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A Triple State Time Variant Cost Function Unit Commitment with Significant Vehicle to Grid Penetration

Morteza Aien[1]*, Aboulfazl Esmaeili[2], Mahmud Fotuhi Firuzabad[3]

[1]Department of Engineering, Vali-E-Asr Rafsanjan University, Rafsanjan, Iran,aien@vru.ac.ir
[2]Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran

Abstract

Hastening the power industry toward smart operation juxtaposed with the unrivaled restructuring and privatization agendas, some of the ubiquitous smart grid advantages are glanced more and more. Recently, the vehicle to grid (V2G) technology, as one of these beneficial aspects, has found a worldwide attention due to its important advantages. The V2G technology can raise the system operation efficiency, if well committed. Unit commitment (UC) is an operation problem to find the optimal schedule of generation units. In a typical UC problem, the generation units have two operational states, producing power or not, while a V2G may have an additional state i.e. consuming power due to its capability of having bi-directional power flow. In this work, this feature is modeled by the third state i.e. -1 for V2G power consumption. In addition, this work considers different cost function coefficients for different time intervals. The binary particle swarm optimization (BPSO) method is used to solve this sophisticated problem. The proposed methodology is justified through two dimensionally different case studies. What makes the results particularly interesting is that when V2Gs are taken into account, the total operation cost of the system decreases and also the V2G owners can obtain considerable profits.

Keywords: Particle swarm optimization, plug-in electric vehicles, unit commitment, vehicle to grid.
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Nomenclature

The main symbols used in the manuscript are defined below for quick reference; others will be explained as required in the text.

A. Indices

h	Hydro units index, numbering from 1 to NH (total number of hydro units)
i	Thermal units index, numbering from 1 to NT (total number of thermal units)
t	Hour index, numbering from 1 to T
v	V2G parking index, numbering from 1 to NV

B. Variables

$PT(i,t)$	Generation of thermal unit i at time t [MW]
$PVG(v,t)$	Power production of v th V2G parking lot at time t [MW]
$PVD(v,t)$	Power consumption of v th V2G parking lot at time t [MW]
$U(i,t)$	On/Off status of unit i at time t
$X^{off}(i,t)$	Duration that thermal unit i is off until time t [hours]
$PH(h,t)$	Power production of h th hydro unit at time t [MW]
$EVS(v,t)$	PEV battery stored energy in v th V2G parking lot at time t [MWh]
$EVG(v,t)$	Energy production of v th V2G parking lot at time t [MWh]
$N^c(v,t)$	Number of charging PEVs in v th V2G parking lot at time t
$N^{dc}(v,t)$	Number of discharging PEVs in v th V2G parking lot at time t
$N^i(v,t)$	Number of idle PEVs in v th V2G parking lot at time t
$SOC(v,t)$	State of charge (SOC) of PEVs in v th V2G parking lot at time t [%]

C. Parameters

$a(i,t)$	No load cost coefficient of i th thermal unit at time t [$\$/h$]
$b(i,t)$	Linear cost coefficient of i th thermal unit at time t [$\$/MWh$]
$c(i,t)$	Quadratic cost coefficient of i th thermal unit at time t [$\$/((MW)^2h)$]
$c\_\cos t(i)$	Cold start-up cost of i th unit[$]
c_s_hour	Duration time that i th unit needs to up from cold status [hours]
$D(t)$	Total demand power at time t [MW]
$F^{\max}$	Maximum fuel consumption limit
$h\_\cos t(i)$	Hot start-up cost of thermal unit i [$]
$losses(t)$	Total system losses in time t [MW]
$MD(i)$	Minimum down time of i th unit [hours]
$MU(i)$	Minimum up time of i th unit [hours]
$N(v,t)$	Number of PEVs in v th V2G parking lot at time t
$P^{\min}(i)$	Minimum generation of i th unit [MW]
$P^{\max}(i)$	Maximum generation of i th unit [MW]
$P^{\max}(h)$	Maximum generation of h th hydro unit [MW]
$PVG^{\max}(v)$	Maximum generation limit of v th V2G parking lot [MW]
$PVG^{\min}(v)$	Minimum generation limit of v th V2G parking lot [MW]
$RD(i)$	Ramp down rate of i th unit [MW/min]
$RU(i)$	Ramp up rate of i th unit [MW/min]
$R(t)$	Total system reserve in time t [MW]
$MPD(t)$	Market price for V2G consumption power at time t [$/MWh]
$MPG(t)$	Market price for V2G generation power at time t [$/MWh]
$z(i)$	Number of prohibited zones of unit i
$\alpha c(i), \beta c(i), \gamma c(i)$	Emission cost function coefficients of i th thermal unit
$\alpha(i), \beta(i), \gamma(i)$	Emission coefficients of i th thermal unit
$\rho gt(t)$	Market factor for thermal generation
$\eta(v)$	Battery efficiency of v th PEV
$\rho r(t)$	Market factor for reserve at time t
$\rho gh(t)$	Market factor for hydro generation at time t
$\rho gv(t)$	Market factor for V2G generation at time t
$C(R(i,t))$	Reserve cost function of unit i [$]
EC	Emission cost function [$]
FC	Fuel cost function of a thermal unit [$]
$SD(i)$	Shut down cost function of i th unit [$]
$SU(i)$	Start- up cost function of i th unit [$]

