Trading Framework for Demand Response Aggregators using Information-gap Decision Theory to Address Uncertainty and Risk-Management

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***Abstract*— In this work a new trading framework for demand response (DR) aggregators is proposed using a non-probabilistic model. In this model, DR is acquired from consumers to sell it to the purchasers by aggregators. Two programs, i.e., time-of-use (TOU) and reward-based DR program, are implemented to obtain DR from consumers. Then, the obtained DR is sold to buyers via two considered agreements, i.e., fixed DR contracts and DR options. The information-gap decision theory is also employed to consider the uncertainties for risk-averse aggregators. Consumer's participation behavior is considered as an uncertain parameter. A robustness function is proposed to examine the immunity of the model against adverse variations of uncertain parameters. The feasibility of the proposed model is studied on the real-world data.**

***Keywords*— Demand response aggregator, Information-gap decision theory, Reward-based DR, Time-of-use, Uncertainty**

I. Nomenclature

Indices

b	Index referring to block of fixed DR contact
c	Index referring to consumers
f	Index referring to fixed DR contract
j	Index of reward-based DR steps
op	Index referring to DR options agreement
p	Index of time periods
t	Index of time horizon

Parameters

B_0	DR aggregator's expected profit [\$]
B_c	DR aggregator's critical profit [\$]
$D_0(c,t)$	Initial load of customer at time interval t
$\lambda_0(c,p)$	Initial price/tariff of customer during period p
$\tilde{\lambda}_{f,b}^{DR}(t)$	Expected price of fixed DR contract [\$/MWh]
$\tilde{\lambda}_{op}^{DR}(t)$	Expected price of DR options agreement [\$/MWh]
$\lambda(c,p)$	TOU tariffs of customer
$d(t)$	The period duration
$E(c,t,p)$	Elasticity of each customer at time interval t associated with price/tariff during period p
f_{op}^{pen}	The penalty of refusing the DR options agreement [MWh]
$\widetilde{PF}(t)$	Factors of taking part of customers in the reward-based DR program
$\bar{P}_j^{DR,rw}(t)$	Reduced load steps in reward-based DR programs [MWh]
$\bar{R}_j^{DR,rw}(t)$	Given reward [\$/MWh]
σ	Profit deviation factor

Functions

$\tilde{\alpha}(q,r_c)$	Robustness function of IGDT
$R(q,u)$	System model of the IGDT approach
$U(\alpha,\tilde{u})$	Fractional uncertainty model of the IGDT

Variables

$\lambda_{f,b}^{DR}(t)$	Price of fixed DR contract [\$/MWh]
$\lambda_{op}^{DR}(t)$	Price of DR options agreement [\$/MWh]
$P_{f,b}^{DR}(t)$	Power in fixed DR contract [MWh]
$PF(t)$	Factor of taking part of customers in reward-based DR program
$P_{op}^{DR}(t)$	Power in DR options agreement [MWh]
q	Decision variables in the IGDT approach
$\mathrm{TOU}(t)$	Time-of-Use capacity resulted from entire customers at time horizon t [MWh]
U	Uncertainty variables in the IGDT approach
A	The horizon of the uncertain parameter
$\tilde{\alpha}$	Optimal robustness function value

Binary Variables

$v_j^{DR.rw}(t)$	Binary variable determining the reduced load level
$v_{op}^{DR}(t)$	A binary variable whether the DR options agreement is applied or not

J.P.S. Catalão acknowledges the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under Projects SAICT-PAC/0004/2015 - POCI-01-0145-FEDER-016434, POCI-01-0145-FEDER-006961, UID/EEA/50014/2013, UID/CEC/50021/2013, UID/EMS/00151/2013, 02/SAICT/2017 - POCI-01-0145-FEDER-029803, and also funding from the EU 7th Framework Programme FP7/2007-2013 under GA no. 309048.

