Modeling the Microgrid Operator Participation in Day-ahead Energy and Reserve Markets considering Stochastic Decisions in the Real-time Market

Salah Bahramara, Pouria Sheikhahmadi, Gianfranco Chicco, *Fellow, IEEE*, Andrea Mazza, *Senior Member, IEEE*, Fei Wang, *Senior Member, IEEE*, and João P. S. Catalão, *Fellow, IEEE*

***Abstract*—The penetration of the distributed energy resources in the distribution networks is facilitated by the structure of the microgrids (MGs). The MG operator (MGO) can schedule the MG resources to meet the local load and participate in the wholesale markets. In this paper, a new model is developed for the MGO participation in the day-ahead (energy and reserve) and the real-time (RT) energy markets under uncertainties. For this purpose, the effect of the uncertainties of demand and generation from renewable energy sources on the MGO decisions is represented in a two-stage stochastic model. The MGO bids in the DA and RT markets are modeled as the first and the second stage decisions, respectively. Moreover, the information gap decision theory (IGDT) method is used to model the behavior of the MGO to address the uncertainties of the RT energy market price and the probability of calling the reserve. The results show that as the RT price uncertainty radius increases, the energy sold to the RT market decreases/increases in the risk-averse/risk-taker strategy. Furthermore, to manage the uncertainty related to the probability of calling the reserve, the reserve capacity provided by the MGO in the risk-averse and the risk-taker strategies decreases and increases, respectively.**

Keywords*—*Microgrid, day-ahead energy and reserve market, two-stage stochastic, distributed energy resources, uncertainty.

I. NOMENCLATURE

Acronyms

DA	Day-ahead
DER	Distributed energy resources
DG	Distributed generation
EES	Electrical energy storage
MG	Microgrid
RES	Renewable energy source
RT	Real-time

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S. Bahramara is with the Department of Electrical Engineering, Sanandaj Branch, Islamic Azad University, Sanandaj, Iran (e-mail: s_bahramara@yahoo.com).

P. Sheikhahmadi is with the Department of Electrical and Computer Engineering, University of Kurdistan, Sanandaj, Iran (e-mail: pouria.sheikhahmadi@yahoo.com).

G. Chicco and A. Mazza are with the Dipartimento Energia "Galileo Ferraris," Politecnico di Torino, Torino 10129, Italy (e-mails: gianfranco.chicco@polito.it; andrea.mazza@polito.it).

F. Wang is with the Department of Electrical Engineering, North China Electric Power University, Baoding 071003, China, also with the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources (North China Electric Power University), Beijing 102206, China, and also with the Hebei Key Laboratory of Distributed Energy Storage and Microgrid (North China Electric Power University), Baoding 071003, China (e-mail: feiwang@ncepu.edu.cn).

J.P.S. Catalão is with the Faculty of Engineering of the University of Porto, and INESC TEC, 4200-465 Porto, Portugal (e-mail: catalao@fe.up.pt).

Indices/sets

e/E	Index/cardinality of EES
f/F	Index/cardinality of RESs
i,j	Indices of buses of MGs
k/K	Index/cardinality of DG
l/L	Index/cardinality of loads
t/T	Index/cardinality of time
ω/W	Index/cardinality of scenarios

Parameters

C_t^{RES}	The bid of RESs to provide energy [$/MWh]
C_t^{DG}	The bid of DGs to provide energy [$/MWh]
$C_t^{ES_c}$	The bid of EES to charge energy [$/MWh]
$C_t^{ES_d}$	The bid of EES to discharge energy [$/MWh]
$C_t^{DG\_Re}$	The bid of DGs to provide reserve [$/MWh]
$C_t^{ES\_Re}$	The bid of EES to provide reserve [$/MWh]
$\overline{\mathrm{E}}_e^{\mathrm{ES}}$	The maximum energy capacity of EES [MWh]
$\underline{\mathrm{E}}_e^{\mathrm{ES}}$	The minimum energy capacity of EES [MWh]
$\overline{\mathrm{I}}_{i,j}^{\mathrm{MGN}}$	The maximum current capacity of feeders [p.u.]
$\widehat{\mathrm{P}}_{l,t}^{\mathrm{MGL\_DA}}$	The forecast amount of MG active load [MW]
$\widehat{\mathrm{Q}}_{l,t}^{\mathrm{MGL\_DA}}$	The forecast amount of MG reactive load [Mvar]
$P_{l,t,\omega}^{\mathrm{MGL\_RT}}$	The amount of MG active load in RT [MW]
$Q_{l,t,\omega}^{\mathrm{MGL\_RT}}$	The amount of MG reactive load in RT [Mvar]
$\widehat{\mathrm{P}}_{f,t}^{\mathrm{RES}}$	The forecast output power of RES [MW]
$P_{f,t}^{\mathrm{RES}}$	The output power of RES in RT [MW]
$\overline{\mathrm{P}}_k^{\mathrm{DG}}$	The maximum capacity of DG [MW]
$\overline{\mathrm{P}}_e^{\mathrm{ch}}$	The maximum power charging of EES [MW]
$\overline{\mathrm{P}}_e^{\mathrm{dch}}$	The maximum power discharging of EES [MW]
$\overline{\mathrm{P}}^{\mathrm{MG}}$	The maximum trading active power with grid [MW]
RU_k	The ramp-up limitation of DG [MW/h]
RD_k	The ramp-down limitation of DG [MW/h]
$\mathrm{R}_{i,j}^{\mathrm{MGN}}$	The resistance of feeders [p.u.]
$\mathrm{S}^{\mathrm{base}}$	Base power for per unit (p.u.) calculations [MVA]
$\overline{\mathrm{V}}_i^{\mathrm{MGN}}$	The maximum voltage limitation of buses [p.u.]
$\underline{\mathrm{V}}_i^{\mathrm{MGN}}$	The minimum voltage limitation of buses [p.u.]
$\bar{Z}_{i,j}^{\mathrm{MGN}}/R_{i,j}^{\mathrm{MGN}}/X_{i,j}^{\mathrm{MGN}}$	The impedance/resistance/reactance of feeders [p.u.]
$\zeta^{\mathrm{RT\_E}}/\zeta^{\mathrm{Re}}$	The risk-aversion parameters
η^{ch}/η^{dch}	The charging/discharging efficiency of EES
$\lambda_t^{\mathrm{DA\_E}}$	The DA energy market price [$/MWh]
$\lambda_t^{\mathrm{RT\_E}}$	The RT energy market price [$/MWh]
λ_t^{Re}	The reserve market price [$/MWh]
ρ_ω	The probability of scenarios
φ^{Re}	The probability of deploying reserve [%]

Variables

$i_{i,j,t,\omega}^{\text{MGN}}$ The current of feeders [p.u.]
$p_{f,t}^{\text{RES}}$ The power generation of RESs in markets* [MW]
$p_{k,t}^{\text{DG}}$ The power generation of DGs in markets [MW]
$p_{k,t}^{\text{DG\_Dep}}$ The reserve deployment by DGs in RT [MW]
$p_{e,t}^{\text{ES}_\text{c}}$ The power charging of EES in markets [MW]
$p_{e,t}^{\text{ES}_\text{d}}$ The power discharging of EES in markets [MW]
$p_{k,t}^{\text{ES\_Dep}}$ The reserve deployment by EES in RT [MW]
$p_{t}^{\text{MG\_E}_\text{in}}$ The power purchased by MG from markets [MW]
$q_{t}^{\text{MG\_E}_\text{in}}$ The reactive power received from the grid [Mvar]
$p_{t}^{\text{MG\_E}_\text{out}}$ The power sold by MG to markets [MW]
$p_{t}^{\text{MG\_Dep}}$ The reserve deployment by MG in RT [MW]
$p_{k,t}^{\text{DG\_Re}}$ The reserve provided by DGs [MW]
$p_{e,t}^{\text{ES\_Re}}$ The reserve provided by EES [MW]
$p_{t}^{\text{MG\_Re}}$ The reserve provided by MG [MW]
$p_{i,j,t,\omega}^{\text{Flow}}$ The active power flow in feeders [MW]
$q_{i,j,t,\omega}^{\text{Flow}}$ The reactive power flow in feeders Mvar]
$p_{i,j,t,\omega}^{\text{Loss}}$ The active power loss of feeders [MW]
$q_{i,j,t,\omega}^{\text{Loss}}$ The reactive power loss of feeders [Mvar]
$U_{k,t}^{\text{ch}}$ Binary variable used for power charging in markets
$U_{k,t}^{\text{dch}}$ Binary variable used for power discharging in markets
$U_{t}^{\text{MG\_in}}$ Binary variable used for power purchased from markets
$U_{t}^{\text{MG\_out}}$ Binary variable used for power sold to markets
$v_{i,t,\omega}^{\text{MGN}}$ The voltage of buses [p.u.]
$\alpha^{\text{RT\_E}}/\alpha^{\text{Re}}$ The uncertainty radius

Functions

$C^{\text{DA\_E}}$ Energy cost of the MGO in the DA market
$C^{\text{DA\_DER\_E}}$ Energy cost of the DER in the DA
$C^{\text{DER\_Re}}$ Reserve cost of the DER in the DA
$R^{\text{DA\_Re}}$ Revenue of the MGO from the reserve market
$C_{\omega}^{\text{RT\_E}}$ Energy cost of the MGO in the RT in each scenario
$C_{\omega}^{\text{RT\_DER\_E}}$ Energy cost of the DER in the RT in each scenario
$C_{\omega}^{\text{DER\_Dep}}$ Cost of reserve deployment of DER in the RT
$R_{\omega}^{\text{RT\_Re}}$ Revenue of the MGO from reserve deployment
TC^{DA} Total cost in the DA operation
TC_{ω}^{RT} Total cost of the MGO in the RT in each scenario

*Remark: For simplification, the indices DA and RT are ignored in some variables. Instead, the term "markets" is mentioned for these variables.

II. Introduction

Although distributed energy resources (DERs) have numerous benefits for the power systems, their presence puts the system operators in different challenges. The complexity of the distribution network operation problem increases with the presence of the DERs. Furthermore, the management of the DERs in the wholesale energy markets is a major challenge for the independent system operator (ISO). Microgrids (MGs) are appropriate solutions for managing the DERs in the power system [1]. On the one hand, the DERs are integrated into the MG structure to meet the local load, where the MG operator (MGO) is responsible for the operation of the local system. On the other hand, the MGO aggregates the bids of its local DERs to participate in the wholesale energy and reserve markets. Therefore, in the presence of the MGs, the complexity of the ISO and the distribution system operator (DSO) problems decreases, as the ISO and the DSO are only collaborating with the MGO rather than with several DERs.

The MGO supplies the local demand of the MG through both participating in the wholesale energy markets and the optimal scheduling of the MG resources. In addition, the MGOs can provide the reserve capacity for the market regarding the flexible energy resources of the MGs, i.e., the dispatchable distributed generators (DGs) and the electrical energy storage (EES). For this purpose, several models have been developed in the literature to investigate the MGO decisions in the day-ahead (DA) energy markets or in the DA energy and reserve markets. Participation in the RT energy market creates a new opportunity for the MGO to trade energy in this market for greater profits [2].

Modeling the MGO strategies to participate in both the DA (energy and reserve) and RT energy markets is a new challenge addressed in this paper. In this case, the uncertain trend in the RT energy market price and the probability of calling the reserve place the MGO at greater risk in its decision-making process in both the DA and RT markets.

Therefore, an appropriate risk management tool is required to assist the MGO decisions in markets that encounter these uncertain parameters. Modeling the uncertain behavior of the RT market price through the probability distribution function (PDF) leads to a large forecasting error. Moreover, it is challenging to construct a PDF to model the uncertainty of the probability of calling the reserve.

