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# Operation of energy hubs with storage systems, solar, wind and biomass units connected to demand response aggregators

## Abstract

Energy Hubs (EHs) play an important role in sustainable cities; they are multi-carrier energy systems that can satisfy different energy needs of consumers by relying on the conversion and storage of energy sources as well as renewable energy sources. With efficient and reliable energy supply, EHs may significantly contribute in developments of sustainable cities. In this paper, day-ahead scheduling of EHs is done, while they are connected to demand response aggregators. The studied EH includes photovoltaic and wind renewable sources, biomass, hydrogen electrolyzer, combined heat and power unit, solar heater, boiler, electric, thermal and hydrogen storage systems. Besides electric grid and gas network as input sources, EH may purchase electricity from demand response aggregators. Information gap decision theory (IGDT) is employed as a risk-aware method to handle uncertainties of electric, thermal and hydrogen demands, photovoltaic and wind power, solar heat and electricity prices. The scheduling is carried out from the perspective of the uncertainty free, risk-averse and risk-seeking decision-makers. The problem is formulated as a mixed-integer model and is solved using CPLEX solver in General algebraic modeling system (GAMS). The impact of risk awareness and deviation factors of critical and target costs on day-ahead scheduling and EH operation costs is investigated. The results show that the transaction with demand response aggregator decreases EH operation cost by 20.1%. The results also show that electric, thermal and hydron storage systems respectively decrease the operation cost by 3%, 1.7% and 2.1%.

**Keywords**: energy hubs, storage, information gap decision theory, risk, uncertainty

**Nomenclature**

**Acronyms**

| | |
|---|---|
| BPP | Biomass power plant |
| CHP | Combined heat and power |
| COP | Coefficient of performance |
| DR | Demand response |
| EH | Energy hub |
| ESS | Electric storage system |
| HE | Hydrogen Electrolyzer |
| HSH | Heat of solar heater |
| HSS | Hydrogen storage system |
| IGDT | Information gap decision theory |
| MILP | Mixed-integer linear programming |
| MINLP | Mixed-integer nonlinear programming |

| | |
|---|---|
| NG | Natural gas |
| PV | Photovoltaic |
| RD | Ramp-down |
| RDRL | Ramp-down rate limit |
| RU | Ramp-up |
| RURL | Ramp-up rate limit |
| SD | Shut down |
| SU | Start up |
| SUED, SDED | Shift-up/down electric demand |
| SUHD, SDHD | Shift-up/down hydrogen demand |
| SUTD, SDTD | Shift-up/down thermal demand |
| TES | Thermal energy storage |
| TOU | Time of use |
| TSS | Thermal storage system |
| UC | Unit commitment |
| **Indices** | |
| $boil$ | Boiler |
| $ch$ | Charging mode of storage system |
| $Conv$ | PV converter |
| $dch$ | Discharging mode of storage system |
| $E$ | Electric |
| $grid$ | Grid |
| $H$ | Hydrogen |
| $ini$ | Initial value |
| $max$ | Maximum value |
| $min$ | Minimum value |
| $sh$ | Shed power |
| $t$ | Time |
| $TR$ | Transformer |
| **Parameters** | |
| OF | Objective function (EH operation cost) |
| $DR$ | Demand response |
| $PR$ | Price |
| $P$ | Electric power |
| $T$ | Thermal power |
| $H$ | Hydrogen power |
| $W$ | Wind power |
| $PV$ | PV power |
| $BP$ | Biomass power |
| $ef$ | Efficiency |
| $LO$ | Value of lost loads |
| $L$ | Storage loss factor |
| $R$ | End energy of storages |
| $IE$ | Initial energy of storages |
| $K$ | Efficiency of storages |
| $Fch$ | Charging power of storage |
| $Fdch$ | Discharging power of storage |
| $k$ | Commitment status of components |
| $v$ | Start-up index |
| $m$ | Shut-down index |
| $n$ | Storages charging and discharging status of at time t |
| $Q$ | COP of components |
| $D$ | Demand |
| $\rho$ | Target cost deviation factor, |
| $\beta$ | Critical cost deviation factor |
| $\alpha$ | Robustness horizon |
| $DPF_{up}$, $DPF_{down}$ | Demands participation factor for shift-up/down |
| $n_{DR,up}$, $n_{DR,down}$ | Shift-up/down status of demands DR |
| $DRI$ | DR incentive amount for demands |
| $DRC$ | Incentives paid to demands |
| $f(X,u)$ | Costs |
| $X$ | Decision vector |

| | |
|---|---|
| $u$ | Uncertain input data |
| $\bar{u}$ | Nominal value of uncertain input data |
| $U$ | A set of uncertainties |
| $f_{cr}$ | Maximum tolerable cost |
| $\bar{f}$ | Nominal optimal cost |
| $f_{targ}$ | Target cost |

## 1. Introduction

In recent years, energy consumption in various sectors is significantly increasing. In the meantime, meeting the multiple energy needs of consumers is of considerable importance. Therefore, the need for a hub with the ability to satisfy the different energy needs of consumers and address its issues is felt more than ever. Energy Hub (EH) is a multi-carrier energy system that can satisfy the different energy needs of consumers by relying on the conversion and storage of energy sources [1-4]. EHs are units including multiple energy carriers that can supply various energy demands by converting, storing, and conditioning these carriers [5]. EHs are eco-friendly systems because they often use renewable energy sources to meet energy demands [6, 7]. Renewable energy sources are natural and clean resources that increase the flexibility and reliability, while reducing the cost of the EH operation. Biomass is a type of energy resource that can be produced from waste, wood chips, etc. [8, 9]. The employment of PV, wind, and biomass energies is a promising resource to achieve reliable, efficient, and environmentally friendly EHs [10]. Optimal use of renewable energy sources and the conversion of waste into energy in order to decrease emission and increase reliability are important ways of achieving the sustainable cities. As energy hubs employ PV, wind, biomass and other renewable energy sources to supply the needed energies by consumers, the optimal operation of renewable-integrated energy hubs is of particular important. Therefore, with efficient and reliable energy supply, EHs may significantly contribute in development and enhancement of sustainable cities. However, renewable energy sources require energy storages for operation continuity. Energy storage systems in the EH can improve power quality, increase efficiency, reduce operation costs and mitigate the variations of renewable energy resources, while enabling the continuous utilization of renewable energy sources [11, 12]

EH units use several converters and energy storage as well as renewable energy sources to supply different loads, while it can purchase its required energy from the electricity network, gas network or other sources such as demand response (DR) aggregators and etc. DR aggregator is a coordinator of large number of distributed DR resources that could participate in wholesale electricity markets as an intermediary between the independent system operator and consumers [13, 14]. Indeed, DR aggregator is an alternative source of electricity supply for the consumers. DR Aggregators' power is provided by decreasing the load by energy consumers [15]. In addition, DR aggregators can provide the electricity with lower price than power grid at some hours of the day and in this way, reduce system operation cost.

In some researches in the literature, DR aggregators have been used the power and energy systems. In Ref. [16], a bi-Level method has been presented for optimal operation of distribution networks including DR aggregator in order to minimize operating cost and maximize profit. The method has been tested on the IEEE 15-Bus and 33-Bus networks. The simulation results show the effectiveness of the proposed bi-level method in reduction of the operation cost, however, uncertainty of DR aggregator has not been considered in this study. In Ref. [17], optimization methods based on robust and lexicographic has been used for the optimal operation of a distribution system based on day-ahead and real-time market horizons including the electricity market, electric vehicle parking lot aggregators and DR aggregators. The uncertainty of electrical demand, wind and PV sources, DR aggregators, electric vehicle aggregators and market prices has been considered, while the problem has not been investigated from risk-aware perspective. The studies performed on 70-bus system show the improvement of the day-ahead and real-time revenues using proposed method.

In Ref. [18], short-term scheduling problem of the electricity retailers including DR aggregator and renewable sources has been addressed. Two-stage stochastic method has been utilized for considering uncertainty of wind and PV, market prices, electric demand and DR. The results of solving the problem in two cases of without uncertainties and stochastic case indicate that the retailer’s profit in the stochastic model including DR and renewables is increased. In Ref. [19], a market-based approach has been proposed for optimization of industrial and residential DR aggregators in order to increase the profit of the energy market participants. However, uncertainty of DR aggregator has not been considered in this study. The presented method has been tested on the Danish sector of the Nordic Electricity Market. The results indicate the efficiency of the suggested method in achieving the optimal consumer’s cost.

In Ref. [20], the scheduling problem of DR aggregators has been investigated using bi-level method with the aim of maximizing profit in the Nordic energy market. The stochastic method based on risk has been represented for considering uncertainties DR aggregator, prices and demand.  Finally, the impact of load reduction on the decision-making process of the DR aggregator and profit of aggregator has been evaluated. In Ref. [21], a bidding approach for DR aggregators has been employed using game theory in electricity market based on customer benefit and market price. The uncertainty of the market price has been taken into account using the robust optimization. The simulation results demonstrate that operator profit is reduced by increment of the robustness level and the price deviation. Table 1 displays the major features of researches carried out on demand response aggregators.

Table 1. The main features of researches conducted on DR aggregators

| **Ref.** | **Area of study** | **Uncertainty of DR aggregator** | **Uncertainty considering method** | **Risk-awareness** |
|---|---|---|---|---|
| [16] | Operation of distribution networks | × | × | × |
| [17] | Operation of distribution networks | ✓ | Robust and lexicographic optimization | × |
| [22] | Industrial companies | × | × | × |
| [18] | Scheduling of the electricity retailers | ✓ | Two-stage stochastic | × |
| [19] | Optimization of residential and industrial DR aggregators | × | × | × |
| [20] | Scheduling DR aggregators | ✓ | Bi-level stochastic | ✓ |

| | | | | |
|---|---|---|---|---|
| [21] | Electricity market | × | Robust optimization | × |

The optimal operation of the EHs including DR aggregators can be carried out using unit commitment (UC) with the objective of minimizing operation costs, while all constraints are met [10]. UC in EH is a complex MILP problem with the uncertainties of the input data including prices, renewable energy and demands [23-27]. Uncertainty of input data is one of the significant challenges faced by system operators [28, 29]. In the literature, various strategies have been presented to handle the uncertainty of input data in the optimal operation of energy systems such as stochastic methods [30, 31], robust optimization method [32] and interval based optimization method [33].

The methods of robust optimization and interval optimization incvolve precise uncertainty set of the input data. Furthermore, these methods usually require two optimizations for each objective function that increases computational time [33]. Risk-based stochastic methods have the benefit of producing results that include more information than the deterministic method and scenario-based optimization approach by taking into account the uncertainties associated with the various input variables. However, these methods require the probability density function (PDF) of all uncertainties, which can make it difficult to implement these methods effectively [34]. These limitations and shortcomings can be addressed using other methods such as information gap decision theory (IGDT), which do not require prior knowledge of uncertain parameters. In addition, this method has the advantage of less computational burden [35, 36]. Therefore, IGDT method has been utilized for modeling uncertainties of input data in energy systems such as microgrid, transmission & distribution systems and etc. [36]. In risk-averse IGDT which is commonly used the achievement of the operation cost not high than target operation cost is guaranteed. In this regard, IGDT method has been employed in some researches to model uncertainties of input data in power and energy systems.

In Ref. [10], IGDT has been employed for unit commitment in an EH including demands of electric, thermal and cooling, storages, PV, wind turbine, by considering the uncertainties of demands, renewables and electricity price, while the effect of risk on EH operation cost and components has been studied. The results show a significant sensitivity of EH operation cost with respect to the uncertain input data. In Ref. [30], IGDT has been used in order to handle uncertainties in an EH. A commercial building has been considered as the case study and time-of-use (TOU) has been used as DR program; however, no attention has been paid to start-up and shut-down costs and DR costs, and ramp-up/down limitations have been neglected.

In [37], the hybrid stochastic-IGDT has been utilized for considering uncertainty of electrical demand, PV and wind resources in an isolated microgrid. In the presented model, the uncertainty of electrical demand, PV and wind resources has been considered using stochastic method, while failures have been modeled using IGDT. The effect of DR programs and failures on optimal scheduling of energy system has been assessed. However, the scheduling problem has not been tackled from the perspective of the risk-awareness.

In [38], hybrid stochastic-IGDT method has been used for considering uncertainty of demand and PV in an energy system including PV, CHP, heat pump, absorption chiller, thermal and electric storages and demands of heat, cooling, and electricity. In the presented model, the uncertainty of PV has been considered using stochastic method, and the uncertainty of demand has been modeled using IGDT under the risk-averse and risk-seeking strategies. However, the uncertainty of the market price has not been considered and the effect of DR programs on the operation of the energy system has not been investigated.

In [39], IGDT based on risk-averse and risk-seeking models has been presented for taking into account uncertainty of PV and wind resources in a multi-energy system including seven hydropower plants, a virtual wind power plant and a virtual solar power plant. The results show that presented model increases the flexibility of the system against risk. Furthermore, IGDT reduces the computational time compared with stochastic optimization method.

By reviewing the above researches and to the best of our knowledge, no research work has been presented to employ DR aggregators for optimal operation of energy hubs. In this study, the optimal operation of EH is carried out with the presence of the DR aggregators. As the proposed model is a MILP, the achievement of the global optimum is guaranteed. The studied EH includes PV and wind renewable sources, biomass, combined heat and power (CHP), hydrogen electrolyzer (HE), solar heater, boiler, electric storage system (ESS), hydrogen storage system (HSS) and thermal storage system (TSS). In the presented model, the EH is able to purchase electricity from both power grid and DR aggregators, so, the proposed EH can import electricity from power grid and DR aggregator, and gas from natural gas network for supplying electric, thermal and hydrogen demands.

In the proposed model, uncertainties of electric, thermal and hydrogen demands, PV, solar heat and wind and, the price of electricity purchased from power grid and DR aggregators are handled using IGDT, which guarantees to achieve the target operation cost with the presence DR aggregators. DR aggregators include some demands that are willing to curtail their consumption in some hours to make a profit. DR aggregators, as effective market entities, play a remarkable role in electricity and energy markets between demands and system operators. In this regard, the proposed EH model is investigated from the prospective of the risk-averse and risk-seeking using decision-making based on IGDT since the optimal decision-making of the operator depends on his/her perspective in dealing with uncertainties. The impact of risk awareness on EH day-ahead scheduling and operation costs is studied.

The main contributions of this paper are as follows:

- ✓ DR aggregator has been employed as an input source of electric energy, in addition to the power grid and its effect on EH performance has been investigated.
- ✓ Day-ahead EH scheduling has been carried out based on the perspectives of the risk-seeking and risk-averse decision makers with the consideration of the uncertainties of electric, thermal and hydrogen demands, PV, solar heat, wind and the price of electricity purchased from power grid and DR aggregator.
- ✓ The effect of deviation factors, critical and target cost on EH scheduling has been investigated.

- ✓ DR effect on EH operation cost has been discussed for electric, thermal and hydrogen demands.
- ✓ Effect of energy storage systems on EH operation costs have been evaluated with the consideration of their storage loss.

The rest of the paper is organized as follows. Section 2 describes IGDT. Section 3 presents the proposed model. Section 4 discusses solution methodology. In section 5, simulation results are explained, and section 6 expresses conclusions.

## 2. IGDT method

IGDT is a non-possibilistic method used for considering uncertain input data. IGDT may be applied with respect to either risk-seeking or risk-averse perspectives. In this section, principles and formulation of IGDT are described briefly, however more details can be found in [10]. The general formulation of optimization problem is as follows:

$$\begin{aligned} &\min f(X,u) \\ &g(X,u) = 0 \\ &h(X,u) \leq 0 \end{aligned} \tag{1}$$

In IGDT, the set $U$ is defined as below.

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

### 2.1. Risk-averse model

In the risk-averse model, the robustness horizon should be maximized in a way that the deviation from uncertainties in the robustness set does not lead to a cost greater than the critical cost [10]. Indeed, the main purpose is to find decision variables in a way to protect decision-makers against the undesirable deviations risk of uncertainties [40]. The following is the risk-averse model.

$$\max \alpha(X,u) \tag{3}$$

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

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

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

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

### 2.2. Risk-seeking model

In the risk-seeking model, the target cost is pre-defined and the primary goal is to find opportunity horizon or uncertainty horizon and decision variables to make target cost achievable [40]. The following is the risk-seeking model.

$$\min \alpha(X,u) \tag{8}$$

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

$$g(X,u) = 0 \tag{10}$$
$$h(X,u) \leq 0 \tag{11}$$
$$f_{targ} = (1-\rho)\bar{f} \tag{12}$$

## 3. Problem formulation

Formulation of optimal EH operation problem including objective function and constraints is given as Equations (13) - (85). In sub-section 3.1, uncertainties are not considered in the model; Subsections 3.2 and 3.3 define the UC model for EH based on risk-averse and risk-seeking models, respectively.

### 3.1. UC in EH without consideration of uncertainties

Problem formulation of EH scheduling with the aim of minimizing operation costs is presented in this section. Equations (13)-(85) present the formulation of proposed model for UC in EH including objective function, constraints and other components.

#### 3.1.1. Objective function

In the proposed model, the objective function is EH operation cost as it is shown in Equation (13). According to Equation (13), the EH operation cost is equal to the sum of the costs of incentive payment to responsive consumers, load shedding costs, start-up and shut-down costs of components, costs of NG, electricity purchased from power grid and DR aggregator minus incentive payment to EH for using biomass. Here it is assumed that the boiler and CHP are committed before starting the operation horizon. Total incentives paid to demands can be obtained by Equation (15). Using Equations (16), (17) and (18), incentives paid to electrical, thermal and hydrogen demands can be determined, respectively [41].

$$\begin{aligned} OF_t = & \sum_t PR_{grid,t} \,.\, P_{grid,t} + \sum_t PR_{dragg.,t} \,.\, P_{dragg.,t} + \sum_t PR_{NG,t} \,.\, P_{NG,t} \\ & + \sum_t \left(v_{boil,t}.SU_{boil} + m_{boil,t}.SD_{boil}\right) + \sum_t \left(v_{HE,t}.SU_{HE} + m_{HE,t}.SD_{HE}\right) \\ & - \sum_t \left(v_{BPP,t}.SU_{BPP} + m_{BPP,t}.SD_{BPP}\right) + \sum_t \left(v_{CHP,t}.SU_{AC} + m_{CHP,t}.SD_{AC}\right) \\ & + LO_t + DRC_t \quad \forall t \end{aligned} \tag{13}$$

$$LO_t = \sum_t \left(LO_e.P_{sh,t} + LO_T.T_{sh,t} + LO_h.H_{sh,t}\right) \quad \forall t \tag{14}$$

$$DRC_t = DRC_{E,t} + DRC_{T,t} + DRC_{H,t} \quad \forall t \tag{15}$$

$$DRC_{E,t} = \sum_t DRI_E\left(DR_{E,up,t} + DR_{E,down,t}\right) \quad \forall t \tag{16}$$

$$DRC_T = \sum_t DRI_T\left(DR_{T,up,t} + DR_{T,down,t}\right) \quad \forall t \tag{17}$$

$$DRC_H = \sum_t DRI_H\left(DR_{H,up,t} + DR_{H,down,t}\right) \quad \forall t \tag{18}$$

### 3.1.2. Energy balance constraints

Energy balance between load and generation must be maintained in the optimal operation of EH. Constraints (19)-(22) indicate the balance constraints between generation and electrical, thermal and hydrogen demands, respectively. According to constraint (19), it can be seen that at all times, the total power purchased from power grid and DR aggregator, produced power by CHP, produced power by biomass power plant, produced power by PV and wind, electric load shed, ESS discharge power and shift-down in electric demand cannot be less than the sum of electric demand, shift-up in demand, ESS charge power and electric power fed into HE.

$$\begin{aligned} P_{grid,t} ef_{TR} + P_{dragg.,t} + P_{chp,t} + P_{bpp,t} + ef_{conv}\,\mathrm{PV_t} + \mathrm{W_t} + PS_{sh,t} + F_{ESS,dch,t} \\ + DR_{E,down,t} \geq \mathrm{D_{E,t}} + DR_{E,up,t} + F_{ESS,ch,t} + \frac{\mathrm{H}_{HE},\mathrm{t}}{\mathrm{Q}_{HE}} \quad \forall t \end{aligned} \tag{19}$$

Total thermal power produced by boiler, produced heating by CHP, thermal load shed, TSS discharging power, shift-down in thermal demand, and heat produced by solar heater cannot be less than the sum of thermal demand, shift-up in thermal demand and TSS discharging power in accordance with constraint (20).

$$T_{boil,t} + T_{chp,t} + TS_{sh,t} + F_{TSS,dch,t} + DR_{T,down,t} + \mathrm{HSH_t} \geq \mathrm{D}_{T,\mathrm{t}} + DR_{T,up,t} + F_{TSS,ch,t} \quad \forall t \tag{20}$$

According to Equation (21), it can be seen that the amount of gas purchased from gas network must be equal to the sum of the amount of gas fed into the CHP and boiler.

$$P_{NG,t} = \frac{P_{chp,t}}{ef_{P,chp}} + \frac{T_{boil,t}}{ef_{boil}} \quad \forall t \tag{21}$$

Total hydrogen produced by electrolyzer, hydrogen load shed, HSS discharging power and shift-down in hydrogen demand cannot be less than the sum of hydrogen demand, shift-up in hydrogen demand and HSS charging power according to constraint (22),

$$\mathrm{H_{HE,t}} + H_{sh,t} + F_{HSS,dch,t} + DR_{hy,down,t,s} \geq \mathrm{D}_{H,\mathrm{t}} + DR_{H,up,t} + F_{HSS,ch,t} \quad \forall t \tag{22}$$

### 3.1.3. Boiler constraints

Boiler operation is depending on the constraints (23)-(29). Constraints (23)-(26) indicate the relationship between start-up and shut-down status of the boiler and commitment status; initially, the boiler is assumed to be online. Due to the constraints (27), at any time, the thermal power generated by the committed boiler is within the pre-determined allowable range. Constraints (28) - (29) prevent a rapid increase / decrease in the boiler thermal power; these constraints do not allow thermal power fluctuations to exceed or fall below the ramp-up rate limit and ramp-down rate limit, respectively [42, 43].

$$v_{boil,t} - m_{boil,t} = n_{boil,t} - n_{boil,t-1} \quad \forall t \neq 1 \tag{23}$$

$$v_{boil,t} = 0 \qquad \forall t = 1 \tag{24}$$

$$m_{boil,t} = 1 - n_{boil,t} \qquad \forall t = 1 \tag{25}$$

$$v_{boil,t} + m_{boil,t} \leq 1 \qquad \forall t \tag{26}$$

$$T_{boil,min} k_{boil,t} \leq T_{boil,t} \leq T_{boil,max}\, k_{boil,t} \qquad \forall t \tag{27}$$

$$T_{boil,t+1} - T_{boil,t} \leq RU_{boil} \qquad \forall t \neq 24 \tag{28}$$

$$T_{boil,t-1} - T_{boil,t} \leq RD_{boil} \qquad \forall t \neq 1 \tag{29}$$

### 3.1.4. CHP constraints

As shown in Figure 1, due to the relationship between power and heat, the CHP unit's operating point must be placed in a predetermined area called the feasible operating region (FOR). The four vertex points A, B, C, and D are used to determine FOR of a CHP. In FOR, A, B, C and D are maximum power point, maximum heat point, minimum power point, and minimum heat point, respectively. Constraints (30)-(34) are used to determine FOR of a CHP [44].