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II. INTRODUCTION

Demand Response (DR) is suitable for electricity markets if it is available in a large volume. To this end, a well-known solution is utilized in market environment, i.e., aggregation of DR programs. Therefore, a DR aggregator could help enhance the contribution of consumers in DR schemes. The interaction between the electricity consumers and independent market operators (ISO) would be facilitated by this new entity, i.e., the DR aggregator, which implements various DR strategies on customers to obtain DR and sells it to the purchasers.

There are two main DR programs, named as time-based DR and incentive-based DR programs. In this work, it has utilized from both types, i.e., time-of-use (TOU) and reward-based DR programs. The elasticity matrix is used to model the TOU program, while the reward-based program is modeled through taking into account the behavior of consumers as an uncertain parameter. Two agreements are considered to sell the acquired DR to purchases, namely, fixed DR contracts and DR options. In the fixed DR contract, a specific amount of DR is sold in a determined tariff and time by the aggregator, while in DR options, the aggregator has a right to not apply the DR in real time. The proposed model is considered a profit maximization problem. To this end, the information-gap decision theory (IGDT) approach is employed to address the uncertainty. Moreover, the horizon of the uncertainty is maximized and the aggregator reaches to a solution that guarantees a predetermined profit of the aggregator.

Several earliest investigations have studied DR programs in detail. For instance, a category of DR programs' promotion is investigated in [1]. In [2] and [3], various features of DR were reviewed in detail. Furthermore, benefits versus barriers of employed DR technologies in electricity markets were discussed in [4]. In addition, the DR aggregator's role as a new entity is studied in some studies. For example, in [5], a new pool-based structure for DR market was proposed which enables DR aggregator to trade its acquired DR, whereas the aspects of DR aggregation in markets were presented in [6].

In [7] was reviewed the capability of utilizing DR programs in industrial sectors as ancillary services. Furthermore, DR was considered as an energy resource of retailers in [8]. Authors in [9] had introduced a hierarchical market mechanism, where aggregator plays a broker role between consumers and ISOs. The performance of DR aggregator as a participant in balancing/ancillary service markets was modeled by considering the uncertainty of renewable energy resources as well as market prices in [10]. In [11] was proposed a new offering strategy that DR was used by wind producers. Thus, the wind producers and the DR aggregator set an agreement to cope with the power generation uncertainty.

As stated in [12], a decomposition algorithm was developed to facilitate using DR by aggregators, whose goal was maximizing social welfare. In [13] DR was defined as a new energy resource, i.e., DR eXchange, in which the bilateral contracts were not considered. A bottom-up approach was developed in [14] that the aggregator transformed its available DR through thermostatically controllable consumptions to take part in reserve electricity market.

By analyzing the behavior of consumers on participating in DR programs, it would helpful that aggregators may do their scheduling under a DR trading framework.

This is the main motivation behind of proposed modeling work. In this context, a trading framework for DR aggregators is taken into account while handling the risk through the IGDT-based approach. The remainder of this work is organized as follows: the IGDT approach is introduced in Section III. The proposed trading framework and then the mathematical formulation are presented in Section IV. Section V gives the information about the data, and then discusses the results in detail. Finally, Section 6 concludes the proposed model.

III. INFORMATION GAP-DECISION THEORY

IGDT approach is defined as maximization of the horizon of uncertainty which results in a solution which ensures a specified value of the objective [15]. In addition, the IGDT process is usually explained by three terms including system and uncertainty models as well as performance requirement.

A. System Model

System model, $R(q,u)$, declares the input/output form of the investigated model. In other words, a system model is the reward which a decision maker receives for selected values of decision variable q, whereas uncertain parameter u, is considered. In the proposed model, the DR aggregator's total profit can be interpreted as a system model.

B. Uncertainty Model

This element is an unbound family of nested sets centered around the expected value [16]. It should be mentioned that there is various information-gap uncertainty models. However, a common uncertainty model, which is used in this paper, is the fractional uncertainty model which is [17]:

$$U(\alpha,\tilde{u}) = \left\{u: \left|\frac{u-\tilde{u}}{\tilde{u}}\right| \leq \alpha\right\}, \alpha \geq 0 \quad (1)$$

As α increases, the decision maker would obtain broader ranges of deviations of the uncertain value. The uncertainty model indicates that the horizon of uncertainty α is dependent on the parameter u.

