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Unit Commitment with Vehicle-to-Grid using Particle Swarm Optimization

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***Abstract*— Vehicle-to-Grid (V2G) technology has drawn great interest in the recent years. Success of the V2G research depends on efficient scheduling of gridable vehicles in limited parking lots. V2G can reduce dependencies on small expensive units in the existing power systems as energy storage that can decrease running costs. It can efficiently manage load fluctuation, peak load; however, it increases spinning reserves and reliability. As number of gridable vehicles in V2G is much higher than small units of existing systems, unit commitment (UC) with V2G is more complex than basic UC for thermal units. Particle swarm optimization (PSO) is used to solve the UC with V2G, as PSO can reliably and accurately solve complex constrained optimization problems easily and quickly without any dimension limitation and physical computer memory limit. In the proposed model, binary PSO is used to optimize the on/off states of power generating units and in the same model, discrete version of PSO is used to optimize the scheduling of the gridable vehicles in the parking lots to reduce the dimension of the problem. Finally, simulation results show a considerable amount of profit for using V2G after proper UC with V2G scheduling of gridable vehicles in constrained parking lots.**

***Index Terms*— Unit commitment, V2G, particle swarm optimization, gridable vehicles, generating units, parking lots, profit.**

I. INTRODUCTION

UNIT commitment (UC) involves efficiently scheduling on/off states of all available resources in a system. Unit commitment with vehicle-to-grid (UC-V2G) involves intelligently scheduling existing generating units and large number of gridable vehicles for V2G technology in limited and restricted parking lots so that maximum benefit can be achieved. In addition to fulfill a large number of practical constraints, the optimal UC-V2G should meet the forecast load demand calculated in advance, plus spinning reserve requirements at every time interval such that the total cost is minimum. Its purpose is to reduce bad environmental effects such as carbon emissions and as to increase profit. UC-V2G is a combinatorial optimization problem with both binary and continuous variables. The number of combinations of generating units and gridable vehicles grows exponentially in UC-V2G problems. UC is known as one of the most difficult problems in power systems optimization. Unit commitment with V2G is even more complex than typical UC of conventional generating units, as number of variables in UC with V2G is much higher than typical UC problems.

A bibliographical survey on UC methods reveals that various numerical optimization techniques have been employed to approach the UC problem since the last 3-decade. Among these methods, priority list (PL) methods [1-3] are very fast, however they are highly heuristic and generate schedules with relatively higher operation cost. Branch-and-bound (BB) methods [4-7] have the danger of a deficiency of storage capacity and increasing the calculation time enormously for a large-scale UC problem. Lagrangian relaxation (LR) methods [8-12] concentrate on finding an appropriate co-ordination technique for generating feasible primal solutions, while minimizing the duality gap. The main problem with an LR method is the difficulty encountered in obtaining feasible solutions.

The meta-heuristic methods [13-38] are iterative techniques that can search not only local optimal solutions but also a global optimal solution depending on problem domain and execution time limit. In the meta-heuristic methods, the techniques frequently applied to the UC problem are genetic algorithm (GA), tabu search (TS), evolutionary programming (EP), simulated annealing (SA), etc. They are general-purpose searching techniques based on principles inspired from the genetic and evolution mechanisms observed in natural systems and populations of living beings. These methods have the advantage of searching the solution space more thoroughly. However, difficulties are their sensitivity to the choice of parameters, balance between local and global searching abilities, proper information sharing and conveying mechanism, converging to local minima, convergence rate, constraint management and so on.

There are two popular swarm inspired methods in computational intelligence areas: Particle swarm optimization (PSO) and ant colony optimization (ACO). Inspired by the food-seeking behavior of real ants, Ant Systems, attributable to Dorigo *et al.*, need huge memory like dynamic programming even for a moderate size of UC problem, and difficult to solve it in real-time and physical computer storage capacity. However, PSO is simple and promising, and it requires less computation time and memory, though it requires an extra transformation for solving discrete optimization problems [19-26].

Fuzzy UC models are also available in [39-44]. However, they are imprecise and need sufficient previous statistics to model the imprecision.

V2G researchers have mainly concentrated on interconnection of energy storage of vehicles and grid [45-51]. Their goals are to educate about the environmental and economic benefits of V2G and enhance the product market. However, success of V2G researches greatly depends on the efficient scheduling

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of gridable vehicles in limited and restricted parking lots, i.e., maximization of profit. This paper makes a bridge between UC and V2G research areas and is the first one to consider UC with gridable vehicles. It extends the area of unit commitment bringing in the V2G technology and making it a success.

