Risk-based Energy Procurement of Retailer in the Presence of Demand Response Exchange

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A retailer can sign multiple contracts with participation in demand response program (DRP). The energy sources considered for retailers include pool market and forward contracts. In this paper, several new DRP schemes are proposed for a retailer which is containing pool-order DR, forward DR and reward-base DR. proposed model is an agreement that retailer will participate it, if is useful. Pool market price uncertainty modeling is one of the main challenges in power system modeling which information gap decision theory (IGDT) is proposed for this uncertainty. In IGDT approach, the robustness and opportunity functions are used to study of different strategies in the presence of pool market price uncertainty. Robustness function is used in the risk-averse strategy while opportunity function is used in the risk-taker strategy. The proposed IGDT risk-constraint strategies of electricity retailer in presence of pool-order DR, forward DR and reward-base DR are modeled via mixed-integer non-linear programming which is solved using SBB solver under GAMS optimization software. To validate the proposed model, two cases are studied and positive effects of proposed DR scheme on the risk-averse, risk-neutral, risk-taker strategies are investigated, and the results are compared with each other.

keywords: *Demand response (DR) programs; electricity retailer; forward DR and pool-order DR; reward-base DR; information gap decision theory (IGDT).*

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NOMENCLATURE

A. Parameters:

$d(t)$ Time period

$f_{po}^{pen}(t)$ Penalty of not running pool-order DR in time period t ($)

$P_{f,b}^{DR,MAX}(t)$ Highest demand in block b of forward DR f in time period t (MWh)

$\bar{P}_{j}^{DR}(t)$ Demand in jth step of reward-base DR in time period t (MWh)

$P_{f,b}^{MAX}(t)$ Highest demand in block b of forward contract in time period t (MWh)

$P_{po}^{MAX}(t)$ Highest demand in pool-order DR in time period t (MWh)

$P^{req}(t)$ Value of purchased power by retailer in period t (MWh)

$\bar{R}_{j}^{DR}(t)$ Highest value in jth step of reward-base DR in time period t ($/MWh)

$\lambda_{po}(t)$ Price of pool-order DR in period t ($/MWh)

$\lambda_{f,b}^{DR}(t)$ Price of block b of forward DR f option in time period t ($/MWh)

$\lambda_{f,b}^{F}(t)$ Price of the block b of forward contract f in time period t ($/MWh)

$\tilde{\lambda}^{p}(t)$ Forecasted pool market price ($/MWh)

ω Percentage increase in cost for retailer (%)

Y Percentage decrease in cost for retailer (%)

C_b Minimum expected cost of retailer ($)

C_r Critical cost for robustness function ($)

C_o Critical cost for opportunity function ($)

B. Numbers:

N_{BDR} Number of blocks in forward DR

N_F Number of forward contracts

N_{FB} Number of blocks in forward contracts

N_{FDR} Number of contract in forward DR

N_J Number of steps in reward-base DR

N_{po} Number of pool-order options

C. Variables:

$C(FDR)$ Total cost of forward DR program ($)

$C(F)$ Total cost of forward contracts ($)

$C(PO)$ Total cost of pool-order options ($)

$EC(P)$ Total cost of power procurement from pool market ($)

$EC(RDR)$ Total cost of reward-base DR ($)

$P^{DR}(t)$ Purchased power from reward-base DR in time period t (MWh)

$P_{po}(t)$ Purchased power from pool-order in time period t (MWh)

$P^{DR}_{f,b}(t)$ Purchased power from block b of forward DR f in time period t(MWh)

$P^{F}_{f,b}(t)$ Purchased power from block b of forward contract f in time period t(MWh)

$P^{p}(t)$ Purchased power from the pool market in time period t (MWh)

$R^{DR}(t)$ Value of reward in time period t ($/MWh)

$R^{DR}_{j}(t)$ Value of reward of step j in time period t ($/MWh)

$v_{DR,j}(t)$ Binary variable that shows which step is executed in time period t 0,1

$v_{po}(t)$ Binary variable which is 1 if pool-order is run in time period t 0,1

$\lambda^{p}(t)$ Actual pool market price ($/MWh)

D. Functions:

$C(p, \lambda)$ Procurement cost function of retailer ($)

$\hat{\alpha}(C_r)$ Robustness function (%)

$\hat{\beta}(C_o)$ Opportunity function (%)

1. INTRODUCTION

The electricity retailer can purchase power from pool market and forward contracts in order to supply the consumers' demand [1]. Also, retailer can use DRPs in order to balance the price on the electricity market [2]. In DRPs, peak load is managed by electricity retailer [3] in which the load profile is flatted and purchased cost is reduced.

A. Literature review

Retailers usually work to fill the gap between consumers and the wholesale market. Ref [4] used hybrid approach based on binary imperialist competitive algorithm and binary particle swarm optimization to procure optimal energy for retailer. An optimal strategy for retailer is presented in [5], which retailer can provide its energy from both pool and bilateral contract options. Retailer problems when setting up a contract for both sides of the suppliers and end-use in order to achieve maximum profits by considering acceptable risk levels are presented in [6]. Also, retailer contracts with consumers should also be set up to allow consumers to choose it. In ref [7], contracts setting problem is provided to maximize profits with an acceptable level of risk. Ref [8] created a multi-stage randomized optimization approach that leads to model the uncertainties of electricity prices and loads. Retailer policies to determine the optimum price for the electricity selling and procure f are investigated by stochastic programming in [9]. In ref [10], the financial risk arising from the uncertainty of market prices has been addressed. Ref [11] presented a stochastic programming in order to determine the selling price of electricity to consumers based on the time-of-use (TOU) of DRP and manage a set of contracts to cover its demand and avoid risks in a medium-term period. In ref [12], a model presented for the retailer, in which consumers shift their loads based on TOU-DRP, taking market price changes into account. In [13], energy management of retailer is modeled by using a bi-level programming approach. In [14], a robust optimization method is presented in order to obtain optimal bidding strategy for retailer which also demand response program is used in [15]. The uncertainty of the pool price for retailers is considered in [16] which various strategies are obtained for selling to consumers.

