Robust Flexible Unit Commitment in Network-Constrained Multi-Carrier Energy Systems

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***Abstract*—The coordinated operation of different energy systems, such as electrical, gas, and heating, can improve the efficiency of the whole energy system and facilitate the larger penetration of renewable energy resources in the electricity generation portfolio. However, appropriate models considering various technical constraints of the energy carriers (e.g., gas system pressure limit and heat losses in the district heating networks) are needed to effectively assess the true impact of integrated energy system (IES) operation on the overall system's performance. This paper proposes a flexible unit commitment (UC) problem for coordinated operation of electricity, natural gas, and district heating networks, called multi-carrier network-constrained unit commitment (MNUC), to minimize the operation cost of the IES. Besides, an integrated demand response (IDR) program is considered as a promising solution to improve consumers' electrical, gas, and heat consumption patterns and increase the power dispatch of combined heat and power units. Multi-energy storage systems are also included in the proposed model to decrease the impact of multi-energy network constraints on the overall system's performance. To model the uncertainties involved in the operation of the three networks, a combined robust/stochastic approach is preferred in the MNUC problem considering multi-carrier energy storage systems and the IDR program. Numerical results show that the whole operation cost of the IES has decreased by %2.58 considering the IDR program and multi-energy storage systems.**

***Index Terms*—Integrated energy system, gas network, district heating network, unit commitment, robust optimization, stochastic optimization.**

NOMENCLATURE

Decision Indices

t	Time intervals
w	Scenarios
i	Generation units
wf	Wind power plants
gw	Gas suppliers
gs	Gas storages
hs	Heat storages
es	Electrical storages
j	Electrical loads
g	Gas loads
hl	Heat loads
b	Power system buses
h	DHN nodess
m	Gas system nodes
L	Power system lines
hp	Heat pipelines
pl	Gas pipelines

Decision Parameters

NT	Sum of time periods
NG, NJ, NHL	Sum of gas/ electrical/ heat loads
NES, NHS, NGS	sum of electrical/ heat/ gas storage systems
NW	Sum of scenarios
NGW	Sum of gas wells
NWF	Sum of wind power units
GU, NC EU	Sum of gas-fired/ CHP/ non-gas fired units
$GW_{\text{gw}}^{\max}$, $GW_{\text{gw}}^{\min}$	Max/ min natural gas injection
p_w	Probability of scenarios
$P_{wf,t}$	Forecasted wind power
$P_i^{\min}$,$P_i^{\max}$	Max/ min power produced by power generation units
R_i^{up},R_i^{dn}	Ramp up/ down of power generation units
T_i^{on},T_i^{off}	Minimum on/ off time of power generation units
η_{xs}^{+},η_{xs}^{-}	Efficiency of charge/ dischrage of electrical/ gas/ heat storages
$X_{xs}^{-\min}$,$X_{xs}^{-\max}$	Min/ max discharge capacity of electrical/ gas/ heat storages
$X_{xs}^{+\min}$,$X_{xs}^{+\max}$	Min/ max charge capacity of electrical/ gas/ heat storages
$XS_{xs}^{\min}$,$XS_{xs}^{\max}$	Max/ min capacity of electrical/ gas/ heat storages
$XL_{z,t,s}$	Electrical/ gas/ heat demands
α_z	Participation factor of electrical/ gas/ heat loads in demand response programs
ΔD_z^{dn},ΔD_z^{up}	Ramp down/ up of shiftable demands
X_L	Line reactance
$PF_L^{\max}$	Capacity of transmission line
T_0	Environment temperature
$T_h^{\min}$, $T_h^{\max}$	Limitation of temperature in DHN nodes
$HP_{hp}^{\min}$,$HP_{hp}^{\max}$	Limitation of mass flow rate in DHN pipelines
$C_{m,n}$	Gas pipelines constant

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$\pi_m^{\min}$, $\pi_m^{\max}$	Limitation of pressure in gas network nodes
	Decision Variables
$P_{i,t,w}$	Power generation of units
$H_{i,t,w}$	Heat generation of CHP units
$GW_{gw,t,w}$	Gas supply of gas wells
$XL_{z,t,s}^{dr}$	Electrical/ gas/ heat demands after implementing demand response
$P_{es,t,w}^{+}$, $P_{es,t,w}^{-}$	Charge/discharge power of electrical storage
$G_{gs,t,w}^{-}$, $G_{gs,t,w}^{+}$	Released/Stored gas of gas storage
$H_{hs,t,w}^{-}$, $H_{hs,t,w}^{+}$	Released/Stored heat of heat storage
$ES_{es,t,w}$	State of charge of electrical storage
$GS_{gs,t,w}$	State of charge of gas storage
$HS_{hs,t,w}$	State of charge of heat storage
$\Delta E_{j,t,w}$	Adjustable electric demand
$\Delta G_{g,t,w}$	Adjustable gas demand
$\Delta H_{hl,t,w}$	Adjustable heat demand
$PF_{L,t,w}$	Power flow through electrical lines
$F_{pl,t,w}$	Gas flow through gas pipelines
$HP_{hp,t,w}$	Mass flow rate of heat pipelines
$T_{h,t,w}$	Hot water temperature in the pipelines
$\delta_{h,t,w}$	Bus angle of power system
$\pi_{m,t,w}$	Gas system pressure

I. Introduction

A. *Motivation*

THE interdependency of various energy systems is increasing due to a higher amount of gas-fired power plants, combined heat and power (CHP) units, gas/electric district heating networks (DHNs), different types of energy storage technologies, and integrated demand response programs (IDRPs) [1]–[3]. According to the 2014 Annual Energy Outlook [4], gas utilization for electricity production will increase to 35% of the total electricity supply in the U.S. by 2040, which leads to higher interdependency between power and gas systems in the future. DHNs were designed in the second half of 19$^{\text{th}}$ century to satisfy heat demand in an area with higher efficiency and less pollution [5]. In a DHN, heat is produced at a central station and transferred to heat consumers as hot water or steam through a network of underground pipelines. Heat is mainly produced by gas-fired CHP units [6]. Gas-fired-based CHP units generate electricity at the same time as heat, which is a highly efficient model of electricity production and decreases the requirement for large power plants [7]. The larger adoption of such technologies increases interdependency between energy systems such as power, gas, and district heating networks. This way, the concept of integrated energy systems (IESs) was born to take advantage of applying alternative energy resources and interconnected systems to provide high-quality service to consumers. It is expected that an IES reduces the overall cost of operation for the end-users while expedites the adoption of renewable energy sources (RES) without jeopardizing the security and integrity of the power grid. It is not, however, possible without a realistic and optimal mechanism for an IES operation.

B. *Literature review*

Some of the literature focused on solving the unit commitment (UC) problem in power systems without considering the interdependence between various energy carriers. In [8], a novel method was proposed to calculate startup cost in the UC problem. The authors of [9] introduced a new stochastic approach to solve the UC problem, where the Lambda-iteration technique is used to obtain the optimal dispatch of units. A risk-based scheme for maintenance scheduling and UC is investigated in [10] to reduce the total operation cost, including the risk cost, production cost and maintenance cost. The authors of [11] solved a flexible UC based on the Modified Harmony Search Algorithm, where the effect of plug-in electric vehicles on the daily operation has been evaluated. A stochastic network-constrained UC (NUC) problem is proposed in [12] to evaluate the impact of hydrogen-based energy storage systems and DRPs on the total operation cost.

