Research Article

Research on ISFLA-Based Optimal Control Strategy for the Coordinated Charging of EV Battery Swap Station

Xueliang Huang,^{1,2} Hao Qiang,^{1,3} Qidong Zhang,¹ and Haijuan Li¹

¹ School of Electrical Engineering, Southeast University, Nanjing 210096, China

² Jiangsu Key Lab of Smart Grid Technology and Equipment, Zhenjiang 212009, China

³ School of Information Science and Engineering, Changzhou University, Changzhou 213164, China

Correspondence should be addressed to Xueliang Huang; xlhuang@seu.edu.cn

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As an important component of the smart grid, electric vehicles (EVs) could be a good measure against energy shortages and environmental pollution. A main way of energy supply to EVs is to swap battery from the swap station. Based on the characteristics of EV battery swap station, the coordinated charging optimal control strategy is investigated to smooth the load fluctuation. Shuffled frog leaping algorithm (SFLA) is an optimization method inspired by the memetic evolution of a group of frogs when seeking food. An improved shuffled frog leaping algorithm (ISFLA) with the reflecting method to deal with the boundary constraint is proposed to obtain the solution of the optimal control strategy for coordinated charging. Based on the daily load of a certain area, the numerical simulations including the comparison of PSO and ISFLA are carried out and the results show that the presented ISFLA can effectively lower the peak-valley difference and smooth the load profile with the faster convergence rate and higher convergence precision.

1. Introduction

Over the past decades, many issues, such as energy shortages, serious environmental pollution, and global warming, have increasingly become worldwide concerns. EVs have emerged as a new traffic tool. Compared with internal combustion engine vehicles (ICEVs), which burn fossil fuels, EVs are driven by electricity. They demonstrate considerable advantages in solving the energy crisis and reducing the emissions of carbon dioxide, as well as in providing a means to drastically reduce the man-made pollution. More and more governments, car manufacturers, and energy companies are getting active in development and production of EVs [1].

With the large-scale introduction of EVs, the power grid will face a significant challenge. Many domestic and foreign scholars have carried out researches on the impact of EVs on power distribution system [2–7], which mainly focus on the coordinated charging of EVs but rarely involve the optimal control strategy for the coordinated charging of EV battery swap station. Here, the coordinated charging means that the batteries are controlled to orderly charge for achieving an

optimal objective such as minimizing the power losses or maximizing the grid load factor. Tian et al. established a mathematical model of dispatching strategy based on different objective functions which were solved by particle swarm optimization (PSO). The results show that the coordinated charging can lower the peak-valley difference and smooth the load profile [8].

The SFLA is a global optimization algorithm proposed by Eusuff et al. [9, 10]. It is a memetic metaheuristic that is based on the evolution of memes carried by interactive individuals and a global exchange of information among the frog population. The SFLA draws its formulation from two other search techniques: the local search of the “particle swarm optimization” technique and the competitiveness mixing of information of the “shuffled complex evolution” technique. It locates a global optimum by combining global information exchange and local search, simulating the process of a group of frogs’ population-based cooperative seeking food. The strategies of local search and global information exchange make frog leap out of local optimum towards the global optimum solution (food place) with high probability. The algorithm

has been developed to arrive at near-optimum solutions to complex and large-scale optimization problems which cannot be solved by gradient based mathematical programming techniques [11]. The SFLA has also been applied successfully to solving engineering problems such as traveling salesman problem (TSP) [12, 13], unit commitment (UC) problem [14–16], embedding virtual networks [17], speech emotion recognition [18], cognitive radio system [19], and other types of issues.

In this paper, based on the characteristics of the EV battery swap station, the ISFLA-based optimal control strategy for coordinated charging has been investigated. Through the discretization of the solution vector, an ISFLA based on the reflecting method to deal with the boundary constraint is proposed. The comparison of PSO and ISFLA shows that the presented ISFLA can lower the peak-valley difference and smooth the load profile with the faster convergence rate and higher convergence precision.

