IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received June 11, 2019, accepted June 22, 2019, date of publication June 28, 2019, date of current version July 16, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2925559

A Real-Time EV Charging Scheduling for Parking Lots With PV System and Energy Store System

WEI JIANG AND YONGQI ZHEN
College of Electronics and Information Engineering, Shanghai University of Electric Power, Shanghai 200090, China

Corresponding author: Wei Jiang (zzm7406@sina.com)

This work was supported by the National Natural Science Foundation of China under Grant 61202369 and Grant 61401269.

ABSTRACT The problem of electric vehicle (EV) charging scheduling in commercial parking lots has become a meaningful study in recent years, especially for the parking lots near the workplace that serve fixed users. This paper focuses on the optimization of the EV charging in the parking lot integrating energy storage system (ESS) and photovoltaic (PV) system. A smart charging management system is first established. The charging optimization problem is formulated as a cost minimization problem. Then, grey wolf optimizer (GWO) is introduced as a method to find the optimal solution. Considering the constraint conditions in the optimization problem, an improved binary grey wolf optimizer (IBGWO) is proposed, which can improve the convergence speed and optimization accuracy. Finally, a real-time EV charging scheduling strategy based on short-term PV power prediction and IBGWO is proposed. Several cases are simulated to analyze the performance of the proposed strategy. The experimental results show that the proposed IBGWO is superior in solving the proposed charging scheduling problem compared with other meta-heuristic algorithms. Moreover, the proposed strategy can effectively improve the utilization rate of the PV power and reduce the electricity cost of operators.

INDEX TERMS Electric vehicle, charging management, real-time strategy, grey wolf optimizer.

I. INTRODUCTION

In recent years, the increasing public awareness of environmental pollution and fossil fuels depletion is leading to the dramatic expansion of electric vehicles (EVs) [1]–[3]. At present, it is difficult for many EV owners to install the charging infrastructure in their home parking garages [4]. To alleviate this problem, it has been hypothesized that parking lots can be utilized as recharging stations [5]. For urban residents, a reliable alternative is to charge their EVs in the parking lot near their workplace, because their working time is longer than the charging time of their EV requirement. EVs are important for the development of sustainable energy and it is feasible and environment- friendly to charge EVs with photovoltaic (PV) Power. So the PV system can be installed in the parking lot with large space to provide power for EVs [6]. However, a large number of uncontrolled EV charging can result in negative impact on the grid [7]. To alleviate this problem, energy storage system (ESS) consisting of lithium batteries can be installed in these locations [8], [9].

The associate editor coordinating the review of this manuscript and approving it for publication was Yilun Shang.

The owner of parking lot makes a profit by providing charging service for EVs. Since the parking time of each EV is generally longer than the time required for charging at workplace, a reasonable charging plan that determines each EV when and how much to charge is needed. It can not only avoid the problems mentioned in the literatures [7], but also reduce the operation cost.

Charging scheduling problem with various goals have been widely studied. Coordinated charging of EVs can decrease the passive influence of the charging load and maximize the benefit of charging operators. In [10], a locally optimal scheduling scheme is suggested to solve the charging problem of large-scale EVs, which consider when the charging of each EV begins and ends. Reference [11] proposes a decentralized algorithm to update the charging profile of each EV by control signal, the EV charging problem is formulated as an optimal problem that how to fill the electric load valley. Reference [12] investigates charging coordination problem for multiple dwellings, two kinds of control strategies are proposed to shift charging load to off-peak periods. In [13], in order to prevent overloading of feeders and minimize the variance of the aggregate load in the distribution system, an effective charging algorithm is proposed. In [14], considering the influence of battery charging characteristics on EV charging scheduling process, an intelligent multi-charging system is designed to maximize the profit of charging operator. Under the charging and transformer capacity constraints, an optimized strategy for multiple PEV aggregators is proposed in [15] to achieve coordination between controlling charging load and minimizing the electrical cost within the time-of-use (TOU) price. In [16], considering market price change and user-selected charging time, a real-time control strategy is adopted to coordinate the charging behavior of EVs, which reduces the charging cost and the impact on the grid. A two-layered management system is proposed in [17] to handle the charging behavior of regular and irregular EVs, so as to maximize economic benefits and the number of EV which meet charging demands. Reference [18] uses an on-off strategy to transform the real-time scheduling problem into a binary optimization problem, charging loads of EVs are coordinated based on dynamic electrical price (EP). Reference [19] proposes a two-stage approximate dynamic programming based on short-term prediction and long-term estimation to optimize the parking lot charging management.

Although a lot of research has been done on coordinated charging of EVs, it is necessary to further study the coordination of renewable energy and ESS to minimize the operation cost in EV charging management. Reference [20] introduces a new coordinated charging model for the parking lot with PV energy and ESS, which considers the influence of charging price on the choices of EV drivers. In [21], a dynamic cost optimization scheduling based on the real-time information of EV charging demands and the PV power generation is developed to control the charging process of each EV in the parking lot, but ESS is not considered. To minimize the mean waiting time of EVs in a charging station with renewable energy and ESS, a constrained markov decision process is proposed in [22]. A heuristics-based strategy is proposed to optimize the EV charging for a charging station with ESS in [23], and the relationship between operation cost and ESS capacity is explored. A hybrid algorithm is proposed in [24] to optimize the management of ESS and PV power based on the fluctuation of EP, which is only suitable for large-scale charging strategy. When the EV charging load is low, it will cause the waste of PV power.

In this paper, a smart charging management system (SCMS) is designed to minimize the operation cost of the parking lot owners. This system integrates PV energy, ESS, and power grid to provide charging service to the EV. The main procedures and contributions of this paper are as follows:

1) An EV charging optimization problem with characteristics of an EV parking lot that integrates PV generation and ESS is formulated as a mixed integer linear programming problem. The goal of optimization is to minimize the operation cost of the parking lot.
2) An improved grey wolf optimizer is proposed to solve the charging scheduling problem of EVs. Through population initialization and mutation, the convergence speed and optimization accuracy of the algorithm are improved, and the efficiency of solving the problem is enhanced.
3) A real-time charging scheduling strategy is proposed to manage the charging process of EVs. It can optimize the charging scheduling according to the change of EV load, and maximize the utilization of PV power.

The rest of this paper is organized as follows. Section II describes the system model of a commercial parking lot and the problem formulation. Section III introduces the improved grey wolf optimizer. An efficient real-time strategy for charging scheduling is presented in Section IV. Afterwards, several necessary case studies are introduced in Section V. Finally, Section VI presents the conclusion and discussion of the proposed research.

II. SYSTEM MODEL

In this paper, considering the regularity of parking modes of EVs, the types of EVs are divided into two groups: regular EVs and irregular EVs. Regular EVs tend to follow a set time on working days, they travel mainly between their home and workplace. The owners of regular EVs pay a fixed fee for a period of time (Monthly or quarterly) to the parking owner. Irregular EVs represent customers who travel unconventionally, their arrival and parking time are random. Compared with regular EVs, the parking pattern of irregular EVs is unpredictable.

