Applied Energy 187 (2017) 449–464

Contents lists available at ScienceDirect

Applied Energy

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

Optimal stochastic energy management of retailer based on selling price determination under smart grid environment in the presence of demand response program

Sayyad Nojavan *, Kazem Zare, Behnam Mohammadi-Ivatloo

Faculty of Electrical and Computer Engineering, University of Tabriz, P.O. Box: 51666-15813, Tabriz, Iran

HIGHLIGHTS

- Stochastic energy management of retailer under smart grid environment is proposed.
- Optimal selling price is determined in the smart grid environment.
- Fixed, time-of-use and real-time pricing are determined for selling to customers.
- Charge/discharge of ESS is determined to increase the expected profit of retailer.
- Demand response program is proposed to increase the expected profit of retailer.

ARTICLE INFO

Article history:
Received 11 July 2016
Received in revised form 19 October 2016
Accepted 8 November 2016

Keywords:
Selling price determination
Electricity retailer
Smart grid
Fixed pricing
Time-of-use pricing
Real-time pricing and demand response program

ABSTRACT

In this paper, bilateral contracting and selling price determination problems for an electricity retailer in the smart grid environment under uncertainties have been considered. Multiple energy procurement sources containing pool market (PM), bilateral contracts (BCs), distributed generation (DG) units, renewable energy sources (photovoltaic (PV) system and wind turbine (WT)) and energy storage system (ESS) as well as demand response program (DRP) as virtual generation unit are considered. The scenario-based stochastic framework is used for uncertainty modeling of pool market prices, client group demand and variable climate condition containing temperature, irradiation and wind speed. In the proposed model, the selling price is determined and compared by the retailer in the smart grid in three cases containing fixed pricing, time-of-use (TOU) pricing and real-time pricing (RTP). It is shown that the selling price determination based on RTP by the retailer leads to higher expected profit. Furthermore, demand response program (DRP) has been implemented to flatten the load profile to minimize the cost for end-user customers as well as increasing the retailer profit. To validate the proposed model, three case studies are used and the results are compared.

1. Introduction

In the smart grid environment, determination of selling price to end-user customers by the electricity retailer is necessary [1]. In this issue, the electricity retailer should procure demand of customers from power market [2], distribution generation units [3], bilateral contracts [4], wind turbine [5], photovoltaic system [6], energy storage systems [7,8], and demand response program [9,10] under uncertainties modeling [11]. Therefore, it is essential that the retailer manage the purchased power from alternative energy resources to maximize his own expected profit. High selling price makes the customers not purchase from this retailer and leads to reduction of retailer profit. Also, low selling price decreases the expected profit of retailer. Therefore, the retailer should determine the optimal selling price with the aim of maximizing the expected profit. Furthermore, the retailer can determine the selling price based on fixed price, time-of-use price or real-time price. Finally, the retailer should manage the uncertainty of pool market price, demand of end-user, wind speed, irradiation and temperature. Finally, demand response program can be used by the retailer as an option enabled via smart grid technology to increase the expected profit.

* Corresponding author.
E-mail addresses: sayyad.nojavn@tabrizu.ac.ir (S. Nojavan), kazem.zare@tabrizu.ac.ir (K. Zare), bmohammadi@tabrizu.ac.ir (B. Mohammadi-Ivatloo).

http://dx.doi.org/10.1016/j.apenergy.2016.11.024

Nomenclature

Index

- b — bilateral contract index
- h — the generation block index of DG units
- i — the minimum OFF-time and ON-time limits modeling index
- j — DG unit index
- s — scenario index
- t — time period index
- z — segment index in the price-quota curve

Sets

- B — number of bilateral contracts
- H — number of production blocks of the DG units
- I — the maximum amount of minimum OFF-time and ON-time value of DG units running from 1 to max {$\mathrm{MUT_j}$, $\mathrm{MDT_j}$}
- J — number of DG units
- S — number of scenarios
- T — number of time periods
- Z — number of segments in the price-quota curve

Parameters

- $\mathrm{Dn_{j,i}}$ — auxiliary variable for modeling of the MDT constraint
- $D^{offer}(l,z,t,s)$ — offered energy of client group in the price-quota curve (kW)
- $DRP^{\max}$ — maximum percentage of demand that can be participated in DRP (%)
- $G^{a}_{t,s}$ — irradiation of sun in each time and scenario (W/m^2)
- G_{a_0} — irradiation of sun at the standard condition (W/m^2)
- $NOCT$ — normal operating cell temperature of PV system (°C)
- ρ_s — the probability of scenario
- $P^{\max}_{b}$ — maximum limit of bilateral contracts (kW)
- $P^{\min}_{b}$ — minimum limit of bilateral contracts (kW)
- $P^{MAX}_{j,h}$ — rated block power of DG units in a piecewise linear cost modeling (kW)
- $P^{PV}_{t,s}$ — available power of PV system (kW)
- $P^{M}_{Max,0}$ — maximum power of PV panel at the standard condition (kW)
- $P^{wind}_{t,s}$ — available power of wind-turbine (kW)
- p_r — nominal power of wind-turbine (kW)
- $P^{\max}_{charge}$ — maximum power limit in charging mode (kW)
- $P^{\max}_{disc}$ — maximum power limit in discharging mode (kW)
- R^{up}_{j} — ramp up rate limit of DG units (kW/h)
- R^{down}_{j} — ramp down rate limit of DG units (kW/h)
- $Sdg_{j,h}$ — rated block cost of DG units in a piecewise linear cost modeling ($/kWh)
- $SP^{offer}(l,z,t)$ — offered price of client group in the price-quota curve ($/kWh)
- $T^{a}_{t,s}$ — temperature at each time and scenario (°C)
- $T_{M,0}$ — module temperature at the standard condition (°C)
- $\mathrm{Up_{j,i}}$ — auxiliary variable for modeling of the MUT constraint
- $\mathrm{V^{w}_{t,s}}$ — wind speed (m/s)
- V_r, V_{ci}, V_{c0} — rated, cut-in and cut-out wind speed (m/s)
- $X^{\max}_{b}$ — maximum limit of stored energy in the energy storage system (kW)
- $X^{\min}_{b}$ — minimum limit of stored energy in the energy storage system (kW)
- χ — charging efficiency of energy storage system (%)
- η — discharging efficiency of energy storage system (%)
- $\lambda_{b,t}$ — energy price of bilateral contracts ($/kWh)
- $\lambda_{t,s}$ — the price for pool market ($/kWh)

Variables

- $A(l,z,t)$ — binary variable for selecting the selling price offered by the retailer to the client group from the price-quota curve [0,1]
- C_B — energy procurement cost from the bilateral contracts ($)
- C_P — energy procurement cost from the pool market ($)
- C_{DG} — energy procurement cost from the DG units ($)
- $D(l,t,s)$ — supplied demand to the client group by the retailer (kW)
- $DRP(l,t,s)$ — free variable for possibility of DRP implementation (positive for demand increase and negative for demand decrease) (kW)
- $D^{DRP}(l,t,s)$ — supplied new demand considering demand response program to the client group by the retailer (kW)
- $P_{b,t}$ — energy procurement from the bilateral contracts (kW)
- P^{BC}_{t} — total energy procurement from the bilateral contracts (kW)
- $P^{charge}_{t,s}$ — charged power of energy storage system (kW)
- $P^{disc}_{t,s}$ — discharged power of energy storage system (kW)
- $P^{P}_{t,s}$ — energy procurement from the pool market (kW)
- $P^{DG}_{j,h,t,s}$ — purchased power from the DG units (kW)
- $R_R(l,t)$ — the revenue obtained from the client group ($)
- s_b — binary variable for selecting the bilateral contracts [0,1]
- $SP(l,z,t)$ — price of the interval of the price-quota curve for the client group ($/kWh)
- $SP^{RTP}(l,t)$ — real-time selling price by the retailer for the client group ($/kWh)
- $SP^{Fixed}(l)$ — fixed selling price by the retailer for the client group ($/kWh)
- $SP^{TOU}_{L}(l)$ — time-of-use selling price in low load level by the retailer for the client group ($/kWh)
- $SP^{TOU}_{M}(l)$ — time-of-use selling price in medium load level by the retailer for the client group ($/kWh)
- $SP^{TOU}_{P}(l)$ — time-of-use selling price in peak load level by the retailer for the client group ($/kWh)
- $U^{charge}_{t,s}$ — binary variable for charging mode of energy storage system [0,1]
- $U^{disc}_{t,s}$ — binary variable for discharging mode of energy storage system [0,1]
- $U^{DG}_{j,t}$ — binary variable for on or off statues of DG units [0,1]
- $X^{b}_{t,s}$ — stored energy in the energy storage system (kWh)

Abbreviations

- BCs — bilateral contracts
- DG — distributed generation
- DRP — demand response program
- ESS — energy storage system
- FP — fixed pricing
- GAMS — general algebraic modeling system
- MINLP — mixed-integer non-linear programming
- PM — pool market
- PV — photovoltaic
- RTP — real-time pricing
- RESs — renewable energy sources
- TOU — time-of-use pricing
- WT — wind turbine

1.1. Literature review

The researches on retailer for determination of selling price is generally categorized to three time periods containing long-term, medium-term and short-term planning. In long-term planning, the review of papers is summarized in Table 1. Table 1 is divided based on objective function, type of selling price determination, solution methodology, uncertainty modeling, participation in demand response program and considering the smart grid technologies. According to Table 1, it is obvious that [12] minimizes total cost without pricing, uncertainty modeling, DRP and smart grid technology, and maximizing the expected profit considering uncertainty modeling using scenario-based stochastic model is considered in [13] without pricing.

Furthermore, the review of papers related to medium-term planning of retailer is summarized in Table 2, which is categorized in similar way to Table 1. Refs. [14–33] are reviewed and compared in Table 2. According to Table 2, the objective function of these references is minimizing cost [14,15,28–30], maximizing profit [16–28,31–33] or minimizing selling price [32,33]. The types of considered selling price is no pricing [14,15,29,30], fixed pricing [16–24,26–28,31–33] and TOU pricing [25]. Also, the solution method is based on hybrid binary imperialist competitive algorithm-binary particle swarm optimization (BICA–BPSO) [14] or GAMS optimization package [15–33]. Furthermore the uncertainty model includes Monte Carlo simulation (MCS) [16], scenario based method [17–28,32,33], robust optimization approach (ROA) [29,30] and information gap decision theory (IGDT) [31]. Only, in Refs. [15,26,27,30], demand response program is considered while in none of the 20 references the smart grid technologies are considered.

Finally, Table 3 summarizes the researches related to short-term scheduling of retailer in electricity market. Also, Table 3 is organized similar to Tables 1 and 2, which Refs. [34–46] are reviewed and compared with each other. The objective function of short-term planning is maximizing profit [35–39,42–46] or minimizing cost [34,39–41,45,46]. Unlike medium-term planning, real-time pricing [36,45] as well as fixed pricing [35,39,42–44,46] and time-of-use pricing [37] are used as types of selling price in short-term scheduling. Also, Stackelberg game [45], genetic algorithm [34,38] or GAMS [35–37,39–44,46] are used to solve the problem. Furthermore, in Refs. [34–39] the uncertainty modeling is not considered. Also, scenario based method [40–43], robust optimization approach (ROA) [44,45] and information gap decision theory (IGDT) [46] are used as uncertainty modeling approaches. In none of the references the smart grid technologies are used while in Refs. [47,45], demand response program is considered.

