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Chance-Constrained Scheduling of Hybrid Microgrids under Transactive Energy Control

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Abstract: The uncertainties related to renewable energy resources (RERs) and energy markets have a direct impact on the scheduling of hybrid microgrids and stand as a challenge in renewable-based systems. Due to this, many mathematical methods are employed for modeling uncertainties, but applying a suitable approach is important for reaching accurate results.This paper presents the chance-constrained programming technique to model the fluctuations in renewable outputs and electricity market prices to effectively deliberate the probabilistic nature of them. In this respect, the transactive energy concept is used to provide the energy sharing possibility for hybrid microgrids with a high portion of renewables for clean electricity generation. The interaction between the the electrical and gas network as a result of using the gas-fired devices in each microgrid, is also included in this study. To test the effectiveness of the suggested framework, the IEEE-10 bus case study with five commercial hybrid microgrids is selected and the scheduling of microgrids is carried out in the interconnected electricity and gas networks. The different impacts of the proposed method are analyzed by considering two cases: optimal scheduling of hybrid microgrids without uncertainty modeling (Case I) and with it (Case II). In Case I and II, numerical results indicated $22378.067 expected operation cost for Case II in comparison with $26014.359 for Case I, which proves the effectiveness of the proposed model in probabilistic modeling of the system as well as achieving the economic benefits for hybrid microgrids.

Highlights:

- Optimal chance-constrained DA scheduling of hybrid microgrids is effectively conducted.
- The CCP method is used for probabilistic evaluation of problem in the presence of RERs.
- Transactive energy technology is employed for managing energy trading in the system.
- LHS and FFS methods are applied for scenario generation and reduction, respectively.
- The interactions between electricity and gas networks are effectively modeled.

Keywords: Transactive energy, electrical and thermal energy storage, renewable energy resources, chance-constrained programming, hybrid microgrids, interconnected electricity and gas network, clean energy production

Nomenclature

Indices

t	Index of time	Sp_t^{Fore}	The forecasted wind speed (m/s)
s	Index for number of scenarios	Sp_h^{Ra}	The rated wind speed related to wind turbine *h* (m/s)
h	Index for number of hybrid microgrids	$Sp_h^{C.i}$	The cut-in speed related to wind turbine *h* (m/s)
m,n	Index for natural gas nodes	$Sp_h^{C.o}$	The cut-out speed related to wind turbine *h* (m/s)
M	Index for microgrids	**Variables**	

Parameters		P_t^{bid}, P_t^{A}	The amount of bid and actual power
$P_{n,t}^{L}, Q_{n,t}^{L}$	Active and reactive power demands	$P_{h,t}^{Wind}$	The amount of wind turbine production
η_{Bc}, η_{Bd}	Charging and discharging efficiency of battery energy storage system (BESS)	$P_{h,t}^{PV}$	The amount of PV production
$\rho_t^{\mathrm{Re}+}, \rho_t^{\mathrm{Re}-}$	Up and down regulation prices in RT market	$P_{h,t}^{CCHP}$	The amount of PGU production
ρ_t^{DA}	Electricity price in DA market	$P_{cha,h,t}^{BAT}$	Charging rate of BESS in microgrid h at time t
$\varepsilon^{+}, \varepsilon^{-}$	Relative differences between ρ_t^{DA} and $\rho_t^{\mathrm{Re}+}, \rho_t^{\mathrm{Re}-}$	$P_{dis,h,t}^{BAT}$	Discharging rate of BESS in microgrid h
P_0, Υ_0	Gas pressure and density in normal condition	$P_{n,t}^{IL}$	The amount of IL
$\mathrm{T}_{e0}, \mathrm{E}_0$	Gas temperature and volume in normal condition	P, Υ	The pressure and density of gas in pipelines
$\mathrm{A}^{Gas}, \mathrm{B}^{Gas}$	Gas compressibility factor and constant	$\mathrm{T}_e, \mathrm{E}_{mn}$	The gas temperature and volume in pipelines
ℓ_{mn}, d_{mn}	The length and internal diameter of pipe *m-n*	$\psi_{mn,t}$	The amount of LP
$\psi_{mn}^{Initial}$	The amount of initial LP in normal condition	$p_{Gas,mnt}^{Comp}$	The amount of gas consumption by compressor
$\psi_{mn,t}^{\max}, \psi_{mn,t}^{\min}$	Maximum and minimum amount of LP between node *m-n*	$p_{G,mnt}^{Gas,Tot}$	The total amount of purchased gas from the gas grid
ψ_{mn}^{End}	The final LP of the day	$p_{L,mnt}^{Gas}$	The amount of gas load
ξ	Constant for converting the gas volume to the energy (GJ/m^3)	$p_{G,mnt}^{Gas}$	The amount of purchased gas from gas grid for thermal demand
Δt	Decision time interval	$p_{CCHP,ht}^{Gas}$	The amount of gas consumed by CCHP
ϖ, G	Air constant and specific gravity ratio	f_{mn}^{Gas}	The amount of gas flow between *m-n*
υ_{mn}	Dimensionless friction factor	Dir_{mn}	Gas direction between *m-n*
ϕ^{Air}, ϕ^{Gas}	Air and gas constants related to G	$\mathrm{P}_m, \mathrm{P}_n$	Gas pressure in node *m* and *n*
$\alpha_{1,2,3,mn}$	Coefficients for the compressor gas flow	$f_{Gas,mn}^{comp}$	Gas flow in compressor
$\beta_{1,2,3,mn}^{Comp}$	Coefficients for the compressor gas consumption	$HP_{t,mn}^{Comp}$	Horse power of compressor
$PT_{mnt}^{Comp,up}$, $PT_{mnt}^{Comp,down}$	The lower and upper bounds for inlet and outlet pressure of compressor	C_t^{Dev}	Cost of power deviation between the actual and bid electricity
$\rho_t^{Se}, \rho_{Gas,t}^{Se}$	The electricity and gas selling prices	$C_{m,t}^{IL}$	Cost of interrupted load
$\rho_{Gas,t}^{Pu}$	Gas purchasing price	$Fe_{h,t}^{PGU}$	Fuel consumed by PGU
M, N	Indicate the total number of buses	$Fe_{h,t}^{BO}$	Fuel consumed by boiler
H, T	Indicate the total number of hybrid microgrids and time intervals	$Ploss_t$	The amount of power loss at time *t*
$CO_{h,t}^{L}, HE_{h,t}^{L}$	Cooling and heating load	$COc_{h,t}$	Cooling energy provided for cooling component
η_{Co}, η_{He}	Thermal efficiency related to cooling and heating components	$HEc_{h,t}$	Heating energy provided for heating component
$P_{\max,h}^{wind}$	Maximum wind power production	$SCOc_{h,t}$	Thermal energy prepared for cooling component from thermal storage
PV^{η}, PV_h^{size}	Efficiency and size of solar panel	$SHEc_{h,t}$	Thermal energy prepared for heating component from the storage

PGU_h^{size}	Size of PGU in microgrid *h*	$COs_{h,t}$	Thermal energy prepared for the storage from cooling process
PV_t^{sol}	Solar radiation at time *t*	$HEs_{h,t}$	Thermal energy prepared for the storage from heating process
a^{pgu}, b^{pgu}	Coefficients of PGU for fuel to electricity conversion	$Q_{h,t}^{Wind}$	Reactive power output of wind turbine *h*
BO_h^{size}	Size of boiler in microgrid *h*	$X_{h,t}^{PGU}$	ON/OFF status of PGU
η^{PGU}, η^{BO}	PGU and boiler efficiency	$TEs_{h,t}^{cchp}$	Thermal energy delivered to the storage by CCHP unit
Ba_h^{size}, Te_h^{size}	Size of BESS and thermal storage	$X_{dis,h,t}^{BAT}$	Discharging state of BESS
$\lambda_{\min}^{Ba}, \lambda_{\min}^{Te}$	Coefficients of BESS and thermal storage for minimum storage limit	$X_{cha,h,t}^{BAT}$	Charging state of BESS
$EBa^{initial}$	Initial electricity stored in BESS	$P_{h,t}^{BAT}$	The amount of electricity stored in BESS
$\lambda_{\min}^{Ba,cha}, \lambda_{\max}^{Ba,cha}$	Lower and upper coefficients for charging limits of BESS	$X_{dis,h,t}^{THE}$	Discharging state of thermal storage
$\lambda_{\min}^{Ba,dis}, \lambda_{\max}^{Ba,dis}$	Coefficients for minimum and maximum discharging limits of BESS	$X_{cha,h,t}^{THE}$	Charging state of thermal storage
$ETe^{initial}$	Initial thermal energy stored in thermal storage	$E_{cha,h,t}^{THE}$	Charging rate of thermal storage
η_{Td}, η_{Tc}	Discharging and charging efficiency of thermal storage	$E_{h,t}^{THE}$	The amount of thermal energy stored in the storage system
$\lambda_{\min}^{Te,cha}, \lambda_{\max}^{Te,cha}$	Coefficients for minimum and maximum charging limits of the storage system	$E_{dis,h,t}^{THE}$	Discharging rate of thermal storage
$\lambda_{\min}^{Te,dis}, \lambda_{\max}^{Te,dis}$	Coefficients for minimum and maximum discharging limits of the storage system	$P_{n,t}^{Inje}(V_t, \theta_t)$	Active power injection
$P_{n,t}^{IL,up}$	Maximum amount of IL	$Q_{n,t}^{Inje}(V_t, \theta_t)$	Reactive power injection
$P_{n,t}^{L,up}, P_{n,t}^{L,down}$	Lower and upper bounds for the energy load	$S_{n,t}(V_t, \theta_t)$	Complex power at time *t* and node *n*
$P_{Min}^{Exch}, P_{Max}^{Exch}$	Lower and upper bounds for energy sharing with the power grid	$P_{n,t}^{El,Gen}$	Active power production
$S_{n,t}^{UP}$	Upper bound limit for complex power	$Q_{n,t}^{El,Gen}$	Reactive power production
V_n^{up}, V_n^{down}	The up and down voltage at node *n*	$V_{n,t}$	Voltage magnitude at time *t* and node *n*
$p_{L,mnt}^{Gas,heat}$	Gas thermal loads	$p_{L,mnt}^{Gas,cchp}$	The amount of gas consumption by CCHP unit