The owner of the parking lot is responsible for providing the required charging power of EVs from the electricity market. In order to minimize the electricity cost of parking owners, a smart charging management system (SCMS) that controls the charging process of each EV based on the fluctuation of EP is proposed. The charging time of each regular EV can be calculated by the SCMS according to its arrival time, departure time and charging demand which set by its owners. After obtaining these information, the charging scheduling of regular EVs that aims to choose appropriate time slots to charge can be set up in advance.

To ensure the benefits of EV owners, it is assumed that: each EV in the parking lot should be charged to its 90% of upper SOC limit before departure and the charging behavior of regular EVs can be obtained by SCMS in advance. In order to simplify the discussion, the efficiency of EV batteries and vehicle-to-grid (V2G) is not considered.

A. BASIC STRUCTURE OF THE SYSTEM

SCMS is proposed in this paper, as show in Fig. 1. The grid is connected to the system via a transformer. The PV system is connected to the bus through a DC-AC converter, and the power it generates is first supplied to charge the EVs. When the PV power is insufficient to satisfy the EV demand, the power of grid or ESS is used to meet the EV load. If there is excess PV power, it will be supplied to the ESS or converted to AC power by the bidirectional inverter to feed into the grid. The key role of ESS in the system is that it can store the grid power in low EP periods

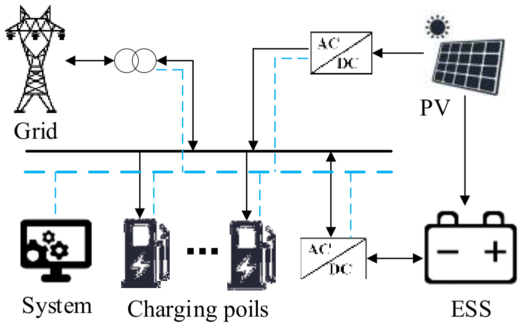

FIGURE 1. The structure of SCMS.

or the excess PV power, and release it to the EV when EP is high.

B. ESTABLISHMENT OF CHARGING MODEL

In order to satisfy EVs with different charging needs and improve the quality of service, the charging modes of EVs are divided into three types: M_0(0KW), M_1 (7KW), and M_2 (19.2KW). M_1 and M_2 are both belong to level 2 of the charging pattern [25]. The charging mode of each EV is determined based on its parking time and charging demand. The variable $i \in \{1, 2 \cdots I\}$ represents the number of EVs that need to be recharged in one day. Let $R_{p,i}$ denote the parking time of EV_i and Dem_i denote its charging demand. Their charging time in M_1 and M_2 is denoted by $R^1_{c,i}$ and $R^2_{c,i}$ respectively. If the parking time of an EV is less than charging time in M_2, the charging demand of this EV will not be satisfied. Therefore, SCMS will reject the requirement of the EV to enter the parking lot for charging and its charging mode is denoted as M_0. Then the choice of charging mode (CM) for EV_i is defined as follows

$$CM_i = \begin{cases} M_1 & R_{p,i} \geq R^1_{c,i} \\ M_2 & R^1_{c,i} > R_{p,i} \geq R^2_{c,i} \\ M_0 & otherwise \end{cases} \quad \forall i \in I, \tag{1}$$

where

$$R^1_{c,i} = \frac{Dem_i}{7}, \quad R^2_{c,i} = \frac{Dem_i}{19.2} \quad \forall i \in I \tag{2}$$

For EVs charged in M_1, SCMS can adjust their charging time to the periods of low EP by on-off strategy. It is more practical to turn charging on or off rather than adjust the charging rate when controlling charging of a large number of EVs. The charging process of these EVs can be delayed at any time under certain restrictions. When charging power is high, frequent charging will do harm to battery life. Therefore, for EVs charged in M_2, once they start charging, the process will not be interrupted, SCMS just need to determine when they start charging in the optimization scheduling.

It is assumed that each EV visits the parking lot once in 24 hours. Let one day be divided into T time slots and each slot t is half an hour. A binary variable k^i_t is proposed to represent the charging state of EV_i in the time slot t. $k^i_t = 1$ denotes EV_i is in charging and $k^i_t = 0$ is in idle state.

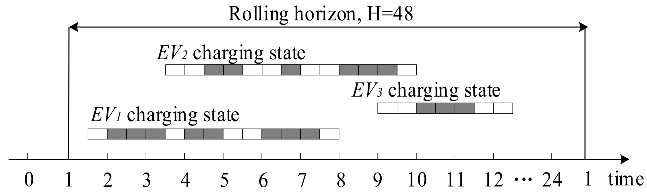

FIGURE 2. Charging state of EVs in parking time.

$[a_i, d_i]$ denotes the parking time slot range of EV_i. $R_{c,i}$ represents the number of time slots to fulfil the charging task. The parking time and required charging time of each EV is updated in real time by SCMS. The remaining charging time should not be less than the remaining parking time. The charging time constraint that EV_i should satisfy can be given by

$$\sum_{t=a_i}^{d_i} k^i_t = R_{c,i}, \quad \forall i \tag{3}$$

It should be noted that the EV_i charged in M_2 keeps $k^i_t = 1$ during the charging periods. In order to better explain the charging strategy, it is assumed that EV_1 and EV_2 are charged in M_1 and EV_3 is charged in M_2, and their charging states in rolling horizon are as shown in Fig.2. Each square represents a time slot and the length of the square bar represents the parking time of each EV, the gray square represents that the EV is charging in this period whereas blank square represents that the EV is in idle state. The rolling horizon is the charging optimal range. The charging period of each EV is scheduled by SCMS in this scope.

Let P_i denote the charging power of the EV_i and P^{EV}_t represents the total charging load of the parking lot from the connected EVs in time slot t. P^{EV}_t is calculated by

$$P^{EV}_t = \sum_{i \in I} k^i_t P_i, \quad \forall t \tag{4}$$

C. ENERGY SUPPLY MODEL OF THE PARKING LOT

To meet the charging demand of EV P^{EV}, the power provided by ESS P^{ESS}, PV system $P^{PV,EV}$ and grid $P^{grid,EV}$ are supplied to charge the EVs. Therefore, the total charging power of all EVs P^{EV} during slot t can be calculated by

$$P^{EV}_t = P^{ESS,EV}_t + P^{PV,EV}_t + P^{grid,EV}_t, \quad \forall t \tag{5}$$

1) ESS MODEL

Let SOC_t denote the state of charge (SOC) of the battery energy storage system in time slot t. It can be calculated by

$$SOC_t = \frac{E^{Rem}_t}{E^{Total}}, \quad \forall t \tag{6}$$

where E^{Rem}_t and E^{Total} respectively denote the remaining capacity of ESS in time slot t and the total capacity of ESS.

Let ΔP^{ESS}_t denote the output power of the ESS, the η^{ESS}_c and η^{ESS}_d respectively denote the converter efficiency of the ESS in charging and discharging process. Therefore, the dynamic adjustment of SOC can be shown as (7).