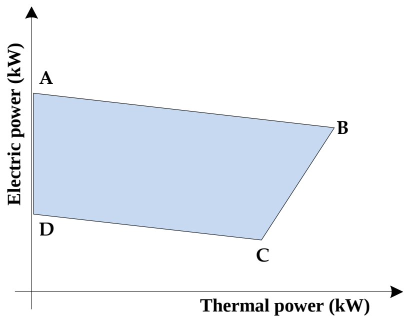


Fig.1. FOR of type I CHPs

$$0 \leq P_{chp,t} \leq P_{chp,A} \,.\, k_{chp,t} \qquad \forall t \tag{30}$$

$$0 \leq T_{chp,t} \leq T_{chp,B} \,.\, k_{chp,t} \qquad \forall t \tag{31}$$

$$P_{chp,t} - P_{chp,A} - \frac{(P_{chp,A} - P_{chp,B})(T_{chp,t} - T_{chp,A})}{T_{chp,A} - T_{chp,B}} \leq 0 \qquad \forall t \tag{32}$$

$$P_{chp,t} - P_{chp,B} - \frac{(P_{chp,B} - P_{chp,C})(T_{chp,t} - T_{chp,B})}{T_{chp,B} - T_{chp,C}} \geq -M(1 - k_{chp,t}) \qquad \forall t \tag{33}$$

$$P_{chp,t} - P_{chp,C} - \frac{(P_{chp,C} - P_{chp,D})(T_{chp,t} - T_{chp,C})}{T_{chp,C} - T_{chp,D}} \geq -M(1 - k_{chp,t}) \quad \forall t \tag{34}$$

### 3.1.5. HE constraints

The constraints (35)-(41) are defined to the HE [45]. The constraints (40) and (41) ensure that the increase and decrease of HE hydrogen do not exceed its ramp-up rate limitation and ramp-down rate limitation, respectively.

$$v_{HE,t} - m_{HE,t} = n_{HE,t} - n_{HE,t-1} \qquad \forall t \neq 1 \tag{35}$$

$$v_{HE,t} = 0 \qquad \forall t = 1 \tag{36}$$

$$m_{HE,t} = 1 - n_{HE,t} \qquad \forall t = 1 \tag{37}$$

$$v_{HE,t} + m_{HE,t} \leq 1 \qquad \forall t \tag{38}$$

$$H_{HE,min}k_{HE,t} \leq H_{HE,t} \leq H_{HE,max}\, k_{HE,t} \qquad \forall t \tag{39}$$

$$H_{HE,t+1} - H_{HE,t} \leq \; RU_{HE} \qquad \forall t \neq 24 \tag{40}$$

$$H_{HE,t-1} - H_{FC,t} \leq \; RD_{HE} \qquad \forall t \neq 1 \tag{41}$$

### 3.1.6. BPP constraints

The constraints (42)-(48) are defined for the BPP [45]. The constraints (47) and (48) ensure that the increase and decrease of BPP power do not exceed its ramp-up rate limitation and ramp-down rate limits, respectively.

$$v_{BPP,t} - m_{BPP,t} = n_{BPP,t} - n_{BPP,t-1} \qquad \forall t \neq 1 \tag{42}$$

$$v_{BPP,t} = 0 \qquad \forall t = 1 \tag{43}$$

$$m_{BPP,t} = 1 - n_{BPP,t} \qquad \forall t = 1 \tag{44}$$

$$v_{BPP,t} + m_{BPP,t} \leq 1 \qquad \forall t \tag{45}$$

$$BP_{BPP,min}k_{BPP,t} \leq BP_{BPP,t} \leq BP_{BPP,max}\, k_{BPP,t} \qquad \forall t \tag{46}$$

$$BP_{BPP,t+1} - BP_{BPP,t} \leq \; RU_{BPP} \qquad \forall t \neq 24 \tag{47}$$

$$BP_{BPP,t-1} - BP_{BPP,t} \leq \; RD_{BPP} \qquad \forall t \neq 1 \tag{48}$$

### 3.1.7. Storage systems constraints

The constraints (49)-(69) are used for ESS operation [43, 46-49]. Constraints (49) and (50) limit the charging as well as discharging power of ESS to their predefined intervals. Constraint (51) states that every time, the energy level of ESS must not be less than the minimum limitation or higher than the upper limit. According to the constraint (52), it can be seen that it is not possible to charge and discharge ESS, simultaneously. The constraint (53) indicates that during the operation horizon, the initial energy level of ESS and its final energy level are equal [50-53]. According to Equations (54) and (55), at any given time, the energy level of ESS is obtained as follows: the sum of initial energy level and energy level during charging minus the sum of storage waste and discharging energy. The constraints of TSS and HSS can also be defined according to constraints (56) - (62) and (63) - (69), respectively [44, 54, 55].

$$n_{ESS,ch,t}Fch_{ESS,min} \leq F_{ESS,ch,t} \leq n_{ESS,ch,t}Fch_{ESS,max} \quad \forall t \tag{49}$$

$$n_{ESS,dch,t}Fdch_{ESS,min} \leq F_{ESS,dch,t} \leq n_{ESS,dch,t}Fdch_{ESS,max} \quad \forall t \tag{50}$$

$$R_{ESS,min} \leq R_{ESS,t} \leq R_{ESS,max} \quad \forall t \tag{51}$$

$$n_{ESS,ch,t} + n_{ESS,dch,t} \leq 1 \quad \forall t \tag{52}$$

$$IE_{ESS,ini} = R_{ESS,end} \tag{53}$$

$$R_{ESS,t} = R_{ESS,t-1} - \frac{F_{ESS,dch,t}}{K_{ESS,dch}} + K_{ESS,ch}F_{ESS,ch,t} - L_{ESS}\left(\frac{R_{ESS,t} + R_{ESS,t-1}}{2}\right) \quad \forall t \neq 1 \tag{54}$$

$$R_{ESS,t} = IE_{ESS,ini} - \frac{F_{ESS,dch,t}}{K_{ESS,dch}} + K_{ESS,ch}F_{ESS,ch,t} - L_{ESS}\left(\frac{R_{ESS,t} + R_{ESS,t-1}}{2}\right) \quad \forall t = 1 \tag{55}$$

$$n_{TSS,ch,t}Fch_{TSS,min} \leq F_{TSS,ch,t} \leq n_{TSS,ch,t}Fch_{TSS,max} \quad \forall t \tag{56}$$

$$n_{TSS,dch,t}Fdch_{TSS,min} \leq F_{TSS,dch,t} \leq n_{TSS,dch,t}Fdch_{TSS,max} \quad \forall t \tag{57}$$

$$R_{TSS,min} \leq R_{TSS,t} \leq R_{TSS,max} \quad \forall t \tag{58}$$

$$n_{TSS,ch,t} + n_{TSS,dch,t} \leq 1 \quad \forall t \tag{59}$$

$$IE_{TSS,ini} = R_{TSS,end} \tag{60}$$

$$R_{TSS,t} = R_{TSS,t-1} - \frac{F_{TSS,dch,t}}{K_{TSS,dch}} + K_{TSS,ch}F_{TSS,ch,t} - L_{TSS}\left(\frac{R_{TSS,t} + R_{TSS,t-1}}{2}\right) \quad \forall t \neq 1 \tag{61}$$

$$E_{TSS,t} = IE_{TSS,ini} - \frac{F_{TSS,dch,t}}{K_{TSS,dch}} + K_{TSS,ch}F_{TSS,ch,t} - L_{TSS}\left(\frac{R_{TSS,t} + R_{TSS,t-1}}{2}\right) \quad \forall t = 1 \tag{62}$$

$$n_{HSS,ch,t}Fch_{HSS,min} \leq F_{HSS,ch,t} \leq n_{HSS,ch,t}Fch_{HSS,max} \quad \forall t \tag{63}$$

$$n_{HSS,dch,t}Fdch_{HSS,min} \leq F_{HSS,dch,t} \leq n_{HSS,dch,t}Fdch_{HSS,max} \quad \forall t \tag{64}$$

$$n_{HSS,ch,t} + n_{HSS,dch,t} \leq 1 \quad \forall t \tag{65}$$

$$IE_{HSS,ini} = R_{HSS,end} \tag{66}$$

$$R_{HSS,t} = R_{HSS,t-1} - \frac{F_{HSS,dch,t}}{K_{HSS,dch}} + Q_{HSS}F_{HSS,ch,t} - L_{HSS}\left(\frac{R_{HSS,t} + R_{HSS,t-1}}{2}\right) \quad \forall t \neq 1 \tag{67}$$

$$R_{HSS,t} = IE_{HSS,ini} - \frac{F_{HSS,dch,t}}{K_{HSS,dch}} + Q_{HSS}F_{HSS,ch,t} - L_{HSS}\left(\frac{R_{HSS,t} + R_{HSS,t-1}}{2}\right) \quad \forall t = 1 \tag{68}$$

$$R_{HSS,min} \leq R_{HSS,t} \leq R_{HSS,max} \quad \forall t \tag{69}$$

### 3.1.8. Shift-up and shift-down constraints of demands

Constraints (70) - (81) present shift-up and shift-down constraints of responsive demands [55, 56]. According to constraints (70) - (72), it can be seen that at all times and for all scenarios, the amounts of SUED, SUTD and SUHD have been bounded via multiplying the demands by the SUED, SUTD and SUHD participation factors. Constraints (73) - (75) show that the amounts of SDED, SDTD and SDHD have been bounded via multiplying the demands by the SDED, SDTD and SDHD participation factors. Also, constraints (76) - (78) show that at no time and in no scenario the demands can be shifted up and down, simultaneously. Given the constraints of Equations (79) - (81), the sum of SUEDs and SDEDs, SUTDs and SDTDs, and SUHDs and SDHDs over operation horizon are equal.

$$DR_{e,up,t} \leq DPF_{e,up}.\mathrm{D}_{\mathrm{e,t}}.n_{DR,e,up,t} \quad \forall t \tag{70}$$

$$DR_{T,up,t} \leq DPF_{T,up}.\mathrm{D}_{\mathrm{T,t}}.n_{DR,T,up,t} \quad \forall t \tag{71}$$

$$DR_{h,up,t} \leq DPF_{h,up}.\mathrm{D}_{h,\mathrm{t}}.n_{DR,h,up,t} \quad \forall t \tag{72}$$

$$DR_{e,down,t} \leq DPF_{e,down}.\mathrm{D}_{\mathrm{e,t}}.n_{DR,e,down,t} \quad \forall t \tag{73}$$

$$DR_{T,down,t} \leq DPF_{T,down}.\mathrm{D}_{\mathrm{T,t}}.n_{DR,T,down,t} \quad \forall t \tag{74}$$

$$DR_{h,down,t} \leq DPF_{h,down}.\mathrm{D}_{h,\mathrm{t}}.n_{DR,h,down,t} \quad \forall t \tag{75}$$

$$n_{DR,e,up,t} + n_{DR,e,down,t} \leq 1 \quad \forall t \tag{76}$$

$$n_{DR,T,up,t} + n_{DR,T,down,t} \leq 1 \quad \forall t \tag{77}$$

$$n_{DR,h,up,t} + n_{DR,h,down,t} \le 1 \quad \forall t \tag{78}$$

$$\sum_t DR_{e,up,t} = \sum_t DR_{e,down,t} \quad \forall t \tag{79}$$

$$\sum_t DR_{T,up,t} = \sum_t DR_{T,down,t} \quad \forall t \tag{80}$$

$$\sum_t DR_{h,up,t} = \sum_t DR_{h,down,t} \quad \forall t \tag{81}$$

### 3.2. Risk-averse IGDT-based UC in EH

The risk-averse IGDT-based UC model is described here, which maximizes robustness horizon, while ensuring that the EH operation cost does not exceed a critical/acceptable operation cost. In this decision making mode, it is sufficient to make sure that the EH operation cost is not worse than the given target operating cost for the worst realization of uncertain input data. To ensure that it is not worse than the target operation cost $(1 + \alpha_{D_E})\mathrm{D}_{\mathrm{E,t}}$, $(1 + \alpha_{D_T})\mathrm{D}_{\mathrm{T,t}}$, $(1 + \alpha_{D_H})\mathrm{D}_{H,\mathrm{t}}$, $\left(1 + \alpha_{PR_{dragg.}}\right)PR_{dragg.,t}$ and $\left(1 + \alpha_{PR_{grid}}\right)PR_{grid,t}$ are the worst realization of electric, thermal and hydrogen demands and prices electricity and demand response aggregator, respectively, while $(1 - \alpha_{PV})\mathrm{PV}_{\mathrm{t}}$, $(1 - \alpha_{HSH})HSH_{\mathrm{t}}$ and $(1 - \alpha_{W})\mathrm{W}_{\mathrm{t}}$ are the worst realization of PV, HSH and wind power. Against the risk of unfavorable deviations of demands, PV/wind power and electricity prices, this mixed-integer model hedges EH operator [10].

$$max(\alpha) \tag{82}$$

$$\alpha = min\left(\alpha_{D_E}, \alpha_{D_T}, \alpha_{D_H}, \alpha_{PR_{grid}}, \alpha_{PR_{dragg.}}, \alpha_W, \alpha_{PV}, \alpha_{HSH}\right) \tag{83}$$

$$OF \le OF_{cr} \tag{84}$$

$$OF_{cr} = (1 + \beta).\overline{OF} \tag{85}$$

$$\begin{aligned} OF = {} & \sum_t \left(1 + \alpha_{PR_{grid}}\right) PR_{grid,t}\, .P_{grid,t} + \sum_t \left(1 + \alpha_{PR_{dragg.}}\right) PR_{dragg.,t}\, .P_{dragg.,t} \\ & + \sum_t PR_{NG,t}\, .P_{NG,t} + \sum_t (v_{boil,t}.SU_{boil} + m_{boil,t}.SD_{boil}) \\ & + \sum_t (v_{HE,t}.SU_{HE} + m_{HE,t}.SD_{HE}) - \sum_t (v_{BPP,t}.SU_{BPP} + m_{BPP,t}.SD_{BPP}) \\ & + \sum_t (v_{CHP,t}.SU_{AC} + m_{CHP,t}.SD_{AC}) + \sum_t (LO_E.P_{sh,t} + LO_T.T_{sh,t} + LO_H.H_{sh,t}) \\ & + DRC_t \quad \forall t \end{aligned} \tag{86}$$

$$\begin{aligned} & P_{grid,t} ef_{TR} + P_{dragg.,t} + P_{chp,t} + P_{bpp,t} + ef_{conv}\,(1 - \alpha_{PV})\mathrm{PV}_{\mathrm{t}} + (1 - \alpha_W)\mathrm{W}_{\mathrm{t}} + PS_{sh,t} + P_{ESS,dch,t} \\ & \quad + DR_{E,down,t} \ge \left(1 + \alpha_{D_E}\right)\mathrm{D}_{\mathrm{E,t}} + DR_{E,up,t} + P_{ESS,ch,t} + \frac{\mathrm{H}_{HE},\mathrm{t}}{\mathrm{Q}_{HE}} \quad \forall t \end{aligned} \tag{87}$$

$$\begin{aligned} & H_{boil,t} + H_{chp,t} + TS_{sh,t} + P_{TSS,dch,t} + DR_{T,down,t} + (1 - \alpha_{HSE})\mathrm{HSH}_{\mathrm{t}} \\ & \quad \ge \left(1 + \alpha_{D_T}\right)\mathrm{D}_{T,\mathrm{t}} + DR_{T,up,t} + F_{TSS,ch,t} \quad \forall t \end{aligned} \tag{88}$$

$$\mathrm{H}_{\mathrm{HE,t}} + H_{sh,t} + H_{HSS,dch,t} + DR_{H,down,t} \ge \left(1 + \alpha_{D_H}\right)\mathrm{D}_{H,\mathrm{t}} + DR_{H,up,t} + H_{HSS,ch,t} \quad \forall t \tag{89}$$

### 3.3. Risk-seeking IGDT-based UC in EH

The risk-seeking IGDT-based UC model is presented in this subsection, in which the minimal opportunity horizon is chosen in such a manner that a target operation cost may be achieved. The optimum realization of uncertain input data must lead to the target cost. In order for a target operating cost to be achieved. $(1+\alpha_E)\mathrm{D}_{\mathrm{E,t}}$, $(1+\alpha_{D_T})\mathrm{D}_{\mathrm{T,t}}$, $(1+\alpha_{D_H})\mathrm{D}_{H,\mathrm{t}}$, $\left(1+\alpha_{PR_{dragg.}}\right)PR_{dragg.,t}$ and $\left(1+\alpha_{PR_{grid}}\right)PR_{grid,t}$, are the best realization of electric, thermal and hydrogen demands and prices of electricity and demand response aggregator, respectively, while $(1+\alpha_{PV})\mathrm{PV_t}$, $(1-\alpha_{HSH})HSH_{\mathrm{t}}$ and $(1+\alpha_W)\mathrm{W_t}$ are the best realization of PV, HSE and wind power, respectively. The EH operator's goal in this model is to profit from favorable demand variations, PV/wind generation, and energy pricing [10].

$$min(\alpha) \tag{90}$$

$$\alpha = max\left(\alpha_{D_E}, \alpha_{D_T}, \alpha_{D_H}, \alpha_{PR_{grid}}, \alpha_{PR_{dragg.}}, \alpha_W, \alpha_{PV}, \alpha_{HSH}\right) \tag{91}$$

$$OF \geq OF_{targ} \tag{92}$$

$$OF_{targ} = (1-\beta).\overline{OF} \tag{93}$$

$$\begin{aligned} OF = &\sum_t \left(1-\alpha_{PR_{grid}}\right) PR_{grid,t}\,.P_{grid,t} + \sum_t \left(1-\alpha_{PR_{dragg.}}\right) PR_{dragg.,t}\,.P_{dragg.,t} \\ &+ \sum_t PR_{NG,t}\,.P_{NG,t} + \sum_t \left(v_{boil,t}.SU_{boil} + m_{boil,t}.SD_{boil}\right) \\ &+ \sum_t \left(v_{HE,t}.SU_{HE} + m_{HE,t}.SD_{HE}\right) - \sum_t \left(v_{BPP,t}.SU_{BPP} + m_{BPP,t}.SD_{BPP}\right) \\ &+ \sum_t \left(v_{CHP,t}.SU_{AC} + m_{CHP,t}.SD_{AC}\right) + \sum_t \left(LO_E.PS_{sh,t} + LO_T.TS_{sh,t} + LO_H.H_{sh,t}\right) \\ &+ DRC_t \quad \forall t \end{aligned} \tag{94}$$

$$\begin{aligned} &P_{grid,t}ef_{TR} + P_{dragg.,t} + P_{chp,t} + P_{bpp,t} + ef_{conv}\,(1+\alpha_{PV})\mathrm{PV_t} + (1+\alpha_W)\mathrm{W_t} + PS_{sh,t} + P_{ESS,dch,t} \\ &\quad + DR_{E,down,t} \geq \left(1-\alpha_{D_E}\right)\mathrm{D_{E,t}} + DR_{E,up,t} + P_{ESS,ch,t} + \frac{\mathrm{H}_{HE},\mathrm{t}}{\mathrm{Q}_{HE}} \quad \forall t \end{aligned} \tag{95}$$

$$\begin{aligned} &T_{boil,t} + T_{chp,t} + TS_{sh,t} + P_{TSS,dch,t} + DR_{T,down,t} + (1+\alpha_{HSH})\mathrm{HSH_t} \\ &\quad \geq \left(1-\alpha_{D_T}\right)\mathrm{D}_{T,\mathrm{t}} + DR_{T,up,t} + F_{TSS,ch,t} \quad \forall t \end{aligned} \tag{96}$$

$$\mathrm{H_{HE,t}} + H_{sh,t} + H_{HSS,dch,t} + DR_{H,down,t,s} \geq \left(1-\alpha_{D_H}\right)\mathrm{D}_{H,\mathrm{t}} + DR_{H,up,t} + H_{HSS,ch,t} \quad \forall t \tag{97}$$

## 4. Solution methodology

In this research, UC problem in EH is solved with the aim of day-ahead scheduling in such a way that the EH operation cost is minimized and all constraints are met. The problem is formulated as a mixed-integer model and is solved with CPLEX solver in GAMS. The CPLEX is a desirable solver for the problems of the linear, mixed-integer and quadratic programming. The CPLEX solver utilizes the algorithms of the primal simplex, dual simplex, the interior point barrier and the mixed integer, and a network optimizer along with the quadratic capability for tackling the optimization problems.

