A Novel Hybrid Two-Stage Framework for Flexible Bidding Strategy of Reconfigurable Micro-Grid in Day-Ahead and Real-Time Markets

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Abstract

Microgrids are going to be used in the future intelligent grids as a promising technology to enable widespread utilization of renewable energy sources in a high-efficient and reliable manners. It is known that reconfiguration of micro-grids, using tie-line and sectionalizing switches, can provide more operational flexibility. Additionally, coordinated scheduling of flexible loads and energy storage systems within a micro-grid can play an important role in the optimal scheduling of micro-grid; thus lowering the costs. This paper proposes an optimal bidding strategy for a micro-grid in day-ahead and real-time markets, based on AC power flow model, considering the hourly reconfiguration of the micro-grids. Fuel cell-based hydrogen energy storage and multiple shiftable loads are considered in the proposed method according to the load's activity schedule. A reconfigurable micro-grid incorporates energy production and consumption of its local components to trade power in both day-ahead and real-time markets in order to maximize its profit as a private entity. The bidding problem faces issues due to the high level of uncertainties, consisting of wind power generation and electric load as well as variations of market prices. A hybrid two-stage bi-level optimization model is proposed to manage such uncertainties so that wind power, load demand, and day-ahead market prices are handled through scenario-based stochastic programming, and an information gap decision theory is applied to model the uncertainty of real-time market prices under two strategies, namely risk-seeker and risk-averse. The numerical simulation results confirm the effectiveness of the proposed model.

Keywords- Two-stage stochastic optimization, information gap decision theory reconfigurable microgrid, demand response, hydrogen energy storage, hybrid optimization approach.

Nomenclature

Index:

t	Index of time periods
i	Index of micro-turbine (MT) units
l	Index of loads
m	Index of load type
wi	Index of wind turbines
s	Index of scenarios in the second stage
w	Index of scenarios in the first stage
b, b'	Index of electrical buses
h	Index of hydrogen storage systems
L	Index of transmission lines
lp	Index of loops

Constants:

NT	Number of time intervals
NL	Number of loads
NU	Number of MT units
NM	Number of load types
NWI	Number of wind farms
NB	Number of buses
NH	Set of hydrogen storage facility
NW	Number of scenarios in first stage
NS	Number of scenarios in second stage
NPL_{lp}	Number of lines in each loop
NCS_{lp}	Initial number of closed switches regardless of reconfiguration
k_1, k_2, k_3	Generation coefficient of wind turbine
r, c	Weibull distribution function coefficients
γ	Shiftable load factor

$DR_{l,m,s}^{\max}$	The maximum value of the shiftable load
$V^{\min}/V^{\max}$	Minimum / maximum value of bus voltage
S_L	Rated capacity of line L in kVA
S_{wi}	Rated generation capacity of wind turbine in kVA
$P_{w,i}^{R}$	Rated active power generation of wind turbine
$P_i^{\max}, P_i^{\min}$	Min/Max active power generation of MT unit i
$Q_i^{\max}, Q_i^{\min}$	Min/Max reactive power generation of MT unit i
R_i^{dn} / R_i^{up}	Ramp up/down of MT unit i
SDC_i / SUC_i	Shut-down/ Start-up cost of MT i
$Z_{b,b'}$	Ampedance of line between b and b'
$\theta_{b,b'}$	Ampedance angle of line between b and b'
$f(\varphi)$	Weibull PDF
$P_h^{P2H,\min} / P_h^{P2H,\max}$	Min/ Max of HES facility in P2H mode
$P_h^{H2P,\min} / P_h^{H2P,\max}$	Min/ Max of HES facility in H2P mode
$\eta_h^{P2H}, \eta_h^{H2P}$	P2H/H2P efficiency of HES facility
$HS_h^{\max}, HS_h^{\min}$	Max/min NG stored in NG storage system
C^{curt}	The cost of wind power curtailment
C^{dr}	The cost of DR
λ_t^{c}	Contracted power price

Variables:

F_i^{C}	Cost function of MT unit i
F_h^{HP} / F_h^{PH}	HES facility cost function in H2P/P2H mode
$SU_{i,t,w}, SD_{i,t,w}$	Start-up / Shut-down cost of MT unit i at time t in scenario w
$P_{i,t,w} / P_{i,t-1,w}$	Generated active power by MT unit i at time t / $t-1$ in scenario w
$Q_{i,t,w}$	Generated reactive power by MT unit i at time t in scenario w
$P_{h,t,w,s}^{H2P} / P_{h,t,w,s}^{P2H}$	The amount of HES facility h charging/ discharging at time t in scenario w and s
$EM_{t,w}$	Purchased active power from the DAM at time t in scenario w

$QEM_{t,w}$	Purchased reactive power from the DAM at time *t* in scenario *w*
$RM_{t,w,s}$	Purchased active power from the RTM at time *t* in scenario *w* and *s*
$QRM_{t,w,s}$	Purchased reactive power from the RTM at time *t* in scenario *w* and *s*
OF_b	Objective function
$I_{i,t,w} / I_{i,t-1,w}$	Binary on/off status of unit *i* at time t/t-1 in scenario *w*
$\lambda_{t,w}^{D}$	DAM price at time *t* and in scenario *w*
$\lambda_{t,s}^{R}$	RTM price at time *t* in scenario *s*
$d_{l,t,w,s}^{DR}$	Amount of active load *l* participate in DR at time *t* in scenario *w* and *s*
$q_{l,t,w,s}^{DR}$	Amount of reactive load *l* participate in DR at time *t* in scenario *w* and *s*
$P_{wi,t,w,s}^{curt}$	Power curtailment of wind turbine *wi* at time *t* in scenario *w* and *s*
$P_{wi,t,s}^{f}$	Wind turbine *wi* active power output at time *t* in scenario *s*
$Q_{wi,t,s}^{f}$	Wind turbine *wi* reactive power output at time *t* in scenario *s*
$PF_{L,t,w,s}$	Active power flow of line *L* at time *t* in scenario *w* and *s*
$QF_{L,t,w,s}$	Reactive power flow of line *L* at time *t* in scenario *w* and *s*
$\delta_{b,t,w}$	Voltage angle of network buses at time *t* in scenario *w*
$I_{h,t,s}^{P2H}, I_{h,t,s}^{H2P}$	Storing/Releasing rate of NG storage system at time *t* in scenario *s*
$HS_{h,t,w,s}$	Stored fuel in NG storage system at time *t* in scenario *w* and *s*
$M_{h,t,w,s}$	Amount of released hydrogen from HES facility for hydrogen-based applications in scenario *w* and *s*
$V_{b,t,w,s}$	b^{th} bus voltage at time *t* in scenario *w* and *s*

1. Introduction

1.1. Motivation

In recent years, distributed energy resources (DERs), especially renewable energy sources (RESs), have received much attention, such that total global renewable energy share can reach up to 36% by 2030 [1]. This new trend in electrical energy production, along with various loads supplied by DERs, led to the emergence of a new electrical network called microgrids (MGs). MGs are small-scale distribution network consist of multiple loads, generation units (renewable and non-renewable units), energy storage technologies, etc., controlled by the central controller to provide different goals such as reliability improvement, power loss minimization, operation cost minimization and reduction in carbon emission [2-5]. The MGs can connect/disconnect to/from the upstream grid to operate in both grid-connected and islanded modes. Furthermore, providing a flexible structure for MG can improve its benefits in both operational ways. In other words, the optimal structure can affect MG performance [6]. The control structure of MG is enabled by modifying the open or closed state of the remotely controllable switches (RCS) under the reconfiguration process. Adding the reconfiguration capability to the MG introduces the next generation of MG called reconfigurable micro-grid (RMG) that is highly regarded nowadays [7]. One of the well-known concepts for MG flexibility that facilitate the achievement of multiple goals is the demand response program (DRP). According to the Department of Energy (DOE), DPR is the modification of energy consumption to better match the demand for power with the supply [8]. Also, one of the most promising facilities to manage the electricity by fuel cells and store the excess output of RES during off-peak times is the generation and storage of hydrogen. The extra efficiency and high density of hydrogen enable the installation of fuel cell-based hydrogen energy storage (HES) in the MG, providing numerous advantages, in particular facilitation of the integrating more RES to the MG in both grid-connected and islanding modes. However, a critical issue of the associated scheduling of RMG systems integrated with RES and fuel cell-based HES considering DRP is to consider the effects of uncertainties caused by wind power, load demand, and energy price that meets the local demand while maximizing the total profit of RMG's operator.

1.2. Literature review

Many researchers have investigated the optimal scheduling of MGs in both islanded and grid-connected modes considering multiple types of RESs. The introduction of a stochastic linear programming approach for optimal scheduling of a grid-connected MG based on local environmental and economic conditions has been described in [9]. In [10], for planning and designing of RES-based MGs, a new two-stage stochastic programming has been proposed to tackle uncertainties introduced by RESs. In [11], an optimal control strategy for power flow management in MGs with energy storage systems, RESs, and electric vehicles (EVs) has been presented. Due to different types of uncertainty caused by RESs, load demand, and charging/discharging behaviors of EV, the problem has been reformulated as a stochastic chance-constrained optimization. In [12], a chance-constrained energy management model for an islanding MG has been developed following the objective of minimizing the generation cost, ESS degradation cost, and emission cost. The generated power by RES is considered as an uncertain parameter, and a novel ambiguity set has been proposed to capture the uncertainty. A hybrid robust-stochastic framework has been defined in [13] to handle the uncertainties of CHP based MG considering electrical and thermal storage systems. The authors in [14] have been studied a hybrid robust-stochastic approach for managing the uncertainty of day-ahead and real-time energy prices, as well as photovoltaic (PV) and wind power production in the optimal scheduling problem of MG.

In addition to conventional MGs scheduling, studies on RMGs as the next generation of MGs have attracted much attention over the past years. RMG is a new type of MG equipped by remotely controllable switches to provide a flexible structure [15]. In [16], MG management has been presented in a grid-connected mode using reconfiguration and unit commitment. In [6], risk-based optimal scheduling of RMG has been investigated in the presence of wind power generation. Authors in [17], have addressed the joint stochastic reserve and energy scheduling problem in MGs. The proposed approach implemented a novel energy management system making use of controlled switches. For optimal scheduling of smart neighboring RMGs, a new framework has been introduced in [18]. The proposed model provides a flexible structure for coupling the neighboring RMGs through to different connection levels. In [19], a novel robust optimization approach for the optimal design of MGS through reconfigurable topology considering uncertain parameters has been presented. The optimal chance-constrained scheduling of RMG considering the islanding operation constraints in the presence of wind, solar, and load demand uncertainties was developed by [20].

Numerous researchers have evaluated the implementation of DR on MG performance. In [21], the operation and pricing strategies with DR for the MG retailers have been investigated. The utilization of the proposed approach on real datasets, demonstrating about 6% profit gain while improving the MG reliability. An optimum economic dispatch of grid-connected MG consisting of RES in the presence of incentive-based DR has been investigated by [22]. The proposed model is implemented in two practical cases, which causes significant benefits to the MG from both supply and demand point of view. Authors in [23], have proposed the optimization modeling of dynamic price-based DR considering high penetration of RESs in a grid-connected MG. The particle swarm optimization approach is implemented to solve the optimization problem, while the uncertainty of RESs has been neglected. In [24], the effects of incentive-based DRP on the operation cost and performance of MG have been analyzed. The scenario-based approach is used to model the high-level uncertainties in MG such as transmission and upstream lines outages, RES output, and load demand. For reducing the mismatch between consumption and generation in the hybrid islanded MG including RES and storage systems, DRP has been implemented in [25]. The utilization of DRP led to a reduction in the number of installed batteries and PV panels as well as net present cost. Authors in [26], have analyzed the effects of RES forecasting and its uncertainties on the economic dispatch problem of islanded MG considering DRP. The utilization of the proposed approach shows a 3% increase in the MG dispatch costs because of the forecast uncertainty. In [27, 28], a smart MG scheduling consisting of renewable units and controllable loads has been studied. The responsible loads can participate in DR programs based on time-of-use (TOU) and real-time pricing (RTP) schemes.

Due to the limited life cycle, high cost and restricted operating conditions, batteries energy storage may not be the most impressive method for large scale applications. Hydrogen-based power storage is continually achieving more recognition as a visible alternative. HES as another large-scale storage facility similar to the compressed air energy storage (CAES) and pump storage has an important role in enhancing the balance between consumption and generation [29]. A novel remote monitoring framework for smart MG integrated with RES and hydrogen has been introduced in [30] for improving the operation of MG and provide effective real-time monitoring. A real-time energy management strategy for a RES and hydrogen-based MG has been presented in [31], where the operation cost of the MG is minimized. The optimal energy and reserve management of grid-tied MGs integrated by PV, wind, fuel cell-based hydrogen storage/production have been presented in [32]. The fluctuations of load and RES power output are incorporated by assuming a known probability distribution function (PDF). A multi-scenario, chance-constrained, and tree-based model predictive control (MPC) strategy for a hydrogen-based MG has been designed in [33]. In [34], an optimal load sharing of RES/ hydrogen-based MG integrated with a hybrid energy storage system has been developed. In [35], a novel energy management of islanded MG equipped with RES, electrical storage, and hydrogen production/ storage has been presented. The intermittency of load demand and RES are considered as uncertain parameters which are addressed by the stochastic approach.

