Journal of Power Sources 195 (2010) 898–911

Contents lists available at ScienceDirect

Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

Intelligent unit commitment with vehicle-to-grid —A cost-emission optimization

Ahmed Yousuf Saber*, Ganesh Kumar Venayagamoorthy

Real-Time Power and Intelligent Systems Laboratory, Missouri University of Science and Technology, Rolla, MO 65409-0040, USA

ARTICLE INFO

Article history:
Received 23 June 2009
Received in revised form 9 August 2009
Accepted 10 August 2009
Available online 20 August 2009

Keywords:
Cost
Emission
Gridable vehicles
Particle swarm optimization
UC
V2G

ABSTRACT

A gridable vehicle (GV) can be used as a small portable power plant (S3P) to enhance the security and reliability of utility grids. Vehicle-to-grid (V2G) technology has drawn great interest in the recent years and its success depends on intelligent scheduling of GVs or S3Ps in constrained parking lots. V2G can reduce dependencies on small expensive units in existing power systems, resulting in reduced operation cost and emissions. It can also increase reserve and reliability of existing power systems. Intelligent unit commitment (UC) with V2G for cost and emission optimization in power system is presented in this paper. As number of gridable vehicles in V2G is much higher than small units of existing systems, UC with V2G is more complex than basic UC for only thermal units. Particle swarm optimization (PSO) is proposed to balance between cost and emission reductions for UC with V2G. PSO can reliably and accurately solve this complex constrained optimization problem easily and quickly. In the proposed solution model, binary PSO optimizes on/off states of power generating units easily. Vehicles are presented by integer numbers instead of zeros and ones to reduce the dimension of the problem. Balanced hybrid PSO optimizes the number of gridable vehicles of V2G in the constrained parking lots. Balanced PSO provides a balance between local and global searching abilities, and finds a balance in reducing both operation cost and emission. Results show a considerable amount of cost and emission reduction with intelligent UC with V2G. Finally, the practicality of UC with V2G is discussed for real-world applications.

1. Introduction

The power and energy industry – in terms of (a) economic importance and (b) environmental impact – is one of the most important sectors in the world since nearly every aspect of industrial productivity and daily life are dependent on electricity. Unit commitment (UC) involves cost efficient scheduling (on/off states) of available generating resources in a system. Various numerical optimization techniques have been employed to approach the UC problem. Priority list methods [1] are very fast; however, they are highly heuristic. Branch-and-bound methods [2,3] have the danger of a deficiency of storage capacity. 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, evolutionary programming (EP), simulated annealing (SA), etc. They are general-purpose searching techniques. However, difficulties are their sensitivity to the choice of parameters, balance between local and global searching abilities, etc. There are also two popular swarm inspired methods in the field of computational intelligence: Particle swarm optimization (PSO) and ant colony optimization (ACO). ACO was pioneered by Dorigo et al. [15] from the inspiration of food-seeking behavior of real ants. It is a memory and computational intensive algorithm especially when dealing with large-scale optimization problems. However, PSO is simpler, and requires less memory and computational time.

The power and energy industry represents a major portion of global emission, which is responsible for 40% of the global CO_2 production followed by the transportation sector (24%) [19]. The estimated costs of an unabated climate change are as much as 20% of the global domestic product (GDP). However, by taking the appropriate measurements these costs could be limited to around 1% of GDP [20]. Climate change caused by greenhouse gas (GHG) emissions is now widely accepted as a real condition that has potentially serious consequences for human society and industries need to factor this into their strategic plans [21]. So environment friendly modern planning is essential. However, power

* Corresponding author at: Real-Time Power and Intelligent Systems Laboratory (http://rtpis.org), Missouri University of Science and Technology, 240 Emerson Electric Co. Hall, 301W. 16th St., Rolla, MO 65409, USA. Tel.: +1 573 647 1471; fax: +1 573 341 4532.

E-mail addresses: aysaber@ieee.org (A.Y. Saber), gkumar@ieee.org (G.K. Venayagamoorthy).

0378-7753/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.jpowsour.2009.08.035

systems researchers have addressed only traditional UC problems to minimize cost in the existing articles. They have never included emission in unit commitment problems, though it is an important factor as mentioned above. Some researchers have included emission in economic dispatch problems only (not in unit commitment) [22,23].

Vehicle-to-grid (V2G) researchers have mainly concentrated on interconnection of energy storage of vehicles and grid [24–30]. Their goals are to educate about the environmental and economic benefits of V2G and enhance the product market. However, success of V2G technology greatly depends on the efficient scheduling of gridable vehicles in limited and restricted parking lots.

Ideally gridable vehicles for V2G technology should be charged from renewable sources. A gridable vehicle can act as a small portable power plant (S3P). An intelligent scheduling of S3Ps and conventional generating units can reduce operation cost and emission. In this paper, unit commitment with vehicle-to-grid (UC–V2G) is introduced where UC–V2G involves intelligently scheduling existing units and large number of gridable vehicles in limited and restricted parking lots. It reduces both operation cost and emission with proper and intelligent optimization. In addition to fulfilling a large number of practical constraints, the optimal UC–V2G should meet the forecast load demand calculated in advance, parking lot limitations, state of charge of gridable vehicles, charging–discharging efficiency, spinning reserve requirements, etc. at every time interval such that the total operation cost and emission are minimal. The overall objective is to reduce bad environmental effects such as carbon emissions and to increase profit. The optimization of 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. Unit commitment with V2G is more complex than typical UC of conventional generating units, as number of variables in UC with V2G is much higher than typical UC problems, and both cost and emission are minimized in the objective function of UC–V2G.

The proposed PSO based solution approach improves balance between local and global searching abilities, and balances reduction between operation cost and emission. Both cost and emission are minimized for UC with V2G; in addition, reserve and reliability of power systems is increased, and the negative impact of climate change is decreased. This paper makes a bridge between UC and V2G research areas and considers UC with gridable vehicles in V2G framework. It extends the area of unit commitment bringing in the V2G technology and making it a success.