In addition, ΔP_h^{ESS} should satisfy the follow (8)-(10) at any time slot, where $P^{c,ESS}$ and $P^{d,ESS}$ represent the charging power and discharge power of ESS, $P^{PV,ESS}$, $P^{grid,ESS}$, and $P^{ESS,grid}$ represent the power from PV to ESS, grid to ESS and ESS to grid.

$$SOC_t = SOC_{t-1} + \frac{\Delta P_t^{ESS} \cdot \Delta t}{E^{Total}}, \quad \forall t, \tag{7}$$

where

$$\Delta P_t^{ESS} = P_t^{c,ESS} - P_t^{d,ESS}, \quad \forall t \tag{8}$$
$$P_t^{c,ESS} = \left(P_t^{PV,ESS} + P_t^{grid,ESS}\right) \cdot \eta_c^{ESS}, \quad \forall t \tag{9}$$
$$P_t^{d,ESS} = \left(P_t^{ESS,EV} + P_t^{ESS,grid}\right) / \eta_d^{ESS}, \quad \forall t \tag{10}$$

2) PV POWER MODEL

The power generated by PV system can be charged for EVs, sold to the grid and stored in ESS. The power balance among them can be expressed by

$$P_t^{PV} = P_t^{PV,grid} + P_t^{PV,EV} + P_t^{PV,ESS}, \quad \forall t \tag{11}$$

where P^{PV} is the generated power of PV system, $P^{PV,grid}$ is the power from the PV to the grid.

3) GRID POWER MODEL

The EV or ESS can be directly charged by grid, and the ESS and PV system can also sell excess power to the grid. Accordingly, the grid power in period t can be expressed by (12)-(14). $P^{grid,b}$ and $P^{s,grid}$ represent the power purchased from the grid and the power sold to the grid.

$$P_t^{grid} = P_t^{grid,b} - P_t^{s,grid}, \quad \forall t \tag{12}$$
$$P_t^{grid,b} = P_t^{grid,EV} + P_t^{grid,ESS}, \quad \forall t \tag{13}$$
$$P_t^{s,grid} = P_t^{ESS,grid} + P_t^{PV,grid}, \quad \forall t \tag{14}$$

D. DESCRIPTION OF EV MODEL

Due to the lack of real-world EV charging data, the EV arrival behavior and their charging demands are generated following the Poisson distribution [19]. For the vehicles arriving at the parking lot, the arrival/departure rates are modeled by giving higher arrival rate in the morning and higher departure rate in the afternoon. The parking time of EVs is set to be longer in the morning and shorter in the afternoon, which refers to the real data of workplace.

E. PROBLEM FORMULATION

In this paper, the objective is to minimize the electricity cost of parking lot, while satisfying the charging needs for connected EVs. Therefore, the optimization problem for the parking lot can be formulated as follows:

$$\min \ Cost = \sum_{t=1}^{T} \left(P_t^{grid,b} U_t^b - P_t^{s,grid} U_t^s\right) \cdot \Delta t \tag{15}$$

$$\text{Subject to} \quad SOC_{\min} \le SOC_t \le SOC_{\max}, \quad \forall t \tag{16}$$
$$0 \le P_t^{c,ESS} \le P_t^{c,\max}, \quad \forall t \tag{17}$$
$$0 \le P_t^{d,ESS} \le P_t^{d,\max}, \quad \forall t \tag{18}$$
$$0 \le P_t^{grid} \le P_t^{grid,\max}, \quad \forall t \tag{19}$$

U_h^b and U_h^s represent the price of electricity purchased from the grid and sold to the grid respectively. The upper and lower limits of SOC are as shown in (16). $P^{c,max}$ and $P^{d,max}$ represent the maximum charge and discharge power of the ESS. The transformer capacity constraint (19), defines the upper limit of total power that can be obtained from the grid.

III. THE GREY WOLF OPTIMIZER

The Grey Wolf Optimizer (GWO) originates from the simulation of hierarchical system and predation behavior of grey wolf population in nature, and achieves the goal of optimization through wolf group tracking, encirclement, pursuit, and attacking prey. Compared with other meta-heuristic optimization algorithms, GWO has the advantages of simple principle, few parameters and strong global search ability. It has been proved to be superior to Particle Swarm Optimization (PSO) algorithm in accuracy and convergence speed [26]. GWO is used to study complex and constrained problems in recent years and it is proved to be a suitable solution [27], [28].

A. CONTINUOUS VALUED GWO

In GWO, the wolf group is divided into four grades: α leads the predation action, β makes the auxiliary decision, δ carries out the specific action arrangement, ω obeys the orders of the first three to track the prey. In the searching process for the best solution, the current best individual in the population is recorded as α, the current suboptimal individual is recorded as β, the current third best individual is recorded as δ, and the remaining individuals are recorded as ω, and the position of the prey corresponds to the global optimal solution of the optimization problem.

In the hunting process of grey wolves, their encircling behavior can be modeled mathematically as

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(n) - \vec{X}(n)\right| \tag{20}$$
$$\vec{X}(n+1) = \vec{X}_p(n) - \vec{A} \cdot \vec{D} \tag{21}$$
$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{22}$$
$$\vec{C} = 2 \cdot \vec{r}_2 \tag{23}$$

where $\vec{D}$ is the distance between each wolf and the prey, $\vec{X}_p(n)$ is the position vector of the prey in the iteration n; $\vec{X}(n)$ is the position vector of the grey wolf individual in the iteration n; $\vec{A}$ and $\vec{C}$ are coefficient vector; $\vec{a}$ decreases linearly from 2 to 0 as the number of iterations; $\vec{r}_1$ and $\vec{r}_2$ are random numbers between [0,1].

Among grey wolves, α, β, and δ are closest to the prey. Therefore, for other grey wolves, the position of prey is determined according to the positions of α, β, and δ. Their positions are updated by:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{24}$$

$$\begin{aligned}\vec{X}_1 &= \vec{X}_\alpha - A_1 \cdot \vec{D}_\alpha\\ \vec{X}_2 &= \vec{X}_\beta - A_2 \cdot \vec{D}_\beta\\ \vec{X}_3 &= \vec{X}_\delta - A_3 \cdot \vec{D}_\delta \end{aligned} \tag{25}$$

$$\begin{aligned}\vec{D}_\alpha &= \left|C_1 \cdot \vec{X}_\alpha(t) - \vec{X}(t)\right|\\ \vec{D}_\beta &= \left|C_2 \cdot \vec{X}_\beta(t) - \vec{X}(t)\right|\\ \vec{D}_\delta &= \left|C_3 \cdot \vec{X}_\delta(t) - \vec{X}(t)\right| \end{aligned} \tag{26}$$

where A_1, A_2, A_3 are calculated by (22), C_1, C_2, C_3 are calculated by (23).

B. IMPROVED BINARY GREY WOLF OPTIMIZER (IBGWO)

According to the previous introduction, the EV charging scheduling problem is transformed to a linear programming problem to determine the charging state of each EV in a specific time range. Since the charging state of each EV in any time slot is represented by 0 or 1, a binary grey wolf algorithm is designed to solve the charging optimal problem.

