

طريقة معتمدة لبرمجة الأعداد الصحيحة والمختلطة لتخطيط مشاركة الوحدات في نظام الشبكات الذكية

* ر. قديري اناري، ** م. رشيدى نجاد و *** م. فتوحى

* قسم الهندسة الإلكترونية لشعبة العلوم والدراسات بالجامعة الحرة الإسلامية في طهران.

** قسم الهندسة الإلكترونية في جامعة شهيد باهنر كرمان الإيرانية

*** المركز العالي لرقابة وإدارة نظام القوة للكهرباء بقسم الهندسة الإلكترونية في جامعة صنعتي شريف الإيرانية

خلاصة

إن أنظمة الطاقة المستقبلية المعروفة بالشبكات الذكية من المتوقع أن تحتوي مستويات أعلى من الذكاء وتتعامل مع معلومات وتكنولوجيا اتصالات جديدة في جميع مناحي شبكات الطاقة. إن مصادر متطلبات الإستجابة (DRR) وناقلات الطاقة تعتبران برنامجين يمكن إستخدامهما في محيط الشبكات الذكية. يمكن إستخدام (DRR) كموقع طلب لمحطة طاقة إفتراضية (مصدر) لزيادة الأمان والثقة بشبكة الخدمات ولها القابلية لتوفير فوائد كثيرة بتطوير الفعالية الإقتصادية في أسواق الكهرباء الإجمالية. ثم إعداد نموذج إقتصادي يتجاوب مع المعطيات ومبني علي المرونة في السعر ومتطلبات المستخدمين. وعلي الجانب الأخر يمكن إستخدام مركبات طاقة (GV) كمحطات طاقة متنقلة لتحسين الأداء وأمان محطات الطاقة. في هذه الورقة تم إستخدام برمجة للأعداد الصحيحة والمختلطة (MIP) لحل مشاركة الوحدة (UC) بإستخدام (DRR) و (GV). ثم تعديل المعادلة الموضوعية لتتضمن كلا العاملين السابقين. ثم تطبيق هذه الطريقة المقترحة في نظام وحدة ناقلة تحتوي علي عشر وحدات لبيان تأثير بيئة الشبكة الذكية علي مشكلة مشاركة الوحدة (UC) ومدى الإستفادة من تطبيق (DRR) و (GR) في سوق الكهرباء..

A mixed integer linear programming based approach for unit commitment in smart grid environment

R. GHADIRIANARI*, M. RASHIDINEJAD** AND M. FOTUHI-FIRUZABAD***

* *Department of Electrical Engineering, Tehran Science and Research Branch, Islamic Azad University, Tehran, Iran, ghadiri_reza@yahoo.com, Corresponding Author.*

***Department of Electrical Engineering, Shahid Bahonar University of Kerman, Kerman, Iran.*

*** *Centre of Excellence in Power System Control and Management, Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran.*

Abstract

The future of power systems known as smart grids is expected to involve an increasing level of intelligence and incorporation of new information and communication technologies in every aspect of the power grid. Demand response resources and gridable vehicle are two interesting programs which can be utilized in the smart grid environment. Demand response resources can be used as a demand side virtual power plant (resource) to enhance the security and reliability of utility and have the potential to offer substantial benefits in the form of improved economic efficiency in wholesale electricity markets. An economic model of incentive responsive loads is modelled based on price elasticity of demand and customers' benefit function. On the other hand, a gridable vehicle can be used as a small portable power plant to improve the reliability as well as security of the power system.

This paper formulates a mixed-integer programming approach to solve the unit commitment problem with demand response resources and gridable vehicles. The objective function of the unit commitment problem has been modified to incorporate demand response resources and gridable vehicles. The proposed method is conducted on the conventional 10-unit test system to illustrate the impacts of smart grid environment on the unit commitment problem. Moreover the benefits of implementing demand response resources and gridable vehicle in electricity markets are demonstrated.

Keywords: Demand response; mixed-integer programming; smart grid; unit commitment.

NOMENCLATURES

$A()$	Incentive of DR programs of an hour.	P_{GV}^{Max}	Maximum power obtainable from one GV.
$AS_m()$	Slope of segment m in linearized total incentive curve.	$PR_0()$	Initial electricity price of an hour.
$a(), b(), c()$	Fuel cost coefficients of a unit.	$PR()$	Spot electricity price of an hour.
$B_0()$	Customer's income of an hour when the demand is at nominal value.	$PEN(\Delta D())$	Total penalty for customers who do not curtail load according to predetermined contract level of an hour.
$B(D_{DR}())$	Customer's income of an hour after implementing DRPs.	$Pen()$	Penalty of an hour.
b_m	Slope of segment m in linearized fuel cost curve.	$p(\Delta D())$	Total incentive for customers of DRPs of an hour.
$D()$	Power demand of an hour.	$p_m()$	Generation of segment m in linearized fuel cost curve.
$D_{DR}()$	Power demand of an hour after implementing DRPs.	$q_m()$	Generation of segment m in linearized emission curve.
$E()$	Self and cross elasticity of an hour.	r, s	Coefficients to reinforce the effect of Penalty and award in incentive-based programs, respectively.
$Em()$	Emission function of a unit.	$RDR()$	Ramping down limit of a unit.
$\underline{Em}()$	Lower limit on the emission of a unit.	$RUR()$	Ramping up limit of a unit.
$e_m()$	Slope of segment m in linearized emission curve.	$S(D_{DR}())$	Customer's benefit of DRPs of an hour.
$F()$	Fuel cost function of a unit.	$SC_n()$	Cost of the interval n of the stairwise startup cost function of unit j .
$\underline{F}()$	Lower limit on the fuel cost of a unit.	$SU()$	Start-up cost of a unit.
$IC()$	Contract level of Incentive-based programs of an hour.	$SD()$	Shutdown cost of a unit.
i	Denotes a unit.	T	Number of hours for the scheduling period.
$MU(), MD()$	Minimum up/down time of a unit.	t	Hour index.
m	Segment index for linearized fuel cost and total incentive curve.	$TU(, 0), TC(, 0)$	Number of hours a unit has been on/off at the beginning of the scheduling period.

