This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2017.2788890, IEEE Transactions on Smart Grid

Self-Scheduling of Demand Response Aggregators in Short-Term Markets Based on Information Gap Decision Theory

Morteza Vahid-Ghavidel, *Student Member, IEEE*, Nadali Mahmoudi, *Member, IEEE,* Behnam Mohammadi-ivatloo, *Member, IEEE*

***Abstract*— This paper proposes a new self-scheduling framework for demand response aggregators, which contributes over the existing models in following aspects. The proposed model considers the uncertainties posed from consumers and electricity market prices. Further, the given model applies the information-gap decision theory (IGDT) in the self-scheduling problem, which guarantees the predefined profit by the aggregator and avoids computational burdens caused by scenario-based methods such as stochastic programming approaches. The DR aggregator procures DR from two proposed programs, i.e. reward-based DR and time-of-use (TOU). Then, the obtained DR is offered into day-ahead and balancing markets. An IGDT-based profit function is proposed, which leads to a bilevel program. The given bilevel model is then transformed into an equivalent single-level model by developing a non-KKT method, which is solved through commercial solvers available in General Algebraic Modeling System (GAMS). The feasibility of the problem is studied using a case study with realistic data of electricity markets.**

***Index Terms*— Demand response aggregator, information-gap decision theory, electricity markets, time-of-use, reward-based DR, uncertainty**

NOMENCLATURE

Indices

t	Index referring to time horizon
j	Index referring to reward-based DR steps
p	Index referring to time periods
c	Index referring to consumers

Parameters

$\tilde{\lambda}_t^{DA}$	Expected day-ahead market price [$/MWh]
$\tilde{\lambda}_t^{+}, \tilde{\lambda}_t^{-}$	Expected excess/deficit condition's imbalance prices [$/MWh]
$\widetilde{PF}_t$	Participation factors of consumers in the reward-based DR program
$D_0(c,t)$	Initial demand of consumer c in time interval t
$E(c,t,p)$	Elasticity of consumer c in time interval t related to price in period p
$\lambda_0(c,p)$	Initial price of consumer c in period p
$\lambda(c,p)$	TOU price of consumer c in period p
B_0	Expected maximum deterministic profit of the DR aggregator [$]
B_c	Critical profit [$]
σ	Profit deviation factor
M	A sufficiently large constant
$\bar{P}_{t,j}^{DR,rw}$	The steps of the reduced load in the reward-based DR program [MWh]
$\bar{R}_{t,j}^{DR,rw}$	The reward given in in the reward-based DR program [$/MWh]

Functions

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

Variables

α	The horizon of the uncertain parameter
$\tilde{\alpha}$	Optimal robustness function value
q	Decision variables of the IGDT model
u	Uncertainty variables of the IGDT model
PF_t	Participation factor of consumers in the reward-based DR program
TOU_t	Time-of-Use program volume obtained from all consumers over the time horizon t [MWh]
λ_t^{DA}	Day-ahead market price [$/MWh]
$\lambda_t^{+}, \lambda_t^{-}$	Excess/deficit condition's imbalance price [$/MWh]
P_t^{DA}	The offered power in the day-ahead market [MWh]
P_t^{+}, P_t^{-}	Excess/deficit amount of power traded in the balancing market [MWh]
$\underline{B}_t^{+}$	The minimum profit of the aggregator when the excess condition occurs [$]
$\underline{B}_t^{-}$	The minimum profit of the aggregator when the deficit condition occurs [$]

Binary Variables

$v_{t,j}^{DR.rw}$	A binary variable that determines the level of the reduced load in the reward-based DR
β_t	A binary variable that determines excess or deficit conditions

I INTRODUCTION

INDEPENDENT system operators (ISOs) are developing new demand response (DR) actions to encourage active participations of demand side resources in electricity markets. The aggregation of DR programs has been known as an appropriate solution to enhance the participation of consumers in electricity markets in different countries. For instance, the Australian Energy Market Commission (AEMC) has advised more active DR aggregators as a main solution in enhancing DR outcomes [1]. Federal Energy Regulatory Commission (FERC) also placed Order 719 in 2008, through which DR aggregators are required to be treated as similar to other generators in the wholesale market [2]. A similar rule is valid in other electricity markets such as some Canadian and Singapore markets. DR aggregators, as new market entities, play an arbitrator role in electricity

M. Vahid-Ghavidel and B. Mohammadi-ivatloo are with University of Tabriz, Iran (mv.ghavidel@ieee.org; mohammadi@ieee.org). N. Mahmoudi is with the University of Queensland, Australia (n.mahmoudi@uq.edu.au).

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markets between consumers and ISOs. These entities carry out DR programs on consumers to resell the obtained DR through various electricity markets.

The intermediary role poses two key challenges to DR aggregators, where they have to take into account not only the consumers behavior when implementing DR programs, but also minimizing their exposures to the risk of uncertain electricity markets when selling DR products. These challenges are indeed the main motivations behind our work. We propose a short-term framework through which DR programs such as time of use (TOU) and reward-based programs are considered on the demand side, while the DR aggregator is enabled to trade the DR product in day-ahead and balancing markets. To this end, a bilevel profit-maximization model based on the information gap decision theory (IGDT) is mathematically formulated, which enables the DR aggregator to ensure its desired profit considering both risks from demand and supply sides. The proposed model accurately captures the uncertainty of the consumers' behavior, through a developed participation factor, as well as that of market prices. The proposed IGDT-based model guarantees the predetermined desired profit expectations provided that the realized uncertain parameters fall into the maximized uncertainty horizon. In order to solve the proposed bilevel model using commercially-available tools, it is required to transform it into an equivalent single level problem. Due to the non-convexity of the lower-level problem, the common approach of Karush-Kuhn-Tucker (KKT) conditions is not valid to derive the single-level model and as such, a new procedure is proposed in this paper to carry out this task.

A number of studies in the literature address various DR programs in detail. Detailed DR programs such as individual consumers' DR [3], building energy management [4], heating and cooling control [5], various incentive-based DR [6], new tariff designs [7] are amongst the most popular DR programs applied to consumers.