As proposed in [29], the updated position vector of grey wolf (24) is transformed to binary by the following equation

$$x_g^{n+1} = \begin{cases} 1 & sigmoid\left(\frac{x_1 + x_2 + x_3}{3}\right) \geq rand \\ 0 & otherwise \end{cases} \tag{27}$$

where *rand* is a random number between [0, 1], x_g^{n+1} is the updated binary position in dimension g at iteration n, and $sigmoid(a)$ can be represented as

$$sigmoid\,(a) = \frac{1}{1 + e^{-10[x-0.5]}} \tag{28}$$

1) ENCODING OF BINARY VARIABLES

It is assumed that the number of grey wolves is W. The charging state of EV_i of *wth* wolf during time slot t of iteration n can be denoted as $k_{t,w}^{i,n}$. Therefore, a dimension of I-by-T matrix is constructed for each wolf to find the optimal solution. In the charging scheduling horizon, the matrix of all EVs of *wth* wolf at iteration n is represented by K_w^n. The charging state solution of all grey wolves can be expressed as $K\,(n) = \{K_1^n, K_2^n, \cdots, K_W^n\}$. K_w^n is given by

$$K_w^n = \begin{bmatrix} k_{1,w}^{1,n} & k_{1,w}^{2,n} & \mathrm{L} & k_{1,w}^{T,n} \\ k_{2,w}^{1,n} & k_{2,w}^{2,n} & \mathrm{L} & k_{2,w}^{T,n} \\ \mathrm{L} & \mathrm{L} & \mathrm{L} & \mathrm{L} \\ k_{I,w}^{1,n} & k_{I,w}^{2,n} & \mathrm{L} & k_{I,w}^{T,n} \end{bmatrix} \tag{29}$$

2) INITIAL POPULATION

The initial population is generated randomly. When solving the charging state coding problem, in order to improve the convergence speed of the algorithm, all individuals in the population must be effective. Each individual should be guaranteed to contain enough 1 to satisfy the conditional constraints of (3)-(4).

3) MUTATION

After selecting α, β, and δ, other grey wolves need to update their positions according to these three, and the individuals after iteration may not meet the previous constraints. Therefore, mutation is used to change the number of 0 and 1 in these individuals randomly. Mutation provides an opportunity for the individuals that are not in the current population and can avoid local optimum effectively.

4) FITNESS FUNCTION

To evaluate the performance of grey wolf individuals, the fitness value of each individual is calculated by using (30), which μ is coefficient that prevents fitness value from being negative. φ is a penalty factor. When $P_t^{grid} > P^{grid,\max}$, φ is a large positive number. When $P_t^{grid} \leq P^{grid,\max}$, φ is equal to 1. By setting the penalty factor φ, individuals who do not meet the constriction can be effectively excluded in the search process.

$$fitness = \frac{1}{\varphi \cdot (Cost + \mu)} \tag{30}$$

Algorithm 1 Improved Grey Wolf Algorithm

Input: The population size, variable dimension and maximum iteration number.
Output: The position of α, fitness value of α.
1: Initialize a constrained population
2: Initialize a, A, and C.
3: Calculate the fitness values of all wolves by (30)
4: Find the α, β, δ solutions
5: **While** the criteria for stopping not satisfied **do**
  For each ω wolf
    Update the current position by (27)
    If the constraints(3) not met
      Mutate the position of individuals.
    End if
  End for
6: Update a, A, and C.
7: Evaluate the fitness of each wolf.
8: Update α, β, δ.
9: **End while**

In order to apply the IBGWO to solve the charging scheduling problem, the entire process of the IBGWO is shown in Algorithm 1 according to the previous description.

IV. PREDICTION AND OPTIMAL METHODOLOGY

At the beginning of each period, the SCMS needs to update input information about EVs, EP and PV power generation. Due to uncertainty and fluctuation of input information in future, the charging decision made in time slot t may not be the optimal charging decision for future time periods. The control system needs to update the charging decision within a limited time interval. Therefore, a real-time charging scheduling strategy based on a short-term prediction of PV power generation and IBGWO is proposed to solve the problem.

A. PREDICTION OF PV POWER GENERATION

The support vector machine (SVM) model [30] is chosen for short-term prediction. The weather types are divided into sunny, cloudy and rainy in different seasons. Then the average generations of different weather types are calculated according to the history data. Based on the current real-time weather forecast, SCMS selects the PV power generation data with similar weather characteristics as the forecast trend and update PV generation forecast data with short-term forecast in real time. Then, previously predicted data will be replaced by the updated data and the scheduling of next time slot is optimized according to the updated data.

B. REAL-TIME CHARGING SCHEDULING STRATEGY

Based on the prediction of PV power generation and algorithm 1, a real-time charging scheduling strategy is shown in algorithm 2. The SCMS keeps updating the current time, the information of PV power, EP and working status of each EV. Once the time is the beginning of each period, real-time charging scheduling strategy will be performed to optimal the charging decision. Firstly, charging optimization is performed without ESS, ensuring that PV power is firstly used to charge the EV. Secondly, find whether there is excess PV power in the optimization interval, the excess power will be charged to ESS at suitable charging periods or sold to the grid at suitable selling periods. Thirdly, find the ESS charging and discharging periods according to the EP, discharge when EP exceeds a certain value and charge when EP is low. Next, based on the updated P^{grid} and P^{ESS}, the algorithm 1 is used to solve the optimization problem. Finally, according to the best individual of the output, the EV charging scheduling is updated. The SCMS controls the operation and records the working status of each EV in real time.

Algorithm 2 Real-Time Charging Scheduling Strategy

Repeat Update time
  while current time is beginning of period **do**
    Update input: EP, P^{PV}, P^{EV}, $P^{grid,max}$, SOC_t.
    Update charging scheduling for EVs without ESS by algorithm 1.
    Update P^{grid} by (5) with $P^{ESS} = 0$.
    If there is excess PV energy **then**
      Find the periods can charge to ESS
      If no period to change ESS
        Find the periods can sell PV power to grid.
        Determine the best selling periods by comparing the electricity cost.
        Update P^{ESS} and P^{grid}.
      End if
    End if
    Find the appropriate charge periods and discharge periods of ESS according to the EP.
    Update P^{ESS} and P^{grid}.
    Solve the problem (15) by algorithm 1.
    Store the best individual α and the *Cost*.
    Update charging scheduling for all the EVs.
  End while
End

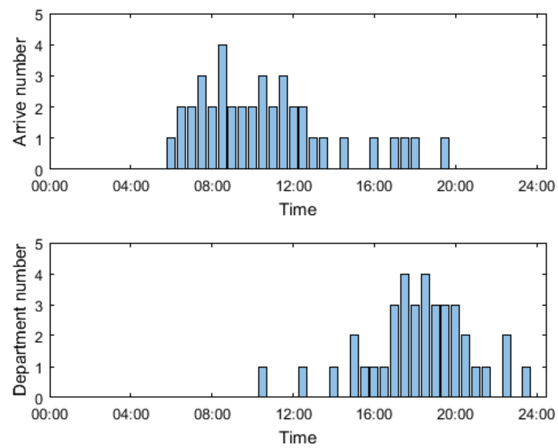

FIGURE 3. Arrival and departure time distribution of EVs.

V. CASE STUDIES

To verify the performance of the proposed strategy in charging scheduling on daily electricity cost, several simulation cases are studied, and the relevant results are discussed in this section.

