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Robust optimization of renewable-based multi-energy micro-grid integrated with flexible energy conversion and storage devices

Amir Aris Lekvan [a], Reza Habibifar [b], Mehran Moradi [a], Mohammad Khoshjahan [c], Sayyad Nojavan [d], Kittisak Jermsittiparsert [e,f,*]

[a] Department of Electrical and Computer Engineering, Tarbiat Modares University, Iran
[b] Electrical Engineering Department, Sharif University of Technology, Iran
[c] Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX, 77843, USA
[d] Department of Electrical Engineering, University of Bonab, Bonab, Iran
[e] MBA School, Henan University of Economics and Law, Zhengzhou, China
[f] Political Science Association of Kasetsart University, Bangkok, Thailand

A R T I C L E I N F O

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Multi-energy microgrid
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A B S T R A C T

This paper presents a new model for optimal scheduling of renewable-based multi-energy microgrid (MEM) systems incorporated with emerging high-efficient technologies such as electric vehicle (EVs) parking lots, power-to-gas (P2G) facility, and demand response programs. The proposed MEM is equipped with wind energy, multi-carrier energy storage technologies, boiler, combined heat and power unit, P2G, EVs, and demand response with the aim of total operational cost minimization. Meanwhile, the system operator can participate in three electricity, heat, and gas market to meet local demands as well as achieve desired profits through energy exchanges. The proposed MEM is exposed to high-level uncertainties due to wind energy, demand, the initial and final state of charge of EVs, arrival and departure times of EVs, as well as power price. A hybrid robust/stochastic framework is used to capture all random variables and distinguishes between the level of conservatism in the decision-making procedure. The electricity price uncertainty is addressed by a robust approach, while a stochastic framework models other uncertainties of the system. Simulations are provided for different cases, which results revealed that the integrated scheduling of MEM in the presence of emerging technologies, incorporated with vehicle-to-grid (V2G) capability, reduces the total operational cost by 14.2 %.

1. Introduction

1.1. Motivation

Reasonable operations of multi-carrier energy systems will be able to offer the high-efficiency utilization of renewable energy sources (RES), as well as the reliability improvement of energy supply. Multi-energy microgrids (MEMs) integrated by multiple energies can provide high energy supply flexibility for not only electrical end-users but thermal or gas consumers. The emerging of the flexible sources in a MEM can facilitate the integration of high penetration of RES and offer significant benefits from technical and environmental points of view. EVs are regarded as the main element of the modern energy system to reduce the emission pollution, as well as mitigate the fluctuation nature of RES via mobility capability. Incorporating the MEM with EV parking lot lets to multiple benefits such as operation cost and emission minimization, load management, and high integration of RES. Meanwhile, the power to gas (P2G) technology as a highly efficient gas storage technology links the electricity and natural gas (NG) sectors in the MEM. The P2G converts surplus power produced by RES into the NG via the electrochemical process. The produced NG saved and injected into the MEM to supply local NG load, utilize as primary fuel for the NG-based generation units such as boiler unit and combined heat and power (CHP), or sold to the NG network. Also, demand response (DR) as one of the key flexible resource offers more flexibility for the power system (Robert, Sisodia, & Gopalan, 2018). The load-shifting capability led to increasing interests in DR program, which enable the MEM's operator to schedule demand at

* Corresponding author at: MBA School, Henan University of Economics and Law, Zhengzhou, China & Political Science Association of Kasetsart University, Bangkok, Thailand.

E-mail addresses: amir.aris@yahoo.com (A.A. Lekvan), rhabibifar@alum.sharif.edu (R. Habibifar), mehran.moradi@modares.ac.ir (M. Moradi), mohammad.khoshjahan@ieee.org (M. Khoshjahan), sayyad.nojavan@ubonab.ac.ir (S. Nojavan), k.jermsittiparsert@gmail.com (K. Jermsittiparsert).

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Nomenclature

Index
- i Index of EVs
- m Categories of EVs
- s Index of scenarios
- t Index of times

Parameters
- C^{DR} Cost of demand response program based shiftable capability
- C^{ES} Electrical storage operation cost for discharge mode
- C^{GS} Gas storage operation cost for discharge mode
- N_T Number of time horizon
- N_M Number of EV's categories
- N_i Number of EVs
- N_m^{arr} Number of EVs from category m which arrived to the parking lot
- $P_{chp}^{min}/P_{chp}^{max}$ Min/max power produced by CHP unit
- $P_{chp}^{A}/P_{chp}^{B}/P_{chp}^{C}/P_{chp}^{D}$ For power generation points of CHP in the corresponding operation region
- $H_{chp}^{A}/H_{chp}^{B}/H_{chp}^{C}/H_{chp}^{D}$ For heat generation points of CHP in the corresponding operation region
- M The large auxiliary number
- $R_{chp}^{Up}/R_{chp}^{Dn}$ Ramp up/ramp down rate of CHP
- UT_{chp}/DT_{chp} Minimum up/down times of CHP
- e_m Electrical vehicle from category m
- η_i The CHP efficiency
- η^{Boil} The boiler efficiency
- $H_{Boil}^{\min}/H_{Boil}^{\max}$ Min/max produced heat by boiler unit
- $P^{D,\min}P^{D,\max}$ Min/max power discharged by electrical storage
- $P^{CH,\min}/P^{CH,\max}$ Min/max power charged by electrical storage
- es^{CH}/es^{D} Efficiency coefficient for Charging/discharging mode
- $ES^{\min}/ES^{\max}$ Min/max energy capacity of electrical storage
- $H^{D,\min}/H^{D,\max}$ Min/max discharged heating by heat storage
- $H^{CH,\min}/H^{CH,\max}$ Min/max charged heating by heat storage
- eh^{CH}/eh^{D} Efficiency coefficient for charging/discharging modes of heat storage
- eh The heat loss coefficient for heat storage
- $HS^{\min}/HS^{\max}$ Min/max energy capacity of heat storage
- η_{P2G} The efficiency of P2G
- $P^{\mathrm{P2G},\max}$ Max power consumed by the P2G during charging
- $G^{D,\max}$ Max produced natural gas by the P2G during discharging
- $GS^{\min}/GS^{\max}$ Min/max energy capacity of the P2G
- $S_m^{\max}$ Max state of charge of EV's battery
- $P_{e_m}^{Dis,\max}$ Maximum power discharging of EV from category m
- $P_{e_m}^{Ch,\max}$ Maximum power charging of EV from category m
- $E_e^{\max}$ Maximum energy capacity of EV
- η_e^{ch}/η_e^{Dis} Charging/discharging efficiency of EV
- C_{bi} Investment cost of batteries of EV to grid services
- L_c Life cycle of EV Battery
- E_b Average capacity of EV battery
- D_{dod} Depth of discharge of battery
- Δt Sampling time to count available EV in the parking lot
- λ_t^g NG price at time t

Variables
- OF Objective function
- $\lambda_{t,s}^e$ Hourly electricity price at time t and scenario s
- $P_{t,s}^{\mathrm{P2G}}$ Inlet electricity into P2G at time t and scenario s
- $d^{t,s}$ Electricity demand at time t and scenario s
- $P_{chp,t,s}/P_{chp,t-1,s}$ The generated power by CHP at time t /t-1
- $P_{t,s}^{D}/P_{t,s}^{CH}$ The electricity discharged/charged value by ESS at time t and scenario s
- $DR_{t,s}$ The value of demand which participate in DR program at time t and scenario s
- $GC^{t,s}$ The value of consumed NG by CHP unit at time t and scenario s
- $GB^{t,s}$ T he value of consumed NG by boiler unit at time t and scenario s
- $GL_{t,s}$ The natural gas load at time t and scenario s
- $G_{t,s}^{D}/G_{t,s}^{CH}$ The value of discharged/charged heating by heat storage at time t and scenario s
- $I^{chp,t,s}$ Binary variable for CHP operation at time t and scenario s
- $H^{chp,t,s}$ The produced heat by CHP at time t and scenario s
- $I^{Boil,t,s}$ Binary variable for boiler operation at time t and scenario s
- $H^{Boil,t,s}$ The produced heat by boiler at time t and scenario s
- $Ie_{t,s}^{D}/Ie_{t,s}^{CH}$ Binary variable for discharging/charging mode of electrical storage at time t and scenario s
- $ES_{t,s}/ES_{t-1,s}$ Energy capacity of electrical storage at time t/t-1 and scenario s
- $Ih_{t,s}^{D}/Ih_{t,s}^{CH}$ Binary variable for discharging/charging mode of heat storage at time t and scenario s
- $H_{t,s}^{D}/H_{t,s}^{CH}$ The discharged/charged heating by heat storage at time t and scenario s
- $HS_{t,s}/HS_{t-1,s}$ Heat volume of heat storage at time t/t-1 and scenario s
- $GS_{t,s}/GS_{t-1,s}$ P2G energy capacity at time t/t-1 and scenario s
- $E^{t,s}$ The amount of power purchased from electricity market at time t and scenario s
- $G^{t,s}$ The amount of NG purchased from gas market at time t and scenario s
- $HL_{t,s}$ The heating load at time t and scenario s
- $DR_{t,s}^{up}/DR_{t,s}^{down}$ The value of load which participate in DR program at time t and scenario s
- $P_{e,t,s}^{Dis}$ The amount of power discharging of EV at time t and scenario s
- $P_{e,t,s}^{Ch}$ The amount of power charging of EV at time t and scenario s
- $E^{e,t,s}/E^{e,t-1,s}$ The energy capacity o EV at time t/t-1 and scenario s
- $E_{e,t,s}^{arr}$ The increased energy related to entering the EVs to the parking lot at time t and scenario s
- $E_{e,t,s}^{Dep}$ The decreased energy related to departing the EVs from the parking lot at time t and scenario s
- $Sl_{i,s}$ The initial energy of the EV when arrived into the parking lot at time t and scenario s
- $w^{i,t,s}$ Binary variable for EV status: equals to 1 if EV connected to grid at time t at time t and scenario s, otherwise is 0

peak hours and save energy to minimize total operation cost. Incorporating P2G, DR program based on shiftable loads, as well as EV parking lots in MEM while provides an appropriate framework to supply electrical, gas and thermal loads, creates an opportunity for the operator to participate in multi-carrier markets and exchange power, heat and NG with corresponding networks. However, RES based wind energy power output, electrical demand, as well as power price uncertainties impose the operation of MEM and should be captured via a useful approach. Furthermore, the arrival and departure time, as well as the state of charge of EVs parking lots should be modeled to achieve a more realistic model.