Modeling DR aggregators and their challenges in electricity markets are addressed in some recent studies. Some investigations consider the challenges of participating DR aggregators in electricity markets, while considering DR in a lumped volume [8]–[10]. That is, these studies do not consider how DR aggregators obtain their DR from consumers. Authors in [11] propose a new bidding strategy for DR aggregators in day-ahead markets using stochastic programming and robust optimization. As found in [12], market participants can negotiate with other market players through demand response exchange markets, but in the considered model the balancing market is not taken into account. DR is considered as a real-option contract where the aggregator can sell its DR in electricity markets [13], though the uncertainty of the demand side is disregarded. In [14] a bilevel model is proposed where DR is represented by coexistence of elastic and inelastic loads. A few studies in the literature take into account both demand and supply sides. As indicated in [15], a study of interaction between households, the ISO and DR aggregators has been done in a hierarchical market. In [16], an optimal bidding strategy for a large price-responsive consumer is proposed through which both market prices and wind power are uncertain parameters. However, the effects of implementing DR programs such as time-based and incentive-based DR programs are not studied. A coupon-based DR program is proposed in [17], where the uncertain nature of wind power and real-time market prices are discussed. Reference [18] introduces a two-stage two-level optimization program of a retailer by assuming the uncertainties of the market prices and the end-users' consumption patterns under DR programs. The consumers' behavior under TOU programs and the level of market prices are investigated in [19] through a multi-agent simulation model. A new DR program as a coupon incentive-based DR is proposed in [20], which investigates scenario-based DR dispatch through reward-based models. In [21], authors present a DR aggregation framework in which the aggregator offers different contracts for reducing load on peak hours in only day-ahead markets. Reference [22] analyzes the benefits and challenges of introducing DR programs in the German balancing markets. As found in [23], authors propose an optimal bidding strategy by implementing DR and CHP cogeneration. The given model uses the IGDT technique while considering only day-ahead market prices as an uncertain parameter and disregarding how DR is obtained from the demand side. Authors in [24] introduce a bottom-up procedure that the aggregator converts provided DR through thermostatically controlled loads to participate in reserve markets. In [25], authors propose a two-stage structure for participation in balancing and day ahead markets focusing on thermal heating DR load. A bidding strategy based on the game theory is proposed in [26], where the objective of the aggregator is reducing the load through load curtailment programs while minimizing the consumers' inconvenience. As stated in [27], the DR is acquired from TOU and reward-based DR programs while selling it to purchasers through long-term contracts such as fixed DR contracts and DR options. In [28], authors present a bottom-up bidding framework for DR aggregators in electricity markets. Various DR programs are considered on the demand side while long-term to short-term options are modeled for selling DR. A recent review of demand response programs, their benefits and barriers in different countries is provided in [29]. The risk is modeled in some studies such as [27] and [28], through the conditional value-at-risk (CVaR) measure. Scenario-based risk measures such as CVaR and value-at-risk (VaR) focus on achieving optimal schedules based on a limited number of scenarios; whereas IGDT-based models determine optimal schedules in order to reach a desired profit in a maximized uncertainty region. The significance of the proposed IGDT-based DR self-scheduling is that it optimizes the robustness of operation schedules using the available uncertain parameter forecasts such that a minimum acceptable profit is guaranteed. Further, IGDT-based problems pledge the predetermined level of the profit unlike the scenario-based models. In the IGDT model, assumptions about the nature of uncertain parameters and presumption on the size of the uncertainty are not required. Therefore, it is not rational and possible to compare the obtained results from IGDT-based problems with other methods such as stochastic programming.

Having mentioned the most relevant studies, it can be stated that there is no such a model that comprehensively develops self-scheduling for DR aggregators while

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modeling both sides' uncertainties through appropriate risk measures such as IGDT. As such, the contributions of this work are declared as follows.

1-Our model develops a short-term self-scheduling for DR aggregators, which simultaneously addresses both uncertainties of consumers and electricity markets.

2-An IGDT-based risk model is proposed to obtain the robustness function considering uncertain parameters including market prices and customers' participation factors.

3-The proposed optimal self-scheduling model is formulated in a bilevel problem, which is non-convex in the lower level. Therefore, a new method is introduced to transform the bilevel model into a single-level problem, which could be solved through commercial solvers.

Table I clearly compares the most relevant studies to our work by giving their approaches, benefits and drawbacks, and then highlights our contributions.

The rest of the paper is structured as follows. Section II addresses the methodology. The proposed IGDT-based model is given in Section III, whereas its formulation is provided in Section IV. Section V details the data, and then explicitly delivers the results with in depth discussions. Last section concludes the paper.

I METHODOLOGY

Framework

The proposed DR trading framework is depicted in Fig. 1. Energy flow direction is indicated by arrows. Note that the

TABLE I
SUMMARY OF THE PREVIOUS RESEARCH WORK

Paper	Solution approach	Pros.	Cons.
[7]	Bilevel programming	- Proposes a pricing scheme by load serving entities for consumers	- Uncertainty is not examined
[11]	Stochastic programming and robust optimization	- Proposes a new bidding strategy for DR aggregators in day-ahead markets	- Balancing market is not modeled - Uncertainty of consumers is disregarded
[13]	Real options approach	- DR is considered as a real option contract	- Demand side participation behavior is not considered
[16]	Bilevel stochastic programming	- Proposing an optimal bidding strategy for a large price-responsive consumer	- No study on the effects of implementing DR programs such as time-based and incentive-based DR programs
[21]	MILP	- Presents a DR aggregation framework in which the aggregator offers different contracts for reducing load on peak hours	- Balancing market is not considered - Uncertainty of consumers is not modeled.
[23]	IGDT-based approach	- Proposes an optimal bidding strategy by implementing DR and CHP cogeneration	- Not considering the balancing market - Disregarding how DR is obtained from the demand side
Our proposed Model	IGDT-based bilevel programming	- Simultaneously addresses the uncertainty of both sides - Converting the bilevel form to single-level problem through a non-KKT method	- Not including long term contracts

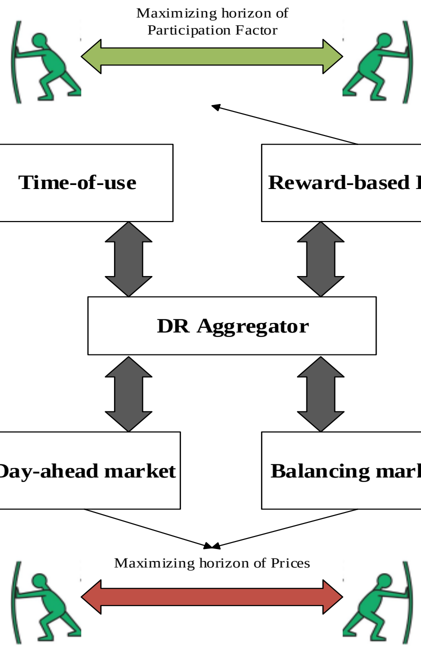

Fig. 1. The proposed DR trading framework

double-sided arrows show that the energy flow can be either from end-users to the pool market or in the opposite direction. The DR aggregator obtains energy from TOU and reward-based DR programs. These programs are acquired from three types of consumers, i.e. residential, commercial and industrial. Each type is offered unique TOU tariffs and an individual reward-based DR. On the other hand, the DR product is traded in an energy pool with day-ahead and balancing markets. We consider two uncertain parameters including market prices and consumers' participation factors. The IGDT approach is utilized to address the risk measure, where the decision maker's goal is to maximize the horizon of the uncertainty while the critical profit is met or exceed. Note that the DR aggregator offers in the day-ahead and balancing markets while any deficit/excess of its offers should be cleared in the balancing market. The balancing market mechanism is based on the market given in [30]. Accordingly, if the aggregated DR is more than the scheduled value, its excess is cleared with a positive imbalance price which is lower than or equal to the cleared day-ahead price. In a similar way, if the aggregated DR is less than the scheduled amount of energy, its deficit in DR will be cleared with a negative imbalance price which is greater than or equal to the cleared day-ahead price. Therefore, if a market player seeks to avoid the economic loss in the day-ahead market, it should prevent any mismatch scheduling in this market.