1. Introduction

Unit commitment (UC) is one of the most challenging and ubiquitous techno-economic decision performing processes in power system operation problem. Its objective is to find an optimal schedule of generation units minimizing the operation cost to satisfy the requested demand, subject to some system and units' constraints. The UC problem has been solved in centralized power systems to determine when to startup or shutdown thermal and hydro units firstly. As the second part of its duty, it must dispatch online generators to meet the system demand and spinning reserve requirements while satisfying units' constraints over a specific short-term time interval, so that the total operation cost is minimized [1]. Generally, it is a nonlinear, mixed integer, non-convex and constrained optimization problem [2]. Till now, a variety of numerical optimization techniques which can be grouped in two main groups i.e. classical and meta-heuristic methods, have been used to solve this problem. Classical methods use mathematical expression of the problem to find the optimal solution such as dynamic programming (DP) [3], [4] and Lagrange relaxation (LR) [5], [6] among the rest. Meta-heuristic methods are methods such as genetic algorithm (GA) [7], taboo search (TS) [8], and particle swarm optimization (PSO) [9] - [12] methods. It could be argued that a classic method guarantees to reach the optimal solution but by the cost of execution time. On the contrary, meta-heuristic methods have less computational burden but do not guarantee to reach the optimal solution [13].

According to the environment friendly policies which force the power industry to go toward the restructuring and reregulation, the smart grid concepts are highlighted more and more. The demand response (DR), demand side management (DSM), and electric vehicles (EVs) integration to the power grid can be named as some of the opportunities for potential environmental impacts of the smart grids [14]. Vehicle to grid (V2G) is one of the most important issues among these key opportunities. As V2Gs can receive/inject energy from/to grid, they have received worldwide attention in recent years. However, efficient V2G-parking scheduling results in: reduce the dependencies on small expensive units, their stored energy decreases running costs and increases spinning reserve, efficiently managing the load and renewable energy generation fluctuation, emission effects and cost deceleration [14], [15]. Increasing the number of plug-in electric vehicles (PEVs) in the transportation system, V2G-parkings seem the same as generation resources with the exception that a V2G-parking can have three states: consuming energy, generating energy and idle states. In the traditional UC problem, thermal units have only two states, being on (1) or off (0). Therefore, a new state can be introduced in the UC problem considering V2G technology. Hence, the UC problem with V2G will be more complex than the traditional one. In [10], the PSO method is used to solve the UC problem considering V2G technology. Simulation results show considerable profits for using V2G technology. In [16], the integration of aggregated PEV fleets and renewable energy resources is studied using stochastic security constrained unit commitment (SCUC) in which the Monte Carlo method is used to model the uncertainties. The role of PEV aggregators as a source of spinning reserve in power systems is studied in [17]. In [11], the PSO method is used to study on the problem of optimal V2G charge/discharge scheduling in constrained parking lots. The effect of PEVs on the cost-based UC problem is investigated in [15]. In [18], a PSO-based methodology for cost and emission optimization in modern power systems UC problem considering V2G technology is proposed. According to the reviewed literature, the PSO method can be used to solve UC with V2G problem. It can reliably and accurately solve very complex constrained optimization problems without any dimension limitation [9]-[12]. It can solve very big problems without any physical computer memory limits [10], [11]. Based on these features, PSO is used for solving the UC problem in a context of V2G.

In this work, it is for the first time proposed to model the V2G behavior in the UC problem using the following three states: generating energy by 1, idle state by 0 and consuming energy by -1. Secondly, it suggests using the real time market price for V2G energy transactions. Note that in this work, the energy consumption of PEVs for transportation purpose is also considered. Generally, the system load and market price are considered to be time variant. Furthermore, the time variable can influence the operation cost and the market price in another manner. There are many countries around the world having different climate regimes. In some regions, the temperature variations during a day and night are significant, where power plant efficiencies may change within a daily period [19], [20]. As a general rule, reduction of efficiency at hot hours of day leads to operation cost increase. So, as the third part of contribution, this work considers this cost increase by variation of cost functions coefficients during the hot hours. On the other hand, this work considers different cost function coefficients for different time intervals.

2. UC Problem Considering V2G Technology

Unit commitment relates to the optimal scheduling on/off status of power system generation resources in a given time horizon. With development of smart grid and V2G technology concepts, PEV owners can make profit by charging their batteries in off peak times and inject power to the grid at the peak times. V2G technology has some important advantages including: reduce dependencies on small expensive units, decrease power system operation cost , load profile management, increasing spinning reserve and reliability, reduction of fuel consumption and pollution emission , among the rest [10], [11]. In order to utilize these opportunities, the system operator must control V2G behavior [10], [11], [16], [21]-[23]. To this end, the system operator must consider it in the UC problem. In contrast to the thermal units, V2Gs have three states; receiving power from the grid or consumption state that we propose to model by -1, idle state by 0 and finally inject power to the grid or generation state that is modeled by 1. Hereby, UC problem with V2G is more complicated than the routine UC problem. It tackles to intelligently scheduling thermal and V2G-based units so that minimum operation cost and optimal condition for PEV owners can be achieved.

