Information Gap Decision Theory (IGDT)-based Robust Scheduling of Combined Cooling, Heat and Power Energy Hubs

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Abstract-Energy hubs (EHs) are units wherein multiple energy carriers can be converted, stored and conditioned to simultaneously supply different energy demands. In this paper, a new model is proposed for unit commitment in renewable EHs with electric, thermal and cooling demands, different storage systems, combined heat and power (CHP) unit, boiler, electric chiller, absorption chiller, PV module, wind turbine and battery charging station (BCS). Using information gap decision theory (IGDT), day-ahead EH scheduling is done from risk-neutral, risk-averse and risk-seeking perspectives, considering the uncertainties of electric demands, BCS demands, heat demands, cooling demands, PV and wind power and electricity prices. Comprehensive models are used for storage systems considering their degradation, charging loss, discharging loss and storage loss; the ramp-up and ramp-down rate limits, start-up and shut-down costs of CHP, boiler and cooling components are considered. The effect of risk as well as effect of critical cost deviation factor and target cost deviation factor on EH operation cost and schedule of EH components is investigated. The findings indicate that the sensitivity of EH operation cost may be very different with respect to different sets of uncertain input data. The findings also show the significant effect of risk-awareness on schedule of EH components and its operation cost.

Keywords: energy hubs, CCHP hubs; information gap decision theory, optimisation; risk, uncertainty

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Nomenclature

Acronyms

EH Energy hub

MCS Monte Carlo Simulation

CHP Combined heat and power

CCHP Combined cooling heat and power

EES Electric energy storage

TES Thermal energy storage

CES Cooling energy storage

P2G Power to gas

PV Photovoltaic

EMS Energy management system

NG Natural gas

MILP Mixed-integer linear programming

MINLP Mixed-integer nonlinear programming

PEM Point estimate method

EHP Electric heat pump

PHEV Plug-in hybrid electric vehicle

COP Coefficient of performance

Indices

t time

$grid$ Grid

NG Natural gas

min Minimum value

max Maximum value

ini Initial value

e Electric demand

h Heat demand

c	Cooling demand
$boil$	Boiler
chp	CHP
AC	Absorption chiller
EC	Electric chiller
TF	Transformer
$Conv$	PV converter
BES	Battery energy storage
TES	Thermal energy storage
CES	Cooling energy storage
$P2G$	Power to gas storage
ch	Charging mode of storage system
dch	Discharging mode of storage system
$shed$	Shed power

Parameters and variables

π	Price
P	Electric power
H	Thermal power
C	Cooling power
D	Demand
BCS	BCS demand
$Wind$	Wind power
PV	PV power
eff	Efficiency
VLL	Value of lost load
COP	Coefficient of performance
RU	Ramp-up rate
RD	Ramp-down rate
SU	Cost of a single start-up

SD Cost of a single shut-down

RC Replacement cost of storage system

$TCDC$ Total charge/discharge capacity of storage system

SLF Storage loss factor

E Energy level of storage system

Pch Charging power of storage

$Pdch$ Discharging power of storage

$EHOC$ EH's operation cost

u Commitment status of components

y Start-up indicator of components

z Shut-down indicator of components

1. Introduction

Energy hubs (EHs) are units in which multiple energy carriers can be converted, stored and conditioned to supply different energy demands [1-5]. The inputs of EHs may be electric power from a grid, electric power from a wind/photovoltaic (PV) unit, natural gas from a gas network, heat from a district heating network, cooling power from a cooling network, water from a water network, hydrogen, biomass, etc and the outputs of EH may be electricity, heat, cooling, water, gas, water or hydrogen demands. Within the EH, the input energy carriers are converted, stored and conditioned using components such as combined heat and power (CHP) units, boilers, gas turbines, transformers, electric/absorption chillers, electric heat pumps (EHPs), electric energy storage (EES), thermal energy storage (TES) and cooling energy storage (CES) units. Nowadays, large residential/commercial buildings, industrial complexes, etc are being structured or can be structured as EH [6-8]. Some advantages of EHs that have made them very popular energy systems, are as below [9].

- In EHs, there exist redundant connections between input and output nodes. For instance, in order to supply electricity demand, EH operator may either directly use the purchased electricity from power grid or use the purchased gas from gas network to feed CHPs and produce the needed power. This redundancy enhances the reliability of energy supply [1].
- The redundant connections between input and output nodes of EH and the resulted higher degree of freedom may result in reduction of operation cost and emissions [10].
- A significant portion of EH energy demand is commonly supplied with renewable energy resources, so EHs are considered environmentally-friendly energy systems [11, 12].

EHs have energy management systems (EMSs) that typically minimise their operation cost on a day-ahead basis. EMS conducts unit commitment (UC) which determines ON/OFF status and operating point of converters, status, charging/discharging power of storage systems and purchased electricity/heat/cooling power/water in a way that EH operation cost is minimised. EH operation cost typically includes cost of purchased electricity/heat/cooling power/water, start-up and shut-down cost of converters and degradation cost of storage systems. In EMS module, the forecasted values of electricity/heat/cooling/water demands and electricity prices as well as power of wind turbines and PV modules are used. These forecasts are uncertain, whereas their values affect the operation cost of EHs [9]. The deviation of the demands, renewable power and prices from forecasted values introduce a significant risk in EH operation cost [13, 14].

In literature, different strategies have been used to deal with the uncertainties of demands, PV and wind power and electricity prices in EH operation. Those strategies can be classified into risk-neutral stochastic methods, risk-aware stochastic methods and robust methods.

[4, 15-20] used risk-neutral probabilistic method wherein some scenarios are generated and the most probable scenarios are selected with their probability of occurrence and the expected operation cost of EH is minimised. For instance in [15], risk-neutral stochastic method has been used to deal with the uncertainties of wind power, electricity demand and prices in an EH with CHP units, boiler, EES, TES, transformer and responsive demands. In risk-neutral stochastic method, EH operator is concerned of the risks of unfavorable deviations of uncertain data from their forecasted values and the possible excessive operation cost because the risk is not considered in the model. On the other hand, [21-23] used risk-averse stochastic method with conditional value at risk to decrease the risks of unfavorable deviations of input data from forecasted values, however, they do not guarantee the achievement of an acceptable operation cost. As an example, [21] uses conditional value at risk for dealing with uncertainties of electricity, heat and NG demands, electricity price and wind power in an EH with CHP units, wind turbine, boiler, TES, compressed air energy storage (CAES) and P2G.

In this research, information gap decision theory (IGDT) as a risk-aware method is used to deal with uncertainties of demands, wind and PV power and electricity prices in EH operation. IGDT-based decision making is done both from risk-averse and risk-seeking perspectives and the effect of risk awareness on EH operation cost and schedule of the components are investigated. An EH with CHP unit, boiler, electric chiller, absorption chiller, EES, TES, CES, P2G, transformer, PV module with its DC/AC converter, wind turbine and battery charging station (BCS) is studied in which the inputs are the electricity purchased from power grid and NG purchased from NG network and the outputs are electric, heat and cooling demands.

The main features of this research are listed out as below:

- Day-ahead CCHP EH scheduling has been done from risk-neutral, risk-averse and risk-seeking perspectives considering uncertainties of electric demand, BCS demand, heat demand, cooling demand, PV power, wind power and electricity price.
- BCS has been integrated into EH to charge the electric vehicles.
- The effect of consideration of risk on EH operation cost and the schedule of EH components has been investigated.
- The effect of critical cost deviation factor and target cost deviation factor on EH operation and the schedule of EH components has been investigated.
- The ramp-up and ramp-down rate limits, start-up and shut-down costs of cooling components have been considered.

2. Information gap decision theory (IGDT)

IGDT is a non-probabilistic and non-possibilistic method for dealing with models including uncertain input data. An optimisation problem can be represented as (1). Without loss of generality, we assume a minimisation problem that aims to minimise the cost.

$$\begin{gathered} \min f(X,u) \\ g(X,u)=0 \\ h(X,u)\leq 0 \end{gathered} \qquad (1)$$

Where $y=f(X,u)$ denotes cost, X and u respectively represent decision vector and uncertain input data.

The forecasted (nominal) values of uncertain input data are represented by $\bar{u}$ and the set U, named as uncertainty set is defined including all values u whose deviation from forecasted values does not exceed $\alpha\bar{u}$.

$$U(\alpha,u)=\left\{u:\left|\frac{u-\bar{u}}{\bar{u}}\right|\leq\alpha\right\} \qquad (2)$$

Where α is named uncertainty horizon [24].

IGDT may be used either from risk-averse or risk-seeking perspectives. In risk-averse IGDT, the decision maker would be satisfied if the cost is equal to or less than a pre-specified critical value. In risk-averse IGDT model, decision maker aims to maximise the uncertainty horizon (or robustness horizon) in a way that any deviation of uncertain input data within robustness set results in a cost not worse than critical cost. The risk-averse IGDT-based model of (1) is as below.

$$\min \alpha(X,u) \quad (3)$$

$$f(X,u) \leq f_{cr} \quad \forall u \in U \quad (4)$$

$$g(X,u) = 0 \quad \forall u \in U \quad (5)$$

$$h(X,u) \leq 0 \quad \forall u \in U \quad (6)$$

$$f_{cr} = (1+\beta)\bar{f} \quad (7)$$

Where α is robustness horizon, $\bar{f}$ is the nominal optimal cost which is achieved if uncertain input data are equal to the forecasted (nominal) uncertain data. f_{cr} is the maximum tolerable cost and β is critical cost deviation factor. Actually, in risk-averse IGDT, the main purpose is to set the decision variables in a way that hedges decision maker against the risk of unfavorable deviations of uncertain input data or in other words, risk-averse IGDT guarantees the achievement of the minimum requirements [24, 25]. Lower values of critical cost leads to lower values of robustness horizon.

In risk-seeking IGDT which is modeled as below, a target cost f_{targ} is pre-specified and the aim is to find decision variables and uncertainty horizon (or opportunity horizon) that makes the f_{targ} achievable. Actually, the most favorable deviations of uncertain input data make the cost equal to f_{targ}.

$$\min \alpha(X,u) \quad (8)$$

$$f(X,u) \leq f_{targ} \quad (9)$$

$$g(X,u) = 0 \quad (10)$$

$$h(X,u) \leq 0 \quad (11)$$

$$f_{targ} = (1-\rho)\bar{f} \quad (12)$$

Where α is referred to as opportunity horizon, f_{targ} is the target cost and ρ is the target cost deviation factor [24, 25]. The optimist risk-seeker decision maker hopes to benefit from desirable deviations of uncertain input data from forecasted values. Lower values of f_{targ} results in lower values of opportunity horizon.

3. The Proposed Model

In this research, a CCHP EH as Fig.1 is used and in this section, the model for UC in this EH is introduced within three subsections; in 3.1, the model is introduced ignoring the uncertainties; in 3.2 and 3.3, risk-averse and risk-seeking IGDT-based UC model are respectively introduced for CCHP EH.

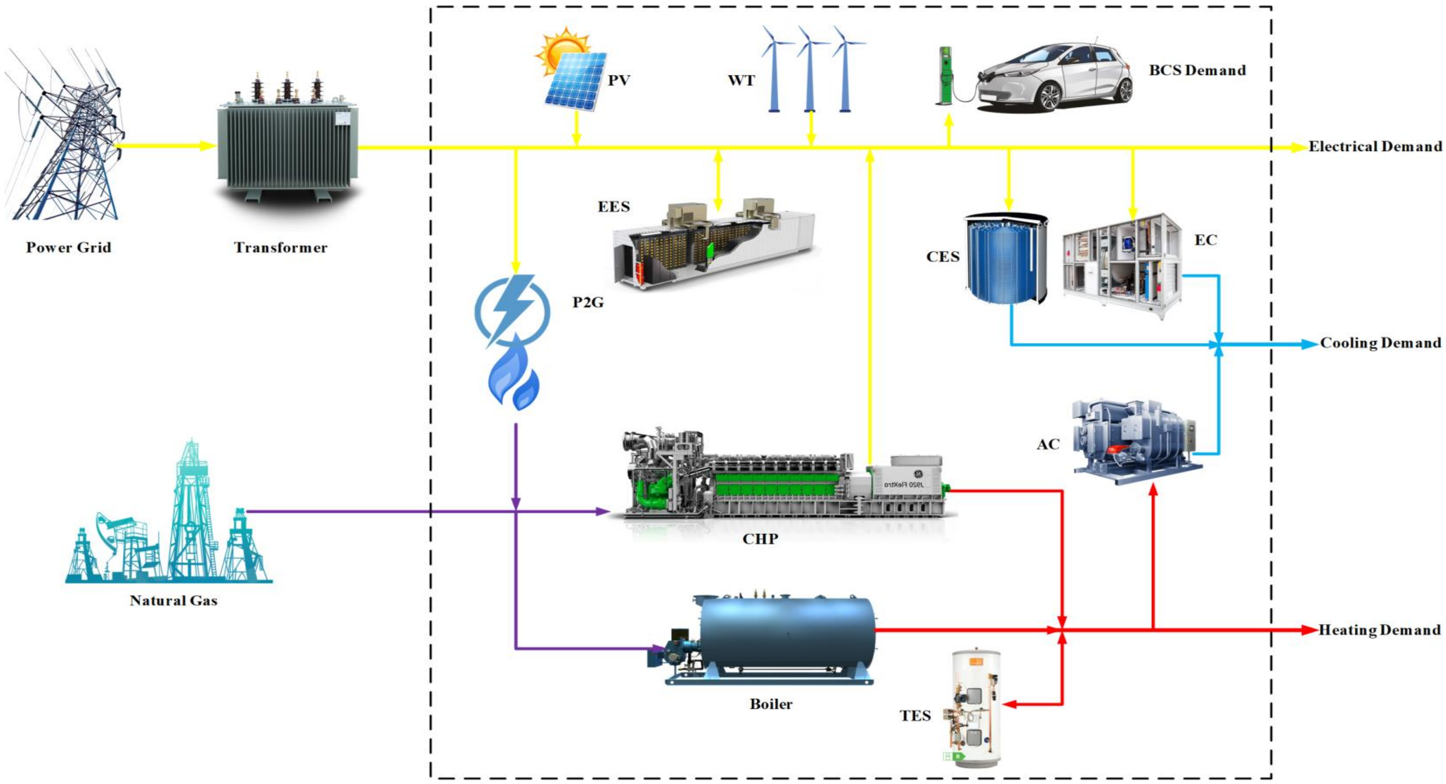

Fig.1. Scheme of the studied EH

3.1. UC in EH without consideration of uncertainties

The proposed MILP model for UC in EH, ignoring the uncertainties is characterised by (13)-(93). CHP, boiler, electric and absorption chillers are assumed committed prior to the beginning of operation horizon. The EH operation cost is represented as (13) and respectively includes the cost of purchased electricity, cost of purchased NG, start-up and shut-down costs of boiler, CHP, electric chiller and absorption chiller, demand shed costs and degradation cost of storage systems [9]. Degradation cost of storage systems are determined as (14)-(17) and are proportional to the sum of charging and discharging power over operation horizon [18].

