

Research on SFLA-Based Bidirectional Coordinated Control Strategy for EV Battery Swapping Station

Guo Zhao^{1,2}, Jiang Guo^{1,2} and Hao Qiang³

Abstract: As a good measure to tackle the challenges from energy shortages and environmental pollution, Electric Vehicles (EVs) have entered a period of rapid growth. Battery swapping station is a very important way of energy supply to EVs, and it is urgently needed to explore a coordinated control strategy to effectively smooth the load fluctuation in order to adopt the large-scale EVs. Considering bidirectional power flow between the station and power grid, this paper proposed a SFLA-based control strategy to smooth the load profile. Finally, compared simulations were performed according to the related data. Compared to particle swarm optimization (PSO) method, the presented SFLA-based strategy can effectively lower the peak-valley difference with the faster convergence rate and higher convergence precision. It is important for the swapping station that energy exchanging mode can supply energy for large-scale EVs with a smoother load profile than one-way charging mode.

Keywords: SFLA, bidirectional coordinated control, battery swapping station, optimization.

1 Introduction

In recent decades, the issues of energy shortage and environment pollution have increasingly become worldwide concerns. As a new green traffic tool, EVs have been demonstrated 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 [Williams, DeBenedictis, Ghanadan et al. (2012); Aziz, Oda, Mitani et al. (2015); Du, Wang and Lv (2016)]. As the large-scale EVs participate in power grid operation, the power load would rise significantly. The charging behavior of EVs is of randomness and intermittence, and the impact of large-scale EVs on the grid would gradually appear as follows: the EVs charging time may be concentrated, thus resulting in local load peak and drastic fluctuations in the load of power grid. Therefore, coordinated

¹ Key Laboratory of Hydraulic Machinery Transients (Wuhan University), Ministry of Education, Wuhan 430072, China.

² School of Power and Mechanical Engineering, Wuhan University, Wuhan 430072, China.

³ School of Urban Rail Transit, Changzhou University, Changzhou 213164, China.

charging is urgent to effectively smooth the load profile. Furthermore, it could potentially provide flexible services to the grid, e.g. load shifting, balancing power, and frequency response [Zhang, Zhang, Xiong et al. (2014); Yang, Zhang, Niu et al. (2015); Zhao, Huang and Qiang (2015); Xia, Lai, Zhong et al. (2016); Vahedipour-Dahraie, Rashidzaheh-Kermani and Najafi (2017)].

Enabling bidirectional power flow, V2G services offer a wide range of benefits and revenues. And in fact, the coordinated strategies proposed in most researches are applied to control over the charging/discharging behavior of huge EVs batteries. Aggregated many batteries, battery swapping stations could be regarded as energy storage power stations, which effectively could carry out the coordinated strategies to achieve the benefits and revenues offered by V2G. Rao R. et al. [Tan, Ramachandaramurthy and Yong. (2016)] proposed an optimization charging mode (OCM) and simulated the impacts of OCM on the power grid side and generation side. Xie P. et al [Xie, Li, Zhu et al. (2016)] applied Monte-Carlo stochastic simulation method to estimate the equivalent controllable capacity of battery swapping stations, presented the lumped S2G equivalent model subject to SOC limits and CC constrains, and proposed a filter-based AGC coordinated strategy. Zhang Q.D. et al. [Zhang, Huang, Chen et al. (2015)] used genetic algorithm to solve the scheduling model which took the economic operation of battery swapping stations and the optimal switching frequency of charging/discharging machine as the goals. Yang J. et al. [Yang and Sun (2015)] proposed a modified genetic algorithm to study the electric vehicles battery swap station location and inventory problem which was formulated as an integer program. Sun L. et al. [Sun, Wang, Liu et al. (2015)] analyzed the start-up characteristics of a generator powered by batteries and proposed a bi-level optimisation-based network reconfiguration model to determine the restoration paths with an objective of maximizing the overall generation capability, and solved this problem by the well-established particle swarm algorithm. Kang Q. et al. [Kang, Wang, Zhou et al. (2015)] presented a novel centralized charging strategy of EVs under the battery swapping scenario by considering optimal charging priority and charging location (station or bus node in a power system) based on spot electric price, and introduces a dynamic crossover and adaptive mutation strategy into a hybrid algorithm of particle swarm optimization and genetic algorithm to implement the charging strategy.