The information gap decision theory (IGDT) method can be used to model the uncertainties of parameters with unknown PDFs or parameters that are difficult to be predicted with low forecasting errors [3]. The MGO decision problem in the markets is then formulated in this paper as a risk-based model using the IGDT approach to manage the uncertainties of the RT market price and the probability of calling the reserve.

A. Literature review and contributions

Appropriate decision-making models have been proposed in the previous studies to model the MGO decisions in the wholesale DA energy market. The MG operation problem has been formulated as a two-level model considering the demand response programs (DRPs) under uncertainty in [4]. The uncertainty of the output power of the renewable energy sources (RESs), as well as that of the demand in a MG, have been modeled through a two-stage robust optimization approach in [5].

The MGO participates in the wholesale energy market in [6] to meet the required energy of its system, including the plug-in electric vehicles. For this purpose, a robust optimization model has been developed to model the MGO decisions under the uncertainty of the energy market price. The MGO decisions in the DA energy market have been modeled in [7] considering the uncertainties of demand and the outage probabilities of the RESs. The DA scheduling problem of a MG including the RESs and the EESs has been modeled as a scenario-based stochastic optimization problem in [8]. The authors of [9] have proposed a two-stage robust model for optimal DA scheduling of a MG considering the uncertainty of the real-time (RT) energy market price.

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TABLE I: COMPARISON BETWEEN THE MODEL PROPOSED IN THIS PAPER AND THE PREVIOUS MODELS

Ref.	Decision maker	DA operation		RT operation		Uncertain parameters				Uncertainty modeling approach[a]
		Energy market	Reserve market	Energy market	Power imbalance	Demand	RESs	RT price	Probability of calling the reserve	
[4]	MGO	✓	-	-	-	✓	✓	-	-	-
[5]	MGO	✓	-	-	-	✓	✓	-	-	-
[6]	MGO	✓	-	-	-	-	-	-	-	-
[7]	MGO	✓	-	-	-	-	✓	-	-	-
[8]	MGO	✓	-	-	-	✓	✓	-	-	-
[9]	MGO	✓	-	-	-	-	✓	✓	-	-
[10]	MGO	✓	-	-	-	✓	✓	✓	-	-
[11]	MGO	✓	-	-	-	✓	✓	-	-	-
[12]	Aggregator	✓	-	-	✓	✓	✓	✓	-	-
[13]	MGO	✓	✓	-	-	-	✓	-	-	-
[14]	MGO	✓	✓	-	-	✓	✓	-	-	-
[15]	MGO	✓	✓	-	-	✓	✓	-	-	-
[16]	MGO	✓	✓	-	-	✓	✓	-	-	-
[17]	MGO	✓	✓	-	✓	✓	✓	-	-	-
[18]	MGO	✓	✓	-	✓	✓	-	✓	-	Stochastic
[19]	MGO	✓	✓	-	✓	-	-	✓	-	Robust
[20]	Aggregator[b]	✓	✓	-	✓	-	-	✓	✓	Stochastic
[21]	Aggregator[b]	✓	✓	-	✓	✓	✓	-	-	-
This paper	MGO	✓	✓	✓	-	✓	✓	✓	✓	IGDT

[a] To clarify the contribution, this paper have been compared with [13]-[21] focusing on the approaches of modeling the uncertainties of the RT price and the probability of calling the reserve. The reason for this comparison is the decision maker's participation in both the DA energy and reserve markets in [13]-[21] as well as in the present paper.

[b] In these studies, the participation of the aggregator in the regulation market is modeled, and the probability of calling the regulation capacity is addressed in [20].

TABLE II: DECISION VARIABLES MODELED IN THE CONSTRAINTS OF THE DA AND RT OPERATION MODELS

Details of modeling		Ref.			
		[17], [20], and [21]	[18]	[19]	This paper
Constraints of the DA operation model	Power balance	DA bids in the markets, power imbalance, and RT stochastic scheduling of the resources	-	DA bids in the markets and DA scheduling of resources	DA bids in the markets and DA scheduling of resources
	Resources	-	-	DA bids in the markets	DA bids in the markets
	Power trading with grid	-	-	DA bids in the energy market only	DA bids in the energy and reserve markets
Constraints of the RT operation model	Power balance	-	RT stochastic scheduling of the resources, power imbalance, and stochastic bids in the energy and reserve markets	DA bids in the markets, power imbalance, and RT deterministic decisions to reschedule the resources	DA bids in the markets, RT bids in the energy market, RT stochastic scheduling of resources, power flow among feeders, power loss, and the amount of the reserve capacity deployed in the RT
	Resources	RT stochastic scheduling of the resources and power imbalance	RT stochastic scheduling of the resources	DA scheduling of resources and RT deterministic decisions to reschedule the resources	DA scheduling of resources, RT stochastic scheduling of resources, and the amount of the reserve capacity of the resources deployed in the RT operation
	Power trading with grid	-	-	DA bids in the energy market only, and power imbalance	DA bids in the markets, RT bids in the energy market, and the amount of the reserve capacity deployed in the RT
	Power flow	-	-	-	Power flow in the feeders, power loss, bus voltage, and feeder current

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The energy management problem of a hybrid AC/DC MG has been modeled using a robust optimization approach in [10] considering the DA energy market price. The DA scheduling problem of a MG has been modeled in [11], where a machine learning method has been used to model the uncertain behavior of the demand and the RESs. The DA decision-making problem of the demand-side resource aggregators is modeled as a risk-based model to manage the uncertainties of the demand, the RT energy price, and the output power of the RESs in [12].

The bidding strategies of the MGO in the DA energy and reserve markets have been modeled considering the uncertainties of the RESs in [13]. The DA energy and reserve scheduling of the MGs with electric vehicles has been modeled with a robust optimization approach in [14]. The MGO bids in the DA energy and reserve markets have been determined using a risk-based approach in [15]. The IGDT approach has been used in [16] to model the uncertainties of MGO bid acceptance in the DA reserve market.

The participation problem of a MGO in the DA energy and reserve market considering the RT energy market has been formulated as a two-stage stochastic model in [17]. The decision problem of a hydrogen-based MG in the DA energy and reserve markets as well as the RT energy market has been addressed in [18]. In this study, the uncertainties of the market price and the hydrogen demand have been modeled through the stochastic approach. A robust optimization approach has been developed in [19] to model the optimal scheduling of a MG to satisfy both the electrical and the thermal loads considering the MGO participation in the wholesale markets. In this model, the bidding strategies of the MGO in the DA energy and ancillary service market are optimized for obtaining the minimum cost to meet the MG power balance in the RT operation.

The optimal decisions of an electric vehicle aggregator in the DA energy and regulation markets are determined under uncertainties in [20]. In this study, the aggregator decides about purchasing energy from the DA market, providing up and down regulation for the market so that the energy deviation between the DA and the RT markets is minimized. The participation problem of an aggregator in the DA energy and the regulation market is formulated as a two-stage stochastic model in [21] to manage the uncertainties of the demand, the output power of the PV system, the outdoor temperature, the prosumers' preferences, and the house occupancy. The objective function of the aggregator is formulated considering the DA cost/revenue from participating in the energy and regulation markets, the expected imbalance cost, and the revenue from providing the regulation capacity in the RT operation.

A comparison between the model proposed in this paper and the models presented in the previous studies is given in Table I and Table II. As shown in these tables, the model proposed in this paper has two contributions, which are described as follows.

- The first contribution is modeling the MGO participation in the RT energy market besides its participation in the DA energy and reserve market. As shown in these tables, this issue has not been addressed in the previous studies. The MGO decisions in the DA energy and reserve market have been investigated considering uncertainties in [13-16]. However, the effect of the MGO participation in the RT market on its DA decisions was not addressed. As shown in Table I, there are two approaches to model the RT operation in the problem of the decision makers, namely, the energy market approach and the power imbalance approach. In the power imbalance approach addressed in [17-21], the aim of the decision maker is to minimize the power imbalance (i.e., the deviation of the RT power trading with the main grid from the DA scheduled power) to avoid receiving the imbalance penalty in the RT operation. Therefore, although it is mentioned that the MGO's decisions in the DA markets are determined with respect to the RT energy market in [17-21], the MGO does not participate in the RT energy market and it only tries to manage its own power imbalance in the RT operation. The main differences between the model proposed in this paper (the energy market approach) and those proposed in [17-21] are as the follows:

- In the models proposed in [17-21], the decision makers are settled regarding the imbalance prices. In this case, the power delivered on the day of operation is metered, then the power imbalance and consequently the imbalance prices are calculated. The imbalance prices are published on the next day of the real operation day. Conversely, in the model proposed in this paper, the MGO is settled in the RT energy market, and the MGO bids are sent to the market a short time before the day of operation. Details of the timeline of the MGO participation in the DA and RT markets are described in sub-section III.C.
- In this paper, the aim of the MGO is to obtain greater profits from employing different strategies to participate in the DA energy and reserve markets and in the RT energy market, or either of these with regard to the market prices. Instead, the aim of the decision makers in [17-21] is to manage their power imbalance.
- The energy market approach proposed in this paper leads to a different mathematical model compared to the models proposed in the power imbalance approach in [17-21], as described in Table II. The aim of the proposed models in [17], [20], and [21] is to optimize the DA bids in the markets and to manage the power imbalance considering the RT stochastic scheduling of the resources. Therefore, only the power balance constraint in the DA model and the technical constraints of the resources are modeled in these studies, as shown in Table II. In [18], all the decision variables are scenario-dependent, therefore, only the power balance constraint and the technical constraints of the resources in the RT model have been modeled. The model proposed in [19] aims to manage the power imbalance by revising the DA scheduling of the resources in the RT operation (i.e., the RT deterministic decisions about rescheduling the resources). Conversely, the DA bids in the energy and reserve market and the RT bids in the energy market in this paper are optimized considering the RT stochastic decisions of the resources, the amount of the reserve capacity deployed in the RT operation, and the power flow variables. Therefore, as described in Table II, different models are used in this paper compared to [19]. These different models consider the power balance constraint and technical constraints of the resources in the RT model, as well as the power trading constraint with the grid in both the DA and the RT models. The previous studies [17]-[21] have not modeled the power flow constraints that have important effects on the RT operation of the MGO.

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- The second contribution of this paper is modeling the risk-based decisions of the MGO to manage the uncertainties of the RT energy price and the probability of calling the reserve using the IGDT approach. As shown in Table I, in the previous studies addressing the participation problem of the decision makers, i.e., the aggregator and the MGO, in the energy and reserve market, only the uncertainties related to both the RT energy price and the probability of calling the reserve are modeled in [20] using the stochastic approach. However, modeling the risk-based decisions of the decision maker in facing these uncertainties is not addressed. Therefore, the contribution of this paper is not only proposing the IGDT approach to model the risk-based decisions of the MGO in the DA (energy and reserve) and the RT energy markets, but also modeling the MGO participation in the RT energy market, besides the DA energy and reserve market.

The modeling of the MGO decisions in the RT energy market presented in this paper leads to a different mathematical model compared to the power imbalance approach proposed in the previous studies [17]-[21].

In this paper, a mathematical formulation is developed to model the mutual effect of the MGO decisions in the DA and RT markets under uncertainties. The demand and RES output power uncertainties are modeled using appropriate PDFs. For this purpose, some scenarios are generated, on which the MGO problem is formulated as a two-stage stochastic model. Since the timeline of participation in the DA and RT markets is different, the MGO decisions in the DA market are considered as first-stage decisions. Furthermore, the stochastic decisions of the MGO in the RT energy market are modeled as second-stage decisions. Then, to model the risk-based behavior of the MGO to manage the uncertainties of the RT energy market price and the probability of calling the reserve, the IGDT approach is used. Therefore, the main contributions of this paper are the following:

- Modeling the MGO bids in the DA energy and reserve markets considering the stochastic decisions in the RT energy market.
- Proposing a risk-based model that uses the IGDT approach to manage the effect of the uncertainties related to the RT energy price and the probability of calling the reserve on the MGO bids in the DA (energy and reserve) and RT energy markets.