N	Number of units.	$UT()$, $DT()$	Number of hours a unit need to remain on/off if on/off at the beginning of the scheduling period.
N_{GV}	Number of gridable vehicles.	$u()$	Unit status indicator where 1 means on and 0 means off.
N_{GV}^{Max}	Maximum number of gridable vehicles.	$v_m()$	Award of segment m in linearized total incentive curve.
$NS()$	Number of segments for the piece-wise linearized total incentive curve.	W_E	Weight coefficient of emission in objective function.
$NSE()$	Number of segments for the piece-wise linearized emission curve.	W_F	Weight coefficient of generation cost in objective function.
$NSF()$	Number of segments for the piece-wise linearized fuel cost curve.	$y()$	Startup indicator.
n	Segment index for stair-wise emission curve.	$z()$	Shutdown indicator.
$P()$	Generation of a unit.	$\alpha()$, $\beta()$, $\delta()$	Emission coefficients of a unit.
$\underline{P}(), \overline{P}()$	Minimum/maximum generating capacity.	$\Gamma()$	Demand ratio parameter of an hour.
P_{GV}	Power obtainable from one GV.	η	The potential of DR programs implementation.

INTRODUCTION

Having effect on nearly every aspect of industrial productivity and daily life, the power industry – in terms of (a) economic importance and (b) environmental effect – is one of the most important sectors in the world. Unit Commitment (UC) involves the determination of on/off status of generation units and the value of generators power production to meet the forecasted demand for a specified time horizon (Afkousi-Paqaleh *et al.*, 2010). The optimal schedule should minimize the system production costs during the scheduling period, while satisfying load demand, spinning reserve requirements as well as physical and operational constraints of each individual unit (Cheng *et al.*, 2002; Hosseini *et al.*, 2007; Zhao *et al.*, 2006). Being a non-convex, mixed-integer combinatorial optimization problem several mathematical, heuristic and hybrid methods have been proposed for solving the UC problem. The mathematical approaches include priority list (PL), dynamic programming (DP), integer and mixed-integer programming (IP/MIP), linear programming (LP), branch and bound (BB) (Padhy, 2004; Ouyang & Shahidehpour, 1991; Tseng *et al.*, 2000; Li *et al.*, 1997; Ruiwei *et al.* 2013; Chaoyue *et al.* 2013). Due to some limitations in application and results of the mathematical methods heuristic approaches have been proposed (Swarup & Yamashiro, 2003; Kazarlis *et al.*, 1996; Huang, 2001; Mantawy *et al.*, 2002; Annakkage *et al.*, 1995; Sarjiya *et al.* 2013).

The Smart Grid is a set of software and hardware tools capable of routing power more proficiently, and therefore reducing the need for excess capacity and upgrade of the existing system. The main difference between the current grid and the smart grid is that the last is a transformed electricity and distribution network which uses two-way communications, advanced intelligent technologies to enhance the efficiency and reliability of power supply. Being equipped with ICT-based (Information and Communication Technologies) optimization technology, smart grids are capable of communicating with demand side loads that offer a variety of options to make the grid load and the production more predictable and adaptable (Battaglini *et al.*, 2009).

In these circumstances, Demand Response Programs (DRPs) are useful tools for the Independent System Operator (ISO), which can be activated within a relatively short time in case of critical system conditions. Federal Energy Regulatory Commission (FERC) reported the results of DR implementations in US utilities and power markets in August 2006 (FERC, 2006). DR can be classified according to how load changes are brought about. Based on the FERC report, DRPs are divided into two basic categories namely; Time-Based Rate (TBR) programs and Incentive-Based Programs (IBP). The aim is to make it attractive for customers to use less power during peak load periods (FERC, 2008). In DRPs, the customer signs a contract with the ISO or the local utility, to reduce its demand as and once requested. The utility benefit is reduction of its peak load and thus saving costly generation reserves, restoring quality of service, reducing environmental emission and reliability improvement. The customer benefits from DRPs are particularly from incentives provided by the local utility or ISO and also reduction in electricity bill. More detailed explanations about DRPs are provided in section II of this paper. In order to evaluate the impact of DRPs on the UC problem, developing of price responsive demand model is necessary. Economic models of price responsive loads for DRPs have been addressed in (Bompard *et al.*, 2007; Aalami *et al.*, 2008a; Aalami *et al.*, 2008b, Goel *et al.*, 2007; Yu & Yu, 2006; Goel *et al.*, 2006; Su & Kirschen, 2009; Pourmousavi & Nehrir, 2014; Zhanle *et al.*, 2013; Ma *et al.* 2013).

The focuses of Vehicle-to-Grid (V2G) researchers have mainly been on interconnection of energy storage of vehicles and grid (Kempton *et al.*, 2005; Tomic & Kempton, 2007; Kempton & Tomic, 2005a; Kempton & Tomic, 2005b; Williams & Kurani, 2006). Their aim is to educate about the environmental and economic benefits of V2G and improvement of the power market. However, success of V2G technology mainly depends on the efficient scheduling of Gridable Vehicles (GVs) considered restricted number of parking lots. Ideally speaking, gridable vehicles for V2G technology should be charged from renewable sources. A gridable vehicle can be considered as a small portable power plant (Saber & Venayagamoorthy, 2010b).

In this paper, UC problem in smart grid environment is investigated. DRPs and V2Gs are considered as the main programs of the smart grid. The economic model of price responsive loads for DRPs has been extracted by using the concept of “price

elasticity of demand” and “customers’ benefit function” as proposed in (Aalami *et al.*, 2010a; Aalami *et al.*, 2010b). It is considered that ISO prizes the customers for load reduction, but does not penalize their violence. Modeling V2G involves intelligently scheduling existing units and large number of gridable vehicles in limited and restricted parking lots.

A mixed-integer programming (MIP) framework is proposed in this study that formulates the unit commitment problem with DRRs and V2G. There is mathematical proof that the mixed-integer linear programming can render the optimum solution (Li & Shahidehpour, 2005). However, since there is a need for linearization of the offered cost curves, reaching the optimum solution of the original problem might not be feasible. A mixed-integer representation of IBPs and GVs has been modeled. The proposed model is used to determine loads provided by DRRs and schedule commitment status of generating units. The obtained results demonstrate that operation cost can be significantly reduced in the presence of DRPs and GVs with proper and intelligent optimization. The proposed approach is carried out on the conventional 10-unit test system to illustrate the influences of smart grid on the UC problem and electricity market.

SMART GRIDS

In this section DR and V2G programs as two of the main segments of the smart grids are discussed.

DEMAND RESPONSE PROGRAMS

Exploration of DRPs was assigned to the United States of America by strategic plan of International Energy Agency (IEA) (IEA, 2010). In the FERC report, DR is divided into two basic categories namely; TBR programs and IBPs. Each of these categories is composed of several programs as indicated in Fig.1. In TBR programs, Time of Use (TOU), Real Time Pricing (RTP) and Critical Peak Pricing (CPP), the electricity price changes for different periods according to the electricity supply cost.

