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Optimization of Bi-Directional V2G Behavior With Active Battery Anti-Aging Scheduling

SHUANGQI LI[1], (Student Member, IEEE), JIANWEI LI[1], (Member, IEEE), CHANG SU[2], AND QINGQING YANG[3], (Member, IEEE)

[1]National Engineering Laboratory for Electric Vehicles and Collaborative Innovation Center of Electric Vehicles in Beijing, School of Mechanical Engineering, Beijing Institute of Technology (BIT), Beijing 100081, China
[2]Department of Sustainable Development, University of Birmingham, Birmingham B15 2TT, U.K.
[3]Faculty of Engineering, Environment and Computing, Coventry University, Coventry CV1 5FB, U.K.

Corresponding author: Jianwei Li (jianwei.li@eng.ox.ac.uk)

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ABSTRACT The bi-directional linkage between the power grid and electric vehicles (EVs) enables flexible, cheap and fast-responding use of vehicle batteries in the grid. However, the battery aging effects due to the additional operation cycles caused by Vehicle-to-Grid (V2G) service and the concern of the battery degradation are the main reason that keeps the customer from being the named prosumer of the grid. This paper proposes a novel active battery anti-aging V2G scheduling approach. Firstly, to evaluate the battery aging effect in V2G service, the battery degradation phenomenon is quantified by a novel use of rain-flow cycle counting (RCC) algorithm. Then, the V2G scheduling is modeled as a multi-objective optimization problem, in which the minimal battery degradation and grid load fluctuation are designed as the optimization objectives. Finally, a multi-population collaborative mechanism, which is particularly designed for the V2G scheduling problem, is also developed to improve the practicability and performance of the heuristic optimization based V2G scheduling method. The proposed methodologies are verified by numerical analysis, which highlights that the proposed V2G scheduling method can minimize battery charge/discharge cycles by optimizing the time and scale of each V2G participant while providing the same services to the grid as expected.

INDEX TERMS Electric vehicle, vehicle to grid, active battery anti-aging and heuristic algorithm.

I. INTRODUCTION

Energy is an essential part of modern life and energy management is an eternal topic in modern society. Electric vehicles (EVs) and power grid are two important components of the energy system. Instead of the one-way energy flow from the grid to EVs, their bi-directional link enables the flexible, cheap and fast-responding application of the vehicle batteries in the power grid [1], [2]. Therefore, it leads to the concept of Vehicle-to-Grid (V2G) that effectively integrates EVs into the grid as distributed energy resources [3].

Currently, many studies have investigated the V2G technology for better use of EV penetrations [4]–[6]. Liu *et al.* [7] established a V2G behavior scheduling model based on Blockchain technology to improve grid operation stability. The simulation results showed that the proposed scheme can reduce the grid power fluctuation level and overall charging cost significantly. Clement-Nyns *et al.* [8] proposed an online plug-in hybrid EV charging coordination approach based on the dynamic programming algorithm, in which the optimal charging profile was formulated by minimizing power loss. A large number of reports can be found from the literature, but many fundamental problems and critical challenges still exist: (1) The battery degradation phenomenon is rarely considered in V2G scheme, which may result in economic loss and dispelling the V2G participants' enthusiasm; (2) The essential of V2G scheduling is a large-scale, non-gradient and multi-objective optimization problem and the global optimal solution is hard to find.

A. ACTIVE BATTERY ANTI-AGING V2G MANAGEMENT

Battery degradation is the main reason that keeps the EV customer from being the named prosumer of the grid [9]–[11]. To encourage the enthusiasm of V2G participants, it is necessary to suppress the battery degradation phenomenon in the

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V2G scheduling issue [12], [13]. The battery aging mechanism and its lifetime prediction have already been well studied in recent years [14]. Wang *et al.* [15] investigated deep-learning algorithm-driven battery remaining useful life prediction method, the long short-term memory neural network was employed in their work to learn the long-term dependencies in the lithium-ion battery degraded capacities. The experiment results indicated that the battery capacity estimation error can be limited within 2.5%. An electrochemical mechanism model was established in David A. Howey's work [16] to quantify grid-connected Lithium-ion battery degradation annual cost, which can predict the battery capacity fade with an error of 5%. Jafari *et al.* [17] proposed a method to quantify the grid-connected Lithium-ion battery degradation phenomenon during V2G services based on the General Arrhenius Equation, and the model accuracy was validated under different scenarios and climates. However, the existing researches mainly emphasize the impact of battery aging on the V2G services, but few of them study the methods to reduce battery degradation actively by scheduling V2G behaviors optimally.

RCC algorithm has been widely used in many fields, such as fatigue damage analysis [18], remaining useful life prediction [19] and energy storage systems [20]. In this paper, the minimal battery lifetime degradation is designed as one of the optimization objectives and quantified by a novel use of the RCC algorithm.

B. THE HEURISTIC ALGORITHM BASED V2G SCHEDULING METHOD

The inherent features of V2G scheduling optimization, i.e. high-dimensional and large scale, cannot be neglected [21], [22]. Moreover, in active battery anti-aging V2G scheduling, the objective to minimize grid load fluctuations conflicts with minimizing battery degradation. The trade-off is actually a Pareto-optimal point searching problem. In addition, the objective function in V2G scheduling is usually not simply linear or quadratic, so the conventional convex optimization method is not applicable [23]. Further, introducing the battery degradation index turns the optimization objective into a non-continuous, non-derivable and non-gradient function, and the conventional gradient descent algorithms are no longer effective [24].

