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Optimal resilient operation of hub energy system considering uncertain parameters

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ABSTRACT

The high potential of hub energy in power systems has considerable profits to improve resiliency and sustainability of system. Variable energy sources embedded in multi-carrier energy systems could be used to propose a robust operation model for improve resiliency of multi-carrier systems during high risk time intervals such as extreme weather condition. Thermal energy sector could be rescheduled for storing heat generated by combined heat and power (CHP) units and boilers in certain periods to coordinate with electrical sector when required. Such cooperation increase operator's capability to manage electrical grid during time intervals with high uncertainty of outages due to extreme weather condition. Accordingly, in this paper an information gap decision theory (IGDT) method is used to model uncertainty of power outages in optimal system operation. By applying the IGDT method, distribution network operator is able to employ an appropriate methodology to have a robust optimal operation. Also, such methodology leads to make suitable decisions during high risk time intervals such as extreme weather condition. The simulation results proved that proposed model improves the performance and resilience of system by cooperation between thermal and electrical sectors. Also, the chance of electrical grid for successful islanding process increased by reduction in power imbalance during high risk time intervals.

1. Introduction

In Presidential Policy Directive 21 issued back in 2013, the energy section was introduced as a crucial element, especially regarding its role in making the necessary functions and processes much easier across all basic infrastructures. Researchers have established the significance and delicate interrelationship between carriers of energy years ago. Since there seems to exist certain unused synergies and supplementary features belonging to various energy carriers, these networks of energy possess physical interconnection and can be investigated as a unified network. Although traditional models have taken a different approach to energy networks in studying them with separated features from planning and execution viewpoints, and merely some interrelationships between energy systems have been taken into account in recent researches. Achieving high efficiency rates, more resilient systems and minimizing operating costs have been direct positive results of integration of energy system. Combined heat and power (CHP) plants are capable of generating both heat and power at the same time, and make the efficiency rate of CHP rise to up to 90%. Meanwhile, CHP units can limit gas pollutant emissions by about 15%. Also, it is possible to consider more maneuvering ability to systems using CHP units during crisis. It is of outmost significance to obtain idea set points of operation of energy networks generation; that is why they have been focused in various researches [1–3].

The most recent literature on different aspects of integrated energy systems would seemingly be classified into two major groups. In the first, research projects focused on investigating and exploring the role of disruptions and lack of certainty in integrated networks. Models with constraints in terms of security for gas and power networks have been introduced by some other studies to study the impact of interruptions in gas/electricity systems reliability/ resiliency [4,5], while others have advanced sophisticated models to explore arrangement of demand taking into account power output of sources that are considered renewable energy [6,7]. In current CHP plants, the researchers present a unit commitment (UC) where influence of heat storage is assessed and analyzed. In order to clarify the unknown aspects of power market price and wind output capacity, a risk analysis of integrated CHP has been conducted [8]. In [9], the robust model has been applied by the authors to assess the degree of uncertainty in terms of load on the programming of systems with

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Abbreviations

T	Time duration
NE	Power plants number
NGW	Gas suppliers number
t	Time interval
n	Power plant
$SU_{n,t}/SD_{n,t}$	Start-up/shut-down cost for non-gas-fueled power unit
su_n/sd_n	Start-up/shut-down price of non-gas-fueled power unit
$SUG_{n,t}/SDG_{n,t}$	Start-up/shut-down gas consumption of gas-fired power plant
sug_n/sdg_n	Start-up/shut-down gas usage rate of gas-fueled power unit
$P_{n,t}$	Plant power supply
F	Operation cost of plants
O	Objective function
$P_n^{\min}/P_n^{\max}$	Min/max power thresholds for plants
R_n^{up}/R_n^{dn}	Ramp up/down of units
$I_{n,t}$	On/off status of plant
$P_{wf,t}$	Wind turbine output
S_t	Wind speed
$D_{j,t}$	Electricity demand
$PF_{L,t}$	Power flow through lines
$V_{b,t}/\delta_{b,t}$	Voltage and angle in bus number b
x_L	Reactance of line number L
$\mathrm{PF}_{\mathrm{L}}^{\max}$	Transmission capacity of line number L
$F_{pl,t}$	Gas transmission capacity
$\pi_{m,t}$	gas pressure in system node
$\pi_m^{\min}/\pi_m^{\max}$	Min/max gas pressure thresholds in node
$GW_{g,t}$	Supplied gas
$GL_{l,t}$	Gas load
$GW_g^{\min}/GW_g^{\max}$	Min/max gas supply
$GL_l^{\min}/GL_l^{\max}$	Min/max gas load
a_n, b_n, c_n, d_n, e_n, f_n	Gas consumption/operation cost coefficients of the power unit
$P_{water,t}$	Power usage of the water carrier
$P_{desa,t}$	Power usage of the desalination system
$P_{pu,w,t}$	Power usage of the water well pump
$P_{pu,st,t}$	Power usage of the water source pump
$B_{hs,t}$	The thermal energy level of the thermal storage system
$HS_{hs,t}^{ch}$	Thermal energy charge of the thermal storage system
$HS_{hs,t}^{dis}$	Thermal energy discharge of the thermal storage system
η_{hs}^{ch}	Thermal energy charging efficiency of the thermal storage system
η_{hs}^{dis}	Thermal energy discharging efficiency of the thermal storage system
η_{hs}	Thermal storage efficiency
$B_{hs}^{\mathrm{Min}}/B_{hs}^{\mathrm{Max}}$	Min/max heat storage capacity of the thermal storage system
$B_{hs}^{\mathrm{Max,charge}}/B_{hs}^{\mathrm{Max,discharge}}$	Maximum charge/discharge rate of the thermal storage system
$P_{n,t}^{\min}/P_{n,t}^{\max}$	Thresholds for plant power supply
$P_{wf,r}$	Rated wind turbine output
$V_b^{\min}/V_b^{\max}$	Voltage limits for bus number b
$s_{ci}/s_r/s_{co}$	Wind turbine cut-in/ rated and cut-off speeds
WL_t	Water load at each time
$W_{desa,t}$	Water generation of the desalination system
x,y,z	Wind turbine output parameters
$C(q,l)$	System model
l	Uncertain nature of energy loads
q	Decision variable
$\hat{\alpha}(C_r)$	Resistance rate of the optimal energy management schedule
$\hat{\beta}$	Minimum amount of α
$l_{m,h}$,$\hat{l}_{m,h}$	Real and predicted load
C_r	Critical amount
C_b	Lowest bound of the operation cost
α	Uncertainty rate
$\hat{\beta}(C_0)$	The lowest rate of uncertainty that network operation cost cannot surpass a critical amount C_r

various chillers, in which, in order to satisfy the cooling load, they have proposed a day-ahead scheduling scheme. In [10], in order to cope with the uncertain aspects of this problem, the researchers have introduced an optimum robust energy management problem for these systems that includes the wholesale price and demand of system.

Yet, another study was conducted focusing on the beneficial/environmental aspects in CHPs. In integrated hub systems, bi-level programming has been proposed by some studies to cope with the financial advantages of hub systems in some levels [11–14]. In [11], a resilient operation for system is introduced based on reinforcement of some gas system during natural crisis. In that work, authors evaluated the impacts of each gas line in total operation of hub system and prosed some solutions for system upgrade by considering CHP unit on trade-of between heat and power generation. In [12], upper/lower levels are studied by considering existing various constraints of hub system by a bi-level framework [12]. In [13], two contradictory goals of cutting costs and restricting pollutant gas emissions were considered by the researchers for operating power and gas systems. A bi-level model is proposed in [14] that investigate the scheduling and operating such networks in upper/lower levels. A robust model was presented by authors in [15] to handle the uncertainty of power market prices while running CHP units. In [16], a bi-level model for operators of CHP system/ private owner of CHP in upper/lower levels to profit maximally, has been introduced. In [17], authors embarked on investigating the certain network-constrained optimal output program of CHP based system while those in [18] have presented a program for studying Gas/ power energy hub designs in a systematic way by taking into account not only stakeholders but also other viewpoints from both technical and economic perspectives. Researchers have analyzed the influence that capacity of storage and forecasted horizon can have operating cost of multi-carrier in [19].

A multi-carrier system has been proposed that includes unified systems of gas and electricity in [20]; interrelated hub systems in [21]; and resilient multi-carrier network in [22]. In order to achieve the ideal set points of the energy system units, researchers have proposed an approximated flow scheme in [23]. Authors have focused on and studied the features and positive aspects of the concept of energy hub, which merely has the capability of handling energy hubs having an equal inputs and

Table 1
Comparison between proposed robust operation model and similar researches.

