Chapter 9

Demand Response Role for Enhancing the Flexibility of Local Energy Systems

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This chapter investigates the distributed energy resources (DER) integration to local energy systems and brings new solutions to improve the flexibility of the entire network. The main concept of the local energy system, including diverse multi-carrier energy systems, is to supply the consumer's energy demands, i.e. electricity, heating and cooling loads. In order to enhance the flexibility of the local energy system, an energy management framework is suggested in this chapter to tackle the DER's uncertainties and enhancing the flexibility of the entire network by adopting the effects of demand response (DR) programs, as well as the effects of electrical energy storage (EES) devices. The flexibility can be provided by electrical and non-electrical energy providers. However, the effectiveness of the electrical flexibility provision is much more important than the others. Since the electrical load balance must be met instantaneously, and there is no interruption allowed, the efforts will be concentrated on the electricity flexibility provision. However, considering the flexibility of a non-electrical system, like thermal loads in a multi-carrier energy system, can improve the net flexibly provisions by the electrical system. Therefore, in the model, developed in this book chapter, the flexibility provision from the whole energy system

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would be studied. The main contribution of this chapter is introducing a centralized framework for determining the operating points of the multi-carrier energy system and improving the flexibility of the local energy systems, considering the price-based DR programs. The mentioned centralized framework can provide the desired solution for the energy vector system and energy communities, considering the flexibility from the consumer engagement in the DR programs. Moreover, the flexibility can be provided by the electrical energy storage devices to the local energy systems.

Nomenclature

Indices

t	Time index
s	Season index
em	Index of emission
k	Index of energy hub number
i	Index of energy hub type

Abbreviations

CHP	Combined heat and power
EH	Electrical heater
EHP	Electrical heat pump
AC	Absorbed chiller
EES	Electrical energy storage
TES	Thermal energy storage

Scalars

η^{T}	Transformer electricity efficiency
$\eta_{P}^{CHP} / \eta_{H}^{CHP}$	CHP electrical/ heating efficiency
η^{Boiler}	Boiler efficiency
η^{EH}	EH efficiency
$\eta_{H}^{EHP} / \eta_{C}^{EHP}$	EHP heating/cooling efficiency
$\eta_{Ch}^{EES} / \eta_{Dis}^{EES}$	EES charging/discharging efficiency
η^{AC}	AC efficiency
λ_{em}	Emission cost
λ^{EES}	EES operation cost
λ^{TES}	TES operation cost
$P^{EES,Ch.,Max} / P^{EES,Dis.,Max}$	Max charging/discharging rate of EES
$P^{TES,Ch.,Max} / P^{TES,Dis.,Max}$	Max charging/discharging rate of TES
$P^{Min,CHP} / P^{Max,CHP}$	Min/Max electrical power of CHP
$H^{Min,CHP} / H^{Max,CHP}$	Min/Max Heating power of CHP

$Cap^{Min,Boiler} / Cap^{Max,Boiler}$	Min/Max capacity of Boiler
$Cap^{Min,EH} / Cap^{Max,EH}$	Min/Max EH capacity
$Cap^{Min,EHP} / Cap^{Max,EHP}$	Min/Max capacity of EHP
$Cap^{Min,AC} / Cap^{Max,AC}$	Min/Max capacity of AC
$Cap^{Min,EES} / Cap^{Max,EES}$	Min/Max capacity of EES
$Cap^{Min,CHP} / Cap^{Max,CHP}$	Min/Max capacity of CHP
G_0^a	Irradiation of sun at the standard condition
$P_{Max,0}^M$	Max power of solar panel at the standard condition
$\mu_{P\max}$	Thermal sensitivity of the solar panel
$NOCT$	The normal operating temperature of the solar panel
$T_{M,0}$	solar panel temperature at the standard condition
p_r	Wind turbine nominal power
$v_{ci} / v_{co} / v_r$	Cut-in/Cut-out and rated speed of wind turbine
$LPF^{e,sh,up} / LPF^{e,do,up}$	Load participation factor of shift up/shift down power by Shiftable DR
$LPF^{(e,h,c),tr,up} / LPF^{(e,h,c),tr,do}$	Load participation factor of shift up/shift down power by Transferable IDR
$LPF^{(e,h,c),cu,up} /$ $LPF^{(e,h,c),cu,do}$	Load participation factor of shift up/shift down power by Curtailable IDR
$\varphi_1 / \varphi_2 / \varphi_3$	Rebounded load factors
$P_l^{Flow,\max} / Q_l^{Flow,\max}$	Maximum rate of active/reactive power flow
$V_i^{\max}$	Maximum rate of voltage magnitude at each bus
$\delta_i^{\max}$	Maximum rate of voltage angle at each bus

Parameters

$\lambda_{k_i,s,t}^{Buy}$	Electricity purchase price
$\lambda_{k_i,s,t}^{Sell}$	Electricity sell price
$\lambda_{k_i,s,t}^{\mathrm{Ref}}$	Reference tariff
$\lambda_{k_i,s}^{DR}$	Operation cost of DR programs
$\lambda_{k_i,s}^{ENS}$	Penalty price of ENS
$\lambda_{k_i,s,t}^{Gas}$	Gas price
EF_{em}^{G}	Emission factor for up-stream grid
EF_{em}^{CHP}	Emission factor for CHP
EF_{em}^{B}	Emission factor for Boiler
$G_{sc,s,t}^a$	Irradiation of sun
$\alpha_{k_i}^{initial}$	Initial energy factor of EES/TES
$T_{sc,s,t}^a$	Temperature
$v_{s,t}^w$	Wind speed

Variables

TOC	Total operation cost

$P_{k_i,s,t}^{G \to H}$	Transferred power from up-stream grid to energy hub
$P_{k_i,s,t}^{M \to H} / P_{k_i,s,t}^{H \to M}$	Transferred power between energy hubs
$P_{k_i,s,t}^{H \to G}$	Transferred power from energy hub to up-stream grid
$f_{k_i,s,t}^{CHP}$	CHP Fuel cost
$f_{k_i,s,t}^{Boiler}$	Boiler Fuel cost
$f_{k_i,s,t}^{EES}$	EES operation cost
$f_{k_i,s,t}^{TES}$	TES operation cost
$P_{k_i,sc,s,t}^{ENS}$	Energy not served
$P_{k_i,s,t}^{CHP}$	Electrical power of CHP
$H_{k_i,s,t}^{CHP}$	Heating power of CHP
$H_{k_i,s,t}^{Boiler}$	Heating power of Boiler
$P_{k_i,s,t}^{EES,Ch.} / P_{k_i,s,t}^{EES,Dis.}$	Charging/Discharging power of EES
$P_{k_i,s,t}^{TES,Ch.} / P_{k_i,s,t}^{TES,Dis.}$	Charging/Discharging power of TES
$P_{k_i,s,t}^{EH} / H_{k_i,s,t}^{EH}$	Electrical /Heating power of EH
$P_{k_i,s,t}^{EHP} / H_{k_i,s,t}^{EHP} / C_{k_i,s,t}^{EHP}$	Electrical /Heating/Cooling power of EHP
$H_{k_i,s,t}^{AC} / C_{k_i,s,t}^{AC}$	Heating /Cooling power of AC
$E_{k_i,s,t}^{EES}$	Stored Energy in EES
$E_{k_i,s,t}^{TES}$	Stored Energy in TES
$P_{k_i,s,t}^{PV}$	Available photovoltaic power
$P_{k_i,s,t}^{Wind}$	Available Wind power
$P_{k_i,s,t}^{e,sh,up} / P_{k_i,s,t}^{e,sh,do}$	Shift-up/shift-down power by shiftable DR program
$P_{k_i,s,t}^{e,pb,up} / P_{k_i,s,t}^{e,pb,do}$	Shift-up/shift-down power by TOU DR program
G_l^{Line} / B_l^{Line}	Susceptance/conductance of network branches
$P_{s,l,t}^{Flow} / Q_{s,l,t}^{Flow}$	Active/ reactive power flow of network branches
$V_{s,i,t}$	Voltage magnitude at each bus
$\delta_{s,i,t}$	Voltage angel at each bus
$P_{k_i,s,t-N_x}^{(e,h,c),tr,up} / P_{k_i,s,t}^{(e,h,c),tr,do}$	Shifted-up/shifted-down power by transferable IDR program
$P_{k_i,s,t}^{(e,h,c),cu,up} / P_{k_i,s,t}^{(e,h,c),cu,do}$	Shifted-up/shifted-down power by curtailable IDR program

Decision Variables

$I_{k_i,s,t}^{CHP}$	Binary variable of CHP operation
$I_{k_i,s,t}^{Boiler}$	Binary variable of Boiler operation
$I_{k_i,s,t}^{EH}$	Binary variable of EH operation
$I_{k_i,s,t}^{EHP,C} / I_{k_i,s,t}^{EHP,H}$	Binary variable of EHP operation in cooling/heating mode

$I_{k_i,s,t}^{AC}$	Binary variable of AC operation
$I_{k_i,s,t}^{EES,Ch.}$ / $I_{k_i,s,t}^{EES,Dis.}$	Binary variable of EES operation in charging/discharging mode
$I_{k_i,s,t}^{TES,Ch.}$ / $I_{k_i,s,t}^{TES,Dis.}$	Binary variable of TES operation in charging/discharging mode
$I_{k_i,s,t}^{e,sh,up}$ / $I_{k_i,s,t}^{e,sh,do}$	Binary variable of shift up/shift down power by shiftable DR program
$I_{k_i,s,t}^{e,pb,up}$ / $I_{k_i,s,t}^{e,pb,do}$	Binary variable of shift up/shift down power by TOU DR program
$I_{k_i,s,t}^{(e,h,c),tr,up}$ / $I_{k_i,s,t}^{(e,h,c),tr,do}$	Binary variable of shift up/shift down power by Transferrable IDR program

9.1. Introduction

The role of consumers has been significantly changed over the past two decades with the power system restructuring. Thus, local energy systems as one of the key components of distribution systems can highly impact the electricity market, system reliability, and policies[1]. Besides, the natural gas (NG) consumption has substantially increased since 2007, specifically after introducing the integrated NG and power systems operation [2,3]. NG is accounted for the cleanest fossil fuel which is easily available in most parts. It is also a fast-response energy carrier for the power plant operation. Accordingly, the integrated operation of NG and power system has captured attention recently. This is important, particularly due to the fact that not only it leads to increased flexibility and efficiency, but also helps to supply different types of load demand, such as cooling and heating loads[4,5]. However, the integrated operation of such systems is associated with severe challenges as the constraints of each system operation would affect the other one. Moreover, converting different energy carriers to other types involves some difficulties as the combined generation of heating, cooling and electrical power is accompanied by uncertainties. Furthermore, the concern on emission policies and reliability issues has increased [6,7]. One effective solution to system reliability issues is to change the system flexibility. The flexibility can be increased by using the integrated operation of different energy systems, demand response (DR) programs, electrical energy storage (EES) systems, and model predictive control tools along with renewable energies

[8]. In this respect, this chapter investigates the role of DR programs and their effects on distributed energy resources (DERs), EES systems, and the operation of multi-carrier energy systems.