$$EHOC = \sum_t \pi_{grid,t} . P_{grid,t} + \sum_t \pi_{NG,t} . P_{NG,t} + \sum_t (y_{boil,t} . SU_{boil} + z_{boil,t} . SD_{boil}) + \sum_t (y_{chp,t} . SU_{chp} + z_{chp,t} . SD_{chp}) + \sum_t (y_{EC,t} . SU_{EC} + z_{EC,t} . SD_{EC}) + \sum_t (y_{AC,t} . SU_{AC} + z_{AC,t} . SD_{AC}) + \sum_t (VLL_e . P_{shed,t} + VLL_h . H_{shed,t} + VLL_C . C_{shed,t}) + \mathrm{degc_{BES}} + \mathrm{degc_{TES}} + \mathrm{degc_{CES}} + \mathrm{degc_{P2G}} \quad (13)$$

$$\mathrm{degc_{BES}} = \frac{RC_{BES}}{TCDC_{BES}} \sum_t (P_{BES,ch,t} + P_{BES,dch,t}) \quad (14)$$

$$\text{degc}_{\text{TES}} = \frac{RC_{TES}}{TCDC_{TES}} \sum_t (P_{TES,ch,t} + P_{TES,dch,t}) \quad (15)$$

$$\text{degc}_{\text{CES}} = \frac{RC_{CES}}{TCDC_{CES}} \sum_t (P_{CES,ch,t} + P_{CES,dch,t}) \quad (16)$$

$$\text{degc}_{\text{P2G}} = \frac{RC_{P2G}}{TCDC_{P2G}} \sum_t (P_{P2G,ch,t} + P_{P2G,dch,t}) \quad (17)$$

The balance constraints for electric, thermal, cooling and NG power are respectively represented as (18)-(21). As per (18), at each time, sum of the imported power from grid times transformer efficiency, CHP power, wind power, PV power times its converter's efficiency, electric power shed and discharging power of BES should not be less than sum of electric demand, BCS demand, charging power of BES, CES and P2G and electric power fed into electric chiller. As per (19), at each time, sum of thermal power generated by boiler and CHP, thermal demand shed and discharging power of TES should not be less than sum of thermal demand, charging power of TES and thermal power fed into absorption chiller. As per (20), at each time, sum of cooling power generated by electric and absorption chillers, cooling demand shed and discharging power of CES should not be less than cooling demand of EH. As per (21), at each time, sum of imported NG and NG discharged by P2G should be equal to the NG consumed by CHP and boiler.

$$P_{grid,t} eff_{TF} + P_{chp,t} + \text{Wind}_\text{t} + eff_{conv}\,\text{PV}_\text{t} + P_{shed,t} + P_{BES,dch,t} \geq \text{D}_{\text{e,t}} + \text{BCS}_\text{t} + P_{BES,ch,t} + P_{CES,ch,t} + P_{P2G,ch,t} + \frac{\text{C}_{\text{EC,t}}}{\text{COP}_{\text{EC}}} \quad \forall t \quad (18)$$

$$H_{boil,t} + H_{chp,t} + H_{shed,t} + P_{TES,dch,t} \geq \text{D}_{\text{h,t}} + P_{TES,ch,t} + \frac{\text{C}_{\text{AC}},\text{t}}{\text{COP}_{\text{AC}}} \quad \forall t \qquad (19)$$

$$\text{C}_{\text{EC,t}} + \text{C}_{\text{AC,t}} + C_{shed,t} + P_{CES,dch,t} \geq \text{D}_{\text{c,t}} \quad (20)$$

$$P_{NG,t} + P_{P2G,dch,t} = \frac{P_{chp,t}}{eff_{P,chp}} + \frac{H_{boil,t}}{eff_{boil}} \qquad (21)$$

The operation of the boiler is subject to constraints (22)-(28). Constraints (22)-(25) represent the relationship among commitment status, start-up status and shut-down status of boiler assuming that it is initially online. Constraints (26) ensure that at each time, the generated thermal power of committed boiler is confined within its pre-specified allowed range. Constraints (27)-(28) preclude quick increase/decrease in thermal power of boiler; they do not allow the violation of thermal power increase from ramp-up rate limit and do not allow the violation of thermal power decrease from ramp-down rate limit [26].

$$y_{boil,t} - z_{boil,t} = u_{boil,t} - u_{boil,t-1} \qquad \forall t \neq 1 \qquad (22)$$
$$y_{boil,t} = 0 \qquad \forall t = 1 \qquad (23)$$
$$z_{boil,t} = 1 - u_{boil,t} \qquad \forall t = 1 \qquad (24)$$
$$y_{boil,t} + z_{boil,t} \leq 1 \qquad \forall t \qquad (25)$$
$$H_{boil,min} u_{boil,t} \leq H_{boil,t} \leq H_{boil,max}\, u_{boil,t} \qquad \forall t \qquad (26)$$
$$H_{boil,t+1} - H_{boil,t} \leq RU_{boil} \qquad \forall t \neq 24 \qquad (27)$$
$$H_{boil,t-1} - H_{boil,t} \leq RD_{boil} \qquad \forall t \neq 1 \qquad (28)$$

Operation of the electric chiller is subject to constraints (29)-(35). Constraints (29)-(32) express the relationship among commitment status, start-up status and shut-down status of electric chiller assuming that it is initially ON. Constraints (33) ensure that at each time, the cooling power of committed electric chiller is confined within its pre-specified allowed range. Constraints (34)-(35) do not allow quick increase/decrease in cooling power of electric chiller; they do not allow the violation of cooling power increase from ramp-up rate limit and also do not allow the violation of cooling power reduction from ramp-down rate limit.

$$y_{EC,t} - z_{EC,t} = u_{EC,t} - u_{EC,t-1} \qquad \forall t \neq 1 \qquad (29)$$
$$y_{EC,t} = 0 \qquad \forall t = 1 \qquad (30)$$
$$z_{EC,t} = 1 - u_{EC,t} \qquad \forall t = 1 \qquad (31)$$
$$y_{EC,t} + z_{EC,t} \leq 1 \qquad \forall t \qquad (32)$$
$$C_{EC,min} u_{EC,t} \leq C_{EC,t} \leq C_{EC,max}\, u_{EC,t} \qquad \forall t \qquad (33)$$
$$C_{EC,t+1} - C_{EC,t} \leq RU_{EC} \qquad \forall t \neq 24 \qquad (34)$$
$$C_{EC,t-1} - C_{EC,t} \leq RD_{EC} \qquad \forall t \neq 1 \qquad (35)$$

The operation of the absorption chiller is subject to constraints (36)-(42). Constraints (36)-(39) express the relationship among commitment status, start-up status and shut-down status of absorption chiller assuming that it is initially ON. Constraints (40) ensure that at each time, the cooling power of committed absorption chiller is confined within its pre-specified allowed range of cooling power. Constraints (41)-(42) do not allow quick increase/decrease in cooling power of absorption chiller and limit the increase/decrease of cooling power to ramp-up/down rate limits.

$$y_{AC,t} - z_{AC,t} = u_{AC,t} - u_{AC,t-1} \qquad \forall t \neq 1 \qquad (36)$$
$$y_{AC,t} = 0 \qquad \forall t = 1 \qquad (37)$$
$$z_{AC,t} = 1 - u_{AC,t} \qquad \forall t = 1 \qquad (38)$$
$$y_{AC,t} + z_{AC,t} \leq 1 \qquad \forall t \qquad (39)$$
$$C_{AC,min} u_{AC,t} \leq C_{AC,t} \leq C_{AC,max}\, u_{AC,t} \qquad \forall t \qquad (40)$$
$$C_{AC,t+1} - C_{AC,t} \leq RU_{AC} \qquad \forall t \neq 24 \qquad (41)$$
$$C_{AC,t-1} - C_{AC,t} \leq RD_{AC} \qquad \forall t \neq 1 \qquad (42)$$

The operation of the absorption chiller is subject to constraints (43)-(57). Constraints (43)-(46) express the relationship among commitment status, start-up status and shut-down status of CHP assuming that it is initially ON. Constraints (47) and (48) respectively ensure that at each time, the power and heat of committed CHP are confined within the pre-specified allowed ranges. Constraints (49)-(50) do not allow sudden increase/decrease in CHP power, while constraints (49)-(50) preclude sudden changes in CHP’s thermal power.

$$y_{chp,t} - z_{chp,t} = u_{chp,t} - u_{chp,t-1} \qquad \forall t \neq 1 \qquad (43)$$
$$y_{chp,t} = 0 \qquad \forall t = 1 \qquad (44)$$
$$z_{chp,t} = 1 - u_{chp,t} \qquad \forall t = 1 \qquad (45)$$
$$y_{chp,t} + z_{chp,t} \leq 1 \qquad \forall t \qquad (46)$$
$$P_{chp,min} u_{chp,t} \leq P_{chp,t} \leq P_{chp,max}\, u_{chp,t} \qquad \forall t \qquad (47)$$
$$H_{chp,min} u_{chp,t} \leq H_{chp,t} \leq H_{chp,max}\, u_{chp,t} \qquad \forall t \qquad (48)$$
$$P_{chp,t+1} - P_{chp,t} \leq RU_{P,chp} \qquad \forall t \neq 24 \qquad (49)$$
$$P_{chp,t-1} - P_{chp,t} \leq RD_{P,chp} \qquad \forall t \neq 1 \qquad (50)$$
$$H_{chp,t+1} - H_{chp,t} \leq RU_{H,chp} \qquad \forall t \neq 24 \qquad (51)$$

$$H_{chp,t-1} - H_{chp,t} \leq \ RD_{H,chp} \qquad \forall t \neq 1 \qquad (52)$$

Due to the interrelation of heat and power, the operating point of a CHP unit should be within a pre-specified region, referred to as feasible operating region (FOR) which has been shown as Fig.2 [27]. The FOR of a CHP is characterised by four vertex points A, B, C and D. In FOR, A is maximum power point, B is maximum heat point, C is minimum power point and D is minimum heat point. FOR of a CHP is characterised by constraints (53)-(57) [27].

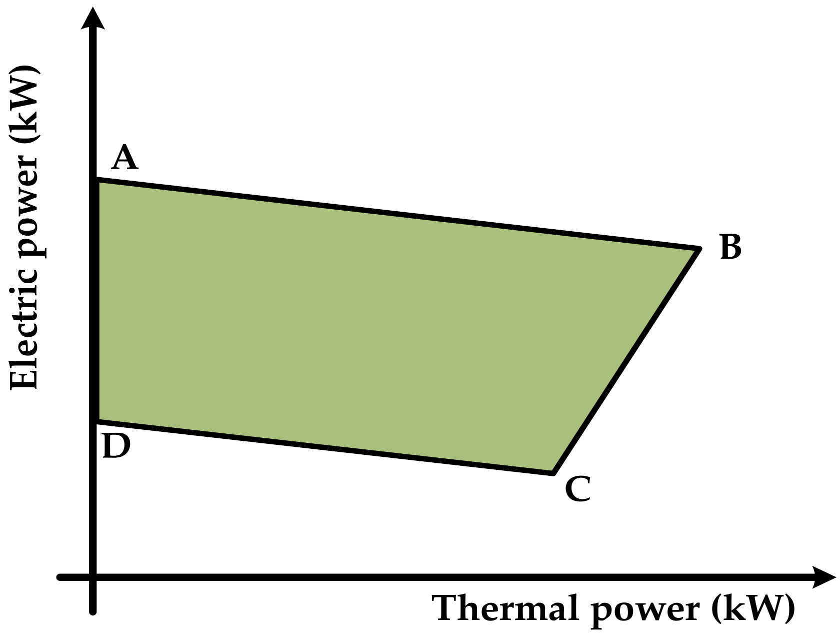

Fig.2. FOR of type I CHPs

$$0 \leq P_{chp,t} \leq P_{chp,A} \,.\, u_{chp,t} \qquad \forall t \qquad (53)$$

$$0 \leq H_{chp,t} \leq H_{chp,B} \,.\, u_{chp,t} \qquad \forall t \qquad (54)$$

$$P_{chp,t} - P_{chp,A} - \frac{(P_{chp,A} - P_{chp,B})(H_{chp,t} - H_{chp,A})}{H_{chp,A} - H_{chp,B}} \leq 0 \qquad \forall t \qquad (55)$$

$$P_{chp,t} - P_{chp,B} - \frac{(P_{chp,B} - P_{chp,C})(H_{chp,t} - H_{chp,B})}{H_{chp,B} - H_{chp,C}} \geq -M(1 - u_{chp,t}) \qquad \forall t \qquad (56)$$

$$P_{chp,t} - P_{chp,C} - \frac{(P_{chp,C} - P_{chp,D})(H_{chp,t} - H_{chp,C})}{H_{chp,C} - H_{chp,D}} \geq -M(1 - u_{chp,t}) \quad \forall t \qquad (57)$$