B. *Paper organization*

The rest of the paper is organized as follows. The problem description is presented in Section III. This problem is mathematically formulated in Section IV. The numerical results are described in Section V. The last section contains the conclusions.

III. PROBLEM DESCRIPTION

The cyber-physical structure of the bidding strategy problem of the MGO in energy and reserve markets is described in Fig. 1. The DER owners send their bids and the technical constraints of the resources to the MGO. Moreover, the forecast data related to the RES output power, MG demand, and energy and reserve market prices are sent to the MGO by a service provider. Regarding this data, the MGO solves its optimization problem (described in the next section) in the energy management system (EMS) center.

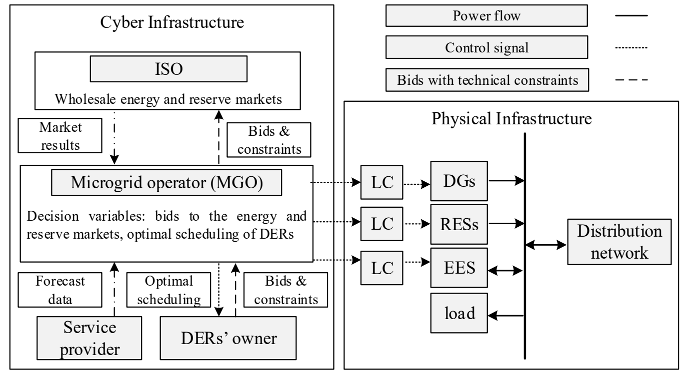

Fig.1. The cyber-physical infrastructure of the problem.

The output results of the optimization problem are the optimal bids of the MGO in the energy and reserve markets. The MGO sends its bids and technical constraints of trading energy and reserve capacity with the main grid to the ISO. The ISO is responsible for clearing the wholesale energy and reserve markets. Discussing the clearing process of the wholesale markets is beyond the scope of this paper. After clearing the wholesale markets, the market results are presented to the MG. The control signals are sent from the MG central control (MGCC) to the local controllers (LCs) of the MG resources. As far as these signals are concerned, the DERs trade energy with the distribution network.

A. *Modeling uncertainties of demand and RESs*

The uncertain behavior of the demand is modeled using the normal PDF. The Rayleigh PDF is used to model the wind speed uncertainty. The Weibull PDF with the specific parameters described in [22] is used to model the uncertain solar irradiance. To model these uncertainties in the decision problem of the MGO, these PDFs are discretized into certain intervals. Details of determining the value and the probability of the uncertain parameters in each interval are described in [23]. As for the probability of each interval of uncertain parameters, a large number of samples are generated. Then, the scenarios are obtained through the scenario tree construction method. In this method, the stages of the scenario tree are the time steps of the problem, and the generated samples are considered as the nodes. This method generates 1000 scenarios, which are then reduced to 15 using the fast-forward scenario reduction technique.

B. *Two-stage stochastic formulation*

As for the scenarios obtained in the previous sub-section, the decision problem of the MGO is modeled as a two-stage stochastic optimization model. In this model, there are two sets of decision variables before and after the occurrence of the scenarios. The first-stage decisions are bids of the MGO in the DA energy and reserve markets, which are determined before the scenarios occur. The MGO bids in the RT market are considered as the second-stage decisions determined after the scenarios occur. The MGO decisions about the optimal scheduling of the DERs are considered in both stages.

C. *Timeline*

The MGOs participate in the wholesale markets as price-taker (self-scheduling) players, due to the low capacity of the MGs in comparison with the other energy market players.

In this case, the bids of the MGOs in the markets are of the quantity-only type, -with no price. In fact, the MGOs accept the market price to trade energy with the market and provide reserve for the market. The deadline for submitting bids in the DA energy and reserve markets is usually before noon on the day before the actual operation (e.g., 10 a.m. at California ISO (CAISO)). The deadline for submitting the bids to the RT energy market starts after the publication of the DA market results until shortly before the real operation (i.e., 75 min before the real operation at CAISO). Therefore, the model proposed in this paper is used by the MGO before the deadline for submitting bids in the DA markets. For the RT market, the MGO waits to see the forecast data, with respect to which it submits the bids to that market. These bids can be considered as the same bids obtained from the proposed model in this paper. Otherwise, the MGO can use the new models for participating in the RT market by considering the results obtained from the DA markets and the values of the uncertain parameters.

IV. Mathematical Modeling

The bidding strategy of the MGO in the markets is modeled as (1)-(59). The MGO aims to minimize its expected total cost (ETC) over the operation time period as modeled in (1). The first term of (1) models the total cost of the MGO in the DA operation, and the second term is used to model the expected cost of the MGO in the RT operation. These terms are described in the next two sub-sections. The time step is one hour and is not explicitly indicated in the equations.

$$\text{Min } ETC = \sum_{\omega=1}^{W} \rho_{\omega} \left(TC^{\text{DA}} + TC_{\omega}^{\text{RT}}\right) \tag{1}$$

A. The DA problem for the MGO

The total cost of the MGO in the DA market is modeled as (2) made up of four terms. The first term is the cost of trading energy with the DA energy market as described in (3). The second term is the revenue of the MGO from providing the reserve capacity to the market, modeled in (4). The third and fourth terms express the costs of MG resources to provide energy and reserve for the system, modeled in (5) and (6), respectively.

$$TC^{\text{DA}} = C^{\text{DA\_E}} - R^{\text{DA\_Re}} + C^{\text{DA\_DER\_E}} + \text{C}^{\text{DER\_Re}} \tag{2}$$

$$C^{\text{DA\_E}} = \sum_{t=1}^{T} \lambda_t^{\text{DA\_E}} \left(p_t^{\text{MG\_DA\_E}_{\text{in}}} - p_t^{\text{MG\_DA\_E}_{\text{out}}}\right) \tag{3}$$

$$R^{\text{DA\_Re}} = \sum_{t=1}^{T} \lambda_t^{\text{Re}} p_t^{\text{MG\_Re}} \tag{4}$$

$$C^{\text{DA\_DER}} = \sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} \left[\begin{array}{l} \sum_{f=1}^{F} \text{C}_t^{\text{RES}} p_{f,t}^{\text{RES\_DA}} + \sum_{k=1}^{K} \text{C}_t^{\text{DG}} p_{k,t}^{\text{DG\_DA}} + \\ \sum_{e=1}^{E} \text{C}_t^{\text{ES}_d} p_{e,t}^{\text{ES}_d\text{\_DA}} - \sum_{e=1}^{E} \text{C}_t^{\text{ES}_c} p_{e,t}^{\text{ES}_c\text{\_DA}} \end{array} \right] \tag{5}$$

$$C^{\text{DER\_Re}} = \sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} \left[\sum_{k=1}^{K} C_t^{\text{DG\_Re}} p_{k,t}^{\text{DG\_Re}} + \sum_{e=1}^{E} C_t^{\text{ES\_Re}} p_{e,t}^{\text{ES\_Re}} \right] \tag{6}$$

The technical constraints of the DA problem are as follows:

- Equations (7) and (8) show the active and reactive power balance constraints of the system in the DA operation.

$$\begin{aligned} &\sum_{f=1}^{F} p_{f,t}^{\text{RES\_DA}} + \sum_{k=1}^{K} p_{k,t}^{\text{DG\_DA}} + \sum_{e=1}^{E} p_{e,t}^{\text{ES}_d\text{\_DA}} + p_t^{\text{MG\_DA\_E}_{\text{in}}} \\ &\quad = \sum_{l=1}^{L} \hat{\text{P}}_{l,t}^{\text{MGL\_DA}} + \sum_{e=1}^{E} p_{e,t}^{\text{ES}_c\text{\_DA}} + p_t^{\text{MG\_DA\_E}_{\text{out}}} : \forall t \end{aligned} \tag{7}$$

$$q_t^{\text{MG\_DA\_E}_{\text{in}}} = \sum_{l=1}^{L} \hat{\text{Q}}_{l,t}^{\text{MGL\_DA}} : \forall t \tag{8}$$

- The reserve capacity that the MGO can provide to the market is supplied from the DG and the EES as shown in (9).

$$p_t^{\text{MG\_Re}} = \sum_{k=1}^{K} p_{k,t}^{\text{DG\_Re}} + \sum_{e=1}^{E} p_{e,t}^{\text{ES\_Re}} \quad : \forall t \tag{9}$$

- The power generation of the RESs in the DA market is lower than or equal to their forecast power as modeled in (10).

$$0 \le p_{f,t}^{\text{RES\_DA}} \le \hat{\text{P}}_{f,t}^{\text{RES}} \quad : \forall f, t \tag{10}$$

- The sum of the power generation of the DGs and the DG capacity to provide reserve are lower than or equal to their maximum power as described in (11). Ramp-up and ramp-down limitations of DGs are modeled in (12) and (13), respectively.

$$p_{k,t}^{\text{DG\_DA}} + p_{k,t}^{\text{DG\_Re}} \le \overline{\text{P}}_k^{\text{DG}}, p_{k,t}^{\text{DG\_DA}}, p_{k,t}^{\text{DG\_Re}} \ge 0 : \forall k, t \tag{11}$$

$$\left(p_{k,t+1}^{\text{DG\_DA}} + p_{k,t+1}^{\text{DG\_Re}}\right) - \left(p_{k,t}^{\text{DG\_DA}}\right) \le \text{RU}_k \quad : \forall k, t \tag{12}$$

$$\left(p_{k,t}^{\text{DG\_DA}} + p_{k,t}^{\text{DG\_Re}}\right) - \left(p_{k,t+1}^{\text{DG\_DA}}\right) \le \text{RD}_k \quad : \forall k, t \tag{13}$$

- The power and energy constraints of the EESs to provide energy and reserve for the system are modeled in (14)-(20). The difference between the discharge and charge power plus the reserve provided by the EESs is less than or equal to the maximum discharge power of the EESs as modeled in (14). This equation shows that when the MGO decides to charge the EESs, its capacity to provide the reserve for the system increases. Equations (15)-(17) are used to limit the maximum charge and discharge power of the EESs and to prevent simultaneous charging and discharging of the EESs. The time-based behavior of the energy stored in the EESs is shown in (18). The limits of the energy stored in the EESs are described in (19). Moreover, the energy stored in the EESs in the last time step of the operation is equal to its initial value. The energy capacity of the EESs to provide reserve for the system is lower than or equal to the energy stored in the EESs minus its minimum value in (20).

$$\left(p_{e,t}^{\text{ES}_d\text{\_DA}} - p_{e,t}^{\text{ES}_c\text{\_DA}}\right) + p_{e,t}^{\text{ES\_Re}} \le \overline{\text{P}}_e^{\text{dch}} \quad : \forall e, t \tag{14}$$

$$0 \le p_{e,t}^{\text{ES}_c\text{\_DA}} \le \overline{\text{P}}_e^{\text{ch}} U_{e,t}^{\text{ch\_DA}} \quad : \forall e, t \tag{15}$$

$$0 \le p_{e,t}^{\text{ES}_d\text{\_DA}} \le \overline{\text{P}}_e^{\text{dch}} U_{e,t}^{\text{dch\_DA}} \quad : \forall e, t \tag{16}$$

$$U_{e,t}^{\text{ch\_DA}} + U_{e,t}^{\text{dch\_DA}} \le 1 \quad : \forall e, t \tag{17}$$

$$E_{e,t}^{\text{ES\_DA}} = E_{e,t-1}^{\text{ES\_DA}} + p_{e,t}^{\text{ES}_c\text{\_DA}} \eta^{\text{ch}} - \frac{p_{e,t}^{\text{ES}_d\text{\_DA}}}{\eta^{\text{dch}}} \quad : \forall e, t \tag{18}$$