A) *Objective Function*

The objective function of this problem consists of the fuel cost, start-up cost, shut down cost, emission cost, and reserve cost as the following [10]:

Fuel cost of a thermal unit is usually expressed as a second order function of the unit output power as:

$$FC(i,t) = [a(i,t) + b(i,t) \times PT(i,t) + c(i,t) \times PT^2(i,t)\ ]U(i,t) \quad (1)$$

Start-up cost for restarting a decommitted thermal unit relates to the boiler temperature. The cold startup needs more fuel to warm up the boiler. In contrast, in the hot startup less energy is required to restart the unit. Here, the start-up cost for PEVs is considered to be zero.

$$SU(i,t)=\begin{cases} h\_\cos t & if \quad MD(i)\le X^{off}(i,t)\le T^{off}(i) \\ c\_\cos t & if \quad X^{off}(i,t)>T^{off}(i)\end{cases} \quad (2)$$

$$T^{off}(i)=MD(i)+c\_s\_hour(i) \quad (3)$$

Equation 3 represents the time that a unit has been off when is started from cold situation. When decommitting a unit, a shutdown cost, i.e. $SD(i)$ can be applied. The emission cost of generating power can be applied in the cost function as the external cost:

$$EC(PT(i,t))= [\alpha c(i)+\beta c(i)\times PT(i,t)+\gamma c(i)\times PT^2(i,t)]U(i,t) \quad (4)$$

The units can offer their surplus capacity in the reserve market with a reserve cost, i.e. $C(R(i,t))$ to achieve profit.

Therefore, the objective function of UC in presence of V2G penetration is as follows [10]:

$$Min\left[\sum_{t=1}^{T}\left\{\begin{array}{l}\sum_{i=1}^{NT}\left\{\rho gt(t)\begin{bmatrix}[FC(PT(i,t))+SU(i,t)\\+EC(P(i,t))]\\+SD(i,t)\times(1-U(i,t))\\+(1/\rho gt(t))\rho r(t)\times C(R(i,t))\end{bmatrix}U(i,t)\right\}\\+\sum_{h=1}^{NH}\left\{\rho gh(t)\begin{bmatrix}SU(h,t)\times U(h,t)\\SD(h,t)\times(1-U(h,t))\end{bmatrix}U(h,t)\right\}\\+\sum_{v=1}^{NV}\left\{\rho gv(t)\begin{bmatrix}MPG(t)\times PVG(v,t)\\-MPD(t)\times PVD(v,t)\end{bmatrix}U(v,t)\right\}\end{array}\right\}\right] \quad (5)$$

B) *Constraints*

The generated power by committed units must be equal to sum of the demanded load and total losses, which can be formulated as the following:

$$\left\{\begin{array}{l}\sum_{i=1}^{NT}[PT(i,t)\times U(i,t)]\\+\sum_{h=1}^{NH}\left[PH(h,t)\times U(h,t)\right]\\+\sum_{v=1}^{NV}[PVG(v,t)\times U(v,t)]\end{array}\right\}=\left\{\begin{array}{c}D(t)+losses(t)\\+\sum_{v=1}^{NV}\left[PVD(v,t)\times U(v,t)\right]\end{array}\right\} \quad (6)$$

Maintaining the system reliability requires a specific value of reserve all the time that can be formulated as:

$$\sum_{t=1}^{T}\left\{\begin{array}{c}\sum_{i=1}^{NT}[P^{\max}(i)\times U(i,t)]+\sum_{h=1}^{NH}[P^{\max}(h,t)\times U(h,t)]\\+\sum_{v=1}^{NV}\left[PVG^{\max}(v,t)\times U(v,t)\right]\end{array}\right\}\ge \sum_{t=1}^{T}\left\{\begin{array}{c}\sum_{v=1}^{NV}[PVD(v,t)\times U(v,t)+R(t)]\\+losses(t)+D(t)\end{array}\right\} \quad (7)$$

Each unit must generate within its operation limits as:

$$P^{\min}(i)<P(i,t)<P^{\max}(i) \quad (8)$$

Commitment/decommitment time of each unit should be more than its minimum up/down time.

$$\begin{cases}[X^{on}(i,t)-MU(i)]\times[U(i,t-1)-U(i,t)]\ge 0\\ [X^{off}(i,t-1)-MD(i)]\times[U(i,t-1)-U(i,t)]\ge 0\end{cases} \quad (9)$$

Each unit can increase/decrease its generation in a time interval according to its ramp up/down rate:

$$\begin{cases}P(i,t)-P(i,t-1)\le RU(i); \quad if\ P(i,t)\ge P(i,t-1)\\ P(i,t-1)-P(i,t)\le RD(i); \quad if\ P(i,t-1)\ge P(i,t)\end{cases} \quad (10)$$

At the system operation interval, a minimum reserve capacity must be provided by the committed units.