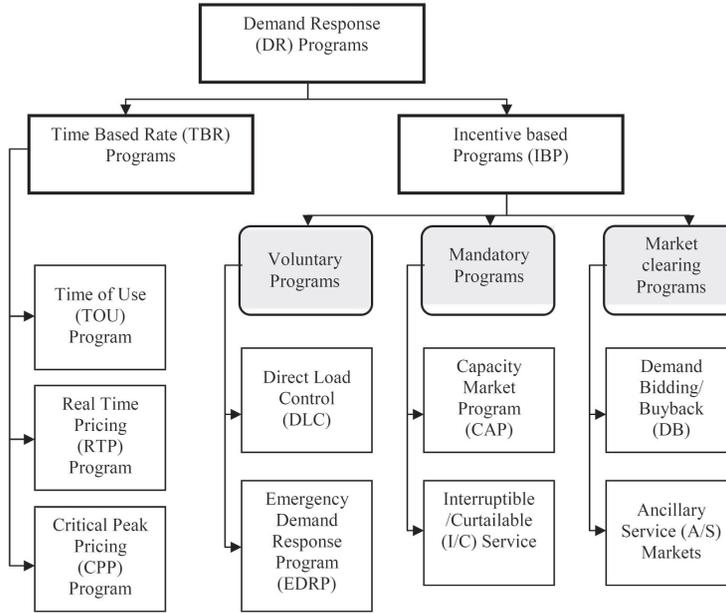


Fig. 1. Categories of demand response programs

In these programs there isn't any incentive or penalty for customer response. IBPs include, DLC, EDRP, Capacity Market Program (CAP), Interruptible/Curtailable (I/C) service, Demand Bidding (DB) and Ancillary Service (A/S) programs. The aforementioned programs can be classified into three main subgroups namely; voluntary, mandatory and market clearing programs. DLC and EDRP are voluntary programs and if customers do not curtail consumption, they are not penalized. I/C and CAP are mandatory programs and enrolled customers are subject to penalties if they do not curtail when directed. DB and A/S are market clearing programs, where large customers are encouraged to offer or to provide load reductions at a price at which they are willing to be curtailed and to identify how much load they would be willing to curtail at the posted prices. A/S programs allow customers to bid load curtailments in electricity markets as operating reserves. More detailed explanations of DRPs can be found in (FERC, 2006).

Vehicle-to-Grid

Plug-in Hybrid Electric Vehicles (PHEVs) are hybrid electric vehicles that can draw and store energy from an electric grid to supply propulsive energy for the vehicle energy consumption. This simple functional change enables a PHEV to displace energy from petroleum with multi-source electric energy (Quinn *et al.*, 2010). This has important

and generally beneficial influence on petroleum consumption, pollution, as well as on the performance and makeup of the electric grid. Because of these characteristics and their near-term availability, PHEVs are seen as one of the most promising means to enhance the sustainability of the energy sectors (Bradley & Frank, 2009).

Generally, PHEVs have many economic benefits and have a short payback period to the owners (Baha et. al. 2013a), they help improve the light duty vehicles fleets' fuel economy and decrease petroleum consumption considerably (Baha et. al. 2014) and are expected to have high penetration rate in the near future (Baha et. al. 2013b).

A widespread adoption of electric vehicles will need to be taken into account in all activities within power systems. However, some activities will more likely be subject to more severe modifications, in technical as well as in operational terms, than others. This can easily be understood since the vehicles will be connected to lower network levels and hence entities active on these levels will be affected more (Galus *et al.*, 2010). Among which UC problem is one of activities that is considerably influenced by the PHEVs.

PROPOSED MATHEMATICAL FRAMEWORK

Conventional Unit Commitment Formulation

UC involves determining generating outputs of all units from an initial hour to satisfy load demands associated with start-up and shut-down schedule over a time horizon. The objective function is to find the optimal schedule such that the total operating costs are minimized while satisfying the load demand, spinning reserve requirements, emission allowance limit as well as other operational constraints.

The objective function for unit commitment problem comprises the start-up costs, shut-down costs of de-committed units, the fuel costs as well as the emission level of generating units which can be presented as:

$$\begin{aligned}
 & \text{Min} \sum_{i=1}^N \sum_{t=1}^T [F(i, t)u(i, t) \\
 & + SU(i)u(i, t)(1 - u(i, t - 1)) \\
 & + SD(i)u(i, t - 1)(1 - u(i, t))]
 \end{aligned} \tag{1}$$

Responsive Load Economic Model

In order to evaluate the impact of participation of customers in DR programs on load profile characteristics, development of responsive load economic models are necessary. Scheppe and his co-workers formalized and developed the concept of

spot pricing of electricity in 1989. They envisaged a system where customers would adjust their demand up/down depending on the spot price (Schweppe *et al.*, 1989). Kirschen showed how this model could be taken into consideration when scheduling generation and setting the price of electricity in a pool based electricity market (Kirschen *et al.*, 2000). In the author's previous studies (Aalami *et al.*, 2010a; Aalami *et al.*, 2010b), economic model of responsive load by consideration of penalty and award has been presented. In this paper, the above models are developed which include variable penalties and awards based on the level of demand for customers in case of no responding and responding to load reduction respectively.

1) Price Elasticity of Demand

Elasticity is defined as the demand sensitivity with respect to the price (Kirschen & Strbac, 2005):

$$E(t, t) = \frac{P(t)}{D(t)} \frac{\partial D(t)}{\partial P(t)} \quad (2)$$

According to (2), the price elasticity of the t -th period versus j -th period can be defined as (Kirschen & Strbac, 2005):

$$E(t, j) = \frac{P(j)}{D(t)} \frac{\partial D(t)}{\partial P(j)} \quad (3)$$

2) Modeling of Single Period Elastic Loads

Suppose that the customer changes his demand from $D(t)$ (initial value) to $D_{DR}(t)$, based on the value which is considered for the incentive and the penalty mentioned in the contract.

$$\Delta D(t) = D_{DR}(t) - D(t) \quad (4)$$

If $A(t)$ \$ is paid as incentive to the customer in t -th hour for each MWh load reduction, the total incentive for participating in incentive-based programs will be as:

$$p(\Delta D(t)) = A(t)[D(t) - D_{DR}(t)] \quad (5)$$

If the customer who has been enrolled in the mentioned DR programs does not commit to his obligations according to the contract, he will be faced with penalty. The total penalty, will be accounted as following:

$$\text{PEN}(\Delta D(t)) = \text{pen}(t) \cdot \{IC(t) - [D(t) - D_{DR}(t)]\} \quad (6)$$