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$$\underline{\mathrm{E}}_e^{\mathrm{ES}} \le E_{e,t}^{\mathrm{ES\_DA}} \le \overline{\mathrm{E}}_e^{\mathrm{ES}} \ :\forall e,t \ , E_{e,ini}^{\mathrm{ES}} = E_{e,t=T}^{\mathrm{ES\_DA}} \ :\forall e \tag{19}$$

$$E_{e,t}^{\mathrm{ES\_Re}} \le E_{e,t}^{\mathrm{ES\_DA}} - \underline{\mathrm{E}}_e^{\mathrm{ES}} \qquad :\forall e,t \tag{20}$$

- The reserve capacity that the MG can provide for the market when the MGO purchases/sells energy from/to the DA market is modeled as (21) and (22), respectively. Equations (23)-(25) are used to limit the MGO bids in the DA market to the maximum capacity of the MG power trading with the main grid.

$$p_t^{\mathrm{MG\_Re}} \le \overline{\mathrm{P}}^{\mathrm{MG}} + p_t^{\mathrm{MG\_DA\_E_{in}}} \quad , p_t^{\mathrm{MG\_Re}} \ge 0 \ :\forall t \tag{21}$$

$$p_t^{\mathrm{MG\_DA\_E_{out}}} + p_t^{\mathrm{MG\_Re}} \le \overline{\mathrm{P}}^{\mathrm{MG}} \qquad :\forall t \tag{22}$$

$$0 \le p_t^{\mathrm{MG\_DA\_E_{in}}} \le \overline{\mathrm{P}}^{\mathrm{MG}} U_t^{\mathrm{MG\_DA\_in}} \quad :\forall t \tag{23}$$

$$0 \le p_t^{\mathrm{MG\_DA\_E_{out}}} \le \overline{\mathrm{P}}^{\mathrm{MG}} U_t^{\mathrm{MG\_DA\_out}} \quad :\forall t \tag{24}$$

$$U_t^{\mathrm{MG\_DA\_in}} + U_t^{\mathrm{MG\_DA\_out}} \le 1 \quad :\forall t \tag{25}$$

B. The RT problem for the MG

The total cost of the MGO in the RT market, modeled as (26), is made up of four terms. The first term is the cost of trading energy with the RT energy market as described in (27). The second term is the revenue of the MGO from the deployment of the reserve in the actual operation, modeled in (28). The cost of MG resources to provide energy and reserve for the system is considered in the third and the fourth terms modeled in (29) and (30), respectively.

$$TC_\omega^{\mathrm{RT}} = C_\omega^{\mathrm{RT\_E}} - R_\omega^{\mathrm{RT\_Re}} + C_\omega^{\mathrm{RT\_DER\_E}} + C^{\mathrm{DER\_Dep}} \tag{26}$$

$$C_\omega^{\mathrm{RT\_E}} = \sum_{t=1}^{T} \lambda_t^{\mathrm{RT\_E}} \left(p_{t,\omega}^{\mathrm{MG\_RT\_E_{in}}} - p_{t,\omega}^{\mathrm{MG\_RT\_E_{out}}} \right) \tag{27}$$

$$R_\omega^{\mathrm{RT\_Re}} = \sum_{t=1}^{T} \lambda_t^{\mathrm{RT\_E}} p_t^{\mathrm{MG\_Re\_Dep}} \tag{28}$$

$$C_\omega^{\mathrm{RT\_DER\_E}} = \sum_{t=1}^{T} \begin{bmatrix} \sum_{f=1}^{F} \mathrm{C}_t^{\mathrm{RES}} P_{f,t,\omega}^{\mathrm{RES\_RT}} + \sum_{k=1}^{K} \mathrm{C}_t^{\mathrm{DG}} p_{k,t,\omega}^{\mathrm{DG\_RT}} + \\ \sum_{e=1}^{E} \mathrm{C}_t^{\mathrm{ES}_d} p_{e,t,\omega}^{\mathrm{ES_d\_RT}} - \sum_{e=1}^{E} \mathrm{C}_t^{\mathrm{ES}_c} p_{e,t,\omega}^{\mathrm{ES_c\_RT}} \end{bmatrix} \tag{29}$$

$$C^{\mathrm{DER\_Dep}} = \sum_{t=1}^{T} \left[\sum_{k=1}^{K} C_t^{\mathrm{DG}} p_{k,t}^{\mathrm{DG\_Dep}} + \sum_{e=1}^{E} C_t^{\mathrm{ES\_dch}} p_{e,t}^{\mathrm{ES\_Dep}} \right] \tag{30}$$

- The active and reactive power balance constraints of the MG in the reference bus (i.e., the bus which connects the MG to the main grid), as well as other buses, are modeled in (31)-(34).

$$\begin{aligned} &\sum_f \left(P_{f,t}^{\mathrm{RES\_DA}} + P_{f,t,\omega}^{\mathrm{RES\_RT}} \right) + \sum_k \left(p_{k,t}^{\mathrm{DG\_DA}} + p_{k,t,\omega}^{\mathrm{DG\_RT}} + p_{k,t}^{\mathrm{DG\_Dep}} \right) + \\ &\sum_e \left(p_{e,t}^{\mathrm{ES_d\_DA}} + p_{e,t,\omega}^{\mathrm{ES_d\_RT}} + p_{e,t}^{\mathrm{ES\_Dep}} \right) + \left(p_t^{\mathrm{MG\_DA\_E_{in}}} + p_{t,\omega}^{\mathrm{MG\_RT\_E_{in}}} \right) \\ &- \left(p_t^{\mathrm{MG\_DA\_E_{out}}} + p_{t,\omega}^{\mathrm{MG\_RT\_E_{out}}} + p_t^{\mathrm{MG\_Dep}} \right) - \left(p_{e,t}^{\mathrm{ES_c\_DA}} + p_{e,t,\omega}^{\mathrm{ES_c\_RT}} \right) \\ &- \sum_l \mathrm{P}_{l,t,\omega}^{\mathrm{MGL\_RT}} = \sum_j (p_{i,j,t,\omega}^{\mathrm{Flow}} + p_{i,j,t,\omega}^{\mathrm{Loss}}) \quad :\forall t,\omega,i=1 \end{aligned} \tag{31}$$

$$\begin{aligned} &\sum_f \left(P_{f,t}^{\mathrm{RES\_DA}} + P_{f,t,\omega}^{\mathrm{RES\_RT}} \right) + \sum_k \left(p_{k,t}^{\mathrm{DG\_DA}} + p_{k,t,\omega}^{\mathrm{DG\_RT}} + p_{k,t}^{\mathrm{DG\_Dep}} \right) \\ &+ \sum_e \left(p_{e,t}^{\mathrm{ES_d\_DA}} + p_{e,t,\omega}^{\mathrm{ES_d\_RT}} + p_{e,t}^{\mathrm{ES\_Dep}} \right) - \left(p_{e,t}^{\mathrm{ES_c\_DA}} + p_{e,t,\omega}^{\mathrm{ES_c\_RT}} \right) \\ &- \sum_l \mathrm{P}_{l,t,\omega}^{\mathrm{MGL\_RT}} = \sum_j (p_{i,j,t,\omega}^{\mathrm{Flow}} + p_{i,j,t,\omega}^{\mathrm{Loss}}) \quad :\forall t,\omega,i \ne 1 \end{aligned} \tag{32}$$

$$\begin{aligned} &\left(q_t^{\mathrm{MG\_DA\_E_{in}}} + q_{t,\omega}^{\mathrm{MG\_RT\_E_{in}}} \right) - \sum_l Q_{l,t,\omega}^{\mathrm{MGL\_RT}} = \\ &\qquad \sum_j (q_{i,j,t,\omega}^{\mathrm{Flow}} + q_{i,j,t,\omega}^{\mathrm{Loss}}) \quad :\forall t,\omega,i=1 \end{aligned} \tag{33}$$

$$\sum_l Q_{l,t,\omega}^{\mathrm{MGL\_RT}} + \sum_j (q_{i,j,t,\omega}^{\mathrm{Flow}} + q_{i,j,t,\omega}^{\mathrm{Loss}}) = 0 \quad :\forall t,\omega,i \ne 1 \tag{34}$$

- The reserve deployment of the MG and its resources in the RT operation is defined through multiplying the reserve capacity with the probability of calling the reserve, as modeled in (35).

$$\begin{aligned} &p_t^{\mathrm{MG\_Dep}} = \varphi^{\mathrm{Re}} p_t^{\mathrm{MG\_Re}} \ , \ p_{k,t}^{\mathrm{DG\_Dep}} = \varphi^{\mathrm{DG\_Re}} p_{k,t}^{\mathrm{DG\_Re}} , \\ &\qquad p_{e,t}^{\mathrm{ES\_Dep}} = \varphi^{\mathrm{ES\_Re}} p_{e,t}^{\mathrm{ES\_Re}} \quad :\forall t \end{aligned} \tag{35}$$

- The sum of the power generation of the RESs in the DA and RT operation is limited as (36).

$$0 \le p_{f,t}^{\mathrm{RES\_DA}} + p_{f,t,\omega}^{\mathrm{RES\_RT}} \le \mathrm{P}_{f,t,\omega}^{\mathrm{RES}} \quad :\forall f,t,\omega \tag{36}$$

- The technical constraints of the DGs in the RT operation are described in (37)-(39) considering the reserve deployment.

$$p_{k,t}^{\mathrm{DG\_DA}} + p_{k,t,\omega}^{\mathrm{DG\_RT}} + p_{k,t}^{\mathrm{DG\_Dep}} \le \overline{\mathrm{P}}_k^{\mathrm{DG}} \quad :\forall k,t,\omega \tag{37}$$

$$\begin{aligned} &\left(p_{k,t+1}^{\mathrm{DG\_DA}} + p_{k,t+1,\omega}^{\mathrm{DG\_RT}} + p_{k,t+1}^{\mathrm{DG\_Re\_Dep}} \right) \\ &\qquad - \left(p_{k,t}^{\mathrm{DG\_DA}} + p_{k,t,\omega}^{\mathrm{DG\_RT}} \right) \le \mathrm{RU}_k \quad :\forall k,t,\omega \end{aligned} \tag{38}$$

$$\begin{aligned} &\left(p_{k,t}^{\mathrm{DG\_DA}} + p_{k,t,\omega}^{\mathrm{DG\_RT}} + p_{k,t}^{\mathrm{DG\_Re\_Dep}} \right) \\ &\qquad - \left(p_{k,t+1}^{\mathrm{DG\_DA}} + p_{k,t+1,\omega}^{\mathrm{DG\_RT}} \right) \le \mathrm{RD}_k \quad :\forall k,t,\omega \end{aligned} \tag{39}$$

- The power and energy constraints of the ESS in the RT operation are modeled as (40)-(46).

$$p_{e,t}^{\mathrm{ES}_d\mathrm{\_DA}} + p_{e,t,\omega}^{\mathrm{ES_d\_RT}} + p_{e,t}^{\mathrm{ES\_Dep}} \le \overline{\mathrm{P}}_e^{\mathrm{dch}} \quad :\forall e,t,\omega \tag{40}$$

$$0 \le p_{e,t,\omega}^{\mathrm{ES_c\_RT}} \le \overline{\mathrm{P}}_e^{\mathrm{ch}} U_{e,t,\omega}^{\mathrm{ch\_RT}} \quad :\forall e,t,\omega \tag{41}$$

$$0 \le p_{e,t,\omega}^{\mathrm{ES_d\_RT}} \le \overline{\mathrm{P}}_e^{\mathrm{dch}} U_{e,t,\omega}^{\mathrm{dch\_RT}} \quad :\forall e,t,\omega \tag{42}$$

$$U_{e,t,\omega}^{\mathrm{ch\_RT}} + U_{e,t,\omega}^{\mathrm{dch\_RT}} \le 1 \quad :\forall e,t,\omega \tag{43}$$

$$\begin{aligned} &E_{e,t,\omega}^{\mathrm{ES\_RT}} = E_{e,t-1,\omega}^{\mathrm{ES\_RT}} + \left(\left(p_{e,t}^{\mathrm{ES_c\_DA}} + p_{e,t,\omega}^{\mathrm{ES_c\_RT}} \right) \eta^{\mathrm{ch}} \right) - \\ &\quad \left(\left(p_{e,t}^{\mathrm{ES_d\_DA}} + p_{e,t,\omega}^{\mathrm{ES_d\_RT}} + p_{e,t,\omega}^{\mathrm{ES\_Dep}} \right) / \eta^{\mathrm{dch}} \right) : \forall e,t,\omega \end{aligned} \tag{44}$$

$$\underline{\mathrm{E}}_e^{\mathrm{ES}} \le E_{e,t,\omega}^{\mathrm{ES\_RT}} \le \overline{\mathrm{E}}_e^{\mathrm{ES}} \qquad :\forall e,t,\omega \tag{45}$$

$$E_{e,ini}^{\mathrm{ES}} = E_{e,t=T,\omega}^{\mathrm{ES\_RT}} \ :\forall e,\omega \tag{46}$$

- The relation among the amount of power trading of the MGO with the RT market, its offers in the DA market, and the reserve deployment in the RT is shown in (47) and (48).