## 5. Simulation results

An EH with ESS, HSS, TSS, PV and wind renewable sources, biomass, CHP, HE, solar heater and boiler are investigated in the study. NG, electricity and DR aggregator are considered as EH inputs in order to fulfill EH needs for Electric, Heating and Hydrogen. The analyzed EH model is shown in Figure 2. Demands for electricity, heating and hydrogen are responsive, and load shedding is considered. EH pays a fixed and a TOU rate for NG and, electricity and DR aggregator, respectively. The hub can supply the electrical energy needed to supply loads by purchasing from the power grid or DR aggregator, or through PV, wind renewable energy or biomass. Biomass power plant’s fuel is supplied by waste materials. Therefore, the electric energy produced by biomass is free of charge. Biomass is a renewable source of energy derived from biological materials. Incentive-based DR programs are used for electrical, thermal and hydrogen demands in this study. In the incentive-based DR programs, consumers receive incentive for Shift-up and shift-down of the loads from peak hours to non-peak hours in order to decrease the EH operation costs.

Figure 3 depicts time factors (normalized with respect to their peak) of demands, PV, solar heat and wind power [10]. Tables 2-3 provide the data for the boiler and CHP, whereas Table 4 lists the other EH inputs [10]. The operation horizon is one day, while the operation resolution is one hour.

In 5.1, optimal operation of EH is presented without considering uncertainties. In 5.2, optimal operation of EH with consideration of uncertainties of electric, thermal and hydrogen demands, PV, heat of solar heater, wind, and the price of electricity purchased from power grid and DR aggregator is addressed from the perspective of the risk-averse and risk-seeking decision makers. In 5.3, decision variables for risk-averse and risk-seeking decision-making and deterministic are compared.

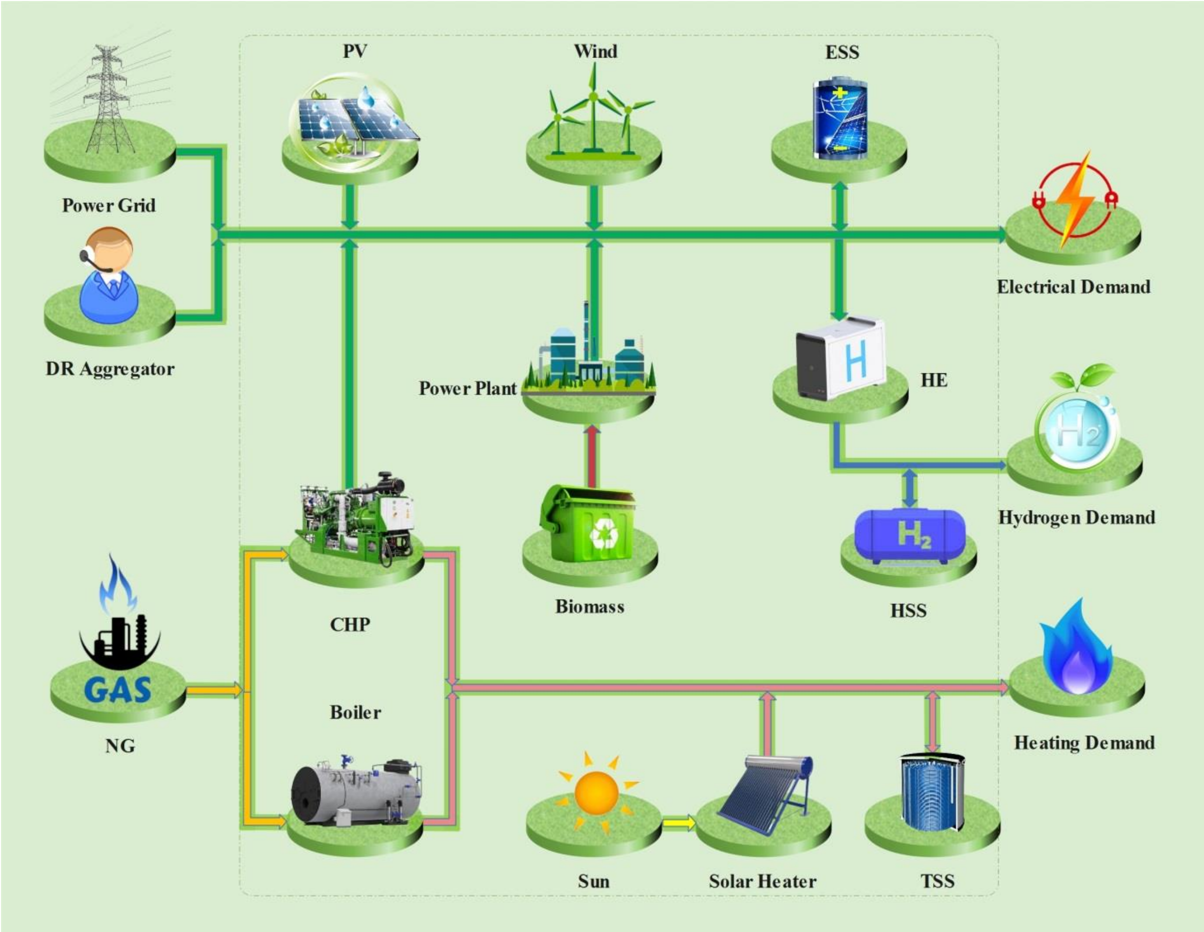


Fig.2. Scheme of the studied EH

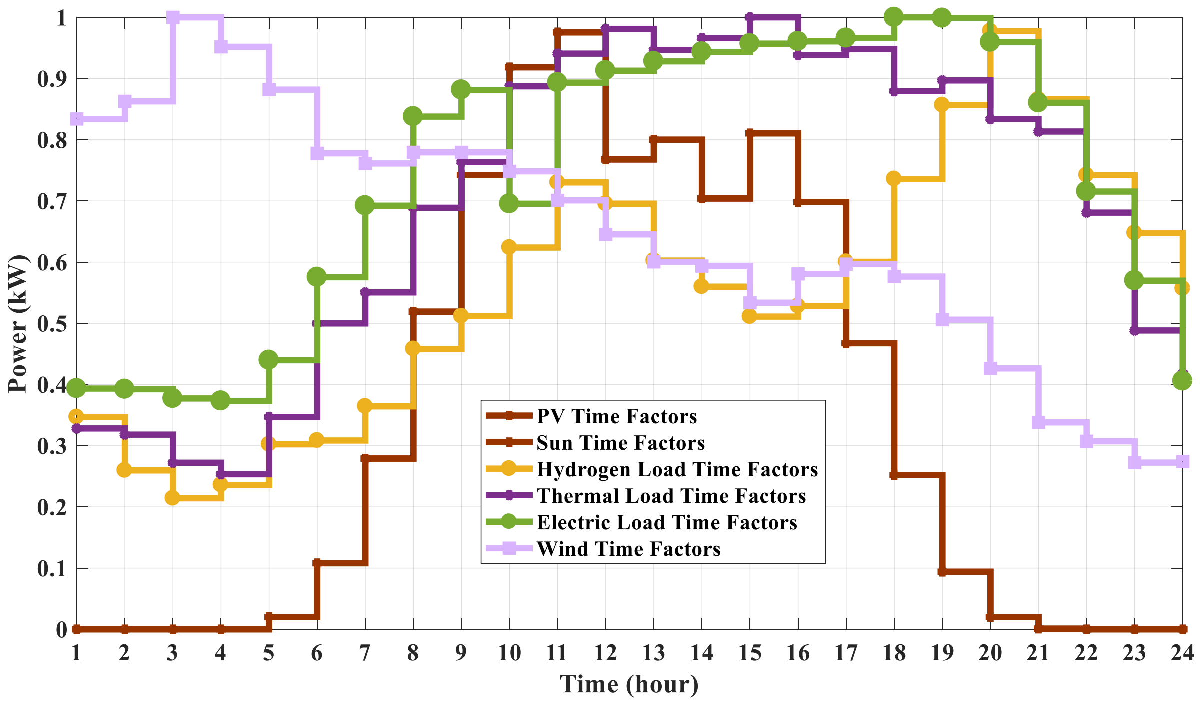


Fig.3. Time factors of demands and, PV, solar and wind power

Table 2. Boiler data

| Min. power (kW) | Max. power (kW) | Efficiency | RU (kW/h) | RD (kW/h) | SU cost ($) | SD cost ($) |
|---|---|---|---|---|---|---|
| 40 | 340 | 0.85 | 45 | 300 | 20 | 20 |

Table 3. CHP data

| Power efficiency | Thermal efficiency | Power RU (kW/h) | Power RD (kW/h) | Heat RU (kW/h) | Heat RD (kW/h) | SU cost ($) | SD cost ($) | $A_p$ | $A_h$ | $B_p$ | $B_h$ | $C_p$ | $C_h$ | $D_p$ | $D_h$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.46 | 0.36 | 110 | 250 | 60 | 210 | 15 | 15 | 293.3 | 0 | 245.6 | 200 | 55 | 141 | 65 | 153 |

Table 4. Input data of EH operation problem

| | | | |
|---|---|---|---|
| Max. purchasable electricity | 450 kW | Electric DR incentive | 1 Cents/kWh |
| Max. purchasable electricity | 420 kW | Hydrogen DR incentive | 0.4 Cents/kWh |
| Max. purchasable NG | 380 kW | Thermal DR incentive | 0.5 Cents/kWh |
| Peak electric load | 610 kW | Biomass incentive | 2 Cents/kWh |
| Peak thermal load | 400 kW | Peak hours of electricity tariff for power grid | 12-14, 19-22 |
| Peak hydrogen load | 300 kW | Mid-peak hours of electricity tariff for power grid | 11, 15-18 |
| NG price | 3 Cents/kWh | Off-Peak hours of electricity tariff for power grid | 23-10 |
| Lost electric load | 1 $/kWh | TOU peak price of power grid | 20 Cents/kWh |
| Lost thermal load | 0.5 $/kWh | TOU mid-peak price of power grid | 12 Cents/kWh |
| Lost hydrogen load | 0.5 $/kWh | TOU off-peak price of power grid | 6 Cents/kWh |
| PV capacity | 80 kW | Peak hours of electricity tariff for DR aggregator | 12-14, 19-22 |
| PV efficiency | 0.9 | Mid-peak hours of electricity tariff for DR aggregator | 9-11, 15-18 |
| Wind capacity | 80 kW | Off-Peak hours of electricity tariff for DR aggregator | 23-8 |
| Sun capacity | 80 kW | TOU peak price of DR aggregator | 24 Cents/kWh |
| Biomass capacity | 80 kW | TOU mid-peak price of DR aggregator | 16 Cents/kWh |
| Participation factor for DR | 0.2 | TOU off-peak price of DR aggregator | 4 Cents/kWh |

## 5.1. Optimal operation of EH without considering uncertainties

The problem of UC in EH without considering uncertainties is solved in this section. The various components of EH operation cost is shown in Table 5.

Table 5. Different components of EH operation cost

| **Components** | **Cost ($)** |
|---|---|
| Total purchased electricity | 1087.300 |
| Purchased electricity from power grid | 759.764 |
| Purchased electricity from DR aggregator | 327.536 |
| Purchased NG | 230.696 |
| The Incentive amount paid to EH for biomass | 32.64 |
| Start-up and shut-down | 0 |
| Load shed | 0 |
| Electric demand response | 16.185 |
| Thermal demand response | 5.304 |
| Hydrogen demand response | 2.595 |

| | |
|---|---|
| Total demand response | 24.084 |
| **Total cost of EH operation ($)** | **1309.441** |

According to Table 5, the cost of the EH operation is $1309.441 and there is no load shed, because the EH's energy sources completely meet all electrical, thermal and hydrogen demands, and these demands are responsive. As demonstrated in Table 5, the purchase of NG and electricity accounts for 98.19 percent of EH operating expenses. The procurement of natural gas and electricity accounts for 17.2% and 81.01% of EH operation expenses, respectively; 1.81% of EH operating expenses are made up of incentives provided in response to electricity, thermal and hydrogen demands. In addition, as can be seen from Table 5, biomass source decreases EH operation cost by 2.43%. Figure 4 depicts energy carriers price during 24 hours. Electricity is obtained from the power grid and DR aggregator on a TOU pricing scheme for the studied EH, while NG has a flat price. According to Figure 4, the price of gas is cheaper than all energy sources and has a fixed price at all hours. However, the price of electricity purchased from the power grid and DR aggregator varies during hours. As DR aggregator competes with the power grid in selling electricity, it provides cheaper electricity for some hours.

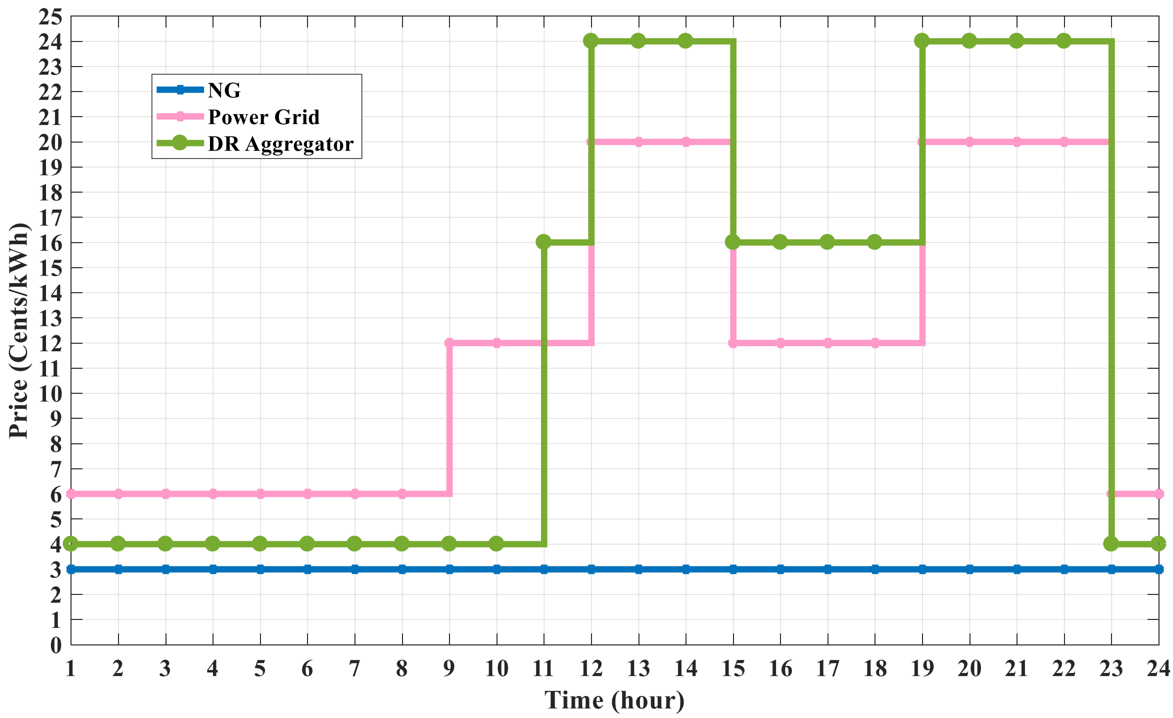


Fig.4. Energy carriers price during 24 hours

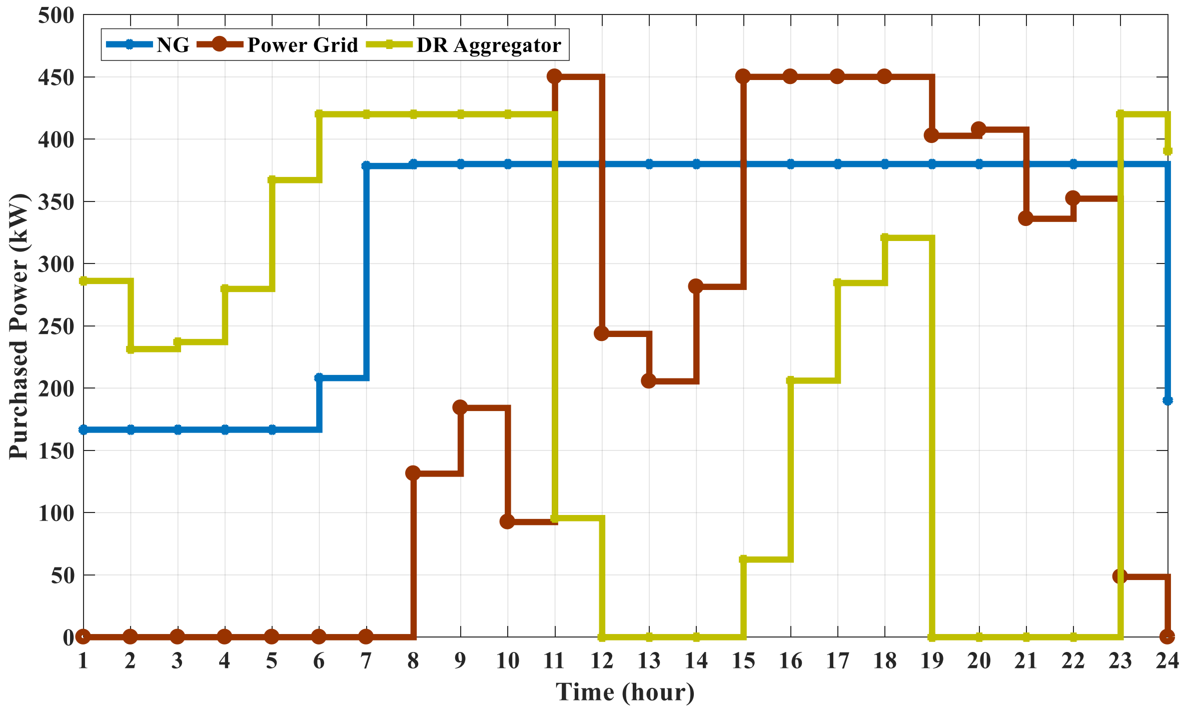


Fig.5. Purchased gas from NG and, purchased electricity from power grid and DR aggregator

Figure 5 illustrates purchased gas from NG network and purchased electricity from power grid and DR aggregator. In the study, purchased electrical energy from power grid and DR aggregator has a TOU tariff, while purchased gas from NG has a fixed tariff. In the model, hub can purchase electricity from power grid and DR aggregator. Therefore, the studied energy hub has two sources to purchase electricity. However, each of them has different tariffs during 24 hours. There are three inputs; electricity, DR aggregator and gas inputs, as well as three demands. The EH may obtain gas by buying from the NG, and the electricity can be obtained by purchasing from the power grid and DR aggregator, or from PV and wind renewable sources, and biomass.