The basic concepts of DRPs are described in [17]. Consumer behavior against price fluctuations is discussed in [18]. Reward-based DRP is described in [19,20]. Formulation of DRP is presented in [21]. A study about coupon-based method is investigated in [22], where the market price determines amount of incentive to the consumer. There is detailed explanation about incentive-based methods in [23], where energy cost and peak-to-average ratio are minimized through a game theory approach. Refs [24,25] provided the description of price-based DRP. The consumer can adjust its energy consumption by using real-time prices based on presented model in [24]. A comprehensive formulation of TOU is given in [25]. The technical aspects of DRP are presented in [26–30]. New markets for DRP exchange have been proposed in [31,32]. Based on the pool-market, the market operator collects offers and clears market to maintain balance, but in [32] market clearing scheme uses Walrasian auctions, in which price is updated in response to adjusting the market price. Ref [33–36] paid to evaluate the three economic types of DRPs, known as load curtailment, load shifting and fuel substitution. DRP can be an option to reduce the retailer's risk. In [37], authors counteract the uncertainty of the pool market which use interruptible loads. In [38], two types of interruptible loads contract (pay-in-advance and pay-as-you-go) are evaluated. Ref [39] used self-production to reduce pool market volatility. Ref [40] indicates that distribution companies can use interruptible loads as energy resources. According to the presented model in [41], distribution companies used interruptible loads to participate in the market. Distribution companies used real-time pricing and TOU to improve consumers' energy consumption [42]. IGDT is one of the main methods which used in uncertainty modeling in power market problems. For example in ref [43] proposes an

IGDT to obtain the bidding strategy of MG. in addition in ref [44] authors considered a price-taker generation station producer that participates in a day-ahead market using IGDT. According to the abovementioned matter, most papers have been reviewed the DRP from consumer point of view and few papers reviewed DRP from the points of retailers. Most of previous papers, DR has mostly addressed as technical aspects and basic concepts has not considered DR contract options. Only [19,20] have reviewed the economic aspects of DRP.

B. Novelty and contributions

In this paper, new DRP is proposed to reduce retailer's cost. There are difference between the new method and the previous method [19, 20] in the DRP exchange type. In new method, DRP is directly exchanged between DRP buyer and seller. The methods in this plan include various agreements for the DRP transaction, which may be long-term or short-term agreements. These contracts include as follows:

1 Forward-DR: this type of contracts is safe agreements that take place at a specific volume and price for specific period [45,46].

2 Pool-order: to counter against the small fluctuation of pool price, this plan uses the well-known financial concept which is presented during price increment [45,46].

3 Reward-based DRP [47]: this type of DRP is a consumer incentive scheme to further load reduction and receive more reward from retailer, also considered contract is a real-time source for presenting DRP method.

The abovementioned contract allows the retailers to decide on different conditions and choose the suitable contracts. In normal conditions, retailers use forward-DRP contract. Also when the pool price has increased, the pool-order will be used. Finally, they can hope to real-time contracts (reward-base DR). Retailer uses DRP and contracts in this paper to minimize their costs, also information gap decision theory is proposed to model the pool price uncertainty. Robust and opportunistic are strategies derived from the robustness and opportunity functions of IGDT technique for retailers, which are used to model various uncertainty states. Also, deterministic results without pool market price uncertainty modeling are used as risk-neutral strategy. Furthermore, robust results are used in the risk-averse strategies while opportunistic results are used in the risk-taker strategies. IGDT has several differences in comparing to robust optimization approach. Robust optimization approach is analyzed solution optimally under forecasting errors in two risk-neutral strategy and risk-averse strategy which risk-averse strategy modeled worst condition for uncertain parameter. Nevertheless, IGDT is analyzed effects of various amounts of deviation from optimal solution on the uncertain parameter.

C. Paper organization

The paper is organized as follows: New proposed DRP schemes for retailer as well as wholesale market suppliers are formulated in Section 2. IGDT approach is presented in Section 3 and it is applied to the proposed model in Section 4. Section 5 presents the risk-averse, risk-neutral and risk-taker results for a retailer, based on proposed IGDT approach. Finally, the conclusion is presented in Section 6.

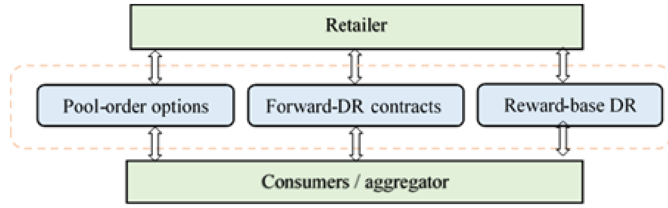

Fig. 1. Available DR programs for energy supply of retailer

2. PROBLEM FORMULATION

Retailer can trade with consumers through several contracts and meet the DRP requirement. These contracts are shown in Fig. 1. These contracts may differ in terms of price, volume and execution time. Details of these contracts will be described in the relevant section. In this paper, consumers just able to sell DRP to retailers, but generally they can sell their DRP in other markets [48,49]. Also the retailer does not care about the technical aspects of DR programs.