In this paper, the expected profit of electricity retailer in the presence of smart grid technologies is maximized. In the proposed model, the power pool market, bilateral contracts and DG units plus renewable energy sources containing wind turbine, PV system as well as energy storage system are used as alternative energy options thorough the smart grid by the retailer. Also, the selling price by the retailer is determined in three case including fixed pricing, time-of-use pricing and real-time pricing. Furthermore, demand response program is used as flexible option to increase the expected profit. Finally, the scenario-based stochastic framework is used for uncertainty modeling of pool market price, demand of end-user, wind speed, irradiation and temperature.

The differences of proposed work with previous works are clearly presented in the last row of Table 3 for more clarification. In this paper, the stochastic expected profit maximization problem of electricity retailer is proposed based on real-time selling pricing determination in the smart grid which is much closer to reality unlike the fixed pricing and time-of-use pricing. Also, the charge and discharge power management of energy storage system and utilizing of demand response program are used through smart grid technologies. Finally, the uncertainties of demand, pool market price and renewable output power are modeled based on scenario approach.

1.2. Demand response program modeling

In the smart grid environment, demand response programs can be used for flexible load management to reduce peak load and decrease the purchased energy cost which are introduced in [48]. In this paper, the time-of-use rate of demand response programs has been provided [49]. In this program, the load profile is flatten because some percentage of load can be shifted from peak time periods to off-peak time periods which will lead to expected operation cost reduction as the energy price is high in peak periods in comparison with off-peak periods. In other words, total load has not changed in all time periods, but it can be transferred from peak periods to the other periods. Also, decreased load should be equal to the increased load during the operation times. In addition, the increased and decreased load must be less than the percentage of base load. Finally, it is worth mentioning that these amounts are set to 20% in this paper.

1.3. Novelty and contributions

Based on our scientific information, no selling price determination for an electricity retailer in the smart grid environment has been reported in the literature. Therefore, in this paper this issue is considered. In the proposed model, the selling price is determined in three approaches using fixed pricing, time-of-use pricing and real-time pricing and compared with each other. In the smart grid, it is necessary that the selling price be determined based on real-time pricing by the retailer to increase the expected profit. Also, the all uncertainties of price, demand and renewable energy are considered in the stochastic framework. Also, demand response program is used as virtual generation unit in peak periods which uses load management to increase the expected profit of retailer. Therefore, the novelty and contributions of this research can be listed as:

1. Optimal selling price is determined in the smart grid environment.
2. Fixed pricing, time-of-use pricing and real-time pricing are determined for selling to client group.
3. Demand response program is investigated for client group demand to increase the flexibility of demand and to increase the expected profit of retailer.

Table 1
Review of papers in long-term planning.

Ref.	Objective function	Selling Price	Solution methodology	Uncertainty model	Considering demand response program	Considering smart grid technologies
[12]	Min cost	No pricing	Regression analysis and survival analysis	No	No	No
[13]	Max profit	No pricing	Simulation package	Scenario	No	No

Table 2
Review of papers in medium-term planning.

Ref.	Objective function	Selling price	Solution methodology	Uncertainty model	Considering demand response program	Considering smart grid technologies
[14]	Min cost	No pricing	BICA–BPSO	No	No	No
[15]	Min cost	No pricing	GAMS	No	Yes	Yes
[16]	Max profit	Fixed Pricing	GAMS	MCS	No	No
[17]	Max profit	Fixed Pricing	GAMS	Scenario	No	No
[18]	Max profit	Fixed Pricing	GAMS	Scenario	No	No
[19]	Max profit	Fixed Pricing	GAMS	Scenario	No	No
[20]	Max profit	Fixed Pricing	GAMS	Scenario	No	No
[21]	Max profit	Fixed Pricing	GAMS	Scenario	No	No
[22]	Max profit	Fixed Pricing	GAMS	Scenario	No	No
[23]	Max profit	Fixed Pricing	GAMS	Scenario	No	No
[24]	Max profit	Fixed Pricing	GAMS	Scenario	No	No
[25]	Max profit	TOU Pricing	GAMS	Scenario	No	No
[26]	Max profit	Fixed Pricing	GAMS	Scenario	Yes	Yes
[27]	Max profit	Fixed Pricing	GAMS	Scenario	Yes	Yes
[28]	Max profit Min cost	Fixed Pricing	GAMS	Scenario	No	No
[29]	Min cost	No pricing	GAMS	ROA	No	No
[30]	Min cost	No pricing	GAMS	ROA	Yes	Yes
[31]	Max profit	Fixed Pricing	GAMS	IGDT	No	No
[32]	Max profit Min selling price	Fixed Pricing	GAMS	Scenario	No	No
[33]	Max profit Min selling price	Fixed Pricing	GAMS	Scenario	No	No

Table 3
Review of papers in short-term planning.

Ref.	Objective function	Selling price	Solution methodology	Uncertainty model	Considering demand response program	Considering smart grid technologies
[34]	Min cost	No pricing	GA	No	No	No
[35]	Max profit	Fixed pricing	GAMS	No	No	No
[36]	Max profit	RTP pricing	GAMS	No	No	No
[37]	Max profit	TOU pricing	GAMS	No	No	No
[38]	Max profit	No pricing	GA	No	No	No
[39]	Max profit Min cost	Fixed pricing	GAMS	No	Yes	Yes
[40]	Min cost	No pricing	GAMS	Scenario	No	No
[41]	Min cost	No pricing	GAMS	Scenario	No	No
[42]	Max profit	Fixed pricing	GAMS	Scenario	No	No
[43]	Max profit	Fixed pricing	GAMS	Scenario	No	No
[44]	Max profit	Fixed pricing	GAMS	ROA	No	No
[45]	Max profit Min cost	RTP pricing	Stackelberg game	ROA	Yes	Yes
[46]	Max profit Min cost	Fixed pricing	GAMS	IGDT	No	No
Current paper	Max profit	Fixed pricing TOU pricing RTP pricing	GAMS	Scenario	Yes	Yes

4. The client group demand, pool market price, renewable energy output power uncertainties are modeled using the scenario-based stochastic framework.
5. The renewable energy resources containing PV system and wind turbines are used as energy procurement sources of retailer in the smart grid.
6. Determination of charging/discharging decisions of energy storage system for proper status operation.

1.4. Structure of paper

The structure of proposed paper is targeted as follows. A stochastic framework for optimal selling price determination and bilateral contracting problem for an electricity retailer in the smart grid environment under uncertainties is modeled in Section 2. Section 3 presents the comparison results of fixed, time-of-use and real-time pricing for selling to the client group in a case study. Finally, the relevant conclusions are presented in Section 4.

2. Problem formulation

The objective of retailer is to maximize the expected profit (revenue minus cost) in the energy market. The revenue is obtained from selling energy to the end users. Also, total procurement cost of retailer includes the purchased costs of energy from pool market, bilateral contracts and distributed generation units (DGs). In the proposed short-term scheduling for the retailer, it should be mentioned that the operation cost of renewable energy resources such as wind turbine and PV system as well as charging/discharging of energy storage system are ignored.

2.1. Bilateral contracts cost modeling

The energy procurement cost due to bilateral contracts, which the retailer is faced with, can be modeled as (1) according to [47].

$$C_B = \sum_{b}^{B}\sum_{t=1}^{T}\lambda_{b,t}P_{b,t} \tag{1}$$

It should be noted that the bilateral contracts variables are classified as first-stage or here-and-now. In other words, these decisions are made before realization of stochastic process.

The allowable limits and energy procurement from bilateral contracts are expressed in (2) and (3), respectively [50].

$$P_b^{\min}s_b < P_{b,t} < P_b^{\max}s_b \quad \forall b,t \tag{2}$$

$$P_t^{BC} = \sum_{b=1}^{B}P_{b,t}; \quad \forall t \tag{3}$$

2.2. Pool market cost modeling

The purchased energy procurement cost from the pool market can be calculated as (4) [51].

$$C_P = \sum_{s=1}^{S}\rho_s \times \sum_{t=1}^{T}\lambda_{t,s}P_{t,s}^{P} \tag{4}$$

It should be mentioned that the pool market prices uncertainty is modeled by scenario-based stochastic framework. Also, the variable used for purchased power from the pool market is classified as second-stage or wait-and-see. In other words, these decisions are made after realization of stochastic process.

2.3. Operation cost of DG units modeling

A piecewise linear operation cost modeling of DG units is expressed in (5) according to Fig. 1 [52]. The technical constraints are presented in Eqs. (6)–(13) based on [53].

$$C_{DG} = \sum_{s=1}^{S}\rho_s \times \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{h=1}^{H}Sdg_{j,h}P_{j,h,t,s}^{DG} \tag{5}$$

$$0 \leqslant P_{j,h,t,s}^{DG} \leqslant P_{j,h}^{MAX} - P_{j,h-1}^{MAX} \quad \forall j,t,s,h = 2,\ldots,N \tag{6}$$

$$0 \leqslant P_{j,1,t,s}^{DG} \leqslant P_{j,1}^{MAX} \quad \forall j,t,s \tag{7}$$

$$\sum_{h=1}^{H}P_{j,h,t,s}^{DG} - \sum_{h=1}^{H}P_{j,h,t-1,s}^{DG} \leqslant R_j^{up} \times U_{j,t}^{DG}; \quad \forall j,t,s \tag{8}$$

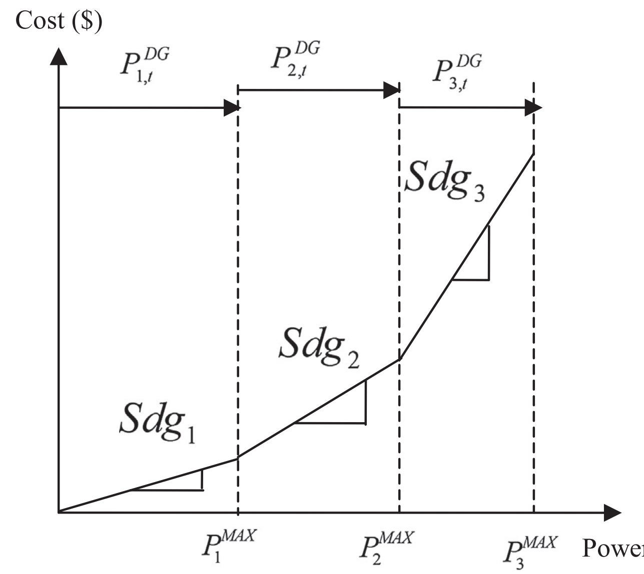

Fig. 1. Linear operation cost model of DG units.

$$\sum_{h=1}^{H}P_{j,h,t-1,s}^{DG} - \sum_{h=1}^{H}P_{j,h,t,s}^{DG} \leqslant R_j^{down} \times U_{j,t-1}^{DG}; \quad \forall j,t,s \tag{9}$$

$$U_{j,t}^{DG} - U_{j,t-1}^{DG} \leqslant U_{j,t+Up_{j,i}}^{DG}; \quad \forall j,t,i \tag{10}$$

$$U_{j,t-1}^{DG} - U_{j,t}^{DG} \leqslant 1 - U_{j,t+Dn_{j,i}}^{DG}; \quad \forall j,t,i \tag{11}$$

$$\mathrm{Up}_{j,i} = \left\{\begin{matrix} i & i \leqslant \mathrm{MUT_j} \\ 0 & i \succ \mathrm{MUT_j} \end{matrix}\right\} \tag{12}$$

$$\mathrm{Dn}_{j,i} = \left\{\begin{matrix} i & i \leqslant \mathrm{MDT_j} \\ 0 & i \succ \mathrm{MDT_j} \end{matrix}\right\} \tag{13}$$

The purchased energy from DGs is limited by Eqs. (6) and (7). Also, the ramp up/down rate limits is expressed in constraints (8) and (9), respectively. Finally, Eqs. (10) and (11) describe the minimum up/down time constraints. Also, the auxiliary variables $\mathrm{Up_{i,j}}$ and $\mathrm{Dn_{i,j}}$ are defined in (12) and (13) for linear modeling of minimum up/down time constraints of DGs [53,54].