Although, the integrated multi- energies microgrid provides multiple advantages for end-users and utility, coordination of different energy carriers coupled with new energy production and conversion components such as EVs, P2G, DRP, and multi-carrier energy storage in MEM will cause a lot of complexity in terms of scheduling and management. Furthermore, the fluctuation of load demand, power price, wind power output, and EVs behavior imposed the optimal operation of MEM, which needs further development.

1.2. Related works

The combination attitude of multiple energy carriers has been studied in different dimensions. Co-optimization of energy networks, including electrical and NG systems, was first studied by Geidl and Andersson (2007). In this framework, the optimal operation of the integrated energy system considering operational constraints related to voltage limitation, as well as gas pressure, has been investigated. The different energy sectors can be simultaneously produced through highly efficient co-production units like the combined cooling, heating, and power (CCHP) (Cho, Smith, & Mago, 2014; Liu, Shi, & Fang, 2014). Once deployed in the energy storage technologies, distribution energy networks, CCHP plant and the RES units can form a multi-energy microgrid. In Li and Xu (2018), The optimally coordinated energy dispatch of MEM in both islanded and grid-connected modes, including fuel-cell, boiler, CHP, wind, and solar energy to minimize operational cost, was investigated. The stochastic optimal operation of MEM considering RES and parking-lots based EVs uncertainties was developed in Shafie-khah et al. (2019). The proposed MEM integrated with both electrical and thermal generation units, such as the CHP unit incorporated with the DR program. A mixed-integer linear programming (MILP) optimization model to determine the technology placement and energy dispatch of MEM was developed in Mashayekh, Stadler, Cardoso, and Heleno (2017), considering the limitations of electrical and heat transfer. The integrated MEM considering line rating and market condition with the aim of operational cost minimization was investigated by Markov and Rajaković (2019). The main focus of this work has therefore been placed on MEM connection with the power market through the additional line. The optimal energy dispatch between energy hub systems decomposed into different sub-problems and solved via the branch-and-bound method in Moeini-Aghtaie, Dehghanian, Fotuhi-Firuzabad, and Abbaspour (2013). The comprehensive model of NG network based on the transient model was developed in Zlotnik, Roald, Backhaus, Chertkov, and Andersson (2016). According to NG price variation and its effects on NG fired-units operation, the integrated NG and electricity systems co-optimized. The stochastic scheduling of coordinated NG and electricity systems was developed in Zhang, Che, Shahidehpour, Alabdulwahab, and Abusorrah (2016). The DR program is incorporated with a multi-carrier energy system as a virtual generation unit while the load demand and RES power output are considered as uncertain parameters. The optimal scheduling of electrical and NG distribution networks coupled via interconnected energy hub systems based on the stochastic approach was developed by Jin et al. (2016). In Amir and Azimian (2020), the economic dispatch of MEM deployments under multiple uncertainties, including electrical and thermal demands, power price, and solar irradiation was investigated. The proposed MCMS incorporated with dispatchable and non-dispatchable generation units, energy storage devices, and DR program. Authors in Khaloie et al. (2020), proposed a novel bidding strategy framework for an integrated energy system in the deregulated electricity market. The proposed approach consists of two objective functions, the first one copes with profit maximization, while the second minimize the emission pollution.

The emergence of high-flexible technologies such as the P2G facility makes the interconnection between NG and electricity systems. The P2G facility converts surplus power into NG; after that, the produced NG stored and injected into the NG network at higher NG prices. Using excessive RES into NG results in a reduction of power curtailment produced by the unpredictable generation unit (Zeng, Fang, Chen, Li, & Zhang, 2016; Zeng, Zhang, Fang, & Chen, 2017). Authors in Clegg and Mancarella (2015) evaluated the effects of the P2G facility in a multi-carrier system. The main objective of the proposed model is to utilize the appropriate potential of P2G to facilitate the integration of high penetration of RES. In Shabanpour-Haghighi and Seifi (2015), a robust strategy for the daily scheduling of coordinated power and NG networks in the presence of a P2G facility was developed. Authors in Lyseng et al. (2018) investigated the potential of P2G to diminish the curtailment of RES. In addition, the co-optimize capacity sizing of solar and wind energy, and electrolyzer was investigated in this paper. Numerical results show that the integration of P2G with RES leads to the reduction of RES curtailment. In Nazari-Heris, Mirzaei, Mohammadi-Ivatloo, Marzband, and Asadi (2019), P2G technology is developed to offer the high integration of wind energy in the distribution networks. The interconnection of electricity and NG networks via P2G and NG-based generation power plant is presented as a two-stage multi-objective programming with the aim of minimize the environmental pollution and operational cost. The optimal strategy of integrated scheduling of the P2G and NG –based generation plants in the regulation market, based on the stochastic programming approach, was developed by Li et al. (2018).

Demand response (DR) as emerging flexible technology has an important role in the optimal management of multi-energies systems. Generally, DR programs are categorized into two primary groups, consists of price-based and incentive-based DR programs (Jordehi, 2019). In Neyestani, Yazdani-Damavandi, Shafie-Khah, Chicco, and Catalão (2015), the optimal operation of a smart energy hub under the stochastic demand response was investigated. The interval optimization approach for a multi-energy system considering an integrated DR program was developed by Su, Zhou, and Tan (2020). The dynamic switching of energy-carrier, including NG and power to respond to the power price considering load demand and solar power uncertainties, were investigated in the presented strategy. In Haghifam, Dadashi, Zare, and Seyedi (2020), optimal scheduling of smart distribution networks in the presence of DR aggregators and microgrid utilities based on the Game theory was proposed. The dynamic economic dispatch model of a multi-flexible energy system incorporated with price-based DR was developed by Niu, Tian, Zhu, and Yue (2020). Integrated DR with the proposed multi-energy system offers multiple ancillary services for the power grid. Authors in Li, Roche, Paire, and Miraoui (2019), proposed a price decision approach for multiple MEM based on a MILP model integrated with the DR program. Each MEM can purchase or sell the power to another. The energy management model of the smart multi-energy system based microgrid considering DR programs was investigated by Wang et al. (2018). In Wang, Zhong, Ma, Xia, and Kang (2017), the comprehensive concept and key factors of integrated DR programs in the multi-energy systems considering electricity, thermal and gas sectors was investigated. The renewable and CCHP-based microgrid in the presence of DR program was developed by Saberi, Pashaei-Didani, Nourollahi, Zare, and Nojavan (2019). The proposed model is formulated as a multi-objective problem with the aim of operational cost and emission minimization.

The appropriate potential of electrical vehicle parking lot to facilitate the integration of RES, and emission pollution reduction has attracted more attention in energy systems. The incentive mechanism for EVs participation in the DR programs based on a contract theory approach was developed by Zhou, Wang, Guo, and Zhang (2019). The contract optimization problem falls into the category of the difference of convex programming and the iterative convex-concave procedure algorithm was applied to solve it. The environmental and economic evaluation of optimal scheduling of renewable-based microgrid in the presence of EVs, wind and solar energy was investigated by Liu et al. (2020). The modified harmony search algorithm was applied to solve the multi-objective problem. The integrated energy system including group of grid-connected islands in the presence of EVs incorporated with a DR to provide storage capacity for electrical energy from RES was presented in Pfeifer, Dobravec, Pavlinek, Krajačić, and Duić (2018). The results revealed that the interconnections between islands increased the share of energy from RES while vehicle to grid (V2G) capability enables utilization of cooperation between energy sectors. To mitigate the fluctuations of wind farms power output, authors in Raoofat et al. (2018), investigated a power smoothing service using the DR program of EVs connected to the neighboring systems. The results of this study demonstrated the effectiveness of the proposed approach in the mitigating of wind power fluctuations as well as charging the EVs. In Jabari, Jabari, Mohammadi-ivatloo, and Ghafouri (2019), the optimal short-term integration of combined desalination, heating and power considering DR programs based on real-time pricing for multiple loads in the presence of the participation of aggregated PEV for different cases has been investigated. The bi-level optimization model for the optimal scheduling of a smart distribution utility integrated with the EV parking lots, as well as wind and solar energy has been investigated by Sadati, Moshtagh, Shafie-khah, Rastgou, and Catalão (2019). A new methodology for EVs operation problem with multiple vehicle types in public transport system was developed by Yao, Liu, Lu, and Yang (2020). Numerical results of the proposed method show annual operational costs reduction by 15.93 % compared with the conventional model. In Habibifar, Lekvan, and Ehsan (2020), a risk-constrained optimal operation of EV's aggregators to participate in freuencyy regulation and energy markets was evaluated considering load and price uncertainty.

