IGDT Opportunity Method in the Trading Framework of Risk-Seeker Demand Response Aggregators

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***Abstract*—In this study, a non-probabilistic program is proposed to a trading framework for demand response (DR) aggregators. Both sides of the aggregator, including upper side and down side of this entity, have been taken into account. In the down-side of the aggregator, two popular programs are considered such as reward-based program and time-of-use (TOU) program, where DR is obtained from these resources. The acquired DR is being sold to the purchasers in the other side of the aggregator through DR options and fixed DR contracts. To the aim of increasing the desired target profit of risk-seeker aggregator, an opportunity function of information-gap decision theory (IGDT) is used to handle the uncertainty, which is solved in General Algebraic Modeling System (GAMS) software. This model is implemented in a realistic case study.**

***Index Terms*--Demand response, DR aggregator, Opportunity, Risk management.**

I. NOMENCLATURE

Indices

t	Time horizon index
j	Index of reward-based DR steps
p	Index of time periods
c	Consumer index
f	Fixed DR contract index
b	Index related with fixed DR contact block
op	Index related with DR options agreement

Parameters

$\tilde{\lambda}_{f,b}^{DR}(t)$	Likely price for DR-contract
$\tilde{\lambda}_{op}^{DR}(t)$	Likely price for DR-agreement
$\widetilde{PF}(t)$	factors dedicated for consumers participation in the reward-based DR program
$D_0(c,t)$	Initial demand related to consumer c in time interval t
$E(c,t,p)$	Elasticity related to consumer c in time interval t related to the price in period p
$\lambda_0(c,p)$	Initial price related to consumer c in period p
$\lambda(c,p)$	TOU price related to consumer c in period p
$d(t)$	Duration of each period
f_{op}^{pen}	penalty related to rejection of DR agreement [MWh]
B_0	Deterministic expected profit related to DR aggregator maximum [$]
B_w	Desired target profit related to DR aggregator [$]
σ	Factor related to profit deviation
$\bar{P}_j^{DR,rw}(t)$	load reduction step in the reward-based DR [MWh]
$\bar{R}_j^{DR,rw}(t)$	Given reward in reward-based DR [$/MWh]

Variables

β	Horizon related to uncertain parameter
$\tilde{\beta}$	The function of optimal robustness value
q	Decision variables within IGDT
u	Uncertainty variables within IGDT
$PF(t)$	Factor related to consumers participation in reward-based DR
TOU(t)	Obtained TOU volume from consumers within time horizon t [MWh]
$\lambda_{f,b}^{DR}(t)$	Fixed contract price of DR
$\lambda_{op}^{DR}(t)$	Agreement price on DR options
$P_{f,b}^{DR}(t)$	DR contracted power[MWh]
$P_{op}^{DR}(t)$	DR options agreement power[MWh]

Binary Variables

$v_j^{DR.rw}(t)$	Reduced load level in reward-based DR
$v_{op}^{DR}(t)$	Binary variable for application of DR options agreement

II. INTRODUCTION

DR - Demand Response - is becoming more and more important in the electricity markets field, especially if it can be traded in large volumes. In this sense, the aggregation of DR programs seems to be a crucial step for the future smart grid. Indeed, the concept of DR aggregator would be an enabler to the contribution in DR programs of the end-user customers. Moreover, this new entity, the DR aggregator, could act as the interface amongst the independent market operator (ISO) and the electricity consumer, implementing DR programs on consumers in an optimal and coordinated way.

The main motivation underlined in our work is to model and analyze the behavior of consumers that participate in DR programs to assist aggregators for DR scheduling in a trading context. In this context, this paper proposes an information-gap decision theory (IGDT)-based approach for considering the trading background for DR aggregators while considering also risk management.

Typically there exist two basic DR programs, namely the incentive-based and the time-based DR programs. In this paper, we use both of them, that is, a reward-based DR program and a time-of-use (TOU) program. TOU program is modeled by considering the elasticity matrix, whereas the reward-based program is implemented by considering the conduct of end-user customers as an uncertain factor. In order to trade the attained DR, there are two possible agreements. Either a fixed DR contract is considered, where a fixed price and time is determined by the aggregator, or DR options are considered, in which the aggregator may or may not utilize in real time the DR.

