Multi-objective Risk-Constrained Optimal Bidding Strategy of Smart Microgrids: An IGDT-based Normal Boundary Intersection Approach

Navid Rezaei, Abdollah Ahmadi, *Student Member, IEEE*, Amirhossein Khazali, Jamshid Aghaei, *Senior Member, IEEE*[1]

***Abstract*— Microgrids face with various uncertainty resources which may put their reliable and beneficial bidding strategy at risk. In the literature, to handle the uncertainties, distinctive methodologies from fuzzy to stochastic techniques have been implemented widely. However, they dominantly suffer from dependency to the uncertainty models and are highly computational. In this paper, to overcome the challenges, a new approach based on information gap decision theory (IGDT) is proposed to provide a promising risk-managing bidding strategy. The uncertainties are modeled effectively without relying on the model in both robust and opportunistic frameworks. The problem is formulated as an effective multi-objective optimization problem considering to the impacts of different uncertainties. Normal boundary intersection technique is utilized to generate evenly distributed Pareto Frontier. Analyzing the IGDT-based numerical results, applied to a test microgrid over a 24 h time horizon, verifies the effectiveness of the proposed bidding strategy structure confronting to the severe uncertainties.**

***Index Terms*—Microgrid, Bidding strategy, Energy management, Information gap decision theory, Uncertainty.**

NOMENCLATURE

Indices

$d \in D$	index of DRRs
$i \in I$	index of DGs
$h \in H$	Index of scheduling time horizon
$s \in S$	index of ESSs
$l \in L$	index of blocks in piece-wise demand response offer package
$v \in V$	index of PVs
$w \in W$	index of WTs

Parameters

π_h^{En}	forecasted price of energy market at hour h
π_h^{SR}	forecasted price of spinning reserve market at hour h
π_h^{Retail}	value of microgrid retail-rate at hour h
a_i	fixed operation cost of DG i
b_i	first-order operation cost of DG i
SUC_i / SDC_i	start-up/shut-down cost of DG i
SRC_i	the cost of spinning reserve of DG i
WTC_w	the cost associated with WT w
PVC_v	the cost associated with PV v
ESC_s	the degradation cost associated with ESS s
$DRC_{d,l}^{En}$	the cost associated with block l in DRR d offer package
DRC_d^{SR}	the cost associated with spinning reserve of DRR d
VLL_{mg}	the microgrid value of lost load
$P_i^{\min}$ / $P_i^{\max}$	the upper/lower level of active power generation of DG i
RMP_i^{up} / RMP_i^{dn}	ramp-up/down limit of DG i
ST_i^{up} / SH_i^{dn}	start-up/shut-down ramp of DG i
T_i^{MUP} / T_i^{MDN}	the minimum up/down time of DG i
$P_s^{ch\max}$ / $P_s^{dch\max}$	the upper/lower level of charge/discharge power of ESS s
$E_s^{\min}$ / $E_s^{\max}$	the upper/lower level of stored energy of ESS s
$LOAD_h^{FRC}$	forecasted load consumption at hour h
$P_{w,h}$	forecasted active power output of WT w at hour h
$P_{v,h}$	forecasted active power output of PV v at hour h
$\psi_{d,l,h}$	the energy reduction offer block l of DRR d at hour h
EXC_{mg}	maximum exchange level of microgrid interconnection
σ_{robust} / $\sigma_{opportunistic}$	uncertainty budget in robust/opportunistic strategy

Variables

α_{robust} / $\alpha_{opportunistic}$	robust/opportunistic risk-controlling variable
P_h^{ex}	exchanged energy with the main grid at hour h
R_h^{ex}	exchanged reserve with the main grid at hour h
$P_{i,h}$	the active power output of DG i at hour h
$R_{i,h}$	scheduled reserve of DG i at hour h
$P_{d,l,h}$	accepted offered demand associated to block l in DRR d offer package at hour h
$R_{d,h}$	scheduled reserve associated with DRR d at hour h
$E_{s,h}$	stored energy of ESS s at hour h
$P_{s,h}^{ch}$ / $P_{s,h}^{dch}$	the charge/discharge active power of ESS s at hour h
SL_h^{mg} / LSH_h^{mg}	microgrid served/shed load at hour h
$r_{i,h}$ / $t_{i,h}$	binary variable indicating the start-up/shut-down state of DG i at hour h
$w_{i,h}$	binary variable indicating commitment state of DG i at hour h
$\tau_{s,h}^{ch}$ / $\tau_{s,h}^{dch}$	binary variable indicating charge/discharge state of ESS s at hour h
$T_{i,h}^{on}$ / $T_{i,h}^{off}$	time duration in which DG i is ON/OFF before hour h

I. INTRODUCTION

A. Motivations

RECENTLY, in the light of the smart grid concept to provide the ever-increasing energy utilization in a more

[1] Manuscript received January 22, 2018; revised April 19, 2018 and June 8, 2018; accepted June 20, 2018. (Corresponding Author: Navid Rezaei.)
N. Rezaei is with the Department of Electrical Engineering, University of Kurdistan, Sanandaj, Iran. P.C.: 66177-15177 (e-mail: n.rezaei@uok.ac.ir).

A. Ahmadi is with the Australian Energy Research Institute and the School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, NSW 2032, Australia. (e-mail: a.ahmadi@student.unsw.edu.au).

A. H. Khazali is with the Department of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran (e-mail: amirhossein.khazali@gmail.com).

J. Aghaei is with the Department of Electrical and Electronics Engineering, Shiraz University of Technology, Shiraz, Iran (e-mail: aghaei@sutech.ac.ir).

automated and controllable architecture [1]-[2], Distributed Energy Resources (DERs) have been widely utilized by Distribution System Operator (DSO) to reliably enrich the overall system performance. Despite the techno-economic-environmental advantages for both the end-user consumers and the DSO, individual integration of the DER units may have adverse impacts on the system stability, relaying and power quality issues. Moreover, small-scale and intermittent features restrict active and beneficial participation of the DER units in energy and/or ancillary service market environments [3].

Conquering operational limitations corresponding to the DER units and bringing about a unified, integrated and competitive operational portfolio in a cost-effective and low-carbon context, microgrid idea has been devised. Microgrids are recognizing as promising, controllable and with high operational flexibility aggregators of dispatchable Distributed Generations (DGs), non-dispatchable Renewable Energy Sources (RESs) including Wind Turbine (WT) and Photovoltaic (PV) units, Energy Storage Systems (ESSs) and Demand Response Resources (DRRs) which can appropriately behave as efficient market participants. In order to present a beneficial market behavior, Microgrid Central Controller (MGCC) should adopt a robust optimistic bidding strategy [4].

Comparing to the bidding strategy problem for other conventional market players such as generation companies (GENCOs) [5] and large consumers [6], or the newly added participants like large-scale ESSs [7] and Electric Vehicle (EV) aggregators [8], the MGCC faces to a more complicated problem. First, he has to consider uncertainties associated with load consumption fluctuations and/or renewable output intermittencies while at the same time should take care of the market price variations. More significantly, the online satisfaction of the supply-demand balance requirement leads the microgrid bidding strategy more sophisticated. Oppositely, difficulties stem from transmission congestion limitation are not apparent in the trading strategy of the low-voltage microgrids. Meanwhile, the MGCC can take advantage of its consumers responsibility by encouraging them participating in demand response programs. Demand response refers to the modifications in the energy consumption patterns for rescuing the system from a reliability-based emergence or mitigating the market price spikes. By this way, microgrid uncertainties can be handled in a more economic-environmental manner.

Accordingly, in order to properly characterize optimal buying/selling active power exchange with the market operator, subject to the uncertainties and system balance constraint, in this paper and as the-first-of-its-kind, a robust Information Gap Decision Theory (IGDT)-based methodology is proposed to establish a tailored bidding strategy framework. Indeed, the uncertainties are the main factors which bound up with the beneficial performance of the microgrids. IGDT helps the MGCC managing the microgrid operational strategy against the inevitable uncertainties in a simple and immune manner without requiring probability distribution function or membership function of the associated variables. Also, the proposed IGDT method provides exact and reliable solutions taking into account useful and harmful risks associated with the differences between forecasted and realized values of the uncertain variables. By this way, the MGCC can set the microgrid bidding strategy in both Risk-Averse (RA) and Opportunity Seeking (OS) portfolios. Furthermore, to simultaneously consider decision-making the procedure of the MGCC against the various microgrid uncertainty resources, the bidding strategy problem is transformed to a Multi-Objective Mathematical Programming (MOMP) one. The constructed MOMP structure is solved using Normal Boundary Intersection (NBI) as an effective superior Pareto set generator and the best compromise solution is selected with the aid of fuzzy decision-making tool.

