Optimization of Vehicle-to-Grid Scheduling in Constrained Parking Lots

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***Abstract*— An automatic Vehicle-to-Grid (V2G) technology can contribute to the utility grid. V2G technology has drawn great interest in the recent years. Success of the sophisticated automatic V2G research depends on efficient scheduling of gridable vehicles in constrained parking lots. Parking lots have constraints of space and current limits for V2G. However, 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 only thermal units. Particle swarm optimization (PSO) is proposed to solve the V2G, as PSO has been demonstrated to 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 optimizes the on/off states of power generating units easily. Vehicles are presented by signed integer number instead of 0/1 to reduce the dimension of the problem. Typical discrete version of PSO has less balance between local and global searching abilities to optimize the number of charging/discharging gridable vehicles in the constrained system. In the same model, balanced PSO is proposed to optimize the V2G part in the constrained parking lots. Finally, results show a considerable amount of profit for using proper scheduling of gridable vehicles in constrained parking lots.**

***Index Terms*— V2G, particle swarm optimization, gridable vehicles, constrained parking lots.**

I. Introduction

ENVIRONMENT friendly modern technologies are essential to protect global warming. Thus research on V2G is very important in power systems. Unit commitment (UC) involves efficiently scheduling on/off states of all available resources in a system. V2G scheduling 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 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. The optimization of 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 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.

Various numerical optimization techniques have been employed to approach the UC problem. Priority list (PL) methods [1] are very fast; however, they are highly heuristic. Dynamic programming (DP) can find global solution by exploring all combinations. However, DP and branch-and-bound methods [2-3] have the danger of huge memory requirement, and their execution time increases exponentially for large-scale UC problems. Lagrangian relaxation (LR) methods [4-6] 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 [7-18] 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 mechanisms, 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 [12-14].

Gridable vehicles can be used to level the real fluctuating load demand. Efficient V2G scheduling can reduce generation cost if gridable vehicles are charged from the grid at off-

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peak load and discharge to the grid at peak load. V2G researchers have mainly concentrated on interconnection of energy storage of vehicles and grid [19-25]. 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 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 in V2G. It extends the area of unit commitment bringing in the V2G technology and making it a success.

The authors have reported different cases on unit commitment with V2G in [26-27]. Gridable vehicles are charged from renewable energy sources in [26]. Gridable vehicles are charged from the grid at off-peak load; however, V2G scheduling suffers from balance of local and global searching abilities in [27]. In this paper, the authors have concentrated on solution quality, as it is an off-line optimization process. Gridable vehicles of V2G in constrained parking lots are intelligently optimized to improve balance between local and global searching abilities of the signed integer number of vehicles at each hour. Results are therefore significantly improved here.

II. UC-V2G Problem Formulation

A. Nomenclature and Acronyms

The following notations are used in this paper.

N	:	Number of units
H	:	Scheduling hour
$I_i(t)$	:	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
$R(t)$	:	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
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 problems, 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.

V2G scheduling is an optimization problem. The objective of the V2G scheduling 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. In this paper, simplified start up cost is applied as follows:

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

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

3. Shut-down cost

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

Therefore, the objective function of the V2G scheduling is

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

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.

C. Constraints

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

1. Gridable vehicle balance in V2G

Negative and positive signs are used for charging and discharging number of vehicles connected in the grid, respectively. Only predefined registered/forecast gridable vehicles are considered for the optimum V2G scheduling. Vehicles are charged from the grid and discharge to the grid during 24 hours. After the scheduling period, they will be come back to the initial state.

$$\sum_{t=1}^{H} N_{V2G}(t) = 0. \quad (5)$$

$$\sum_{t=1}^{H} |N_{V2G}(t)| = FREQ * N_{V2G}^{max}. \quad (6)$$

Here $FREQ$ is maximum charging-discharging frequency during the scheduling 24 hours.

2. Charging-discharging frequency

Multiple charging-discharging facilities of gridable vehicles are considered 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 at off-peak load when price is low (or free for wind/solar power) and will discharge to the grid at peak load when price is high.