The problem considered in this paper involves the maximization of profit, and the IGDT approach is engaged for handling uncertainty. In the following sections, the method will be enlightened with more specifics.

In the literature there are numerous works that have addressed DR programs. For example, in [1] a group of DR programs' has been researched. In [2] and [3], a number of different DR characteristics has been assessed. In addition, the pros and cons of considering DR approaches in the energy systems field was thoroughly debated in [4]. The importance of the DR aggregator, as a new agent in the field, was also reviewed.

Ref. [5] proposed a novel framework based on a pool for DR market, to allow trades for the DR aggregator, while wholesale markets were addressed in conjunction with DR aggregators in [6].

Ref. [7] assessed the ability to use DR programs in industry as a part of the ancillary services. In [8] a hierarchical market tool was proposed so that the aggregator could make the link between the ISO and the consumer. Renewables and market prices uncertainty was considered in [9] while studying the performance of the DR aggregator in the electricity market.

In [10], the authors have proposed a decomposition approach to enable the use of DR by the aggregator, so that social welfare could be maximized.

In [11], DR exchange was defined as a novel energy entity where bilateral contracts where not contemplated. Finally, in [12], thermostatically-controlled-loads were considered as a potential DR for an aggregator through a bottom-up methodology for contributing in the electricity market.

III. PROBLEM FORMULATION

The studied model is composed of residential, commercial and industrial electricity consumers each one with specific DR services like reward-based and TOU programs.

Afterward, the obtained DR is exchanged with buyers via DR options agreements and fixed DR contacts. In peak times, DR is obtained from consumers while in other times (off-peak and mid peak), it is proposed to the buyers to motivate them to increase their consumption.

At first, uncertainty is not taken into account and the model is studied under deterministic condition. Also, it is assumed that aggregator of DR is informed about load behavior under simulations.

A. Fixed DR Contracts

According to fixed DR contracts, an agreement is achieved between the aggregated and the buyer to trade the acquired DR in block b of f^{th} contract including certain values of price and DR, i.e. $\lambda_{f,b}^{DR}(t)$ and $P_{f,b}^{DR}(t)$.

Equation (1) is used to model the fixed DR contract and equation (2) is used to limit the value of DR in each block.

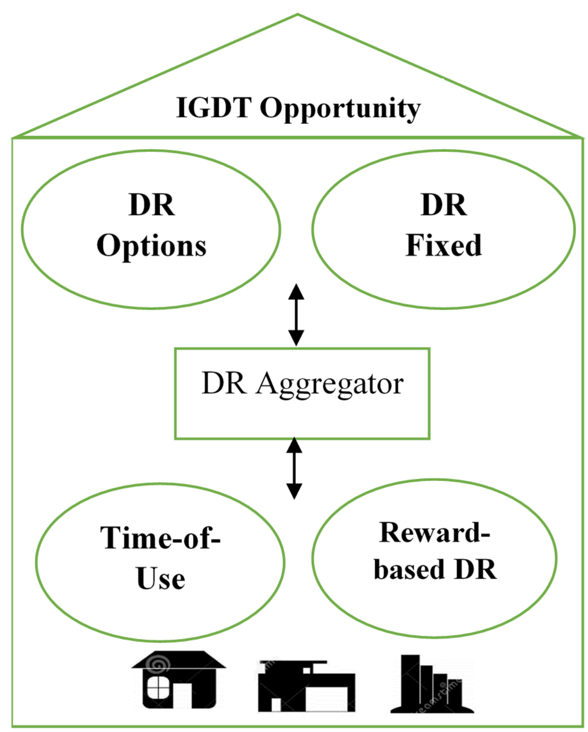

Figure 1. DR aggregator structure

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

$$p_{f,b}^{DR,min} \le p_{f,b}^{DR}(t) \le p_{f,b}^{DR,max} \ ,\forall t \quad (2)$$

It is noteworthy that N_b and N_f are the number of available blocks and contracts, respectively

B. DR Option Agreement

The aggregator examines the profitability of signed DR and then attests to set an agreement with the buyer. If the agreement is canceled by the aggregator, the aggregator will be responsible to pay the penalty fee to the buyer. So, with considering these conditions, this agreement can be expressed as:

$$P(ODR) = \sum_{t=1}^{T}\sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t).d(t) - \left(1 - v_{op}^{DR}(t)\right).f_{op}^{pen}(t)] \quad (3)$$

$$p_{op}^{DR,min} \le p_{op}^{DR}(t) \le p_{op}^{DR,max} \ ,\forall op = 1,2,\dots,N_{op} \quad (4)$$

It should be noticed that equation (4) is used to limit the value of agreed DR in the agreement.