1. Introduction

1.1 Motivation and background

In recent decades, microgrids have been nominated as a key structure in providing the heating, cooling, and electricity demand of consumers [1]. They are deemed as the small-scale versions of a modern grid that create the possibility of a successful transition from the centralized utility towards a decentralized system [2]. Microgrids generally include various distributed energy resources (DERs) like combined cooling, heating and power (CCHP) units, distributed generators (DGs), wind turbines, and solar photovoltaic (PV) systems to meet the electrical and thermal energy in a local scale [3]. Greenhouse gas emission reduction, governmental incentives for using renewable energy resources (RERs) as the uncontaminated electricity generation systems, resiliency and reliability improvement, and total cost reduction [4] are some significant local goals followed in the microgrid's development policies [5]. Nowadays, the usage of RERs for energy production takes into account as a priority research topic [6]. Hence, the combination of cost-effective devices such as wind turbines and solar systems as RERs with conventional energy generation units such as DGs has introduced new concepts of microgrids that are called hybrid microgrids [7]. At the same time as the expansion of energy markets and the advent of RERs, accurate analyzing of the microgrids has been challenged in the power grid [8]. Due to this, almost all researches in the field of microgrids such as optimal planning, operation, scheduling, and energy management of microgrids are approximately carried out in accompanying with the assessment of RERs impacts. For example, optimal sizing of RERs and combined heat and power (CHP) units are conducted in [9] for the hybrid microgrids considering the volatility of RERs. In this regard, a great need is felt for incorporating the hybrid microgrids with innovative technologies that can facilitate the way of balancing energy for renewable-based systems in a reliable and sustainable manner. Additionally, engaging gas-fired systems as the standby units for the stochastic producers in hybrid microgrids has somehow required the system to integrate the electrical and gas networks for realistic modeling of microgrids.

1.2 Relevant literature

Energy management of the hybrid microgrids in the presence of intelligent devices and RERs is considered as a key topic that a large part of the studies about the microgrids is devoted to this issue. The importance of optimal energy management in the hybrid microgrids is more highlighted by emerging the grid-edge technologies and energy conversion systems that inspire the necessity for integration of the hybrid energy networks and developing the interdependent energy infrastructures [10]. Recently, several methods are exerted for managing energy of hybrid microgrids in literature. For example, in [11], the optimal operation management of the microgrid clusters has been done using the chance-constrained model based on the predictive control to manage the local operation of the microgrid clusters without focusing on proposing the effective strategy for the operation of the renewable-based microgrid. An effective overview of the different power management strategies of hybrid microgrids is presented in [12] considering the various operation modes and system structures along with a comprehensive assessment of power control and management schemes in the transient and steady states of the problem. However, this work does not cover the probabilistic modeling of the system that is necessary in the presence of renewable systems. The energy management goals are intended in [13] for the multi-carrier microgrids by applying an interactive multi-agent system for controlling and managing various devices. Also, the authors in [14] developed a new approach for energy management of the multi-carrier energy system based on the self-scheduling technique to maximize the system's profit by interacting in the different local energy markets. This is while the new energy managing and controlling technique is proposed in [15] for the hybrid microgrid that is focused on enhancing the reliability of continuous energy supply as well as power quality. The authors in [16] propose a novel fuzzy system integrated with a gray wolf optimization method (FL-GWO) for energy management and optimal sizing of ESSs in hybrid microgrids based on the meta-heuristic approach to minimize the harmful effects of greenhouse gas emissions. On the other hand, for shaving the peak load as well as maximizing the financial profit, the authors proposed a hierarchical energy management system in [17] considering the principle of bidding strategy in neighborhood grids. Moreover, a hierarchical distributed predictive control technique is proposed in [18] aiming to focus on solving the energy management problem in a typical microgrid considering the coordination of DERs.

In power grids with a high portion of renewables, integration of the DERs is introduced as one of the effective manners to overcome the challenge of increasing the penetration of RERs across the power system [19]. In this regard, the integration of the microgrids as small scale power systems can be one of the promising way to overcome the challenges ahead of the optimal scheduling of different types of DERs [20]. To this end, optimal scheduling of the renewable-based microgrids is accomplished especially for the energy management and integration of RERs. For example, a multi-objective genetic algorithm optimization method is presented in [21] for scheduling of community microgrids intending the minimization of both the operational and emission cost. In this research, although the paper pursues to optimize several objectives, the volatilities in the stochastic generators' outputs are ignored in the system modeling. Moreover, the authors in [22] have proposed the multi-carrier energy framework for scheduling of microgrids fortified with a wind-solar-biogas hybrid system, in which a special plan is not intended to capture the intermittencies in the microgrid. In such frameworks with the numerous RERs, modeling the behaviors of the uncertain parameters is a central challenge for the researchers, which is scrutinized using various mathematical based methods. For this aim, a robust optimization is posed in [23] to deal with the intermittent nature of RERs based on the ensemble weather forecasts for improvement of the hybrid microgrid's performance. In this work, as the robust model is suggested, the proper strategy is not provided for facilitating the operation of RERs. This is while an information gap decision theory (IGDT) is proposed in [24] to accomplish the optimal bidding strategy for microgrids considering uncertain changes in the energy market to reduce the electricity purchasing cost. In [25], in spite of presenting a prediction-based optimization strategy for managing energy to balance it in the microgrid, realistic modeling of the microgrid is overlooked due to a lack of analyzing the fluctuations in the energy supply-side.

All of the mentioned approaches have been used for modeling the various types of uncertainties related to the RERs and energy markets. However, the probabilistic nature of problems containing the RERs is not considered effectively by them and fluctuations caused by uncertainties associated with RERs and energy markets are not also exerted under the mentioned techniques. This is while the smart grid structure is moving towards the maximum use of RERs [26] in the integrated paradigm of energy networks [27], which will lead to a probabilistic environment of network and will make it necessary to investigate the probabilistic nature of the grid [6]. Thereby, a chance-constrained model as a stochastic programming approach is adopted in some research works to do so [28]. For instance, a chance-constrained programming (CCP) model is proposed in [29] for the day-ahead (DA) scheduling of the electricity market by focusing on the reliability and economic aspects. In another work [30], an optimal control strategy is formulated based on the CCP method for maximizing the economic benefits and system robustness in the power flow management of microgrids integrated with RERs and electrical vehicles (EVs).

1.3 Research gaps and contributions

Some of the mentioned references have noted the energy management issue by applying various optimization approaches and models, while some others have focused on the environmental and economic aspects of the optimal scheduling of hybrid microgrids. Generally, gas-fueled generation systems such as DGs and CHP are the backup units for the hybrid microgrids and are almost taken into account as the inseparable components. Modeling of the natural gas grid in the presence of such devices for achieving the results with high accuracy is essential in the electric power system researches. This is while with the advent of new technologies such as the power-to-gas, energy hubs, and etc., it will be possible to convert different types of energy into each other in the future smart grids, hence the scheduling of electricity and gas networks together would be necessary. However, in none of the mentioned references, optimal scheduling and energy management of hybrid microgrids are carried out in the combined electrical and gas networks and the restrictions of gas networks are also ignored in their formulations. In addition, electrical and thermal energy trading possibility as a vital way for supplying the energy load of hybrid microgrids in the emergency conditions is not reflected and evaluated effectively. Meanwhile, many technologies regarding energy sharing are being developed, which will provide a significant basis for energy exchanging in smart networks, so the massive energy trading in future smart grids will be inevitable. Therefore, the new observation about the energy exchanging in the future smart grids will need reliable and sustainable technologies that can handle the high level of energy trading predicted for the new structure of the power grid [31], in which transactive energy is applied for this aim in this research. Indeed, transactive energy has appeared as a reliable technology for balancing energy in the multi-energy systems under the economic and control mechanisms [32]. On the other hand, a large number of aforementioned researches have employed the uncertainty quantification techniques for capturing the volatility of renewables and energy market uncertainties, but in none of them, not the fluctuations of renewable systems and energy market simultaneously nor the probabilistic nature of problem are modeled even the integration of numerous DERs is not considered effectively. To sum up, considering the complete literature review in the previous subsection, the research gaps can be summarized as follows. 1) The interactions between the natural gas system and the electricity network are not optimally taken into account in the scheduling of the hybrid microgrids, in which the gas-fired systems play an inevitable role. 2) Although energy trading models are recognized as one of the promising methods for the sustainability of microgrids and facilitating the establishing energy balance in the renewable-based system, an effective energy sharing strategy is not offered yet for optimal scheduling of the hybrid microgrid. 3) Given the intermittency feature of the renewable systems, deploying a suitable technique that can allow violation for uncertain parameters can be useful for realistic modeling of the problem, which this issue is disregarded in the probabilistic modeling of the hybrid microgrids.

