

Enhancing Uncertainty Management in EHs: Incorporating Heating and Cooling Assets and Leveraging Demand Response Programs

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The energy hub (EH) is a key component in modern energy systems that integrates multiple energy resources and carriers to meet energy demands. This paper investigates an EH composed of conventional generation units, renewable energy resources (RERs), energy storage systems (ESSs), and heating and cooling assets. It tries to optimize EH owner profits while minimizing costs through mathematical programming. Additionally, it addresses uncertainty management in EH arising from RERs outputs, utilizing a chance constraint - information gap decision theory - robust optimization (CC-IGDT-RO) approach derived from optimization with uncertain data and feasibility robustness theorems. Furthermore, it introduces flexibility services as an alternative means to effectively address this uncertain energy management component. A comparative analysis with existing literature demonstrates the robustness and applicability of the proposed framework, which is 42% lower in the costs within conventional EHs, and providing 10% more flexibility in comparison with cases in review.

Keywords: EH, energy systems, flexibility, management, renewable energy resource, uncertainty.

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Nomenclature

t	Index of time	H_{GB}^{max}	Capacity of gas boiler
e	Index of electricity	P_{EC}^{max}	Capacity of electrical chiller
h	Index of heating energy	P_{AC}^{max}	Capacity of absorption chiller
c	Index of cooling energy	P_{GT}^{max}	Maximum production of gas turbine
res	Index of renewable energy resources	p_{grid}^{max}	Maximum purchased power from grid
wt	Index of wind Turbine	$p_{sell,t}^{max}$	Maximum sold power to the UG
pv	Index of photovoltaic	E_{es}^{max}	Maximum stored electrical energy in BSS
st	Index of solar thermal	E_{hs}^{max}	Maximum stored heating energy in HSS
x	Index of energy storage	E_{cs}^{max}	Maximum stored cooling energy in ISS
$P_{e.demand,t}$	Electrical demand	$p_{es,dis}^{max}$	Maximum discharged power of BSS
$P_{h.demand,t}$	Heating demand	$p_{hs,dis}^{max}$	Maximum discharged power of HSS
$P_{c.demand,t}$	Cooling demand	$p_{cs,dis}^{max}$	Maximum discharged power of ISS
$price_t^e$	Price of purchasing electrical energy	E_{es}^{min}	Minimum stored electrical energy in BSS
$price_t^{sell}$	Price of selling electrical energy	E_{hs}^{min}	Minimum stored heating energy in HSS
$price_t^{gas}$	Price of purchasing natural gas	E_{cs}^{min}	Minimum stored cooling energy in ISS
H_{GB}^{max}	Capacity of gas boiler	$u_{hs,t}$	The binary variable related to heating electrical storage system (HESS)
P_{EC}^{max}	Capacity of electrical chiller	$u_{cs,t}$	The binary variable related to cooling electrical storage system (CESS)

η_{trans}	Efficiency of transformer
η_k	Efficiency of inverter
$\eta_{e.GT}$	Efficiency of gas turbine for producing electricity
$\eta_{h.GT}$	Efficiency of gas turbine for producing heating energy
η_{HE}	Efficiency of heat exchanger
η_{GB}	Efficiency of gas boiler
C_{EC}	Efficiency of electrical chiller
C_{AC}	Efficiency of absorption chiller
$P_{h.GT.t}$	The produced heating energy by gas turbine
$P_{h.GB.t}$	The produced heating energy by gas boiler
$P_{e.in.t}$	The actual purchasing power from the UG
$P_{WT.ac.t}$	The generated ac Power by WT
$P_{PV.dc.t}$	The generated dc Power by PV
$P_{h.ST.t}$	The generated heating energy by ST
$P_{h.HE.t}$	The produced heating energy by heat exchanger
$P_{c.EC.t}$	The produced cooling energy by electrical chiller
$P_{c.AC.t}$	The produced cooling energy by absorption chiller
$P_{AC.t}$	The consumed heating power by the absorption chiller
$P_{e.EC.t}$	The consumed power by the electrical chiller
$P_{GT.t}$	The consumed gas by the gas turbine
$P_{GB.t}$	The consumed gas by the gas boiler
$P_{e.dis.t}$	The discharge rate of BSS
$P_{h.dis.t}$	The discharge rate of HSS
$P_{c.dis.t}$	The discharge rate of ISS
$P_{e.ch.t}$	The charge rate of BSS
$P_{h.ch.t}$	The charge rate of HSS
$P_{c.ch.t}$	The charge rate of ISS
$E_{es.t}$	The stored electrical energy in BSS
$E_{hs.t}$	The stored heating energy in HSS
$E_{cs.t}$	The stored cooling energy in BSS

1. Introduction

Sustainable, clean, secure, and affordable energy supply is becoming one of the biggest challenges of the present day due to technological advancements and the growing need for a variety of energy sources. Dependence on energy carriers, deteriorating infrastructure, environmental concerns, and rising energy demand are the problems that prompted researchers to explore ways to effectively manage energy systems. Modern energy systems encompass a wide array of technologies, including smart grids, demand-side management programs, energy storage systems, and renewable energy resources (RERs) such as solar, wind, hydro, and geothermal, aimed at addressing the aforementioned challenges [1].