2. Shuffled Frog Leaping Algorithm

As a bioinspired optimization technique, the SFLA is a meta-heuristic optimization method, which imitates and models the behavior of frogs searching for food laid on discrete stones randomly located in a pond. In SFLA there is a population, which consists of a set of frogs (solutions). The set of frogs is partitioned into subsets referred to as memeplexes. Different memeplexes are considered as different cultures of frogs, and each memeplex performs a local search. Within each memeplex, the individual frogs hold ideas, which can be influenced by those of other frogs, and evolve through a process of memetic evolution. Frog leaping improves an individual's meme and enhances its performance towards the goal. After a predefined number of memetic evolution steps, ideas are passed among memeplexes in a shuffling process. The local search and the shuffling processes continue until the defined convergence criteria are satisfied.

The SFLA involves a population of possible solutions defined by a set of p randomly generated frogs denoted as $Q = [X_1, X_2, \dots, X_p]^T$, where $X_i = (x_1, x_2, \dots, x_{is})$ is the position of the i th frog in the S dimension search space. All the frogs are sorted in a descending order according to their fitness, and the population is divided into m memeplexes, each containing n frogs (i.e., $p = m \times n$), in such a way that the first frog goes to the first memeplex, the second frog goes to the second memeplex, the m th frog goes to the m th memeplex, and the $(m + 1)$ th frog goes back to the first memeplex, and the process continues in this manner.

In each memeplex the frogs with the best and the worst fitness are represented by X_b and X_w , respectively. The best frog in the whole population is denoted by X_g . During memeplex evolution, the worst frog X_w leaps toward the best frog X_b , which is formulated as the following updating rule:

$$\begin{aligned} D &= \text{rand}(0, 1) \times (X_b - X_w), \\ X_{w,\text{new}} &= X_w + D, \quad -D_{\max} \leq D \leq D_{\max}, \end{aligned} \quad (1)$$

where D denotes the updated step size for frog leaping, $\text{rand}(0,1)$ generates a random number between $[0, 1]$, and $D_{\max}$ is the maximum distance in one leaping.

If $X_{w,\text{new}}$ has better fitness, the worst frog X_w will be replaced. Otherwise, the calculations in (1) are repeated with replacement of X_b by X_g . If no improvement occurs in this case, a new solution is randomly generated within the feasible space to replace the worst frog X_w . Then, the calculations continue for a specific number of iterations. After a pre-specified number of memetic evolutionary steps within each memeplex, to ensure global exploration, ideas passed within memeplexes are combined in the shuffling process. All the frogs are resorted, and the population is redivided into m memeplexes. The concurrently implemented local search and global shuffling continue alternatively until predefined convergence criteria are satisfied.

3. Charging Optimization Model for EV Battery Swap Station

Large-scale charging behavior of the EV will have a serious impact on the grid. Coordinated charging of the EV battery swap station can reduce the difference between the growing load peak and off-peak and save the costs of grid operation.

3.1. Charging Power Model of the EV Battery Charger. In the EV battery swap station, the typical strategy for battery charging is a two-stage method. The first stage has a constant current and limited pressure and the second stage has a constant pressure and limited current. Charging load power can be expressed as

$$P(t) = \begin{cases} I_{\max} U(t), & 0 \leq t \leq T_C, \\ U_{\max} I(t), & T_C < t \leq T_F, \end{cases} \quad (2)$$

where $I_{\max}$ and $U_{\max}$ denote the maximum charging current and voltage, respectively. T_C is the duration of charging with a constant current and T_F is the total charging duration. These parameters are constants determined by the battery type and charging characteristics.

In the first stage, to facilitate the modeling and analysis, the charging voltage is treated as the linear representation of $U_{\max}$. And in the second stage, the charging current is exponentially declined with time [20]. Then (2) can be rewritten as

$$P(t) = \begin{cases} I_{\max} U_{\max} \left[(1 - k) \frac{t}{T_C} + k \right], & 0 \leq t \leq T_C, \\ U_{\max} I_{\max} e^{-\alpha(t - T_C)}, & T_C < t \leq T_F, \end{cases} \quad (3)$$

where α and k are also constants determined by the battery type and charging characteristics.