B. Literature review

In recent years, many types of research have addressed the bidding strategy problem of the microgrids. The main goal of the MGCC is to maximize the total microgrid benefit by optimizing the exchanging amounts of the energy and ancillary service bids in the day-ahead markets while at the same time maintaining the microgrid system requirements. Authors in [9], conducted a stochastic based optimal scheduling strategy of a microgrid in an electricity market. They have developed a comfort aware thermal model to assess the role of Heating, Ventilation and Air-Conditioning (HVAC) systems in the bidding strategy of the microgrid. In [4], bidding strategy of a microgrid in a joint day-ahead energy and spinning reserve market was solved using a scenario-based stochastic programming framework. Although the fluctuations in load and renewable resources have been taken into account, however, the market price uncertainty was not considered. Analogously, Shayeghi and Sobhani [10], developed a comprehensive stochastic based market participation strategy for a microgrid increasing renewable penetration level. Stochastic based models suffer the drawback of the interdependency to the variable probabilistic densities and may become computationally inefficient in the case of complex problems. Authors in [11] have proposed a risk-averse bidding strategy model that concentrates on minimizing the expected regret value over considering to a subset of worst case scenarios. They used Conditional Value-at-Risk (CVaR) index ensuring the robustness of the day-ahead bidding results. Comparing to the CVaR, the IGDT not only looks upon the associated model risks without adding complexity to the formulation, but it also does not stand on generating random scenarios which can potentially intensify the risk assessing errors [12]. Reference [13], through defining an effective incentive-based demand response program, took advantage of customer consumption reduction capability to cope with price and RES uncertainties and increase microgrid total benefit in a pool market. The corresponding bidding strategy was optimized using a stochastic programming considering to CVaR as a risk metric. Wang *et al.* [14], have focused on synergy among DER units to evaluate ramping capabilities of the microgrids in the ancillary service markets. They adopted a hybrid stochastic/Robust Optimization (RO) approach to cope with uncertainties. Likewise, authors in [15] have used a RO-based approach to model the uncertainty of upstream grid prices. A price-based time-of-use demand response program was utilized by the MGCC to reduce the procurement energy costs in the bidding strategy problem of microgrids. Despite that both RO and IGDT methodologies belong to risk-hedge, interval-based optimization technique category, IGDT as a strong performance satisfier provides the associated confidence interval in a more comprehensive and user-friendly manner which, unlike its rival, can be simply extended to the opportunistic based optimization functions [5,12]. Furthermore, in the case of lacking of effective and adequate input data, IGDT seems to procure more reliable decisions. An optimal stochastic/robust bidding strategy of a microgrid in the day-ahead markets was proposed in [16] with the purpose of minimizing total net cost. To handle the microgrid uncertainties in the market environment, some of the researchers proposed Artificial Intelligence (AI) learning methods. Authors in [17], utilized reinforcement learning approach to obtain approximate auction strategy of the microgrids concerning to the demand variations and stochastic nature of the markets. Likewise, a partially observable Markov decision making-based probabilistic approach was used in [18] to microgrid agent behavior during bidding process. Hidden Markov approach is another AI-based learning technique which employed by [19] to model the uncertainty of the load demands and renewable generations to provide a truthful bidding strategy. Although these algorithms are efficient and interactive, comparing to the IGDT, they may suffer from scalability and possibly non-stationary solutions, particularly in the face of the highly-constrained optimization problems.

By a detailed reviewing the literature and thorough focusing on the microgrid appropriative researches, owing to best of our knowledge, no work has been dedicated to provide a risk-constrained bidding strategy framework for microgrids which is optimized using the IGDT methodology and evaluated against multiple uncertainties through an NBI-based MOMP portfolio. The comparison between different researches in the field of the microgrid bidding strategy is summarized in Table I.

TABLE I
TAXONOMY TABLE OF THE MICROGRID BIDDING STRATEGY PROBLEM

Reference	Uncertain Parameter			Uncertainty Modeling Strategy				Problem Constraints				Objective structure	
	RES	Load	Price	Stochastic	IGDT	RO	AI	DR	Generation Reserve	ESS	Risk	Single-objective	Multi-objective
[4]	*	*		*					*	*		*	
[9]	*	*	*	*				*		*		*	
[10]	*		*	*				*		*		*	
[11]		*	*	*				*			*	*	
[12]	*	*	*	*				*		*	*	*	
[14]	*		*	*		*			*	*		*	
[15]	*	*		*		*		*		*		*	
[16]	*		*	*		*				*		*	
[17]			*				*			*		*	
[18]			*				*			*		*	
This paper		*	*	*	*			*	*	*	*	*	*

From Table I, the novel and comprehensive approach of this paper can be demonstrated. Comparatively, the full energy and reserve constraints considering to the all DERs are considered. Both single and multi-objective paradigms are evaluated under both robust and stochastic frameworks regarding to the simultaneous load and market price uncertainties.

C. Paper scopes and contributions

In order to increase the performance efficiency of the microgrids in the energy and spinning reserve markets, in this paper, a NBI-based MOMP risk-constrained IGDT-constructed optimization framework is developed. The microgrid both robust and opportunistic behaviors confronting the uncertainties are precisely formulated using the IGDT. The derived model is simulated over a typical microgrid, and total benefit is optimized over a 24 h time horizon. Thanks to the smart grid technologies, the MGCC can utilize the DRRs coordinated with the DGs and RESs such a way the microgrid hourly supply-demand balance is obtained while the associated day-ahead benefit-based objective function is maximized. In gist, the main contributions of the paper can be highlighted as the following:

- Providing, for the first time, a new IGDT- based risk-constrained bidding strategy framework for the smart microgrids.
- Developing the precise robust (RA) and opportunistic (OS) decision-making models for the MGCC facing to the operational uncertainties.
- Efficient solving a NBI- constructed multi-objective optimization problem to cope with various uncertainty resources on the basis of the developed IGDT model.

D. Paper organization

The rest of the paper is laid out as follows. Paper methodology including the principles of the IGDT and the NBI-MOMP are explained in Section II. Section III describes the developed deterministic and risk-constrained models while providing the detailed formulations considering to the system uncertainties. Illustrative implementations are evaluated in Section IV in a typical microgrid considering to the both single and multi-objective frameworks. Moreover, for the verification, the numerical results are compared with stochastic and Monte Carlo Simulation (MCS) methodologies. Lastly, in Section V some relevant conclusions are extracted.

II. METHODOLOGY

A. IGDT method

The IGDT as a recent uncertainty handling method aims to find out an optimal solution that ensures a specified expectation of the system target while at the same time deviations from the forecasted values associated with the uncertain variables are minimized [20, 21]. Indeed, IGDT provides required risk managing decisions when available required information is very restricted. The IGDT is particularly suitable in cases with severe uncertainty levels or with insufficient historical data. Since it models the gap between realized and forecasted values without requiring any data, e.g. probability distributions. In [20] various uncertainty models have been identified, however, in this paper, to model the microgrid different uncertainty resources, envelope-based model is utilized. In an envelope-bound uncertainty model, the gap between the realized (ϑ) and forecasted ($\overline{\vartheta}$) values of the microgrid uncertain variables can be simply explained as:

$$H_{mg}(\varsigma,\overline{\vartheta}) = \left\{ \vartheta \left| -\varsigma.\overline{\vartheta} \le \vartheta - \overline{\vartheta} \le \varsigma.\overline{\vartheta} \right. \right\}; \varsigma \ge 0 \tag{1}$$

The uncertain behavior of the microgrid uncertain variables are demonstrated using $H_{mg}(.)$ and can be managed by optimizing the value of ς as the model risk-controlling (uncertainty horizon) variable. The value of the ς is optimized subject to guaranteeing an expected value of the system objective function as can be described in (2).

$$OF_{mg}^{IGDT}(X,\delta) \le \left|1 \pm \delta\right| OF_{mg}^{DET}(X); \delta \ge 0 \tag{2}$$

where, parameter δ is Uncertainty Budget (UB) which characterizes the level of expected objective function. OF_{mg}^{IGDT} and OF_{mg}^{DET} are the IGDT-based and the deterministic values of the system objective function, respectively. The set of decision variables which should be optimized subject to the operational constraints are indicated by X. Noteworthy, according to the objective direction of the MGCC (i.e., minimizing or maximizing), interdependency between uncertain variable and the objective function and the considered robust (RA) or opportunistic (OS) decision making procedure, the $\pm$ signs are varied.

