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Unit commitment problem of power system with plug-in electric vehicles

***Abstract**. The electric vehicle (EV) has become a popular topic because of the increasing scarcity of energy sources and growing environmental pollution. Unit commitment (UC) with plug-in hybrid electric vehicle (PHEV) for cost optimization is presented in this paper. The profile of charging load and vehicle-to-grid (V2G) power of PHEV is forecasted, and various scenarios with different PHEV control strategy are simulated. Quantum-inspired binary particle swarm optimization algorithm with heuristic strategy has been employed to solve the UC problem. Results show that PHEVs will significantly affect the UC problem. PHEVs bring on new load demand to power system, which will increase the generation cost. However, the coordinated charging strategy and reasonable usage of V2G power can reduce the generating cost.*

***Streszczenie.** W artykule przedstawiono problem optymalizacji kosztów ładowania pojazdów elektrycznych (ang. Plug-in Hybrid Electric Vehicle) pod względem doboru jednostek wytwórczych. Badaniom poddano różne metody regulacji przepływu energii do ładowania odbiorników w postaci pojazdów elektrycznych. Wykazany został wpływ nowego rodzaju obciążenia na zwiększenie kosztów wytwarzania energii. (**Problem zobowiązań energetycznych jednostek wytwórczych w systemie energetycznym, zawierającym podłączane pojazdy elektryczne**)*

Keywords: electric vehicle; unit commitment; vehicle to grid; quantum-inspired binary particle swarm optimization.
Słowa kluczowe: Pojazdy elektryczne, zobowiązanie energetyczne jednostki wytwórczej, Vehicle to grid (V2G), optymalizacja roju cząstek.

Introduction

Electrification has become a major trend for the future transportation, due to the increasing scarcity of energy sources and the growing environmental pollution. Currently, many governments and automobile manufactures focus on the research and promotion of electric vehicles (EVs) [1]. Although the deployment of EVs could reduce the dependence on fossil fuel and emissions of CO_2, a large number of EVs will significantly affect the operation and management of the power grid [2].

The impact of EV on power system is demonstrated in many levels, such as generation, transmission and distribution [3-5]. The unit commitment problem is to determine the on/off state of units and load demand allocation in each time period of planning horizon. The impact of EVs on the unit dispatch is mainly reflected in two aspects: Firstly, the uncertainty of charging behaviour will affect the load demand, and this affection will spread to the unit commitment results. Ref. [6] analyzed the impact of different charging modes on the unit commitment results, but it did not consider the users' driving habits in the modelling process. Secondly, the vehicle to grid (V2G) technique makes it possible that EV can provide energy back to the grid, which can reduce the output of traditional units. Intelligent unit commitment with V2G for cost and emission optimization is presented in Ref. [4], that EVs can replace the traditional small size unit to provide power, so as to achieve cost saving and emission reduction.

The UC problem is a large-scale, non-linear, mixed-integer combinatorial optimization problem with constraints. It is difficult to find the exact solution to the problem, so near-optimal solutions are preferred. Many methods have been developed to solve UC problem in the past decades. There are some classical methods including priority list method (PLM) [7, 8], dynamic programming (DP) [9-11], mixed-integer programming (MIP) [12], and lagrangian relaxation (LR) [13-15]. These methods are usually rigorous in mathematical analysis but have some weakness when solving UC problem. PLM is fast because of its heuristics, but it often can't find the best solution. DP has to face the curse of dimensionality, and the calculation time will increase if some constraints are taken into account. MIP requires some assumptions, which will limit the solution space. LR is a mature theoretical optimization algorithm that is widely used to solve the large-scale combinatorial optimization problem. However, it may suffer from numerical convergence problem, and some strict constraints make the calculation be complicated.

Besides the classical methods mentioned above, some meta-heuristic approaches have been used to solve the UC problem. Specifically, there are genetic algorithm (GA) [16, 17], simulated annealing (SA) [18, 19], tabu search (TS) [20], particle swarm optimisation (PSO) [21], and so on. These methods have advantage of more likely finding the global optimal solution. However, their common drawback is time-consuming, especially for a large-scale UC problem.