The increasing penetration of renewable energy generation units (such as wind power) into the MG and other renewable sources with probabilistic nature, as well as load fluctuation, led to more complexity of MG scheduling. To deal with the uncertainties of RES and load demand in MG, multiple studies have been investigated. Authors in [36], have presented a two-stage adaptive robust optimization approach for scheduling of grid-connected MG considering the RES uncertainty. In [37] the problem of MG optimal scheduling in the presence of multiple uncertainties caused by RES power output, electrical vehicle behavior, and load demand has been reformulated as a stochastic chance-constrained optimization model. For handling the uncertainty in the MG scheduling problem, a scenario-based robust energy management has been introduced in [38]. By optimizing the worst-case scenario, the MG performance will become robust against the possible realization of uncertain parameters. Due to the intermittent nature of RESs and its effects on the hybrid MG performance, a scenario-robust mixed-integer linear programming has been presented in [39, 40]. To capture the uncertainty of RES in the islanded MG, a novel ambiguity set with no information about the probability distribution has been introduced in [41]. The proposed method is reformulated as a tractable second-order conic programming.

However, due to the lack of sufficient information about uncertain input parameters, they cannot be described using PDF. The information gap decision theory (IGDT) is an approach to handle uncertainties in such a situation. The IGDT method is used to make risk-seeker (RS) and risk-averse (RA) decision against severe uncertainty of input parameters. This approach has been widely used by researchers in various problems, including power and natural gas integration, electric vehicle (EV) management, biding strategy of combined heat and power (CHP) unit, security-constrained unit commitment (SCUC) etc. [42-49]. A non-probabilistic decision-making based on the IGDT approach for a CHP unit to participate in day-ahead market has been presented in [44]. In [45], the IGDT-based optimal robust scheduling of integrated natural gas and electricity networks in the presence of CAES and DR has been presented. To manage the revenue risk of EVs aggregator and restraining the system in confronting different uncertain parameters (such as energy price and RES power output), the IGDT approach has been utilized in [47]. In [48], the integration of electric and natural gas systems considering power price uncertainty handled with the IGDT approach has been proposed. The main objective of the method presented is to minimize the operation cost while satisfying the interdependency constraints between electricity and natural gas networks. In

[49], a multi-objective IGDT model has been introduced to provide a flexible risk-based bidding strategy for an MG, where the uncertainties related to the power price and electric load are managed effectively in both robust and opportunistic frameworks.

1.3. Contribution

The major gaps in the reviewed literature can be summarized as follows:

- In some literature e.g. [2-5, 8-13, 49], the bidding strategy problem of MG has been solved without considering dynamic reconfiguration capability. These studies have ignored the role of tie-line and sectionalizing switches in the reduction of power losses and the energy purchase cost from the power market, as well as more appropriate management of the uncertainties in real-time dispatch.
- In most of the studies e.g. [6-20, 49], the effect of the MG participation in both day-ahead and real-time markets has not been considered simultaneously. This issue leads to a reduction in decision-making flexibility and the profit of the MG operator.
- Although in a few studies e.g. [18-26[49], the effect of flexible loads on the MG profit has been evaluated, the activity intervals of such loads based on their type have been ignored. Not paying attention to such an issue does not provide a realistic scheduling model.
- Most of the reviewed literature e.g. [13-46, 49], has only applied one of the stochastic or robust optimization approaches to handle the uncertainty of system, while the MG operator is reluctant to employ an identical conservatism level to manage system uncertainties.

To cover these challenges, this paper develops the optimal bidding strategy problem of MG in both day-ahead and real-time by presenting a novel hybrid two-stage bi-level optimization framework for achieving high flexibility in the MG. Additionally, the HES facility and multiple shiftable loads according to their activity interval are integrated into the introduced strategy to make a high-performance and smarter MG considering the dynamic reconfiguration capability of the grid. In addition, an AC-power flow model is considered to realize the constraints of RMG in detail. The RMG consists of local energy production and consumption components, which can buy electricity in both day-ahead and real-time markets and utilize the distributed energy resources under its ownership to maximize its profit as a private company. Table I shows the contributions of the proposed model compared with other works. The main contributions of this paper can be summarized as follows:

1- Presenting an optimal bidding strategy problem for an MG to participate in both real-time and day-ahead markets considering dynamic reconfiguration capability.
2- Considering the energy smart technologies such as the HES facility and DRP to improve flexibility and profit of MG. The fuel-cell based HES is introduced as a high-efficiency storage facility, which is effective in managing the on-peak condition of the power price.
3- Modelling shiftable loads based on their activity intervals in DRP. This pattern leads to solving a more accurate day-ahead scheduling problem to attain more dependable results.
4- Proposing a two-stage bi-level optimization framework to handle the uncertainties of RMG in both day-ahead scheduling and real-time dispatch and achieving more reliability for MG operator. The presented hybrid optimization model considers the benefits of the scenario-based stochastic approach and IGDT model, simultaneously.
5- The uncertainties of the power output of wind turbine, electrical demand, and the day-ahead market (DAM) price are modeled as scenario-based stochastic programming, while an IGDT is utilized to manage the uncertainty of real-time market (RTM) price under two strategies of RS and RA without the need for PDF.

Table I. Comparison of main contributions with literature review.

Ref	Modeling the constraints of network	Reconfiguration capability	DR	Activity interval of loads based on their type	Real-time market	Uncertain parameters	Modeling the uncertainties
[8]	DC-power flow	No	Yes	No	No	Wind, PV and load	Stochastic
[13]	———	No	No	No	No	Load, energy price	Hybrid robust/stochastic
[14]	———	No	No	No	Yes	Wind, PV, day-ahead and real-time energy prices	Hybrid robust/stochastic
[15]	AC-power flow	Yes	No	No	No	Wind, PV, load, energy price	Stochastic
[19]	AC-power flow	Yes	No	No	No	Wind, PV, load, energy price	Robust
[28]	AC-power flow	Yes	Yes	Yes	No	———	Deterministic
[40]	AC-power flow	No	No	No	No	Wind, PV, load, energy price	Robust
[42]	———	No	Yes	No	No	Load	IGDT
[43]	AC-power flow	No	Yes	No	No	Energy price and load	IGDT
[49]	———	No	Yes	No	No	Energy price and load	IGDT
Proposed model	AC-power flow	Yes	Yes	Yes	Yes	Wind, load, day-ahead and real-time energy prices	Hybrid two-stage IGDT/stochastic

2. Problem description

2.1 MG components

This paper proposes an MG with reconfiguration capability that includes renewable resources, conventional units, a number of residential and commercial buildings with associated loads, hydrogen-based energy storage technology. Renewable units include wind turbines, and conventional producing units are introduced as non-renewable generating units such as micro-turbines (MTs). The MG loads are divided into two separate types, flexible and non-flexible loads. Flexible loads are scheduled based on their activity plan to maximize the profit of MG. The hydrogen storage system is also introduced as a viable option to reduce energy purchases during peak hours, which leads to an increase in the MG profit. Reconfiguration capability of the MG creates another suitable opportunity to increase the MG profit and reduce the energy purchase cost from the electricity market by reducing the power losses.

It is also worth noting that the reconfiguration has been well used for a variety of purposes, worldwide. In real-world applications, a computational tool for automatic reconfiguration process in modern distribution systems based on smart grid concepts has been developed for real-time and short-term reconfiguration. In such a situation, the functionality and information of remote controller components like remote-controllable switches installed in MGs were implemented in a computer system aiming to enable reconfiguration in normal conditions. For example, an automatic reconfiguration based on smart grid concepts has been investigated by [50], tested on the real power utility of Brazil. The common types of devices including Re-closer, automatic Sectionalizes, and remotely controllable switches, are embedded in the utility. Each switching necessary for optimal reconfiguration is analyzed from network constrains point of view at each time period. Another reconfiguration application in the real world is related to automatic network reconfiguration at Split Airport where remote control and supervision ABB's RTU540 and PLC modules function were installed [51]. Considering all system restrictions, automatic reconfiguration via installed devices to find optimal configuration, and diminish a power failure is applied. More information about the real-world application and automatically installed devices can be found in [52]. It should be noted that switching can cause transient effects on any horizon and situation. Therefore, to control the transient effect, appropriate dynamic stability tools like dampers and filters can be used. It should be mentioned that the proposed method is for fully automated smart MGs that facilitate daily reconfiguration.

2.2 Market model

Everyday the MG should submit its hourly bids through forecasting electricity prices into the DAM several hours before energy delivery. The MG can appear in the power market as a seller and buyer. However, in this paper, the MG operator prefers to participate in the power market as the buyer due to the high loading profile in peak-price hours. Also, the MG can participate in the RTM to cover the part of the demand due to the power deviation from the day-ahead schedule. It is the typical approach that the MG submits buying bids at high prices to assure that its submitted demand is accepted in the market. So, the bidding strategy of the MG will be optimized if the submitted demand under an accurate optimization approach is calculated. The market operator is liable for determining the market clearing prices after receiving all offers and bids from all market players [53, 54]. The power exchange between the MG and the market operator is determined based on the market-clearing prices. These prices can be predicted by the MG operator since the MG is considered as a price-taker in the electricity market due to the small size, so the amount of its demand doesn't affect the market-clearing price [14].

2.3 Decision-making framework

The main purpose of the proposed problem is to maximize the profit of the RMG operator by participating in day-ahead and real-time markets and utilizing its own distributed energy resources. The introduced model may be understood as a three-stage programming model [55]. Based on the proposed model shown in Fig. 1, in the first stage, the MG bids its power demand to the DAM while the day-ahead and real-time energy market prices, electric loads, and output of wind power have not yet been realized by scenarios. In the second stage, the scenarios associated with the DAM are realized and DAM prices are considered as pre-specified. The output of wind power and electric loads are also achieved by different scenarios right before the RTM clearing at each hour. The MG operator provides a balance between production and consumption, considering installed technologies and purchased electricity from the RTM under various scenarios of wind power and electric load. This step is carried out and the needed demand value from the RTM is obtained before the RTM is implemented. In the third stage, the RTM price is realized using the IGDT approach, and the RTM supplies the unbalanced power. Since no decisions are made in the third stage, the three-stage programming model turns into a two-stage programming model [14, 55].

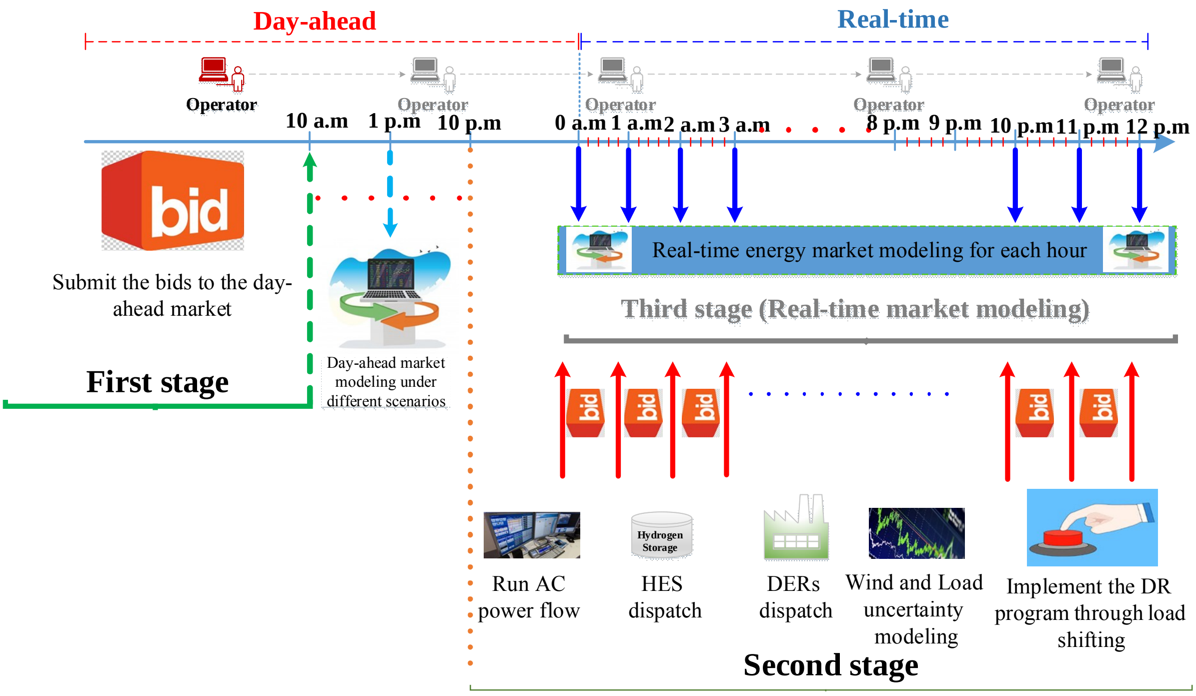

Fig. 1. The structure of the proposed three-stage model.