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Equations (49)-(51) are used to model the fact that the MG can trade energy with the main grid just in one direction.

$$p_t^{\mathrm{MG\_DA\_E_{in}}} + p_{t,\omega}^{\mathrm{MG\_RT\_E_{in}}} - p_t^{\mathrm{MG\_Dep}} \le \overline{\mathrm{P}}^{\mathrm{MG}} \quad :\forall t,\omega \quad (47)$$

$$p_t^{\mathrm{MG\_DA\_E_{out}}} + p_{t,\omega}^{\mathrm{MG\_RT\_E_{out}}} + p_t^{\mathrm{MG\_Dep}} \le \overline{\mathrm{P}}^{\mathrm{MG}} \quad :\forall t,\omega \quad (48)$$

$$0 \le p_{t,\omega}^{\mathrm{MG\_RT\_E_{in}}} \le \overline{\mathrm{P}}^{\mathrm{MG}} U_{t,\omega}^{\mathrm{MG\_RT\_in}} \quad :\forall t,\omega \quad (49)$$

$$0 \le p_{t,\omega}^{\mathrm{MG\_RT\_E_{out}}} \le \overline{\mathrm{P}}^{\mathrm{MG}} U_{t,\omega}^{\mathrm{MG\_RT\_out}} \quad :\forall t,\omega \quad (50)$$

$$U_{t,\omega}^{\mathrm{MG\_RT\_in}} + U_{t,\omega}^{\mathrm{MG\_RT\_out}} \le 1 \quad :\forall t,\omega \quad (51)$$

- Eqs. (52)-(59) are used to model the power flow constraints. The limitations of the feeder currents and the bus voltages are modeled in (52) and (53), respectively. Also, the squares of the feeder currents and the bus voltages are constrained by (54) and (55). In (56), the magnitude of the voltage at the final bus is calculated in terms of the magnitude of voltage at the initial bus, the active and reactive power flows, the magnitude of the feeder current, and the electrical parameters of the lines. The relation among the apparent, the active, and the reactive power is defined in (57). The active and reactive power losses of each feeder are calculated as (58) and (59), respectively. To maintain the linear form of the model, the square magnitudes of the voltage, current, active power, and reactive power are replaced with the linear terms as in [24].

$$-\overline{\mathrm{I}}_{i,j}^{\mathrm{MGN}} \le i_{i,j,t,\omega}^{\mathrm{MGN}} \le \overline{\mathrm{I}}_{i,j}^{\mathrm{MGN}} \quad :\forall i,j,t,\omega \quad (52)$$

$$\underline{\mathrm{V}}_i^{\mathrm{MGN}} \le v_{i,t,\omega}^{\mathrm{MGN}} \le \overline{\mathrm{V}}_i^{\mathrm{MGN}} \quad :\forall i,t,\omega \quad (53)$$

$$(\underline{\mathrm{V}}_i^{\mathrm{MGN}})^2 \le v_{i,t,\omega}^{\mathrm{MGN\_sqr}} \le (\overline{\mathrm{V}}_i^{\mathrm{MGN}})^2 \quad :\forall i,t,\omega \quad (54)$$

$$0 \le i_{i,j,t,\omega}^{\mathrm{MGN\_sqr}} \le (\overline{\mathrm{I}}_{i,j}^{\mathrm{MGN}})^2 \quad :\forall i,j,t,\omega \quad (55)$$

$$v_{i,t,\omega}^{\mathrm{MGN\_sqr}} - 2(\mathrm{R}_{i,j}^{\mathrm{MGN}} p_{i,j,t,\omega}^{Flow} + \mathrm{X}_{i,j}^{\mathrm{MGN}} q_{i,j,t,\omega}^{Flow}) - \left(Z_{i,j}^{\mathrm{MGN}}\right)^2 i_{i,j,t,\omega}^{\mathrm{MGN\_sqr}} - v_{j,t,\omega}^{\mathrm{MGN\_sqr}} = 0 \quad :\forall i,j,t,\omega \quad (56)$$

$$v_{i,t,\omega}^{\mathrm{MGN\_sqr}} i_{i,j,t,\omega}^{\mathrm{MGN\_sqr}} = p_{i,j,t,\omega}^{Flow\_sqr} + q_{i,j,t,\omega}^{Flow\_sqr} \quad (57)$$

$$p_{i,j,t,\omega}^{\mathrm{Loss}} = (\mathrm{R}_{i,j}^{\mathrm{MGN}} i_{i,j,t,\omega}^{\mathrm{MGN\_sqr}})\mathrm{S}^{\mathrm{base}} \quad :\forall i,j,t,\omega \quad (58)$$

$$q_{i,j,t,\omega}^{\mathrm{Loss}} = (\mathrm{X}_{i,j}^{\mathrm{MGN}} i_{i,j,t,\omega}^{\mathrm{MGN\_sqr}})\mathrm{S}^{\mathrm{base}} \quad :\forall i,j,t,\omega \quad (59)$$

C. *IGDT-based optimization model*

The IGDT approach is used to model the uncertainties of the RT energy market price and the probability of calling the reserve. In this approach, the amount of the uncertain parameter is a function of the uncertainty radius. Therefore, the amount of the RT energy market price ($\lambda_t^{\mathrm{RT\_E}}$) and the probability of calling the reserve (φ^{Re}) are defined as functions of their related uncertainty radius, i.e., $\alpha^{\mathrm{RT\_E}}$ and α^{Re}, as modeled in (62)-(63) and (66)-(67), respectively. In the model proposed in this paper, when the MGO wants to be risk-averse/risk-taker, the MGO increases the uncertainty radius related to the uncertain parameter for which the amount of that parameter decreases/increases and consequently the ETC of the MGO increases/decreases. Modeling details are described as follows.

Eqs. (60)-(63) are used to model the uncertainty related to the RT energy market price in the decision problem of the MGO in the markets. When the uncertain parameter is set as its forecast values, the base value of the ETC of the MGO, named ETC_b, is calculated. Regarding the effect of the uncertain parameter on the objective function, two strategies can be considered for the MGO; risk-averse and risk-taker strategies. In the risk-averse strategy, the MGO aims to obtain an objective function that is robust against the uncertain parameter in the worst case. Since the MGO profit from participating in the markets decreases when the RT energy market price is lower than the forecast prices in the model proposed in this paper, the worst case is defined as the case in which the lowest RT energy market price is considered. For this purpose, the relation among the considered RT energy market price, the forecast price, and the uncertainty radius ($\alpha^{\mathrm{RT\_E}}$) is defined as (62). Therefore, when the uncertainty radius is maximized as (60), the worst case is obtained for the risk-averse MGO. In the risk-taker strategy, the best objective function is obtained for the MGO. For this purpose, maximizing the uncertainty radius results in a RT energy market price higher than the forecast price, as modeled in (63).

Eqs. (64)-(67) are used to model the uncertainty of the probability of calling the reserve. Since a decrease in the probability of calling the reserve reduces the profit of the MGO, the worst case is defined as the case in which the lowest probability is obtained. Therefore, the uncertainty radius (α^{Re}) is maximized to obtain the robust objective function in this case, with respect to which the least probability of calling the reserve is obtained, as described in (66). Furthermore, Eq. (67) is used to model the risk-taker MGO facing the uncertainty of the probability of calling the reserve, since increasing this probability decreases the ETC of the MGO. It should be noted that $\xi^{\mathrm{RT\_E}}$ and ξ^{Re} are defined as the risk aversion parameters related to the RT energy market price and the probability of calling the reserve, respectively. The MGO can control its own risk level in the decision-making process by changing this parameter from 0 to 1. Moreover, both of the optimization problems described in (60)-(63) and (64)-(67) are solved considering Eqs. (7)-(25) and (31)-(59).

$$\max \ \alpha^{\mathrm{RT\_E}} \quad (60)$$

$$ETC \le ETC_b\left(1+\zeta^{\mathrm{RT\_E}}\right) \quad , \quad 0 \le \zeta^{\mathrm{RT\_E}} \le 1 \quad (61)$$

$$\lambda_t^{\mathrm{RT\_E}} \le \left(1-\alpha^{\mathrm{RT\_E}}\right)\overline{\lambda}_t^{\mathrm{RT\_E}} \quad (62)$$

$$\lambda_t^{\mathrm{RT\_E}} \le \left(1+\alpha^{\mathrm{RT\_E}}\right)\overline{\lambda}_t^{\mathrm{RT\_E}} \quad (63)$$

$$\max \ \alpha^{\mathrm{Re}} \quad (64)$$

$$ETC \le ETC_b\left(1+\zeta^{\mathrm{Re}}\right) \quad , \quad 0 \le \zeta^{\mathrm{Re}} \le 1 \quad (65)$$

$$\varphi^{\mathrm{Re}} \le \left(1-\alpha^{\mathrm{Re}}\right)\overline{\varphi}^{\mathrm{Re}} \quad (66)$$

$$\varphi^{\mathrm{Re}} \le \left(1+\alpha^{\mathrm{Re}}\right)\overline{\varphi}^{\mathrm{Re}} \quad (67)$$

The resulting mixed integer linear programming (MILP) optimization model has been implemented in GAMS 24.1.2 and it has been solved via CPLEX12 solver on a PC with 2.8-GHz Core i5 and 6 GB RAM. The model statistics contains 1910003 single equations, 846531 single variables, and 21600 discrete variables.

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V. Numerical Results

The effectiveness of the proposed model is confirmed by applying it to the 15-bus MG test system depicted in Fig. 2 [25]. The MG load (MGL) and the forecast output power of WTs and PVs are shown in Fig. 3 and Fig. 4, respectively. The bids of the DERs and their technical constraints are given in Table III [26, 27]. The bids of the RESs sent to the MGO are 2 \$/MWh. The distribution transformer capacity is 5 MVA, and the power factor of the related load consumption is assumed to be 0.95. Therefore, the maximum active power exchange of the MG with the main grid is 4.75 MW. The maximum current of the feeders is 5 kA, and the minimum and maximum limitations of the MG bus voltages are 0.36 kV and 0.44 kV, respectively. The DA and RT energy market prices and the reserve market price are shown in Figs. 5 and 6, respectively [28].