Several studies examined the operation of IESs from different perspectives in recent years. A robust framework for the NUC in the integrated power and gas systems is introduced in [13], where the possibility of transmission line outages on the integrated system performance has been studied. The authors proposed a risk-based stochastic approach for co-optimization of power and gas systems in [14] considering power-to-gas (P2G) storage and DR programs, where the main objective was to minimize the operation cost of the energy in the IES. In [15], the authors linearized the gas network constraints for the day-ahead scheduling of a gas and power integrated system, where the uncertainties associated with load demand and DR resources have been assessed. An approximate linearization approach is introduced for non-linear technical constraints of a gas network in [16] to optimally schedule an IES. A computationally tractable market-based coordination of power and gas systems is presented in [17], where the market prices are identified iteratively while the exchange of proprietary information, such as power and gas transmission line data, is avoided. A two-stage stochastic and robust scheme is studied in [18] and [19] for coordinated operation of power and gas networks in the presence of electricity and gas demand uncertainties, respectively.

Moreover, several algorithms for optimal operation of integrated power and heat systems have been introduced in the literature. A NUC formulation for integrated power and heat systems is developed in [20] considering CHP technology and DHN, where the variability of wind power generation is managed by a heat storage system. The authors studied the flexibility of heat and electricity demands in [21] considering an aggregator, where a two-level problem was designed for maximizing social welfare through independent system operator (ISO) as well as minimizing the cost of energy purchased by aggregators. In [22], the authors have proposed a joint hourly UC formulation in an integrated power system and DHN by characterizing thermal storage, the inertia of pipelines, and heat demand. "decomposition–coordination framework" for large-scale non-linear power and heat systems is proposed in [7], where the impact of the proposed model has been investigated on the flexibility and operation cost of the system.

The integrated power, gas, and DHN operation has been scarcely investigated in the literature. In [23]–[26], the authors proposed energy management frameworks for multi-carrier energy systems based on the energy flow model, where the constraints of power, gas and DHNs are modeled. In [23], the impact of DHN on optimization of multi-carrier energy networks were analyzed by applying an evolutionary optimization approach. In [24], a market trading model for an integrated gas, DHN, and power network is proposed based on the energy flow of each network as well as their interconnection, where market equilibrium is attained by implementing a mixed-integer linear programming. In another effort, the authors have presented an integrated optimization model for energy flow in power, gas, and DHNs simultaneously in [25] considering various links among the carriers, such as boilers and CHPs. In [26], an energy flow model for an integrated power, gas and heat system has been introduced in the presence of uncertainties related to solar power output, heat and power demand.

C. *Contributions*

It can be seen from the literature review that the operation of an IES with multi-energy storage and IDRPs have not been investigated properly. Moreover, only the energy flow problem has been investigated in an IES of power, gas, and DHN. The major gaps in the existing literature are listed below:

1) In some of the literature, e.g., [8]–[12], interdependency between power network with other energy networks has been ignored in the UC problem.
2) In [4], [13], [15]–[19], [27], interdependency between power and DHN as well as gas and DHN has not been formulated in the UC problem.
3) The effect of gas network pressure limits on the power and heat dispatch of CHP plants has not been investigated in the UC problem in [6], [7], [20]–[22], [27].
4) In a few studies, e.g., [23]–[26], an energy flow model is preferred to the UC problem, which is not sufficient for the operation of a practical IES.
5) Flexible technologies such as multi-carrier energy storage systems and IDRPs have not been formulated in the UC problem in [4], [7], [13], [15]–[27].

This paper presents a UC formulation constrained by power, gas, and heat networks, which is called multi-carrier NUC (MNUC), to investigate the mutual impact of the three energy carriers in an IES. In particular, the effect of gas pressure drop in the gas network is modelled accurately, which may happen in winter due to the increase in natural gas demand. Additionally, heat losses of the DHN are formulated to evaluate its impact on the IES performance.. This way, the proposed MNUC model allows the simultaneous application of several emerging technologies (e.g., IDRPs) in day-ahead scheduling under optimal conditions of the integrated power, gas, and heat systems. Moreover, a combined robust/stochastic approach is developed to adequately represent uncertain parameters of the IES. In this approach, the uncertainties associated with electric, thermal and gas load demands are modeled using Monte Carlo simulation, while the uncertainty of wind power production is handled by using a robust framework based on information gap decision theory (IGDT). This way, there is no need for probability distribution functions of the underlying uncertainties. The main contributions of this paper are summarized below:

1) Integrating the gas pressure constraint and heat losses in the proposed UC formulation (despite energy flow models in [23]–[26]) for the day-ahead scheduling of the IES.
2) Introducing a combined robust/stochastic optimization framework for the proposed MNUC problem to manage uncertainties in an effective and tractable manner. The proposed approach enables the system operator to use both the benefits of a scenario-based modeling method as well as a robust optimization technique to manage uncertainties of the system simultaneously.
3) Integration of multi-energy storage systems (i.e., electricity, gas and heat) as well as the application of electricity, gas, and heat-based DR programs in the MNUC to assess its impact on the energy efficiency, optimal utilization, minimization of the overall operation cost, and better management of resources in an uncertain environment.

The remainder of this paper is organized as follows. Formulation of the proposed robust MNUC problem are developed and described in Section II. Section III introduces the case study, simulation results, and discussion. Finally, Section IV concludes this paper.

II. Problem Description and Formulation

Multi-carrier energy storage technologies and IDRPs can play a vital role in increasing the connection between electricity, gas, and district heating networks. This interconnection can lead to the interoperability of the IES that facilitates a higher uptake of intermittent RES with minimum cost. IDRPs consist of flexible electrical, gas and heat DR resources. Electrical DR programs affect electricity market prices, load demand profile, intermittent RES curtailment, and operating cost of the power system. Electrical DR programs are typically integrated in the wholesale electricity markets through aggregators by reducing and/or shifting load demand at certain times. The offers from aggregators will be added to the NUC problem to determine the optimal dispatch of plants and flexible loads [28]. When there is a link between gas/heat networks with an electricity grid, it allows the implementation of DR programs for gas systems and DHNs that can benefit electricity grid operation. More specifically, it is helpful by improving the flexibility of consumers in decreasing or increasing gas and heat consumption at particular times. In the gas system, the process of DR aggregator is similar to that of the power network when the end-users consume gas directly [3].

Similar to electricity load aggregators, a gas aggregator deals with gas consumers to alter their consumption by shifting or curtailment. Accordingly, the aggregator offers the flexibility of the gas consumers and intended prices to the gas system operator (GSO). Finally, GSO determines hourly dispatch considering flexible gas loads. Unlike electricity and gas operators, the DHN operator (DHNO) is a buyer of gas and electricity and a seller of heat to end-users in the form of steam or hot water [29]. Accordingly, the DHN aggregator can be defined as an independent entity that can manage the end-users' heat demand. This way, the DHN aggregator provides flexibility for the DHN operator in line with the flexibility of steam or hot water consumers [29].

In the proposed IES model, the ESO, GSO and DHNO are managed under a single entity, which is called the integrated energy system operator (IESO). In this arrangement, multi-carrier energy suppliers, demand, aggregators, and storage units provide their hourly bids to the IESO so that it solves an integrated MNUC problem to determine the hourly schedules of all units and participants from gas, electricity and heat systems.