B. NBI – based multi-objective optimization method

Generally, a MOMP problem can be stated as follows

$$Min / Max\ OF(X) = \left[OF_1(X), OF_2(X), \ldots, OF_n(X)\right]^T \tag{3}$$
$$s.t. \quad C(X) = 0, D(X) \le 0; X \in FR$$

where $OF(X)$, $C(X)$ and $D(X)$ are objective functions, equality and inequality constraints in optimization problem. *FR* shows the feasibility region of the problem.

In the decision-making process, Pareto Frontier plays a key role in establishing a posteriori or a priori solution. In the literature, several multi-objective optimization techniques (such as epsilon constraint and weighting methods) have been introduced to generate Pareto Frontier. Producing uniformly distributed set of Pareto points without relying on the relative ratios between competitive objective functions, leads the NBI to be taken as a more promising MOMP solution methodology [22], [23]. The fundamental structure of the NBI can be mathematically formulated as:

$$Max\ \Upsilon \tag{4}$$
$$s.t.\ \overline{\Phi}\rho + \Upsilon\hat{n} = \overline{OF}(X)$$
$$C(X) = 0,\ D(X) \le 0;\ X \in FR$$

where, $\overline{\Phi}$ and $\overline{OF}(X)$ are normalized payoff table and scaled objective functions, respectively. The corresponding payoff table (Φ) consists of the minimum values associated with the objective functions. The pay-off matrix is calculated as $\Phi = \begin{pmatrix} OF_1(X_1) & OF_1(X_2) \\ OF_2(X_1) & OF_2(X_2) \end{pmatrix}$, where the diagonal elements show the amounts of functions when they are considered as objective functions to be optimized (referred as utopia amounts). On the other hand off-diagonal elements are the amounts of functions when they are not considered to be optimized and are referred as nadir amounts. $\hat{n}$ is a quasi-normal vector. Υ and ρ are a perpendicular scalar to the utopia line and weighted values associated with the Pareto points along the Convex Hull of Individual Minima (CHIM). A set of points consists of convex combination of each row of the payoff table constructs the CHIM that can be expressed as in (5):

$$Po\ \mathrm{int}(\rho) = \left\{ \overline{\Phi}\rho, \rho \in FR, \sum_{k=1}^{n} \rho_k = 1; \rho_k \ge 0 \right\} \tag{5}$$

A near-uniform distribution of the points on the Pareto Frontier is attained by solving (4) for each ρ_k.

In order to eliminate units for all objective functions, each objective function is normalized as follows:

$$\overline{OF_k}(X) = \left[\frac{OF_k(X) - OF_k^U}{OF_k^N - OF_k^U} \right] \tag{6}$$

where, OF_k^N and OF_k^U are indicating Nadir and Utopia points of *k*-th objective functions, respectively.

The Nadir ($OF^N = \left[OF_1^N, \ldots, OF_k^N, \ldots, OF_n^N\right]^T$) and Utopia ($OF^U = \left[OF_1^*(X_1^*), \ldots, OF_k^*(X_k^*), \ldots, OF_n^*(X_n^*)\right]^T$) points are defined as the points where all the objective functions are in their worst and best possible values, respectively. $OF_k^*(X_k^*)$ represents the individual minimum of *k*-th objective function [22], [23]. Illustrative representation of the NBI mechanism for two objective functions can be shown as in Fig. 1. As it can observed, any point $P(\rho_1, \rho_2)$ in the normalized space on the CHIM can be formulated as $P(\rho_1, \rho_2) = \begin{bmatrix} \rho_1\overline{\Phi}_{11} + \rho_2\overline{\Phi}_{12} \\ \rho_1\overline{\Phi}_{21} + \rho_2\overline{\Phi}_{22} \end{bmatrix}$. The distance Υ between the utopia line and the Pareto surface for a specific amount for ρ_1 and ρ_2 is calculated as $\Upsilon \begin{bmatrix} \hat{n}_1 \\ \hat{n}_2 \end{bmatrix} = \begin{bmatrix} \rho_1\overline{\Phi}_{11} + \rho_2\overline{\Phi}_{12} - \overline{OF}_1(X) \\ \rho_1\overline{\Phi}_{21} + \rho_2\overline{\Phi}_{22} - \overline{OF}_2(X) \end{bmatrix}$. By (4) the main optimization problem can be detached to a number of single objective optimization problems for different values of ρ_1 and ρ_2.

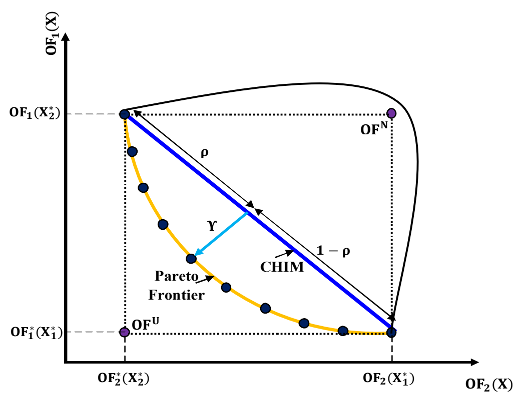

Fig. 1. The NBI mechanism for two-objective functions

III. Model Description and Problem Formulation

In this section, the mathematical formulation of the proposed bidding strategy problem is demonstrated. First the deterministic model is built-up. Afterwards the risk-constrained IGDT based structure is presented. Both robust and opportunistic frameworks are developed according to uncertainties associated with microgrid load and market price deviations. Finally, the corresponding multi-objective portfolio is denoted. In this paper, it is assumed that the microgrid can participate into a joint energy and spinning reserve market. The MGCC is responsible for maximizing the total daily benefit of the microgrid.

A. Deterministic bidding strategy model

The objective function comprises of two main terms including market participation revenue and operational cost functions as represented in (7). The associated functions of the microgrid day-ahead revenue and cost can be characterized by (8) and (9), respectively.

$$\max BENEFIT_{MG} = \max\left\{REVENUE_{MG} - COST_{MG}\right\} \quad (7)$$

$$REVENUE_{MG} = \sum_{h=1}^{H}\left[\pi_h^{En} P_h^{ex} + \pi_h^{SR} R_h^{ex} + \pi_h^{\text{Retail}} SL_h^{mg}\right] \quad (8)$$

$$\begin{aligned} COST_{MG} &= \sum_{h=1}^{H}\begin{Bmatrix} DG\_COST_h + RES\_COST_h \\ +ESS\_COST_h + DRR\_COST_h \\ +Payback\_LSH\_COST_h \end{Bmatrix} \\ &= \sum_{h=1}^{H}\sum_{i=1}^{I}\{a_i w_{i,h} + b_i P_{i,h} + SUC_i r_{i,h} + SDC_i t_{i,h} + SRC_i R_{i,h}\} \\ &+ \sum_{h=1}^{H}\left\{\sum_{w=1}^{W} WTC_w P_{w,h} + \sum_{v=1}^{V} PVC_v P_{v,h}\right\} \\ &+ \sum_{h=1}^{H}\sum_{s=1}^{S} ESC_s\left\{\eta_{ch} P_{s,h}^{ch} + P_{s,h}^{dch}/\eta_{dch}\right\} \\ &+ \sum_{h=1}^{H}\sum_{d=1}^{D}\left\{\sum_{l=1}^{L} DRC_{d,l}^{En} P_{d,l,h} + DRC_d^{SR} R_{d,h}\right\} + \sum_{h=1}^{H} VLL_{mg} LSH_h^{mg} \end{aligned} \quad (9)$$

The MGCC is in the task to supply the microgrid energy and reserve demands reliably. According to (8), the MGCC can gain revenue from selling energy and reserve in the wholesale market and at the same time from selling electricity to the consumers in accordance with the microgrid retail rate. Since, P_h^{ex} is a free variable, the MGCC should reconcile between maximizing revenue of selling to and minimizing cost of buying energy from the main grid. Besides, the MGCC must minimize the microgrid operational costs which consist of the costs corresponding to the DGs (*DG_COST*) including start-up, shut-down, energy and reserve procurement costs of the DGs. The next term in the cost function represented by (9), is the cost associated with the policy of increasing RES penetration and mitigating associated imbalances (*RES_COST*). The ESS degradation cost during charging/discharging cycles is also added to the microgrid daily costs (*ESS_COST*). Moreover, with respect to the load demands, the MGCC should pay an incentive cost to motivate the DRRs (*DRR_COST*) for effective participation of the end-user customers and while on the other hand predicting a payback cost to minimize the involuntary load shedding risks imposed to the end-user consumers (*Payback_LSH_COST*) [4], [9].