In terms of the model implementation, the DR aggregator would forecast both markets' prices on the day prior to energy delivery. Then, it decides on the reward to be offered to customers, while modeling their behavior and uncertainty. Further, TOU prices are offered. Having the information of both demand and supply sides, the DR aggregator runs its self-scheduling model and determines its shares from both sides while taking into account its risk through the IGDT model.

II INFORMATION GAP DECISION THEORY

The IGDT model aims to ensure that the expected profit of the DR aggregator is achieved, while the region of the

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uncertainty is maximized. Fig. 2 illustrates how the IGDT model works. As depicted, the DR aggregator aims to obtain at least its critical profit (denoted by Bc in the Y axis), while trying to extend the uncertainty horizons of both participation factors and market prices as much as possible (see the uncertainty horizon in Fig. 2, depicted as α in the X axis). Note that the critical profit, i.e. B_c, is guaranteed to be met or exceed as declared in $B^* \geq B_c = (1-\sigma) \times B_0$, where it is a percentage of the deterministic profit, i.e. B_0. σ is used for declaring the risk-averseness of the DR aggregator. (This will be explained in more detail in the following, where a thorough discussion of problem formulations is provided.)

The IGDT model is described using three components, namely the system model, the uncertainty model, and the performance requirement, explained below [31]:

System Model: The system model is represented in an input/output structure described in *R(q,u)*, which indicates the reward of the decision maker for the selected values of the decision variable q considering the uncertain parameter *u*. In our work, *R(q,u)* represents the profit of the DR aggregator.

Uncertainty Model: The uncertainty model can be characterized by several approaches using IGDT, denoted here by $U(\alpha, \tilde{u})$ [31]. A common function used for declaring the uncertainty model is the fractional uncertainty model which is mathematically represented as follows:

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

where, $U(\alpha, \tilde{u})$ indicates the gap between the known forecasted (expected) values denoted here by $\tilde{u}$ and what is required to be known, i.e. u. The horizon of the uncertain parameter is denoted by α. For higher values of α, the range of possible variations of the uncertain parameter becomes greater. Note that the information-gap uncertainty model has *Contraction* and *Nesting* nature. Contraction nature declares that $U(0, \tilde{u})$ is the singleton set $\{\tilde{u}\}$ [32]. Nesting nature indicates that $U(\alpha^{(1)}, \tilde{u}) \subseteq U(\alpha^{(2)}, \tilde{u})\ if\ \alpha^{(1)} \subseteq \alpha^{(2)}$. Note that due to the variable nature of α, the solution will find the lower and upper bounds of the uncertainty horizon. This uncertainty model definition expresses that the length of the uncertainty horizon depends on the values of the uncertain parameter.

Performance Requirement: Based on the risk management strategy of the decision maker, we can specify various performance models in the IGDT structure. However, the robustness function is considered here due to its ability of indicating the worst-case scenarios. This robustness function is proper for risk-averse aggregators. The IGDT-based robustness function is modeled in such a

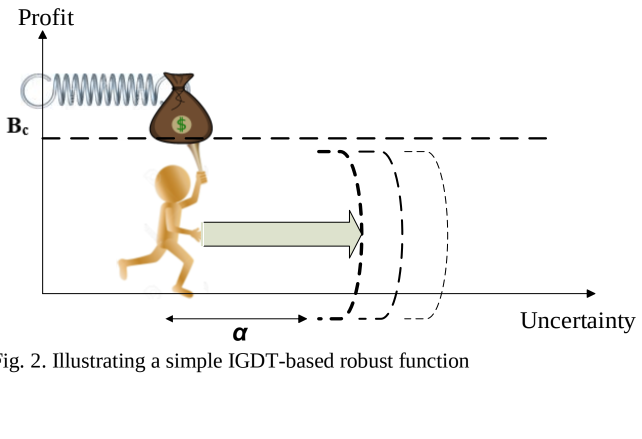

Fig. 2. Illustrating a simple IGDT-based robust function

way to be immune against the unfavorable deviations of the uncertain parameter. An IGDT robustness function, $\tilde{\alpha}(q, r_c)$, is described as the maximum value of α such that the minimum favorable or desired reward of the decision-making problem is fulfilled, i.e.:

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

In the above context, r_c is the critical profit of the performance model which is pledged to be equal or better than that value.

The proposed IGDT-based model is a bilevel problem which can be modeled using the following formulation [33]:

$$\underset{x}{Max}\ f^{up}(x, y^*) \qquad (3)$$

$$s.t.:$$

$$g^{up}(x, y^*) \leq 0 \qquad (4)$$

$$y^* = arg\left\{\underset{y}{min}\ f^{lo}(x, y)\right. \qquad (5)$$

$$s.t.:$$

$$g^{lo}(x, y) \leq 0 \qquad (6)$$

$$h^{lo}(x, y) = 0 \qquad (7)$$

where *up* (*lo*) is used for identifying the upper (lower) level of the bilevel program. Equations (3) and (4) are for the upper level, then the lower level is defined in (5) – (7).

III FORMULATION

In this section, we introduce our model's formulation in the following orders. First, it is assumed that there is no uncertain parameter, i.e. market prices and participation factors are perfectly known. In this condition, the deterministic self-scheduling is delivered. Then the uncertain parameters (uncertain market prices and participation factors) are taken into account.

A. Deterministic DR aggregator self-scheduling

The DR aggregator aims to determine its optimal DR volume to trade in the day-ahead and balancing markets. It is assumed that the aggregator is price taker in these markets. In this stage, we consider that the DR aggregator can accurately forecast its market prices as well as customers' participation factors. The deterministic problem is then formulated in (8) – (18).