In this study, the UC problem considering EV is addressed. Since the pure electric vehicles are not widespread used yet, the plug-in electric vehicle (PHEV) is the study object in this research. In order to consider the actual driving behaviours of drivers, the travel data of 2009 National Household Travel Survey (NHTS) [22] is employed in this study. Thereafter, the profile of PHEVs' charging load is forecasted. Coordinated charging strategy aiming to mineralize the peak-valley difference is proposed. In addition, the V2G capacity of PHEV is predicted, which can be used for the spinning reserve. To solve the UC problem, quantum-inspired binary particle swarm optimization (QBPSO) algorithm with heuristic strategy has been employed. The algorithm has been implemented and tested on a test system with 10 units.

The Profile of PHEV's Charging Load

A) Assumptions and modelling

In order to forecast the load profile of PHEV, the charging power and charging interval should be identified.

The charging power of PHEV can be obtained by

$$P_i^{PHEV} = q_C E_i^{PHEV} / \eta_C \tag{1}$$

where q_C is the charging rate usually between 0.2C～1C (the C-rate signifies charge or discharge rate, charge rate of 1C means it costs one hour to fully charge the battery from empty state); E_i^{PHEV} is the capacity of the ith PHEV's battery and varies with vehicle types; η_C is the charging efficiency.

The charging interval contains two elements: charging duration and start time of charging. The charging duration depends on the battery's charge rate and initial state of charge (SOC) before charging. We assume that the charging process will last before the battery is full. Thus the charging duration could be defined as follows:

$$t_i^{Need} = (1 - SOC_i) / q_C \tag{2}$$

Since it is assumed that the charging behaviour is always after the last trip, SOC_i relates to the daily mileage of the ith PHEV, which can be expressed as:

(3) $$SOC_i = \begin{cases} (1-d_i / D_i^{\max}) \times 100\%, d_i < 0.9 D_i^{\max} \\ 10\% \qquad\qquad\qquad\quad, d_i > 0.9 D_i^{\max} \end{cases}$$

(4) $$D_i^{\max} = E_i^{PHEV} / Q_i$$

where d_i is the daily mileage of the ith PHEV, D_i^{max} is the vehicle's all electric driving range, Q_i is the power consumption per mile. It should be noted that equation (3) is based on the following assumption: when the battery energy is sufficient, PHEV is driven in all-electric mode; when the proportion of the remaining energy is below 10%, PHEV gets power from the internal combustion engine.

In this study, it is assumed that the start time of charging is associated with the charging pattern. Coordinated charging is an effective strategy to make the power grid more flexible to accommodate PHEV. It can be performed by direct management of the system operator or by electricity price mechanism. In this study, the direct manage mode is preferred, and the goal of the coordinated charging strategy is minimizing the peak-valley difference of load.

B) Coordinated charging strategy

The objective of the coordinated charging strategy is minimizing the peak-valley difference. The control variable is every vehicle's charging state in each time interval. The optimization model can be described as follows:

1) Objective:

(5) $$\begin{cases} \min G = \max[P_{base}(t_i) + \sum_{j=1}^{\lambda N_v} P_j^{PHEV}(t_i) X_j(t_i)] \\ \qquad - \min[P_{base}(t_i) + \sum_{j=1}^{\lambda N_v} P_j^{PHEV}(t_i) X_j(t_i)] \\ t_i \in [1, 24] \end{cases}$$

where G is peak-valley difference of the load curve; $P_{base}(t_i)$ is base load on time t_i ; $P_j^{PHEV}(t_i)$ is charging power of the jth PHEV; $X_j(t_i)$ is charging state of the PHEV on time t_i, and "1" means the vehicle is on charging, "0" means the vehicle is not on charging; N_v is the vehicle population; λ is the penetration of PHEV.

2) Constraints：

(6) $$\sum_{t_i=1}^{24} X_j(t_i) = t_j^{Need}$$

(7) $$\prod_{t_i=T_j^C}^{T_j^C + t_j^{Need}} X_j(t_i) = 1$$

(8) $$T_j^C > T_j^{trip}$$

where t_j^{Need} is the charging duration of jth PHEV; T_j^C is the start time of jth PHEV's charging behaviour; T_j^{trip} is the end time of the last trip of jth PHEV.