The utilization of Renewable Energy Resources (RERs) has been advocated in several studies as part of an integrated and contemporary framework that enhances the performance of modern energy systems. On the other hand, compared to conventional

synchronous machine-based power generation, renewable energy generation systems are considered more affordable and cleaner [2]. Although integrating renewable energy resources (RERs) into power systems has benefits, control problems persist, raising several significant issues such as high fault current, limited fault ride-through capabilities, reduced power quality, and uncertainty. Shafiu Alam et al. provide a thorough and in-depth analysis of the problems and solutions associated with RERs integration into the grid [3].

One of the proposed solutions to implement RERs in energy systems and address their penetration challenges is through the use of an energy hub (EH). EH's electrical energy-producing assets include microturbines, combined heat and power generation technologies, and RERs such as solar photovoltaic (PV) panels and wind turbines (WTs). Various resources such as boilers, electric heaters, electric heat pumps, absorption chillers, and air conditioners are utilized to meet electrical, cooling, and heating requirements. EH also has energy storage devices for electrical, thermal, or cooling energy [4]. EH enables the production, transmission, conversion, and storage of various energy carriers by establishing a coupling connection between input energy carriers and output energy flows. Moreover, excess energy from RERs in EH can be stored or used in electric vehicles and heating and cooling systems, reducing reliance on traditional energy sources and lowering costs for system owners [5]. The main objective of the EH owner is to schedule an effective program to manage EH operations with the aim of reducing costs [6]. Results from simulations indicate that the suggested technique would lead to a significant decrease in operating and emission expenses, as well as a reduced risk level for the EH. With the integration of plug-in electric vehicles, fuel cell power plants, and real-time pricing (RTP) demand response (DR) programs, the expenses related to operation, emissions, and risk are reduced by 37.39%, 32.11%, and 33.16%, respectively. Additionally, the integration of plugged-in electric vehicles, fuel cell power plants, and time-of-use (TOU) based DR programs leads to a 10.47%, 9.03%, and 11.64% reduction in the operation's emissions and risk costs, respectively. By engaging in demand response programs (DRP), lowering system costs, and preserving system stability through load balancing, the energy system becomes more flexible. According to DRPs, which can facilitate interaction and coordination between the supply side and demand side, leading to a mutually beneficial situation for energy consumers and suppliers, consumers are encouraged to consciously adjust their energy consumption in response to price or incentive signals provided by energy companies. In light of this, [7] describes a two-stage operation optimization technique for a modern energy system that includes DR and Energy Storage Systems (ESSs). The suggested method, which addresses the MES's optimal scheduling problem, divides the optimization problems on the demand side and supply side into two parts. The electricity, cooling, and heating demand curves are first optimized within the consumer comfort requirements using a genetic algorithm (GA). The recommended methodology offers an efficient and cost-effective operating strategy, reducing operational expenses by 3.6% compared to the traditional GA method. Moreover, research by Allahviridzadeh et al. suggests an ideal load dispatch model for the EH system by considering how thermal and electric energy are coupled [8]. For the integrated design and operation of an EH with electrical and thermal energy storage devices, Mansouri et al. provide a two-stage stochastic model. According to the simulation results, the decision to install larger asset capabilities and consequently increase investment costs by 8.07% is driven by the consideration of uncertainties. Their framework alters the demand curve for electricity, cooling, and heating loads, which reduces operating costs by 15.1%. Finally, the findings demonstrate that storage systems with peak-hour discharge enhance system flexibility while simultaneously lowering operational expenses [9].

Some scholars focus on uncertainties raised within the topic of the EH and its assets. For instance, a paper presents a unique model for