The heuristic algorithm is one of the most effective ways to deal with the complex optimization problem, and the Particle Swarm Optimization (PSO) algorithm is a typical heuristic algorithm. At present, the PSO algorithm has been widely used in the Hybrid Energy Storage System [25], Path Planning [26] and systems identification [27], etc.. The PSO algorithm was regarded as one of the most successful approaches to solve the large-scale and multi-objective optimization problem. In recent years many researchers have developed many different methods to improve the performance of PSO algorithm [28]–[30]. Li *et al.* [31] proposed an information-sharing mechanism to improve the PSO algorithm performance in the large-scale optimization problem. The proposed methods were validated effectiveness under various test environments. The fuzzy logic method was used in literature [32] to improve the effectiveness of the PSO algorithm in the multi-objective optimization problem. The experiment results in a V2G scheduling system indicated that the proposed method can improve the system performance effectively. However, to the authors' best knowledge, there is no published literature considering both the large-scale and multi-objective optimization problems in V2G scheduling at present. Thus, to improve the performance of the PSO algorithm based V2G behaviors management system, a multi-population collaborative mechanism (MCM) is developed in this paper.

Keeping in the view of above perspective and issues, to suppress the battery aging effect in V2G services and improve the performance of the V2G scheduling system, a novel active battery anti-aging V2G scheduling method is proposed in this paper. The key contributions are as follows: (1) The battery degradation phenomenon during V2G services is quantified by a novel RCC algorithm; (2) A mathematical optimization model is established for the active battery anti-aging V2G scheduling problem, in which the minimal battery degradation and grid load fluctuation are designed as the optimization objectives; (3) A multi-population collaborative mechanism is developed with the ability to solve the large-scale, multi-objective, and non-gradient optimization problem in active battery anti-aging V2G scheduling.

This article is organized as follows: Section II briefly introduces the architecture of the intelligent V2G scheduling system, in which the system working principles and information flows are defined. The background materials of the algorithm used in our work are detailed in Section III. The proposed battery degradation quantification method and active battery anti-aging V2G scheduling method are described in Section IV. Results and comparisons are provided in Section V, followed by concluding remarks in Section VI.

II. THE ACTIVE BATTERY ANTI-AGING V2G SCHEDULING SYSTEM

The framework of the proposed battery anti-aging V2G scheduling system is shown in Fig. 1. The system is divided into 4 parts: information prediction module, user information collection module, V2G behaviors management module, and EV smart charger. The optimal V2G behavior control strategies are achieved through the cooperation of four modules.

A. USER INFORMATION COLLECTION MODULE

The User information collection module is used to collect household electricity load and EV's charging demand data on the basis of Information and Communications Technology (ICT) [33]. The real-time V2G charging demand information is sent to the information prediction module for future use, and at the same time, the charging requirements of the EVs that have just been connected to the grid (within recent

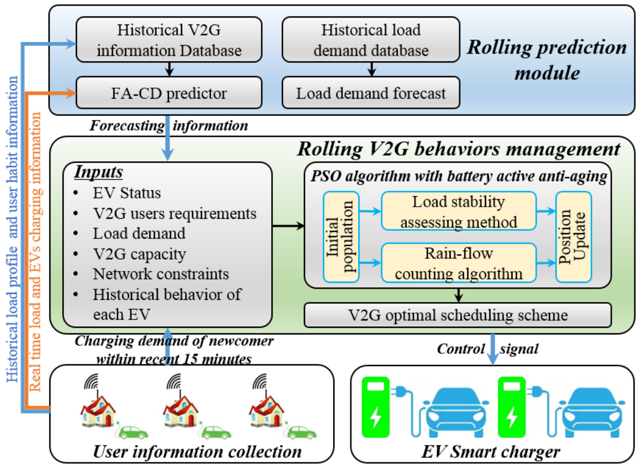

FIGURE 1. The architecture of the active battery anti-aging V2G scheduling system.

15 minutes) are sent to the rolling V2G behaviors management module.

B. ROLLING PREDICTION MODULE

A historical V2G information database, as well as a historical baseload demand database corresponding the V2G participants in different districts, are established in this module. Meanwhile, future arriving EVs' charging demand, discharging capacity [34] and future load demand [35] are forecasted based on the established database, provided as an important data foundation for V2G scheduling.

C. ROLLING V2G BEHAVIOR MANAGEMENT MODULE

The V2G behaviors management module formulates the V2G charge/discharge control strategies for every grid-connected EV on the basis of the collected user demand and grid load state information. The optimization objectives are to minimize grid load fluctuation and battery degradation. The control strategies are sent to EV smart charger.

D. EV SMART CHARGER

According to the charge/discharge strategies, the EV Smart charger controls the charge/discharge power of every grid-connected EV in real-time by power electronic devices.

E. SYSTEM OPERATION TIME LOGIC

The above presented V2G scheduling system operates in a rolling way with the controlling interval of 15 minutes. In each time of V2G scheduling, the EV charging information and baseload is predicted by the prediction module through historical data and real-time information, and the V2G behaviors of the EVs that have just been connected to the grid (within recent 15 minutes) are scheduled. The above-mentioned prediction-decision V2G scheduling process is carried out repeatedly with the system operation.

The information collection & communication technology [33], the grid load [35], [36] & V2G capacity estimation [37], [38] approach and the smart charging pile technology [39] has been well studied in the existing literature. Therefore, in the rest part of this paper, we mainly focus on the V2G behavior management method.