3. 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

$$\sum_{i=1}^{N} I_i(t)\, P_i(t) + P_v\, N_{V2G}(t) = D(t) + Losses. \quad (7)$$

4. Spinning reserve

To maintain system reliability, adequate spinning reserves are required.

$$\sum_{i=1}^{N} I_i(t)\, P_i^{max}(t) + P_v^{max}\, N_{V2G}(t) \geq D(t) + R(t). \quad (8)$$

5. Generation limits

Each unit has generation range, which is represented as

$$P_i^{min} \;\leq\; P_i(t) \;\leq\; P_i^{max}. \quad (9)$$

6. State of charge

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

7. Constrained parking lot

Each parking lot has space and current limitations. Therefore a limited number of vehicles can charge/discharge to/from the grid in a constrained parking lot at a given time instant.

$$N_{V2G}(t) \;\leq\; N_{V2G}^{max}(t) \quad (10)$$

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.

$$\left.\begin{array}{lll} (1 - I_i(t+1))MU_i & \leq & X_i^{on}(t), \text{ iff } I_i(t) = 1 \\ I_i(t+1)MD_i & \leq & X_i^{off}(t), \text{ iff } I_i(t) = 0 \end{array}\right\}. \quad (11)$$

10. Ramp rate

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

$$P_i^{min}(t) \;\leq\; P_i(t) \;\leq\; P_i^{max}(t) \quad (12)$$

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:

$$\left.\begin{array}{lllll} P_i^{min} & \leq & P_i & \leq & P_{i,1}^{u} \\ P_{i,j-1}^{l} & \leq & P_i & \leq & P_{i,j}^{u}, \quad j = 2, 3, \ldots, Z_i \\ P_{i,Z_i}^{l} & \leq & P_i & \leq & P_i^{max} \end{array}\right\}. \quad (13)$$

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. Initial status

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

III. Proposed Method

A. Particle swarm optimization

Particle swarm optimization (PSO) is similar to other swarm based evolutionary algorithms. Each potential solution, called a particle, flies in multi-dimensional problem space with a velocity, which is dynamically adjusted according to the flying experiences of its own and its colleagues. PSO is an intelligent iterative method where Velocity and position of each particle are calculated as below.

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

$$x_{ijt} = x_{ijt} + v_{ijt}. \quad (15)$$

In the above velocity equation, 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.

B. Data structure of the proposed PSO for V2G scheduling

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

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

PSO can easily optimize an $N \times H$ binary matrix for generating units because possible state of a generating unit is either 1 or 0 only. On the other hand, basic PSO has less balance between local and global searching abilities for the optimization of an $H \times 1$ signed integer column vector for gridable vehicles, as possible number of charging/discharging number of gridable vehicles varies from -$N_{V2G}^{max}(t)$ to +$N_{V2G}^{max}(t)$ at hour t. The authors have used binary PSO for the optimization of generating units and balanced (regulated) PSO for the optimization of gridable vehicles.

Besides, some extra storage is needed for $pbest_i$, $gbest$ and temporary variables, which is acceptable and under typical computer memory limit. For the V2G scheduling problem, dimension 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/vehicles and t=time.

C. Binary PSO for generating units

Scheduling of thermal units is a binary optimization problem. A continuous searching space can be converted to a valid binary searching space by a probability distribution. To extend the real-valued PSO to binary space, the authors calculate probability from the velocity to determine whether x_{ijt} will be in on state or off (0/1).

$$v_{ijt} = 4.0, \text{ if } v_{ijt} > 4.0. \tag{16}$$

$$Pr(v_{ijt}) = \frac{1}{1 + \exp(-v_{ijt})}. \tag{17}$$

$$x_{ijt} = \begin{cases} 1, & \text{if } \mathcal{U}(0,1) < Pr(v_{ijt}) \\ 0, & \text{otherwise.} \end{cases} \tag{18}$$

D. Balanced PSO for V2G vehicles

Vehicles are presented by signed integer numbers (positive sign indicates discharging state and negative sign indicates charging state) instead of 0/1 to reduce the dimension of the problem. At each hour, optimal number of changing/discharging gridable vehicles is needed to determine so that the operating cost is minimum. In the proposed balanced PSO, changes of velocity depend on iteration. To make a fine tuning (balance) in complex searching space, initially velocity changes rapidly for global search and then velocity changes slowly for local search. A balancing factor is included in velocity calculation (at the end of (19)). Signed integer number of vehicles is formulated by rounding off the real value of a new particle location in balanced PSO.