2.4. Wind-turbine and photovoltaic system models

The available power from wind turbine in each time period and scenario is a function of related speed. Therefore, the available power of wind turbine can be calculated using Eq. (14) according to Ref. [53]. Also, it should be noted that the Weibull distribution curve is used to generate scenarios for wind speed.

$$P_{t,s}^{wind} = \begin{cases} 0 & \mathrm{V_{t,s}^{w}} < V_{ci} \\ p_r \times \left(\frac{\mathrm{V_{t,s}^{w}} - V_{ci}}{\mathrm{V}_r - V_{ci}}\right)^3 & \mathrm{V}_{ci} < \mathrm{V_{t,s}^{w}} < V_{cr} \\ p_r & \mathrm{V}_r < \mathrm{V_{t,s}^{w}} < V_{c0} \\ 0 & \mathrm{V_{t,s}^{w}} > V_{c0} \end{cases} \tag{14}$$

Furthermore, the available power from photovoltaic system in each time period and scenario can be computed using Eq. (15) according to Ref. [54]. Also, the normal distribution curve is used to generate scenario for radiation and temperature uncertainty modeling in stochastic model.

$$P_{t,s}^{PV} = \frac{G_{t,s}^{a}}{G_{a_0}} \times \left\{ P_{Max,0}^{M} + \mu_{P\max} \times \left(T_{t,s}^{a} + G_{t,s}^{a} \times \frac{NOCT - 20}{800} - T_{M,0} \right) \right\} \tag{15}$$

2.5. Energy storage system modeling

The technical constraints of ESS are presented in Eqs. (16)–(21) according to [54]. The initial condition and energy of ESS is captured in (16). Eqs. (17) and (18) consider the power limits of charging and discharging modes. The lower and upper limits of stored energy in ESS are captured in Eq. (19). Eq. (20) shows the binary mode of charge and discharge which cannot be operated simultaneously. The energy dynamic model of ESS is shown in Eq. (21). It should be mentioned that the variables related to ESS are second-stage or wait-and-see. In other words, these variables are dependent on scenario.

$$X_{t_0}^{b} = X_0^{b} \tag{16}$$

$$P_{t,s}^{charge} \leq P_{charge}^{\max} \times U_{t,s}^{charge}; \quad \forall t, s \tag{17}$$

$$P_{t,s}^{disc} \leq P_{disc}^{\max} \times U_{t,s}^{disc}; \quad \forall t, s \tag{18}$$

$$X_{b}^{\min} \leq X_{t,s}^{b} \leq X_{b}^{\max}; \quad \forall t, s \tag{19}$$

$$U_{t,s}^{charge} + U_{t,s}^{disc} \leq 1; \quad \forall t, s \tag{20}$$

$$X_{t,s}^{b} = X_{t-1,s}^{b} + \chi \times P_{t,s}^{charge} - \frac{P_{t,s}^{disc}}{\eta}; \quad \forall t, s \tag{21}$$

2.6. Demand supplied by the retailer considering demand response program

It should be mentioned that the clients are flexible versus the determination of selling real-time pricing by the retailer ($SP(l,t)$). Also, the retailer sets a quantity from client demand based on price-quota curve of the clients that is offered to the retailer to procure their demand ($D(l,t,s)$) according to Fig. 2. This figure shows the price-quota curve of clients for one hour.

Furthermore, the clients can use the time-of-use (TOU) rates of demand response program to minimize the energy procurement cost [55]. In TOU program, the clients can shift some percentage of demand from peak period to off-peak period to flatten the load profile and to minimize the cost. Therefore, the participation of clients has advantages for end-user customers and retailer.

The supplied demand by the retailer considering DRP is computed by equations shown in below:

$$D(l,t,s) = \sum_{z=1}^{Z} D^{offer}(l,z,t,s) A(l,z,t); \quad \forall l, t, s \tag{22}$$

$$D^{DRP}(l,t,s) = D(l,t,s) + DRP(l,t,s); \quad \forall l, t, s \tag{23}$$

$$DRP(l,t,s) \leqslant +DRP^{\max} \times D(l,t,s); \quad \forall l, t, s \tag{24}$$

$$DRP(l,t,s) \geqslant -DRP^{\max} \times D(l,t,s); \quad \forall l, t, s \tag{25}$$

$$\sum_{t=1}^{T} DRP(l,t,s) = 0; \quad \forall l, s \tag{26}$$

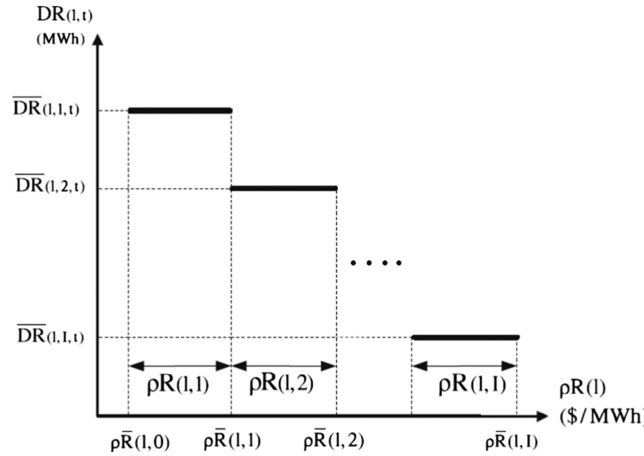

Fig. 2. Price-quota curve of the demand supplied by the retailer.

$$SP(l,t) = \sum_{z=1}^{Z} SP(l,z,t) \quad ; \quad \forall l, t \tag{27}$$

$$SP^{offer}(l,z-1,t) A(l,z,t) \leq SP(l,z,t) \leq SP^{offer}(l,z) A(l,z,t); \quad \forall l, z, t \tag{28}$$

$$\sum_{z=1}^{Z} A(l,z,t) = 1; \quad \forall l, t \tag{29}$$

Through Eqs. (22)–(29), it is clear that the demand of each client group supplied by the retailer in each period is a function of selling price. Also, constraints (23)–(26) show the new demand based on demand response program. It is emphasized that the small part of demand that can be shifted from peak period to off-peak period to flatten the demand curve whereas total consumed energy over the planning horizon is fixed [56]. According to Eq. (23), the new demand with time-of-use rate of demand response program consideration is equal to the amount of primary demand plus $DRP(l,t,s)$. If demand increases, the variable $DRP(l,t,s)$ would be positive and if demand decreases, it would be negative. As it can be seen from Eq. (23), due to improvement of intelligent network technology, we can transfer some amount of demand from peak periods to off-peak periods. Also, as expressed in constraints (24) and (25) the increasing/decreasing demand should not exceed the percentage of based demand which is presented by $DRP^{\max}$. In the proposed paper, the maximum amount of increasing/decreasing demand is considered to be 20%. Also, Eq. (26) expresses that the total load does not decrease or increase and it is just transferred from peak periods to off-peak periods meaning that the increasing load and decreasing load should be equal during a day.

The revenue obtained from client l in time period t by selling energy to the end-user customers can be computed as following:

$$R_R(l,t) = \sum_{s=1}^{S} \rho_s \times SP(l,t) D^{DRP}(l,t,s) \tag{30}$$

The energy balance constraint for a retailer in each time period is indicated as following:

$$\sum_{b=1}^{B} P_{b,t} + \sum_{j=1}^{J}\sum_{h=1}^{H} P_{j,h,t,s}^{DG} + P_{t,s}^{P} + P_{t,s}^{wind} + P_{t,s}^{PV} + P_{t,s}^{disc} = \sum_{l=1}^{L} D^{DRP}(l,t,s) + P_{t,s}^{charge} \quad \forall t, s \tag{31}$$

Finally, the objective function of retailer can be expressed in (32) which is expected profit (revenue minus cost) in energy market. The revenue is obtained from selling energy to the end users that is presented in first term of objective function. Also, the purchased energy cost from pool market, DGs and bilateral contracts are presented in second, third and fourth terms of objective function.

$$Max \sum_{s=1}^{S} \rho_s \times \left\{ \sum_{t=1}^{T}\sum_{l=1}^{L} SP(l,t) D^{DRP}(l,t,s) - \sum_{t=1}^{T} \lambda_{t,s} P_{t,s}^{P} - \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{h=1}^{H} S_{j,h}^{DG} P_{j,h,t,s}^{DG} \right\} - \sum_{b}^{B}\sum_{t=1}^{T} \lambda_{b,t} P_{b,t} \tag{32}$$

2.7. Determination of real-time price (RTP), fixed price and time-of-use (TOU) price

The proposed objective function (32) should be maximized subject to constraints (1)–(31). In the proposed model, the selling price is generally modeled based on time index. Therefore, this selling price is similar to real-time pricing that should be determined by the retailer according to constraint (33) in the proposed model.

$$SP(l,t) = SP^{RTP}(l,t) \tag{33}$$

Also, the constraint (33) should be replaced with constraint (34) in fixed price determination by the retailer in time periods. According to constraint (34), the selling price is determined fixed based on decision maker of retailer for all time periods.

$$SP(l,t) = SP^{Fixed}(l) \tag{34}$$

Furthermore, the constraint (33) should be replaced with constraint (35) in determination of time-of-use pricing by the decision maker of retailer. The constraint (35) emphasizes that the selling price is determined for low, medium and peak periods by the retailer.

$$SP(l,t) = \left\{ \begin{array}{ll} SP_{L}^{TOU}(l) & \text{for } t \in low\ load\ level \\ SP_{M}^{TOU}(l) & \text{for } t \in medium\ load\ level \\ SP_{P}^{TOU}(l) & \text{for } t \in peak\ load\ level \end{array} \right\} \tag{35}$$

In order to model the uncertainty of pool market prices, demand, temperature, irradiation and wind speed, the forecast error distribution curves are divided into five intervals with the width of one standard deviation [57]. In uncertainty modeling, the used values for parameter in deterministic solution are considered as mean values. The standard deviation for uncertain parameters is considered to be 10%. Fig. 3 shows a sample discrete form of the predication error probability distribution function. It is essential that for every available scenario two values be computed [57]:

1. By integrating the area below the probability distribution curve in every period, we can acquire each scenario's probability.
2. The realized prediction error in each relevant scenario is considered to be the average amount of period.

Table 4 shows the amount and its probability in each relevant scenario.

Therefore, for five uncertainty parameters in this paper, five scenarios are independently generated based on probability distribution function. Therefore, total number of scenarios will be $5^5 = 3125$. Since the proposed model is complex and to decrease the computing time, the scenarios are reduced to five scenarios based on scenario reduction technique by Kantorovich distance approach [58].

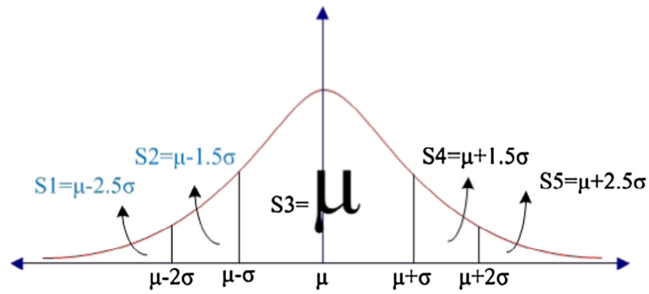

Fig. 3. Probability distribution function for uncertainty parameters.

The proposed stochastic framework of selling price determination by the retailer in the smart grid environment under demand response program is modeled using MINLP and it is solved using SBB solver [59] under GAMS [60] optimization package.