There are many research works, devoted so far to investigate the impacts of DR programs on the operating costs, emission, and load demand curve of the system. In this regard, Ref. [9] presents a comprehensive model for the optimal planning and operation of the energy hub considering the uncertainties of generation and consumption. A price-based demand response program is considered in the model and the impacts of this program on equipment' capacity and operating costs are fully investigated. Examination of the results proves that applying the DR program reduces the capacity of equipment and thus the cost of investment. The results also show that the DR program modifies the load demand curve by transferring part of the load from peak hours to off-peak hours.

The authors present a MILP optimization model with the aim of increasing the flexibility of multi-energy communities in [10]. In the mentioned model, all flexible equipment such as CHP, EHP, EB, TES and BES are considered. Finally, the simulation results prove the effectiveness of the model. In Ref. [11], in order to improve the flexibility of electromechanical heating systems using demand response programs, a hierarchical optimization algorithm is presented.

A new management model for the optimal scheduling of a multi-carrier energy hub has been introduced in [12]. In the proposed hub, three types of assets have been considered: dispersed generating systems (DGs) such as micro combined heat and power (mCHP) units, storage devices such as battery-based ESSs, and heating/cooling devices such as electrical heater, heat-pumps and absorption chillers. The optimal scheduling and management of the examined energy hub assets in line with electrical transactions with distribution network has been modeled as a mixed-integer non-linear optimization problem. In this regard, optimal operating points of DG units as well as

ESSs are calculated based on a cost-effective strategy. Ref. [13] developed a scenario-based stochastic multi-objective framework to minimize the operating cost and emission of three interconnected energy hubs. The impact of price-based DR program has been studied and the epsilon-constraint technique is used to solve the problem. The results derived from the simulation show that the DR program is capable of effectively reducing the operating cost and the dependency on the upstream network. A robust optimization model has been used in Ref. [14] to address the market price uncertainties in the context of optimal scheduling of an energy hub. The studied energy hub is equipped with TES and ESS systems while taking into consideration TOU-based and real-time pricing (RTP) based DR programs. The model addresses environmental issues and it is formulated as a MILP problem, and investigated through three different case studies. The simulation results show that RTP mechanism is associated with a more desired performance. Renewable energies are known as the most famous DERs and they have been largely integrated with local energy systems. Although renewable energies involve negligible operating cost and emission, they can bring serve challenges to power systems due to their intermittent power generation [15]. A conditional value-at-risk model with integrated DRPs has been proposed in Ref. [16] for the optimal operation of a resourced energy hub with a wind turbine and compressed-air energy storage (CAES) systems. It is noteworthy that the uncertainties of the problem are characterized using a scenario-based optimization technique and an efficient scenario reduction method is used to alleviate the number of primary scenarios. The simulation results show that the CAES system can effectively compensate for the volatile renewable power generation and improve flexibility. Besides, applying DRPs to electrical and heating load demand has successfully resulted in lowering the operating cost of the system. Ref. [17] introduced a design and operation model for an energy hub, taking into consideration shifting-load DR programs and uncertainties, relating to the load demand and wind power generation. A scenario-based stochastic programming approach along with an effective scenario reduction method in GAMS – SCENRED has been employed to tackle the uncertainties. The results obtained revealed that the uncertainties cause the capacity of assets to rise which in turn leads to increased capital costs. On the contrary, applying DR programs effectively reduces the need for higher assets capacities and consequently, decreases the total cost. Ref. [18] develops an energy management model for the microgrids in the presence of renewable energies and DR programs. The studied microgrid is comprised of active loads, besides micro combined heat and power (CHP) unit, an auxiliary boiler and an EES system to supply electrical and heating load demands. The DR program is based on shifting the load demand, and a scenario-based stochastic framework has been deployed to handle the impacts of the uncertainties arisen by the load demand, market price, and renewable power generation. According to the results, it can be deduced that the DR program is capable of mitigating the operating cost both in grid-connected and islanded operation modes. Ref. [19] utilizes a robust optimization framework for the optimal operation of a local energy system, including CHP unit, TES, and a boiler. The mentioned model takes into account the uncertainties and a TOU-based DR program is used which results in mitigating the operating cost of the system by modifying the consumption pattern of the consumer. System flexibility is accounted as one of the most important issues in local energy systems, where it is influenced by several direct and indirect factors. Thus, it has captured attention during recent years. In this regard, Ref. [20] presents a MILP-based scheduling model for an energy hub, considering the uncertainties caused by load demand, renewable power generation, and market price. The energy hub is resourced with a CHP unit, a wind turbine, an EES system, as well as a power-to-gas (P2G) storage system. A shifting-load DR has also been applied. The simulation results show that the P2G storage system, besides the DR program would lead to reducing the operating costs and enhancing the system flexibility. A day-ahead scheduling model has been developed for a multi-carrier energy system, aimed at minimizing the energy supply cost. The studied system comprises a photovoltaic (PV) system and a wind turbine along with EES and ETS systems. A shiftable and curtailable (interruptible) loads based DR program has also been considered. The problem has been formatted as a mixed-integer non-linear programming (MINLP) model, solved using DICOPT solver in GAMS. The results obtained indicate that the DR program would impact the elastic loads which in turn leads to increased system flexibility and reduced operating cost.

Ref. [21] proposes a DR-oriented operational model for a multi-carrier energy system, including EES and TES systems. The objective function of the problem is a quadratic function and the problem is tackled using the genetic algorithm (GA) to optimize the operating cost. The roles of storage systems and DR program in enhancing the system flexibility and operating cost have been studied. Ref. [22] uses a two-stage model to implement the price-based residential DR programs in multi-carrier energy systems. The first stage is solved to derive the received price signals. The system operator uses the results obtained from the first stage to minimize energy losses. The consumers are ensured that they would not tolerate a higher cost in the second stage than that of obtained in the first stage to motivate them to participate in the DR program. The results reported by the simulation show that the mentioned model can successfully mitigate the energy losses and enhance the operational indexes.

Ref. [23] presents a stochastic optimization model for the participation of a local energy system in the electricity market. In this model, flexible loads are also considered. The problem is modeled as a MILP problem and the objective function is to maximize the aggregator's profit. Finally, the simulation results show that the proposed model is able to find the bidding curves.

Ref. [24] proposes a scheduling framework for a prosumer microgrid, taking into account DR programs and an EES system. Besides, the studied microgrid is equipped with solar PV panels. The problem has been modeled as a linear programming (LP) problem solved using MATLAB. The simulation results verify the effective role of the coordinated operation of the DR program and EES system in decreasing the cost and improving the system flexibility. A tri-objective optimization model has been developed in Ref. [25] to minimize the operating cost, the expected energy not supplied (EENS), and the mismatch between the load curve and renewable power generation profile. The DR program has been included in the model and the resulted multi-objective problem has been solved using the epsilon-constraint technique. Recently and along with the substantial penetration of multi-carrier energy systems in distribution networks, DR programs have also been applied to heating and cooling load demands, known as the integrated demand response (IDR). Ref. [26] provides a comprehensive review of the IDR programs, and future aspects. An integrated model has been used in Ref. [27] for the operation of a multi-carrier energy system, including electricity, NG, and heat and equipped with IDR programs, P2G systems, and energy storage systems. A coordinated operation model has been suggested for the flexible loads together with other assets. Finally, the model has been simulated on two test systems and the results show that the operation of storage systems would be useful, but highly constrained by the physical limitations. On the other hand, the IDR programs are not directly impacted by technical constraints but limited by the consumer discomfort index. Ref. [28] presents a two-stage MILP model for the planning of a multi-carrier energy system considering the IDR program. The proposed model uses a matrix structure in which operation constraints are expressed in detail. Also, the effect of using the IDR program on equipment capacity, total cost and load demand curve has been thoroughly investigated.

Ref. [29] has carried out optimal day-ahead scheduling of a hydrogen-based smart energy system using a robust optimization model, taking into account IDR programs and market price uncertainty. The IDR programs are applied to both electrical and heating loads. The hydrogen storage system is used to convert the surplus renewable power to hydrogen to supply the required hydrogen of the hydrogen-based assets. The objective function of the problem is the total cost minimization where the integrated operation of IDR programs and the hydrogen storage system would help reduce the operating costs by 7.8% and raise the system robustness against market price uncertainty by 30%. The impacts of pumped-storage units for increasing the operational flexibility of power systems have been examined in [30] . Ref. [31] developed an integrated planning model for multi-carrier energy systems where the energy hub's interconnection and IDR programs have been considered. The problem is solved, aimed at minimizing the load supply cost. The results obtained indicate that the presented model is capable of reducing the installed capacity of the assets and planning cost. A multi-stage LP model has been used in Ref. [32] for the operation of a multi-carrier energy system, taking into consideration renewable energies, storage systems and IDR programs. It is noteworthy that IDR programs have been applied to all types of load demands. In this respect, first, the nodes arrangement and virtual nodes insertion are used to transform the complex energy hub into some simple energy hubs. Then, the coupling matrix of each simple hub is obtained. Such a technique linearizes the primary non-linear optimization problem and significantly alleviates the computational burden. The simulation results verify that the integrated operation model can reduce the operating cost and enhance the operation robustness.

This chapter first reviews the DR programs and their roles in local energy systems, particularly multi-carrier energy systems. Afterward, an operation model is proposed to evaluate the impacts of DRPs, distributed generation (DG) units, and storage systems on the system scheduling and flexibility. Moreover, the impact of each item on the operating and emission costs would be discussed.

9.2. Demand response programs for local energy systems.

Local energy systems had always been passive elements in power systems before introducing DR programs. Besides, they were deprived of having the chance to reduce their costs. After the power system restructuring and adding DR programs to such systems, local energy systems can actively participate in electricity markets to mitigate their costs or provide the system with ancillary services. In this respect, they would help enhance reliability and mitigate the fluctuations, which in turn results in reduced energy bills [33]. Thus, DR programs have been widely accepted in many countries.

9.2.1 Comprehensive assessment of DR programs

DR programs are essential for the sustainable development of electricity markets, as the interaction between the generation and demand can lead to a more competitive environment. In addition, deploying the potential of consumers to change their consumption pattern results in a more efficient market. Therefore, DR-based policies are always supported by decision-making entities. The resulting equilibrium would be required for dynamic markets and providing consumers with diverse power options. In general, DR programs can be defined as the response of end-user to market prices. The response of the end-user would be controlling the asset's load demand, reducing the load demand, and partially/fully interrupting the lead demand. The entities that may ask for DR programs are independent system operator (ISO), service-providing entities, and distribution companies. Price response also includes RTP, dynamic pricing, critical peak pricing (CPP), TOU pricing. Demand response can be described more accurately as modifying the power consumption with respect to the usual consumption, in response to the market price or incentive to motivate the consumer to change the consumption pattern. This happens during the periods at which the energy prices are high or the system reliability is vulnerable. Overall, DR programs would be interpreted as reducing the consumption over the critical peak periods. The critical periods are those with high wholesale market prices over the day or those at which the system's reserve is not sufficient due to any failure or extreme weather conditions. A DR program is considered a complementary action to increase system efficiency. Seven major benefits of DR programs are: enhanced system reliability, reduced operating cost, increased market efficiency, risk management, reduced environmental emissions, mitigated market power, and improved services to consumers. According to the research conducted by the electric power research institute (EPRI), DR programs reduce the peak-load demand of the US by 45,000 MW, i.e. 6% of the peak demand. The main challenge in properly implementing DR programs is to select the best program with respect to the type of the load and system conditions. Fig. 1 shows different types of DR program. As this figure depicts, DR programs are categorized into price-based end incentive-based ones.