Unit commitment with V2G is introduced for the first time in this paper. The rest of the paper is organized as follows. In Section II, problem formulation and constraints of the UC-V2G are discussed. The proposed method, applied distributions and important operations are explained in Section III. Simulation results are reported in Section IV. Finally, conclusion is drawn in Section V.

II. UC-V2G PROBLEM FORMULATION

A. Nomenclature and Acronyms

The following notations are used in this paper.

N : Number of units
H : Scheduling hour
K : Number of buses with loads
L : Number of transmission lines
$I_i(t)$: ith unit status at hour t (1/0 for on/off)
$P_i(t)$: Output power of ith unit at time t
P_i^{max} : Maximum output limit of ith unit
P_i^{min} : Minimum output limit of ith unit
$P_i^{max}(t)$: Maximum output power of unit i at time t considering ramp rate
$P_i^{min}(t)$: Minimum output power of unit i at time t considering ramp rate
$D(t)$: Load demand at time t
$D_K(t)$: Load at bus K at time t
$R(t)$: System reserve requirement at hour t
MU_i/MD_i : Minimum up/down time of unit i
$X_i^{on}(t)$: Duration of continuously on of unit i at time t
$X_i^{off}(t)$: Duration of continuously off of unit i at time t
$\mathcal{SC}_i()$: Start-up cost function of unit i
$\mathcal{FC}()$: Fuel cost function
$h\text{-}cost_i$: Hot start cost of ith unit
$c\text{-}cost_i$: Cold start cost of ith unit
$c\text{-}s\text{-}hour_i$: Cold start hour of ith unit
RUR_i : Ramp up rate of unit i
RDR_i : Ramp down rate of unit i
$\overline{F}_l$: Real power flow limit on transmission line l
Γ_l : The matrix relating generator output to power flow on transmission line l
P_v : Capacity of each vehicle
$N_{V2G}^{max}(t)$: Maximum parking lot capacity at hour t
$N_{V2G}(t)$: No. of vehicles connected to the grid at hour t
N_{V2G}^{max} : Total vehicles in the system
SoC : State of charge
$Effi$: Efficiency
ELD : Economic load dispatch
$\mathcal{TC}$: Total cost

B. Objective Function

Usually large cheap units are used to satisfy base load demand of a system. Most of the time, large units are therefore on and they have slower ramp rates. On the other hand, small units have relatively faster ramp rates. In unit commitment problem, main challenge is to properly schedule small expensive units to handle uncertain, fluctuating and peak loads. Gridable vehicles of V2G technology will reduce dependencies on small/micro expensive units. But number of gridable vehicles in V2G is much higher than small/micro units. So profit, spinning reserve, reliability of power systems vary on scheduling optimization quality.

UC-V2G is an optimization problem. The objective of the UC-V2G is to minimize total running cost which includes mainly fuel cost and startup cost.

1. Fuel cost

Fuel cost of a thermal unit is expressed as a second order function of each unit output as follow:

$$\mathcal{FC}_i(P_i(t)) = a_i + b_i P_i(t) + c_i P_i^2(t) \tag{1}$$

where a_i, b_i and c_i are positive fuel cost co-efficients.

2. Start-up cost

The start-up cost for restarting a decommitted thermal unit, which is related to the temperature of the boiler, is included in the model. If the unit is cold which means that it has been shut down for a long time, it is necessary to consume more fuel to warm up the boiler. If the unit has been decommitted for a short while (which satisfies the minimum down time), less energy will be needed to restart the unit. In this study, a step function of time-dependent start-up cost is simplified using transition hour (H_i^{off}) from hot to cold start which is defined in (2) and (3). Start-up cost will be high cold cost ($c\text{-}cost_i$) when down time duration (X_i^{off}) exceeds cold start hour ($c\text{-}s\text{-}hour_i$) in excess of minimum down time (MD_i) and will be low hot cost ($h\text{-}cost_i$) when down time duration does not exceed $c\text{-}s\text{-}hour_i$ in excess of minimum down time as follows [3]:

$$\mathcal{SC}_i(t) = \begin{cases} h\text{-}cost_i & : MD_i \le X_i^{off}(t) \le H_i^{off} \\ c\text{-}cost_i & : X_i^{off}(t) > H_i^{off} \end{cases} \tag{2}$$

$$H_i^{off} = MD_i + c\text{-}s\text{-}hour_i. \tag{3}$$

3. Shut-down cost

Shut-down cost is constant and the typical value is zero in standard systems.