The operational constraints associated with DGs are as follows:

$$P_i^{\min} w_{i,h} \le P_{i,h} \le P_i^{\max} w_{i,h}; \quad \forall i \in I, \forall h \in H \quad (10)$$

$$P_{i,h} \le P_{i,h-1} + RMP_i^{up} w_{i,h-1} + ST_i^{up}\left[w_{i,h} - w_{i,h-1}\right] + P_i^{\max}(1 - w_{i,h}); \quad \forall i \in I, \forall h \in H \quad (11)$$

$$P_{i,h} \ge P_{i,h-1} - RMP_i^{dn} w_{i,h} - SH_i^{dn}\left[w_{i,h-1} - w_{i,h}\right] - P_i^{\max}(1 - w_{i,h-1}); \quad \forall i \in I, \forall h \in H \quad (12)$$

$$\left[T_{i,h-1}^{on} - T_i^{MUP}\right].\left[w_{i,h-1} - w_{i,h}\right] \ge 0; \quad \forall i \in I, \forall h \in H \quad (13)$$

$$\left[T_{i,h-1}^{off} - T_i^{MDN}\right].\left[w_{i,h-1} - w_{i,h}\right] \ge 0; \quad \forall i \in I, \forall h \in H \quad (14)$$

$$r_{i,h} + t_{i,h} \le 1; \quad \forall i \in I, \forall h \in H \quad (15)$$

$$P_{i,h} + R_{i,h} \le P_i^{\max} w_{i,h}; \quad \forall i \in I, \forall h \in H \quad (16)$$

$$0 \le R_{i,h} \le R_i^{\max} w_{i,h}; \quad \forall i \in I, \forall h \in H \quad (17)$$

Constraint (10) stands for physical energy generation restriction of the DGs. Ramp up/down limitations are developed precisely by (11) and (12). Minimum up/down time limitations are described by (13) and (14). Constraint (15) avoids concurrent starting-up or shutting-down of a DG. Spinning reserve procurement constraints are represented by (16) and (17). Interdependency of the energy and reserve capacities is explained by (16) and (17) shows the admissible reserve capacity limitation. Through (17), the MGCC take a conservative strategy for participating in reserve market while ensuring the microgrid reliability-based reserve requirements [4]. Notably, in this paper, it is assumed that the microgrid resources such as ESSs, DRRs and DGs are not participated directly into markets. Since the energy and reserve capacities are managed coordinately in a centralized manner by the MGCC to provide a unified bidding strategy for the whole microgrid concerning the energy balance and reliability restrictions of the microgrid particularly in the face of unexpected severe uncertainties and at the same maximizing its benefit.

The ESS operational restrictions are demonstrated as:

$$E_{s,h} = E_{s,h-1} + \eta_{ch} P_{s,h}^{ch} - P_{s,h}^{dch}/\eta_{dch}; \quad \forall s \in S, \forall h \in H \quad (18)$$

$$0 \le P_{s,h}^{ch} \le P_s^{ch\max} \tau_{s,h}^{ch}; \quad \forall s \in S, \forall h \in H \quad (19)$$

$$0 \le P_{s,h}^{dch} \le P_s^{dch\max} \tau_{s,h}^{dch}; \quad \forall s \in S, \forall h \in H \quad (20)$$

$$\tau_{s,h}^{ch} + \tau_{s,h}^{dch} \le 1; \quad \forall s \in S, \forall h \in H \quad (21)$$

$$E_s^{\min} \le E_{s,h} \le E_s^{\max}; \quad \forall s \in S, \forall h \in H \quad (22)$$

$$E_{s,H} = E_{s,0}; \quad \forall s \in S \quad (23)$$

The ESS energy balance model is captured in (18). Constraint (18) indicates the stored energy in the ESS for each hour. The ESS is charged with the power $P_{s,h}^{ch}$ with the charging efficiency η_{ch} and discharges with the power $P_{s,h}^{dch}$ and the discharging efficiency of η_{dch}. It is worth to mention that the charging interval is assumed to be 1 hour. $E_{s,h}$ expresses the stored energy in scenario s and for hour h. Constraints (19) and (20) depict the limits of the charging and discharging power of the ESS. The operation logic of the ESS is ensured by (21). It indicates that the ESS can operate whether in the charging or discharging state and it cannot operate in both modes simultaneously. Upper and lower energy limit of the ESS is stated by (22). In other words, the amount of stored energy is imposed by (22) for the ESS. Constraint (23) presents that ESS has equal initial and final energy levels.

Equation (23) forces that the amounts of stored energy in the initial and final hours to be identical to ensure the amount of required stored energy during the operation time horizon.

The microgrid end-user consumers can be participated in providing energy and reserve services. They can submit their energy reduction offers to the MGCC in the context of an interruptible/curtailable demand response program. If it is required to utilize the DRR capability, the MGCC is in charge to pay as their submitted offers. In this paper, a simple piece-wise demand reduction model of the DRRs is developed. Fig. 2, shows the represented price-demand piece-wise offer package of the DRRs.

Mathematical formulations associated with the DRRs can be simply described by (24) to (27):

$$P_{d,l,h} \le \psi_{d,l,h}; \qquad \forall d \in D, \forall l = 1, \forall h \in H \tag{24}$$

$$P_{d,l,h} \le \psi_{d,l,h} - \psi_{d,l-1,h}; \forall d \in D, \forall l = 2,...,L, \forall h \in H \tag{25}$$

$$P_{d,h} = \sum_{l=1}^{L} P_{d,l,h}; \qquad \forall d \in D, \forall h \in H \tag{26}$$

$$P_{d,h} + R_{d,h} \le \psi_{d,l,h}; \qquad \forall d \in D, \forall l = L, \forall h \in H \tag{27}$$

The microgrid energy and reserve exchange with the main grid should be managed according to the interconnection capacity as explained by (28). The microgrid reserve bid consists of aggregated reserves procured from the DGs and DRRs as stated by (29).

$$\left|P_h^{ex}\right| + R_h^{ex} \le EXC_{mg}; \qquad \forall h \in H \tag{28}$$

$$R_h^{ex} = \sum_{i=1}^{I} R_{i,h} + \sum_{d=1}^{D} R_{d,h}; \qquad \forall h \in H \tag{29}$$

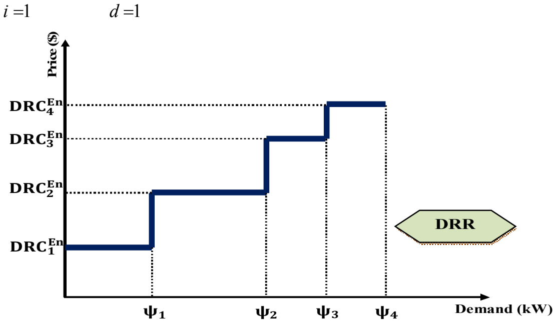

Fig. 2. A four-step DRR price-demand piece-wise offer package

Microgrid hourly energy balance is presented by (30) and (31). Besides, according to (32), the admissible hourly amount of the load shedding is restricted by the MGCC to the forecasted value of the microgrid hourly load. In order to preserve the microgrid system sustainability, maximum reserve requirement should be satisfied as depicted by (33).