$$\sum_{i=1}^{NT}R(i,t)\ge R^{\min}(t) \quad (11)$$

$$F(i,t)\le F^{\max}(i) \quad (12)$$

$$E(P(i,t))\le E^{\max} \quad (13)$$

$$E(PT(i,t))= [\alpha(i)+\beta(i)\times PT(i,t)+\gamma(i)\times PT^2(i,t)]U(i,t) \quad (14)$$

The sum of PEVs at different modes at each hour must be equal to the total number of V2Gs of the system.

$$N^c(v,t)+N^{dc}(v,t)+N^i(v,t)=N(v,t) \quad (15)$$

V2Gs power generation/ consumption is as:

$$EV(v,t)=U(v,t)\begin{bmatrix}-PVD(v,t)\\VG(v,t)\times\eta(v)\end{bmatrix} \quad (16)$$

A minimum SOC of V2Gs must be provided all the times:

$$SOC(v,t)\ge SOC^{\min}(v) \quad (17)$$

3. Particle Swarm Optimization Method

Particle swarm optimization (PSO) is a swarm based evolutionary algorithm [10]. In this method, each particle which is a potential solution moves in multi-dimensional problem space with a given velocity. Each particle updates its velocity according to its flying experiences and the others. The ith particle in swarm at iteration k has a position represented by a d-dimensional vector such as (18). Its velocity is calculated from (20); where $V_d(i,k)$ is the velocity of particle i in the dth dimension. The best position of particle i obtained until iteration k is named as particle best (PB) that represented by $PB(i,j,t,k-1)$. The best previous position among all the particles in iteration k is recorded and called global best (GB) that represented by $GB(j,t,k-1)$. Particles' position is updated by (21).

$$X(i,k)=\left[x_1(i,k),x_2(i,k),...,x_d(i,k)\right] \tag{18}$$

$$V(i,k)=\left[v_1(i,k),v_2(i,k),...,v_d(i,k)\right] \tag{19}$$

$$\begin{aligned}&V(i,j,t,k)=w\times v(i,j,t,k-1)\\&+c_1\times rand_1\times[PB(i,j,t,k-1)-x(i,j,t,k-1)]\\&+c_2\times rand_2\times[GB(j,t,k-1)-x(i,j,t,k-1)]\end{aligned} \tag{20}$$

$$x(i,j,t,k)=x(i,j,t,k-1)+v(i,j,t,k) \tag{21}$$

It must be noted that in (20), $v(i,j,t,k-1)$ is the particle's current velocity and the second term indicates the cognitive part of PSO in which the given particle updates its velocity based on its own experiences. The social part of PSO is given by the third part in which the particle uses the experiences of other particles to update its velocity [10]. Specific weights are devoted to each term. Note that i indicates particle number, j represents generating unit/vehicle, t is the time and k shows the iteration.

C) *Binary PSO for Generation Units*

As the original PSO is a real-valued method, in [24] a method is proposed to extend it to binary space. In which, the authors squashed $v(i,j,t,k)$ using the following logistic functions to find whether $x(i,j,t,k)$ is in on or off state (o/1).

$$\Pr(v(i,j,t,k))=\frac{1}{1+e^{-v(i,j,t,k)}} \tag{22}$$

$$x(i,j,t,k)=\begin{cases}1, \; if \;\; u(0,1)<\Pr(v(i,j,t,k))\\0, otherwise\end{cases} \tag{23}$$

Where, $u(0,1)$ is a uniform random number in range of [0, 1].

4. Case Studies

The proposed method is validated in this section. To this end, a 6-bus test system with 3 generation units and a 118-bus system with 54 units are scheduled in a 24-hour horizon.

A) *The 6-Bus Test System*

This small system is the Wood & Woollenberg 6-bus system. Technical data of this system was taken from [25]. Additional required data are presented in Table 1. For the first case study, some sub-cases are defined to present the V2G effects on the UC problem. In cases with V2G, it is assumed that there are a number of PEVs that have two daily trips presented in Tables 2 and 3. Each V2G parking has various number of PEVs and min/max capacity of power generation and consumption according to its number of PEVs and the energy that PEVs need to trip. PEVs in each V2G parking have various trip patterns. For example, Tables 2 and 3 say that 240 PEVs in parking 1 at 5:00 A.M. travel toward parking 2 and arrive there at 6:00 A.M. These PEVs come back from parking 2 at 12:00 A.M. and arrive to parking 1 at 13:00 P.M. and so on. PEVs need various amount of energy for each trips pattern relating to the paths length. This means that each V2G parking consumes enough energy at suitable hours to charge PEVs so that PEVs in each V2G parking have enough energy for their trips. Amount of energy that each PEV needs to trip is taken from [16]. It is assumed to be a parking lot at each bus.

B) *The base case: No V2G penetration*

In this case, no V2G exists in the system. The load is assumed to have a trend in the scheduling time such as depicted in Fig. 1, with the peak load equal to 240 MW. We interest to find the optimal schedule of generation units. The total operation cost for this case is \$61673. The power generation of the units is depicted in Fig. 2. Inspecting the results more closely, it is obvious that the first unit is the marginal generation unit.

