compared to that of plan #1.

As only a small difference is observed in investment, but the service radius of plan #2 is much wider than plan #1 due to one more charging station constructed, so that it is more convenient for electric car users to charge, hence plan #2 is preferred in reality. Furthermore, the capacities of the CSs are relatively small. There remains a certain expansion space for the future growth of the EV charging load without overloading the distribution line or significantly increasing the loss.

According to the above analysis, although the net investment income reduces by about 11.02%, but the USFD increases by about 19.07%. The significant improvement of EV user satisfaction not only attracts more consumers, but also improves the comprehensive competitiveness of enterprises.

C. COMPARISON

The bi-level programming model has conflicting characteristics, i.e. the upper decision maker and the lower decision maker have different goals and these goals are contradictory. Such a contradiction allows the possibility to find the best tradeoff between the two goals. To demonstrate the advantages of the bi-level planning model of EV CS proposed in this paper, comparisons to other existing single-layer planning models defined in the two following scenarios:

Scenario #1: Establish a single layer EV CS planning model by taking the USFD as the objective and the total investment income of the charging station as a constraint (not less than 8 million CNY).

Scenario #2: Establish a single layer EV CS planning model by taking total investment income as the objective and the USFD as a constraint (not less than 600 units).

The hybrid VNS-PSO algorithm [30] is used to solve the above two scenarios. The parameters of the model and algorithm are the same as section B. The planning results are shown in Table 2.

TABLE 2. Optimal planning results in two scenarios.

Scenarios	1	2
Sites (set)	S-1(5)、S-3(6) S-7(5)、S-9(6)	S-1(5)、S-3(5) S-5(5)、S-8(5)、S-10(6)
Total income (10^4 CNY)	835.47	602.58
Construction costs (10^4 CNY)	2216.58	2421.92
Line reconstruction cost (10^4 CNY)	194.16	254.52
User time-consuming cost (10^4 CNY)	201.84	97.43
USFD	476	604

It can be seen from Table 2 that the total income of scenario #1 is high, but the USFD is low. On the other hand, the USFD of scenario #2 is high, but the total investment income is very low (27.88% lower than that of scenario #1), which is contrary to the basic investment principle. Comparing to the result from the bi-level planning model of the EVCS in Table 1, we can see that the bi-level planning model can reasonably address both interests of the investors and EV users through coupling the UL model with the LL model. And the proposed bi-level model can achieve an effective compromise between investment income and USFD, so that investors and users can be in a relatively balanced state, which is of great significance for the long-term development of enterprises.

D. SENSITIVITY ANALYSIS OF MODEL PARAMETERS

1) DAILY LOAD DIFFERENCE

The load of the distribution system varies with time, and the charge demand is different in different hours during the day.

In order to investigate the influence of the simultaneous rate of load and the charging demand, the rate η is set as 0.5, 0.7 or 0.9, and the planning results are shown in Table 3 by using the proposed IDDE algorithm.

TABLE 3. Optimal planing results with different simultaneous rate.

Scenarios	η =0.5	η = 0.7	η = 0.9
Sites (set)	S-1(4)、S-3(5)、S-5(5)、S-7(5)、S-9(6)	S-1(4)、S-3(5)、S-5(4)、S-8(5)、S-10(5)	S-1(3)、S-3(4)、S-5(4)、S-7(4)、S-10(5)
Total income (10^4 CNY)	718.44	665.92	606.29
Construction costs (10^4 CNY)	2538.16	2343.71	2013.47
Line reconstruction cost (10^4 CNY)	312.48	254.52	208.16
User time-consuming cost (10^4 CNY)	112.53	128.64	147.94
USFD	631	587	522

As can be seen from Table 3 that the final EV charging station planning results are different with different simultaneous rate of charging load and the conventional load, and the corresponding conventional load curve under different simultaneous rate are shown in Fig. 3. According to Table 3 and Fig.3, it can be observed that the conventional load in the distribution network is relatively small when the simultaneous rate is small. Hence, the bus can accept more EV charging demand and the charging station can be equipped with more facilities, in this way, both the charging station investment income and the user satisfaction can be improved. On the contrary, the capacity for incorporating EV charging demand into the distribution system is poor with large simultaneous rate, and the equipment in the charging stations will be reduced, hence the investment income and the user satisfaction will be reduced accordingly. Therefore, existing distribution network loading level differences need to be considered during the charging station planning procedure.

2) EV PENETRATION

EVs will be increasingly favored by consumers with the battery technology being developed and security improvement, and the EV number will increase continuously. The charging station planning will be expanded with the increasing charging demand. Therefore, the penetration of EVs are set as 20% and 30% in this paper, and the optimal planning results of charging stations are listed in Table 4 by using the proposed IDDE algorithm.