III. ALGORITHM BACKGROUND

A. PARTICLE SWARM OPTIMIZATION ALGORITHM

The PSO algorithm is used in this paper to find the optimal V2G strategy. In the PSO algorithm, each candidate solution is denoted as a "particle" without mass or volume in the search-space. The solution set consisting of a large number of particles is called a "Swarm". Each particle is labeled by three properties: velocity, position, and fitness. The position of the particle represents a candidate solution. The velocity determines the flying direction and distance of a particle in each iteration. The particles move in the search-space by updating velocity and gradually approach the optimal solution, and the fitness function is used to evaluate particle quality [40]. In the conventional PSO optimization process, an initial swarm is generated by randomly initializing particle position and velocity firstly. The position and velocity of particle i can be denoted as $X_i = [x_{i1}, x_{i2}, \cdots x_{iD}]$ and $V_i = [v_{i1}, v_{i2}, \cdots v_{iD}]$ respectively. The particle velocity and position are updated by the following equations [41]:

$$V_i^{k+1} = V_i^k + c_1 rand_1(pbest_i^k - X_i^k) + c_2 rand_2(gbest_i^k - X_i^k) \tag{1}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{2}$$

where: k represents iteration times, V_i^k and X_i^{k+1} represent the velocity and position vector of particle i in $k-th$ iteration respectively. $pbest_i^k$ is the personal best position vector of particle i in the $k-th$ iteration, $gbest^k$ represents the global best position vector in the whole swarm, $c1$ and $c2$ are learning factors, $rand1$ and $rand2$ are random numbers obeying uniform distribution within [0, 1].

B. BATTERY DEGRADATION QUANTIZATION METHOD

The battery degradation mechanism has been well studied in previous work. However, the conventional battery degradation quantification method, including the electrochemical model [42] and artificial intelligence algorithm [43], can only quantify the battery degradation phenomenon on a large time scale (several days or weeks) [44]. Nevertheless, the scheduling horizon in V2G management is usually less than one day [45], [46], so it is difficult to quantify battery degradation in V2G applications. Comparing to the conventional battery degradation quantification method, the RCC algorithm can quantify the battery aging phenomenon in a short period (several minutes or hours) [47], which is more suitable for the battery degradation quantification issue in V2G scheduling. Therefore, the RCC algorithm is used in this paper to extract the charging and discharging cycles and quantify the battery degradation phenomenon in V2G service. The application of the RCC algorithm has been well studied in our previous work: hybrid energy storage system in microgrid [48], renewable energy system [49] and energy management system of

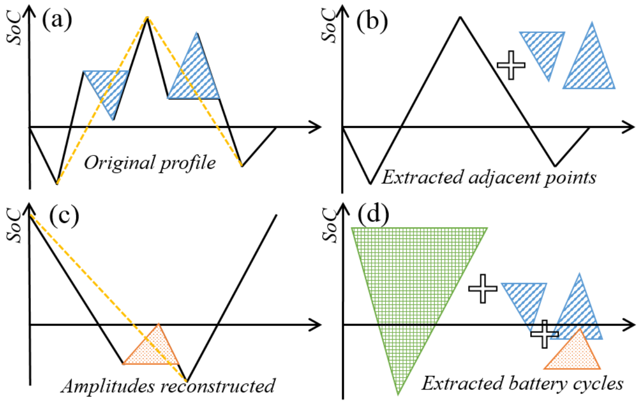

FIGURE 2. **The battery cycle extraction process in the rain-flow cycle counting algorithm. (a) The original profile. (b) The extracted adjacent points. (c) The reconstructed amplitudes. (d) The extracted battery cycles.**

hybrid electric vehicles [50]. Basically, as shown in Fig.2, the cycle counting can be achieved by the following three steps as following: Firstly, the data (for the battery the data is the DOD that presents the battery charge/discharge cycles) is pre-processed by searching for adjacent data points with the reverse polarity so that the local maxima and minima can be found and stored in a matrix. Secondly, compose full cycles by analyzing the turning points and combine these sub-cycles to get full-cycles together with the summing up of the amplitudes. Thirdly, extract and count the number of cycles in varying amplitude store them for later use.

The battery degradation phenomenon can be quantified by analyzing the extracted battery number of cycles and DOD data. The RCC algorithm is used to evaluate the battery aging in V2G scheduling in this paper.

IV. PROPOSED METHODOLOGY

A. ACTIVE BATTERY ANTI-AGING V2G SCHEDULING METHOD

An active battery anti-aging V2G scheduling method is proposed in this section. Firstly, a mathematical optimization model is established for the V2G scheduling issue, in which the minimal battery degradation and grid load fluctuation are designed as the optimization objectives. Then, combine with the PSO algorithm and the RCC algorithm, the system operation principles and information flows are detailed.

The optimization variable in V2G scheduling is the charge/discharge power of every grid-connected EV. The particle dimension is $(n+1) \times (T_u + T_w)$. Where n is the total number of EVs already in the grid. 1 represents the future available V2G capacity of EVs that will connect to the grid in later control steps. T_w and T_u are the number of decision points in the future and past control step respectively. The position of particle I is as follows (3) as shown at the bottom of this page, where: $P_{i,j}$ represents the power state of EV_i in control step j, $P_{n+1,j}$ reflects the utilization degree of future V2G schedulable capacity. In this paper, the historical V2G behaviors are also stored in the particle, it is not schedulable but influence future V2G scheduling directly.

To estimate EV's SoC accurately, the recurrence formula is as follows [50]:

$$SoC_{t+1}^{i} = SoC_{t}^{i} + \frac{\Delta t \times P_t^i \times \eta^i}{C^i} \times 100 \tag{4}$$

where Δt is the control time-step, C^i is the battery capacity of EV_i. η^i is the battery charge/discharge efficiency.

The first optimization objective is to provide load-shifting service, which can be described as to minimize load fluctuation variance [32]:

$$fitness1 = \min\left\{\frac{1}{u+w}\sum_{t=1}^{u+w}\left[\mathbf{P_{load}(t)} + \sum_{i=1}^{n}\mathbf{P_I(t)} - \bar{P}_{AV}\right]^2\right\} \tag{5}$$

where: $\mathbf{P_{load}(t)}$ is the system load in the time slot t, $\bar{P}_{AV}$ is the average grid load level.