$$v_{ijt} = [v_{ijt} + c_1 * rand_1 * (pbest_{ijt} - x_{ijt}) + c_2 * rand_2 * (gbest_{jt} - x_{ijt})] * [1 + \frac{-Range}{MaxIte}(Ite - 1)]. \tag{19}$$

$$x_{ijt} = x_{ijt} + v_{ijt}. \tag{20}$$

$$x_{ijt} = \text{round}(x_{ijt}). \tag{21}$$

$$x_{ijt} = N_{V2G}^{max}(t), \text{ if } x_{ijt} > N_{V2G}^{max}(t). \tag{22}$$

$$x_{ijt} = -N_{V2G}^{max}(t), \text{ if } x_{ijt} < -N_{V2G}^{max}(t). \tag{23}$$

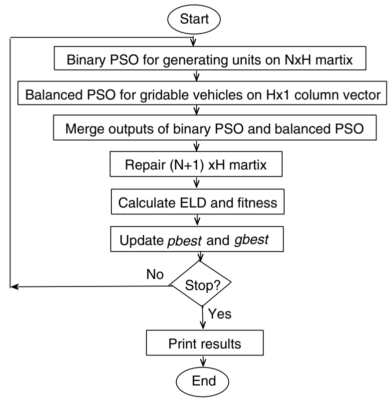

Fig. 1. Algorithmic flowchart of the proposed binary PSO and balanced PSO for V2G scheduling.

E. The proposed algorithm

In the same algorithm, binary PSO is applied for the optimization of generating units and balanced PSO is applied for the optimization of gridable vehicles as below. Flowchart of the proposed method is shown in Fig. 1.

1) Initialize: Initialize a $(N+1) \times H$ matrix for each particle randomly. Set parameters of binary PSO and balanced PSO. Select $pbest$ and $gbest$ locations. Take some temporary variables.
2) Move: For each particle in the current swarm, calculate velocity and location in all dimensions. Apply binary PSO (14, 16-18) on $N \times H$ binary matrix for generating units and balanced PSO (19-23) on $H \times 1$ column vector for gridable vehicles in the same model. Merge the outputs of binary PSO and balanced PSO.
3) Repair and calculate ELD: Check each particle for all the constraints (5-13). Repair each particle location if any constraint is violated there. Then, calculate economic load dispatch of feasible particle locations (solutions) only. It accelerates the process.
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 $gbest$ solution and stop if maximum number of iterations ($MaxIte$) is reached; otherwise increase current iteration number and go back to Step 2.

F. 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 [8].

G. ED Calculation

Load demand is distributed among generating units and gridable vehicles. It is the most computational intensive part of V2G scheduling. Lambda iteration is used to calculate economic dispatch (ED) here. An intelligent method may be used to improve the solution quality.