C) *The variable cost function coefficients-case#1*

The performance of power plant strongly depends on ambient air temperature. Mass flow rate of air decreases in hot hours for the same volumetric flow rate. This causes in reduced power output of turbine, increasing heat rate and consequently an increase in the operation cost [19], [20]. The approximated cycle efficiency of a power plant is expressed as:

$$\eta=1-\frac{T1}{T2} \tag{24}$$

Where, T1 and T2 are inlet and outlet air temperature to and from the compressor, respectively. Equation (24) certifies that the efficiency decreases with the increase in compressor inlet temperature. In this case, the intention is to assess the effect of this matter on the UC solutions. So, case 1 remains the same structure as the base case, except that fuel cost function coefficients are varied at hot hours of day in order to model the plant efficiency changes due to the ambient temperature variations. To this end, it is assumed that the variable cost coefficients, i.e. b and c of the second thermal unit is increased by 5% at hot hours of the day, i.e. from 12 A.M. to 4 P.M. Grid operation cost in this case is \$61926.76. The cost is expectedly more than the base case cost by about \$785.91, which is caused by coefficients variation of the second thermal unit. This means that in regions with high temperature difference between day hours such as day and night times, fuel cost differs from the cost that calculated with constant fuel cost coefficients.

The effect is shown in more detail in Fig. 3. It can be seen that in that hours, the second unit has not been committed due to its higher operation cost. Unit 1, the marginal unit of the base case, has been committed more in this case.

D) *V2G integration-Case#2*

In case 2, V2G parking lots are integrated to the grid. In this case, the plants cost function coefficients are considered to be fixed. Assume that V2Gs charge/discharge their energy at real time market price shown in Fig. 4. Note that the initial number of V2Gs in parking lots 1- 6 is assumed to be 1000, 1000, 1000, 0, 0, and 0 V2Gs, respectively.

The total operation cost in this case is \$59431.54 which has been lowered due to V2G integration by about \$2242.31 compared to the base case. Table 4 presents the on/off status of thermal units and V2G parking lots for this case. Figs. 5 and 6 present the power transactions of thermal units and V2G parking lots for this case, respectively. Note that in Fig. 6, positive values indicate power generation by V2G parking lots and negative values represent their power consumption. Fig. 6 pictorially shows that the V2Gs at parking lots charge in off peak hours and discharge their stored energy in peak hours and make profit.

E) *V2G integration with variable cost function of thermal units-Case#3*

Case 3 is the same as case 2 with the exception that the variation of cost function coefficients is considered. Hot hours are 12:00A.M. to 16:00P.M. again with 5% increase in the second unit cost function. Grid operation cost in this case is \$60763.54. Note that the total benefit obtained by V2G owners due to difference in real time market prices at different hours is \$1439.9 for this case.

F) *V2G encouragement with variable cost functions-Case#4*

Generally, the price signal is recognized as a control policy of the independent system operator (ISO) to manage the load pattern. Hereby, the energy price at different time instants is increased/ decreased to control the load level. So, case 4 is the same as case 3 with the exception that the price for peak time generation/ off peak consumption for V2Gs is different from the real time market price, i.e. in peak/off peak time the price of V2G generation/consumption is 10% over/under market price. Expectedly, this may help to better control the load pattern. Given these conditions, grid operation cost is \$60406.45. What makes the results particularly interesting is that the total operation cost for this case is lower than other cases with variable cost functions. Note that in all cases, the SOC constraint of V2Gs is considered. It must be noted that the maximum iterations and particle size of the method were chosen as 120 and 50, respectively. Note that comparison of the results of PSO method with those of dynamic programming (DP) method certified the accuracy of the PSO method with errors less than 5%.

G) *The IEEE 118-Bus Test System*

The second case study is the IEEE 118-Bus test system with 54 thermal units. Technical data about this system was taken from [26]. In this case study, it is again assumed that 6 V2G parking lots are located in 6 close buses, e.g. buses 82-87. For sake of simplicity and without loss of generality, it is assumed that V2Gs in parking lots have the same trip plan as the first case study and the initial number of V2Gs and the number of traveling V2Gs of Tables 2 and 3 have been multiplied by 8 for this case study. In this case, some subcases are defined again as bellow:

The base case: there are no V2Gs in this case. The total operation cost for this system is \$1519000.

Case 1: in this case, no V2G exists in the system and let assume that the cost functions of thermal units in buses 100, 103, 104, 105, 107, 110, 111, and 112 increase by 10% in hot hours, i.e. 12 A.M. to 16 P.M.. The total operation cost is \$1521700. As implied before, theses variations lead to cost increment.

Case 2: V2Gs exist in the system and the unit cost functions are fixed in the scheduling horizon. For this case, the total cost is \$1465100.

Case 3: the cost functions are the same as those of case 1 and V2Gs exist in the system. The total cost is \$1467300.

Case 4: the same as case 2 but let assume that price for generation at peak times and consumption at off peak hours are different from the real time market price, i.e. in peak time the price of V2G generation is 25% over real time market price and the price for V2G consumption in off peak hours is 25% lower than the real time market price. The total cost of this case is \$1455700. Expectedly, this case has the least cost among all cases.