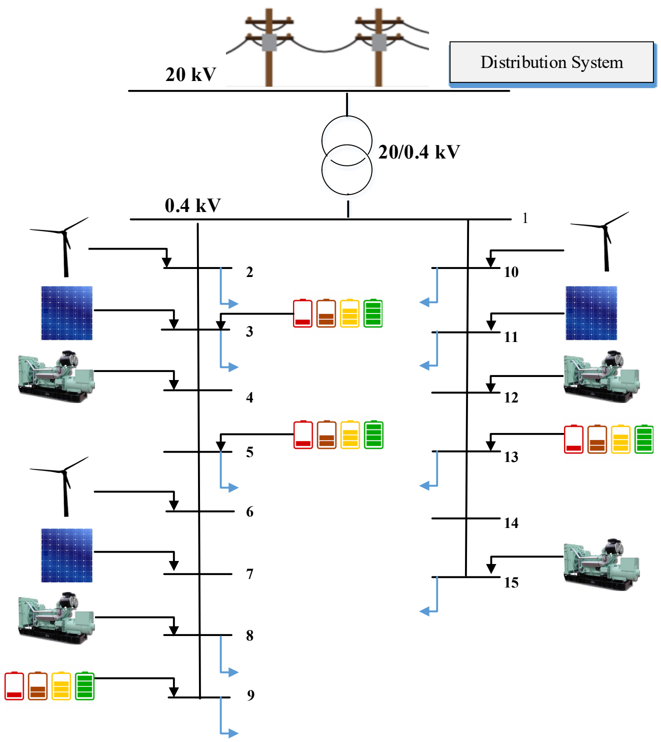

Fig. 2. The 15-bus MG structure used as the test system

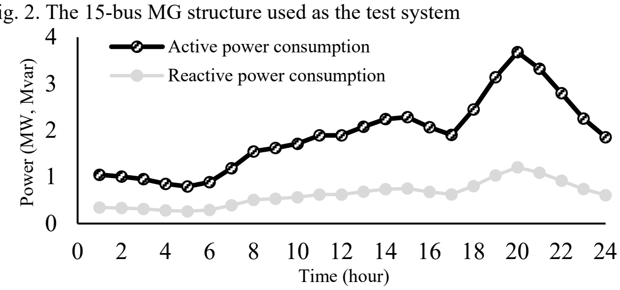

Fig. 3. The forecast MGL in the operation time period.

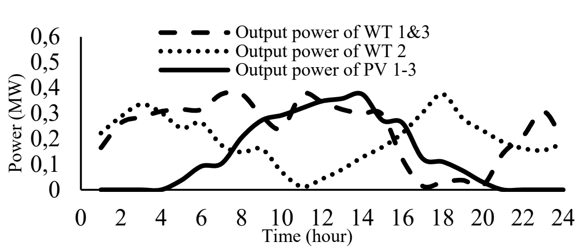

Fig. 4. The forecast output power of the RESs.

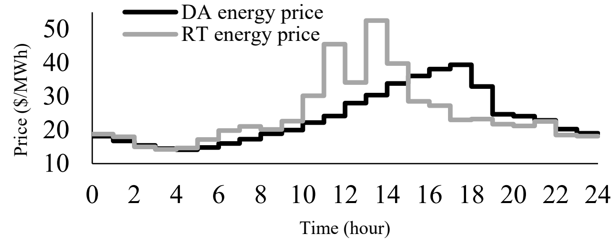

Fig. 5. The DA and RT energy markets prices

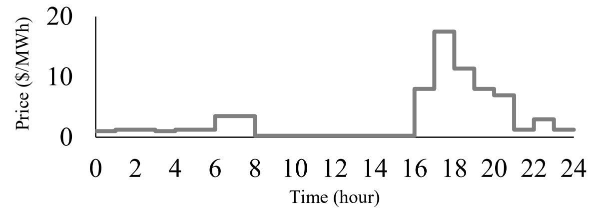

Fig. 6. The reserve market price

TABLE III. Bids and Technical Constraints of the DERs

# DG	$\overline{P}_k^{DG}$	$\underline{P}_k^{DG}$	RU_k	RD_k	P_{DG}^{ini}	C_k^{DG}	$C_k^{DG\_Re}$
1, 2	0.5	0	0.35	0.35	0	13	3.9
3, 4	0.5	0	0.30	0.30	0	10	3
# ES	$\overline{P}_e^{ch}/\overline{P}_e^{dch}$	$\underline{E}_e$	$\overline{E}_e$	η_{ch}, η_{dch}	E_e^{ini}	C_e^{ESch}/C_e^{ESdch}	$C_e^{ES\_Re}$
1, 2	0.5	1	2.5	0.95	1	2.5	0.75
3, 4	0.5	1	2.5	0.90	1	3.0	1.00

The reserve capacity deployment is set as 0.1. For the per unit calculations, the base power is $S^{base} = 1$ MVA, and the base voltages are 20 kV and 0.4 kV for the distribution system and the MG, respectively.

A. The results of the two-stage model

The results, including the MG operation cost, the optimal scheduling of the DERs, and the MGO bids in the energy and reserve markets are shown in Figs. 7-12 and Table IV. The operating cost of the MGO in the DA operation and the RT energy market for the first scenario are given in Table IV.

As shown in this table, the MGO participates in the DA energy market as a consumer, purchasing energy from the market. Also, the MGO prefers to provide the reserve capacity for the reserve market using the EESs due to their operating cost lower than the DGs. On the other hand, the MGO acts as a producer in the RT energy market, where it sells energy to this market.

In all scenarios, the operation cost of the MGO in two cases, i.e., with and without participating in the reserve market, is compared in Fig. 7. The results show that the operating cost of the MGO that participates in both the energy and the reserve markets (75.74 \$) is lower than the operating cost of the MGO that participates in the energy market only (133.76 \$).

The main reason is that the MGO can obtain revenue not only from providing the reserve capacity in the reserve market (during the first-stage decisions) but also from selling the deployment of that capacity based on the RT market price in the RT operation.

The first-stage decisions of the MGO about scheduling the MG resources as well as the bidding strategies in the DA energy and reserve markets are shown in Fig. 8 and Fig. 9. According to Fig. 8, the MGL is considerably supplied by the EESs and the energy purchased from the DA energy market.

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Note that due to the low bid of the EESs and the RESs, the MGO utilizes them either to meet the MGL during the peak-load hours (e.g., hours 18-23) or to decrease the amount of the purchased energy from the DA energy market, especially in high-price hours (e.g., 16, 17, and 19).

It is worth mentioning that the MGO deals with a challenging decision related to the scheduling of the EESs for providing energy and reserve. Therefore, using the proposed co-optimization model, the EESs are charged/discharged in an optimal way to provide both energy and reserve simultaneously.

As concluded from Figs. 8 and 9, for instance, the MGO remarkably charges the EESs in hours 6, 7, 12, and 14 to achieve two main aims. The first aim is to engage the energy stored in the EESs to meet the MGL for decreasing the energy purchased from the DA energy market in high-price hours (e.g., 16 and 17). The second aim is associated with the reserve capacity provided for the reserve market with high prices (e.g., hours 17 and 21), and with the reserve capacity deployed in the RT operation.

The MGO decisions in the RT operation in the first scenario are shown in Fig. 10. There are two main objectives for the MGO to participate in the RT energy market.

TABLE IV. THE OPERATING COST/REVENUE OF THE MG IN SCENARIO 1.

Cost/revenue of the MG in the DA operation ($)				
TC^{DA}	$C^{\mathrm{DA\_E}}$	$R^{\mathrm{DA\_Re}}$	$C^{\mathrm{DA\_DER}}$	
1014.29	1063.45	98.78	49.63	
Cost/revenue of the MG in the RT operation ($)				
$TC_{\omega}^{\mathrm{RT}}$	$C_{\omega}^{\mathrm{RT\_E}}$	$R_{\omega}^{\mathrm{RT\_Re}}$	$C_{\omega}^{\mathrm{RT\_DER}}$	
			$C_{\omega}^{\mathrm{DER\_E}}$	$C_{\omega}^{\mathrm{DER\_Re\_Dep}}$
-905.65	-1338.01	28.09	456.99	3.46

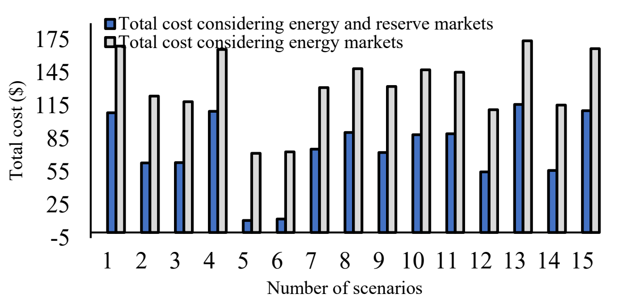

Fig. 7. Total cost of the MG operation in each scenario (TC_{ω})

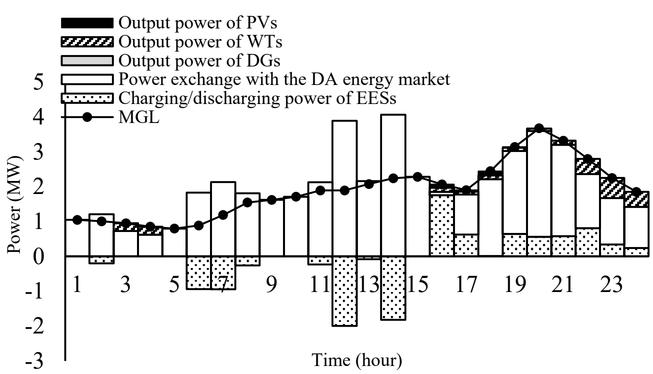

Fig. 8. Power balance in the DA energy market

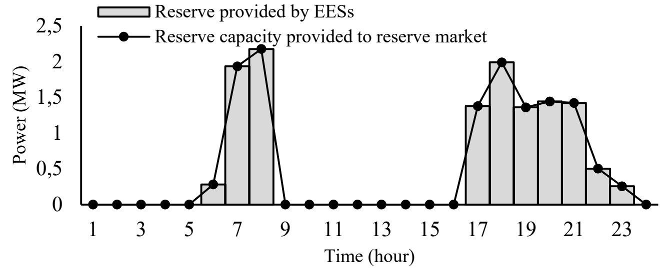

Fig. 9. The energy stored in the EESs to provide reserve capacity

At first, the MGO supplies its power balance constraint in the RT operation in the presence of the RES and demand uncertainties. Secondly, it aims at making much more revenue by selling energy to the RT market as much as possible. According to Fig. 10, it is clear that the MGO can deploy the DGs and the RESs to sell energy as a producer in the RT market at all hours.

It is worth noting that the MGO deploys all resources to sell much more energy to the RT energy market at hours 12 and 14 with the highest market prices (i.e., 45.49$/MWh and 52.54$/MWh, respectively). Moreover, the EESs have a key role in controlling the deviation of the RESs as well as the demand to sell energy to the RT market affordably.

Fig. 11 specifies the demand-supply balance in the RT operation of the MG in scenario 1. In other words, in this figure the MGO decisions about supplying the MGL are shown considering the power loss of the system.

Fig. 12 indicates the energy stored in the EESs in relation to the two-stage decision-making process during the operating time of the MG. In the first-stage decisions, the MGO charges/discharges the EESs to meet the MGL and provide the reserve capacity for the market. The second-stage decisions are made to reschedule the EESs to participate in the RT market.

B. The results for the IGDT approach

This sub-section investigates the decisions of the MGO to manage the uncertainties of the RT market price and the probability of calling the reserve using the IGDT approach. Therefore, the RT market prices are supposed to change from 70% to 130% of the forecast prices.

Note that in the range 70% to 100% of the forecast price, the MGO is a risk-averse decision-maker (Case I). Conversely, in the range 100% to 130% of the forecast price, the risk-taker MGO makes opportunistic decisions (Case II).