Ref #	Type of system	UC problem	Constraints modeling	Resilient operation	Uncertainty modeling	Type of uncertainty-handling method
[8]	Power and heat	✔	✔	–	–	–
[9]	Power and heat	–	–	✔	–	Stochastic
[10]	Power and heat	–	–	–	✔	Robust-stochastic
[11]	Power and gas	–	✔	–	–	–
[12]	Power and gas	–	✔	–	–	–
[30]	Power and gas	✔	✔	–	✔	Stochastic
[17]	Power, gas, and heating	–	✔	✔	–	–
[22]	Power, gas, and heating	–	✔	–	–	–
[28]	Power, gas, and heating	–	–	–	✔	IGDT
[29]	Power, gas, and heating	✔	✔	–	✔	Two-stage stochastic
Proposed model	Power, gas, water, and heating	✔	✔	✔	✔	IGDT

outputs, and makes up optimal solution based on OPF in [24]. Employing dummy variables and virtual units, the authors have presented a scheme in [25] in order to compensate the deficiencies of these methods in terms of coping with irregular equations in the ideal functioning of energy hub that also cause a complicated problem in terms of optimization as a result of the additional variables and a wide range of additional limitations. In [26,27], the researchers have presented an innovative approach for ideal operation of multi-carrier network, having capability of halting rise in new variables when changing irregular equations into regular ones. A method for handling uncertainty developed based on information gap decision theory (IGDT) was implemented by the authors to deal with uncertainty in terms of load during the ideal operation of multi-carrier network with storages, renewable energy sources, and fuel cells in [28]. A multi-objective scheme was proposed by the authors in [29] focused on optimal operational planning for CHP based on a two-stage solution method with state-of-the-art technological advancements.

Table 1 provides a comparison of contributions offered by the proposed model of robust operation with models studied in the literature. As far as authors know, none of the studied papers has employed a robust model to conduct an uncertainty study of resilient hub system. Major drawback of the studies reviewed is the fact that a sophisticated model for operating networks having all carriers is not obtained and functioning of hub as a whole is not explored. Also, resiliency improvement for hub systems is studied rarely. The current study advances a sophisticated model of operation based on IGDT for multi-carrier networks of energy based on which the storage role plants heat production program is taken into account, and the system's supply of thermal and electrical load is studied. Also, maneuvering ability for system during time intervals that electrical part is faced by high possibility of outages is considered. This ability is based on CHP unit rescheduling for heat and power output. Employing the robust model proposed, the operating company of the energy network ought to have the capability of handling the uncertainty in terms of outages for electric grids. Accordingly, this paper applies the IGDT approach to present a model of the outages uncertainty during high risk time intervals in hub system based on the functions of opportunity and robustness. In this paper a robust approach introduced has been incorporated in pilot hub energy system for assessment of performance of proposed approach.

2. Materials and methods

Fig. 1 demonstrates details of proposed robust programming of the hub system, which draws on employing the IGDT method to cope all uncertainties in energy demand and electrical lines' outage. The advanced approach is meant for a multi-carrier network having gas, electricity, heat, and hydro demands and will be evaluated by conducting a selected case study. Taking the uncertainty of power load and power interruptions into account while programming the power output of facilities and the operation of the storage units in terms of charging/discharging based on the IGDT method constitutes the most basic methodology of the model introduced. Therefore, ideal set points of the facilities will be employed in order to determine the total minimized cost of operation of the energy system as a whole. Also, this section presents formulation of operation problem in deterministic conditions and while having an unclear situation using IGDT approach.

The objectives expected for multi-carrier system, that could be appear either in the form of objective function in some various shapes. Rescheduling of energy resource, gas consumption, allowed budgets by considering uncertainties changes operational cost and effects of outages in normal or islanding operation. Resilience as a function of load curtailment and ENS is a related to outages (changes by weather condition) and other outputs of proposed strategy as mentioned before.

2.1. Objective operation

The main goal of ideal function of hub system encompassing electricity, gas, thermal and hydro carriers is to minimize overall expenses of supplying energy demands, penalties for potentials outages included, a formulation of which is depicted in (1). Terms one and two of (1) represent the expenses for operating units which do not use gas while taking energy output and start/shutdown along with the expenses of the consumption of purchased gas into account. The expenses of operating the gas storage are represented by the term three of (1) since gas makes up the main type of fuel consumed by them for generating electrical energy. A set of relevant acronyms of the concepts is presented in Table 1. It must be reminded that the expenses for operating units that consume gas is represented in the term two of (1), as gas constitutes their main fuel consumption for producing electrical energy.

$$O = Min \sum_{t=1}^{T} \left[\sum_{n=1}^{NE} \left[F\left(P_{n,t}\right) + SU_{n,t} + SD_{n,t} \right] + \sum_{g=1}^{NGW} \rho^{gas} GW_{g,t} + \sum_{gs=1}^{NGS} C_s GS_{gs,t}^{out} \right] \tag{1}$$

Outages number and magnitude of load curtailment are key factors in resiliency level and operational cost. One of solutions for improve resilience and enhance economic profits is rescheduling of energy resources. In this paper uncertainties for demand and outages are considered. Wind speed and demand level change during time intervals. Wind speed variations changes probability of lines outage and in sequence it changes ENS of power grid and operation cost. Three different methods are considered to show effect of rescheduling of resources based on risk-taker, risk-neutral, and risk-averse.

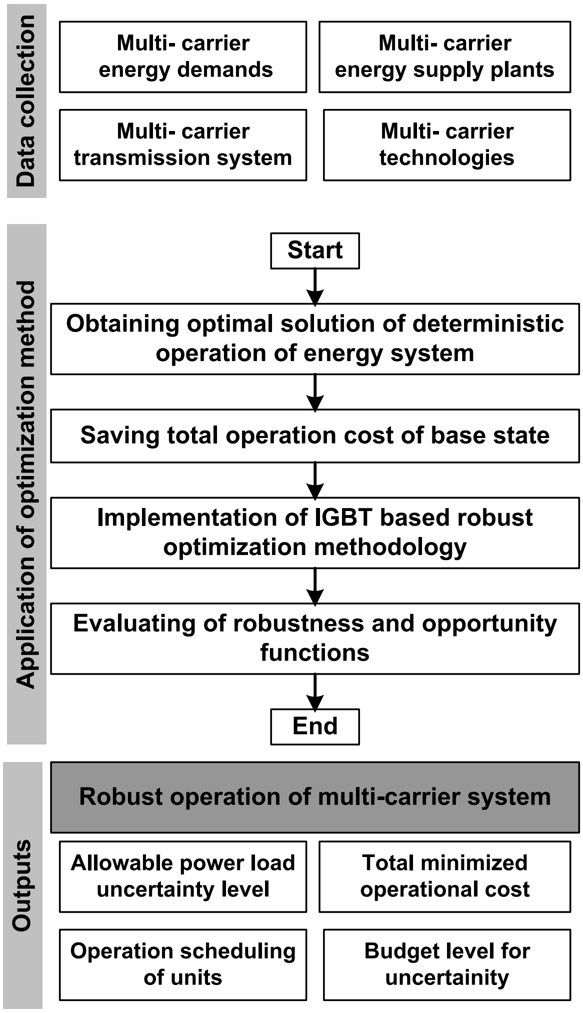

Fig. 1. The proposed schematic for robust scheduling of hub system.

2.2. Power network constraints

This sub-section is dedicated to exploration and discussion of the constraints and limitations of unit commitment in the multi-carrier network generation units. As displayed in Fig. 2, CHP plant has been investigated for supplying heat and power demands; thermal and electricity generation have an interdependency which is known as the feasible operation region (FOR). Linear equations of CHP plant are employed in order to contain output heat and power by CHP plant [31].

$$P_n^{\min} I_{n,t} \le P_{n,t} \le P_n^{\max} I_{n,t} \tag{2}$$

$$P_{n,t} - P_n^A - \frac{P_n^A - P_n^B}{H_n^A - H_n^B} \times (H_{n,t} - H_n^A) \le 0 \quad n \in NC \tag{3}$$

$$P_{n,t} - P_n^A - \frac{P_n^A - P_n^B}{H_n^A - H_n^B} \times (H_{n,t} - H_n^A) \le 0 \quad n \in NC \tag{4}$$

$$P_{n,t} - P_n^B - \frac{P_n^B - P_n^C}{H_n^B - H_n^C} \times (H_{n,t} - H_n^B) \ge -(1 - I_{n,t}) \times M \quad n \in NC \tag{5}$$

$$P_{n,t} - P_n^C - \frac{P_n^C - P_n^D}{H_n^C - H_n^D} \times (H_{n,t} - H_n^C) \ge -(1 - I_{n,t}) \times M \quad n \in NC \tag{6}$$

$$0 \le H_{n,t} \le H_n^A \times I_{n,t} \quad n \in NC. \tag{7}$$

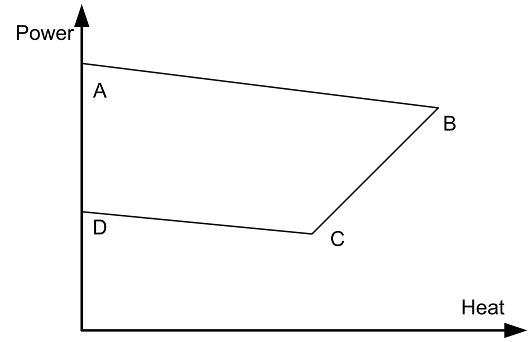

Fig. 2. Limited operation region for CHP unit.