A. *MNUC model*

Traditionally, the NUC model is applied to achieve the minimum daily operation cost with respect to the constraints of the power system, ignoring the network constraints of other energy carriers. Recently, modified NUC problems are reported in the literature for the optimal scheduling of coupled power and heating systems, or power and gas systems. However, the interconnection between the three systems has not been considered. In addition, the pressure shortage of the gas network and increase of heat loss in the DHN are not considered simultaneously in these studies. This can affect energy system operation significantly due to an increase in heat and gas demand during winter. The extra heat losses should be compensated by increasing heat generated in the CHP units,which inevitably leads to higher gas consumption and thus higher operation cost. To address these challenges, this paper offers an MNUC formulation considering the constraints of power, gas and heating networks within the same framework. The main purpose of the proposed MNUC is to achieve the minimum operation cost of IES by simultaneously satisfying constraints associated with the power, gas, and heating network. The dependency between different energy carriers in the MNUC problem is shown in Fig. 1

B. *Stochastic Optimization Model*

1) Objective function: The main objective of the proposed MNUC framework for the IESO is to minimize the operation cost of the integrated power, gas, and heat systems in the presence of multi-carrier smart technologies while respecting the technical constraints of the entire system, which is given in (1). The first term in (1) represents the operation cost of the non-gas-fueled power plants. The second term describes the operation cost of electrical energy storage units. The operation cost of the gas suppliers and natural gas storage units are modelled in the third term in (1). The last term

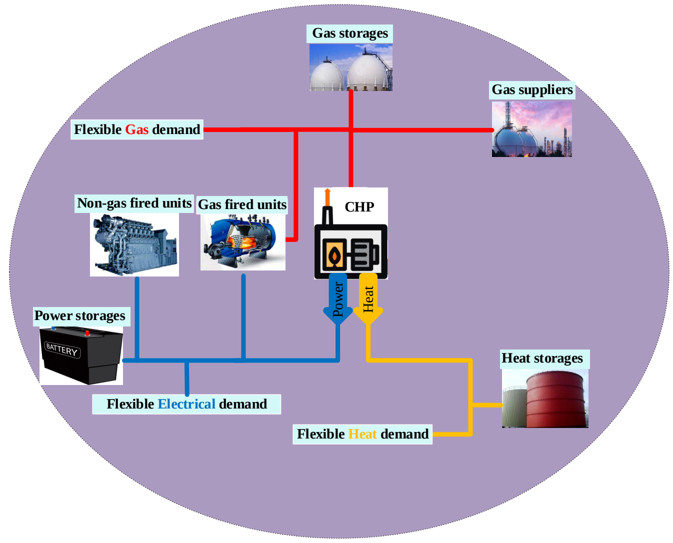

Fig. 1. The dependency between different energy carriers in the MNUC problem

of the objective function accounts for the cost of electric demand response (EDR), gas demand response (GDR), and heat demand response (HDR), respectively.

$$\min \sum_{w=1}^{NW} p_w \sum_{t=1}^{NT} \left[\begin{array}{l} \sum\limits_{i=1}^{EU} \left[F\left(P_{i,t,w}\right) + SU_{i,t} + SD_{i,t} \right] \\ + \sum\limits_{e=1}^{NSE} \left[P_{e,t,w}^{+} C_e^{+} + P_{e,t,w}^{-} C_e^{-} \right] \\ + \left\{ \sum\limits_{gw=1}^{NGW} C_{gw}^{Well} GW_{gw,t,w} + \sum\limits_{gs=1}^{NGS} C_{gs}^{-} G_{gs,t,w}^{-} \right\} \\ + \left\{ \begin{array}{l} \sum\limits_{j=1}^{NJ} C_j^E \left|\Delta E_{j,t,w}\right| + \sum\limits_{g=1}^{NGL} C_g^G \left|\Delta G_{g,t,w}\right| \\ + \sum\limits_{hl=1}^{NHL} C_{hl}^H \left|\Delta H_{hl,t,w}\right| \end{array} \right\} \end{array} \right] \tag{1}$$

2) UC problem constraints: All of the constraints related to the UC problem include the minimum and maximum generation of the power plants (2), the ramp rates of the power plants in continuous time intervals (3) and (4), the minimum up/down times of the units (5) and (6), start-up and shut-down of the power plants (7), (8) and feasible operating regions of the CHP units (13)- (17), as shown in Fig. 2. EU, CU and GU represent sets of non-gas fired units, gas-fired CHP units and non-CHP units, respectively [30].

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

$$\begin{array}{l} P_{i,t,w} - P_{i,t-1,w} \le \left[1 - I_{i,t}(1 - I_{i,t-1})\right] R_i^{up} \\ + I_{i,t}(1 - I_{i,t-1}) P_i^{\min} \end{array} \tag{3}$$

$$\begin{array}{l} P_{i,t-1,w} - P_{i,t,w} \le \left[1 - I_{i,t-1}(1 - I_{i,t})\right] R_i^{dn} \\ + I_{i,t-1}(1 - I_{i,t}) P_i^{\min} \end{array} \tag{4}$$

$$\left(X_{i,t-1}^{on} - T_i^{on}\right)\left(I_{i,\,t-1} - I_{i,t}\right) \ge 0 \tag{5}$$

$$\left(X_{i,t-1}^{off} - T_i^{off}\right)\left(I_{i,t} - I_{i,t-1}\right) \ge 0 \tag{6}$$

$$SU_{i,t} \ge su_i\left(I_{i,t} - I_{i,t-1}\right) \;\; i \in EU \tag{7}$$

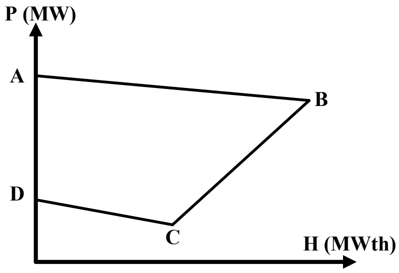

Fig. 2. Feasible operating region of the CHP units

$$SD_{i,t} \geq sd_i \left(I_{i,t-1} - I_{i,t}\right) \;\; i \in EU \tag{8}$$

$$SUG_{i,t} \geq sug_i \left(I_{i,t} - I_{i,t-1}\right) \;\; i \in CU \cup GU \tag{9}$$

$$SDG_{i,t} \geq sdg_i \left(I_{i,t-1} - I_{i,t}\right) \;\; i \in CU \cup GU \tag{10}$$

$$SUG_{i,t} \geq sug_i \left(I_{i,t} - I_{i,t-1}\right) \quad i \in GU \tag{11}$$

$$SDG_{i,t} \geq sdg_i \left(I_{i,t-1} - I_{i,t}\right) \quad i \in GU \tag{12}$$

$$P_{i,t,w} - P_i^A - \frac{P_i^A - P_i^B}{H_i^A - H_i^B} \times (H_{i,t,w} - H_i^A) \leq 0 \;\; i \in CU \tag{13}$$

$$P_{i,t,w} - P_i^A - \frac{P_i^A - P_i^B}{H_i^A - H_i^B} \times (H_{i,t,w} - H_i^A) \leq 0 \;\; i \in CU \tag{14}$$

$$P_{i,t,w} - P_i^B - \frac{P_i^B - P_i^C}{H_i^B - H_i^C} \times (H_{i,t,w} - H_i^B) \geq -(1 - I_{i,t}) \times M \;\; i \in CU \tag{15}$$

$$P_{i,t,w} - P_i^C - \frac{P_i^C - P_i^D}{H_i^C - H_i^D} \times (H_{i,t,w} - H_i^C) \geq -(1 - I_{i,t}) \times M \;\; i \in CU \tag{16}$$

$$0 \leq H_{i,\,t,w} \leq H_i^A \times I_{i,\,t} \;\; i \in CU \tag{17}$$

3) Multi-carrier energy storage systems: In this study, the electricity, gas, and heat storage technologies are considered in the problem formulation. The constraints of the storage systems are defined by (18)-(23). Equation (18) ensured only one of the charging and discharging operation at a given time. Power limits are enforced by (19)-(20) during charging and discharging modes. State of charge is computed in (21) for each hour, and capacity limits of the storage units are enforced by (22). Finally, energy neutrality of the storage units over the entire scheduling period is guaranteed by (23) [31].