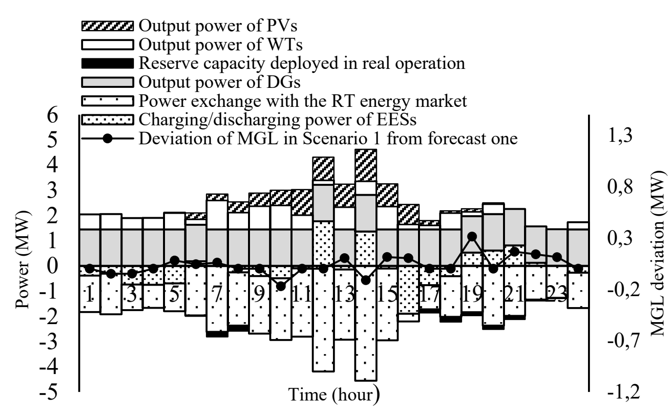

Fig. 10. The MGO decisions in the RT operation

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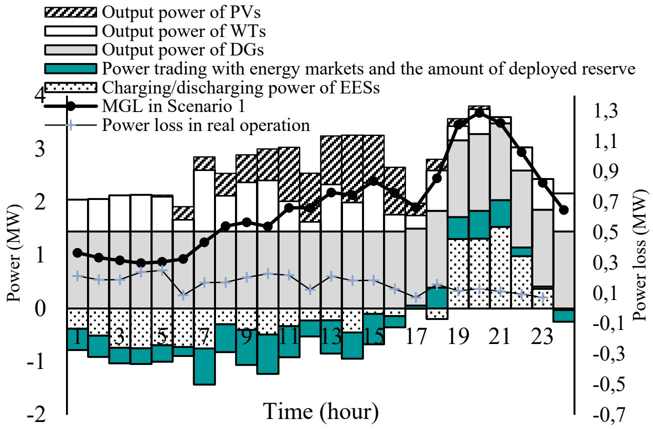

Fig. 11. The demand-supply balance in the real operation

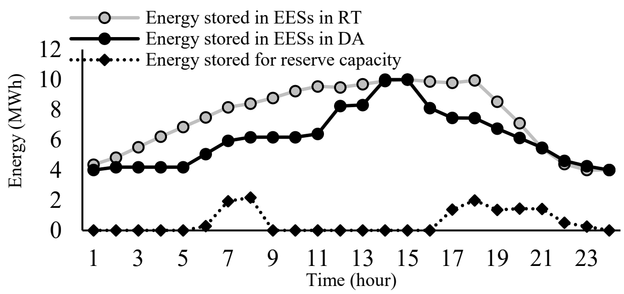

Fig. 12. The energy stored in the EESs in DA and RT operations

For the MGO with a risk-averse strategy (Case III), the probability of calling the reserve is changed from 0.1 to zero when the uncertainty radius increases from 0 to 1. Furthermore, for the risk-taker MGO (Case IV), as the uncertainty radius increases from 0 to 0.5, the probability of calling the reserve increases from 0.1 to 0.15.

In Case I, as shown in Fig. 13(a), the risk-aversion parameter (ξ) increases from 0 to 1. In other words, the risk-averse MGO assumes that the RT market price might be less than the forecast prices.

Therefore, the main findings can be summarized as follows. The uncertainty radius increases from 0 to 0.3, after which the ETC increases from 75.74$ to 252.31$ due to the reduction of the MGO revenues from selling energy to the RT market. In addition, the MGO prefers to decrease the energy sold to the RT market, with the aim of selling more energy to the DA market (from 0 to 8.49 MWh) and increasing the reserve capacity provided for the reserve market from 12.737 MW to 13.815 MW.

In Case II, as shown in Fig. 13(b), the risk-taker MGO makes decisions about the case with RT market prices higher than the forecast prices. As a result, the ETC decreases when the uncertainty radius increases from 0 to 0.3. The main reason is that the energy sold to the RT market increases from 47.673 MWh to 51.169 MWh. On the other hand, the risky MGO tends to decrease the reserve capacity from 12.737 MW to 11.087 MW.

In Case III, as reported in Fig. 13(c), risk-based decisions are made about the lower probability of calling the reserve compared to the forecast probability. In this case, the ETC of the MGO experiences an increase of 26.14$ in the worst case when the uncertainty radius changes from 0 to 1. This ETC increase occurs as the MGO sells a lower amount of the reserve deployed in the RT market. Therefore, as the uncertainty radius increases, the risk-averse MGO decides to provide less reserve capacity for the DA energy market, and the amount of the reserve capacity decreases from 12.737 MW to 8.750 MW.

The behavior of the risk-taker MGO to face the uncertainty in the probability of calling the reserve is described in Fig. 13(d). For this purpose, the uncertainty radius increases from 0 to 0.5. In this case, as the uncertainty radius increases, the risk-taker MGO increases the reserve capacity provided for the market from 12.737 MW to 13.563 MW. This decision decreases the *ETC* of the MGO from 75.74$ to 67.41$.

C. Comparison of the two-stage stochastic and IGDT-based approaches to model the uncertainty of the RT price

As mentioned before, for the parameters with high forecasting errors such as the RT energy market price, the IGDT approach is an appropriate tool to model the uncertainties. Modeling the uncertainty of the RT energy market price through the PDF can be considered another approach.

The effectiveness of the IGDT approach compared to the stochastic model to manage the uncertainty of the RT market price is investigated in this sub-section. For this purpose, the uncertainty of the RT market price is modeled using the Normal PDF. The mean value (μ) of this PDF is equal to the forecast value of the RT energy market price and its standard deviation is considered equal to the standard deviation of a uniform distribution between 70% to 130% of the forecast price, as considered in the IGDT-based model. Then, this PDF is discretized into seven equally spaced steps. The RT market price in these steps changes from 0.7μ to 1.3μ, and the corresponding probabilities are determined by considering the areas given by the Normal probability distribution around these steps.

A new two-stage stochastic model has been developed by modeling the RT market price through the mentioned Normal PDF. The results of solving this model show that the deviation of the worst case cost from the *ETC* is 124.81$. This deviation is equal to 30.35$ when modeling the RT market price uncertainty through the IGDT-based model as developed in this paper.

Therefore, in the IGDT-based model there is a lower deviation between the worst-case cost and the *ETC* than in the two-stage stochastic model. On these bases, the MGO can better manage its risk-based decisions in the worst-case scenario to address the uncertainty of the RT market price in the IGDT-based model.

Furthermore, the high deviation obtained in the two-stage stochastic model shows that when the MGO makes its decisions considering the ETC in this case, it could face a high cost deviation in the worst case.

D. Discussion of the results

The model proposed in this paper addressed two main goals for the risk-based MGO decisions in markets considering uncertainties. The following remarks on the results obtained demonstrate the effectiveness of the proposed model to achieve these goals.

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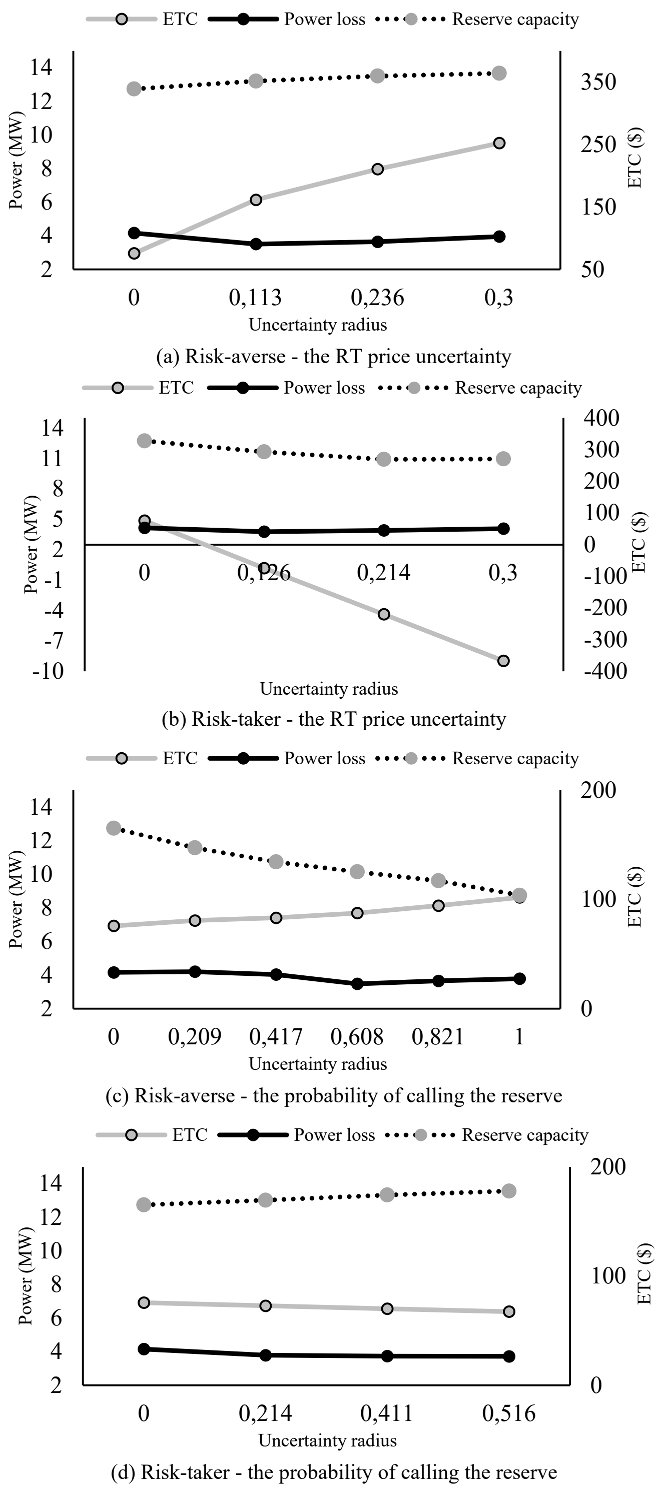

Fig. 13. The sensitivity of the MGO decisions to the uncertain parameters including the type of the risk strategy and the uncertain parameter

The first goal was to propose a new model for MGO to employ different strategies to schedule the MG resources to participate in the DA (energy and reserve) and RT energy markets. For this purpose, the MGO decides to use most of the capacity of its DGs, PVs, and WTs to sell energy to the RT energy market due to the high price in this market. In addition, the EESs are used in both the DA and the RT energy markets to minimize the operating costs of the MG. It should be noted that the EESs supply all the reserve provided by the MGO for the market. Therefore, the results show that the MGO schedules the MG resources optimally to participate in the DA energy and reserve markets as well as in the RT energy market to minimize the ETC.

The second goal was to model the risk-based behavior of the MGO to manage uncertainties (i.e., managing the RT market price and the probability of calling the reserve) by changing its strategies in the markets. The results show that the major concentration of the MGO to manage the uncertainty of the RT market price is on changing its energy sold to the RT energy market. In addition, the MGO prefers to change its reserve capacity provided for the DA reserve market when it encounters the uncertainty about the probability of calling the reserve. In both cases, the IGDT-based model aims to protect the MGO decisions against uncertainties in the worst case.

VI. Conclusions

In this paper, a two-stage stochastic optimization problem has been formulated to co-optimize the MGO bids in the DA energy and reserve markets, considering the stochastic behavior in the RT market. Moreover, the risk-based decisions of the MGO to manage the uncertainties of the RT market price and the probability of calling the reserve have been modeled using the IGDT approach. The main conclusions deriving from the application of this model to the MG test system are the following:

- Using the co-optimization of the MGO participation in the energy and reserve markets, the ETC of the MG operation undergoes a more significant reduction than for the MGO participation in merely the energy markets. The ETC decreases from 133.76$ to 75.74$.
- The proposed two-stage stochastic programming approach ensures that the MGO makes convenient two-stage decisions about the DERs as well as the bids in the DA and RT markets, taking into account the uncertainties. In other words, the MGO can control the deviations of the RESs and the MGL, satisfying the MGL and obtaining more revenue through its participation as a consumer/producer in the DA/RT markets.
- The risk-based decisions of the MGO showed that considering the RT price higher than the forecast price (risk-averse strategy), the energy sold by the MGO to the RT market decreases. To compensate the revenue reduction in the RT market, both the energy sold to the DA energy market and the reserve capacity provided for the reserve market increase. In the risk-taker strategy, the MGO sells more energy to the RT energy market and sells less reserve and energy to the DA markets.
- The risk-based behavior of the risk-averse MGO in the face of the uncertainty in the probability of calling the reserve showed that as the uncertainty radius increases, the MGO decreases the reserve capacity provided for the market. In fact, since the MGO revenues from calling the reserve in the RT market decrease as the uncertainty radius increases, the MGO prefers to provide less reserve capacity for the market. Conversely, the risk-taker MGO increases its reserve capacity for the market as the uncertainty radius increases.