In order to take into account ramp rates of electricity producing CHPs, ramp-up/down constraints are studied as (8) and (9). Moreover, in (10) and (11), the minimum up/down-duration limitations of CHPs are taken into consideration.

$$P_{n,t} - P_{n,t-1} \le R_n^{up} \tag{8}$$

$$P_{n,t-1} - P_{n,t} \le R_n^{dn} \tag{9}$$

$$I_{i,t} - I_{i,t-1} \le I_{i,t+TU_{i,u}} \tag{10}$$

$$TU_{i,u} = \begin{cases} u & u \le MUT_i \\ 0 & u > MUT_i \end{cases} \tag{11}$$

$$I_{i,t-1} - I_{i,t} \le 1 - I_{i,t+TD_{i,u}} \tag{12}$$

$$TD_{i,u} = \begin{cases} u & u \le MDT_i \\ 0 & u > MDT_i \end{cases} \tag{13}$$

Start-up and shut-down expenses of CHP would be taken into account for both gas-consuming or non-gas-consuming units, are explored here. Expenses for the non-gas-consuming plants can be as (14)–(15), while the expenses for gas-fueled units can be presented as (16) and (17).

$$SU_{n,t} \ge su_n(I_{n,t} - I_{n,t-1}) \quad n \in NE \tag{14}$$

$$SD_{n,t} \ge sd_n(I_{n,t-1} - I_{n,t}) \quad n \in NE \tag{15}$$

$$SUG_{n,t} \ge sug_n(I_{n,t} - I_{n,t-1}) \quad n \in NGC \tag{16}$$

$$SDG_{n,t} \ge sdg_n(I_{n,t-1} - I_{n,t}) \quad n \in NGC \tag{17}$$

The multi-carrier system's balance of power should be regarded in order to guarantee the balance between the CHP plant power output and traditional generation units and power demand. Such sense is devised as (18). Power loss happening during power transmission and these constraints are modeled as (19) and (20), respectively.

$$\sum_{n=1}^{NU_b} P_{n,t} + \sum_{e=1}^{NES_b} \left(P_{e,t}^D - P_{e,t}^C\right) + \sum_{wf=1}^{NWf_b} P_{wf,t} - \sum_{j=1}^{NJ_b} D_{j,t} = \sum_{L=1}^{NL_b} PF_{L,t} \tag{18}$$

$$PF_{L,t} = \frac{\delta_{b,t} - \delta_{b',t}}{x_L} \tag{19}$$

$$-PF_L^{\max} \le PF_{L,t} \le PF_L^{\max} \tag{20}$$

2.3. Limitations of gas systems

The passage of gas through the pipelines can be devised in formulae as (21)–(22) and (23), the former representing it with considering compressors, and the latter representing it as without considering them. As these equations illustrate, using a compressor in the gas system will lead to improvement of gas pipeline steam capacity. Equations (24) and (25) put a threshold on pressure of gas and its demand of suppliers, respectively. While (26) and (27) denote the lowest and the highest thresholds of gas demand and its balance, respectively [32].

$$F_{pl,t} = \mathrm{sgn}(\pi_{m,t}, \pi_{n,t}) C_{m,n} \sqrt{\left|\pi_{m,t}^2 - \pi_{n,t}^2\right|} \tag{21}$$

$$\mathrm{sgn}(\pi_{m,t}, \pi_{n,t}) = \begin{cases} 1 & \pi_{m,t} \geq \pi_{n,t} \\ -1 & \pi_{m,t} \leq \pi_{n,t} \end{cases} \tag{22}$$

$$F_{pl,t} \geq \mathrm{sgn}(\pi_{m,t}, \pi_{n,t}) C_{m,n} \sqrt{\left|\pi_{m,t}^2 - \pi_{n,t}^2\right|} \tag{23}$$

$$\pi_m^{\min} \leq \pi_{m,t} \leq \pi_m^{\max} \tag{24}$$

$$GW_g^{\min} \leq GW_{g,t} \leq GW_g^{\max} \tag{25}$$

$$GL_l^{\min} \leq GL_{l,t} \leq GL_l^{\max} \tag{26}$$

$$\sum_{g=1}^{NGW_m} GW_{g,t} + \sum_{gs=1}^{NGS_m} \left(GS_{gs,t}^{out} - GS_{gs,t}^{in}\right) - \sum_{gl=1}^{NGL_m} GL_{gl,t} = \sum_{pl=1}^{NPL_m} F_{pl,t} \tag{27}$$

2.4. Limits of heat storage

According to the multi-carrier energy system under study, heat energy storage technology has been considered in order to explore the probability of heat storing and consumption upon necessity. Formulation (28) can represent the heat which is stored in the thermal energy storage, while taking into account the rates and relevant efficiency of thermal charge/discharge rates at each time, along with any thermal loss of the storage and the latest level up to which heat energy has been stored in the storage. It is essential that the lowest and the highest capacities thermal storage be regarded for system (29). While, charge and discharge rate of heat energy is required to be confined to their maximum amounts as (30) and (31), respectively [33].

$$B_{hs,t} = (1-\eta_{hs}) B_{hs,t-1} + \eta_{hs}^{ch} HS_{hs,t}^{ch} - \frac{HS_{hs,t}^{dis}}{\eta_{hs}^{dis}} - \beta_{\mathrm{loss}} SU_{hs,t} + \beta_{\mathrm{gain}} SD_{hs,t} \tag{28}$$

$$B_{hs}^{\mathrm{Min}} \leq B_{hs,t,s} \leq B_{hs}^{\mathrm{Max}} \tag{29}$$

$$B_{hs,t} - B_{hs,t-1} \leq B_{hs}^{\mathrm{Max,charge}} \tag{30}$$

$$B_{hs,t-1} - B_{hs,t} \leq B_{hs}^{\mathrm{Max,discharge}} \tag{31}$$

2.5. Systems interconnection constraints

Each CHP's consumption of gas can be taken as a function of the electricity and thermal output that can be presented as (32). Likewise, the power-only unit's consumption of gas is related to the electricity produced by the plant that we can present as (33). The gas supply value in feeding CHP is modeled as (34). These gas demands are presented as (35)–(36).

$$\begin{aligned} F_{n,t}^{CHP} = {} & c_n + b_n P_{n,t} + a_n (P_{n,t})^2 + d_n H_{n,t} + e_n (H_{n,t})^2 + f_n H_{n,t} P_{n,t} \\ & + SUG_{n,t} + SDG_{n,t} \quad n \in NC \end{aligned} \tag{32}$$

$$F_{n,t}^{G} = c_n + b_n P_{n,t} + a_n \left(P_{n,t}\right)^2 + SUG_{n,t} + SDG_{n,t} \quad n \in NG \tag{33}$$

$$F_{e,t} = HR_e P_{e,t}^D \tag{34}$$

$$GL_{gl,t} = F_{i,t}^{CHP} \quad \forall gl = i, \ldots, NC \tag{35}$$

$$GL_{gl,t} = F_{i,t}^{G} \quad \forall gl = i, \ldots, NG \tag{36}$$

In order to meet water demand, desalination of water is added to the system under study. The water carrier is interconnected to the power network in such systems whereby electrical energy is used to generate drinkable water. A formulation of power used in the mentioned desalination system could be devised drawing on water supply as (37).

$$P_{desa,t} = Q_{desa,t} \times \eta_{desa} \tag{37}$$

The water demand is provided for power usage CHP, the pump of water well, and pump, a representation of modeled as:

$$P_{water,t} = P_{desa,t} + P_{pu,w,t} + P_{pu,st,t} \tag{38}$$

The water output of the desalination plant ought to meet the water demand of the system, in general.

$$WL_t = W_{desa,t} \tag{39}$$

2.6. Grid constraints

The generated power of wind turbine which corresponds to the hourly wind speed is expressed in Eq. (9).

$$P_{wf,t} = \begin{cases} 0 & \text{if } 0 < s_t < s_{ci} \\ P_{wf,r}(z - y \times s_t + x \times s_t^2) & \text{if } s_{ci} \leq s_t < s_r \\ P_{wf,r} & \text{if } s_r \leq s_t < s_{co} \end{cases} \tag{40}$$

The constraint of wind turbine power is presented in Eq. (41) based on which the generated electrical power of wind turbine should be within the nominal range.

$$0 \leq P_{wf,t} \leq P_{wf,r} \tag{41}$$

The limitations for power generation of each DG plants and voltages are considered as follow:

$$P_{n,t}^{min} \leq P_{n,t} \leq P_{n,t}^{max} \tag{42}$$

$$V_{i,b}^{\min} \leq V_{i,b} \leq V_{i,b}^{\max} \tag{43}$$

2.7. Outage model for power lines

Results of different researches show that extreme weather conditions (Storm) are the main reason for more than half of faults inception in electrical grids [34]. In order to evaluate how a resilient grid modifies operational scheduling by considering weather conditions, outages are distinguished into two classes. In the first class, outages with non-weather caused reasons are modeled by a constant interruption value. In the second class, weather-caused faults are considered. In order to have a proper analysis to evaluate weather condition effect on outage rate, the faults mentioned in the second class are modeled by correlations as presented in [34]. Unfortunately, standard distribution test systems do not have weather-caused events data, so, real normalized data is used in simulations in order to evaluate a resilience grid behavior during different weather conditions. In [34] correlation between events and wind speed for short-time intervals is introduced by using (42)

$$N_w = 0.0012 S_t^2 - 0.0131 S_t \tag{44}$$

It is assumed that average wind speed probability could be predicted in one-hour time intervals. In this paper, average wind speed for all time intervals is used. Wind speed affects number of outages. It is clear that wind flow patterns and wind speed profiles changes by time and it is possible to estimate some wind patterns for each area.