Table.1.
Thermal Units Data- Case Study 1

Unit	*SU (\$)*	*SD (\$)*	*UP time (hours)*	*Down time (hours)*
1	100	40	4	3
2	200	60	3	2
3	80	10	2	1

Table.2.
PEVs First Trip Plan

Number of PEVs	Departure		Arrival	
	Time	Parking no.	Time	Parking no.
240	5:00	1	6:00	2
720	6:00	1	9:00	6
480	7:00	2	10:00	4
720	8:00	3	10:00	5
240	9:00	2	11:00	5

Table.3.
PEVs Second Trip Plan

Number of PEVs	Departure		Arrival	
	Time	Parking no.	Time	Parking no.
240	12:00	2	13:00	1
480	14:00	4	17:00	2
720	15:00	6	18:00	1
240	19:00	5	21:00	2
720	20:00	5	22:00	3

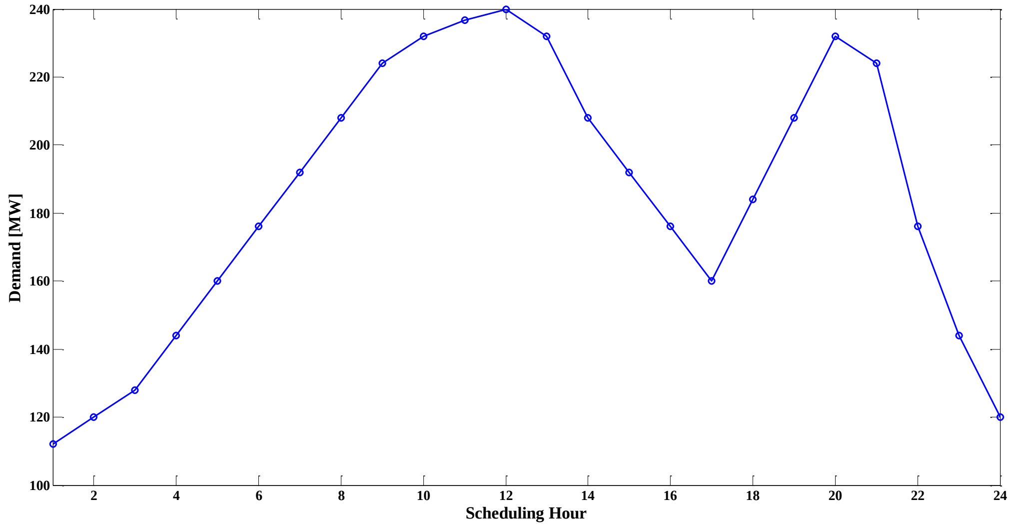

Fig. 1. The load pattern for the base case

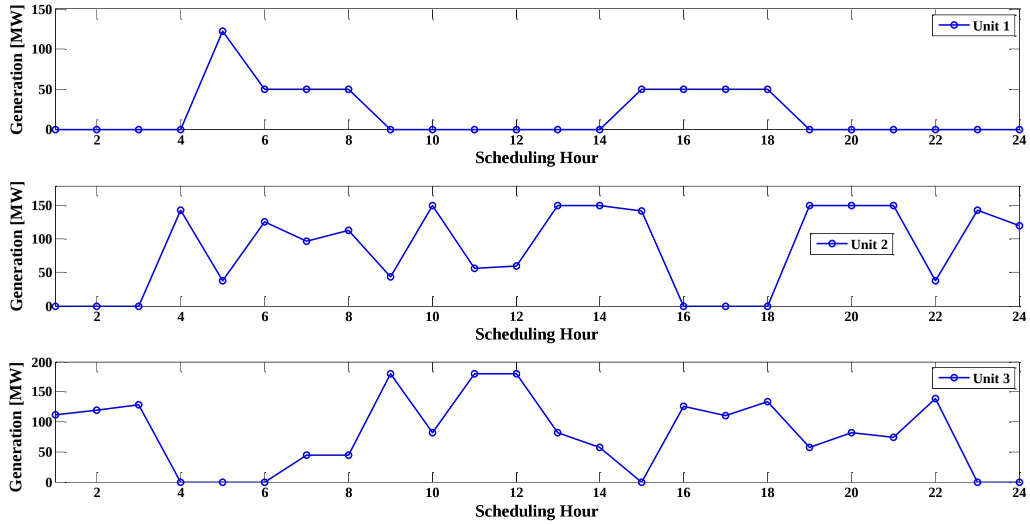

Fig. 2. Generating unit outputs for the base case

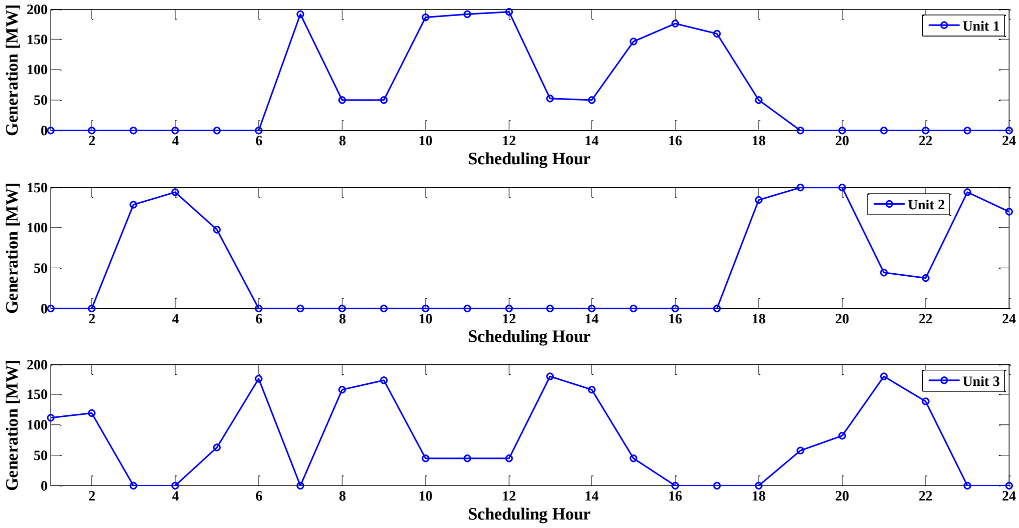

Fig. 3. Generated power of the units for case 1

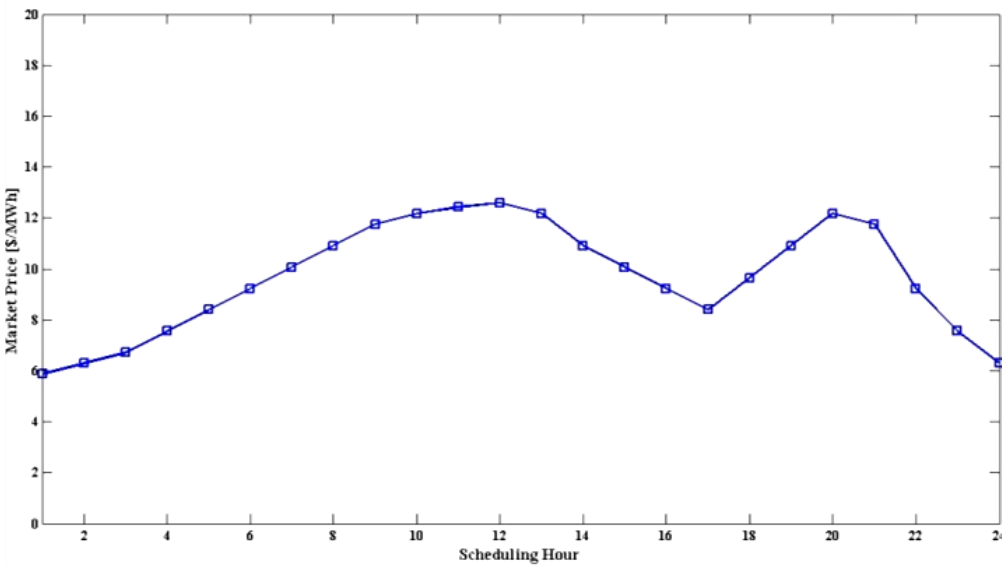

Fig. 4. The real time market price of case 2

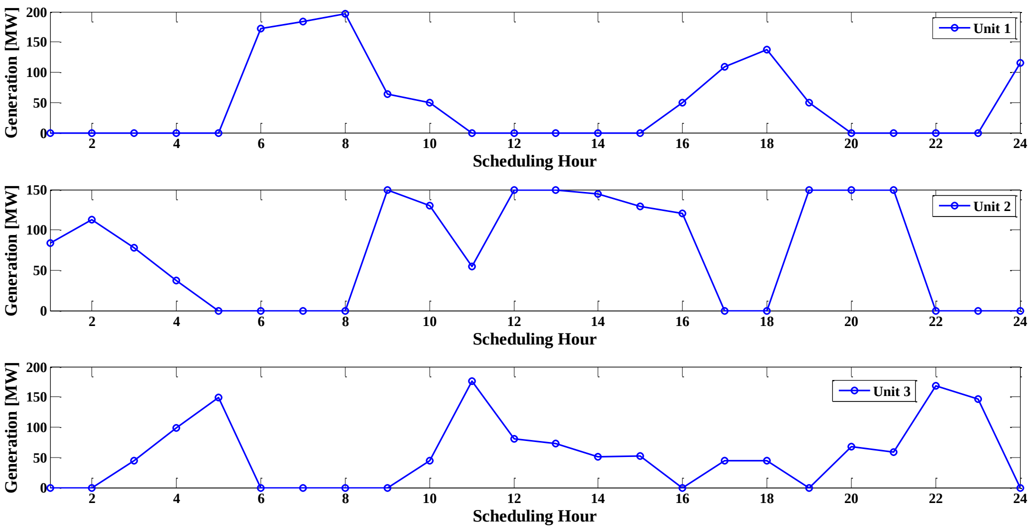

Fig. 5. Power generation of thermal units in case 2

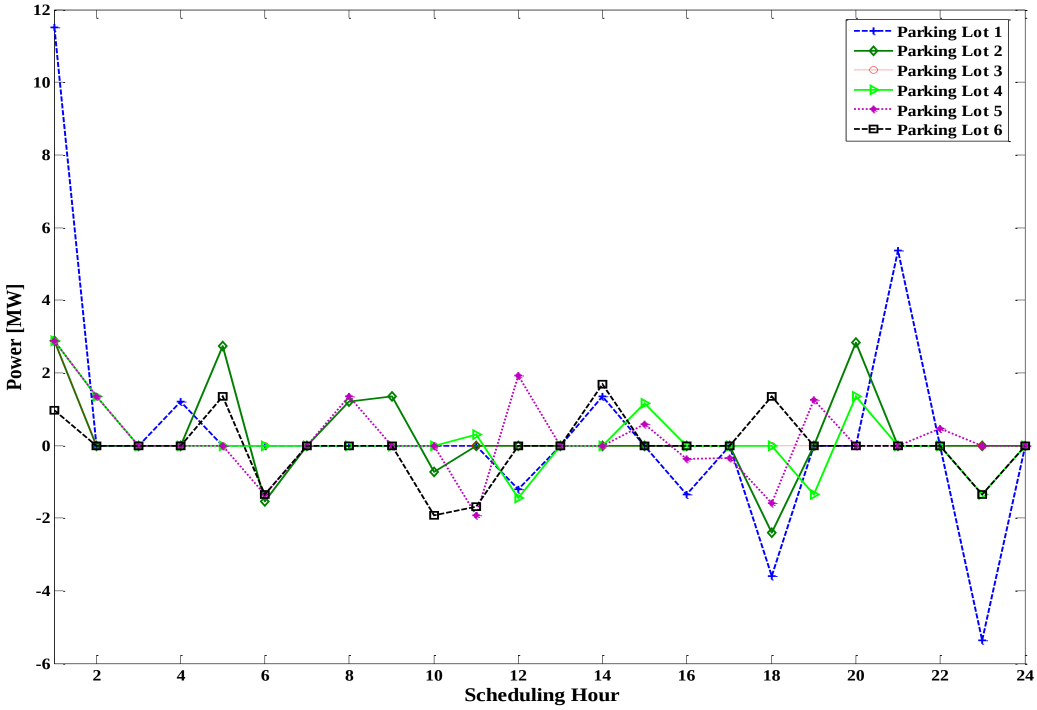