$$I^+_{xs,t,w} + I^-_{xs,t,w} \leq 1 \tag{18}$$

$$X_{xs}^{+\min} I^+_{xs,t,w} \leq X^+_{xs,t,w} \leq X_{xs}^{+\max} I^+_{xs,t,w} \tag{19}$$

$$X_{xs}^{-\min} I^-_{xs,t,w} \leq X^-_{xs,t,w} \leq X_{xs}^{-\max} I^-_{xs,t,w} \tag{20}$$

$$XS_{xs,t,w} = (1 - \eta_{xs}) XS_{xs,t-1,w} + \eta^+_{xs} X^+_{xs,t,w} - \frac{X^-_{xs,t,w}}{\eta^-_{xs}} \tag{21}$$

$$XS_{xs}^{\min} \leq XS_{xs,t,w} \leq XS_{xs}^{\max} \tag{22}$$

$$XS_{xs,0} = XS_{xs,24,w} \tag{23}$$

where $X \in \{E, G, H\}$ and $xs \in \{es, gs, hs\}$ represent electricity, gas, and heat storage technologies, respectively

4) IDRPs: In this work, a generic IDRP model is developed for electricity, gas, and heat aggregators, where aggregators can offer their flexibility bids to the IESO market. This way, the IESO solves a single MNUC problem by considering the conditions of the three energy carriers simultaneously. As a result, the IESO coordinates shiftable power, gas, and heat load demands. Equation (24) represents the maximum adjustable load at each time interval for power, heat and gas load demands. A conservative DR concept is adopted in (25) for the three energy carriers by modelling load's rebound effect. Equation (26) represents electricity, gas and heat load demand after IDRPs implementation. Finally, (27) and (28) model the loads ramp rate in continuous times, where $X \in \{E, G, H\}$ and $z \in \{j, hl, g\}$ (23) [31].

$$\left|\Delta X_{z,t,s}\right| \leq \alpha_x \times XL_{z,t,s} \tag{24}$$

$$\Delta X_{z,t,s} = 0 \tag{25}$$

$$XL^{dr}_{z,t,s} = \left|\Delta X_{z,t,s}\right| + XL_{z,t,s} \tag{26}$$

$$XL^{dr}_{z,t,s} - XL^{dr}_{z,t-1,s} \leq \Delta D^{up}_z \tag{27}$$

$$XL^{dr}_{z,t-1,s} - XL^{dr}_{z,t,s} \leq \Delta D^{dn}_z \tag{28}$$

5) Multi-carrier network constraints: The constraints associated with the power system model are expressed in (29)-(31) including power balance at each time interval and scenario, and the technical constraints of the power transmission lines. Equations (32)-(41) represent the constraints of the DHN [7]. In steady state, the mass flow equation at each time interval and node is expressed by (32). The conversion of generated heat, heat demand, and heat storage charging/discharging to mass flow rates are expressed in (33)-(36), respectively. The energy carrier in the DHN can be steam or liquid water. Without loss of generality, however, we only considered liquid water in this study. Temperature drops in the heat pipelines are indicated in (37), which depends on the flow rate of the pipeline, $(HP_{hp,t,s})$, the length of the pipeline, Le_{hp}, and the heat loss coefficient of the pipeline, k_{hp}, as given in (38). The pipeline heat losses coefficient is also determined by (39). The relevant constraints of the temperature and capacity of the pipeline are also expressed in (40)-(41). Equations (42)-(47) demonstrate the gas flow through the pipelines with/without compressor, the gas pressure limits at each node, the limits of natural gas supply and the gas balance at each time interval and node [4]. Typically, CHP and gas-fired units are big consumers of natural gas, where their consumption is modelled in (48) and (49) in connection with the gas system [7], [32].

$$\begin{aligned}&\sum_{i=1}^{NU_b} P_{i,t,w} + \sum_{e=1}^{NES_b} \left(P^-_{e,t,w} - P^+_{e,t,w}\right) + \sum_{wf=1}^{NWF_b} P_{wf,t} \\ &- \sum_{j=1}^{NJ_b} EL^{dr}_{j,t,w} = \sum_{l=1}^{NL_b} PF_{L,t,w}\end{aligned} \tag{29}$$

$$PF_{L,t,w} = (\theta_{b,t,w} - \theta_{b',t,w})/X_L \tag{30}$$

$$|PF_{L,t,w}| \leq PF_L^{\max} \tag{31}$$

$$\begin{aligned}&\sum_{i=1}^{NC_h} QG_{i,t,w} + \sum_{hl=1}^{NHL_h} QL_{hl,t,w}^{dr}\\&+\sum_{hs=1}^{NHS} (QS_{hs,\,t,w}^{-} - QS_{hs,\,t,w}^{+}) = \sum_{hp=1}^{NHP_h} HP_{hp,\,t,w}\end{aligned} \tag{32}$$

$$QG_{i,t,w} = 3600\; H_{i,\,t,\,w}/(T_{h,\,t,\,w} - T_{h,t,\,w}^{back})\, c \quad i \in CU \tag{33}$$

$$QS_{hs,\,t,s}^{-} = 3600\; H_{hs,t,s}^{-}/(T_{h,t,s} - T_{h,t}^{back})\, c \tag{34}$$

$$QS_{hs,\,t,w}^{+} = 3600\; H_{hs,t,w}^{+}/(T_{h,\,t,w} - T_{h,t}^{back})\, c \tag{35}$$

$$QL_{hl,t,w}^{dr} = 3600\; HL_{hl,t,w}^{dr}/(T_{h,t,w} - T_{h,t}^{back})\, c \tag{36}$$

$$\Delta T_{hP,t,w} = E_{hp,t,\,w}\, HP_{hp,t,w} \tag{37}$$

$$1000\, c (HP_{hp,t,w})^2 \times E_{hp,t,\,w} - 3.6 k_{hp}(1+\beta) Le_{hp} = 0 \tag{38}$$

$$k_{hp} = T_{hp} - T_0/R_1 + R_2 \tag{39}$$

$$T_h^{\min} \leq T_{h,\,t,w} \leq T_h^{\max} \tag{40}$$

$$HP_{hp}^{\min} \leq HP_{hp,\,t,w} \leq HP_{hp}^{\max} \tag{41}$$

$$F_{pl,t,w} = \mathrm{sgn}(\pi_{m,t,w}, \pi_{n,t,w})\; C_{m,n}\sqrt{\left|\pi_{m,t,w}^2 - \pi_{n,t,w}^2\right|} \tag{42}$$

$$\mathrm{sgn}(\pi_{m,t,w}, \pi_{n,t,w}) = \begin{cases} 1 & \pi_{m,t,s} \geq \pi_{n,t,w} \\ -1 & \pi_{m,t,s} < \pi_{n,t,w} \end{cases} \tag{43}$$