2.8. Island operation

Forecasting of power imbalance value, where the virtual equivalent inertia constant of the whole micro grid is needed is difficult to determine. Moreover, some energy resources, which link to power grid through inverters have no inertia. In this paper, it is tried to prove that new method that lead to reduce power imbalance value during high risk time intervals. The base idea of this task is based on reduction in power imbalance and maximum usage of sources during high risk time interval due to reduce ENS penalty costs. It is obvious that incensement in the inertia of power grid, number of resource could inject power and power generation level and in other side, reduction in power demand are key parameters in successful islanding. In this study, power imbalance value during high risk time intervals is considered as a factor to evaluate resilience of islanding against extreme weather condition. Note that predict of the power imbalance value is an important data in load shedding process and ENS value based on the response of the system, which can automatically take the line outages into consideration. The power imbalance value based on system inertia could be formulated in the following:

$$\frac{2H_i}{f_n}\frac{df_i}{dt} = P_{m_i} - P_{e_i} \quad (i = 1, 2, 3, \ldots, N) \tag{45}$$

$$\Delta P = \sum_{i=1}^{N} \Delta P_i = \frac{2\sum_{i=1}^{N} H_i}{f_n}\frac{df_c}{dt} = \xi \frac{df_c}{dt} \tag{46}$$

3. System's IGDT based optimal operation

The main difference between IGBT approach and stochastic programming is related to rare events and their outcome. There are some serious different in modeling uncertainties in both approaches. For problems with known probabilistic model and enough data the stochastic approaches is easier to use. However, in cases that there is not enough data or accurate model, IGBT approach has more reliable results due to IGBT ability to classify data based on non-determined parameters. Decision making process to select best possible solution in the presence of high level uncertainty is more reliable in IGBT approach because it considers less assumption in structure of uncertainty structure. So, IGBT is able to consider priorities and risks in decision making process and evaluate their impacts on final decision. IGBT is based on quantitative models but it lets to analyze solutions and strategies in uncertainties impact on objective function. IGBT is useful for problems with high levels of uncertainty and limited data.

The power load model, lines outage caused by weather condition and nature of resilient operation caused to select IGBT approach due to non-accurate models and their impact on objective function. It could be construed as a risk-aversion potential of IGDT.

3.1. Developing a model of the uncertainty

An uncertainty modeling of fractional info-gap is performed as (40) in order to study uncertainty factor in hub energy systems i.e. the power load [35].

$$U(\alpha, \widetilde{l}_{m,h}) = \left\{ l_{m,h} : \frac{|l_{m,h} - \widetilde{l}_{m,h}|}{\widetilde{l}_{m,h}} \leqslant \alpha \right\}, \quad \alpha \geqslant 0 \tag{47}$$

In the resulting equation, real and predicted load are denoted as $l_{m,h}$ and $\widetilde{l}_{m,h}$, and α defines the uncertain parameter. The scheme introduced in (45) constitutes an envelope-bound info-gap scheme. Also, gap magnitude is within proportion of anticipated value.

3.2. fundamental of IGDT

It is of outmost significance to devise a plan for modeling the uncertainty of essential input parameters in the energy networks since they vary remarkably in terms of certain features e.g. demand. In fact, the IGDT approach seems to present an efficient tool for devising model of the functions of robustness and opportunity of the energy systems vis-a-vis changes in system parameters [35]. The researchers in the current study have examined the probabilistic character of demand that is named l, while, decision parameter is named q.

It is necessity to mention that the objectives expected for multi-carrier system, that could be appear either in the form of objective function in some various shapes. Assessment of such obligatory criteria could be conducted in terms of robustness and opportunity functions as follows:

$$\widehat{\alpha} = \max_{\alpha}\{\alpha : maximum\ total\ cost\ which\ is\ is\ not\ higher\ than\ a\ specified\ cost\} \tag{48}$$

$$\hat{\beta} = \min_{\beta}\{\alpha : minimum\ total\ cost\ which\ is\ less\ than\ a\ specified\ cost\} \tag{49}$$

The robustness function evaluates robustness of a hub system relative to potential decrease in electrical loads outages and inviolability of grid relative to overall expense of operation. Put another way, the robustness function is a factor whereby one can define the maximum uncertainty value attainable by the uncertain parameter. It could be construed as a risk-aversion potential of IGDT. A formula could be devised in which the robustness function might be presented as [35]:

$$\hat{\alpha}(C_r) = \max_{\alpha}\{\alpha : \max(C(q, l)) \leqslant C_r\} \tag{50}$$

where $\hat{\alpha}(C_r)$ represents robustness of operational planning against probabilistic factors. While it must be noted that an increase in terms of robustness of operational planning might be achieved by adopting more values of $\hat{\alpha}(C_r)$.

Opportunity function acts as a means by which the profit value can be measured and it might be obtained from probabilistic character of demand. In other words, it is a means for describing opportunity of receiving advantages from the optimum deviation of probabilistic characters.

$\hat{\beta}$ denotes lowest value of α which constitutes the minimum cost of the operation. A limited value of $\hat{\beta}$ represents situation in which the lowest operation cost is obtained in presence of a certain level of uncertainties, that could be presented as follow:

$$\hat{\beta}(C_o) = \min_{\beta}\{\alpha : \min(C(q, l)) \leqslant C_o\} \tag{51}$$

3.3. Robustness function

One can obtain robust status of decision-making for a multi-carrier network operation utilizing the next equation:

$$\alpha(C_r) = \max\left\{\alpha : \left(\min_{l \in U(\alpha, \widetilde{l}_{m,h})} \cos t^{total} \leqslant C_r\right) = (1+\omega)C_b\right\} \tag{52}$$

according to which, $\hat{\alpha}(C_r)$ denotes uncertainties with high possibilities that total operation cost of hub energy may not go beyond a critical level which is set as C_r. Meanwhile, C_b denotes multi-carrier network's lowest bound of the operation cost, which is anticipated to pay, and w denotes the cost change factor which can be employed for developing and designing a model of growth cost of system. Considering a multi-carrier network whose major characteristic is risk aversion, function of robustness that proposed by IGDT method is maximizing parameter of uncertainty whenever the needed cost of operation is fulfilled.

$$\hat{\alpha}(C_r) = \max \alpha \tag{53}$$

$$\left\{ \sum_{t=1}^{T} \left[\sum_{n=1}^{NE} \left[F\left(P_{n,t}\right) + SU_{n,t} + SD_{n,t} \right] + \sum_{g=1}^{NGW} \rho^{gas} GW_{g,t} + \sum_{gs=1}^{NGS} C_s GS_{gs,t}^{out} \right] \right\} \leq C_r \tag{54}$$

$$l_{m,h} \geq (1+\alpha)\tilde{l}_{m,h} \tag{55}$$

$$l_{m,h} \leq (1-\alpha)\tilde{l}_{m,h} \tag{56}$$

Regarding α, representing the rate of uncertainty, cost of multi carrier network operation will fall in upper bound provided that maximum outage amount allowed by IGDT is loaded in α (reign of uncertainty)—that is, $l_{m,h} \leqslant (1+\alpha)\,\tilde{l}_{m,h}$. As mentioned in Eq. (52), may be presented in a straightforward version, by which the negative uncertain parameter impact swing on objective function is taken into account:

$$\hat{\alpha}(C_r) = \max \alpha, \tag{57}$$

$$\left\{ \sum_{t=1}^{T} \left[\sum_{n=1}^{NE} \left[F\left(P_{n,t}\right) + SU_{n,t} + SD_{n,t} \right] + \sum_{g=1}^{NGW} \rho^{gas} GW_{g,t} + \sum_{gs=1}^{NGS} C_s GS_{gs,t}^{out} \right] \right\} \leq C_r \tag{58}$$

$$l_{m,h} = (1+\alpha)\tilde{l}_{m,h}. \tag{59}$$

In order to achieve the desired value of the objective function, all of system's elements limits in terms of equality and inequality ought to be met. The desired solution of (55) acts as a guarantor based on which if outage uncertainty rate (α) is less than considered upper bound ($\hat{\alpha}$), total cost of hub energy operation will not go beyond definite level of cost (C_r).