C. Time-of-Use program

Based on time-of-use (TOU) program, various prices are offered to energy consumers within different time periods in a day so that consumers can modify their electricity usage habit in accordance with the offered prices. It should be noticed that consumer's participation in TOU and their elasticity are proportional with each other. This program is modeled in equation (5).

$$TOU(t) = \sum_{c=1}^{N} D_0(c,t) \sum_{p=1}^{P} E(c,t,p)\left(\frac{\lambda(c,p) - \lambda_0(c,p)}{\lambda_0(c,p)}\right), \forall t \quad (5)$$

D. Reward-based DR program

This program is modeled via equations (6)-(10). Equation (6) is used to model the reduction of load in this program in which $PF(t)$ represents participation level of consumers ranging from 0 (unattainable) to 1 (attainable). Value of donated reward is expressed in (7) which is limited in (8).

$$P^{DR}(t) = \sum_{j=1}^{N_J} PF(t).\bar{P}_j^{DR}(t).v_j^{DR}(t) \ ,\forall t,\forall j \quad (6)$$

$$R^{DR}(t) = \sum_{j=1}^{N_J} R_j^{DR}(t) \ ,\forall t,\forall j \quad (7)$$

$$\bar{R}_{(j-1)}^{DR}(t).v_j^{DR}(t) \le R_j^{DR}(t) \le \bar{R}_j^{DR}(t).v_j^{DR}(t), \forall t,\forall j \quad (8)$$

$$\sum_{j=1}^{N_J} v_j^{DR}(t) = 1 \ ,\forall t,\forall j \quad (9)$$

$$v_j^{DR}(t) \in \{0,1\} \quad (10)$$

It should be noticed that various reduction levels of load can be chosen in this program which is explained completely in [13].

E. Deterministic Trade of DR Aggregator

Aggregator seeks to maximize its benefit obtained from trading DR with buyers in different time periods. So, the objective function can be expressed as:

$$Obj.Func:\ B_0 = Max \sum_{t=1}^{T}\left[\sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t).d(t) + \sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t).d(t) - \left(1 - v_{op}^{DR}(t)\right).f_{op}^{pen}(t)] - \sum_{j=1}^{N_J} PF(t).\bar{P}_j^{DR}(t).R_j^{DR}(t)\right] \quad (11)$$

S.t:

$$\sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t) + \sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t). = P^{DR}(t) - TOU(t) \ ,\forall t \quad (12)$$

Constraint associated to fixed DR contract (2) (13)

Constraint associated to DR option agreement (4) (14)

TOU program constraint (5) (15)

Constraints pertaining to reward-based program (6) – (10) (16)

It is noteworthy that the first and second parts of objective function expressed in (11) are obtained benefits from DR contracts and DR agreements programs and the last part represents total cost of reward-based DR program. It is noteworthy that energy balance limitation is expressed in (12) according to which available resources should satisfy demand sides.

F. IGDT-based Trade of DR Aggregator

In this section, opportunity function of IGDT is used to model the uncertainty of participation level of consumers in DR while procured DR by buyers are considered to be decision variables ($u_t = PF(t)$ and$q(t) = \{p_{op}^{DR}(t),\ p_{f,b}^{DR}(t)\}$). For this, the fractional info-gap uncertainty model of IGDT is employed. It should be noticed that the forecasted value of participation level of consumers is available ($\tilde{u}_t = \widetilde{PF}(t)$).