A. PARAMETER SETTING

Based on the Section II, it is assumed that the specifications of EVs are the same and their battery capacities are set as 50 kWh according to common EV capacities such as BYD e5 and Geely EV450. The arrival/department time distribution and SOC distribution of EVs on working days are shown in Fig.3 and Fig.4. Their detailed time information and charging demands are listed in Table 1. Specific parameters of ESS are listed in Table 2 and the TOU price is shown in Table 3. It is assumed that the price of electricity sold is one-fifth of electricity purchased. The data of PV power generation in this paper can be obtained from [31], [32]. All the cases are simulated on the plat of MATLAB installed on a personal computer with an Intel Core i5 (3.4GHz) processor and 4GB random-access memory.

According to the parameters set in the previous, several case studies are described as follows to simulate the operation of a parking lot in one day.

Case1: The parking lot with the grid connection only and the EV is charged from the arrival time and the charging process is uninterruptible. It should be noted that there is no limit to the power supply of the grid to meet the EV charging needs. The performance of this case is the basis for evaluating other studied cases.

Case 2: The parking lot with the grid connection only. This case is optimized by the on-off strategy based on IBGWO to get the running status and electrical cost of the parking lot. The transformer capacity constraint should be observed.

Case 3: The parking lot with ESS and without PV system. This case is generated to test the role of ESS in the parking lot based on case 2.

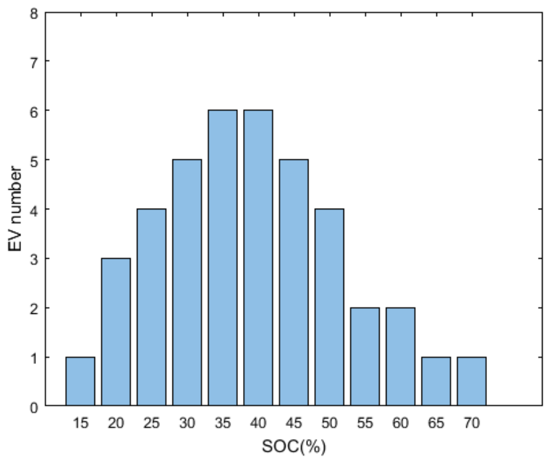

FIGURE 4. SOC distribution of EVs.

TABLE 1. The information of EVs.

ID	t_a	t_d	*Dem* (kwh)	ID	t_a	t_d	*Dem* (kwh)
1	6:00	15:30	27.5	21	10:30	19:30	37.5
2	6:30	17:30	37.5	22	10:30	18:30	30
3	6:30	17:00	37.5	23	10:30	19:00	32.5
4	7:00	16:30	35	24	11:00	18:00	25
5	7:00	12:30	27.5	25	11:00	20:00	32.5
6	7:30	15:00	42.5	26	11:30	19:30	30
7	7:30	14:00	27.5	27	11:30	20:30	27.5
8	7:30	17:30	37.5	28	11:30	17:30	15
9	8:00	17:30	35	29	12:00	19:00	22.5
10	8:00	18:00	35	30	12:00	17:00	25
11	8:30	15:00	25	31	12:30	20:30	20
12	8:30	10:30	30	32	12:30	20:00	32.5
13	8:30	18:30	40	33	13:00	16:00	30
14	8:30	18:00	35	34	13:30	20:00	32.5
15	9:00	18:30	35	35	14:30	21:30	30
16	9:00	17:00	32.5	36	16:00	21:00	22.5
17	9:30	19:30	40	37	17:00	22:30	17.5
18	9:30	19:00	32.5	38	17:30	21:00	20
19	10:00	18:30	27.5	39	18:00	22:30	30
20	10:00	20:00	35	40	19:30	23:30	25

TABLE 2. Parameter settings of ESS.

Variable	Value
η_c^{ESS}	0.99
η_d^{ESS}	0.99
SOC_{min}	0.2
SOC_{max}	0.9
$p^{c,max}$	20
$p^{d,max}$	20
E^M	300
$p^{grid,max}$	60

Case 4: The parking lot with ESS and PV. This case is generated to evaluate the effectiveness of the proposed system.

Case 5: Considering that the number of charging cars will be greatly reduced at the weekend, We chose ten EVs from Table 1 to be charged in that day. Their ID numbers are 11, 13, 15, 17, 19, 21, 22, 27, 29, and 34. This case is generated to evaluate the charging scheduling of the system at the weekend.

TABLE 3. TOU electricity price.

Time	price
22:00-6:00	0.364
6:00-8:00, 11:00-13:00, 15:00-18:00, 21:00-22:00	0.752
8:00-11:00, 13:00-15:00, 18:00-21:00	1.222

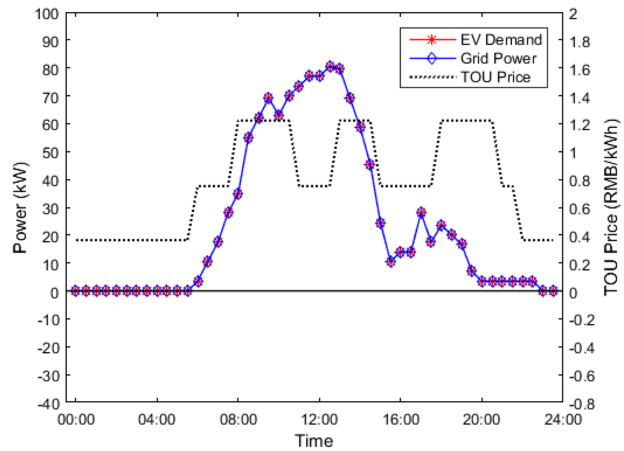

FIGURE 5. Power curves of the EV charging in Case 1.

B. RESULTS AND ANALYSIS

1) PERFORMANCE IN DIFFERENT CASES

As shown in Fig.5, in the case 1, if the EV starts charging from the arrival time, the peak load will exceed the set transformer capacity limit in order to meet the total charging demand of EVs. So, the EVs that arrive at the parking lot after the grid power reaches the limit will not be charged in the actual situation. This is clearly not what parking lot operators want. Then the on-off strategy and IBGWO are used to complete the simple scheduling of EV charging. From the Fig.6, by comparing with Fig.5, we can find that the IBGWO and on-off strategy can effectively shift EV load to the periods with low EP without exceeding the grid power limits. Since only the grid provides the power in the parking lot, the EV charging load is equal to the power of grid in these cases.

Due to the addition of ESS, We can see that the power of grid is greatly reduced in Fig. 7 during the high EP periods.

The ESS releases the stored energy to charge the EV in the high EP periods, compared with case 2, it reduces the EV charging load during the low EP period. This is conducive to charging the ESS under the maximum grid power limit during the low EP periods, and storing energy for the next high EP time to obtain the maximum economic benefit. At the end of the high EP periods, the ESS will discharge to the minimum capacity limit. Therefore, the ESS is fully utilized to charge EVs under constraints in this case, its total output power is limited by its maximum capacity.