3. Problem formulation based on two-stage stochastic programming

A. Objective function

The objective of the proposed model is to maximize the profit of the RMG in a day-ahead scheduling framework. The formulated function under the two-stage stochastic programming is as (1), where the first stage includes the cost of power purchase from DAM. On the other hand, the second stage contains the production cost of energy sources owned by the MG operator and the cost of power purchase from the RTM.

$$\begin{aligned} OF_b = max \sum_{w=1}^{NW} \pi_w \Bigg[& -\sum_{t=1}^{NT} \lambda_{t,w}^{D} EM_t + \sum_{s=1}^{NS} \pi_s \Bigg(\sum_{t=1}^{NT} \sum_{l=1}^{NL} \lambda_t^{C} d_{l,t,w,s}^{DR} - \sum_{t=1}^{NT} \lambda_t^{R} RM_{t,w,s} \\ & - \sum_{t=1}^{NT} \sum_{i=1}^{NU} \left(C(P_{i,t,w,s}) + SU_{i,t,w,s} + SD_{i,t,w,s} \right) - \sum_{t=1}^{NT} \sum_{h=1}^{NH} \left(F_h^{HP}(P_{h,t,w,s}^{H2P}) + F_h^{PH}(P_{h,t,w,s}^{P2H}) \right) \\ & - \sum_{t=1}^{NT} \sum_{l=1}^{NL} \sum_{m=1}^{NM} C^{dr} \left| dr_{l,m,t,w,s} \right| - \sum_{t=1}^{NT} \sum_{wi=1}^{NWI} C^{curt} P_{wi,t,w,s}^{curt} \Bigg) \Bigg] \end{aligned} \quad (1)$$

The first term in (1) refers to the purchased power cost from the DAM. Oppositely, the revenue obtained from power sold to the contracted customers is represented by the second term. The third term of objective function relates to the purchased power cost from the RTM. The operation cost of the gas-fired based MT is signified by the fourth term. The fifth term deals with the HES charging and discharging. The cost of incentive-based DR is given by the sixth term. The last line in (1) deals with wind power curtailment cost. The purchased power from the DAM (EM_t) is considered as *"here and now"* variable, and demand supplied by MG operator ($d_{l,t,w,s}^{DR}$), the purchased power from RTM ($RM_{t,w,s}$), the power generated by MTs ($P_{i,t,w,s}$), startup/shutdown costs of units ($SU_{i,t,w,s}/SD_{i,t,w,s}$), charge and discharge power of HES ($P_{h,t,w,s}^{P2H}$ and $P_{h,t,w,s}^{H2P}$), the scheduled flexible load ($dr_{l,m,t,w,s}$) and wind power curtailment ($P_{wi,t,w,s}^{curt}$) are stated as *"wait and see"* variables.

B. MTs constraints

The set of constraints related to MTs operation are represented by (2)-(9). The active and reactive power output limits are respectively expressed in (2) and (3). The up and down ramp rate limitations for consecutive intervals are established by constraints give in (4) and (5), respectively. The MT unit must be turned on/off for a certain time before it can start-up or shut-down which are expressed as a minimum up and down-time, respectively represented by constraints in (6) and (7). The constraints in (8) and (9) represent the start-up and shut-down cost limits.

$$P_i^{\min} I_{i,t,w,s} \le P_{i,t,w,s} \le P_i^{\max} I_{i,t,w,s} \tag{2}$$

$$Q_i^{\min} I_{i,t,w,s} \le Q_{i,t,w,s} \le Q_i^{\max} I_{i,t,w,s} \tag{3}$$

$$P_{i,t,w,s} - P_{i,t\text{-}1,w,s} \le \left[1 - I_{i,t,w,s}(1 - I_{i,t-1,w,s})\right] R_i^{up} + I_{i,t,w,s}(1 - I_{i,t-1,w,s}) P_i^{\min} \tag{4}$$

$$P_{i,t-1,w,s} - P_{i,t,w,s} \le \left[1 - I_{i,t-1,w,s}(1 - I_{i,t,w,s})\right] R_i^{dn} + I_{i,t-1,w,s}(1 - I_{i,t,w,s}) P_i^{\min} \tag{5}$$

$$(X_{i,t-1,w,s}^{on} - T_i^{on})(I_{i,t-1,w,s} - I_{i,t,w,s}) \ge 0 \tag{6}$$

$$(X_{i,t-1,w,s}^{off} - T_i^{off})(I_{i,t,w,s} - I_{i,t-1,w,s}) \ge 0 \tag{7}$$

$$SU_{i,t,w,s} \geq SUC_i \left(I_{i,t,w,s} - I_{i,t-1,w,s} \right)$$
$$SU_{i,t,w,s} \geq 0 \tag{8}$$

$$SD_{i,t,w,s} \geq SDC_i \left(I_{i,t-1,w,s} - I_{i,t,w,s} \right)$$
$$SDC_{i,t,w,s} \geq 0 \tag{9}$$

C. HES constraints

The HES cannot be operated in both hydrogen-to-power and power-to-hydrogen modes simultaneously which is stated as (10). The charging and discharging powers are bounded by the upper and lower limits in each scenario, as shown in constraints (11) and (12), respectively. The amount of energy stored in HES at the t^{th} time and the s^{th} scenario, as dictated in (13), is calculated by considering remaining energy level from previous time plus/minus the charging/discharging power and hydrogen applied in other energy applications in current time. It is noticeable that since capacity of HES is expressed in kilowatt-hours (kWh), the hydrogen used in other energy applications is also stated in kWh. The limitation of stored energy level at the t^{th} time and the s^{th} scenario is expressed by constraint in (14). In addition, the constraint in (15) represents the limit related to equality of initial and final value of stored energy level at the t^{th} time and the s^{th} scenario.

$$I_{h,t,w,s}^{P2H} + I_{h,t,w,s}^{H2P} \leq 1 \tag{10}$$

$$P_h^{P2H,\min} I_{h,t,w,s}^{P2H} \leq P_{h,t,w,s}^{P2H} \leq P_h^{P2H,\max} I_{h,t,w,s}^{P2H} \tag{11}$$

$$P_h^{H2P,\min} I_{h,t,w,s}^{H2P} \leq P_{h,t,w,s}^{H2P} \leq P_h^{H2P,\max} I_{h,t,w,s}^{H2P} \tag{12}$$

$$HS_{h,t,w,s} = HS_{h,t\text{-}1,w,s} + \eta_h^{P2H} P_{h,t,w,s}^{P2H} - \frac{P_{dis,t,s}^{H2P}}{\eta_h^{H2P}} - M_{h,t,w,s} \tag{13}$$

$$HS_h^{\min} \leq HS_{h,t,w,s} \leq HS_h^{\max} \tag{14}$$

$$HS_{h,0,w,s} = HS_{h,24,w,s} \tag{15}$$

D. Demand response constraints

Generally, the DR programs are categorized into two groups: the price-based DR and the incentive-based DR. The characteristics and behavior of residential and commercial consumers for participating in DR programs are different which are mainly rooted in the time of activity and customer's tendency for participating in DR programs. Hence, in this paper, an incentive-based program through shifting capability of loads is considered. The system includes both residential and commercial consumers. Based on their activity plan, the MG operator can schedule the shiftable loads during the time horizon. The constraint in (16) expresses the consumption value after the implementation of DR program. The total amount of load shedding at the current time must be shifted to other intervals and is represented by constraint (17). The amount of shiftable load is bounded by the maximum value as dictated in constraint (18), where the maximum value is calculated using (19). Finally, (20) represents the relationship between the active and reactive load consumption participating in the DR.

$$d_{l,t,w,s}^{DR} = d_{l,t,s} + \sum_{m=1}^{NM} dr_{l,m,t,w,s} \tag{16}$$

$$\sum_{t=t_m}^{NT_m} dr_{l,m,t,w,s} = 0 \tag{17}$$

$$\left| dr_{l,m,t,w,s} \right| \le DR_{l,m,s}^{\max} \tag{18}$$

$$DR_{l,m,s}^{\max} = \gamma\, d_{l,t,s} \tag{19}$$

$$q_{l,t,w,s}^{DR} = \tan\phi\; d_{l,t,w,s}^{DR} \tag{20}$$

E. Wind power generation

The generated power by WT depends on wind speed and due to its probabilistic nature, the power output of WT is significantly fluctuating. To model the uncertainty of wind speed, the scenario-based stochastic approach is used. As [6, 16], it is assumed that wind speed is subjected to the Weibull distribution and the Weibull density function is calculated using (21). The power generated by WT as a function of wind speed is expressed by (22) and, (23) expresses the relationship between the active and reactive power output. A part of the wind power generation can be curtailed (spilled) but based on (24), this value could not exceed the actual wind generation at each scenario.

$$f(\varphi)=\frac{r}{c}\left(\frac{\varphi}{c}\right)^{r-1}\exp\left[-\left(\frac{\varphi}{c}\right)^{r}\right] \tag{21}$$

$$P^{f}_{wi,w,t,s}=\begin{cases}0 & 0\le \varphi_{wi,w,t,s}\le \varphi_{cut-in}\\ (k_1+k_2\varphi_{wi,t,s}+k_3\varphi^2_{wi,t,s})P^R_{wi} & \varphi_{cut-in}\le \varphi_{wi,w,t,s}\le \varphi_{rated}\\ P^R_{wi} & \varphi_{rated}\le \varphi_{wi,w,t,s}\le \varphi_{cut-out}\\ 0 & \varphi_{cut-out}\le \varphi_{wi,w,t,s}\end{cases} \tag{22}$$

$$(P^{f}_{wi,t,s}-P^{curt}_{wi,t,w,s})^2+(Q^{f}_{wi,t,w,s})^2\le S^2_{wi} \tag{23}$$

$$P^{curt}_{wi,t,w,s}\le P^{f}_{wi,t,w,s} \tag{24}$$

F. Power flow constraints of reconfigurable MG

The limits of active and reactive power balance are respectively expressed by (25) and (26). The AC power flow calculations are given in (27) and (28), and the amount of power that flows in each line should be restricted by rated value, expressed by constraint in (29). The node voltages must be bounded by minimum and maximum values, expressed in (30). As discussed previously, reconfiguration is the process of changing the topology of MG by modifying the open and close states of multiple switches. At each time, the radial structure of RMG should be established. Therefore, the optimal structure obtained should not contain any loops. For this purpose, the number of open switches after reconfiguration, at each time and in each scenario, must be equal to the initial number of open switches, as expressed in (31), where, NCS_{lp} denotes the initial number of closed switches in each loop (*lp*) without reconfiguration capability. In this situation, equation (32) satisfies the radial constraint and prevent making any loop in the topology, where NPL_{lp} denotes the number of power lines in each loop. It should be noted that since finding the loops in the RMG is done offline and only once after the equipment has been installed, therefore, in this paper, loops that may be created in the optimal structure are already known. The limitation of switching in the whole scheduling horizon is defined as (33), where $K_{L,t,w,s}$ is a variable binary that shows the state of open and closed switches during the reconfiguration process. N_L^{Swich} is the maximum number of switching actions in the whole scheduling horizon that is assumed to be 6 in this paper.

$$EM_t + RM_{t,w,s} + \sum_{i=1}^{NU_b} P_{i,t,w,s} + \sum_{wi=1}^{NWI} P^f_{wi,t,w,s} + \sum_{h=1}^{NH_b} P^{H2P}_{h,t,w,s} - \sum_{h=1}^{NH_b} P^{P2H}_{h,t,w,s} - \sum_{l=1}^{NL} d^{dr}_{l,t,w,s} = \sum_{L=1}^{NLI_b} PF_{L,t,w,s} \quad (25)$$

$$QEM_t + QRM_{t,w,s} + \sum_{i=1}^{NU_b} Q_{i,t,w,s} + \sum_{wi=1}^{NWI} Q^f_{wi,w,t,s} - \sum_{l=1}^{NL_b} Q^{dr}_{l,t,w,s} = \sum_{L=1}^{NLI_b} QF_{L,t,w,s} \quad (26)$$

$$PF_{L,t,w,s} = \left(\frac{V^2_{b,t,w,s}}{Z_{b,b'}} \cos(\theta_{b,b'}) - \frac{V_{b,t} V_{b',t,w,s}}{Z_{b,b'}} \cos(\delta_{b,t} - \delta_{b',t} + \theta_{b,b'}) \right) K_{L,t,w,s} \quad (27)$$

$$QF_{L,t,w,s} = \left(\frac{V^2_{b,t,w,s}}{Z_{b,b'}} \sin(\theta_{b,b'}) - \frac{V_{b,t} V_{b',t,w,s}}{Z_{b,b'}} \sin(\delta_{b,t} - \delta_{b',t} + \theta_{b,b'}) \right) K_{L,t,w,s} \quad (28)$$

$$PF^2_{L,t,w,s} + QF^2_{L,t,w,s} \le S^2_L \quad (29)$$

$$V_b^{\min} \le V_{b,t,w,s} \le V_b^{\max} \quad (30)$$

$$\sum_{L=1}^{NLI_{lp}} K_{L,t,w,s} = NCS_{lp} \quad (31)$$

$$\sum_{L=1}^{NLI_{pl}} K_{L,t,w,s} \le NPL_{lp} - 1 \quad (32)$$

$$\sum_{t=1}^{NT} \left| K_{L,t,w,s} - K_{L,t-1,w,s} \right| \le N_L^{Swich} \quad (33)$$

3. Proposed hybrid stochastic-IGDT framework

In this paper, a novel hybrid model is utilized for modeling the uncertainty of the predicted electricity demand, wind power, DAM and RTM prices in the bidding strategy problem of the RMG which is formulated as a two-stage bi-level optimization problem. The decision structure of the proposed model to handle the uncertainties is illustrated in Fig. 2. In the proposed model, the MG can participate in the RTM to increase its flexibility and achieving more profit. Variations of RTM price play an important role in the submitted bids of the MG operator to the DAM. Since the RTM prices mainly depend on unpredictable market conditions; this issue makes it hard to be achieved by its stochastic process in day-ahead scheduling [14, 55]. Therefore, in this paper, the uncertainty of the power price in the RTM is achieved through the IGDT-based non-probabilistic method, while the forecasted electricity demand, wind power, and DAM price are modeled based on Monte Carlo simulation.