optimizing EHs, addressing the complexities of energy transmission and production, particularly in gas and electricity networks, and factoring in market uncertainties and diverse energy carriers. The model's effectiveness is demonstrated through its application on a micro-energy grid, with a particular focus on electric vehicle recharge modes and a novel algorithm. The model showed a 50% improvement over other methods in achieving optimal microgrid performance [10]. Moreover, [11] presents a new approach to home energy management systems by developing a micro EH that aggregates flexible resources across multiple homes and integrates distributed energy systems, all underpinned by detailed appliance modeling. The effectiveness of the hub, demonstrated through real-world data, shows significant improvements in grid control levels, reductions in operational costs, and carbon emissions. This highlights its potential in optimizing energy consumption and enhancing power flexibility. In fact, flexibility services and the implementation of required reserves may assist the system operator in overcoming the prediction fluctuations and uncertainties of RERs within the system. Flexibility services include various approaches that system operators choose to manage the system's functioning, such as economically balancing supply and demand with available assets. These services also include DRPs, provision of flexible generation units, preparation of flexible ramping products, and frequency response services [12]. Some researchers focus on implementing these services in the EH. This is achieved by employing various mathematical approaches to manage uncertainties, such as stochastic programming (SP), robust optimization (RO), information gap decision theory (IGDT), chance-constrained (CC) optimization, and hybrid approaches that combine two of the mentioned methods. In this study, Mirzaei et al. [13] introduced a stochastic security-constrained unit commitment problem for an EH, considering the coordinated operation of price-based DR and Hybrid Energy Storage (HES) systems in the face of uncertainties in demands, market prices, and wind speed. Another approach for allocating flexibility services can be examined through the framework developed by Pourghaderi et al. in [14] which is designed to address the intra-hourly flexibility needs of energy systems. To leverage the potential of distributed energy resources (DERs), a local market is established within the distribution network. Their work focuses on procuring excess energy from the system's assets to address unbalanced energy situations, which occur when the predicted output of Distributed Energy Resources (DERs) is inaccurate. Yang et al. also introduce a stochastic scheduling approach for an EH, incorporating risk constraints and considering uncertainties in renewable generation and load demands. They use the conditional value at risk technique to assess risks. The proposed method, which incorporates a new slime mold algorithm based on coughing and chaos theory, demonstrates significant flexibility in EH management. This leads to reductions in operational costs and emission costs, showcasing the effectiveness of the approach in optimizing energy management [15]. Another study introduces an optimal load dispatch model for an EH, which includes various units and utilizes a data-driven, two-stage robust optimization approach to tackle uncertainties in electricity prices. The study demonstrates that the proposed model, effectively solved using the column and constraint generation algorithm, can reduce total costs by deploying energy storage units and participating in DRPs. This approach achieves a balance between economy and robustness compared to other methods [16].

The literature lacks some assets within the EHs under study, and the implementation of a mathematical framework that results in a simple and validated uncertainty management framework with a more accurate feasible region for the problem's robust solutions should be addressed in the research. Regarding these issues, this paper aims to study the optimal operation of the EH in two scenarios. Firstly, an objective function is optimized to minimize

customer costs using mathematical programming. After that, various DRPs are implemented, and the study evaluates the impact of energy storage devices on the optimal operation of an EH. The study also addresses the management of uncertainty in the EH resulting from RERs outputs. It involves optimization with uncertain data and feasibility robustness theorems, along with the implementation of CC and IGDT, aiming to improve the accuracy of net-load prediction. The net-load prediction fluctuation, which is calculated using the aforementioned framework, is managed by flexibility services that leverage the assets' capabilities in the EH. In summary, the main contribution of this research and its novelties lie in the following points:

- Implementation of the DR program in a EH, consisting of electrical, heating, cooling and ESSs, with the prospect of interaction between EH and the main grid.
- Provision of flexibility services in the EH to manage expenses (42% reduction in operational costs) and enhance assets' capability to provide power for sale to the main grid (10% greater flexibility compared to existing research in the literature).
- Realization of flexibility services with a new mathematical approach that is validated by its accuracy and high processing speed compared to other frameworks in the literature.
- Addressing the uncertainty stemming from RERs output and EH's expenses by offering an ancillary service (flexible ramping products) without incurring any tariffs to the distribution system operator, a novel contribution in the literature.

2. Modeling of the EH

The EH is a display platform for modern energy systems consisting of various converters and energy storage technologies. Input carriers, such as electrical energy, natural gas, and thermal energy, directly supply output loads. The converters receive an additional amount of incoming energy. The load requirements are transmitted through the output port after converting the size and type of the input carriers. Storage devices may also be used to store input energies, which can reduce the cost of purchasing energy from the power market. The EH is modeled as shown in Fig. 1. The electrical, heating, and cooling components of the understudied EH are shown in Fig. 1, and they will be discussed in subsequent subsections.

2.1. Electrical Units

The output power of renewable energy sources ($P_{e,ret}$), the generated electrical power by the gas turbine, and the input electrical energy from the power market ($P_{e,int}$) are added together to supply the input electrical energy for the electrical system in the EH ($P_{e,in,act}$). The purchased electrical energy from grid ($P_{grid,t}$) is multiplied by the transformer's efficiency (η_{trans}), as shown in Eq. (2), to produce the input electrical energy ($P_{e,in,t}$). On the other hand, the gas turbine ($P_{e,GT,t}$) is used to produce some of the AC electrical power according to Eq. (3). According to Eq. (4), the researched EH uses solar panels and wind turbines as renewable electricity resources. Inverters are used to convert the PV system's DC output electrical power to AC power.