To address the mentioned gaps, this paper is focused on modeling the probabilistic nature of the optimal scheduling of hybrid microgrids problem using the mathematical-based CCP approach. In order to create both electrical and thermal energy exchanging possibilities, this paper has applied the transactive energy concepts as the sustainable energy trading-based technology in establishing a time-to-time energy balance using reliable strategies. In this study, each of the hybrid microgrids is equipped with the CCHP units not only to provide the thermal energy demand but also to support the RERs in meeting the electricity demand of microgrids. Due to the operation of gas-fired CCHP units in each microgrid, this paper is structured to evaluate the DA stochastic scheduling of microgrids in the interconnected electricity and gas grids considering the restrictions of both of them. In this paper, in addition to the CCHP units, each of the microgrids consists of a wind turbine, PV panel, electrical and thermal storage. Because of the fluctuations in the wind turbine and PV panel outputs due to the uncertain behaviors of wind velocity and solar radiation along with the volatility of electricity price in the energy market, we have used the Latin hyperbolic sampling (LHS) and fast forward selection (FFS) methods for scenario creation and reduction. Because of existence nonlinear equations in natural gas modeling and AC power flow formulation along with binary variables in modeling the CCHP units, the CCP-based optimal DA scheduling problem is a mixed-integer nonlinear program (MINLP) problem, which is solved using SBB and DICOPT solvers in the General Algebraic Modeling System (GAMS) software.

The main novelties and contributions of this paper are briefly explained as follows:

- The CCP-based model is proposed for analyzing the probabilistic nature of the problem by deploying the LHS and FFS approaches for the scenario creation and reduction processes in the presence of RERs.
- Transactive energy strategy is proposed to manage the energy exchanging of microgrids with the main grid to increase system reliability and resiliency.
- Due to the correlations between the electricity and gas grids, the optimal DA scheduling problem is solved for the interconnected electrical and natural gas networks aiming to achieve the results with higher accuracy.

The main objective of this work is to suggest a CCP-based model for optimal DA scheduling of the hybrid microgrids with a high penetration of clean energy generation systems in the interconnected electrical and gas networks. Due to considering the energy sharing possibility in the proposed model, transactive energy technology is applied to control the energy sharing between hybrid microgrids and the energy network. Improving the economic benefits of the hybrid microgrids, maximum usage of pollutant-free energy generation units, and the reliability of continuous energy supplying by operating controllable units in the deregulated environment are taken into account as the main achievements of the proposed model.

1.4 Organization of paper

The rest of this paper is organized as follows: the key models about the gas system, CCP model, and scenario generation and reduction approaches are expressed in Section II. The CCP-based DA scheduling formulations of hybrid microgrids are presented in Section III. In Section IV, the simulation results of this paper are fully described. Finally, Section V draws the main conclusions and briefly outlines the future works.

2. Key models

2.1 Electricity price model

This paper is targeted to suggest the CCP-based model for optimal scheduling of hybrid microgrids in the DA market. In this market, hybrid microgrids can submit an hourly bid that presents their status as a producer or a consumer on the next trading day. In the energy trading market, the hybrid microgrid will be a consumer if its power bid is less than zero, otherwise, it is a producer [33]. The fluctuations in energy demand and production could lead to the deviations between the actual and bid powers, which can be expressed as follows:

$$\Delta P_t^{dev} = P_t^f - P_t^{bid} \quad \forall\, t \tag{1}$$

$$P_t^f = \sum_{h=1}^{H} (P_{h,t}^{Wind} + P_{h,t}^{PV} + P_{h,t}^{CCHP} + P_{dis,h,t}^{BAT} - P_{cha,h,t}^{BAT}) - \sum_{n=1}^{N} (P_{n,t}^{L} - P_{n,t}^{IL}) \tag{2}$$

Power deviation between the bid and actual power is called imbalance power ΔP_t^{dev} and its corresponding cost is obtained from the following equation:

$$C_t^{dev} = \begin{cases} \rho_t^{\mathrm{Re}+}.\Delta P_t^{dev} & , \ \Delta P_t^{dev} < 0 \\ \rho_t^{\mathrm{Re}-}.\Delta P_t^{dev} & , \ \Delta P_t^{dev} \geq 0 \end{cases} \tag{3}$$

Moreover, DA market price has been used to set up the up and down-regulation prices in the real-time balancing (RT) market as follow:

$$\begin{cases} \rho_t^{\mathrm{Re}+} = (1+\varepsilon^{+}).\rho_t^{DA} \\ \rho_t^{\mathrm{Re}-} = (1-\varepsilon^{-}).\rho_t^{DA} \end{cases} \tag{4}$$

2.2 Gas system model

2.2.1. Linepack and gas flow models

Linepack (LP) is the pressured natural gas, which is stored in the gas pipelines across the natural gas network. The LP magnitude in the pipelines depends directly on the average pressure of gas and its variation will lead to an increase or decrease the amount of LP in the pipelines [34, 35]. Gas in pipelines is described by some variables that are shown in Fig. 1.

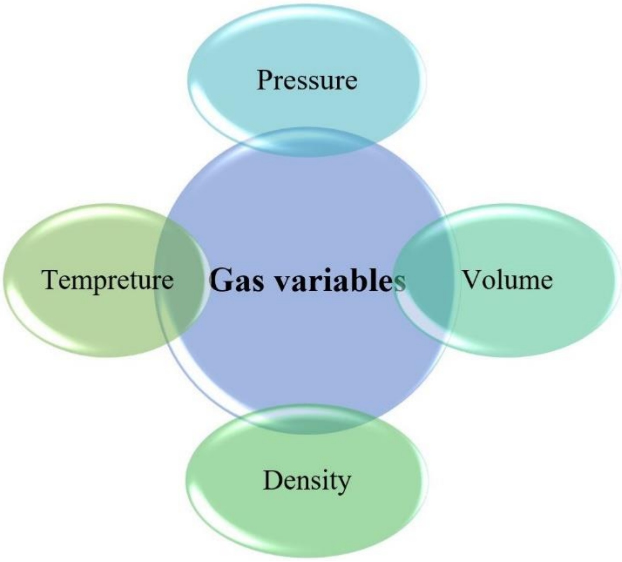


Fig. 1. Gas variables in pipelines.

The relationship between gas variables is described based on Boyle's law that is given as [36]:

$$\frac{\mathrm{P}}{\Upsilon \mathrm{T}_e} = \frac{\mathrm{P}_0}{\Upsilon_0 \mathrm{T}_{e0}} = \mathrm{A}^{Gas}.\mathrm{B}^{Gas} \tag{5}$$

$$\mathrm{P}_{mn}^{Ave}.\mathrm{E}_{mn} = \mathrm{P}_0.\mathrm{E}_0 \tag{6}$$

$$\mathrm{E}_{mn} = \pi.\ell_{mn}.d_{mn}^2 / 4 \tag{7}$$

Generally, the amount of LP in the pipelines depends on the initial natural gas stored in pipelines and varies along with changes in the gas supply and demand $\Delta p_{mn,t}^{Gas}$. In this paper, gas suppliers are gas network and gas storage while thermal demand, gas storage, compressor load, and the CCHP gas load are considered as gas consumers. The amount of LP in the steady-state is given as [37]:

$$\psi_{mn}^{Initial} = \xi.\mathrm{P}_{mn}^{Aver}.\mathrm{E}_{mn} / \Upsilon_0.\mathrm{T}_{e0}.\mathrm{A}^{Gas}.\mathrm{B}^{Gas} \tag{8}$$

$$\psi_{mn,t+1} = \psi_{mn,t} + \Delta p_{mn,t}^{Gas}.\Delta t \tag{9}$$

$$\Delta p_{mn,t}^{Gas} = p_{G,mnt}^{Gas,Tot} - p_{L,mnt}^{Gas} - p_{Gas,mnt}^{Comp} \tag{10}$$

$$p_{G,mnt}^{Gas,Tot} = p_{G,mnt}^{Gas} + p_{CCHP,ht}^{Gas} \quad \forall t \tag{11}$$

Moreover, the gas flow equation in the pipe *m*-*n* typically depends on the pressure at node *m* and *n*. Generally, Weymouth's formula is used for modeling the gas flow in pipelines according to the following equations [38, 39]:

$$f_{mn}^{Gas} = Dir_{mn}.\varpi.\frac{\mathrm{T}_{e0}}{\mathrm{P}_0}.\sqrt{\left|\frac{(\mathrm{P}_m^2 - \mathrm{P}_n^2).d_{mn}^5}{G.\upsilon_{mn}.\ell_{mn}.\mathrm{T}_e.\mathrm{B}^{Gas}}\right|} \tag{12}$$

$$Dir_{mn} = \begin{cases} +1 & \text{if} \quad \mathrm{P}_m - \mathrm{P}_n > 0 \\ -1 & \text{if} \quad \mathrm{P}_m - \mathrm{P}_n < 0 \end{cases} \tag{13}$$

$$\upsilon_{mn} = \frac{0.032}{d_{mn}^{(1/3)}} \tag{14}$$

$$\varpi = \sqrt{\pi^2.\phi^{Air} / 64} \;\; , \;\; G = \frac{\phi^{Air}}{\phi^{Gas}} = \frac{1}{0.6} = 1.6667 \tag{15}$$

where, equations (12) and (13) present the gas flow and direction equations, respectively.