2. UC–V2G problem formulation

2.1. Nomenclature and acronyms

The following notations are used in this paper.

c-s-hour_i	cold start hour of *i*th unit
h-cost_i	hot start-up cost of *i*th unit
c-cost_i	cold start-up cost of *i*th unit
$D(t)$	load demand at time *t*
H	scheduling hours
$I_i(t)$	*i*th unit status at hour *t* (1/0 for on/off)
MU_i/ MD_i	minimum up/down time of unit *i*
N	number of units
$N_{V2G}^{max}(t)$	maximum number of discharging vehicles at hour *t*
$N_{V2G}(t)$	no. of vehicles connected to the grid at hour *t*
N_{V2G}^{max}	total vehicles in the system
$P_i(t)$	output power of *i*th unit at time *t*
$P_i^{max/min}$	maximum/minimum output limit of *i*th 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
P_v	capacity of each vehicle
$R(t)$	system reserve requirement at hour *t*
RUR_i	ramp up rate of unit *i*
RDR_i	ramp down rate of unit *i*
S3P	small portable power plant
$X_i^{on}(t)$	duration of continuously on of unit *i* at time *t*
$X_i^{off}(t)$	duration of continuously off of unit *i* at time *t*
$\mathcal{FC}_i()$	fuel cost function of unit *i*
$\mathcal{SC}_i()$	start-up cost function of unit *i*
$\mathcal{EC}_i()$	emission cost function of unit *i*
	state of charge
	efficiency

2.2. 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. Besides, each unit has different cost and emission characteristics that depend on amount of power generation, fuel type, generator unit size, technology and so on. In UC with

emission 0pinning 0p5earchr-317.8(0pinability)-296.6(0p5e417.8(0p

Therefore, the objective (fitness) function for cost-emission optimization of unit commitment with V2G is

$$\begin{aligned}\min \mathcal{TC} &= \mathcal{W}_c \times (\text{Fuel} + \text{Start}-\text{up}) + \mathcal{W}_e \times \text{Emission}\\ &= \sum_{i=1}^{N}\sum_{t=1}^{H} [\mathcal{W}_c(\mathcal{FC}_i(P_i(t)) + \mathcal{SC}_i(1 - I_i(t-1)))\\ &\quad + \mathcal{W}_e(\ _i\mathcal{EC}_i(P_i(t)))]I_i(t)\end{aligned} \tag{5}$$

subject to 6–13 constraints.

$_i$ is the emission penalty factor of unit *i*. Weight factors $\mathcal{W}_c$ and $\mathcal{W}_e$ are used to include ($\mathcal{W} = 1$) or exclude ($\mathcal{W} = 0$) cost and emission in the fitness function. It increases flexibility of the system. Different weights may also be possible to assign different precedence of cost and emission in the fitness function. Any other cost may be included or any existing type of cost may be excluded from the objective function according to the system operators' demand.

2.3. Constraints of UC with V2G

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

1. *Gridable vehicle balance in UC with V2G.*
   Only predefined registered/forecasted gridable vehicles are considered for the optimum scheduling in UC with V2G. Total number of registered gridable vehicles is known (fixed) and it is assumed that they are charged from renewable sources. All the vehicles discharge to the grid during a predefined scheduling period (24 h).

$$\sum_{t=1}^{H} N_{V2G}(t) = N_{V2G}^{max}. \tag{6}$$

2. *Charging–discharging frequency.*
   Vehicles are charged from renewable sources and discharge to the grid. Multiple charging–discharging facilities of gridable vehicles may be considered. It should vary depending on life time and type of batteries. For simplicity, charging–discharging frequency is one per day in this study.
3. *System power balance.*
   Gridable vehicles are considered as S3Ps. Power supplied from committed units and selected (some percentage of total vehicles) S3Ps must satisfy the load demand and the system losses, which is defined as

$$\sum_{i=1}^{N} I_i(t)P_i(t) + P_V N_{V2G}(t) = D(t) + \text{Losses}. \tag{7}$$

4. *Spinning reserve.*
   To maintain system reliability, adequate spinning reserves are required.

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

5. *Generation limits.*
   Each unit has generation range, which is represented as

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

6. *State of charge* ( ).
   Each vehicle should have a desired departure state of charge level.
7. *Number of discharging vehicles limit.*
   All the vehicles cannot discharge at the same time. For reliable operation and control, limited number of vehicles will discharge at a time. This constraint also applies for power transfer, current limit.

$$N_{V2G}(t) \leq N_{V2G}^{max}(t). \tag{10}$$

8. *Efficiency* ( ).
   Charging and inverter efficiencies ( ) should be considered.
9. *Minimum up/down time.*
   Once a unit is committed/uncommitted, there is a predefined minimum time after it can be uncommitted/committed respectively.

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

10. *Ramp rate.*
    For each unit, output is limited by ramp up/down rate at each hour as follows:

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

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:

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

where $P_{i,j}^{l}$ and $P_{i,j}^{u}$ are lower and upper bounds of the *j*th 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.

3. Proposed solution approach

3.1. Particle swarm optimization

Particle swarm optimization 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.

$$\begin{aligned}V_{ijt} &= w \times V_{ijt} + c_1 \times \text{rand}_1 \times (\text{pbest}_{ijt} - x_{ijt})\\ &\quad + c_2 \times \text{rand}_2 \times (\text{gbest}_{jt} - x_{ijt}).\end{aligned} \tag{14}$$

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

In the above velocity equation, the first term indicates the current velocity of the particle (inertia); second term presents the cognitive part of the particle 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 derived from the swarm.

3.2. Data structure

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 $H \times 1$ 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 $H \times 1$ integer column vector for gridable vehicles, as possible number of connected gridable vehicles varies from 0 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 of V2G.

Besides, some extra storage is needed for $pbest_i$, *gbest* and temporary variables, which is acceptable and under typical computer memory limit. For the UC with V2G problem, dimension of a particle $\mathcal{P}$ is $(N+1) \times H$. Dimensions of location and velocity are presented by three indices as x_{ijt} and V_{ijt}, respectively in the rest of the paper for simplicity where i = particle number, j = generating unit/no. of vehicles and t = time.

3.3. 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 or off (0/1) state. In (18), $\mathcal{U}(0,1)$ generates a real number between 0 and 1.

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

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

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

3.4. Balanced PSO for V2G vehicles

Number of connected vehicles to grid is presented by an integer number instead of zero or one for each vehicle to reduce the dimension of the problem. At each hour, optimal number of gridable vehicles is needed to determine so that the operating cost and emission are 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 (the last term of (19)). Integer number of vehicles is formulated by rounding off the real value of a new particle location in balanced PSO.

$$V_{ijt} = [V_{ijt} + c_1 \times rand_1 \times (pbest_{ijt} - x_{ijt}) + c_2 \times rand_2 \times (gbest_{jt} - x_{ijt})] \quad 1 + \frac{-Range}{Max\,Ite}(Ite - 1) \quad . \tag{19}$$

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

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

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

$$x_{ijt} = 0, \quad \text{if } x_{ijt} < 0. \tag{23}$$

3.5. Proposed algorithm for UC with V2G

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 economic dispatch*. Check each particle for all the constraints (6–13). Repair each particle location if any constraint is violated there. Then, calculate economic dispatch (see Section 3.7) of feasible particle locations (solutions) only. It accelerates the process.
(4) *Evaluate fitness*. Evaluate each feasible location in the swarm using the objective function. According to the operators' demand, price and (or) emission are considered in the fitness function. Update *pbest* and *gbest* locations.
(5) *Check and stop/continue*. Print the *gbest* solution and stop if maximum number of iterations (*Max Ite*) is reached; otherwise increase current iteration number and go back to Step (2).

3.6. Constraints management

Stochastic random PSO particles (solutions) do not always satisfy all the constraints. Constraints are handled in two ways – direct repair and indirect penalty methods [8]. A direct repair for the constraints of UC with V2G is given below.