The operation of BES is subject to the constraints (58)-(64) [18]. Constraints (58) and (59) respectively bound charging and discharging power of BES to their allowable ranges. Constraints (60) ensure that at each time the energy level of BES does not exceed its maximum allowable energy level and does not fall below its minimum allowable energy level. Constraints (61) do not allow simultaneous charge and discharge of BES and constraint (62) ensures that the energy level of BES at the end of operation horizon equals its initial energy level. Constraints (63) and (64) express the energy level of BES at time t versus its energy level at the previous time period; they consider charging loss, discharging loss and storage loss of BES. Actually, $eff_{BES,ch}$, $eff_{BES,dch}$ and SLF_{BES} are the factors that determine energy efficiency of BES.

$$u_{BES,ch,t}Pch_{BES,min} \leq P_{BES,ch,t} \leq u_{BES,ch,t}Pch_{BES,max} \quad \forall t \quad (58)$$
$$u_{BES,dch,t}Pdch_{BES,min} \leq P_{BES,dch,t} \leq u_{BES,dch,t}Pdch_{BES,max} \quad \forall t \ (59)$$
$$E_{BES,min} \leq E_{BES,t} \leq E_{BES,min} \quad \forall t \ (60)$$
$$u_{BES,ch,t} + u_{BES,dch,t} \leq 1 \quad \forall t \quad (61)$$
$$E_{BES,ini} = E_{BES,end} \quad (62)$$
$$E_{BES,t} = E_{BES,t-1} - \frac{P_{BES,dch,t}}{eff_{BES,dch}} + eff_{BES,ch}P_{BES,ch,t} - SLF_{BES}\left(\frac{E_{BES,t} + E_{BES,t-1}}{2}\right) \quad \forall t \neq 1 \qquad (63)$$
$$E_{BES,t} = E_{BES,ini} - \frac{P_{BES,dch,t}}{eff_{BES,dch}} + eff_{BES,ch}P_{BES,ch,t} - SLF_{BES}\left(\frac{E_{BES,t} + E_{BES,t-1}}{2}\right) \quad \forall t = 1 \qquad (64)$$

The operation of TES is subject to the constraints (65)-(71) [18]. In this research, hot water tank is used as TES. Constraints (65) and (66) respectively bound charging and discharging power of TES to their allowable ranges. Constraints (67) ensure that at each time the energy level of TES does not violate its maximum allowable energy level and does not fall below its minimum acceptable energy level. Constraints (68) do not allow simultaneous charge and discharge of TES and constraint (69) ensures that the energy level of TES at the end of operation horizon equals its initial energy level. Constraints (70) and (71) express the relation of the energy level of TES at two successive time periods and consider charging loss, discharging loss and storage loss of TES.

$$u_{TES,ch,t}Hch_{TES,min} \leq H_{TES,ch,t} \leq u_{TES,ch,t}Hch_{TES,max} \quad \forall t \quad (65)$$
$$u_{TES,dch,t}Hdch_{TES,min} \leq H_{TES,dch,t} \leq u_{TES,dch,t}Hdch_{TES,max} \quad \forall t \ (66)$$
$$E_{TES,min} \leq E_{TES,t} \leq E_{TES,min} \quad \forall t \ (67)$$
$$u_{TES,ch,t} + u_{TES,dch,t} \leq 1 \quad \forall t \quad (68)$$
$$E_{TES,ini} = E_{TES,end} \quad (69)$$
$$E_{TES,t} = E_{TES,t-1} - \frac{H_{TES,dch,t}}{eff_{TES,dch}} + eff_{TES,ch}H_{TES,ch,t} - SLF_{TES}\left(\frac{E_{TES,t} + E_{TES,t-1}}{2}\right) \quad \forall t \neq 1 \qquad (70)$$
$$E_{TES,t} = E_{TES,ini} - \frac{H_{TES,dch,t}}{eff_{TES,dch}} + eff_{TES,ch}H_{TES,ch,t} - SLF_{TES}\left(\frac{E_{TES,t} + E_{TES,t-1}}{2}\right) \quad \forall t = 1 \qquad (71)$$

The operation of CES is subject to the constraints (72-(78). In this research, ice storage technology is used as CES in which electric power is used to produce ice, the ice is stored as cooling power storage and the ice is melted to produce cooling power when discharging is needed. Actually, electric power is the input of CES and cooling power is its output. Constraints (72) and (73) respectively bound charging and discharging power of CES to their allowable ranges. Constraints (74) ensure that at each time the energy level of CES does not violate its maximum allowable energy level and does not fall below its minimum acceptable energy level. Constraints (75) do not allow simultaneous charge and discharge of CES and constraint (76) ensures that the energy level of CES at the end of operation horizon equals its initial energy level. Constraints (77) and (78) express the energy level of CES at time t versus its energy level at the previous time period and consider charging loss, discharging loss and storage loss of CES.

$$u_{CES,ch,t}Pch_{CES,min} \le P_{CES,ch,t} \le u_{CES,ch,t}Pch_{CES,max} \quad \forall t \quad (72)$$
$$u_{CES,dch,t}Pdch_{CES,min} \le P_{CES,dch,t} \le u_{CES,dch,t}Pdch_{CES,max} \quad \forall t \ (73)$$
$$E_{CES,min} \le E_{CES,t} \le E_{CES,min} \quad \forall t \ (74)$$
$$u_{CES,ch,t} + u_{CES,dch,t} \le 1 \quad \forall t \quad (75)$$
$$E_{CES,ini} = E_{CES,end} \quad (76)$$
$$E_{CES,t} = E_{CES,t-1} - \frac{P_{CES,dch,t}}{eff_{CES,dch}} + COP_{CES}P_{CES,ch,t} - SLF_{CES}\left(\frac{E_{CES,t} + E_{CES,t-1}}{2}\right) \quad \forall t \ne 1 \qquad (77)$$
$$E_{CES,t} = E_{CES,ini} - \frac{P_{CES,dch,t}}{eff_{CES,dch}} + COP_{CES}P_{CES,ch,t} - SLF_{CES}\left(\frac{E_{CES,t} + E_{CES,t-1}}{2}\right) \quad \forall t = 1 \qquad (78)$$

The operation of P2G is subject to the constraints (79)-(86). P2G takes electric power during its charging and converts, stores and can discharge it as NG. The conversion of electricity into NG in P2G occurs in two stages; electrolysis and methanization. In electrolysis, the electricity breaks down water into hydrogen and oxygen and in the second stage, referred to as methanization, the produced hydrogen is combined with carbon dioxide to produce methane (NG) [28]. Constraints (79) and (80) respectively bound charging and discharging power of P2G to their allowable ranges. Constraints (81) ensure that at each time the energy level of P2G does not go beyond its maximum allowable energy level and does not fall below its minimum acceptable energy level. Constraints (82) do not allow simultaneous charge and discharge of P2G and constraint (83) ensures that the energy level of P2G at the end of operation horizon matches its initial energy level. Constraints (84) and (85) express the relation of energy level of P2G at two successive time periods and consider charging loss, discharging loss and storage loss of P2G [16, 18].

$$u_{P2G,ch,t}Pch_{P2G,min} \le P_{P2G,ch,t} \le u_{P2G,ch,t}Pch_{P2G,max} \quad \forall t \quad (79)$$
$$u_{P2G,dch,t}Pdch_{P2G,min} \le P_{P2G,dch,t} \le u_{P2G,dch,t}Pdch_{P2G,max} \quad \forall t \ (80)$$
$$E_{P2G,min} \le E_{P2G,t} \le E_{P2G,min} \quad \forall t \ (81)$$
$$u_{P2G,ch,t} + u_{P2G,dch,t} \le 1 \quad \forall t \quad (82)$$
$$E_{P2G,ini} = E_{P2G,end} \quad (83)$$
$$E_{P2G,t} = E_{P2G,t-1} - \frac{P_{P2G,dch,t}}{eff_{P2G,dch}} + eff_{P2G,ch}P_{P2G,ch,t} - SLF_{P2G}\left(\frac{E_{P2G,t} + E_{P2G,t-1}}{2}\right) \quad \forall t \ne 1 \qquad (84)$$
$$E_{P2G,t} = E_{P2G,ini} - \frac{P_{P2G,dch,t}}{eff_{P2G,dch}} + eff_{P2G,ch}P_{P2G,ch,t} - SLF_{P2G}\left(\frac{E_{P2G,t} + E_{P2G,t-1}}{2}\right) \quad \forall t = 1 \qquad (85)$$

3.2. Risk-averse IGDT-based UC in EH

Here, the risk-averse IGDT-based UC model is introduced which maximises robustness horizon in a way that the EH operation cost is guaranteed to not go beyond a critical/acceptable operation cost. To guarantee that EH operation cost is not worse than the specified target operation cost, it is sufficient to ensure that it is not worse than the target operation cost for the worst realization of uncertain input data. The worst realization of electric, thermal, cooling and BCS demands and electricity prices are respectively $\left(1+\alpha_{D_e}\right)\mathrm{D}_{\mathrm{e,t}}$, $\left(1+\alpha_{D_h}\right)\mathrm{D}_{\mathrm{h,t}}$,$\left(1+\alpha_{D_c}\right)\mathrm{D}_{\mathrm{c,t}}$, $(1+\alpha_{BCS})\mathrm{BCS_t}$ and $\left(1+\alpha_{\pi_{grid}}\right)\pi_{grid,t}$, while the worst realization of PV and wind power are

$(1-\alpha_{PV})\mathrm{PV_t}$ and $(1-\alpha_{Wind})\mathrm{Wind_t}$. This MINLP model hedges EH operator against the risk of unfavorable deviations of demands, PV/wind power and electricity prices.

$$max(\alpha) \quad (86)$$

$$\alpha = min\left(\alpha_{D_e}, \alpha_{D_h}, \alpha_{D_c}, \alpha_{BCS}, \alpha_{\pi_{grid}}, \alpha_{Wind}, \alpha_{PV}\right) \quad (87)$$

$$EHOC \leq EHOC_{cr} \quad (88)$$

$$EHOC_{cr} = (1+\beta).\overline{EHOC} \quad (89)$$

$$EHOC = \sum_t \left(1+\alpha_{\pi_{grid}}\right)\pi_{grid,t}.P_{grid,t} + \sum_t \pi_{NG,t}.P_{NG,t} + \sum_t \left(y_{boil,t}.SU_{boil} + z_{boil,t}.SD_{boil}\right) + \sum_t \left(y_{chp,t}.SU_{chp} + z_{chp,t}.SD_{chp}\right) + \sum_t \left(y_{EC,t}.SU_{EC} + z_{EC,t}.SD_{EC}\right) + \sum_t \left(y_{AC,t}.SU_{AC} + z_{AC,t}.SD_{AC}\right) + \sum_t \left(VLL_e.P_{shed,t} + VLL_h.H_{shed,t} + VLL_C.C_{shed,t}\right) + \mathrm{degc_{BES}} + \mathrm{degc_{TES}} + \mathrm{degc_{CES}} + \mathrm{degc_{P2G}} \quad (90)$$

$$P_{grid,t}eff_{TF} + P_{chp,t} + (1-\alpha_{Wind})\mathrm{Wind_t} + (1-\alpha_{PV})eff_{conv}\,\mathrm{PV_t} + P_{shed,t} + P_{BES,dch,t} \geq \left(1+\alpha_{D_e}\right)\mathrm{D_{e,t}} + (1+\alpha_{BCS})\mathrm{BCS_t} + P_{BES,ch,t} + P_{CES,ch,t} + P_{P2G,ch,t} + \frac{\mathrm{C_{EC,t}}}{\mathrm{COP_{EC}}} \quad \forall t \quad (91)$$

$$H_{boil,t} + H_{chp,t} + H_{shed,t} + P_{TES,dch,t} \geq \left(1+\alpha_{D_h}\right)\mathrm{D_{h,t}} + P_{TES,ch,t} + \frac{\mathrm{C_{AC},t}}{\mathrm{COP_{AC}}} \quad \forall t \quad (92)$$

$$\mathrm{C_{EC,t}} + \mathrm{C_{AC,t}} + C_{shed,t} + P_{CES,dch,t} \geq \left(1+\alpha_{D_c}\right)\mathrm{D_{c,t}} \quad (93)$$

Subject to constraints (14)-(17), (21)-(85)

3.3. Risk-seeking IGDT-based UC in EH

In this subsection, the risk-seeking IGDT-based UC model is introduced wherein the minimum opportunity horizon is determined in a way that a target operation cost becomes achievable. To make a target operation cost achievable, the best realization of uncertain input data must lead to the target cost. The best realization of electric, thermal, cooling and BCS demands and electricity prices are respectively $\left(1-\alpha_{D_e}\right)\mathrm{D_{e,t}}$, $\left(1-\alpha_{D_h}\right)\mathrm{D_{h,t}}$,$\left(1-\alpha_{D_c}\right)\mathrm{D_{c,t}}$, $(1-\alpha_{BCS})\mathrm{BCS_t}$ and $\left(1-\alpha_{\pi_{grid}}\right)\pi_{grid,t}$, while the best realization of PV and wind power are respectively $(1+\alpha_{PV})\mathrm{PV_t}$ and $(1+\alpha_{Wind})\mathrm{Wind_t}$. In this model, EH operator aims to benefit from favorable deviations of demands, PV/wind power and electricity prices.