$$F_{pl,t,w} \geq \mathrm{sgn}(\pi_{m,t,w}, \pi_{n,t,w})\; C_{m,n}\sqrt{\left|\pi_{m,t,w}^2 - \pi_{n,t,w}^2\right|} \tag{44}$$

$$\pi_m^{\min} \leq \pi_{m,t,w} \leq \pi_m^{\max} \tag{45}$$

$$GW_{gw}^{\min} \leq GW_{gw,t,w} \leq GW_{gw}^{\max} \tag{46}$$

$$\begin{aligned}&\sum_{gw=1}^{NGW_m} GW_{gw,t,w} + \sum_{g=1}^{NGS_m} (G_{gs,t,w}^{-} - G_{gs,t,w}^{+})\\&- \sum_{g=1}^{NG_m} GL_{g,t,w}^{dr} = \sum_{pl=1}^{NPL_m} F_{pl,t,w}\end{aligned} \tag{47}$$

$$\begin{aligned}&GL_{g,t,s} = c_i + b_i P_{i,t,s} + a_i (P_{i,t,s})^2 + d_i H_{i,t,s} + e_i (H_{i,t,s})^2\\&+ f_i H_{i,t,s} P_{i,t,s} + SUG_{i,t} + SDG_{i,t} \quad \forall g = i, ..., CU\end{aligned} \tag{48}$$

$$GL_{g,t,s} = c_i + b_i P_{i,t,s} + a_i (P_{i,t,s})^2 \quad \forall g = i, ..., GU \tag{49}$$

C. Hybrid robust/stochastic framework

In this paper, a combined robust/stochastic optimization framework is used to manage the uncertainty of the integrated power, gas, and heat systems. Monte Carlo simulation is used to model the uncertainties associated with electric, heat, and gas load demands, and an IGDT-based robust approach is applied to model wind power uncertainty. The IGDT-based robust approach has several advantages over scenario-based modeling and well-known robust optimization methods [33]:

1) The IGDT approach does not need a probability distribution function to model the uncertain parameter, which is a less computationally-expensive option compared to the stochastic model.
2) Unlike well-known robust optimization methods, where the maximum prediction error of an uncertain parameter is considered as the input to the problem, it is treated as the output of the optimization problem. As a result, the IESO can manage a certain level of prediction error of an uncertain parameter by changing its operation cost to an acceptable level.

The mathematical representation of the uncertainty is given in (50), where $\bar{\nu}$ is the forecasted value of the uncertain parameter v. Furthermore, ϵ shows the maximum permissible deviation of an unknown parameter from its predicted value.

$$u = u(\bar{\nu}, \varepsilon) = \left\{ \nu : \left| \frac{\nu - \bar{\nu}}{\bar{\nu}} \right| \leq \varepsilon \right\} \tag{50}$$

Equation (52) represents the mathematical model of the IGDT-based approach, where of_b and Δ_C are defined as the initial and guaranteed amounts of the objective function, respectively. In addition, x is the problem decision variable. β_r is the robustness degree versus an increase of the objective function with regard to the basic status value [34].

$$\alpha(x, \Delta_C) = max\left\{ \varepsilon : \left(\underset{\nu \in U(\bar{\nu}, \varepsilon)}{max}\; of \leq \Delta_C = (1+\beta_r) of_b \right) \right\} \tag{51}$$

In the risk-averse model, the unknown parameter creates an undesirable impact on the value of objective function. So, the IESO faces a higher operation cost with respect to the undesirable deviation of the uncertain parameter, which is defined as a two-level model by (52)-(54) [33].

$$\alpha = max\; \varepsilon \tag{52}$$

$$max \sum_{w=1}^{NW} p_w \sum_{t=1}^{NT} \left[\begin{array}{l} \sum_{i=1}^{EU} [F(P_{i,t,w}) + SU_{i,t} + SD_{i,t}] \\ + \sum_{e=1}^{NSE} [P_{e,t,w}^{+} C_e^{+} + P_{e,t,w}^{-} C_e^{-}] \\ + \sum_{gw=1}^{NGW} C_{gw}^{Well} GW_{gw,t,w} \\ + \sum_{gs=1}^{NGS} C_{gs}^{-} G_{gs,t,w}^{-} \\ + \left\{ \begin{array}{l} \sum_{j=1}^{NJ} C_j^E \left|\Delta E_{j,t,w}\right| \\ + \sum_{g=1}^{NGL} C_g^G \left|\Delta G_{g,t,w}\right| \\ + \sum_{hl=1}^{NHL} C_{hl}^H \left|\Delta H_{hl,t,w}\right| \end{array} \right\} \end{array} \right] \leq \Delta_C \tag{53}$$

$$\text{Eqs. } (2) - (49) \tag{54}$$

The forecast error of wind power generation in a robust approach is modeled in a way that it would result in higher operating costs. Since a decrease in the generated wind power will make the higher operating cost of the integrated system, the two-level problem presented in (52)-(54) can be defined as a one-level problem as follows:

$$\alpha = max\ \varepsilon \tag{55}$$

$$\sum_{w=1}^{NW} p_w \sum_{t=1}^{NT} \left[\begin{array}{l} \sum\limits_{i=1}^{EU} \left[F\left(P_{i,t,w}\right) + SU_{i,t} + SD_{i,t} \right] \\ + \sum\limits_{e=1}^{NSE} \left[P_{e,t,w}^{+} C_e^{+} + P_{e,t,w}^{-} C_e^{-} \right] \\ + \sum\limits_{gw=1}^{NGW} C_{gw}^{Well} GW_{gw,t,w} \\ + \sum\limits_{gs=1}^{NGS} C_{gs}^{-} G_{gs,t,w}^{-} \\ + \left\{ \begin{array}{l} \sum\limits_{j=1}^{NJ} C_j^E \left| \Delta E_{j,t,w} \right| \\ + \sum\limits_{g=1}^{NGL} C_g^G \left| \Delta G_{g,t,w} \right| \\ + \sum\limits_{hl=1}^{NHL} C_{hl}^H \left| \Delta H_{hl,t,w} \right| \end{array} \right\} \end{array} \right] \leq \Delta_C \tag{56}$$

$$\Delta_C = (1 + \beta_r) of_b \tag{57}$$

$$\begin{array}{l} \sum\limits_{i=1}^{NU_b} P_{i,t,w} + \sum\limits_{e=1}^{NES_b} \left(P_{e,t,w}^{-} - P_{e,t,w}^{+} \right) + \sum\limits_{wf=1}^{NWF_b} (1 - \varepsilon) P_{wf,t} \\ - \sum\limits_{j=1}^{NJ_b} EL_{j,t,w}^{dr} = \sum\limits_{l=1}^{NL_b} PF_{L,t,w} \end{array} \tag{58}$$