Apart from grid stability and economy, the battery degradation phenomenon resulted by participating in V2G is also considered in this paper:

$$fitness2 = \min\left\{\sum_{i=1}^{n} N_i^{cycle} + N_i^{h-cycle}\right\} \tag{6}$$

N_i^{cycle} and $N_i^{h-cycle}$ are the battery number of cycles and half-cycles of EV_i in V2G scheduling, which can be calculated by the RCC algorithm described in Section III.B.

When formulating V2G strategy, the travel demands of V2G participant should be satisfied, the battery charging process should be completed before departure [32]:

$$SoC_i^{end} \geq SoC_i^{set} \tag{7}$$

$$\mathbf{P_I} = \begin{bmatrix} \underbrace{\begin{matrix} P_{1,1} & \cdots & P_{1,j} & \cdots & P_{1,u} \\ P_{2,1} & \cdots & P_{2,j} & \cdots & P_{2,u} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{i,1} & \cdots & P_{i,j} & \cdots & P_{3,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{n,1} & \cdots & P_{n,j} & \cdots & P_{n,u} \\ P_{n+1,1} & \cdots & P_{n+1,j} & \cdots & P_{n+1,u} \end{matrix}}_{Historical\ V2G\ power\ profile} & \underbrace{\begin{matrix} P_{1,u+1} & \cdots & P_{1,u+w} \\ P_{2,t+1} & \cdots & P_{2,u+w} \\ \vdots & \ddots & \vdots \\ P_{3,u+1} & \cdots & P_{i,u+w} \\ \vdots & \ddots & \vdots \\ P_{n,u+1} & \cdots & P_{n,u+w} \\ P_{n+1,u+1} & \cdots & P_{n+1,u+W} \end{matrix}}_{Pending\ scheduling} \end{bmatrix} \tag{3}$$

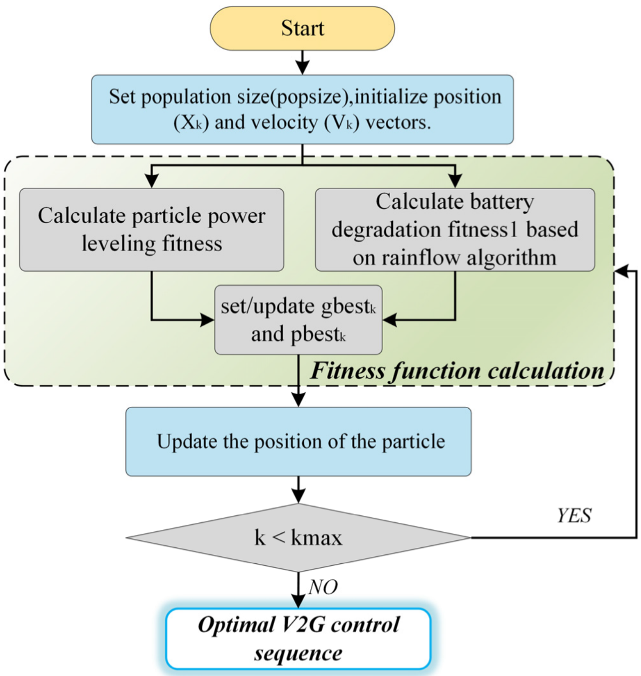

FIGURE 3. The active battery anti-aging V2G scheduling method.

Battery life is mainly influenced by the number of cycles, DOD and charge/discharge rate. The number of cycles has been considered in the objective function, the DOD and charge/discharge rate are restricted by the following constraints in this paper:

$$-P_{i,disch\arg}^{\max} \leq P_{i,t} \leq P_{i,ch\arg e}^{\max} \tag{8}$$

$$SoC_{\min} \leq SoC_{i,t} \leq SoC_{\max} \tag{9}$$

The flowchart of the proposed active battery anti-aging V2G scheduling method is shown in Fig. 3. The system operation process can be divided into four steps:

The status of the grid-connected EVs are collected, including the serial number i of each EV, accessing time t_{start}^{i}, preset departure time t_{end}^{i}, the SoC_i^{start} when EV_i accesses the grid, and the preset minimal SoC_i^{set} at departure. Then the population size Q is determined, and an initial swarm satisfying the constraints(7 $\sim$ 9) is generated.

1) Two fitness functions are formulated and the fitness value of the particles is calculated based on the defined fitness functions. The fitness function 1 and 2 are used to evaluate swarm's grid load stabilizing performance and battery degradation suppression performance respectively. With the guidance of both fitness functions, the generated V2G strategy could stabilize grid load fluctuation and reduce V2G participants' battery degradation costs at the same time.
2) The personal and global best solution $pbest_k$ and $gbest_k$ are found through the fitness value, and particle position X_i and velocity V_i are updated following equation (1) and (2).

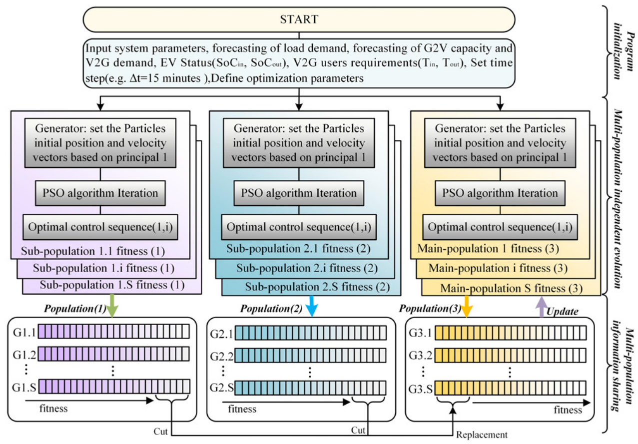

FIGURE 4. The proposed multi-population collaborative mechanism.