$$SL_h^{mg} = LOAD_h^{FRC} - LSH_h^{mg} - \sum_{d=1}^{D} P_{d,h}; \qquad \forall h \in H \tag{30}$$

$$P_h^{ex} = \sum_{i=1}^{I} P_{i,h} + \sum_{d=1}^{D} P_{d,h} + \sum_{s=1}^{S} \left\{ P_{s,h}^{dch} / \eta_{dch} - \eta_{ch} P_{s,h}^{ch} \right\}$$
$$+ \sum_{w=1}^{W} P_{w,h} + \sum_{v=1}^{V} P_{v,h} - SL_h^{mg} - LSH_h^{mg}; \qquad \forall h \in H \tag{31}$$

$$LSH_h^{mg} \le LOAD_h^{FRC} \qquad \forall h \in H \tag{32}$$

$$\sum_{i=1}^{I} \left\{ P_i^{\max} - P_{i,h} - R_{i,h} \right\} + \sum_{d=1}^{D} \left\{ \psi_{d,l,h} - P_{d,h} - R_{d,h} \right\}$$
$$+ \left\{ EXC_{mg} - \left| P_h^{ex} \right| - R_h^{ex} \right\}$$
$$+ \sum_{s=1}^{S} \eta_{dch} (E_{s,h} - E_s^{\min}) \ge R_h^{mg,\max}; \qquad \forall h \in H \tag{33}$$

B. IGDT-based risk-constrained bidding strategy model

The IGDT-based risk-constrained models corresponding to the market price and load variation uncertainties are formulated in the robust and opportunistic structures by (34) to (37).

- *Market price uncertainty*

$$\max \alpha_{robust}^{price} \tag{34}$$
$$s.t. \qquad (9)\ to\ (33)$$
$$REVENUE_{MG}^{robust} = (1 - \alpha_{robust}^{price}) REVENUE_{MG}$$
$$BENEFIT_{MG}^{robust} \ge (1 - \sigma_{robust}^{price}) BENEFIT_{MG}$$

$$\min \alpha_{opportunistic}^{price} \tag{35}$$
$$s.t. \qquad (9)\ to\ (33)$$
$$REVENUE_{MG}^{opportunistic} = (1 + \alpha_{opportunistic}^{price}) REVENUE_{MG}$$
$$BENEFIT_{MG}^{opportunistic} \ge (1 + \sigma_{opportunistic}^{price}) BENEFIT_{MG}$$

where, $REVENUE_{MG}^{robust}$ and $BENEFIT_{MG}^{robust}$ are the risk-averse daily revenue and benefit of the microgrid, respectively. $REVENUE_{MG}^{opportunistic}$ and $BENEFIT_{MG}^{opportunistic}$ are the risk-seeker daily revenue and benefit of the microgrid, respectively.

- *Microgrid load consumption uncertainty*

$$\max \alpha_{robust}^{Load} \tag{36}$$
$$s.t. \qquad (8)-(29)\ and\ (31)-(33)$$
$$SL_h^{mg} = (1 + \alpha_{robust}^{Load}) LOAD_h^{FRC} - LSH_h^{mg} - \sum_{d=1}^{D} P_{d,h}; \qquad \forall h \in H$$
$$BENEFIT_{MG}^{robust} \ge (1 - \sigma_{robust}^{Load}) BENEFIT_{MG}$$

$$\min \alpha_{opportunistic}^{Load} \tag{37}$$
$$s.t. \qquad (8)-(29)\ and\ (31)-(33)$$
$$SL_h^{mg} = (1 - \alpha_{opportunistic}^{Load}) LOAD_h^{FRC} - LSH_h^{mg} - \sum_{d=1}^{D} P_{d,h}; \qquad \forall h \in H$$
$$BENEFIT_{MG}^{opportunistic} \ge (1 + \sigma_{opportunistic}^{Load}) BENEFIT_{MG}$$

Worth to be mentioned that an analogous IGDT-based optimization framework can also be applied concerning the RES output power uncertainties. In this paper, for the sake of the notational conciseness and more emphasizing on the model conceptual understanding, it is assumed that the MGCC has sufficient data about the RES productions and besides through providing appropriate promising in-site imbalance control strategies can effectively mitigate the associated intermittencies [24]. A portion of the dedicated operational costs to the RESs can be assigned to the associated uncertainty management strategies.

C. MOMP IGDT-based bidding strategy model

The proposed IGDT-based MOMP problem can be written in the form of a Mixed Integer Non-Linear Programming (MINLP) framework which can be solved using the NBI method considering to a particular UB. The robust and opportunistic multi-objective models taking the uncertainties relating to the market price and the microgrid load consumption deviations into account is developed by (38) and (39), respectively. The corresponding payoff tables are built through solving the single objective problems provided by (34) to (37).

$$\max\ (\alpha_{robust}^{price}, \alpha_{robust}^{Load}) \tag{38}$$
$$s.t.\qquad (9)-(29)\ and\ (31)-(33)$$
$$REVENUE_{MG}^{robust} = (1-\alpha_{robust}^{price})REVENUE_{MG}$$
$$SL_h^{mg} = (1+\alpha_{robust}^{Load})LOAD_h^{FRC} - LSH_h^{mg} - \sum_{d=1}^{D} P_{d,h};\quad \forall h \in H$$
$$BENEFIT_{MG}^{robust} \geq (1-\sigma_{robust}^{MOMP})BENEFIT_{MG}$$

$$\min\ (\alpha_{opportunistic}^{price}, \alpha_{opportunistic}^{Load}) \tag{39}$$
$$s.t.\qquad (9)-(29)\ and\ (31)-(33)$$
$$REVENUE_{MG}^{opportunistic} = (1+\alpha_{opportunistic}^{price})REVENUE_{MG}$$
$$SL_h^{mg} = (1-\alpha_{opportunistic}^{Load})LOAD_h^{FRC} - LSH_h^{mg} - \sum_{d=1}^{D} P_{d,h};\quad \forall h \in H$$
$$BENEFIT_{MG}^{opportunistic} \geq (1+\sigma_{opportunistic}^{MOMP})BENEFIT_{MG}$$

IV. Illustrative Implementations

The proposed IGDT-based risk constrained bidding strategy decision-making approach is tested on a typical low-voltage microgrid shown in Fig. 3. The MINLP problems about the deterministic, the IGDT-based single objective and the MOMP demonstrated models are solved by DICOPT under General Algebraic Modeling System (GAMS) [25]. The derived formulations have been performed on a platform with Intel Core 2 Duo CPU and 4 GB of RAM. The forecasted values of the day-ahead energy and reserve market prices, retail-rate prices, WT and PV output active power generations and load consumption are represented in Fig. 4. The operational costs related to WTs and PVs are 10.63 and 54.84 \$/kWh, respectively [4], [26]. The microgrid installed capacity of the WTs and PVs are 250 and 140 kW, respectively. Besides, the portfolio of the considered microgrid, consists of five DGs, two DRRs, and an ESS. The technical and economic parameters of the DGs including two Micro-Turbines (MTs), two Fuel Cells (FCs) and a Gas Turbine (GT) are summarized in Tables II and III, respectively [4], [26]. The DRRs' price-demand offer packages are also listed in Table IV. In this paper, the incentive based Demand Bidding/Buyback (DB) demand response program type is considered which has high dispatchability and compatibility characteristics [27]. The value of the microgrid lost load (VLL_{mg}) is set to 300 \$/kWh. The main grid interconnection exchange capacity is limited to 800 kW. The capacity of the ESS has been chosen as 90 kWh and the charging and discharging maximum values are set equal to 90 kW. The charge and discharge efficiencies are set equal to 0.95. The minimum and maximum admissible energy stored in the ESS is set to 10 and 90 kWh, respectively. The degradation cost of the ESS is 5 \$/kWh [4]. The State-Of-Charge (SOC) of the ESS is defined as the ratio of the stored energy and the ESS capacity. The initial ESS stored energy is 30 kWh. It is also assumed that all the DGs and RESs are operating such a way the technical voltage/reactive power requirements are satisfied and the associated power factors are fixed at unity. Furthermore, since the microgrid is small and resources are considered close together, the active power losses and thermal stresses can be neglected. The expected value of the microgrid daily benefit ($\mathrm{BENEFIT_{MG}}$) derived by solving the deterministic model is 3457.69\$.