3. Numerical simulation

In this section, a case study is used to show the results of selling price determination in three cases containing fixed pricing, time-of-use pricing and real-time pricing. Also, the results of these cases are compared with each other. Table 5 provides the size of each problem, which is expressed as the number of binary variables, real variables and equations for more clarification about the complexity of proposed model.

3.1. Data

Three load levels containing the valley, shoulder and peak periods are assumed for daily demand which is presented in Table 6. Also, data of twelve bilateral contracts are presented in Table 7 containing the maximum and minimum energy and related price for the peak and all load levels. Table 8 provides the characteristics of self-distributed generation units. Furthermore, Table 9 presents the forecasted daily temperature, irradiation and wind speed for a sample day [53]. Finally, Tables 10 and 11 provide the parameters of PV system [54], wind turbine [54] and energy storage system, respectively. According to Tables 9 and 10 and Eqs. (14) and (15), the available power by wind turbine and PV system in all scenarios are shown in Fig. 4(a) and (b), respectively. Also, Fig. 5 shows the relationship between selling price and demand of client groups which are supplied by the retailer. This figure comprises 100 steps as a stepwise price-quota curve for each client. The forecasted pool price and the load curve of retailer for the time periods are depicted in Figs. 6 and 7, respectively. It should be mentioned that the maximum percentage of demand which can be shifted from

Table 4
Probability of scenarios approximated normal distribution function.

Scenario number	Value of each relevant scenario	Probability of each relevant scenario
S1	$\mu - 2.5\sigma$	0.0123
S2	$\mu - 1.5\sigma$	0.136
S3	μ	0.682
S4	$\mu + 1.5\sigma$	0.136
S5	$\mu + 2.5\sigma$	0.023

Table 5
Computational size of the proposed model.

Options	Case 1		Case 2		Case 3	
	Without DRP	With DRP	Without DRP	With DRP	Without DRP	With DRP
Number of binary variables	927	927	7827	7827	7827	7827
Number of real variables	4163	4883	18,332	19,052	18,032	18,752
Number of equations	7248	8343	27,717	28,812	21,117	22,212

Table 6
Classification of daily load levels.

Level	Hours of the day
Valley (V)	1, 2, 3, 4, 5, 6, 7, 8
Shoulder (S)	9, 10, 11, 12, 13, 14, 15, 16
Peak (P)	17, 18, 19, 20, 21, 22, 23, 24

peak period to off-peak period to flatten the demand curve is assumed to be 20% ($DRP^{\max} = 0.20$).

3.2. Case 1: fixed pricing determination

In this case, the selling price is determined as fixed pricing ($SP(l,t) = SP^{Fixed}(l)$) for all time periods. Therefore, the proposed objective function (32) is maximized subject to constraints (1)–(31) and (34) with and without demand response program.

The simulation results of case 1 with and without demand response program are presented in Table 12. It can be seen from Table 12 that the expected profit of retailer with and without DRP is 1123.666 $ and 1036.756 $, respectively in which the expected profit is increased 8.38% due to implementation of DRP. Also, the fixed selling price for residential, commercial and industrial with and without DRP are presented in Table 10. For implementation of DRP, the fixed selling price is decreased 1.50%, 1.42% and 1.35% for residential, commercial and industrial, respectively. This is favorable for both retailer and end-user customers.

The supplied load by the retailer from price-quota curves for clients with and without DRP is shown in Fig. 8. Also, the power procurement from PM, BC and all DG units with and without considering DRP in the third scenario are shown in Figs. 9–11, respectively. Finally, the charged and discharged power and stored energy level of ESS in the third scenario are depicted in Figs. 12 and 13, respectively.

3.3. Case 2: time-of-use pricing determination

In time-of-use pricing model, the retailer determines the selling price for low, medium and peak periods according to Eq. (35).

Table 7
Bilateral contracts specification.

Contract number	Validity level	Min	Max	Price
1	V, S, P	50	15	0.040
2	P	40	10	0.043
3	V, S, P	50	15	0.050
4	P	40	10	0.048
5	V, S, P	70	25	0.032
6	P	60	20	0.041
7	V, S, P	70	25	0.051
8	P	60	20	0.048
9	V, S, P	70	25	0.043
10	P	60	20	0.058
11	V, S, P	70	25	0.052
12	P	60	20	0.057

V: valley; S: shoulder; P: peak.

Unlike the fixed pricing, the time-of-use pricing by the retailer is closer to reality. In this case, the proposed objective function (32) is maximized subject to constraints (1)–(31) and (35) with and without demand response program.

Table 13 presents the simulation results of case 2 with and without DRP. According to Table 13, 562% more profit is achieved due to implementation of DRP while the expected profit of retailer with and without DRP is 1170.850 $ and 1108.541 $, respectively. Also, the time-of-use selling price for low, medium and peak periods for residential, commercial and industrial customers with and without DRP are depicted in Fig. 14. According to Fig. 14, it can be seen that the time-of-use selling price in DRP mode is less than without DRP mode. Therefore, these results are favorable for both retailer and end-user customers.

Furthermore, Fig. 15 shows the supplied load by the retailer for clients with and without DRP. Also, Figs. 16–18 depict the energy purchased from PM, BC and all DG units with and without considering DRP in the third scenario, respectively. Finally, Figs. 19 and 20 express the charged and discharged power and stored energy level of ESS in the third scenario, respectively.

3.4. Case 3: real time pricing determination

In the smart grid environment, determination of selling price using real-time pricing by the retailer is much closer to reality unlike the fixed pricing and time-of-use pricing. Therefore, the proposed objective function (32) should be maximized subject to constraints (1)–(31) and (33) with and without demand response program. Furthermore, the real-time pricing should be determined by the retailer according to constraint (33) ($SP(l,t) = SP^{RTP}(l,t)$).

The simulation results of case 3 with and without DRP are presented in Table 14. It should be mentioned that 2.94% more profit is gained due to implementation of DRP while the expected profit of retailer with and without DRP is 1210.002 $ and 1175.436 $, respectively. Also, Fig. 21 depicts the real-time selling pricing for each time periods with and without DRP. According to Fig. 21, it can be seen that real-time selling pricing in DRP mode is less than without DRP mode. Therefore, these results are favorable for both retailer and end-user customers.

In case 3, the supplied load of clients by the retailer with and without DRP is shown in Fig. 22. Also, the power procurement from PM, BC and all DG units with and without considering DRP in the third scenario are shown in Figs. 23–25, respectively. Finally, the charged and discharged power and stored energy level of ESS in the third scenario are depicted in Figs. 26 and 27, respectively.

3.5. Comparison results of cases 1, 2 and 3

The comparison results of different cases containing the expected costs of purchasing from PM, BCs, DG units and the expected total cost as well as expected revenue, expected profit and percentage of profit increase versus case 1 (without DRP) in three cases are presented in Table 15. According to Table 15, in fixed pricing, the expected profit of retailer with and without demand response program is $1123.666 and $1036.756, respec-

Table 8
Distributed generations data.

Parameters	First DG	Second DG	Third DG
Maximum power output	150	180	200
Minimum power output	0	0	0
S_1^{DG}	0.030	0.037	0.044
S_2^{DG}	0.036	0.040	0.049
S_3^{DG}	0.039	0.045	0.054
P_1^{MAX}	60	80	100
P_2^{MAX}	110	120	150
P_3^{MAX}	150	180	200
MUT_j	2	2	2
MDT_j	2	2	2
R_j^{up}	80	90	100
R_j^{down}	80	90	100

Table 9
Forecasted daily wind speed, temperature and irradiation for a sample day.

Time (h)	Wind speed	Temperature	Insulation
1	10.5	24.7	0
2	13.5	24.5	0
3	14.9	24.3	0
4	15.6	24.4	0
5	19.5	24.5	93.5
6	20.6	26.5	219
7	14.4	27.5	467.5
8	14.1	28	637.5
9	11.3	28.5	780
10	9.7	28.8	916
11	7.0	29	1100
12	5.9	29.7	1033
13	8.9	29.8	850
14	9.5	30	680
15	10.4	29.8	595
16	8.8	29.5	255
17	7.1	29	212.5
18	8.3	27.7	153
19	9.9	26.5	63
20	7.5	24.8	0
21	8.8	25	0
22	9.8	24.8	0
23	9.2	24.6	0
24	8.4	24.8	0

Table 10
Wind-turbine/PV system parameters data.

Wind-turbine		PV system	
Parameters	Values	Parameters	Values
p_r	1200	$P_{Max,0}^{M}$	700
V_{ci}	2	G_{a_0}	1000
V_r	14	$T_{M,0}$	25
V_{c0}	25	$NOCT$	44

Table 11
Energy storage system parameters data.

Parameters	Values
X_b^{max}	1000
X_b^{min}	50
P_{charge}^{max}	600
P_{disc}^{max}	600
χ	90
η	80

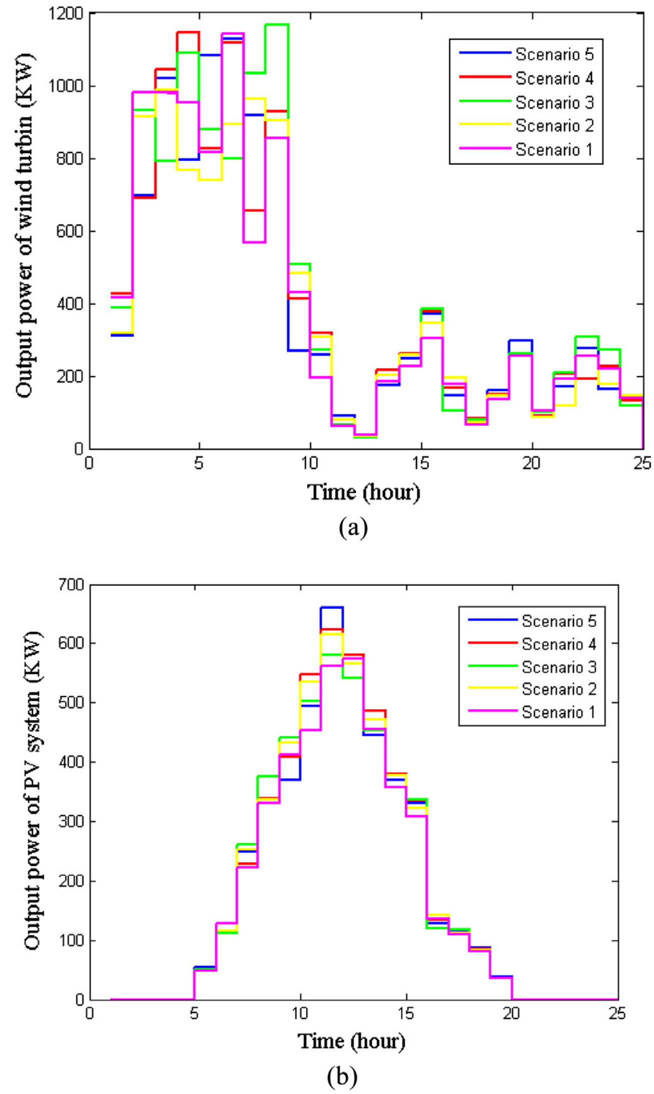

Fig. 4. Available power in all scenarios; (a) wind turbine and (b) PV system.