C) Charging load of PHEV with coordinated charging

The only control variable of the above optimism model is the charge state $X_j(t_i)$ in each interval. However, the solving process will become extremely complex when large numbers of vehicles exist. Under constrains of equations (6) and (7), we can conclude that the charge state can be determined if we know the start point T_j^C. It can be expressed by：

(9) $$X_j(t_i) = \begin{cases} 1, & t_i \in [T_j^C, T_j^C + t_j^{Need}] \\ 0, & t_i \notin [T_j^C, T_j^C + t_j^{Need}] \end{cases}$$

In addition, the vehicle stopped earlier will have higher priority to be arranged. Therefore, the goal of the coordinated charging model can be transformed to obtaining the value of T_j^C. The solving process of this model can be viewed as a multi-stage decision-making process. The task of each stage is to decide T_j^C of each PHEV to maintain the minimal peak-valley difference of load. The coordinated charging model can be solved by following steps:

Step0: Compute charging power and charging duration of each PHEV;

Step1: Pick a vehicle according to the order of end time of its last trip. Predict all possible load curves considering the charging load of the PHEV we picked. Select the charging start time which cause the minimal peak-valley difference, and record it;

Step2: Update the load curve according to the charging power, charging duration and charging start time;

Step3: If all the vehicles have been arranged, then stop. If not, go to step 1.

Hence, the total charging power load in t_i is given by

(10) $$P_{Total}^{PHEV}(t_i) = \sum_{j=1}^{\lambda N_v} P_j^{PHEV}(t_i) X_j(t_i)$$

Power capacity of V2G

PHEV can provide electricity energy back to the power grid by V2G technique. In this study, the V2G power is used for spinning reserve. However, its premise is that the PHEV users' travel will not be affected. Therefore, it is assumed that only the vehicle whose SOC is bigger than the threshold value can be used to discharge to the grid. The power provided by a PHEV in each time interval is:

(11) $$SR_j^{PHEV}(t_i) = \begin{cases} q_D E_j^{PHEV} \eta_D, SOC_j(t_i) \geq SOC_{\lim} \\ 0 \qquad\qquad\quad, SOC_j(t_i) < SOC_{\lim} \end{cases}$$

where $SR_j^{PHEV}(t_i)$ is the power provided by the jth PHEV at t_i; q_D is discharging rate， usually is 0.2C ～ 1C; η_D is discharging efficiency; SOC_{lim} is the threshold value; $SOC_j(t_i)$ is SOC of the jth PHEV at t_i, which can be described as follows:

(12) $$SOC_j(t_i) = \begin{cases} (1-d_j(t_i) / D_j^{\max}) \times 100\%, d_j(t_i) < 0.9 D_j^{\max} \\ 10\% \qquad\qquad\qquad\qquad\quad, d_j(t_i) \geq 0.9 D_j^{\max} \end{cases}$$

where, $d_j(t_i)$ is the distance already travelled travel range by jth PHEV until t_i.

Since the frequent alternation of charging and discharging in short interval will do great harm to batteries, it is assumed that PHEVs can't offer power to grid when it is charging. Also, moving vehicles can't provide power. The total reserve capacity of large-scale PHEVs at interval t_i is given by:

(13) $$SR_{Total}^{PHEV}(t_i) = \sum_{j}^{\lambda N_v} SR_j^{PHEV}(t_i) Z_j(t_i)(1 - X_j(t_i))$$

where $Z_j(t_i)$ is the travel state of the jth PHEV at t_i, which is represented by "0" or "1". "0" means the PHEV is on the road, "1" means the PHEV is stopped and available to discharge to grid.

Optimal Unit Commitment Formulation

A) Objective function

The unit commitment problem is an optimization problem that arranges the start-up and shut-down schedule of generating units in near future so that the total cost is minimized. Its objective is：

(14)

$$\min F = \sum_{i=1}^{24} \sum_{j=1}^{N} [u_j(t_i) f_j(P_j(t_i)) + u_j(t_i)(1 - u_j(t_{i-1})) Cu_j(t_i)]$$

where F is the total production cost; $f_i(P_j(t_i))$ is the fuel cost of unit j at time t_i; $Cu_j(t_i)$ is the start-up cost of unit j at time t_i; $u_j(t_i)$ is the status of unit j at time t_i ("1" means on, "0" means off); N is the number of generators.