The penetration of RES, along with the energy price and energy consumption fluctuations, imposed the optimal scheduling and management of integrated energy systems. There are multiple uncertainty modeling which are captured in the literature to mitigate the challenges caused by uncertain parameters. The comprehensive decision making under uncertainty in modern energy systems was investigated by Hemmati, Mohammadi-Ivatloo, and Soroudi (2020) and Soroudi and Amraee (2013). Authors of Habibifar, Khoshjahan, and Ghasemi (2020), focused on the optimal day-ahead scheduling of multi-carrier energy system based on the energy hub concept, considering wind, load, and energy price uncertainty. The proposed energy hub can participate in gas and day-ahead energy market to supply electrical, gas, and thermal loads. The optimal operation of energy hub consists of cooling, heating, and electrical demands incorporated with DR program and RES was investigated by Rakipour and Barati (2019). To handle system uncertainties, including three types of consumption: cooling, heating, and electrical, and RES power production, the stochastic programming method was implemented. In Najafi, Falaghi, Contreras, and Ramezani (2016), the optimal stochastic operation of energy hub was studied where the hourly electricity price, and wind energy are captured as uncertain parameters. The risk-based optimally energy management model of energy hub systems based on a MILP model was developed by Soroudi and Keane (2015). The main goal of the proposed model is to minimize the total operation costs. The optimal stochastic scheduling of the RES-based residential energy hub incorporated with EVs and solar systems was investigated by Bahrami, Toulabi, Ranjbar, Moeini-Aghtaie, and Ranjbar (2017). The chance-constrained optimal operation of smart reconfigurable microgrid in the presence of wind, solar, and load uncertainties has been evaluated by Hemmati, Mohammadi-Ivatloo, Abapour, and Anvari-Moghaddam (2020). A two-stage stochastic operation of coordinated electricity and NG network considering compressed air storage system and DR program was developed by Mirzaei et al. (2019). The risk-based two-stage stochastic scheduling of renewable-based reconfigurable microgrids in the presence of wind and power price uncertainties with the aim of profit maximization was investigated by Hemmati, Mohammadi-Ivatloo, Ghasemzadeh, and Reihani (2018).

1.3. Contribution and novelty

The development of distributed energy sources will increase the dependency of energy carriers, like heating, gas, and power. On this basis, the cross-impact of multiple energy carriers should be developed under the concept of MEM under the integrated and comprehensive model. However, the integration of emerging flexible technologies like EVs parking lots, DR program, and P2G facility with considering multi-energy market (thermal, gas, and electricity markets) with the hybrid optimization approach has rarely been studied in the literature. Therefore, this paper evaluates the optimal operation of MEM integrated with P2, EVs parking lot, and DR program based on the hybrid robust/stochastic approach. The proposed model is associated with multiple random variables, consists of wind energy, load demand, power price, arrival and departure times, and state of charge of EVs. The scenario-based stochastic approach is used, while a robust optimization strategy is applied to model the power price uncertainty. The comprehensive scheduling model, considering the multi-energy market concept for the system operator to purchase the required energy which has been ignored in the literature. Briefly, the main contributions of this paper are outlined as follows:

1 Proposing a novel multi-energy microgrid incorporated with multiple generation and consumption sectors.
2 Integrating the power-to-gas facility as a connection point between power and NG grids to increase the flexibility of the operator's decision-making.
3 Evaluating the comprehensive model of EVs parking lot as a mobile load or generation unit in MEM.
4 Proposing the hybrid robust/stochastic framework to address high-level uncertainty, including wind energy, load demand, EVs behavior, as well as price fluctuation. The hybrid framework uses the advantages of both methods simultaneously to address the uncertainties of the system.
5 Considering responsible demand to participate in the DR program as a flexible resource. which provides the more flexibility for the operator contributing the higher economic benefits.
6 Establishing the MEM connection and participation in electrical, thermal, and gas markets. The MEM's operator can participate in both markets to purchase the required energy.

1.4. Paper organization

The rest of this paper is organized as follows: Section 2 presents the problem description and P2G concept. The problem formulation of MEM scheduling integrated with multiple components contains objective function and constraints related to multiple are represented in Section 3. Section 4 presents the hybrid robust/stochastic strategy to address system uncertainties and reformulated the proposed MEM operation model. Numerical results and investigates the performance of the proposed model are given in Section 5. Finally, Section 6 concludes the paper.

2. Problem description

The optimal operation of a multi-energy microgrid system in the presence of multiple flexible and conventional resources imposed by high-level uncertainty. Firstly, for more information about the P2G mechanism of P2G and its operation in the energy system is developed. Secondly, the main problem of MEM operation with the aim of operational cost minimization will be described.

2.1. P2G mechanism

The P2G storage, as a flexible emerging resource, makes a connection between multiple energy sectors. The surplus produced energy by wind is given to P2G when the power price reaches a lower value. The P2G converted the electricity into the NG and saved it in the tanks. When the NG prices reach high values, P2G releases the converted NG to the system and causes the operator unwanted to buy the NG from the upstream network. The conversion mechanism of power to the NG by P2G facility consists of two main processes. Firstly, the electrolyzer process breakdown water to oxygen and hydrogen by consumed the electricity as a chemical reaction: $2H_2O \rightarrow O_2 + 2H_2$. Secondly, the generated hydrogen in the mentioned reaction is combined with carbon dioxide and formed the mechanization reaction as: $4H_2 + CO_2 \rightarrow 2H_2O + CH_4$. In addition to NG production in whole process, the generated hydrogen in the first reaction is used singly. It should be noted that the generation of hydrogen is more impressive than the whole operation process of the P2G. The generated hydrogen can be applied in the hydrogen-based industries and hydrogen market. Fig. 1 shows the overall schematic of the P2G facility, gas and hydrogen application in grids. The P2G operation modeling and integration with a multi-energy system will be described in future sections.

2.2. Multi-energy microgrid operation

The MEM's operator seeks to minimize the total operation cost through optimizing the CHP, boiler, EVs, and multiple energy storage to meet local electrical, gas, and thermal loads. Furthermore, the operator sings the contract with responsible loads for participating in the incentive-based DR program and to smooth the load profile. In this way, the responsible loads in lieu of incentive in their bills, reduce load demand at peak hours and enhance the economic benefits. Besides, the whole operation of MEM is imposed by high-level uncertainty caused by electrical price, load demand, wind power energy, and EVs behavior, including arrival and departure time, and state of charge (SoC) levels. Therefore, hybrid robust/stochastic is used in which electricity price is modeled via a robust approach while multiple scenarios generated for other uncertain parameters based on the stochastic approach. Fig. 2 shows the overall view of the proposed MEM operation considering all components. The system operator in connection with multi-energy markets, including power, thermal, and NG markets to supply the required energy for the optimal operation of the MEM. EVs as a mobile load or generation, mitigate the wind energy integration. In addition, EVs can shifts the load from peak load consumption times to off-peak times. At off-peak hours, EVs are charged at parking, when the power price reaches maximum amounts, EVs are discharged and inject the power through power-to-grid capability and makes the operator unwanted to purchase power from the electricity network. Furthermore, the operator makes a contract with shiftable electrical loads via the DR program as shown in Fig. 2. Hence, relying on responsible loads, the operator shifted load from peak hours to off-peak intervals and satisfy the economic benefits. It should be noted that besides the responsible loads, the system's operator can manage the energy consumption of EVs through optimal charging and discharging schemes. Also, thermally controllable devices are applied to provide more flexibility on the demand side. The MEM central controller analyzes all the required input and forecasted data to find the optimal set points of generation units to meet the local electrical, gas, and thermal loads with the aim of operational cost minimization. Also, all the contracts between MEM's operator with responsible loads, optimum set points of operation of multiple generation units as well as upstream networks have been evaluated by the central controller via the proposed model.

All infrastructures in the proposed MEM in Fig. 2 are described as follows:

2.3. Electrical demand

The electrical demands are the main consumers in the MEM which are supplied through the electrical bus with the electricity infrastructure. As we know, there are multiple consumers in the system, including commercial, industrial, and residential consumers. The percentage of electrical loads consist of shiftable loads that can participate in the DR program. The electrical demand can be supplied by power purchased, wind energy, EVs, CHP, and electrical storage.

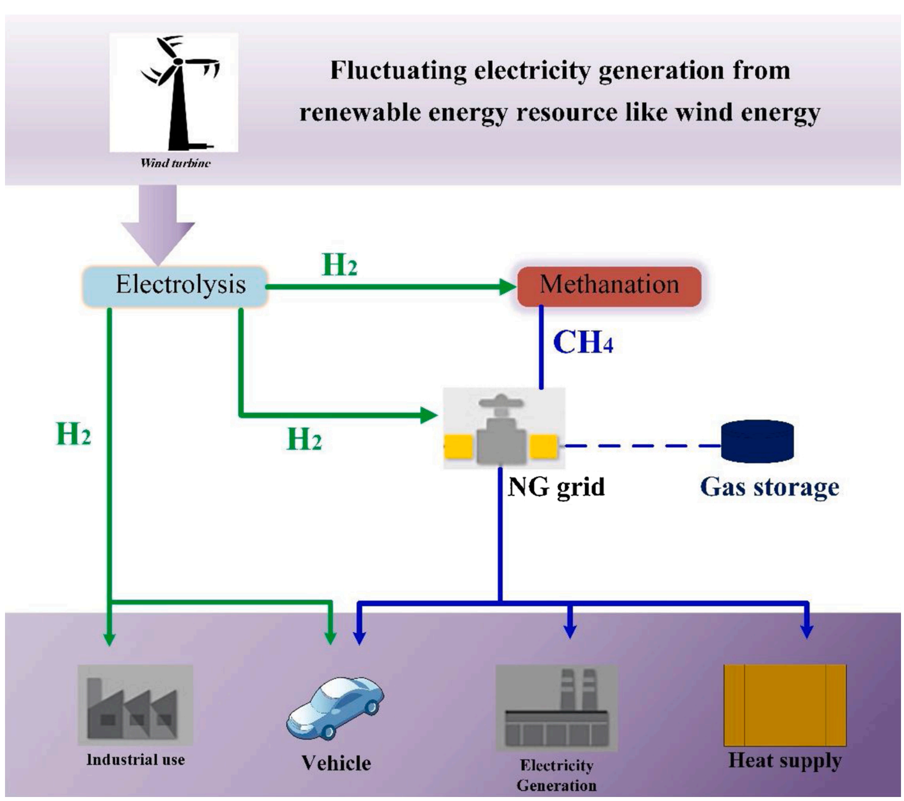

Fig. 1. The overall schematic of P2G facility and its applications.