2.2.2. Compressor station model

Compressors play a crucial role in compensating the drop of pressure in pipelines. The difference between the gas pressure at the inlet and outlet of this device and gas flow are two important factors in determining the amount of gas consumption in the compressor. Compressor station status can be exhibited using the following equations:

$$f_{Gas,mn}^{comp} = Dir(\mathrm{P}_m, \mathrm{P}_n).\frac{HP_{t,mn}^{Comp}}{\alpha_{1,mn} - \alpha_{2,mn}.\left[\dfrac{\max(\mathrm{P}_m, \mathrm{P}_n)}{\min(\mathrm{P}_m, \mathrm{P}_n)}\right]^{\alpha_{3,mn}}} \tag{16}$$

$$p_{Gas,mnt}^{Comp}(HP_{mnt}^{Comp}) = \beta_{1,mn}^{Comp} + \beta_{2,mn}^{Comp}.HP_{mnt}^{Comp} + \beta_{3,mn}^{Comp}.(HP_{mnt}^{Comp})^2 \tag{17}$$

$$PT_{mnt}^{Comp,down} \le \frac{\max(\mathrm{P}_m, \mathrm{P}_n)}{\min(\mathrm{P}_m, \mathrm{P}_n)} \le PT_{mnt}^{Comp,up} \tag{18}$$

where, equations (16) and (17) express the gas flow of compressor and the amount of its gas consumption, respectively.

2.3. Stochastic programming model

Increasing the penetration of the RERs as the popular energy resources with zero environmental problems and free fuel costs has been led to an increase in their exploitation throughout the electrical power system [40]. The dependency on weather changes and intermittent nature of the RERs outputs necessitates considering various states of their outputs (here called as a scenario) in the modeling phase. On the other hand, we are also faced with volatility behaviors of energy prices and loads as the other uncertain parameters in the energy market modeling. Therefore, in order to near realistic modeling of the optimal scheduling of hybrid microgrids, we consider the energy prices, wind speed, and intensity of sunlight as the uncertain parameters. In addition, numerous scenarios are created using the LHS method and the number of them is reduced to the rational amount by applying the FFS method to provide the problem simulation process with an acceptable computational burden.

2.3.1. Latin hyperbolic sampling method

Over the past decades, several techniques are introduced to effectively generate scenarios for various uncertain parameters in probabilistic-based problems [41]. One of the most famous of them is the Monte-Carlo simulation (MCS) method, which is exerted in several scenario-based research works [41]. However, as this method is simple for stochastic analysis, it serves a longer time for convergence and full coverage of the sample space cannot be guaranteed under its paradigm in the high-reliability systems [42]. Thereby, Latin hyperbolic sampling (LHS) was proposed in [43] as an effective scenario creation approach to consider all elements of the whole sample space with various probability and also establish the interaction between multiple random variables [44]. Given the mentioned features, this method is widely applied in stochastic programming problems in recent studies [45, 46] with various goals. The full description of the LHS method can be accessed in [47].

2.3.2. Fast forward selection method

In order to avoid the computational complexity caused by handling the numerous generated scenarios for uncertain parameters, scenario reduction methods are introduced and used in stochastic-based problems in recent decades [48]. Scenario reduction methods are widely applied for decreasing the number of created scenarios to a reasonable number of them in some researches [49, 50]. The fast forward selection approach is one of the scenario reduction methods that is used to reduce the computational burden in practical problems. For example, this method is considered in [51] to alleviate the number of created scenarios for wind speed and save the problem-solving time. In the FFS approach, some scenarios with minimum distance in comparison with other scenarios are selected as the candidate scenarios based on minimizing the Kantorovich distance between the generated scenarios [52]. The algorithm of the FFS method, along with more required information about its process, can be accessed in [53].

2.3.3. Chance-constrained programming model

The chance-constrained model has been developed as the stochastic programming technique and is employed for scenario-based optimization problems in recent years [54]. Indeed, CCP, as one of the powerful tools, uses confidence levels and can be applied for modeling the decision systems through handling the probabilistic version of problems [55]. In the CCP method, confidence levels are considered for holding the probabilistic constraints at least the confidence level σ, which is determined by the decision-maker as the safety margin [56]. In other words, probabilistic analysis of the uncertain parameters is carried out with the aim of incorporating their randomness into the stochastic problem modeling process [57]. Typically, the CCP problem can be formulated as follow:

$$\min_{x} g(x, \vartheta) \tag{19}$$

$$\text{s.t} \quad \Pr\{f_q(x, \vartheta) \geq 0, \quad q = 1, \cdots, \tau\} \geq \sigma \tag{20}$$

where, $g(x, \vartheta)$ presents the objective function with random variables. ϑ is the vector of τ random variables, which its cumulative distribution function is:

$$G_{\vartheta_k}(z) = \Pr(\vartheta_k \leq z), \ (k = 1, \cdots \tau) \tag{21}$$

In equation (20), the set of joint chance constraints are measured with *Pr()* in which all set of constraints are presented by $f_1, \cdots, f_\tau$ with random variable. In addition, the parameter σ shows the confidence level, which is entered into the probabilistic constraints and determined by the decision-maker.

3. Problem formulation

3.1. System architecture of hybrid microgrids

Given the environmental concerns, all of the hybrid microgrids are powered with wind turbines and solar panels to produce clean energy without fuel costs. Because of the dependency of RERs outputs on the climate changes, their energy production would be uncertain and their standalone operation may cause unbalances between energy supply and demand at some times. To compensate such stochastic nature, a CCHP unit is considered for each microgrid not only as a backup system to provide the required electrical energy but also to meet the heating and cooling energy demand. The CCHP units are consisted of three main components, namely power generation unit (PGU) for supporting the electrical energy generation in the system, boiler for supplying the thermal energy, and heating and cooling systems to feed the thermal storage. Moreover, electrical and thermal storages are operated to capture the surplus of energy generated at some times and injecting it into the system at a later time. The existence of the electrical energy storage in the presence of RERs is essential for establishing the energy balance through storing the surplus energy produced by wind turbines in the hours that the wind velocity is suitable for wind turbine production and then sold back stored energy in the peak times when the electricity consumption is greater than its production. In order to increase the system reliability in providing the microgrids demand, the energy sharing possibility is also intended based on the transactive energy paradigm for the hybrid microgrids. The schematic of hybrid microgrids is demonstrated in Fig. 2. According to this figure, the relationships between all microgrid's components are shown in the interconnected structure of the electrical and gas network. In Fig. 2, the black and red solid lines respectively present the electricity and gas flows. In addition, the dashed line represents the thermal energy flow.