TABLE II
Economic Characteristics of the DGs

DG	a(\$)	b(\$/kWh)	SUC(\$)	SDC(\$)	SRC(\$/kW)
MTs	85.06	4.37	9	8	2.20
FCs	255.18	2.84	16	9	1.50
GT	212.00	3.12	12	8	1.70

TABLE III
Technical Characteristics of the DGs

DG	P^{min} (kW)	P^{max} (kW)	RMP^{up}/RMP^{dn} (kW)	ST^{up}/SH^{dn} (kW)	T^{MUP}/T^{MDN} (h)
MTs	30	150	250	100	2
FCs	20	100	250	100	2
GT	35	200	280	120	2

TABLE IV
DRR Offer Packages

DRR1	Demand (kW)	0-25	25-65	65-95	95-120
	Offered Price (\$)	0.3	0.48	0.60	0.75
DRR2	Demand (kW)	0-40	40-60	60-85	85-135
	Offered Price (\$)	0.25	0.45	0.65	0.80

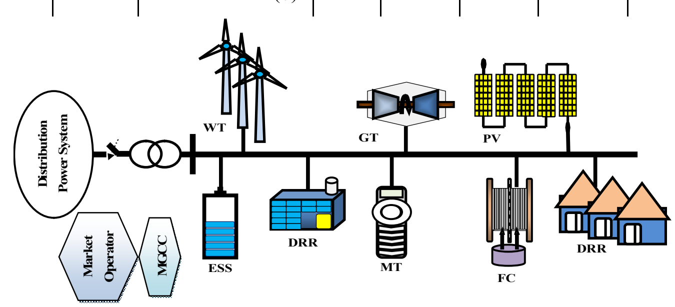

Fig. 3. A typical microgrid test system with various energy resources

The robust and opportunistic optimization frameworks regarding to the only market price uncertainty has been solved according to (34) and (35), respectively. Fig. 5 shows the variations of the price robustness index (α_{robust}^{Price}) concerning the changing of the UB (σ_{robust}^{Price}) and the changes of the daily benefit versus to the corresponding robustness index. Obviously, in the robust strategy, by decreasing the wholesale market prices, it is expected that the total benefit is also reduced. Worth mentioning, in α_{robust}^{Price} equals to 0.0381, the microgrid benefit becomes zero. Likewise, for the opportunistic case, it is assumed that by increasing the market prices, the microgrid day-ahead benefit becomes higher. The increasing trend of the benefit function versus to the price opportunity index ($\alpha_{opportunity}^{Price}$) is depicted in Fig. 6. It seems that after the point in which UB ($\sigma_{opportunity}^{Price}$) is 0.283, the increasing trend of the benefit function is saturated and has no changes. It is because of the techno-economic operational constraints of the microgrid environment. In this point, the microgrid daily benefit is 4436.19\$.

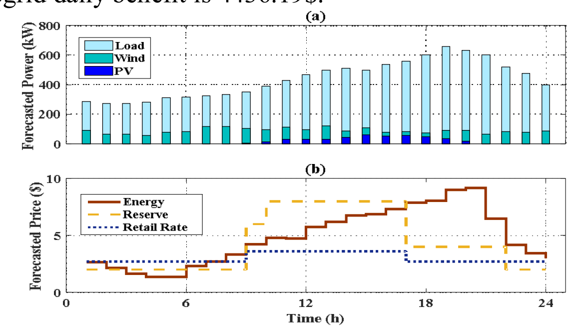

Fig. 4. Forecasted values of (a) microgrid RES and load (b) market prices.

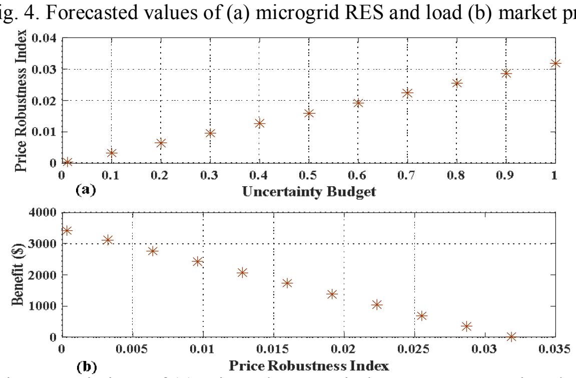

Fig. 5. Variations of (a) price robustness index versus uncertainty budget and (b) microgrid daily benefit versus price robustness index

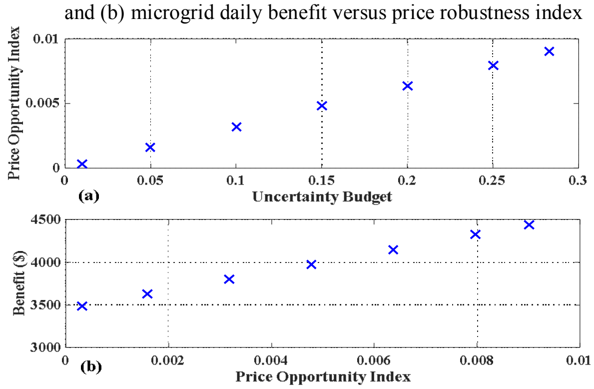

Fig. 6. Variations of (a) price opportunity index versus uncertainty budget and (b) microgrid daily benefit versus price opportunity index

The IGDT-based robust and opportunistic optimization results regarding the only load consumption uncertainty are illustrated in Figs. 7 and 8, respectively. According to (36), through increasing the microgrid load consumption level, it is expected that the benefit lessens. The main restrictions are the hourly supply-demand balance and interconnection capacity limitation constraints which limit the revenues gained from selling energy to the end-user customers. The microgrid benefit reaches zero when load robustness index (α_{robust}^{Load}) is equal to 0.1731. Analogously, the trends of the microgrid benefit versus to the load opportunity index ($\alpha_{opportunity}^{Load}$) is a growing one, which saturates when UB ($\sigma_{opportunity}^{Load}$) reaches to 1.3950, which corresponds to the point in which $\alpha_{opportunity}^{Load}$ equals to 0.5326. In this point, microgrid total benefit is 8281.11\$. Generally, in OS strategies, the higher feasible UBs lead to greater benefits while in the RA strategies higher UBs provide more conservative decisions. Therefore, the MGCC should utilize a decision regarding to the risk variations of the uncertainty budgets.

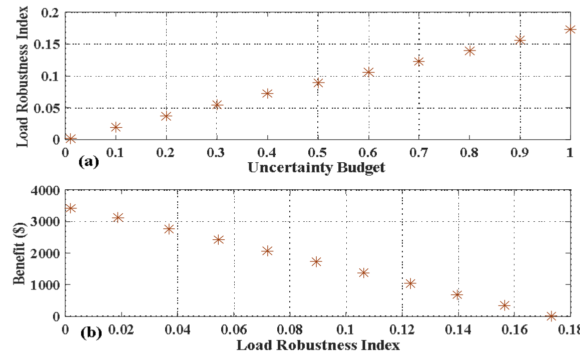

Fig. 7. Variations of (a) load robustness index versus uncertainty budget and (b) microgrid daily benefit versus load robustness index

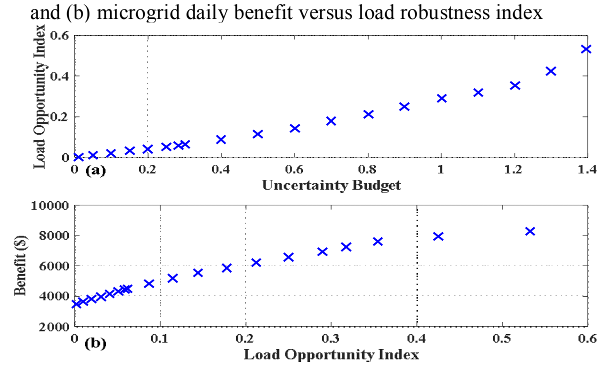

Fig. 8. Variations of (a) load opportunity index versus uncertainty budget and (b) microgrid daily benefit versus load opportunity index