According to Figure 5, the hub buys the power needed to supply loads from DR aggregator during hours 23-10, because in these hours, the price of power supply from DR aggregator is cheaper than the price of electricity from the power grid. The hub, on the other hand, buys the power needed to supply loads from the grid during the remaining hours. Because in those hours, the purchase price of power from the power grid is cheaper than the purchase price of electricity from DR aggregator. However, in some hours, such as hours 11 and 15-18, when more power is needed than the grid capacity, the hub, after using all the grid capacity, buys the remaining needed power from DR aggregator.

The schedule of electrical, hydrogen and thermal energies in EH, comprising energy sources, converters, energy storage systems is shown in Figures 6-8. The heat demand may be met by the boiler, solar heater, the CHP or the combination of them. A HE is used to meet the hydrogen needs.

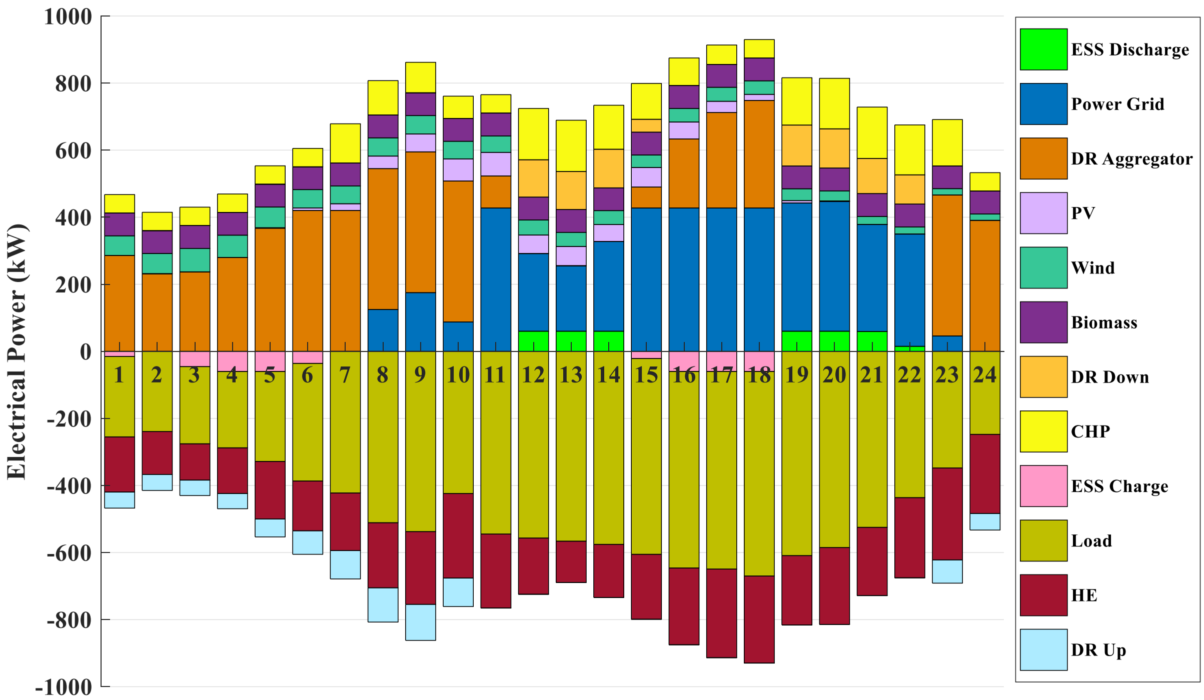


Fig.6. Electrical energy balance in EH

Figure 6 shows the electrical energy balance in the EH. According to the Figure 6, the distributed power in the EH in the hour 1 is 467.52 kW, While PV do not generate any power and the hub does not buy power from the grid in hour 1. In hour 1, 164.52 kW is used for producing hydrogen in HE; 240 kW is used to supply electrical demand; 15 kW is used to charge the ESS, respectively and 48 kW shift-up occurred in the electricity demand. At all hours except hours 12 to 15 when the price of electricity consumption is at its highest, the electricity purchased from the grid is used to supply electricity demand.

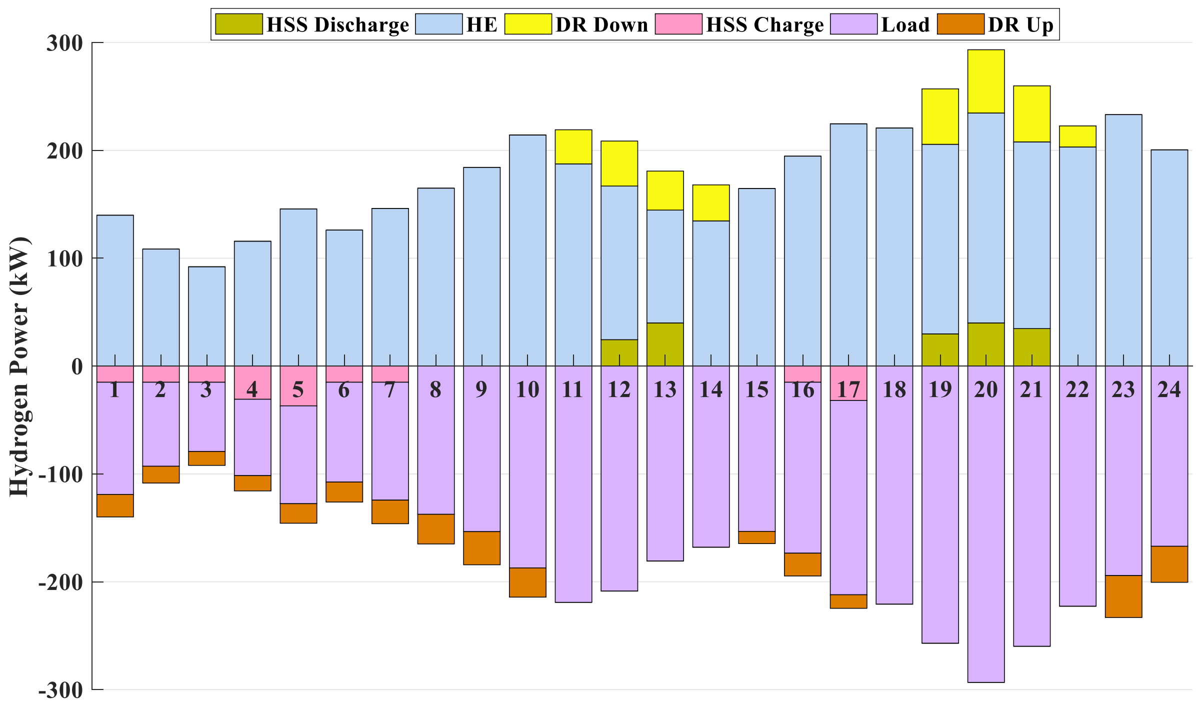

Fig.7. Hydrogen energy balance in EH

Figure 7 shows that during hour 1, HE generates 140 kW of hydrogen power. HSS is charged with 15 kW of this power. The hydrogen demand is supplied by 104 kW, with a 21 kW shift-up in the hydrogen demand. According to Figure 7, the hydrogen storage system is charged at low load and is discharged at high load to help supply of load.

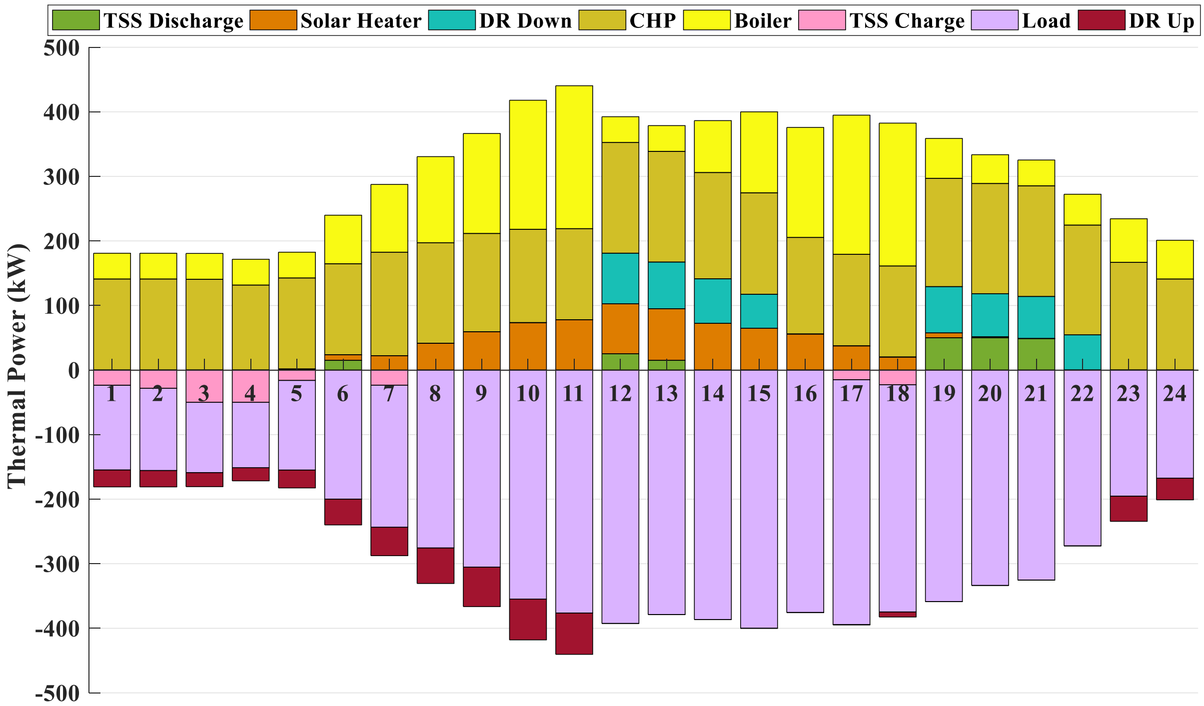


Fig.8. Thermal energy balance in EH

Figure 8 shows the thermal power distribution at the hours 1-24. Thermal power generated by CHP and boiler at hour 1 is 141 kW and 40 kW, respectively. The thermal demand is supplied by 131 kW, with a 26.50 kW shift-up in the hydrogen demand, while TSS is charged with 23.50 kW of thermal power.

### 5.1.1. Sensitivity analysis of EH operation cost with respect to input data

The sensitivity of the EH operation cost with respect to input data is investigated in this section. In this regard, by changing the data from 0.5 to 1.5 based on the Forecast error of 10%, the sensitivity of electric, thermal and hydrogen demands, PV and wind power, and the prices of the electricity, DR aggregator and gas with respect to the EH operation costs are analyzed. The simulation results of sensitivity analysis are presented in Table 6. It is worth noting that the value of $\beta$ is multiplied by the corresponding input data.

Table 6. Sensitivity analysis of EH operation cost with respect to input data

| | Demand | | | Power | | Price | | |
|---|---|---|---|---|---|---|---|---|
| $\beta$ | Electric | Thermal | Hydrogen | PV | Wind | Power grid | DR Aggregator | Gas |
| 0.5 | 634.60 | 1154.36 | 990.65 | 1355.49 | 1369.91 | 844.55 | 886.84 | 1188.11 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0.6 | 756.63 | 1154.36 | 1053.67 | 1346.27 | 1357.80 | 960.26 | 1001.56 | 1215.47 |
| 0.7 | 883.39 | 1158.66 | 1116.92 | 1337.05 | 1345.69 | 1062.90 | 1104.04 | 1239.89 |
| 0.8 | 1020.48 | 1205.68 | 1180.75 | 1327.84 | 1333.59 | 1153.74 | 1203.99 | 1263.30 |
| 0.9 | 1164.37 | 1253.95 | 1244.98 | 1318.64 | 1321.49 | 1233.45 | 1276.59 | 1286.37 |
| 1 | 1309.44 | 1309.44 | 1309.44 | 1309.44 | 1309.44 | 1309.44 | 1309.44 | 1309.44 |
| 1.1 | 1455.20 | 1372.72 | 1373.79 | 1300.24 | 1297.39 | 1385.41 | 1342.19 | 1332.51 |
| 1.2 | 1604.19 | 1442.18 | 1438.97 | 1291.03 | 1285.33 | 1434.19 | 1373.90 | 1355.17 |
| 1.3 | 1754.82 | 1599.25 | 1505.56 | 1281.83 | 1273.28 | 1460.51 | 1401.57 | 1377.22 |
| 1.4 | 1910.79 | 1855.07 | 1574.34 | 1272.63 | 1261.21 | 1477.62 | 1420.95 | 1399.24 |
| 1.5 | 2084.34 | 2116.55 | 1647.65 | 1263.43 | 1249.15 | 1494.73 | 1438.42 | 1421.26 |

As can be seen from Table 6, the EH operation costs are more sensitive to electric demand, the purchasing price of electricity from the power grid and the purchasing price of electricity from DR aggregator. While, the sensitivity with respect to thermal and hydrogen demands, PV power, wind power and gas price is less. The results show that increasing the electric demand by 10%, 20%, 30%, 40% and 50% increases the EH operation cost respectively by 11.11%, 22.5%, 34.01%, 45.92% and 59.17%. While, decreasing the electric demand by 10%, 20%, 30%, 40% and 50% decreases the EH operation cost respectively by 11.07%, 22.06%, 32.53%, 42.21% and 51.53%. Figure 11 displays the sensitivity of EH operation cost with respect to input data. As can be seen from Figure 11, the considerable increment of EH operation cost at higher $\beta$ values of demands is due to the imposition of the load shedding cost to the hub.

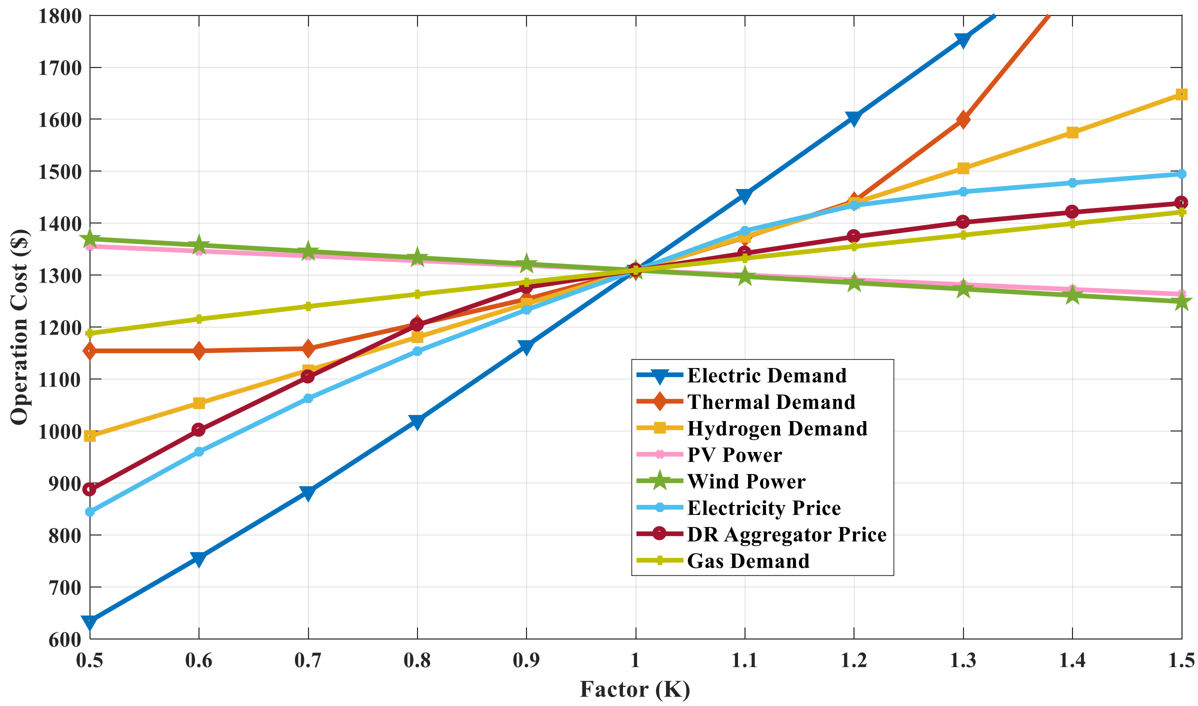


Fig.11. Sensitivity of EH operation cost with respect to input data

### 5.1.2. Energy storage systems

Energy storage systems increase EH flexibility in supplying loads and reduce operation costs by charging during low-load hours and discharging during high-load hours. In this section, the effect of the electrical, hydrogen and thermal storage systems on EH operation cost is evaluated. Table 7 displays specifications of electrical, hydrogen and thermal storages.

Table 7. Input data of electrical, hydrogen and thermal storage systems

| | Storages | | |
|---|---|---|---|
| | ESS | TSS | HSS |
| Min. charging power (kW) | 15 | 15 | 15 |
| Max. charging power (kW) | 60 | 50 | 40 |
| Min. discharging power (kW) | 15 | 15 | 15 |
| Max. discharging power (kW) | 60 | 50 | 40 |
| Charging efficiency | 0.90 | 0.95 | 0.95 |
| Discharge efficiency | 0.90 | 0.95 | 0.95 |
| Min. energy (kWh) | 15 | 15 | 15 |
| Max. energy (kWh) | 220 | 180 | 150 |
| Initial energy (kWh) | 15 | 15 | 15 |
| Storage loss factor | 0.001 | 0.001 | 0.001 |

The charging and discharging power of ESS, TSS and HSS, as well as their impact on the EH operation costs, are explored in this section. The charging and discharging power of storages, as well as their contribution in the cost of EH operation are shown in Figures 10-11.

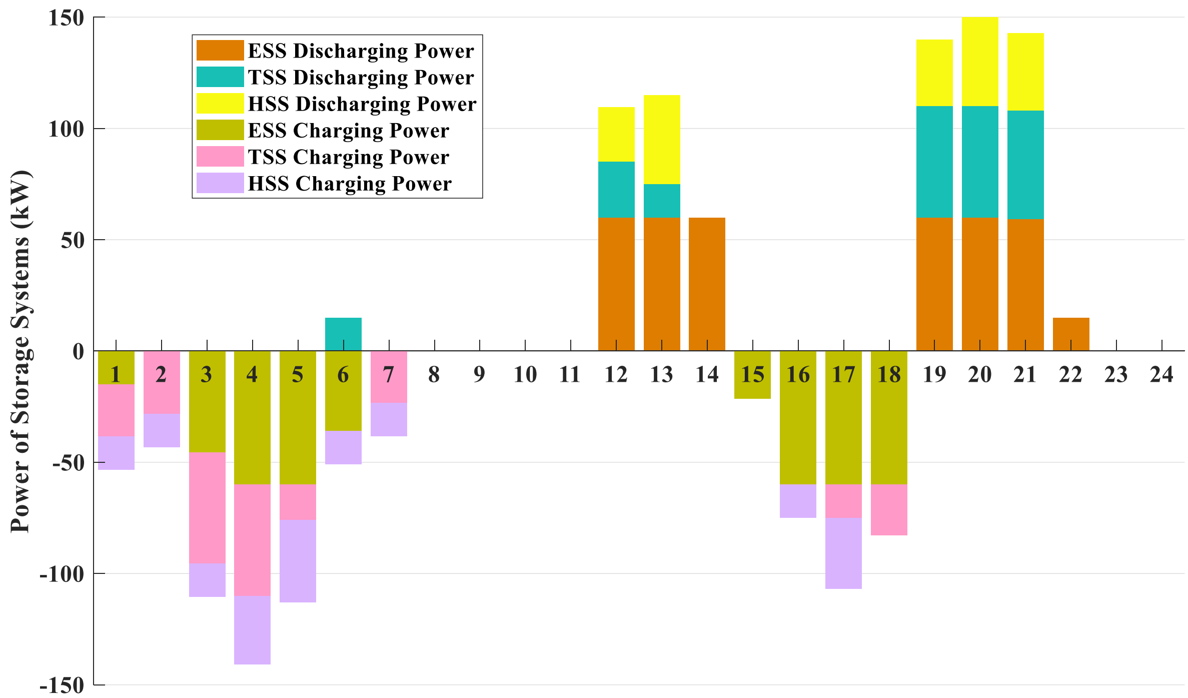


Fig.10. Charging and discharging power of electrical, hydrogen and thermal storage systems

Figure 10 illustrates the charging and discharging power of storage systems, including electrical, hydrogen and thermal. As demonstrated in Figure 10, storage systems are charged when electricity demand and price are at their lowest, and discharged when price and demand are at their highest, reducing the cost of EH operations. The ESS is charged during hours 1 and 3-5 and 15-18 when prices and demand are low, then discharged at hours 12-14 and 19-22, as shown in Figure 10. TSS is also charged during hours 1-5, 7 and 17-18 when thermal demand is low, and is released to supply thermal demand during hours 6, 12-13 and 19-21. The HSS is also charged during hours 1-7 and 16-17, when hydrogen demand is low, and discharged at hours 12-13 and 19-21. The EH storage systems often run in idle mode because of the significant expense of storage losses.