Therefore, the objective function of UC-V2G is

$$\begin{aligned} \min \ \mathcal{TC} = & \text{ Fuel cost + Start-up cost + V2G cost} \\ = & \sum_{i=1}^{N}\sum_{t=1}^{H}[\mathcal{FC}_i(P_i(t)) + \mathcal{SC}_i(1 - I_i(t-1))]I_i(t) \\ & + \sum_{t=1}^{H}[P_v N_{V2G}(t)] \end{aligned} \tag{4}$$

subject to (5-13) constraints.

Any new type of cost may be included or any existing type of cost may be excluded from the objective function according to the system operators' demand in the deregulated market. Different weights may also be assigned to different types of cost depending on their relative importance in the changing environment.

C. Constraints

The constraints that must be satisfied during the optimization process are as follows:

1. Gridable vehicle balance in V2G

Total scheduled vehicles during 24 hours is the predefined registered/forecast gridable vehicles for V2G technology.

$$\sum_{t=1}^{H} N_{V2G}(t) = N_{V2G}^{max}. \tag{5}$$

2. System power balance

The generated power from all the committed units and gridable vehicles must satisfy the load demand and the system losses, which is defined as

$$\sum_{i=1}^{N} I_i(t)\, P_i(t) + P_v\, N_{V2G}(t) = D(t) + Losses. \tag{6}$$

3. Spinning reserve

To maintain system reliability, adequate spinning reserves are required.

$$\sum_{i=1}^{N} I_i(t)\, P_i^{max}(t) + P_v^{max}\, N_{V2G}(t) \geq D(t) + R(t). \tag{7}$$

4. Generation limits

Each unit has generation range, which is represented as

$$P_i^{min} \;\leq\; P_i(t) \;\leq\; P_i^{max}. \tag{8}$$

5. State of charge

Each vehicle should have a desired departure state of charge (SoC) level.

6. Vehicle parking limits

Each parking lot has space limit for parking vehicles. This constraint is also valid for current limit.

$$N_{V2G}(t) \;\leq\; N_{V2G}^{max}(t) \tag{9}$$

7. Charging-discharging frequency

Frequency of charging-discharging of gridable vehicles is considered as 1 per day. It should vary depending on life time and type of batteries. Vehicles will be charged either from wind/solar power or from utility grid during off-peak load when price is low (or free for wind/solar power) and will discharge at peak load when price is high.

8. Efficiency

Charging and inverter efficiencies should be considered.

9. Minimum up/down time

Once a unit is committed/decommitted, there is a predefined minimum time after it can be decommitted/committed again.

$$\left.\begin{array}{lcl} (1 - I_i(t+1))MU_i & \leq & X_i^{on}(t), \text{ iff } I_i(t) = 1 \\ I_i(t+1)MD_i & \leq & X_i^{off}(t), \text{ iff } I_i(t) = 0 \end{array}\right\}. \tag{10}$$

10. Ramp rate

For each unit, output is limited by ramp up/down rate at each hour as follow:

$$P_i^{min}(t) \;\leq\; P_i(t) \;\leq\; P_i^{max}(t) \tag{11}$$

where $P_i^{min}(t) = \max\ (P_i(t-1) - RDR_i,\ P_i^{min})$ and $P_i^{max}(t) = \min\ (P_i(t-1) + RUR_i,\ P_i^{max})$.

11. Prohibited operating zone

In practical operation, the generation output P_i of unit i must avoid unit operation in the prohibited zones. The feasible operating zones of unit i can be described as follows:

$$\left.\begin{array}{lclcl} P_i^{min} & \leq & P_i & \leq & P_{i,1}^{u} \\ P_{i,j-1}^{l} & \leq & P_i & \leq & P_{i,j}^{u}, \quad j = 2,3,\ldots,Z_i \\ P_{i,Z_i}^{l} & \leq & P_i & \leq & P_i^{max} \end{array}\right\}. \tag{12}$$

where $P_{i,j}^{l}$ and $P_{i,j}^{u}$ are lower and upper bounds of the jth prohibited zone of unit i, and Z_i is the number of prohibited zones of unit i.

12. Transmission constraints

Generation must be distributed throughout the system to prevent transmission lines from being overloaded:

$$-\overline{F}_l \;\leq\; F_l(t) = \sum_{i=1}^{N} \Gamma_{l,i} P_i(t) - \sum_{i=1}^{K} \Gamma_{l,k} D_k(t) \;\leq\; \overline{F}_l\,; \quad l = 1,2,\ldots,L. \tag{13}$$

13. Initial status

At the beginning of the schedule, initial states of all the units and vehicles must be taken into account.