In order to investigate the optimal control strategy for coordinated charging, the total charging duration T_F is divided equally into M sections, and the duration T_M of each section can be derived as T/M . According to the equal area

rule, the charging power of each section can be expressed with the average power:

$$\bar{P}_j = \frac{\int_{(j-1)T_M}^{jT_M} P(t) dt}{T_M}, \quad 1 \leq j \leq M. \quad (4)$$

Then an integer C is defined to satisfy the following expression:

$$CT_M \leq T_C \leq (C+1)T_M. \quad (5)$$

Substituting (3) and (5) into (4) yields the multisection charging power model of battery charger:

$$\bar{P}_j = \begin{cases} U_{\max} I_{\max} \left[\frac{(1-k)(2j-1)T_M}{2T_C} + k \right] & 0 < j \leq C \\ U_{\max} I_{\max} \left[\frac{(1-k)(T_C^2 - C^2 T_M^2)}{2T_C} + k(T_C - CT_M) - \frac{e^{\alpha(T_C - CT_M - T_M)} - 1}{\alpha} \right] & C < j \leq C+1 \\ U_{\max} I_{\max} \frac{e^{\alpha[T_C - (j-1)T_M]} - e^{\alpha(T_C - jT_M)}}{\alpha} & C+1 < j \leq M. \end{cases} \quad (6)$$

Obviously, the accuracy of (6) is relative to M . A larger M implies the higher precision of the model with the greater amount of computation, and vice versa.

3.2. Optimization Objective Function of the EV Battery Charging Power. According to the “technical guide for electric vehicle battery-swap station” presented by the State Grid Corporation of China (SGCC), a single EV battery charger is used to charge a single battery box. Inside the battery box, the battery pack consists of a plurality of battery cells. The battery mentioned in this paper refers to the battery pack. There are two types of batteries in the EV battery swap station, namely, the regulated battery connected to the EV battery charger and participating in the grid charging optimization by controlling its charging start time and the full charged reserve battery disconnected to the charger and used when not meeting the demand for swapping battery. Only the regulated-battery is considered in this paper.

In order to investigate the optimal control strategy for coordinated charging of the EV battery swap station, some assumptions are made as follows.

(1) All batteries are of the same type. The initial-charging SOC of each battery is the same and set to 20%, and the end-charging SOC is also the same and set to 100%.

(2) Corresponding to the above multisection charging power model of the battery charger, one optimization period T_O is also divided into multisections (M_O) with each section having the same duration T_M . And $M_O = T_O \cdot M/T$. Then

in one optimal period T_O , the number N_b of batteries needed for charging can be expressed as

$$N_b = \sum_{j=1}^{M_O} b_j \quad 1 \leq j \leq M_O, \quad (7)$$

where b_j is the predicted number of batteries swapped into the station during the j th section. For optimal control, it is necessary to number these batteries needed for optimal charging. From the b_0 batteries, uncharged and reserved in the swap station at the beginning of the T_O , to the batteries swapped into the station during the T_O , the batteries are numbered consecutively until N_b . The other batteries swapped into the station of the T_O are not indexed again and charged during the next optimization period.

(3) For the battery i , $t_{\text{in}}(i)$ and $t_{\text{out}}(i)$ denote its swap-in time and swap-out time, respectively:

$t_{\text{in}}(i) = 0$: battery i is one of the batteries b_0 ;

$t_{\text{in}}(i) = t_j$: battery i is swapped in during the j th optimization section;

$t_{\text{out}}(i) = t_k$: battery i is swapped out during the k th optimization section;

$t_{\text{out}}(i) = M_O + 1$: battery i is remained in the station.