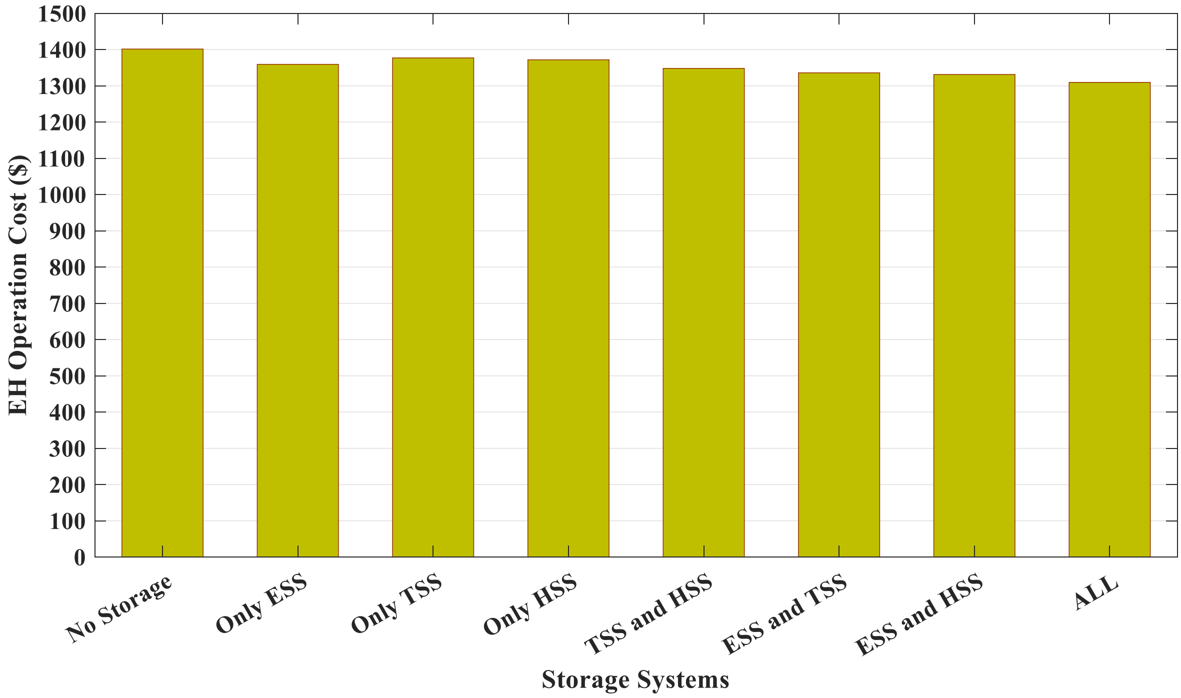


Fig.11. Effect of storages on EH operation cost

Figure 11 shows the impact of storages on the cost of EH operation. Various combinations of these storage systems are utilized to investigate the influence of ESS, HSS and TSS on EH operation costs. The impact of various storage systems on the cost of EH operations depends on a variety of parameters, including the EH model and components, energy carrier pricing profiles, demand profiles, charge/discharge/storage efficiencies, storage capacity, and so on. According to Figure 11, the operation cost of EH without storage systems is $1401.5, however when ESS, TSS and HSS are present, the cost of EH operation is decreased by 3%, 1.7% and 2.1%, respectively. As a result, TSS has marginal impact on reducing the cost of EH operation, but ESS and HSS have a large impact.

### 5.1.3. DR aggregator

In the research, DR aggregator is used as an EH resource for electricity. The EH can purchase the electricity required to supply the loads from the power grid and DR aggregators. Furthermore, DR aggregator can provide the electricity with lower price than power grid at some hours of the day and in this way, reduces EH operation cost. In this subsection, the effect of DR aggregator on EH operation cost is discussed. Table 8 shows different components of EH operation cost.

Table 8. Different components of EH operation cost

| Components | Cost ($) | | | |
|---|---|---|---|---|
| | No Power grid and DR aggregator | Power grid and DR aggregator | Only power grid | Only DR aggregator |

| | | | | |
|---|---|---|---|---|
| Total purchased electricity | 0 | 1087.300 | 1216.442 | 1214.779 |
| Purchased electricity from power grid | 0 | 759.764 | 1216.442 | 0 |
| Purchased electricity from DR aggregator | 0 | 327.536 | 0 | 1214.779 |
| Purchased NG | 273.6 | 230.696 | 240.759 | 229.738 |
| The Incentive amount paid to EH for biomass | 32.64 | 32.64 | 32.64 | 32.64 |
| Start-up and shut-down | 24 | 0 | 0 | 0 |
| Load shed | 6187.752 | 0 | 198.917 | 249.936 |
| Electric demand response | 4.286 | 16.185 | 0 | 0 |
| Thermal demand response | 1.319 | 5.304 | 0 | 0 |
| Hydrogen demand response | 0 | 2.595 | 198.917 | 249.936 |
| Total demand response | 5.606 | 24.084 | 15.764 | 15.386 |
| **Total cost of EH operation ($)** | **6458.310** | **1309.441** | **1639.243** | **1677.200** |

Figure 12 depicts the effect of purchased electricity sources on EH operation cost. The effect of different electricity sources on EH operation cost is determined by a variety of parameters including the studied EH model, components, energy carrier pricing profiles, purchasable electricity capacity from electricity sources, demand profiles and so on. According to Figure 12, the operation cost of EH without DR aggregator is $1639.243, while the EH operation cost with the presence of DR aggregator is $1309.441. In this case, the cost of EH operation is decreased by 20.1%. On the other hand, DR aggregator acts as a redundant source for the studied EH model. When EH is disconnected from power grid, EH can purchase the electricity needed for supplying demands from DR aggregator. Furthermore, the EH can purchase the cheaper electricity from DR aggregator than power grid in some hours, therefore, DR aggregator can be considered as a suitable alternative for electricity import in EH.

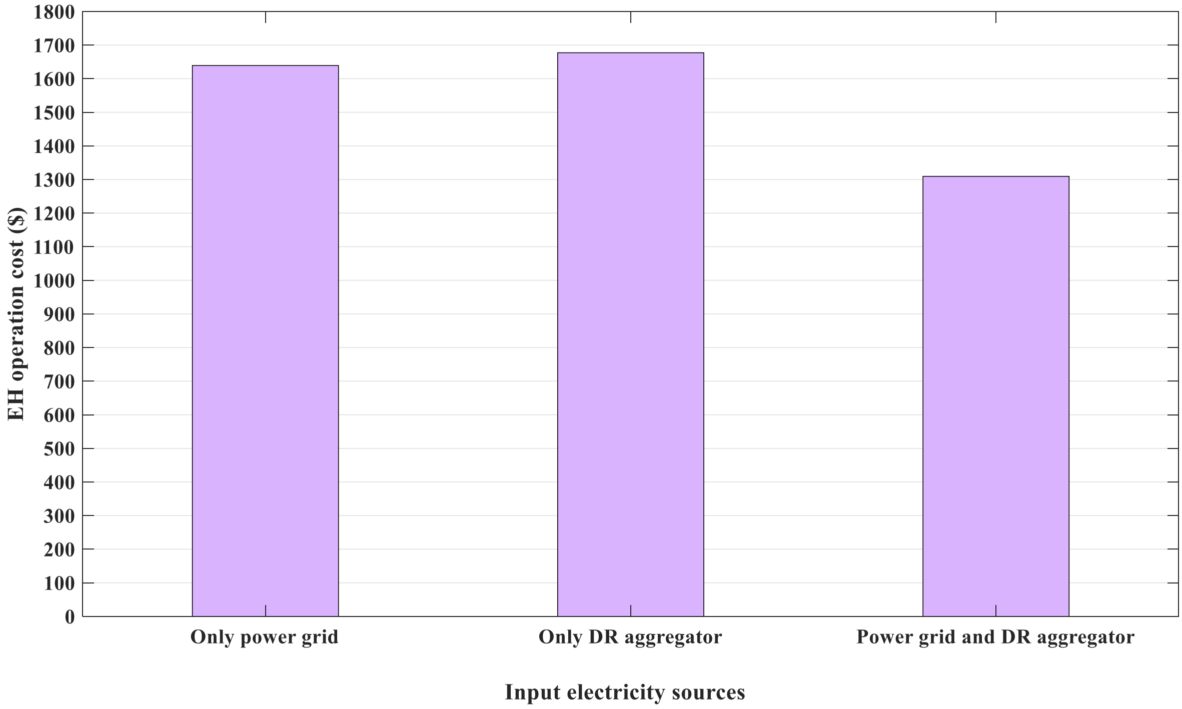


Fig.12. Effect of electricity sources on EH operation cost

Table 9 presents comparison of purchased electricity from power grid and DR aggregator, purchased gas from NG and produced power by CHP in the presence of different electricity sources during 24 hours.

As it can be seen from Table 9, the EH purchases electricity from power grid or DR aggregator for supplying demands when each one of them is available. In this case, when more power is needed than the grid capacity, the EH, after using all the grid capacity, purchases the rest of power needed to supply demands from CHP. Furthermore, the EH purchases electricity from power grid, DR aggregator or both of them according to the electricity price and grid capacity during 24 hours when both of power grid and DR aggregator sources are available.

Table 9. Comparison of decision variables for different electricity sources

| | Power grid and DR aggregator | | | Only power grid | | Only DR aggregator | |
|---|---|---|---|---|---|---|---|
| Hour | Purchased electricity from grid (kW) | Purchased electricity from DR Aggregator (kW) | CHP power (kW) | Purchased electricity (kW) | CHP power (kW) | Purchased electricity (kW) | CHP power (kW) |
| 1 | 0 | 286.12 | 55 | 301.18 | 55 | 286.12 | 55 |
| 2 | 0 | 231.37 | 55 | 250.30 | 55 | 231.37 | 55 |
| 3 | 0 | 237.01 | 55 | 182.93 | 55 | 240.20 | 55 |
| 4 | 0 | 279.69 | 55 | 283.71 | 55 | 290.36 | 55 |
| 5 | 0 | 367.12 | 55 | 354.13 | 75.53 | 370.78 | 55 |
| 6 | 0 | 420 | 55 | 408.83 | 140.23 | 420 | 55 |
| 7 | 0 | 420 | 117.26 | 450 | 133.30 | 420 | 99.61 |
| 8 | 131.30 | 420 | 102.63 | 450 | 117.65 | 420 | 120.72 |
| 9 | 184.13 | 420 | 90.97 | 450 | 130.67 | 420 | 130.67 |
| 10 | 92.47 | 420 | 66.62 | 450 | 106.32 | 420 | 106.32 |
| 11 | 450.00 | 95.63 | 55 | 450 | 129.19 | 420 | 106.44 |
| 12 | 243.59 | 0 | 153.15 | 450 | 118.29 | 420 | 118.29 |
| 13 | 205.46 | 0 | 153.15 | 450 | 121.59 | 420 | 122.85 |
| 14 | 281.37 | 0 | 131.25 | 450 | 97.24 | 420 | 118.90 |
| 15 | 450 | 62.32 | 106.90 | 450 | 72.89 | 420 | 94.54 |
| 16 | 450 | 206.02 | 82.54 | 450 | 82.83 | 420 | 82.83 |
| 17 | 450 | 284.44 | 58.19 | 450 | 68.35 | 420 | 68.35 |
| 18 | 450 | 320.70 | 55 | 450 | 120.74 | 420 | 120.74 |
| 19 | 402.69 | 0 | 141.38 | 450 | 108.88 | 420 | 108.88 |
| 20 | 407.61 | 0 | 150.62 | 450 | 118.12 | 420 | 118.12 |
| 21 | 336.04 | 0 | 153.15 | 450 | 110.63 | 420 | 121.32 |
| 22 | 352.19 | 0 | 148.92 | 450 | 148.92 | 420 | 113.51 |
| 23 | 48.41 | 420 | 138.20 | 450 | 138.20 | 420 | 138.20 |
| 24 | 0 | 390.66 | 55 | 342.96 | 119.84 | 390.66 | 55 |

## 5.2. Optimal operation of EH with consideration of uncertainties

The UC of the studied EH has 192 uncertain data including electric, thermal and hydrogen demands, PV, heat of solar heater and wind and the price of electricity purchased from power grid and DR aggregator. In the section 5.1, UC is addressed ignoring uncertainty of input data. However, the sensitivity analysis of the EH with respect to uncertain variables demonstrates that EH performance is sensitive to changes in input data, particularly electric demand and, the purchasing price of electricity purchased from the power grid and DR aggregator. This means that undesirable deviations of uncertain variables from forecasts will lead to higher operation costs than the EH operation cost without considering uncertainties. Thus, a robust decision-making method must be employed to ensure acceptable operation costs. Within robustness horizon, no deviation in uncertain variables leads to the higher operation costs than the pre-specified critical/acceptable operation costs of the EH. In this regard, the separate and simultaneous effect of uncertain input data on the studied model is discussed for both IGDT based risk-averse and risk-seeking decision makers. Indeed, the optimal decision-making of the operator or decision maker depends on his/her perspective in dealing with uncertainties. In other words, it is essential to study the impact of uncertainties on the EH day-ahead scheduling and operation costs from the perspective of an optimistic risk-seeker operator, a pessimistic risk-averse operator and a neutral uncertainty-free operator in order to achieve the optimal solution. Therefore, risk-averse, risk-seeking and uncertainty-free decision-making situations are utilized in this study.

### 5.2.1. Risk-averse day-ahead EH scheduling

The risk-averse IGDT is a model for considering uncertainty of input data. In the risk-averse IGDT model, the uncertainty horizon or robustness horizon should be maximized in such a way that the deviation from uncertainties in the robustness set does not result in a cost greater than the critical cost. The goal of risk-averse IGDT is not to minimize the operation cost of the EH, but the objective is to maximize the robustness horizon such that operation costs at the worst realisations of demands, solar heat, PV and wind power and purchased electricity prices from power grid and DR aggregator does not exceed critical cost. Although the robustness increases the operation cost of the EH, it protects the operator from the possibility of adverse variances in demand, PV/wind generation, and energy prices from forecasted values. In fact, operator considers the risk of increasing the demand and reducing generation resources in risk-averse IGDT in order to balance load and generation.

#### 5.2.1.1. EH scheduling with separate consideration of uncertainties

In this sub-section, uncertainty of electric, thermal and hydrogen demands, heat of solar heater, PV and wind power and the price of electricity purchased from power grid and DR aggregator are considered separately. In this regard, the impact of each of uncertain variables on the EH operation cost from the risk-averse perspective is investigated. Table 10 indicates robustness horizon for different deviation factors of critical operation cost. Also, Figure 13 shows tolerable deviation of input data to guarantee a certain critical operation cost. According to the results in Table 10 and Figure 13, for the critical operation cost of $1374.91 or critical cost deviation factor of 0.05, the maximum robustness horizon considering the uncertainties of electric, thermal and hydrogen demands, PV, heat of solar heater and wind, and, the price of electricity purchased from power grid and DR aggregator is 0.0422, 0.0986, 0.0959, 0.7107, 0.8416, 0.5413, 0.0862 and 0.1916, respectively.

The simulation results show that the deviations of electric demand and purchased electricity price from power grid is crucial in operation of the EH. For instance, if the critical cost deviation factor is 0.01, the robustness horizon of the electric demand is 0.0085. it means that the EH operation cost will not be more than 1% higher than nominal operation cost if the electric demand deviate within a 0.85% band concentered at their forecasted values. Also, for the critical cost deviation factor of 0.01, the robustness horizon of the purchased electricity price from power grid and DR aggregator is 0.0172 and 0.0171, respectively. It means that if the purchased electricity price from power grid and DR aggregator deviates within the range of 1.72% and 1.71% of the forecasts, the EH operation cost will not be more than 1% higher than the nominal operation cost.

As can be seen from Table 10, the operation cost of the EH is guaranteed not to be higher than \$1374.91, if electric, thermal and hydrogen demands, PV, heat of solar heater and wind power, and purchased electricity prices from power grid and DR aggregator deviate within 4.22%, 9.86%,9.59%, 71.07%, 84.16%, 54.13%, 8.62% and 19.16% band concentered at their forecasted values. As another instance, the operation cost of the EH is guaranteed not to be higher than \$1964.161, if electric, thermal and hydrogen demands respectively deviate within 40.39%, 42.21% and 72.09% band concentered at their forecasted values and, PV, heat of solar heater and wind power, and purchased electricity prices from power grid and DR aggregator deviate within 1% band concentered at their forecasted values.