$$B_0 = Max \sum_{t=1}^{T}[P_t^{DA}.\lambda_t^{DA} + P_t^{+}.\lambda_t^{+} - P_t^{-}.\lambda_t^{-}] - \sum_{t=1}^{T}\sum_{j=1}^{N_J} PF_t.P_{t,j}^{DR,rw}.R_{t,j}^{DR,rw} \qquad (8)$$

$$S.t.:$$

$$P_t^{DA} + P_t^{+} - P_t^{-} = P_t^{DR.rw} - TOU_t\ ,\forall t \qquad (9)$$

$$TOU_t = \sum_{c=1}^{N} D_0(c,t) \sum_{p=1}^{P} E(c,t,p)\left(\frac{\lambda(c,p)-\lambda_0(c,p)}{\lambda_0(c,p)}\right), \forall t \qquad (10)$$

$$P_t^{DR.rw} = \sum_{j=1}^{N_J} PF_t.\bar{P}_{t,j}^{DR.rw}.v_{t,j}^{DR.rw}\ ,\forall t, \forall j \qquad (11)$$

$$R_t^{DR.rw} = \sum_{j=1}^{N_J} R_{t,j}^{DR.rw}\ ,\forall t, \forall j \qquad (12)$$

$$\bar{R}_{t,(j-1)}^{DR,rw}.v_{t,j}^{DR.rw} \leq R_{t,j}^{DR.rw} \leq \bar{R}_{t,j}^{DR,rw}.v_{t,j}^{DR.rw}, \forall t, \forall j \qquad (13)$$

$$\sum_{j=1}^{N_J} v_{t,j}^{DR.rw} = 1\ ,\forall t, \forall j \qquad (14)$$

$$P^{min} \leq P_t^{DA} \leq P^{Max}\ ,\forall t \qquad (15)$$

$$0 \leq P_t^{+} \leq P_t^{DR.rw} - TOU_t\ ,\forall t \qquad (16)$$

$$0 \leq P_t^{-} \leq P^{Max}\ ,\forall t \qquad (17)$$

$$v_{t,j}^{DR.rw} \in \{0,1\} \qquad (18)$$

The given deterministic model is formulated as a profit maximization problem, presented in (8). The first term of this equation refers to the revenue of selling DR to the day-ahead market. The revenue of selling the excess amount of

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DR in the balancing market is declared in the second term. The 3rd term represents the cost of buying power from the balancing market in the deficit condition. Lastly, the cost of the proposed reward-based DR comes as the last term. Note that it is considered that consumers have smart meters and then the cost of these facilities is not mentioned in objective function. As such, the TOU program does not pose any cost to the DR aggregator since it represents distinct tariffs instead of incentives given to consumers. Equation (9) refers to the power balancing constraint. The acquired power of DR programs, i.e. TOU and reward-based DR, must be equal to the power traded in DA and balancing markets for each time interval. The balancing trading procedure includes either positive imbalance or negative imbalance values. The time-of-use program is defined in equation (10). According to this program, during a day, customers receive different price tariffs, such as peak and off-peak tariffs. As such, they regulate their electricity usage habit relying on their elasticity to price changes. $\lambda_0(c,p)$ shows the initial price dedicated to consumer c in period p while $\lambda(c,p)$ shows the offered TOU price. The elasticity of consumer c during time t than period p is declared by $E(c,t,p)$.

Equation (11) indicates the reward-based DR program, which is explained as follows. With reference to Fig. 3, when the DR aggregator offers greater rewards in a stepwise style, the volume of the load reduction increases. The vertical axis of the figure, indicated by $\bar{P}_{t,j}^{DR,rw}$, is the steps of the reduced load and the horizontal axis ($\bar{R}_{t,j}^{DR,rw}$) shows the amount of the reward. The complete reward-based DR procedure is declared in equations (11)–(14) and (18), where, $P_t^{DR.rw}$ is the amount of the total reduced load through enforcing the reward-based DR program. PF_t is the participation factor that simulates the behavior of consumers' uncertainty. The participation factor ranges between 0 to 1, which zero indicates that the reward-based DR program is unattainable and the value 1 declares that the whole forecasted DR is obtained. In equation (12), $R_{t,j}^{DR,rw}$ is the total reward of the related program that is paid to the consumer. Equation (13) limits the reward offered to consumers. As stated in (14), it is assumed that the DR aggregator can select only one level (j) of the load reduction in the DR curve for each time interval. Note that various uncertainties exist due to the behavior of customers on the demand side which is also dependent on their geographical location. Indeed, the participation factor introduced in this paper thoroughly takes into account these uncertainties. The response of customers depending on their characteristics and geographical location is modelled through this factor, ranging between zero and 1. That is, if a specific customer's participation factor ranges between, e.g. 0.9 and 1, it indicates that the customer is likely to respond to the offered reward with the expectation of up to 10% uncertainty. Note also that, determining a very accurate range of participation factors requires a deep and comprehensive behavioral study of customers including psychological investigations, which is beyond this work's focus.

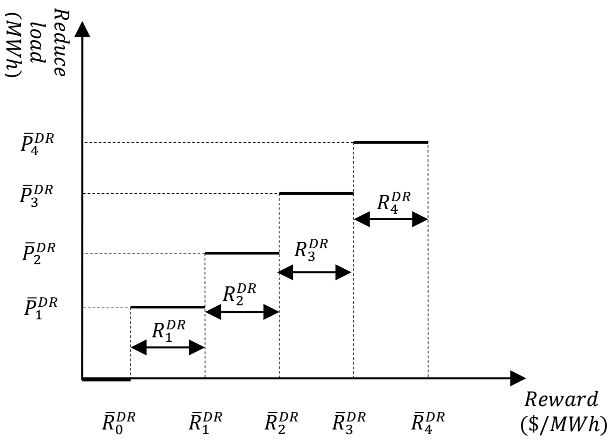

Fig. 3. Reward-based DR stepwise curve

The traded power of the DR aggregator should be higher and lower than its minimum and maximum capacities, as declared in (15). Further, the amount of the excess condition, i.e. P_t^+ must be positive and lower than the whole DR, because the maximum amount of P_t^+ occurs when the aggregator trades no power in the DA market (see Eq. (16)). Lastly, constraint (17) limits the amount of the deficit condition whose maximum value occurs when there is no DR but the aggregator offers its maximum in the DA market.

B. The IGDT-based DR aggregator self-scheduling

This section models the uncertainty of consumers' behavior (through participation factors) and market prices including DA, positive and negative imbalance prices, illustrated by $u_t = \{PF_t, \lambda_t^{DA}, \lambda_t^+, \lambda_t^-\}$ for each time t. The decision variables are the offered power in the DA market and the excess and deficit amounts of power traded in the balancing market, denoted by $q = \{P_t^{DA}, P_t^+, P_t^-\}$. To address these uncertainties, the IGDT method is used here. The forecasted (or expected) values of the uncertain parameters, indicated by $\tilde{u}_t = \{\widetilde{PF}_t, \tilde{\lambda}_t^{DA}, \tilde{\lambda}_t^+, \tilde{\lambda}_t^-\}$, are assumed to be accessible. The *fractional info-gap uncertainty* model is used to define the uncertainty model of the participation factor and the DA market price. However, as for the uncertainty of the imbalance prices, only the upper bound of the fractional info-gap uncertainty model is utilized since the worst-case scenario is considered in the IGDT robust function. It should be noted that the decision making in deterministic self-scheduling is completely different from the IGDT-based model, where the robust self-scheduling is considered in a way to be immune against the unfavorable deviations of uncertain parameters.

1. IGDT-based robust self-scheduling

The robust formulation is proposed in (19)-(30).