The battery can be swapped into and swapped out of the station at any time in one section. To facilitate the optimal control, we suppose that the battery could be charged from the section next to that of swapping in and be swapped out of the station from the section next to that of full charged. Then the start-charging time $T_S(i)$ of the battery i is between $t_{\text{in}}(i) + 1$ and $t_{\text{out}}(i) - M$:

$$t_{\text{in}}(i) + 1 \leq T_S(i) \leq t_{\text{out}}(i) - M. \quad (8)$$

To ensure that all batteries are full charged at the end of the T_O , the swapped-in batteries during the last M sections of the T_O are no longer charged. Then the start-charging time $T_S(N_b)$ of the battery N_b would meet

$$b_0 + \sum_{j=1}^{T_S(N_b)-1} b_j \leq N_b \leq b_0 + \sum_{j=1}^{T_S(N_b)} b_j, \quad (9)$$

$$T_S(N_b) \leq M_O - M.$$

If there are i_{f0} full charged batteries at the beginning of the T_O and all swapped out in the t_f section, the new full charged batteries would be swapped out from the t_f section. Then

$$\sum_{j=1}^{t_f-1} b_j \leq i_{f0} \leq \sum_{j=1}^{t_f} b_j, \quad t_f \geq M+1. \quad (10)$$

(4) The battery is the core of EV and quite expensive. Many times of start and stop charging would greatly reduce its life, in which case the battery charging continuity constraint is introduced.

Based on assumptions (1) and (4), the charging duration of all batteries is the same. In this paper, the minimum variance of the load profile including the charging loads generated by the EV battery swap station is the optimization objective and is expressed as

$$\min F = \frac{\min \left[\sum_{j=1}^{M_O} (P_{d,j} + \sum_{i=1}^N C_{i,j} P_{i,j} - P_{avr})^2 \right]}{M_O}$$

$$\text{S.T.} \begin{cases} b_0 + \sum_{j=1}^{T_S(N_b)-1} b_j \leq N_b \leq b_0 + \sum_{j=1}^{T_S(N_b)} b_j \\ T_S(N_b) \leq M_O - M \\ \sum_{j=1}^{t_f-1} b_j \leq i_{f0} \leq \sum_{j=1}^{t_f} b_j \\ t_f \geq M + 1 \\ t_{in}(i) + 1 \leq T_S(i) \leq t_{out}(i) - M, \end{cases} \quad (11)$$

where

$$P_{avr} = \frac{\sum_{j=1}^{M_O} (P_{d,j} + \sum_{i=1}^N C_{i,j} P_{i,j})}{M_O}, \quad (12)$$

$P_{d,j}$: the predicted daily load power of the j th section excluding the charging load generated by EV swap station;

N : the total number of EV battery chargers;

$C_{i,j}$: the charging decision variable of the i th battery during the j th section: "1" means charging and "0" is discharging. Based on assumption (4),

$$C_{i,j} = \begin{cases} 1 & T_S(i) \leq j \leq T_S(i) + M - 1, \\ 0 & \text{else;} \end{cases} \quad (13)$$

$P_{i,j}$: the charging load of the i th battery during the j th section.

4. ISFLA-Based Optimal Control Strategy for Coordinated Charging

There are N chargers controlled by the control center of the EV battery swap station. From (11), the optimal control of the battery coordinated charging is a multivariable, nonlinear, and discrete integer optimization problem. Using the reflecting method to deal with the boundary constraint, an improved shuffled frog leaping algorithm (ISFLA) is proposed to achieve the optimal control strategy for coordinated charging of EV battery swap station.

4.1. Definition of Frog Position. In this paper, the position of the virtual frog consists of the start-charging time of every battery needed for coordinated charging, so the dimension

of solution space is equal to the number N_b of the regulated battery. The i th frog can be expressed as

$$X_i = (T_{is}(1), T_{is}(2), \dots, T_{is}(N_b)). \quad (14)$$

Based on the assumptions,

$$T_{is}(h) \in \begin{cases} [1, M_O - M] & 1 \leq h \leq b_0, \\ [K + 2, M_O - M] & \sum_{j=0}^K b_j + 1 \leq h \leq \sum_{j=0}^{K+1} b_j, \end{cases} \quad (15)$$

where $0 \leq K \leq M_O - M - 2$.

4.2. Inner-Memeplex Evolution. T_{is} is an integer, and the position of the frog with the worst fitness is adjusted as the following modified rule:

$$d_j = \text{rand}(0, 1) \times (T_{bs}(j) - T_{ws}(j)), \quad 0 \leq j \leq N_b, \quad (16)$$

$$T_{w_new}(j) = T_{ws}(j) + [d_j], \quad -d_{j,\max} \leq d_j \leq d_{j,\max},$$

where $[d_j]$ means an integer rounded to d_j .