C. Performance Requirement

In IGDT structure, a performance model can be defined as a function of decision variables and uncertain parameters. There are two different performance models in IGDT approach which depend on the decision maker's risk management strategy: robustness function and opportunity function. Because of the ability of modeling worst cases through a robustness function, this performance function is chosen in this problem which is suitable for risk-averse decision makers. Note that a risk-averse aggregator seeks to trade DR in a way to be immune against unfavorable deviations of the uncertain parameter from its forecasted value. Robustness function, denoted here by $\tilde{\alpha}(q,r_c)$, is explained as the maximum value of the uncertainty horizon α while the minimum requested reward of decision maker r_c is fulfilled, i.e.:

$$\tilde{\alpha}(q,r_c) = Max_{\alpha}\left\{\alpha: \begin{Bmatrix} minimum\ requirement\ r_c \\ is\ always\ fulfilled \end{Bmatrix}\right\} \quad (2)$$

IV. PROBLEM FORMULATION

The proposed trading framework is shown in the Fig. 1. As depicted in Fig. 1, there are three types of electricity consumers at the bottom side of the aggregator, known as residential, commercial and industrial sectors.

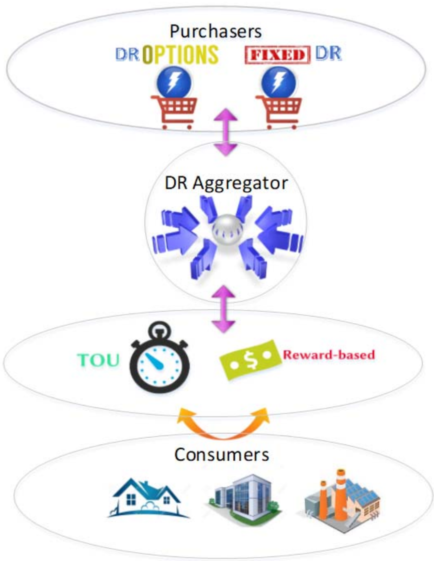

Fig. 1. The proposed DR trading framework.

It is assumed that each sector has a particular DR program including the TOU program and reward-based DR program. Then, the acquired DR is traded with purchasers through two types of forward contracts which are fixed DR contacts and DR options agreements.

It should be noted that, the double-sided arrows express that the energy could be flowed either from customers to the DR buyers or vice versa. In the proposed method, the DR aggregator acquires DR from consumers during peak periods while trading it with purchasers. Then, during off-peak periods, the consumers are encouraged to use more energy which is supplied by the DR aggregator. To this end, it is supposed that there is no uncertain parameter. Assuming this in the trading framework, the DR aggregator has perfect information about the uncertain parameter, i.e. the behavior of the consumers. In this part, the deterministic results are obtained. Next, the uncertainty will be taken into account. In this stage, the result of the proposed trading framework is studied under uncertainty.

A. Fixed DR Contracts

The fixed DR contract is defined as follows:

$$P(FDR) = \sum_{t=1}^{T} \sum_{f=1}^{N_f} \sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t).d(t) \tag{3}$$

$$p_{f,b}^{DR,min} \leq p_{f,b}^{DR}(t) \leq p_{f,b}^{DR,max} \quad ,\forall t \tag{4}$$

Note that constraint (4) limits the amount of each block.

B. DR Option Agreement

In the proposed DR option agreement, the aggregator sets an agreement with purchasers to exercise the signed contract of DR only if it is cost-effective. The presented agreement is formulated as follows:

$$P(ODR) = \sum_{t=1}^{T} \sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t).d(t) - \left(1 - v_{op}^{DR}(t)\right).f_{op}^{pen}(t)] \tag{5}$$

$$p_{op}^{DR,min} \leq p_{op}^{DR}(t) \leq p_{op}^{DR,max} \quad ,\forall op = 1,2,\dots,N_{op} \tag{6}$$

As shown in (5), the first term denotes the revenue from celling DR to purchasers and the second term denotes the penalty of the aggregator, if it does not exercise this contract. Then, the DR value is imposed through equation (6).