A. Pool-order DR

At the time of pool price fluctuations, retailer can set a pool-order options contract with DRP sellers. In fact, this contract is set for market price upturn times and will run when the DRP cost is lower than the procurement cost from the pool market. At the contract running time, the retailer decides to run or not to perform the contract by compar the market price. If the contract is not executed, the retailer must pay a predetermined amount as a penalty. Meanwhile, retailers not have to choose this contract because will choose contract to prevent further losses when pool prices is increased. The mathematical model of this contract is presented in Eqs. (1) - (3). Furthermore, the overall structure of this contract is shown in Fig. 2.

$$C(PO) = \sum_{t \in T} \sum_{po=1}^{N_{po}} [P_{po}(t).\lambda_{po}(po).\nu_{po}(t).d(t) + (1-\nu_{po}(t)).f_{po}^{pen}(t) \tag{1}$$

$$0 \leq P_{po}(t) \leq P_{po}^{Max}(t) \quad \forall po = 1, 2, ..., N_{po} \tag{2}$$

$$P_{po}^{total}(t) = \sum_{po=1}^{N_{po}} P_{po}(t).\nu_{po}(t) \tag{3}$$

Eq. (1) shows the overall cost of pool-order options for the specified time horizon. This equation consists of two parts. The first part shows the cost of the pool-order option and the second part shows the penalty for not executed contract. Eq. (2) determines the power limit of each pool-order options. Finally, the total pool-order power is expressed in Eq. (3).

B. Forward DR

Forward DRP contracts are agreements that are signed before the start of the time horizon. Forward DR contract is created by adapting forward contracts to DRP, in which the exchange product is DRP [45]. These contracts have different price blocks, which in each block has different volume and price. These types of contracts usually have a certain price, which is determined as follows:

- Unmatched market: in this method, the price is negotiated directly between the buyer and the seller.

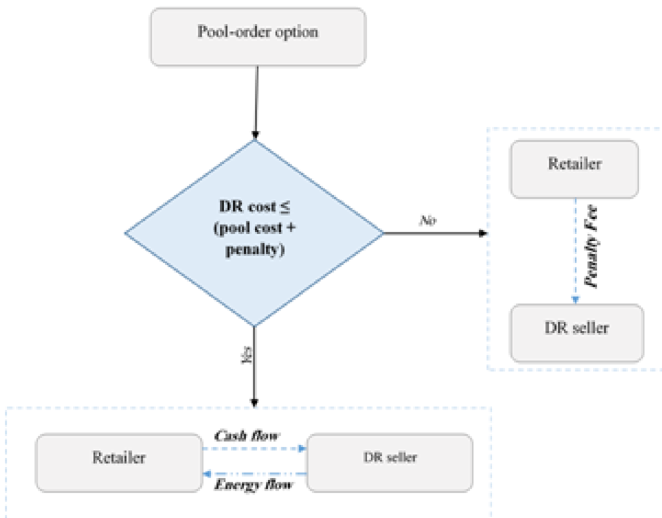

Fig. 2. Configuration of pool-order option

- Bourse-trade market: in this market, contracts are signed with standardized price and volume. The advantage of this type of trading is that prices are settled through a centralized clearing center.

Because this type of exchange is done directly between the seller and the buyer, direct settlement is used for pricing. The total cost of this contract is calculated as follows:

$$C(FDR) = \sum_{t \in T} \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t).d(t) \tag{4}$$

Furthermore, Eqs. (4) and (5) show the forward DRP cost and the boundary size of each contract, respectively. Finally, Eq. (6) shows the overall forward-DRP's power in during period.

$$0 \leq P_{f,b}^{DR}(t) \leq P_{f,b}^{DR,Max}(t) \tag{5}$$

$$P^{FDR}(t) = \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} P_{f,b}^{DR}(t) \tag{6}$$

C. Reward-base DR

The reward-based DRP is shown in Fig. 3. In this DRP, the consumers more reduce their demand while the rewards will increase which receive from the retailer. In this method, increased rewards are stepwise. This paper has assumed that the full potential reward-based DRP is used by consumers. The all equations for this scheme are presented in (7)-(10).

$$P^{DR}(t) = \sum_{j=1}^{N_J} \bar{P}_j^{DR}(t).\nu_{DR,j}(t) \tag{7}$$

$$R^{DR}(t) = \sum_{j=1}^{N_J} R_j^{DR}(t) \tag{8}$$

$$\bar{R}_{j-1}^{DR}(t).\nu_{DR,j}(t) \leq R_j^{DR}(t) \leq \bar{R}_j^{DR}(t).\nu_{DR,j}(t) \tag{9}$$

$$\sum_{j=1}^{N_J} \nu_{DR,j}(t) = 1 \tag{10}$$

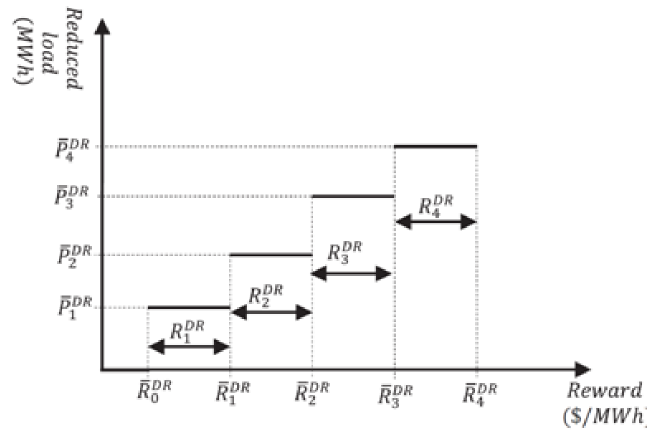

Fig. 3. The reward-base DR curve

Eq. (7) shows the total reduced demand by the consumers and Eq. (8) shows the reward paid by retailer. Constraint of reward in each step is presented by Eq. (9). Number of reward-based DRP choices is shown in Eq. (10). The total expected cost of the reward-based DRP is provided by Eq. (11).