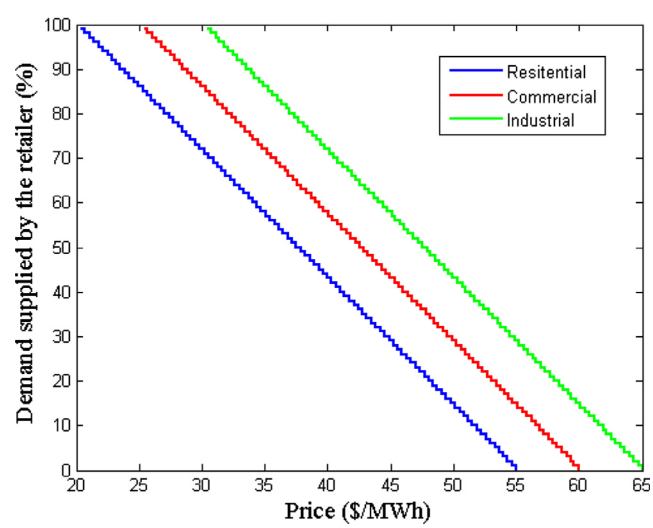

Fig. 5. Price-quota curves.

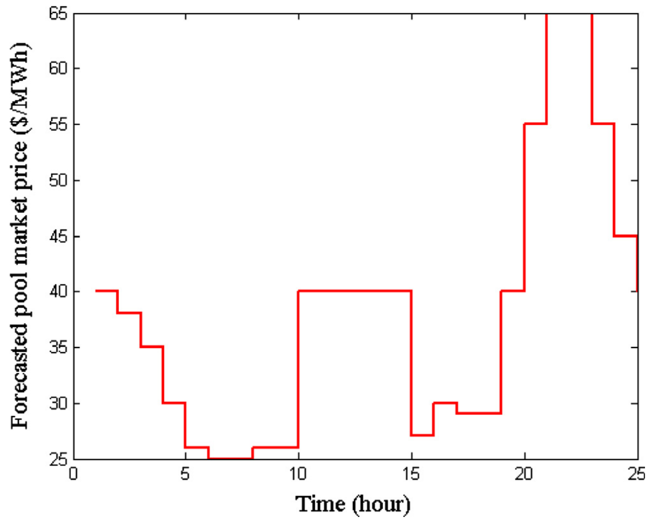

Fig. 6. Forecasted pool price.

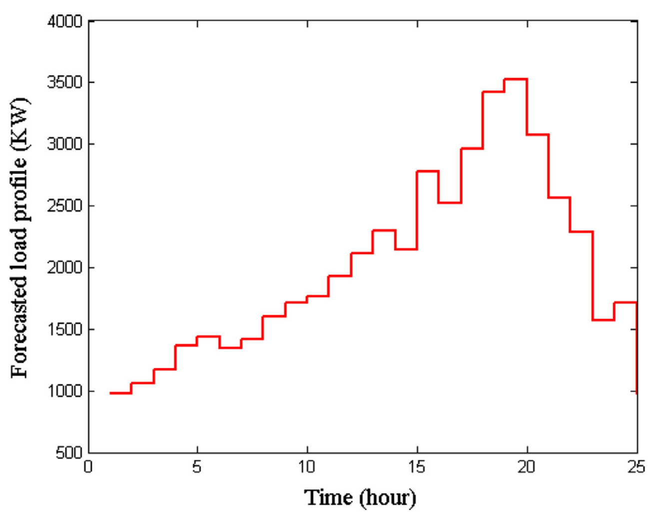

Fig. 7. Forecasted load curve of retailer.

Table 12
Simulation results of case 1.

Parameters	Without DRP	With DRP
Expected profit ($)	1036.756	1123.666
Expected revenue ($)	2222.538	2331.381
Expected total cost ($)	1185.782	1207.715
Expected cost of purchased of pool market ($)	897.042	908.595
Expected cost of purchased of DG units ($)	163.140	173.520
Expected cost of purchased of bilateral contracts ($)	125.600	125.600
Fixed selling price for residential ($/MWh)	46.600	45.900
Fixed selling price for commercial ($/MWh)	49.150	48.450
Fixed selling price for industrial ($/MWh)	51.700	51.000

tively which has 8.38% more profit due to implementation of demand response program. Furthermore, in time-of-use pricing, 6.92% more profit is gained due to implementation of time-of-use pricing while the expected profit of retailer without demand response program is $1108.541. Also, in time-of-use pricing and utilizing of demand response program, the expected profit of retailer is $1170.850 which is 12.93% more profit. Finally, determination of selling price based on real-time pricing by the retailer is

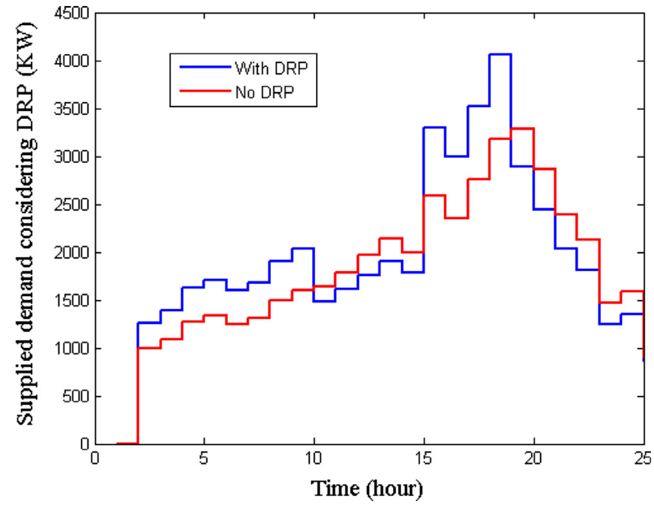

Fig. 8. Supplied load of clients by the retailer in case 1.

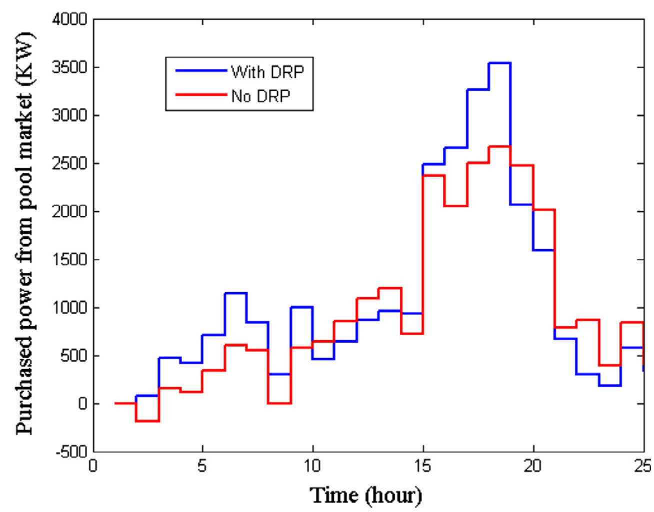

Fig. 9. Power procurement from the PM in case 1.

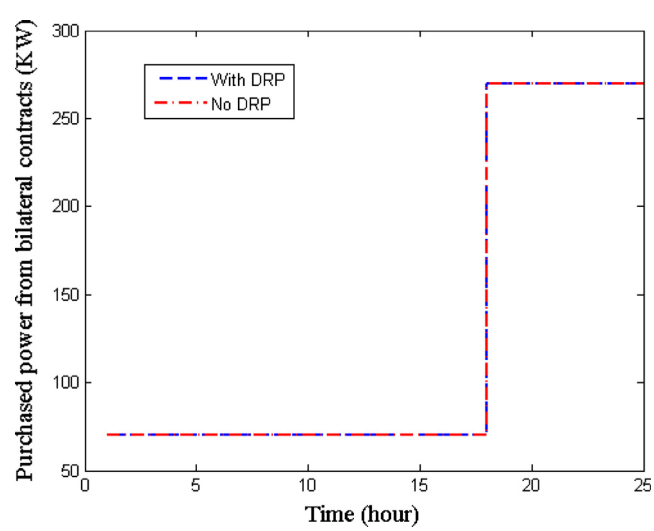

Fig. 10. Power procurement from the BC in case 1.

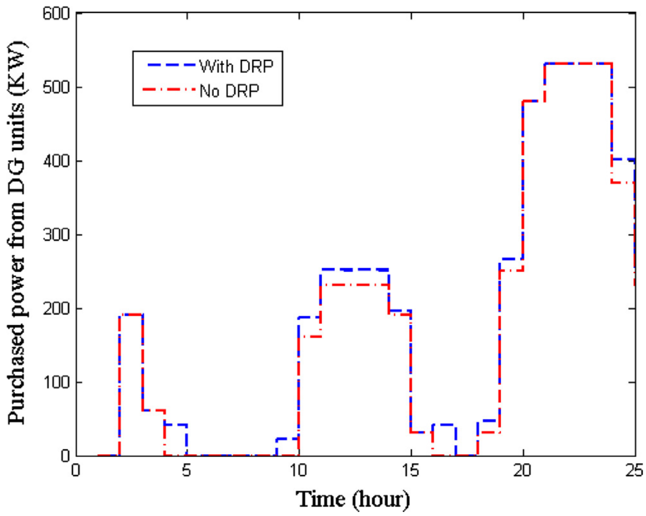

Fig. 11. Power procurement from the DG units in case 1.

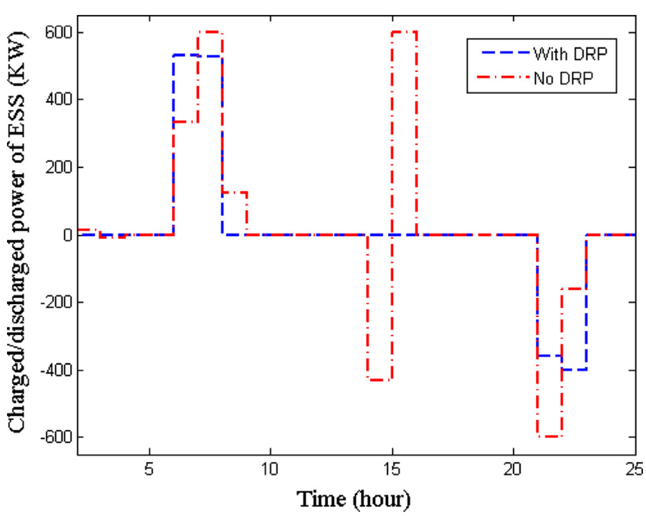

Fig. 12. Charged and discharged power of ESS in case 1.

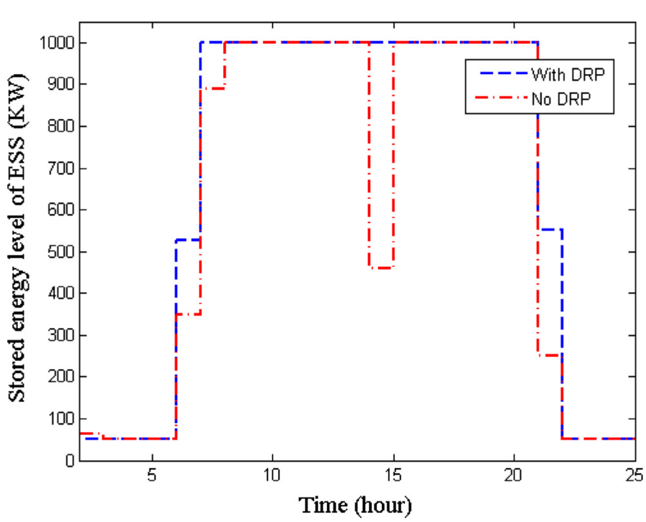

Fig. 13. Stored energy level of ESS in case 1.

Table 13
Simulation results of case 2.