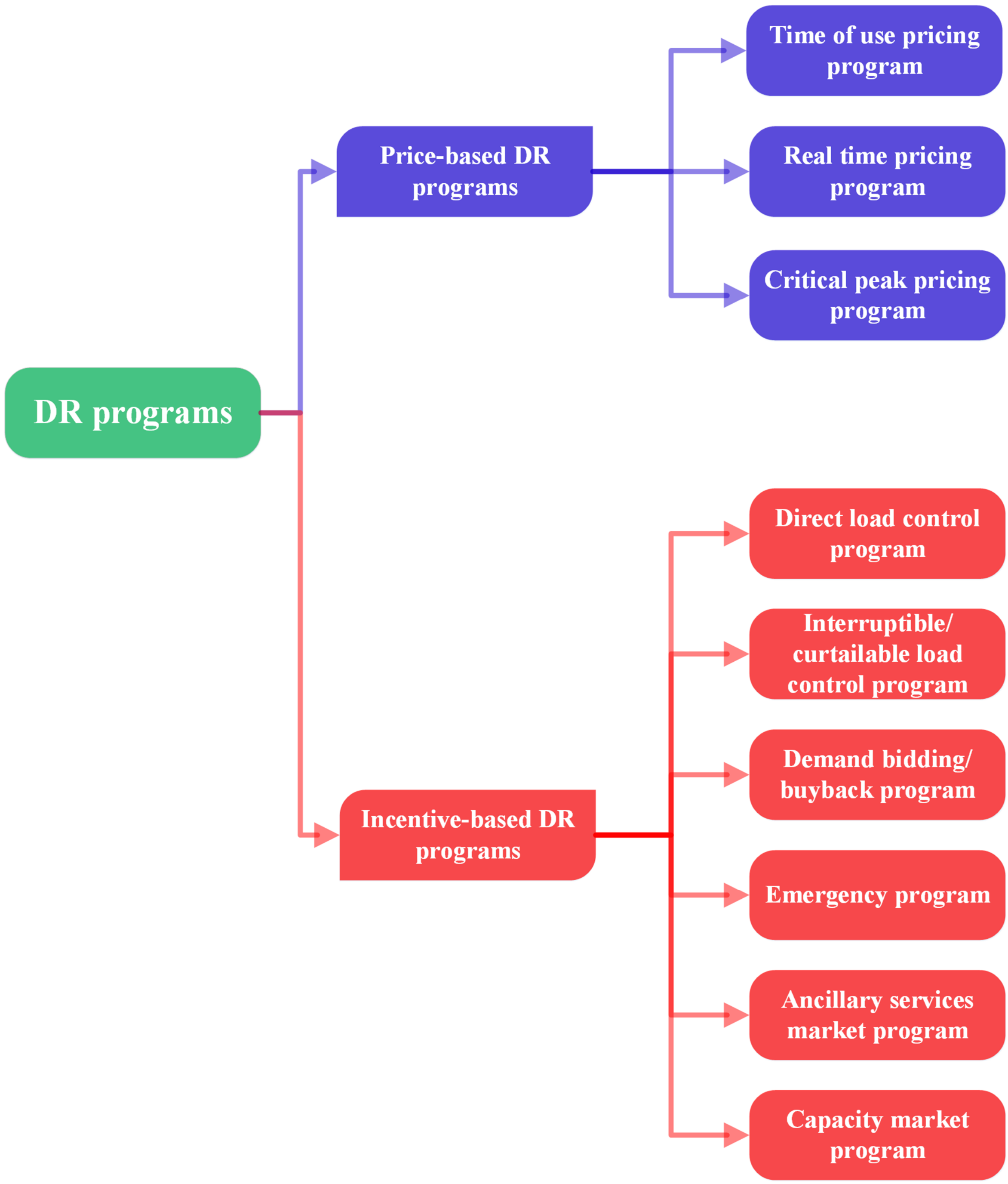

Fig. 1. DR programs classification [34].

9.2.1.1 Price-based Demand Response Programs

A price-based DRP leads to substantial modifications in the power consumption patterns in response to the market price variations. These DRPs are categorized into TOU mechanism, RTP, and CPP. If the variations in the market price over different time intervals of the day are considerable, consumers would react to price signals and reduce their bill [35].

- **Time-of-use Pricing**

TOU pricing is the most used mechanism all over the world. By using this mechanism, the 24 hours of the day are divided into three or four periods as: peak, off-peak, and valley periods. Each of these periods is associated with a fixed price. These prices may vary for different hours of the day, different days of the week, or seasons of the year. The differences in the prices are the incentive for consumers to reduce their consumption or shift their leads to other periods. These programs are mandatory and arbitrary programs. Consumers are able to participate in arbitrary programs and give up after the agreed period. Mandatory programs are designed for all consumers and they have to participate. Once the consumer tends to reduce the consumption over the peak periods and shift the peak load to off-peak hours, the load factor improves, and prices would drop in most cases. The main point in implementing such a program is to precisely measure the consumption, issuance of electricity bills, and training consumers. Hence, advanced energy meters are required for each consumer. These meters need smart systems and advanced calculations to issue the electricity bill. Recently, the way priced-based DR programs are implemented has substantially changed with the recent advances in internet technology. Accordingly, advanced digital meters with advanced communication systems, providing the consumers with the several capabilities to observe their consumption and decide on shifting their load demand, will be installed and used [36].

- **Real-time Pricing**

RTP is another price-based DRP, with hourly-varying pricing. The type of this DR program is arbitrary. Once the consumers enter this program, they should continue with the contract for a given period. The more substantial the variations of the market prices, the more the load shifting of consumers will be [37,38].

- **Critical peak Pricing**

The CPP is a combination of the TOU and RTP mechanisms. CPP is associated with a pre-determined high price designed by distribution companies to apply over peak intervals. These tariffs are called for a limited number of days or hours of the day with relatively short cautions. The consumers will receive a price discount over off-peak hours in this mechanism. It is worth mentioning that these tariffs are not yet common and used only in some regions [39].

9.2.1.2 Incentive-based Demand Response Programs

These programs are planned by distribution companies, service-providing entities, and local system operators with respect to the price consideration and the specific features of generators and the system. These programs offer some incentives to consumers to reduce or shift their load demand. Such incentives may be constant or variable in time. Once, the system reliability is vulnerable or market prices are too high, the load demand should be reduced. It is noteworthy that the consumers that are not able to commit to their contracts, would be penalized. Incentive-based DR programs provide the system operator with different options to solve the market problems of a region. These programs would help solve the system reliability issues. For instance, centralized loads would be mitigated to reduce transmission system congestion. These DR programs include direct load control (DLC), interruptible/curtailable services, Demand Bidding/buyback programs, emergency DRPs, capacity market programs, and ancillary service market programs [40].

- **Direct load Control**

The consumers having assets with the capability to turn off or be used for a shorter period of time can participate in DLC programs. Some of these assets are residential central air conditioning systems, boilers, electric pumps and electric heaters (EHs). In this respect, consumers should be equipped with a telecommunication receiver/transmitter to be able to participate in this program. It is noteworthy that once consumers opt to participate in the DLC program, they cannot quit the program.

- **Interruptible/curtailable services**

Interruptible services can be utilized by ISOs in the cases where there is not sufficient operating reserve in restructured power systems. In these programs, consumers make a contract with the service provider to change the power consumption with previously-provided information.

- **Demand Bidding/Buyback programs**

Demand bidding/buyback programs can be used when a consumer decides to give up consuming electricity with a pre-determined price. Such programs are arbitrary as the consumer is able to determine the amount and the time at which he/she tends to participate. These programs were introduced in 1993 and they are available as a DR program. By using this mechanism, if consumers make a contract with the service provider and determine the amount of their load to reduce, they can make a higher profit, compared to the case without these programs. From the economic point of view, it can be said that the profit made by reducing the load demand is higher than the cost of energy purchased from generation companies (GENCOs) with high prices.

- **Emergency Demand Response programs**

Once the system's reserve decreases, some consumers reduce their load demand and receive incentives instead. These consumers are end-users and load aggregators. The end-users usually include large industrial and commercial units that can reduce their load demand for at least 100 kW during emergency cases. These programs are deployed for cases with vulnerable reliability. These programs are similar to DLC programs in terms of the communication systems and actions taken to reduce the load demand. The consumer receives the incentive immediately after verification of the action taken.

- **Capacity market programs**

Consumers offer the load curtailment as the capacity of the system to replace the conventional generation. In this respect, consumers provide a pre-specified interruptible load to deal with contingent events and fluctuations. If they commit to their contracts when it is needed, they receive incentives; otherwise, they will be penalized.

- **Ancillary service Market Programs**

As it is obvious, consumers offer their interruptible or shiftable load in the ancillary service market as the operating reserve. In case they have to interrupt or reduce their load demand, they will be paid by the ISO according to the spot market price. In the past, PJM ISO and other ISOs relied only upon generation units to provide the required ancillary services. However, today there are numerous reliable sources other than generation units to provide the system with fast response services.

- **Integrated Demand Response Programs for Multi-Carrier Energy Systems**

IDR programs are used in multi-carrier energy systems, planned to simultaneously supply electrical, heating and cooling load demands [41]. The operation of these systems involves more constraints while some of them are inter-related. Thus, it is of high significance to prevent the coincidence of their peak loads for the sake of having am efficient operation. Accordingly, IDR programs are used and applied to all the three mentioned types of load demands simultaneously. In this respect, they are applied to each load demand separately through the power balance equations. It is worth noting that participating in IDR programs is associated with more limitations compared to the case with DR programs. Thus, different methods are used to implement these programs. Load-based IDR programs would be more desired than price-based IDR programs, as they may cause some other problems. For instance, if the three types of load demands are simultaneously shifted to another time interval, a new peak load would be created. The consumer will receive an incentive using this mechanism from the system operator. Generally, there are three types of load-based IDR programs, utilized according to the application and the consumer's behavior. These three load-based IDR programs are as follows:

- **Shiftable IDR**

Consumers shift their peak-load demand to off-peak hours through this program and receive an incentive. The mechanism of this program is similar to that of shiftable DR while it is used for all load demand types. It should be noted that the total amount of load demand would remain unchanged and only a fraction of the load demand is shifted.

- **Transferable IDR**

The load demand is shifted to other intervals using the transferable IDR programs. In this respect, the time interval between these shifts remains fixed, i.e. the load demand reduces in a time interval and after a specific period, it increases by the reduced amount (e.g. 8 hours). Consequently, the load demand would be transformed from peak intervals to valley intervals. It is noted that the maximum transferable load is different for each type.

- **Curtailable IDR**

The load demand can be curtailed at a specific time using this program and it will be rebounded over the subsequent time intervals (e.g. 3 hours), immediately after the load curtailment. For example, if the load is curtailed at hour 18, it will be rebounded at hours 19, 20, and 21. The percentage of the load rebounded would be logically estimated. For instance, if a consumer curtails a fraction of the load demand at hour 18, the most probable hour to rebound the load demand is hour 19. Then, the remaining load demand will be rebounded over hours 20 and 21. As mentioned above, each of the three IDR programs can be employed. However, shiftable IDR programs are the most prevalent ones.