(i) If total number of vehicles is not satisfied, difference between left and right sides of (6) is randomly distributed among 24 h.
(ii) System power balance, generation limit and ramp rate constraints are satisfied in ED of UC with V2G.
(iii) Nearest (upper/lower) valid limit is assigned for inequality constraints.

The above repair accelerates convergence. If solutions are still invalid after repair, penalty is added to discourage the invalid solutions.

3.7. ED calculation

Load demand is distributed among generating units and selected number of gridable vehicles. It is the most computational intensive part of UC with V2G. Capacity of 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 $\times N_{V2G}(t) \times P_V \times (1 - \quad)$ and the remaining demand $[D(t) - \quad \times N_{V2G}(t) \times P_V \times (1 - \quad)]$ 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. An intelligent method may be used to improve the solution quality.

4. Results and discussion

All calculations have been run on Intel(R) Core(TM)2 Duo 2.66 GHz CPU, 3 GB RAM, Microsoft Windows XP OS and Visual C++ compiler. A 10-unit system is considered for simulation with 50,000 gridable vehicles, which are charged from renewable sources. Vehi-

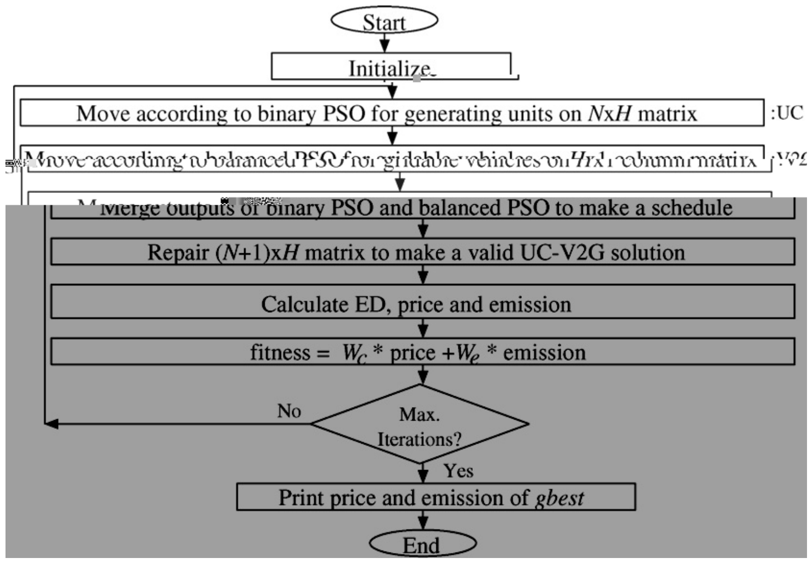

Fig. 1. Algorithmic flowchart of the proposed binary PSO and balanced PSO for UC with V2G.

cles are charged from renewable sources and they discharge to the grid so that the total running cost and emission are minimal; however, the load demand and constraints are fulfilled. Load demand and unit characteristics of the 10-unit system are collected from Ref. [14]. Emission coefficients and penalty factor equation are given in Appendix A. In order to perform simulations on the same condition of Refs. [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 h. The proposed method is stochastic and convergence depends on proper setting of parameter values.

Parameter values are $\mathrm{SwarmSize} = 30$; $\mathrm{MaxIterations}=1000$; trust parameters $c_1=1.5$, $c_2=2.5$; total number of vehicles = 50,000; balance of search, $\mathrm{Range} = 0.6$; maximum battery capacity = 25 kWh; minimum battery capacity = 10 kWh; average battery capacity, $P_V = 15$ kWh; maximum number of discharging vehicles at each hour, $N_{V2G}^{max}(t) = 10\%$ of total vehicles; total number of gridable vehicles in the system, $N_{V2G}^{max} = 50,000$; charging–discharging frequency = 1 per day; scheduling period = 24 h; departure state of charge, = 50%; efficiency, = 85%.

In fitness function, both cost and emission are considered (i.e., $\mathcal{W}_c = 1$ and $\mathcal{W}_e = 1$) and randomly selected results with and without gridable vehicles are shown in Tables 1 and 2, respectively. Running cost is \$559,367.06 (fuel cost plus start-up cost) and emission is 257,391.18 tons when 50,000 gridable vehicles are considered in the 10-unit system during 24 h (Table 1). On the other hand, running cost and emission are \$565,325.94 and 260,066.35 tons, respectively when gridable vehicles are not considered in the same system (Table 2). Thus V2G saves (\$565,325.94 – \$559,367.06=) \$5958.88 and reduces (260,066.35 – 257,391.18 tons=) 2676.17 tons emission per day in the 10-unit small system.

Effect of both cost and emission in fitness function of UC with V2G is shown in Fig. 2. Though value of fitness function is continuously decreasing, individual cost and emission are frequently fluctuating (both increasing and decreasing) up to 200 iterations. In the proposed method, variations of cost and emission are small, and finally both production cost and emission are moderate after program execution. From Fig. 2, emission variation is higher than cost variation because values of second order emission coefficients are much higher than that of fuel cost coefficients.

According to Tables 1 and 2, emission is always lower; however, maximum capacity of the system and reserve are always higher (except at 4th hour) when gridable vehicles are considered in unit commitment with V2G. Only at 4th hour, reserve is lower and emission is higher, which are tolerable, as spinning reserve (10%) is satisfied; however, it is happened because the method is stochastic and it makes balance between cost and emission optimization. Minimum reserve is 124.3 MW at 24th hour using gridable vehicles in V2G technology and it is 110.0 MW at the same hour without using V2G. Average reserve is 213.60 MW using V2G technology and it is only 185.70 MW without using V2G. Figs. 3–5 give a detailed description visually. So V2G increases reliability of the system as well.

Cost and emission are also tested separately as a fitness function of the same system. Table 3 shows the results when only cost (fuel cost plus start-up cost) is considered in the fitness

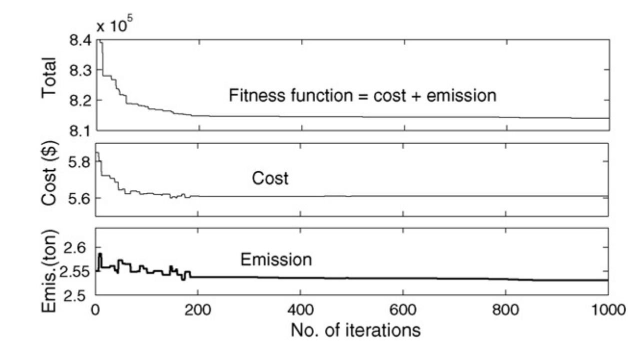

Fig. 2. Cost plus emission in fitness function of UC with V2G.