3.4. Opportunity function

Uncertainty of outage is a concept denoting the increase or decrease in demand caused by forecasting error. Robustness against a decrease in the demand was brought up and investigated in previous sub-section and the current sub-section will focus on explaining the positive impact on reduction in terms of demand based on proposing an opportunity function.

It is possible to get the opportunity function for multi-carrier network operation by exploring as follow:

$$\hat{\beta}(C_o) = \min \left\{ \alpha : \max_{l \in U(\alpha, \tilde{l}_{m,h})} \cos t^{total} \leqslant C_o = (1-\psi) C_b \right\}, \tag{60}$$

where $\hat{\beta}_{(C0)}$ denotes uncertainty lowest rate based on which the total cost of operation that is impossible to go beyond a critical value i.e. C_r. C_b denotes the lowest bound energy hub operation cost anticipated to pay, and factor of cost change applied for developing a model of the reduced cost of system is denoted by ψ. For a risk-averse hub system, robustness function for the proposed IGDT is pushing the uncertain parameter to its maximum level whenever the needed operation cost is met.

$$\hat{\beta}(C_o) = \min \alpha, \tag{61}$$

$$\left\{ \sum_{t=1}^{T} \left[\sum_{n=1}^{NE} \left[F\left(P_{n,t}\right) + SU_{n,t} + SD_{n,t} \right] + \sum_{g=1}^{NGW} \rho^{gas} GW_{g,t} + \sum_{gs=1}^{NGS} C_s GS_{gs,t}^{out} \right] \right\} \leq C_o, \tag{62}$$

$$l_{m,h} \leq (1+\alpha)\,\tilde{l}_{m,h}, \tag{63}$$

$$l_{m,h} \geq (1-\alpha)\tilde{l}_{m,h}, \tag{64}$$

Regarding the uncertainty rate of α, cost of operation will the lowest provided that the minimum amount of curtailed load allowed by IGDT is ordered at reign of uncertainty, α, equal to $l_{m,h} \leqslant (1-\alpha)\,\tilde{l}_{m,h}$. Accordingly, opportunity function, whereby positive impact of variation in uncertain term in objective function is considered, may be presented in a briefed version presented as follow:

$$\hat{\beta}(C_o) = \min \alpha \tag{65}$$

$$\left\{ \sum_{t=1}^{T} \left[\sum_{n=1}^{NE} \left[F\left(P_{n,t}\right) + SU_{n,t} + SD_{n,t} \right] + \sum_{g=1}^{NGW} \rho^{gas} GW_{g,t} + \sum_{gs=1}^{NGS} C_s GS_{gs,t}^{out} \right] \right\} \leq C_o \tag{66}$$

$$l_{m,h} = (1-\alpha)\tilde{l}_{m,h} \tag{67}$$

Like the robustness function as mentioned before, the desired value of objective function is obtainable only if the equality and inequality constraints are taken into account.

4. Simulation results

In order to assess the suggested robust operation modeling, while adopting IGDT method, an energy hub including gas, electricity, thermal demand, and water carriers is simulated. Schematic of simulated system is presented in Fig. 3. The test system consists a 6-bus electrical grid, a 6-node natural gas network. Also, two nodes for heat and water are considered, as well. Heat storage and thermal node are linked to each other. Also, heat exchange between heat storage and thermal node is based on network operation strategy. The data related to simulated hub energy system are taken from [34–37]. The main features of the heat energy storage technology are demonstrated in Table 2. The demands for gas, electricity, thermal demand, and water are displayed in Fig. 4. Gas price is assumed fix rate and equal by 2 \$/kcf.

4.1. The analysis of robustness solution

As Fig. 5 displays it, the solution of robustness function with related constraints are used to perform a robustness analysis. The cost of robustness means desired amount of objective function while taking negative impact on variation in uncertain parameter into consideration. As presented in (55)–(57), robustness function is applied to take into account and consider the relationship between negative impacts of uncertain term changes on the objective function. The relationship between robustness function and cost of robustness based on which the cost of operation increases by considering higher values for robustness function, so, hub operator has to agree to higher costs in order to achieve the robust operation strategy by considering potential demand

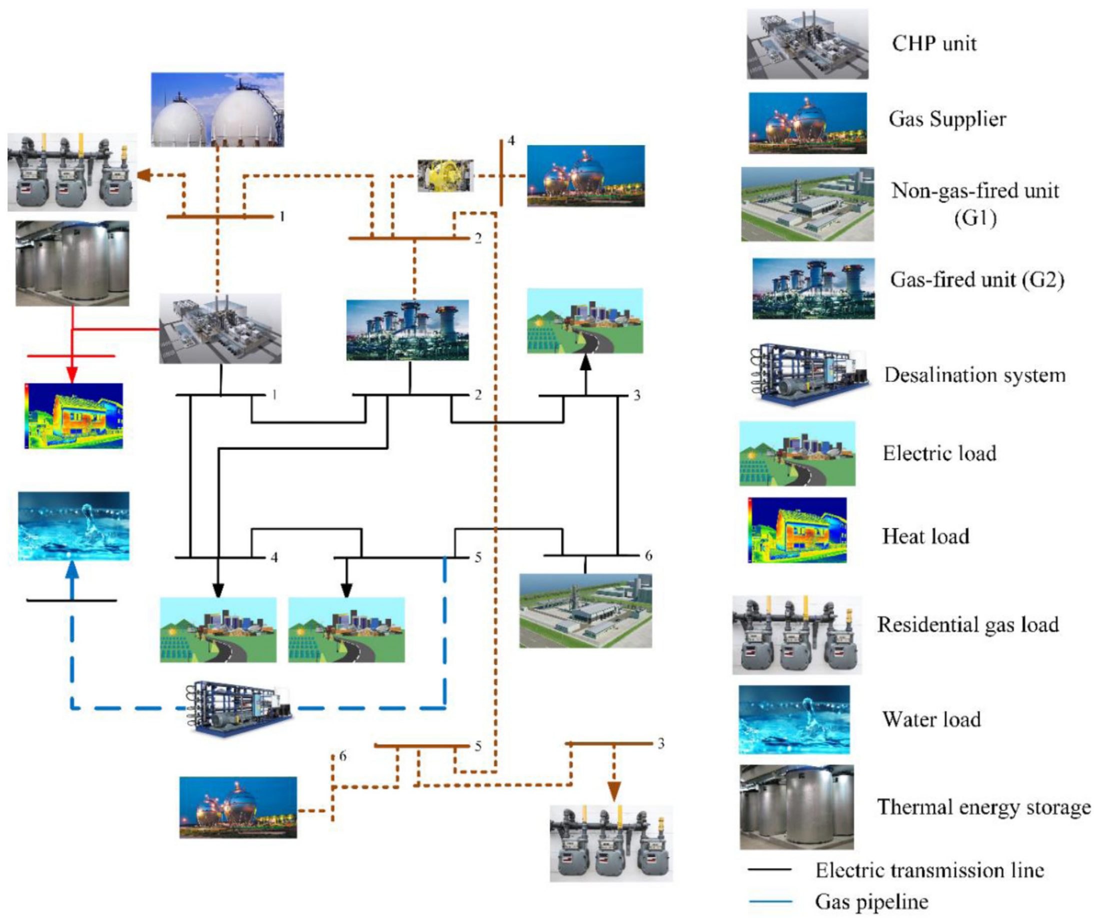

Fig. 3. Schematic of test system.

Table 2
Thermal storage parameters [36–39].

Data of thermal storage						
B_{hs}^{Max}(MWth)	B_{hs}^{Min}(MWth)	$B_{hs}^{Max,\ charge}$ (MWth)	$B_{hs}^{Max,\ discharge}$ (MWth)	$B_{hs}^{Min,\ charge}$ $B_{hs}^{Min,\ discharge}$ (MWth)	η_{hs}	η_{hs}^{ch}, η_{hs}^{dis}
60	0	15	15	0	95%	90%

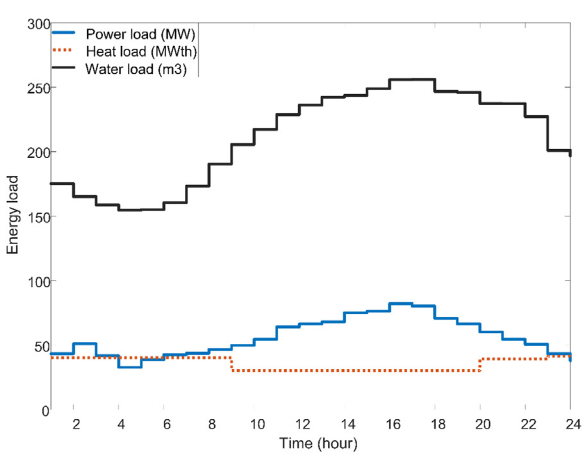

Fig. 4. The energy demand of hub system.