$$P_{e,in,act} = P_{e,in,t} + P_{e,GT,t} + P_{e,ret} \quad (1)$$

$$P_{e,in,t} = \eta_{trans} \times P_{grid,t} \quad (2)$$

$$P_{e,GT,t} = \eta_{e,GT} \times P_{GT,t} \quad (3)$$

$$P_{e,ret} = \eta_k \times P_{PV,dct} + P_{WT,act} \quad (4)$$

Additionally, extra electricity produced can be sold to the power grid ($P_{sell,t}$). Since the electrical chiller is utilized to meet the structure's cooling needs, the electrical system in the EH should provide the electrical chiller's input power ($P_{e,EC,t}$). As a result, the electrical system's power balance constraint will be as follows:

$$P_{e,demand,t} = P_{e,in,act,t} - P_{sell,t} - P_{e,EC,t} \quad (5)$$

2.2. Heating Units

Electricity and natural gas are the two primary input carriers for the energy center under study. According to Eq. (6), the gas turbine and the gas boiler both get a portion of the input natural gas ($P_{gas,in,t}$). As shown by (7) and (8), the gas turbine and gas boiler both use natural gas to produce heat. On the other hand, (8) shows that the gas turbine also produces heat in addition to electrical energy. Based on (9), the heating exchanger in the EH is utilized to modify the temperature of the heat generated by the gas turbine ($P_{h,GT,t}$). Using (10), the total heat produced ($P_{h,t}$), is computed. A portion of the necessary heating demand can also be met by solar thermal energy, which is represented by the letters $P_{h,ST,t}$.

$$P_{gas,in,t} = P_{GT,t} + P_{GB,t} \quad (6)$$

$$P_{h,GB,t} = \eta_{GB} \times P_{GB,t} \quad (7)$$

$$P_{h,GT,t} = \eta_{h,GT} \times P_{GT,t} \quad (8)$$

$$P_{h,HE,t} = \eta_{HE} \times P_{h,GT,t} \quad (9)$$

$$P_{h,t} = P_{h,GB,t} + P_{h,ST,t} + P_{h,HE,t} \quad (10)$$

The following input requirements for an absorption chiller and the total amount of heating power produced must be met:

$$P_{h,demand,t} = P_{h,t} - P_{c,AC,t} \quad (11)$$

2.3. Cooling Units

According to (12), the two methods for providing total cooling energy are an electric chiller and an absorption chiller. The electrical system and heating EH mentioned above, respectively, produce the necessary electrical chiller input and heating input of the absorption chiller.

$$P_{c,t} = P_{c,EC,t} + P_{c,AC,t} \quad (12)$$

$$P_{c,EC,t} = C_{EC} \times P_{e,EC,t} \quad (13)$$

$$P_{c,AC,t} = C_{AC} \times P_{AC,t} \quad (14)$$

2.4. Energy Storage Systems (ESSs)

During off-peak hours, the ESSs store energy at a cheap cost and during peak hours, they inject energy into the power grid. (15) demonstrates the dynamic model of energy storage devices. The BESs, HESs, and CESs are referred to as x in the following equations. Energy storage device capacity and charging and

discharging power are also constrained by (16) - (18). In (17) - (18), the binary variable $u_{xs,t}$ is employed to prevent concurrently charging and discharging ESSs. If energy storage is charging at the t -th time interval, $u_{xs,t}$ is equal to 1.

$$E_{xs,t+1} = E_{xs,t} + \left(\eta_{xs,ch} \times P_{x,ch,t} - \frac{P_{x,dis,t}}{\eta_{xs,dis}} \right) \quad (15)$$

$$E_{xs}^{min} \leq E_{xs,t} \leq E_{xs}^{max} \quad (16)$$

$$P_{x,ch,t} \leq u_{xs,t} \times P_{xs,ch}^{max} \quad (17)$$

$$P_{x,dis,t} \leq (1 - u_{xs,t}) \times P_{xs,dis}^{max} \quad (18)$$

The EH's electrical, heating, and cooling balance restrictions will be as follows:

$$P_{e,demand,t} = P_{e,in,act,t} + P_{e,dis,t} - P_{e,ch,t} - P_{c,ch,t} - P_{sell,t} - P_{e,EC,t} \quad (19)$$

$$P_{h,demand,t} = P_{h,t} + P_{h,dis,t} - P_{h,ch,t} - P_{c,AC,t} \quad (20)$$

$$P_{c,demand,t} = P_{c,t} + P_{c,dis,t} \quad (21)$$

The best performance of the examined EH will be demonstrated in Section 3 in accordance with the beforementioned equations.