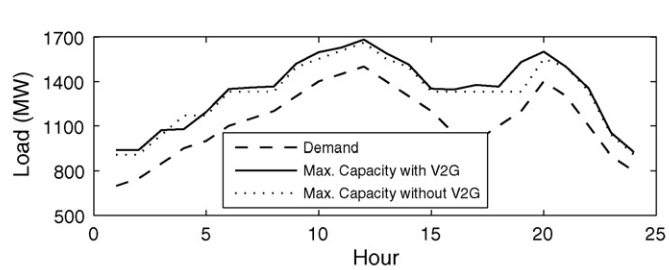

Fig. 3. Maximum capacity with and without V2G.

Table 1
Schedule and dispatch of generating units and gridable vehicles for 10-unit system with 50,000 gridable vehicles (both cost and emission are considered in the fitness function).

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

Table 2
Schedule and dispatch of generating units without gridable vehicles for 10-unit system (both cost and emission are considered in the fitness function).

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)	V2G/S3P (MW)	Emission (ton)	Maximum 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	6,827.0	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	7,547.2	910.0	750.0	160.0
3	455.0	265.0	0.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	7,728.0	1040.0	850.0	190.0
4	455.0	235.0	130.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	7,965.0	1170.0	950.0	220.0
5	455.0	285.0	130.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	8,653.9	1170.0	1000.0	170.0
6	455.0	359.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	0.00	10,225.6	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	11,304.6	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	12,410.0	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	12,927.2	1497.0	1300.0	197.0
10	455.0	455.0	130.0	130.0	162.0	32.9	25.0	10.0	0.0	0.0	0.00	13,557.8	1552.0	1400.0	152.0
11	455.0	455.0	130.0	130.0	162.0	72.9	25.0	10.0	10.0	0.0	0.00	13,866.1	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	14,153.7	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	13,557.8	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	12,927.2	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	12,410.0	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	9,302.4	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	8,536.1	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	10,225.6	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	12,410.0	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	13,557.8	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	12,927.2	1497.0	1300.0	197.0
22	455.0	340.1	130.0	130.0	0.0	20.0	25.0	0.0	0.0	0.0	0.00	10,112.7	1335.0	1100.0	235.0
23	455.0	315.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	8,510.3	1040.0	900.0	140.0
24	455.0	345.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	8,423.3	910.0	800.0	110.0

Total emission = 260,066.35 ton. Total running cost = $565,325.94 (fuel cost plus start-up cost).

Table 3
Schedule and dispatch of generating units and gridable vehicles for 10-unit system with 50,000 gridable vehicles (only cost is considered in the fitness function).

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)	V2G/S3P (MW)	No. of vehicles	Emission (ton)	Maximum capacity (MW)	Demand (MW)	Reserve (MW)
1	455.0	235.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.45	1482	6,708.6	928.9	700.0	228.9
2	455.0	287.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.16	1123	7,434.3	924.3	750.0	174.3
3	455.0	249.4	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.54	2438	7,516.6	1071.1	850.0	221.1
4	455.0	355.9	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.08	1424	9,266.5	1058.2	950.0	108.2
5	455.0	383.8	130.0	0.0	25.0	0.0	0.0	0.0	0.0	0.0	6.16	967	10,088.6	1214.3	1000.0	214.3
6	455.0	348.5	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	11.46	1798	10,000.2	1354.9	1100.0	254.9
7	455.0	397.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	12.04	1889	11,030.4	1356.1	1150.0	206.1
8	455.0	445.7	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	14.30	2243	12,170.4	1360.6	1200.0	160.6
9	455.0	455.0	130.0	130.0	65.6	20.0	25.0	0.0	0.0	0.0	19.37	3038	12,900.7	1535.7	1300.0	235.7
10	455.0	455.0	130.0	130.0	154.8	20.0	25.0	10.0	0.0	0.0	20.11	3154	13,532.7	1592.2	1400.0	192.2
11	455.0	455.0	130.0	130.0	162.0	53.5	25.0	10.0	10.0	0.0	19.48	3055	13,855.7	1646.0	1450.0	196.0
12	455.0	455.0	130.0	130.0	162.0	80.0	25.0	10.0	10.0	10.0	23.31	3656	14,201.1	1708.6	1500.0	208.6
13	455.0	455.0	130.0	130.0	154.7	20.0	25.0	10.0	0.0	0.0	20.25	3176	13,531.8	1592.5	1400.0	192.5
14	455.0	455.0	130.0	130.0	62.7	20.0	25.0	0.0	0.0	0.0	22.23	3487	12,899.0	1541.5	1300.0	241.5
15	455.0	449.8	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	10.12	1588	12,276.9	1352.2	1200.0	152.2
16	455.0	301.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	8.99	1410	9,153.6	1350.0	1050.0	300.0
17	455.0	250.2	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	9.75	1529	8,404.7	1351.5	1000.0	351.5
18	455.0	349.1	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	10.89	1709	10,011.2	1353.8	1100.0	253.8
19	455.0	430.5	130.0	130.0	25.0	0.0	25.0	0.0	0.0	0.0	4.55	714	12,054.3	1426.1	1200.0	226.1
20	455.0	455.0	130.0	130.0	151.8	20.0	25.0	10.0	0.0	0.0	23.10	3623	13,512.6	1598.2	1400.0	198.2
21	455.0	455.0	130.0	130.0	74.5	20.0	25.0	0.0	0.0	0.0	10.39	1630	12,909.8	1517.8	1300.0	217.8
22	455.0	353.8	130.0	130.0	0.0	20.0	0.0	0.0	0.0	0.0	11.17	1752	10,114.9	1272.3	1100.0	172.3
23	455.0	306.9	0.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	8.05	1263	8,373.6	1056.1	900.0	156.1
24	455.0	333.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.81	1852	8,202.2	933.6	800.0	133.6

Total running cost = $558,003.01 (fuel cost plus start-up cost). Total emission = 260,150.45 ton.

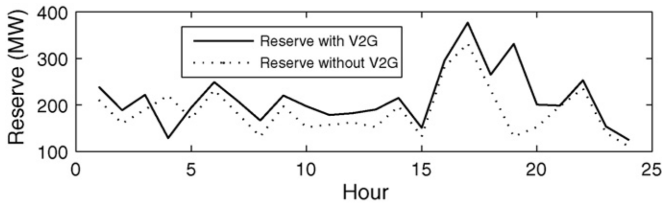

Fig. 4. Reserve power with and without V2G.

