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Demand Side Management for EV Charging/Discharging Behaviours with Particle Swarm Optimization*

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***Abstract*— In this paper, the electric vehicle charging and discharging behaviours from the demand side is discussed. A large-scale charging of electric vehicles could jeopardize the safety and economics of the power grid operation. It is hence necessary to investigate the charging/discharging pattern involved in EVs and knowledge-based modelling technique is used to model their behvaiour. An improved particle swarm optimization algorithm is proposed to control large scale EV charging/discharging with the aid of pricing mechanism for the minimized cost for electric vehicle users as the objective. Simulation experiments are implemented to prove the effectiveness of the proposed algorithm.**

***Index Terms*— Demand side management, Charging/Discharging behaviour, Electrical vehicles, Particle swarm optimization**

I. Introduction

The charging/discharging behaviour of the electric vehicles (EVs) could have effect on the safety and economy of the power grid operation. How to take measures to avoid the negative effect of EVs on the grid under the current technology background or even the assistance of Vehicle to Grid (V2G) technology to make reasonable use of storage distribution characteristics of EVs for power grid operational optimization is the compulsory problem to be solved before the popularity of the electric vehicles in reality. The pricing mechanism setting during EV charging/discharging is the core of the problem, which could directly affect the EV charging behaviour and the cost recovery of the charging facility put into use. Besides, it will have positive effect on the users to participate the grid load optimization and backup service from the grid [2].

Demand side management (DSM) is an advanced energy management technology to manage the energy usage and saving operation still in its initial growth stage [3]. From the economic point of view, DSM can avoid the switch on backup generator in high cost so that the whole cost can be reduced and alleviate the burden of grid expansion. Besides, it can increase energy usage efficiency and reduce greenhouse gas emission. From the system operation perspective, DSM will contribute the reliability at high peak and safety at emergency moments of the system. From the end-users point of view, the implement of DSM can encourage users to optimize their energy usage behaviour thus reducing their electricity bills [5].

Based on the investigation, it demonstrates that 80% of the time of personal EVs is in still state on daily basis. Experts and scholars therefore assume that the energy from EVs can be reloaded back to the grid to satisfy the demand during load intense period and EVs can be charged from grid so as to achieve the peak shaving and valley filling function. It is the rudimentary idea of V2G (vehicle to grid).

According to the statistical data of the driving habits of inhabitants provided by Traffic Department of US in 2003, a simulation model is developed to investigate the impact of different charging behaviours of future electric vehicle users to the power grid load [12]. It found out that there would be high pressure on the power grid due to the EVs charging in large scale. Christophe and George [6] discuss the possibility of reverse power supply from EVs to the grid with the aid of dynamic batteries. Moreover, the strategy, structure and technical requirement involved in V2G are discussed and the responsibilities for all participants are evaluated as well, which provides theoretical support for future V2G market construction.

Lund and Kempton [9] think V2G technology can be used to schedule the charging time of EVs flexibly and correspond to the randomicity of the power supply of the wind energy, solar energy such clean energy resources. Due to the limitation of battery storage capacity of single EV, V2G technology can only be a valuable resource with accumulated large number of EVs [2]. Discrete particle swarm algorithm is adopted to develop optimal charging/discharging time plan model based on V2G technology, where the charging time of EVs is used as a constraint [10]. A binary particle swarm algorithm is used to built an optimal energy storage scheduling model with the maximum benefits of customers as the objective [7]. In paper [1], it analyzes the variables involved in EV charging/discharging to the grid and the impact model under different charging strategies is developed. Zhen and Roger proposed a systematic design scheme for charging management to adapt to fast charging station and simulation experiments have been used to prove its effectiveness [13].

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The price structure and coordinated strategy adopted by power companies will induct the EV charging/discharging behaviour, which is the key problem related to whether the future EVs can be developed with the grid harmoniously. Therefore, time-of-time (ToU) prices are used to study the interaction relationship between the power grid and EV users with the aid of demand side management.