Table 10. Robustness horizon for different deviation factors of critical operation cost

| $\beta$ | Critical operation cost (\$) | $\alpha_{D_e}$ | $\alpha_{D_T}$ | $\alpha_{D_h}$ | $\alpha_{PV}$ | $\alpha_{HSH}$ | $\alpha_{wind}$ | $\alpha_{\pi_{grid}}$ | $\alpha_{\pi_{dragg.}}$ |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1309.440 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.01 | 1322.535 | 0.0085 | 0.0202 | 0.0192 | 0.1423 | 0.1792 | 0.1086 | 0.0172 | 0.0171 |
| 0.02 | 1335.629 | 0.0169 | 0.0405 | 0.0384 | 0.2846 | 0.3559 | 0.2168 | 0.0345 | 0.0549 |
| 0.03 | 1348.724 | 0.0253 | 0.0604 | 0.0576 | 0.4266 | 0.5227 | 0.3251 | 0.0517 | 0.1017 |
| 0.05 | 1374.913 | 0.0422 | 0.0986 | 0.0959 | 0.7107 | 0.8416 | 0.5413 | 0.0862 | 0.1916 |
| 0.07 | 1401.101 | 0.0591 | 0.1354 | 0.1340 | 0.9948 | 1 | 0.7571 | 0.1207 | 1 |
| 0.09 | 1427.290 | 0.0758 | 0.1716 | 0.1715 | 1 | 1 | 0.9732 | 0.1777 | 1 |
| 0.1 | 1440.385 | 0.0842 | 0.1895 | 0.1901 | 1 | 1 | 1 | 0.2200 | 1 |
| 0.3 | 1702.273 | 0.2479 | 0.3244 | 0.5295 | 1 | 1 | 1 | 1 | 1 |
| 0.4 | 1833.217 | 0.3271 | 0.3733 | 0.6386 | 1 | 1 | 1 | 1 | 1 |
| 0.5 | 1964.161 | 0.4039 | 0.4221 | 0.7209 | 1 | 1 | 1 | 1 | 1 |

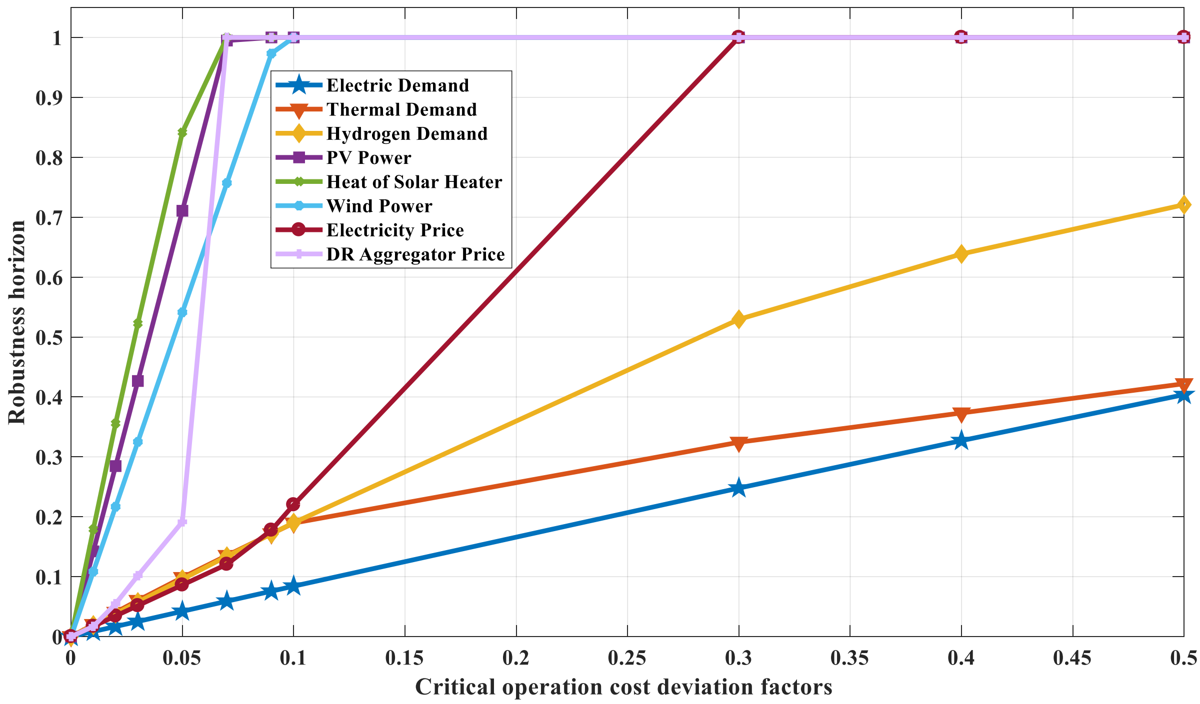


Fig.13. Tolerable deviation of input data to guarantee a certain critical operation cost

#### 5.2.1.2. EH scheduling with simultaneous consideration of uncertainties

In this sub-section, uncertainties of electric, thermal and hydrogen demands, PV, heat of solar heater and wind, and the price of electricity purchased from power grid and DR aggregator are simultaneously considered from the risk-averse perspective. In other words, the objective of EH scheduling considering all uncertainties is to maximize the total robustness horizon ($\alpha_{Total}$) in a way the operation costs at the worst realization of electric, thermal and hydrogen demands, PV, heat of solar heater and wind power, and purchased electricity prices from power grid and DR aggregator does not exceed critical cost. The ($\alpha_{Total}$) is equal to ($\alpha_{D_e} + \alpha_{D_T} + \alpha_{D_h} + \alpha_{HSH} + \alpha_{wind} + \alpha_{\pi_{grid}} + \alpha_{\pi_{dragg.}}$). It is worth stating that the EH scheduling with the consideration of the all uncertainties is done for $\beta = 0.05$. Table 11 displays the total robustness horizon for 0.05 deviation factor of critical operation cost. According to the Table 11, the total robustness horizon is equal to 0.842 for 0.05 deviation factor of critical operation cost. The robustness horizon is maximized at 0.842 when the robustness horizon of electric, thermal and hydrogen demands, PV and wind power, and purchased electricity prices from power grid and DR aggregator is equal to 0 and the robustness horizon of heat of solar heater is equal to 0.842. Indeed, the operation cost of the EH is guaranteed not to be higher than $1374.91, if electric, thermal and hydrogen demands, PV and wind power, and purchased electricity prices from power grid and DR aggregator are at their forecasted values and, heat of solar heater deviate within 84.2% band concentered at its forecasted value.

Table 11. Total robustness horizon for 0.05 deviation factor of critical operation cost

| $\beta$ | Critical operation cost ($) | $\alpha_{Total}$ | $\alpha_{D_e}$ | $\alpha_{D_T}$ | $\alpha_{D_h}$ | $\alpha_{PV}$ | $\alpha_{HSH}$ | $\alpha_{wind}$ | $\alpha_{\pi_{grid}}$ | $\alpha_{\pi_{dragg.}}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.05 | 1374.913 | 0.842 | 0 | 0 | 0 | 0 | 0.842 | 0 | 0 | 0 |

The schedule of electrical and thermal energies in EH, including demands, energy generation resources, converters, energy storage systems, and DR program is indicated in Figures 14 and 15 in hours 1-24.

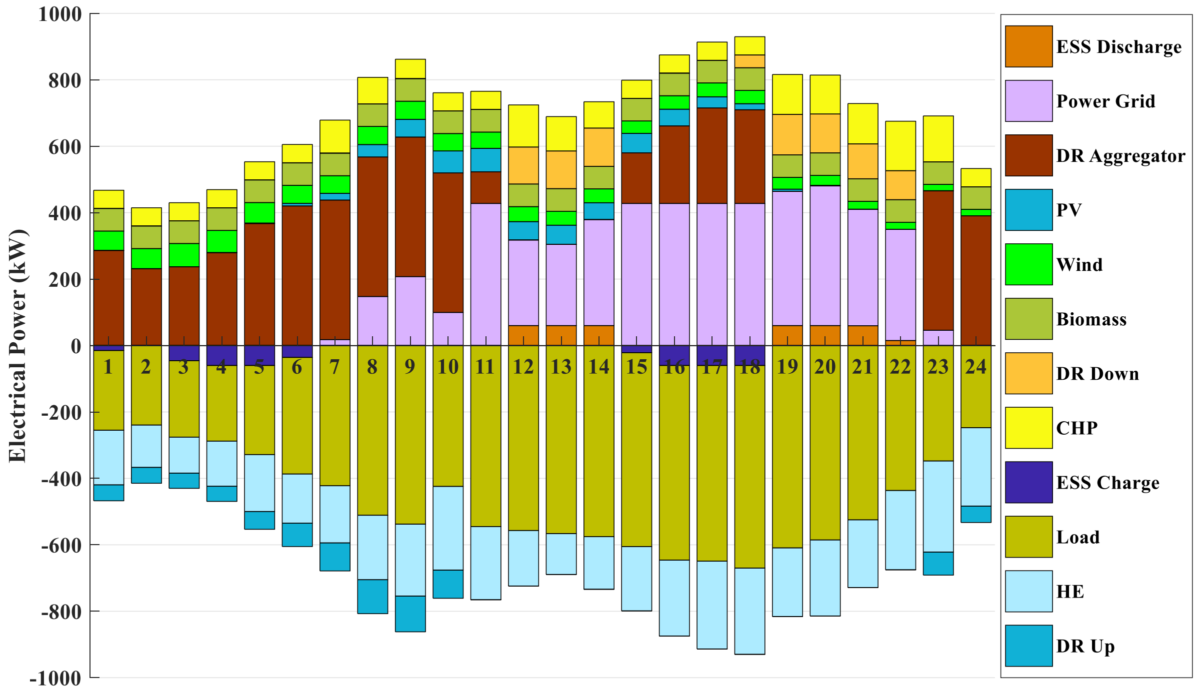


Fig.14. Electrical energy balance in EH

As can be seen from Figure 14, the purchased electrical power from power grid and DR aggregator is increased and the electrical power generated by CHP is decreased with respect to the forecasted values, while the electrical power of the other components is equal to their forecasted values. This is due to an 84.2% reduction in heat of solar heater compared to the forecasted value. This reduction in generating heating energy and consequently inability to supply thermal demand leads to the compensation of heating energy by CHP. Therefore, in this case generated electricity by CHP is reduced with respect to the forecasted value in order to provide more heating energy. By reducing the electricity generated by the CHP, the EH must purchase the electricity needed to supply demands from power grid and DR aggregator. Thus, the purchased electricity by the EH in this case is higher than purchased electricity without considering uncertainties.

According to the Figure 14, by reducing the electricity generated by the CHP in hours 7-10, 12-17 and 19-21, the EH purchases the electricity needed to supply electric demands from power grid and DR aggregator due to the electricity price and grid capacity. For instance, the purchased electricity price from DR aggregator is cheaper than purchased electricity price from power grid in hours 7-10. Although, in the same hours, the EH has to purchase electricity needed from power grid due to DR aggregator capacity. In hours 15-18, the purchased electricity price from power grid is cheaper than purchased electricity price from DR aggregator. Although, in the same hours, the EH has to purchase electricity needed from DR aggregator due to the power grid capacity.

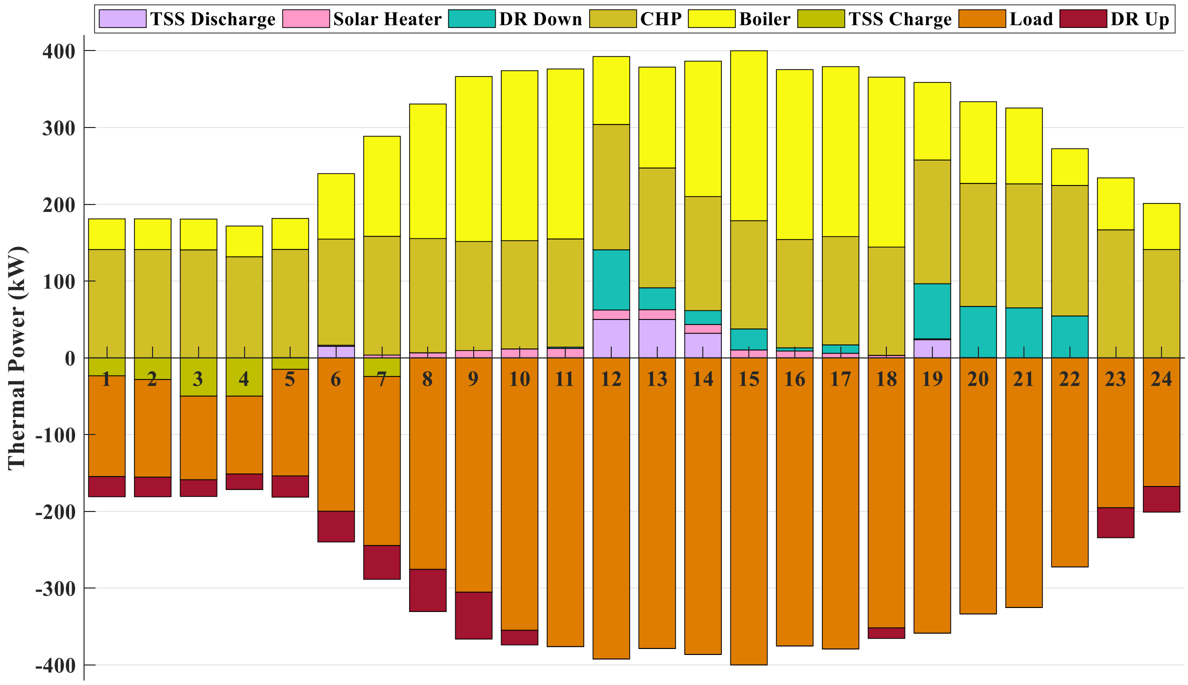


Fig.15. Thermal energy balance in EH

Figure 15 shows the thermal power at the hours 1-24. Due to the 84.2% reduction in heat of solar heater in comparison with the forecasted value, and the reduction of generating heating energy and consequently inability to supply thermal demand leads, heating energy is supplied by CHP and boiler.

### 5.2.2. Risk-seeking day-ahead EH scheduling

The risk-seeking IGDT is a model for considering uncertainties. In the risk-seeking IGDT model, the opportunity horizon or uncertainty horizon must be minimized in such a way that the best deviation from uncertainties in the opportunity set lead to the target operation cost. In other words, the objective of the risk-seeking IGDT is to acquire the minimum deviations of uncertainties in such a way the best amount of demands, PV, heat of solar heater and wind power, and purchased electricity prices from power grid and DR aggregator leads to the target operation cost. In the risk-seeking model, the decision in UC is made from the point of view of an optimistic decision maker.

#### 5.2.2.1. EH scheduling with separate consideration of uncertainties

This subsection discusses the EH scheduling with the consideration of the uncertainty of electric, thermal and hydrogen demands, PV, heat of solar heater and wind, and, the price of electricity purchased from power grid and DR aggregator, in order to evaluate the effect of uncertain variables on the EH operation costs from the perspective of an optimistic risk-seeker operator. Table 12 displays the required deviation of input data to achieve the certain target cost. According to the Table 12, for the target operation cost of $1243.97 or deviation factor of 0.05, the minimum opportunity horizon considering the uncertainties of electric, thermal and hydrogen demands, PV, heat of solar heater and wind, and, the price of electricity purchased from power grid and DR aggregator is 0.1137, 0.0959, 0.7116, 0.9645, 0.5431, 0.0862, 0.1525 and 0.0423, respectively. Consideration of a target cost deviation factor of 0.05 means that decision maker obtains decision variables and opportunity horizons in order to achieve an operation cost 5% lower than nominal cost. As per Table 12, for target cost of $1243.968 with target cost deviation factor of 5%, electric, thermal and hydrogen demands, PV, heat of solar heater and wind power, and purchased electricity prices from power grid and DR aggregator must deviate within 11.37%, 8.59%, 71.16%, 96.45%, 54.31%, 8.62%, 15.25% and 4.23% band concentered at their forecasted values.

Table 12. Comparison of the required deviation of input data to maintain the chance of achieving a certain target cost

| $\rho$ | Target operation cost ($) | $\alpha_{D_e}$ | $\alpha_{D_T}$ | $\alpha_{D_h}$ | $\alpha_{PV}$ | $\alpha_{HSH}$ | $\alpha_{wind}$ | $\alpha_{\pi_{grid}}$ | $\alpha_{dragg.}$ |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1309.4410 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.01 | 1296.34659 | 0.0215 | 0.0192 | 0.1423 | 0.1876 | 0.1087 | 0.0332 | 0.0407 | 0.0085 |
| 0.03 | 1270.15777 | 0.0661 | 0.0577 | 0.4270 | 0.5652 | 0.3260 | 0.0643 | 0.1227 | 0.0254 |
| 0.05 | 1243.96895 | 0.1137 | 0.0959 | 0.7116 | 0.9645 | 0.5431 | 0.0862 | 0.1525 | 0.0423 |
| 0.1 | 1178.49690 | 0.2610 | 0.1919 | NA | NA | NA | 0.1708 | 0.2269 | 0.0845 |
| 0.15 | 1113.02485 | NA | 0.2883 | NA | NA | NA | 0.2476 | 0.2912 | 0.1268 |
| 0.2 | 1047.55280 | NA | 0.3853 | NA | NA | NA | 0.3161 | 0.3555 | 0.1693 |
| 0.25 | 982.080750 | NA | 0.4829 | NA | NA | NA | 0.3812 | 0.4182 | 0.2121 |
| 0.3 | 916.608700 | NA | 0.5821 | NA | NA | NA | 0.4378 | 0.4757 | 0.2551 |
| 0.35 | 851.136650 | NA | 0.6890 | NA | NA | NA | 0.4943 | 0.5294 | 0.2991 |
| 0.4 | 785.664600 | NA | 0.8109 | NA | NA | NA | 0.5509 | 0.5833 | 0.3443 |

### 5.2.2.2. EH scheduling with simultaneous consideration of uncertainties

This subsection presents uncertainty of electric, thermal and hydrogen demands, PV, heat of solar heater and wind, and, the price of electricity purchased from power grid and DR aggregator from the point of view of risk-seeking, simultaneously. In other words, the objective of EH scheduling considering the all uncertainties is to minimize the total opportunity horizon or uncertainty horizon ($\alpha_{Total}$) in a way the best realization of demands, PV, heat of solar heater and wind power, and purchased electricity prices from power grid and DR aggregator leads to the target operation cost. The ($\alpha_{Total}$) is equal to ($\alpha_{D_e} + \alpha_{D_T} + \alpha_{D_h} + \alpha_{HSH} + \alpha_{wind} + \alpha_{\pi_{grid}} + \alpha_{\pi_{dragg.}}$). It is worth stating that the EH scheduling with the consideration of the all uncertainties is done for $\beta = 0.05$. Table 13 shows the total robustness horizon for 0.05 deviation factor of critical operation cost. According to the Table 13, the total opportunity horizon is equal to 0.0423 for 0.05 deviation factor of target operation cost. The total opportunity horizon is minimized at 0.0423 when the opportunity horizon of thermal and hydrogen demands, PV and wind power, and purchased electricity prices from power grid and DR aggregator is equal to 0 and the opportunity horizon of electric demand is equal to 0.0423. In fact, the operation cost of the EH is guaranteed to be equaled $1243.97, if thermal and hydrogen demands, PV, heat of solar heater and wind power, and purchased electricity prices from power grid and DR aggregator are set at their forecasted values and, electric demand be deviated within 4.23% band concentered at its forecasted value.

Table 13. Total opportunity horizon for 0.05 deviation factor of target operation cost

| $\rho$ | Target operation cost ($) | $\alpha_{Total}$ | $\alpha_{D_e}$ | $\alpha_{D_T}$ | $\alpha_{D_h}$ | $\alpha_{PV}$ | $\alpha_{HSH}$ | $\alpha_{wind}$ | $\alpha_{\pi_{grid}}$ | $\alpha_{\pi_{dragg.}}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.05 | 1243.96895 | 0.0423 | 0.0423 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

The schedule of electrical and thermal energies in EH, including demands, energy generation resources, converters, energy storage systems, and the DS program is shown in Figures 16 and 17 in hours 1-24.

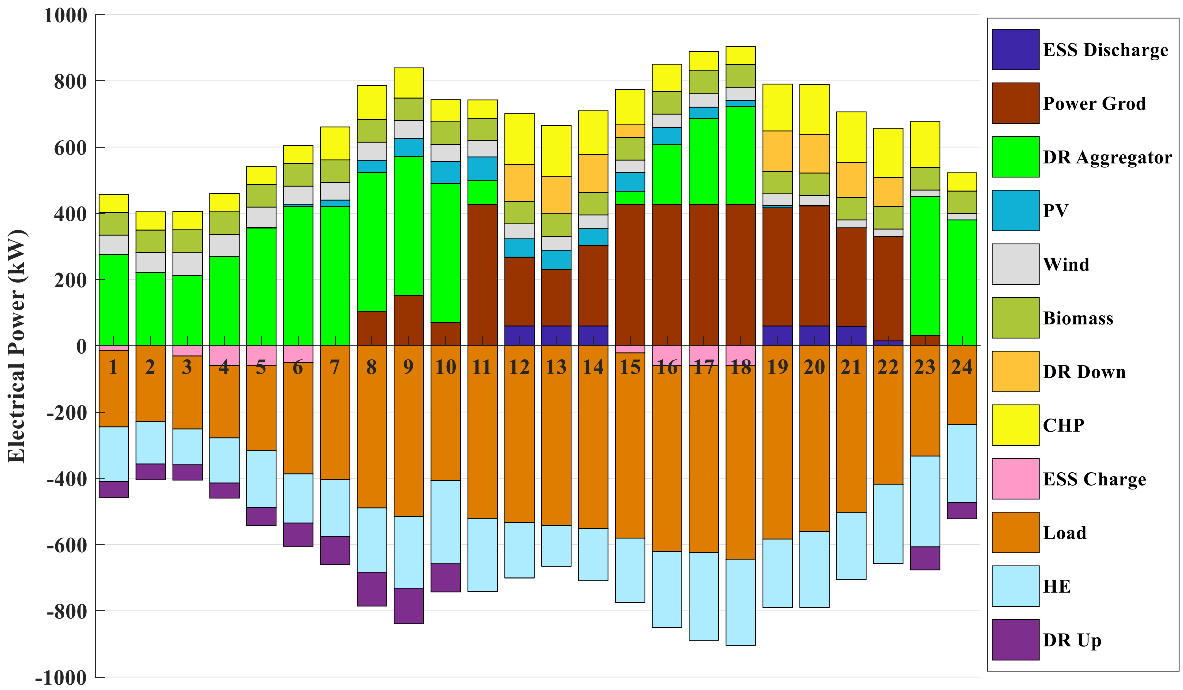


Fig.16. Electrical energy balance in EH

As can be seen from Figure 16, the purchased electrical power from power grid and DR aggregator is decreased with respect to the forecasted values. While, the electrical power of the other components is equal to their forecasted values. This is due to a 4.23% reduction in electric demand compared to the forecasted value. This reduction in electric demand leads to reduce the purchased electrical power from power grid and DR aggregator and consequently reduction of the EH operation cost. Thus, the purchased electricity by the EH in this case is lower than purchased electricity without considering uncertainties. Figure 17 shows the thermal power dispatch at the hours 1-24. As can be seen from Figure 17, thermal power dispatch in this case is equal to the forecasted values.