The safe region established by IGDT technique cannot be always increased as much as feasible. There are various obstacles that affect the management level of system uncertainty. IGDT method trends to maximize the system resistance level against the existing uncertainties while satisfying the other goal that can limit the increment of robustness level. For instance, consider a bidding strategy problem for an MG that participates in the power market as a buyer to supply demand. If the power price is described as an uncertain parameter, the MG operator should increase its operating budget to be robust versus the possible increment in the power price. The budget limitation is an effective factor that can affect decision-maker strategies against the power price uncertainty .

The IGDT-based technique is known as a bi-level optimization problem, where both the uncertainty set and operator profit should be maximized simultaneously [44, 45]. In the proposed model, the RTM price forecasting error radius is maximized in the upper level, while in the lower level, a two-stage stochastic problem is solved to maximize the operator profit. Hence, the mentioned model is formulated as a two-stage bi-level optimization problem.

The IGDT approach has some benefits compared with the stochastic programming and robust optimization, which can be categorized as follows [45]:

1. The IGDT unlike the stochastic programming, does not need a PDF to handle the uncertain parameters of the problem.

2. In stochastic optimization, problem-solving time is high due to the generation of various scenarios. While the solving-time of problems that use the IGDT approach is less due to a lack of scenarios.

3. Compared to the robust optimization including only one RA strategy for an uncertain parameter, the IGDT model studies two RA and RS approaches that enhance the decision-making range of the RMG operator. Besides, in robust optimization, the uncertainty radius of the uncertain parameter is specified before the problem solving, while in the IGDT approach this radius is determined after the optimization problem-solving process.

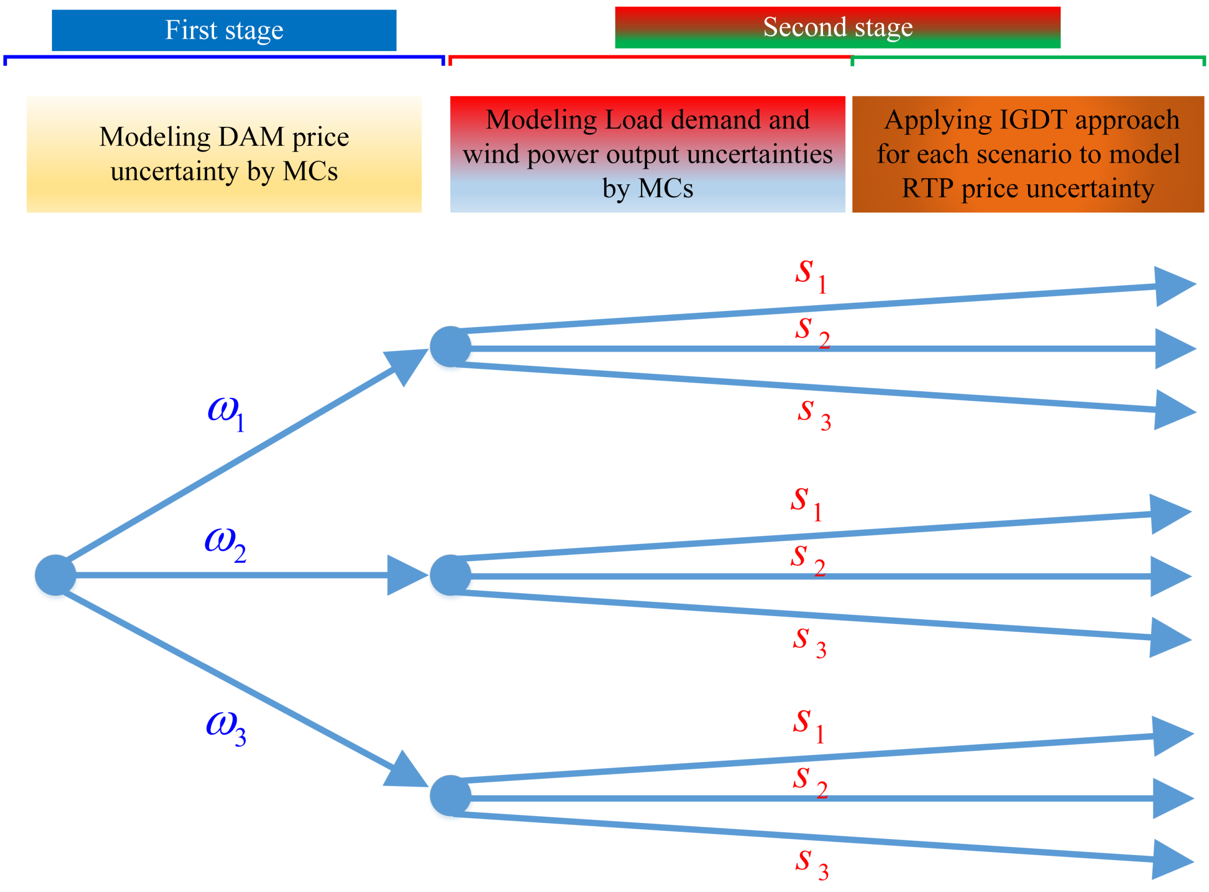

Fig. 2. The decision structure of the proposed hybrid optimization model to handle the uncertainties

3.1 Mathematical description of IGDT technique

The uncertainty in an optimization problem is expressed as (33), where the forecasted value of uncertain parameter is shown by $\bar{\Psi}$. The ε is the maximum permissible variation of an uncertain parameter from its forecasted value, which is defined as the unknown uncertainty radius of decision-maker.

$$U = U(\bar{\Psi}, \varepsilon) = \left\{ \Psi : \left| \frac{\Psi - \bar{\Psi}}{\bar{\Psi}} \right| \leq \varepsilon \right\} \tag{34}$$

In the IGDT model, both RS and RA approaches are considered which are defined using (35) and (36), respectively, where Δ_C^r and Δ_C^o are the satisfactory values of the objective function depending on β_r and β_ρ, which are obtained by the decision maker. β_r is the robustness level against the increment of the objective function concerning the basic condition value (OF_b). β_ρ is the opportuneness level against the decrease of the objective function with respect to the basic condition value.

$$\alpha_r(X, \Delta_C^r) = \max\left\{ \varepsilon : \left(\min_{\Psi \in U(\bar{\Psi}, \varepsilon)} OF \geq \Delta_C^r = (1 - \beta_r) OF_b \right) \right\} \tag{35}$$

$$\alpha_\rho(X, \Delta_C^o) = \min\left\{ \varepsilon : \left(\max_{\Psi \in U(\bar{\Psi}, \varepsilon)} OF \geq \Delta_C^o = (1 + \beta_\rho) OF_b \right) \right\} \tag{36}$$

3.2 Mathematical model of proposed two-stage bi-level framework

In the RA approach, the uncertain parameter has an unfavorable impact on the objective function. Hence, in this approach, the RMG operator considers a lower profit due to the unfavorable variation of the RTM price from its predicted value. It is provided by (37)-(41) as a two-stage bi-level optimization problem.

$$\alpha_r = \max \ \varepsilon \tag{37}$$

$$\begin{aligned}
\min \sum_{w=1}^{NW} \pi_w \Bigg[& -\sum_{t=1}^{NT} \lambda_{t,w}^{D} EM_t + \sum_{s=1}^{NS} \pi_s \Bigg(\sum_{t=1}^{NT} \sum_{l=1}^{NL} \lambda_t^C d_{l,t,w,s}^{DR} - \sum_{t=1}^{NT} \lambda_t^R RM_{t,w,s} \\
& - \sum_{t=1}^{NT} \sum_{i=1}^{NU} \left(C(P_{i,t,w,s}) + SU_{i,t,w,s} + SD_{i,t,w,s} \right) - \sum_{t=1}^{NT} \sum_{h=1}^{NH} \left(F_h^{HP}(P_{h,t,w,s}^{H2P}) + F_h^{PH}(P_{h,t,w,s}^{P2H}) \right) \\
& - \sum_{t=1}^{NT} \sum_{l=1}^{NL} \sum_{m=1}^{NM} C^{dr} \left| dr_{l,m,t,w,s} \right| - \sum_{t=1}^{NT} \sum_{wi=1}^{NWI} C^{curt} P_{wi,t,w,s}^{curt} \Bigg) \Bigg] \geq \Delta_C^r
\end{aligned} \tag{38}$$

$$\Delta_C^r = (1-\beta_r) OF_b \tag{39}$$

$$(1-\varepsilon)\,\overline{\lambda}_t^R \leq \lambda_t^R \leq (1+\varepsilon)\,\overline{\lambda}_t^R \tag{40}$$

s.t. (2)-(33) (41)

In the RS approach, the MG operator considers a higher profit due to a profitable variation of RTM price from its forecasted value which is formulated as a two-stage bi-level problem in (42) -(46).

$$\alpha_\rho = \min \ \varepsilon \tag{42}$$

$$\begin{aligned}
\max \sum_{w=1}^{NW} \pi_w \Bigg[& -\sum_{t=1}^{NT} \lambda_{t,w}^{D} EM_t + \sum_{s=1}^{NS} \pi_s \Bigg(\sum_{t=1}^{NT} \sum_{l=1}^{NL} \lambda_t^C d_{l,t,w,s}^{DR} - \sum_{t=1}^{NT} \lambda_t^R RM_{t,w,s} \\
& - \sum_{t=1}^{NT} \sum_{i=1}^{NU} \left(C(P_{i,t,w,s}) + SU_{i,t,w,s} + SD_{i,t,w,s} \right) - \sum_{t=1}^{NT} \sum_{h=1}^{NH} \left(F_h^{HP}(P_{h,t,w,s}^{H2P}) + F_h^{PH}(P_{h,t,w,s}^{P2H}) \right) \\
& - \sum_{t=1}^{NT} \sum_{l=1}^{NL} \sum_{m=1}^{NM} C^{dr} \left| dr_{l,m,t,w,s} \right| - \sum_{t=1}^{NT} \sum_{wi=1}^{NWI} C^{curt} P_{wi,t,w,s}^{curt} \Bigg) \Bigg] \geq \Delta_C^o
\end{aligned} \tag{43}$$

$$\Delta_C^o = (1+\beta_\rho) OF_b \tag{44}$$

$$(1-\varepsilon)\,\overline{\lambda}_t^R \leq \lambda_t^R \leq (1+\varepsilon)\,\overline{\lambda}_t^R \tag{45}$$

s.t. (2)-(33) (46)

3.3 Single-level formulation

It can be seen that a decrease in RTM price has a positive impact on the profit of the MG operator. On the other hand, an increase in the RTM price has an unfavorable impact on the profit of the RMG operator. Hence, in the introduced RA approach, the minimum profit is related to the time when the RTM price is enhanced in comparison with the forecasted value. Therefore, the proposed two-stage bi-level optimization problem in (37)-(41) is reformulated to a two-stage single-level problem as expressed by (47)-(51).