The paper is organized as follows. In Section 2, the EV charging and discharging behaviour is modelled and the constraints are discussed as well. Section 3 describes an improved particle swarm optimization algorithm to optimize the charging/discharging from system point of view. Simulation results are illustrated in Section 4. Conclusions are given in Section 5.

II. The electric vehicle charging/discharging behaviour analysis

Here, the initial state of charge (SoC) of each EV and the required power is considered together with the length of charging/discharging process. Then the comprehensive model of the behaviours of the large amount of EVs is discussed. The number and length of the charging/discharging EVs, their on/off status and active power are regarded as the optimized variables for the least tariff objective.

A. EV behaviour description

According to the data, over 90% of cars are in parked state on the daily basis [4]. It indicates that under the well constructed charging facilities, car users can choose the charging time freely. Here, the behaviours of the pure electric vehicles including buses and personal cars are investigated including their driving time, charging periods such factors.

1) Electric buses: More and more pure electric buses are running on the road in Beijing, Guangzhou, Shenzhen such cities in China. Based on the current development situation and future tendency, the driving distance, charging pattern and periods are analyzed for the electric vehicles behaviours characteristics description.

- Driving distance: Based on the data provided by the Shenzhen Traffic Department, the averaged driving distance of each routine is 20km. The distance is followed by the normal distribution with expectation value 20 km and variance 5km and the averaged speed is 25km/h.
- Charging mode: The battery replacement is used as the main charging method during operational period and battery charging is used during the rest of the time. The SoC of the battery should not below 0.3 or the battery should be replaced to satisfy the requirement for the next single trip.
- Charging periods: Suppose the operational duration is between 6-22pm. The batteries can be replaced anytime. The battery can be charged in 24 hours.

TABLE I

THE CLASSIFICATION OF THE EV SOC

SoC	0-20%	20-40%	40-60%	60-80%	80-100%
No.k	1	2	3	4	5

2) Personal electric cars: Compared to electric buses, the personal electric cars are mainly used for going to work place and the averaged driving time per day is twice.

- Driving distance: The driving distance is between 40km to 60km [11]. Suppose the distance during morning for work and during evening to home is the same, then the single mileage is followed the uniform distribution among 20km to 30km.
- Charging mode: Battery charging is the main charging mode for personal electric cars.
- Charging periods: If the battery SoC is below 0.2, the battery should be charged or when it can not satisfy for the next expected journey. Besides, the battery should be fully charged for one time or the SoC should be at least above 0.6.

The charging/discharging period and the driving period of the two types of EVs are shown in Fig.1. As for electric buses, the battery can be charged for all 24 hours. On the other hand, the personal cars can be charged at off-driving periods, i.e., the green rectangles in Fig.1. For simplicity, the full charge and discharge of all vehicles takes 5 hours. Then the SoC variation is 20% per hour. The SoC of the EVs can be divided into 5 conditions, which is demonstrated in Table I. The SoC can be changed from k^{th} to $(k+1)^{th}$ or $(k-1)^{th}$ status during one-hour charge/discharge.

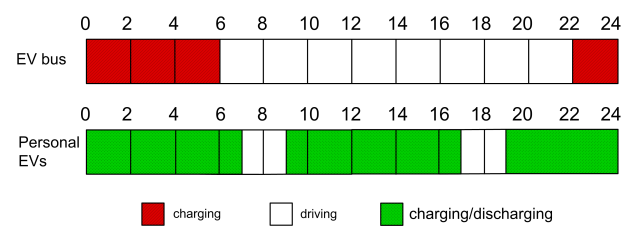

Fig. 1. The charging/discharging time periods per day

Suppose the starting time is T_{in}, initial SoC is SOC_{in}, leaving time is T_{out}, the minimum SoC when leaving is SOC_{out}. The parameters for certain type of EVs is $\{T_{in}(j), T_{out}(j), SOC_{in}(j), SOC_{out}(j)\}$, where j is the number of EVs. $N(j,t)$ is the number of j type at t moment and $N(j,k,t)$ is the number of EVs when j type of EV at t moment and their SoC is in k status, where $N_c(j,k,t), N_d(j,k,t)$ denote the charging and discharging number. During t time period, each type of EVs has

$$0 \leq N_c(j,k,t) + N_d(j,k,t) \leq N(j,k,t) \tag{1}$$

The EVs which can finish their full charging/discharging in an hour will be omitted, i.e.,

$$\left\{\begin{array}{l} \mathrm{N_c(j,1,t)=0} \\ \mathrm{N_d(j,6,t)=0} \end{array}\right. \tag{2}$$