14. Must run units

These units include prescheduled units that must be online due to operating reliability and/or economic considerations.

15. Must out units

Units, which are on forced outages and maintenance, are unavailable for commitment.

III. PROPOSED METHOD

PSO is similar to the other evolutionary algorithms in that the system is initialized with a population of random solutions. Each potential solution, call particles, flies in the D-dimensional problem space with a velocity which is dynamically adjusted according to the flying experiences of its own and its colleagues. The location of the ith particle is represented as $X_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]^T$. The best previous position of the ith particle is recorded and called $pbest_i$. The index of the best $pbest$ among all the particles is represented by the symbol g. The location $pbest_g$ is also called $gbest$. The rate of the velocity for the ith particle is represented as $V_i = [v_{i1}, v_{i2}, \ldots, v_{iD}]^T$. The modified velocity and position of each particle is calculated using the current velocity and the distance from $pbest$, $gbest$ as (14) and (15).

$$\begin{aligned} v_{ijt} = w * v_{ijt} + c_1 * rand_1 * (pbest_{ijt} - x_{ijt}) + \\ c_2 * rand_2 * (gbest_{jt} - x_{ijt}). \end{aligned} \tag{14}$$

$$x_{ijt} = x_{ijt} + v_{ijt}. \tag{15}$$

In (14), the first term indicates the current velocity of the particle (inertia), second term presents the cognitive part of PSO where the particle changes its velocity based on its own thinking and memory, and the third term is the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge [23]. All the terms are multiplied by appropriate parameters. For UC-V2G problem, dimension D of a particle $\mathcal{P}$ is $(N+1)$ times H.

Dimensions of location and velocity are presented by 3 indices as x_{ijt} and v_{ijt}, respectively in the rest of the paper for simplicity where i=particle number, j= generating unit/vehicle and t=Time.

Binary PSO for generating units: To extend the real-valued PSO to binary space, Kennedy and Eberhart calculate probability from the velocity to determine whether x_{ijt} will be in ON state or OFF (0/1). They squashed v_{ijt} using the following logistic function.

$$Pr(v_{ijt}) = \frac{1}{1+\exp(-v_{ijt})}. \tag{16}$$

$$x_{ijt} = \begin{cases} 1, & \text{if } \mathcal{U}(0,1) < Pr(v_{ijt}) \\ 0, & \text{otherwise.} \end{cases} \tag{17}$$

Discrete PSO for V2G vehicles: At each hour, optimal number of gridable vehicles is needed to determine so that operating cost is minimum. When integer solutions (not necessarily 0 or 1) are needed, one of the options is rounding off the real values of new positions in PSO.

$$x_{ijt} = \text{round}(x_{ijt}). \tag{18}$$

By using discrete PSO instead of binary PSO, dimension of UC-V2G is reduced.

A. Data structure and algorithm of PSO for UC-V2G

In the proposed method, each PSO particle has the following fields for UC-V2G problem,

Particle $\mathcal{P}_i$ {
  Generating unit : An $N \times H$ binary matrix X_i;
  Vehicle : An $1 \times H$ interger column vector Y_i;
  Velocity : An $(N+1) \times H$ real-valued matrix V_i;
  Fitness : A real-valued cost $\mathcal{TC}$;
  }.

Besides, some extra storage is needed for $pbest_i$, $gbest$ and temporary variables, which is acceptable and under typical computer memory limit.

The proposed PSO algorithm for UC-V2G is shown below:

1) Initialize
    - Set swarm size ($SwarmSize$), maximum number of generations ($GenerationNumber$), c_1, c_2, w, etc.
    - Initial random location: Generate $SwarmSize$ particles randomly.
    - Initial random velocity: Generate initial velocities for all particles in all dimensions randomly.
    - Initial $pbest$ and $gbest$: Initially each particle is itself $pbest_i$. Evaluate all particles and the best is assigned to $gbest$.
2) Move: Calculate velocity and location in all dimensions of the current swarm using (14-15). Use binary PSO (16-17) for generating units and discrete PSO (14-15, 18) for gridable vehicles in the same algorithm.
3) Repair and calculate ELD: Repair each particle location if any constraint is violated there. It accelerates the process. Then, calculate economic load dispatch of each feasible particle location (solution).
4) Evaluate fitness: Evaluate each feasible location in the swarm using the objective function. Update $pbest$ and $gbest$ locations.
5) Check and stop/continue: Print the $gbest$ and stop if $GenerationNumber$ is reached; otherwise increase iteration generation number and go back to Step 2.