$$\text{Eqs. } (2) - (28) \text{ and Eqs. } (30) - (49) \tag{59}$$

The proposed hybrid problem-solving process is presented in Fig. 3

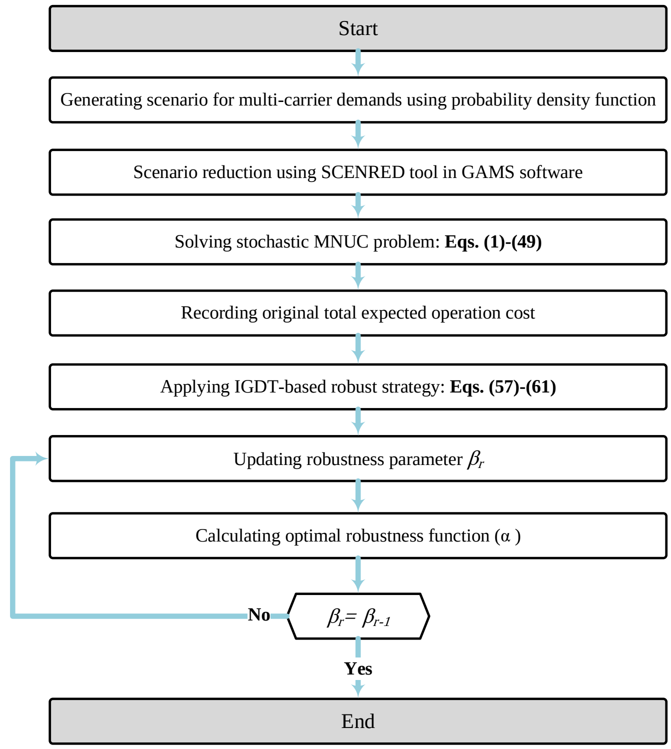

Fig. 3. The proposed hybrid problem-solving process

III. Implementation and Simulation Results

In order to evaluate the effectiveness of the proposed model, a multi-carrier IES, as shown in Fig. 4, consisting of a 30-node heating network, 6-bus electrical grid, and a 6-node natural gas network is considered. Characteristics of the power, gas, and heating systems are given in [7], [15]. The predicted wind power production and energy demands is demonstrated in Fig. **??** [28]. The proposed MNUC model is a mixed-integer nonlinear problem (MINLP) that is solved by applying Discrete and Continuous Optimizer (DICOPT) solver in GAMS which is a high-level modeling language being employed for mathematical programming as well as non-convex optimization. Hence, the DICOPT optimal solutions can be globally optimal with a fair degree of confidence so that has been employed in some literature such as [1], [14], [35]. The main problem is separated into two sub-problems in DICOPT. The NLP sub-problem is solved using CONOPT solver and the MIP sub-problem is taken care of by CPLEX solver.

Four simulation cases are considered to evaluate the performance of the proposed MNUC formulation.

Case study 1: In this case, the impact of the technical constraints of the natural gas system and DHN is analyzed on the UC problem, while uncertainties of the integrated system and intelligent multi-carrier technologies are ignored. Fig. 6 shows the hourly dispatch of generation units in this case study. It can be observed from Fig. 6(a) that when the natural gas and DHN constraints are not considered, the CHP plant is dispatched at all intervals to satisfy electricity and heat demands. G_1 with a maximum capacity of 20 MW is scheduled between $t = 13$ and $t = 21$. G_2, as the most expensive power plant in the system, is dispatched between $t = 14$ and $t = 18$ to partially fulfill load demand during on-peak hours. Under these conditions, the total operation cost of the IES is $\$267,323.30$. Considering the limitations of the natural gas system, the hourly participation of G_1 and G_2 increased, as shown in Fig. 6(b), due to the limitations of the fuel supplied to the CHP plant as a result of gas pressure drop at node 1 in the natural gas network. In Fig. 7, it can be seen that power generated by the CHP plant has decreased during elevated gas demand, which indicates the dependence of the system's planning on the constraints of the natural gas system. Consequently, the total operation cost increased to $\$275,422.33$. The impact of heat losses on the temperature drop in the DHN pipelines and the increase in the heat generated by the CHP power plant are shown in Figs. 8 and 9. The temperature drop in the pipelines, hence an increase in heat consumption, exacerbated the amount of fuel consumption, which resulted in a reduction of the CHP plant output power. Therefore, as shown in Fig. 6(c), the lower generation of the CHP plant increased the hourly participation of G_1 and G_2, which further resulted in raising the overall operation cost of the IES to $\$277,971.88$.

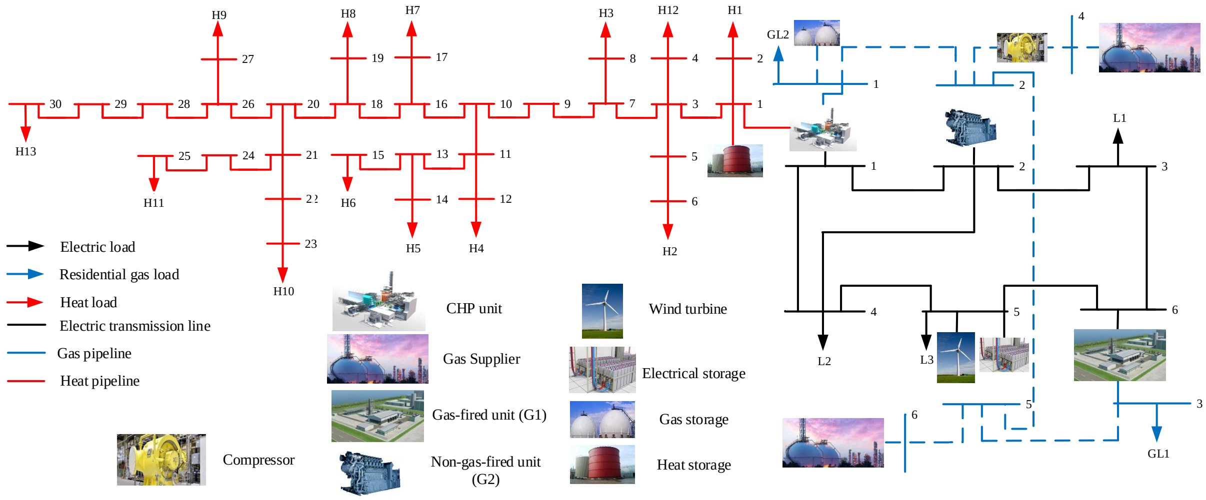

Fig. 4. The integrated electricity, gas and heating network under study

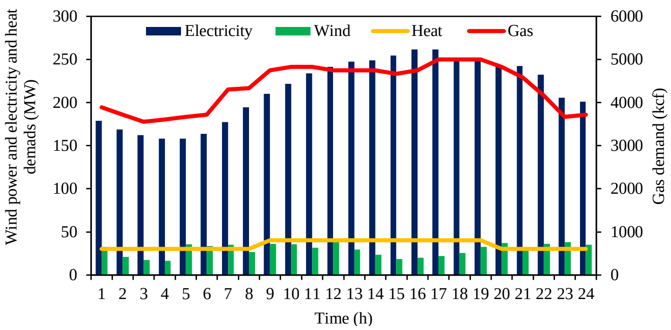

Fig. 5. The forecasted wind power and multi-energy demands

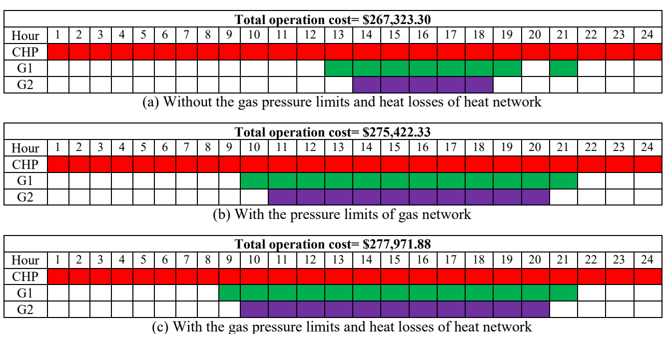

Fig. 6. The power plants schedules with gas and DHN constraints (Case 1)