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

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

$$P^{min} \leq P_t^{DA} \leq P^{Max} \quad ,\forall t \tag{21}$$

$$B^* = \Big\{Min_{\lambda_t^{DA},\lambda_t^+,\lambda_t^-,PF_t} \sum_{t=1}^{T} [P_t^{DA}.\lambda_t^{DA} + P_t^+.\lambda_t^+ - P_t^-.\lambda_t^-] - \sum_{t=1}^{T}\sum_{j=1}^{N_J} PF_t.P_{t,j}^{DR,rw}.R_{t,j}^{DR,rw} \tag{22}$$

$$(9),(10),(11),(12),(13),(14),(18) \tag{23}$$

$$0 \leq P_t^+ \leq P_t^{DR.rw} - TOU_t \quad ,\forall t \tag{24}$$

$$0 \leq P_t^- \leq P^{Max} \quad ,\forall t \tag{25}$$

$$P_t^+.P_t^- = 0 \quad ,\forall t \tag{26}$$

$$(1-\alpha).\widetilde{PF}_t \leq PF_t \leq (1+\alpha).\widetilde{PF}_t \quad ,\forall t \tag{27}$$

$$(1-\alpha).\tilde{\lambda}_t^{DA} \leq \lambda_t^{DA} \leq (1+\alpha).\tilde{\lambda}_t^{DA} \quad ,\forall t \tag{28}$$

$$(1-\alpha).\tilde{\lambda}_t^+ \leq \lambda_t^+ \quad ,\forall t \tag{29}$$

$$(1-\alpha).\tilde{\lambda}_t^- \leq \lambda_t^- \quad ,\ \forall t\Big\} \tag{30}$$

The proposed IGDT-based robust self-scheduling is represented in a bilevel problem as the minimum requirement of the profit (in the lower level) is dependent on the uncertainty horizon which is solved through the upper-

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level model. Equations (19)–(21) state the upper-level formulation, which determine the maximum possible value of the uncertainty horizon (α) in order to guarantee the predetermined profit denoted by B_c. As stated in (20), B_c is the critical profit which is a percentage of the deterministic profit i.e. B_0. B_0 is determined from solving the deterministic problem described in section IV-A. Equation (21) is the same as (15).

The lower-level problem is formulated in (22)–(30), which determines the minimum possible profit considering the uncertainty horizon. The objective function is represented in a robustness function which indicates the worst-case scenarios. Therefore, equation (22) determines the lowest profit of the DR aggregator for a certain schedule and uncertainty horizon, i.e. P_t^{DA} and α, which are determined in the upper level. Term 1 of this equation refers to the revenue of selling DR in the day-ahead market. The revenue and cost of selling/buying the excess and deficit DR in the balancing market are declared in the second and third terms, respectively. Lastly, the cost of the proposed reward-based DR is given in the last term. Constraints (23)–(25) are described in section IV-A. Constraint (26) implies that excess and deficit modes do not occur in the same time interval. In (27)–(30), the fractional information-gap uncertainty models are given [34].

Note that, for the sake of simplicity, we consider the same time volatility levels and forecasting errors for participation factors and market prices. In case of different uncertainty horizons for these parameters, different optimization problems must be solved for each parameter. The problem will then be modeled as a multi-objective optimization program, which could be solved using the ε-constraint method [35].

2. Equivalent single level formulation

Since constraint (26) makes our problem non-convex, the commonly-used approach of using the 1st order necessary optimality conditions is not valid to transform the bilevel model into a single-level problem. Thus, a new procedure is introduced, which is explained as follows. The lower-level problem aims to determine the uncertain parameters' values, such as market prices and the participation factors of customers that cause to the lowest profit for certain values of the uncertainty horizon, i.e. α as well as the scheduled amount of P_t^{DA}. Therefore, two conditions are taken into account for each hour, as declared below.

A- Excess condition:

This condition takes place in a situation that the acquired DR is more than the offered power in the DA market ($P_t^{DA} \leq P_t^{DR.rw} - TOU_t$). Thus, the given equation in (22) can be replaced by (13):

$$\underline{B_t^+} = Min_{\lambda_t^{DA},\lambda_t^+,PF_t}\left\{P_t^{DA}.\lambda_t^{DA} + \lambda_t^+([P_t^{DR.rw} - TOU_t] - P_t^{DA}) - \sum_{j=1}^{N_J} PF_t.P_{t,j}^{DR,rw}.R_{t,j}^{DR,rw}\right\} \quad (31)$$

As shown in (31), $\underline{B_t^+}$ is the minimum profit of the aggregator when the excess condition takes place. In addition, in this situation, declining the DA market price would result in decreasing the positive imbalance price and participation factors, and thus, the profit of the aggregator. Note that Eq. (31) accounts for two terms encountering the participation factor (PF), i.e. the second term (where $P_t^{DR.rw}$ inherently includes PF as given in Eq. (11)), and the last term. In order to achieve the worst-case scenario, i.e. the lowest profit, both states, i.e. $PF_t = (1-\alpha).\widetilde{PF_t}$ and $PF_t = (1+\alpha).\widetilde{PF_t}$ are examined, where the first state is driven to result in the lowest profit. Therefore, the possible lowest profit will occur at the minimum values of $PF_t, \lambda_t^{DA}, \lambda_t^+$ as stated in (32) – (34).

$$PF_t = (1-\alpha).\widetilde{PF_t} \quad ,\forall t \quad (32)$$

$$\lambda_t^{DA} = (1-\alpha).\tilde{\lambda}_t^{DA} \quad ,\forall t \quad (33)$$

$$\lambda_t^+ = (1-\alpha).\tilde{\lambda}_t^+ \quad ,\forall t \quad (34)$$

B- Deficit condition

Unlike the excess condition, in this situation the amount of the acquired DR is less than the power offered in the DA market ($P_t^{DA} \geq P_t^{DR.rw} - TOU_t$). As such, equation (22) is replaced by (35):

$$\underline{B_t^-} = Min_{\lambda_t^{DA},\lambda_t^-,PF_t}\left\{P_t^{DA}.\lambda_t^{DA} - \lambda_t^-(P_t^{DA} - [P_t^{DR.rw} - TOU_t]) - \sum_{j=1}^{N_J} PF_t.P_{t,j}^{DR,rw}.R_{t,j}^{DR,rw}\right\} \quad (35)$$

$\underline{B_t^-}$ is the minimum profit of the DR aggregator when the deficit condition takes place. Similarly to the excess condition, lower DA market prices lead to a decrease in negative imbalance prices and participation factors, and thus, the aggregator profit will decrease. Therefore, the possible lowest (worst-case) profit will be at the minimum values of $PF_t, \lambda_t^{DA}, \lambda_t^-$ as stated in (36)–(38).