The function of fuel cost $f_i(P_j(t_i))$ is in the form of:

$$f_j(P_j(t_i)) = a_j + b_j P_j(t_i) + c_j(P_j(t_i))^2 \tag{15}$$

where, a_j, b_j, c_j represent the cost coefficients of jth unit.

The start-up cost of jth generator is:

$$Cu_j(t_i) = \begin{cases} Cu_j^H, & T_j^{MD} \le Toff_j(t_{i-1}) \le T_j^{MD} + T_j^{Cold} \\ & and\ u_j(t_i) - u_j(t_{i-1}) = 1 \\ Cu_j^C, & Toff_j(t_{i-1}) > T_j^{MD} + T_j^{Cold} \\ & and\ u_j(t_i) - u_j(t_{i-1}) = 1 \\ 0, & others \end{cases} \tag{16}$$

where Cu_j^H is the hot start-up cost of jth unit; Cu_j^C is the cold start-up cost; $Toff_j$ is the continuously off time of jth unit up to time t_{i-1}; T_j^{MD} is the minimum down time; T_j^{Cold} is the cold start time.

B) Constrains

1) Power Balance Constrain

$$\sum_{j=1}^{N} u_j(t_i) P_j(t_i) = P_{Total}(t_i) = P_{base}(t_i) + P_{Total}^{PHEV}(t_i) \tag{17}$$

where $P_j(t_i)$ is the output of unit j at t_i, $P_{base}(t_i)$ is the base load at t_i, $P_{Total}^{PHEV}(t_i)$ is the charging load of PHEVs at time t_i.

2) Supply Constrains

$$u_j(t_i) P_j^{\min} \le P_j(t_i) \le u_j(t_i) P_j^{\max} \tag{18}$$

where P_j^{min}, P_j^{max} are minimum and maximum output of unit j.

3) Reserve Capacity Constrains

$$\sum_{j=1}^{N} u_j(t_i) P_j^{\max} \ge P_{base}(t_i) + \max\{SR_{Sys}(t_i) - SR_{Total}^{PHEV}(t_i), 0\} \tag{19}$$

where $SR_{Sys}(t_i)$ is the system reserve requirement at time t_i, $SR_{Total}^{PHEV}(t_i)$ is the reserve offered by PHEV at time t_i.

4) Minimum On and Off Time Constrains

$$\begin{cases} (Ton_j(t_{i-1}) - T_j^{MU})(u_j(t_{i-1}) - u_j(t_i)) \ge 0 \\ (Toff_j(t_{i-1}) - T_j^{MD})(u_j(t_i) - u_j(t_{i-1})) \ge 0 \end{cases} \tag{20}$$

where $Ton_j(t_{i-1})$ and $Toff_j(t_{i-1})$ are continuously on time and off time of unit j up to time t_{i-1}, T_j^{MU} and T_j^{MD} are minimum up and down time of unit j.

QBPSO Algorithm with Heuristic Strategies

UC problem involves two sub-problems: unit commitment and economic load dispatch. The unit commitment sub-problem needs to determine the start-up and shut-down schedule of the generation units, considering the load demand, spinning reserve requirements and on/off time constrains of the units. The economic load dispatch sub-problem needs to allocate the system demand and spinning reserve among the running units.

An internal/external two layer optimization methodology is used in this study. The external layer optimization solves the unit commitment problem by quantum-inspired binary particle optimization algorithm. The internal layer optimization solves the economic load dispatch problem by interior point algorithm. In detail, module of interior point algorithm in the MATLAB will be used in this study.

QBPSO is a novel particle swarm algorithm, inspired by the fundamental theory of particle swarm and features of quantum computing [23]. It preserves the diversity of population, and has faster convergence speed and global optimization ability.