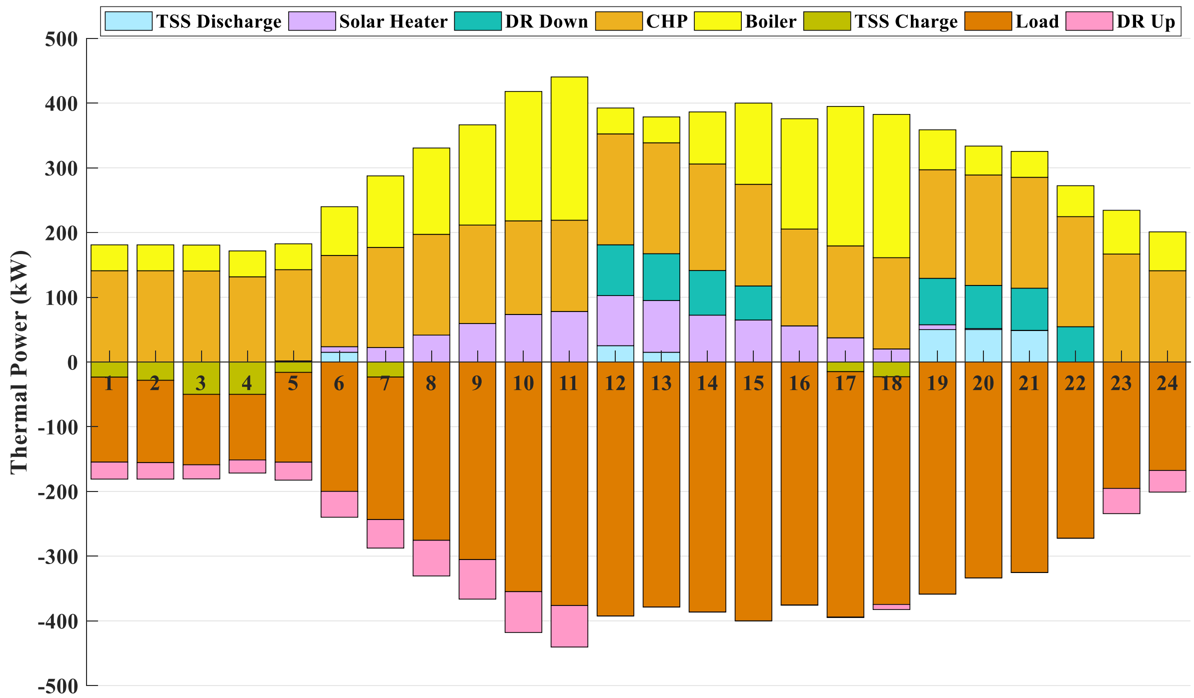


Fig.17. Thermal energy balance in EH

## 5.3. Comparison of decision variables for risk-averse, risk-seeking and uncertainty-free decision making

This subsection presents the comparison and impact of decision variables on UC in EH for risk-averse, risk-seeking and uncertainty-free decision making with the consideration of the price uncertainty of electricity purchased from power grid and DR aggregator. The results are shown in Tables 14 and 15 and Figures 18-25.

Table 14 presents the comparison of purchased electricity from power grid, purchased electricity from DR aggregator, purchased gas from NG and produced power by CHP for risk-averse, risk-seeking and uncertainty-free decision making, considering price uncertainty of electricity purchased from power grid. According to the Table 14, at hours 12-14 and 19-22, EH operator purchases less electricity from power grid in the risk-averse decision-making than uncertainty-free decision-making in order to hedge himself against risk of purchased electricity price deviations from power grid. In this case, DR aggregator as a redundant source provides more electricity for supplying electric demands. When EH purchases less electricity from power grid, the EH can purchase the electricity needed for supplying demands from DR aggregator. Furthermore, the EH can purchase the cheaper electricity from DR aggregator than power grid in some hours. Therefore, the DR aggregator can be considered as a suitable alternative for EH operation and supplying demands in the risk-averse decision-making. On the contrary, in the risk-seeking decision-making, EH purchases more electricity from power grid than uncertainty-free decision-making despite the price uncertainty of electricity purchased from power grid in the hope of decreasing its operation cost. Figures 18-21 show purchased electricity from power grid and DR aggregator, purchased gas from NG and produced power by CHP for risk-averse, risk-seeking and uncertainty-free decision making, considering price uncertainty of electricity purchased from power grid, respectively. Figures 18 and 19 show that at hours 12-14 and 19-22, risk-averse EH operator decreases the electricity purchase from power grid and increases electricity purchase from DR aggregator. While, risk-seeking EH operator increases the electricity purchase from power grid and decreases electricity purchase from DR aggregator. As it can be seen from Figures 20 and 21, the purchased gas from NG and produced power by CHP in both risk-averse and risk-seeking decision-making is almost equal to the same amounts in deterministic due to the availability of redundant electricity sources in the EH model studied.

Table 14. Comparison of decision variables for risk-averse, risk-seeking and uncertainty-free decision making considering price uncertainty of electricity purchased from power grid

| | Uncertainty Free ($\beta = 0$) | | | | Risk-averse decision making ($\beta = 0.1$) | | | | Risk-seeking decision making ($\rho = 0.1$) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hour | Purchased electricity from grid (kW) | Purchased electricity from DR Aggregator (kW) | Purchased gas (kW) | CHP power (kW) | Purchased electricity from grid (kW) | Purchased electricity from DR Aggregator (kW) | Purchased gas (kW) | CHP power (kW) | Purchased electricity from grid (kW) | Purchased electricity from DR Aggregator (kW) | Purchased gas (kW) | CHP power (kW) |
| 1 | 0 | 286.12 | 166.62 | 55 | 0 | 286.12 | 166.62 | 55 | 0 | 286.12 | 166.62 | 55 |
| 2 | 0 | 231.37 | 166.62 | 55 | 0 | 231.37 | 166.62 | 55 | 0 | 231.37 | 166.62 | 55 |
| 3 | 0 | 237.01 | 166.62 | 55 | 0 | 237.01 | 166.62 | 55 | 0 | 237.01 | 166.62 | 55 |
| 4 | 0 | 279.69 | 166.62 | 55 | 0 | 279.69 | 166.62 | 55 | 0 | 279.69 | 166.62 | 55 |
| 5 | 0 | 367.12 | 166.62 | 55 | 0 | 367.12 | 166.62 | 55 | 0 | 367.12 | 171.32 | 55 |
| 6 | 0 | 420 | 208.11 | 55 | 0 | 420 | 208.11 | 55 | 0 | 420 | 208.11 | 55 |
| 7 | 0 | 420 | 378.40 | 117.26 | 0 | 420 | 378.40 | 117.26 | 65.53 | 420 | 261.05 | 55 |
| 8 | 131.30 | 420 | 380 | 102.63 | 131.30 | 420 | 380 | 102.63 | 181.43 | 420 | 293.81 | 55 |
| 9 | 184.13 | 420 | 380 | 90.97 | 143.67 | 420 | 380 | 90.97 | 184.13 | 420 | 380 | 90.97 |
| 10 | 92.47 | 420 | 380 | 66.62 | 92.47 | 420 | 380 | 66.62 | 92.47 | 420 | 380 | 66.62 |
| 11 | 450.00 | 95.63 | 380 | 55 | 450.00 | 81.29 | 380 | 55 | 450 | 65.07 | 380 | 96.69 |
| 12 | 243.59 | 0 | 380 | 153.15 | 0 | 217.07 | 380 | 153.15 | 255.31 | 0 | 380 | 153.15 |
| 13 | 205.46 | 0 | 380 | 153.15 | 0 | 201.10 | 380 | 153.15 | 223.15 | 0 | 380 | 139.05 |
| 14 | 281.37 | 0 | 380 | 131.25 | 0 | 273.21 | 380 | 131.25 | 298.51 | 0 | 380 | 114.70 |
| 15 | 450 | 62.32 | 380 | 106.90 | 450 | 106.67 | 380 | 106.90 | 450 | 100.62 | 380 | 90.35 |
| 16 | 450 | 206.02 | 380 | 82.54 | 450 | 211.93 | 380 | 82.54 | 450 | 112.05 | 380 | 82.83 |
| 17 | 450 | 284.44 | 380 | 58.19 | 450 | 290.34 | 380 | 58.19 | 450 | 228.79 | 380 | 58.59 |
| 18 | 450 | 320.70 | 380 | 55 | 450 | 320.70 | 380 | 55 | 450 | 265.45 | 380 | 65.25 |
| 19 | 402.69 | 0 | 380 | 141.38 | 0 | 382.55 | 380 | 141.38 | 447.59 | 0 | 380 | 141.38 |
| 20 | 407.61 | 0 | 380 | 150.62 | 0 | 387.23 | 380 | 150.62 | 450 | 0 | 380 | 150.62 |
| 21 | 336.04 | 0 | 380 | 153.15 | 0 | 319.24 | 380 | 153.15 | 391.92 | 0 | 380 | 148.55 |
| 22 | 352.19 | 0 | 380 | 148.92 | 0 | 334.58 | 380 | 148.92 | 352.51 | 0 | 380 | 148.62 |
| 23 | 48.41 | 420 | 380 | 138.20 | 48.41 | 420 | 380 | 138.20 | 135.99 | 420 | 229.43 | 55 |
| 24 | 0 | 390.66 | 190.24 | 55 | 0 | 390.66 | 190.24 | 55 | 0 | 390.66 | 190.24 | 55 |

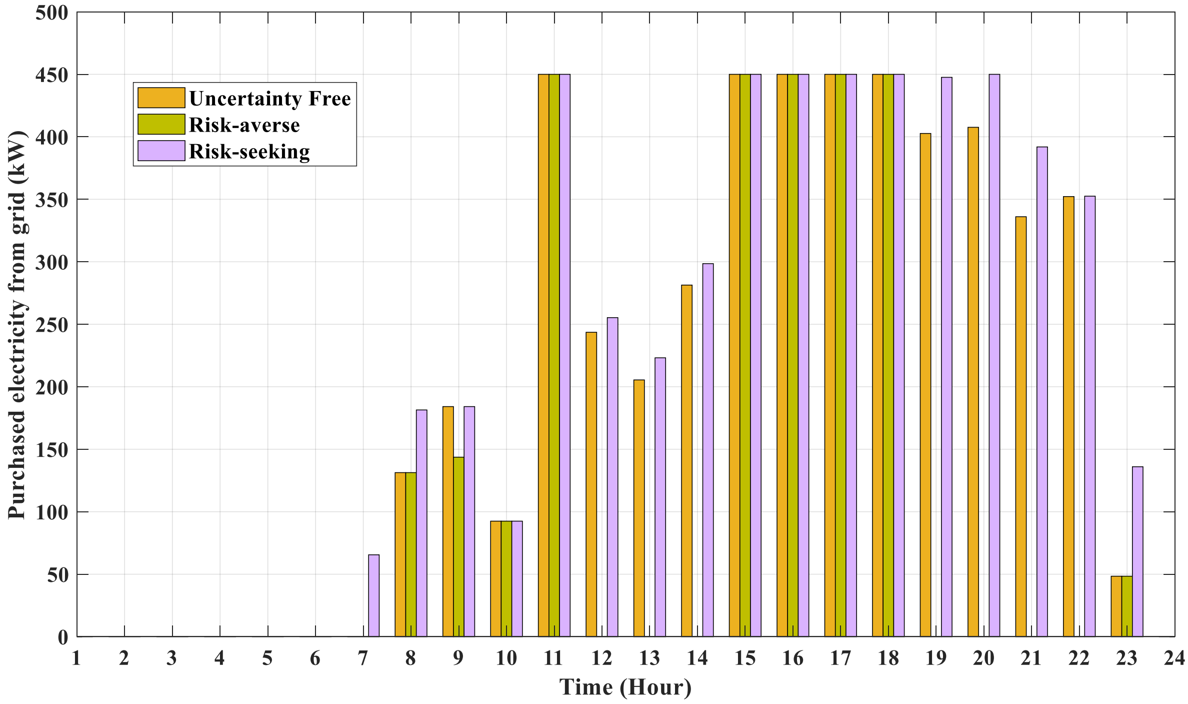


Fig.18. Purchased electricity from power grid for risk-averse, risk-seeking and uncertainty-free decision making considering price uncertainty of electricity purchased from power grid

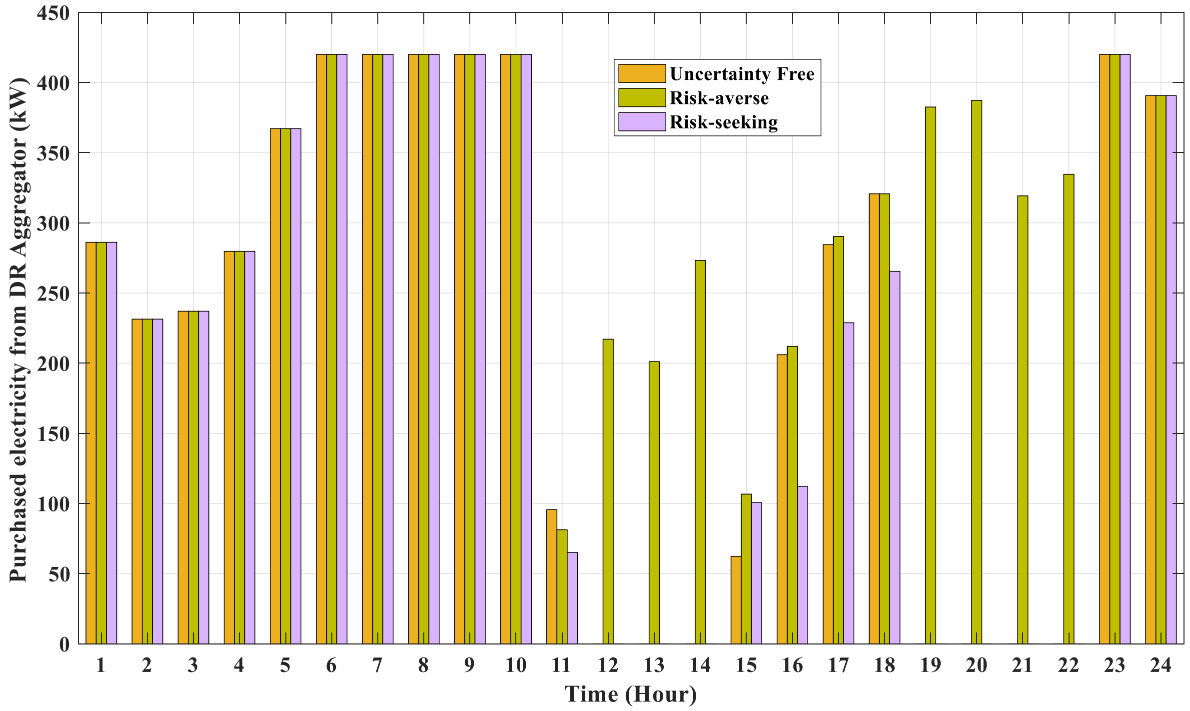


Fig.19. Purchased electricity from DR Aggregator for risk-averse, risk-seeking and uncertainty-free decision making considering price uncertainty of electricity purchased from power grid

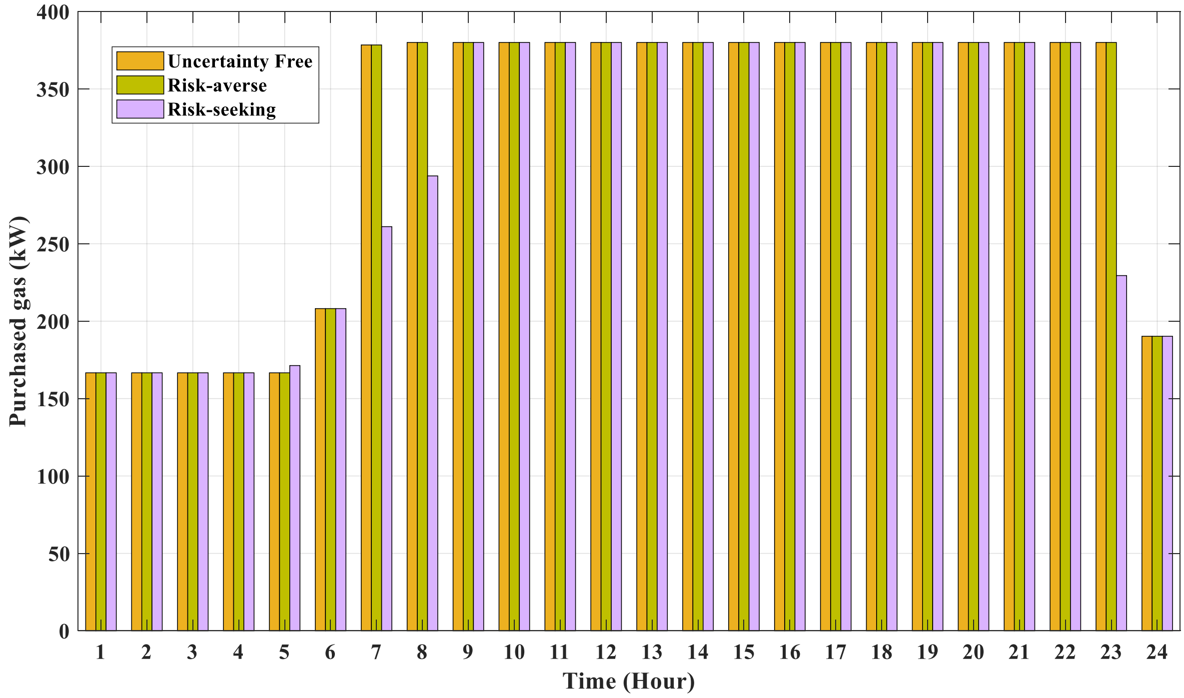


Fig.20. Purchased gas for risk-averse, risk-seeking and uncertainty-free decision making considering price uncertainty of electricity purchased from power grid

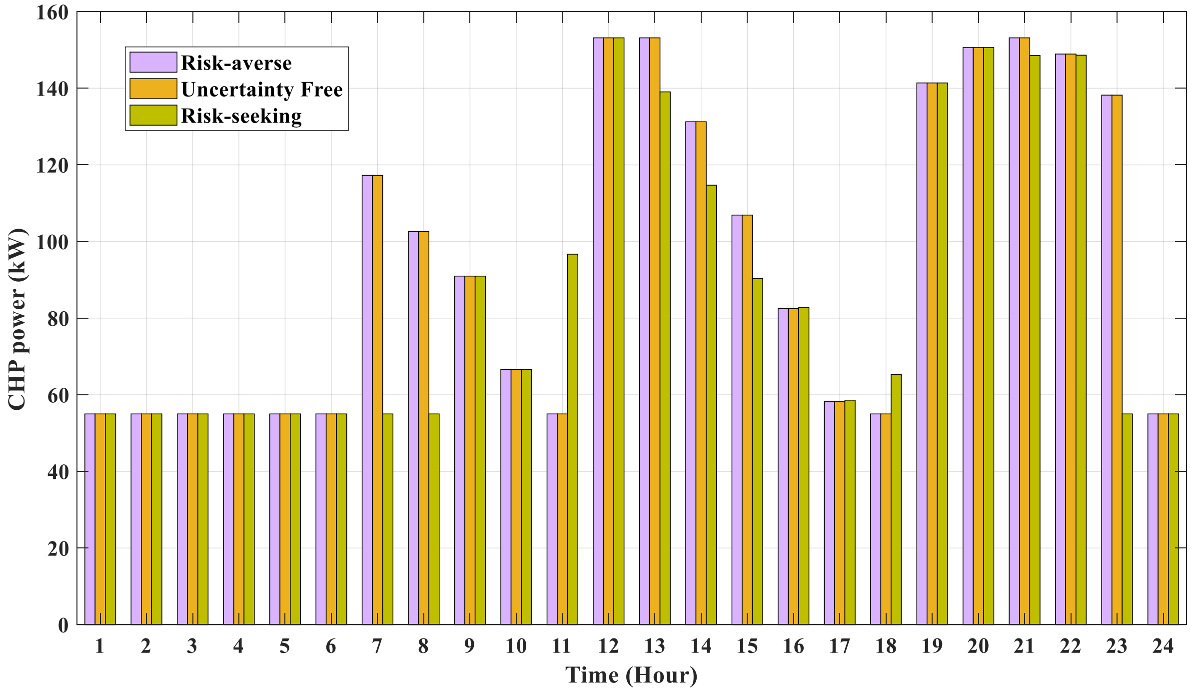


Fig.21. CHP power for risk-averse, risk-seeking and uncertainty-free decision making considering price uncertainty of electricity purchased from power grid

Table 15 shows the comparison of purchased electricity from power grid and DR aggregator, purchased gas from NG and produced power by CHP for risk-averse, risk-seeking and uncertainty-free decision making considering price uncertainty of electricity purchased from DR aggregator.