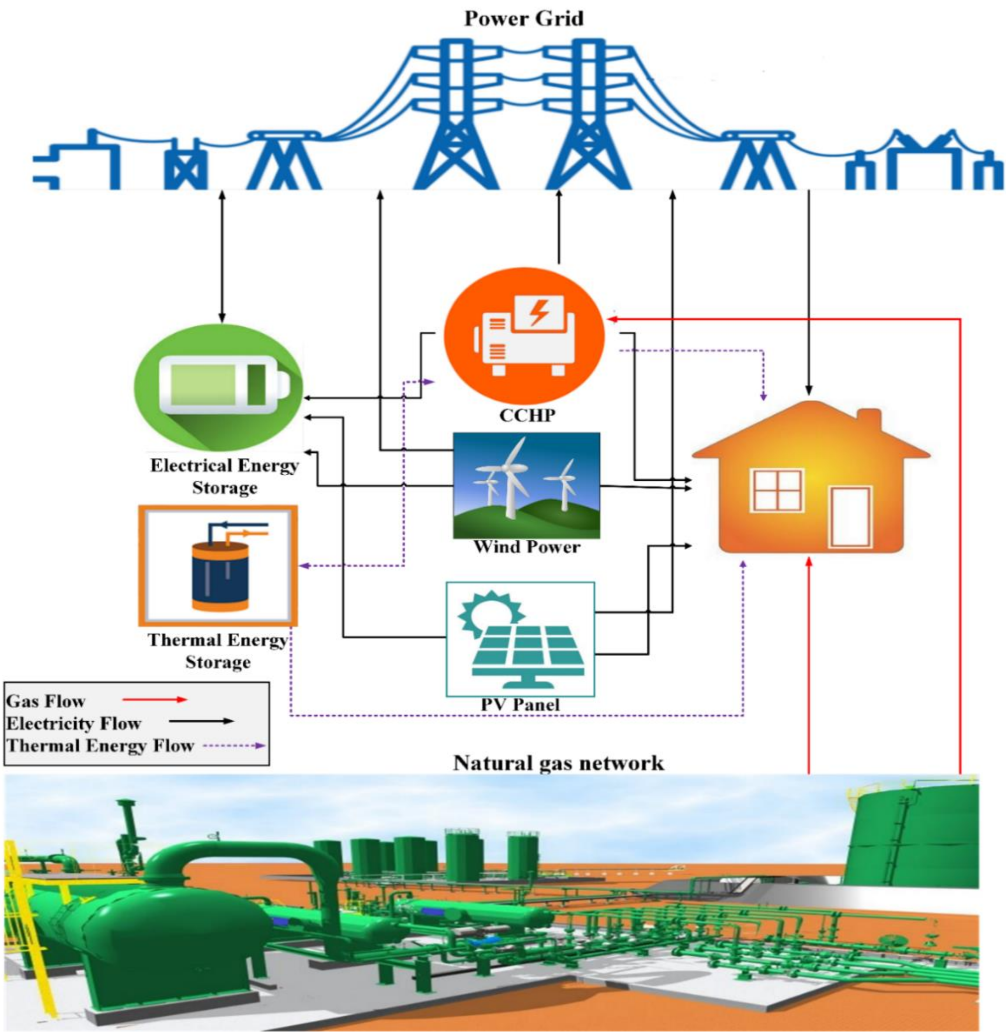


Fig. 2. The schematic of hybrid microgrids.

3.2. Objective function and constraints

3.2.1. Objective function

This paper is structured to minimize the energy cost of hybrid microgrids in the system with a high penetration of renewables. Due to this, all microgrids attempt to optimize their bidding strategies to have a successful presence in the DA electricity and wholesale gas markets. This objective is scheduled to realize using the following function:

$$F_h = \sum_{t=1}^{T}\sum_{n=1}^{N}(P_{n,t}^{IL} - P_{n,t}^{L}).\rho_t^{Se}.\Delta t - \sum_{t=1}^{T} P_t^{bid}.\rho_t^{DA}.\Delta t - \sum_{t=1}^{T} C_t^{Dev} + \sum_{m=1}^{M}\sum_{t=1}^{T} C_{m,t}^{IL}$$
$$+\sum_{t=1}^{T}\rho_{Gas,t}^{Pu}.(Fe_{h,t}^{PGU} + Fe_{h,t}^{BO}) + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\rho_{Gas,t}^{Pu}.p_{G,mnt}^{Gas} - \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\rho_{Gas,t}^{Se}.p_{L,mnt}^{Gas} \quad \forall\ h \tag{22}$$

$$\min\ E[\mathrm{Cost}] = \sum_{s=1}^{S}\mathrm{Prob}_s.(F_{h,s}) \tag{23}$$

where, E[Cost] is the objective function and denotes the expected cost, which should be minimized during the optimization process. Applying the CCP method on the cost-based objective function will add a new constraint related to the objective function as follows:

$$p(F_h \le F_h^{Upper}) \ge \sigma \qquad \forall h \tag{24}$$

where, F_h^{Upper} is the maximum value of energy cost for each microgrid. In (22), the first term models the revenue of selling electricity to the consumers. The next term models the revenue (cost) by selling (purchasing) electricity to (from) the power grid. The third and fourth terms present the cost of imbalance energy and interrupted load (IL). Moreover, the fifth term of objective F_h represents the fuel cost of CCHP units. Finally, the last two terms of objective F_h model the cost of purchasing natural gas from the wholesale gas market and revenue of selling natural gas, respectively. Equation (24) expresses that the energy cost of each hybrid microgrid should not be greater than a specified value (F_h^{Upper}), but the probability of violating this constraint is considered using a confidence level σ based on the CCP method. On the other hand, when σ is set to 95%, i.e., the upper bound of this constraint can fluctuate in five percent of generated scenarios.

3.2.2. Constraints

In this research, the optimal chance-constrained DA scheduling problem is conducted subject to the complete constraints of different sectors. The subscript *s* is also omitted from the variables to avoid information repetition. The set of constraints is given below.

3.2.2.1. Electricity demand-supply balance constraint

In the electrical power system, the electricity supply and demand should be balanced as the following constraint:

$$\sum_{h=1}^{H}(P_{h,t}^{Wind}+P_{h,t}^{PV}+P_{h,t}^{CCHP}+P_{dis,h,t}^{BAT})=P_{t}^{bid}+\sum_{n=1}^{N}(P_{n,t}^{L}-P_{n,t}^{IL})+P_{cha,h,t}^{BAT}+Ploss_{t}\quad \forall t \tag{25}$$

3.2.2.2. Thermal energy balance constraints

Similar to the electricity balance constraint, the energy balance should be established between thermal energy supply and demand, which are given as:

$$(COc_{h,t}+SCOc_{h,t}).\eta_{Co}=CO_{h,t}^{L}+COs_{h.t}\qquad \forall h\ ,\ \forall t \tag{26}$$

$$(HEc_{h,t}+SHEc_{h,t}).\eta_{He}=HE_{h,t}^{L}+HEs_{h.t}\qquad \forall h\ ,\ \forall t \tag{27}$$

3.2.2.3. Wind power constraint

Wind turbine output depends on the forecasted, rated, cut in, and cut out wind velocity. The constraint regarding wind turbine production is given as:

$$P_{h,t}^{Wind}=\begin{Bmatrix} 0 & Sp_{t}^{Fore}<Sp_{h}^{C.i}\ ,Sp_{t}^{Fore}>Sp_{h}^{C.o} \\ P_{\max,h}^{wind}\times\left(\dfrac{Sp_{t}^{Fore}-Sp_{h}^{C.i}}{Sp_{h}^{Ra}-Sp_{h}^{C.i}}\right)^{3} & Sp_{h}^{C.i}\le Sp_{t}^{Fore}\le Sp_{h}^{Ra} \\ P_{\max,h}^{wind} & Sp_{h}^{Ra}\le Sp_{t}^{Fore}\le Sp_{h}^{C.o} \end{Bmatrix} \tag{28}$$

$$P_{h,t}^{Wind}\ /\ \sqrt{(P_{h,t}^{Wind})^{2}+(Q_{h,t}^{Wind})^{2}}=\text{Constant} \tag{29}$$

3.2.2.4. PV panel constraint

The electricity produced by PV panels directly depends on the PV size, efficiency, and solar radiation. Therefore, PV production will follow the below constraint:

$$P_{h,t}^{PV}\le PV_{h}^{size}.PV^{\eta}.PV_{t}^{sol}\qquad \forall h\ ,\ \forall t \tag{30}$$

3.2.2.5. CCHP constraints

In a CCHP unit, the PGU is consisted of a gas turbine to provide electricity and support the system for heating energy production over the scheduling horizon [58]. The energy generation in the PGU and boiler depends on the ON/OFF status of PGU and their size according to the following constraints.

$$Fe_{h,t}^{PGU} \le X_{h,t}^{PGU}.PGU_h^{size} \quad \forall h \ , \ \forall t \tag{31}$$

$$Fe_{h,t}^{BO} \le BO_h^{size} \quad \forall h \ , \ \forall t \tag{32}$$

$$P_{h,t}^{CCHP} \le (Fe_{h,t}^{PGU} - X_{h,t}^{PGU}.a^{pgu}) / b^{pgu} \quad \forall h \ , \ \forall t \tag{33}$$

$$COc_{h,t} + HEc_{h,t} + TEs_{h,t}^{cchp} \le Fe_{h,t}^{BO}.\eta^{BO} + Fe_{h,t}^{PGU}.\eta^{PGU} \quad \forall h \ , \ \forall t \tag{34}$$

Equation (34) presents that thermal energy produced by the CCHP for supporting the thermal storage or cooling and heating components.

3.2.2.6. Battery energy storage (BESS) constraints

$$X_{dis,h,t}^{BAT} + X_{cha,h,t}^{BAT} \le 1 \quad \forall h \ , \ \forall t \tag{35}$$

$$Ba_h^{size}.\lambda_{\min}^{Ba} \le P_{h,t}^{BAT} \le Ba_h^{size} \quad \forall h \ , \ \forall t \tag{36}$$

$$P_{h,t}^{BAT} = (P_{cha,h,t}^{BAT} - P_{dis,h,t}^{BAT}).\Delta t + EBa^{initial} \quad \forall h \ , \ t = 1 \tag{37}$$

$$P_{h,t}^{BAT} - P_{h,t-1}^{BAT} = (P_{cha,h,t}^{BAT} - P_{dis,h,t}^{BAT}).\Delta t \quad \forall h \ , \ \forall t \ge 2 \tag{38}$$

$$\lambda_{\min}^{Ba,cha}.X_{cha,h,t}^{BAT}.Ba_h^{size} \le P_{cha,h,t}^{BAT} \le \lambda_{\max}^{Ba,cha}.X_{cha,h,t}^{BAT}.Ba_h^{size} \quad \forall h \ , \ \forall t \tag{39}$$

$$\lambda_{\min}^{Ba,dis}.X_{dis,h,t}^{BAT}.Ba_h^{size} \le P_{dis,h,t}^{BAT} \le \lambda_{\max}^{Ba,dis}.X_{dis,h,t}^{BAT}.Ba_h^{size} \quad \forall h \ , \ \forall t \tag{40}$$

Equation (35) states the impossibility of simultaneous charging and discharging of the BESS. Equation (36) states the electricity stored in BESS should be kept in the permissible range. Equations (37) and (38) present the charging and discharging activities while charging and discharging of BESS limits over the scheduling horizon are represented in (39) and (40), respectively.