Unlike deterministic problem in which the total profit of aggregator was due to be maximized, in opportunity function of IGDT, aggregator seeks trading to obtain the maximum possible profit from advantageous divergences of the uncertain parameter. This strategy is called risk-seeking strategy. So, the objective of opportunity function of IGDT is to minimize uncertainty parameter (β) while satisfying the requirements. Opportunity function of IGDT is mathematically modeled as:

$$Obj\ Func:\ \ \bar{\beta} = Min\ \beta \tag{17}$$

$$S.t:\quad B^* \geq B_w = (1+\sigma).B_0 \tag{18}$$

$$\begin{aligned} B^* = max\Bigg\{\sum_{t=1}^{T}\Bigg[&\sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t).d(t) \\ &+\sum_{op=1}^{N_{op}}[P_{op}^{DR}(t).\lambda_{op}^{DR}(t).d(t) \\ &-\left(1-v_{op}^{DR}(t)\right).f_{op}^{pen}(t) \\ &-\sum_{j=1}^{N_J} PF(t).\bar{P}_j^{DR}(t).R_j^{DR}(t)\Bigg]\Bigg\} \end{aligned} \tag{19}$$

$$(1-\beta).\widetilde{PF}_t \leq PF_t \leq (1+\beta).\widetilde{PF}_t \quad ,\forall t \tag{20}$$

$$(12)-(16) \tag{21}$$

As it can be seen, total benefit of aggregator proportionally increases with the increase of participation factor. It can be observed that the maximum benefit of aggregator is achievable if the value of uncertain parameter is the minimum.

In order to increase the value of B^*, the level of participation should be the maximum so that $PF(t) = (1+\beta).\widetilde{PF}(t)$. Thus, the updated model can be expressed as:

$$Obj\ Func:\ \ \bar{\beta} = Min\ \beta \tag{22}$$

$$S.t:\quad B^* \geq B_c = (1+\sigma).B_0 \tag{23}$$

$$B^* = \sum_{t=1}^{T}\Big[\sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t)\lambda_{f,b}^{DR}(t)\,d(t) + \sum_{op=1}^{N_{op}} P_{OP}^{DR}(t)\lambda_{op}^{DR}(t)d(t) - \Big(1 - v_{op}^{DR}(t)\Big) f_{op}^{pen}(t) - \sum_{j=1}^{N_J}\widetilde{PF}(t)(1+\beta).\bar{P}_j^{DR}(t)\,R_j^{DR}(t)\Big] \tag{24}$$

$$(7)-(10) \tag{25}$$

$$P_t^{DR} = \sum_{j=1}^{N_J}\widetilde{PF}(t).(1+\beta).\bar{P}_j^{DR}(t).v_j^{DR}(t),\forall t,\forall j \tag{26}$$

$$(12)-(15) \tag{27}$$

IV. Case Study

A. Data Preparation

This programming is formulated as a mixed integer non-linear program (MINLP). The SBB [14] solver has been used under General Algebraic Modeling System (GAMS) [15] for obtaining the results. Different factors related to profit deviation, i.e. σ, is considered to study the proposed model. Since the model is non-linear, this model could be linearized through using several methods such as implementing linear cutting algorithms [16] or reformation-linearization techniques [17]. Nevertheless, linearization is not the purpose of the authors in this work.

The simulation of the proposed program is run by a PC with 6GB RAM and 2.43 GHz CPU.

The load of a long day is taken into account, which is data used from [18]. Two time periods are considered, which divides the day in two, that is: on-peak and off-peak. From 09am to 10pm is considered as on-peak period and the remaining hours are assumed as off-peak. The DR aggregator's trading procedure is that the DR is being bought from the consumers and then it is being sold to the customer during on-peak hours. During the off-peak period, this method will be vice versa.

According to Fig. 1, three groups of consumers are taken into account, i.e. commercial, residential, and industrial. The aggregator acquires DR from the consumers through two DR programs including reward-based DR program and TOU program. Thus, the aggregator trades the attained DR to the purchaser by considering two forward contracts such as DR options agreement and fixed DR contract. The TOU prices are taken from ref. [18] and the elasticity data, i.e. Table I, from ref. [19]. Note that the reward-based DR curve has 25 steps for each type of consumers.