If the charging/discharging happens at t period, the number of the EVs at $t+1$ in different status will be changed to:

$$\begin{aligned} &\mathrm{N(j,1,t+1)= N(j,1,t)-N_d(j,1,t)-N_c(j,1,t)+N_c(j,2,t)} \\ &\mathrm{N(j,k,t+1)= N(j,k,t)-N_d(j,k,t)-N_c(j,k,t)+} \\ &\qquad\qquad \mathrm{N_d(j-1,k,t)+N_c(j+1,k,t), k=2,\cdots,5} \\ &\mathrm{N(j,6,t+1)= N(j,6,t)-N_d(j,16t)-N_c(j,6,t)+N_c(j,5,t)} \end{aligned} \tag{3}$$

Based on the the statistical data, the amount of the cars are increased 5% each year and the number of electric cars in 2016, 2020 and 2024 year are predicted as (unit: thousand):

Year	Total	Electric buses	Personal cars
2016	300	240 (80%)	60 (20%)
2020	700	420 (60%)	280 (40%)
2024	1,600	640 (40%)	960 (60%)

B. Objective function

The objective is to achieve the least electricity bills for the electric car owners, including the charging cost, discharging cost (battery weary) and discharging benefits from the gird, which can be described in the following inequalities:

$$\min_{Q,p_i\in R} Q \tag{4}$$

$$R = r_1 + r_2 \tag{5}$$

$$s.t. \sum_{i\in \mathrm{N}_1} Q_{C,i} + \sum_{j\in \mathrm{N}_2} Q_{C,j} - \sum_{j\in \mathrm{N}_2} Q_{D,j} + \sum_{j\in \mathrm{N}_2} Q_{v2g,j} \geq Q \tag{6}$$

$$Q_c \geq 0, \forall i \in R, Q_D \leq 0, Q_{v2g} \leq 0, \forall i \in N_2 \tag{7}$$

$$1^T W = 1, 0 \leq W \leq 1 \tag{8}$$

$$Q_{Ci} = P_i \times W \times L_c, \forall i \in R \tag{9}$$

$$Q_{Di} = P_i \times W \times L_D, \forall i \in N_2 \tag{10}$$

where the ToU charging prices and discharging prices(Chinese Unit: ¥Yuan), L_C, L_D, are shown in Fig.2.

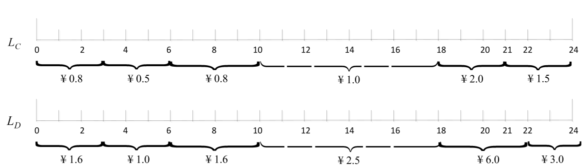

Fig. 2. The charge/discharge ToU prices for electric cars

The final optimal objective is shown in Eq.(4) to obtain the least electricity bills Q. Eq.(5) denotes that there are two types of electric vehicles, N_1 and N_2 denoting electric buses and personal cars, respectively. The electricity bills generated from the two groups are larger or equal to the least tariffs Q, shown in Eq.(6), where $Q_{C,i}$ is the charging cost, $Q_{D,i}$ is the benefits from discharge and $Q_{v2g,i}$ is the battery weary from discharge. The discharge cost Q_{v2g} will be discussed later. The charge cost Q_C and Q_{v2g} are equal or larger than 0 and Q_D is equal or less than 0, denoting that it will or will not be charged with or without electricity bills, shown in Eq.(7) and Eq.(8). The electricity bill Q_i of each vehicles i can be calculated according to the power matrix, scheme matrix W and ToU prices, which is represented by Eq.(9). The benefits from discharging is shown in Eq.(10).