$$min(\alpha) \quad (94)$$

$$\alpha = max\left(\alpha_{D_e}, \alpha_{D_h}, \alpha_{D_c}, \alpha_{BCS}, \alpha_{\pi_{grid}}, \alpha_{Wind}, \alpha_{PV}\right) \quad (95)$$

$$EHOC \geq EHOC_{targ} \quad (96)$$

$$EHOC_{targ} = (1-\beta).\overline{EHOC} \quad (97)$$

$$EHOC = \sum_t \left(1-\alpha_{\pi_{grid}}\right)\pi_{grid,t}.P_{grid,t} + \sum_t \pi_{NG,t}.P_{NG,t} + \sum_t \left(y_{boil,t}.SU_{boil} + z_{boil,t}.SD_{boil}\right) + \sum_t \left(y_{chp,t}.SU_{chp} + z_{chp,t}.SD_{chp}\right) + \sum_t \left(y_{EC,t}.SU_{EC} + z_{EC,t}.SD_{EC}\right) + \sum_t \left(y_{AC,t}.SU_{AC} + z_{AC,t}.SD_{AC}\right) + \sum_t \left(VLL_e.P_{shed,t} + VLL_h.H_{shed,t} + VLL_C.C_{shed,t}\right) + \mathrm{degc_{BES}} + \mathrm{degc_{TES}} + \mathrm{degc_{CES}} + \mathrm{degc_{P2G}} \quad (98)$$

$$P_{grid,t}eff_{TF} + P_{chp,t} + (1+\alpha_{Wind})\mathrm{Wind_t} + (1+\alpha_{PV})eff_{conv}\,\mathrm{PV_t} + P_{shed,t} + P_{BES,dch,t} = \left(1-\alpha_{D_e}\right)\mathrm{D_{e,t}} + (1-\alpha_{BCS})\mathrm{BCS_t} + P_{BES,ch,t} + P_{CES,ch,t} + P_{P2G,ch,t} + \frac{\mathrm{C_{EC,t}}}{\mathrm{COP_{EC}}} \quad \forall t \quad (99)$$

$$H_{boil,t} + H_{chp,t} + H_{shed,t} + P_{TES,dch,t} = \left(1-\alpha_{D_h}\right)\mathrm{D_{h,t}} + P_{TES,ch,t} + \frac{\mathrm{C_{AC},t}}{\mathrm{COP_{AC}}} \quad \forall t \quad (100)$$

$$\mathrm{C_{EC,t}} + \mathrm{C_{AC,t}} + C_{shed,t} + P_{CES,dch,t} = \left(1-\alpha_{D_c}\right)\mathrm{D_{c,t}} \quad (101)$$

Subject to constraints (14)-(17), (21)-(85)

4. Results and analysis

In this section, the results of UC in EH are presented in different scenarios. An EH with CHP unit, boiler, electric chiller, absorption chiller, EES, TES, CES, P2G, transformer, PV module with its DC/AC converter, wind turbine and BCS is studied. The scheme of the studied EH is shown as Fig.1 in which the inputs are the electricity purchased from power grid and NG purchased from NG network and the outputs are electric, heat and cooling demands. The proposed MILP model is solved with CPLEX solver in general algebraic modeling system (GAMS) which guarantees the achievement of the global optimum; only in the case that in risk-averse IGDT all uncertainties are simultaneously considered, the resulted MINLP model is solved with DICOPT solver. Operation horizon is 24 hours and operation resolution is 1 hour. Throughout the paper, hour (h), $ and kWh are the default units for time, cost and power.

The data of boiler, CHP, chillers and storage systems are respectively tabulated as Tables 1-4. Day-ahead forecasts of EH demands, PV and wind power, and electricity prices can be found as figures 3-5 [29]. Value of lost electric, thermal and cooling loads are respectively 30 $/kWh, 15 $/kWh and 10 $/kWh. Maximum purchasable electric power from grid (transformer capacity) and maximum purchasable natural gas are respectively 1000 kW and 900 kW. Transformer efficiency is 0.95 and the efficiency of PV's DC/AC converter is 0.9. Capacities of PV and wind units are respectively 80 kW and 100 kW, operation cost of PV and wind units are assumed zero and they are owned by EH owner. Peak electric demand (excluding BCS), thermal demand and cooling demand are respectively 800 kW, 400 kW and 250 kW. The peak of electricity price is 10 cents/kWh and the price of NG is 3 cents/kWh.

Table 1. boiler data

Minimum power	Maximum power	Ramp-up limit	Ramp-down limit	Start-up cost	Shut-down cost	efficiency
30	320	50	290	20	20	0.8

Table 2. CHP data

Power efficiency	Thermal efficiency	Power ramp-up limit	Power ramp-down limit	Heat ramp-up limit	Heat ramp-down limit	Start-up cost	Shut-down cost	A_p	$A_□$	B_p	$B_□$	C_p	$C_□$	D_p	$D_□$
0.45	0.35	100	240	50	200	15	15	290.4	0	243.2	196	54	138	64	150

Table 3. Electric and absorption chiller data

Cooling unit	Minimum power	Maximum power	Ramp-up limit	Ramp-down limit	Start-up cost	Shut-down cost	COP
Electric chiller	35	150	40	115	5	10	3
Absorption chiller	40	190	40	150	4	4	0.8

Table 4.Data of storage systems

Storage system	Minimum charging power	Maximum charging power	Minimum discharging power	Maximum discharging power	Charging efficiency	Discharge efficiency	Minimum energy	Maximum energy	Initial energy	Storage loss factor	Replacement cost	Charge-discharge capacity
BES	10	50	10	50	0.9	0.9	20	200	20	0.01	20000	1e7
TES	10	40	10	40	0.9	0.9	20	150	20	0.01	5000	1e7
CES	10	30	10	30	2	0.95	20	100	20	0.01	5000	5e7
P2G	0	30	0	30	0.9	0.9	0	150	0	0.01	5000	5e7

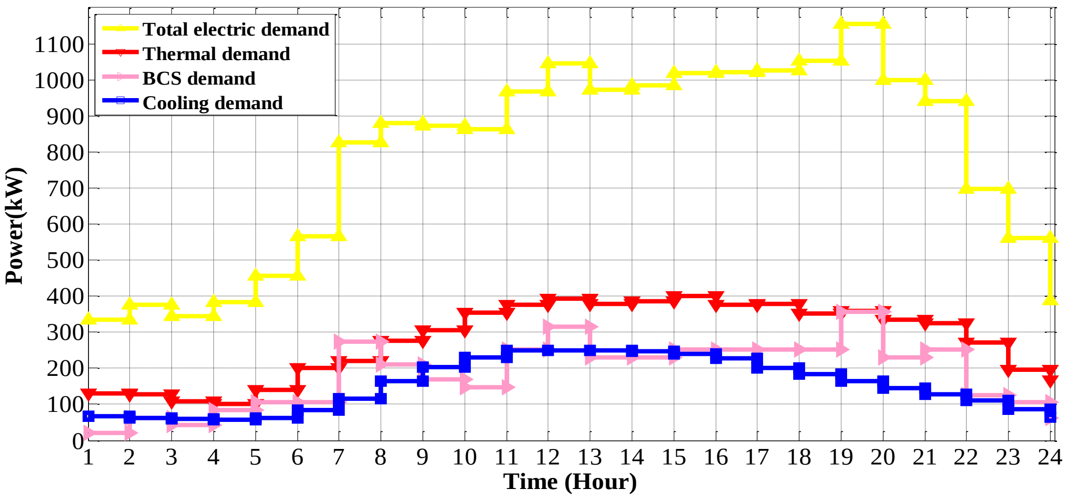

Fig.3. EH demands during scheduling horizon

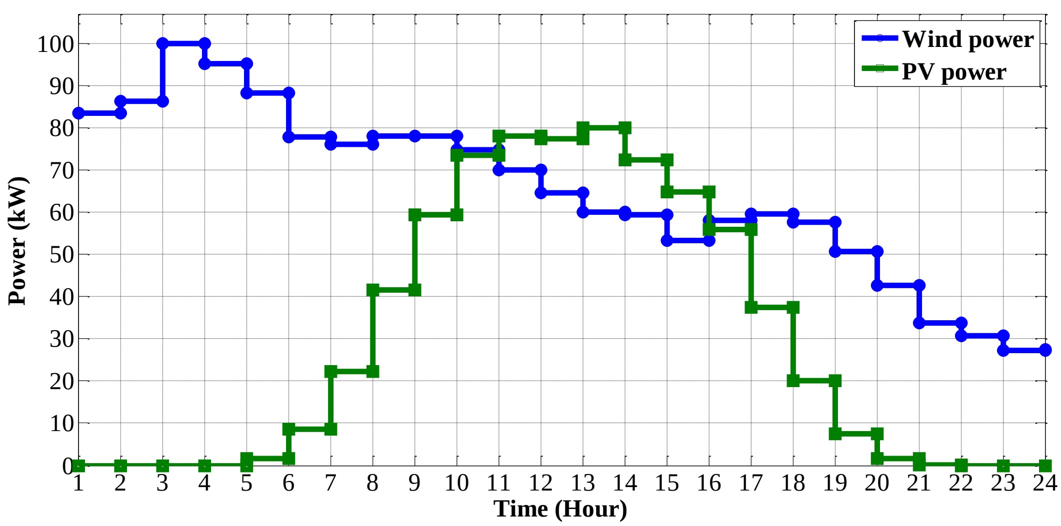

Fig.4. Forecasted PV and wind power

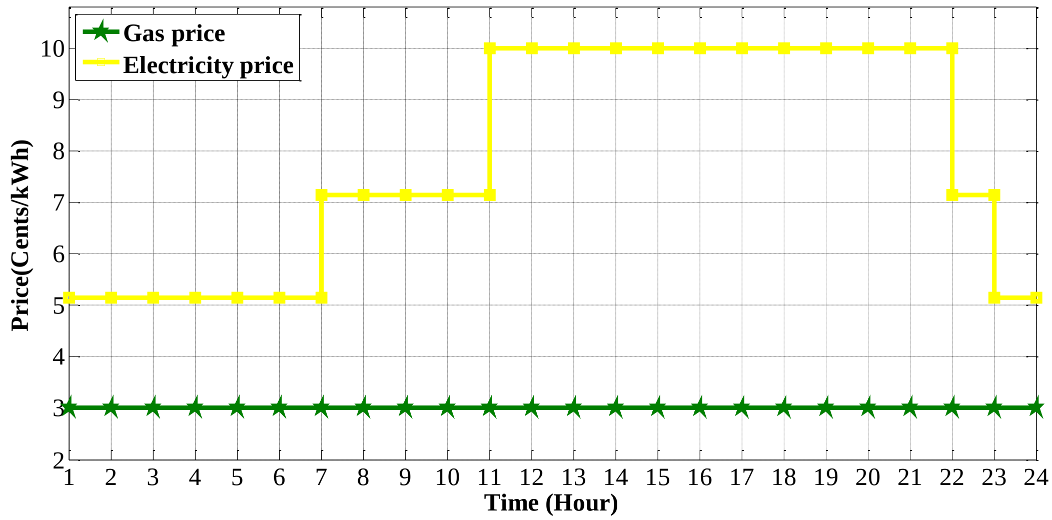

Fig.5. Electricity and natural gas price

In this section, the results are presented as six subsections; in 4.1, UC in EH is solved ignoring the uncertainties of EH demands, PV/wind power and electricity prices. In 4.2, the sensitivity of EH operation cost with respect to different sets of uncertain input data is determined; In 4.3, the uncertainties are taken into account and UC in EH is solved from the perspective of a risk-averse decision maker and a robust decision is made for the specified critical operation cost. In 4.4, the uncertainties are taken into account and UC in EH is solved from the perspective of an optimist decision maker who targets to achieve a prespecified daily operation cost. In 4.5, the decision variables are compared in risk-neutral, risk-averse and risk-seeking scenarios. Finally, in 4.6 the effect of critical cost deviation factor/target cost deviation factor on decision variables is investigated.

4.1. Day-ahead EH scheduling without uncertainties

In this scenario, UC in EH is done without considering the uncertainties of demands, wind and PV power and electricity prices. As per the results, in this scenario, EH operation cost is $1605.076 including $1166.694 as cost of purchased electricity, $433.5409 as the cost of purchased NG, $4 as start-up and shut-down costs and $0.8416 as storage degradation costs. No load shedding is needed for electric, thermal and cooling demands. The purchased electricity and NG can be seen in Fig.6. The schedule of CHP, boiler, electric chiller, absorption chiller, PV module and wind turbine have been illustrated as Fig.7 and the schedule of storage systems have been illustrated as Fig.8. Shadow prices of electricity, heat, cooling energy and NG can be seen as Fig.9.