$$PF_t = (1-\alpha).\widetilde{PF_t} \quad ,\forall t \quad (36)$$

$$\lambda_t^{DA} = (1-\alpha).\tilde{\lambda}_t^{DA} \quad ,\forall t \quad (37)$$

$$\lambda_t^- = (1-\alpha).\tilde{\lambda}_t^- \quad ,\forall t \quad (38)$$

Note that, in a condition which the amount of the acquired DR is more (less) than the offered power to the DA market, i.e. $P_t^{DA} \leq (1-\alpha).\{P_t^{DR.rw} - TOU\}$ ($P_t^{DA} \geq (1+\alpha).\{P_t^{DR.rw} - TOU\}$), it is obvious that we are at the excess (deficit) condition. But, when $(1-\alpha).\{P_t^{DR.rw} - TOU\} \leq P_t^{DA} \leq (1+\alpha).\{P_t^{DR.rw} - TOU\}$, both situations could happen. In order to clarify this, we introduce a binary variable (β_t) for each time interval to identify excess (β_t=1) or deficit (β_t=0) conditions. As a result, the equivalent single-level formulation is delivered in equations (39)-(51). Note that in this approach, equation (22) in the lower level of the given bilevel model is replaced by two new equations that indicate excess and deficit conditions. As such, this equation which addresses the overall minimum profit, is replaced by equations (31)-(34), which indicates the minimum profit in the excess condition, and equations (35)-(38), which indicates the minimum profit in the deficit condition.

$$Obj\ Func: \ \bar{\alpha} = Max\ \alpha \quad (39)$$

$$S.t: \quad B^* \geq B_c = (1-\sigma).B_0 \quad (40)$$

$$P^{min} \leq P_t^{DA} \leq P^{Max} \quad ,\forall t \quad (41)$$

$$B^* = \sum_{t=1}^{T} \underline{B_t^+}.\beta_t + \underline{B_t^-}.(1-\beta_t) \quad ,\forall t \quad (42)$$

$$\underline{B_t^+} = P_t^{DA}.\lambda_t^{DA} + \lambda_t^+([P_t^{DR.rw} - TOU_t] - P_t^{DA}) - \sum_{j=1}^{N_J} PF_t.P_{t,j}^{DR,rw}.R_{t,j}^{DR,rw} \quad (43)$$

$$\underline{B_t^-} = P_t^{DA}.\lambda_t^{DA} - \lambda_t^-(P_t^{DA} - [P_t^{DR.rw} - TOU_t]) - \sum_{j=1}^{N_J} PF_t.P_{t,j}^{DR,rw}.R_{t,j}^{DR,rw} \quad (44)$$

$$P_t^{DA} \leq P_t^{DR.rw} - TOU_t + (1-\beta_t).M \quad ,\forall t \quad (45)$$

$$P_t^{DA} \geq P_t^{DR.rw} - TOU_t - \beta_t.M \quad ,\forall t \quad (46)$$

$$PF_t = (1-\alpha).\widetilde{PF_t} \quad ,\forall t \quad (47)$$

$$\lambda_t^{DA} = (1-\alpha).\tilde{\lambda}_t^{DA} \quad ,\forall t \quad (48)$$

$$\lambda_t^+ = (1-\alpha).\tilde{\lambda}_t^+ \quad ,\forall t \quad (49)$$

$$\lambda_t^- = (1-\alpha).\tilde{\lambda}_t^- \quad ,\forall t \quad (50)$$

$$(10),(11),(12),(13),(14),(18) \quad (51)$$

The objective function, i.e. maximizing the uncertainty

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horizon in (39), is now formulated in a single level problem with new constraints as follows. Constraints (40) and (41) are the same as the upper-level constraints of (20) and (21) in the bilevel model. The total profit of the DR aggregator in the whole period is now shown in equation (42), which is the sum of the DR aggregator's profit in all time intervals. As stated before, $\beta_t = 1$ is for identifying the excess condition and $\beta_t = 0$ is for identifying the deficit condition for each time interval t. Excess ($\underline{B}_t^+$) and deficit ($\underline{B}_t^-$) profits are shown in separate functions, given in (43) and (44). Note that excess or deficit conditions are now declared in (45) and (46). In the above formulation, M is a sufficiently large constant i.e. $M \geq P^{Max}$. The remaining constraints are explained earlier in the bilevel model.

The algorithm of the proposed DR aggregator self-scheduling is shown in Fig. 4. First, the deterministic profit (B_0) of the DR aggregator is calculated using the forecasted inputs ($\widetilde{PF}_t, \tilde{\lambda}_t^{DA}, \tilde{\lambda}_t^+, \tilde{\lambda}_t^-$). The second step calculates the maximum achievable profit of the DR aggregator for the deterministic case. Then, we use B_0 and σ to calculate the critical profit of the DR aggregator, denoted by B_c. As described before, B_c is the lowest possible desired profit of the DR aggregator. Finally, the output of the previous step is used for implementing the IGDT-based self-scheduling program in the DA energy market considering all uncertainties.

Note that the IGDT approach uses the forecasted amounts of uncertain variables ($\widetilde{PF}_t, \tilde{\lambda}_t^{DA}, \tilde{\lambda}_t^+, \tilde{\lambda}_t^-$) as well as the profit deviation factor, denoted by σ, instead of probability distribution functions used in other approaches such as stochastic programming. σ is used for declaring the risk-averseness of the DR aggregator. There is a direct relationship between the profit deviation factor and the risk-averseness of the DR aggregator. That is, as σ increases, the DR aggregator becomes more risk-averse and more robust of its scheduling.

IV SIMULATION RESULTS AND DISCUSSIONS

A. *Data preparation*

The proposed model is formulated in a mixed-integer nonlinear programming (MINLP) approach and is solved for different profit deviation factors, i.e. σ, using DICOPT [36] and SBB [37] solvers under General Algebraic Modeling System (GAMS) [38]. The simulation indicates that the results are the same through both solvers, which ensures that the proposed model results in a reasonable optimal solution. Note that the proposed nonlinear IGDT-based model with bi-linear nonlinearity can be linearized using several techniques such as reformulation-linearization techniques [39] or using linear cutting plane algorithms [40] with the cost of some oversimplifications. However, the focus of this paper is not linearizing the IGDT-based model. The simulation is carried out using a PC System with 6GB RAM and 2.43GHz CPU speed. The proposed program generates 3,818 real variables, 1,824 binary variables and 3,947 constraints. The solution takes about 140 seconds.

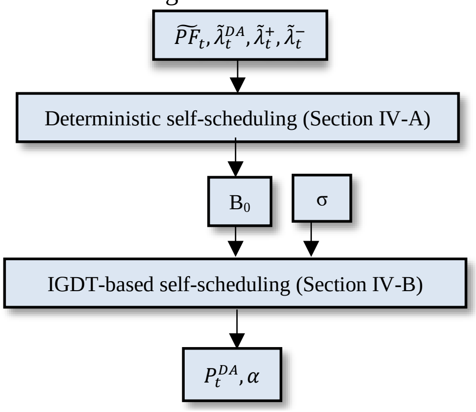

Fig. 4. The steps of proposed DR aggregator self-scheduling model

The load data is taken from [27]. In this study, we consider a working day in summer in Queensland, Australia. The given day is divided into two periods including peak and off-peak. In a day horizon, 9am to 10pm is considered as the peak period and the rest of the day is assumed as off-peak hours. Further, it is considered that the DR aggregator can buy DR from customers to sell it into the energy pool in peak periods, while the reverse flow occurs in off-peak periods. Three types of consumers are considered here including residential, commercial and industrial. We use TOU prices from retail tariffs in Queensland, Australia [41], as declared in TABLE II. The elasticity matrix is given in Table III [42]. According to Fig. 3, it is assumed that there are 25 unique steps for the reward-based DR curve for each consumer type. The expected DA market prices and the expected participation factors are driven from [43] and [44], respectively, for each hour. Furthermore, the positive and negative imbalance prices are assumed 0.9 and 1.1 of the DA market prices, respectively [45].