9.3. Flexibility Assessment of Local Energy Systems in The Presence of Energy Storage Systems and DR programs

System flexibility is accounted as one of the most important issues in local energy systems, impacted by some factors both directly and indirectly. The most influencing factors are the uncertainties in the load demand and generation, DG units and energy storage systems. Moreover, the connection between the local energy systems and IDR programs highly affects the system flexibility. The negative impacts of renewable energies' uncertainties on system flexibility can be effectively addressed by storage systems, P2G converters, and model predictive control methods. TES, EES, and cooling thermal energy storage systems can be utilized in local energy systems. These devices would help enhance the system flexibility. CAES system has also been widely used to provide the system with efficient electromechanical energy storage. These devices store the compressed air by consuming electricity and discharge the compressed air to produce electricity when it is needed. In general, the principle of storage systems operation is on the basis of absorbing electricity to charge over off-peak and valley periods and discharge over peak periods to improve the system reliability by load flattening. P2G converters have also been used to use the surplus power generation, particularly surplus renewable power generation, to produce gas and improve the system efficiency and flexibility. DR programs can also be applied to upgrade the system flexibility by shifting the peak load demand to other periods and reducing the total operating cost. Such programs would also help stabilize the voltage at the connection point of consumers and improve the reliability by alleviating the peak load demand. If DR programs are applied to other types of load demand rather than only electrical loads, their impact on the system flexibility would be more highlighted.

9.4. Energy Management Framework for DER Integrated Distribution Networks

This section presents an energy management system (EMS) for multiple local energy systems, connected to a 33-bus distribution network. These local energy systems include three residential, industrial, and commercial energy hubs with transactive energy trading capability. In this respect, each hub is equipped with a CHP unit to evaluate the impacts of DERs on the system, besides RES's scheduling and flexibility. Moreover, the residential and commercial hubs include PV panels and the industrial hub includes a wind turbine. Furthermore, TES and EES systems have been used to investigate their roles in the optimal operation of energy hubs. The impacts of DR programs on the system scheduling & flexibility have been studied through considering five different programs. In this respect, two conventional DR programs, applied to electrical loads and three IDR programs, applied to heating and cooling loads, have been used in this chapter. It is noteworthy that the network constraints and power flow of lines have been modeled to avoid any unreal power transaction among the energy hubs. Fig.2 illustrates the conceptual model of the energy hubs in this study including industrial, commercial and residential energy hubs.

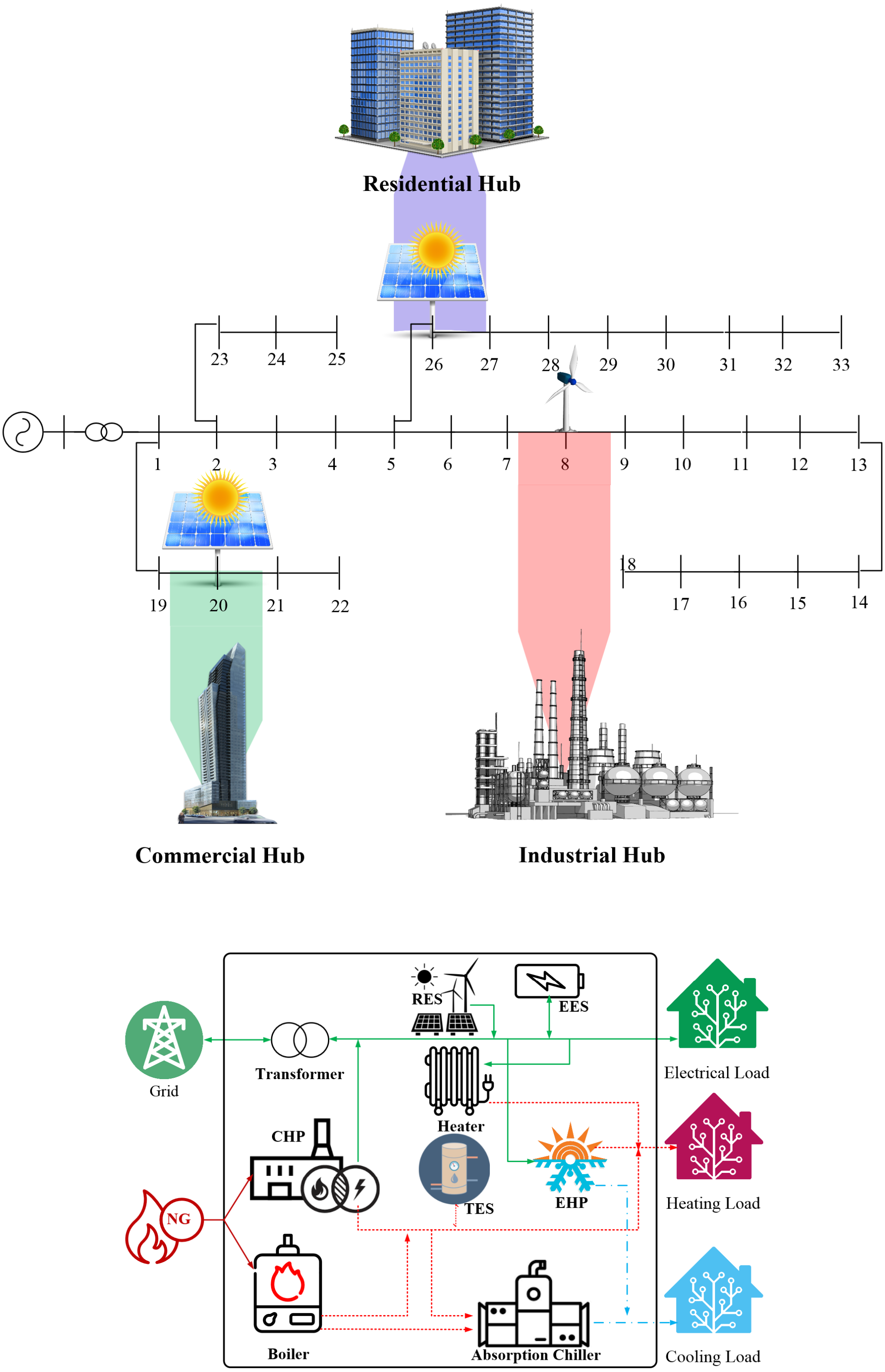

Fig. 2. Conceptual model of energy hubs in this study

The presented problem has been modeled as a single-objective optimization problem as follows:

- **Objective function**

The objective function of the problem is expressed in (1a), comprised of the operating costs of generation and storage assets, The first and second items of this function state the energy purchase cost and profit of each hub, made by selling energy relating to each hub respectively. $f_{k_i,sc,s,t}^{CHP}$, $f_{k_i,sc,s,t}^{Boiler}$, $f_{k_i,sc,s,t}^{EES}$, and show the operating costs of CHP units, boiler, EES, and TES systems $f_{k_i,sc,s,t}^{TES}$ respectively. $P_{k_i,sc,s,t}^{ENS}$ and $\lambda_{k_i,s}^{ENS}$ are the amount of energy not supplied (ENS) and its corresponding cost respectively. The last part of the objective function also shows the cost due to emission, propagated by the CHP unit and boiler, and also the cost due to transacting power with the upstream grid. SO_2, CO_2, and NO_2 emissions have been taken into account in this chapter.

$$Min: \ TOC =$$

$$\sum_{s=1}^{N_s}\omega_s\sum_{t=1}^{N_T}\sum_{k_i\in K}\left[\begin{array}{l}\left(\dfrac{P_{k_i,s,t}^{G\to H}+P_{k_i,s,t}^{M\to H}}{\eta^T}\lambda_{k_i,s,t}^{Buy}\right)-\left(P_{k_i,s,t}^{H\to G}+P_{k_i,s,t}^{H\to M}\right)\eta^T\lambda_{k_i,s,t}^{Sell}\\ +f_{k_i,s,t}^{CHP}+f_{k_i,s,t}^{Boiler}+f_{k_i,s,t}^{EES}+f_{k_i,s,t}^{TES}+P_{k_i,sc,s,t}^{ENS}\lambda_{k_i,s}^{ENS}+(P_{k_i,s,t}^{(e,h,c)\ +}+P_{k_i,s,t}^{(e,h,c)\ -})\lambda_{k_i,s}^{DR}\\ +\sum_{em=1}^{EM}\lambda_{em}EF_{em}^{G}P_{k_i,s,t}^{G\to H}+\lambda_{em}EF_{em}^{CHP}P_{k_i,s,t}^{CHP}+\lambda_{em}EF_{em}^{B}H_{k_i,s,t}^{Boiler}\end{array}\right] \tag{1a}$$

- **Operating cost of energy hubs' assets**

Eqs. (1b)-(1e) indicate the operating cost of CHP units, boiler, EES, and TES systems respectively. Eq. (1b) shows that the operating cost of the CHP units is a function of the heat and power generation, as well as the NG price. It is noted that $P_{k_i,sc,s,t}^{CHP}$ and $H_{k_i,sc,s,t}^{CHP}$ are the electrical power and heat generation of the CHP units respectively, while their associated efficiencies are stated by η_P^{CHP} and η_H^{CHP} respectively. The operating cost of the boiler is expressed as the product of the NG consumption and the NG price. The heat generation of the boiler, its efficiency, and the NG price are denoted by $H_{k_i,sc,s,t}^{Boiler}$, η^{Boiler}, and $\lambda_{k_i,s,t}^{Gas}$ respectively. As Eqs. (1d)-(1e) indicate, the operating costs of EES and TES systems depend upon the charging and discharging power and their operation duration.

$$f_{k_i,s,t}^{CHP} = \left(\frac{P_{k_i,s,t}^{CHP}}{\eta_P^{CHP}} + \frac{H_{k_i,s,t}^{CHP}}{\eta_H^{CHP}} \right) \lambda_{k_i,s,t}^{Gas} \tag{1b}$$

$$f_{k_i,s,t}^{Boiler} = \left(\frac{H_{k_i,s,t}^{Boiler}}{\eta^{Boiler}} \right) \lambda_{k_i,s,t}^{Gas} \tag{1c}$$

$$f_{k_i,s,t}^{EES} = \lambda^{EES} \left(P_{k_i,s,t}^{EES,Ch.} + P_{k_i,s,t}^{EES,Dis.} \right) \tag{1d}$$

$$f_{k_i,s,t}^{TES} = \lambda^{TES} \left(P_{k_i,s,t}^{TES,Ch.} + P_{k_i,s,t}^{TES,Dis.} \right) \tag{1e}$$

- **CHP model**

The CHP operation is characterized using the equalities and inequalities presented in (2a)-(2e). The combined heat and power generation is limited as expressed in (2a). Besides, the power and heat outputs are also constrained as (2b) and (2c) respectively. It is noted that $I_{k_i,sc,s,t}^{CHP}$ is a binary variable, specifying the turn off/on status of the CHP unit. Expression (2d) and (2e) show the power and heat flow of this asset.