$$EC(RDR) = \sum_{t \in T} \left[\sum_{j=1}^{N_J} \bar{P}_j^{DR}(t).R_j^{DR}(t).d(t) \right] \tag{11}$$

D. Pool market

Pool market as a power market is always available to the retailer, in which the pool price uncertainty is considered as uncertain variable. In this paper, this uncertain variable is modeled by IGDT technique. The total cost of pool market is modeled as follow:

$$EC(P) = \sum_{t \in T} P^p(t).\lambda^p(t).d(t) \tag{12}$$

E. Forward contract market

Forward contract is also considered as a contract for the future, which is one of the power purchasing sources for the retailer. This contract is set in constant blocks, in which each blocks has a specific power and price. These blocks have incremental steps for price and power. The overall cost of forward contract is shown as below:

$$C(F) = \sum_{t \in T} \sum_{f=1}^{N_F} \sum_{b=1}^{N_{FB}} P_{f,b}^F(t).\lambda_{f,b}^F(t).d(t) \tag{13}$$

$$0 \leq P_{f,b}^F(t) \leq P_{f,b}^{MAX}(t) \tag{14}$$

In the forward contract, the power boundaries are modeled in Eq. (14). Finally, total power for each period t is obtained by Eq. (15).

$$P^F(t) = \sum_{f=1}^{N_F} \sum_{b=1}^{N_{FB}} P_{f,b}^F(t) \tag{15}$$

F. Power balance and objective function

Power balance constraint is provided in Eq. (16) which procured power is equal to demand. Finally, the proposed objective function for a retailer is presented in Eq. (17) which total procurement cost from pool market, forward contracts, pool-order DRP, forward DRP and reward-base DRP are presented.

$$P^{erq}(t) = P^{p}(t) + P^{F}(t) + P_{po}^{total}(t) + P^{FDR}(t) + P^{DR}(t) \quad \textbf{(16)}$$

$$Min \;\; C(p,\lambda) = Ec(P) + C(F) + C(PO) + C(FDR) + C(RDR) \quad \textbf{(17)}$$

3. IGDT TECHNIQUE

One of the main problems in the power system is the uncertainty problem. This uncertainty may occur for various parameters in the power system (for example pool price, consumers demand and etc.). Also, this uncertainty may have desirable or undesirable effects. These effects are examined by the IGDT method [50–53]. IGDT method has two robustness and opportunity functions which are used to assess the desirable and undesirable effects, respectively. IGDT consists of three parts: system model, operation requirements and uncertainty modeling.

A. System model

System output/input structure exists in $C(p,\lambda)$ model which IGDT is applied and used to describe the system model. In this model p is the decision variable and λ is uncertainty parameter. It should be mentioned that purchased power from alternative energy sources are the decision variable while pool market price is considered as uncertainty parameter in the proposed model.

B. Operation requirements

Operation requirements describe the expected performance for retailer in different circumstances. These expectations are analyzed in various functions such as opportunity and robustness, which set these functions for certain problems. The robustness and opportunity functions of retailer will be as follow:

$$\hat{\alpha}(C_r) = \max_{\alpha} \{\alpha : \; \max(C(p,\lambda)) \le C_r \} \quad \textbf{(18)}$$

$$\hat{\beta}(C_o) = \min_{\alpha} \{\alpha : \; \min(C(p,\lambda)) \le C_o \} \quad \textbf{(19)}$$

As shown in Eq. (18) which is considered as robustness function, retailers are resistant against increasing pool prices, with considering the risk-averse strategy and paying more money. $\hat{\alpha}$ is degree of resistance against increasing pool price. Therefore, the maximum value of $\hat{\alpha}$ is desirable. Also the total cost of retailers must be less than the constant value, C_r .

Also, for opportunity function expressed in Eq. (19), retailer will benefit from decreasing pool price with taking risk-seeking strategy, which leads to reduction in total costs. $\hat{\beta}$ is minimum value of α. Since $\hat{\beta}$ represent the minimum pool price reduction, so that the minimum $\hat{\beta}$ value is desired. Also the total cost of retailers must be less than the constant value, C_o. Also, in the abovementioned equation, C_r is bigger than C_o.

C. Uncertainty modeling

By obtaining information about the uncertainty parameter (λ), it can be modeled using fractional error model based on IGDT approach which is introduced in next section.

4. PROPOSED IGDT-BASED RISK-CONSTRAINT FORMULATION

In this section, IGDT technique has been applied to pool market price uncertainty.

A. Uncertainty modeling

To model the uncertainty in the problem, a fractional info-gap uncertainty model is used in Eq. (20). Meanwhile, the uncertainty parameter in this problem is pool price.

$$U(\alpha,\tilde{\lambda}^{p}(t)) = \left\{ \lambda^{p}(t) \;\; : \;\; \frac{\left|\lambda^{p}(t) - \tilde{\lambda}^{p}(t)\right|}{\tilde{\lambda}^{p}(t)} \le \alpha \right\}, \alpha \ge 0 \quad \textbf{(20)}$$

The proposed uncertainty model in Eq. (20) is a fractional info-gap uncertainty model, in which the scale of gap is proportional to the forecasted value, $\tilde{\lambda}^{p}(t)$.