In addition, the fixed DR contract contains 6 blocks for on-peak with 90kW maximum demand and 6 blocks for off-peak hours with 30kW. Regarding DR option agreements, eight agreements for the whole day is assumed. It is noteworthy that the DR aggregator has the right not to exercise the agreement. However, the penalty fee must be paid to the purchaser. The value of this penalty is equal to 10% of the whole value.

B. Results

In the first step, the behavior of the aggregator is being studied while the uncertain parameters are perfectly known and the model is optimized without any uncertainty.

In other words, the deterministic behavior of the model is being discussed and it is assumed the aggregator could forecast the uncertain parameter perfectly, which is the factor dedicated for consumers participation in reward-based DR program *PF(t)*.

Deterministic modelling is ensured in equations (10) – (15). The deterministic expected profit related to DR aggregator B_0 is around \$202,000. Thus, the opportunity model is being simulated considering several deviation factors that indicates the corresponding desired target profits, i.e. $B_w = (1+\sigma) \times B_0$, refer to equations (21) – (26). However, the results of some σ are investigated more in detail, i.e. σ = {0, 0.01, 0.1}. σ=zero is indicating the deterministic results, and the other values are used to address the opportunity. As in σ=zero, the results of the suggested model without uncertainty is derived. Then, the effects of opportunity function are being studied. For example, if σ=0.01 be selected, the model is simulated in a way that assures the aggregator that its profit will be $B_w = (1+0.01) * B_0 = \$204{,}000$

In this model, by changing the desired target profit, various values of opportunity parameter are being derived, as depicted in Fig. 2. It is noticeable that if the aggregator is tending to gain high values of desired target profit, the higher favorable price deviations from the forecasted values are required. For instance, if the aggregator wishes to obtain B_w= *\$224,000* profit instead of B_0= *\$209,000*, the uncertain factor must be at least %85 higher than the forecasted ones.

According to Fig.2, an enhanced risk-averse behavior would be developed by the aggregator as the opportunistic function increases.

The behavior of TOU program implement is shown in Fig. 3. It is obvious that the program encourages consumers to transfer time of utilizing the electricity equipment during off-peak periods rather than on-peak periods. Further, the results of TOU are the same for all uncertain factors.

To study more in detail about the impact of employing IGDT opportunity model, two deviation factors are taken into account, i.e. σ= {0, 0.01, 0.1}. Thus, σ=0 is for a risk-neutral behavior, becoming risk-seeker with the augmentation of the profit deviation factor. Where the corresponding desired target profits will be $B_{w1} = (1+0.01) * B_0 = \$204{,}000$, $B_{w2} = (1+0.1) * B_0 = \$224{,}000$. And their corresponding opportunistic function value $\bar{\beta}$ would be 0.035 and 0.85.

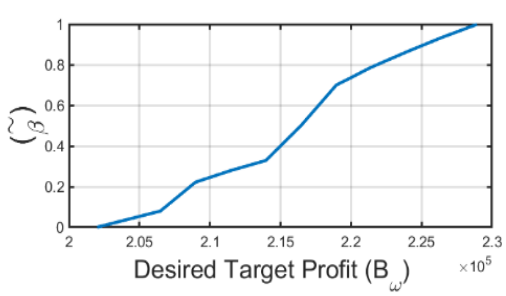

Figure 2. Optimum opportunistic function value ($\bar{\beta}$) versus desired target profit.

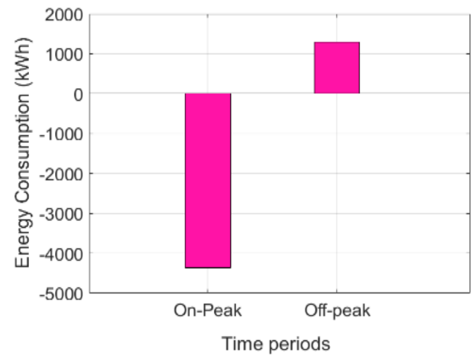

Figure 3. Time-of-Use program results

It means that if the uncertain parameter favorable spike would be more or equal than 0.035 of the forecasted values, it would gain the desired profit target which is more than the critical profit, B_0. Since this amount of spike of the uncertain parameter is so noticeable, i.e. $\overline{\beta_2} = 0.85$. Then the aggregator could expect of the desired target profit $B_{w2} = \$224{,}000$, if and only if the uncertain parameter values would be 85% greater or equal of the forecasted ones.