4.3. Boundary Constraint. Dealing with the boundary constraint may affect the performance of the algorithm. In general, there are three basic approaches, namely, absorbing, reflecting, and damping. Using the reflecting method, when the updating position of the frog after t iterations is beyond a certain boundary, the frog would return within the boundary with the original speed but in the opposite direction. In this paper, the reflecting method is chosen to deal with the boundary constraint and the position evolution of the frog obeys the following rule.

When $d_j > 0$,

$$T_{ws_new}(j) = \begin{cases} T_{ws}(j) - [d_j] & T_{ws}(j) = M_O - M, \\ \min(T_{ws}(j) + [d_j], M_O - M) & T_{ws}(j) < M_O - M; \end{cases} \quad (17)$$

when $d_j < 0$,

$$T_{ws_new}(j) = \begin{cases} T_{ws}(j) - [d_j] & T_{ws}(j) = t_{in}(j) + 1, \\ \max(T_{ws}(j) + [d_j], t_{in}(j) + 1) & T_{ws}(j) > t_{in}(j) + 1. \end{cases} \quad (18)$$

4.4. Steps of the ISFLA. The overall process of the ISFLA can be described in the following main steps.

Step 0 (initialize the parameters). Set the parameters of p , n , ite_m , and ite_p . p is number of frogs in the whole population. n is the number of frogs in each memeplex. ite_m is the maximum number of iterations for each memeplex. ite_p is the maximum number of shuffling iterations for whole population. Therefore, $m = p/n$ is the number of memeplexes.

TABLE 1: Basic parameters of battery.

Type	$U_{\max}$ (V)	$I_{\max}$ (A)	Constant current charging duration (min)	Constant voltage charging duration (min)
Li-Ion	58.8	120	90	150

Step 1 (initialize the population). The initial population is formed by p randomly generated frogs: $X_1, X_2, \dots, X_p$. Compute the fitness value $F(X_i)$ according to (11) for each frog X_i .

Step 2 (shuffle the frogs). Firstly sort the p frogs in order of decreasing fitness, and then partition all the p frogs into m memplexes. The first frog goes to the first memplex, the second frog goes to the second memplex, the m th frog goes to the m th memplex, the $(m+1)$ th frog goes back to the first memplex, and at last the p th frog goes to the m th memplex.

Step 3 (memetic evolution). Repeat the following operations for ite_m times: firstly find the worst frog X_w and the best frog X_b in each memplex, then update X_w according to (16)–(18), and yield X_{w_new} . If X_{w_new} has a better fitness, replace X_w by X_{w_new} . Otherwise, repeat the updated strategy with X_g replacing X_b . If this still cannot produce a better solution, replace the X_w by a randomly generated frog.

Step 4 (check convergence). If the convergence criteria are met, stop and output the best frog X_g in the whole population. Otherwise, return to Step 2.

In this ISFLA, the convergence criteria are defined as the maximum number of shuffling iterations for whole population (ite_p).

5. Numerical Simulation

In this paper, the optimization objective is one area's daily load profile which includes the charging loads generated by the EV battery swap station. The optimization period T_O is set to a day and divided into 24 sections with the duration T_M of one hour.

5.1. Parameters of EV Battery. In the EV market, there are different battery types such as NiMH, Lead Acid, and Li-Ion. And the market share of Li-Ion with its technical advantages has increased annually. The “E6 pioneer” EV developed by BYD Co., Ltd., has been configured a Li-Ion battery with the energy density of 100 W·h per kilogram (i.e., a battery of 600 kg can store power of 60 kW·h for each charging). Its parameters are shown in Table 1.

In consideration of the charging continuity constraint and based on the battery parameters, the average charging power of each section in the multisection charging model can be calculated and shown in Table 2.

5.2. Area Daily Load. A certain area daily load power before regulation can be predicted and shown in Table 3.

TABLE 2: Average charging power of each section.