As can be seen from Table 1 and Table 4, the optimal planning results are various with different EV penetration. Specifically, with the penetration improvement, the number of equipment in CSs increases and the investment income increases accordingly. Besides, the consumer waiting time for charging also reduces with more charging equipment, hence,

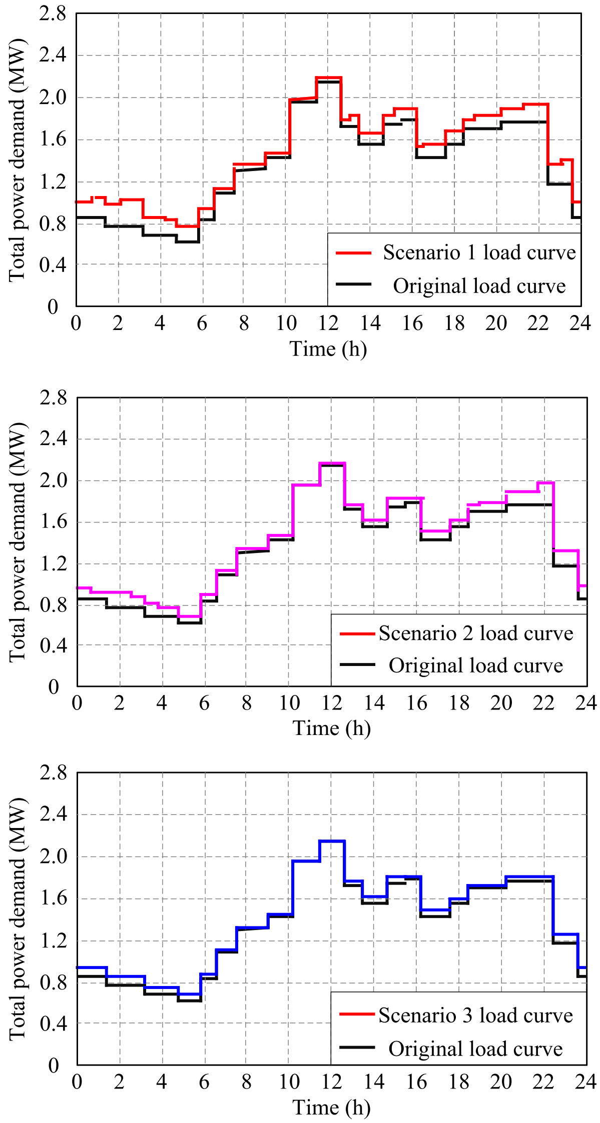

FIGURE 3. Conventional load curves of bus 18 with different simultaneous rate.

TABLE 4. Optimal planning results with different ev penetration.

Penetration	20%	30%
Sites (set)	S-1(8)、S-3(8)、S-5(8)、S-8(9)、S-10(9)	S-1(11)、S-3(13)、S-5(12)、S-8(14)、S-10(13)
Total income (10^4Yuan)	948.32	1482.76
Construction costs (10^4Yuan)	3624.93	4474.58
Line reconstruction cost (10^4Yuan)	254.52	254.52
User time-consuming cost (10^4Yuan)	117.86	109.32
USFD	603	625

the USFD is also improved at the same time. In this case, the EV penetration is the main factor influencing the allocation results. The total power demand curves under different

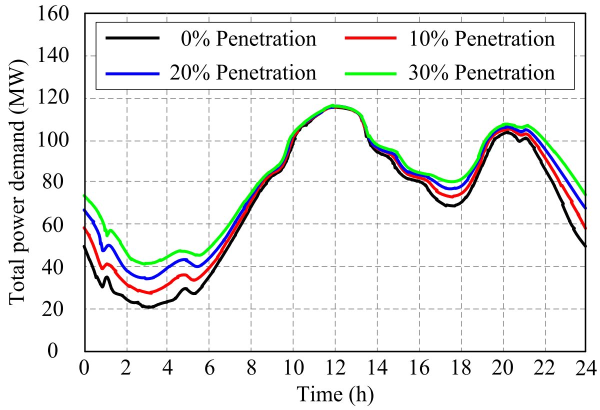

FIGURE 4. Total power demand curve with different EV penetration.

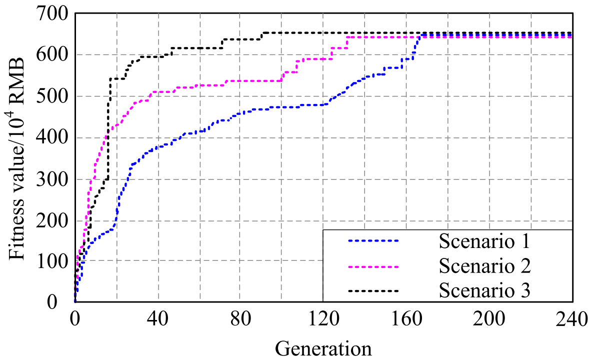

FIGURE 5. Optimal fitness evolution curves in the three scenarios.