TABLE I
SCHEDULE AND RESERVE POWER OF 10-UNIT SYSTEM WITH 50,000 GRIDABLE VEHICLES

Time (H)	U-1	U-2	U-3	U-4	U-5	U-6	U-7	U-8	U-9	U-10	Vehicles	Max. capacity (MW)	Demand (MW)	Reserve (MW)
1	1	1	0	0	0	0	0	0	0	0	-47115	1210.4	700.0	510.4
2	1	1	0	0	0	0	0	0	0	0	-44824	1195.8	750.0	445.8
3	1	1	0	1	0	0	0	0	0	0	+25110	1200.1	850.0	350.1
4	1	1	1	1	0	0	0	0	0	0	+18424	1287.5	950.0	337.5
5	1	1	1	1	0	0	0	0	0	0	-46054	1463.6	1000.0	463.6
6	1	1	1	1	1	0	0	0	0	0	-4723	1362.1	1100.0	262.1
7	1	1	1	1	1	0	0	0	0	0	0	1332.0	1150.0	182.0
8	1	1	1	1	1	0	0	0	0	0	0	1332.0	1200.0	132.0
9	1	1	1	1	1	1	1	0	0	0	+15080	1593.1	1300.0	293.1
10	1	1	1	1	1	1	1	1	0	0	-581	1555.7	1400.0	155.7
11	1	1	1	1	1	1	1	1	1	0	+32701	1815.5	1450.0	365.5
12	1	1	1	1	1	1	1	1	1	1	+26199	1829.0	1500.0	329.0
13	1	1	1	1	1	1	1	1	0	0	+17208	1661.7	1400.0	261.7
14	1	1	1	1	1	1	1	0	0	0	+274	1498.7	1300.0	198.7
15	1	1	1	1	1	0	0	0	0	0	+4247	1359.1	1200.0	159.1
16	1	1	1	1	1	0	0	0	0	0	-4439	1360.3	1050.0	310.3
17	1	1	1	1	1	0	0	0	0	0	-324	1334.1	1000.0	334.1
18	1	1	1	1	1	0	0	0	0	0	+13076	1415.4	1100.0	315.4
19	1	1	1	1	1	0	1	0	0	0	+16839	1524.3	1200.0	324.3
20	1	1	1	1	1	1	1	1	0	0	+20719	1684.1	1400.0	284.1
21	1	1	1	1	1	1	1	0	0	0	+1014	1503.5	1300.0	203.5
22	1	1	1	1	0	1	0	0	0	0	-47890	1555.3	1100.0	455.3
23	1	1	1	0	0	0	0	0	0	0	-4055	1065.9	900.0	165.9
24	1	1	0	0	0	0	0	0	0	0	+9109	968.1	800.0	168.1
Total running cost = $554,737.84														

Notes: '-' indicates charging from the grid and '+' indicates discharging to the grid.

TABLE II
SCHEDULE AND RESERVE POWER OF 10-UNIT SYSTEM WITHOUT GRIDABLE VEHICLES

Time (H)	U-1	U-2	U-3	U-4	U-5	U-6	U-7	U-8	U-9	U-10	Vehicles	Max. capacity (MW)	Demand (MW)	Reserve (MW)
1	1	1	0	0	0	0	0	0	0	0	0	910.0	700.0	210.0
2	1	1	0	0	0	0	0	0	0	0	0	910.0	750.0	160.0
3	1	1	0	0	1	0	0	0	0	0	0	1072.0	850.0	222.0
4	1	1	0	0	1	0	0	0	0	0	0	1072.0	950.0	122.0
5	1	1	1	0	1	0	0	0	0	0	0	1202.0	1000.0	202.0
6	1	1	1	1	1	0	0	0	0	0	0	1332.0	1100.0	232.0
7	1	1	1	1	1	0	0	0	0	0	0	1332.0	1150.0	182.0
8	1	1	1	1	1	0	0	0	0	0	0	1332.0	1200.0	132.0
9	1	1	1	1	1	1	1	0	0	0	0	1497.0	1300.0	197.0
10	1	1	1	1	1	1	1	0	1	0	0	1552.0	1400.0	152.0
11	1	1	1	1	1	1	1	0	1	1	0	1607.0	1450.0	157.0
12	1	1	1	1	1	1	1	1	1	1	0	1662.0	1500.0	162.0
13	1	1	1	1	1	1	1	1	0	0	0	1552.0	1400.0	152.0
14	1	1	1	1	1	1	1	0	0	0	0	1497.0	1300.0	197.0
15	1	1	1	1	1	0	0	0	0	0	0	1332.0	1200.0	132.0
16	1	1	1	1	1	0	0	0	0	0	0	1332.0	1050.0	282.0
17	1	1	1	1	1	0	0	0	0	0	0	1332.0	1000.0	332.0
18	1	1	1	1	1	0	0	0	0	0	0	1332.0	1100.0	232.0
19	1	1	1	1	1	0	0	0	0	0	0	1332.0	1200.0	132.0
20	1	1	1	1	1	1	1	1	0	0	0	1552.0	1400.0	152.0
21	1	1	1	1	1	1	1	0	0	0	0	1497.0	1300.0	197.0
22	1	1	0	0	1	1	1	0	0	0	0	1237.0	1100.0	137.0
23	1	1	0	0	1	0	0	0	0	0	0	1072.0	900.0	172.0
24	1	1	0	0	0	0	0	0	0	0	0	910.0	800.0	110.0
Total running cost = $563,741.83														