B. Robustness function

In robustness function, maximum value of resistance against pool price uncertainty is shown by$\hat{\alpha}(C_r)$. Retailer in robust performance with paying more money wants to choose the risk-averse strategy. Based on the abovementioned content, robustness function of IGDT technique can be modeled as follows:

$$\hat{\alpha}(C_r) = \max \left\{ \alpha \; : \; \left(\max_{l \in U(\alpha,\tilde{\lambda}^{p}(t))} \;\; \cos t^{total} \le C_r = \; (1+\omega)C_b \right) \right\} \quad \textbf{(21)}$$

In the taken risk-averse strategy by retailer, the uncertainty parameter is maximized while all requirements of retailer are satisfied.

$$\hat{\alpha}(C_r) = \max \; \alpha \quad \textbf{(22)}$$

Subject to:

$$Max \left\{ Ec(P) + C(F) + C(PO) + C(FDR) + C(RDR) \right\} \le C_r \quad \textbf{(23)}$$

$$(1-\alpha)\tilde{\lambda}^{p}(t) \le \lambda^{p}(t) \le (1+\alpha)\tilde{\lambda}^{p}(t) \quad \textbf{(24)}$$

$$Eqs.(1) - (16) \quad \textbf{(25)}$$

In order to considering of maximum increase of the uncertain parameter $\lambda^{p}(t) = (1+\alpha)\tilde{\lambda}^{p}(t)$ will be taken into account. Therefore, the robustness function for risk-averse strategy will be simplified as follows:

$$\hat{\alpha}(C_r) = \max \; \alpha \quad \textbf{(26)}$$

Subject to:

$$Max \left\{ Ec(P) + C(F) + C(PO) + C(FDR) + C(RDR) \right\} \le C_r \quad \textbf{(27)}$$

$$\lambda^{p}(t) = (1+\alpha)\tilde{\lambda}^{p}(t) \quad \textbf{(28)}$$

$$Eqs.(1) - (16) \quad \textbf{(29)}$$

C. Opportunity function

Any reduction of the uncertainty parameter will increase possible benefit for the retailer which is modeled by using opportunity function. Retailer can take advantage of these benefits with taking the risk-taker strategy into account. Also, based on the mentioned content above, opportunity function of IGDT technique can be formulated as follows:

$$\hat{\beta}(C_o) = \min \left\{ \alpha \; : \; (\min_{l \in U(\alpha,\tilde{\lambda}^{p}(t))} \;\; \cos t^{total} \le C_o) = \; (1-\Upsilon)C_b \right\} \quad \textbf{(30)}$$

For a risk-taker retailer, the objective of using the IGDT technique is to maximize the benefits of reducing the uncertainty parameter while the requirements of retailer are satisfied:

$$\hat{\beta}(C_o) = \min \alpha \quad (31)$$

Subject to:

$$Min\{Ec(P) + C(F) + C(PO) + C(FDR) + C(RDR)\} \leq C_o \quad (32)$$

$$(1-\alpha)\tilde{\lambda}^p(t) \leq \lambda^p(t) \leq (1+\alpha)\tilde{\lambda}^p(t) \quad (33)$$

$$Eqs.(1) - (16) \quad (34)$$

$\lambda^p(t) = (1-\alpha)\tilde{\lambda}^p(t)$ Will be taken into account in order to consider the reduction of the uncertain parameter. Therefore, the opportunity function for risk-averse strategy will be simplified as follows:

$$\hat{\beta}(C_o) = \min \alpha \quad (35)$$

Subject to:

$$Min\{Ec(P) + C(F) + C(PO) + C(FDR) + C(RDR)\} \leq C_o \quad (36)$$

$$\lambda^p(t) = (1-\alpha)\tilde{\lambda}^p(t) \quad (37)$$

$$Eqs.(1) - (16) \quad (38)$$

5. CASE STUDY

This scheme consists of 32 periods, which include summer and winter days. Each period is comprised of the one week's average peak time. Peak times are different for each season, so that for the summer from 11 am to 9 pm, and for the winter is from 6–10 am to 4–10 pm. It should be noted that only peak times of working days (Monday–Friday) are used. According to the considered method in [54,55], these periods consist of 12 weeks of January–March, 17 weeks of June–September and 3 weeks of December which daily load profiles of Queensland in 2012 has been used [56].

In this study, forward contracts included three contracts (F1-F3) which each contract covers some part of the years. F1-F3 contracts are set for 12 weeks of January–March, 17 weeks of June–September and 3 weeks of December, respectively. These contracts consist of 6 blocks, which each block is different in price and maximum power size. Forward price used are taken from Queensland region 2012 [57]. Maximum power for each block of forward contracts at each time period is 450MW.

Four options are considered for pool-order DRP. As noted earlier, this option is set to few increases in the market price and is negotiated in a certain volume of demand and price. Maximum demand for pool-order options is 50MW. As mentioned earlier, retailers should pay a penalty if they do not perform the pool-order. Amount of this penalty is equal to 15% of the each contract cost for retailer. This plan is eight months long, with a forward DRP contract for each month. For forward DRP contract six blocks are considered and each block with a maximum demand value of 75MW is limited.

For reward-based DRP, 14 steps with different incentives considered to reduce the demand. Capacity of DRP in this plan considered 30% of the total Australia demand in which obtained on the basis of trials. Figs. 4- 6 and Tables 1 and 2 show and present the input data for each above options.