B. Constraints Management

Stochastic random PSO particles (solutions) may not always satisfy all the constraints. Constraints may be handled in two ways - direct repair and indirect penalty methods.

1) If total number of vehicles is not satisfied, difference between left and right sides of (5) is randomly distributed among 24 hours.
2) System power balance is satisfied in ED.
3) Nearest (upper/lower) valid limit is assigned for inequality constraints.

If solutions are still invalid after repair, penalty is added to discourage the invalid solutions.

C. ED Calculation

Load demand is distributed among generating units and gridable vehicles. Usually power from each vehicle is constant (P_v). At hour t, if schedule is $[I_1(t), I_2(t), \ldots, I_N(t), N_{V2G}(t)]^T$ then power from vehicles is $N_{V2G}(t) * P_v * Effi$ and the remaining demand $(D(t) - N_{V2G}(t) * P_v * Effi)$ is fulfilled by running units of schedule $[I_1(t), I_2(t), \ldots, I_N(t)]^T$. Lambda iteration is used to calculate economic dispatch (ED) here.

IV. SIMULATION RESULTS

All calculations have been run on Intel(R) Core(TM)2 Duo 2.66GHz CPU, 2.96 GB RAM, Microsoft Windows XP OS and Visual C++ compiler. Base 10-generator system is considered for simulation with 50,000 gridable vehicles which are charged from renewable source. Load demand and unit characteristics of the 10-unit system are collected from [22]. In order to perform simulations on the same condition of [13, 15-16, 18, 22], the spinning reserve requirement is assumed to be 10% of the load demand, cold start-up cost is double of hot start-up cost, and total scheduling period is 24 hours. Convergence depends on proper setting of parameter values.

Parameter values are $SwarmSize$ = 30; $GenerationNumber$ = 1,000; trust parameters c_1 = 1.4, c_2 = 2.6; total number of vehicles = 50,000; maximum battery capacity = 25 KWh; minimum battery capacity = 10 KWh; average battery capacity, P_v = 15 KWh; maximum parking lot capacity at each hour, $N_{V2G}^{max}(t)$ = 10% of total vehicles; charging-discharging frequency = 1 per day; scheduling period = 24 hours; departure state of charge, SoC = 50%; efficiency = 85%.

TABLE I
Dispatch Schedule and Reserve Power of UC with 50,000 Gridable Vehicles

Time (H)	U-1 (MW)	U-2 (MW)	U-3 (MW)	U-4 (MW)	U-5 (MW)	U-6 (MW)	U-7 (MW)	U-8 (MW)	U-9 (MW)	U-10 (MW)	Vehicles (MW)	Max. capacity (MW)	Demand (MW)	Reserve (MW)
1	455.0	229.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.14	940.3	700.0	240.3
2	455.0	282.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12.27	934.5	750.0	184.5
3	455.0	261.5	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.44	1046.9	850.0	196.9
4	455.0	330.4	130.0	0.0	25.0	0.0	0.0	0.0	0.0	0.0	9.52	1221.0	950.0	271.0
5	455.0	384.2	130.0	0.0	25.0	0.0	0.0	0.0	0.0	0.0	5.74	1213.5	1000.0	213.5
6	455.0	355.8	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	4.17	1340.3	1100.0	240.3
7	455.0	391.7	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	18.25	1368.5	1150.0	218.5
8	455.0	442.7	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	17.28	1366.6	1200.0	166.6
9	455.0	455.0	130.0	130.0	62.1	20.0	25.0	0.0	0.0	0.0	22.88	1542.8	1300.0	242.8
10	455.0	455.0	130.0	130.0	162.0	26.9	25.0	10.0	0.0	0.0	6.02	1564.0	1400.0	164.0
11	455.0	455.0	130.0	130.0	162.0	42.2	25.0	10.0	10.0	0.0	30.71	1668.4	1450.0	218.4
12	455.0	455.0	130.0	130.0	162.0	80.0	25.0	10.0	10.0	10.0	23.63	1709.3	1500.0	209.3
13	455.0	455.0	130.0	130.0	155.7	20.0	25.0	10.0	0.0	0.0	19.20	1590.4	1400.0	190.4
14	455.0	455.0	130.0	130.0	77.4	20.0	25.0	0.0	0.0	0.0	7.48	1512.0	1300.0	212.0
15	455.0	446.6	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	13.34	1358.7	1200.0	158.7
16	455.0	303.6	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	6.38	1344.8	1050.0	294.8
17	455.0	256.3	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	3.65	1339.3	1000.0	339.3
18	455.0	348.8	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	11.18	1354.4	1100.0	254.4
19	455.0	400.5	130.0	130.0	25.0	20.0	25.0	0.0	0.0	0.0	14.57	1526.1	1200.0	326.1
20	455.0	455.0	130.0	130.0	152.5	20.0	25.0	10.0	0.0	0.0	22.46	1596.9	1400.0	196.9
21	455.0	455.0	130.0	130.0	71.2	20.0	25.0	0.0	0.0	0.0	13.70	1524.4	1300.0	224.4
22	455.0	339.6	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	20.34	1372.7	1100.0	272.7
23	455.0	312.7	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.21	1044.4	900.0	144.4
24	455.0	329.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.22	940.4	800.0	140.4
Total running cost = $559,081.36														