B. *Case study and discussion*

1- Deterministic self-scheduling of the DR aggregator

This section provides the results of the case without uncertainty, where all the expected values for participation factors and market prices are perfectly known. The optimal power offered in the DA market is shown in subsection IV-B, where we show all cases. The optimal expected profit of the DR aggregator when there is no uncertainty (i.e. B_0) is just above $344,900.

As depicted in Fig. 5, customers consume more energy during off-peak periods and reduce it during peak periods in the TOU program. Note that the TOU program is only affec-

TABLE II
Time-of-Use Prices

		$\lambda_0(c,p)$ ($/MWh)	$\lambda(c,p)$ ($/MWh)
Residential	Peak	294	346
	Off Peak	294	213
Commercial	Peak	255	281
	Off Peak	255	205
Industrial	Peak	331	424
	Off peak	331	135

TABLE III
ELASTICITY MATRIX

		Peak	Off Peak
Residential	Peak	-0.15	0.05
	Off Peak	0.02	-0.03
Commercial	Peak	-0.16	0.06
	Off Peak	0.03	-0.04
Industrial	Peak	-0.2	0.1
	Off peak	0.07	-0.08

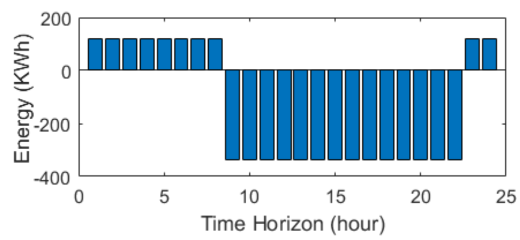

Fig. 5. TOU results

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ted by the elasticity of consumers, and thus, its outcome is independent of uncertainties (i.e. the TOU result in Fig. 5, is the same for the remaining cases.).

2- IGDT Robust self-scheduling by the DR aggregator

Having the deterministic self-scheduling, the IGDT robust approach can now be examined (see the algorithm in Fig. 4). The optimal scheduling program for different values of σ is solved, which carries out different critical profits, i.e. $B_C = (1 - \sigma) \times B_0$. To this end, we consider three cases.

- ***Case1***: In this case, only the participation factor is assumed uncertain while market prices are known. As such, the goal of this stage is to maximize the horizon of this uncertainty that assures obtaining the critical profit.
- ***Case2:*** This case assumes that the participation factor is perfectly known and only market prices are uncertain. Again, the DR aggregator aims to maximize the horizon of this uncertainty to ensure achieving the critical profit.
- ***Case3***: The impact of both uncertainties associated with participation factors and market prices are studied in this case, through which the DR aggregator maximizes the horizon of both uncertainties while ensuring the critical profit is met.

The key results of IGDT decisions are listed in Tables IV-VI. Note that letter D stands for the deficit condition and letter E stands for the excess one. That is, the DR aggregator would encounter the deficit condition if the traded DR in the day-ahead market is less than its scheduled DR in this market, and on the other hand, the excess condition is applied to the aggregator if its DR in the day-ahead market is higher than its scheduled volume.

Table IV shows the results obtained from various deviation factors in case 1 for a sample hour of the peak period. As discussed in the problem formulation, the deviation factor, i.e. σ, is defined to model the minimum desired profit of the DR aggregator. Case 1 results in deviation factors between 0 and 0.35 for obtaining different critical profits B_c. It states that for σ more than 0.35, the optimal IGDT robustness value (α) will be unacceptable, as the cost of implementing the proposed method (robustness cost) will be greater than the DR aggregator total income. In reality, a risk-averse DR aggregator would usually schedule in such a way that its critical profit (Bc) is not less than 15-25% of the expected maximum profit based on the forecasted parameters, i.e. $B0$. Therefore, we choose an arbitrary value in this range around 20%, i.e. σ= 0.199. When the deviation factor is σ=0.199, the critical profit is $B_c = (1 - 0.199) \times \mathrm{B}_0$ = $276,270. According to Table IV, the critical profit in the given deviation factor is achieved only if the participation factor errors result in no more than $\overline{\alpha} = 0.55$ or 55%.

Table V provides the results for various deviation factors, which are obtained in case 2. Having the same deviation factor *σ=0.199* as case 1, the desired critical profit, $276270, is achieved only when the market price error is no more than $\bar{\alpha} = 0.13$ or 13%.

Lastly in case 3, the key results of IGDT decisions are listed in TABLE VI. Again, when the deviation factor is *σ=0.199*, both market prices and participation factor errors should not be more than $\bar{\alpha} = 0.115$ or 11.5%, to ensure the profit is equal to or greater than the critical profit of $276270.

Concluding the given cases, it is obvious that considering all uncertainties in case 3, being the closest case to the reality, results in a lower acceptable uncertainty horizon. It is also worth mentioning that when the deviation factor becomes close to zero, the DR aggregator tends to become a risk-neutral player. For example, for *σ=0.01*, the critical profit is around $341,000, which is very close to the risk-neutral profit, being equal to the deterministic profit, i.e. $B_c=B_0$. Note also that while case 1 involves some deviation factors resulting in the deficit condition (see Table IV, column 4), case 2 (Table V, column 4), as well as case 3 has excess DR to sell in this market in all deviation factors (Table VI, column 4).

Figure 6 displays the optimal robustness against various critical profits. It is evident that in all three cases the robustness value decreases linearly as the critical profit grows. The high amounts of optimal robustness occur when the DR aggregator expects a lower profit, while the extreme opposite case results in around $350,000 profit at no robustness. It should also be emphasized that case 1, which involves only uncertain participation factors, expects more robustness at the same profit than other cases. The worst case here refers to the lowest values of participation factors, day-ahead market prices and positive/negative imbalance prices. Implementing IGDT robustness function in

TABLE IV

OPTIMAL ROBUSTNESS FUNCTION FOR CASE 1 FOR A SAMPLE HOUR

σ	α	Bc ($)	D or E*
0.010	0.028	341410	E
0.048	0.134	328382	E
0.086	0.24	315354	E
0.123	0.346	302326	D
0.161	0.451	289298	E
0.199	0.557	276270	E
0.237	0.663	263242	D
0.274	0.769	250214	E
0.312	0.875	237186	D
0.350	0.981	224158	E