In QBPSO, quantum bit (Q-bit) is defined as the smallest unit, which may be in the "1" state or "0" state. A Q-bit is described by a pair of numbers (α, β), which satisfy the constraint $\alpha^2+\beta^2=1$. A Q-bit particle as a string of n Q-bits can be defined as follow:

$$p_i = \begin{bmatrix} \alpha_{i1} & \alpha_{i2} & \cdots & \alpha_{in} \\ \beta_{i1} & \beta_{i2} & \cdots & \beta_{in} \end{bmatrix} \tag{21}$$

where $\alpha_{ij}^2+\beta_{ij}^2=1$, j=1,2,⋯,n. The state of the jth element in particle p_i takes a value of 0 or 1 by the probability of α_{ij}^2 or β_{ij}^2. In the initialization step, both α and β of each particle equal to $1/\sqrt{2}$ in order to make "0" state and "1" state occur with equal probability.

The position vector of ith particle $X_i=\{x_{i1},\ldots, x_{im}\}$ is determined by the value of β_{ij}^2 stored in the ith Q-bit string:

$$x_{ij} = \begin{cases} 1, & rand_j < \beta_{ij}^2 \\ 0, & otherwise \end{cases} \quad (j = 1, 2, \cdots m) \tag{22}$$

where $rand_j$ is random number uniformly distributed between 0 and 1. m is the length of the Q-bit string.

Instead of velocity updating in traditional particle swarm optimization, rotation angle updating is used in QBPSO. Determining the rotation angle requires information on the following aspects: the current position, the best position of the ith particle and the group's best position so far.

$$\Delta\theta_{ij}^{k+1} = \theta \times \{\gamma_{1i}^k \times (x_{ij}^{P,k} - x_{ij}^k) + \gamma_{2i}^k \times (x_j^{G,k} - x_{ij}^k)\} \tag{23}$$

where θ is the magnitude of rotation angle, γ_{1i}^k and γ_{2i}^k are two factors determining the direction of evolution towards personal best and group best, $x_{ij}^{P,k}$ is the personal best of the jth element in the ith particle, $x_j^{G,k}$ is the group best of the jth element, x_{ij}^k is the current position, k is the current iteration number.

The magnitude of rotation angle θ affects the performance of the algorithm. The values from 0.001π to 0.05π are recommended for θ, and a dynamic rotation angle approach is adopted for enhancing the convergence characteristics:

$$\theta = \theta_{\max} - (\theta_{\max} - \theta_{\min}) \times \frac{k}{K_{\max}} \tag{24}$$

where k is the current iteration number, K_{max} is the maximum iteration number, $\theta_{min}=0.001\pi$ and $\theta_{max}=0.05\pi$.

The factors γ_{1i}^k and γ_{2i}^k can be obtained in the following way:

$$\gamma_{1i}^k = \begin{cases} 0, & Fit(X_i) \ge Fit(Pb_i^k) \\ 1, & otherwise \end{cases} \tag{25}$$

$$\gamma_{2i}^k = \begin{cases} 0, & Fit(X_i) \ge Fit(Gb^k) \\ 1, & otherwise \end{cases} \tag{26}$$

where Fit(*) is the fitness of the particle, Pb_i^k is the personal best of ith particle, Gb^k is the group best.

The Q-bit is updated by rotation gate as following:

$$\begin{bmatrix} \alpha_{ij}^{k+1} \\ \beta_{ij}^{k+1} \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta_{ij}^{k+1}) & -\sin(\Delta\theta_{ij}^{k+1}) \\ \sin(\Delta\theta_{ij}^{k+1}) & \cos(\Delta\theta_{ij}^{k+1}) \end{bmatrix} \begin{bmatrix} \alpha_{ij}^k \\ \beta_{ij}^k \end{bmatrix} \tag{27}$$

The unit commitment problem is difficult to be solved because of many constraints. In this study, the following heuristic strategies are used to help with finding the optimal solution:

1) Start-up priority of units

The start-up priority of units is determined referring to their per MW cost with their maximum output. The lower the cost is, the higher the priority will be:

(28) $$Priority_i = [a_i + b_i P_i^{\max} + c_i (P_i^{\max})^2] / P_i^{\max}$$

2）Spinning reserve constraints handling

Once the particle violates the spinning reserve constrains（19），additional units will be started according to their priority until the constraints are satisfied.