C. Time-of-Use Program

In the proposed model, two tariffs are defined which are for peak periods and off-peak periods. There is a direct relation between the elasticity of consumers and their participation in TOU program participation. The mathematical formulation of this program is indicated in (7).

$$TOU(t) = \sum_{c=1}^{N} D_0(c,t) \sum_{p=1}^{P} E(c,t,p) \left(\frac{\lambda(c,p) - \lambda_0(c,p)}{\lambda_0(c,p)} \right), \forall t \tag{7}$$

D. Reward-Based DR Program

As depicted in Fig. 2, more reduction in the amount of consumer's electricity usage occurs when the aggregator submits higher rewards through the stepwise manner. The whole formulation of this program is written as follows:

$$P^{DR}(t) = \sum_{j=1}^{N_J} PF(t).\bar{P}_j^{DR}(t).v_j^{DR}(t), \forall t, \forall j \tag{8}$$

$$R^{DR}(t) = \sum_{j=1}^{N_J} R_j^{DR}(t), \forall t, \forall j \tag{9}$$

$$\bar{R}_{(j-1)}^{DR}(t).v_j^{DR}(t) \leq R_j^{DR}(t) \leq \bar{R}_j^{DR}(t).v_j^{DR}(t), \forall t, \forall j \tag{10}$$

$$\sum_{j=1}^{N_J} v_j^{DR}(t) = 1, \forall t, \forall j \tag{11}$$

$$v_j^{DR}(t) \in \{0,1\} \tag{12}$$

The whole amount of the reduced load through applying this DR program is indicated in (8). The equation (9) refers to the paid reward of the participants in this program. In addition, constraint (10) imposes the amount of the reward paid to consumers. In this model, it is assumed that one level, i.e., j of load reduction in Fig. 2 can be chosen.

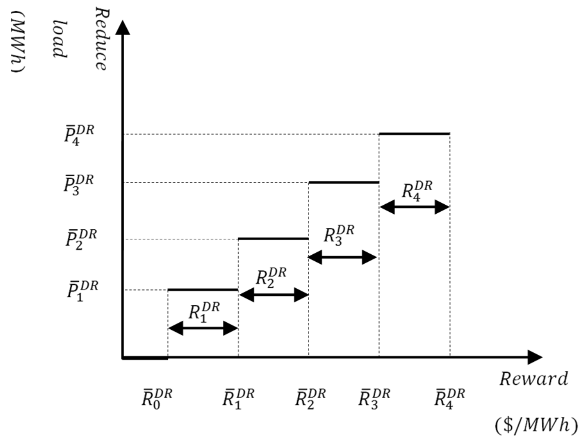

Fig. 2. The proposed DR trading framework.

E. Deterministic Trading Framework of the DR Aggregator

The goal of a DR aggregator is determining an optimal amount of DR to buy from customers and sell it to purchasers during peak periods and vice versa during off-peak ones. As mentioned before, in the first stage of IGDT method, it is considered that the DR aggregator is able to perfectly predict the behavior of the consumers in taking part in the reward-based DR program. The model is formulated as follows:

$$
\begin{aligned}
Obj.Func:\ B_0 = Max \sum_{t=1}^{T} \Bigg[& \sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t).d(t) \\
& + \sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t).d(t) \\
& - \left(1 - v_{op}^{DR}(t)\right).f_{op}^{pen}(t)] \\
& - \sum_{j=1}^{N_J} PF(t).\bar{P}_j^{DR}(t).R_j^{DR}(t) \Bigg]
\end{aligned} \tag{13}
$$

S.t:

$$
\begin{aligned}
\sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t) + \sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t). \\
= P^{DR}(t) - TOU(t)\ ,\forall t
\end{aligned} \tag{14}
$$

The limitation constraint of Fixed DR contract (3) (15)

The limitation constraint of DR option agreement (5) (16)

TOU program constraint (7) (17)

Reward-based program constraints (8) – (12) (18)

As shown in (14), the deterministic approach is modeled as a profit maximization program. First and second terms referring the income of aggregator by selling DR via fixed DR agreement and DR options. Then, the last term refers to the cost of reward-based DR program.