Parameters	Without DRP	With DRP
Expected profit ($)	1108.541	1170.850
Expected revenue ($)	2112.107	2256.109
Expected total cost ($)	1003.567	1085.258
Expected cost of purchased of pool market ($)	714.827	786.019
Expected cost of purchased of DG units ($)	163.140	173.640
Expected cost of purchased of bilateral contracts ($)	125.600	125.600

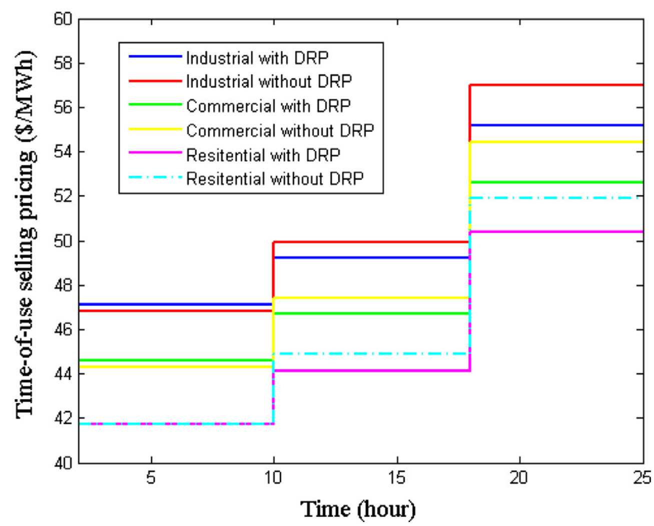

Fig. 14. Time-of-use selling pricing with and without DRP in case 2.

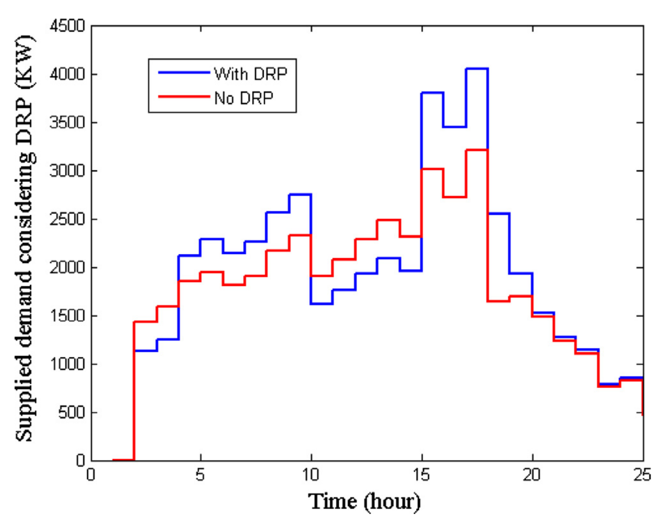

Fig. 15. Supplied load of clients by the retailer in case 2.

much closer to reality unlike the fixed pricing and time-of-use pricing. Therefore, 13.37% more profit is gained due to implementation of real-time pricing while the expected profit is 1175.436. Also, it can be seen from Table 15 that the expected profit in case 3 is higher than cases 1 and 2 because the retailer determined selling price based on real-time pricing and utilized demand response program simultaneously which leads to 16.71% more profit.

Finally, Figs. 28–30 depicted the comparison results of selling price determination based on fixed pricing, time-of-use pricing

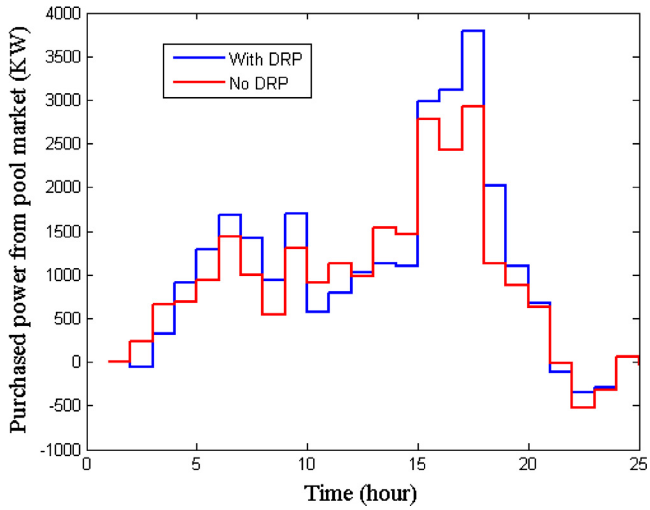

Fig. 16. Power procurement from the PM in case 2.

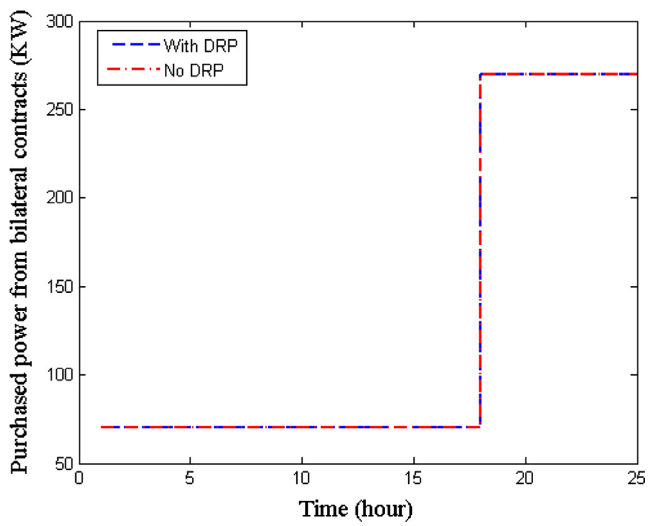

Fig. 17. Power procurement from the BC in case 2.

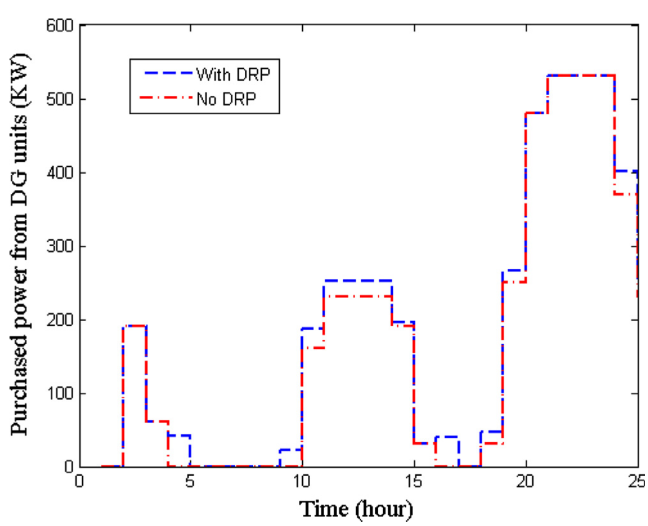

Fig. 18. Power procurement from the DG units in case 2.

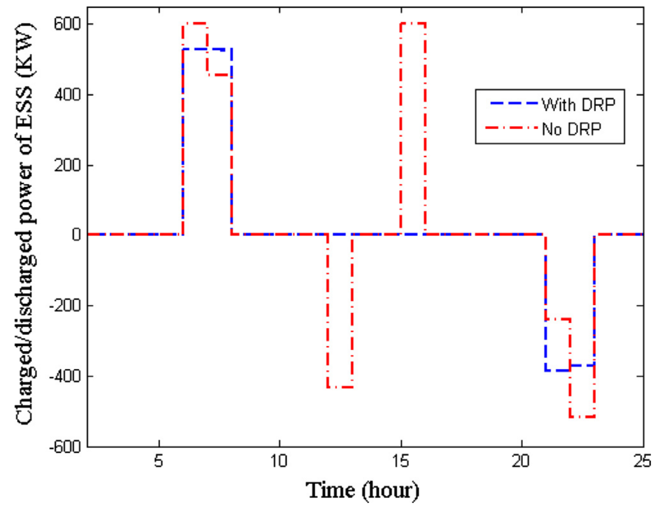

Fig. 19. Charged and discharged power of ESS in case 2.

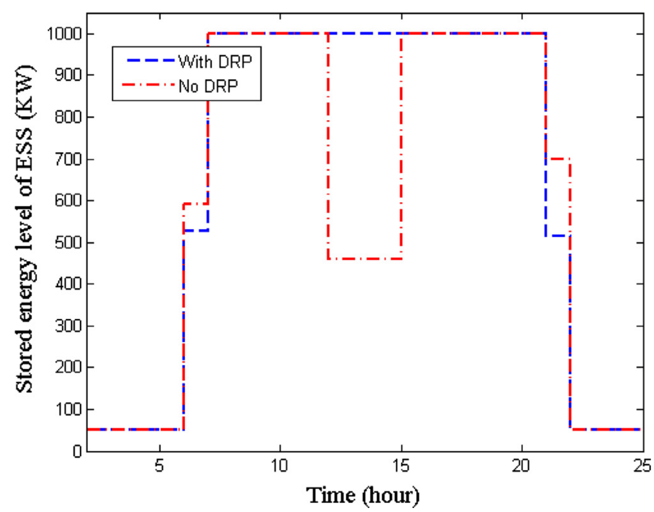

Fig. 20. Stored energy level of ESS in case 2.

Table 14
Simulation results of case 3.

Parameters	Without DRP	With DRP
Expected profit ($)	1175.436	1210.002
Expected revenue ($)	2180.976	2283.321
Expected total cost ($)	1005.541	1073.319
Expected cost of purchased of pool market ($)	755.201	812.370
Expected cost of purchased of DG units ($)	163.140	173.750
Expected cost of purchased of bilateral contracts ($)	87.200	87.200

and real-time pricing for residential, commercial and industrial consumers by the retailer. According to Figs. 28–30, it can be seen that fixed pricing, time-of-use pricing and real-time selling pricing in demand response program mode is less than without demand response program mode. Therefore, these results are favorable for both retailer and end-user customers. In other words, demand response program reduces the selling price which is beneficial for

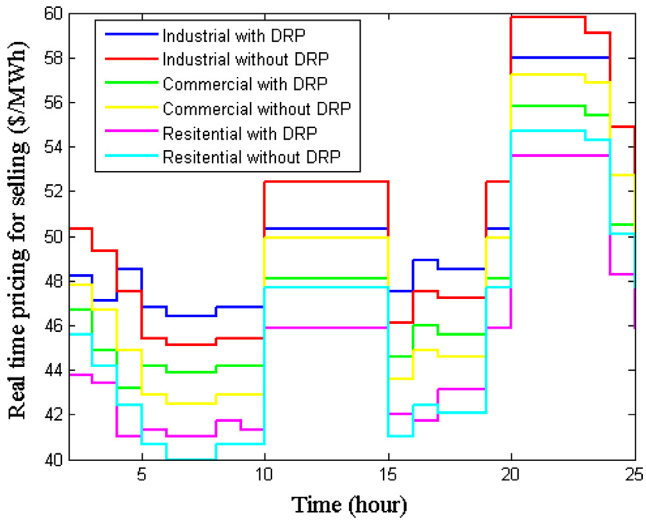

Fig. 21. Real-time selling pricing with and without DRP in case 3.

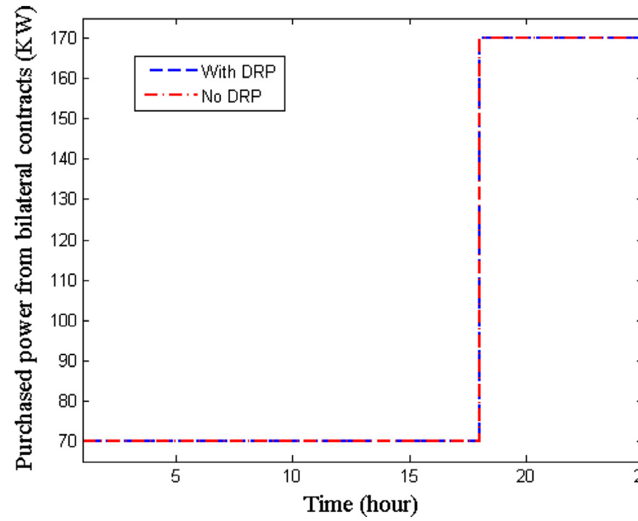

Fig. 24. Power procurement from the BC in case 3.