$$Cap^{Min,CHP} I_{k_i,s,t}^{CHP} \le P_{k_i,s,t}^{CHP} + H_{k_i,s,t}^{CHP} \le Cap^{Max,CHP} I_{k_i,s,t}^{CHP} \tag{2a}$$

$$P^{Min,CHP} I_{k_i,s,t}^{CHP} \le P_{k_i,s,t}^{CHP} \le P^{Max,CHP} I_{k_i,s,t}^{CHP} \tag{2b}$$

$$H^{Min,CHP} I_{k_i,s,t}^{CHP} \le H_{k_i,s,t}^{CHP} \le H^{Max,CHP} I_{k_i,s,t}^{CHP} \tag{2c}$$

$$\begin{aligned} P_{k_i,s,t}^{CHP} = {} & P_{k_i,s,t}^{CHP \to EL} + P_{k_i,s,t}^{CHP \to EES} + P_{k_i,s,t}^{CHP \to EHP} + P_{k_i,s,t}^{CHP \to EH} \\ & + P_{k_i,s,t}^{CHP \to M} + P_{k_i,s,t}^{CHP \to G} \end{aligned} \tag{2d}$$

$$H_{k_i,s,t}^{CHP} = H_{k_i,s,t}^{CHP \to HL} + H_{k_i,s,t}^{CHP \to AC} + H_{k_i,s,t}^{CHP \to TES} \tag{2e}$$

- **Boiler model**

The boiler model is characterized using (3a) and (3b) where the heat generation is constrained as shown in (3a) and the heat flow is stated in (3b). It should be noted that $Cap^{Max,Boiler}$ and $Cap^{Min,Boiler}$ are the lower and upper bounds of the heat generation, where the minimum heat generation is assigned to model "zero" in this chapter. Besides, $I^{Boiler}_{k_i,sc,s,t}$ is a binary variable, determining the turn/off status of the boiler. As Eq. (3b) indicates, the heat generated by the boiler can be directly used by the consumer or indirectly used by the absorption chiller (AC) to supply the cooling power. Otherwise, it can be stored in the TES system.

$$Cap^{Min,Boiler} I^{Boiler}_{k_i,s,t} \leq H^{Boiler}_{k_i,s,t} \leq Cap^{Max,Boiler} I^{Boiler}_{k_i,s,t} \tag{3a}$$

$$H^{Boiler}_{k_i,s,t} = H^{Boiler \to HL}_{k_i,s,t} + H^{Boiler \to AC}_{k_i,s,t} + H^{Boiler \to TES}_{k_i,s,t} \tag{3b}$$

- **Electrical heater model**

The equalities and inequalities presented in (4a)-(4d) are used to model the electrical heater (EH) operation. The heat generated by the EH is limited as shown in (4a) while Eq. (4b) represents the heat generation equation of the EH as the product of electricity consumption and the respective efficiency. The power and heat flow equations of the EH are stated in (4c) and (4d) respectively.

$$Cap^{Min,EH} I^{EH}_{k_i,s,t} \leq H^{EH}_{k_i,s,t} \leq Cap^{Max,EH} I^{EH}_{k_i,s,t} \tag{4a}$$

$$H^{EH}_{k_i,s,t} = P^{EH}_{k_i,s,t} \eta^{EH} \tag{4b}$$

$$P^{EH}_{k_i,s,t} = P^{G \to EH}_{k_i,s,t} + P^{CHP \to EH}_{k_i,s,t} + P^{EES \to EH}_{k_i,s,t} + P^{RES \to EH}_{k_i,s,t} + P^{M \to EH}_{k_i,s,t} \tag{4c}$$

$$H^{EH}_{k_i,s,t} = H^{EH \to HL}_{k_i,s,t} + H^{EH \to TES}_{k_i,s,t} \tag{4d}$$

- **Electric heat pump**

The heating power generation and cooling power generation equations of the electric heat pump (EHP) are represented in (5a) and (5b) respectively. It is noteworthy that the heating power and cooling power and their associated binary variables are denoted by $H_{k_i,sc,s,t}^{EHP}$ and $C_{k_i,sc,s,t}^{EHP}$, $I_{k_i,sc,s,t}^{EHP,H}$, and $I_{k_i,sc,s,t}^{EHP,C}$ respectively. The EHP is capable of operating in one of the heating and cooling modes at a time. In this regard, the conflicting conditions have been avoided using (5c). The heating power and cooling power generation equations are the functions of the electricity consumption and respective efficiencies, as indicated in (5d) and (5e) respectively. The electrical power, heating power, and cooling power flow equations are expressed in (5f)-(5h) respectively.

$$Cap^{Min,EHP} I_{k_i,s,t}^{EHP,H} \le H_{k_i,s,t}^{EHP} \le Cap^{Max,EHP} I_{k_i,s,t}^{EHP,H} \tag{5a}$$

$$Cap^{Min,EHP} I_{k_i,s,t}^{EHP,C} \le C_{k_i,s,t}^{EHP} \le Cap^{Max,EHP} I_{k_i,s,t}^{EHP,C} \tag{5b}$$

$$0 \le I_{k_i,s,t}^{EHP,H} + I_{k_i,s,t}^{EHP,C} \le 1 \tag{5c}$$

$$H_{k_i,s,t}^{EHP} = P_{k_i,s,t}^{EHP} \eta_H^{EHP} \tag{5d}$$

$$C_{k_i,s,t}^{EHP} = P_{k_i,s,t}^{EHP} \eta_C^{EHP} \tag{5e}$$

$$P_{k_i,s,t}^{EHP} = P_{k_i,s,t}^{G\to EHP} + P_{k_i,s,t}^{CHP\to EHP} + P_{k_i,s,t}^{EES\to EHP} + P_{k_i,s,t}^{RES\to EHP} + P_{k_i,s,t}^{M\to EHP} \tag{5f}$$

$$H_{k_i,s,t}^{EHP} = H_{k_i,s,t}^{EHP\to HL} + H_{k_i,s,t}^{EHP\to TES} \tag{5g}$$

$$C_{k_i,s,t}^{EHP} = C_{k_i,s,t}^{EHP\to CL} \tag{5h}$$

- **Absorption chiller model**

The constraints and energy flow of the AC are stated in Eqs. (6a)-(6d). The minimum and maximum limits of the generation of the AC are represented in (6a). Eq. (6b) shows the cooling power generation of the AC, depending upon the input heating power and the associated efficiency.

The input heating energy flow and the output cooling energy flow are shown in (6c) and (6d) respectively.

$$Cap^{Min,AC} I^{AC}_{k_i,s,t} \leq C^{AC}_{k_i,s,t} \leq Cap^{Max,AC} I^{AC}_{k_i,s,t} \tag{6a}$$

$$C^{AC}_{k_i,s,t} = H^{AC}_{k_i,s,t} \eta^{AC} \tag{6b}$$

$$H^{AC}_{k_i,s,t} = H^{CHP \to AC}_{k_i,s,t} + H^{Boiler \to AC}_{k_i,s,t} + H^{TES \to AC}_{k_i,s,t} \tag{6c}$$

$$C^{AC}_{k_i,s,t} = C^{AC \to CL}_{k_i,s,t} \tag{6d}$$

- **EES and TES model**

The EES and TES systems are modeled using the constraints represented in (7a)-(7k). The energy stored in the EES system is limited as (7a). The energy balance of this device is expressed in (7b) which is the function of the energy available at time *t-1* and the charging and discharging power. The charging power and discharging power of the EES system should be in the feasible operating interval of this device as shown in (7c) and (7d) respectively. As constraint (7e) emphasizes, the EES system is capable of operating in either charging or discharging modes at a time. The initial energy and final energy stored in the device are also limited as stated in (7f) and (7g) respectively. Eqs. (7h) and (7i) indicate the energy flows of the EES system in the charging and discharging modes respectively. The energy flows of the TES system are indicated in (7j) and (7k) respectively.

$$Cap^{Min,EES} \leq E^{EES}_{k_i,s,t} \leq Cap^{Max,EES} \tag{7a}$$

$$E^{EES}_{k_i,s,t} = E^{EES}_{k_i,s,t-1} + \left(P^{EES,Ch.}_{k_i,s,t} \eta^{EES}_{Ch} \right) - \left(\frac{P^{EES,Dis.}_{k_i,s,t}}{\eta^{EES}_{Dis}} \right) \tag{7b}$$

$$0 \leq P^{EES,Ch.}_{k_i,s,t} \leq P^{EES,Ch.,Max} I^{EES,Ch.}_{k_i,s,t} \tag{7c}$$

$$0 \leq P^{EES,Dis.}_{k_i,s,t} \leq P^{EES,Dis.,Max} I^{EES,Dis.}_{k_i,s,t} \tag{7d}$$

$$0 \leq I^{EES,Ch.}_{k_i,s,t} + I^{EES,Dis.}_{k_i,s,t} \leq 1 \tag{7e}$$

$$E_{k_i,s,t=T}^{EES} = E_{k_i,s,t=0}^{EES} \tag{7f}$$

$$E_{k_i,s,t=0}^{EES} = \alpha_{k_i}^{initial} Cap^{Max,EES} \tag{7g}$$

$$P_{k_i,s,t}^{EES,Ch.} = P_{k_i,s,t}^{G\to EES} + P_{k_i,s,t}^{CHP\to EES} + P_{k_i,s,t}^{PV\to EES} + P_{k_i,s,t}^{M\to EES} \tag{7h}$$

$$P_{k_i,s,t}^{EES,Dis.} = P_{k_i,s,t}^{EES\to EL} + P_{k_i,s,t}^{EES\to G} + P_{k_i,s,t}^{EES\to EHP} + P_{k_i,s,t}^{EES\to EH} + P_{k_i,s,t}^{EES\to M} \tag{7i}$$

$$H_{k_i,s,t}^{TES,Ch} = H_{k_i,s,t}^{CHP\to TES} + H_{k_i,s,t}^{Boiler\to TES} + H_{k_i,s,t}^{EH\to TES} + H_{k_i,s,t}^{EHP\to TES} \tag{7j}$$

$$H_{k_i,s,t}^{TES,Dis} = H_{k_i,s,t}^{TES\to HL} + H_{k_i,s,t}^{TES\to AC} \tag{7k}$$

- **Renewable energies model**

Eq. (8a) shows the power generation equation of the solar PV panels, in which $P_{k_i,sc,s,t}^{PV}$ is the power output of the panel. Besides, $G_{sc,s,t}^{a}$, G_0^a, $P_{Max,0}^{M}$, $T_{sc,s,t}^{a}$, $NOCT$, and $T_{M,0}$ are the hourly solar irradiance, standard solar irradiance, nominal capacity of the PV system, hourly temperature, normal operating cell temperature, and the standard temperature respectively. The power produced by the wind turbine follows the conditional equation presented in (8b). The renewable energy flow equations are shown in (8c) and (8d).