TABLE II
Dispatch Schedule and Reserve Power of UC Without Gridable Vehicles

Time (H)	U-1 (MW)	U-2 (MW)	U-3 (MW)	U-4 (MW)	U-5 (MW)	U-6 (MW)	U-7 (MW)	U-8 (MW)	U-9 (MW)	U-10 (MW)	Vehicles (MW)	Max. capacity (MW)	Demand (MW)	Reserve (MW)
1	455.0	244.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	910.0	700.0	210.0
2	455.0	295.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	910.0	750.0	160.0
3	455.0	370.0	0.0	0.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1072.0	850.0	222.0
4	455.0	455.0	0.0	0.0	39.9	0.0	0.0	0.0	0.0	0.0	0.00	1072.0	950.0	122.0
5	455.0	389.9	130.0	0.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1202.0	1000.0	202.0
6	455.0	359.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1332.0	1100.0	232.0
7	455.0	410.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1332.0	1150.0	182.0
8	455.0	455.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1332.0	1200.0	132.0
9	455.0	455.0	130.0	130.0	84.9	20.0	25.0	0.0	0.0	0.0	0.00	1497.0	1300.0	197.0
10	455.0	455.0	130.0	130.0	162.0	32.9	25.0	0.0	10.0	0.0	0.00	1552.0	1400.0	152.0
11	455.0	455.0	130.0	130.0	162.0	72.9	25.0	0.0	10.0	10.0	0.00	1607.0	1450.0	157.0
12	455.0	455.0	130.0	130.0	162.0	80.0	25.0	42.9	10.0	10.0	0.00	1662.0	1500.0	162.0
13	455.0	455.0	130.0	130.0	162.0	32.9	25.0	10.0	0.0	0.0	0.00	1552.0	1400.0	152.0
14	455.0	455.0	130.0	130.0	84.9	20.0	25.0	0.0	0.0	0.0	0.00	1497.0	1300.0	197.0
15	455.0	455.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1332.0	1200.0	132.0
16	455.0	309.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1332.0	1050.0	282.0
17	455.0	260.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1332.0	1000.0	332.0
18	455.0	359.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1332.0	1100.0	232.0
19	455.0	455.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1332.0	1200.0	132.0
20	455.0	455.0	130.0	130.0	162.0	32.9	25.0	10.0	0.0	0.0	0.00	1552.0	1400.0	152.0
21	455.0	455.0	130.0	130.0	84.9	20.0	25.0	0.0	0.0	0.0	0.00	1497.0	1300.0	197.0
22	455.0	455.0	0.0	0.0	144.9	20.0	25.0	0.0	0.0	0.0	0.00	1237.0	1100.0	137.0
23	455.0	420.0	0.0	0.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	1072.0	900.0	172.0
24	455.0	345.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	910.0	800.0	110.0
Total running cost = $563,741.83														

Randomly selected results with and without gridable vehicles are shown in Tables I and II, respectively. Running cost is \$563,741.83 without V2G and it is \$559,081.36 considering V2G. Therefore, total running cost is reduced by \$4,660.47 for only gridable vehicles; however, other constraints are the same during the schedule 24 hours. Minimum reserve is 140.4 MW using V2G technology and it is 110.0 MW without using V2G. Average reserve is 221.69 MW using V2G technology and it is only 181.54 MW without using V2G.