The RA and OS MOMP IGDT-based problems are solved according to (38) and (39), respectively. The associated payoff tables regarding to the price and load uncertainties in either robust or opportunistic structures can be simply extracted using the aforementioned single objective frameworks. The selected UBs in robust and opportunistic problems are 0.4 and 0.2, respectively. The Pareto front has been carried out using the NBI methodology. The best compromise solutions are acquired by applying the fuzzy decision making approach [23]. The day-ahead microgrid energy and spinning reserve bid quantities corresponding to the RA and OS MOMP IGDT based optimization problems are represented in Figs. 9 and 10, respectively. Evidently, in the hours the energy in the wholesale market is inexpensive, the MGCC imports energy to the microgrid. Furthermore, in the peak hours with higher energy market and lower reserve market prices, the bidding strategy is directed at strengthening the microgrid energy market participation role. During peak hours (hours 17 to 23), prices in reserve market are downtrend while the energy prices ascend. Consequently, the MGCC allocates the resource capacities to further participating in the energy market. As a result, the reserve bids in these hours become zero.

The scheduled values of energy and reserve resources in MOMP frameworks are depicted in Figs. 11 and 12. Obviously, in hours 17 to 23, according to the higher energy prices, amounts of the generated energy by DGs and DRRs have been increased and the ESS has discharged. Hence, the microgrid can attain higher revenues. Likewise, in off-peak hours (hours 2 to 6), the resource capacities have been mainly allocated for reserve procurement. ESS has been charged accordingly. Worth mentioning that, state of charge (SOC) of the ESS is managed according to safe energy variation range during the charging/discharging procedures.

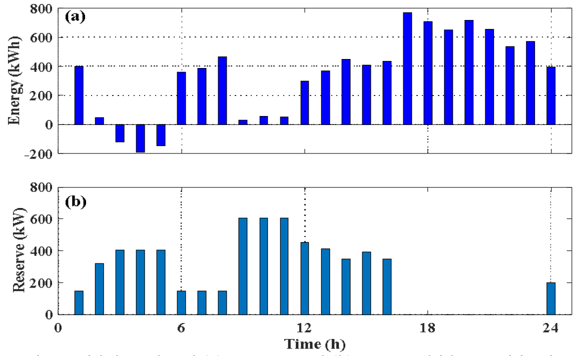

Fig. 9. Microgrid day-ahead (a) energy and (b) reserve bid quantities in the robust case

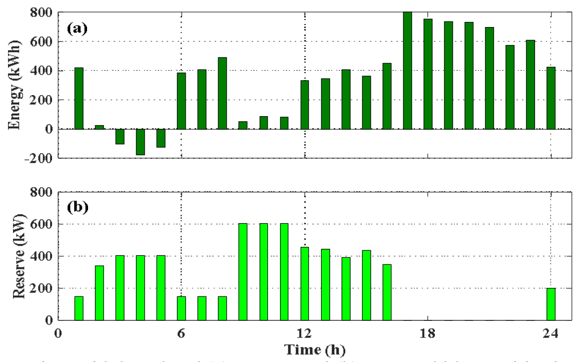

Fig. 10. Microgrid day-ahead (a) energy and (b) reserve bid quantities in the opportunistic case

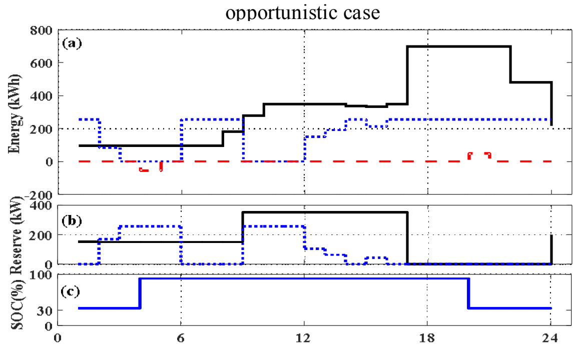

Fig. 11. Hourly values of (a) energy and (b) reserve of DGs (solid), DRRs (dotted) and the ESS (dashed), (c) SOC of the ESS in the robust case

The breakdown of the microgrid benefit function is represented in Table V. Both the RA and OS strategies are solved for the particular UBs concerning the price and load uncertainties simultaneously. For instance, in the RA strategy, for UB equal to 0.4, the robustness indices corresponding to price and load uncertainties have been calculated within 0.0065 and 0.0367, respectively. Total benefits of the microgrid during the RA and OS strategies are 2072.8$ and 4149.1$. It can be recognized that the MGCC can optimistically manage the microgrid market participation role while at the same minimizing the operational costs without imposing involuntary load shedding to the consumers. To verify the IGDT-based results, the bidding strategy model is solved using MCS methodology. First, 1000 random scenarios are generated concerning to the load and price uncertainties.

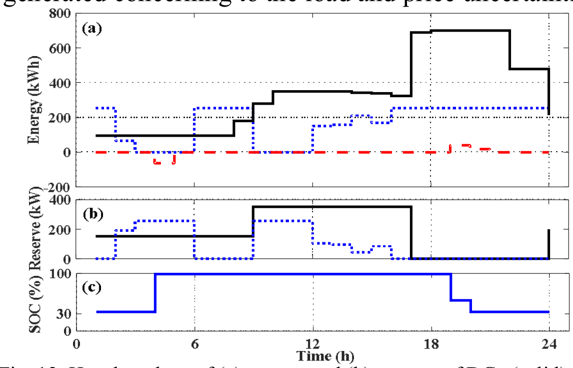

Fig. 12. Hourly values of (a) energy and (b) reserve of DGs (solid), DRRs (dotted) and ESS (dashed), (c) SOC of the ESS in the opportunity case

TABLE V
BREAKDOWN OF THE MICROGRID MOMP DAILY BENEFIT FUNCTIONS ASSOCIATED WITH THE BEST COMPROMISE SOLUTIONS

IGDT-based Operational Index	OS strategy $\sigma^{MOMP}_{opportunistic}=0.2$	RA strategy $\sigma^{MOMP}_{robust}=0.4$
α^{Price}	0.0004	0.0065
α^{Load}	0.0377	0.0367
DG Energy Cost	47416.16	47535.03
RES Cost	46399.93	46399.93
ESS Cost	586.01	526.25
DRR Energy Cost	1260.33	1321.27
DG Reserve Cost	7480.00	7480.00
DRR Reserve Cost	1795.04	1673.69
Payback LSH Cost	0	0
Energy Market Revenue	53850.79	51075.15
Reserve Market Revenue	34664.62	33447.28
Retail Rate Revenue	20571.22	22486.56
Total Cost	104937.47	104936.17
Total Revenue	109086.63	107008.99
Total Benefit	4149.16	2072.82

The histograms of the generated scenarios for the price and load variations are represented in Figs. 13 and 14, respectively. Comparing the derived results by the IGDT with the average values of the MCSs, presents that each UB can be whether economic, conservative or opportunistic. For instance, in the case of the price uncertainty, the strategies with RA-UBs equal to 0.003 and 0.03 are economic and conservative, respectively. Likewise, the strategies with OS-UBs equal to 0.001 and 0.009 are economic and opportunistic, respectively. From Fig. 14, it can be observed that while UBs reaches to higher values in both OS and RA strategies, the decision makings change from the economic to the niggardly or greedy ones. The MGCC with OS-UB equals to 0.02, makes an economic decision while for 1.39, he takes a perfect risk seeking strategy. A fully conservative decision making can be obtained for RA-UB equals to 0.15. Generally, higher distances from the MCS average values yield to more conservative or opportunistic strategies. UBs lead to economic strategies which are closer to the MCS average values.