With the popularization of EVs, battery swapping stations will increase rapidly and arouse more and more attentions. In this paper, we mainly investigated the bidirectional power flow between the station and power grid and designed a SFLA-based control strategy to smooth the load profile. Compared to particle swarm optimization (PSO) method, the presented SFLA-based strategy can effectively lower the peak-valley difference with the faster convergence rate and higher convergence precision.

2 Optimization model of EV battery swapping station

According to the “technical guide for electric vehicle battery-swap station” presented by the State Grid Corporation of China (SGCC), one charger for EV is used to charge one battery box. In the battery box, there is a battery pack, which consists of a plurality of battery cells. The battery mentioned in this paper refers to the battery pack. There are

two types of battery in EV battery swapping stations, which are called regulated batteries, connected to EV battery chargers and participating in the grid coordinated control, and full-charged reserve batteries, disconnected to chargers and only used when not meeting the demand for swapping battery. Only regulated batteries are considered in this paper.

In order to investigate the bidirectional coordinated control strategy for EV battery swapping stations, some assumptions are made as follows.

- 1) Under normal circumstances, there are sufficient chargers, and batteries in the state can meet the user's needs.
- 2) Irrespective of the diversity of batteries [Chen, Li and Hong (2015)], all batteries are considered of the same type, and with the same initial charging state (SOC_b) of 20% and the same end-charging SOC of 100%.
- 3) In optimization model, meeting the energy exchange purpose is a priority. And the constraint of battery continuous charging would be ignored. Furthermore, we assume that the charging or discharging power would be achieved within an allowable range.
- 4) At the beginning of optimization period, set as 0:00, the regulated batteries with full charge are only swapped out for the user's demand, and don't perform the charge and discharge operations.

2.1 Optimization objective function

In energy exchange model, EV battery-swap stations can play its positive role in smoothing the load fluctuation and improving the grid operation. Then, the minimum variance of the load profile including the charging load generated by EV battery-swap stations in one area is treated as the optimization objective.

In view of assumption (3), batteries would not be charged by the typical two-stage method mentioned in Qiang (2015). Therefore, one optimization period T_O could be arbitrarily divided into multi-sections (M_b), and each section has the same duration T_b .

$$T_b = T_O / M_b \tag{1}$$

Obviously, a larger M_b implies the higher precision of the model with the greater amount of computation, and vice versa.

Then, the optimization objective can be expressed as Huang, Qiang, Zhang et al. (2013).

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

$$P_{avr} = \sum_{j=1}^{M_b} (P_{d,j} + \sum_{i=1}^N P_{i,j}) / M_b \tag{3}$$

where $P_{d,j}$ represents the predicted daily load power of the j^{th} section excluding the charging load generated by EV swap station; N is the total number of EV battery chargers; $P_{i,j}$ stands for the charging or discharging power of the i^{th} battery in the j^{th} section. A positive $P_{i,j}$ indicates that the battery is charging, and a negative $P_{i,j}$ indicates that the battery in a discharged state. If $P_{i,j}$ equals to zero, it indicates that the battery is in the off-working state.

2.2 Constraints

In addition to meeting the user demand for battery replacement, EV battery swapping station plays an active role as energy storage unit in the grid operation. Then, the charging or discharging power and battery capacity must be considered.

2.2.1 Power constraint

The overlarge power may cause damage to the charge-discharge device, which is used to exchange energy between the batteries and grid. Therefore,

$$\begin{aligned}
 -P_{dmax} &\leq P_{i,j} \leq P_{cmax} \\
 P_{dmax} &= \min[P_{device_dmax}, P_{battery_dmax}] \\
 P_{cmax} &= \min[P_{device_cmax}, P_{battery_cmax}]
 \end{aligned} \tag{4}$$

where P_{device_dmax} and P_{device_cmax} respectively represent the maximum charging and discharging power of devices; $P_{battery_dmax}$ and $P_{battery_cmax}$ stand for those of batteries.