Next, as shown in Fig. 8, with the coordination of PV system and ESS, the demand for EV charging is more concentrated in the periods of low EP. During periods of high EP, only small or no power of grid is purchased from the grid. PV system and ESS play an important role in reducing the power of grid. The charging and discharging number of ESS

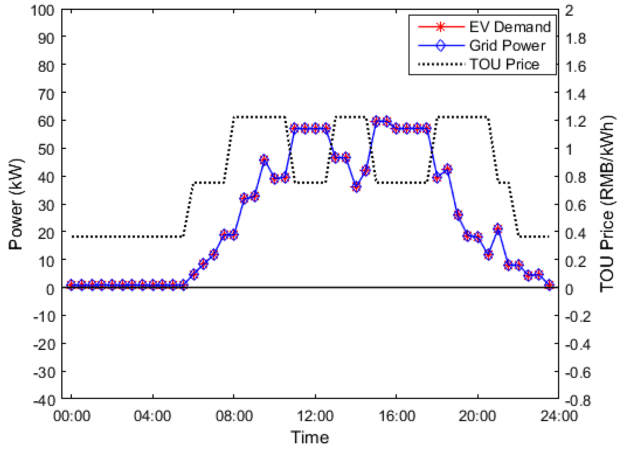

FIGURE 6. Power curves of the EV charging in Case 2.

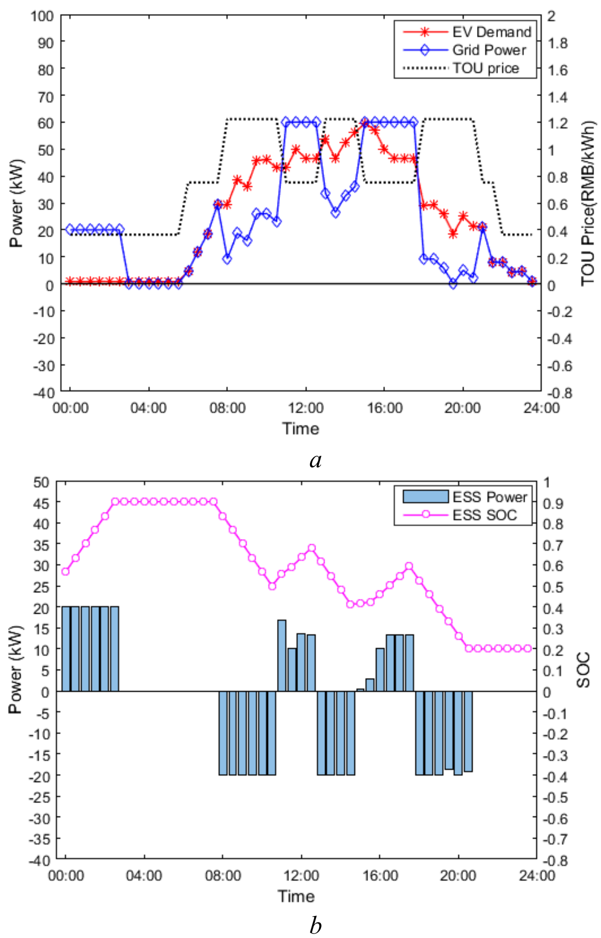

FIGURE 7. Results of the charging scheduling in Case 3. a) Power curves. b) The output power and SOC of ESS.

is reduced and it is beneficial to extend the life of ESS. If the PV power predicted value is more than actual value, the grid power will complement the error value (such as $t = 21$ to $t = 24$). If the predicted value is less than the actual value, the excess PV power will be used to offset the corresponding value of grid power supplied to the system (such as $t = 25$ to $t = 27$) or be sold to the grid (such as $t = 15$ to $t = 19$).

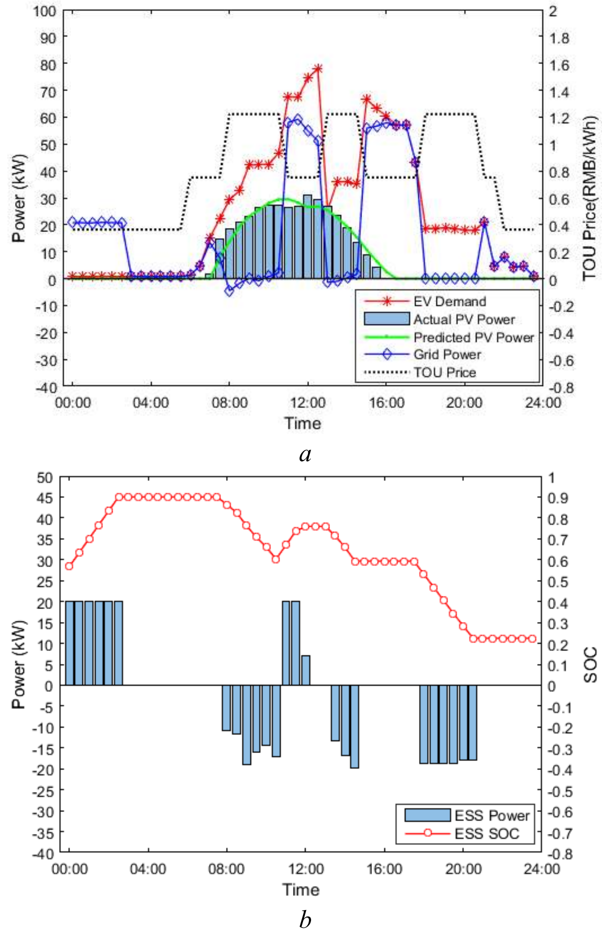

FIGURE 8. Results of the charging scheduling in Case 4. a) Power curves. b) The output power and SOC of ESS.

Compared with Case 3, the grid power is reduced during the low EP periods, which provides tolerance for the PV power prediction error.

When the charging load is low in the future optimization range, as shown in Fig. 9, it is obvious that the PV power in the optimized range is much more than the EV load. From $t = 15$ to $t = 30$, excess PV power is stored in the ESS for charging the coming EVs or sold to the grid according to the EP. Under the premise of ensuring that ESS stores enough power to meet the charging demands of EVs arriving in the future, SCMS chooses to sell excess PV power to the grid during periods of high EP, as shown in $t = 19$ to $t = 21$ and $t = 26$ to $t = 29$. If the excess PV power is always given priority to charge the ESS, it is likely that there will be excess PV power in the low EP period after the capacity limit of ESS is reached, and they will have to be sold to the grid at a low price. Compared with this, our proposed strategy has better economic benefits. In the optimization process, only a small amount of power is purchased from the grid to make up the prediction error value, which greatly reduces the cost and improves the utilization rate of PV power generation.

As can be seen from the several cases, the ESS and PV system is critical for reducing the overall charging cost.