$$\alpha_r = \max \varepsilon \tag{47}$$

$$\begin{aligned}
&\sum_{w=1}^{NW} \pi_w \Bigg[-\sum_{t=1}^{NT} \lambda_{t,w}^{D} EM_t + \sum_{s=1}^{NS} \pi_s \Bigg(\sum_{t=1}^{NT} \sum_{l=1}^{NL} \lambda_t^{C} d_{l,t,w,s}^{DR} - \sum_{t=1}^{NT} \lambda_t^{R} RM_{t,w,s} \\
&\quad - \sum_{t=1}^{NT} \sum_{i=1}^{NU} \left(C(P_{i,t,w,s}) + SU_{i,t,w,s} + SD_{i,t,w,s} \right) - \sum_{t=1}^{NT} \sum_{h=1}^{NH} \left(F_h^{HP}(P_{h,t,w,s}^{H2P}) + F_h^{PH}(P_{h,t,w,s}^{P2H}) \right) \\
&\quad - \sum_{t=1}^{NT} \sum_{l=1}^{NL} \sum_{m=1}^{NM} C^{dr} \left| dr_{l,m,t,w,s} \right| - \sum_{t=1}^{NT} \sum_{wi=1}^{NWI} C^{curt} P_{wi,t,w,s}^{curt} \Bigg) \Bigg] \geq \Delta_C^{r}
\end{aligned} \tag{48}$$

$$\Delta_C^{r} = (1-\beta_r) OF_b \tag{49}$$

$$\lambda_t^{R} = (1+\varepsilon)\, \overline{\lambda}_t^{R} \tag{50}$$

s.t. (2)-(33) (51)

Consequently, in the proposed RS approach, the maximum profit is obtained when the RTM price is decreased in comparison with the forecasted value. Therefore, the proposed two-stage bi-level optimization problem in (42)-(46) is reduced to a two-stage single-level problem as presented by (52)-(56). The flowchart related to the two-stage single-level problem solving process is represented in Fig. 2.

$$\alpha_\rho = \min \varepsilon \tag{52}$$

$$\sum_{w=1}^{NW}\pi_w\left[-\sum_{t=1}^{NT}\lambda_{t,w}^{D}EM_t+\sum_{s=1}^{NS}\pi_s\left(\sum_{t=1}^{NT}\sum_{l=1}^{NL}\lambda_t^{C}d_{l,t,w,s}^{DR}-\sum_{t=1}^{NT}\lambda_t^{R}RM_{t,w,s}\right.\right.$$
$$-\sum_{t=1}^{NT}\sum_{i=1}^{NU}\left(C(P_{i,t,w,s})+SU_{i,t,w,s}+SD_{i,t,w,s}\right)-\sum_{t=1}^{NT}\sum_{h=1}^{NH}\left(F_h^{HP}(P_{h,t,w,s}^{H2P})+F_h^{PH}(P_{h,t,w,s}^{P2H})\right) \tag{53}$$
$$\left.\left.-\sum_{t=1}^{NT}\sum_{l=1}^{NL}\sum_{m=1}^{NM}C^{dr}\left|dr_{l,m,t,w,s}\right|-\sum_{t=1}^{NT}\sum_{wi=1}^{NWI}C^{curt}P_{wi,t,w,s}^{curt}\right)\right]\geq\Delta_C^{o}$$

$$\Delta_C^{o}=(1+\beta_\rho)OF_b \tag{54}$$

$$\lambda_t^{R}=(1-\varepsilon)\,\overline{\lambda}_t^{R} \tag{55}$$

s.t. (2)-(33) (56)

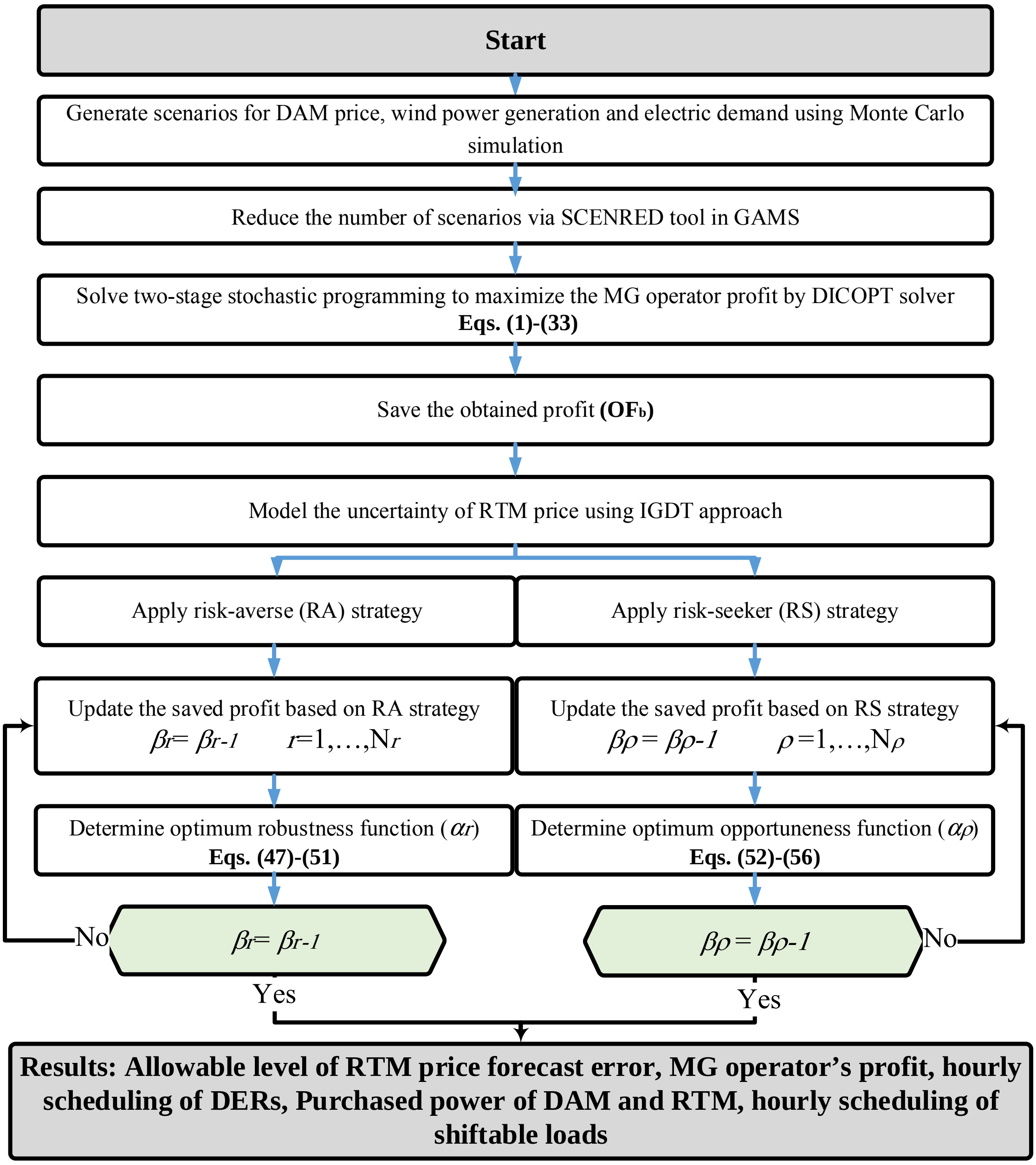

Fig. 3. Proposed two-stage single-level problem solving process

4. Simulation and results

The proposed approach is examined on a 10-bus MG test system [2] integrated with the wind turbine and HES facility in the presence of DR program, as depicted in Fig. 4. The forecasted data for day-ahead and real-time power price, as well as the wind power output and daily load demand, are presented in Figs. 5 and 6, respectively [2]. The contract price between local consumers and the MG operator is 16 ¢/kWh. The residential and commercial load activity status for each time is provided in Table II [56]. The proposed model is a mixed-integer nonlinear problem (MINLP) that is solved by applying Discrete and Continuous Optimizer (DICOPT) solver in GAMS which is a high-level modeling language being employed for mathematical programming as well as non-convex optimization. Hence, the DICOPT optimal solutions can be globally optimal with a fair degree of confidence so that has been employed in some literature such as [44-46, 49, 57, 58]. The main problem is separated into two sub-problems in DICOPT. The NLP sub-problem is solved using CONOPT solver and the MIP sub-problem is taken care of by CPLEX solver. The options of the DICOPT solver for solving the proposed MINLP problem are set as optca= 0.0 and optcr= 0.0. optca option shows an absolute termination tolerance for a global solver. If the absolute gap is not bigger than optca, the solver will stop. optcr option determine a relative termination tolerance for a global solver. it is noticeable that after finding a solution proven to be optimal within the tolerance specified with optcr the solver will stop and thus the solution time may be reduced. However, changing this option may cause the true integer optimum to be missed [44-46, 49, 57, 58].

To demonstrate the effectiveness of the proposed method, the following cases are studied:

Case 1: The evaluation for the effects of smart technologies (DR program, HES and reconfiguration capability) on the profit of RMG's operator under the deterministic self-scheduling approach.

Case 2: Impact assessment of smart technologies on the optimal management of the RMG, considering high-level uncertainty under the hybrid two-stage IGDT-stochastic approach.

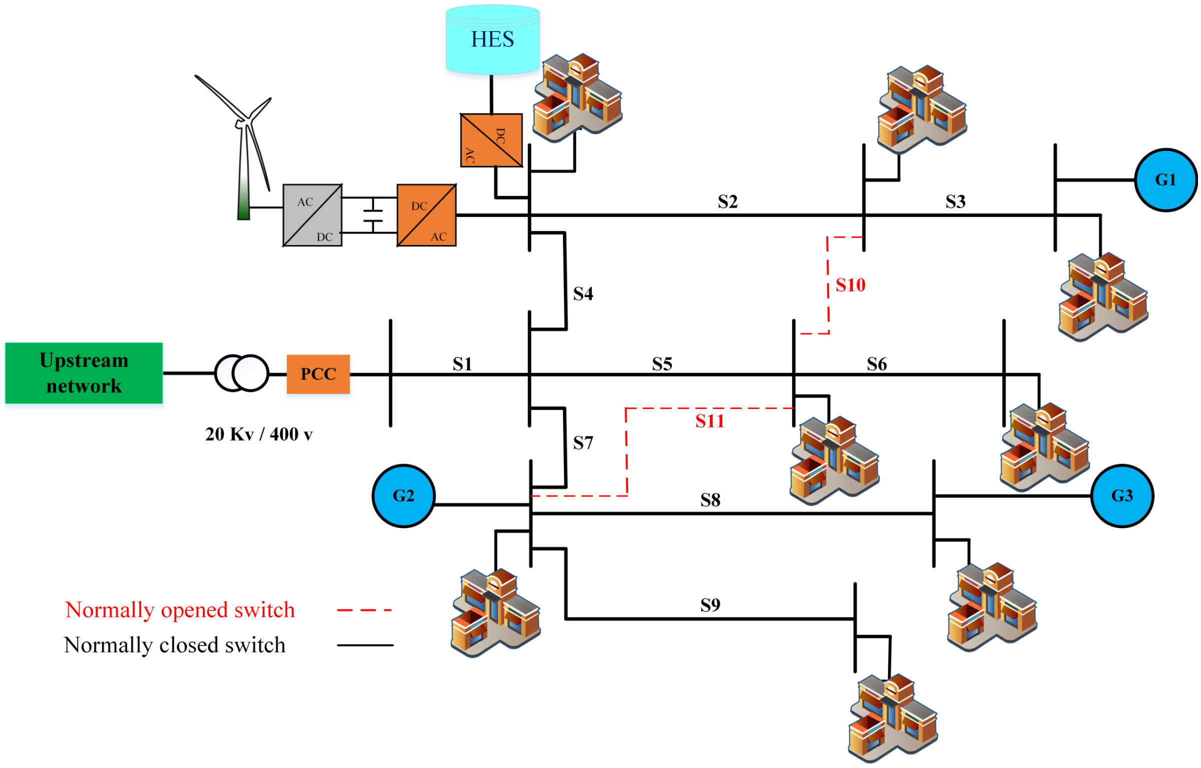

Fig. 3. The structure of the 10-bus MG test system

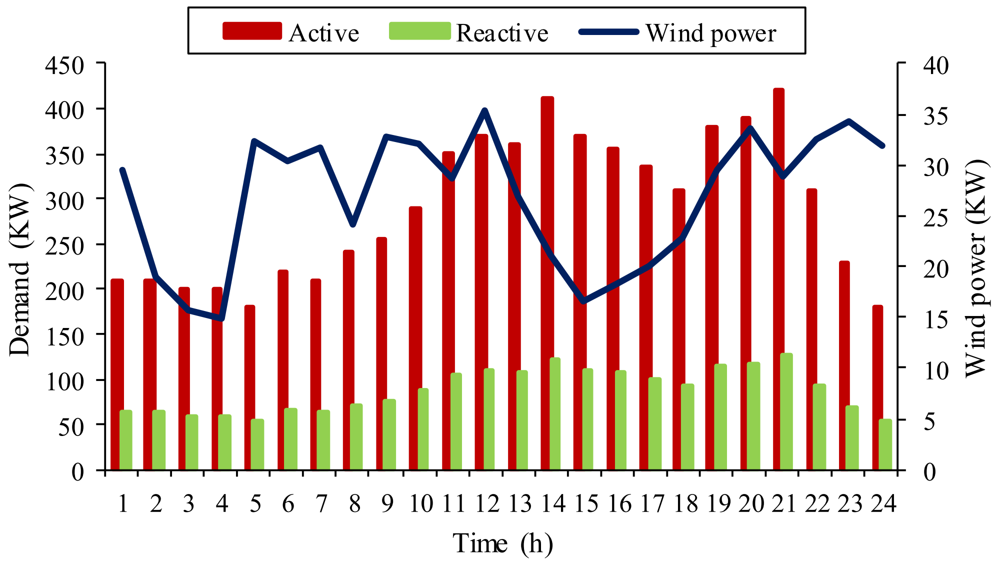

Fig. 4. The forecasted day-ahead and real-time prices.