The discharging cost Q_{v2g} mainly denote the maintenance cost of battery loss caused by discharging. For simplicity, the discharging cost is proportional to the discharging power during each time period, i.e.,

$$Q_{v2g} = \beta P_v \tag{11}$$

where β is the discharging cost ($/MV); P_v is the discharging power of a EV, and it is assumed constant here. The optimal appliance usage plan table will be selected with particle swarm optimization algorithm.

III. Particle swarm optimization algorithm

Particle swarm optimization (PSO) is an optimal tool and a random swarm optimal technology, proposed by Kennedy and Eherhart in 1995[8]. In the algorithm, the inhabitance in the bird swarm movement model can be regarded as the possible position of the solution, where the whole swarm is moved to the solution through information transferring individually. The bird in the swarm is abstracted as particle without quality and volume, and their velocities are affected by their own and swarm historical movement state information. The historical and local optimal positions are used to coordinate the particle itself and its swarm relationship so that the swarm particles can seek optimal operation in complex solution domain.

The particle swarm algorithm is described as follows. A swarm is composed of m particles searching in D-dimensional space with certain flight speed. During flight, each particle will change its position based on its own searched best historical point and the best point globally or neighboring. The i^{th} particle is composed of three $D-$dimensional vector,

- Current position: $x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$;
- Current speed: $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$;
- Best historical position: $p_i = (p_{i1}, \cdots, p_{i2}, p_{iD})$;
- Best global position: $p_g = (p_{g1}, \cdots, p_{g2}, p_{gD})$;

where $i = 1, 2, \cdots, m$. The update formula is described as:

$$v_{id} = \omega v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{12}$$

$$x_{id} = \left\{\begin{array}{ll} 0 & r \geq 1/\left(1 + exp(-v_{id})\right) \\ 1 & r \geq 1/\left(1 + exp(-v_{id})\right) \end{array}\right. \tag{13}$$

where $d \in (1, 2, \cdots, D)$ denotes the space dimension, ω is the inertia coefficient; c_1 and c_2 are the learning factors; r_1, r_2 and r are the random numbers in the range of $[0, 1]$. Binary Particle Swarm Optimization (BPSO) is proposed by Kennedy and Eberhart targeted on binary variable issues [11], where the location is updated as:

$$x_{i,d} = \begin{cases} 1 & if\ \rho < s(v_{i,d}) \\ 0 & else \end{cases} \tag{14}$$

where $s(v_{i,d}) = \frac{1}{1+e^{-v_{i,d}}} \in [0, 1]$, ρ is the random number in [0,1].

An improved weight adjustment is used in the algorithm. The weight ω will decrease according to the step t from the maximum value to the least value. Here, the maximum value is 0.9 and the least value is 0. PSO is more suitable for global optimization issues and it is used to obtain the optimal charging/discharging time for electric vehicles.

IV. Simulation experiments

Matlab simulation tool is used to test the algorithm. The particle number is decided by the problem to be solved, generally set as 20-40. Here, one day is evenly divided into 24 time slots, hence, there are 24 particles in the program. The maximum repeated time is 1000. The number of the charging EVs, discharging EVs and SOC are also considered in the program. The diagram of the particle swarm optimization algorithm is as follows:

- *Start*
- Parameter settings: threshold ε, particle number D, maximum repeat times N_{max}
- Initial particle position: $x_i^{(0)} = (x_{i1}, x_{i2}, \cdots, x_{iD})$
- Initial particle velocity: $v_i^{(0)} = (v_{i1}, v_{i2}, \cdots, v_{iD})$
- Evaluate the fitness function of each particle: $\widetilde{f}_i^{(0)}$ (normally the minimized objective function)
- To find the global optimization $gbest_i^{(0)} = \min(\widetilde{f}_1^{(0)}, \widetilde{f}_2^{(0)}, \cdots, \widetilde{f}_D^{(0)})$, $pbest_i^{(0)} = x_i^{(0)}$, $k = 0$
- 1: k=k+1; update $v_i^{(k)}$ and $x_i^{(k)}$
- 2: Evaluate the fitness of x_i, update $pbest_i^{(k)}$ and $gbest^{(k)}$, if $\left(\tilde{f}^{(k-1)} - \tilde{f}^{(k)}/\tilde{f}^{(k)} > \varepsilon\ and\ k < N_{\max}\right)$, go to 1 step, or
- *End*