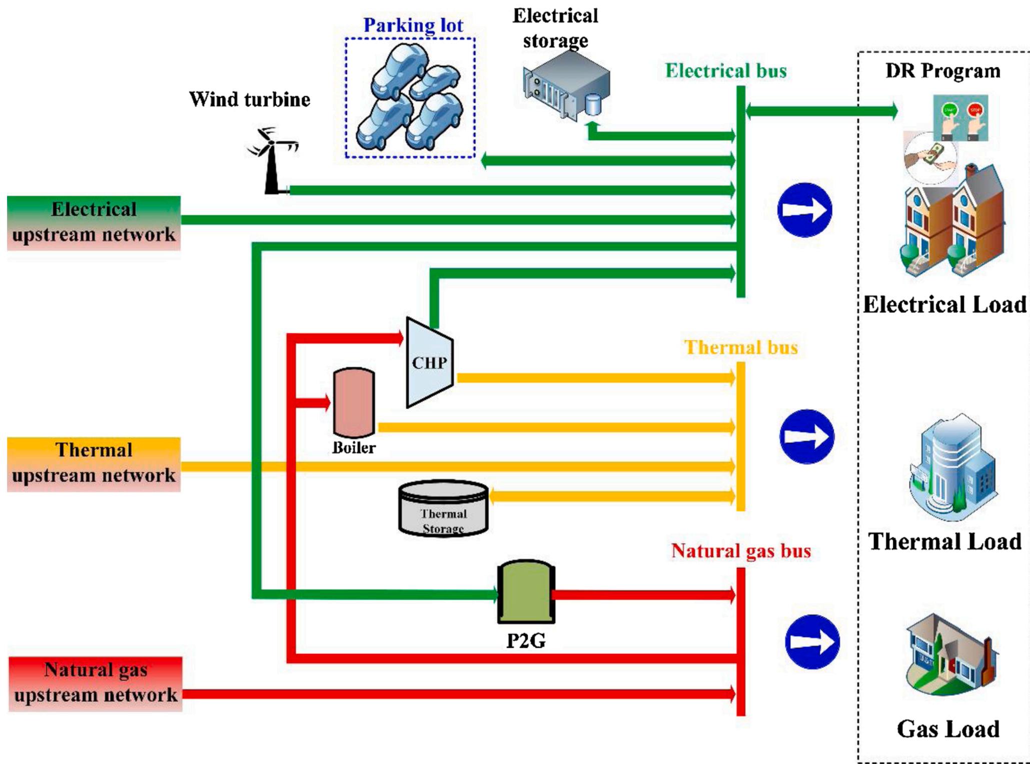

Fig. 2. The overall schematic of proposed MEM incorporated with multiple components.

2.4. Gas demand

The proposed MEM has gas loads besides electrical and thermal loads. The natural gas injected into the MEM to supply gas load, as well as a primary fuel for CHP, and boiler unit. Also, the P2G facility generates the gas to complete the gas infrastructure.

2.5. Thermal demand

Besides electrical and gas loads, there are thermal loads in the MEM. Thermal loads using heating energy supplied by thermal purchased, thermal energy storage, boiler, and heating output by the CHP unit.

2.6. Energy storage technologies

Electrical and thermal energy storage technologies are embedded in the MEM as a flexible source. The operator can serve the energy at off-peak hours in the electrical and thermal storage. Then, the stored heating and power in electrical and thermal storage are released at peak hours to meet local demand. It should be noted that electrical energy storage mitigates the fluctuation of wind energy.

2.7. EVs parking lot

EVs parking lot as an efficient type of vehicle can be supplied by an external power source through the embedded battery. EVs in the MEM can operate as mobile loads which can provide more flexibility via optimal charge and discharge scheme. During charging time, EVs can be charged in the parking, while discharging EVs inject power to the network via vehicle-to-grid (V2G) technology.

2.8. DR program

The DR program has been considered as an impressive and flexible tool in the modern power system. The basic concept behind DR is to motivate electricity end-users to reduce/manage/reschedule their consumption by offering incentives and discounts on the electricity bills. The system operator encourages consumers to diminish energy consumption in low wind energy periods which occur at peak hours and increase the energy consumption in high-value wind production.

2.9. Natural gas-based units

Gas boiler and CHP unit are two natural gas-based generation units that use the gas as an input. The CHP unit produces the power and heat, simultaneously based on its feasible operation region. The gas boiler uses the natural gas to generate the heating energy to serve the thermal load, that has a significant role in the MEM.

2.10. Problem formulation

The proposed MEM scheduling in the presence of multiple generation and consumption is formulated in this section. The main objective of the MEM's operator is to minimize the total operation cost which represented by (1). The exchanged power, NG and heat cost between MEM's operator and multi-energy markets are expressed by first, second and third terms of (1), respectively. The operation cost of electrical energy storage in the discharging mode is represented by the fourth term of (1). In the same way, the operation costs of P2G facility, heat storage and EVs parking-lots in the discharging mode are established by fifth and sixth terms of (1), respectively. The wind power curtailment cost is expressed by the seventh term. The MEM sings the contract with responsible consumers who participate in the DR program; the eighth term represents the DR cost. Finally, the degradation cost of EVs is expressed by the ninth term of the objective function (1) which is a function of the investment cost of EV's battery, while it has an inverse connection with battery capacity, lifetime, and an average depth of discharge (DOD) (Cao et al., 2020).

$$OF = Min \sum_{s=1}^{NS} \pi_s \left(\begin{array}{l} \sum_{t=1}^{N_t} \left(\lambda_t^e E_{t,s} + \lambda_t^g G_{t,s} + \lambda_t^h H_{t,s} + C^{ES} P_{t,s}^D + C^{GS} G_{t,s}^D + C^{HS} H_{t,s}^D \right. \\ \left. + C^{EV} P_{t,s}^{EV,D} + C^{Wind} P_{w,t,s} + C^{DR}\left(DR_{t,s}^{up} + DR_{t,s}^{dn}\right) + \frac{1000 C_{bi}}{L_c E_b D_{dod}} \right) \end{array} \right) \tag{1}$$

2.11. *Problem constraints*

The proposed optimal scheduling of MEM coupled with CHP, boiler, electrical and thermal storage, P2G facility, EVs parking lots, DR program, and wind energy is restricted by multiple limitations related to the operation of components and energy networks which are presented in this section.

2.11.1. *CHP unit constraint*

CHP is one of the heat and power generation sources. The main idea of CHP unit operation is to employ waste heat during power generation. The CHP scheduling is expressed by feasible region operation, which makes a connection between the produced heat and power. Fig. 3 shows the feasible region for the CHP operation which makes a connection between produced heat and power.

The main complexity of CHP operation is related to a feasible operation region (Nazari-Heris, Mohammadi-ivatloo, & Nazarpour, 2019). There are four boundary points that assign the value of generated heat and electricity by CHP. Constraints (2)–(6) are related to the feasible operation region of CHP, which restricted the power and heat value of four boundary points. The ramp-up/down power limitation are calculated in (7) and (8). Constraints (9)–(12) and (12)–(16) respectively express the minimum up and downtime restrictions. Constraint (17) interrelates the produced heat and electricity by the CHP.

$$P_{chp}^{min} I^{chp,t,s} \le P^{chp,t,s} \le P_{chp}^{max} I^{chp,t,s} \tag{2}$$

$$P^{chp,t,s} - P_{chp}^{A} - \frac{P_{chp}^{A} - P_{chp}^{B}}{H_{chp}^{A} - H_{chp}^{B}} \times \left(H^{chp,t,s} - H_{chp}^{A}\right) \le 0 \tag{3}$$

$$P^{chp,t,s} - P_{chp}^{B} - \frac{P_{chp}^{B} - P_{chp}^{C}}{H_{chp}^{B} - H_{chp}^{C}} \times H^{chp,t,s} - H_{chp}^{B}) \ge -\left(1 - I^{chp,t,s}\right) \times M \tag{4}$$

$$P^{chp,t,s} - P_{chp}^{C} - \frac{P_{chp}^{C} - P_{chp}^{D}}{H_{chp}^{C} - H_{chp}^{D}} \times \left(H^{chp,t,s} - H_{chp}^{C}\right) \ge -\left(1 - I^{chp,t,s}\right) \times M \tag{5}$$

$$0 \le H^{chp,t,s} \le H_{chp}^{A} \times I^{chp,t,s} \tag{6}$$

$$P^{chp,t,s} - P^{chp,t-1,s} \le R_{chp}^{Up} \tag{7}$$

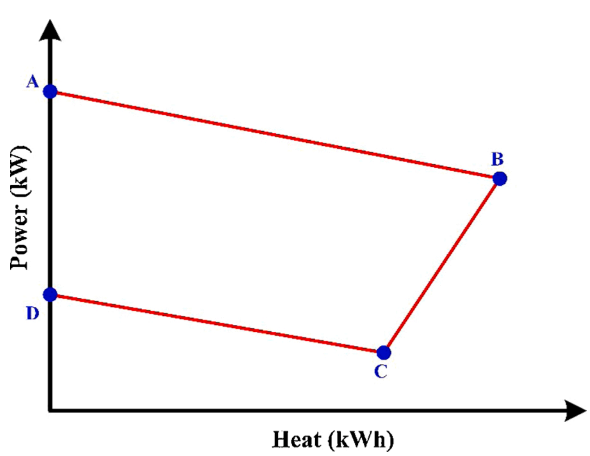

Fig. 3. Feasible operation region for CHP unit.