*D (E) stands for deficit (Excess) conditions

TABLE V

OPTIMAL ROBUSTNESS FUNCTION FOR CASE 2 FOR A SAMPLE HOUR

σ	α	Bc ($)	D or E*
0.010	0.006	341410	E
0.048	0.031	328382	E
0.086	0.057	315354	E
0.123	0.083	302326	E
0.161	0.110	289298	E
0.199	0.139	276270	E
0.237	0.168	263242	E
0.274	0.199	250214	E
0.312	0.231	237186	E
0.350	0.265	224158	E

TABLE VI

OPTIMAL ROBUSTNESS FUNCTION FOR CASE 3 FOR A SAMPLE HOUR

σ	α	Bc ($)	D or E*
0.010	0.005	341410	E
0.048	0.025	328382	E
0.086	0.046	315354	E
0.123	0.068	302326	E
0.161	0.092	289298	E
0.199	0.115	276270	E
0.237	0.141	263242	E
0.274	0.168	250214	E
0.312	0.195	237186	E
0.350	0.225	224158	E

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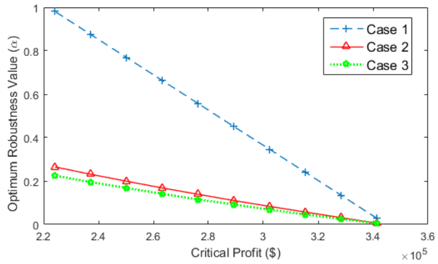

Fig. 6. Optimum robustness function value versus critical profit

scheduling strategy imposes cost to the DR aggregator. To explain this cost, consider that forecasted uncertain parameters do not involve any errors. Then the observed uncertain parameters are the same as the forecasted values. In this situation, if we implement the IGDT robust model, the obtained profit of the risk-neutral DR aggregator is greater than the risk-averse DR aggregator. The difference between the risk-neutral aggregator's profit and the risk-averse aggregator's profit defined as the robustness cost (RC). Figure 7 indicates the robustness cost for various robustness function values of $\bar{\alpha}$. It is obvious that by increasing $\bar{\alpha}$, the robustness cost will increase. In other words, more robust self-scheduling imposes more costs when forecasted values are observed, which decreases the profit of the aggregator.

Figure 8 depicts the day-ahead scheduling in all cases for σ=0.199. The DR aggregator buys DR from consumers to offer it into the pool market during peak hours, i.e. 9-22 while in off-peak hours, this procedure will be reverse. It is interesting to illustrate that while case 1 has the lowest sale in the day-ahead market, cases 2 and 3 account for the highest volume, with approximately the same amounts. This indicates that considering the market uncertainties will result in higher scheduling in the market. This is discussed in such a way that since the considered aggregator tends to manage the risk, modeling the uncertainty of market prices causes the DR aggregator to avoid waiting for the balancing market which may involve a high level of the risk due to price uncertainties.

The achieved reward-based DR is shown in Fig. 9. The reward-based DR in case 1 has the lowest share. However, the highest reduced energy corresponds when we consider no uncertain parameter (deterministic programming). But when the uncertain parameters are taken into account, case 2 gives better results. More energy is reduced in peak hours

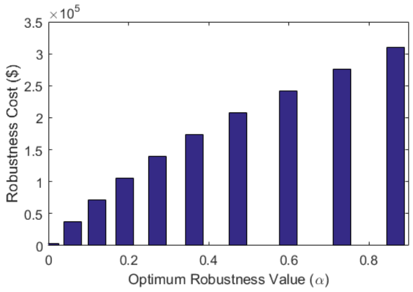

Fig. 7. Robustness Cost versus optimal robustness function value

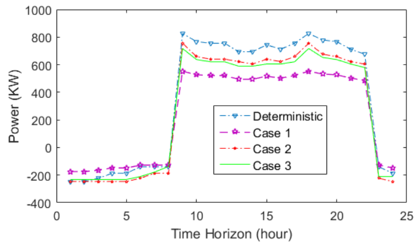

Fig. 8. Optimal daily schedule

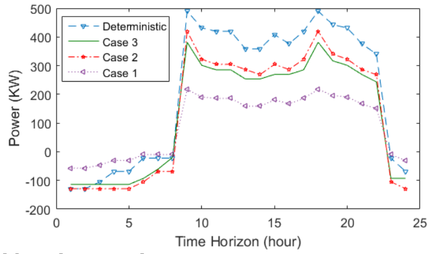

Fig. 9. Reward-based DR results

while more growth in consuming energy occurs in off-peak periods. That is, when the uncertainty of customers' behavior through participation factors is modeled, the share of the reward-based DR declines, and when this is disregarded it increases. Further, when both uncertainties are considered, the share of this program takes the middle position.

1- CONCLUSIONS

This paper develops an IGDT-based short-term self-scheduling for DR aggregators, which simultaneously takes into account the uncertainty of both market prices and the participation factor of end users in the DR program. Two common types of DR programs, named as time-based and incentive-based programs, are covered, while on the market side, the most active markets, i.e. day-ahead and balancing markets, are properly addressed in our self-scheduling model. The proposed IGDT-based robust model results in a bilevel problem. Due to the non-convexity of the problem, a non-KKT procedure is proposed to transform it into an equivalent single-level program. The IGDT-based robustness function is modeled in a way to guarantee a minimum level of the predetermined critical profit. The problem is solved on a realistic case study with the following findings. Considering the uncertainties of both market prices and consumers' behavior results in the lowest robustness compared to modeling either uncertainties. Further, the results indicate that modeling the uncertainty of market prices enforces the DR aggregator to have a higher share in the day-ahead market and thus avoid waiting for the balancing market due to its higher risk.

This work expresses various attitudes of implementing the proposed self-scheduling model by examining different uncertain parameters. Using the results, the DR aggregator can find the impact of each uncertain parameter and can then focus on improving the forecasting accuracies of the uncertain parameters considering their impacts. This work can be further improved by considering long-term contracts and markets (such as forward contracts). Moreover, this work has only studied the behavior of risk-averse DR aggregators through the robust IGDT-based program. The behavior of a risk-seeker aggregator can be modeled through the opportunity IGDT-based model in the future work.

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Morteza Vahid-Ghavidel (S'16) was born in Tabriz, Iran, in 1992. He received his B.Sc. and M.Sc. degrees in electrical engineering from the University of Tabriz, Tabriz, Iran, in 2015 and 2017, respectively. At present, he is a Research Assistant with the Smart Energy Systems Laboratory. His research interests include optimization in power systems under uncertainty, individual and aggregated demand response and electricity market.

Nadali Mahmoudi (S'08, M'15) received his Ph.D. in electrical power engineering from the University of Queensland, Brisbane, Australia in 2015. His research interests include demand response, electricity markets, renewable energy, optimization, and stochastic programming

Behnam Mohammadi-ivatloo (S'09–M'12) received the B.Sc. degree in electrical engineering from University of Tabriz, Tabriz, Iran, in 2006, and the M.Sc. and Ph.D. degree from Sharif University of Technology, Tehran, Iran, in 2008, all with honors.

He is currently an Associate Professor with Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran. His main area of research is economics, operation, and planning of intelligent energy systems in a competitive market environment.

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