2.2.2 Battery capacity constraint

According to the battery specification, there are upper and lower limits to battery capacity. Namely, the battery would be charged up to the upper limit and stopped discharging when its capacity drops down to the lower limit. Based on the assumption (2), all the batteries have the identical capacity and it can be expressed as

$$Q_{min} \leq Q \leq Q_{max} \tag{5}$$

where Q_{max} and Q_{min} are the upper and lower limits of battery capacity when charging or discharging. Considering the relationship between SOC and capacity of batteries, it is easy to deduce that at any time the SOC should meet

$$SOC_{min} = Q_{min} / Q_{full} \leq SOC \leq Q_{max} / Q_{full} = SOC_{max} \tag{6}$$

where Q_{full} stands for the battery capacity in the full charge state.

For the battery i , $t_{in}(i)$ denotes its swap-in section. And according to the assumption, the charging or discharging operation of the battery would be performed from the next section $t_{in}(i)+1$. Then at the beginning of section j , its capacity $Q_{i,j}$ can be expressed as the accumulation of the initial capacity deduced with the SOC_b and the change of capacity from the section $t_{in}(i) + 1$ to j due to charging or discharging,

$$Q_{i,j} = SOC_b \times Q_{full} + \sum_{k=t_{in}(i)+1}^{j-1} (P_{i,k} \times T_b) \tag{7}$$

Substitute Eq. (7) into Eq. (6) and yield

$$\frac{SOC_{min} \times Q_{full} - Q_{i,j}}{T_b} \leq P_{i,j} \leq \frac{SOC_{max} \times Q_{full} - Q_{i,j}}{T_b} \tag{8}$$

In order to reduce the variables of the model, the further assumption is made

$$\begin{aligned} \text{SOC}_{\min} &= \text{SOC}_b \\ \text{SOC}_{\max} &= \text{SOC}_e = 1 \end{aligned} \quad (9)$$

Substitute Eq. (7) and Eq. (9) into Eq. (8), then yield

$$- \sum_{k=t_{\text{in}}(i)+1}^{j-1} P_{i,k} \leq P_{i,j} \leq (\text{SOC}_e - \text{SOC}_b) \times Q_{\text{full}} / T_b - \sum_{k=t_{\text{in}}(i)+1}^{j-1} P_{i,k} \quad (10)$$

2.2.3 User demand constraint

As the main means of energy supply to EVs, the primary function of swap station is to provide sufficient full-charged batteries to satisfy the user's demands. Therefore, it is obvious that the charging or discharging operation of the battery would be done during the section $t_{\text{in}}(i)+1$ to the section $t_{\text{out}}(i)-1$, where $t_{\text{out}}(i)$ denotes the swap-out section of the i^{th} battery. Then the section j would be an integer and meet

$$t_{\text{in}}(i) + 1 \leq j \leq t_{\text{out}}(i) - 1 \quad (11)$$

Batteries must be full-charged when they are swapped out. So,

$$Q_{i,t_{\text{out}}(i)-1} + P_{i,t_{\text{out}}(i)-1} \times T_b = Q_{\text{full}} \quad (12)$$

Evidently, $P_{i,t_{\text{out}}(i)-1}$ is non-negative. So the battery would not be discharged in the section $t_{\text{out}}(i) - 1$.

Substitute Eq. (7) into Eq. (12) and yield the charging power in the section $t_{\text{out}}(i)-1$.

$$0 \leq P_{i,t_{\text{out}}(i)-1} = (1 - \text{SOC}_b) Q_{\text{full}} / T_b - \sum_{k=t_{\text{in}}(i)+1}^{t_{\text{out}}(i)-2} P_{i,k} \leq P_{\text{cmax}} \quad (13)$$

Through the above analysis, it is important to note that the full-charged regulated batteries could be charged only after discharged, while the batteries swapped into station would be discharged just after charged.

3 SFLA-based energy exchange optimal control strategy

3.1 Shuffled frog leaping algorithm

SFLA is a bio-inspired optimization technique and imitates and models the behavior of frogs searching for food laid on discrete stones randomly located in a pond [Huang, Qiang, Zhang et al. (2013); Eusuff and Lansey (2003); Ebrahimi, Hosseinian and Gharehpetian (2011)]. 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 memplexes in a shuffling process. The local search and the shuffling processes continue until the defined convergence criteria are satisfied.