The IGDT technique is used to assess the retailer's risks. This issue will be studied in two cases which include with DRP and without DRP modes. The proposed models are solved using

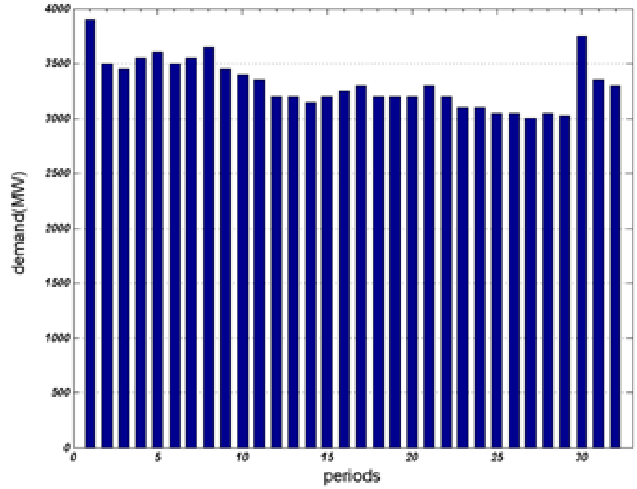

Fig. 4. Demand amount required by the retailer

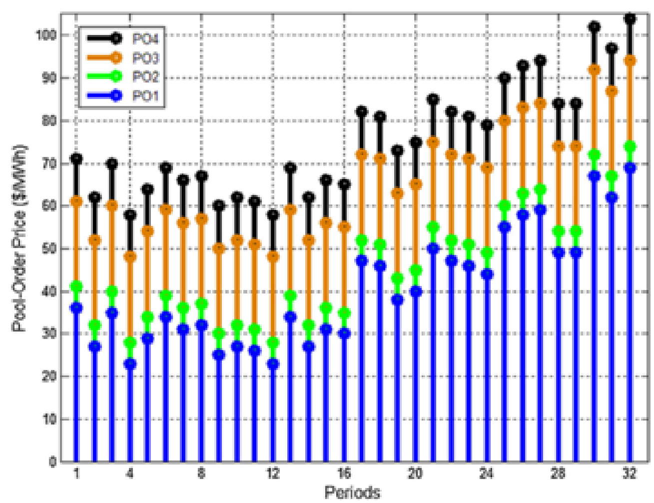

Fig. 5. Pool-order option prices

Table 1. Forward contract prices ($/MWh)

	B1	B2	B3	B4	B5	B6
F1	40	45	50	55	60	65
F2	38	42	46	50	54	58
F3	39	44	49	54	59	64

CPLEX solver [58] under GAMS environment [59] in which a risk-based performance for retailers is provided in the presence of pool-order DR, forward DR and reward-base DR programs.

A. Robustness and opportunity functions

In the risk-neutral strategy, optimal performance of retailer obtained without considering the robustness and opportunity functions based on IGDT approach. In other words, cost function, Eq. (17), is minimized subject to constraints (1)-(16) by considering forecasted pool market price. In this strategy, retailer reduce their costs due to implementation of pool-order DRP, forward

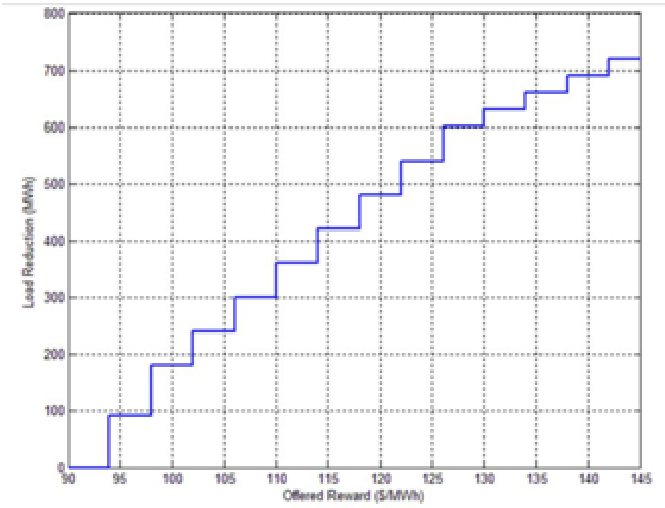

Fig. 6. Amount of reward for each reduce demand

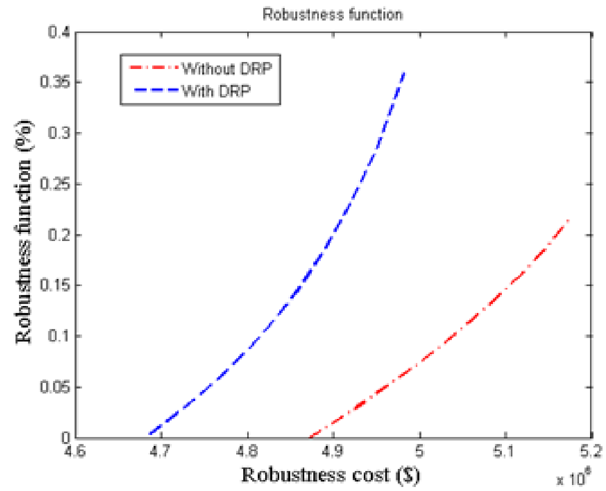

Fig. 7. Robustness function

Table 2. Forward DR prices ($/MWh)

	B1	B2	B3	B4	B5	B6
FDR1	35	37	39	41	43	45
FDR2	32	34	36	38	40	42
FDR3	29	31	33	35	37	39
FDR4	33	35	37	39	41	43
FDR5	45	47	49	51	53	55
FDR6	51	53	55	57	59	61
FDR7	56	58	60	62	64	66
FDR8	69	71	73	75	77	79