In the swarm particles, the position of each particle is the exchange power between EVs and grid. The charging scenario without any additional guidance is shown in Fig.3. As discussed in Section II, the The EV users can choose any time for their charging periods at any time. Under the time-of-use prices circumstances, the generated electricity bills are high accordingly. With the adoption of PSO to adjust the peak periods control together with the potential of energy resale

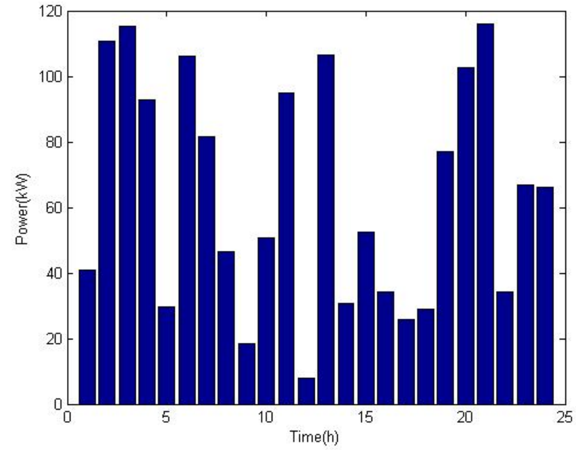

Fig. 3. The charging scenario without optimization

TABLE II

THE POWER EXCHANGE BETWEEN SINGLE EV AND GRID

Time/H	1	2	3	4	5	6	7	8
Power/kWH	0	0	-6.9	0	12	-6.9	12	0
Time/H	9	10	11	12	13	14	15	16
Power/kWH	0	-6.9	-6.9	-6.9	0	12	-6.9	-6.9
Time/H	17	18	19	20	21	22	23	24
Power/kWH	-6.9	12	-6.9	0	0	0	12	0

back to the grid, the power consumption in each time slots for each electric vehicle can be assigned optimally to shift the charging periods to low cost periods. The charging scenario is illustrated in Fig.4. Here, only personal EVs will participate the vehicle to grid activities, therefore, their power exchange between each other are discussed and one is list in Table II. It can be seen that if better charging/discharging period can be chosen with variable electricity prices, the EV owners can be benefit from the electricity trade, $Fittness = -12.34$, i.e., the user can gain 12.34 ¥per day. This could reduce the cost of EV users and become the incentive for electric vehicles market prosperity. Finally, a group of EVs with the optimization scheme and without optimization is shown in Fig.5. The required power from the high peak periods can be shift to valley periods. Further research will be carried to investigate the large-scale EV charging behaviour to the grid in details.

V. Conclusions

In this paper, the charging/discharging issues involved in large-scale electric vehicles is discussed. The electric vehicles can be classified into electric buses and electric personal cars. Considering the conditions of electric vehicles applications, the charging/discharging behaviours are discussed in details. The least tariff generated from EVs for the users are used as the objective with the application of particle swarm optimization algorithm. Simulation experimental results have