IV. 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. A 10-unit system is considered for simulation with 50,000 gridable vehicles. It is assumed that there are no renewable sources in the system and power electronics modules on the gridable vehicles can control bi-directional power flow between the vehicles and grid. Vehicles are charged from the grid at off-peak loads and they discharge at peak loads so that the total running cost is minimum; however, the load demand and constraints are fulfilled. Load demand and unit characteristics of the 10-unit system are collected from [14]. In order to perform simulations on the same condition of [7, 9-11, 14], 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. The proposed method is stochastic and convergence depends on proper setting of parameter values.

Parameter values are $SwarmSize$ = 30; $MaxIte$ = 1,000; trust parameters c_1 = 1.4, c_2 = 2.6; total number of vehicles = 50,000; balance of search, $Range$ = 0.6; maximum battery capacity = 25 KWh; minimum battery capacity = 10 KWh; average battery capacity, P_v = 15 KWh; maximum parking lot capacity at each hour, $N_{V2G}^{max}(t)$ = 50,000 vehicles; multiple charging-discharging facilities; scheduling period = 24 hours; departure state of charge, SoC = 50%; efficiency = 85%.

Randomly selected results with and without gridable vehicles are shown in Tables I and II, respectively. Running cost is

TABLE III

POWER FROM GENERATING UNITS DURING 24 HOURS CONSIDERING 50,000 GRIDABLE VEHICLES

	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	9225.6	2574.7	2547.9	769.6	256.6	225.0	50.0	20.0	10.0	0.0
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 (MW)	0.0	-453.9	364.7	467.9	-755.1	-75.1	0	-12.9	-10.0	-10.0	0.0

Notes: V2G Effect = Results with V2G - Results without V2G.
A negative value of V2G effect indicates an expensive unit and a positive value of V2G effect indicates a cheap unit.

TABLE IV

TEST RESULTS OF THE PROPOSED PSO FOR V2G SCHEDULING (10 RUNS)

Method	Total cost					Execution time		
	Best ($)	Worst ($)	Average ($)	Std. ($)	Diff. (%)	Maximum (sec)	Minimum (sec)	Average (sec)
With V2G (using balanced PSO)	554,509.53	559,987.85	557,584.44	2087.17	0.988	31.42	23.81	28.91
With V2G (not using balanced PSO)	557,180.67	561,593.56	558,917.58	1319.86	0.792	29.67	25.55	27.224
Without V2G	563,741.83	565,443.39	564,743.51	646.65	0.301	23.47	19.22	21.24

\$563,741.83 without V2G and it is \$554,737.84 considering V2G. There is no free renewable energy source in the system. Therefore, total running cost is reduced by \$9,003.99 for only gridable vehicles that are charged from the grid at off-peak hours and discharge to the grid at peak hours; however, other constraints are the same during the schedule 24 hours for Tables I and II. Minimum reserve is 132.0MW at 8th hour using V2G technology and it is 110.0MW at 24th hour without using V2G. Average reserve is 291.96MW using V2G technology and it is only 181.54MW without using V2G.

Fig. 2 shows that the load curve has both peaks and valleys, and maximum capacity of the system is always higher when V2G is considered. In the system, spinning reserve is 10%. Fig. 3 shows reserves with and without considering V2G. The system with V2G is more reliable than traditional system with only generating units. The system with lower spinning reserve (e.g., 5%) has lower running cost; however, it is less reliable. Operators expect that large cheap units will mainly satisfy base load and other small expensive units will fulfill fluctuating, peak loads. Gridable vehicles of V2G reduce dependencies on small expensive units.

A negative value of V2G effect indicates an expensive unit and a positive value of V2G effect indicates a cheap unit. Table III shows that U-1 and U-7 produce same constant powers, as they are cheap and generating maximum power. U-2, U-5 to U-6 and U-8 to U-10 produce less power when gridable vehicles are connected in the system, as they are expensive units; however, U-3 and U-4 generate more power when gridable vehicles are connected, as they are relatively cheap and the proposed PSO method makes balance between the increasing and decreasing power generations.