3) Step 2 and 3 are performed repeatedly, and the particle position is continuously updated before the evolution times k reaches maximum iteration times $k_{\max}$. The global optimal solution $gbest_{k\max}$ is outputted as the optimal V2G control strategy.

B. THE MULTI-OBJECTIVE AND LARGE-SCALE OPTIMIZATION METHOD FOR ACTIVE BATTERY ANTI-AGING V2G SCHEDULING

Particle prematurity and homoplasy are the main obstacles that limiting the performance of the conventional PSO algorithm on multi-objective and large-scale optimization problems.

Prematurity appears in large-scale optimization problems [51]. PSO algorithm inclines to be stuck in local optimum because of prematurity, and the evolution process may stop before acquiring the actual global optimal solution. Two methods are applicable for expanding the search range: one is to expand the population size, but the computation complexity is also increased tremendously; the other is to weaken the attraction of the global best solution, which may cause convergence difficulty [52]. The homoplasy appears when dealing with the multi-objective optimization problem, limiting much of the search-space and depriving the potential of the algorithm to find a coordinating optimal solution [53].

In the active battery anti-aging V2G scheduling issue, to obtain the optimal V2G control strategy, it is necessary to explore an effective method to overcome the prematurity and homoplasy obstacles. Therefore, in this section, a multi-population collaborative mechanism is developed and provided as a possible solution for the dilemma raised above. The flowchart of the proposed MCM method is shown in Fig. 4, and system operation principles can be described by the following 4 steps:

1) ALGORITHM CONFIGURATION INITIALIZATION

To satisfy the swarm diversity requirements, the initial population in the proposed MCM method is divided into several groups, labeled as sub-population and main-population.

These populations are independent and assigned with different fitness functions. The main-population represents the coordination between several optimization objectives, and the sub-population can enrich the diversity of the main-population. Meanwhile, to improve the algorithm efficiency in the large-scale optimization problem, reducing the demand on population size and computing resources, the sub-population and main-population are divided into several sub-groups again. Each sub-group has the same objective function and constraints, but the initial particles are different. During the evolution, the particles in different sub-groups evolve in different directions, several evolution centers are generated in the optimization process and the homoplasy can be avoided effectively. In this paper, two sub-populations and one main-population are set, and every sub-population and main-population is further divided into S sub-group with the particle number *popsize*.

2) POPULATION INITIALIZATION

The particle position and velocity in the sub-population and main-population are initialized in this step. The initial position influences the optimization efficiency directly, to reduce the required computing resources occupation, the particles should be distributed in the search-space as evenly as possible, while the particle validity should also be guaranteed. The particles in different populations are given different initialization principles to improve algorithm performance and efficiency. Firstly, to generate better load-shifting particles for sub-population 1, in principle 1, constraints on grid peak power are tightened, while the constraints on charging/discharging rate and DOD are loosened. The corresponding initialization principle is as follows:

$$\text{P1 } ST: \begin{cases} P_Z^{\max} < 2 \times \bar{P}_{AV} \\ SoC_i^{end} \geq SoC_i^{set} \\ -1.5 \times P_{i,disch\arg}^{\max} \leq P_i^t \leq 1.5 \times P_{i,ch\arg e}^{\max} \\ 0 \leq SoC_{i,t} \leq SoC_{\max} \\ P_i^t = 0 \text{ while } A_i^t = 0 \end{cases} \tag{10}$$

To generate better battery protection particles for sub-population 2, in principle 2, maximum charge/discharge cycles are limited, as well as the constraints on charge/discharge rate and DOD are tightened:

$$\text{P2 } ST: \begin{cases} N_i^{cycle} < 5 \\ SoC_i^{end} \geq SoC_i^{set} \\ -0.8 \times P_{i,disch\arg}^{\max} \leq P_i^t \leq 0.8 \times P_{i,ch\arg e}^{\max} \\ 1.5 \times SoC_{\min} \leq SoC_{i,t} \leq SoC_{\max} \\ P_i^t = 0 \text{ while } A_i^t = 0 \end{cases} \tag{11}$$

In principle 3, particles are generated for the main-population, the balance between the various optimization objectives is more valued, so all the constraints are treated equally:

$$\text{P3 } ST: \begin{cases} P_Z^{\max} < 3 \times \bar{P}_{AV} \\ N_i^{cycle} < 7 \\ SoC_i^{end} \geq SoC_i^{set} \\ -P_{i,disch\arg}^{\max} \leq P_i^t \leq P_{i,ch\arg e}^{\max} \\ SoC_{\min} \leq SoC_{i,t} \leq SoC_{\max} \\ P_i^t = 0 \text{ while } A_i^t = 0 \end{cases} \tag{12}$$

3) POPULATION EVOLUTION

Particle velocity and position are updated based on the formula (1) and (2) in this step. The fitness functions in sub-populations and main-population are as follows:

$$\begin{cases} fitness\ \ function(1) = 0.8 \times fitness1 + 0.2 \times fitness2 \\ fitness\ \ function(2) = 0.2 \times fitness1 + 0.8 \times fitness2 \\ fitness\ \ function(3) = 0.5 \times fitness1 + 0.5 \times fitness2 \end{cases} \tag{13}$$

Fitness function (1) focuses on peak-shifting performance, so particles in sub-population 1 have a better effect on peak-shifting. *Fitness function (2)* focuses on battery life protection performance, so particles in sub-population 2 have a better effect on battery degradation suppression. *Fitness function (3)* is the fitness function of main-population, with high requirement on both optimization objectives, the best solution for multi-objective optimization can be found in main-population.