As per the figures, the schedule of electric/thermal/cooling resources depends on their efficiencies and operational constraints and the variations of electric/thermal/cooling demands. Due to the coupling of electric, thermal and cooling components, any change in electric/thermal/cooling demand may change the operating point of all electric/thermal/cooling components. From the perspective of the dispatch of electric power, at low electric demand hours 1-5, CHP is operated at its minimum power vertex, i.e., point C with $P = 54\ kW, H = 138\ kW$ and the remaining electric power is either produced by wind/PV units or imported from power grid. For instance, at hour 1 when electric demand and BCS demand are respectively 314.72 kW and 21 kW, BES and CES are respectively charged with 10 kW and 11.288 kW and $\frac{35\ kW}{3} = 11.67\ kW$ is consumed by electric chiller, wind turbine and CHP unit respectively produce 83.39 kW and 54 kW and 243.4578 kW is imported from power grid. At hour 6 with an increase in electric demand, CHP's operating point changes to a point with higher electric power as $P = 143.2\ kW, H = 165.3446\ kW$. At hour 8 with further increase in electric and heat demands, CHP's operating point is changed into B as its maximum heat point with $P = 243.2\ kW, H = 196\ kW$. CHP continues its operation at this point until hour 23 when a sharp decrease in electric power demand changes its operating point to the minimum power point (C).

From the perspective of the dispatch of thermal power, at low thermal demand hours 1-5 when CHP operates at its minimum electric power point and produces 138 kW thermal power, boiler supplies the remaining thermal demand of EH. For instance, at hour 1 when thermal demand is 131.28 kW and absorption chiller needs $\frac{40\ kW}{0.8}$=50 kW thermal power, TES is charged with 10 kW, CHP and boiler respectively produce 138 kW and 53.28 kW to keep the balance of thermal power in the hub. From hour 6, with increase in thermal and electric demands, CHP switches to its maximum heat operating point. At hour 23 with the sharp decrease in thermal and electric demands, CHP only produces 138 kW and the boiler respectively produces 57.32 kW and 30 kW at hours 23 and 24. The interesting point is that at hour 24 the marginal price of heat is zero and the increase in heat demand will not increase the operation cost of EH, because the thermal demand of EH at this time is less than the sum of minimum thermal power of CHP and boiler.

From the perspective of cooling power dispatch, at low cooling demand hours 1-5, the cooling demand of EH is lower than sum of minimum cooling power of electric chiller and absorption chiller, so both chillers are operated at their minimum cooling power to avoid shut-down and start-up costs and the marginal price of cooling power is zero as the increase in cooling demand adds nothing to EH operation cost. For instance, at hour 1 when cooling demand is as low as 66.7 kW, electric chiller and absorption chiller respectively produce 35 kW and 40 kW and the 11.2882 kW is used to charge CES. At hours 6-8, with increase in cooling demand, the minimum power of chillers is no longer sufficient to supply it, so the cooling power of electric chiller as the cheaper cooling power resource is increased, while absorption chiller is still operated at minimum power. At hour 9, with the sharp increase in cooling demand, power of electric chiller reaches its upper limit and absorption chiller performs as the marginal source of cooling power.

At hour 18 with decrease in cooling demand, cooling power of absorption chiller drops to its minimum and electric chiller as the marginal cooling power resource produces 143.95 kW. At hour 19 with further decrease in cooling demand, it is no longer economical to keep absorption chiller committed, so it is shut-down at this hour. At hours 19-24, electric chiller and CES supply cooling demand of EH. The increase in marginal price of cooling power at hours such as 19 is due to the high marginal prices of electricity at those hours.

As per Fig.8, at low electric demand hours 1 and 3-6 BES is in charging mode and at high electric demand hours 11-14, it is discharged. TES is charged at low heat demand hours 1, 3-5, 7-9 and is discharged at high heat demand hours 10, 12, 14-15. CES is also charged at low cooling demand hours 1, 10 and is discharged at high cooling demand hours 8, 9, 11-13, 19. Through charging at low demand hours and discharge at high demand hours, storage systems reduce operation cost of EH.

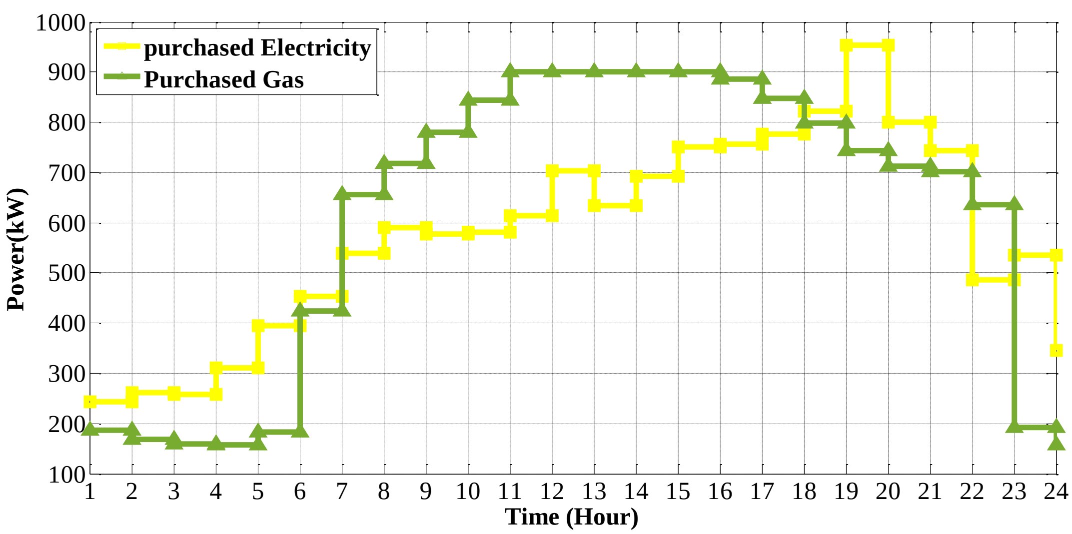

Fig.6.Purchased electricity and natural gas

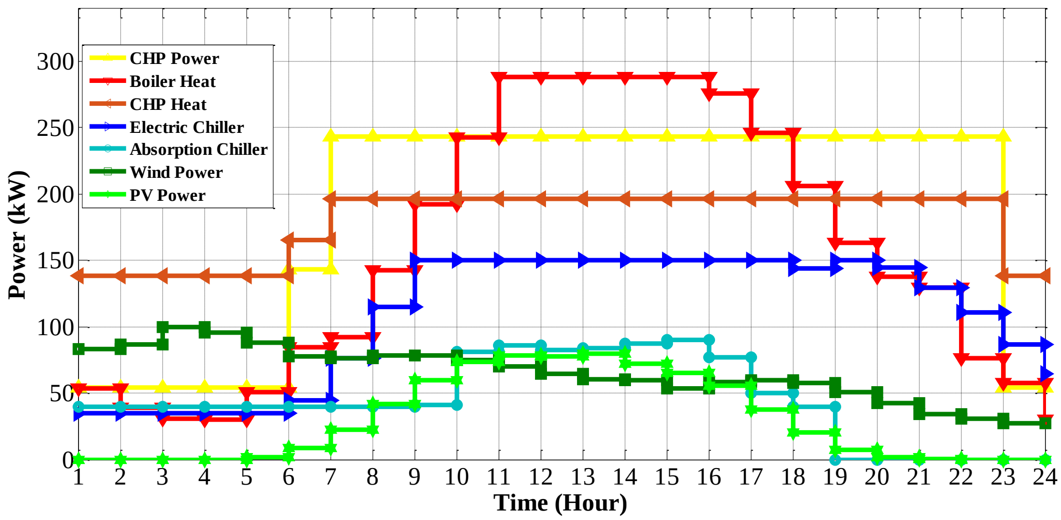

Fig.7. Power of CHP, boiler, PV, wind, PV and chillers

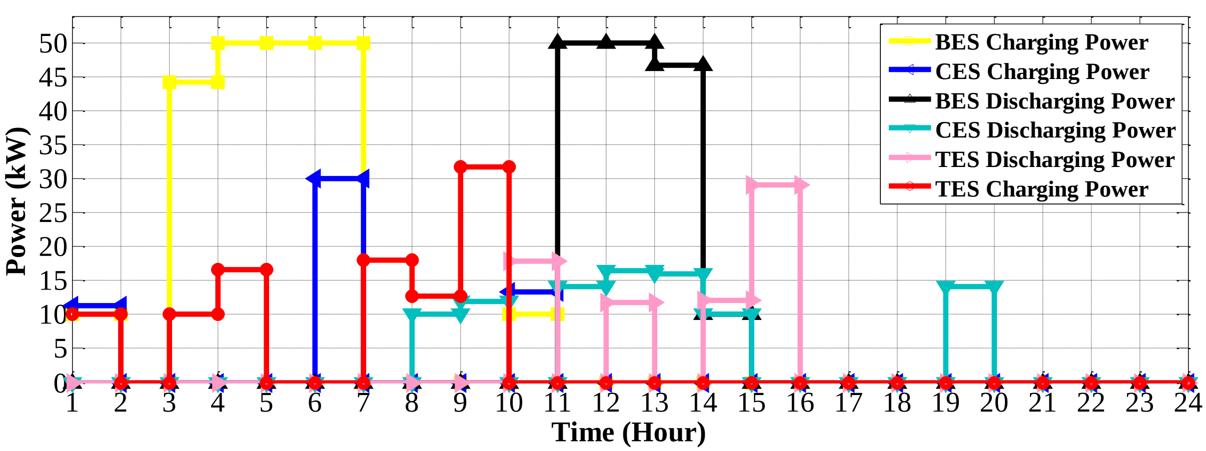

Fig.8. Charging and discharging power of storage systems

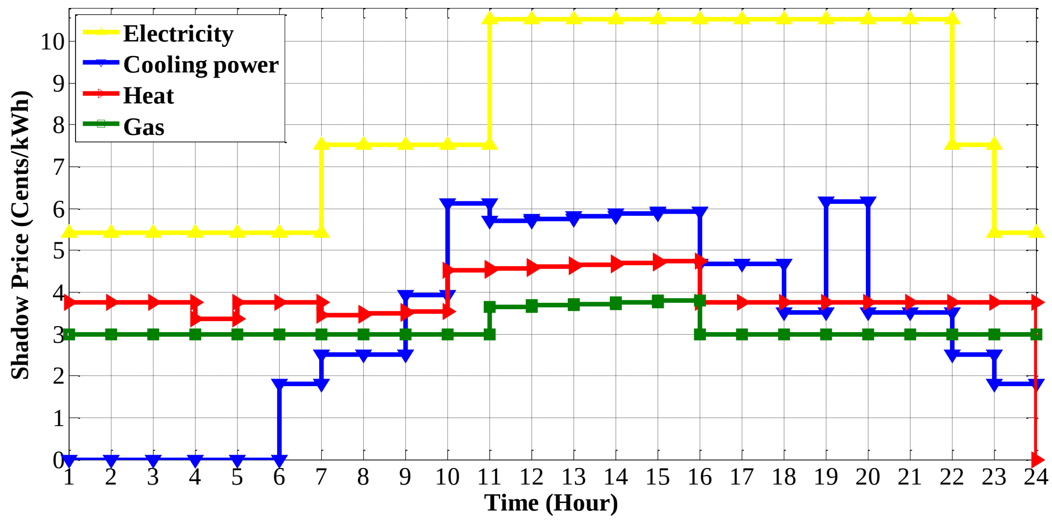

Fig.9. Shadow prices of electricity, thermal, cooling energy and natural gas

4.2. Sensitivity analysis of EH operation cost with respect to changes in different sets of input data

In this scenario, the sensitivity of EH operation cost with respect to different sets of input data is investigated and the results are tabulated as Table 5. The notation K at the first column indicates that the corresponding set of input data is multiplied by K. The results show that at most of K values, EH operation cost is more sensitive to its electric demands, electricity prices, NG prices and BCS demands and is less sensitive with respect to thermal and cooling demands, PV and wind power. The results show that 10, 20, 30 and 40 percent decrease in electric demand respectively decrease EH operation cost by 7.9%, 15.81%, 23.71% and 31.62%. On the other hand, 10, 20, 30 and 40 percent increase in electric demand respectively increase EH operation cost by 7.92%, 38.76%, 195% and 1055.6%. The severe increase in EH operation cost at higher K values of demands is due to the high demand shed costs imposed to EH. The sensitivity of EH operation cost with respect to different sets of input data has been illustrated as Fig.10.