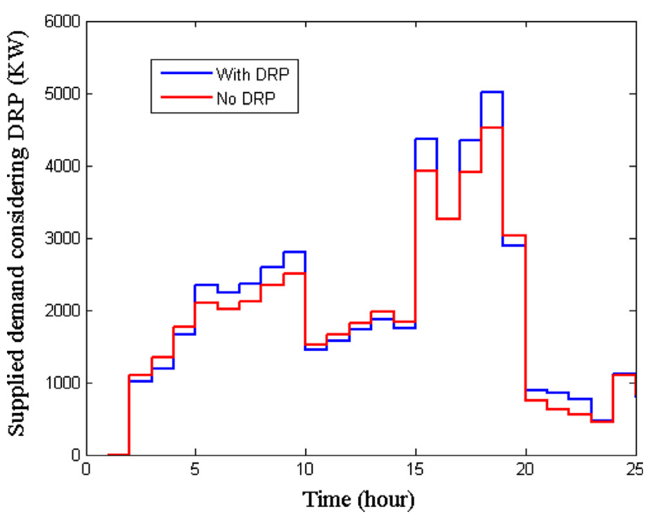

Fig. 22. Supplied load of clients by the retailer in case 3.

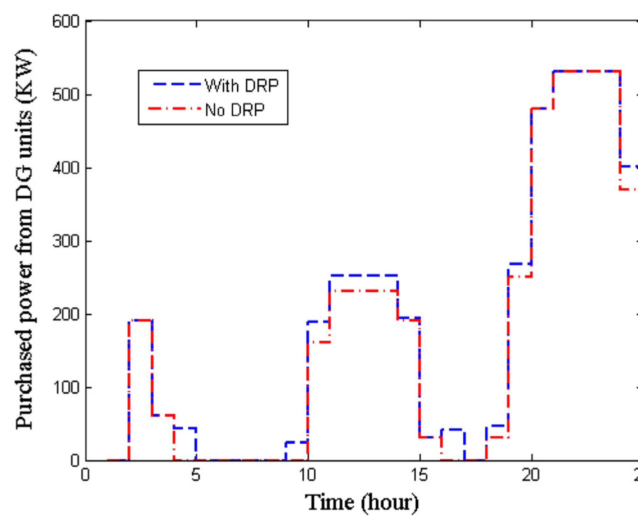

Fig. 25. Power procurement from the DG units in case 3.

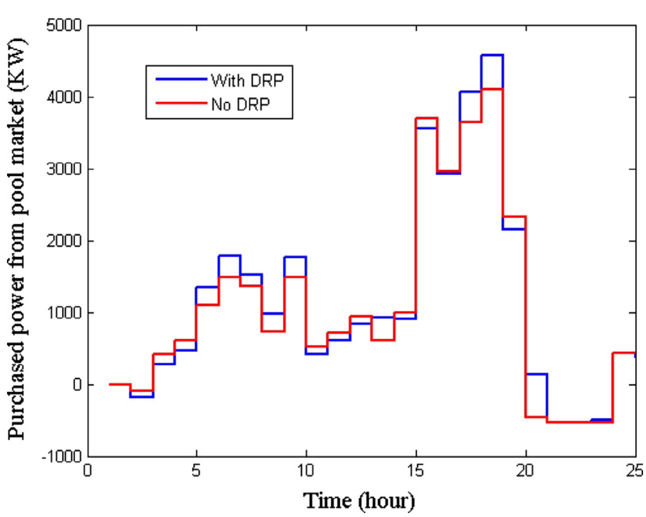

Fig. 23. Power procurement from the PM in case 3.

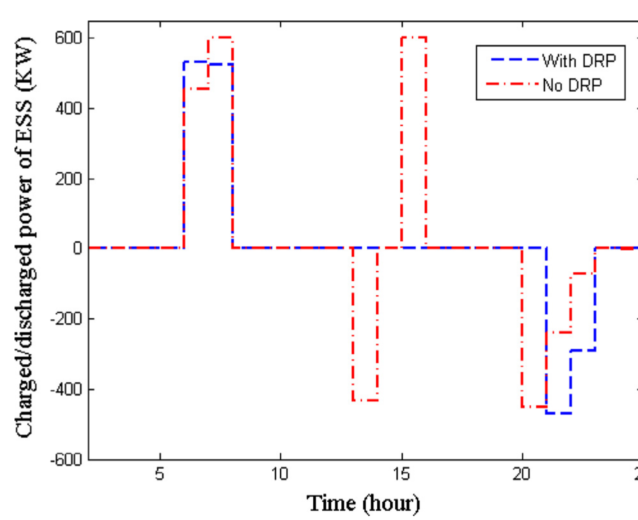

Fig. 26. Charged and discharged power of ESS in case 3.

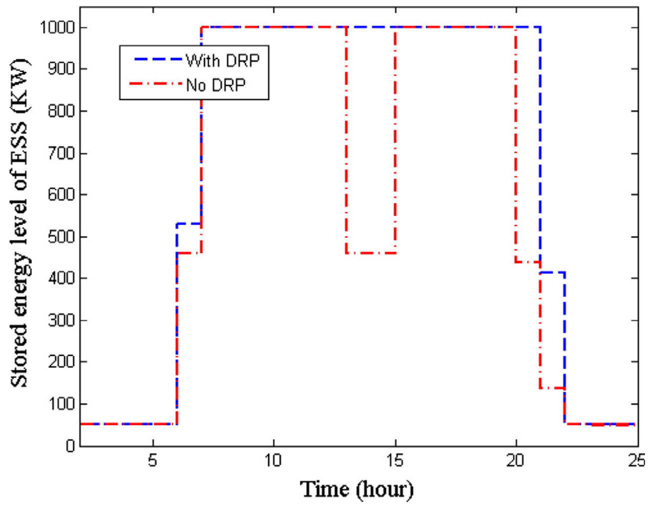

Fig. 27. Stored energy level of ESS in case 3.

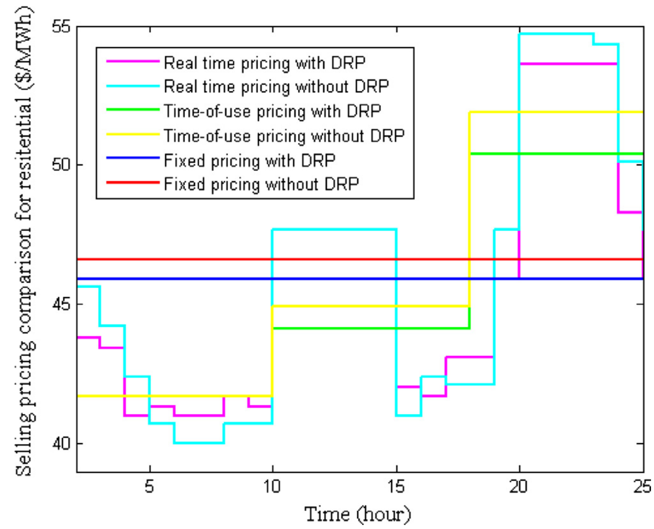

Fig. 28. Comparison results of selling price for residential customers.

customers and increases the expected profit which is useful for retailer which is a win-win strategy between retailer and customers. Furthermore, selling price determination based on real-time pricing and utilized demand response program simultaneously is much closer to reality which leads to retailer expected profit increase.

4. Conclusion

In this paper, the selling price determination problem by the retailer in the presence of demand response program under the smart grid environment is proposed. To demonstrate the efficiency of proposed model, three cases including fixed pricing, time-of-use pricing and real-time pricing with and without demand response program are considered. In the proposed model, the pool market price, demand of clients, wind speed, irradiation and temperature are considered as stochastic framework and are modeled using a scenario approach. The comparison results of three cases show that the expected profit in case 3 (real-time selling pricing) is increased 16.71% and 12.93% in comparison with cases 1 and 2, respectively. Also, the simulation results show the positive effects of demand response program for both retailer (increasing the expected profit) and end-user clients (decreasing the selling price). Finally, from the proposed model it can be concluded that the selling price determination based on real-time pricing by the retailer as well as participation in demand response program leads to retailer expected profit increase and decreases the selling price for end-user customers that is favorable for both retailer and end-user customers.

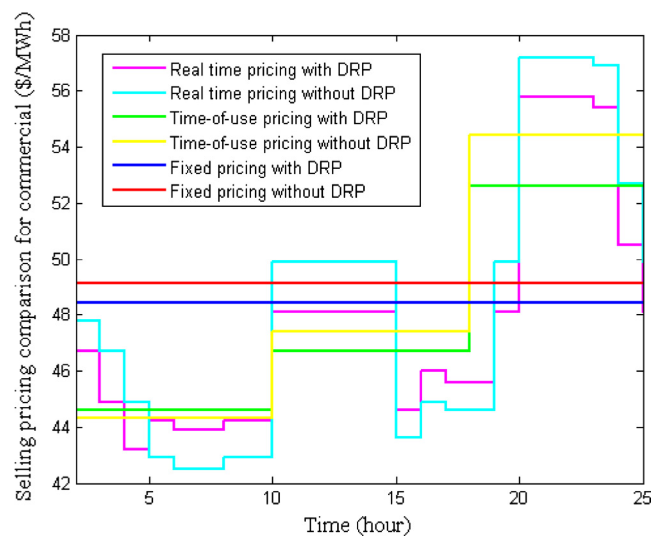

Fig. 29. Comparison results of selling price for commercial customers.

Table 15
Comparison results of cases 1, 2 and 3.

Cases	Case 1		Case 2		Case 3	
Parameters	Without DRP	With DRP	Without DRP	With DRP	Without DRP	With DRP
Expected cost of purchased of PM ($)	897.042	908.595	714.827	786.019	755.201	812.370
Expected cost of purchased of DG units ($)	163.140	173.520	163.140	173.640	163.140	173.750
Expected cost of purchased of BCs ($)	125.600	125.600	125.600	125.600	87.200	87.200
Expected total cost ($)	1185.782	1207.715	1003.567	1085.258	1005.541	1073.319
Expected revenue ($)	2222.538	2331.381	2112.107	2256.109	2180.976	2283.321
Expected profit ($)	1036.756	1123.666	1108.541	1170.850	1175.436	1210.002
Increased profit (%)	0	8.38%	6.92%	12.93%	13.37%	16.71%

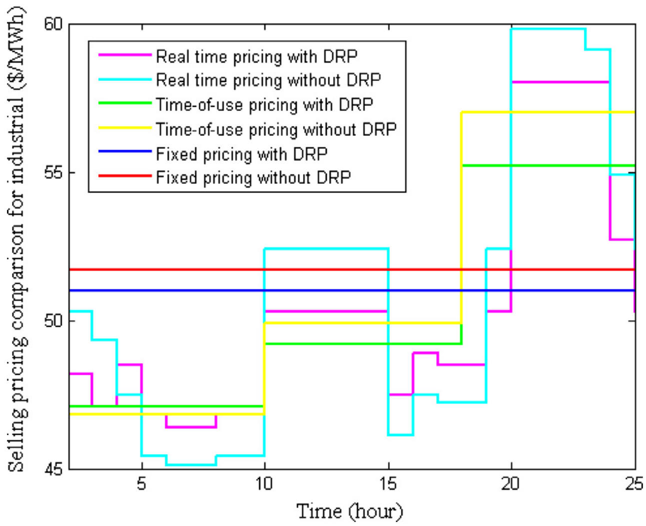

Fig. 30. Comparison results of selling price for industrial customers.