4) MULTI-POPULATION INFORMATION SHARING

After the sub-population and main-population evolved N times independently, particles in sub-population and main-population are exchanged, and the variety of main-population is enriched. The sub-group in sub-populations and main-population are extracted and denoted as *G1.1,G1.2,…,G1.S; G2.1,G2.2,…,G2.S; G3.1,G3.2,…,G3.S.* As illustrated in Fig. 3, the particles in each sub-population are arranged according to their fitness, the color from shallow to dark represents the fitness from low to high. The inferior particles in main-population would be gradually eliminated and replaced by those superior particles in sub-population.

After the replacement, particles are generated again for sub-population under the initialization principal in step 2 for keeping the population size. Then turn to step 3, the particle velocity and position are updated iteratively.

V. RESULTS AND DISCUSSIONS

A. SIMULATION ENVIRONMENT SETUP AND DATASET DESCRIPTION

The V2G participants' behavior data were collected by Beijing Electric Vehicles Monitoring and Service Center, which is affiliated to National Engineering Laboratory for Electric Vehicles and serves as a national big data platform for electric vehicles in China. The monitoring data of a residential area with 40 households were downloaded from the established big data platform and served as the basic simulation data of

TABLE 1. An example charging segment of the collected datasets.

Vehicle stamp	Grid-connected time	Grid-connected SoC (%)	Departure time	Departure SoC (%)	Battery capacity (kw·h)
201807285801	18:10	32	07:25	80	90
201807285802	20:45	24	06:10	76	75
…	…	…	…	…	…
201807285842	17:45	48	08:30	95	120
201807285843	18:30	42	06:45	85	85

this paper. As shown in Table 1, the individuals' travel behavior data, including the vehicle tamp, vehicle grid-connected time and SoC, departure time and SoC, battery system parameters, etc. are further extracted from the collected data set to simulate the users' V2G behaviors and verify the proposed scheduling method.

The baseload demand curve used in our work is also obtained from the aforementioned residential area by Smart Meter technology. It is worth noting that unusual dates such as the Chinese Spring Festival Holiday, the New Year holiday, and the weekends are excluded from the data set in advance. The detailed information of the simulation platform is shown in Table 2.

In order to reach the optimal performance of the proposed V2G scheduling algorithm, we prepared multiple algorithm parameter settings. However, not all results are reported in the paper, the comparison is only made with the optimal settings of each algorithm. The parameters of the conventional PSO algorithm and proposed MCM method are set as follows for better performance through multiple experiments:

Parameter of PSO algorithm

$$\begin{cases} \text{Interation times} \in \{50\} \\ \text{Population size} \in \{60000\} \\ \text{learning factor} \in \{\text{c}1 = 0.8, c2 = 0.5\} \\ \text{Penalty factor} \in \{500, 500\} \\ \text{Inertia weight} \in \{0.4\} \end{cases}$$

Parameter of MCM algorithm

$$\begin{cases} \text{Interation times} \in \{50\} \\ \text{Number of sub-groups} \in \{5\} \\ P\text{opulation size} \in \{20000, 20000, 20000\} \\ \text{Particle exchange times}\{2\} \\ \text{Particle exchange position}\{10{,}20\} \\ \text{Particle exchange length}\{1500\} \\ \text{Learning factor} \in \{\text{c}1 = 0.8, c2 = 0.5\} \\ \text{Penalty factor} \in \{500, 500\} \\ \text{Inertia weight} \in \{0.4\} \end{cases}$$

The most active V2G period (16:00-24:00 and 00:00-08:00) is taken into consideration in this study, the baseload profile in this period is shown in Fig. 5.

In the random charging scenario, it is assumed that EV owners would immediately charge their cars with rated power upon arriving home until the batteries are fully charged. As shown in Fig. 5, most EVs are connected to the grid during

TABLE 2. The parameters of the simulation environment.

Parameters	Value
Controlling interval	15mins
Number of vehicles	47
V2G period	16:00-24:00 and 00:00-08:00
Number of households	40
Baseload sampling interval	15mins
Maximum and minimum battery SoC	90% & 10%
Maximum battery V2G charging and discharging power	10kw & 20kw

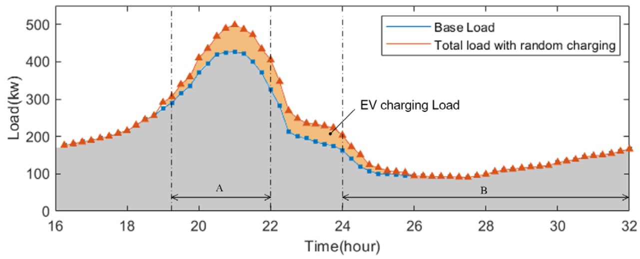

FIGURE 5. The power system baseload and total load profile when EVs random charging.

19:00-22:00 (zone A), while the baseload also booms in this period and peaks at around 21:00, as a result, the grid peak load is elevated to 504kw. While after 00:00 (zone B), most of the EVs have been fully charged and the minimum grid load is only 97.5kw. To ensure the safe, stable and economic grid operation, it is necessary to suppress the grid load fluctuation.