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 dimensions search space. All the frogs are sorted in a descending order according to their fitness, and the population is divided into m memplexes, each containing n frogs (i.e., $p=m \times n$), in such a way that 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, and the $(m+1)^{th}$ frog goes back to the first memplex, and the process continues in this manner.

In each memplex 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 memplex evolution, the worst frog X_w leaps toward the best frog X_b , which is formulated as the following updating rule

$$\begin{aligned} \Delta X &= rand(0,1) \times (X_b - X_w) \\ X_{w_new} &= X_w + \Delta X, \quad -\Delta X_{max} \leq \Delta X \leq \Delta X_{max} \end{aligned} \tag{14}$$

where, ΔX denotes the updated step size for frog leaping; $rand(0,1)$ generates a random number between $(0, 1)$; and ΔX_{max} is the maximum distance in one leaping. If X_{w_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 prespecified number of memetic evolutionary steps within each memplex, to ensure global exploration, ideas passed within memplexes are combined in the shuffling process. All the frogs are resorted, and the population is redivided into m memplexes. The concurrently implemented local search and global shuffling continue alternatively until predefined convergence criteria are satisfied.

3.2 SFLA_based optimization model

To achieve the minimum variance of the load profile including the load generated by EV battery swapping stations in one area, the position of the virtual frog consists of the charging or discharging power of each battery in each section. Based on Eq. (13), the charging power in the last section could be derived by the powers in other sections. It indicates that the number of independent variable of the i^{th} battery is $t_{out}(i) - t_{in}(i) - 2$. Then the position vector of frog can be defined as

$$X = \underbrace{(P_{1,t_{in}(1)+1}, \dots, P_{1,t_{out}(1)-2})}_{\text{battery 1}}, \dots, \underbrace{(P_{k,t_{in}(k)+1}, \dots, P_{k,t_{out}(k)-2})}_{\text{battery } k}, \dots, \underbrace{(P_{N_b,t_{in}(N_b)+1}, \dots, P_{N_b,t_{out}(N_b)-2})}_{\text{battery } N_b} \tag{15}$$

And the dimension D of the vector is

$$D = \sum_{i=1}^{N_b} (t_{out}(i) - t_{in}(i) - 2) \quad (16)$$

Then the updating rule of position on each dimension within each memplex could be expressed as

$$\begin{aligned} \Delta P(j, t) &= rand(0, 1) \times (P_b(j, t) - P_w(j, t)) \quad 0 \leq j \leq N_b, t \in [t_{in}(j) + 1, t_{out}(j) - 1] \\ P_{w_new}(j, t) &= P_w(j, t) + \Delta P(j, t) \quad -\Delta P_{max}(j, t) \leq \Delta P(j, t) \leq \Delta P_{max}(j, t) \end{aligned} \quad (17)$$

where $P_b(j, t)$ and $P_w(j, t)$ represent the $P_{j, t}$ of the best and worst frog position vectors within a memplex respectively; $P_{w_new}(j, t)$ represents the updated power. If there is a better fitness with $P_{w_new}(j, t)$, replace P_w with $P_{w_new}(j, t)$. Otherwise, use $P_g(j, t)$, which is the $P_{j, t}$ of the best frog position vector within the whole population, to replace $P_b(j, t)$ and repeat iterative update. If there is still no improvement, randomly generate a $P_{w_new}(j, t)$ and substitute the original $P_w(j, t)$ for further iteration.

3.3 Steps of SFLA

The overall process of SFLA consists of the following main steps.

Step 1: Initialize the parameters, which include the number of frogs (p) in the whole population, the number of frogs (n) in each memplex, the maximum iteration number (ite_m) for each memplex and the maximum shuffling iteration number (ite_p) for the whole population. Obviously, the whole population is divided into m (p/n) memplexes.