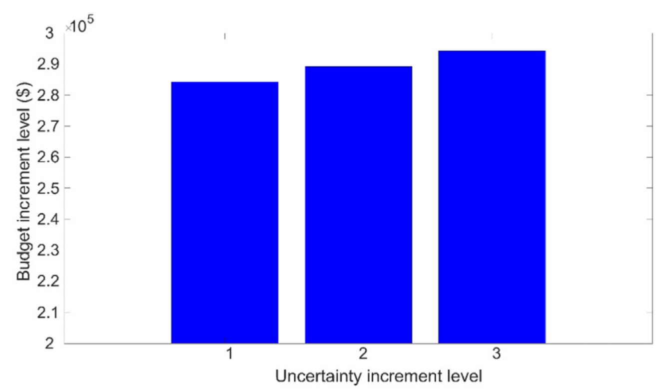

Fig. 5. The relationship between robustness function and operation cost.

growth. Drawing on interpretation of results, a $5000 additional budget for system operation will be beneficial in terms of overcoming a 4% change in power demand by reduction in outages side effects. In addition, if one increases the operation cost by $10,000, the robust model presented here can cope with a 6% uncertainty in outages. It is noteworthy that operation cost of hub excess $5000 for each step for robustness function.

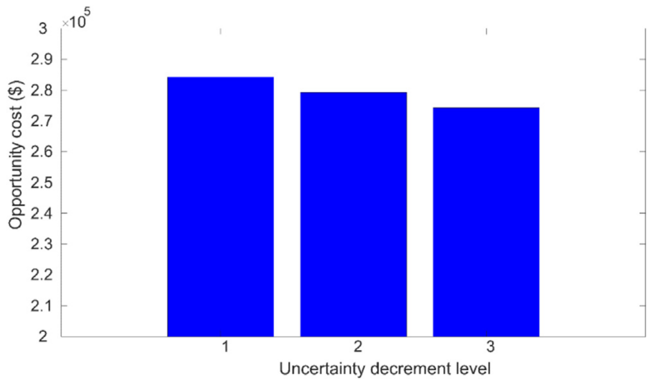

Fig. 6. The relation between opportunity function and operation cost.

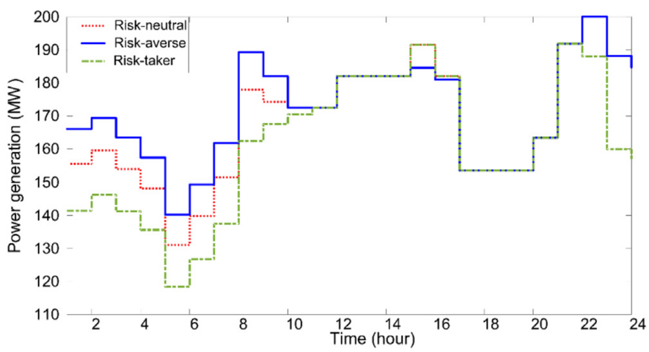

Fig. 7. Output of schedule for CHP plant.

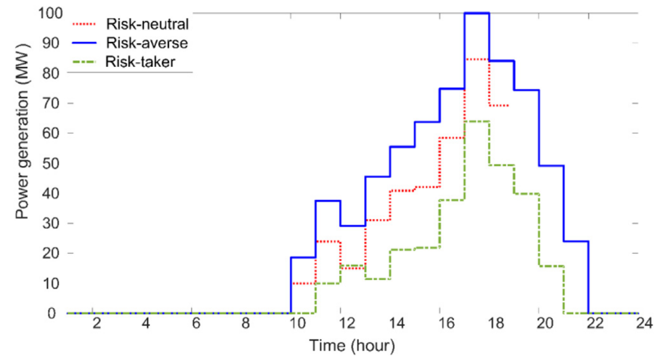

Fig. 8. Generation schedule for gas-fired G1 plant.

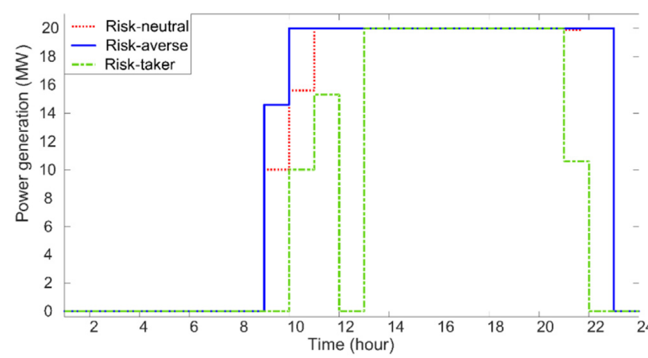

Fig. 9. Generation schedule for non-gas-fueled G2 plant.

4.2. The opportunity solution analysis

As demonstrated in Fig. 6, the opportunity function is investigated based on taking suitable solution of opportunity function (52) with related constraints into account. The opportunity cost is a desired value by considering positive effects of variation in uncertainty in objective function. A representation of opportunity function can be depicted in (58)–(60), that is based on positive penetration of changes in uncertainty level of objective function. Fig. 6, shows relationship between opportunity function and opportunity cost. According to its analysis, cost of hub system operation decreases by robustness function reduction. Put another way, system operator needs to spend less in order to obtain a programming of the system that is robust. Also results show that operation cost decreases by $5000 by a 3.9% electricity demand reduction. Moreover, a $10,000 reduction in operation cost is achieved by an 8.1% electricity demand reduction. It must be stated that hub system operation cost $2000 steps is selected for opportunity function.

4.3. IGDT-based robust operation of hub system

This sub-section provides detailed description of investigating the IGDT-based operation of energy hub. As demonstrated in Figs. 7–9, the desired output programming for three different scenarios named risk-taker, risk-neutral, and risk-averse by considering various uncertainty level for demand and lines outages is clarified. As reported results make it easy to understand, the consideration of risk-taker method lead to injecting less power, as outages decreases. What is more, taking risk-averse method positively into account influences the power generation according to an increment in electric loads curtailment.

Figs. 10 and 11 demonstrate optimal gas usage of G1 and G2 plants for risk-seeker, risk-neutral, and risk-averse scenarios, respectively. Obviously, risk-taker method is influential as G1 and G2 units used less gas as demand is reduced. Moreover, consideration of risk-averse method leads to an increase in gas usage by growth power demand of hub system.

The effects of outage probability on operational planning during extreme weather condition are studied. In this section the performance of islanding ability is evaluated. The best status for island operation will be obtained when the generation of power is near to demand. It is obvious that in grid connected systems it is not easy target. So, any actions that help to reduce demand and increase output of DGs, CHP and energy resources are important in ENS reduction and load shedding value. In this paper, it is shown that proposed resilient operation method increase power generation in order to enhance resilience and decrease ENS. As shown in Figs. 7–9, there are considerable changes in output and working point of CHP and DGs during time intervals with high level of outages may cause by weather condition in various scenarios. Fig. 7 shows that power output of CHP is increased 5.5% in risk-averse method and also it increased 3.2% in risk-neutral method in compare with risk-taker method. Also G1 and G2 plants outputs are increased 113.6% and 52.5% in risk-averse and risk-neutral methods in compare with risk-taker method. It is noticeable that wind turbine inertia is same for all possible islanding scenarios. As mentioned in Section 2.8, power imbalance is main factor in chance of successful islanding process and magnitude of load shedding and in sequence ENS penalty cost.

Heat output of the CHP unit for 24-h time scheduling time horizon is presented in Fig. 12. According to this figure, during ($t = 5$ till $t = 8$) and when heat production is less than heat demand ($t = 9$ till $t = 12$), this plant supplies heat much higher than heat demand presented in Fig. 4, highlighting impact of heat storage system. Meanwhile, in Fig. 13, the heat charge/discharge

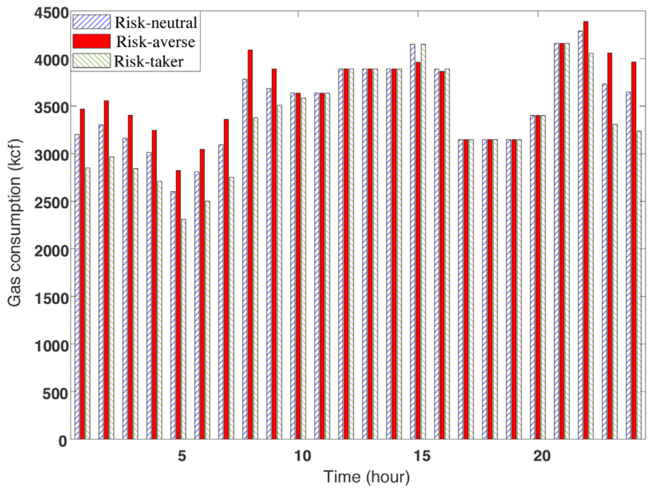

Fig. 10. Gas consumption of CHP unit.