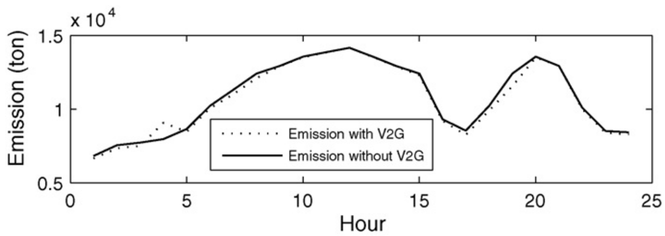

Fig. 5. Emission with and without V2G.

function (i.e., $\mathcal{W}_c = 1$ and $\mathcal{W}_e = 0$). Using the proposed method, running cost is \$558,003.01 where all the constraints are satisfied and for this running cost, emission is 260,150.45 tons. Therefore the cost is reduced by (\$559,367.06 – \$558,003.01=) \$1364.05 and for the \$1364.05 cost reduction, emission is increased by (260,150.45 – 257,391.18 tons =) 2759.27 tons. According to Table 3, most of the time large cheap units are running; large amount of power is delivered from V2G at peak load hours; emission is always high; and reserve, cost are low. Effect of only cost in fitness function of UC with V2G is shown in Fig. 6. Cost is continuously decreasing; however, emission is fluctuating up to 200 iterations. From Fig. 6, variations of emission and total cost are high when only fuel cost is considered in the fitness function and as the cost is low, emission is very high, which is not tolerable for environment.

Similarly Table 4 shows the results when only emission is considered in the fitness function (i.e., $\mathcal{W}_c = 0$ and $\mathcal{W}_e = 1$). Using the proposed method, emission is 249,661.71 tons, where only emission is the fitness function and all constraints are fulfilled; however, running cost is \$570,754.78. Therefore emission is reduced by (257,391.18 – 249,661.71 tons=) 7729.47 tons; however, cost is increased by (\$570,754.78 – \$559,367.06=) \$11,387.72 for the small system. From Table 4, sometimes small expensive units are also committed even at off-peak load; power delivered from V2G does not vary greatly between peak and off-peak loads; emission is always low; and reserve, cost are high. Effect of only emission in fitness function of UC with V2G is shown in Fig. 7. Emission is rapidly decreasing; however, cost fluctuates slowly up to 500 iterations. As emission is low, the cost is high, which may not be acceptable when only emission is considered in the fitness function of UC with V2G.

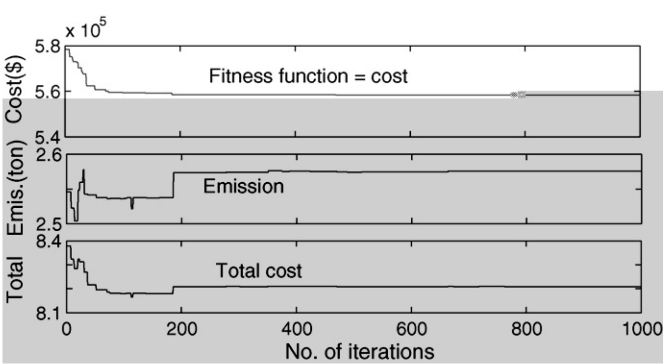

Fig. 6. Cost in fitness function of UC with V2G.

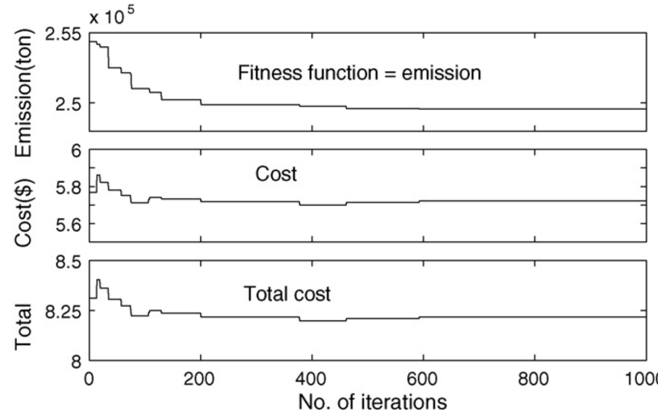

Fig. 7. Emission in fitness function of UC with V2G.

Load curve of the 10-unit system has both peaks and valleys (Fig. 3). Emission comparison is shown in Fig. 8. Emission is always high when only price is considered in the fitness function to generate low cost schedule. On the other hand, emission is always low and cost is very high when only emission is considered in the fitness function to generate environmental friendly schedule. However, difference is small at peaks (12th and 20th h) and valleys (16th and 17th h) of the load for the optimization method. From Tables 3 and 4, total emission is reduced by (260,150.45 – 249,661.71 tons=) 10,488.74 tons per day or 3,828,390.1 tons per year and cost is increased by (\$570,754.78 – \$558,003.01=) \$12,751.77 per day or \$4,654,396.05 per year for different fitness functions. In the proposed method, fitness function (5) is flexible using weights $\mathcal{W}_c$ and $\mathcal{W}_e$ for giving precedence of cost and emission, respectively. For practical use, values of $\mathcal{W}_c$ and $\mathcal{W}_e$ should be chosen carefully considering price, environmental effects, consumers and system operators' demand.

So there is a trade-off between cost and emission. However, fitness function of unit commitment with V2G, considering both cost and emission, can make a balance between the cost and emission where both cost and emission are moderate (Tables 1 and 2 and Fig. 2). Besides, V2G helps to reduce both cost and emission in power systems (Tables 1 and 2). Therefore intelligent unit commitment with V2G, for both cost and emission optimization, is essential in power systems.

The main challenge of unit commitment is to properly schedule small expensive units, as large cheap units are always on. 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. Table 5 shows the effect of V2G on each unit considering both cost and emission in the fitness function. Usually a negative value of V2G effect indicates a relatively expensive (or more polluting) unit

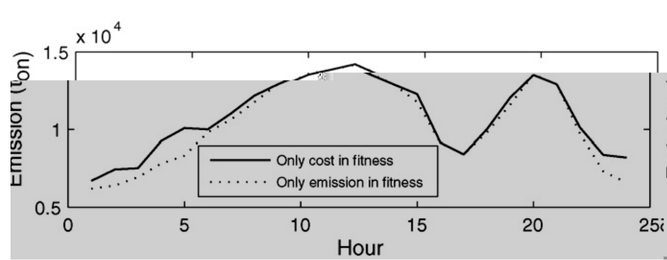

Fig. 8. Emission comparison.

Table 4
Schedule and dispatch of generating units and gridable vehicles for 10-unit system with 50,000 gridable vehicles (only emission is considered in the fitness function).

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)	V2G/S3P

Table 5
Power from generating units during 24 h 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	V2G/S3P
With V2G (MW)	10,920.0	8937.8	2340.0	2730.0	1241.9	282.4	225.0	73.0	20.0	10.0	318.8
Without V2G (MW)	10,920.0	9139.4	2470.0	2600.0	1289.8	331.7	225.0	82.9	20.0	10.0	0.0
V2G effect (MW)	0.0	−201.6	−130.0	130.0	−47.9	−49.3	0	−9.9	0.0	0.0	318.8

Notes: V2G effect = results with V2G − results without V2G. Usually a negative value of V2G effect indicates an expensive or more polluting unit.

in the system. In this instance U-1, U-7, U-9 and U-10 produce same constant powers, as U-1 is the cheapest unit and it always generates maximum power; however, U-7, U-9 and U-10 are expensive and they generate minimum power whenever they are committed. U-2, U-3, U-5, U-6 and U-8 generate less power (negative value of V2G effect) when V2G is considered, because they are either (relatively) costly or more polluting units. In this instance U-4 generates more power (positive value of V2G effect) when V2G is considered, because the proposed method makes balance between the cost and emission, and it satisfies all the constraints of the system.