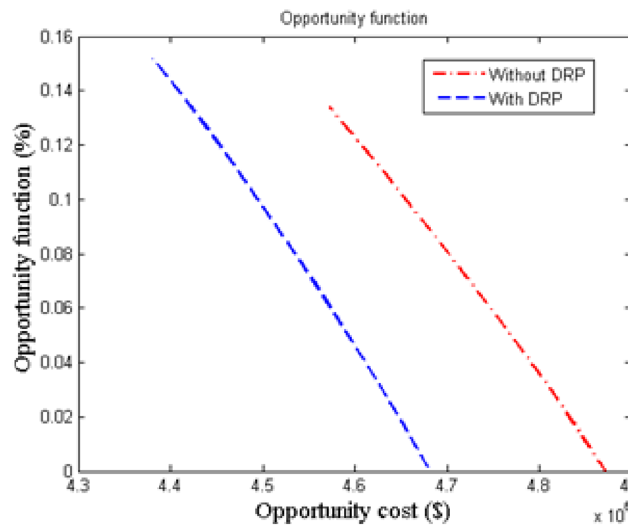

Fig. 8. Opportunity function

DRP and reward-based DRP, which retailer cost with DRP and without DRP are 4,681,597.4 $ and 4,873,026.5 $, respectively. It can be seen that the total cost in with DRP mode has reduced 3.93 %.

Fig. 7 shows purchased cost in the risk-averse strategy. This strategy is achieved by solving the robustness function (26) and taking into account constraints (27)-(29). According to Fig.7, for example the retailer with payment 4,903,026.5 $ withstand against possible increasing pool market prices. However, it should be noted that the degree of robustness ($\hat{\alpha}$) in with DRP and without DRP is 20.4 % and 1.6 %, respectively. This means that the retailer pays 4,903,026.5 $ which is robust to the 20.4 % in DRP mode, and 1.6 % in without DRP mode. So by using DRP the retailer is more robust to the increasing pool market prices.

Furthermore, Fig. 8 shows purchased cost in the risk-taker strategy. This strategy is achieved by solving the opportunity function, Eq. (35), and taking constraints (36)-(38) into account. According to Fig. 8, for example, in 11% reduction of pool market price, purchased costs are 4,471,597.4 $ and 4,633,026.5 $ for with DRP and without DRP modes, respectively. This means that the retailer can increase their benefits in a certain price reduction if DRP is used.

B. Comparison risk-based results

In this section, we will look at analysis and will compare the results. This analysis will be compared to three different retailer strategies which are risk-averse, risk-neutral and risk-taker strategies. These strategies determine the optimal retailer performance in different conditions.

B.1. Analysis results of DRP schemes

Retailer has three DRP options (Forward DRP, Pool-order options and reward-base DRPs) to supply its Demand. Fig. 9 shows Forward DRP with three different strategies (risk-averse, risk-neutral and risk-taker) for the retailer. Retailer purchases more DRP by taking risk-averse strategy in comparison with risk-neutral strategy. So, forward DRP is safe option for retailers when the prices are increasing. Also, retailer purchases less DRP in the risk-taker strategy in comparison with risk-neutral strategy which retailer purchases more power from pool market in the risk-taker strategy and vice versa. A summary of the obtained results of this problem for retailer is presented in Table 3.

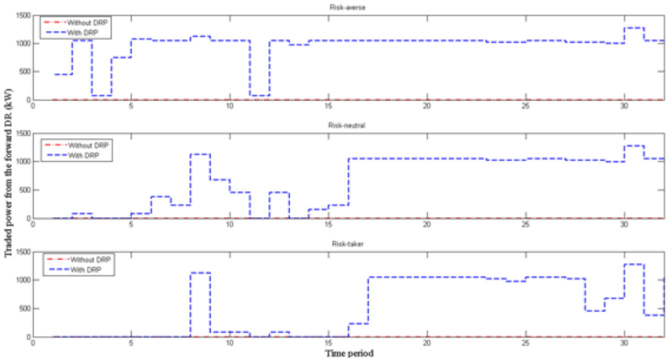

Fig. 9. Purchased power from the forward DR

Table 3. Retailer cost in different condition

Various cost ($)	With DR	Without DR
Deterministic cost (Risk-neutral strategy)	4,681,597.4	4,873,026.5
Robustness cost (Risk-averse strategy)	4,981,597.4	5,173,026.5
Opportunity cost (Risk-taker)	4,381,597.4	4,573,026.5

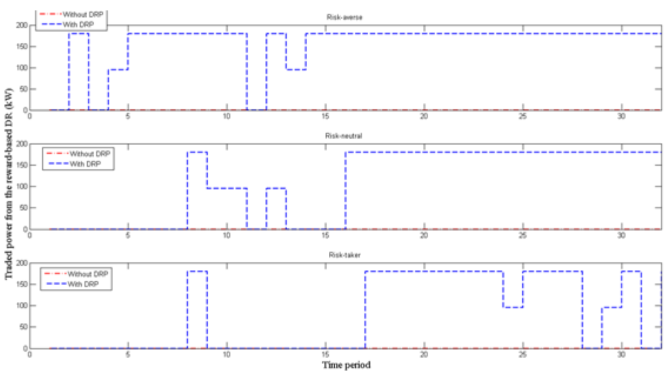

Fig. 10. Purchased power from the reward-base DR

Fig. 10 shows reward-base DRP with three different strategies (risk-averse, risk-neutral and risk-taker) for the retailer. It is seen that in the risk-averse strategy, retailer make the most of this option. So, reward-based DRP is also safe option for retailers when the prices are increasing and vice versa.