3）Minimum up and down time constraints handling

Minimum up and down time constraints (20) make the unit commitment problem more complicated. The following processes are adopted to adjust particles that violating these constrains：

(29) $$\begin{cases} u_j(t_i) = 0, \;\; when \;\; Toff_j(t_{i-1}) < T_j^{MD} \\ \qquad and \;\; u_j(t_{i-1}) = 0, u_j(t_i) = 1 \\ u_j(t_i) = 1, \;\; when \;\; Toff_j(t_{i-1}) \geq T_j^{MD} \\ \qquad and \;\; u_j(t_{i-1}) = 0, u_j(t_i) = 1 \end{cases}$$

(30) $$\begin{cases} u_j(t_i) = 1, \;\; when \;\; Ton_j(t_{i-1}) < T_j^{MU} \\ \qquad and \;\; u_j(t_{i-1}) = 1, u_j(t_i) = 0 \\ u_j(t_i) = 0, \;\; when \;\; Ton_j(t_{i-1}) \geq T_j^{MU} \\ \qquad and \;\; u_j(t_{i-1}) = 1, u_j(t_i) = 0 \end{cases}$$

4）De-commitment strategy

Once the particle has excess spinning reserve, the running units will shut down according to their priority until the spinning reserve constraint is satisfied.

The flow chart of the computational procedure is illustrated in Fig. 1.

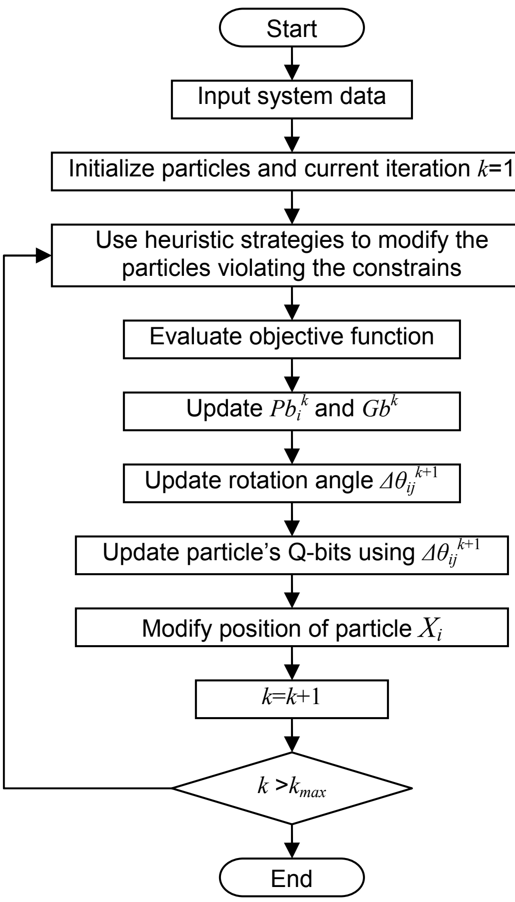

Fig.1. Flow chart of the computational procedure

Simulation results and analysis

A) Test system

A test system with 10 generators is used for simulation. The system data is given in Ref. [21]. Referring to the ratio of the installed capacity to the car ownership in U.S. [20], it is assumed that there are 0.39 million cars in the 10-unit system. The travel data of the cars is a random sample of the data in NHTS, which include the number of daily trips, the duration of each trip, the mileage of each trip, etc. [21]. By processing the travel data, the daily travel distance (d_i in Eq.3)、the end time of daily driving (T_j^{trip} in Eq.8)、the cumulative driving distance ($d_j(t_i)$ in Eq.12) and their driving state in each interval ($Z_j(t_i)$ in Eq.13) can be obtained. The proportion of various types of PHEV and their battery capacity are shown in Table 1. It is assumed that the power consumption per mile is 0.3kWh, charging and discharging efficiency (η_C, η_D) are 0.9, and the threshold value SOC_{lim} is 0.7.

Table 1. The percentage of PHEV with different battery capacity

Vehicle Type	PHEV20	PHEV33	PHEV40	PHEV60
Proportion	38%	28%	20%	14%
Battery Capacity /kWh	6	9.9	12	18

B) Prediction of PHEVs' charging load

The load pattern considering PHEV with uncoordinated charging and coordinated charging are investigated. For the uncoordinated charging scenario, it is assumed that all PHEVs will start charging when their last trip is over. It shows from Fig.2 that the evening peak is increased significantly due to the charging behaviour of PHEVs. The peak load of evening becomes even higher than that of daytime when PHEVs' penetration reaches 30%. The reason for this phenomenon is that most vehicles end their last trip in the evening, and the uncoordinated charging makes the charging load overlap the original evening peak. Therefore, uncoordinated charging is seen as the "worst-case" scenario [3].