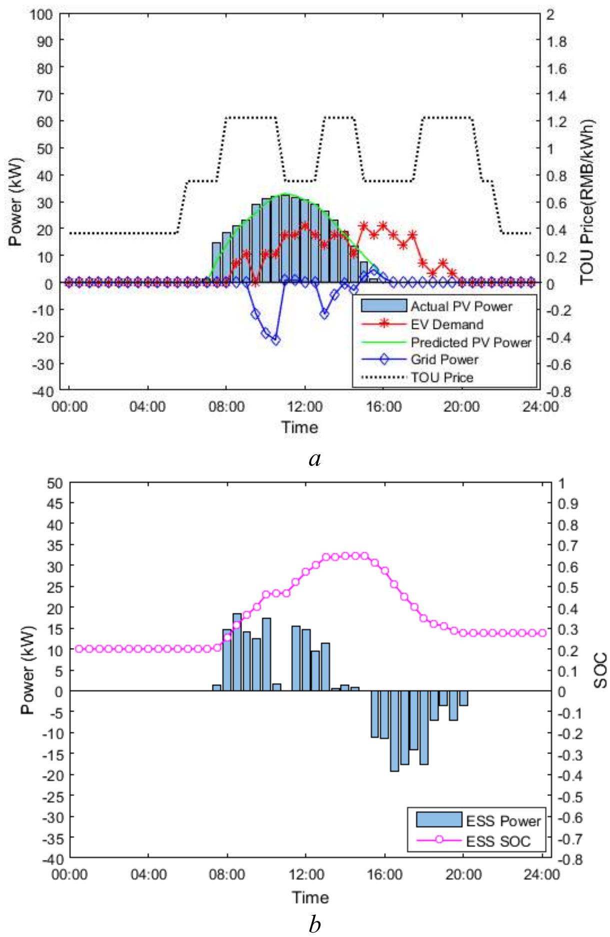

FIGURE 9. Results of the charging scheduling in Case 5. a) Power curves. b) The output power and SOC of ESS.

The accuracy of PV power generation prediction also has an important impact on the reduction of system operation cost. The comparison of the 5 different case studies in this paper is summarized in Table 4. Compared with Case 1, Case 2 reduced the cost by 2.7% under the transformer capacity limit. Although the savings is very less without ESS, the strategy is effectively to reduce the operation cost of the system. When PV system and ESS are added to the SCMS, the operation cost is greatly reduced. Compared with Case 2, the cost is reduced by 12.3% and 55.0% respectively in Cases 3 and 4. On weekends, the cost is negative because that the PV power generation is abundant and excess power is sold to the grid for profit under the premise of meeting EV load. Compared with the ESS management strategy in [24], the PV power utilization rate is greatly improved.

2) COMPARISON WITH OTHER APPROACHES

In order to better prove the effectiveness of the improved algorithm in solving the proposed problem, we compare the improved algorithm with GA [33], PSO [34], BGWO.

According to the literature or our experimental process, the parameters of each algorithm are set to produce the best results. As shown in Table 5, the performance of several algorithms in solving case 4 is listed. From the comparison of average and best cost, it can be seen that BGWO obtains better results than GA and PSO, but their average running time is longer. Compared with BGWO, the average cost and best cost of IBGWO are reduced by 1.3% and 1.0% respectively, and the running time is reduced by 50.6%. It is proved that the improved method proposed in this paper enhances the stability and efficiency of the BGWO, which greatly improves the practicability of the algorithm in solving real-time scheduling problems.

TABLE 4. The settings of the cases.

Case ID	IBGWO	On-off Strategy	ESS	PV	Cost (RMB)
1	NO	NO	NO	NO	1249.63
2	YES	YES	NO	NO	1215.31
3	YES	YES	YES	NO	1065.67
4	YES	YES	YES	YES	546.74
5	YES	YES	YES	YES	-9.24

TABLE 5. Performance comparison of cases 4.

Approach	Avg. Cost (RMB)	Best Cost(RMB)	Avg. Time(s)
GA	556.76	555.26	158.59
PSO	557.52	553.44	97.89
BGWO	554.93	552.47	89.64
IBGWO	547.67	546.74	44.26

VI. CONCLUSIONS

In this paper, we designed a smart charging management system for the parking lot integrating PV system and ESS. This system completes a collaborative power flow scheduling among the grid, ESS, and PV system to charge EVs and the corresponding model is also established. We assume that the daily regular EVs in future 24 hours are predictable. The vehicle arrival behavior modeled by Poisson stochastic process is generated to simulate real-life parking behavior. The charging scheduling problem is transformed into an optimization problem of electricity cost minimization. Then, an improved grey wolf optimizer is proposed to solve the charging scheduling problem of EVs.

Through population initialization and mutation, the convergence speed and optimization accuracy of the algorithm are improved. A real-time scheduling strategy based on an improved IBGWO and short-term PV power prediction is proposed to make the charging decision. Through the simulation results of different cases, it can be observed that the proposed strategy can improve the utilization rate of PV power generation and maximize the ESS energy storage benefit, and achieve efficient charging optimization scheduling in the parking lot. Compared with other algorithms, the proposed IBGWO can achieve better results.

Some limitations of this study are as follows. The price and lifespan of ESS and PV system are not considered in this paper. The charging scheduling of irregular EVs has not been studied. These are the future works need to investigate.

REFERENCES

[1] L. Hua, J. Wang, and C. Zhou, "Adaptive electric vehicle charging coordination on distribution network," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2666–2675, Nov. 2014. doi: 10.1109/TSG.2014.2336623.

[2] L. Cheng, Y. Chang, Q. Wu, W. Lin, and C. Singh, "Evaluating charging service reliability for plug-in EVs from the distribution network aspect," *IEEE Trans. Sustain. Energy*, vol. 5, no. 4, pp. 1287–1296, Oct. 2014. doi: 10.1109/TSTE.2014.2348575.

[3] R. A. Verzijlbergh, M. O. W. Grond, Z. Lukszo, J. G. Slootweg, and M. D. Ilic, "Network impacts and cost savings of controlled EV charging," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1203–1212, Sep. 2012. doi: 10.1109/TSG.2014.2336623.

[4] D. Wu, H. Zeng, C. Lu, and B. Boulet, "Two-stage energy management for office buildings with workplace ev charging and renewable energy," *IEEE Trans. Transport. Electrific.*, vol. 3, no. 1, pp. 225–237, Mar. 2017. doi: 10.1109/TTE.2017.2659626.

[5] J. Babic, A. Carvalho, W. Ketter, and V. Podobnik, "Evaluating policies for parking lots handling electric vehicles," *IEEE Access*, vol. 6, pp. 944–961, 2018. doi: 10.1109/ACCESS.2017.2777098.

[6] P. Nunes, R. Figueiredo, and M. C. Brito, "The use of parking lots to solar-charge electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 66, pp. 679–693, Dec. 2016. doi: 10.1016/j.rser.2016.08.015.

[7] S. W. Hadley and A. A. Tsvetkova, "Potential impacts of plug-in hybrid electric vehicles on regional power generation," *Electr. J.*, vol. 22, no. 10, pp. 56–68, 2009.

[8] P. Kassing, A. Sumper, T. Müeller, and M. Heißwolf, "Battery storage systems feasibility study for revenue models in Germany," in *Proc. Int. Conf. Modern Power Syst. (MPS)*, Jun. 2017, pp. 1–5.

[9] I. Rahman, P. M. Vasant, M. Singh, M. Abdullah-Al-Wadud, and N. Adnan, "Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle charging infrastructures," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 1039–1047, May 2016. doi: 10.1016/j.rser.2015.12.353.