TABLE 5. Average CPU time and fitness values of different algorithms.

Scenarios	CPU time (min)	UL fitness	LL fitness
1	26.21	663.26	585
2	21.58	650.83	578
3	14.94	665.92	587

TABLE 6. Average calculation time and fitness value based on different algorithms.

Algorithm	Calculation time (min)	UL fitness	LL fitness
IDDE	14.94	665.92	587
IGA	16.58	661.15	583
IPSO	15.63	663.53	584

EV penetration levels are depicted in Figure 4. It is worth noting that the potential users who need fast charging service at 2-3am mainly include the night taxi cars and cruisers in the city, as well as the public highway buses. Although the charging demand is quite low in this period, it needs to be considered in planning stage.

As shown in Fig.4, with the gradually increasing EV penetration, the total power demand has been promoted. Apparently, compared valley period, less power demand is caused by EV charging in peak time. This is because that the charging power is limited according to (11), with the goal of encouraging the drivers charge their vehicles at more appropriate period to enable the global peak-shift.

E. COMPUTATIONAL PERFORMANCE COMPARISON

To verify the effectiveness of the proposed IDDE algorithm compared to the standard DDE algorithm which does not have the mutation operator τ to select the update strategy, the following three scenarios are considered:

Scenario #1: In the standard DDE algorithm, the update strategy DE/rand/1/bin is used during the mutation operation.

Scenario #2: In the standard DDE algorithm, the update strategy DE/best/1/bin is used during the mutation operation.

Scenario #3: In the proposed IDDE algorithm, the mutation operator κ is introduced during the mutation operation, and the update strategy is adaptively selected according to the criterion.

In order to avoid the influence of the randomness of the algorithm, the algorithms used in the three scenarios are run 10 times separately from the optimization planning problem of the charging station, and the optimal values are taken as the global optimal solution. The optimal fitness evolution curves for the three scenarios are depicted in Figure 5, and the average CPU calculation time and fitness values are shown in Table 5.

We can see from Table 5 and Fig. 5 that the DDE algorithm using the update strategy DE/rand/1/bin converges slowly. However, as the number of iterations increases, it gradually approaches the global optimal solution. While the DDE algorithm using the update strategy DE/best/1/bin converges faster, but it is easy to fall into the local optimal solution. The proposed IDDE algorithm combines the advantages of the two update strategies. In the early stage of evolution, the probability of using the update strategy DE/rand/1/bin is large, and the diversity of the population can be effectively maintained, and the global convergence of the algorithm is ensured. In the later period, the probability of using the update strategy DE/best/1/bin gradually increases, which ensures the local search ability and improves the convergence speed. Furthermore, comparisons with the improved genetic algorithm (IGA) and improved particle swarm optimization (IPSO) are also performed. The average CPU time of 10 runs and fitness value for each algorithm are shown in Table 6. It can be seen from Table 6 that the solution obtained by IDDE algorithm is better than IGA and IPSO algorithm, and the average CPU time of IDDE algorithm is smaller than IGA and IPSO algorithm, which further proves the convergence performance.

VI. CONCLUSION

From the enterprise investor's point of view, the charging station planning should maximize the investment income and ensure the user satisfaction level at the same time. The bi-level allocation model for EV CS planning, coordinating investor benefits and user satisfaction degree, is proposed in this paper. The upper-level model takes the maximization of investment income as the goal considering the power grid constraints and investment constraint. The lower model takes the maximal user satisfaction as the goal considering the capacity constraints of the charging station. Case studies demonstrated that through the coupling of the upper- and lower-level models, an effective compromise can be achieved between the investment income and the user satisfaction, which provides a new idea for the planning of EV CS. Besides, the impact from daily load difference and EV penetration are also analyzed. It should be noted that different utilities other than the power company are regarded as one kind of investors in this paper. As more different investors considered in planning CSs, the "gaming" may exist to provide better charging services to benefits of different investors and users, which would be studied further.

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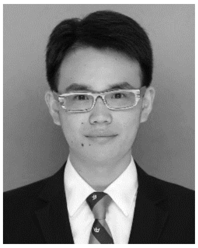

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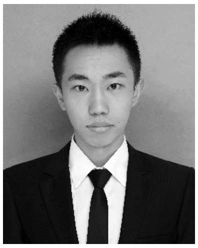

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