F. The IGDT-Based Trading Framework of DR Aggregator

In this part, the uncertainty of the consumers' contribution to the DR program is considered. To declare the uncertainty model of participation factors, the fractional info-gap is utilized. The aim of a decision maker in the IGDT under uncertainty is trading in a way to be immune against variations of uncertainties. The mathematical formulation of the robust IGDT-based model is written as follow:

$$Obj\ Func:\ \bar{\alpha} = Max\ \alpha \tag{19}$$

$$S.t: \qquad B^* \geq B_c = (1-\sigma).B_0 \tag{20}$$

$$
\begin{aligned}
B^* = min \Bigg\{ \sum_{t=1}^{T} \Bigg[& \sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t).d(t) \\
& + \sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t).d(t) \\
& - \left(1 - v_{op}^{DR}(t)\right).f_{op}^{pen}(t) \\
& - \sum_{j=1}^{N_J} PF(t).\bar{P}_j^{DR}(t).R_j^{DR}(t) \Bigg]\Bigg\}
\end{aligned} \tag{21}
$$

$$(1-\alpha).\widetilde{PF}_t \leq PF_t \leq (1+\alpha).\widetilde{PF}_t \quad ,\forall t \tag{22}$$

(15) – (18) (23)

Note that the DR aggregator's profit B^* in constraint (21) monotonically decreases by decreasing the participation factor, i.e. $PF(t)$, which is considered as an uncertain parameter. Therefore, to decrease B^*, the participation factor must be selected as follows: $PF(t) = (1-\alpha).\widetilde{PF}(t)$. Thus, the formulation would be converted to new form:

$$Obj\ Func:\ \bar{\alpha} = Max\ \alpha \tag{24}$$

$$S.t: \qquad B^* \geq B_c = (1-\sigma).B_0 \tag{25}$$

$$
\begin{aligned}
B^* = \textstyle\sum_{t=1}^{T} \Big[& \textstyle\sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t).d(t) + \\
& \textstyle\sum_{op=1}^{N_{op}} P_{OP}^{DR}(t).\lambda_{op}^{DR}(t).d(t) - \left(1 - v_{op}^{DR}(t)\right).f_{op}^{pen}(t) - \\
& \textstyle\sum_{j=1}^{N_J} \widetilde{PF}(t).(1+\alpha).\bar{P}_j^{DR}(t).R_j^{DR}(t) \Big]
\end{aligned} \tag{26}
$$

(9) – (12) (27)

$$P_t^{DR} = \sum_{j=1}^{N_J} \widetilde{PF}(t).(1-\alpha).\bar{P}_j^{DR}(t).v_j^{DR}(t)\ ,\forall t, \forall j \tag{28}$$

(15) – (18) (29)

The given robust IGDT-based model's results depend on the value of the critical profit, i.e. B_c. This means that the aggregator's profit cannot be less than B_c if all the uncertain parameters' forecast errors are less than $\bar{\alpha}$.

V. Case Study

A. Input Data

The proposed model expresses a mixed integer non-linear program (MINLP) that has been solved by SBB [18] solver through GAMS [19] for diverse profit deviation factors σ.

It is noteworthy that the proposed non-linear IGDT-based problem can be linearized by utilizing reformation-linearization techniques [20] or employing linear cutting algorithms [21].

However, the proposed work focus is not linearizing the proposed program. The model is simulated using a PC system with 2.43 GHz CPU speed and 6 GB RAM.

The data that is related to the load is derived from [22], where it has studied a day in Queensland, Australia. It is assumed that the studied day includes two time periods namely, peak, i.e. 9am to 10pm and off-peak, i.e. 10pm to 9am.

The aggregator buys DR from customers during peak periods and sells the acquired DR to the purchasers, while this process is vice versa in off-peak periods.