3. Optimal Utilization of EH

The objective of an EH is to reduce the overall costs of integrated energy systems so that the limitations on converter and distribution system capacity may be defined. Decision variables are:

$$\{P_{e,in,act,t}, P_{sell,t}, P_{h,GT,t}, P_{h,GB,t}, P_{c,EC,t}, P_{c,AC,t}, P_{h,HE,t}\}$$

This research aims to reduce the expenses of acquiring electrical energy and natural gas while increasing the revenues from selling excess electricity to the power grid. These goal functions can be combined linearly to form (22) as an indication.

$$OF = \sum_{t=1}^{24} price_t^e \times P_{grid,t} + \sum_{t=1}^{24} price_t^{gas} \times P_{gas,in,t} - \sum_{t=1}^{24} price_t^{sell} \times P_{sell,t} \quad (22)$$

3.1. Constraints of the Optimization Problem

According to (23) and (24), where $u_{grid,t}$ is equal to 1 if the electrical power is purchased from the UG at the t -th time interval, the buying and selling of electrical energy are, respectively, prohibited. Additionally, (25) - (28) specify the limits relating to the capacity of converters such the gas turbine, gas boiler, electrical chiller, and absorption chiller.

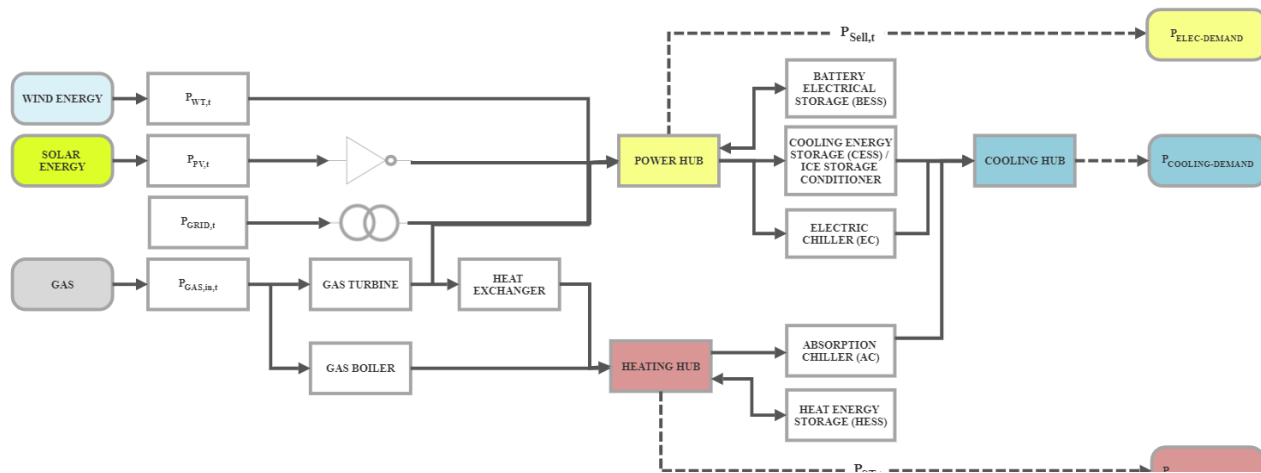


Fig. 1. Schematic of understudied EH

$$P_{\text{grid},t} \leq P_{\text{grid}}^{\text{max}} \times u_{\text{grid},t} \quad (23)$$

$$P_{\text{sell},t} \leq P_{\text{sell},t}^{\text{max}} \times (1 - u_{\text{grid},t}) \quad (24)$$

$$P_{e,GT,t} \leq P_{GT}^{\text{max}} \quad (25)$$

$$P_{h,GB,t} \leq H_{GB}^{\text{max}} \quad (26)$$

$$P_{c,EC,t} \leq P_{EC}^{\text{max}} \quad (27)$$

$$P_{c,AC,t} \leq P_{AC}^{\text{max}} \quad (28)$$

3.2. Demand Response Program

Consumers alter their consumption curves in DR programs by reducing and changing their demand in response to changes in price. The main restrictions on the TOU rate of the DR program for the best performance of the EH may be found in the following equations.

$$P_{e,demand,t,new} = P_{e,demand,t} + P_{e,shift,t} \quad (29)$$

$$|P_{e,shift,t}| \leq E_{xs}^{\text{max}} \times P_{e,demand,t} \quad (30)$$

$$\sum_{t=1}^{24} P_{e,shift,t} = 0 \quad (31)$$

Equation (29) is a formative equation for the new load curve. The daily DR program's power transmission will be less than the energy storage device's load curve, and the total amount of transmitted electricity will be zero, as per (30) and (31).

$$P_{e,demand,t,new} = P_{e,demand,t} \left[1 + E \times \frac{\text{price}_t^e - \text{price}_t^{e,base}}{\text{price}_t^{e,base}} \right] \quad (32)$$

Using (32), where E is the demand-price elasticity coefficient, the new load pattern that results from the implementation of the real-time DRP can be described.