Number of vehicles connected to grid is not directly proportional to the load demand. Schedule of vehicles (amount of power delivered from V2G) depends on non-linear price curves, emission curves, load demand, constraints, fitness function and balance between cost and emission. The proposed method can handle these factors efficiently and results are shown in Tables 1, 3 and 4. When only cost is considered, most of the vehicles are connected at peak loads or concentrated at peak hours (see Table 3) where high correlation between load demand and delivered power from V2G is 0.70305. However, vehicles are intelligently distributed (not concentrated) during 24-h scheduling period where load demand and delivered power from V2G are weakly correlated (0.079289) to make balance between cost and emission (see Table 1). Fig. 9 shows this fact visually where both cost and emission are minimized.

Regarding the optimization algorithm, the proposed method solves UC with V2G problem efficiently. Stochastic results are shown in Table 6. The best, worst, and average findings of the proposed method from 10 runs are reported together. Two sets of data are given at each entry of the tables, as both cost and emission are considered in the fitness function. First set is for cost and second set is for emission. In each set, first element is the production cost and second element is emission for the production cost. For 10-unit system with 50,000 vehicles and 10% spinning reserve, best results is \$559,685 production cost with 255,764 tons emission or \$560,254 production cost with 255,206 tons emission. Both are considered as best because first one is the lowest production cost and second one is the lowest emission. Results of different systems are also included in Table 6. For 20-unit system, the base 10-unit system is duplicated (copied 2 times) and the load demand is multiplied by two. The system converges for both small and large units. According to Table 6, a system with 5% spinning reserve needs less production cost than the same system with 10% spinning reserve; however, emission is near about the same and sometimes it is even higher because emission coefficients of U-3 and U-4 are much higher than others. The system with lower spinning reserve (e.g., 5%) has lower

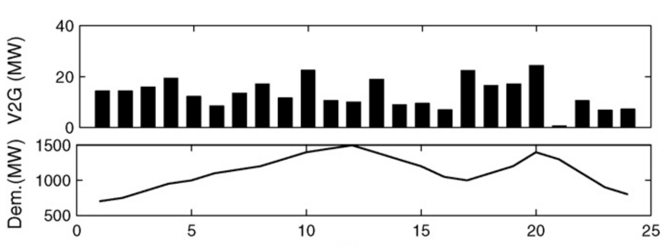

Fig. 9. Power delivered from V2G.

running cost; however, it is less reliable. The proposed method is a generalized optimization method for UC with V2G. Thus it can handle a new UC–V2G system of different input characteristics and constraints.

So the system always converges. 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 (see Figs. 2, 6 and 7). Therefore, the proposed PSO holds the above fine-tuning characteristic of a good optimization method. The method is stochastic; however, variation of results at different time is tolerable and results are not biased. These facts strongly demonstrate the robustness of the proposed method for optimization of both cost and emission in UC with V2G.

Table 7 shows the comparison of the proposed method to recent methods, e.g., integer-coded GA (ICGA) reported in Ref. [7], Lagrangian relaxation and genetic algorithm (LRGA) reported in Ref. [9], genetic algorithm (GA), dynamic programming (DP) and Lagrangian relaxation (LR) reported in Ref. [10], evolutionary programming (EP) reported in Ref. [11], and hybrid particle swarm optimization (HPSO) reported in Ref. [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 7, because (a) the DP cannot search all the states of the V2G scheduling; (b) it is very difficult to obtain feasible solutions and to minimize the duality gap in LR for V2G scheduling; (c) most of the cases, SA generates random infeasible solutions in each iteration by a random bit flipping operation from the huge matrix of UC with V2G; (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 6 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 (moderate speed) system. Execution time is acceptable, as it is in second. Execution time does not vary too much because swarm size and number of iterations are the same for all the systems. However, it is faster when gridable vehicles are considered because ED is the most computational expensive part of UC with V2G and less amount of power will be dispatched from generating units which is usually faster to calculate when gridable vehicles are connected. 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 the proposed method.

Battery size of an EV is larger than that of a HEV/PHEV. Performance of each EV and HEV/PHEV affects the results of UC with V2G. Results considering EVs (25 kWh each for around 100 miles drive) or HEVs/PHEVs (average 10 kWh) are shown in Table 8. Emission

Table 6
Test results of the proposed PSO for UC with V2G.

System	Total cost/emission				Execution time		
	Best (cost, emission)	Worst (cost, emission)	Average (cost, emission)	Std. dev. (cost, emission)	Maximum (s)	Minimum (s)	Average (s)
10% spinning reserve							
10-unit with 50,000 vehicles	($559,685, 255,764 ton) [a] ($560,254, 255,206 ton) [b]	($560,254, 255,206 ton) ($559,685, 255,764 ton)	($560,094, 255,448 ton)	($213.2, 258.1 ton)	28.84	27.19	28.22
10-unit without vehicles	($565,356, 260,735 ton) ($565,949, 259,711 ton)	($565,949, 259,711 ton) ($565,888, 260,666 ton)	($565,740, 260,097 ton)	($277, 485.8 ton)	34.98	33.03	34.68
20-unit with 100,000 vehicles	($1,115,572, 516,563 ton) ($1,116,486, 513,695 ton)	($1,116,724, 514,050 ton) ($1,115,572, 516,563 ton)	($1,116,111, 515,111 ton)	($452, 1138 ton)	33.52	31.50	32.74
20-unit without vehicles	($1,128,196, 523,035 ton) ($1,129,042, 521,243 ton)	($1,129,042, 521,243 ton) ($1,128,667, 523,443 ton)	($1,128,720, 522,173 ton)	($395, 986 ton)	39.28	37.20	38.09
5% spinning reserve							
10-unit with 50,000 vehicles	($553,090, 255,760 ton) ($553,636, 255,186 ton)	($553,636, 255,186 ton) ($553,090, 255,760 ton)	($553,385, 255,594 ton)	($241.1, 303.2 ton)	28.23	27.66	27.92
10-unit without vehicles	($558,757, 259,867 ton) ($559,568, 259,086 ton)	($559,568, 259,086 ton) ($559,070, 259,870 ton)	($559,131, 259,677 ton)	($358, 488 ton)	33.19	32.42	32.71
20-unit with 100,000 vehicles	($1,102,742, 516,045 ton) ($1,103,188, 510,581 ton)	($1,103,188, 510,581 ton) ($1,103,302, 517,098 ton)	($1,103,077, 514,574 ton)	($274.7, 2929.1 ton)	31.05	29.41	30.68
20-unit without vehicles	($1,112,294, 526,909 ton) ($1,112,942, 521,308 ton)	($1,112,942, 521,308 ton) ($1,112,294, 526,909 ton)	($1,112,610, 523,742 ton)	($290.1, 2868.3 ton)	37.82	36.04	37.32

[a] Best value for cost.
[b] Best value for emission.

and operation cost are lower; and maximum system capacity and average reserve are higher when EVs are considered in the system. However, EVs are more costly than HEVs.