Number of vehicles connected to grid is not directly proportional to the load demand. Fig. 4 shows that vehicles are connected to grid and the number of vehicles connected to grid is changing at each hour. Positive number of vehicles indicates discharging to the grid and negative number of vehicles indicates charging from the grid. It is frequently changing to obtain balance for optimization. Maximum number of vehicles is connected to discharge batteries to the grid during peak load hours (11th, 12th, 13th hours). On the other hand, most of the vehicles are connected to charge batteries from the grid during off-peak load hours (1st, 2nd, 5th, 6th, 22nd, 23rd hours). It depends on load curve, non-linear price curves and constraints. Parking lot capacity is considered here. An optimization method is therefore essential to solve this complex system.

Regarding the optimization algorithm for V2G, balanced PSO solves V2G scheduling problem efficiently. Stochastic results are shown in Table IV. The best, worst, and average findings of the proposed method are reported together. Balanced PSO generates better results when balancing factor is applied. Average result is \$557,584.44 when balancing factor is used. On the other hand, it is \$558,917.58 when balancing factor is not used and other conditions are the same. However, balanced PSO needs slightly more time. The system always converges. The variation is tolerable. Results are not biased. These facts strongly demonstrate the robustness of the proposed PSO for V2G scheduling.

Table V shows the comparison of the proposed method to the most recent methods, e.g., integer-coded GA (ICGA) reported in [7], Lagrangian relaxation and genetic algorithm

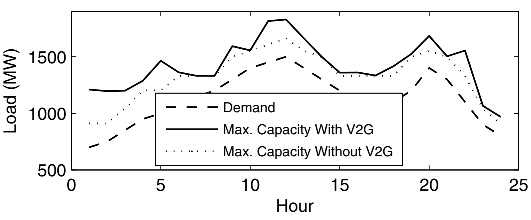

Fig. 2. Maximum capacity with and without V2G.

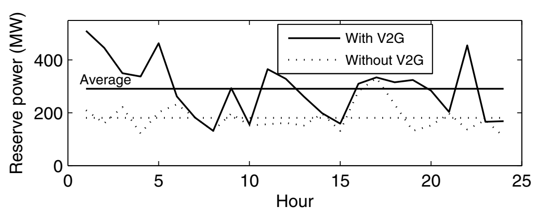

Fig. 3. Reserve power with and without V2G.

TABLE V
COMPARISON OF TOTAL RUNNING COST - ICGA, LRGA, GA, DP, LR, EP, AG, HPSO AND THE PROPOSED PSO

	Total cost ($)														
	ICGA			LRGA			GA			DP			LR		
	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			AG			HPSO			Proposed balanced PSO		
	Best	Worst	Avg.	Best	Worst	Avg.	Best	Worst	Avg.	Best	Worst	Avg.
Without V2G	564551	566231	565352	-	-	564005	563942	565785	564772	563741.8	565443.3	564743.5
With V2G		-			-			-		554509.5	559987.8	557584.4

(LRGA) reported in [9], genetic algorithm (GA), dynamic programming (DP) and Lagrangian relaxation (LR) reported in [10], evolutionary programming (EP) reported in [11], and hybrid particle swarm optimization (HPSO) reported in [14] 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.

The proposed method is superior to other mentioned methods in Table V, because (a) DP cannot search all the states of a large-scale problem such as the V2G scheduling and it does not have information sharing and conveying mechanisms [28]; (b) it is very difficult to obtain feasible solutions and to minimize the duality gap in LR for a large-scale problem such as V2G scheduling; (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 needs less memory and simple calculations; (iii) it has no dimension limitation; (iv) 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.

Table IV shows execution time of the proposed method. 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. Execution time is acceptable, as it is in second. Scheduling with V2G spends more average time because size of the problem increases when gridable vehicles are considered. 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 in balanced PSO.