[10] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1095–1105, Sep. 2012. doi: 10.1109/TSG.2011.2173507.

[11] L. Gan, U. Topcu, and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 940–951, May 2013. doi: 10.1109/TPWRS.2012.2210288.

[12] W. Qi, Z. Xu, Z.-J. M. Shen, Z. Hu, and Y. Song, "Hierarchical coordinated control of plug-in electric vehicles charging in multifamily dwellings," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1465–1474, May 2014. doi: 10.1109/TSG.2014.2308217.

[13] A. Ghavami, K. Kar, and A. Gupta, "Decentralized charging of plug-in electric vehicles with distribution feeder overload control," *IEEE Trans. Autom. Control*, vol. 61, no. 11, pp. 3527–3532, Nov. 2016. doi: 10.1109/TAC.2016.2516240.

[14] Z. Wei, Y. Li, Y. Zhang, and L. Cai, "Intelligent parking garage EV charging scheduling considering battery charging characteristic," *IEEE Trans. Ind. Electron.*, vol. 65, no. 3, pp. 2806–2816, Mar. 2018. doi: 10.1109/TIE.2017.2740834.

[15] Z. Xu, Z. Hu, Y. Song, W. Zhao, and Y. Zhang, "Coordination of PEVs charging across multiple aggregators," *Appl. Energy*, vol. 136, pp. 582–589, Dec. 2014. doi: 10.1016/j.apenergy.2014.08.116.

[16] S. Deilami, A. S. Masoum, P. S. Moses, and M. A. S. Masoum, "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile," *IEEE Trans. Smart Grid*, vol. 2, no. 3, pp. 456–467, Sep. 2011. doi: 10.1109/TSG.2011.2159816.

[17] M. S. Kuran, A. Carneiro Viana, L. Iannone, D. Kofman, G. Mermoud, and J. P. Vasseur, "A smart parking lot management system for scheduling the recharging of electric vehicles," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 2942–2953, Nov. 2015. doi: 10.1109/TSG.2015.2403287.

[18] L. Yao, W. H. Lim, and T. S. Tsai, "A real-time charging scheme for demand response in electric vehicle parking station," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 52–62, Jan. 2017. doi: 10.1109/TSG.2016.2582749.

[19] L. Zhang and Y. Li, "Optimal management for parking-lot electric vehicle charging by two-stage approximate dynamic programming," *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 1722–1730, Jul. 2017. doi: 10.1109/TSG.2015.2505298.

[20] A. S. Awad, M. F. Shaaban, T. H. M. El-Fouly, E. F. El-Saadany, and M. M. A. Salama, "Optimal resource allocation and charging prices for benefit maximization in smart PEV-parking lots," *IEEE Trans. Sustain. Energy*, vol. 8, no. 3, pp. 906–915, Jul. 2017. doi: 10.1109/TSTE.2016.2617679.

[21] Y. Zhang and L. Cai, "Dynamic charging scheduling for EV parking lots with photovoltaic power system," *IEEE Access*, vol. 6, pp. 56995–57005, 2018. doi: 10.1109/ACCESS.2018.2873286.

[22] T. Zhang, W. Chen, Z. Han, and Z. Cao, "Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price," *IEEE Trans. Veh. Technol.*, vol. 63, no. 6, pp. 2600–2612, Jul. 2014. doi: 10.1109/TVT.2013.2295591.

[23] H. Chen, Z. Hu, H. Zhang, and H. Luo, "Coordinated charging and discharging strategies for plug-in electric bus fast charging station with energy storage system," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 9, pp. 2019–2028, 2018. doi: 10.1049/iet-gtd.2017.0636.

[24] K. Chaudhari, A. Ukil, K. N. Kumar, U. Manandhar, and S. K. Kollimalla, "Hybrid optimization for economic deployment of ESS in PV-integrated EV charging stations," *IEEE Trans. Ind. Informat.*, vol. 14, no. 1, pp. 106–116, Jan. 2018. doi: 10.1109/TII.2017.2713481.

[25] M. Yilmaz and P. T. Krein, "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles," *IEEE Trans. Power Electron.*, vol. 28, no. 5, pp. 2151–2169, May 2013. doi: 10.1109/TPEL.2012.2212917.

[26] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014. doi: 10.1016/j.advengsoft.2013.12.007.

[27] L. K. Panwar, S. Reddy, A. Verma, B. K. Panigrahi, and R. Kumar, "Binary grey wolf optimizer for large scale unit commitment problem," *Swarm Evol. Comput.*, vol. 38, pp. 251–266, Feb. 2018. doi: 10.1016/j.swevo.2017.08.002.

[28] R. Sanjay, T. Jayabarathi, T. Raghunathan, V. Ramesh, and N. Mithulananthan, "Optimal allocation of distributed generation using hybrid Grey Wolf optimizer," *IEEE Access*, vol. 5, pp. 14807–14818, Jul. 2017. doi: 10.1109/ACCESS.2017.2726586.

[29] E. Emary, H. M. Zawbaa, and A. E. Hassanien, "Binary grey wolf optimization approaches for feature selection," *Neurocomputing*, vol. 172, pp. 371–381, Jan. 2016. doi: 10.1016/j.neucom.2015.06.083.

[30] J. Shi, W.-J. Lee, Y. Liu, Y. Yang, and P. Wang, "Forecasting power output of photovoltaic systems based on weather classification and support vector machines," *IEEE Trans. Ind. Appl.*, vol. 48, no. 3, pp. 1064–1069, May/Jun. 2012. doi: 10.1109/TIA.2012.2190816.

[31] *California Solar Initiative 15-Minute Interval Data*. Accessed: Apr. 20, 2019. [Online]. Available: https://www.californiadgstats.ca.gov/downloads/

[32] *California Weather Type Information*. Accessed: Apr. 20, 2019. [Online]. Available: https://www.ncdc.noaa.gov/cdo-web/datatools/lcd/

[33] J. A. Domínguez-Navarro, R. Dufo-López, J. M. Yusta-Loyo, J. S. Artal-Sevil, and J. L. Bernal-Agustín, "Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems," *Int. J. Elect. Power Energy Syst.*, vol. 105, pp. 46–58, Feb. 2019. doi: 10.1016/j.ijepes.2018.08.001.

[34] T. K. Maji and P. Acharjee, "Multiple solutions of optimal PMU placement using exponential binary PSO algorithm for smart grid applications," *IEEE Trans. Ind. Appl.*, vol. 53, no. 3, pp. 2550–2559, May/Jun. 2017. doi: 10.1109/TIA.2017.2666091.

WEI JIANG received the Ph.D. degree in communication and information system from Shanghai Jiao Tong University (SJTU), Shanghai, China, in 2008. She is with the College of Electronics and Information Engineering, Shanghai University of Electric Power, where she is currently an Associate Professor. Her research interests include source coding/network information theory, signal processing, and electric power communication.

YONGQI ZHEN received the B.S. degree from Jiangsu Normal University. He is currently pursuing the master's degree with the Shanghai University of Electric Power. He is committed to researching the smart grid and distribution network fault location.