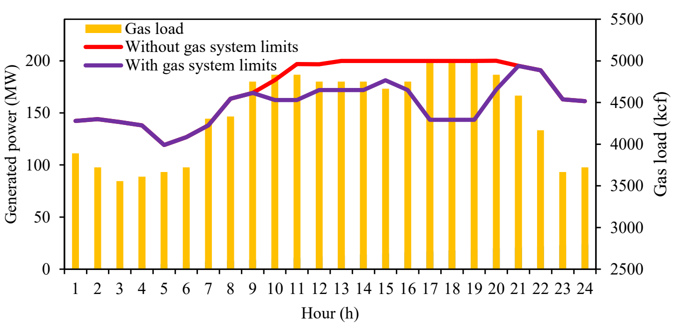

Fig. 7. The impact of gas pressure on the heat and power production of the CHP unit (Case 1)

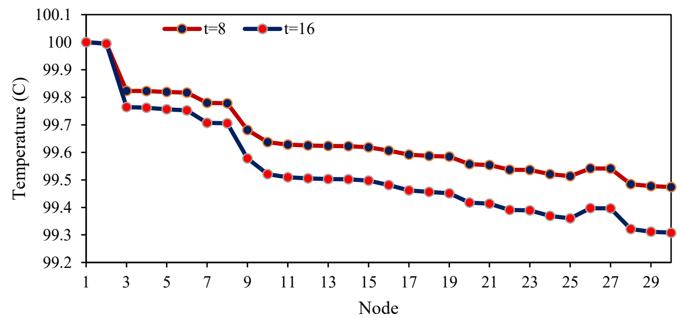

Fig. 8. The effect of heat losses on the temperature (Case 1)

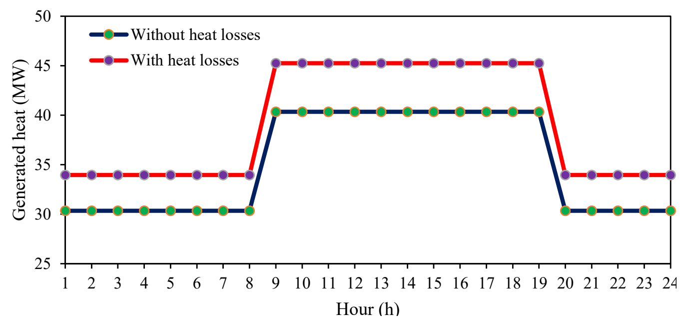

Fig. 9. CHP unit heat generation under heat losses (Case 1)

Case study 2: In this case, IES operation is assessed in the presence of multi-carrier energy storage systems, the results of which are shown in Fig. 10. It can be seen that the hourly participation of expensive power plants is reduced when the power, gas, and heat storage systems are considered simultaneously, which resulted into $\$27,426.34$ reduction in the total operation cost of the IES. The energy stored in multi-carrier energy storage systems is shown in Fig. 11 for one day of operation. The gas and heat storage systems operate as a backup option to lower the negative impact of natural gas pressure limits on the power dispatch of the CHP plant. When the heat storage system is in discharging mode during $t = 8$ to $t = 13$, less heat energy is needed from the CHP plant, which leads to a reduction in the heat production of the plant. As a result, gas fuel is only needed for electricity generation by the CHP unit, which curtails overall gas demand. Furthermore, the gas storage system is charged during the time intervals in which the IES does not suffer from gas pressure drops. The gas storage unit injects natural gas to node 1 in the gas network during the hours when the system experiences a pressure drop ($t = 14$ to $t = 20$), thus more gas will be available for the

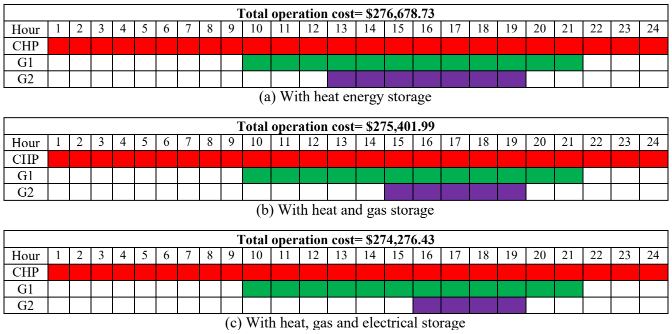

Fig. 10. The impact of multi-carrier storage systems on hourly participation of plants (Case 2)

CHP plant during those hours. Also, the power storage system reduces the hourly participation of expensive power plants by storing electricity during off-peak hours ($t = 1$ to $t = 12$) and delivering power to the grid during on-peak hours ($t = 13$ to $t = 15$).

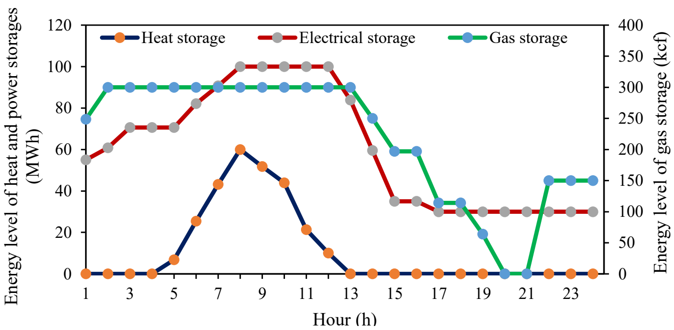

Fig. 11. State of charge of the storage units (Case 2)

Case study 3: This case evaluates the application of IDRPs within the IES considering multi-carrier energy storage units. The amount and cost of shiftable electric, heat, and gas load demands are assumed to be 6% at \$5/MWh, 6% at \$5/MWh, and 3% at \$0.9/kcf, respectively, at a given forecast of each time interval. Figs. 12 and 13 depict the profiles of electricity, gas, and heat demand in Case 3. It can be seen that a part of power, heat and gas load demand has shifted from on-peak to off-peak hours. The shift in heat and gas demand increased the power dispatch of the CHP plant. This increase is due to two reasons: 1) The heat generated by the CHP plant decreased; therefore, the fuel supplied to the CHP plant is only used for electricity generation which increased overall CHP electricity production, 2) the amount of gas delivered to the CHP plant increased due to the lower natural gas pipeline congestion. When the power production of the CHP plant is reduced due to the congestion of natural gas pipelines, shifting load to off-peak intervals is effective in lowering the hourly participation of expensive power plants. In fact, during these intervals ($t = 13$ to $t = 20$), the shiftable power demand is used as a flexibility source to reduce the dependency of the power system to the natural gas system constraints. As it can be observed from Fig. 14(c), the total operation cost dropped to $\$270,970.03$ by considering integrated DR programs. Table I also shows the effect of smart energy technologies on the total operation cost for cases 1 to 3. It can be seen that the total operation cost has been reduced by %2.58 and %1.22 in case 3 compared to cases 1 and 2, respectively.