Fig. 1 shows that the load curve has peaks and valleys, and reserve is always higher when V2G is considered. The system with V2G is more reliable than traditional system with only generating units. Operators expect that large cheap units (U-1 and U-2) will mainly satisfy base load and other small expensive units (U-3 to U-10) will fulfill fluctuating, peak loads. Gridable vehicles of V2G reduce dependencies on small expensive units.

Table III shows that U-1 and U-7 produce same constant powers, as U-1 is the cheapest, thus it is generating always maximum power, and U-7 is expensive, thus it is generating minimum power whenever it is running; U-2, U-5 to U-6 and U-8 to U-10 produce less power when gridable vehicles are

TABLE III
POWER FROM GENERATING UNITS DURING 24 HOURS

	U-1	U-2	U-3	U-4	U-5	U-6	U-7	U-8	U-9	U-10	Vehicles
With V2G (MW)	10920.0	9056.7	2730.0	2210.0	1279.9	269.1	225.0	50.0	20.0	10.0	318.8
Without V2G (MW)	10920.0	9679.5	2210.0	2080.0	1524.7	331.7	225.0	62.9	30.0	20.0	0.0
V2G Effect (%)	0	6.43	-19.04	-5.88	16.05	18.87	0	20.51	33.33	50	-

TABLE IV
TEST RESULTS OF THE PROPOSED PSO FOR UC WITH V2G (10 RUNS)

No. of units	**Success** (%)	**Total cost**				**Execution time**		
		Best ($)	Worst ($)	Average ($)	Variation (%)	Maximum (sec)	Minimum (sec)	Average (sec)
With V2G	100	557,594.52	559,236.25	558,243.30	0.294	22.05	18.5	20.14
Without V2G	100	563,741.83	565,443.39	564,743.51	0.301	23.47	19.22	21.24

connected in the system, as they are expensive units; however, U-3 and U-4 generate more power when gridable vehicles are connected, as the proposed PSO method makes balance between the increasing and decreasing power generations.

Fig. 2 shows that vehicles are connected to grid and the number of vehicles connected to grid is changing at each hour. It is frequently changing for optimization. Number of vehicles connected to grid is not directly proportional to the load demand; however, maximum number of vehicles is connected during the peak load (11th and 12th hours). It depends on load curve, non-linear price curves and constraints. An optimization method is therefore essential to solve this complex system.

Regarding the optimization algorithm for V2G, PSO solves the problem efficiently. Stochastic results are shown in Table IV. The best, worst, and average findings of the proposed method are reported together with their cost variation as a percentage of the best solution. It always converges. The variation is tolerable. Average result is near to the best result. These facts strongly demonstrate the robustness of the proposed PSO for UC with V2G problem.

Table V shows the comparison of the proposed method to the most recent methods, e.g., integer-coded GA (ICGA) reported in [13], Lagrangian relaxation and genetic algorithm (LRGA) reported in [15], genetic algorithm (GA), dynamic programming (DP) and Lagrangian relaxation (LR) reported in [16], evolutionary programming (EP) reported in [18], and hybrid particle swarm optimization (HPSO) reported in [22] with respect to the total cost. "-" indicates that no result is reported in the corresponding article. The proposed method is working properly, as results are comparable with existing methods when only number of gridable vehicles is assigned to zero in the algorithm keeping all other resources and constraints the same.

From Table V, it is obvious that the proposed method is superior to other mentioned methods because (a) the DP cannot search all the states of UC problem in real time; (b) it is very difficult to obtain feasible solutions and to minimize the duality gap in LR; (c) most of the cases, SA generates random infeasible solutions in each iteration by the random bit flipping operation; (d) PSO shares many common parts of GA, EP, etc.; however, (i) it has better information sharing and conveying mechanisms than GA, EP; (ii) it has better dynamics of balance between global and local searching abilities; (iii) it needs less memory and simple calculations; (iv) it has no dimension limitation; (v) it is easy to implement. The proposed PSO generates little bit better results than HPSO just for proper parameter settings, swarm size (in the proposed method, swarm size is 30 instead of 20 in HPSO), ED calculations and efficient programming.