The flexible strategy of appropriating award and penalty in IBPs has been considered based on the level of demand. It means that the “demand ratio parameter” like $\Gamma(t)$ can be defined to classify the level of award and penalty for each hour of scheduling period as following:

$$\Gamma(t) = \frac{D(t)}{\text{Max}\{D(\tau)\}} \quad \tau \in \{1, 2 \dots t \dots T\} \quad (7)$$

Therefore, (8) and (9) can be modified as the following:

$$p(\Delta D(t)) = \Gamma^s(t)A(t)[D(t) - D_{DR}(t)] \quad \forall t \quad (8)$$

$$\text{PEN}(\Delta D(t)) = \Gamma^r(t)\text{pen}(t) \cdot \{\text{IC}(t) - [D(t) - D_{DR}(t)]\} \quad \forall t \quad (9)$$

The customer’s benefit, for the t -th hour will be as:

$$S(D(t)) = B(D(t)) - D(t)PR(t) + p(\Delta D(t)) - \text{PEN}(\Delta D(t)) \quad (10)$$

According to the classical optimization rules, to maximize the customer’s benefit, $\partial S/\partial D(t)$ should be equal to zero; therefore,

$$\frac{\partial S(D(t))}{\partial D(t)} = \frac{\partial B(D(t))}{\partial D(t)} - PR(t) + \frac{\partial p}{\partial D(t)} - \frac{\partial \text{PEN}}{\partial D(t)} = 0 \quad (11)$$

$$\frac{\partial B(D(t))}{\partial D(t)} = PR(t) + \Gamma^s(t)A(t) + \Gamma^r(t)\text{pen}(t) \quad (12)$$

The benefit function, most often used, is the quadratic benefit function (Schweppe *et al.*, 1989):

$$B(D(t)) = B_0(t) + PR_0(t)[D_{DR}(t) - D(t)] \left\{ 1 + \frac{D_{DR}(t) - D(t)}{2E(t)D(t)} \right\} \quad (13)$$

By differentiating the above equation and solving for $\partial B/\partial D(t)$ and substituting the result in (12) we will have:

$$PR(t) + \Gamma^s(t)A(t) + \Gamma^r(t)\text{pen}(t) = PR_0(t) \left\{ 1 + \frac{D_{DR}(t) - D(t)}{E(t)D(t)} \right\} \quad (14)$$

Therefore, customer’s consumption will be as following:

$$D_{DR}(t) = D(t) \left\{ 1 + E(t, t) \left[\frac{PR(t) - PR_0(t) + \Gamma^s(t)A(t) + \Gamma^r(t)\text{pen}(t)}{PR_0(t)} \right] \right\} \quad (15)$$

3) Modeling of Multi Period Elastic Loads

According to the definition of the cross elasticity in (3) with the linearity assumption we have:

$$\frac{\partial D(t)}{\partial PR(j)} : \text{Constant for } t, \quad j=1, 2 \dots 24 \quad (16)$$

Implying the linear relationship between prices and demands:

$$D_{DR}(t) = D(t) \left\{ 1 + \sum_{\substack{j=1 \\ j \neq t}}^{24} E(t, j) \cdot \frac{[PR(j) - PR_0(j) + \Gamma^s(j)A(j) + \Gamma^r(j)\text{pen}(j)]}{PR_0(j)} \right\} \quad (17)$$

4) Load Economic Model

By combining (16) and (17), we will have the responsive load economic model as following:

$$D_{DR}(t) = \eta D(t) \left\{ \begin{array}{l} 1 + E(t, t) \frac{[PR(t) - PR_0(t) + \Gamma^s(t)A(t) + \Gamma^r(t)\text{pen}(t)]}{PR_0(t)} \\ + \sum_{\substack{j=1 \\ j \neq t}}^{24} E(t, j) \frac{[PR(j) - PR_0(j) + \Gamma^s(j)A(j) + \Gamma^r(j)\text{pen}(j)]}{PR_0(j)} \end{array} \right\} \quad (18)$$

Gridable Vehicles Model

Only predefined registered/forecasted GVs are considered for determining the optimum solution (scheduling) in the UC problem. Total number of registered GVs is considered to be fixed and it is assumed that they were charged from renewable sources and not from the grids. All the vehicles will discharge to the grid during the scheduling period (Saber & Venayagamoorthy, 2010b).

$$\sum_{t=1}^T N_{GV}(t) = N_{GV}^{Max} \quad (19)$$

Vehicles are assumed to be charged from renewable sources and discharge to the grid. Multiple charging–discharging facilities of GVs may be available however since it is very dependent on life time and type of batteries. In this study, for sake of simplicity, charging–discharging frequency is one per scheduling horizon.

MIP-Based Unit Commitment with Demand Response and Gridable Vehicles

In this paper, we have focused on voluntary programs of DR. Hence, we assume “A” \$/MWh and zero \$/MWh as the value of incentive and penalty, respectively. In

other words, in these programs it is considered that ISO prizes the customers for load reduction, but does not penalize their violence.

$p(\Delta D(t))$ is a quadratic function of incentive which can be concluded from (5) and (17). Hence, the objective function is a nonlinear mixed-integer optimization problem that is difficult to solve by standard nonlinear programming methods. Next, we describe an alternative mixed-integer linear formulation, MILP-UC, suitable for available MILP software (Li & Shahidehpour, 2005; Carrión & Arroyo, 2006).

The MILP-based model of objective function for unit commitment problem with DR and GV can be formulated as:

$$\begin{aligned}
 \text{Min} \sum_{t=1}^T [& \sum_{m=1}^{NS(i)} v_m(t) AS_m(t) + \sum_{i=1}^N [\underline{F}(i) u_i(t) \\
 & + \sum_{m=1}^{NSF(i)} p_m(i,t) b_m(i) + SC_n(i) \left[u(i,t) - \sum_{n=1}^k u(i,t-n) \right] \\
 & - z(i,t) SD(i) \}] \quad (20)
 \end{aligned}$$

More explanation about each parameter of (18) is outlined in the following.