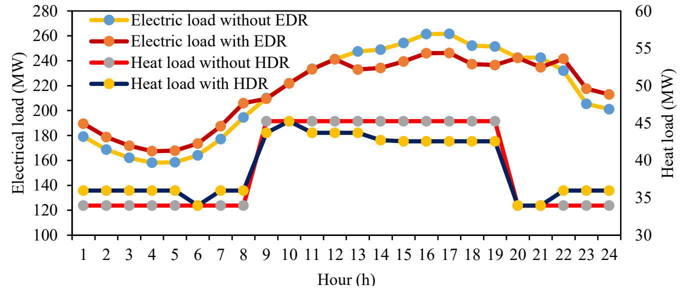

Fig. 12. The effect of DR on the profile of electricity and heat loads (Case 3)

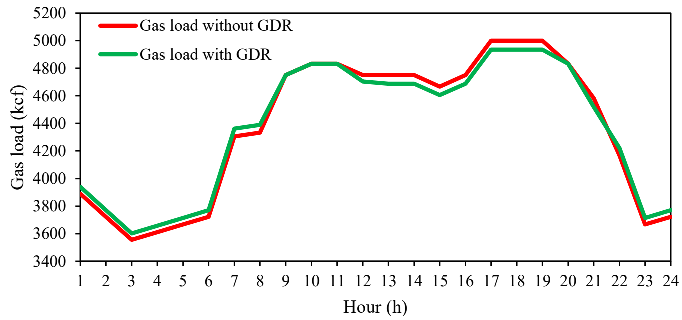

Fig. 13. The effect of DR on gas demand profile (Case 3)

Case study 4: In this case, uncertainties associated with the parameters of the IES are considered in the simulation study. It is assumed that power, heat, and gas load demand follow a normal distribution with 5% standard deviation. 1000 scenarios have been generated using Monte Carlo simulation, which has been reduced to 5 scenarios using the scenario reduction method in GAMS package. The effect of multi-energy demand uncertainties on the predicted operation cost of IES is reported in Table II. As it is anticipated, the expected operation cost has increased under uncertainty modeling compared to the deterministic model due to increased participation of expensive power plants. However, the expected operation cost has dropped from $\$280,685.66$ to $\$274,573.41$ by considering smart energy technologies. In order to model wind power uncertainty, a IGDT-based robust approach has been implemented. The base operation cost of the IES is $\$274,573.41$, which is equal to the expected operation cost of the system considering the uncertainties of multi-carrier energy demand .

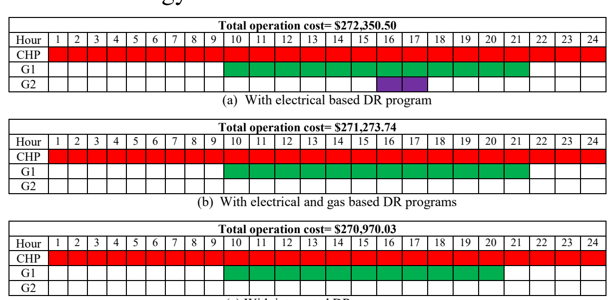

Fig. 14. The effect of integrated DR on hourly scheduling of units (Case 3)

TABLE I

EVALUATING THE EFFECT OF SMART ENERGY TECHNOLOGIES ON THE TOTAL OPERATION COST

Simulation cases	Modeling multi-energy network constraints	Multi-carrier energy storage systems	IDR program	Total operation cost ($)
Case study 1	✓	×	×	277,971.88
Case study 2	✓	✓	×	274,276.43
Case study 3	✓	✓	✓	270,970.03

In the IGDT-based robust approach, the operator can increase the conservatism level of the operation against the wind power uncertainty by increasing the robustness parameter β. To this end, a sensitivity analysis is applied in order to evaluate the effect of the robustness parameter β on the optimal robustness function α and the total operation cost. To do so, the proposed MNUC problem is solved by changing the robustness parameter β, from 0.005 to 0.03 with increment of 0.005, the results of which are shown in Fig. 15. It can be seen that the critical operation cost and the optimal function α increases for higher β values, which means that the operator can cover a wider range of wind power prediction errors at a higher operation cost. When $\beta = 0.01$, the critical operation cost and the optimal function α are $\$27,699.88$ and 0.142, respectively. It means that the IESO can manage 14% of the wind power forecast error by increasing 1% of the operation cost (i.e., the desirable operation cost of the operator). This way, the IESO can handle wind power production uncertainty under a desirable operation cost, which can be associated with various factors such as social welfare, environmental, economical, and technical conditions of the network. In Fig. 16 the impact of uncertainty of wind power production on the hourly participation of the plants is investigated under the resistance parameter β of 0.01 and 0.02. It can be seen that the hourly participation of expensive power plants has increased when $\beta = 0.02$. In fact, by increasing β, the uncertainty of wind power generation increases, which leads to an increase in the participation of more expensive units. However, the system operator will be able to manage 31% of the wind power prediction error by applying a more robust operation strategy.

TABLE II
THE IMPACT OF UNCERTAINTIES ON THE TOTAL OPERATION COST IN CASE 4

	Without smart energy technologies		With smart energy technologies	
	Deterministic	Stochastic	Deterministic	Stochastic
Total operation cost ($)	277,971.88	280,385.66	270,970.03	274,573.41

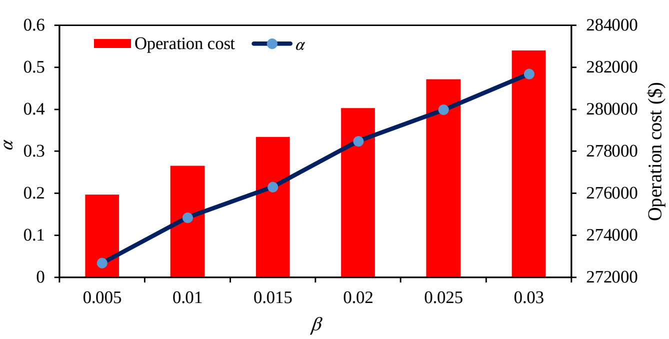

Fig. 15. α and the operation cost versus changes in β in Case 4

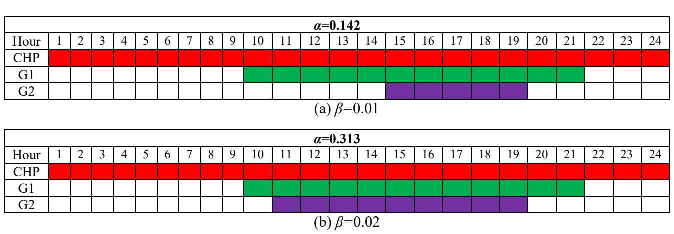

Fig. 16. The effect of β on hourly dispatch of the units (Case 4)

IV. Conclusion

This paper developed a flexible unit commitment (UC) formulation for an integrated electricity, gas, and district heating system. For managing the uncertainties of power, gas and heat load demands as well as wind power, a combination of stochastic and robust optimization methods are used. Additionally, multi-carrier energy storage systems and integrated DR programs were added to the MNUC formulation, and the impact of these technologies are investigated on hourly scheduling of the units and operation cost of the entire system. The proposed model enabled energy system operators to use the advantages of both stochastic and robust techniques simultaneously to mitigate the risks. Besides, the proposed model confirms the effectiveness of the smart energy technologies in reducing the daily operation cost under a realistic energy system model that involves practical constraints of multi-energy networks. The The simulation results show that gas pressure constraints of the natural gas system and heat losses of the DHN reduced the power produced by the CHP plant, which resulted in an increase in the overall cost of IES by %3. In contrast, applying smart energy technologies such as multi-carrier energy storage systems and integrated DR programs could decrease the total operation cost by %2.58.

The work of this paper can be extended by focusing on the optimal scheduling of energy systems consisting of power, gas, hydrogen, cooling, and heating. In addition, the effect of other smart energy technologies such as power-to-gas storage, ice storage, and electric vehicle parking lots will be studied on the energy system's performance in future works.

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