$$P_{k_i,sc,s,t}^{PV} = \frac{G_{sc,s,t}^{a}}{G_0^a}\left[P_{Max,0}^{M} + \mu_{P\max}\left(T_{sc,s,t}^{a} + G_{sc,s,t}^{a}\frac{NOCT-20}{800} - T_{M,0}\right)\right] \tag{8a}$$

$$P_{k_i,s,t}^{Wind} = \begin{cases} 0 & v_{sc,s,t}^{w} \le v_{ci} \\ p_r\left(\dfrac{v_{s,t}^{w} - v_{ci}}{v_r - v_{ci}}\right)^3 & v_{ci} \le v_{s,t}^{w} \le v_r \\ p_r & v_r \le v_{s,t}^{w} \le v_{co} \\ 0 & v_{s,t}^{w} \ge v_{co} \end{cases} \tag{8b}$$

$$P_{k_i,s,t}^{RES} = P_{k_i,s,t}^{PV} + P_{k_i,s,t}^{Wind} \tag{8c}$$

$$P_{k_i,s,t}^{RES} = P_{k_i,s,t}^{RES\to EL} + P_{k_i,s,t}^{RES\to EES} + P_{k_i,s,t}^{RES\to EHP} + P_{k_i,s,t}^{RES\to EH} + P_{k_i,s,t}^{RES\to M} + P_{k_i,s,t}^{RES\to G} \tag{8d}$$

- **Energy transaction between hubs**

This section includes the power flow equations for the transactive energy trading between the three hubs. As Eqs. (9a)-(9c) show, the energy transaction of each hub would be determined with respect to other hubs. Moreover, the power received by each hub from other hubs can be specified using Eqs. (9d)-(9f).

$$P_{k_i,s,t}^{H\to M} = P_{s,t}^{Ind\to Com} + P_{s,t}^{Ind\to Res} \quad , \; i = Industrial \tag{9a}$$

$$P_{k_i,s,t}^{H\to M} = P_{s,t}^{Com\to Ind} + P_{s,t}^{Com\to Res} \quad , \; i = Comercial \tag{9b}$$

$$P_{k_i,s,t}^{H\to M} = P_{s,t}^{Res\to Ind} + P_{s,t}^{Res\to Com} \quad , \; i = Residential \tag{9c}$$

$$P_{k_i,s,t}^{M\to H} = P_{s,t}^{Res\to Ind} + P_{s,t}^{Com\to Ind} \quad , \; i = Industrial \tag{9d}$$

$$P_{k_i,s,t}^{M\to H} = P_{s,t}^{Res\to Com} + P_{s,t}^{Ind\to Com} \quad , \; i = Comercial \tag{9e}$$

$$P_{k_i,s,t}^{M\to H} = P_{s,t}^{Ind\to Res} + P_{s,t}^{Com\to Res} \quad , \; i = Residential \tag{9f}$$

- **Demand response programs models**

This section provides the mathematical formulation of two conventional DR programs, including a price-based DR program and a transferrable load based DR program as well as three IDR programs. These IDR programs include shiftable, transferrable, and curtailable programs. It should be noted that the mentioned IDR programs are applied to electrical, heating, and cooling loads. Furthermore, the impact of each DR and IDR program would be individually studied.

- **Shiftable demand response program**

By using this mechanism, consumers receive an incentive and agree to shift their peak-load demand to off-peak hours. The mathematical relationships, given in (10a)-(10d) show the mechanism of this program. As (10a) indicates, the sum of the amount of reduced load and increased load demands over the scheduling period should be equal. Constraints (10b) and (10c) show the maximum hourly increase and decrease in the load demand. Constraint 10(d) state that the simultaneous increase and decrease in the load demand as a result of the DR program is impossible and should be avoided.

$$\sum_{t=1}^{T} P_{k_i,s,t}^{e,sh,up} = \sum_{t=1}^{T} P_{k_i,s,t}^{e,sh,do} \tag{10a}$$

$$0 \le P_{k_i,s,t}^{e,sh,up}(sc,s,t) \le LPF^{e,sh,up} P_{k_i,s,t}^{s} I_{k_i,s,t}^{e,sh,up} \tag{10b}$$

$$0 \le P_{k_i,s,t}^{e,sh,do} \le LPF^{sh,do} P_{k_i,s,t}^{e} I_{k_i,s,t}^{e,sh,do} \tag{10c}$$

$$0 \le I_{k_i,s,t}^{e,sh,do} + I_{k_i,s,t}^{e,sh,up} \le 1 \tag{10d}$$

- **Time-of-use demand response program**

The mechanism of the TOU program is stated in (11a)-(11f). Eq. (11a) emphasizes that the sum of the increased load demand and reduced load demand must be equal over the scheduling period. $D_{k_i,sc,s,t}^{up}$ and $D_{k_i,sc,s,t}^{do}$ denote the upward and downward load demand respectively, depending upon the hourly electricity price and load elasticity, modeled in (11b) and (11c). $\varepsilon_{k_i}^{up}$ and $\varepsilon_{k_i}^{do}$ indicate the upward and downward load demand elasticities respectively. Moreover, $\lambda_{k_i,s,t}^{Buy}$ and $\lambda_{k_i,s}^{ref}$ are the hourly electricity price and off-peak electricity price respectively. Constraints (11d) and (11e) show the upper and lower bounds of the decrease in the load demand due to the DR program. $B_{k_i}^{up}$ and $B_{k_i}^{do}$ are the maximum upward and downward load variation coefficients, stated in terms of a percentage of the electrical load demand. $I_{k_i,sc,s,t}^{up}$ and $I_{k_i,sc,s,t}^{do}$ are upward and downward load demand variation binary variables respectively, where the conflicting situation is avoided in constraints (11f).

$$\sum_{t=1}^{T} P_{k_i,s,t}^{e,pb,up} = \sum_{t=1}^{T} P_{k_i,s,t}^{e,pb,do} \tag{11a}$$

$$P_{k_i,s,t}^{e,pb,up} \geq \varepsilon^{up}.P_{k_i,s,t}\left(1-\frac{\pi_{k_i,s,t}^{Net}}{\pi_{k_i,s}^{Ref}}\right) \tag{11b}$$

$$P_{k_i,s,t}^{e,pb,do} \geq \varepsilon^{do}.P_{k_i,s,t}\left(1-\frac{\pi_{k_i,s,t}^{Net}}{\pi_{k_i,s}^{Ref}}\right) \tag{11c}$$

$$0 \leq P_{k_i,s,t}^{e,pb,up} \leq P_{k_i,s,t}^{e}.B^{up}.I_{k_i,s,t}^{e,pb,up} \tag{11d}$$

$$0 \leq P_{k_i,s,t}^{e,pb,do} \leq P_{k_i,s,t}^{e}.B^{do}.I_{k_i,s,t}^{e,pb,do} \tag{11e}$$

$$0 \leq I_{k_i,s,t}^{e,pb,do} + I_{k_i,s,t}^{e,pb,up} \leq 1 \tag{11f}$$

- **Shiftable Integrated demand response program**

The shiftable IDR program is modeled using the mathematical formulations presented in (12a)-(12d). Eq. (12a) states that the load demand should remain constant over the scheduling period, i.e. the sum of increases and decreases should be equal. The hourly upward load demand and downward load demand have been characterized through (12b) and (12c) respectively, while constraint (12d) removes the conflicting situation.

$$\sum_{t=1}^{T} P_{k_i,s,t}^{(e,h,c),sh,up} = \sum_{t=1}^{T} P_{k_i,s,t}^{(e,h,c),sh,do} \tag{12a}$$

$$0 \leq P_{k_i,s,t}^{(e,h,c),sh,up} \leq LPF^{(e,h,c),sh,up} P_{k_i,s,t}^{(e,h,c)} I_{k_i,s,t}^{(e,h,c),sh,up} \tag{12b}$$

$$0 \leq P_{k_i,s,t}^{(e,h,c),sh,do} \leq LPF^{(e,h,c),sh,do} P_{k_i,s,t}^{(e,h,c)} I_{k_i,s,t}^{(e,h,c),sh,do} \tag{12c}$$

$$0 \leq I_{k_i,s,t}^{(e,h,c),sh,do} + I_{k_i,s,t}^{(e,h,c),sh,up} \leq 1 \tag{12d}$$

- **Transferrable integrated demand response program**

The mathematical relationships, proposed in (13a)-(13d) are employed to model the transferrable IDR program. In this respect, Eq. (13a) shows that this program should be applied with a determined pace, e.g. 8 hours in this chapter. In other words, if the load increases or decreases, the same amount should be compensated after 8 hours. This hourly upward and downward transferrable load demands are modeled using constraints (13b) and (13c). Furthermore, the conflicting situation is avoided using constraint (13d).

$$P_{k_i,s,t}^{(e,h,c),tr,do} = P_{k_i,s,t+N_x}^{(e,h,c),tr,up} \tag{13a}$$

$$0 \le P_{k_i,s,t}^{(e,h,c),tr,up} \le LPF^{(e,h,c),tr,up} P_{k_i,s,t}^{(e,h,c)} I_{k_i,s,t}^{(e,h,c),tr,up} \tag{13b}$$

$$0 \le P_{k_i,s,t}^{(e,h,c),tr,do} \le LPF^{(e,h,c),tr,do} P_{k_i,s,t}^{(e,h,c)} I_{k_i,s,t}^{(e,h,c),tr,do} \tag{13c}$$

$$0 \le I_{k_i,s,t}^{(e,h,c),tr,do} + I_{k_i,s,t}^{(e,h,c),tr,up} \le 1 \tag{13d}$$

- **Curtailable integrated demand response program**

Constraint (14a) indicates the mechanism of implementing the curtailable IDR program. The load curtailed at each hour must be rebounded over the immediate subsequent three hours. In this regard, φ_1, φ_2, and φ_3 are the rebounded load demand in percent and their values are 60%, 30%, and 10% respectively. Constraints (14b) and (14c) indicate the upward and downward load demand at each hour.

$$P_{k_i,s,t}^{(e,h,c),cu,do} = \varphi_1 P_{k_i,s,t+1}^{(e,h,c),cu,up} + \varphi_2 P_{k_i,s,t+2}^{(e,h,c),cu,up} + \varphi_3 P_{k_i,s,t+3}^{(e,h,c),cu,up} \tag{14a}$$

$$0 \le P_{k_i,s,t}^{(e,h,c),cu,up} \le LPF^{(e,h,c),cu,up} P_{k_i,s,t}^{(e,h,c)} I_{k_i,s,t}^{(e,h,c),cu,up} \tag{14b}$$

$$0 \le P_{k_i,s,t}^{(e,h,c),cu,do} \le LPF^{(e,h,c),cu,do} P_{k_i,s,t}^{(e,h,c)} I_{k_i,s,t}^{(e,h,c),cu,do} \tag{14c}$$

As it was mentioned before, there is a limit for DR program implementation at the same time to show the effectiveness of each DR programs on operational results. Constraints (15a)-(15f) deal with this assumption to avoid multiple integrations of the DR programs at the same time.