Fuel Cost

The quadratic fuel cost function typically used in scheduling problems can be formulated as:

$$F(i, t) = a(i) + b(i)P(i, t) + c(i)P^2(i, t) \quad (21)$$

The cost function in (21) can be accurately approximated by a set of piecewise blocks (Li & Shahidehpour, 2005). For practical purposes, the piecewise linear function is indistinguishable from the nonlinear model if enough segments are used. The analytic representation of this linear approximation is

$$\underline{F}(i) u_i(t) + \sum_{m=1}^{NSF(i)} p_m(i, t) b_m(i) \quad (22)$$

Start-up Cost

Since the time span has been discretized into hourly periods, the startup cost is also a discrete function. The discrete startup cost can be asymptotically approximated by a stair-wise function, which is more accurate as the number of intervals increases (Carrión & Arroyo, 2006). A mixed-integer linear formulation for the stair wise startup cost was proposed in (Carrión & Arroyo, 2006).

$$\begin{aligned}
 SU(i) \geq SC_n(i) \left[u(i, t) - \sum_{n=1}^k u(i, t-n) \right] \quad \forall i, \forall t \\
 \forall k = 1 \dots NS(i) \quad (23)
 \end{aligned}$$

$$SU(i) \geq 0 \quad \forall i, \forall t \tag{24}$$

Note that (23) and (24) only depend on the binary variables associated with the on/off status of generating units.

Shut-down Cost

Shut-down cost is constant for each unit and is modeled by using a shut-down indicator as presented in (18).

Total Incentive for Participation in DR Programs

As shown in Fig. 2, $p(\Delta D(t))$ is a quadratic function of incentive (25), which can be represented as a piecewise linear model (26):

$$p(\Delta D(t)) = A(t)A(t)f(D(t), t, E(t, j)) \tag{25}$$

$$\forall t, \forall j = 1 \dots T$$

$$p(\Delta D(t)) = \sum_{m=1}^{NS(i)} v_m(t) AS_m(t) \tag{26}$$

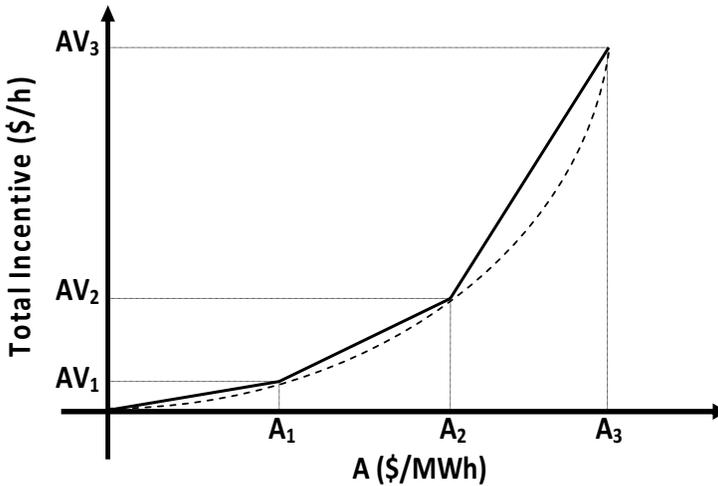


Fig. 2. Piecewise linear total incentive curve for an hour.

The objective function is subject to the following constraints.

Power supplied from committed units, GVs and DR resources must satisfy the load demand.

$$\begin{aligned}
 & \sum_{i=1}^N P(i,t)u(i,t) + P_{GV}N_{GV}(t) = (1-\eta)D(t) \\
 & + \eta D(t) \{1 + E(t,t) \frac{[PR(t) - PR_0(t) + \Gamma^s(t)A(t) + \Gamma^r(t)\text{pen}(t)]}{PR_0(t)} \\
 & + \sum_{\substack{j=1 \\ t \neq j}}^T E(t,j) \frac{[PR(j) - PR_0(j) + \Gamma^s(j)A(j) + \Gamma^r(j)\text{pen}(j)]}{PR_0(j)}\}, \\
 & \forall i, \forall t
 \end{aligned} \tag{27}$$

Unit output limit

$$\underline{P}(i,t)u(i,t) + \sum_{m=1}^{NSF(i)} p_m(i,t) \leq \overline{P}(i,t)u(i,t) \quad \forall i, \forall t \tag{28}$$

Ramping up/down constraints

$$P_i(t+1) - P_i(t) \leq RUR_i \quad \forall i, \forall t \tag{29}$$

$$P_i(t) - P_i(t+1) \leq RDR_i \quad \forall i, \forall t \tag{30}$$

Once a unit is committed, it must remain “on” for a minimum number of hours given in (31). Formulation of minimum on/off time constraints is given as (Li & Shahidehpour, 2005):

$$\sum_{t=1}^{UT(i)} (1 - u(i,t)) = 0, \quad \forall i \tag{31a}$$

$$y(i,t) + \sum_{m=t+1}^{\max[T, t+MU(i)-1]} z(i,m) \leq 1, \tag{31b}$$

$$\forall i, \forall t = UT(i) + 1, \dots, T$$

$$UT(i) = \text{Max}\{0, \text{Min}[T, MU(i) - TU(i,0)u(i,0)]\} \tag{31c}$$

Accordingly, if a unit is shutdown, it must remain “off” for a minimum number of hours given as (Li & Shahidehpour, 2005):

$$\sum_{t=1}^{DT(i)} u(i,t) = 0, \quad \forall i \tag{32a}$$

$$z(i,t) + \sum_{m=t+1}^{\max[T, t+MD(i)-1]} y(i,m) \leq 1, \tag{32b}$$

$$\forall i, \forall t = DT(i) + 1, \dots, T$$

$$DT(i) = \text{Max} \{0, \text{Min} [T, MD(i) - TC(i, 0)(1 - u(i, 0))]\} \quad (32c)$$

The relationship between startup and shutdown indicators and unit status is (Li & Shahidehpour, 2005):

$$y(i, t + 1) - z(i, t + 1) = u(i, t + 1) - u(i, t), \quad \forall i, \forall t \quad (33)$$

The hourly relationship among unit status, startup, and shutdown indicators is enforced by (33). A unit may not be started up and shut down at a given hour, therefore (Li & Shahidehpour, 2005):

$$\begin{aligned} y(i, t) + z(i, t) &\leq 1 \quad \forall i, \forall t \\ 0 &\leq z(i, t) \leq 1 \quad \forall i, \forall t \end{aligned} \quad (34)$$

Spinning reserve (SR) must be sufficient enough to maintain the desired reliability of a power system. SR is usually a pre-specified amount that is either equal to the largest unit or a given percentage of the forecasted load which can be given by the following equation:

$$\begin{aligned} \sum_{i=1}^N \overline{P}(i, t)u(i, t) + P_{GV}^{Max} N_{GV}(t) &\geq SR(t) + (1 - \eta)D(t) \\ + \eta D(t) \{1 + E(t, t) \frac{[PR(t) - PR_0(t) + \Gamma^s(t)A(t) + \Gamma^r(t)\text{pen}(t)]}{PR_0(t)} \\ + \sum_{\substack{j=1 \\ j \neq t}}^T E(t, j) \frac{[PR(j) - PR_0(j) + \Gamma^s(j)A(j) + \Gamma^r(j)\text{pen}(j)]}{PR_0(j)}\} & \quad (35) \\ \forall i, \forall t & \end{aligned}$$

State of charge

This constraint express that each vehicle should have a desired departure state of charge level.