$$P^{chp,t,s} - P^{chp,t-1,s} \le R_{chp}^{Dn} \tag{8}$$

$$UT_{chp} = \max\left\{0, \min\left[N_T, \left(T_{chp}^{On} - X_{chp,t=0}^{On}\right) I^{chp,t=0}\right]\right\} \tag{9}$$

$$\sum_{t=1}^{UT_{chp}} \left(1 - I^{chp,t,s}\right) = 0 \forall t = 1, \ldots, UT_{chp} \tag{10}$$

$$\sum_{k=t}^{t+T_{chp}^{On}-1} I^{chp,k,s} \ge T_{chp}^{On}\left(I^{chp,t,s} - I^{chp,t-1,s}\right) \;\; \forall t = UT_{chp}+1, \ldots, N_T - T_{chp}^{On} + 1 \tag{11}$$

$$\sum_{k=t}^{UT_{chp}} \left(I^{chp,k,s} - I^{chp,t,s} + I^{chp,t-1,s}\right) \ge 0 \qquad \forall t = N_T - T_i^{On} + 2, \ldots NT \tag{12}$$

$$DT_{chp} = \max\left\{0, \min\left[N_T, \left(T_{chp}^{Off} - X_{chp,t=0}^{Off}\right) I^{chp,t=0}\right]\right\} \tag{13}$$

$$\sum_{t=1}^{DT_{chp}} \left(1 - I^{chp,t,s}\right) = 0 \forall t = 1, \ldots, DT_{chp} \tag{14}$$

$$\sum_{k=t}^{t+T_{chp}^{Off}-1} I^{chp,k,s} \ge T_{chp}^{Off}\left(I^{chp,t,s} - I^{chp,t-1,s}\right) \;\; \forall t = DT_{chp}+1, \ldots, N_T - T_{chp}^{Off} + 1 \tag{15}$$

$$\sum_{k=t}^{DT_{chp}} \left(I^{chp,k,s} - I^{chp,t-1,s} + I^{chp,t,s}\right) \ge 0 \qquad \forall t = N_T - T_i^{Off} + 2, \ldots NT \tag{16}$$

$$GC_{t,s} = \frac{P^{chp,t,s}}{\eta_i} \tag{17}$$

2.11.2. *Boiler constraints*

The boiler unit has a major role to supply the heat demands, beside CHP unit. The boiler output heat is limited by the minimum and maximum values as (18). The relationship between produced heat and consumed NG by the boiler is represented by (19).

$$H_{Boil}^{\min} \times I^{Boil,t,s} \le H^{Boil,t,s} \le H_{Boil}^{\max} \times I^{Boil,t,s} \tag{18}$$

$$GB_{t,s} = \frac{H^{Boil,t,s}}{\eta^{Boil}} \tag{19}$$

2.11.3. *ESS constraints*

Electrical energy storage systems (ESS) are applied for multiple goals such as peak shaving, ancillary services, power quality, and etc., (Palizban & Kauhaniemi, 2016). The ESS operation is exclusive by multiple limitations. For both charging and discharging modes, binary variables are considered to prevent simulations operation in charging and discharging as (20). The charged and discharged power value of ESS are restricted by minimum and maximum amounts as expressed by (21) and (22), respectively. Eq. (23) expresses the capacity of ESS at *t* time, taking account the energy capacity at time *t-1*, minus charged power and plus the discharged and at *t* time (Hemmati et al., 2018). Constraint (24) limits the stored energy capacity in ESS by the upper and lower values. The equality condition for initial ($t = 0$) and final ($t = 24$) operation states is expressed by constraint (25).

$$Ie_{t,s}^{D} + Ie_{t,s}^{CH} \le 1 \tag{20}$$

$$P^{D,\min}\ Ie_{t,s}^{D} \le P_{t,s}^{D} \le P^{D,\max}\ Ie_{t,s}^{D} \tag{21}$$

$$P^{CH,\min}\ Ie_{t,s}^{CH} \le P_{t,s}^{CH} \le P^{CH,\max}\ Ie_{t,s}^{CH} \tag{22}$$

$$ES_{t,s} = ES_{t-1,s} + es^{CH} P^{CH}_{t,s} - \frac{P^{D}_{t,s}}{es^{D}} \tag{23}$$

$$ES^{\min} \le ES_{t,s} \le ES^{\max} \tag{24}$$

$$ES_{t=0} = ES_{t=24,s} \tag{25}$$

2.11.4. Heat storage constraints

Thermally activated systems have attracted much attention due to significant capabilities (Delgado, Ramos, Domínguez, Ríos, & Cabeza, 2020). The HES as one of the thermal energy storage system can coupled with other thermal resources to manage the local thermal demands in MEM. The operation of HES is limited by multiple constraints. As the electrical energy storage, the HES for both charging and discharging modes, binary variables are considered to prevent simulations operation in charging and discharging modes which is expressed by (26). The Eqs. (27) and (28) respectively show the lower and upper amount of discharged and charged heat by HES. Constraint (29) determine the current stored heat in the HES at time t. The amount of heat capacity is limited by upper and lower values as represented by (30). The equality constraint condition of initial ($t = 0$) and final ($t = 24$) operation states for HES is calculated by (31).

$$Ih^{D}_{t,s} + Ih^{CH}_{t,s} \le 1 \tag{26}$$

$$H^{D,\min}\, Ih^{D}_{t,s} \le H^{D}_{t,s} \le H^{D,\max}\, Ih^{D}_{t,s} \tag{27}$$

$$H^{CH,\min}\, Ih^{CH}_{t,s} \le H^{CH}_{t,s} \le H^{CH,\max}\, Ih^{CH}_{t,s} \tag{28}$$

$$HS_{t,s} = HS_{t-1,s}(1 - eh) + eh^{CH} H^{CH}_{t,s} - \frac{H^{D}_{t,s}}{eh^{D}} \tag{29}$$

$$HS^{\min} \le HS_{t,s} \le HS^{\max} \tag{30}$$

$$HS_{t=0} = HS_{t=24,s} \tag{31}$$

2.11.5. P2G constraints

The P2G storage converts power to NG and stores it into gas tanks. In the required conditions, the produced NG is injected to supply the NG consumption and primary fuel for the boiler and CHP operation. Constraint (32) shows conversion efficiency for P2G storage. The current NG capacity in P2G at time t is determined in (33). The value of converted electricity and produced NG are limited by (34) and (35). The value of stored NG is limited by upper and lower values as described by (36). The equality constraint condition for initial ($t = 0$) and final ($t = 24$) operation states for P2G is calculated by (37).

$$G^{CH}_{t,s} = \eta_{\mathrm{P2G}} P^{\mathrm{P2G}}_{t,s} \tag{32}$$

$$GS_{t,s} = GS_{t-1,s} + G^{CH}_{t,s} - G^{D}_{t,s} \tag{33}$$

$$0 \le P^{\mathrm{P2G}}_{t,s} \le P^{\mathrm{P2G,max}} \tag{34}$$

$$0 \le G^{D}_{t,s} \le G^{D,\max}_{t} \tag{35}$$

$$GS^{\min} \le GS_{t,s} \le GS^{\max} \tag{36}$$

$$GS_{t=0} = GS_{t=24,s} \tag{37}$$

2.11.6. EVs constraints

The EVs parking lot as mobile load generation can provide multiple advantages for MEM. However, the operation of EVs is restricted by different restrictions. The maximum and minimum values of charged and discharged power limits for each EV are expressed by (38) and (39). It should be noted that in this paper, there are six models of EV. Hence, constraints (40) and (41) show the maximum charged and discharged power of each EV (Cao et al., 2020). The maximum energy capacity of parking lot contains multiple EVs at time t is calculated in (42). To determine the increased (dropped) energy capacity of parking lot based on the energy of arrived EVs (EVs departing), Eqs. (43) and (44) are established. The total stored energy in the parking lot at t time equals the stored energy t-1, plus charged power from EV batteries, as well as the achieved energy by arriving EVs into the parking lot, minus the discharged power of EV batteries, as well as the reduced energy caused by departing of EV from the parking lot, at the t time which is calculated in (45). Constraint (46) calculates the total stored energy of the parking lot limited by the upper and lower values. Finally, the equality condition for the initial and final operation states is shown by (47).

$$0 \le P^{CH}_{e,t,s} \le P^{CH,\max}_{e,t} \tag{38}$$

$$0 \le P^{Dis}_{e,t,s} \le P^{Dis,\max}_{e,t} \tag{39}$$

$$P^{CH,\max}_{t} = \sum_{m=1}^{N_M} \sum_{i}^{N_i} P^{CH,\max}_{e_m,t} w^{i,t,s} \tag{40}$$

$$P^{Dis,\max}_{t} = \sum_{m=1}^{N_M} \sum_{i=1}^{N_i} P^{Dis,\max}_{e_m,t} w^{i,t,s} \tag{41}$$

$$E^{\max}_{e,t} = \sum_{m=1}^{N_M} \sum_{i=1}^{N_i} S^{\max}_{m} w^{i,t,s} \tag{42}$$

$$E^{arr}_{e,t,s} = \sum_{m=1}^{N_M} \sum_{i=1}^{N^{arr}_{m,t}} \left(S^{\max}_{m} - Sl_{i,s}\right) \tag{43}$$

$$E^{Dep}_{e,t,s} = \sum_{m=1}^{N_M} \sum_{i=1}^{N^{arr}_{m,t}} S^{\max}_{m} \tag{44}$$

$$E^{e,t,s} = E^{e,t-1,s} + E^{arr}_{e,t,s} + \eta^{ch}_{e} P^{CH}_{e,t,s} \times \Delta t - \left(E^{Dep}_{e,t,s} + \frac{P^{Dis}_{e,t,s} \times \Delta t}{\eta^{Dis}_{e}} \right) \tag{45}$$

$$0 \le E^{e,t,s} \le E^{\max}_{e,t} \tag{46}$$

$$E^{e,t=0} = E^{e,t=24,s} \tag{47}$$

2.11.7. Demand response constraints

The MEM's operator can sign contract with responsible loads through DR programs as an emerging flexible source. The DR based on shifting capability of responsible loads is considered to participate in DR and provide advantages for both consumers and MEM's operator. The limitations of the responsible loads amount at time t are represented by (48) and (49). The maximum allowed amount of the forecasted load consumption and load shifting of responsible loads are calculated by(50) and (51), respectively, where γ^{DR} is the coefficient that represents the participation level for responsible loads in the DR program equals to 0.1. The maximum allowable load interruption that shifted to the off-peak period is limited by (52). The total load demand of MEM, after applying the DR is calculated by (53).