V. CONCLUSION

In this paper, an innovative risk-constrained bidding strategy for the microgrids in joint energy and reserve markets has been proposed. The uncertainties associated with the wholesale and retail market prices and the microgrid load consumption variations were taken into account. In this work, the IGDT method was employed to model precisely the uncertainty resources and provide an effective non-probabilistic handling strategy. The corresponding optimization problem has been solved using an MINLP formulation in single and multi-objective frameworks. The NBI technique was utilized to generate the Pareto front. The key findings of the paper can be summarized as follows:

- The MGCC can effectively reconcile between benefits margins and uncertainty budgets;
- The microgrid market participation was optimized by providing a coordinated management of the coupled energy and reserve resources procured by DERs;
- Severe uncertainties stem from price and load fluctuations were managed through conducting a new IGDT-based multi-objective auction strategy which has been verified using a proficient stochastic MCS-based comparison;

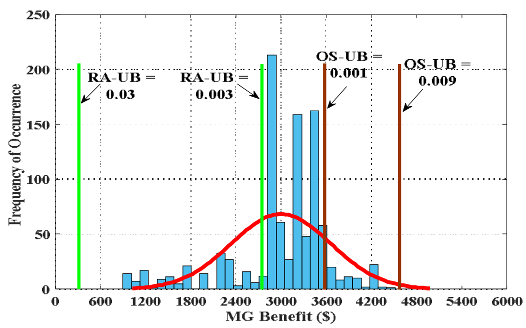

Fig. 13. MG benefit function using MCS and IGDT considering price uncertainty

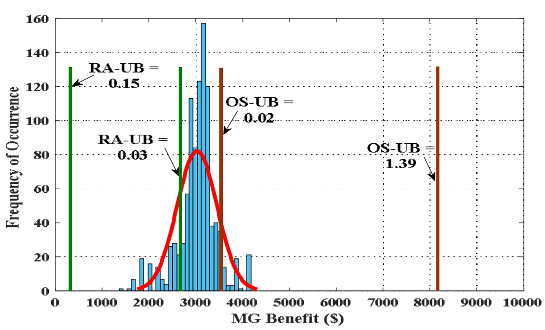

Fig. 14. MG benefit function using MCS and IGDT considering load uncertainty

For the future researches, the microgrid bidding strategy problem can be optimized subject to system security constraints such as voltage limitations, frequency security issues and in the line of the DSO certain requirements.

REFERENCES

[1] X. Bingyin, L. Tianyou, X. Yongduan, "Smart distribution grid and distribution automation", Automation of Electric Power Systems, pp. 1-5, 2009.

[2] M. H. Amini, B. Nabi, M. R. Haghifam, "Load management using multi-agent systems in smart distribution network", IEEE Power and Energy Society General Meeting, pp. 1-5, 2013.

[3] N. Hatziargyriou, Microgrids: Architecture and control, Wiley-IEEE, 2014.

[4] L. Shi, Y. Luo, G. Y. Tu, "Bidding strategy of microgrid with consideration of uncertainty for participating in power market", International Journal of Electrical Power and Energy Systems, Vol. 59, pp. 1-13, 2014.

[5] M. Kazemi, B. Mohammadi-Ivatloo, M. Ehsan, "Risk-constrained strategic bidding of GenCos considering demand response", IEEE Transactions on Power Systems, Vol. 30, pp. 376 - 384, 2015.

[6] S. Nojavan, H. Ghesmati, K. Zare, "Robust optimal offering strategy of large consumer using IGDT considering demand response programs", Electric Power Systems Research, Vol. 130, pp. 46–58, 2016.

[7] Y. Wang, Y. Dvorkin, R. Fern´andez-Blanco, B. Xu, T. Qiu, D. Kirschen, "Look-ahead bidding strategy for energy storage", IEEE Transactions on Sustainable Energy, Vol. 8, pp. 1106 - 1117, 2017.

[8] H. Wu, M. Shahidehpour, A. Alabdulwahab, A. Abusorrah, "A Game theoretic approach to risk-based optimal bidding strategies for electric vehicle aggregators in electricity markets with variable wind energy resources", IEEE Transactions on Sustainable Energy, Vol. 7, pp. 374-385, 2016.

[9] D. T. Nguyen, L. Baole, "Optimal bidding strategy for microgrids considering renewable energy and building thermal dynamics", IEEE Transactions on Smart Grid, Vol. 5, pp. 1608-1620, 2014.

[10] H. Shayeghi, B. Sobhani, "Integrated offering strategy for profit enhancement of distributed resources and demand response in microgrids considering system uncertainties", Energy Conversion and Management, Vol. 87, pp. 756-777, 2014.

[11] Z. Xu, Z. Hu, Y. Song, J. Wang, "Risk-averse optimal bidding strategy for demand-side resource aggregators in day-ahead electricity markets under uncertainty", IEEE Transactions on Smart Grid, Vol. 8, pp. 96 - 105, 2017.

[12] J. Aghaei, V. G. Agelidis, M. Charwand, F. Raeisi, A. Ahmadi, A. Esmaeel Nezhad, A. Heidari, "Optimal robust unit commitment of CHP plants in electricity markets using information gap decision theory", IEEE Transactions on Smart Grid, Vol. 8, pp. 2296-2304, 2017.

[13] D. Tung Nguyen, L. B. Le, "Risk-Constrained Profit maximization for microgrid aggregators with demand response", IEEE Transactions on Smart Grid, Vol. 6, pp. 135 - 146, 2015.

[14] J. Wang, H. Zhang, W. Tang, R. Rajagopal, Q. Xia, C. Kang, Y. Weng, "Optimal bidding strategy for microgrids in joint energy and ancillary service markets considering flexible ramping products", Applied Energy, Vol. 205, pp. 294-303, 2017.

[15] A. Mehdizadeh, N. Taghizadegan, "Robust optimisation approach for bidding strategy of renewable generation-based microgrid under demand side management", IET Renewable Power Generation, Vol. 11, pp. 1446-1455, 2017.

[16] G Liu, Y Xu, K Tomsovic, "Bidding strategy for microgrid in day-ahead market based on hybrid/stochastic optimization", IEEE Transactions on Smart Grid, Vol. 7, pp. 227-237, 2015.

[17] V. Nanduri, T. K. Das, "A Reinforcement Learning Model to Assess Market Power Under Auction-Based Energy Pricing", IEEE Transactions on Power Systems, Vol. 22, pp. 85-95, 2007.

[18] M. H. Cintuglu, O. A. Mohammed, "Behavior Modeling and Auction Architecture of Networked Microgrids for Frequency Support", IEEE Transactions on Industrial Informatics, Vol. 13, pp. 1772-1782, 2017.

[19] D. Li, S. K. Jayaweera, "Distributed Smart-Home Decision-Making in a Hierarchical Interactive Smart Grid Architecture", IEEE Transactions on Parallel and Distributed Systems, vol. 26, no. 1, pp. 75-84, 2015.

[20] Y. Ben-Haim, Info-gap Decision Theory: Decision under severe uncertainty. New York, NY, USA: Academic, 2006.

[21] A. O'Connell, A. Soroudi, A, Keane, "Distribution network operation under uncertainty using information gap decision theory", IEEE Transactions on Smart Grid, to be Published, DOI: 10.1109/TSG.2016.2601120.

[22] I. Das and J. E. Dennis, "Normal-boundary intersection: A new method for generating the Pareto surface in nonlinear multi-criteria optimization problems", SIAM Journal on Optimization, vol. 8, no. 3, pp. 631–657, 1998.

[23] M. Charwand, A. Ahmadi, A. Heidari, A. Esmaeel Nezhad, "Benders decomposition and normal boundary intersection method for multiobjective decision making framework for an electricity retailer in energy markets", IEEE Systems Journal, Vol. 9, pp. 1475-1484, 2015.

[24] M. Shabanzadeh, M. K. Sheikh-Eslami, M-R. Haghifam, "The design of a risk-hedging tool for virtual power plants via robust optimization approach", Applied Energy, Vol. 155, pp. 766-777, 2015.

[25] Generalized Algebraic Modeling Systems (GAMS). <http://www.GAMS.com>.

[26] N Rezaei, M Kalantar, "Smart microgrid hierarchical frequency control ancillary service provision based on virtual inertia concept: An integrated demand response and droop controlled distributed generation framework", Energy Conversion and Management, Vol. 92, pp. 287-301, 2015.

[27] P. Siano, "Demand response and smart grids – a survey", Renewable and Sustainable Energy Reviews, Vol. 30, pp. 461–78, 2014.