The retail tariffs in Queensland, Australia are used for TOU prices of each consumer. The elasticity data is taken from [23]. Furthermore, it is assumed that the modeled fixed DR contract has 6 blocks for each period which its maximum demand is 90 kW during peak periods and 30 kW during off-peaks.

Then, it has defined 4 DR options for every single period. If the aggregator does not exercise the signed contract, it should pay the penalty fee to the purchaser which is 10% of the total agreement's value.

B. Analysis of Results

In this section, first, it is supposed that aggregator has perfect information about the uncertain parameter, i.e., participation factor of the customers in the DR program and can forecast $PF(t)$ with no error. In other words, the optimization program is carried out without considering uncertainty, equations (13)–(18). The aggregator's optimal expected profit, i.e., B_0 is about \$209,000. Afterwards, the proposed IGDT-based robust model (24)–(29) is solved for various values of deviation factor, i.e., σ, which leads to several critical profits, i.e. $B_C = (1-\sigma) \times B_0$. For instance, for $\sigma = 0.11$, the aggregator can ensure that its profit will not be lower than $B_C = \$186{,}000$ if none of the uncertain parameters' forecast error are more than corresponding $\bar{\alpha} = 0.39$.

As illustrated in Fig. 3, the problem is solved for several values of the deviation factor, $\sigma = 0$ to $\sigma = 0.19$, which leads to various optimum robustness function values, i.e. $\bar{\alpha}$. With reference to Fig. 3, it is worth-mentioning that when $\sigma = 0$, the critical profit is equal to the aggregator's expected profit, i.e. $B_c = B_0$, where the aggregator becomes a risk-neutral player.

By increasing the profit deviation factor, the optimum robustness function value will increase, which leads the aggregator to be more risk-averse. Fig. 4 depicts the outcome of TOU program.

Observe that the energy consumption decreases about 4.2 MWh during peak hours, while it increases about 1.3 MWh during off-peak period. In other words, this figure indicates that the customers are encouraged to use more electricity in off-peak periods while reducing their consumption in peak hours. It should be noted that this program is only dependent on the elasticity of consumers. Therefore, the results are not affected by the uncertain parameter.

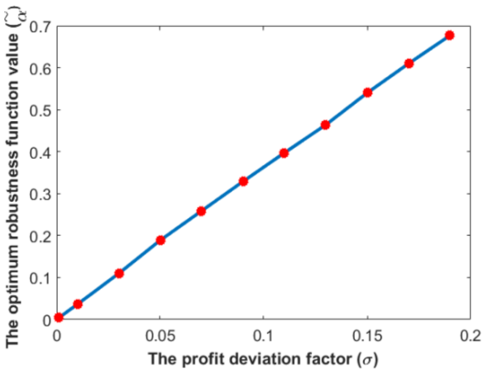

Fig. 3. Optimum robustness function value ($\bar{\alpha}$) versus profit deviation factor (σ).

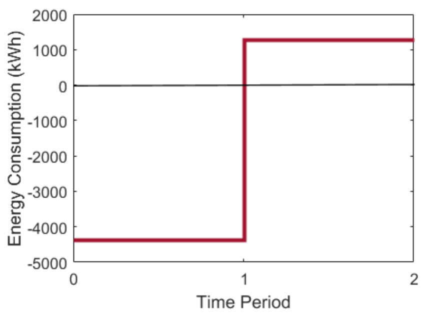

Fig. 4. Time-of-Use program results.

To study the effects of implementing the IGDT-based robust approach on the proposed model, it was chosen an arbitrary profit deviation factor, i.e. $\sigma = 15$ where the critical profit would be equal to $B_c = (1-0.15) \times B_0 = \$177{,}650$. Then, after running the optimization problem, the optimum robustness function value would be $\bar{\alpha} = 53\%$.

To study the effect of the profit deviation factor, the problem is solved through three different $\sigma = \{0, 0.07, 0.15\}$. As stated before, $\sigma = 0$ corresponds to the risk-neutral aggregator and as the profit deviation factor increases, the decision maker becomes more risk-averse.