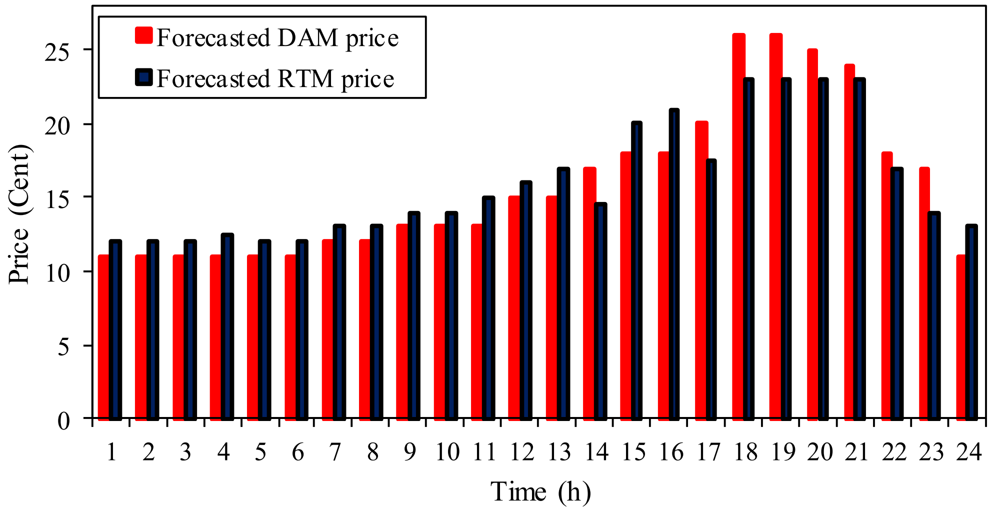

Fig. 5. The daily forecasted wind power and load demand.

Table II. Activity status of residential and commercial loads

Time (h)	Residential	Commercial
1	×	×
2	×	×
3	×	×
4	×	×
5	×	×
6	✓	×
7	✓	×
8	✓	×
9	✓	✓
10	✓	✓
11	✓	✓
12	✓	✓
13	×	✓
14	×	✓
15	×	✓
16	×	✓
17	×	×
18	×	×
19	×	×
20	×	×
21	✓	×
22	✓	✓
23	✓	✓
24	✓	✓

4.1: Simulation results in case 1: In this case, the effects of smart technologies including DR program, reconfiguration capability and HES facility on the profit of RMG are evaluated regardless of the uncertainties. The load participation factor (LPF) for the shiftable loads to take part in the DR program is 10% and the load shifting price is 5¢/kWh. Fig. 6 shows the optimal power dispatch of MTs, as well as purchased power from the upstream network (DAM and RTM). As shown, G1 is the low-cost generation unit and is committed between hours 9 and 23. While, G2 is committed between hours 15 and 22, and G3 is only committed for few hours. The operator often prefers to meet the demand through local resources and purchases the rest from the day-ahead and real-time markets. At hours between 1 and 8, when the power price reaches a lower value (see Fig. 6), the operator supplies the required power by purchasing it from the DAM and RTM. Further, Fig.7 demonstrates the effects of DR program implementation on the MG residential and commercial loads profile as well as the time activity. As illustrated, the part of electricity consumption at peak hour has shifted to an hour where the electricity price is lower.

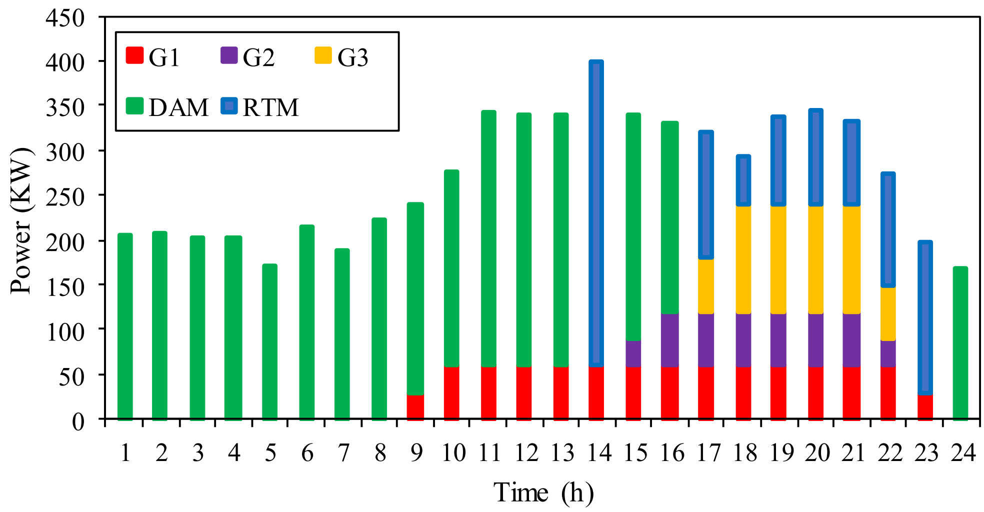

Fig. 6. The daily power dispatch and power purchased from markets.

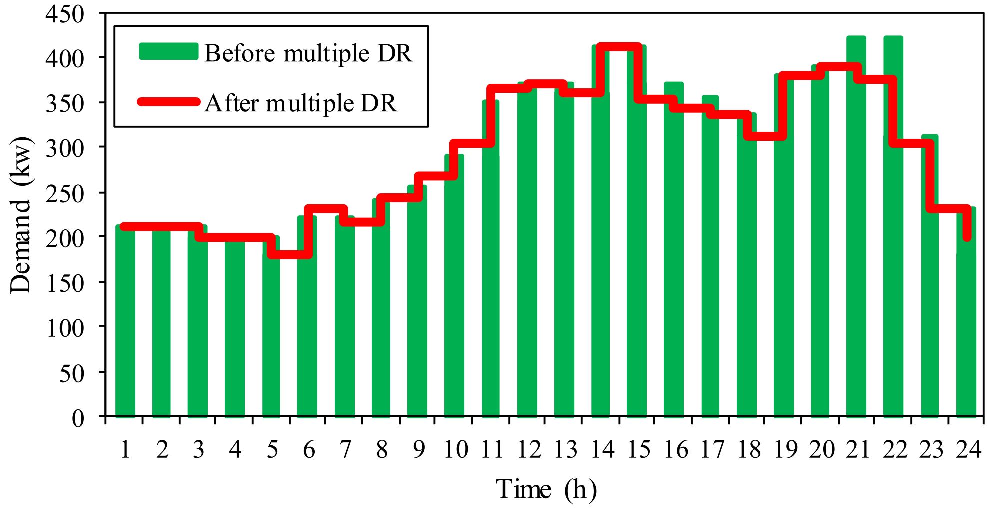

Fig. 7. The effect of DR on the load profile for residential and commercial loads.

The effects of multiple load shifting on the power purchased from DAM and RTM in the presence of HES facility (regardless of the reconfigurable capability) are depicted in Fig. 8. In this situation, the total purchased cost from both markets reduces from ¢67379.42 to ¢65693.80. It should be noted that, without considering the DR program, the cost of the purchased power from DAM is ¢45575.34 while this value reaches ¢4600.70 in the presence of DR. This increase is due to the fact that local consumption is shifted from the hour when the operator purchases the power from the RTM to the hours when purchase is done from the DAM. However, the total purchased power from the upstream network (DAM and RTM) has decreased in the presence of DR. The economic effects of LPF increasing in the DR program are given in Table III. As LPF increases, the system operator can shift higher percentages of the network consumption from peak hours to off-peak hours. This results in a decrease in total power purchased from the DAM and RTM during peak hours. In other words, the increase of LPF has a direct relation by increasing shifted demand value from peak hours to off-peak times. The reduction of the power purchased from the power market, especially during peak hours via increasing LPF, decreases the total purchased costs, and increases the MG profit, consequently.

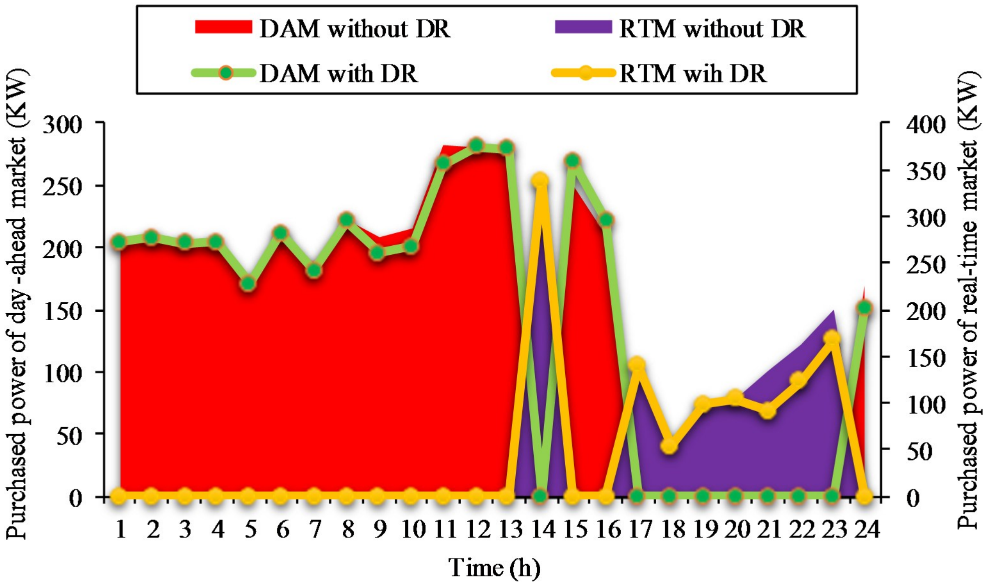

Fig. 8. The effect of multiple DR on the power purchased.

Table III. The effect of increasing participation coefficient of the purchased cost and MG profit

LPF (%)	10	12.5	15	17.5	20
Cost of purchased power from DAM (cent)	46000.70	46107.82	46144.18	46239.70	46370.11
Cost of purchased power from RTM (cent)	19693.10	19445.92	19238.36	18990.03	18707.31
Total profit of MG operator (cent)	15349.27	15391.96	15465.81	15532.64	15601.95

The HES charging/discharging scheme, as well as the state of charge in the presence of DR program (irrespective of reconfigurable capability) is shown in Fig. 9. As illustrated, between hour 1 to hour 6, due to lower electricity prices, the HES operates in the power-to-hydrogen mode. Consequently, the stored hydrogen is converted to power by the fuel-cell facility between hour 18 to hour 21 (higher electricity prices) and meets part of MG demand. Fig. 10, shows the effect of the HES facility on the purchased power from the upstream network (considering the DR program). As can be seen, the injected power by HES facility between hour 18 to hour 21 leads a reduction in purchased power from the upstream network.

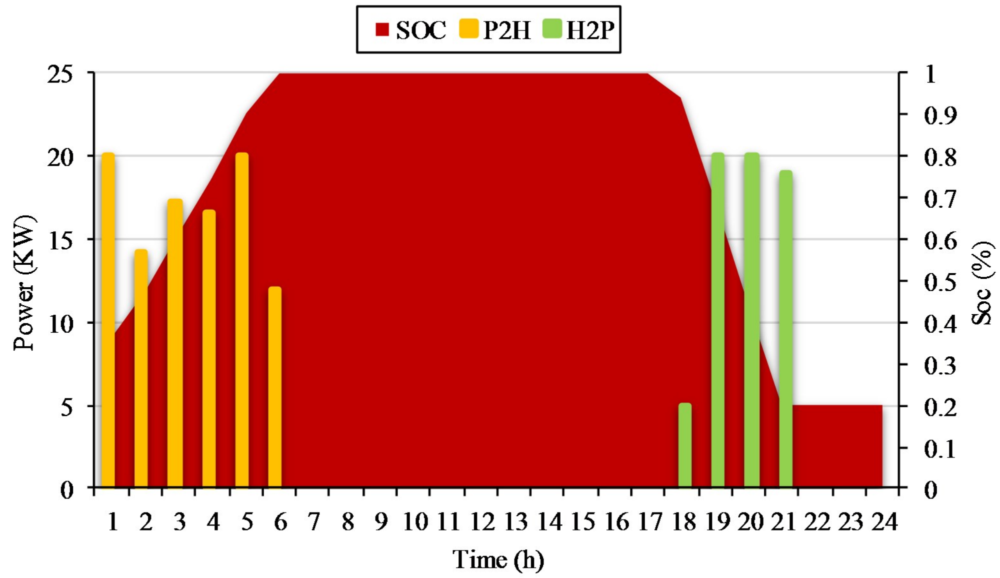

Fig. 9. The HES charging/discharging scheme.