Number of discharging vehicles constraint

All the vehicles cannot be discharged at the same time because of power transfer, current limit. For reliable operation and control of GV, only a limited number of vehicles are assumed to be able to discharge at a time.

$$N_{GV}(t) < N_{GV}^{Max}(t) \quad (36)$$

Efficiency

Charging and inverter efficiencies should be considered.

SIMULATION RESULTS AND DISCUSSION

In this study, the conventional 10-unit test system (Afkousi-Paqaleh *et al.*, 2010) has been used for our simulation studies. Fig. 3 represents the load curve of the 10-unit test system which is divided into three different intervals, namely valley period (00:00am–5:00 am), off-peak period (5:00 am–9:00 am & 14:00 pm–19:00 pm) and peak period (9:00 am–14:00 pm & 19:00 pm–24:00 pm). The potential of DRP implementation is considered to be 40%. It means that only customer representing 40% of the total load signed contracts for participating in the programs. Therefore, ISO will be able to decrease the peak load of the system about 600 MW and to increase the reserve margin and reduce the cost of UC problem as well as the possibility of load shedding. The voluntary IBPs has been introduced in Table I. The price elasticity of demand is provided in Table 2.

Parameter values regarding GV are presented in the following (Saber & Venayagamoorthy, 2010b):

Maximum battery capacity = 25 kWh;

Minimum battery capacity = 10 kWh;

Average battery capacity, $P_{GV} = 15$ kWh;

Maximum number of vehicles for power provision at each hour, $N_{GV}^{Max}(t) = 10\%$ of total GVs;

Total number of GVs in the system, $N_{GV}^{Max} = 50,000$;

Charging–discharging frequency = one per study horizon (24h);

Departure state of charge= 50%;

Efficiency = 85%.

Four different case studies have been considered in order to show the effect of smart grid environment (including DRPs and GVs) on the unit commitment problem. The first case study focuses on the conventional unit commitment problem without consideration of DRPs and GVs. In the second case, the effect of DRPs on the unit commitment problem has been studied. In the third case impact of GVs on UC problem has been investigated. Finally, the effect of both of DRPs and GVs on the unit commitment problem has been studied.

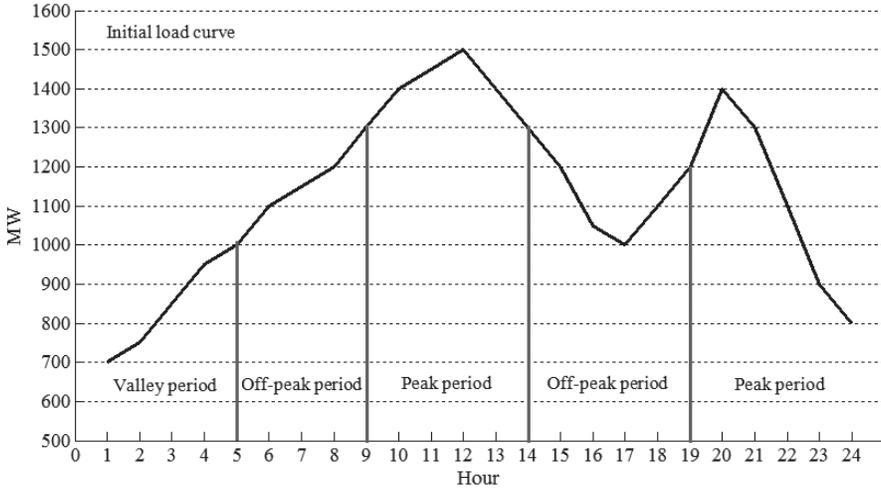


Fig. 3. 10-Unit test system load curve.

Table 1. Statement of Scenarios

Source	Scenario no	Incentive value	Price elasticity
		(\$/MWh)	
DRP	1	4	As Table II
	2	7	As Table II
	3	10	As Table II

Table 2. Price Elasticity of Demand

Hour	1-5	6-9	10-14	15-19	20-24
1-5	-0.04	0.015	0.017	0.015	0.017
6-9	0.015	-0.05	0.02	0.015	0.02
10-14	0.017	0.02	-0.095	0.02	0.005
15-19	0.015	0.015	0.02	-0.055	0.02
20-24	0.017	0.02	0.005	0.015	-0.095

Case 1: Conventional Unit Commitment Problem

In this case, the system includes 10 units with a scheduling time horizon of 24 hours. The generating units' data are given in (Afkousi-Paqaleh *et al.*, 2010). The cost curves for generating units given as a quadratic function in (Afkousi-Paqaleh *et al.*, 2010) are approximated by twenty linear segments between the minimum and maximum

generating units' capacity. Table III gives the MIP-based solutions (outputs) of units for 24-h period for 10-unit based system.

Case 2: Unit Commitment Considering Demand Response Programs

By applying final DR model (17) on the initial load curve of 10-unit system, the new load curve with DRPs is represented in Fig. 4. The MIP-based solutions for the UC problem with DRPs are provided in Table IV. As shown in in this table, the total operation cost of scheduling generation units can be decreased after taking into account the DRPs. The total incentive and units' generation cost have reverse trends that means when one of them is increased the other one will decrease. Hence, obtaining the optimum value of incentive for the DRPs is a very complicated process. The MIP-based optimum values of incentives have been obtained for the DRPs and are presented in Table V. The output powers of generation units are presented in Table VI after implementing DRPs. The shaded boxes highlight the difference in the output power of generating units comparing to the base case. As it can be seen, the expensive generating units are not called on peak interval due to reduction in customers' demand after implementation of DRPs. For example, unit 10 that is the most expensive unit of the 10-unit test system is not brought online at the peak hour.