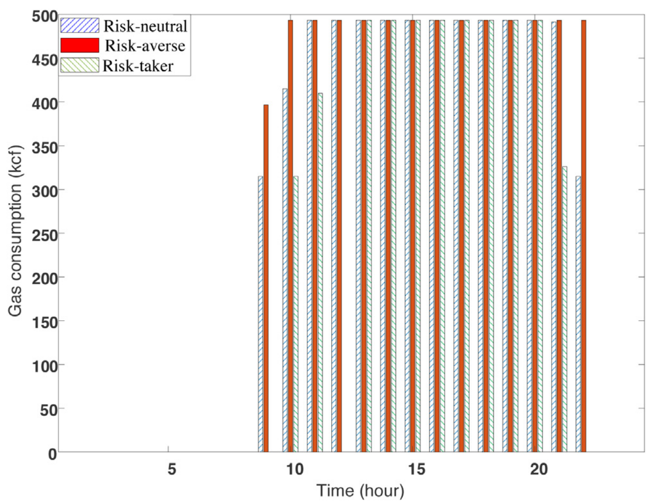

Fig. 11. Gas usage of gas-fueled unit, G2.

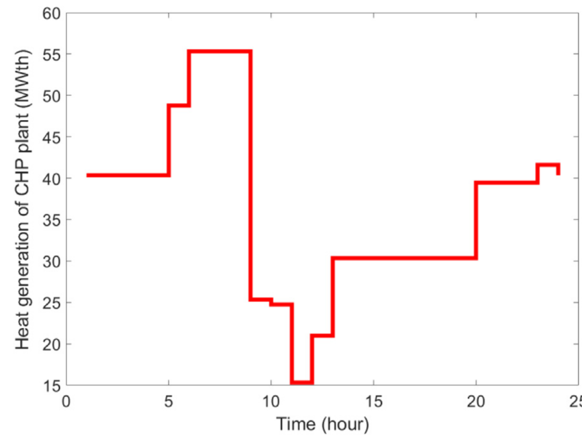

Fig. 12. The CHP plant thermal output.

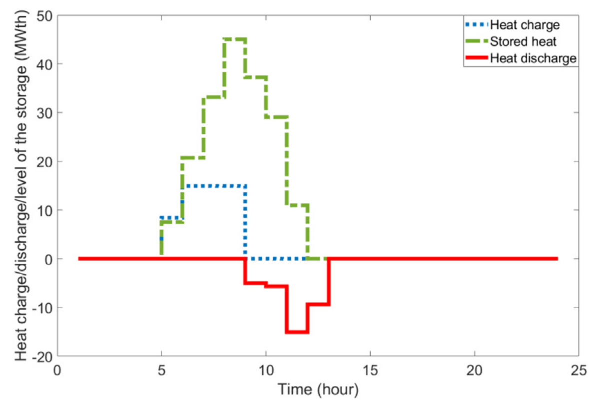

Fig. 13. The thermal storage schedule.

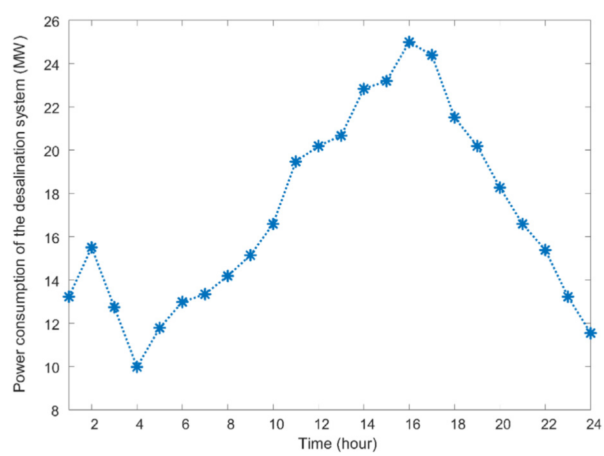

Fig. 14. Electricity consumption of water desalination unit.

of heat energy storage technology is presented in addition to programming for thermal energy stored in this storage based on (26)–(29), that allows storages surplus heat during off-peak periods and discharge it at peak period. By employing suitable optimization solver, the optimal set points of heat energy storage are obtained operation cost of hub system is minimized.

As depicted in Fig. 14, electricity used by the water desalination system in order to meet the presented water demand can be achieved drawing on (31) and (32). It seems that desalination unit used about 405.17 MW energy supplied by bus 5 of electrical grid during 24-h period. As seen in Fig. 15, wind turbine electrical output during the time horizon under study is presented, which is taken in by bus 5 of the power network. The wind turbines installed in the system generate a total power output of 713.92 MW.

5. Conclusion

The main goal of the current study was to introduce an IGDT-based robust operation of hub system having power, gas, heating, and water carriers and taking thermal storage into account at same time. According to the model advanced in this study, the network operator is deemed to be responsible not only for handling an uncertain risk of outages and in sequence power demand but also for evaluating impact of outages variation on hub energy system optimal operation. Accordingly, functions of opportunity and robustness for hub system based on the IGDT approach are analyzed in order to be employed by system operator so that they can contribute to proper decision making on the system operation, considering power demand changes by outages. Results for hub system is presented in three different scenarios, divided to risk-neutral, risk-averse, and risk-taker scenarios. The difference of these scenarios with together is according to positive, negative,

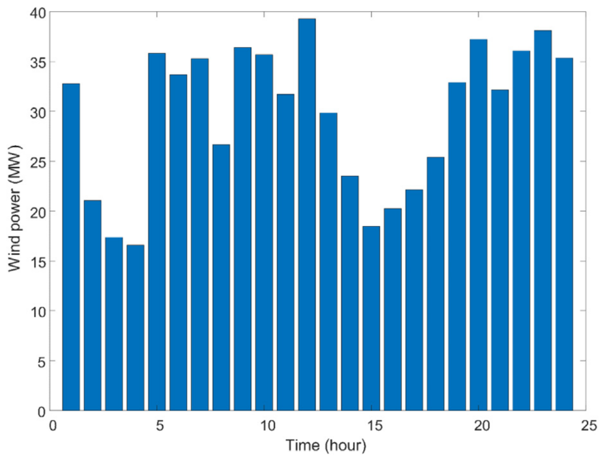

Fig. 15. The wind turbines electrical output.

and neutral aspects of the uncertain parameter. Regarding risk-averse method, system operator makes the decision of spending more for producing sufficient electrical energy so that it can be more robust against outage level and side effects on demand uncertainty. Also, taking risk-taker method into account, operator benefits from within potential decrease in electricity demand due to dependency of operation cost of system on total power used. Simulation results proved that risk-averse method has best resilience against load shedding in islanding operation in compare with risk-neutral and risk-taker methods. In addition, impact of heat storage on system operation analyzed by considering thermal charge/discharge of heat storage along with the programming for heat energy stored, which confirmed the desired programming of the heat energy storage in terms of managing heat demand. The focus of upcoming research projects will be on the exploration of new demand, including an air-conditioning and battery system with the penetration of renewable energy while mot leaving out the role of the uncertainty resulting from physical harms to electrical part [40]. Ultimately, what is of great significance in operation of hub system is resilience which qualifies to be the subject of a future study.