Step 2: Initialize the population, which is formed by p randomly generated frogs X_1, X_2, \dots, X_p . Compute the fitness value $F(X_i)$ according to (2) for each frog X_i . It is noted that in the position vector X , the dimension of every battery is various, and it is relatively difficult to deal with X_1, X_2, \dots, X_p . Therefore, we set the power to “0” in those non-effective sections those are before $t_{in}(i)+1$ and after $t_{out}(i)-1$. Then every battery has the same dimension of M_b . As a result, the position vector of frog can be modified as

$$X = (0, \dots, 0, \underbrace{P_{1, t_{in}(1)+1}, \dots, P_{1, t_{out}(1)-2}}_{\text{battery 1}}, P_{1, t_{out}(1)-1}, 0, \dots, 0, \dots, 0, \underbrace{P_{N_b, t_{in}(N_b)+1}, \dots, P_{N_b, t_{out}(N_b)-2}}_{\text{battery } N_b}, P_{N_b, t_{out}(N_b)-2}, 0, \dots, 0)$$

A optimal period T_o with M_b sections
A optimal period T_o with M_b sections

(18)

Step 3: Shuffle the frogs. Firstly, sort the p frogs in order of decreasing fitness, and then partition all 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 $(m+1)^{\text{th}}$ frog goes back to the first memplex, and at last the p^{th} frog goes to the m^{th} memplex.

Step 4: 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 Eq. (17), 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. In fact, X_{w_new} is obtained by updating the D powers in Eq. (15). The updating flow chart of the i^{th} battery is shown in Figure 1.

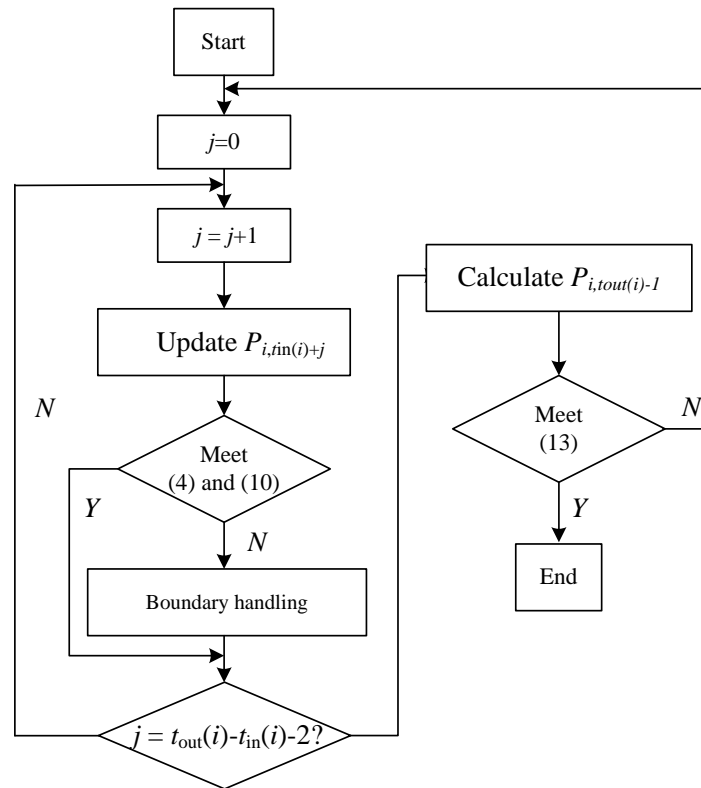


Figure 1: Updating flow chart of the i^{th} battery

In Figure 1, as much as possible in order to satisfy the constraint conditions of Eq. (13), if the updated charging power exceeds a certain boundary, absorption method is used to handle the boundary, setting the power to the boundary value; if the updated discharging power does, reflection method is applied to change (reduce) the power.

Step 5: Check convergence. If the convergence criteria are satisfied, stop and output the best frog X_g in the whole population. Otherwise, return to Step 3.

Step 6: Output the results and quit the program.

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

4 Numerical simulation

In this paper, the optimization period T_o is set to a day and divided into 24 sections with the duration T_b of one hour.

4.1 Parameters of EV battery

In the EV market, there are different types such as NiMH, Lead Acid, and Li-Ion. And the market share of Li-Ion with its technical advantages has increased year by year. 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 main parameters are shown in Table 1.

Table 1: Basic parameters of battery

U_{\max} (V)	I_{\max} (A)	Constant current charging duration (h)	Constant voltage charging duration (h)
58.8	120	1.5	2.5

4.2 Area daily load

In a certain area, its daily load power regardless of EV swap station can be predicted and shown in Table 2.