Table 5. Sensitivity analysis of EH operation cost with respect to different input data

K	operation cost with changes in electric demand	operation cost with changes in BCS demand	operation cost with changes in thermal demand	operation cost with changes in cooling demand	operation cost with changes in wind power	operation cost with changes in PV power	operation cost with changes in electricity price	operation cost with changes in gas price
0.6	1097.587	1443.42	1512.158	1544.677	1653.581	1629.366	1126.094	1398.455
0.7	1224.459	1483.834	1532.537	1565.234	1641.454	1623.294	1250.338	1453.113
0.8	1351.332	1524.248	1555.736	1578.072	1629.328	1617.221	1370.643	1506.933
0.9	1478.204	1564.662	1580.391	1590.842	1617.202	1611.149	1488.235	1557.353
1	1605.076	1605.076	1605.076	1605.076	1605.076	1605.076	1605.076	1605.076
1.1	1732.164	1645.49	1633.934	1621.773	1592.95	1599.004	1717.993	1648.261
1.2	2227.149	1686.065	2680.84	1799.015	1580.824	1592.931	1828.614	1691.102

1.3	4743.24	1726.908	4936.377	3351.337	1568.698	1586.859	1937.490	1732.657
1.4	18548.429	1771.941	7920.778	4982.404	1556.572	1580.787	2044.913	1771.667

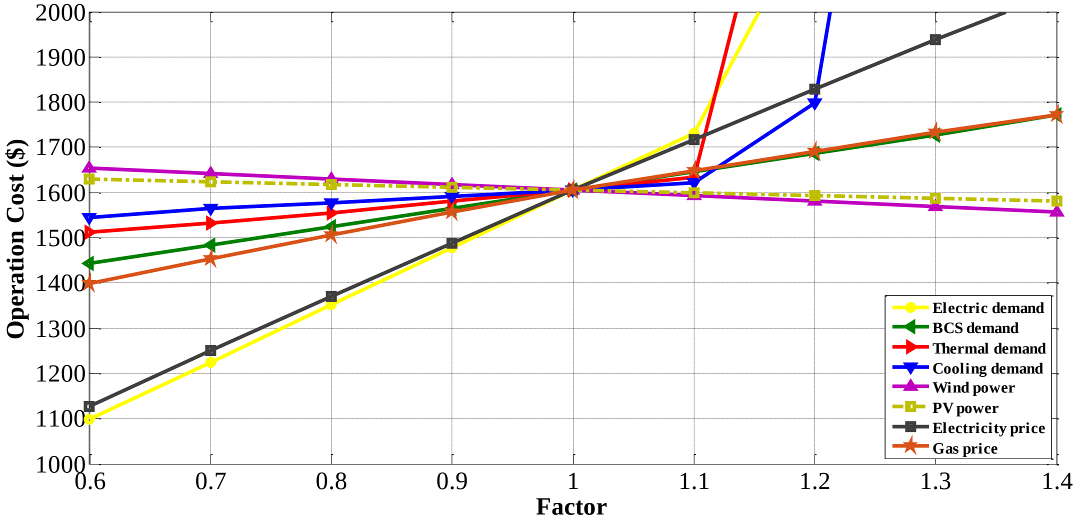

Fig.10. Sensitivity analysis of EH operation cost with respect to different input data

4.3. Risk-averse day-ahead EH scheduling

In the UC for the studied EH, there exists 7 sets of uncertain input data including 7×24=168 uncertain data. In the first scenario (subsection 4.1), UC was solved with forecasted values of demands, PV and wind power and electricity prices, ignoring their uncertainties. However, the results in 4.2 indicated the significant sensitivity of EH operation cost with respect to uncertain input data especially electric demand, BCS demand and electricity prices, so unfavorable deviations of demands, PV/wind power and electricity prices from forecasted values may result in operation costs significantly higher than that achieved in 4.1 ($1605.076). In this subsection, a robust decision making strategy is used that guarantees the achievement of an acceptable/critical operation cost. No deviation of demands, PV/wind power and electricity prices within robustness horizon may lead to an operation cost higher than the pre-specified critical/acceptable operation cost.

In risk-averse IGDT, the objective is not to minimise EH operation cost, but it is to maximise the robustness horizon in a way that operation cost does not exceed critical operation cost and the operational costs are met at the worst realization of demands, PV/wind power and electricity prices. Such a robust decision-making hedges EH operator against the risk of unfavorable deviations of demands, PV/wind power and electricity prices from forecasted values, although the robustness is achieved at a cost and increases the operation cost of EH.

In this subsection, firstly, risk-averse IGDT-based decision making is done in EH considering the uncertainties of a single set of input data. This is to see how robustness horizon changes with uncertainties of different sets of input data. As per the results in Fig.11, with critical cost deviation factor of 0.01 (or critical operation cost of $1621.1), the maximum robustness horizon considering the uncertainties of electric demands, BCS demands, thermal demands, cooling demands, PV power, wind power and electricity prices are respectively 0.0126, 0.0397, 0.0597, 0.097, 0.264, 0.132 and 0.014. For instance, it shows that any deviation of electric demands within a 1.26% band centered at forecasted electric demands would not lead to an operation cost higher than $1621.1. The results indicate that the deviations of electric demands and electricity prices is crucial in EH operation. For instance, with critical cost deviation factor of 0.1, the robustness horizon for electric demands is 0.1262 meaning that the EH operation cost would not be more than 10% higher than nominal operation cost if the electric demands deviate within a 12.62% band centered at their forecasted values or the robustness horizon for electricity prices is 0.143 meaning that the EH operation cost would not be more than 10% higher than nominal operation cost if the electricity prices deviate within a 14.3% band centered at forecasted electricity prices, however at critical cost deviation factor of 0.1, the robustness horizons of other sets of uncertain input data are higher than 15% and it is clear that forecast error of those data is not more than 15%.

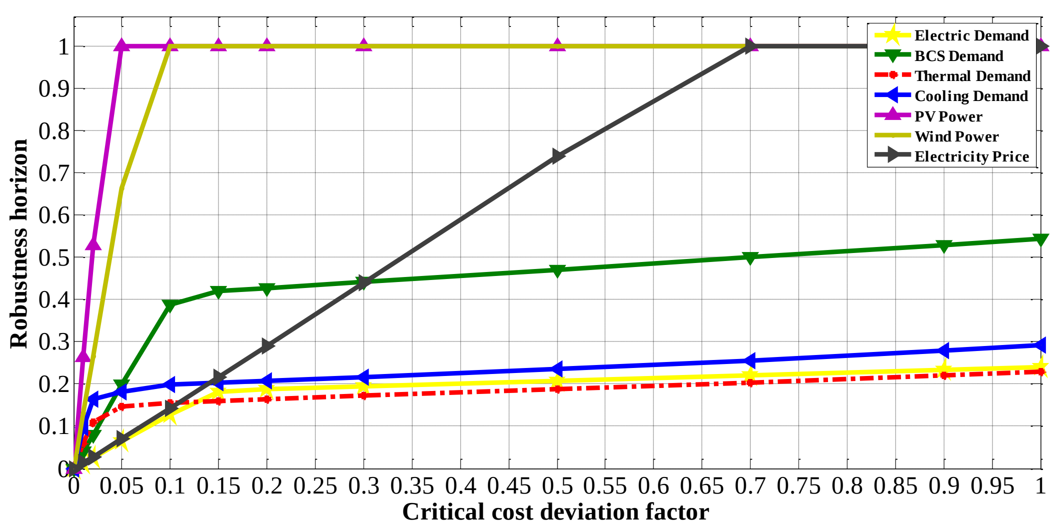

Fig.11. Tolerable deviation of different input data to guarantee a certain critical operation cost

Here, risk-averse IGDT is used while all uncertain input data are simultaneously considered. As mentioned in 3.2, due to the incorporation of “minimum” operator, this model is MINLP and solved with DICOPT solver. The achievement of the global optimum is no longer guaranteed. A new set of constraints has been added to the model according to which the uncertainty horizon of no set of input data can be lower than a pre-specified limit. As per the results, tabulated in table 6, EH operation cost is guaranteed not to be higher than \$1637.2, if electric, thermal, cooling and BCS demands, electricity prices and PV power values deviate within a 1% band centered at their forecasted values and wind power values deviate within a 5.43% band centered at their forecasted values. As another example, EH operation cost is guaranteed not to be higher than \$1685.3, if electric, thermal, cooling and BCS demands and electricity prices deviate within a 5% band centered at their forecasted values.

Table 6. Robustness horizon for different critical operation cost deviation factors

β	Critical operation cost	α_{D_e}	α_{BCS}	α_{D_h}	α_{D_c}	α_{PV}	α_{wind}	$\alpha_{\pi_{grid}}$
0	1605.1	0	0	0	0	0	0	0
0.05	1621.1	0.01	0.01	0.01	0.01	0.756	0.01	0.01
0.1	1637.2	0.01	0.01	0.01	0.01	0.01	0.543	0.01
0.2	1685.3	0.05	0.05	0.05	0.05	1	0.698	0.05
0.3	1765.6	0.05	0.112	0.05	0.102	1	1	0.105
0.4	1845.8	0.05	0.112	0.05	0.102	1	1	0.219
0.5	1926.1	0.05	0.112	0.05	0.102	1	1	0.334
0.6	2086.6	0.1	0.1	0.1	0.1	0.265	0.1	0.1
0.7	2407.6	0.1	0.1	0.1	0.1	0.1	0.222	0.159
0.8	2728.6	0.1	0.1	0.1	0.1	0.1	0.222	0.275
0.9	3049.6	0.1	0.1	0.1	0.1	0.1	0.222	0.392
1	3210.2	0.1	0.1	0.1	0.1	0.1	0.222	0.509

4.4. Risk-seeking day-ahead EH scheduling

In this subsection, the decision in UC is made from the perspective of a risk-seeker optimist decision maker and the opportunity horizons for different target cost deviation factors have been tabulated as Table 7. In this model, the objective is not to minimise operation cost, but it is to find the minimum required deviations of different uncertain input data that makes a target operation cost achievable. The optimist decision maker hopes to benefit from favorable deviations of uncertain input data and achieve the target operation cost. The target cost deviation factor determines the risk-seeking degree of the decision maker. The more risk-seeker an EH operator is, the higher target cost deviation factor he/she chooses. For instance, choosing target cost deviation factor of 0.1 means that decision maker aims to find decision variables and opportunity horizons that makes possible the achievement of an operation cost 10% less than nominal operation cost. As per table 7, for target cost of \$1573, i.e., target cost deviation factor of 2%, electric demands must favorably deviate within a 2.5% band centered at their forecasted values or BCS demands must favorably deviate within a 7.94% band centered at their forecasted values.

Table 7. Comparison of the required deviation of input data to maintain the chance of achieving a certain target cost

ρ	Target operation cost	Electric demand	BCS demand	Thermal demand	Cooling demand	Wind power	PV power	Electricity price

0	1605.1	0	0	0	0	0	0	0
0.01	1589.0	0.01265	0.040	0.0643	0.1133	0.1323	0.2643	0.014
0.02	1573.0	0.025	0.0794	0.1298	0.2416	0.265	0.5286	0.0275
0.05	1524.8	0.0632	0.198	0.3373	0.5886	0.6618	NA	0.069
0.1	1444.6	0.1265	0.397	0.8465	NA	NA	NA	0.1373
0.15	1364.3	0.1898	0.596	NA	NA	NA	NA	0.205
0.2	1284.1	0.2530	0.794	NA	NA	NA	NA	0.2728
0.25	1203.8	0.316	0.993	NA	NA	NA	NA	0.3375
0.3	1123.6	0.379	NA	NA	NA	NA	NA	0.4020
0.4	963.0	0.506	NA	NA	NA	NA	NA	0.5233

4.5. Effect of risk-aware decision-making on decision variables

In this subsection, the effect of risk-aware decision making on decision variables of UC problem in EH is investigated, considering the uncertainty of electricity prices and the results have been presented as Table 8 and figures 12-14. According to the figures 12-14, at hours 1-7 and 22-24, which are light load hours of electricity, risk-averse EH operator purchases significantly less electricity than risk-neutral EH operator and risk-seeking EH operator in order to hedge himself against risk of electricity price deviations. For risk-seeking operator, it is not reasonable to purchase higher electricity in the hope of less electricity price, because it does not need higher electric power at these low-demand hours, therefore, at these hours, risk-neutral operator and risk-seeker operator approximately purchase the same amount of electricity from grid.

On the other hand, at hours 8-21 with heavy electricity demand, risk-seeking EH operator purchases higher electricity than risk-neutral EH operator and risk-averse EH operator in the hope of a low electricity price and decreasing its operation cost. At these hours, risk-averse EH operator cannot significantly reduce its electricity purchase, because purchased electricity and CHP power are the only tools to supply electric demand of EH and CHP is already working with a high power output, so in order to supply its electric demand, EH must buy a high amount of electricity from grid.

Figs. 13-14 approve that at low electric power demand hours 1-7, risk-averse EH operator increases its NG purchase, feeds more NG into CHP and thereby produces more electricity with CHP to compensate the fall in purchase from electric grid.

Table 8. Comparison of decision variables for risk-neutral, risk-averse and risk-seeking decision making considering electricity price uncertainty

Hour	Purchased electricity β=0 (risk-neutral decision making)	Purchased gas β=0(risk-neutral decision making)	CHP power β=0(risk-neutral decision making)	Purchased electricity β=0.1(risk-averse decision making)	Purchased gas β=0.1(risk-averse decision making)	CHP power β=0.1(risk-averse decision making)	Purchased electricity ρ=0.1(risk-seeking decision making)	Purchased gas ρ=0.1(risk-seeking decision making)	CHP power ρ=0.1(risk-seeking decision making)
1	243.4578	186.6	54	163.5199	326.2577	129.941	242.1018	186.6	54
2	261.3018	169.05	54	142.8284	407.6104	166.5497	261.3018	169.05	54
3	258.5358	158.6	54	152.5014	381.3504	154.7327	259.939	158.6	54
4	310.5649	157.5	54	230.3524	326.8376	130.2019	310.5649	157.5	54
5	394.5228	183.5	54	209.0471	549.0598	230.2019	394.5228	183.5	54
6	454.0621	423.9415	143.2	348.7989	607.8444	243.2	470.0357	392.0266	125.8458
7	539.6951	655.7753	243.2	539.3256	634.8398	243.2	557.9627	601.2795	225.8458
8	589.3758	718.2753	243.2	589.5502	697.3398	243.2	589.3758	702.3444	243.2
9	577.3971	780.7753	243.2	577.3971	759.8398	243.2	587.3842	762.2405	243.2
10	581.5204	843.2753	243.2	567.4476	819.0366	243.2	556.9213	824.7405	243.2
11	613.8042	900	243.2	613.8042	881.5366	243.2	613.8042	887.2405	243.2
12	702.9773	900	243.2	702.9773	900	243.2	702.9773	900	243.2
13	633.1504	900	243.2	633.1504	900	243.2	654.2843	896.7912	243.2
14	692.8021	900	243.2	692.8021	900	243.2	703.3284	900	243.2
15	750.1832	900	243.2	750.1832	900	243.2	750.1832	900	243.2
16	756.8779	885.0851	243.2	756.8779	885.0851	243.2	771.5382	885.0851	243.2
17	777.2105	847.8148	243.2	777.2105	847.8148	243.2	777.2105	832.1898	243.2
18	822.1046	797.6444	243.2	822.1046	797.6444	243.2	822.1046	797.6444	243.2
19	953.0547	743.8944	243.2	943.9846	806.3944	243.2	953.0547	743.8944	243.2
20	799.3421	712.4444	243.2	785.307	774.9444	243.2	799.3421	712.4444	243.2
21	743.3242	702.1444	243.2	729.2891	764.6444	243.2	743.3242	702.1444	243.2
22	485.4421	635.8944	243.2	471.407	698.3944	243.2	485.4421	635.8944	243.2
23	535.2404	191.65	54	322.0474	602.0944	243.2	535.2404	191.65	54
24	344.8088	157.5	54	164.3774	516.7625	215.6681	344.8088	157.5	54