Execution time depends on algorithm, computer configuration and efficient program coding. The proposed method is implemented efficiently in Visual C++ and run on a modern system. Table IV shows execution time of the proposed method for UC with V2G. Execution time is acceptable, as it is in second. Execution time is not exponentially growing with respect to the number of gridable vehicles of V2G, as vehicles are treated as a cluster of integer number of vehicles for

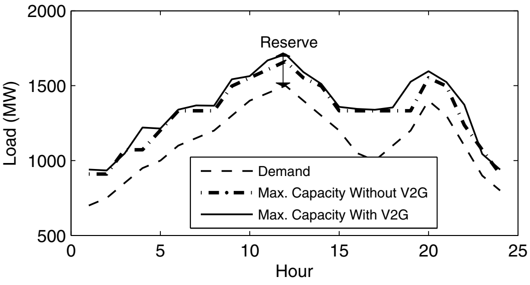

Fig. 1. Reserve power with and without V2G.

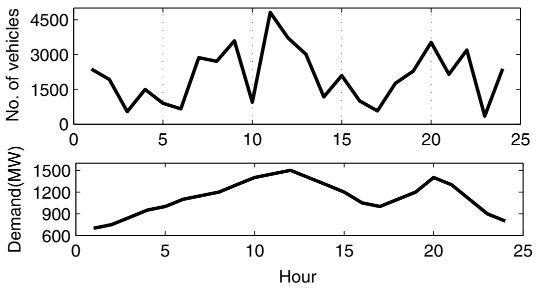

Fig. 2. Vehicles connected to the grid.

TABLE V
COMPARISON OF TOTAL COST - ICGA[13], LRGA[15], GA[16], DP[16], LR[16], EP[18], AG[32], HPSO[22] AND THE AVERAGE FINDING OF THE PROPOSED PSO

	Total cost ($)														
	ICGA[13]			LRGA[15]			GA[16]			DP[16]			LR[16]		
	Best	Worst	Avg.	Best	Worst	Avg.	Best	Worst	Avg.	Best	Worst	Avg.	Best	Worst	Avg.
Without V2G	-	-	566404	-	-	564800	565825	570032	-	565825	N/A	N/A	565825	N/A	N/A
With V2G	-			-			-			-			-		

	Total cost ($)											
	EP[18]			AG[32]			HPSO[22]			Proposed PSO		
	Best	Worst	Avg.	Best	Worst	Avg.	Best	Worst	Avg.	Best	Worst	Avg.
Without V2G	564551	566231	565352	-	-	564005	563942	565785	564772	563,741.8	565443.3	564743.5
With V2G	-			-			-			557594.5	559236.2	558243.3

Notes: '-' indicates that result is not reported in the corresponding reference;
ICGA: Generations = 300, chromosomes = 50, crossover and mutation prob. = not constant;
LRGA: Generations = 500, population size = 60, duality gap = 0.02, crossover and mutation prob. = 0.8, 0.0333 respectively;
GA: Generations = 500, chromosomes = 50, adaptive crossover prob. range = 0.4 to 0.9 and adaptive mutation prob. range = 0.004 to 0.024;
DP: Complete state enumerations for only 10-unit system;
LR: Multiplier increasing factor=0.01 and decreasing factor=0.97;
EP: Generations = 500, population size = 50;
AG: Population size = 70, ini. temperature = 900, crossover prob. = 0.8 and mutation prob. = 0.1;
HPSO: Maximum iterations = 1000, population size = 20, inertia weight, w = 1.0, c_1 = 2.8, c_2 = 1.2;

discrete PSO (not binary PSO).

Fig. 3 shows the convergence of the proposed PSO for UC with V2G. In the beginning, it converges faster, then converges slowly at the middle of generation and then very slowly or steady from the near final iterations. Therefore, the proposed PSO holds the above fine-tuning characteristic of a good optimization method.

V. CONCLUSION

This paper has introduced for the unit commitment with gridable vehicles based on V2G. The authors have solved the UC with V2G using PSO. In this paper, the contributions are the timely introduction of UC with V2G, and effective optimization of UC with V2G using binary and integer versions of PSO in the same algorithm. From this study, it is clear that UC with V2G reduces operational costs, but it increases profit, reserve and reliability. Finally, this study is a first look at UC with V2G. In future, there is enough scope to include other practical constraints of gridable vehicles and parking lots for real applications of V2G technology.

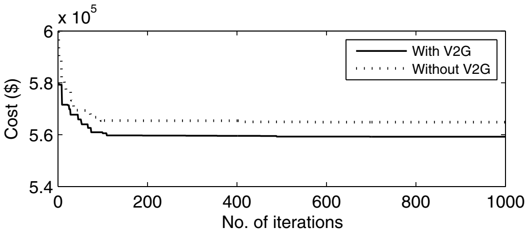

Fig. 3. Convergence of the proposed PSO for UC with V2G.

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