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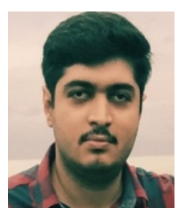
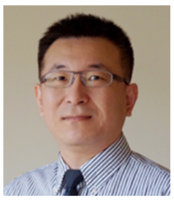
Salah Bahramara received the M.Sc. degree in electrical engineering from Tehran University in 2012 and the Ph.D. degree in electrical engineering from Tarbiat Modares University in 2016. He is currently an Assistant Professor in electrical engineering at Islamic Azad University, Sanandaj Branch, Sanandaj, Iran. His research interests include flexibility in power systems, energy management of microgrids, wholesale and local markets, and bi-level optimization.



Pouria Sheikhahmadi received the B.Sc. and M.SC. degrees in electrical engineering from University of Kurdistan, Sanandaj, Iran, in 2015 and 2018, respectively. He worked in the Kurdistan Electricity Power Distribution Company from 2019 to 2020. He is currently a Research Assistant at University of Kurdistan, Sanandaj, Iran. His research interests include electricity markets, active distribution networks, microgrids, and bi-level optimization.

Gianfranco Chicco (Fellow, IEEE) holds a Ph.D. in Electrotechnics Engineering and is a Full Professor of Electrical Energy Systems at Politecnico di Torino, Italy. He received the title of Doctor Honoris Causa from the Universities Politehnica of Bucharest and “Gheorghe Asachi” of Iasi (Romania) in 2017 and 2018, respectively. He is the Vice-Chair of the IEEE R8 Italy Section. He is the Editor-in-Chief of Sustainable Energy Grids and Networks, a Subject Editor of Energy, and an Editor the IEEE Open Access Journal of Power and Energy and IET Renewable Power Generation. He was the Conference Chair of WESC 2006, IEEE PES ISGT Europe 2017, and UPEC 2020. His research activities include Power System Analysis, Distribution System Analysis and Optimization, Electrical Load Management, Energy Efficiency and Environmental Impact of Multi-Energy Systems, Data Analytics Applied to Power and Energy Systems, and Power Quality.

Andrea Mazza (Senior Member, IEEE) graduated in Electrical Engineering (honors) at Politecnico di Torino (PdT), Torino, Italy, in 2011 and received the Ph.D. degree in Electrical Engineering from PdT in 2015. He is currently an Assistant Professor (Tenure Track) of Power and Energy Systems at PdT. His research activities include distribution system optimization, distribution system reliability and resilience, decision-making methods applied to electricity system and integration of distributed energy resources in the electricity grid. Furthermore, he works on studying the integration of Power-to-X plants in electricity systems and he is also active in the analysis of the optimal integration of different distribution networks (heat, gas, electricity) for increasing the share of renewable-based dispersed generation in the electricity distribution system.



Fei Wang (Senior Member, IEEE) received the B.Sc. degree from Hebei University, Baoding, China in 1993, the M.Sc. and Ph.D. degree in Electrical Engineering from North China Electric Power University (NCEPU), Baoding, China, in 2005 and 2013, respectively. He is currently a Professor with the Department of Electrical Engineering, NCEPU and the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, Baoding and Beijing, China. He is the Director of Institute of Power System Automation, the Director of Smart Energy Network Integrated Operation Research Center (SENIOR) and the Leader of "Double First-Class" research team project at NCEPU. He was a Visiting Professor with the Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, USA, from 2016 to 2017. He was a Researcher with the Department of Electrical Engineering, Tsinghua University, Beijing, China, from 2014 to 2016.

He is an Associate Editor of the IEEE Transactions on Sustainable Energy, the IEEE Transactions on Industry Applications, the IEEE Power Engineering Letters, the IEEE Open Access Journal of Power and Energy, the IET Renewable Power Generation, the Frontiers in Energy Research, the Protection and Control of Modern Power Systems (Springer), and the E-Prime Journal (Elsevier). He was the *Guest Editor-in-Chief* for the Research Topic "*Source-Grid-Load-Storage Collaborative and Interactive Optimization Control Technology of New Types of Active Distribution Network*" of the Frontiers in Energy Research, and the *Guest Editor* for the special issue "*Demand Side Management and Market Design for Renewable Energy Support and Integration*" of the IET Renewable Power Generation. He is an IEEE Senior Member and the Expert Member of *IEC SC8A/WG2*. He supervised more than 80 Postdocs, Ph.D. and M.Sc. students. He has authored or coauthored more than 260 publications, including 100 international journal papers.

He was the recipient of the 2021 Elsevier China Highly Cited Scholar, the *2020 Science and Technology Progress First Award* of Hebei Province, *2018 Technical Invention First Award* of Hebei Province, the *2018 Patent Third Award* of Hebei Province, the *2014 Natural Sciences Academic Innovation Achievement Award* of Hebei Province, the *2018 China Electric Power Science and Technology Progress Third Award*, and the *2014 Outstanding Doctoral Dissertation Award* of NCEPU. He was the General Chair of the 2017 International Seminar of Renewable Energy Power Forecasting and Absorption Technology and 2018 International Seminar of Integrated Energy and Smart Microgrid Technology. He was the member of Series Steering Committee and Program Committee of 1st to 5th *International Conference on Smart Energy Systems and Technologies* (SEST) from 2018 to 2022. He was also the member of Scientific Advisory Board of 14th to 17th *International Conference on Sustainable Development of Energy, Water and Environment Systems* (SDEWES) from 2019 to 2022.

His research interests include renewable energy power/electricity price/electricity load forecasting, electricity market, demand response, smart grid, microgrid and integrated energy system.

João P. S. Catalão (Fellow, IEEE) received the M.Sc. degree from the Instituto Superior Técnico (IST), Lisbon, Portugal, in 2003, and the Ph.D. degree and Habilitation for Full Professor ("Agregação") from the University of Beira Interior (UBI), Covilha, Portugal, in 2007 and 2013, respectively. Currently, he is a Professor at the Faculty of Engineering of the University of Porto (FEUP), Porto, Portugal, and Research Coordinator at INESC TEC. He was also appointed as Visiting Professor by North China Electric Power University (NCEPU), Beijing, China.

He was the Primary Coordinator of the EU-funded FP7 project SiNGULAR ("Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration"), a 5.2-million-euro project involving 11 industry partners. He was also the Principal Investigator of 3 funded projects by FCT (Portuguese National Funding Agency for Science, Research and Technology) and FEDER (European Regional Development Fund). Moreover, he has authored or coauthored more than 975 publications, including 485 international journal papers (more than 165 IEEE Transactions/Journal papers, 218 *Elsevier* and 22 *IET* journal papers), 443 international conference proceedings papers (vast majority co-sponsored by IEEE), 4 books and 43 book chapters, with an *h*-index of 77, an *i10*-index of 419, and more than 23,000 citations (according to Google Scholar), having supervised more than 110 post-docs, Ph.D. and M.Sc. students, and other students with project grants.

He was the inaugural Technical Chair of SEST 2018 — *1st International Conference on Smart Energy Systems and Technologies* (technically co-sponsored by IEEE IES), the General Chair of SEST 2019 (technically co-sponsored by IEEE PES and IEEE IES), the General Co-Chair of SEST 2020 (technically co-sponsored by IEEE PES, IEEE IES and IEEE IAS), and the Honorary Chair of SEST 2021 (technically co-sponsored by IEEE PES, IEEE IES, IEEE IAS and IEEE PELS). He was also the Editor of the books entitled *"Electric Power Systems: Advanced Forecasting Techniques and Optimal Generation Scheduling"* and *"Smart and Sustainable Power Systems: Operations, Planning and Economics of Insular Electricity Grids"* (Boca Raton, FL, USA: CRC Press, 2012 and 2015, respectively).

He is an Associate Editor of the IEEE Transactions on Systems, Man, and Cybernetics: Systems, the IEEE Transactions on Neural Networks and Learning Systems, the IEEE Transactions on Industrial Informatics, the IEEE Transactions on Intelligent Transportation Systems, the IEEE Transactions on Vehicular Technology, the IEEE Transactions on Cloud Computing, and the IEEE Transactions on Industry Applications. He was the Senior Editor of the IEEE Transactions on Smart Grid and the Promotion and Outreach (Senior) Editor of the IEEE Open Access Journal of Power and Energy, 2020-2021, being also a member of the IEEE PES Publications Board. Furthermore, he was an Associate Editor of the IEEE Transactions on Sustainable Energy, 2011-2018, an Associate Editor of the IEEE Transactions on Smart Grid, 2013-2020, an Associate Editor of both the IEEE Transactions on Power Systems and the IEEE Power Engineering Letters, 2017-2021, and an Associate Editor of both the IEEE Systems Journal and the IEEE Access, 2020-2022.

He was the *Guest Editor-in-Chief* for the Special Section on "Real-Time Demand Response" of the IEEE Transactions on Smart Grid, published in December 2012, the *Guest Editor-in-Chief* for the Special Section on "Reserve and Flexibility for Handling Variability and Uncertainty of Renewable Generation" of the IEEE Transactions on Sustainable Energy, published in April 2016, the *Corresponding/Lead Guest Editor* (*Guest Editor-in-Chief*) for the Special Section on "Industrial and Commercial Demand Response" of the IEEE Transactions on Industrial Informatics, published in November 2018, the *Guest Co-Lead Editor* for the Special Section on "Invited Papers on Emerging Topics in the Power and Energy Society" of the IEEE Open Access Journal of Power and Energy, published in October 2020, the *Guest Co-Lead* Editor for the Special Section on "Invited Papers in 2021 on Emerging Topics in the Power and Energy Society" of the IEEE Open Access Journal of Power and Energy, published in November 2021, and the *Guest Editor-in-Chief* for the Special Section on "Demand Response Applications of Cloud Computing Technologies" of the IEEE Transactions on Cloud Computing, published in March 2022.

He was the recipient of the 2011 Scientific Merit Award UBI-FE/Santander Universities, the 2012 Scientific Award UTL/Santander Totta, the 2016-2020 (five years in a row) FEUP Diplomas of Scientific Recognition, the 2017 Best INESC-ID Researcher Award, and the 2018 Scientific Award ULisboa/Santander Universities (with an Honorable Mention in 2017). He was recognized as one of the Outstanding Associate Editors 2020 of the IEEE Transactions on Smart Grid, and also one of the Outstanding Associate Editors 2021 of the IEEE Transactions on Power Systems. He has multiple Highly Cited Papers in Web of Science. He is a *Top Scientist* in Research.com, which lists only scientists having *h*-index equal or greater than 30. He is also among the *0.5% Top Scientists*, according to a study published by a team at Stanford University. Furthermore, he has won 5 *Best Paper Awards* at IEEE Conferences (MELECON, POWERENG, SEGE, EDST, SCEMS) and the MPCE *Best Paper Award* 2019. Moreover, his former M.Sc. and Ph.D. students have won the National Engineering Award in 2011, the 1st Prize in the REN (Portuguese TSO) Award in 2019, and the 1st Prize in the Young Engineer Innovation Award in 2020.

His research interests include power system operations and planning, power system economics and electricity markets, distributed renewable generation, demand response, smart grid, and multi-energy carriers.