3.2.2.7. Thermal storage constraints

$$X_{dis,h,t}^{THE} + X_{cha,h,t}^{THE} \le 1 \quad \forall h \ , \ \forall t \tag{41}$$

$$Te_{h}^{size}.\lambda_{\min}^{Te} \le E_{h,t}^{THE} \le Te_{h}^{size} \quad \forall h\ ,\ \forall t \tag{42}$$

$$E_{h,t}^{THE} = (E_{cha,h,t}^{THE} - E_{dis,h,t}^{THE}).\Delta t + ETe^{initial} \quad \forall h\ ,\ t=1 \tag{43}$$

$$E_{h,t}^{THE} - E_{h,t-1}^{THE} = (E_{cha,h,t}^{THE} - E_{dis,h,t}^{THE}).\Delta t \quad \forall h\ ,\ \forall t \ge 2 \tag{44}$$

$$COs_{h.t} + HEs_{h.t} + TEs_{h,t}^{cchp} \le Te_{h}^{size} \quad \forall h\ ,\ \forall t \tag{45}$$

$$SCOc_{h,t} + SHEc_{h,t} \le E_{dis,h,t}^{THE}.\eta_{Td} \quad \forall h\ ,\ \forall t \tag{46}$$

$$E_{cha,h,t}^{THE} \le (COs_{h.t} + HEs_{h.t} + TEs_{h,t}^{cchp}).\eta_{Tc} \quad \forall h\ ,\ \forall t \tag{47}$$

$$\lambda_{\min}^{Te,cha}.X_{cha,h,t}^{THE}.Te_{h}^{size} \le E_{cha,h,t}^{THE} \le \lambda_{\max}^{Te,cha}.X_{cha,h,t}^{THE}.Te_{h}^{size} \quad \forall h\ ,\ \forall t \tag{48}$$

$$\lambda_{\min}^{Te,dis}.X_{dis,h,t}^{THE}.Te_{h}^{size} \le E_{dis,h,t}^{THE} \le \lambda_{\max}^{Te,dis}.X_{dis,h,t}^{THE}.Te_{h}^{size} \quad \forall h\ ,\ \forall t \tag{49}$$

Equation (41) states the impossibility of simultaneous charging and discharging of the thermal storage. Equation (42) states the permissible range of the storage system for storing the thermal energy. Equations (43) and (44) present the activities related to the charging and discharging of the storage system. The amount of thermal energy content depends on the storage charging and discharging rates expressed in (46) and (47). Moreover, equations (48) and (49) represent the limits of charging and discharging thermal storage over the scheduling horizon.

3.2.2.8. Constraints for the interruptible load (IL)

$$\left|P_{n,t}^{IL}\right| \le P_{n,t}^{IL,up} \quad \forall n \in 1:N\ ,\ \forall t \in 1:T \tag{50}$$

$$P_{n,t}^{L,down} \le P_{n,t}^{L} - P_{n,t}^{IL} \le P_{n,t}^{L,up} \tag{51}$$

In emergency conditions, up to 10% of loads at each bus are considered for the interruption and the amount of IL should not exceed the admissible range in accordance with the constraints (50) and (51).

3.2.2.9. Interconnection exchange constraint

$$P_{Min}^{Exch} \le P_{t}^{bid} \le P_{Max}^{Exch} \quad \forall t \tag{52}$$

Equation (52) presents that the amount of energy sharing between the power grid and hybrid microgrids should be retained in the allowable range.

3.2.2.10. Electricity network constraints

$$P_{n,t}^{Inje}(V_t,\theta_t)+P_{n,t}^{L}-P_{n,t}^{El,Gen}=0 \quad \forall t,\ \forall n \tag{53}$$

$$Q_{n,t}^{Inje}(V_t,\theta_t)+Q_{n,t}^{L}-Q_{n,t}^{El,Gen}=0 \quad \forall t,\ \forall n \tag{54}$$

$$S_{n,t}(V_t,\theta_t)\leq S_{n,t}^{UP} \quad \forall t,\ \forall n \tag{55}$$

$$V_n^{down}\leq V_{n,t}\leq V_n^{up} \quad \forall t,\ \forall n \tag{56}$$

Equations (53) and (54) state the active and reactive power balance constraints in the AC power flow, respectively. Additionally, equations (55) and (56) express that the amount of complex power flow and voltage in the buses must stay in the permissible range.

3.2.2.11. Natural gas network constraints

$$p_{G,mnt}^{Gas,Tot}+\sum_{n=1}^{N}f_{nm}^{Gas}=\sum_{n=1}^{N}f_{mn}^{Gas}+p_{L,mnt}^{Gas}+p_{Gas,mnt}^{Comp} \quad \forall m\in 1:M \tag{57}$$

$$p_{L,mnt}^{Gas}=p_{L,mnt}^{Gas,cchp}+p_{L,mnt}^{Gas,heat} \tag{58}$$

$$\psi_{mn,t}^{\min}\leq\psi_{mn,t}\leq\psi_{mn,t}^{\max} \tag{59}$$

$$\psi_{mn,0}=\psi_{mn}^{Initial}\ ;\ \psi_{mn,T}\geq\psi_{mn}^{End} \tag{60}$$

Natural gas nodal balance is modeled using (57). Equation (58) presents the gas demand, which is consisted of thermal gas loads and CCHP gas demand. The constraint related to the maximum and minimum amount of the linepack is modeled in (59). The final and initial amount of linepack are also presented in (60).

4. Simulation results

In this section, the chance-constrained DA scheduling model is implemented on the modified IEEE10-bus radial system with five commercial hybrid microgrids targeting to minimize hybrid microgrids' cost in the interconnected electricity and gas networks. The single-line diagram of the 10-bus system is shown in Fig. 3 and complete information for this system such as length of pipe, the reactance, and resistance of power lines can also be accessed in [59].

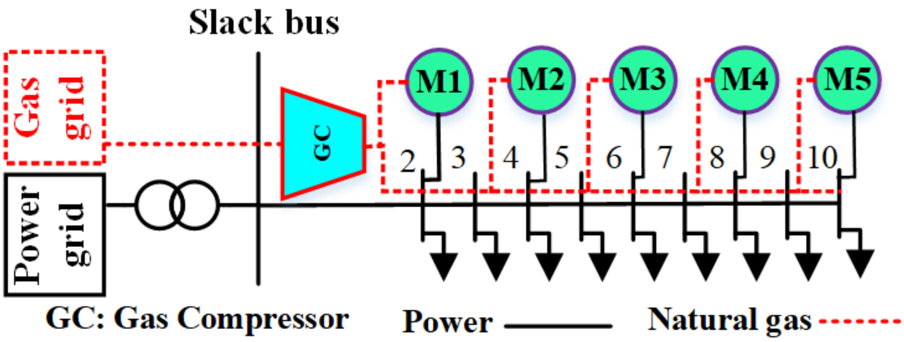


Fig. 3. The single-line diagram of 10-bus interconnected power and gas systems.

Because of the probabilistic nature of this problem engaged with different uncertainties, the CCP approach is applied with a confidence level of 95% for the constraints that include uncertain parameters. In this respect, the electricity and gas prices in the DA and wholesale markets along with the wind speed and intensity of sunlight are assumed as uncertain parameters, which LHS and FFS techniques are also deployed for scenario generation and reduction. This paper has also exerted the transactive energy concept to enable a dynamic energy balance over the scheduling horizon. For this aim, the capacity of energy exchanging with the power grid is set to 3500 kW for the hybrid microgrids. In addition, hybrid microgrids are equipped with the CCHP units as the standby systems for meeting the thermal and electrical energy. This scheduling problem is carried out for the microgrids located in the Chicago area, USA, and is conducted for two sample days in a year, namely July 15 and January 15, considering a 24-hour time horizon for both days. The proposed model is general and is not limited to the special area so that it can be implemented for the regions that have a suitable climate condition for RERs generation and natural gas and electricity networks are available for interactions. The data of electricity and thermal loads of hybrid microgrids, CCHP units, and electrical and thermal storage systems can be found in [60]. Moreover, the profile of thermal loads along with energy price variations during a day is illustrated in Fig. 4. Also, total electrical and thermal energy capacities for each of the hybrid microgrids are presented in Table 1.

Table 1. Total electrical and thermal energy capacities for the hybrid microgrids.