$$P_{k_i,s,t}^{e,+} = P_{k_i,s,t}^{e,sh,up} + P_{k_i,s,t}^{e,pb,up} + P_{k_i,s,t}^{e,tr,up} + P_{k_i,s,t}^{e,cu,up} \tag{15a}$$

$$P_{k_i,s,t}^{h,+} = P_{k_i,s,t}^{h,sh,up} + P_{k_i,s,t}^{h,tr,up} + P_{k_i,s,t}^{h,cu,up} \tag{15b}$$

$$P_{k_i,s,t}^{c,+} = P_{k_i,s,t}^{c,sh,up} + P_{k_i,s,t}^{c,tr,up} + P_{k_i,s,t}^{c,cu,up} \tag{15c}$$

$$P_{k_i,s,t}^{e,-} = P_{k_i,s,t}^{e,sh,do} + P_{k_i,s,t}^{e,pb,do} + P_{k_i,s,t}^{e,tr,do} + P_{k_i,s,t}^{e,cu,do} \tag{15d}$$

$$P_{k_i,s,t}^{e,-} = P_{k_i,s,t}^{h,sh,do} + P_{k_i,s,t}^{h,pb,do} + P_{k_i,s,t}^{h,tr,do} + P_{k_i,s,t}^{h,cu,do} \tag{15e}$$

$$P_{k_i,s,t}^{c,-} = P_{k_i,s,t}^{c,sh,do} + P_{k_i,s,t}^{c,pb,do} + P_{k_i,s,t}^{c,tr,do} + P_{k_i,s,t}^{c,cu,do} \tag{15f}$$

- **Power balance constraints**

Eqs. (16a)-(16c) show the balance equations for the electrical, heating, and cooling power respectively. As Eq.(16a) shows, the electrical load demand is supplied by transacting power with the upstream grid and other energy hubs, and also by the CHP units, EES system, and other RESs. Besides, the heating load demand is supplied using the CHP unit, boiler, EHP, EH, and TES system. The cooling load demand is also supplied using the AC and EHP.

$$P_{k_i,s,t}^{G\rightarrow EL} + P_{k_i,s,t}^{M\rightarrow EL} + P_{k_i,s,t}^{ESS\rightarrow EL} + P_{k_i,s,t}^{RES\rightarrow EL} + P_{k_i,s,t}^{CHP\rightarrow EL} + P_{k_i,s,t}^{e,-} = P_{k_i,s,t}^{EL} + P_{k_i,s,t}^{e,+} - P_{k_i,s,t}^{ENS} \tag{16a}$$

$$H_{k_i,s,t}^{CHP\rightarrow HL} + H_{k_i,s,t}^{Boiler\rightarrow HL} + H_{k_i,s,t}^{EHP\rightarrow HL} + H_{k_i,s,t}^{EH\rightarrow HL} + H_{k_i,s,t}^{TES\rightarrow HL} + P_{k_i,s,t}^{h,-} = H_{k_i,s,t}^{HL} + P_{k_i,s,t}^{h,+} \tag{16b}$$

$$C_{k_i,s,t}^{EHP\rightarrow CL} + C_{k_i,s,t}^{AC\rightarrow CL} + P_{k_i,s,t}^{c,-} = C_{k_i,s,t}^{CL} + P_{k_i,s,t}^{c,+} \tag{16c}$$

- **Power flow constraints**

Eqs. (17a)-(17i) state the linear formulation of the power flow constraints. Eq. (17a) relates to the susceptance and conductance calculations. The active and reactive power flow equations are represented in (17b) and (17c) respectively. Constraints (17d) and (17e) state the maximum active and reactive power flow of lines respectively. The constraints of the voltage magnitude and angle are applied using inequalities (17f) and (17g) respectively. The active and reactive power injections of each bus would be determined by employing Eqs. (18h) and (17i) respectively.

$$G_l^{Line} = \frac{r_l}{r_l^2 + x_l^2}, \quad B_l^{Line} = \frac{x_l}{r_l^2 + x_l^2} \tag{17a}$$

$$P_{s,l,t}^{Flow} = B_l^{Line}\left(\delta_{s,i,t} - \delta_{s,j,t}\right) + G_l^{Line}\left(V_{s,i,t} - V_{s,j,t}\right) \tag{17b}$$

$$Q_{s,l,t}^{Flow} = B_l^{Line}\left(V_{s,i,t} - V_{s,j,t}\right) - G_l^{Line}\left(\delta_{s,i,t} - \delta_{s,j,t}\right) \tag{17c}$$

$$-P_l^{Flow,\max} \le P_{s,l,t}^{Flow} \le P_l^{Flow,\max} \tag{17d}$$

$$-Q_l^{Flow,\max} \le Q_{s,l,t}^{Flow} \le Q_l^{Flow,\max} \tag{17e}$$

$$V_i^{\min}(i) \le V_{s,i,t} \le V_i^{\max} \tag{17f}$$

$$\delta_i^{\min} \le \delta_{s,i,t} \le \delta_i^{\max} \tag{17g}$$

$$P_{n,s,t}^{Gen} + \sum_{l=1|m\to n}^{L} P_{l,s,t}^{flow} = \left(\sum_{k_i \in n} P_{k_i,s,t}^{G\to H} + P_{k_i,s,t}^{M\to H}\right) + \sum_{l=1|n\to m}^{L} P_{l,s,t}^{flow} \tag{17h}$$

$$Q_{n,s,t}^{Gen} + \sum_{l=1|m\to n}^{L} Q_{l,s,t}^{flow} = \sum_{k_i \in n} \tan(\varphi_{k_i})\left(P_{k_i,s,t}^{G\to H} + P_{k_i,s,t}^{M\to H}\right) + \sum_{l=1|n\to m}^{L} Q_{l,s,t}^{flow} \tag{17i}$$

9.5. Simulation results

This section is devoted to solving the proposed scheduling problem through simulating five different case studies, and the results, obtained are discussed. Table 1 provides the required information of the five case studies. The data of the energy hubs' assets are available in Ref. [17]. Furthermore, the load demand data of each hub are presented in Table 2.

Table 1. The studied five cases for DR program assessment.

Case no.	DR	EES	TES	RER's	Coordinate	Uncoordinated
1	×	✓	✓	✓	✓	×
2	✓	✓	✓	✓	✓	×
3	✓	✓	✓	✓	×	✓
4	✓	×	✓	✓	✓	×
5	✓	✓	×	✓	✓	×
6	✓	✓	✓	×	✓	×

Table 2. Load demand data of energy hubs.

Hour	**Industrial**			**Commercial**			**Residential**		
	Spr./Fall	Summer	Winter	Spr./Fall	Summer	Winter	Spr./Fall	Summer	Winter
1	450	450	300	175	175	175	401.46	584.48	190.37
2	450	450	300	175	175	175	400.38	551.92	259.62
3	450	450	300	175	175	175	384.93	520.04	273.40
4	450	450	300	175	175	175	380.90	499.58	304.33
5	600	600	750	175	175	175	448.74	576.18	386.37
6	900	750	1050	175	175	175	587.14	733.46	551.51
7	1200	1050	1350	175	175	175	780.00	893.52	638.60
8	1425	1350	1500	175	175	175	855.06	910.00	730.84
9	1500	1500	1500	280	280	280	899.50	910.00	729.01
10	1500	1500	1500	420	420	420	913.75	910.00	732.25
11	1500	1500	1500	490	490	490	911.65	975.00	780.00
12	1500	1500	1500	490	490	490	931.52	1105.0	780.00
13	1500	1500	1500	490	490	490	947.14	1105.0	780.00
14	1500	1500	1500	490	490	490	962.87	975.00	780.00
15	1500	1500	1500	542.5	525	560	976.69	845.00	845.00
16	1500	1500	1350	542.5	525	560	980.40	845.00	845.00
17	1050	1350	1200	577.5	560	595	985.94	910.00	780.00
18	900	1050	750	595	560	630	1020.5	975.00	715.00
19	600	600	300	665	630	700	1019.2	1040.0	715.00
20	450	450	300	700	700	700	979.17	1170.0	715.00
21	450	450	300	700	700	700	878.02	1300.0	624.00
22	450	450	300	647.5	700	595	729.98	1248.0	596.03
23	450	450	300	595	700	490	581.45	1040.0	397.20
24	450	450	300	385	490	280	414.01	780.00	192.59

Five DR and IDR programs have been simulated to investigate their impacts on the operating cost of the system. The results, obtained are represented in Table 3. The results, derived from simulation of the DR programs for electrical loads show that the price-based DR program performs better, as no payment would be made by the system operator. In other words, consumers shift their load demand with respect to the electricity price, leading to a modified load demand profile and reduced cost. On the contrary, consumers shift their load demand using the load-based DR program, only if they receive an incentive.

Table 3. The simulation results for the five case studies.

	Operation cost ($/day)			
	Shiftable DR			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3356.36	4718.62	2984.14	3474.01
Commercial	1006.39	1401.88	763.52	904.65
Residential	1248.15	2407.16	806.96	969.64
	Price-based DR			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3317.89	4668.27	2945.05	3438.88
Commercial	987.26	1403.32	752.27	886.43
Residential	1218.42	2376.99	790.46	958.61
	Shiftable IDR			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3301.43	4475.41	2941.10	3400.73
Commercial	974.53	1377.45	753.64	884.45
Residential	1212.43	2279.39	789.58	955.20
	Transferable IDR			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3481.46	4742.99	3049.75	3498.88
Commercial	990.60	1381.06	788.50	904.23
Residential	1268.12	2418.77	819.92	971.51
	Curtailable IDR			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3564.38	4881.90	3118.69	3569.00
Commercial	1002.35	1411.21	797.16	909.93
Residential	1310.78	2484.18	833.02	985.26
	Without DR or IDR			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3612.40	4975.28	3172.39	3596.32
Commercial	1010.91	1425.36	798.17	919.32
Residential	1327.97	2540.14	840.98	1000.91

It is noteworthy that both DR programs result in modifying the load demand profile while the price-based DR program would be more beneficial to the system operator. The simulation results for the three IDR programs, applied to electrical, heating, and cooling loads verify that the shiftable IDR program leads to a more desired solution. Transferrable and curtailable IDR programs are ranked the second and third in terms of their results desirability. It is noteworthy that the consumer would be paid using each of these three programs. The superior performance of the shiftable IDR program is due to the fact that it is associated with lower operating limitations. The obtained results for the five case studies also verify that the shiftable IDR program is associated with the best performance compared to others. Although the system operator should pay to consumers, it leads to better results as it is applied to heating and cooling loads as well, and it shifts the load demand to off-peak hours. It has been revealed that the residential energy hub has participated more in the DR programs as it includes more flexible loads compared to the commercial and industrial energy hubs.

Figs. 3-5 depict the impact of shifting IDR program on the electrical load demand curve in summer, the cooling load demand curve in summer, and the heating load demand curve in winter respectively. As can be observed, this IDR program has successfully and effectively modified the load demand curves by shifting the peak load to off-peak hours.