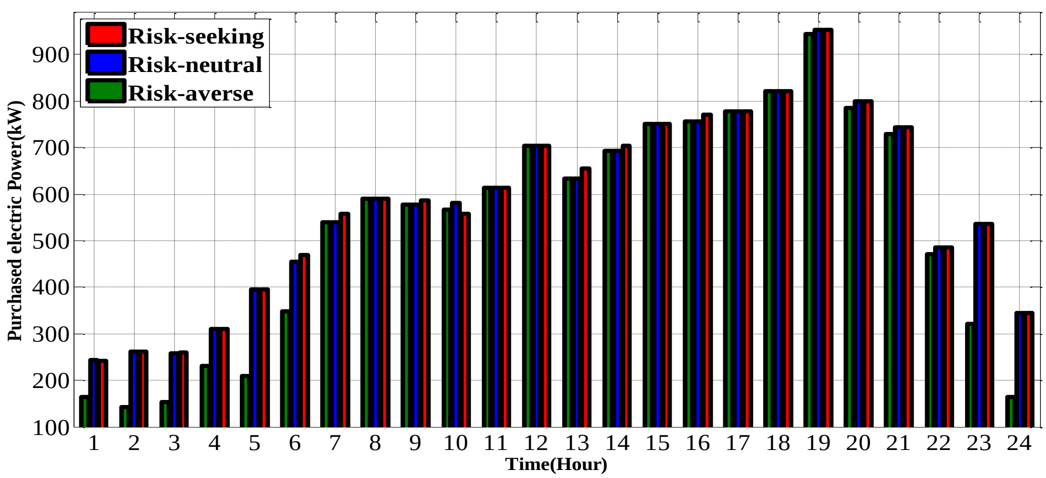

Fig.12. Purchased electricity for risk-neutral, risk-averse and risk-seeking decision making considering electricity price uncertainty

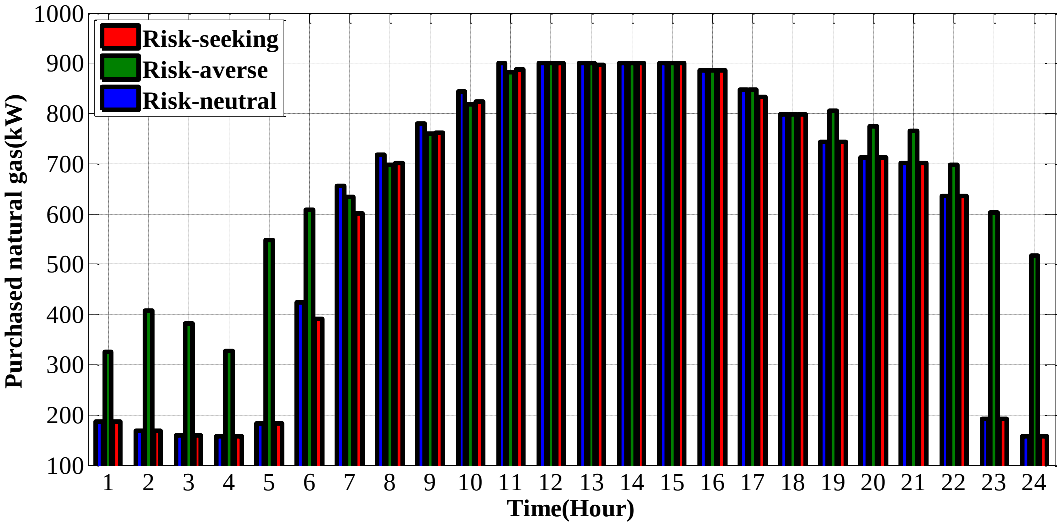

Fig.13. Purchased gas for risk-neutral, risk-averse and risk-seeking decision making considering electricity price uncertainty

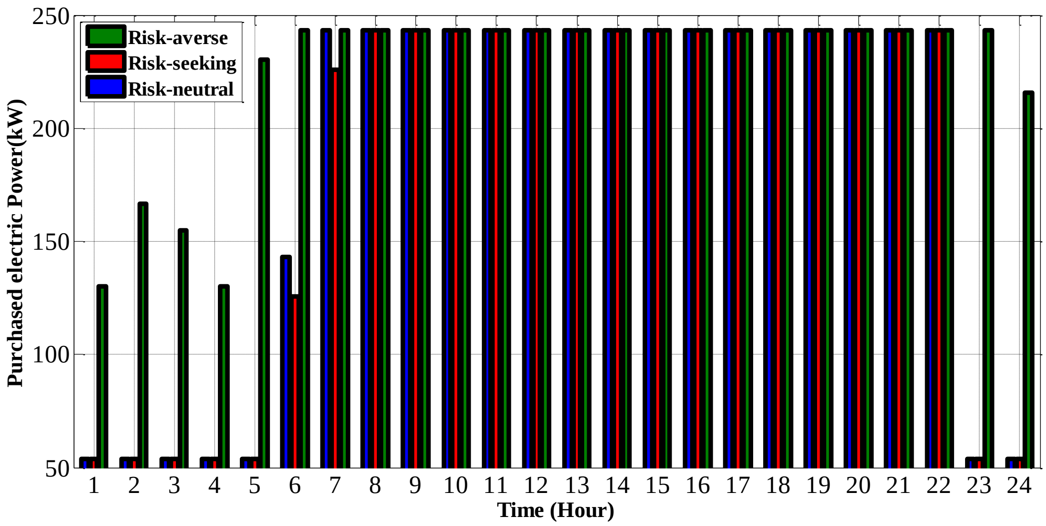

Fig.14. CHP power for risk-neutral, risk-averse and risk-seeking decision making considering electricity price uncertainty

4.6. Effect of critical /target cost deviation factors (β and ρ) on decision variables

In this sub-section, first the effect of critical cost deviation factor on decision variables in risk-averse IGDT is investigated considering the uncertainties of electricity prices. As per Table 9 and figures 15-17, with increase in critical operation cost deviation factor and critical operation cost, purchased electricity from grid decreases and purchased NG, NG fed into CHP and CHP power increases. This is reasonable because in order to hedge himself against the risk of increase in electricity price, EH operator decreases the import from power grid; instead increases the import from NG network and compensates power purchase with feeding more NG into CHP and generation of more electric power from CHP unit. Actually, the risk-averse EH operator sees the electricity price and import from power grid as a threat that may increase its operation cost, so decreases the share of power grid in supplying its electric demands. Table 9 and figures 15-17 compare decision variables for critical cost deviation factors 0.1 and 0.25.

Table 9. Effect of critical operation cost on decision variables in risk-averse scheduling considering electricity price uncertainty

Hour	Purchased electricity $\beta = 0.1$	Purchased gas $\beta = 0.1$	CHP power $\beta = 0.1$	Purchased electricity $\beta = 0.25$	Purchased gas $\beta = 0.25$	CHP power $\beta = 0.25$
1	163.5199	326.2577	129.941	35.49871	596.5248	251.5611
2	142.8284	407.6104	166.5497	55.14665	592.7163	249.8474
3	152.5014	381.3504	154.7327	52.50327	592.4576	249.7309
4	230.3524	326.8376	130.2019	102.6261	596.482	251.5419
5	209.0471	549.0598	230.2019	195.3649	577.9444	243.2
6	348.7989	607.8444	243.2	348.7989	607.8444	243.2
7	539.3256	634.8398	243.2	539.3256	634.8398	243.2
8	589.5502	697.3398	243.2	589.5502	697.3398	243.2
9	577.3971	759.8398	243.2	577.3971	759.8398	243.2
10	567.4476	819.0366	243.2	567.4476	822.3398	243.2
11	613.8042	881.5366	243.2	612.328	884.8398	243.2
12	702.9773	900	243.2	702.9773	900	243.2
13	633.1504	900	243.2	633.1504	900	243.2
14	692.8021	900	243.2	692.8021	900	243.2
15	750.1832	900	243.2	750.1832	900	243.2
16	756.8779	885.0851	243.2	753.5286	900	243.2
17	777.2105	847.8148	243.2	765.4917	900	243.2
18	822.1046	797.6444	243.2	799.1195	900	243.2
19	943.9846	806.3944	243.2	922.9644	900	243.2
20	785.307	774.9444	243.2	760.9649	883.3429	243.2
21	729.2891	764.6444	243.2	710.3418	849.0194	243.2
22	471.407	698.3944	243.2	471.407	698.3944	243.2
23	322.0474	602.0944	243.2	322.0474	602.0944	243.2
24	164.3774	516.7625	215.6681	133.257	582.4611	245.2325

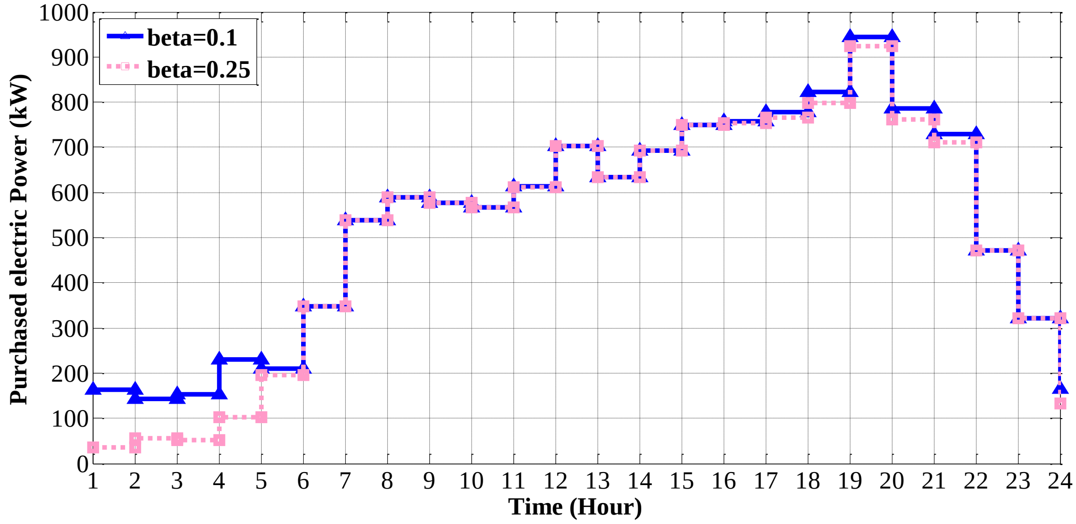

Fig.15. Effect of critical operation cost on purchased electricity in risk-averse scheduling considering electricity price uncertainty

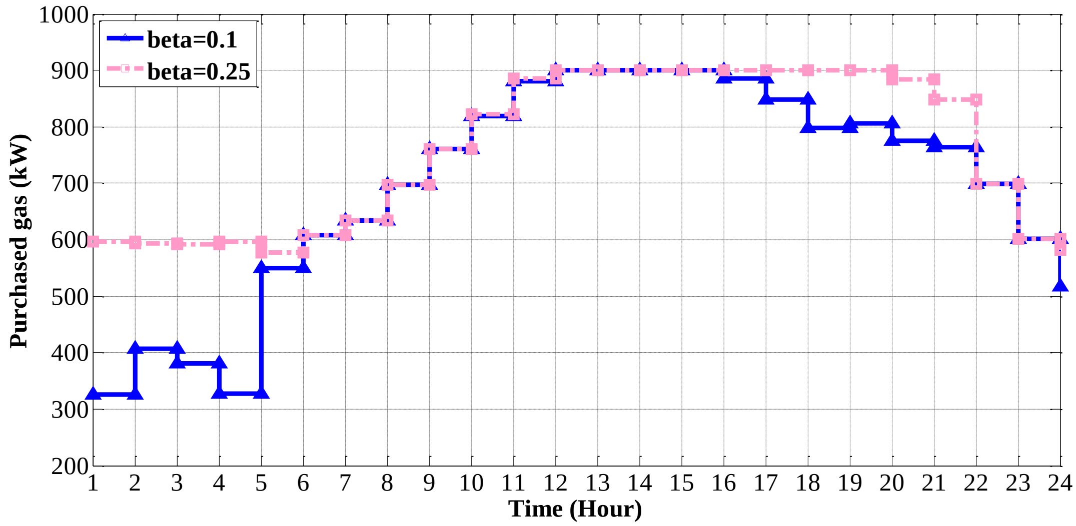

Fig.16. Effect of critical operation cost on purchased NG in risk-averse scheduling considering electricity price uncertainty