5. Practicality of V2G for UC

For future practical applications, number of gridable vehicles in an electric power network can be estimated analytically based on number of electricity clients (customers) in that network. An estimate of gridable vehicles from residential electricity clients may be computed as follows:

$$N_{GV} = NV_{UC-V2G} V_{REC} N_{REC} = \frac{NV_{UC-V2G} V_{REC} X_{RL} L_{min}}{AV_{HLD}} \quad (24)$$

$$AV_{HLD} = \frac{AV_{MEC}}{30 \times 24} \quad (25)$$

where N_{GV} is the number of gridable vehicles (GVs), NV_{UC-V2G} is the percentage of the number of registered GVs for participation in UC with V2G, V_{REC} is the average number of gridable vehicles per residential electricity client, N_{REC} is the number of residential electricity clients, X_{RL} is the percentage of residential loads in the power network, L_{min} is the minimum load in the power network at given time (MW), AV_{HLD} is the average hourly load demand per residential electricity client (kW), and AV_{MEC} is the average monthly electricity consumption per residential electricity client (kWh).

For example: the minimum load, L_{min}, in the 10-unit benchmark system considered in this paper is 700 MW [14]. It can be taken that the average monthly electricity consumption, AV_{MEC}, of a domestic home is about 1500 kWh [31]. Thus average hourly electricity load of a residential client, AV_{HLD}, is 2.0833 kW. If we assume that $X_{RL} = 30\%$, the total number of clients in the region N_{REC}, is 100,801.6 and it can be rounded to 100,000 for simplicity. It is reasonable to assume that in the future, in United States, $V_{REC} = 1$, i.e., on average there will be one gridable vehicle per residential electricity client, and $NV_{UC-V2G} = 50\%$, i.e., 50% register to participant in "UC with V2G". Thus, N_{GV} from (24) is 50,000 and there are a reasonable number of vehicles to be considered on the 10-unit benchmark system for our simulation studies. Likewise, the 20-unit system (double the size of the 10-unit system) with 100,000 gridable vehicles is considered in this paper to show scalability.

The average distance driven with a vehicle is about 20,000 km per year [32], thus each day a vehicle covers an average distance of 54.79 km (20,000/365) and takes roughly less than 2 h of travel time. Therefore, it can be said that on average a vehicle is on the road less than 10% of a day and it is parked more than 90% of a day, either in a parking lot or in a home garage. Vehicles can be controlled in UC with V2G during the 90% time of a day using an automatic intelligent agent when they are parked. It is difficult to determine whether a particular vehicle will be parked or on the road at a particular time. Thus in this model, an individual vehicle is not scheduled. However, UC with V2G determines number of vehicles that need to be connected every hour for 24 h. It is logical that most of the vehicles are parked and depending on the UC with V2G schedule, committed number of vehicles (not specific vehicles) is discharged using an intelligent autonomous agent, as enough number of gridable vehicles is in parking lots or in home garages. Instead of considering individual vehicle, aggregation of vehicles can solve the discharging control problem of mass number of vehicles in UC with V2G. For reliable control operations, maximum number of discharging vehicles limit constraint, given in (10), is imposed so that number of scheduled vehicles at each hour is not too high with respect to the total number of vehicles in the system, which is easy to control. In order to illustrate the concept in this paper, maximum 10% of the vehicles are scheduled for discharging at each hour. This percentage can be made to vary every hour depending on system,

Table 7
Comparison of total running cost – ICGA, LRGA, GA, DP, LR, EP, AG, HPSO and the proposed PSO for 10-unit system.

	Total cost ($)														
	ICGA			LRGA			GA			DP			LR		
	Best	Worst	Average	Best	Worst	Average	Best	Worst	Average	Best	Worst	Average	Best	Worst	Average
Without V2G	–	–	566,404	–	–	564,800	565,825	570,032	–	565,825	N/A	N/A	565,825	N/A	N/A
With V2G		–			–			–			–			–	

	Total cost ($)											
	EP			AG			HPSO			Proposed PSO		
	Best	Worst	Average	Best	Worst	Average	Best	Worst	Average	Best	Worst	Average
Without V2G	564,551	566,231	565,352	–	–	564,005	563,942	565,785	564,772	563,741.8	565,443.3	564,743.5
With V2G		–			–			–		554,509.5	559,987.8	557,584.4

desired reliability, and operators' demand. In Table 1, for the first hour, 2254 vehicles are scheduled for discharging and it is quite feasible that out of 50,000 vehicles at least 2254 vehicles will be parked at this hour and an intelligent autonomous agent (not traditional human control room operators) will be able to control the discharging of 2254 vehicles at the first hour. Similarly it is true for other hours. It is not necessary to control all the vehicles (e.g., 50,000 vehicles) at any given time; however, it is essential to control some percentage of vehicles at a time and this is possible. One vehicle may leave in the middle of the discharging operation and in this case, it will be substituted by another vehicle in a 'parking' status.

In the proposed model, only registered gridable vehicles will be able to participate in UC with V2G. These registered vehicles are in the 'parking' status when not in use (online), i.e., plugged to the grid in parking lots or in home garages when stationary. An intelligent autonomous agent will detect such vehicles when online and depending on their status and the current UC with V2G schedule, vehicles will be selected to discharge automatically using an automatic control system.

It has already been planned that one million plug-in hybrid and electric vehicles will be on the road by 2015 only in United States [33]. Success of the V2G technology depends on efficient scheduling of gridable vehicles when mass number of gridable vehicles will be on the road. Business models and profit for V2G has been reported in Ref. [26]. In this model, a data base will be maintained for the registered vehicles including charging–discharging history. Owners of the registered gridable vehicles will earn profit depending on the amount of charging–discharging from their vehicles. Therefore they will be encouraged to take part in the UC with V2G process by plugging in their vehicles and thus an automatic system will be able to control scheduled number of vehicles for charging–discharging operations. Systems with V2G will be more successful if real-time non-linear price rate (different at daytime and night) is applied for electric energy at different time of a day.

UC is usually carried out for a period of 24 h and it is noted from Table 6 that the execution time with the balanced hybrid PSO for UC with V2G problem on a 20-unit system with 100,000 vehicles is less than 40 s on a standard desktop personal computer (2.66 GHz CPU, 3 GB RAM). Besides, it is seen that the balanced hybrid PSO method always converges for UC with V2G. Thus, the UC with V2G is practically feasible. However, a small computing cluster based on graphic processing units (GPUs), e.g. a cluster of four GPUs, can speed up optimization by at least 50 times, thus reducing the execution time to less than a second, which is acceptable for all practical and real-time solutions for UC with V2G problems.

Table 8
'UC with V2G' with EVs versus HEVs.