3.3. Uncertainty Management with Flexibility Provision

The researchers have developed hybrid approaches containing CC, IGDT, RO, and SP to obtain a better solution to overcome the EH challenges more easily and create a linear and manageable objective function. This paper focuses on the feasibility robustness (FR) lemma, coming from configuration of CC [17] and IGDT-based RO [18], to cover the net-load (load minus RERs production) prediction fluctuation. Firstly, the envelope-bound IGDT-based RO is used for RERs output, and then, the uncertain net-load is covered using CC. The described mathematical approach can be found in (33)-(37).

$$-\Delta \leq f(Y, \tilde{x}) \leq \Delta \quad (33)$$

$$s. t. g(\tilde{x}, e) \geq 0 \quad (34)$$

$$\text{Prob}[h(\tilde{x}, e) \geq 0] \geq \varphi \quad (35)$$

$$\Delta = \text{Expected Value } f(Y, \bar{x}) \text{ with } \varphi \text{ probability} \quad (36)$$

$$\tilde{x}\epsilon\xi = \xi(\bar{x}, \sigma) = \left\{ \tilde{x}: \left| \frac{\tilde{x} - \bar{x}}{\bar{x}} \right| \leq \sigma \right\} \quad (37)$$

where, \tilde{x} represents the uncertain variables containing PV and WT uncertain generation ($P_{e,ret}$), and demand uncertainty ($P_{e,demand,t}$). $h(\tilde{x}, e)$ represents the net-load ($P_{e,demand,t} - P_{e,in,ac,t}$), with probability of φ (between 0 and 1). The σ (between 0 and 1) is the difference between the maximum deviation of uncertainty variables and their estimated or optimum value \bar{x} . Δ is also attained from running the mathematical programming with the maximum values of these uncertain values, obtained from 24-hour

ahead operation. This deviation is filled through provision of assets operational flexibility. The operational flexibility index, which evaluation process is extracted from [19], [20] is calculated in the following:

$$GTUOF(t) = P_{GT}^{\text{max}}(t) - p_{e,GT}(t) \quad (38)$$

$$GTDOF(t) = p_{e,GT}(t) - P_{GT}^{\text{min}}(t) \quad (39)$$

$$BDOF(t) = \min \left(P_{es,dis}^{\text{max}} - P_{e,dis,t}, \frac{2(E_{es,t} - P_{e,dis,t} \Delta T)}{\Delta T_e} \right) \quad (40)$$

$$BCOF(t) = \min \left(P_{es,ch}^{\text{max}} - P_{e,ch,t}, \frac{2(E_{es}^{\text{max}} - E_{es,t} - P_{s,t}^{Ch} \Delta T)}{\Delta T_e} \right) \quad (41)$$

$$UOF(t) = GTUOF(t) + BDOF(t) \quad (42)$$

$$DOF(t) = GTDOF(t) + BCOF(t) \quad (43)$$

$GTUOF(t)$ stands for gas turbines capability to provide upward flexibility services at each hour. $GTDOF(t)$ is for gas turbines capability to provide downward flexibility services. $BDOF(t)$ demonstrates batteries' flexibility provision when are in discharging mode, which concludes upward flexibility provision by these assets. $BCOF(t)$ introduces the batteries' flexibility provision when ESS is in the charging mode, that determines downward flexibility provision by these assets. Finally, $UOF(t)$ and $DOF(t)$ are upward flexibility and downward flexibility provided by the EH, respectively. The flexibility ensures required capability of EH assets to cover net-load prediction fluctuations ($-\Delta$ and Δ).

4. Case Study and Results

A mathematical programming is used to optimize the objective function. EH data is obtained from [21], [22]. The purchase costs of input carriers, such as electricity and natural gas, are the basis of this objective function. This section also provides the estimated operational flexibility offered by various generating units in an energy system. Fig. 2 represents the data for electrical, heating, and cooling demands. Also, the net-load fluctuation margins (σ , φ) are 5%.

4.1. Simulation Results

In this instance, mathematical programming is solved. Table 1 displays the overall expenses associated with the optimization technique. By employing MINLP solution methods, the overall cost of EH without ESSs using RERs is reduced by 7.79% in comparison to optimization problems without RERs. Thus, it is clear that the cost of the EH may reduce with the utilization of RERs.