Fig. 11 shows pool-order DRP with three different strategies (risk-averse, risk-neutral and risk-taker) for the retailer. In this option of DRP scheme, retailer has the highest DRP purchase from consumers or aggregator in the risk-averse strategy which has risen in prices. So, this option is very suitable when the prices increase a little.

B.2. Analysis results of wholesale market suppliers

The retailer also has access to the wholesale markets to supply their demand. Two options of the wholesale market have been used in this study, which are pool market and forward contract.

Fig. 12 analyzed the purchased power from the pool market in three different strategies (risk-averse, risk-neutral and risk-taker) for the retailer. The biggest buying potential from the pool market is in the risk-taker strategy, which is the desire to buy power from the market because this strategy is analyzing the reduction in pool prices. In the risk-averse strategy due to market price rises in this strategy, the purchasing power from the pool decreases. Also, using the DRP in three strategies, the power purchased from the market has dropped.

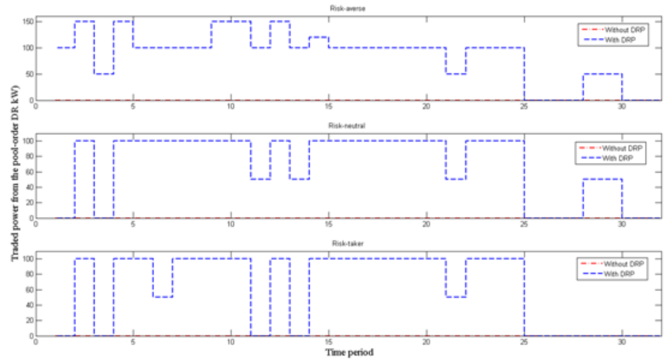

Fig. 11. Purchased power from the reward-base DR

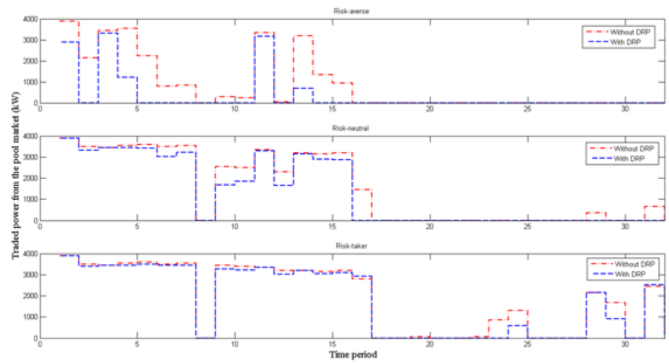

Fig. 12. Purchased power from the pool market

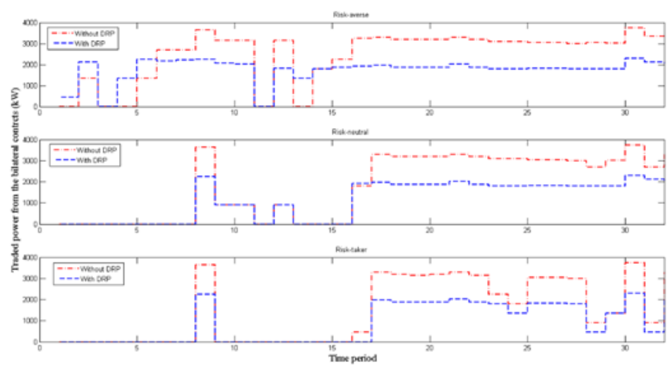

Fig. 13. Purchased power from the forward contracts

Fig. 13 analyzed the power purchased from the forward contract in three different strategies (risk-averse, risk-neutral and risk-taker) for the retailer. According to this figure, it can be seen that the ability to buy forward contract in the risk-averse strategy is more than other strategies. Because in this strategy, the pool market prices have increased and retailer do not want to buy power from pool market. Also, by using the DRP in three strategies, the purchased power from the forward contract market has decreased.

6. CONCLUSION

In this paper, new schemes of DRP and IGDT technique are proposed to model uncertainty of pool price. This technique uses two robustness and opportunity functions which examines the increase and decrease in pool price, respectively. Using of mentioned functions in above , retailer costs are examined at three levels of risk (risk-averse, risk-neutral and risk-taker). According to the obtained results, it is found that in the risk-neutral strategy, the retailer can reduce its cost 3.9 % using the proposed DRP schemes which the costs with DRP and without DRP in the normal condition of pool price are 4,681,597.4 $ and 4,873,026.5 $, respectively. Also, in the risk-averse strategy, retailer with payment of 4,903,026.5 $ can be robust itself amount of 20.4 % in with DRP mode and 1.6 % in without DRP mode against increasing pool market price. In other word, retailer by paying 4,903,026.5 $ can be robust itself amount of 20.4 % and 1.6 % in with DRP and without DRP is respectively. Therefore, by using DRP the retailer is more robust to the increasing pool market prices. Furthermore, in the risk-taker strategy, purchased costs are 4,471,597.4 $ and 4,633,026.5 $ for with DRP and without DRP modes, respectively. Due to reduce pool market price (11%) which will increase their benefit up to 3.6% by implementation of DRP. In other word, in 11% reduction of pool market price, purchased costs are 4,471,597.4 $ and 4,633,026.5 $ for with DRP and without DRP modes, respectively. This means that the retailer can increase their benefits in a certain price reduction if DRP is used. In the proposed model for retailer in order to supply its power, three different risk strategies containing risk-averse, risk-neutral and risk-taker have been investigated. In the risk-averse strategy which price rises is analyzed, retailers tend to buy more power from the DRPs and forward contract, but buy less power from the pool market. In the risk-taker strategy which price reduction is analyzed, retailers tend to buy more power from the pool market and then from the other options.

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