Parameter	EV	HEV
Running cost ($)	556,552.02	560,917.79
Emission (ton)	256,178.95	258,136.03
Maximum capacity (MW)	1708.6	1678.4
Average reserve (MW)	234.06	207.31

6. Conclusion

This paper has made a bridge between researches on UC and V2G, and is the first one to propose UC with gridable vehicles which can be considered as small portable power plants. The V2G concept can be viewed for the smart grid as S3P. Intelligent unit commitment with V2G based on optimal operation cost and reduced emissions in power system has been presented. This complex UC with V2G optimization problem has been solved using a balanced hybrid PSO, handling variables in binary and integer form. The local and global search has been balanced, thus avoiding the possibility of missing the best solution. From the results presented, it is clear that UC with V2G reduces operational cost and emission. In addition, it increases profit, reserve and reliability. Finally, this study is a first look at UC with V2G and in future, there is enough scope to include other practical constraints of V2G technology and unit commitment for real-world applications.

Acknowledgements

This work is supported by the U.S. National Science Foundation (NSF) under NSF EFRI # 0836017 and the CAREER Grant ECCS # 0348221.

Appendix A. Emission characteristics

See Table A.1.

Emission penalty factor:

$$_{i} = \frac{\mathcal{FC}_i(P_i^{max})}{\mathcal{EC}_i(P_i^{max})} \$\,\text{ton}^{-1} \tag{A.1}$$

where $\mathcal{FC}()$ and $\mathcal{EC}()$ are cost and emission functions, respectively.

Table A.1
Generator emission coefficients.

Unit	˛$_i$ (ton h^{-1})	ˇ$_i$ (ton MW^{-1} h^{-1})	$_i$ (ton MW^{-2} h^{-1})
U-1	103.3908	−2.4444	0.0312
U-2	103.3908	−2.4444	0.0312
U-3	300.3910	−4.0695	0.0509
U-4	300.3910	−4.0695	0.0509
U-5	320.0006	−3.8132	0.0344
U-6	320.0006	−3.8132	0.0344
U-7	330.0056	−3.9023	0.0465
U-8	330.0056	−3.9023	0.0465
U-9	350.0056	−3.9524	0.0465
U-10	360.0012	−3.9864	0.0470

References

[1] T. Senjyu, K. Shimabukuro, K. Uezato, T. Funabashi, IEEE Trans. Power Syst. 18 (May (2)) (2003) 882–888.
[2] A.I. Cohen, M. Yoshimura, IEEE Trans. Power Appl. Syst. PAS-102 (February) (1983) 444–451.
[3] Z. Ouyang, S.M. Shahidehpour, IEEE Trans. Power Syst. 6 (August (3)) (1991) 1203–1209.
[4] S. Virmani, E.C. Adrian, K. Imhof, S. Mukherjee, IEEE Trans. Power Syst. 4 (November (4)) (1989) 1373–1380.
[5] J.J. Shaw, IEEE Trans. Power Syst. 10 (August (3)) (1995) 1329–1342.
[6] W.L. Peterson, S.R. Brammer, IEEE Trans. Power Syst. 10 (May (2)) (1995) 1077–1084.
[7] I.G. Damousis, A.G. Bakirtzis, P.S. Dokopoulos, IEEE Trans. Power Syst. 19 (May (2)) (2004) 1165–1172.
[8] T. Senjyu, A.Y. Saber, T. Miyagi, K. Shimabukuro, N. Urasaki, T. Funabashi, IEE Proc., Gen. Transm. Dist. 152 (September (5)) (2005) 705–713.
[9] C.-P. Cheng, C.-W. Liu, C.-C. Liu, IEEE Trans. Power Syst. 15 (May (2)) (2000) 707–714.
[10] S.A. Kazarlis, A.G. Bakirtzis, V. Petridis, IEEE Trans. Power Syst. 11 (February (1)) (1996) 83–92.
[11] K.A. Juste, H. Kita, E. Tanaka, J. Hasegawa, IEEE Trans. Power Syst. 14 (November (4)) (1999) 1452–1459.
[12] Y. Valle, G.K. Venayagamoorthy, S. Mohagheghi, J.-C. Hernandez, R.G. Harley, IEEE Trans. Evol. Comput. 12 (April (2)) (2008) 171–195.
[13] J. Kennedy, R.C. Eberhart, Proc. IEEE Conf. Syst. Man Cybern. (1997) 4104–4109.
[14] T.O. Ting, M.V.C. Rao, C.K. Loo, IEEE Trans. Power Syst. 21 (February (1)) (2006) 411–418.
[15] M. Dorigo, V. Maniezzo, A. Colorni, IEEE Trans. Syst. Man Cybern. Part B 26 (2) (1996) 29–41.
[16] M. Dorigo, L.M. Gambardella, IEEE Trans. Evol. Comput. 1 (1) (1997) 53–65.
[17] T. Satoh, K. Nara, IEEE Trans. Power Syst. 6 (May (2)) (1991) 850–857.
[18] A.H. Mantawy, Y.L. Abel-Mogid, S.Z. Selim, IEEE Trans. Power Syst. 14 (August (3)) (1999) 829–836.
[19] S. Labatt, R.R. White, Carbon Finance: The Financial Implications of Climate Change, John Wiley & Sons, Inc., Hoboken, NJ, 2007.
[20] N. Stern, The Stern Review: the economics of climate change, 2006. Available: www.sternreview.org.uk.
[21] G.K. Venayagamoorthy, G. Braband, Proceedings of the 17th World Congress, The International Federation of Automatic Control, Seoul, Korea, July 6–11, 2008, 2008.
[22] P. Venkatesh, R. Gnanadass, N.P. Padhy, IEEE Trans. Power Syst. 18 (May (2)) (2003) 688–697.
[23] M.A. Abido, IEEE Trans. Evol. Comput. 10 (June (3)) (2006) 315–329.
[24] 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.
[25] J. Tomic, W. Kempton, J. Power Sources 168 (June (2)) (2007) 459–468.
[26] W. Kempton, J. Tomic, J. Power Sources 144 (June (1)) (2005) 268–279.
[27] W. Kempton, J. Tomic, J. Power Sources 144 (June (1)) (2005) 280–294.
[28] B.D. Williams, K.S. Kurani, J. Power Sources 160 (September (1)) (2006) 446–453.
[29] B.D. Williams, K.S. Kurani, J. Power Sources 166 (April (2)) (2007) 549–566.
[30] W. Kempton, T. Kubo, Energy Policy 28 (1) (2000) 9–18.
[31] C. Roe, A.P. Meliopoulos, J. Meisel, T. Overbye, Proceedings of the IEEE Energy 2030, Atlanta, GA, USA, November 17–18, 2008, 2008.
[32] H. Lund, W. Kempton, Energy Policy 36 (September (9)) (2008) 3578–3587.
[33] B. Obama, J. Biden, New energy for America. Available: www.barackobama.com/pdf/factsheet_energy_speech_080308.pdf.