From the authors' prior experience, typical integer version of PSO has less balance between local and global searching abilities to optimize the number of charging/discharging gridable vehicles in the constrained system. Balanced PSO is therefore applied for the optimization of gridable vehicles of V2G in the constrained parking lots. Fig. 5 shows an instant of the internal optimization process at peak hour (e.g., 12th hour). Initially it is random and it gradually updates with less fluctuation for the balanced PSO. Fig. 6 shows the convergence of the proposed method. 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

The authors have introduced V2G scheduling in constrained parking lots for the success of the V2G research. In this paper, they have solved the V2G scheduling using a modern intelligent method. Gridable vehicles are mainly charged from the grid at off-peak load and discharge to the grid at peak load hours. In this paper, the contributions are the timely introduction of V2G scheduling in constrained parking lots, and an effective optimization of the problem using binary and

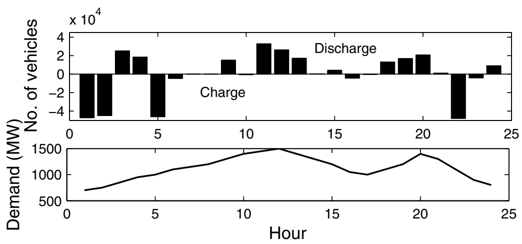

Fig. 4. Vehicles connected to the grid.

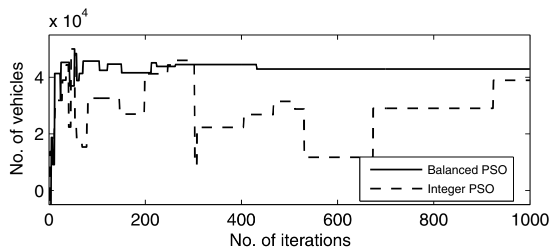

Fig. 5. Optimization of gridable vehicles in balanced PSO.

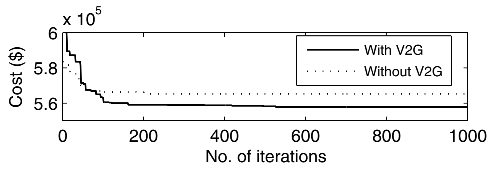

Fig. 6. Convergence of the proposed PSO for V2G.

balanced versions of PSO in the same algorithm. From this study, it is clear that the effective V2G scheduling reduces operational costs; however, it increases profit, reserve and reliability. Finally, this study is a first look at V2G scheduling. In future, there is enough scope to include other practical constraints of gridable vehicles and parking lots for real applications of V2G technology.

REFERENCES

[1] T. Senjyu, K. Shimabukuro, K. Uezato, and T. Funabashi, "A fast technique for unit commitment problem by extended priority list," *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 882-888, May 2003.

[2] Z. Ouyang and S. M. Shahidehpour, "An intelligent dynamic programming for unit commitment application," *IEEE Trans. Power Syst.*, vol. 6, no. 3, pp. 1203-1209, Aug 1991.

[3] A. I. Cohen and M. Yoshimura, "A branch-and-bound algorithm for unit commitment," *IEEE Trans. Power Appa. Syst.*, vol. PAS-102, pp. 444-451, Feb 1983.

[4] S. Virmani, E. C. Adrian, K. Imhof, and S. Mukherjee, "Implementation of a Lagrangian relaxation based unit commitment problem," *IEEE Trans. Power Syst.*, vol. 4, no. 4, pp. 1373-1380, Nov 1989.

[5] John J. Shaw, "A direct method for security-constrained unit commitment," *IEEE Trans. Power Syst.*, vol. 10, no. 3, pp. 1329-1342, Aug 1995.

[6] W. L. Peterson and S. R. Brammer, "A capacity based Lagrangian relaxation unit commitment with ramp rate constraints," *IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 1077-1084, May 1995.

[7] I. G. Damousis, A. G. Bakirtzis, and P. S. Dokopoulos, "A solution to the unit-commitment problem using integer-coded genetic algorithm," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 1165-1172, May 2004.

[8] T. Senjyu, A. Y. Saber, T. Miyagi, K. Shimabukuro, N. Urasaki, and T. Funabashi, "Fast technique for unit commitment by genetic algorithm based on unit clustering," *IEE Proc., Gen. Transm. Dist.*, vol. 152, no. 5, pp. 705-713, Sep 2005.

[9] C.-P. Cheng, C.-W. Liu, and C.-C. Liu, "Unit commitment by Lagrangian relaxation and genetic algorithms," *IEEE Trans. Power Syst.*, vol. 15, no. 2, pp. 707-714, May 2000.