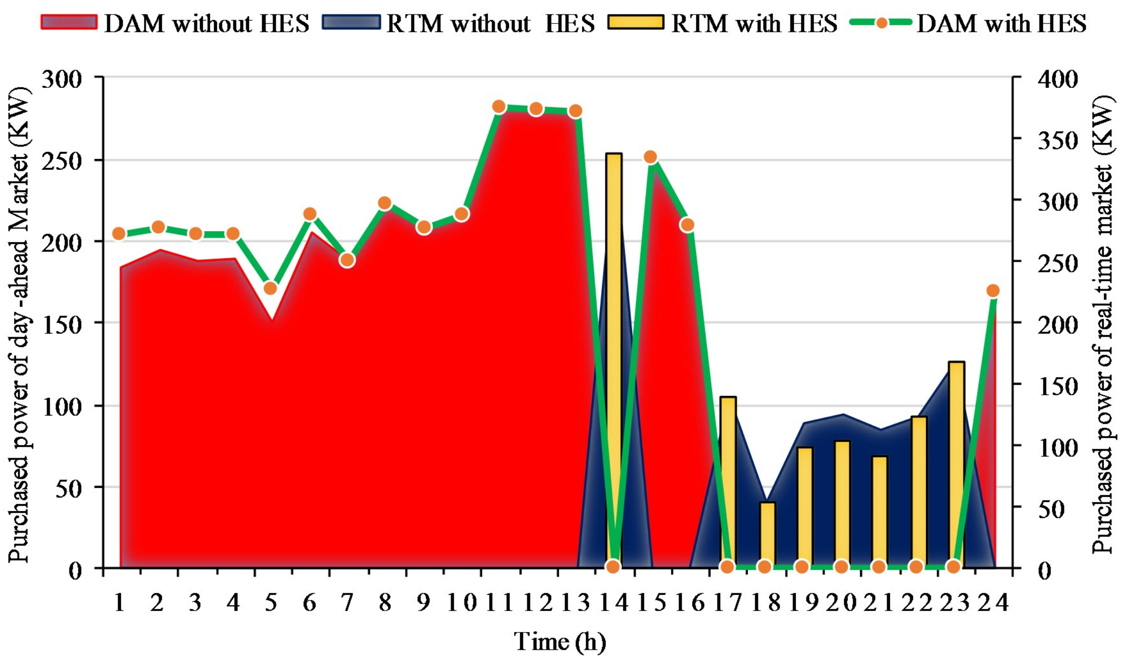

Fig. 10. The effects of HES facility on the purchased power from the markets.

Figs. 11-13 show the optimal MG structure (switches status) for the different situations (with and without DR and HES) in each hour. At each time, the status of switches is changed so that the radial structure restriction is established and power losses is also minimized. As discussed, reconfiguration changes flow of power among distribution feeders resulting in power loss minimization, as well as utilizing the maximum capacity of distribution lines. Taking advantage of reconfiguration capability besides each equipment (DR and HES) has different effects on the architecture of the RMG. In comparison with Fig. 11, the status of switch number four is changed at 12 and 13 p.m. in the presence of DR (Fig. 12). This makes the RMG less reliant on the upstream network, and less power has been purchased during this time period by changing the structure and power supply path. Furthermore, the optimal switches status using DR, HES, and reconfiguration capability in Fig. 13 is completely different from the previous ones, which results in power loss minimization and more less power purchasing with the upstream network. Therefore, the optimal structure in the presence of HES and DR while imposes the power flow and power losses reduces the operational cost and the power purchased from the power market.

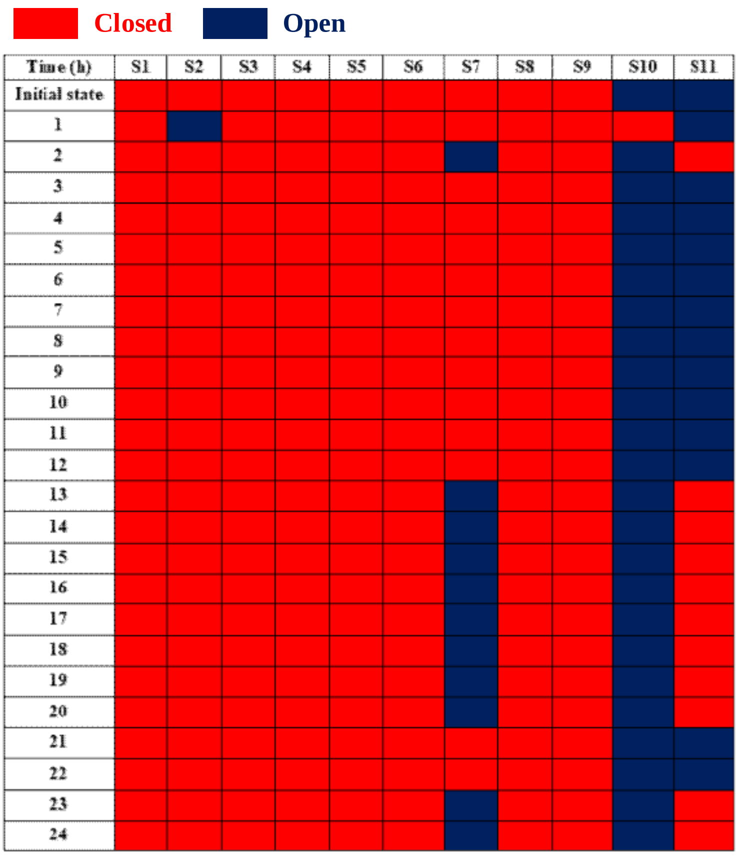

Fig. 11. The optimal RMG structure without DR and HES.

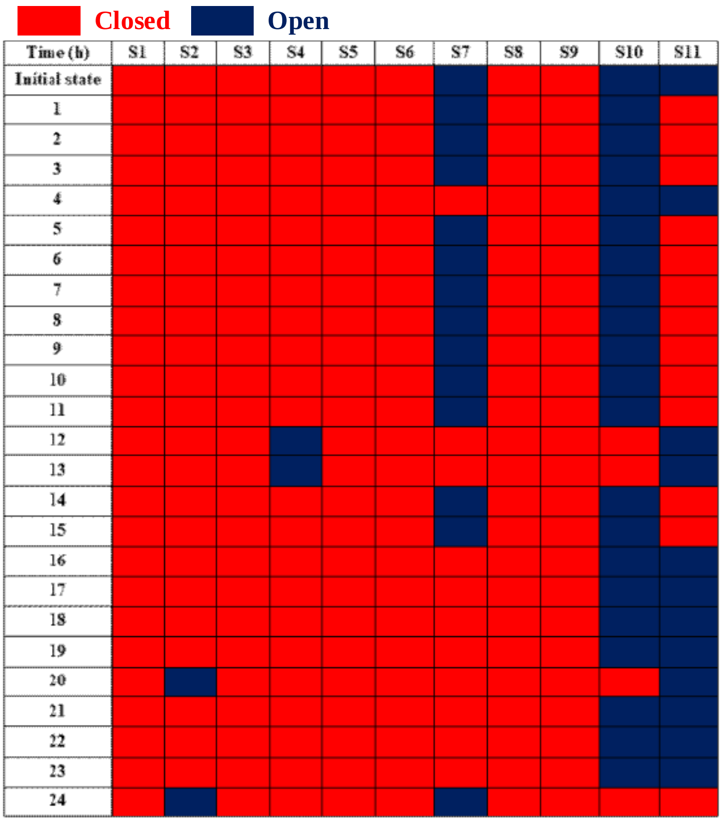

Fig. 12. The optimal RMG structure considering DR while HES is neglected.

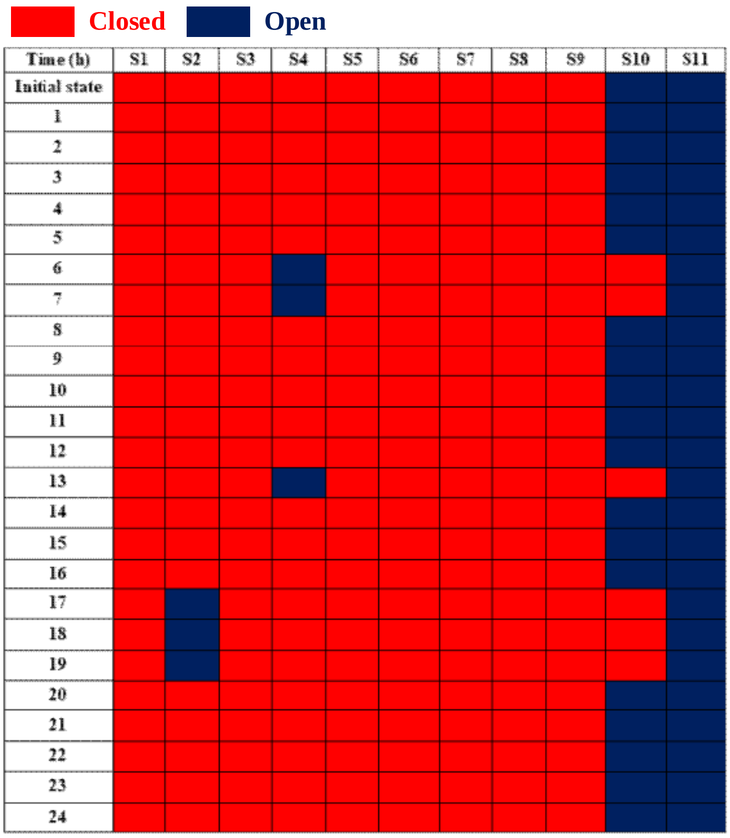

Fig. 13. The optimal RMG structure considering DR and HES.

The effects of reconfiguration on the power loss and RMG profit are shown in Table IV. As shown, by considering the reconfigurable capability, the profit increases to ¢15531.83. Furthermore, the effect of simultaneous consideration of smart technologies on the RMG profit is shown in Table V. As shown, considering all available options, simultaneously, increase the profit more and more compared to the cases where technologies are implemented, individually.

Table IV. The impact of smart technologies on the power loss and profit of RMG

	DR+HES	DR+HES+ Reconfigurable capability
Total power losses (KWh)	121	111.5
Total profit of MG operator (cent)	15349.27	15531.83

Table V. The impact of multiple technologies on the purchased power and the RMG profit

	-	DR	DR+HES	DR+HES+ Reconfigurable capability
Cost of Purchased power from DAM (cent)	43977.92	44866.23	46000.70	45919.60
Cost of Purchased power from RTM (cent)	22316.77	21209.16	19693.10	19595.75
Total profit of MG operator (cent)	14618.97	14967.67	15349.27	15531.83

4.2: Simulation results in case 2: In this case, the evaluation of numerical results is presented considering the high-level system uncertainties including day-ahead and real-time power prices, wind power generation, and load demand. In order to address all the system uncertainties, a two-stage IGDT-stochastic approach is implemented as described in the previous sections. The DAM power price, wind power output, as well as the load consumption uncertainties are modeled by the scenario-based stochastic framework. The DAM and load demand are subjected to the normal distribution function with 10% and 5 % standard deviation, respectively. The wind power generation is subjected to the Weibull distribution and its parameters can be found in [6]. To model the DAM price uncertainty, 100 scenarios are generated by Monte-Carlo Simulations (MCSs) which are reduced to 4 most probable scenarios by the SCENRED tool. In addition, 100 different scenarios are generated to model the wind and load demand uncertainties, which are reduced to 5 scenarios. Table VI demonstrates the impact of the simultaneous consideration of the DR program, HES facility and reconfigurable capability on the RMG profit under the scenario-based stochastic framework, regardless of the uncertainty of RTM price. As shown, using the stochastic approach, the expected profit reaches ¢15156.06. Furthermore, considering the DR and HES facility beside the reconfigurable capability leads to a decrease in the purchased power from the real-time and day-ahead markets, as well as an increase in the RMG profit.