The results of the reward-based DR program is depicted in Fig. 5. It is seen that increasing the profit deviation factor leads to a reduction in the amount of the DR, which is reasonable. It should be emphasized that because of including uncertainty, risk-averse aggregator tends to decline its share from this program. As illustrated, the positive values indicate the DR is obtained from customers to sell it to the buyers during peak periods.

The outcomes of fixed DR contracts is shown in Table I. The obtained DR is sold to the buyers during peak periods while it is bought from them in off-peak periods. With reference to Table I, it is obvious that as the aggregator becomes more risk-averse the traded energy from fixed DR contracts is decreased in peak time and increased in off-peak time. The effects of implementing DR option agreements for different profit deviation factors are declared in Table II. For a risk-neutral aggregator, i.e., $\sigma = 0$, all DR options are exercised. However as the profit deviation factor declines, the decision maker's willingness to use DR options declines.

Note that introducing the IGDT-based procedure to the proposed DR trading framework imposes cost to the aggregator, i.e. robustness cost (RC). In order to explain the RC, it was considered that the uncertain parameter's forecasting error is zero.

In other words, the predicted values of uncertain parameter are exactly equal to the observed values. On this basis, by carrying out the IGDT-based robust process, the risk-neutral player's optimal profit B_0 will be greater than the risk-averse player's profit $B(\sigma)$. Accordingly, RC is the difference between these two profit values, i.e., $RC = B_0 - B(\sigma)$. Fig. 6 declares RC for different values of $\bar{\alpha}$ which correspond to the studied profit deviation factors, i.e., $\sigma = 0$ to $\sigma = 0.19$. It is seen that the growth in the robustness of the program against uncertain factor's forecasting errors enforces higher costs to the aggregator.

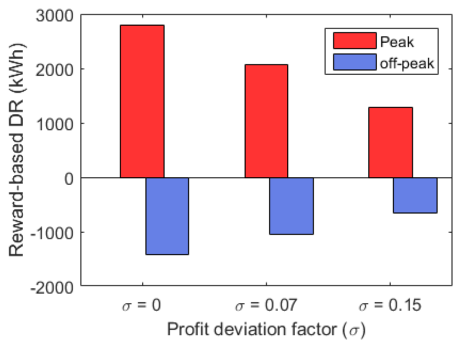

Fig. 5. Reward-based DR results.

TABLE I. FIXED DR ENERGY (KWH)

σ	Peak	Off-peak
0	4560	-1006
0.07	4487	-1069
0.15	3701	-1122

TABLE II. DR OPTION EXERCISMENT (KWH)

σ	Peak	Off-peak
0	ALL	ALL
0.07	2,3,4	1,2,4
0.15	2,3,4	2,4

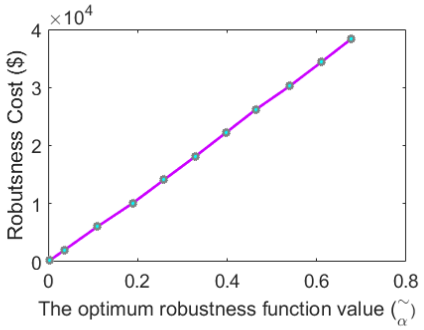

Fig. 6. Robustness cost function of optimum robustness value.

VI. CONCLUSION

A new DR trading framework for aggregators utilizing IGDT-based approach was proposed in this work. The DR aggregator plays as an intermediary role between consumers and power purchasers. Two programs were applied to the consumers. Thus, the aggregator sells the obtained DR to the buyers through two agreements. The IGDT-based robustness function was developed in a way to ensure the lowest level of pre-determined critical profit of the risk-averse aggregator. The problem was assessed on a real-world system. The aggregator would be more active in the DR market through the proposed trading framework. In addition, this modeling indicated that the consumers' behavior in participating in DR programs plays a crucial role in the DR aggregator trading performance through DR buyers. Furthermore, risk-averseness of the model has a direct relation with cost.

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