Capacity	M 1	M 2	M 3	M 4	M 5
Electricity generation (kW)	3750	3625	3875	2000	2625
Heating energy generation (kJ)	63	170	302	502	524

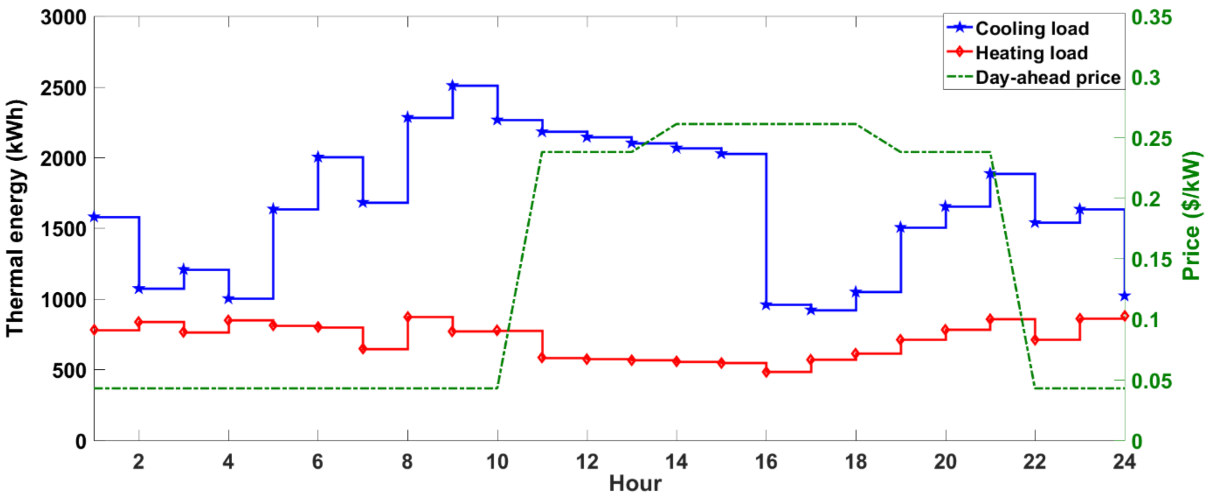


Fig. 4. The profile of the thermal loads and energy price variations during a day.

The complete information regarding the PV panels and electrical and thermal energy prices can be accessible in [47], respectively. Moreover, natural gas network and wind turbine parameters can be reached from [61] and [62], respectively. The existence of the nonlinear equations and binary variables has converted the scheduling problem to the MINLP problem. In this research, GAMS software as a high-level optimization system is used for solving the MINLP problem, which is also designed for modeling different types of optimization problems. In GAMS, SBB and DICOPT are two powerful solvers that are designed and developed for solving the MINLP problems. Hence, the scheduling problem is modeled in GAMS using SBB [63] and DICOPT [64] solvers. The simulation results for the mentioned solvers indicated that all extracted results for them are the same, which ensures that a reasonable optimal solution concluded from the proposed scheduling model. After running the program, the numerical results of hybrid microgrids are extracted in two cases, in which Case I is done without uncertainty modeling, while Case II is considered with uncertainty modeling using the CCP method. Indeed, Case I is considered as a base case for this study without modeling the stochastic performances of uncertain sources while Case II is presented to model the realistic conditions of the system for evaluating the impacts of uncertainty modeling on system economy. Microgrid's energy cost for two cases is tabulated in Table 2. Moreover, Table 3 presents the financial indicators for the DA scheduling problem.

Table 2. Total energy cost of hybrid microgrids in Case I and II ($).

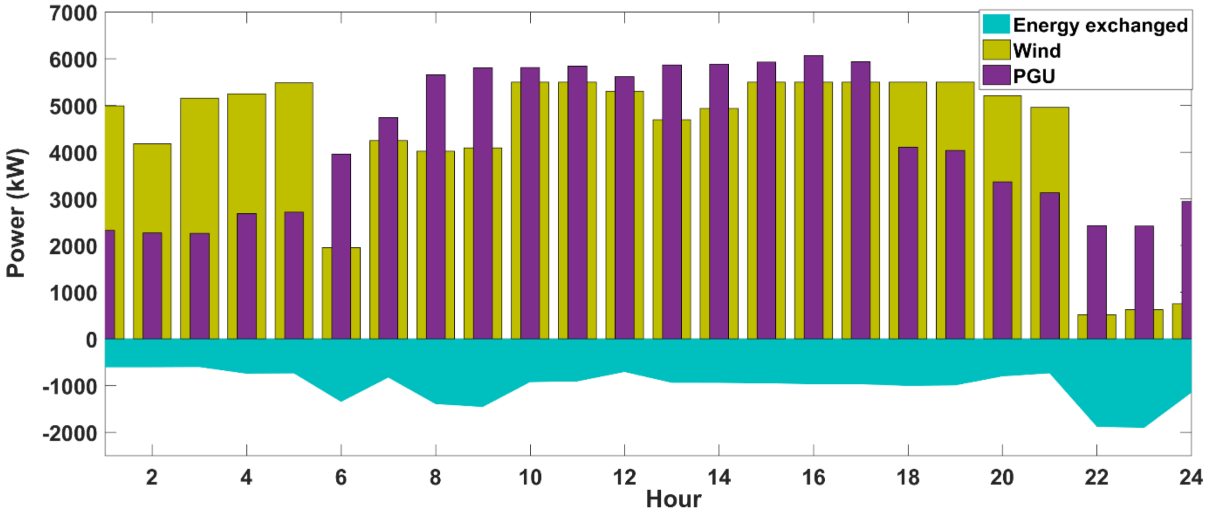
Day	Case Index	M 1	M 2	M 3	M 4	M 5
July 15	**I**	5190.950	5171.768	5195.161	5247.739	5211.741
	II	4463.091	4443.910	4467.302	4519.881	4483.883
January 15	**I**	4940.209	4931.364	4962.438	5028.615	4987.671
	II	4186.014	4154.627	4180.237	4234.633	4190.547

Table 3. Financial indicators for day-ahead scheduling of hybrid microgrids in Case II ($)

Revenue of thermal energy	264.864	Revenue of electrical energy	4419.841
Gas purchase cost	3092.170	Imbalance cost	2253.557
		Electricity purchase cost	5726.394
Total cost of gas sector	2827.306	**Total cost of power sector**	3560.123

After solving the problem by applying the CCP method for July 15 in Case II, the amount of expected operation cost is equal to $22378.067, which is reduced in comparison with $26017.359 in Case I without uncertainty modeling. In addition, for January 15, the amount of expected operation cost for hybrid microgrids is reduced from $24850.297 in Case I to $20946.058 in Case II. Moreover, the total energy cost of each hybrid microgrid for Case I and II are presented in Table 2 for July 15. All microgrids have gained the energy cost based on their scales and interactions in the energy market. Each of the mentioned cases is solved using the SBB and DICOPT solvers and the obtained results from the mentioned solvers are the same, which indicates that the optimality of results is relatively reasonable enough. Moreover, to further analyze microgrids' cost and revenue, the detailed financial information of all microgrids in Case II is also listed in Table 3. Similar to Table 2, all obtained results for the MINLP solvers are also the same in this table. In this study, gas purchased from the wholesale gas market is used for meeting the gas demand of the heating load and CCHP units. The revenue of gas for all microgrids is obtained only from selling energy to thermal loads related to the non-electrical demands that the amount of their gas consumption is very low in comparison with gas consumed by CCHP units. Hence, the magnitude of gas revenue is much lower than the gas purchase cost. In this study, the sum of the cost of interrupted load and electricity purchasing cost from the DA market is considered as the cost of electricity. Purchasing electrical energy from the DA market is conducted to balance the energy supply and demand during the scheduled time intervals. On the other hand, the existence of the power difference between the microgrid's bid and actual power has been led to the power deviation cost. Thereby, to provide this power gap, microgrids have been forced to purchase their required energy in the real-time balancing market when the price of electricity is more than DA market price. Due to this, another high cost as the imbalance cost is imposed for the hybrid microgrids.

The scheduling of DERs and energy trading with the main grid in Case II are displayed in Fig. 5. As obvious from it, the wind turbine generation is high in the morning (1-5 am) which not only meets the electricity demand but also can charge BESS. Because of the low gas fuel price in this time interval, the PGU also generates the electricity to help the full charging of BESS for using its full capacity later. However, during peak times (10-12 am and 1-5 pm), both the wind turbines and PGU produce a high level of electricity to supply the adequate energy needed at peak times. In this respect, the energy trading possibility is also used for establishing the time-to-time energy balance over the scheduling horizon. Indeed, considering the limitation for the energy exchange between the microgrids and the energy network has made the implementation of the proposed model more practical in the real applications.



(R1-3) Fig. 5. The diagram of DERs scheduling and energy traded with the main grid in Case II.

In addition, the PV panel, as the other clean energy resource, is considered in the energy production process of hybrid microgrids. As seen in Fig. 6, PV panels generate the highest amount of energy during peak times (8-12 am and 1-5 pm). Typically, because the intensity of solar radiation is high at noon, PV panels can be a suitable choice for meeting the peak demand. The IL at each bus is also posed as the last option to balance energy in this research, which is happened at high load times according to Fig. 6. Employing the demand response programs such as IL offers more ways for balancing energy that can facilitate the application of the proposed model in practice.