B. THE RESULTS OF V2G SCHEDULING

The results of the conventional PSO algorithm based V2G scheduling [52], [53] are shown in Fig. 6 (a). During grid peak hours, the EVs are scheduled to feed energy back to the grid, the EVs' charging load is no longer overlapping the baseload and the peak load of the grid is reduced successfully. However, the V2G scheduling is inherently characterized as a high-dimensional, large-scale optimization problem, it is very difficult to get the global optimal solution, which is reflected in the following two aspects: Firstly, the conventional PSO algorithm can only realize long term load-shifting, but the grid load fluctuation is not sufficiently suppressed: the load profile keeps fluctuating from 22:00 to 06:00; Secondly, its peak-shaving performance is not satisfying, with only 8% drop compared to baseload profile, which means that only a small part of EVs are scheduled to discharge during peak hours. The aforementioned issue is more serious when considering active battery anti-aging. To further improve the load-shifting ability of the V2G scheduling system, a MCM method is proposed in this paper and the result is shown in Fig. 6 (b). With the proposed mechanism, the V2G scheduling system can not only realize the long-term load-shifting performance but also suppress short-term grid load fluctuation. When compared to random charging, the load peak and load Standard Deviation (STD) is reduced by 32% and 60.4% respectively.

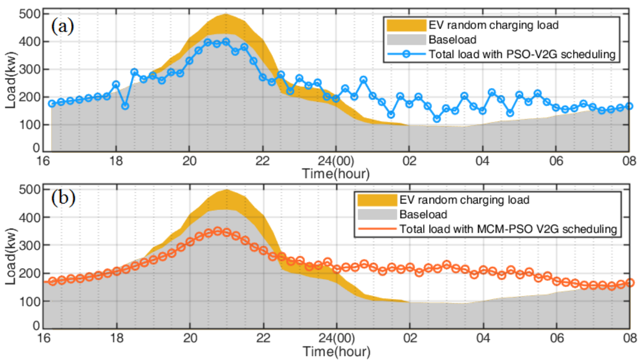

FIGURE 6. Power system load profile (a) under the conventional PSO algorithm and (b) MCM method.

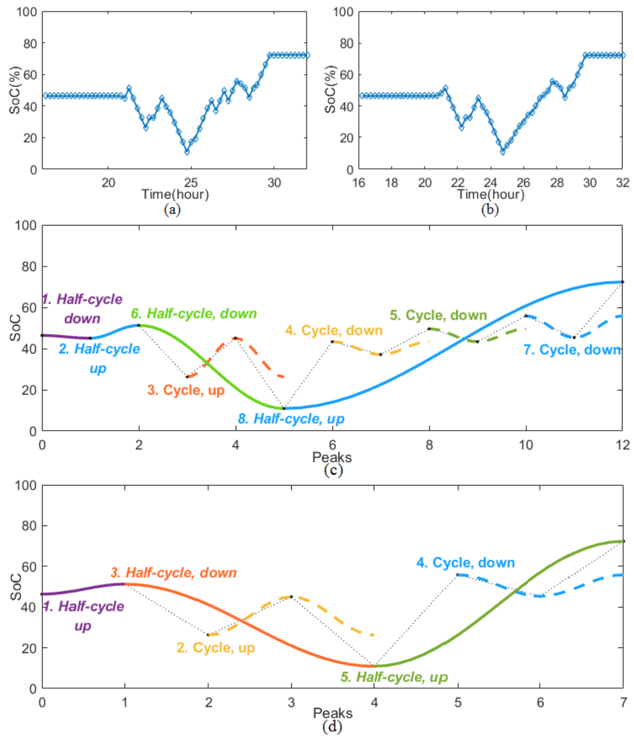

FIGURE 7. The comparison of (b, d) the battery anti-aging V2G scheduling method and (a, c) conventional V2G scheduling method.

To verify the proposed battery anti-aging V2G scheduling method, the battery cycles in the conventional V2G scheduling method [32], [54] and the proposed one are compared in Fig. 7. Subfigure (a) and (b) are the SoC profiles, subfigure (c) and (d) are the corresponding charge/discharge cycles statistics by the RCC algorithm. With the proposed battery degradation suppression method, the battery number of cycles during participating in V2G service are reduced significantly: the number of half-cycles drops from 4 to 3, and the number of full cycles drops from 4 to 2, which indicates that the battery is protected successfully by the proposed anti-aging algorithm.

C. COMPARISON OF DIFFERENT ALGORITHMS PERFORMANCE

The performance of different V2G behavior management methods is compared in Table 3. The coordination of EV

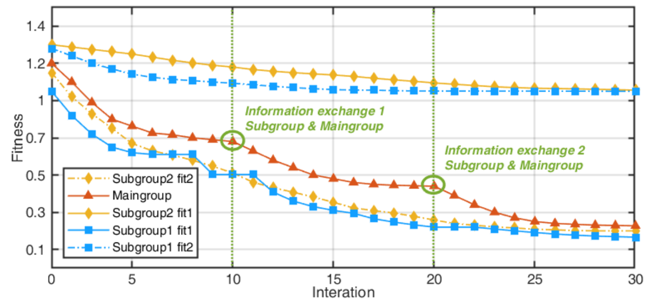

FIGURE 8. The convergence speed of the proposed multi-population collaborative mechanism.

charge/discharge behavior can be realized by using conventional PSO algorithm based V2G management method [32], [52]–[54], which reduces 22.2% peak load and 30.1% grid load STD, but it is not able to further suppress the load fluctuation and has poor performance on peak-shaving service. The proposed MCM method can further decrease the peak load and load STD with 32% and 60.4% respectively, and the grid energy quality is significantly improved. Compared to the conventional V2G scheduling method, the number of full-cycles (NFC) and half-cycle (NHC) in active battery anti-aging V2G scheduling method drops 79.4% and 15.6% respectively, which indicates that the proposed method is capable of suppressing battery degradation phenomenon in V2G service.