According to the Table 15 and considering price uncertainty of electricity purchased from DR aggregator, EH operator purchases less electricity from DR aggregator in the risk-averse decision-making than uncertainty-free decision-making in order to hedge himself against risk of purchased electricity price deviations from DR aggregator. In this case, power grid as a redundant source provides more electricity for supplying electric demands, although, rest of electricity needed for EH is supplied by CHP. In this regard, the EH must purchase more gas from NG for supplying CHP. Therefore, the purchased gas from NG and produced power by CHP in risk-averse decision-making is higher than their corresponding values in uncertainty-free case.

On the contrary, in the risk-seeking decision-making, EH purchases more electricity from DR aggregator than uncertainty-free decision-making despite the price uncertainty of electricity purchased from power grid and DR aggregator in the hope of decreasing its operation cost. Figures 22-25 show purchased electricity from power grid and DR aggregator, purchased gas from NG and produced power by CHP for risk-averse, risk-seeking and uncertainty-free decision making, considering price uncertainty of electricity purchased from DR aggregator, respectively. Figures 22 and 23 indicate that at hours 12-14 and 19-22, risk-averse EH operator increases the electricity purchased from power grid. While, risk-seeking EH operator decreases the electricity purchase from power grid and increases electricity purchase from DR aggregator. As it can be seen from Figures 24 and 25, the purchased gas from NG and produced power by CHP in risk-averse is higher than their counterparts in uncertainty-free case due to the EH need to provide more electricity for supplying demands. While, the purchased gas from NG and produced power by CHP in risk-seeking decision-making is equal to its counterpart in uncertainty-free case due to the availability of redundant electricity sources in the EH model.

Table 15. Comparison of decision variables for risk-averse, risk-seeking and uncertainty-free decision making, considering price uncertainty of electricity purchased from DR Aggregator

| | Uncertainty Free ($\beta = 0$) | | | | Risk-averse decision making ($\beta = 0.1$) | | | | Risk-seeking decision making ($\rho = 0.1$) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hour | Purchased electricity from grid (kW) | Purchased electricity from DR Aggregator (kW) | Purchased gas (kW) | CHP power (kW) | Purchased electricity from grid (kW) | Purchased electricity from DR Aggregator (kW) | Purchased gas (kW) | CHP power (kW) | Purchased electricity from grid (kW) | Purchased electricity from DR Aggregator (kW) | Purchased gas (kW) | CHP power (kW) |
| 1 | 0 | 286.12 | 166.62 | 55 | 0 | 244.518 | 380 | 153.15 | 0 | 286.12 | 166.62 | 55 |
| 2 | 0 | 231.37 | 166.62 | 55 | 323.29 | 0 | 166.62 | 55 | 0 | 231.37 | 166.62 | 55 |
| 3 | 0 | 237.01 | 166.62 | 55 | 2.80 | 21.58 | 380 | 153.15 | 0 | 237.01 | 166.62 | 55 |
| 4 | 0 | 279.69 | 166.62 | 55 | 0 | 162.27 | 380 | 153.15 | 0 | 279.69 | 166.62 | 55 |
| 5 | 0 | 367.12 | 166.62 | 55 | 0 | 249.70 | 380 | 153.15 | 0 | 367.12 | 166.62 | 55 |
| 6 | 0 | 420 | 208.11 | 55 | 0 | 298.11 | 380 | 153.15 | 0 | 420 | 208.11 | 55 |
| 7 | 0 | 420 | 378.40 | 117.26 | 0 | 411.80 | 380 | 152.11 | 0 | 420 | 378.40 | 117.26 |
| 8 | 131.30 | 420 | 380 | 102.63 | 450.00 | 91.96 | 380 | 152.11 | 131.2991 | 420 | 380 | 102.63 |
| 9 | 184.13 | 420 | 380 | 90.97 | 122.51 | 420 | 380 | 149.92 | 143.6666 | 420 | 380 | 90.97 |
| 10 | 92.47 | 420 | 380 | 66.62 | 0 | 420 | 380 | 130.31 | 92.46877 | 420 | 380 | 66.62 |
| 11 | 450.00 | 95.63 | 380 | 55 | 450 | 0 | 380 | 121.63 | 108.5543 | 420 | 380 | 55 |
| 12 | 243.59 | 0 | 380 | 153.15 | 431.46 | 0 | 380 | 112.56 | 0 | 231.41 | 380 | 153.15 |
| 13 | 205.46 | 0 | 380 | 153.15 | 446.05 | 0 | 380 | 121.40 | 0 | 195.19 | 380 | 153.15 |
| 14 | 281.37 | 0 | 380 | 131.25 | 448.02 | 0 | 380 | 150.38 | 0 | 267.43 | 380 | 131.12 |
| 15 | 450 | 62.32 | 380 | 106.90 | 450 | 0 | 380 | 130.83 | 114.1003 | 420 | 380 | 106.77 |
| 16 | 450 | 206.02 | 380 | 82.54 | 450 | 0 | 380 | 118.34 | 224.895 | 420 | 380 | 82.41 |
| 17 | 450 | 284.44 | 380 | 58.19 | 450 | 0 | 380 | 125.10 | 307.4392 | 420 | 380 | 58.06 |
| 18 | 450 | 320.70 | 380 | 55 | 450 | 0 | 380 | 130.64 | 345.4759 | 420 | 380 | 55 |
| 19 | 402.69 | 0 | 380 | 141.38 | 436.05 | 0 | 380 | 131.78 | 0 | 382.55 | 380 | 141.38 |
| 20 | 407.61 | 0 | 380 | 150.62 | 450 | 0 | 380 | 139.47 | 0 | 387.23 | 380 | 150.62 |
| 21 | 336.04 | 0 | 380 | 153.15 | 450 | 0 | 380 | 142.22 | 0 | 319.24 | 380 | 153.15 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 22 | 352.19 | 0 | 380 | 148.92 | 406.18 | 0 | 380 | 135.64 | 0 | 334.58 | 380 | 148.92 |
| 23 | 48.41 | 420 | 380 | 138.20 | 313.20 | 153.53 | 380 | 153.15 | 48.40749 | 420 | 380 | 138.20 |
| 24 | 0 | 390.66 | 190.24 | 55 | 0 | 292.54 | 380 | 153.15 | 0 | 390.66 | 190.24 | 55 |

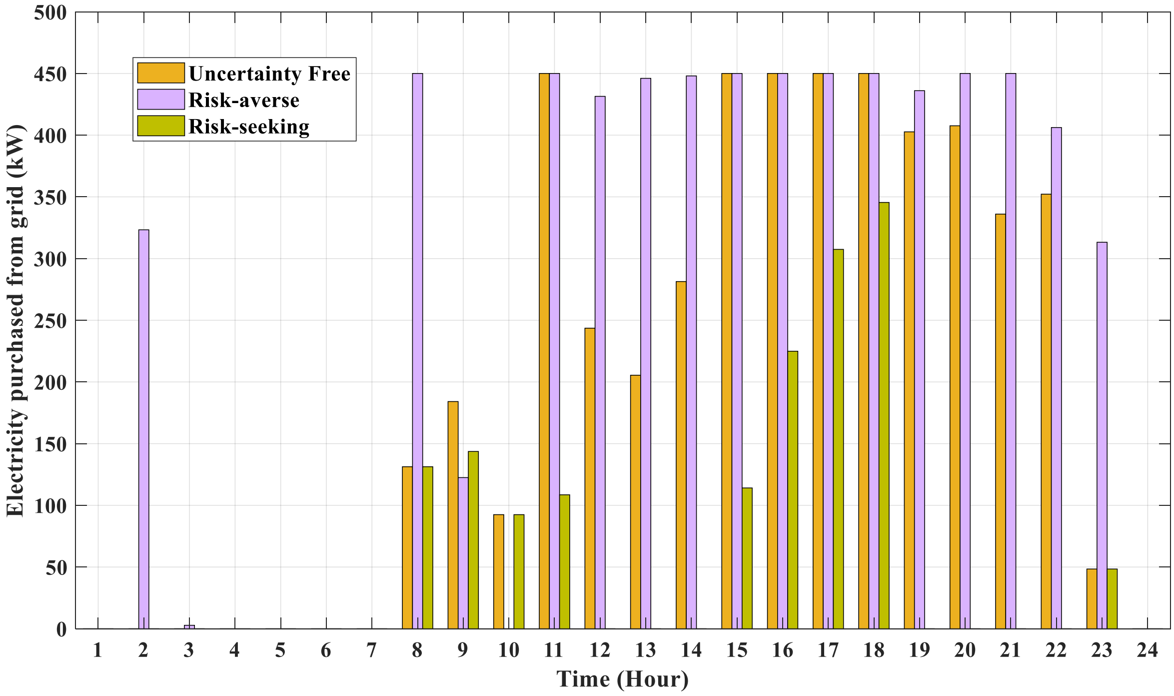


Fig.22. Purchased electricity from grid for risk-averse, risk-seeking and uncertainty-free decision making, considering price uncertainty of electricity purchased from DR Aggregator

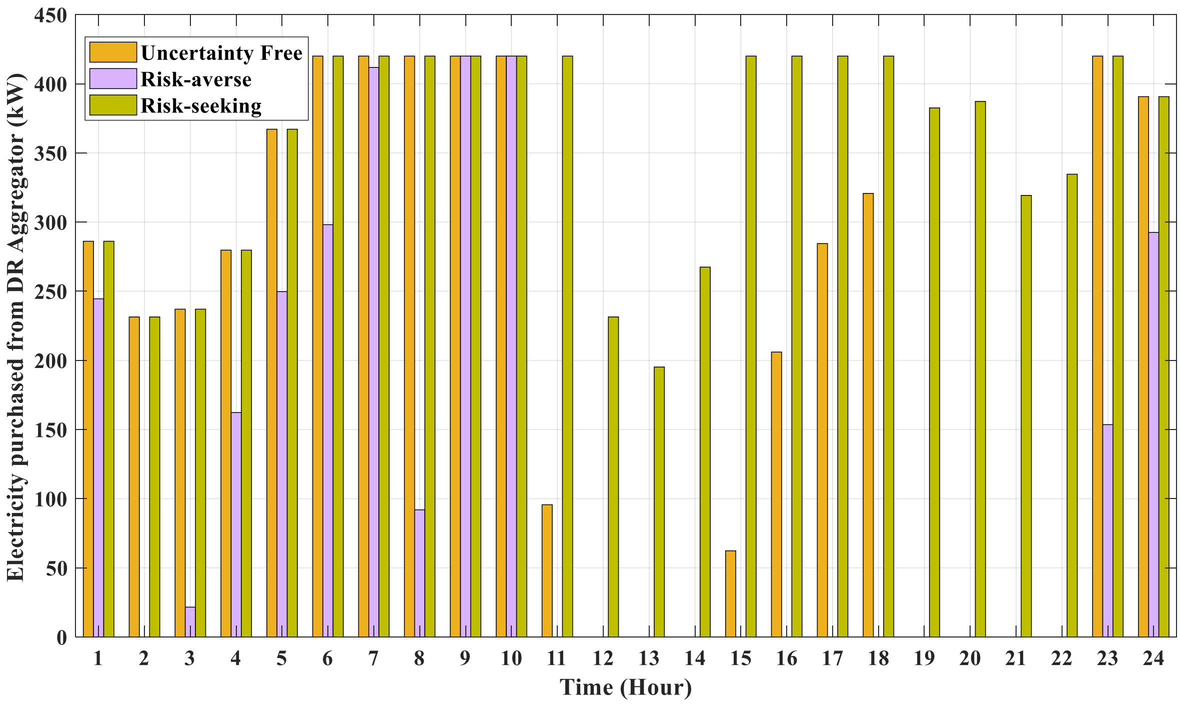


Fig.23. Purchased electricity from DR Aggregator for risk-averse and risk-seeking decision making, and deterministic considering price uncertainty of electricity purchased from DR Aggregator

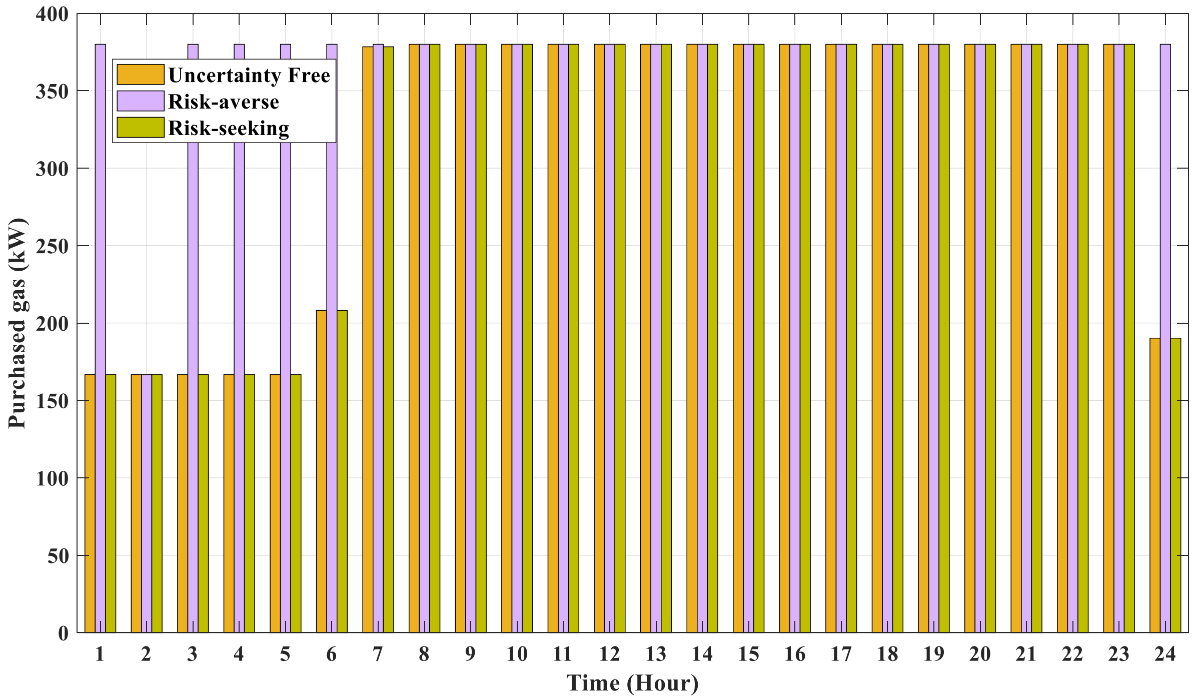


Fig.24. Purchased gas for risk-averse, risk-seeking and uncertainty-free decision making considering price uncertainty of electricity purchased from DR Aggregator

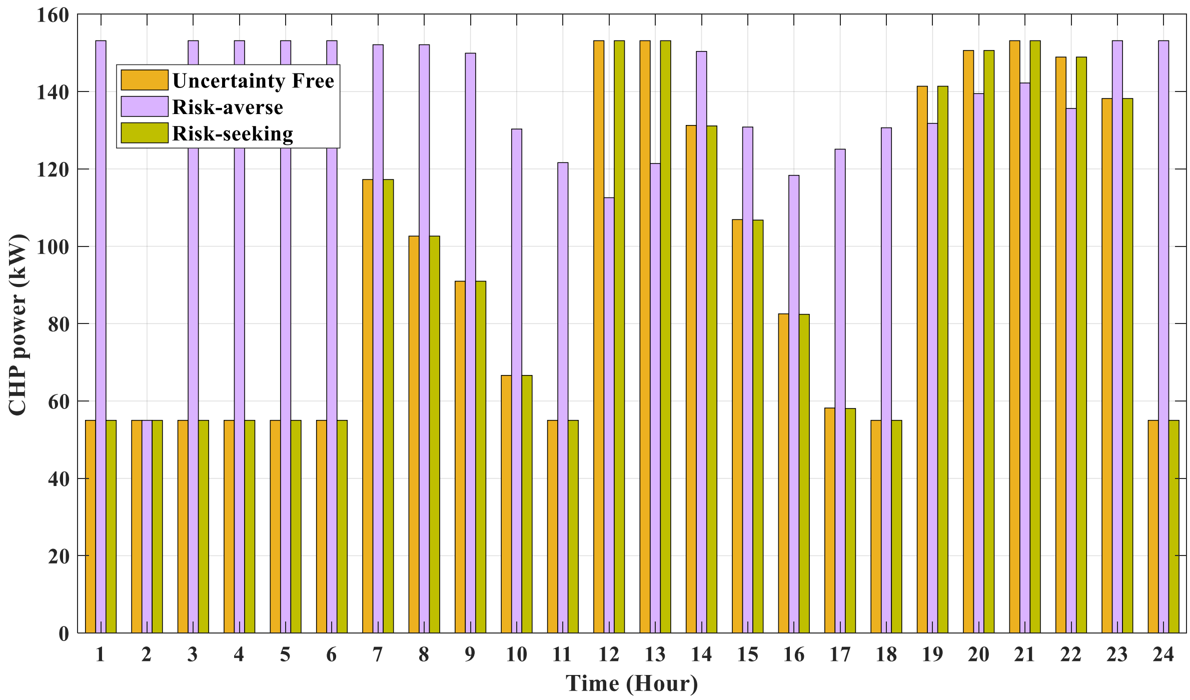


Fig.25. CHP power for risk-averse, risk-seeking and uncertainty-free decision making, considering price uncertainty of electricity purchased from DR Aggregator

## 6. Conclusions

In this paper, day-ahead EH scheduling is performed from the perspective of the uncertainty free, risk-averse and risk-seeking decision-making, and impact of risk and deviation factors of critical and target costs on EH operation costs is investigated, considering uncertainties. In this regard, information gap decision theory (IGDT) is employed as a risk-aware method to handle uncertainties of electric, thermal and hydrogen demands, PV and wind power, solar heat and electricity prices, while, decision factors for risk-averse and risk-seeking decision-making and deterministic are compared. The results of the sensitivity analysis indicate that EH operation costs are more sensitive to electric demand, the purchasing price of electricity from the power grid and DR aggregator. While, the sensitivity with respect to thermal and hydrogen demands, PV power, wind power and gas price is less.

According to the findings, EH operation cost is respectively reduced by 6.8%, 2.43% and 20.1% in the presence of storage systems, biomass source and DR aggregator, respectively. As it can be seen from results, DR aggregator acts as a redundant source for the studied EH model. When EH is disconnected from power grid, EH operator can purchase the electricity needed for supplying demands from DR aggregator. Furthermore, in some hours, the EH can purchase the cheaper electricity from DR aggregator than power grid. The simulations show that the day-ahead EH scheduling from the perspective of risk-averse or risk-seeking operator has a significant impact on the EH operation cost. In fact, risk-averse decision-making protects the operator from the possibility of adverse variances in demands, PV/wind generation, and energy prices from forecasted values.

The comparison of decision variables for risk-averse and risk-seeking decision making shows that EH operator purchases less electricity from power grid in the risk-averse decision-making than uncertainty-free case in order to hedge himself against risk of electricity price deviations. In this case, DR aggregator as a redundant and reliable source provides more electricity for supplying electric demands. On the contrary, in the risk-seeking decision-making, EH purchases more electricity from power grid than uncertainty-free case, despite the price uncertainty of electricity purchased from power grid in the hope of decreasing its operation cost. As a direction for future research, developing other methods of considering uncertainties such as hybrid, robust and etc. for the EH operation is recommended.

### Conflict of interest

The authors declare that there is no conflict of interest for this paper.

### Acknowledgement

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