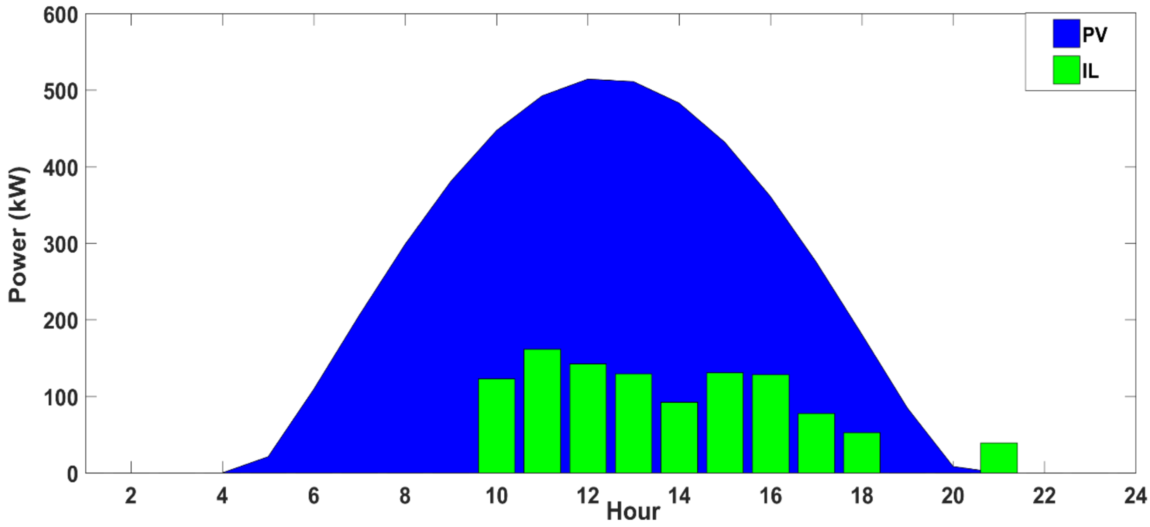


Fig. 6. The behaviors of solar panel and IL during a day in Case II.

Because of the unpredictability of RERs outputs, the hybrid microgrids are equipped with the BESS to store energy when the produced energy is greater than its consumption and to give it back to the system when it is needed. Fig. 7 demonstrates the behaviors of BESS for 24 hours. In order to indicate the important role of the BESS in balancing energy in the systems with a high penetration of the stochastic producers, the amount of energy production is demonstrated in two states: with and without the BESS. As seen in Fig. 7, the BESS is charged in the early morning when the production of wind turbines is high. However, the BESS is discharged during peak times to respond to the high energy demand of this part of the day. At night (6-10 pm), because of lower energy demand, the production of PGU and wind turbines are used for charging BESS. However, reducing the generation of production units in the system at the end of the night (10-12 pm) has led to discharging BESS for supplying the energy load at the mentioned time periods.

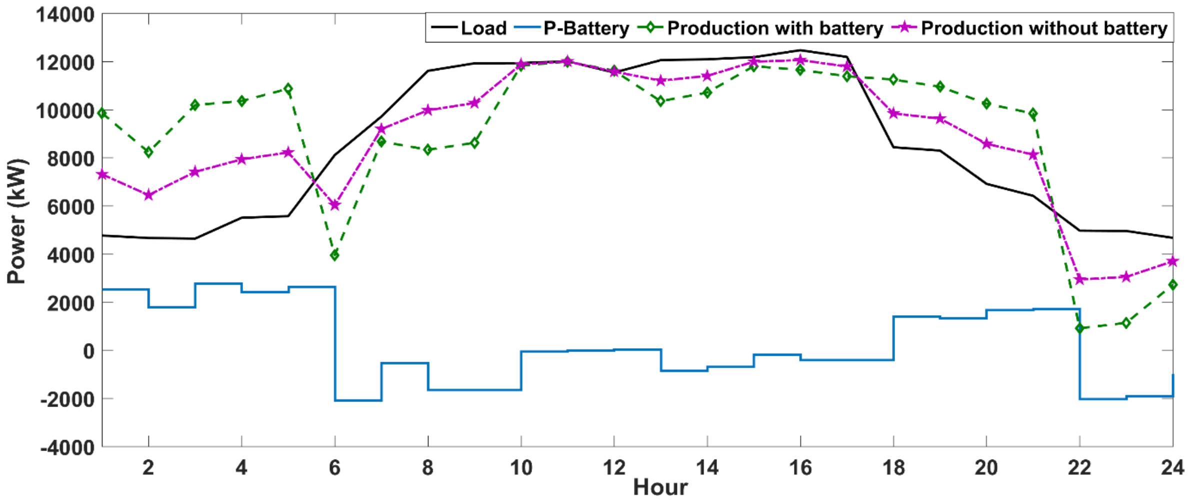


Fig. 7. The BESS scheduling during 24-hours in Case II.

Because of using the gas-fired units like CCHP systems in the hybrid microgrids, the analysis of electrical and natural gas grids in the interconnected mode is crucial to achieve the near reality results. The LP is the key option in the natural gas networks for nodal balancing during the natural gas network interactions. Due to this, the role of LP potential in realizing the dynamic balance between the natural gas supply and demand is shown in Fig. 8. As obvious from this figure, when the gas supply is less than its consumption, the LP is discharged for meeting the surplus gas demand while it is charged at other times when the gas supply is higher.

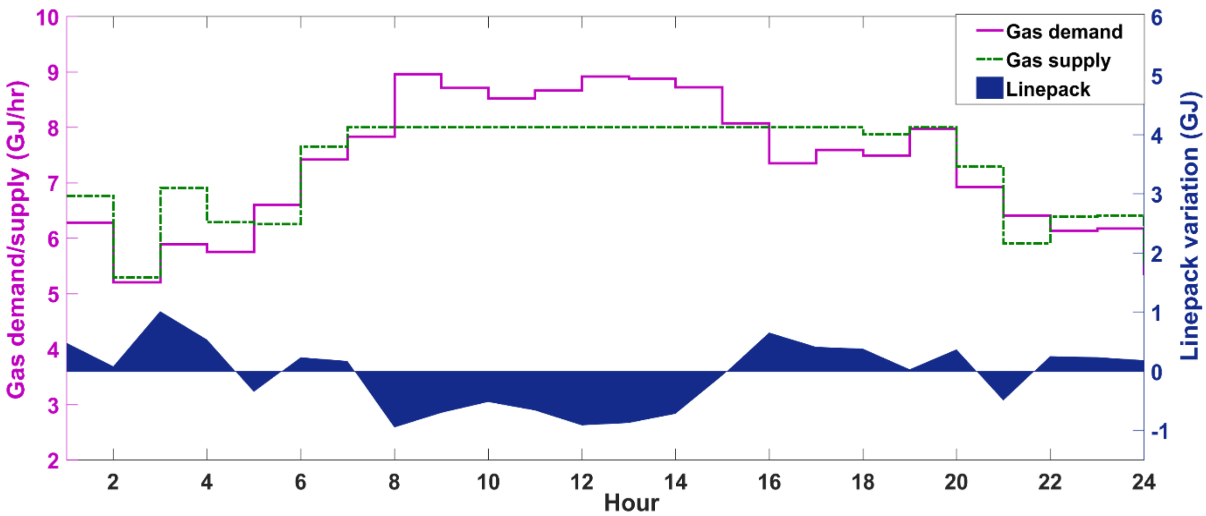


Fig. 8. The linepack variations during a day in Case II.

5. Conclusion

In this article, the optimal chance-constrained DA scheduling of the hybrid microgrids was accomplished to minimize the microgrids' energy cost and maximizing clean energy production by applying the numerous RERs for the energy generation. To this end, five commercial hybrid microgrids were selected considering the possibility of energy trading with the power grid based on the transactive energy architecture. The CCP method was employed for probabilistic evaluation of the problem in the presence of RERs, in which energy prices in the energy market, wind velocity, and solar radiation were intended as the uncertain parameters for this assessment. In order to well study all possible outcomes related to the realization of different uncertain parameters in practice, the LHS and FFS approaches were exerted for scenario generation and reduction. To effectively model interactions between the electrical and natural gas networks, this problem was carried out in a coupled electrical and natural gas networks with electrical and thermal energy demands considering all restrictions of the mentioned grids. The careful analysis of simulation results indicated that all microgrids could meet their energy demands in the network with a high penetration of renewables in a cost-effective manner. In this respect, the amount of operation cost for the hybrid microgrids was reduced by nearly 13.99% in Case II with uncertainty modeling in comparison with Case I. It was also demonstrated that using the transactive energy concept in controlling the energy trading between microgrids and the energy grid could result in establishing a time-to-time energy balance between energy supply and demand in the system with a high share of renewable systems. Another key finding is that the modeling of interactions between the electrical and gas grids could provide a reliable condition for the gas-fired systems to support the RERs targeting continuous energy supply in the deregulated environment.

In addition, considering various behaviors of all uncertain parameters is necessary for reaching feasible and near-optimal results. In this regard, applying the appropriate uncertainty modeling methods will be beneficial that can not only cater to the different behaviors of the uncertain sources in probabilistic modeling of the microgrid but also provide robust conditions for the system. On the other hand, the flexibility and reliability of the systems operated in an uncertain environment are of great importance. To this end, employing appropriate demand-side energy management methods will increase the flexibility of renewable-based systems while enabling dynamic energy balances. These areas of practice could be considered as future works.

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