Table 1. The comparison of total cost of EH by RERs penetration suggestion

Integrated Demand Response Program (IDRP) state with RERs Penetration	Total Cost
IDRP without RERs	23968
IDRP with RERs	22211.8554

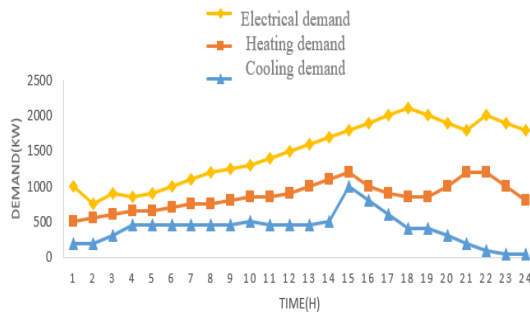


Fig. 2. Electrical, heating, and cooling demands

In the absence of energy storage, the purchased electricity and the purchased natural gas are shown in Fig. 3 and Fig. 4, respectively. Natural gas is bought from the distribution system between 1:00 and 8:00 a.m. since the heating demand is only satisfied by the gas boiler and gas turbine without taking the energy storage devices into account. Since the heating demand has minimum value from 1:00 to 8:00, the cost of buying natural gas is low during this time period. Due to the gas boiler's high efficiency, a higher percentage of the natural gas is transferred into heating energy through gas boiler. As a result of the poor gas-electricity efficiency and the small proportion of natural gas used as input, the gas turbine also produces low-value electrical power. In order to meet the electrical and cooling demands, the gas turbine's power cannot be used; instead, as shown in Fig. 3, it must buy high-value electrical energy from the power market. Since the need for electricity and cooling services is decreasing, the purchased power is lower between 1:00 and 5:00 in the morning. On the other side, between 8:00 and 9:00 a.m., the peak of the day's electricity consumption occurs. Because of this, the most electricity is bought at this time. Due to rising electrical, heating, and cooling needs, the amount of natural gas purchased increases between 8:00 and 16:00. The whole electricity and heating needs are met by the gas turbine and gas boiler between the hours of 8:00 and 11:00 a.m. and 11:00 and 15:00 p.m. Thus, purchasing more electrical power is not required. As depicted in Fig. 3 and Fig. 4, the highest electrical power and the least amount of natural gas are purchased when the need for electricity, heating, and cooling are at their highest values. The optimal operation of the EH under study is also evaluated in this work in relation to the effects of three distinct energy storages (electrical, heating, and cooling). If electrical, heating, and cooling energy storage devices are implemented in the investigated EH, as shown in Fig. 5, the exchange of electrical power with the grid is increased.

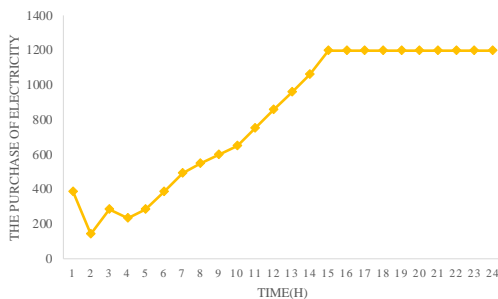


Fig. 3. purchased electricity power

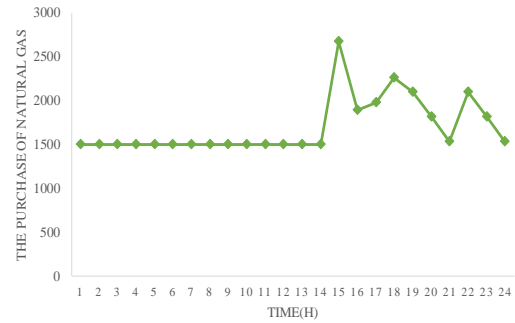


Fig. 4. purchased natural gas

The energy storage for cooling has no significant impact on how well the EH functions. The cost of acquiring electrical energy, when accounting for the cooling storage, is essentially identical to the scenario when there are no storage devices in the EH. The impacts of ESSs on the natural gas that was purchased are shown in Fig. 6. Almost, employing the ESSs results in a fall in the value of bought natural gas. According to Fig. 5, high electrical energy is exchanged with the power grid during periods of low demand and low cost. Fig. 6 shows that the amount of natural gas bought during off-peak times is lower than it is during peak times. Table 2 displays the effects of various energy storage technologies on the EH's overall cost. As shown in Table 2, the overall cost of the EH employing electrical, heating, and cooling storage devices dropped from 20765.02 \$ to 19612.10 \$. The cooling energy storage component has the least impact on the overall cost. Thus, the cost associated with cooling energy storage is essentially identical to the cost in the scenario when energy storage devices are not taken into account. By utilizing Fig. 5 and Fig. 6, one can comprehend this point. The total cost of purchasing natural gas and electricity and the revenue from selling electricity to the grid are used to calculate the operation cost. Additionally, Formulation in 3.2 section is used to simulate DRP prices for both TOU and RTP, and these rates are then contrasted with IDRP rates. By selecting the right kind and size of input carriers, the EH may operate efficiently in IDRPs without being constrained by DRPs. Table 3 compares the overall expenses associated with the EH as a result of various DR initiatives. By employing RTP and TOU rates of DRP instead of an IDRP, costs are reduced. Figure 7 depicts the load curve following the deployment of DR services. As can be observed, due to the fact that the load is reduced during periods of high demand utilizing RTP and TOU, these programs are more successful than IDRP. Customers have the option to shift their consumption to periods of reduced demand, which results in an increase in load during off-peak times. Table 3 presents the efficacy of TOU and the RTP rates of DRP. The revised demand curve that results from the RTP-DRP closely resembles the real load pattern, as seen in Fig. 7. This issue highlights how well RTP performs when compared to TOU. As depicted in Fig. 8, the operational flexibility provided by EH assets can be delivered through upward and downward flexibility to overcome net-load prediction fluctuations. The gas turbines and energy storage units also benefit from uncertainty management of the net-load through the developed CC-IGDT-RO framework. As the simulation results show, heating and cooling storage units have more stand-by times when the developed framework is applied, in comparison with the case study paper mentioned at the beginning of section IV. Also, when the developed framework applied to the case in [13], it shows better cost minimization and improved performance due to consideration of mixed-probability approach in the system. Furthermore, the results show when flexibility is provisioned to cover the net-load prediction fluctuations, the EH operator takes less grid-feed electricity.