Table 2: Predicted daily load without the load generated by EV battery swapping station

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

4.3 Parameters of the EV battery swapping station

At the beginning of one optimization period, there are 600 batteries in the swapping station, including 350 full-charged batteries, 200 un-full 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 can be derived and shown in Table 3.

Table 3: Predicted number of batteries swapped in during each optimization section

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

4.4 Simulation and analysis

According to [Chen, Li and Hong (2015)], the maximum charging and discharging power of battery are set to 8 kW and 6 kW respectively, which are less than those of device. The main parameters of SFLA are shown in Table 4.

Table 4: Parameters of SFLA

Parameter	<i>p</i>	<i>n</i>	<i>m</i>	<i>ite_m</i>	<i>ite_p</i>
Value	200	20	10	5	100

Compared with the traditional one-way charging mode, the energy exchanging mode, bidirectional coordinated control has more efficient at smoothing the fluctuation of power load. Figure 2 shows the load profiles under various conditions and the variances are compared in Table 5.

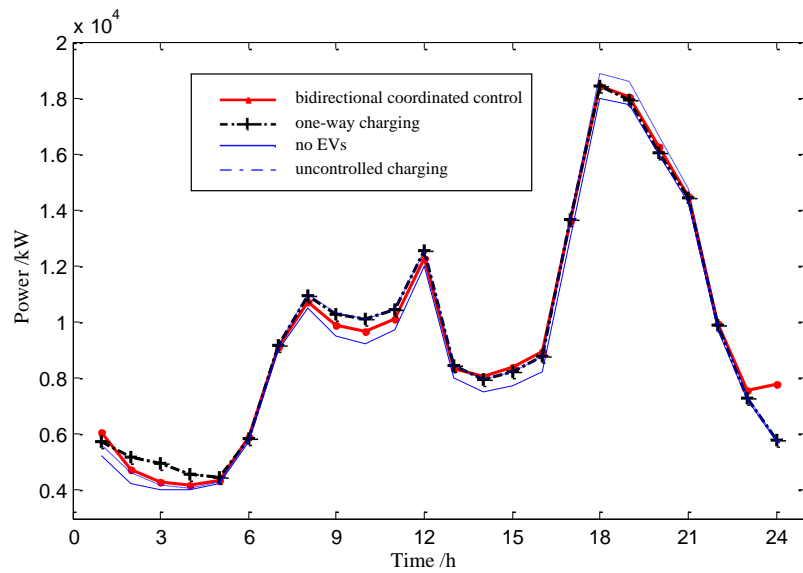


Figure 2: Area load profiles under different conditions

Table 5: Variances under different conditions

Condition	Uncontrolled charging	Based_SFLA coordinated charging	
		One-way charging	Energy exchanging
Variance ($\times 10^7 \text{kW}^2$)	1.836	1.6105	1.5380
Result	-	Declining 12.28%	Declining 16.23%

In Figure 2, the load profile under bidirectional coordinated control is the smoothest. Under this coordinated control, the batteries are recharged in the valley load time period and discharged in the peak load time period. During the daytime, the optimal load profile

is closer to the profile of no EVs. And for making the swapping station the same state at the beginning of every optimization period T_0 , there are many batteries which would be charged to full in the last section. Therefore, at the end of T_0 , the charging power rises obviously. Fortunately, it happened in the night, which is the valley load time period. Furthermore, it is obvious that in Table 5 the coordinated charging can smooth the load fluctuation and shift peak load. And the variance has reduced from $1.836 \times 10^7 \text{ kW}^2$ to $1.538 \times 10^7 \text{ kW}^2$ in energy exchanging mode, which is more efficient to decline 16.23%, greater than that in one-way mode of 12.28%.

Particle swarm optimization (PSO) is usually used to solve optimization problems [Tian, Jing-Han, Jiang, et al. (2012); Han, He, Wang, et al. (2011); Rajanna and Saini (2016); Xuwei, Ke and Potter (2016)]. Then, the compared simulations are carried out with 200 particles and the results are shown in Figure 3.