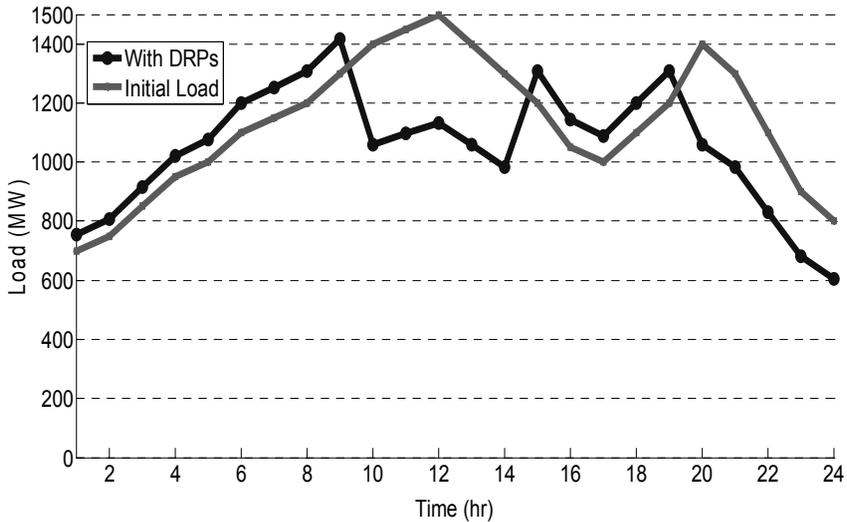


Fig. 4. The impact of DRPs on load profile in case 2

Table 3. Units' Output Power for the Conventional 10-Unit Test System

Hours	Units									
	1	2	3	4	5	6	7	8	9	10
1	455	245	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0
3	455	370	0	0	25	0	0	0	0	0
4	455	455	0	0	40	0	0	0	0	0
5	455	455	0	0	70	20	0	0	0	0
6	455	455	0	130	40	20	0	0	0	0
7	455	390	130	130	25	20	0	0	0	0
8	455	440	130	130	25	20	0	0	0	0
9	455	455	130	130	100	20	0	10	0	0
10	455	455	130	130	162	33	25	10	0	0
11	455	455	130	130	162	73	25	10	10	0
12	455	455	130	130	162	80	25	43	10	10
13	455	455	130	130	162	33	25	10	0	0
14	455	455	130	130	100	20	0	10	0	0
15	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0
19	455	455	130	130	30	0	0	0	0	0
20	455	455	130	130	162	23	25	10	10	0
21	455	455	130	130	85	20	25	0	0	0
22	455	445	0	130	25	20	25	0	0	0
23	455	420	0	0	25	0	0	0	0	0
24	455	320	0	0	25	0	0	0	0	0

Table 4. Total Cost Comparisons of Different Scenarios in Case 2

Scenario no	Source	Cost of Generating Units (\$)	Total Incentive(\$)	Total Cost(\$)
	Base Case	565283.9537	0	565283.9537
1		531285.7933	7003.9	538289.6933
2	DRP	519728.8862	21449.4	541178.2862
3		511579.6245	43774.4	555354.0245

Case 3: Unit Commitment Considering Gridable Vehicles

The MIP-based solutions for the UC problem with GVs are provided in Table VII. The output powers of generation units are presented in this table after implementing GVs. Like before the shaded boxes highlight the difference in the output power of generating units comparing to the base case. The total generation cost of generation units is 552,464.6172 \$. It shows considerable reduction in the UC problem after including GVs comparing to the 565283.9537 \$ for the case 1. As mentioned earlier it is assumed that GVs are charged from renewable resources. In case GVs are charged via power grid their charging power consumption should be considered in the load curve and therefore simulations.

Implementation of GVs has decreased the generation costs by turning off the expensive generating units at peak interval.

The results of the proposed MIP-based approach are compared with those reported in the literature.

In (Saber & Venayagamoorthy, 2010a) the authors studied the impact of GV on unit commitment problem. Particle Swarm Optimization (PSO) was used to determine the best solution. The same assumptions has been considered in this study, that are, using renewable resources for recharging of GVs so the charging power needed for this matter is not supplied from the grid's units and therefore there is no emission for recharging. Shown in Table IX is the comparison of the proposed method with those of PSO form (Saber & Venayagamoorthy, 2010a).

Table 5. Optimum Value and Total Cost of DR Programs in Case 2

Source	A (\$/MWh)	Generation Cost	Total Incentive	Total cost
DRP	5.02	526822.8534	11031.3238	537854.1772

Table 6. 10-Unit Output Power with DRPs in Case 2, Scenario 2

Hours	Units									
	1	2	3	4	5	6	7	8	9	10
1	455	298.31	0	0	0	0	0	0	0	0
2	455	352.12	0	0	0	0	0	0	0	0
3	455	434.74	0	0	25	0	0	0	0	0
4	455	455	0	0	95.35	20	0	0	0	0
5	455	446.16	130	0	25	20	0	0	0	0
6	455	438.56	130	130	25	20	0	0	0	0
7	455	455	130	130	63.04	20	0	0	0	0
8	455	455	130	130	107.52	20	0	10	0	0
9	455	455	130	130	162	54.48	0	10	10	10
10	455	428.18	0	130	25	20	0	0	0	0
11	455	455	0	130	35.97	20	0	0	0	0
12	455	455	0	130	73.76	20	0	0	0	0
13	455	428.18	0	130	25	20	0	0	0	0
14	455	352.59	0	130	25	20	0	0	0	0
15	455	455	130	130	117.52	0	0	10	10	0
16	455	404.08	130	130	25	0	0	0	0	0
17	455	349.60	130	130	25	0	0	0	0	0
18	455	455	130	130	28.56	0	0	0	0	0
19	455	455	130	130	117.52	0	0	10	10	0
20	455	318.18	130	130	25	0	0	0	0	0
21	455	372.59	130	0	25	0	0	0	0	0
22	455	246.42	130	0	0	0	0	0	0	0
23	455	150	75.26	0	0	0	0	0	0	0
24	454.67	150	0	0	0	0	0	0	0	0

As shown in this table the proposed MIP-based solution always result in the same solution while the results obtained by PSO varies considerably. Moreover the proposed method render better solution in comparison with the PSO. It should be noted that since the UC is an operational problem the execution time is very important. Reference (Saber & Venayagamoorthy, 2010a) have not provided the execution time, however, it should be noted the reaching the best solution by PSO is not guaranteed while MIP always render the optimum solution of the linearized problem. The execution time of the proposed method on 2.67GHz Core i5, 4G RAM is 3.72 seconds that is very low.