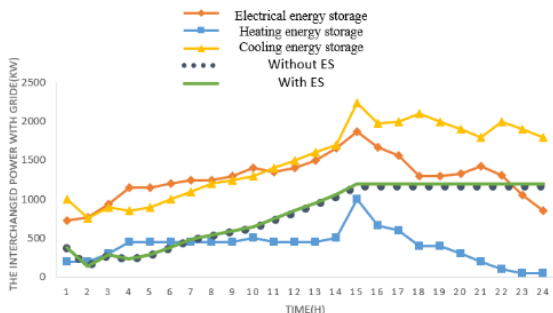


Fig. 5. Effects of energy storage on the electricity power

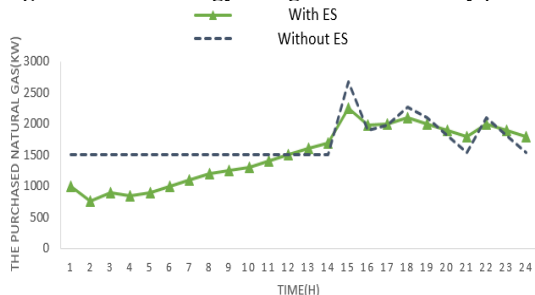


Fig. 6. Effects of energy storage on the purchased natural gas

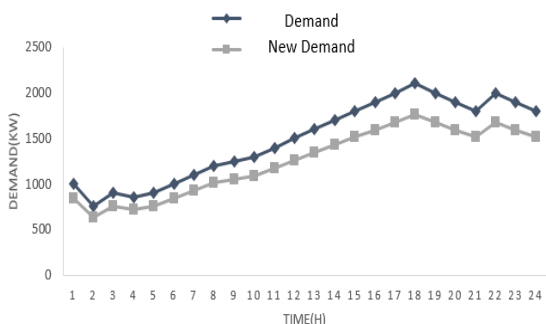


Fig. 7. The load curves

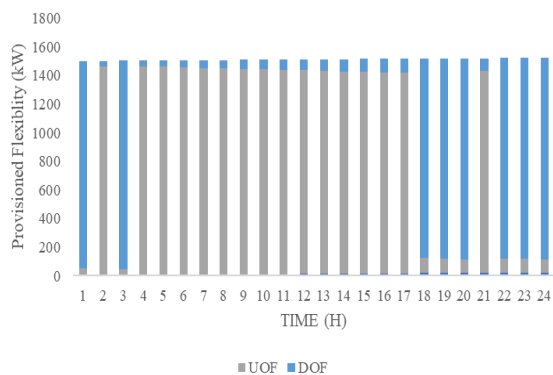


Fig. 8. Operational Flexibility provided by EH assets

Table 2. The comparison of the total cost of EH using different energy storage devices

Total cost with different energy storages by IDRPs (\$)	Value
Without energy storage	20765.02
With cooling energy storage	20668.56
With heating energy storage	20187.034
With electrical energy storage	19986.09
With electrical, cooling and heating energy storages	19612.10

Table 3. The comparison of the total cost of EH using different DRPs

Total cost with ES by DRP	Value
Time of use pricing	19886.59
Real time pricing	19563.09
IDRP	19989.10

4. Conclusions

In this research, the optimal functioning of the sample EH is suggested using mathematical programming. An objective function is optimized, taking into account the cost of obtaining input carriers from the market and the bidirectional exchanges between EH and the power grid. Additionally, a variety of DR methods, including TOU and RTP, are employed in this study, and the results of the simulation indicate that RTP is therefore the most efficient way to alter or reduce client usage in response to pricing changes. In addition, three energy storage systems—BES, HES, and CES—are utilized to lower consumer expenses. The developed CC-IGDT-RO framework also contributes to more enhanced operation of the system while facing uncertainty of any different form. This developed framework is finally managed through providing operational flexibility obtained from electrical assets.

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