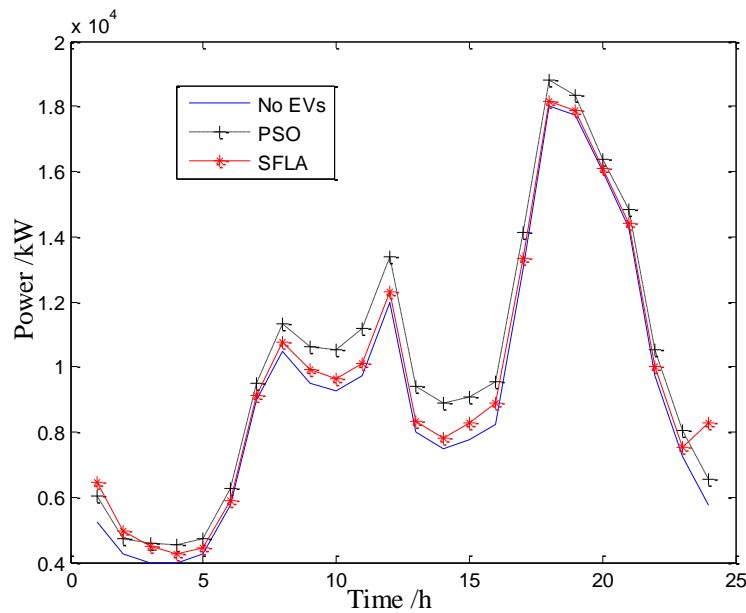


Figure 3: Area load profiles optimized with PSO and SFLA

In Figure 3, SFLA 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 4.

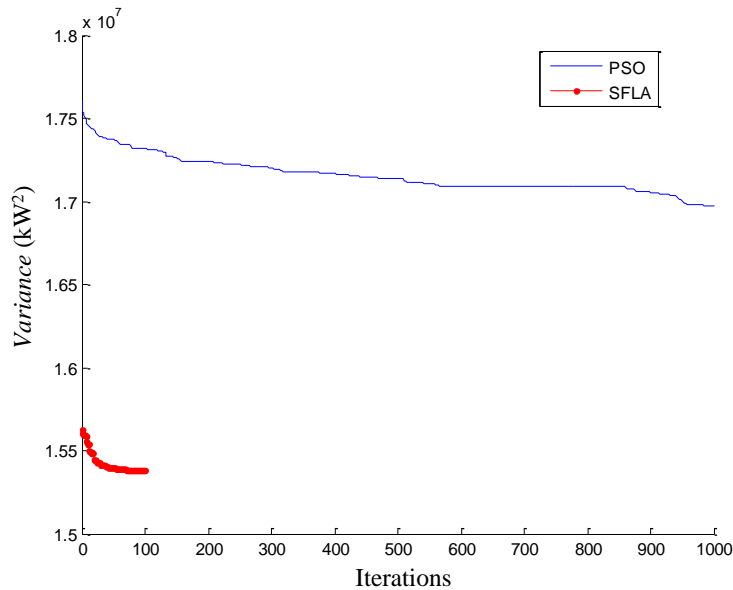


Figure 4: Convergence characteristics of SFLA and PSO

Clearly, the convergence rate of SFLA is much faster (100) than that of PSO (more than 1000) and the minimum variance of the load profile generated by SFLA is less than that generated by PSO, shown in Table 6.

Table 6: Variances generated by PSO and SFLA

Condition	Uncontrolled charging	Coordinated charging	
		PSO	SFLA
Variance ($\times 10^7 \text{kW}^2$)	1.836	1.6967	1.5380
Iterations	-	100	More than 1000
Result	-	Declining 7.59%	Declining 16.23%

5 Conclusion

As a main way of energy supply to EVs, the optimal control strategy for coordinated charging of the swapping station is very important in smoothing the load profile. Considering bidirectional power flow between the station and power grid, this paper presented an optimization model of EV battery swapping station and proposed a SFLA-based control strategy to optimize the operation of station. Compared simulations were carried out and the main conclusions of this paper are as follows:

- For the swapping station, energy exchanging mode can supply energy for large-scale EVs with a smoother load profile than one-way charging mode.

- Compared to particle swarm optimization (PSO) method, the presented SFLA-based strategy can effectively lower the peak-valley difference with the faster convergence rate and higher convergence precision.

Conflict of Interests: The authors declare that there is no conflict of interests regarding the publication of this paper.

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