$$0 \le DR^{up}_{t,s} \le DR^{up,\max}_{t,s} \tag{48}$$

$$0 \le DR^{dn}_{t,s} \le DR^{dn,\max}_{t,s} \tag{49}$$

$$DR^{up,\max}_{t,s} = \gamma^{DR} d_{t,s} \tag{50}$$

$$DR^{dn,\max}_{t,s} = \gamma^{DR} d_{t,s} \tag{51}$$

$$\sum_{t=1}^{NT} DR^{up}_{t,s} = \sum_{t=1}^{NT} DR^{dn}_{t,s} \tag{52}$$

$$d_{t,s}^{DR} = d^{t,s} - DR_{t,s}^{dn} + DR_{t,s}^{up} \tag{53}$$

2.11.8. Energy balance constraints

MEM can provide all the electrical, thermal and gas loads demand through resources (dispatchable and RES), and purchasing/selling energy from/to the corresponding networks. However, for each energy carrier, the energy balance based on local generation and consumption and energy exchanging with the upstream networks must be established. The energy balance restriction of power, thermal and NG sector, are respectively expressed by (54)–(56).

$$E^{t,s} + P_{t,s} - P_{t,s}^{\mathrm{P2G}} + P_{t,s}^{D} - P_{t,s}^{CH} - d^{t,s} + P_{w,t,s} = 0 \tag{54}$$

$$H^{t,s} + H^{chp,t,s} + H^{Boil,t,s} + H_{t,s}^{D} - H_{t,s}^{CH} - HL_{t,s} = 0 \tag{55}$$

$$G^{t,s} + G_{t,s}^{D} - GC^{t,s} - GB^{t,s} - GL_{t,s} = 0 \tag{56}$$

3. Hybrid robust/stochastic strategy

The robust optimization strategy is a basic approach to solve optimization problems associated uncertainty, especially in case of lack of full information or data on the uncertainty behavior. In this strategy, it is assumed that the random parameter belongs to an uncertainty set and the decision-maker tries to make an optimal decision imposed by the effects of the uncertain parameter. In other words, the decision variables will be found in such a way that the objective function remains optimum even if the random variable takes its worst-case amount. The concept of this approach was first introduced by Soroudi and Amraee (2013). In robust optimization, no specified probability distribution function (PDF) is not available to reveal the uncertain parameter behavior.

In this section, a hybrid stochastic/robust is modeled to minimize the operation cost of the MEM by following the worst case of power price uncertainty. The stochastic model of the suggested technique was demonstrated in the previous part. The hybrid framework has benefits in comparison to the pure stochastic. In the hybrid model, the MEM operator has the opportunity to take various risk levels based on the system conditions. An integer parameter Γ_s is considered to model the conservatism level of the optimization problem. With the increment of Γ_s into the given interval of $[0:N_m]$, the MEM operator considers a more robust decision against the power price uncertainty in each scenario. $\Gamma_s = 0$ means that the power price uncertainty is ignored in scenarios and $\Gamma_s = N_m$ means the mentioned parameter uncertainty is completely considered. The objective function of hybrid framework is as follows:

$$OF = Min\left\{ \begin{array}{l} \sum_{s=1}^{NS} \pi_s \left(\begin{array}{l} \sum_{t=1}^{N_t} \left(\lambda_t^{e,\min} E_{t,s} + \lambda_t^{g} G_{t,s} + \lambda_t^{h} H_{t,s} + C^{ES} P_{t,s}^{D} + C^{GS} G_{t,s}^{D} + C^{HS} H_{t,s}^{D} \right. \\ \left. + C^{EV} P_{t,s}^{EV,D} + C^{Wind} P_{w,t,s} + C^{DR}(DR_{t,s}^{up} + DR_{t,s}^{dn}) + \dfrac{1000 C_{bi}}{L_c E_b D_{dod}} \right) \end{array} \right) \\ + \sum_{s=1}^{N_s} \pi_s \left[\max\limits_{\{m||m_s| \le \Gamma_s\}} \sum_{t \in m_s} (\lambda_t^{e,\max} - \lambda_t^{e,\min}).|E_{t,s}| \right] \end{array} \right\} \tag{57}$$

The objective function of (57) has been formulated as a min-max structure. The min-max model of the objective function is associated with the point that while the outer part of the objective function minimizes the operation cost of the MEM, the inner part of the objective function provides the worst-case condition of power price variabilities. The inner part of the objective function can be reformulated as follows:

$$\max_{\{m||m_s| \le \Gamma_s\}} \sum_{t \in m_s} (\lambda_t^{e,\max} - \lambda_t^{e,\min}).|E_{t,s}| = \max\left\{ \sum_{t} (\lambda_t^{e,\max} - \lambda_t^{e,\min}) |E_{t,s}| k_{t,s} \right\} \tag{58}$$

$$\sum_{t=1}^{NT} k_{t,s} \le \Gamma_s : \alpha_s \tag{59}$$

$$0 \le k_{t,s} \le 1 \quad : \beta_{t,s} \tag{60}$$

By applying strong duality technique, the presented model in (58)–(60) can be rewritten as (61)–(66).

$$\min \sum_{t} \beta_{t,s} + \alpha_s \Gamma_s \tag{61}$$

$$\beta_{t,s} \ge 0 \tag{62}$$

$$\alpha_s \ge 0 \tag{63}$$

$$\alpha_s + \beta_{t,s} \ge (\lambda_t^{E,\max} - \lambda_t^{E,\min}) V_{t,s} \tag{64}$$

$$V_{t,s} \ge 0 \tag{65}$$

$$-V_{t,s} \le E^{t,s} \le V_{t,s} \tag{66}$$

Where, α_s and $\beta_{t,s}$ are defined as dual variables and $V_{t,s}$ is stated as the auxiliary variable to provide a straightforward linear problem. So, hybrid framework can be expressed as:

$$OF = Min\left\{ \sum_{s=1}^{NS} \pi_s \left(\begin{array}{l} \sum_{t=1}^{N_t} \left[\begin{array}{l} \lambda_t^{e,\min} E_{t,s} + \beta_{t,s} + \lambda_t^{g} G_{t,s} + \lambda_t^{h} H_{t,s} + C^{ES} P_{t,s}^{D} + C^{GS} G_{t,s}^{D} + C^{HS} H_{t,s}^{D} \\ + C^{EV} P_{t,s}^{EV,D} + C^{Wind} P_{w,t,s} + C^{DR}(DR_{t,s}^{up} + DR_{t,s}^{dn}) + \dfrac{1000 C_{bi}}{L_c E_b D_{dod}} \end{array} \right] \\ + \alpha_s \Gamma_s \end{array} \right) \right\} \tag{67}$$

Table 1
The hourly electrical, heat and natural gas demands, as well as forecasted wind power.

Time (h)	Electric demand (kW)	Heat demand (kWh)	Gas demand (kW)	Wind power generation (kW)
1	175.19	158.4	155.53	32.78
2	165.15	158.4	148.81	21.06
3	158.67	158.4	142.22	17.38
4	154.73	158.4	144.43	16.58
5	155.06	158.4	146.65	35.84
6	160.48	160.0	148.87	33.7
7	173.39	147.20	172.24	35.28
8	190.4	134.40	173.23	26.68
9	205.56	142.40	190.58	36.4
10	217.2	140.80	193.38	35.68
11	228.61	140.80	193.37	31.72
12	236.1	132.80	190.59	39.28
13	242.18	147.20	190.47	29.86
14	243.6	155.20	190.59	23.52
15	248.86	155.20	186.62	18.48
16	255.79	155.20	190.77	20.28
17	256	155.20	200.97	22.16
18	246.74	152.00	200.78	25.4
19	245.97	152.00	200.95	32.9
20	237.35	152.00	193.31	37.24
21	237.31	153.60	183.35	32.16
22	227.14	152.00	166.46	36.08
23	201.05	150.40	146.66	38.1
24	196.75	148.80	148.88	35.36

$$\beta_{t,s} \geq 0 \tag{68}$$

$$\alpha_s \geq 0 \tag{69}$$

$$\alpha_s + \beta_{t,s} \geq (\lambda_t^{E,\max} - \lambda_t^{E,\min}) V_{t,s} \tag{70}$$

$$V_{t,s} \geq 0 \tag{71}$$

$$-V_{t,s} \leq P_{t,s}^{E,ex} \leq V_{t,s} \tag{72}$$

4. Simulation and numerical results

In order to evaluate the proposed hybrid robust/stochastic model in previous sections, a multi-carrier microgrid test system, according to Fig. 2, is studied. The proposed MEM contains CHP, boiler, wind turbine, electrical, heat, and power-to-gas energy storage technologies, and interconnected EVs parking lots. The proposed MEM has the ability to participate in three markets: electricity, gas, and heat, in order to meet local electrical, thermal, and gas demands. The hourly electrical, heat, and NG demands, as well as the forecasted wind energy, are given in Table 1. Also, the daily energy prices, including power, NG, and heat prices are given in Table 2.

All characteristics and data of embedded generation and conversion technologies can be found in Mirzaei et al. (2020). The proposed MEM scheduling is formulated as a MILP model and carried out in the GAMS software that solved by CPLEX solver. To handle the existing uncertain parameters a hybrid robust/stochastic approach was applied such that wind energy, electrical demand and EVs behavior (contains arrival and departure time, and initial and final SoC) were modeled using scenario-based stochastic strategy while the power price is handled via a robust optimization approach, needless any PDF.

The forecasted error of wind power generation follows the Weibull distribution function with corresponding characteristics in Hemmati, Mohammadi-Ivatloo, Abapour et al. (2020). Also, the forecasted error of load demand follows the Normal distribution function with zero mean and 5 % standard deviation. Also, arrival and departure times, and initial and final state of charge of EVs are captured via Normal

Table 2
The hourly electrical, heat, and gas market prices.

Time (h)	Power market price (cent/kWh)	Heat market price (cent/kWh)	Gas market price (cent/Btu)
1	3	2.25	2.1
2	2	1.875	2.1
3	3	2.25	2.1
4	2.5	1.875	2.1
5	2.5	1.875	2.1
6	3.1	2.325	2.1
7	4.5	3.375	3.9
8	4.7	3.525	3.9
9	4.9	3.675	3.9
10	6.2	4.65	3.9
11	9	6.75	3.9
12	13	9.75	3.9
13	16	12	3.9
14	8.5	6.375	3.9
15	8.2	6.15	3.9
16	7	5.25	3.9
17	8	6	3.9
18	6.5	4.875	3.9
19	5.5	4.125	2.1
20	6.5	4.875	2.1
21	7.5	5.625	2.1
22	5	3.75	2.1
23	4.5	3.375	2.1
24	3.5	1.875	2.1

Table 3
The optimal hourly operation of CHP and boiler units.