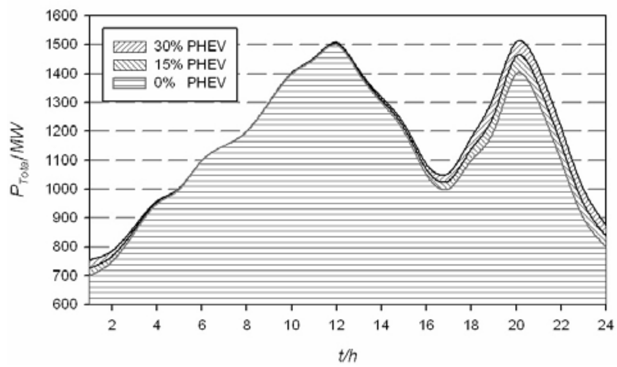

Fig.2. The profile of charging load with uncoordinated charging

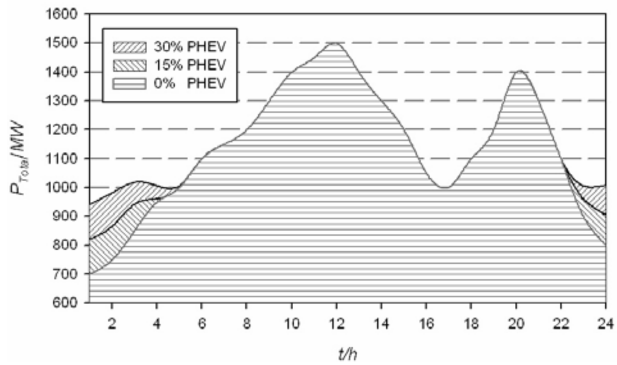

Fig.3. The profile of charging load with coordinated charging

Fig. 3 shows the load pattern considering PHEV with coordinated charging. It can be seen that the charging behaviour have staggered the peak load and filled in the load valley. With the increase of PHEV's penetration, the valley-filling effect becomes more obvious. With 15% penetration of PHEV, the peak-valley difference reduces from 800MW to 678MW. With 30% penetration, the peak-valley difference is further reduced to 557 MW.

C) Prediction of V2G power

Based on the coordinated charging strategy, we can work out the spinning reserve provided by PHEVs, which is shown in Fig.4. It can be seen that the maximum value appears at 6 a.m., because most vehicles complete charging before 6 for their first daily trip. Then, the battery energy will be consumed on the road. The V2G capacity will reach minimum at middle night.

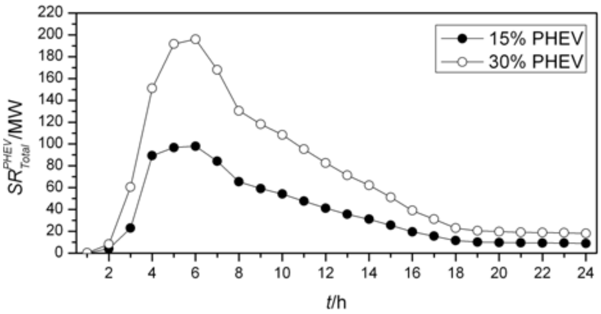

Fig.4. Spinning reserve provided by PHEVs

D) Unit commitment result without considering PHEVs

The spinning reserve requirement is set to be 10% of the load demand. Unit commitment results of 10-unit systems are shown in Table 2 and we can conclude that the QBPSO proposed in this paper has better optimization ability compared with the reference algorithms.

Table 2. Comparison of optimization results （UNIT: USD）

Algorithm	BPSO[21]	LRPSO[24]	IBPSO[25]	QBPSO
Generation cost	565804	565869	564087	563977

E) Unit commitment result considering PHEVs

Three scenarios are considered to investigate the impact of PHEVs on the unit commitment problem:

Scenario1: Adopting uncoordinated charging strategy without considering the V2G power;

Scenario2: Adopting coordinated charging strategy without considering the V2G power;

Scenario3: Adopting coordinated charging strategy, and using PHEVs to provide spinning reserve by V2G technique.