[10] S. A. Kazarlis, A. G. Bakirtzis, and V. Petridis, "A genetic algorithm solution to the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 11, no. 1, pp. 83-92, Feb 1996.

[11] K. A. Juste, H. Kita, E. Tanaka, and J. Hasegawa, "An evolutionary programming solution to the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 14, no. 4, pp. 1452-1459, Nov 1999.

[12] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," *Proc. IEEE Int. Conf. on Neural Networks*, pp. 1942-1948, Perth, Australia, 1995.

[13] J. Kennedy and R. C. Eberhart, "A discrete binary version of the particle swarm algorithm," *Proc. of IEEE Conf. on Systems, Man, and Cybernetics*, pp. 4104-4109, 1997

[14] T. O. Ting, M. V. C. Rao, and C. K. Loo, "A novel approach for unit commitment problem via an effective hybrid particle swarm optimization," *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 411-418, Feb 2006.

[15] M. Dorigo, V. Maniezzo, and A. Colorni, "The ant system: optimization by a colony of cooperating agents," *IEEE Trans. Syst. Man Cybernetics*, vol. 26, no 2, pp. 29-41, Part B 1996.

[16] M. Dorigo and LM. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman," *IEEE Trans Evol. Comput.* vol. 1, no. 1, pp. 53-65, 1997.

[17] T. Satoh and K. Nara, "Maintenance scheduling by using simulated annealing method [for power plants]," *IEEE Trans. Power Syst.*, vol. 6, no. 2, pp. 850-857, May 1991.

[18] A. H. Mantawy, Y. L. Abel-Mogid, and S. Z. Selim, "Integrating genetic algorithms, tabu search, and simulated annealing for the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 829-836, Aug. 1999.

[19] W. Kempton, J. Tomic, S. Letendre, A. Brooks, T. Lipman, "Vehicle-to-grid power: Battery, hybrid and fuel cell vehicles as resources for distributed electric power in California, Davis, CA," *Institute of Transportation Studies*, Report # IUCD-ITS-RR 01-03, 2005.

[20] J. Tomic and W. Kempton, "Using fleets of electric-drive vehicles for grid support," *Journal of Power Sources*, vol. 168, no. 2, pp. 459-468, 1 Jun 2007.

[21] W. Kempton and J. Tomic, "Vehicle to grid fundamentals: Calculating capacity and net revenue," *Journal of Power Sources*, vol. 144, no. 1, pp. 268-279, 1 Jun 2005.

[22] W. Kempton and J. Tomic, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Journal of Power Sources*, vol. 144, no. 1, pp. 280-294, 1 Jun 2005.

[23] B. D. Williams and K. S. Kurani, "Estimating the early household market for light-duty hydrogen-fuel-cell vehicles and other "Mobile Energy" innovations in California: a constraints analysis," *Journal of Power Sources*, vol. 160, no. 1, pp. 446-453, 29 Sep 2006.

[24] B. D. Williams and K. S. Kurani, "Commercializing light-duty plug-in/plug-out hydrogen-fuel-cell vehicles: "Mobile Electricity" technologies and opportunities," *Journal of Power Sources*, vol. 166. no. 2, pp. 549-566, 15 Apr 2007.

[25] W. Kempton and T. Kubo, "Electric-drive vehicles for peak power in Japan," *Energy Policy*, vol. 28, no. 1, pp. 9-18, 2000.

[26] A. Y. Saber and G. K. Venayagamoorthy, "Unit commitment with vehicle-to-grid using particle swarm optimization," *PowerTech 2009*, Bucharest, Romania, 28 June - 2 July, 2009 [submitted].

[27] A. Y. Saber and G. K. Venayagamoorthy, " V2G Scheduling - A modern approach to unit commitment with vehicle-to-grid using particle swarm optimization," *IFAC PP&PSC 2009*, Tampere Hall, Finland, 5-8 July 2009 [submitted].

[28] A. Y. Saber, T. Senjyu, A. Yona, and T. Funabashi, "Unit commitment computation by fuzzy adaptive particle swarm optimisation," *IET Proc., Gen. Transm. Dist.*, vol. 1, no. 3, pp. 456-465, May 2007.