Time (h)	Heat generated by CHP (kWh)	Heat generated by boiler (kWh)	Power generated by CHP (kW)
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	0	80	0
11	87.5	80	83.938
12	87.5	80	231.444
13	87.5	80	231.444
14	87.5	80	83.938
15	87.5	80	83.938
16	87.5	80	83.938
17	87.5	80	83.938
18	0	80	0
19	87.5	80	83.938
20	87.5	80	231.444
21	87.5	80	231.444
22	87.5	80	83.938
23	87.5	80	83.938
24	0	0	0

distribution with zero mean and 5 % standard deviation (Heydarian-Forushani, Golshan, & Siano, 2017). The 1000 scenarios are generated using Monte-Carlo simulation which are reduced to 10 appropriate scenarios using a backward selection approach in the SCENRED tool.

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

Case 1: Optimal operation of multi-energy microgrid considering wind energy, load demand and EV's behavior while power price uncertainty is neglected.

Case 2: Case 1 while the hybrid robust/stochastic strategy is applied to handle price uncertainty, in addition to other random variables.

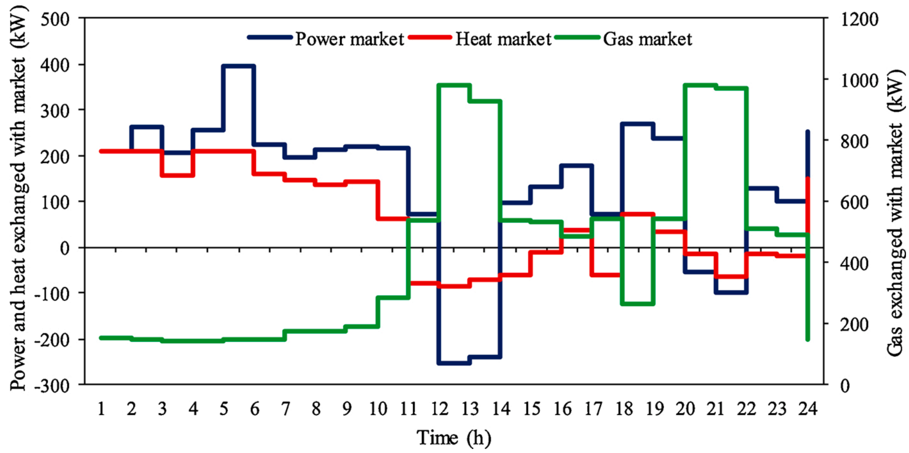

Fig. 4. The hourly energy exchanging between MEM and three markets.

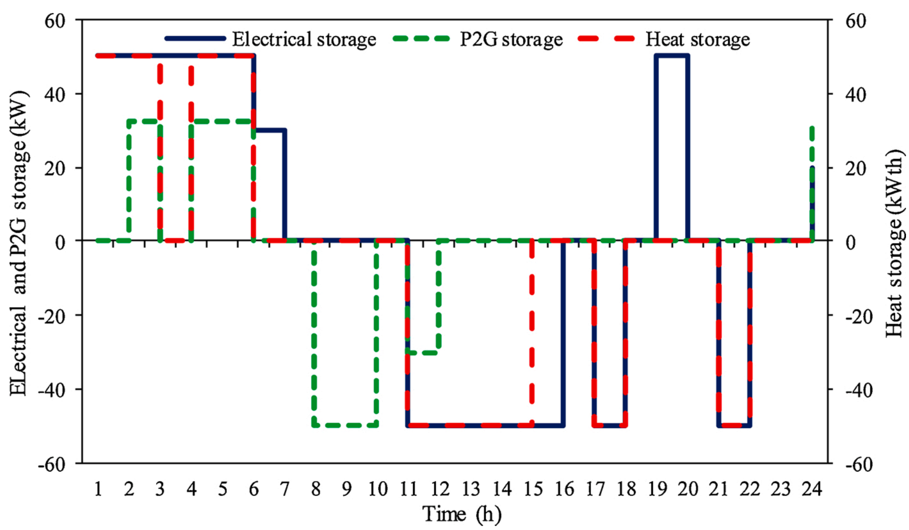

Fig. 5. Optimal charging and discharging scheme of multi-carrier energy storage systems.

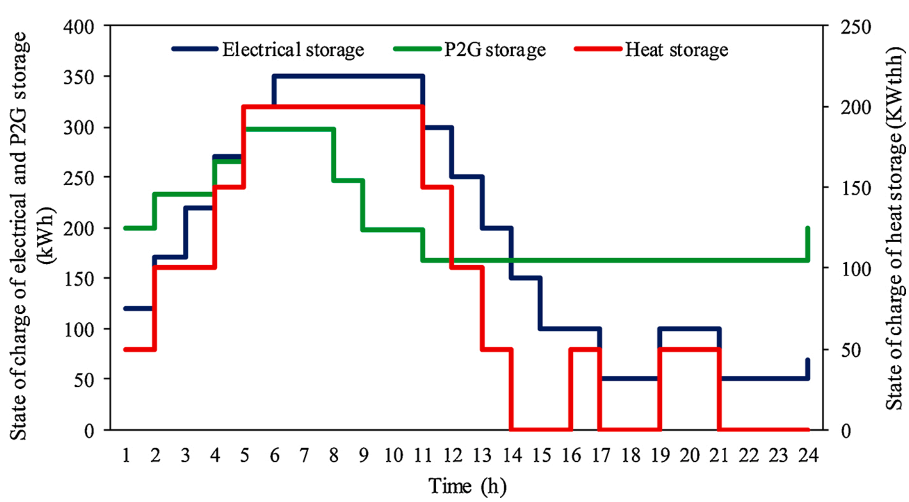

Fig. 6. Optimal state of charge of multi-carrier energy storage.

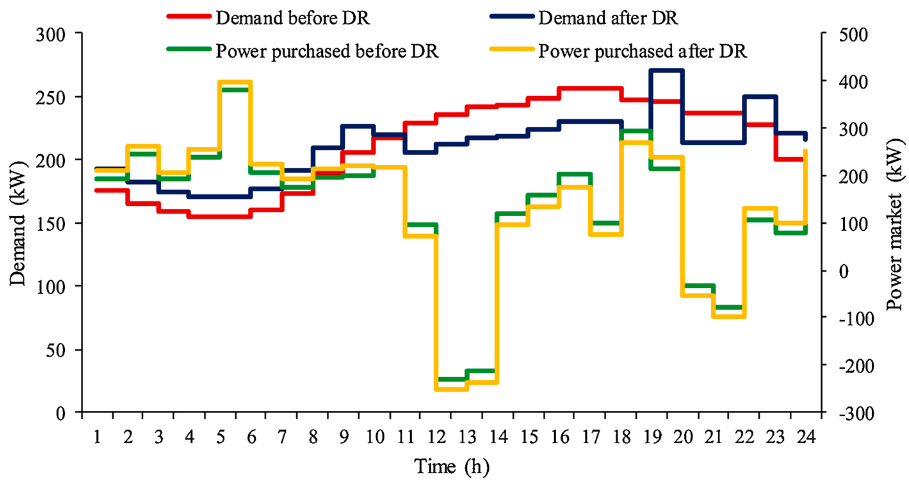

Fig. 7. The effects of DR program on the load profile, as well as power exchange.

4.1. Case 1

In this case, the optimal scheduling of MEM without considering the price uncertainty ($\Gamma = 0$) is evaluated. Table 3 represents the optimal operation of CHP and boiler units while the price uncertainty is neglected. It can be seen from Table 3 that due to the higher electricity price values at hours 12, 13, 20, and 21 p.m. CHP unit operates on the maximum power generation set point according to the feasible operation region. Meanwhile, at other times, between 11 a.m.–23 p.m. when the operator seeks to participate in the thermal market and heat prices reach higher values, he adjusts the CHP operation on the minimum power generation set point to produce heat with the maximum possible capacity. In the same way, the boiler unit is committed at 10 a.m.–23 p.m. due to the higher heat price values.

Fig. 4 depicts the energy exchange including electricity, heat, and gas between MEM and corresponding markets for Case 1. According to Fig. 4, when the electricity prices reach lower values (e.g. hours 1 a.m.–10 a.m.), the operator prefers to supply the required power by purchasing from the electricity market. At higher electricity prices (e.g. 12, 13, 20, and 21 p.m.) MEM's operator sells power to the electricity market. This procedure is established for other energies exchanges. At higher heat prices, operator sells the heat to the thermal market and vice versa. Furthermore, according to Fig. 4, at some hours like 12. 13, 20, and 21 p.m. due to the NG consumption by CHP and boiler units to supply desired heat and power, the amount of purchased NG has increased.

Table 4
Comparison of total operation cost of MEM in the presence of multiple high-efficient technologies.