Section	1	2	3	4
Charging power (kW)	6.45	6.18	2.52	0.85

FIGURE 1: Area load profile under different conditions.

5.3. Parameters of the EV Battery Swap Station. At the beginning of one optimization period, there are 600 batteries in the swap station, including 350 full charged batteries, 200 unfull charged batteries, and 50 reserved batteries. All batteries except the reserved batteries participate in the optimal control of coordinated charging. By predicting the demand of EV owners for swapping batteries during each optimization section, the number b_j can be derived and shown in Table 4.

5.4. Simulation of ISFLA. The main parameters of ISFLA are set and shown in Table 5. Based on ISFLA and PSO, the area load profiles are compared and shown in Figure 1.

In Figure 1, ISFLA and PSO can lower the load peak-valley difference and smooth the load profile. But the convergence characteristics of two algorithms in the numerical simulation differ greatly and are shown in Figure 2.

Clearly, the convergence rate of ISFLA is much faster than that of PSO and the minimum variance of the load profile generated by ISFLA is less than that generated by PSO. Under different conditions, the variances of the load profile are shown in Table 6.

With ISFLA, the distribution of batteries according to the start-charging time in the optimization period T_O is shown in Figure 3.

In Figure 3, during some optimization sections, there is a very small or no difference between the number of starting-charging batteries and that of those swapped into the station. This can explain that the optimized load profile with ISFLA and the load profile with uncoordinated charging almost coincide in some sections in Figure 1.

For a fixed population p , the different number m of partitioned memplexes will affect the convergence rate and the global optimal solution. Some simulations are made of

TABLE 3: Certain area daily load before regulation.

Time (h)	Power (MW)	Time (h)	Power (MW)	Time (h)	Power (MW)	Time (h)	Power (MW)
1	5.25	7	9	13	8	19	17.75
2	4.25	8	10.5	14	7.5	20	16
3	4	9	9.5	15	7.75	21	14.25
4	4	10	9.25	16	8.25	22	9.75
5	4.25	11	9.75	17	13	23	7.25
6	5.75	12	12	18	18	24	5.75

TABLE 4: Predicted number of batteries swapped in during each optimization section.

Time (h)	1	2	3	4	5	6	7	8	9	10	11	12
Number	3	3	1	2	10	18	53	68	46	31	17	24
Time (h)	13	14	15	16	17	18	19	20	21	22	23	24
Number	30	30	37	50	67	42	28	28	25	18	13	6

FIGURE 2: Convergence characteristics of ISFA and PSO.

FIGURE 3: Distribution of batteries starting charging.

TABLE 5: Parameters of ISFLA.

Parameter	p	m	n	ite_m	ite_p
Value	50	10	5	5	100

TABLE 6: Variances under different conditions.

Condition	Uncoordinated charging	Coordinated charging ISFLA	PSO
Variance (kW²)	1.836	1.615	1.737
Result	—	Declining 12.04%	Declining 5.40%

TABLE 7: Global convergence value.

Memplex	5	10	20	40
$F \text{ (kW}^2) \times 10^7$	1.616	1.615	1.6139	1.6137

ISFLA with the parameters of a fixed p (200) and different m and the results are shown in Figure 4 and Table 7.

In Figure 4 and Table 7, the greater the number of memplex is, the faster the algorithm converges with a higher convergence performance. However, the relationship between them is not linear, and how to choose an appropriate memplex considering the convergence rate and global convergence value is a main goal of our further work.

6. Conclusion

As a main way of energy supply to EVs, the optimal control strategy for coordinated charging of the swap station is very important in smoothing the load profile. Based on the characteristics of the EV battery swap station, a multisession charging power model of battery is presented and an ISFLA in reflecting method to deal with the boundary constraint is proposed to achieve coordinated charging of batteries. In numerical simulations, the comparison of PSO and ISFLA is made, and the results show that the presented ISFLA can effectively lower the peak-valley difference and smooth

FIGURE 4: Iterations of ISFLA with different memplexes.

the load profile with the faster convergence rate and higher convergence precision.

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