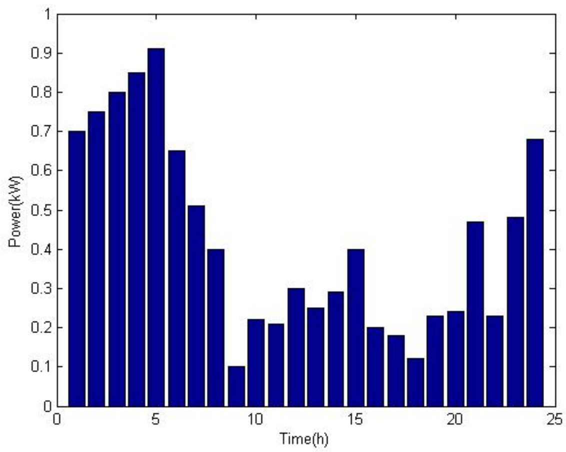

Fig. 4. The charging scenario with optimization

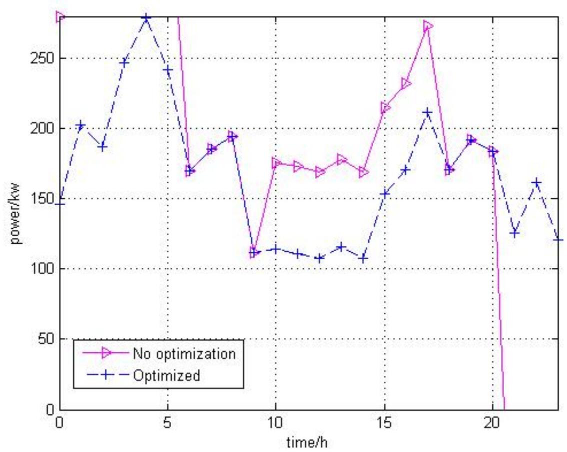

Fig. 5. The power output of EVs with and without optimization

been proved the effectiveness of the algorithm. Future work will investigate the effect of EV charging/discharging to the grid.

REFERENCES

[1] Acha, S., Green, T., Shah, N. (2010). "Effects of Optimised Plug-in Hybrid Vehicle Charging Strategies on Electric Distribution Network Losses", IEEE PES Transmission and Distribution Conference and Exposition, New Orleans, USA. 19th -22nd April, 2010.

[2] Brooks A.N.(2002). "Vehicle-to-grid demonstration project : grid regulation ancillary service with a battery electric vehicle", Final report, Contract number 01-313.

[3] FARUQUI. "Will the smart grid promote s-mart customerdecisions?"EB/OL,2008-07-21. http://www.drsgcoalition.org/resources/other/Smart Grid Smart Customer Decisions.pdf

[4] Fluhr J., Ahlert K.H. and Weinhardt C.(2010)."A stochastic model for simulting the availability of electric vehicles for services to the power grid", Proceedings o the 43rd Hawaii International Conference on System Sciences, Hawaii, USA, 2010:1-10.

[5] Strbac G.(2008). "Demand side management: Benefits and challenges", Energy Policy, 36(12):4419C4426.

[6] Guille C. and Gross G.(2009), "A conceptual framework for the vehicle-to-grid (V2G) implementation", Energy policy, 37(11):4379-4390.

[7] Hutson,Venayagamoorthy,Corzine.2008.Intelligent Scheduling of Hybrid and Electric Vehicle Storage Capacity in a Parking Lot for Profit Maximization in Grid Power Transactions, IEEE Energy 2030 Conference, Atlanta,USA, pp.1-8.

[8] Kennedy J., Eberhart R. (1995). "Particle Swarm Optimization", Proceeding of IEEE International Conferene on Neural Networks, NJ, 1995:1942-1948.

[9] Lund H, Kempton W. (2008). "Integration of renewable energy into the transport and electricity sectors through V2G", Energy Policy, 36(9):3578-3587.

[10] Saber A, Venayagamoorthy G.(2010). "Intelligent Unit Commitment with V2GCA Cost-Emission Optimization",Journal of Power Sources, 195(3):898-911.

[11] Sandels C, Franke U, Ingvar N., et.al. (2010). "Vehicle to grid-Monte Carlo simulations for optimal aggregator stategies", International Conference on Power System Technology, Hangzhou, China, 2010.

[12] Weiller C.(2011). "Plug-in hybrid electric vehicle impacts on hourly electricity demand in the United States", Energy Policy, 39:3766-3778.

[13] Zhen H. and Roger A.D. (2003). "Design and testing of a fuel-cell powered battery charging station". Journal of Power Sources, 115(2):279-287.