The convergence speed of the proposed MCM method is shown in Fig. 8, where the red curve represents the fitness value of the main-population, the blue one and the orange one represent that of sub-population 1 and sub-population 2 respectively. There are two fitness functions in each sub-population, the solid line denotes the particle peak-shaving performance, and dashed dot line denotes the particle battery degradation suppression performance. The load fluctuation suppressing is the mainly considered optimization objective in Sub-population 1, the battery degradation mitigating is that of in Sub-population 2, and two objectives are treated equally in main-population. Each population has independent fitness functions (see Eq. 10 to 12), so the dropping speed of different fitness functions are also different. The fitness 1 drops faster than fitness 2 in sub-population 1, as the fitting function of sub-population 1 mainly focuses on evaluating the peak-shifting performance of candidate solutions. Similarly, for the same reason, fitness 2 drops faster than fitness 1 in sub-population 2, which verifies the effectiveness of proposed population evolution principles. The fitness function of the main-population drops slowly, and the evolution process stops at 5th, 15th, and 25th iteration because of poor swarm diversity. But by exchanging particles between main-population and sub-population, the evolution process is accelerated significantly. The fitness function of the main-population drops from 0.7 to 0.25 after two exchanges at 10th and 20th iteration, which indicates that the proposed MCM method can boost population evolution and improves the V2G scheduling efficiency effectively.

TABLE 3. The result of different V2G management method.

Scenario	Peak (kw)	STD	Minimum SoC(%)	NFC	NHC
Base load	426	101.65	-	-	-
Random charging	504	120.55	18.7	0	30
V2G & conventional PSO	392	84.24	13.4	135	83
V2G & MCM[a]	343	47.71	12.6	117	77
V2G & MCM & Battery active anti-aging	354	56.83	21.2	24	65

[a]MCM: Multi-population collaborative mechanism.

TABLE 4. The calculation time of different algorithm-based V2G scheduling method.

Algorithm	Calculation time (s)			CPU average usage (%)
	Average	Minimum	Maximum	
Conventional PSO	476	42	1042	13
MCM & PSO	135	37	426	86

To verify the effectiveness of the proposed V2G scheduling method, we compare the complexity of different algorithms in the paper. The program is implemented on a high-performance workstation equipped with 2×E5-2690v4 processor, and the MATLAB Parallel Computing Toolbox is employed to improve the efficiency of MCM algorithm: different sub-populations and sub-groups are assigned to different threads of the processor and thus the evolution of the population can be performed in parallel. The calculation time of different V2G scheduling methods in real scenarios is compared in Table 4.

The conventional PSO algorithm is not able to utilize the modern multi-core CPU resources effectively, the average CPU usage is only 13%, and with the proposed MCM method, the CPU computation resources can be used more reasonable (86% on average). As a result, the calculation time of the conventional PSO algorithm within 50 iterations is as long as 476s on average, and this number is reduced to 135s with the MCM method, which validates the effectiveness of the proposed scheduling method. The maximum calculation time of MCM method in the whole scheduling period can be limited within 426s, which indicates that the V2G management system can schedule the charging behaviors of grid-connected EVs in time (15 minutes, 900s).

VI. CONCLUSION AND FUTURE WORK

A battery anti-aging V2G behavior management method is presented in this paper. By using the RCC algorithm based battery degradation quantification method, the minimal battery aging effect was designed as one of the optimization objectives in the mathematical model. Compared to the conventional V2G management method, the battery number of full-cycles and half-cycle are reduced by 79.4% and 15.6% respectively, which indicates that the battery degradation phenomenon during the V2G application is suppressed effectively. The designed multi-population collaborative mechanism can utilize the computational resources reasonably to solve the high-dimensional and multi-objective optimization problem in V2G scheduling. The simulation results revealed that the particle exchange process can boost population evolution and improve the algorithm performance effectively, the peak load and load STD were further reduced by 32% and 60.4% respectively, which validated that the grid energy quality can also be improved by the proposed battery active anti-aging V2G scheduling method.

This paper mainly focuses on suppressing the battery degradation problem in V2G scheduling. It is assumed that the baseload profile and battery state can be predicted and estimated accurately. But the prediction or estimation errors cannot be avoided in real scenarios and may influence the operation of the V2G management system. For instance, the prediction error of baseload and EV charging information may influence the V2G scheduling results and have a negative impact on system peak-shaving performance. Likewise, the battery state estimation error may also influence the V2G scheduling, especially when quantifying the battery degradation phenomenon. Future work can be conducted on studying the influence of the prediction error and how to suppress these influences in V2G scheduling.

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SHUANGQI LI (Student Member, IEEE) was born in Beijing, China. He received the B.Eng. degree in vehicle engineering from the Beijing Institute of Technology, Beijing, China, in 2018. He is currently a Research Assistant with the National Engineering Laboratory for Electric Vehicles, Beijing Institute of Technology. His major research interests include the big data analysis, deep-learning algorithm, and grid-electric vehicles V2G technology.

JIANWEI LI (Member, IEEE) received the B.Eng. degree from North China Electric Power University and the master's and Ph.D. degrees from the University of Bath, U.K. He was a Postdoctoral Researcher with the University of Liege, Belgium. After that, he works an Assistant Professor in the Beijing Institute of Technology. He is currently a Researcher with Oxford University. His research interests include electrical energy storages and hybrid energy storages, electrical vehicles, machine learning for energy storage systems, and microgrids.

CHANG SU received the B.A. degree from the University of Chinese Academy of Social Sciences, Beijing, China, and the M.Sc. degree in development policy and politics from the University of Birmingham. She is currently pursuing the second M.Sc. degree in sustainable development with the University of Birmingham. Her major research interests are energy policy, energy conservation, and environmental sustainability.

QINGQING YANG (Member, IEEE) received the B.Eng. degree from North China Electric Power University, China, and the M.Sc. and Ph.D. degrees from the University of Bath, U.K. She is currently a Lecturer with Coventry University. Her research interests include HVDC control and protection, artificial intelligence applications in power systems, energy storage, and smart grids.