Table 7. 10-Unit Output Power with GVs in Case 3

Hours	Units										GV
	1	2	3	4	5	6	7	8	9	10	
1	455	245	0	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0	0
3	455	395	0	0	0	0	0	0	0	0	0
4	455	455	0	0	38.70	0	0	0	0	0	1.3
5	455	455	0	0	58.12	20	0	0	0	0	31.87
6	455	455	0	130	37.57	20	0	0	0	0	22.42
7	455	410	130	130	25	20	0	0	0	0	0
8	455	455	130	130	30	20	0	0	0	0	0
9	455	455	130	130	78.12	20	0	10	0	0	31.87
10	455	455	130	130	143.12	20	25	10	0	0	31.87
11	455	455	130	130	162	41.12	25	10	10	0	31.87
12	455	455	130	130	162	80	25	11.12	10	10	31.87
13	455	455	130	130	143.12	20	25	10	0	0	31.87
14	455	455	130	130	78.12	20	0	10	0	0	31.87
15	455	455	130	130	30	0	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0	0
19	455	455	130	130	30	0	0	0	0	0	0
20	455	455	130	130	158.12	20	0	10	10	0	31.87
21	455	455	130	130	78.12	20	0	0	0	0	31.87
22	455	445	0	130	31.85	20	0	0	0	0	8.150
23	455	420	0	0	25	0	0	0	0	0	0
24	455	320	0	0	25	0	0	0	0	0	0

Table 9. Comparison of the Results of the Proposed Method with PSO for Case 3

Method	Best Solution	Worst Solution	Average Solution
PSO	554,509.5	559,987.8	557,584.4
MIP	552,464.6	552,464.6	552,464.6

Case Study 4: Unit Commitment Considering DRPs and GVs

In this case both DRPs and GVs are considered in the UC problem. Table X provides the MIP-based solution of the UC problem in the smart grid environment.

Considering both DRPs and GVs resulted in more reduction in generation costs of the system and decreased the peak load considerably. The total cost of the system including costs of generation units and DRPs is 533,023.706 \$.

Table 10. Optimum Value and Total Cost of DR Programs in Case 4

Source	A (\$/MWh)	Generation Cost	Total Incentive	Total cost
DRP	5.02	511574.3060	21449.4	533023.706

It shows significant reduction in the UC problem after including GVs comparing to the 565283.9537 \$ for the case 1, 537854.1772 for case 2 and 552,464.6172 \$ for case 3.

The output powers of generation units are presented in Table XI after implementation of DRPs and GVs. The shaded boxes show the difference in the output power of generating units comparing to the base case.

Table 11. 10-Unit Output Power with DRPs and GVs in Case 4

Hours	Units										GV
	1	2	3	4	5	6	7	8	9	10	
1	455	245	0	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0	0
3	455	395	0	0	0	0	0	0	0	0	0
4	455	455	0	0	38.70	0	0	0	0	0	1.3
5	455	455	0	0	58.12	20	0	0	0	0	31.87
6	455	455	0	130	37.57	20	0	0	0	0	22.42
7	455	410	130	130	25	20	0	0	0	0	0
8	455	455	130	130	30	20	0	0	0	0	0
9	455	455	130	130	78.12	20	0	10	0	0	31.87
10	455	455	130	130	143.12	20	25	10	0	0	31.87
11	455	455	130	130	162	41.12	25	10	10	0	31.87
12	455	455	130	130	162	80	25	11.12	10	10	31.87
13	455	455	130	130	143.12	20	25	10	0	0	31.87
14	455	455	130	130	78.12	20	0	10	0	0	31.87
15	455	455	130	130	30	0	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0	0
19	455	455	130	130	30	0	0	0	0	0	0
20	455	455	130	130	158.12	20	0	10	10	0	31.87
21	455	455	130	130	78.12	20	0	0	0	0	31.87
22	455	445	0	130	31.85	20	0	0	0	0	8.150
23	455	420	0	0	25	0	0	0	0	0	0
24	455	320	0	0	25	0	0	0	0	0	0

Discussions

Fig. 5 shows the difference in market clearing price (MCP) between the all the cases in the study horizon. As it can be seen MCP has been decreased after implementation of DRPs and GVs in the peak period. The MCP reduction demonstrates the capability of DRPs and GVs in peak shaving.

As the presented results show the smart grid has a significant influence on the UC problem and if these influences are not considered thoroughly it might raise some challenges and difficulties in optimal operation of the system.

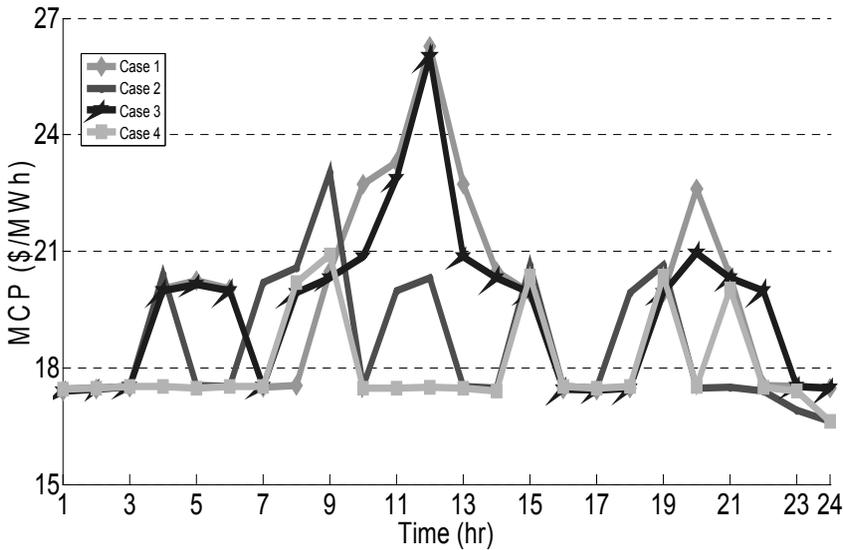


Fig. 5. The impact of different cases on MCP

CONCLUSIONS

A mixed-integer programming approach for solving the UC problem in the smart grid environment has been addressed in this paper. DR and GVs as two of the most important programs of the smart grids are considered in this paper. The objective function of the UC problem has been modified to incorporate DRPs and GVs. The proposed method has been illustrated using the conventional 10-unit test system. Four different cases have been derived to investigate the impact of DRPs and GVs separately and simultaneously. As demonstrated in results section of the paper the proposed MIP-based solution render the optimal solution of the linearized problem. The proposed method gives the better solutions in comparison with those reported in the literature.

Obtained results demonstrate the impacts of smart grid environment on the UC problem and the reveals benefits of implementing DRRs and GV in UC problem. The incorporation of DRPs and GV decreased the operational costs by 5.7%. With the higher degree of penetration of smart grid more reduction in operational costs can be achieved.

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