	–	ESS+HSS + P2G	ESS+HSS + P2G + DR	ESS+HSS + P2G + DR + EV2G
Power operation cost (cent)	15519.273	13602.273	11203.172	9503.551
Gas operation cost (cent)	30989.322	31482.322	31482.322	31482.322
Thermal operation cost (cent)	2994.293	1531.793	1531.793	1531.793
Total operation cost (cent)	50351.920	45465.420	44217.287	42517.666

Figs. 5 and 6, represent the charging and discharging scheme as well as the state of charge of multi-energy storage systems, respectively. It can be seen from Fig. 5 that the electrical storage system is charged at low power price hours and then the energy stored at high power price hours (e.g. 11 p.m.–16 p.m.) is injected into the network. This procedure is established for thermal energy storage. At low heat prices hours,

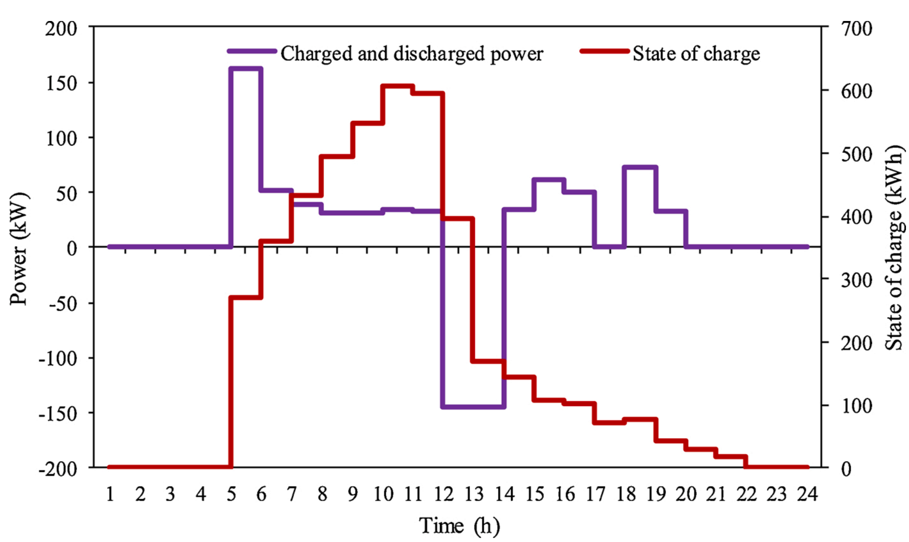

Fig. 8. The hourly charging/discharging scheme and state of charge of EVs parking lot.

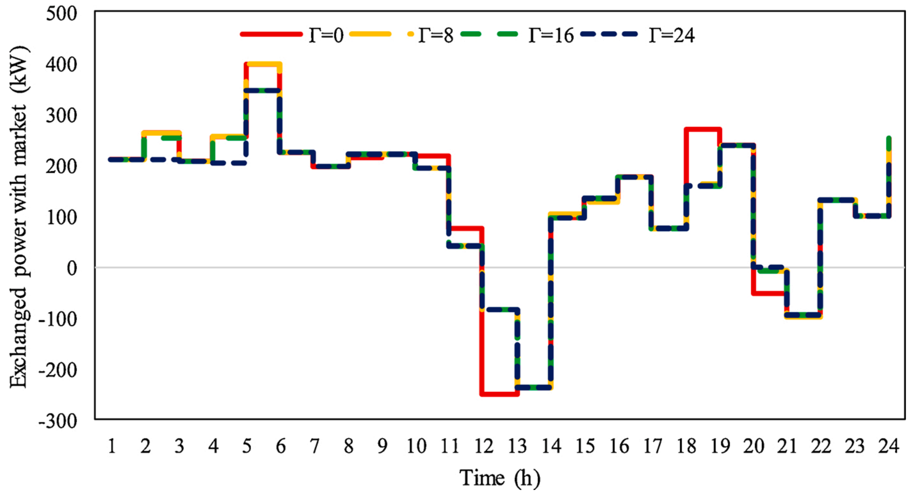

Fig. 9. The effect of increasing the level of conservatism of operator on power exchanges between MEM and upstream network.

thermal storage is charged and operates in discharging mode when the heating price reaches higher values. The P2G converts the electricity to NG at low power price hours, at higher gas prices, the stored NG in P2G tanks is injected into the system to meet required NG.

Fig. 7 shows the effect of the DR program on the network load profile and the amount of power exchanged between the MEM and the electricity market. As can be seen, the electricity demand has shifted from the hours with high electricity prices to the hours with low electricity prices. During the hours when the electrical load has been interrupted, the selling power has increased or the purchasing power from the electricity market has decreased, which has resulted in a reduction of total operation cost of the MEM.

The optimal charging/discharging scheme, as well as the available energy level of EVs parking lot, are depicted in Fig. 8. According to Fig. 8, not EVs have entered into the parking lot until 5 a.m. At 7 a.m., the energy level of the parking lot gradually increased, due to the entry of EVs into the parking lot and purchasing the power from the grid via the grid-to-vehicle (G2V) capability. At 12 and 13 p.m. level of energy in the parking lot has been mainly reduced. When power price reaches higher values at 12 and 13 p.m. the parking lot is discharged and injects power to grid via the V2G capability, results in the reduction of the energy level of the parking lot. Hence, the V2G capability at such periods offers an appropriate economic opportunity for MEM's operator to diminish daily operation costs.

Table 4 demonstrates the daily operation cost of MEM in the presence of emerging high-efficient technologies. According to Table 4, incorporating the MEM with these technologies under an integrated stochastic optimization framework ($\Gamma = 0$), the total operation cost has mainly reduced.

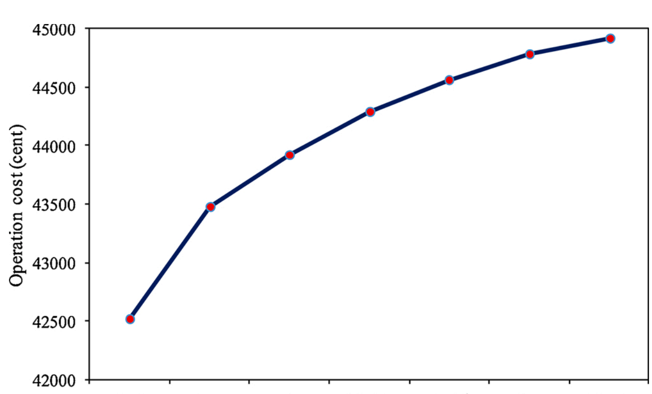

Fig. 10. The effect of increasing the level of conservatism of the operator on the cost of operation of MEM.

Table 5
The effect of increasing the Γ on each of the costs of electricity, gas and heat.

	Γ = 0	Γ = 8	Γ = 16	Γ = 24
Power operation cost (cent)	12554.334	12075.156	12054.095	12623.838
Gas operation cost (cent)	31482.322	30738.580	30891.69	31188.568
Thermal operation cost (cent)	1531.793	1105.230	1105.230	1105.230
Total operation cost (cent)	42517.666	43918.96	44554.844	44917.636

Table 6
Comparison of operational costs under a hybrid robust/stochastic approach for Γ = 8.

Γ = 8	–	ESS+HSS + P2G	ESS+HSS + P2G + DR	ESS+HSS + P2G + DR + EV
Power operation cost (cent)	14678.148	12582.555	11407.760	1105.230
Gas operation cost (cent)	31971.401	32589.361	32591.151	30738.580
Thermal operation cost (cent)	2567.730	1105.230	1105.230	1105.230
Total operation cost (cent)	51217.279	46277.146	45104.141	43918.966

4.2. Case 2

In this case, the optimal operation of the MEM under the hybrid robust/stochastic approach considering price uncertainty besides other ones is investigated. In order to evaluate the uncertainty nature of electricity price under a conservative approach, Γ has been increased from 0 to 24 with eight steps. Fig. 9 shows the effects of Γ changes in the energy exchanges between MEM and the upstream network. By increasing the Γ which increases the level of conservation of the system's operator, the power exchanges decreased. In fact, with an increasing Γ coefficient, the electricity price has been increased during the hour of purchasing power, and has been decreased during the hours of selling power to the grid. This results in the reduction of operator inclinations to exchange power with the upstream network.

The effects of the increasing Γ coefficient on total operation cost is shown in Fig. 10. As can be seen, increasing the Γ, total operation cost increases and the operator raises the level of his conservatism. Table 5 reveals the effects of the increasing Γ coefficient on each electricity, gas, and thermal operation costs, separately. According to Table 5, when $\Gamma = 8$ the heat and gas operation cost decreases, while electricity cost increases. The main reason for the reduction of heat and gas operation costs is related to less utilization of CHP, and more utilization of the boiler unit, conversely. With the further increases of Γ, thermal operation cost is constant, while the NG operation cost due to less utilization of the P2G facility increases.

Table 6 indicates the effects of multiple technologies on uncertainty management under the hybrid robust/stochastic approach for Γ = 8. It can be seen under the hybrid robust/stochastic strategy, the emerging technologies play an appropriate role in reducing the total operation cost of MEM. In fact, in the presence of such technologies, MEM's operator under a lower operational cost, achieves his desired level of conservatism.

5. Conclusion

In this paper, the optimal operation of the renewable-based multi-energy microgrid incorporated with emerging high-efficient technologies was presented. The power-to-gas storage, demand response based shiftable loads, and electrical vehicle parking lot have been embedded in the multi-energy microgrid as high-efficiency components. In addition to EVs, P2G, and DR program, the proposed MEM has been integrated with wind energy, multi-carrier energy storage (heat, electrical, and gas) systems, boiler, combined heat, and power, with the aim of total daily operational cost minimization. Furthermore, bilateral energy exchanges between MEM and electricity, heat, and gas markets were considered to offer active participation of the system operator in three markets to meet local demands as well as achieve desired profits through energy exchanges. The proposed model was formulated based on mixed-integer linear programming under a hybrid robust/stochastic approach to handle existing high-level uncertainties, including wind power output, electricity demand, arrival and departure times, and initial and final state of charge of EVs in a parking lot, as well as electricity prices.

Simulations have shown the following results:

- Deployment of the proposed hybrid/stochastic strategy enables the operator to take advantage of both stochastic and robust approaches simultaneously, as well as to differentiate between the level of conservatism of system uncertainties.
- Multi-carrier energy storage systems integrated with power-to-gas technology reduced the daily operation by 9 %.
- Taking into account the demand response program, along with multi-carrier storage systems, the MEM operator was able to reduce the operational costs by up to 13 %.
- Integrated optimal scheduling of MEM in the presence of emerging technologies, incorporated with vehicle-to-grid (V2G) capability, reduces the total operational cost by 14.2 %.

The efficiency of the proposed MEM operation will be further improved by considering district heating networks, hydrogen storage, fuel-cell, solar energy in the presence of other uncertainty modeling approaches like information gap decision theory were are left for future works.

Declaration of Competing Interest

The authors report no declarations of interest.

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