Figure 4 states the results of implementing opportunity approach on the DR aggregator trading framework. According to this figure, the amount of DR increases as the profit deviation factor, i.e. σ increases. However, the amount of this increment is not noticeable when $\sigma_1 = 0.01$in comparison with the deterministic result. Thus, when the deviation factor is ten times greater than the first one, i.e. $\sigma_2 = 0.1$, the amount of reward-based DR increasing sufficiently. As the DR aggregator wants to gain more profit, the amount of demand is also increasing. Note that the negative values in the Fig.4 refer to DR which is offered to the consumers during off-peak periods. During off-peak intervals the aggregator encourages consumers to consume more energy. Similarly, the positive values in the figure indicates the amount of reward-based, which is acquired from consumers. As stated in the proposed model, there are 2 fixed agreements to sell the obtained DR to the purchasers by the aggregator. The results regarding these agreements are declared in Table I. The results indicate that, having a more risk-seeker behavior from the aggregator, fixed-DR agreements amount is also increased to meet the desired target profit.

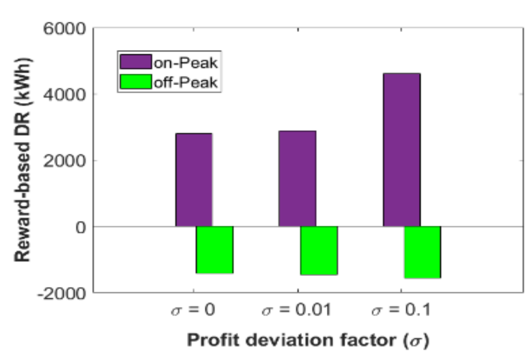

Figure 4. DR results for reward-based

TABLE I
Fixed DR energy (kWh)

σ	Peak	Off-peak
0	4560	-1006
0.01	4658	-1056
0.1	6369	-1152

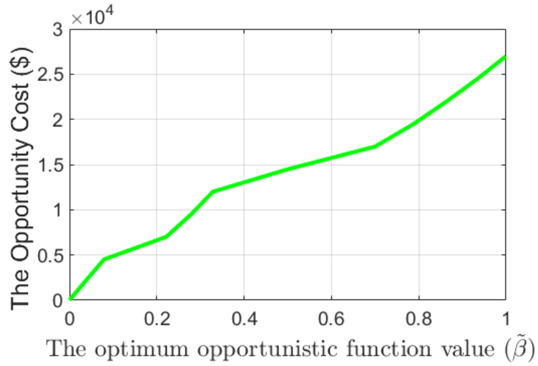

Figure 5. Opportunity cost (OC) versus optimum opportunity value

As the aggregator in opportunity model tends to increase its target profit, it is reasonable that all of the DR option agreements to be exercised in this situation. And the results approve this this claim as well. There are costs which are imposed to the aggregator by employment of the IGDT opportunity approach to the model. This cost is indicated as the opportunity cost (OC).

Hence, by implementing the IDGT opportunity procedure in this situation, the aggregator will encounter with an economic loss if the opportunistic model carried out, but no favorable spikes correlated to the uncertain parameter are seen. This economic loss is the opportunity cost. The opportunity cost is depicted in Fig. 5 for several values of the optimum opportunistic function. It is obvious in Fig. 5 that if the aggregator tends to schedule for higher values of target profit, the cost of the implementing opportunity programming would increase as well.

V. Conclusions

A risk-seeker DR aggregator tends to increase its utility's target profit. To this end, an IGDT-based opportunity function is one of the best functions which can meet the risk-seeker aggregator expectations. The authors have considered both sides of the aggregator through various popular DR programs. The results showed that by implementing the opportunity function to the trading framework of the DR aggregator, the desired target value is being increased if the forecasted favorable spikes of the uncertain parameter are being observed in the actual time. Furthermore, the model demonstrated that the opportunity cost has a direct relation with the desired profit target.

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