CRediT authorship contribution statement

Mehdi Paktinat: Software, Formal analysis, Writing - original draft, Data curation. **Meysam Amirahmadi:** Conceptualization, Methodology, Software, Investigation, Writing – review & editing, Project administration. **Mohammad Tolou-Askari:** Validation, Formal analysis, Writing – review & editing, Supervision. **Farhood Mousavizadeh:** Visualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] V. Chaudhary, H.M. Dubey, M. Pandit, Combined heat–power economic emission dispatch for a microgrid using coyote optimization, in: Artificial Intelligence and Sustainable Computing, in: Algorithms for Intelligent Systems, Springer, Singapore, 2022.
[2] Jiakun Fang, Qing Zeng, Xiaomeng Ai, Zhe Chen, Jinyu Wen, Dynamic optimal energy flow in the integrated natural gas and electrical power systems, Sustain. Energy IEEE Trans. 9 (1) (2018) 188–198.
[3] Changzheng Shao, Yi Ding, Pierluigi Siano, Zhenzhi Lin, A framework for incorporating demand response of smart buildings into the integrated heat and electricity energy system, Ind. Electron. IEEE Trans. 66 (2) (2018) 1465–1475.
[4] António Coelho, Nilufar Neyestani, Filipe Soares, João Peças Lopes, Wind variability mitigation using multi-energy systems, Int. J. Electr. Power Energy Syst. 118 (2020) 105755.
[5] Ling Hao, Mingshan Wei, Fei Xu, Xiaochen Yang, Jia Meng, Panpan Song, Yong Min, Study of operation strategies for integrating ice-storage district cooling systems into power dispatch for large-scale hydropower utilization, Appl. Energy 261 (2020) 114477.
[6] Hong Tan, Wei Yan, Zhouyang Ren, Qiujie Wang, Mohamed A. Mohamed, A robust dispatch model for integrated electricity and heat networks considering price-based integrated demand response, Energy (2021) 121875.
[7] G. Maggio, A. Nicita, G. Squadrito, How the hydrogen production from RES could change energy and fuel markets: A review of recent literature, Int. J. Hydrogen Energy (2019).
[8] Yanjuan Yu, Hongkun Chen, Lei Chen, Cheng Chen, Jun Wu, Optimal operation of the combined heat and power system equipped with power-to-heat devices for the improvement of wind energy utilization, Energy Sci. Eng. (2019).
[9] Bin Liu, Ke Meng, Zhao Yang Dong, Comparison of various solution techniques in dispatching coupled electricity-heat system with independent thermal energy storage, IET Renew. Power Gener. (2019).
[10] M. Sadat-Mohammadi, S. Asadi, M. Habibnezhad, H. Jebelli, Robust scheduling of multi-chiller system with chilled-water storage under hourly electricity pricing, Energy Build. 218 (2020) 110058.
[11] Houhe Chen, Ting Zhang, Rufeng Zhang, Tao Jiang, Xue Li, Guoqing Li, Interval optimal scheduling of integrated electricity and district heating systems considering dynamic characteristics of heating network, IET Energy Syst. Integr. (2020).
[12] Weichun Ge, Fengjiao Yu, Qianwei Liu, Shunjiang Wang, Anlong Su, Chao Pan, Economic dispatch of WT-pv-ES with cogeneration in abnormal regulatory domain, IOP Conf. Ser. Earth Environ. Sci. 446 (2020) 042043.
[13] Suyang Zhou, Rui Pei, Jihua Xie, Wei Gu, Xiaogang Chen, Integrated energy system operation optimization with gas linepack and thermal inertia, IET Renew. Power Gener. (2021).
[14] Q. Zeng, B. Zhang, J. Fang, Z. Chen, A bi-level programming for multistage co-expansion planning of the integrated gas and electricity system, Appl. Energy 200 (2017) 192–203.
[15] Yuchen Fang, Shuqiang Zhao, Nan Wang, Zhiwei Li, Jinshan Liu, Power system stochastic optimal dispatch considering thermal and electrical coordination, Int. J. Electr. Power Energy Syst. 110 (2019) 772.
[16] Himanshu Anand, An efficient approach to schedule generating units of combined heat and power (CHP) generating system, IETE J. Res. (2020) 1.
[17] S. Lu, W. Gu, J. Zhou, X. Zhang, C. Wu, Coordinated dispatch of multi-energy system with district heating network: Modeling and solution strategy, Energy 152 (2018) 358–370.
[18] E. Widl, T. Jacobs, D. Schwabeneder, S. Nicolas, D. Basciotti, S. Henein, T.G. Noh, O. Terreros, A. Schuelke, H. Auer, Studying the potential of multi-carrier energy distribution grids: A holistic approach, Energy 153 (2018) 519–529.
[19] Chaoxian Lv, Hao Yu, Peng Li, Chengshan Wang, Xiandong Xu, Shuquan Li, Jianzhong Wu, Model predictive control based robust scheduling of community integrated energy system with operational flexibility, Appl. Energy 243 (2019) 250.
[20] Xin-Rui Liu, Si-Luo Sun, Qiu-Ye Sun, Wei-Yang Zhong, Time-scale economic dispatch of electricity-heat integrated system based on users' thermal comfort, Energies 13 (2020) 5505.
[21] Cheng Zhou, Jianyong Zheng, Sai Liu, Yu Liu, Fei Mei, Yi Pan, Tian Shi, Jianzhang Wu, Operation optimization of multi-district integrated energy system considering flexible demand response of electric and thermal loads, Energies 12 (2019) 3831.
[22] A. Shabanpour-Haghighi, A.R. Seifi, An integrated steady-state operation assessment of electrical, natural gas, and district heating networks, IEEE Trans. Power Syst. 31 (2015) 3636–3647.
[23] I. Bouwmans, K. Hemmes, Optimising energy systems: Hydrogen and distributed generation, in: Proceedings of the Second International Symposium on Distributed Generation: Power System and Market Aspects, Stockholm, Sweden, 2–4 October, 2002, pp. 1L–7L.
[24] Xun Dou, Jun Wang, Zhen Wang, Tao Ding, Shizhen Wang, A decentralized multi-energy resources aggregation strategy based on bi-level interactive transactions of virtual energy plant, Int. J. Electr. Power Energy Syst. 124 (2021) 106356.
[25] Sang Song, Taesu Cheong, Pattern-based set partitioning algorithm for the integrated sustainable operation of a district heating network, Sustainability 10 (2018) 2774.
[26] A. Shabanpour-Haghighi, A.R. Seifi, Simultaneous integrated optimal energy flow of electricity, gas, and heat, Energy Convers. Manag. 101 (2015) 579–591.

[27] Lesia Mitridati, Jalal Kazempour, Pierre Pinson, Heat and electricity market coordination: A scalable complementarity approach, European J. Oper. Res. (2019).
[28] Yuchen Fang, Shuqiang Zhao, Risk-constrained optimal scheduling with combining heat and power for concentrating solar power plants, Sol. Energy 208 (2020) 937.
[29] Yuchen Fang, Shuqiang Zhao, Nan Wang, Zhiwei Li, Jinshan Liu, Power system stochastic optimal dispatch considering thermal and electrical coordination, Int. J. Electr. Power Energy Syst. 110 (2019) 772.
[30] Wei Wei, Yaping Shi, Kai Hou, Lei Guo, Linyu Wang, Hongjie Jia, Jianzhong Wu, Chong Tong, Coordinated flexibility scheduling for urban integrated heat and power systems by considering the temperature dynamics of heating network, Energies 13 (2020) 3273.
[31] M. Moradi-Dalvand, M. Nazari-Heris, B. Mohammadi-ivatloo, S. Galavani, A. Rabiee, A two-stage mathematical programming approach for the solution of combined heat and power economic dispatch, IEEE Syst. J. (2019).
[32] H. Fan, J. Lu, Z. Li, M. Shahidehpour, S. Zhang, Optimal planning of integrated electricity-gas system with demand side management, IEEE Access 7 (2019) 176790–176798.
[33] Changming Chen, Xin Deng, Zhi Zhang, Shengyuan Liu, Muhammad Waseem, Yangqings Dan, Zhou Lan, Zhenzhi Lin, Li Yang, Yi Ding, Optimal day-ahead scheduling of multiple integrated energy systems considering integrated demand response cooperative game and virtual energy storage, IET Gener. Transm. Dist. (2021).
[34] B. Yousefi-Khangah, S. Ghassemzadeh, S.H. Hosseini, B. Mohammadi-Ivatloo, Short-term scheduling problem in smart grid considering reliability improvement in bad weather conditions, IET Gener. Transm. Dist. 11 (10) (2018) 2521–2533.
[35] Feixiong Chen, Hongjie Deng, Zhenguo Shao, Distributed robust synergistic scheduling of electricity natural gas heating and cooling systems via alternating direction method of multipliers, Int. J. Energy Res. (2021).
[36] Xin-Rui Liu, Si-Luo Sun, Qiu-Ye Sun, Wei-Yang Zhong, Time-scale economic dispatch of electricity-heat integrated system based on users' thermal comfort, Energies 13 (2020) 5505.
[37] J. Li, J. Fang, Q. Zeng, Z. Chen, Optimal operation of the integrated electrical and heating systems to accommodate the intermittent renewable sources, Appl. Energy 167 (2016) 244–254.
[38] Jiawei Wang, Cuo Zhang, Shi You, Yi. Zong, Chresten Træholt, Zhao Yang Dong, Multi-timescale coordinated operation of a CHP plant-wind farm portfolio considering multiple uncertainties, Int. J. Electr. Power Energy Syst. 125 (2021) 106428.
[39] A. Alabdulwahab, A. Abusorrah, X. Zhang, M. Shahidehpour, Stochastic security-constrained scheduling of coordinated electricity and natural gas infrastructures, IEEE Syst. J 11 (2015) 1674–1683.
[40] D. Wang, R. Wu, X. Li, C.S. Lai, X. Wu, J. Wei, Y. Xu, W. Wu, L.L. Lai, Two-stage optimal scheduling of air conditioning resources with high photovoltaic penetrations, J. Clean. Prod. 241 (2019) 118407.