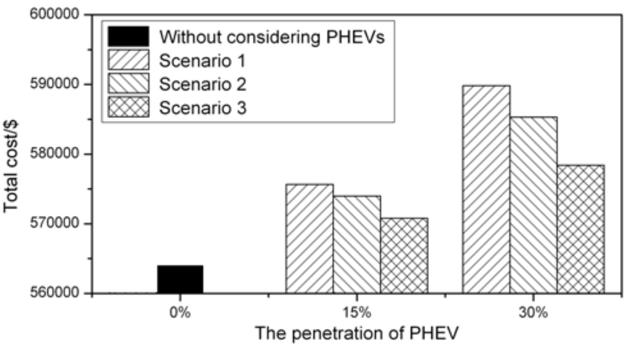

Fig.5. Optimal unit commitment of 10 unit system with PHEV

Fig. 5 illustrates the unit commitment results of these three scenarios. As shown, the generating cost will increase considering the charging load of PHEVs, and the cost will become more and more with the growth of PHEVs' penetration. Nevertheless, different control schemes will make the generating cost vary significantly under the same PHEV penetration. It can be seen that the scenario 1 has the highest cost, and scenario 3 has the lowest cost.

Fuel costs and startup costs for each scenario are represented in Table 3. It shows that the generating cost is dominated by the fuel cost. The fuel cost decreases from scenario 1 to scenario 3 that is why the generating cost also decreases from scenario 1 to scenario 3.

Table 3. Fuel cost and start-up cost （UNIT: USD）

PHEV penetration	15%		
Scenario	1	2	3
Fuel cost	571663	569903	565875
Start-up cost	3980	4090	4910
PHEV penetration	30%		
Scenario	1	2	3
Fuel cost	585794	582124	575308
Start-up cost	4040	3190	3100

In order to make a further analysis of the results, the statistics on the output of each unit is given in Table 4. The generating units are classified into two groups according to the start-up priority index: Unit 1 — Unit 5 are fuel-economical type unit because of the lower per MW cost; Unit 6 — Unit 10 are fuel-consuming type. Table 5 shows the accumulated outputs of each type unit. It is indicated that, from scenario 1 to scenario 3, the accumulated output of the fuel-economical type units increases and that of the fuel-consuming type units is reduced.

Comparing scenario 1 with scenario 2, the load curve of the latter is more flat, which makes it possible that the generating cost becomes lower by raising the output of fuel-economical type units and reducing the output of fuel-consuming type units. Comparing with scenario 2, scenario 3 not only adopts the coordinated charging strategy, but also has PHEVs providing spinning reserve for the grid. Thus it makes output regulation of the unit more flexible, and finally the system can operate in much more economical state.

Table 4. Cumulative statistics of generator's output（UNIT: MW）

	15% PHEV			30% PHEV		
Scenario / Unit No.	1	2	3	1	2	3
1	10920	10920	10920	10920	10920	10920
2	9870	10094	10297	9988	10097	10076
3	2080	2080	1820	2210	2080	1560
4	2340	2210	2080	2470	2600	3120
5	1635	1635	1871	1636	1709	1840
6	409	332	349	454	372	394
7	225	225	175	225	225	100
8	90	83	76	144	83	86
9	30	20	10	50	20	20
10	10	10	10	20	10	0

Table 5. Total output of each type units （UNIT: MW）

	15% PHEV			30% PHEV		
Unit NO.	Case1	Case2	Case3	Case1	Case2	Case3
1-5	26844	26938	26988	27223	27406	27516
6-10	764	670	620	893	710	600

Conmclusions

In this paper, the impact of PHEV on unit commitment is demonstrated. PHEVs bring on new load demand, which increases the generation cost. On the other hand, PHEVs can provide power back to the grid, which is favorable. Simulations show that various control strategies lead to different UC results. The proposed coordinated charging strategy makes the load profile become flat, which generates less generation cost. In addition, PHEVs can provide spinning reserve for power system by the V2G technique, which will reduces the reserve requirement for the traditional units, and further lowers the generation cost.

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