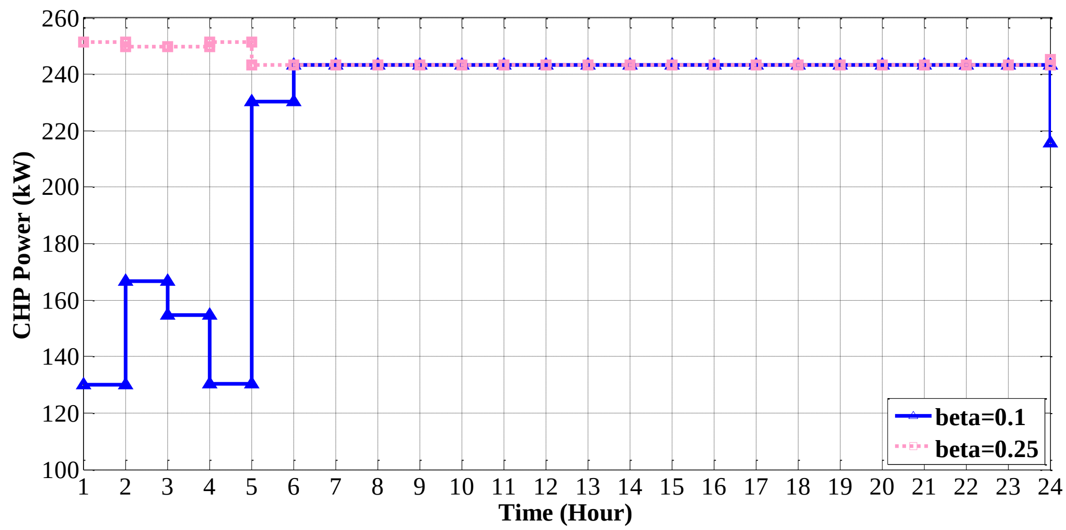

Fig.17. Effect of critical operation cost on CHP power in risk-averse scheduling considering electricity price uncertainty

Here, the effect of target cost deviation factor on decision variables in risk-seeking IGDT is investigated considering the uncertainties of electricity prices. As per Table 10 and figures 18-20, with increase in target operation cost deviation factor and target operation cost, purchased electricity from grid increases and purchased NG, NG fed into CHP and CHP power decreases. Actually, in order to make lower operation costs achievable and get more benefit from favorable deviations of electricity prices, EH operator increases the import from power grid; instead decreases the import from NG network and NG injection into CHP and CHP power generation. Actually, the risk-averse EH operator sees the electricity price and import from power grid as an opportunity to decrease EH operation cost, so increases the share of power grid in supplying its electric demands to make lower operation costs achievable. Table 10 and figures 18-20 compare decision variables for target cost deviation factors of 0.1, 0.15, 0.2 and 0.25.

Table 10. Effect of target operation cost on decision variables in risk-seeking scheduling considering electricity price uncertainty

Hour	Purchased electricity $\rho = 0.1$	Purchased gas $\rho = 0.1$	CHP power $\rho = 0.1$	Purchased electricity $\rho = 0.15$	Purchased gas $\rho = 0.15$	CHP power $\rho = 0.15$	Purchased electricity $\rho = 0.2$	Purchased gas $\rho = 0.2$	CHP power $\rho = 0.2$	Purchased electricity $\rho = 0.25$	Purchased gas $\rho = 0.25$	CHP power $\rho = 0.25$
1	242.1018	186.6	54	242.1018	186.6	54	243.4578	186.6	54	243.4578	186.6	54
2	261.3018	169.05	54	261.3018	169.05	54	261.3018	169.05	54	261.3018	169.05	54
3	259.939	158.6	54	259.939	158.6	54	259.939	158.6	54	259.939	158.6	54
4	310.5649	157.5	54	310.5649	157.5	54	310.5649	157.5	54	310.5649	157.5	54
5	394.5228	183.5	54	394.5228	183.5	54	394.5228	183.5	54	394.5228	183.5	54
6	470.0357	392.0266	125.8458	545.6628	246	54	547.9568	236.7347	54	547.9568	246	54
7	557.9627	601.2795	225.8458	633.5898	469.153	154	738.853	285.25	54	738.853	297.75	54
8	589.3758	702.3444	243.2	589.3758	714.8444	243.2	770.2661	386.3149	71.35421	788.5337	354.4	54

9	587.3842	762.2405	243.2	594.5183	748.3178	236.9348	758.5205	448.3228	71.13274	776.5549	408.4536	54
10	556.9213	824.7405	243.2	556.9213	824.7405	243.2	646.8544	733.045	171.1327	676.2573	669.1758	143.2
11	613.8042	887.2405	243.2	613.8042	887.2405	243.2	613.8042	875.1694	243.2	613.8042	875.1694	243.2
12	702.9773	900	243.2	702.9773	900	243.2	702.9773	893.5726	243.2	702.9773	893.5726	243.2
13	654.2843	896.7912	243.2	661.4001	900	243.1459	655.7157	900	243.2	655.981	900	242.9479
14	703.3284	900	243.2	703.3284	883.8741	243.2	703.3284	883.8741	243.2	703.3284	883.8741	243.2
15	750.1832	900	243.2	750.1832	896.4515	243.2	750.1832	889.5851	243.2	750.1832	889.5851	243.2
16	771.5382	885.0851	243.2	771.6081	885.0851	243.2	771.6081	885.0851	243.2	771.6081	885.0851	243.2
17	777.2105	832.1898	243.2	777.2105	831.9944	243.2	777.2105	831.9944	243.2	777.2105	831.9944	243.2
18	822.1046	797.6444	243.2	822.1046	797.6444	243.2	822.1046	797.6444	243.2	822.1046	797.6444	243.2
19	953.0547	743.8944	243.2	953.0547	743.8944	243.2	953.0547	743.8944	243.2	953.0547	743.8944	243.2
20	799.3421	712.4444	243.2	799.3421	712.4444	243.2	799.3421	712.4444	243.2	799.3421	712.4444	243.2
21	743.3242	702.1444	243.2	743.3242	702.1444	243.2	743.3242	702.1444	243.2	743.3242	702.1444	243.2
22	485.4421	635.8944	243.2	485.4421	635.8944	243.2	684.6	287.95	54	684.6	287.95	54
23	535.2404	191.65	54	535.2404	191.65	54	535.2404	191.65	54	535.2404	191.65	54
24	344.8088	157.5	54	344.8088	157.5	54	344.8088	157.5	54	344.8088	157.5	54

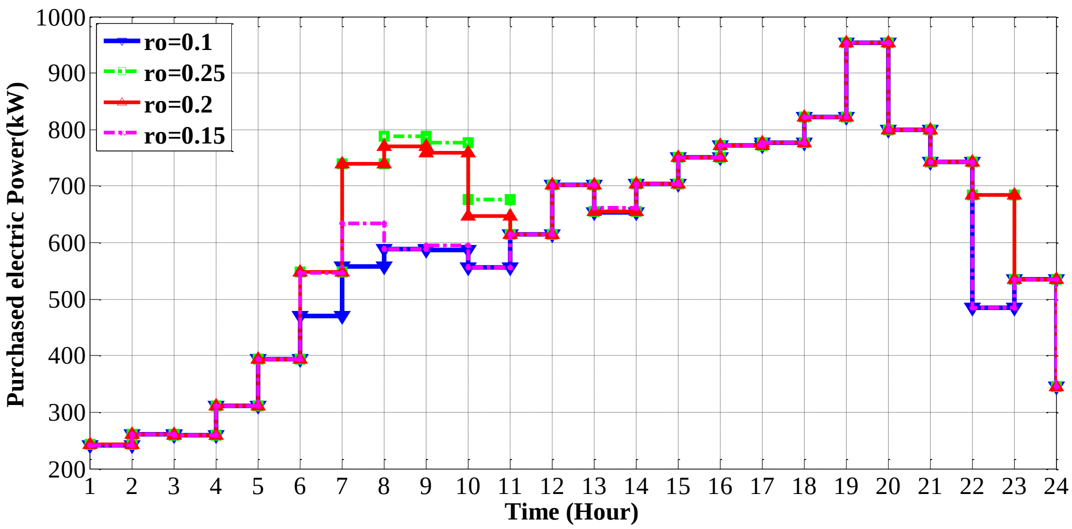

Fig.18 Effect of target operation cost on purchased electricity in risk-seeking scheduling considering electricity price uncertainty

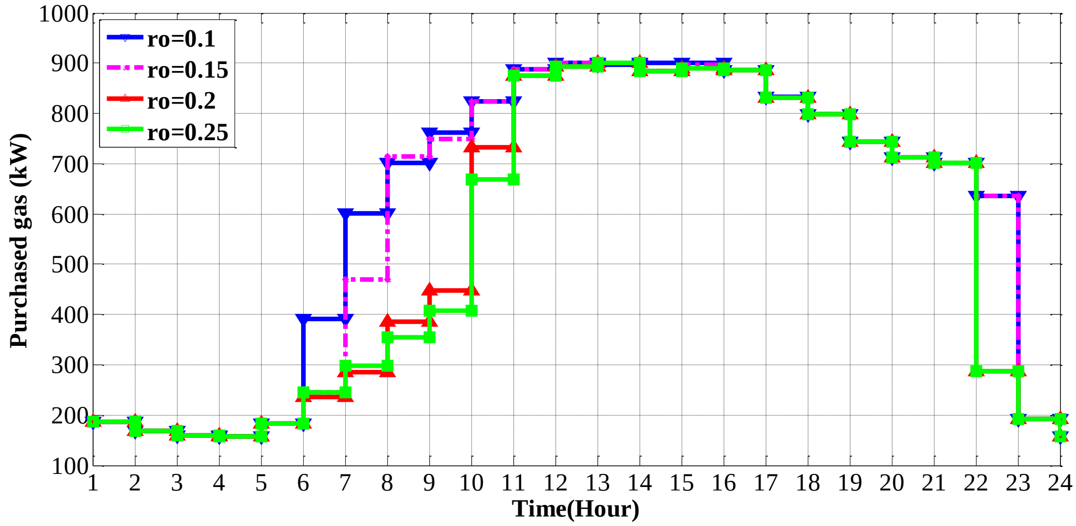

Fig.19. Effect of target operation cost on purchased gas in risk-seeking scheduling considering electricity price uncertainty

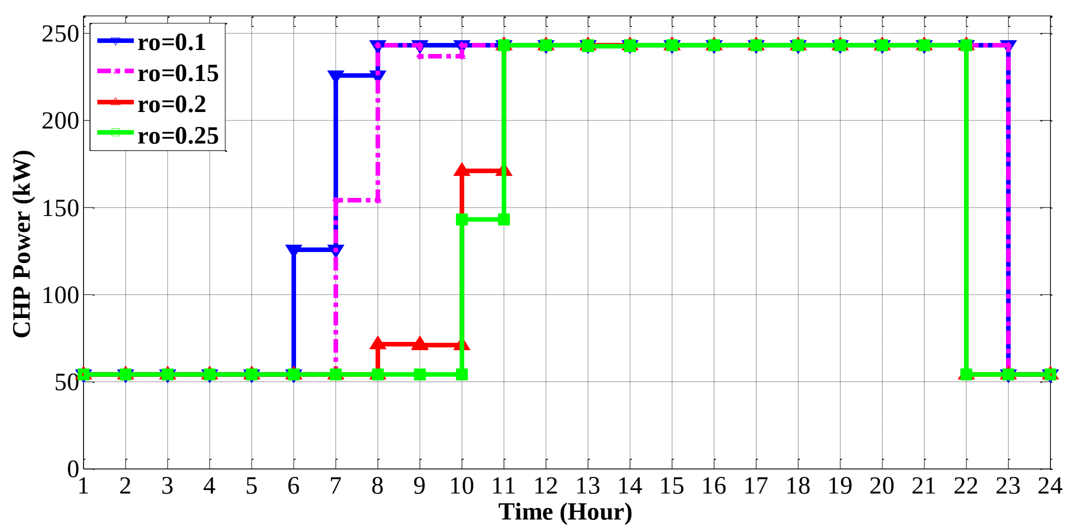

Fig.20 Effect of target operation cost on CHP power in risk-seeking scheduling considering electricity price uncertainty

5. Conclusions

In this paper, a new risk-aware model has been proposed for unit commitment in renewable CCHP EHs with storage systems, CHP, boiler, electric chiller, absorption chiller, PV module, wind turbine and battery charging station (BCS). Using information gap decision theory (IGDT), day-ahead EH scheduling has been done from risk-neutral, risk-averse and risk-seeking perspectives, considering the uncertainties of demands, PV and wind power and electricity prices. The effect of risk as well as effect of critical cost deviation factor and target cost deviation factor on EH operation cost and schedule of EH components has been investigated. The findings indicate the significant effect of risk-awareness on EH operation cost and schedule of its components. According to the results, in risk-averse IGDT-based decision making, the EH operator is hedged against the risk of unfavorable deviations of demands, PV/wind power and electricity prices at the cost of a higher operation cost and in risk-seeking decision making, he/she sets the schedule of components in a way that a target operation cost becomes achievable.

Major findings show that at low electric demand hours, risk- averse EH operator purchases significantly less electricity than risk-neutral operator and risk-seeking operator in order to hedge himself against risk of electricity price deviations, whereas for risk-seeking operator, it is not rational to purchase higher electricity in the hope of less electricity price, because he does not need higher electric power at low-demand hours, therefore, at these hours, risk-neutral operator and risk-seeker operator approximately purchase the same amount of electricity from grid. On the other hand, at hours with heavy electricity demand, risk-seeking EH operator purchases higher electricity than risk-neutral operator and risk-averse operator in the hope of a low electricity price and decreasing its operation cost. At these hours, risk-averse EH operator cannot significantly reduce its electricity purchase, because purchased electricity and CHP power are the only tools to supply EH's electric demand and CHP is already being operated with a high power, so in order to supply its electric demand, EH must purchase a high amount of electricity from grid. As per the results, with increase in critical operation cost, purchased electricity from grid decreases and purchased NG, NG fed into CHP and CHP power increases. The results also show that with increase in target operation cost, purchased electricity from grid increases and purchased NG, NG fed into CHP and CHP power decreases.

Acknowledgement

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