Table VI. The impact of multiple technologies on the purchased power and the RMG profit based on scenario-based stochastic approach

	-	DR	DR+HES	DR+HES+ Reconfigurable capability
Expected cost of purchased power from DAM (cent)	44662.02	45087.19	46150.98	46212.12
Expected cost of purchased power from RTM (cent)	24853.28	21387.71	19965.02	19678.99
Expected total power losses (KWh)	117.9	121	122.1	112.8
Expected total profit of MG operator (cent)	14145.83	14568.17	14927.07	15156.06

To handle the uncertainty of RTM under the RA strategy, a 0.02 step increase in β_r at 0.02 to 0.14 is considered. The basic amount of RMG profit is ¢15156.06 and is obtained by solving the optimization problem in (1) - (32) considering the wind, load, and DAM price uncertainties. Fig. 14 depicts the effect of β_r on the optimal robust function α_r as well as the RMG profit. As the value of β_r increases, α_r also increases, which means that the operator can handle a wider range of the forecasted errors in the RTM price. However, increasing the error range leads to reducing the RMG profit. In other words, by increasing β_r, the operator adopts a more robust strategy in this situation, which makes a less profit value. More specifically, for $\beta_r = 0.04$ and $\beta_r = 0.1$, the RMG profit is respectively equal to ¢14523.47 and ¢13615.75. This means that these values can be guaranteed if the forecasted error of the RTM price in scheduling intervals does not exceed 2.3% and 7.9%, respectively. Fig. 15 shows the effect of β_r changes on the total purchased power from DAM and RTM. As illustrated, increasing β_r under the RA strategy leads to applying a more robust strategy which reduces the purchased power from the RTM, consequently reduces the dependence on the RTM.

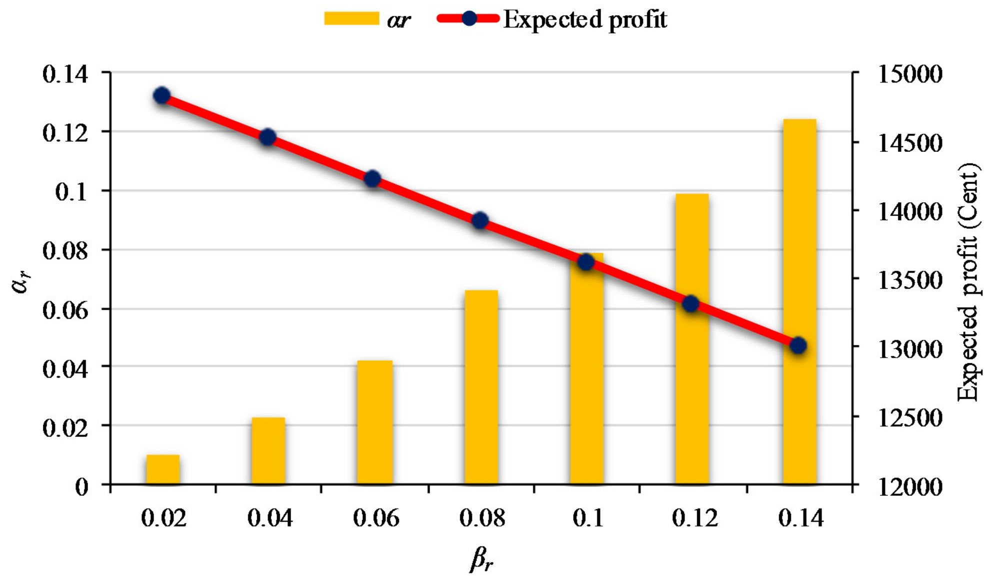

Fig. 14. The effect of β_r on the α_r and RMG profit.

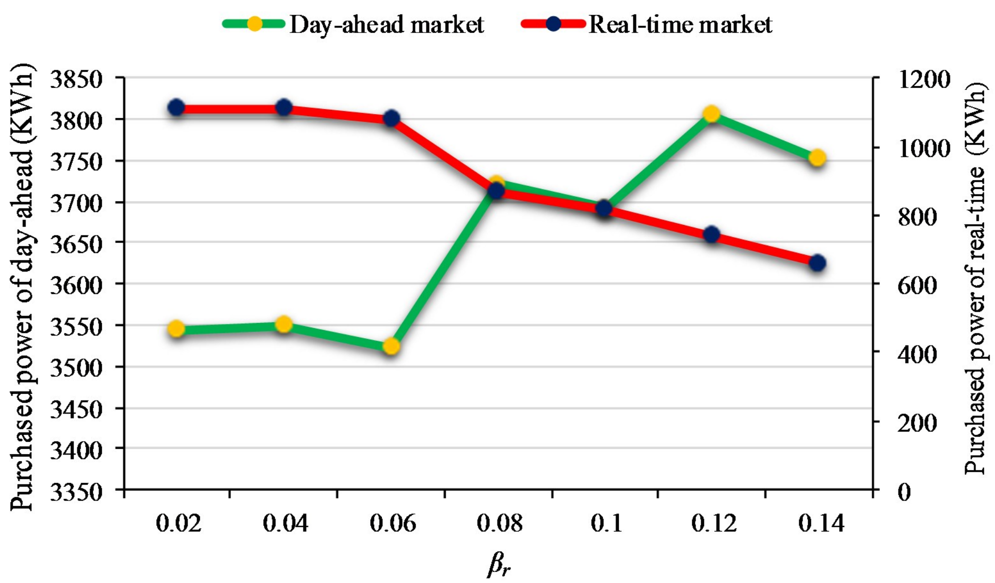

Fig. 15. The effect of β_r on the total purchased power from DAM and RTM.

To model the RTM price uncertainty under the RS strategy, β_ρ is increased from 0.02 to 0.14 by 0.02 step. Fig. 16 depicts the effect of β_ρ on the opportunity function α_ρ and the RMG profit. As the value of β_ρ increases, the value of α_ρ and RMG profit also increase. For example, for $\beta_\rho = 0.08$, the value of α_ρ and RMG profit reach 0.059 and ¢16338.9, respectively. This means that if at least 5.9% of RTM price falls below its forecasted value, the profit reaches ¢163389. In this situation, the operator participates in the RTM and DAM based on the current strategy. Fig. 17 demonstrates the effect of β_ρ on the total purchased power from DTM and RTM. As can be seen, by increasing β_ρ under the RS strategy, the operator prefers to provide the required power by purchasing it from the RTM rather than the DAM and participates in both markets based on the current approach, accordingly.

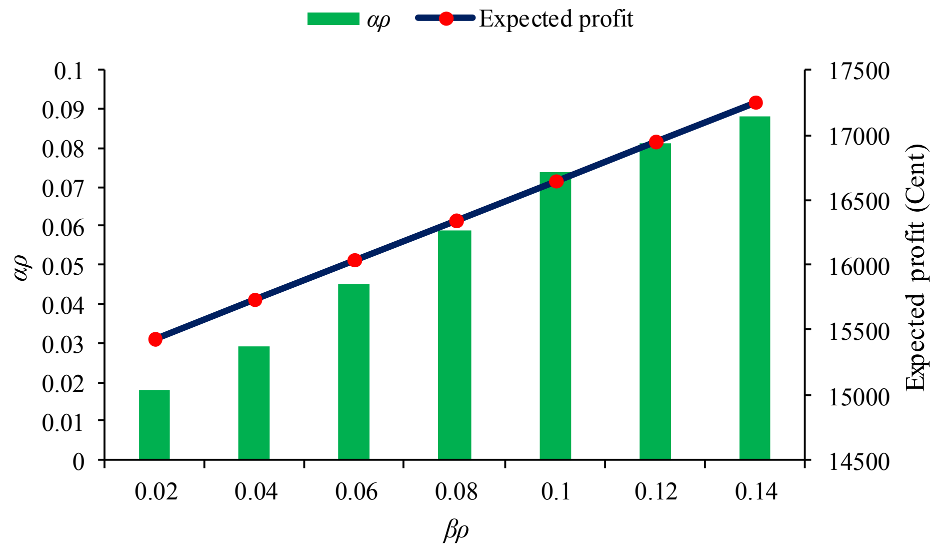

Fig. 16. Evaluate the effect of β_ρ on the opportunity function α_ρ and RMG profit.

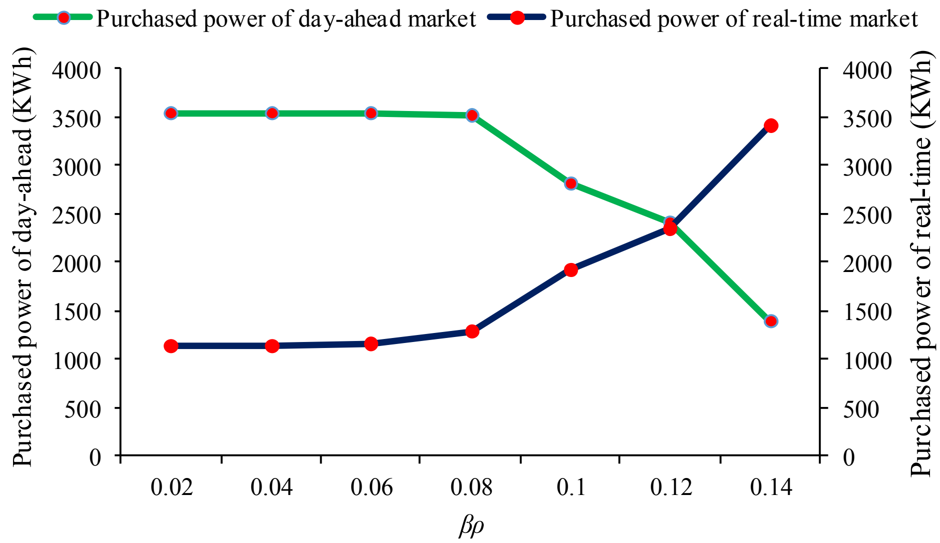

Fig. 17. Evaluate the effect of β_ρ on the total purchased power from DAM and RTM.

- ***"After the fact" analysis***

As mentioned, the IGDT-based bidding strategy solution guarantees a pre-specified profit, provided the after-the-fact prices fall into a maximized price band centered at the forecast prices. The IGDT based scheme obtains the optimal scheduling to reach a target profit, while stochastic approaches attain optimal model based on a limited number of price scenarios [59]. In well-known robust optimization problems, the robustness interval of the unknown parameter is specified before solving the problem [60]. Robust optimization and risk-constrained stochastic approaches are often stated as a 'performance maximization' model, where profit is maximized concerning an uncertainty budget and risk factor. However, IGDT is described as a 'performance satisfying' model, where a robust solution is calculated such that pre-specified expectations are satisfied. In this part, the benefit of the IGDT-based hybrid approach is evaluated by an "after the fact" analysis. For this purpose, robustness function α_r is calculated as 0.079 under the RA strategy (β_r =0.1), where the minimum guaranteed profit is equal to ¢13615.75. It is assumed that the real price of RTM follows one of the following two scenarios:

Scenario 1: The real price of RTM is 7.5% more than the predicted value.

Scenario 2: The real price of RTM is 7.5% less than the predicted value.

As can be observed in Table VII, although the expected profit under the two-stage stochastic programming approach is higher than the proposed hybrid model, it can lead to a lower profit in practice like scenario 1. In addition, it can be seen that the profit in scenario 2 is ¢15812.55, which is more than the guaranteed minimum profit of ¢13615.75. So, the proposed model is robust against the uncertainty of RTM price and can guarantee a minimum profit of ¢13615.75 under the condition that the forecast error of RTM price is not more than 7.9%. To achieve a higher degree of reliability, the MG operator must increase the robustness parameter β_r, which leads to decreasing the expected profit of the MG.

Table VII. The effect of the proposed hybrid model on the profit of the MG operator in reality

	Two-stage stochastic model	Two-stage IGDT-stochastic model
Profit in scenario 1 (¢)	13512.26	13712.24
Profit in scenario 2 (¢)	16570.93	15812.57
Expected profit (¢)	15128.614	13615.75

5. Conclusion

This paper developed an optimal bidding strategy problem for the reconfigurable micro-grid based on the AC-power flow model considering smart energy technologies. The presented strategy was solved to maximize the profit of reconfigurable micro-grid in both real-time and day-ahead markets considering the uncertainties of the system. In addition, to handle the uncertainties of reconfigurable micro-grid in day-ahead scheduling and real-time dispatch, a hybrid two-stage bi-level optimization was applied which simultaneously considered the benefits of scenario-based stochastic programming and information gap decision theory approach. In this regard, the variations of the wind power production, electrical demand, and day-ahead market price were modeled based on scenario-based stochastic programming, while an information gap decision theory was utilized to manage the uncertainty of real-time market price under two strategies including risk-seeker and risk-averse strategies without the need for probability distribution function. The presented model enabled the reconfigurable micro-grid operator to make decisions on system operation with higher reliability and flexibility. Simulation results demonstrated that:

- Dynamic reconfiguration capability could decrease the power losses in the micro-grid by 8%, and increase the profit of the MG operator by 1.1%.
- Optimal scheduling of flexible loads according to their activity plan could increase the operation profit of the micro-grid by 2.9%.

- The micro-grid operator profit increased by 2.4% in presence of hydrogen energy storage.
- Coordinated scheduling of energy smart technologies could increase the profit of the MG by 6.6%
- The proposed hybrid optimization model could increase the operator profit by 1.4%. The hybrid model enabled the operator to differentiate between the risk levels of system uncertainties.

6. Future work

The efficiency of the proposed model will be further improved by considering the reconfigurable multi-carrier micro-grid which supplied the electrical, heating and gas loads, simultaneously. Also, the application of integrated demand response programs in multi-carrier microgrids is left to future work.

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