References

[1] Shahidehpour M, Yamin H, Li Z. Market operations in electric power systems. New York: Wiley; 2002.
[2] Zou P, Chen Q, Xia Q, He C, Kang C. Incentive compatible pool-based electricity market design and implementation: a Bayesian mechanism design approach. Appl Energy 2015;158:508–18.
[3] Del Granado PC, Pang Z, Wallace SW. Synergy of smart grids and hybrid distributed generation on the value of energy storage. Appl Energy 2016;170:476–88.
[4] Gilbert F, Anjos MF, Marcotte P, Savard G. Optimal design of bilateral contracts for energy procurement. Eur J Oper Res 2015;246(2):641–50.
[5] Xiao Y, Wang X, Wang X, Dang C, Lu M. Behavior analysis of wind power producer in electricity market. Appl Energy 2016;171:325–35.
[6] Brusco G, Burgio A, Menniti D, Pinnarelli A, Sorrentino N. The economic viability of a feed-in tariff scheme that solely rewards self-consumption to promote the use of integrated photovoltaic battery systems. Appl Energy 2016;183:1075–85.
[7] Wendel CH, Braun RJ. Design and techno-economic analysis of high efficiency reversible solid oxide cell systems for distributed energy storage. Appl Energy 2016;172:118–31.
[8] Zhang S, Xiong R, Cao J. Battery durability and longevity based power management for plug-in hybrid electric vehicle with hybrid energy storage system. Appl Energy 2016;179:316–28.
[9] Mazidi M, Monsef H, Siano P. Robust day-ahead scheduling of smart distribution networks considering demand response programs. Appl Energy 2016;178:929–42.
[10] Babonneau F, Caramanis M, Haurie A. A linear programming model for power distribution with demand response and variable renewable energy. Appl Energy 2016;181:83–95.
[11] Hu MC, Lu SY, Chen YH. Stochastic–multiobjective market equilibrium analysis of a demand response program in energy market under uncertainty. Appl Energy 2016;182:500–6.
[12] Xie J, Hong T, Stroud J. Long-term retail energy forecasting with consideration of residential customer attrition. IEEE Trans Smart Grid 2015;6(5):2245–52.
[13] Gabriel S, Genc MF, Balakrishnan S. A simulation approach to balancing annual risk and reward in retail electrical power markets. IEEE Trans Power Syst 2002;17(4):1050–7.
[14] Nojavan S, Mehdinejad M, Zare K, Mohammadi-Ivatloo B. Energy procurement management for electricity retailer using new hybrid approach based on combined BICA–BPSO. Int J Electr Power Energy Syst 2015;73:411–9.
[15] Feuerriegel S, Neumann D. Measuring the financial impact of demand response for electricity retailers. Energy Pol 2014;65:359–68.
[16] Nazari M, Foroud AA. Optimal strategy planning for a retailer considering medium and short-term decisions. Int J Electr Power Energy Syst 2013;45(1):107–16.
[17] Gabriel S, Conejo AJ, Plazas MA, Balakrishnan S. Optimal price and quantity determination for retail electric power contracts. IEEE Trans Power Syst 2006;21(1):180–7.
[18] Karandikar RG, Khaparde SA, Kulkarni SV. Quantifying price risk of electricity retailer based on CAPM and RAROC methodology. Int J Electr Power Energy Syst 2007;29(10):803–9.
[19] Karandikar RG, Khaparde SA, Kulkarni SV. Strategic evaluation of bilateral contract for electricity retailer in restructured power market. Int J Electr Power Energy Syst 2010;32(5):457–63.
[20] Carrión M, Conejo AJ, Arroyo JM. Forward contracting and selling price determination for a retailer. IEEE Trans Power Syst 2007;22(4):2105–14.
[21] Kettunen J, Salo A, Bunn DW. Optimization of electricity retailer's contract portfolio subject to risk preferences. IEEE Trans Power Syst 2010;25(1):117–28.
[22] Hatami AR, Seifi H, Sheikh-El-Eslami MK. Optimal selling price and energy procurement strategies for a retailer in an electricity market. Electr Power Syst Res 2009;79(1):246–54.
[23] Ahmadi A, Charwand M, Aghaei J. Risk-constrained optimal strategy for retailer forward contract portfolio. Int J Electr Power Energy Syst 2013;53:704–13.
[24] Mahmoudi N, Eghbal M, Saha TK. Employing demand response in energy procurement plans of electricity retailers. Int J Electr Power Energy Syst 2014;63:455–60.
[25] Hatami A, Seifi H, Sheikh-El-Eslami MK. A stochastic-based decision-making framework for an electricity retailer: time-of-use pricing and electricity portfolio optimization. IEEE Trans Power Syst 2011;26(4):1808–16.
[26] García-Bertrand R. Sale prices setting tool for retailers. IEEE Trans Smart Grid 2013;4(4):2028–35.
[27] Mahmoudi N, Saha TK, Eghbal M. A new demand response scheme for electricity retailers. Electr Power Syst Res 2014;108:144–52.
[28] Carrión M, Arroyo JM, Conejo AJ. A bilevel stochastic programming approach for retailer futures market trading. IEEE Trans Power Syst 2009;24(3):1446–56.
[29] Nojavan S, Mohammadi-Ivatloo B, Zare K. Robust optimization based price-taker retailer bidding strategy under pool market price uncertainty. Int J Electr Power Energy Syst 2015;73:955–63.
[30] Nojavan S, Mohammadi-Ivatloo B, Zare K. Optimal bidding strategy of electricity retailers using robust optimisation approach considering time-of-use rate demand response programs under market price uncertainties. IET Gener Transm Distrib 2015;9(4):328–38.
[31] Charwand M, Moshavash Z. Midterm decision-making framework for an electricity retailer based on information gap decision theory. Int J Electr Power Energy Syst 2014;63:185–95.
[32] Charwand M, Ahmadi A, Siano P, Dargahi V, Sarno D. Exploring the trade-off between competing objectives for electricity energy retailers through a novel multi-objective framework. Energy Convers Manage 2015;91:12–8.
[33] Charwand M, Ahmadi A, Heidari AR, Esmaeel Nezhad A. Benders decomposition and normal boundary intersection method for multiobjective decision making framework for an electricity retailer in energy markets. IEEE Syst J 2015;9(4):1475–784.
[34] Herranz R, Munoz San Roque A, Villar J, Campos FA. Optimal demand-side bidding strategies in electricity spot markets. IEEE Trans Power Syst 2012;27(3):1204–13.
[35] Yusta JM, Ramirez-Rosado IJ, Dominguez-Navarro JA, Perez-Vidal JM. Optimal electricity price calculation model for retailers in a deregulated market. Int J Electr Power Energy Syst 2005;27(5):437–47.
[36] Mahmoudi-Kohan N, Moghaddam MP, Sheikh-El-Eslami MK, Shayesteh E. A three-stage strategy for optimal price offering by a retailer based on clustering techniques. Int J Electr Power Energy Syst 2010;32(10):1135–42.
[37] Hajati M, Seifi H, Sheikh-El-Eslami MK. Optimal retailer bidding in a DA market–a new method considering risk and demand elasticity. Energy 2011;36(2):1332–9.
[38] Ghazvini MA, Soares J, Horta N, Neves R, Castro R, Vale Z. A multi-objective model for scheduling of short-term incentive-based demand response programs offered by electricity retailers. Appl Energy 2015;151:102–18.
[39] Zugno M, Morales JM, Pinson P, Madsen H. A bilevel model for electricity retailers' participation in a demand response market environment. Energy Econ 2013;36:182–97.
[40] Boroumand RH, Zachmann G. Retailers' risk management and vertical arrangements in electricity markets. Energy Pol 2012;40:465–72.
[41] Boroumand RH, Goutte S, Porcher S, Porcher T. Hedging strategies in energy markets: the case of electricity retailers. Energy Econ 2015;51:503–9.
[42] Fleten SE, Pettersen E. Constructing bidding curves for a price-taking retailer in the Norwegian electricity market. IEEE Trans Power Syst 2005;20(2):701–8.
[43] Mahmoudi-Kohan N, Moghaddam MP, Sheikh-El-Eslami MK. An annual framework for clustering-based pricing for an electricity retailer. Electr Power Syst Res 2010;80(9):1042–8.
[44] Wei W, Liu F, Mei S. Offering non-dominated strategies under uncertain market prices. IEEE Trans Power Syst 2015;30(5):2820–1.
[45] Wei W, Liu F, Mei S. Energy pricing and dispatch for smart grid retailers under demand response and market price uncertainty. IEEE Trans Smart Grid 2015;6(3):1364–74.
[46] Khojasteh M, Jadid S. Decision-making framework for supplying electricity from distributed generation-owning retailers to price-sensitive customers. Utilities Policy 2015;37:1–12.
[47] Zare K, Moghaddam MP, Sheikh-El-Eslami MK. Risk-based electricity procurement for large consumers. IEEE Trans Power Syst 2011;26(4):1826–35.
[48] Vardakas JS, Zorba N, Verikoukis CV. A survey on demand response programs in smart grids: pricing methods and optimization algorithms. IEEE Commun Surv Tut 2015;17(1):152–78.

[49] Nojavan S, Zare K, Mohammadi-Ivatloo B. Stochastic energy procurement management for electricity retailers considering the demand response programs under pool market price uncertainty. Majlesi J Energy Manage 2015;4(3).
[50] Zare K, Moghaddam MP, El Eslami MK. Demand bidding construction for a large consumer through a hybrid IGDT-probability methodology. Energy 2010;35(7):2999–3007.
[51] Zare K, Moghaddam MP, El Eslami MK. Electricity procurement for large consumers based on information gap decision theory. Energy Pol 2010;38(1):234–42.
[52] Zare K, Conejo AJ, Carrión M, Moghaddam MP. Multi-market energy procurement for a large consumer using a risk-aversion procedure. Electr Power Syst Res 2010;80(1):63–70.
[53] Nojavan S, allah Aalami H. Stochastic energy procurement of large electricity consumer considering photovoltaic, wind-turbine, micro-turbines, energy storage system in the presence of demand response program. Energy Convers Manage 2015;103:1008–18.
[54] Aalami HA, Nojavan S. Energy storage system and demand response program effects on stochastic energy procurement of large consumers considering renewable generation. IET Gener Transm Distrib 2016;10(1):107–14.
[55] Nojavan S, Qesmati H, Zare K, Seyyedi H. Large consumer electricity acquisition considering time-of-use rates demand response programs. Arab J Sci Eng 2014;39(12):8913–23.
[56] Ghalelou AN, Fakhri AP, Nojavan S, Majidi M, Hatami H. A stochastic self-scheduling program for compressed air energy storage (CAES) of renewable energy sources (RESs) based on a demand response mechanism. Energy Convers Manage 2016;120:388–96.
[57] Mohseni-Bonab SM, Rabiee A, Mohammadi-Ivatloo B. Voltage stability constrained multi-objective optimal reactive power dispatch under load and wind power uncertainties: a stochastic approach. Renew Energy 2016;85:598–609.
[58] Growe-Kuska N, Heitsch H, Romisch W. Scenario reduction and scenario tree construction for power management problems. Power tech conference proceedings, 2003 IEEE Bologna, vol. 3. IEEE; 2003. p. 7.
[59] The GAMS Software Website; 2016 <http://www.gams.com/dd/docs/solvers/sbb.pdf>.
[60] Brooke A, Kendrick D, Meeraus A. GAMS user's guide. Redwood City (CA): The Scientific Press; 1990. Available: <http://www.gams.com/docs/gams/GAMSUsersGuide.pdf>.