Fig. 6. V2G parking lots power generation/consumption- case 2

5. Conclusion

In this work, the unit commitment (UC) problem with vehicle to grid (V2G) penetration is solved by a binary and discrete particle swarm optimization (PSO) approach. Here, V2G is modeled by three states in the UC problem: generating power by 1, idle state by 0 and consuming power by -1. V2Gs in this study benefit from real time market price variations. This encourages V2G owners to charge in off peak hours and discharge in the peak load and consequently make profit due to spot price variations, taking into account their state of charge (SOC) limitations.

A number of V2G parking lots having different number of PEVs that travel in different paths at different times with different traveling times are considered. The proposed methodology is examined through two dimensionally different case studies including a 6-Bus system with three thermal units and a 118-Bus test system with 54 thermal units.

Taking into account the PEVs, the total operation cost of the system decreases and also the PEVs can obtain considerable profits due to variation of real time market prices. V2Gs can help the independent system operator (ISO) to control the load pattern. Variation of ambient temperature can affect the thermal units' efficiency and system operation cost. In this work, this issue is considered in the UC with V2G penetration problem.

Table.4.
Unit Status- Case 2

Hour/ Unit	***Thermal Unit no.***			***Parking Lot no.***					
	1	**2**	**3**	**1**	**2**	**3**	**4**	**5**	**6**
1	0	1	0	1	1	1	1	1	1
2	0	1	0	0	0	0	1	1	0
3	0	1	1	0	0	0	0	0	0
4	0	1	1	1	0	0	0	0	0
5	0	0	1	0	1	0	0	0	1
6	1	0	0	0	-1	0	0	-1	-1
7	1	0	0	0	0	0	0	0	0
8	1	0	0	0	1	0	0	1	0
9	1	1	0	0	1	0	0	0	0
10	1	1	1	0	-1	0	0	0	-1
11	0	1	1	0	0	0	1	-1	-1
12	0	1	1	-1	0	0	-1	1	0
13	0	1	1	0	0	0	0	0	0
14	0	1	1	1	0	0	0	0	1
15	0	1	1	0	0	0	1	1	0
16	1	1	0	-1	0	0	0	-1	0
17	1	0	1	0	0	0	0	-1	0
18	1	0	1	-1	-1	0	0	-1	1
19	1	1	0	0	0	0	-1	1	0
20	0	1	1	0	1	0	1	0	0
21	0	1	1	1	0	0	0	0	0
22	0	0	1	0	0	0	0	1	0
23	0	0	1	-1	0	0	-1	0	-1
24	1	0	0	0	0	0	0	0	0

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