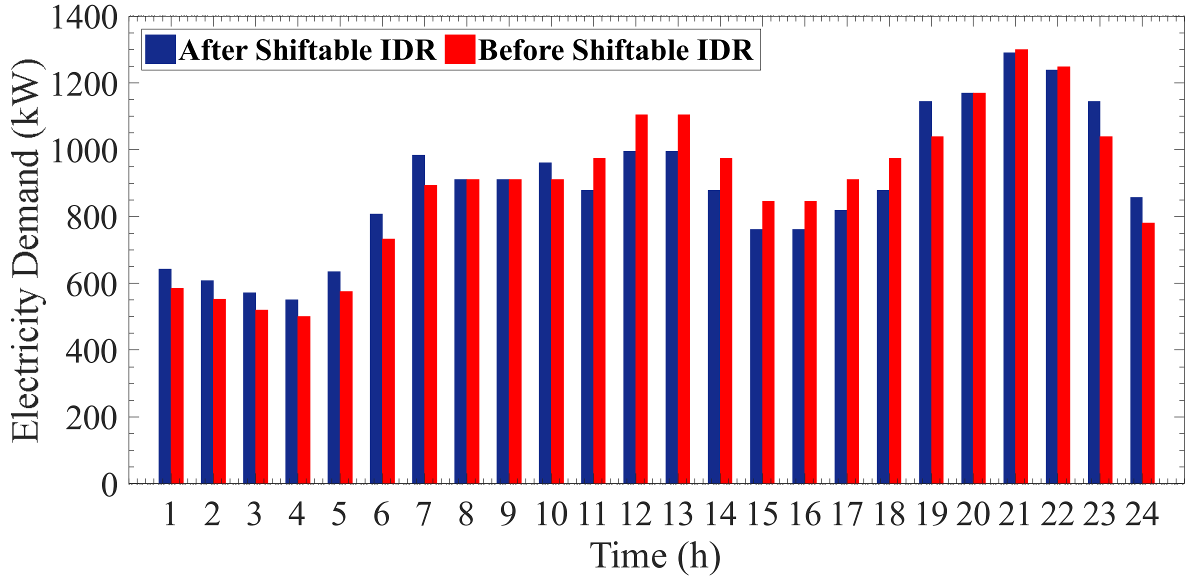

Fig. 3. Electrical load demand in summer.

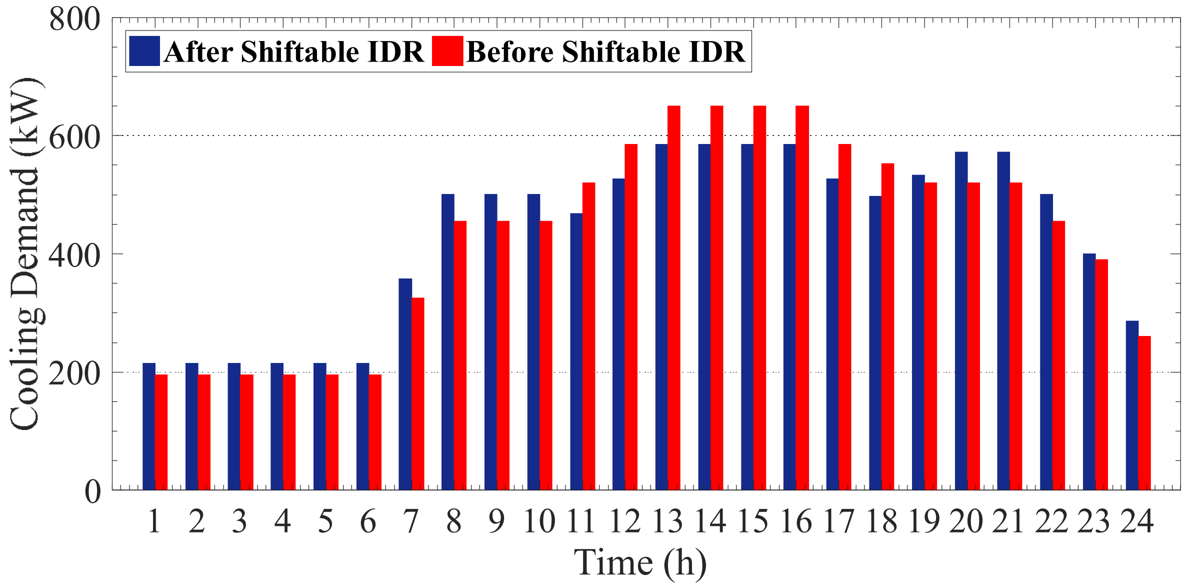

Fig. 4. Cooling load demand in summer.

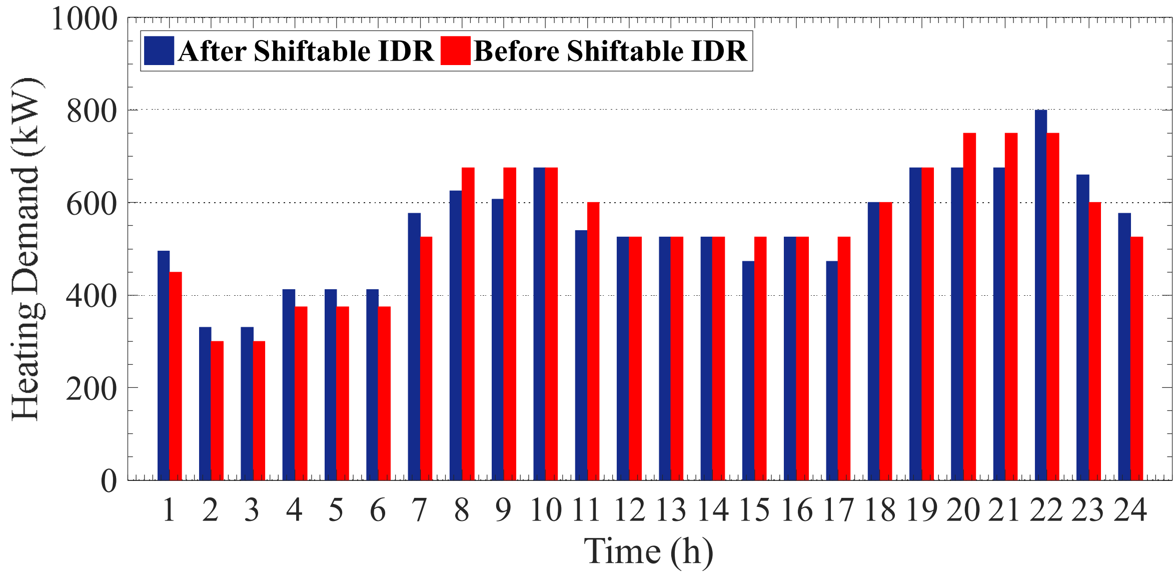

Fig. 5. Heating load demand in winter.

Table 4 represents the results, obtained from the simulating the six case studies with and without IDR programs. As the shiftable IDR program has the most desired performance, it is used for further studying the problem. The comparison made between case studies 1 and 2 shows that the operating cost would be much higher without applying the IDR program in Case 1 compared to Case 2. This difference is more considerable in summer and winter due to their higher load demands compared to spring and fall. Moreover, the commercial energy hub is less impacted by the IDR program as its load demand is less flexible compared to other energy hubs. In Case 3, it is assumed that the three energy hubs are only allowed to transact power with the upstream grid and transactive energy trading between these hubs is not allowed. Accordingly, the operating cost in this case is substantially higher than Case 2. This is due to the fact that they should pay more for emission costs, associated with the energy transaction with the upstream grid. The commercial energy hub is much more affected by this limitation and it should tolerate a higher cost. In this respect, the peak load demands of the commercial and industrial hubs are not coincident and energy trading between these two hubs could have considerably reduced the operating cost of this hub. The impact of this limitation is more than the absence of the IDR program in residential and commercial energy hubs. In this respect, the residential hub could have purchased its required power over the final hours of the day from the industrial hub and decreased its operating costs by not paying for emission costs. It is noted that the load demand of industrial hub is significantly low during these hours and it can sell power to the commercial and residential hubs. The results indicate that in general, the transactive energy trading between the hubs would substantially enhance the system flexibility. Case 4 is simulated without any EES system, showing that a higher cost should be tolerated which is more tangible in the industrial hub as it owns a larger EES system. It is noted that if the hub is equipped with an EES system, it is charged during the initial hours of the day at low prices through absorbing power from the upstream grid or the surplus power generation of the CHP unit. Thus, it can deliver power to the system over the peak-load periods, resulting in reduced load demand and operating costs. The simulation results, obtained in Case 5 indicate that the impact of the absence of the TES system on the operating cost is less significant compared to the EES system. The comparison with Case 2 shows that the effect of lacking the TES system can be more observed in summer and winter, when it is utilized for providing the required heating power of the AC and supplying the heating load demand. The operating cost considerably increases in Case 6 without any renewable energies, i.e. PV panels in residential and commercial hubs and a wind turbine in the industrial energy hub. It is noted that the impact of renewable energies on the operating cost is much more significant compared to other cases.

Table 4. The simulation results for the 6 case studies with and without the shiftable IDR program.

	Operation cost ($/day)			
	Case 1			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3612.40	4975.28	3172.39	3596.32
Commercial	1010.91	1425.36	798.17	919.32
Residential	1327.97	2540.14	840.98	1000.91
	Case 2			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3301.43	4475.41	2941.10	3400.73
Commercial	974.53	1377.45	753.64	884.45
Residential	1212.43	2279.39	789.58	955.20
	Case 3			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3401.92	4551.49	3013.95	3435.05
Commercial	989.80	1458.23	791.46	933.80
Residential	1365.92	2614.69	841.72	952.27
	Case 4			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3397.53	4593.77	3001.95	3473.09
Commercial	986.18	1407.90	780.61	894.19
Residential	1260.39	2329.01	805.45	952.09
	Case 5			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	3310.01	4501.24	2949.61	3425.37
Commercial	978.18	1379.98	757.29	888.10
Residential	1214.61	2282.78	791.85	957.47
	Case 6			
	Spring	**Summer**	**Fall**	**Winter**
Industrial	4525.80	6450.50	4349.58	5174.02
Commercial	1029.63	1526.07	836.76	937.70
Residential	1388.68	2571.90	869.25	983.54

Table 5 represents the annual cost due to emissions in each case. The results show that the impacts of the studied cases on the operating cost are different and the cases in which energy hubs pay more for emission are different as well. It is worth mentioning that the lowest cost relates to Case 2 with all assets. Besides, the industrial hub tolerates the highest cost in Case 6, where there is no wind turbine as its capacity is relatively high. Accordingly, the industrial hub should purchase more power from the upstream grid, which in turn leads to a higher emission cost. The highest costs of the residential and commercial hubs occur in Case 3, where the transactive energy trading between hubs is not allowed. A substantial fraction of their load demand could have been supplied by the industrial hub, while without any access to the industrial hub, they have to purchase power from the upstream grid and pay more for emission.

Table 5. Emission costs for the 6 case studies and for each hub.

Energy hub units	**Emission cost ($/year)**					
	Case 1	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**
Industrial	218260.21	196188.69	209272.361	203439.49	197186.96	315663.40
Commercial	103639.36	102746.42	115912.99	104145.05	106374.95	110911.37
Residential	160766.16	145154.50	188975.13	149009.74	145238.42	174660.23

9.6.Conclusion Remarks

10. This chapter investigated the impacts of five DR and IDR programs on the scheduling of local energy hubs. First, a comprehensive review was carried out on the background of DR programs in local energy systems. Then, the mechanism of local energy systems and IDR programs in such systems were described. In this respect, a MILP framework was developed for the optimal scheduling of multiple energy hubs, connected to a 33-bus distribution network. The studied hubs were industrial, commercial, and residential. After determining the most desired IDR program, i.e. shiftable IDR program, showing a better performance compared to other programs, six case studies were simulated and analyzed. In this respect, the impacts of different assets and capabilities on the operating and emission costs were investigated. The results obtained from the simulation showed that renewable energies have the most significant impact

on the emission cost of the industrial hub, while the other two hubs were mainly affected by the transactive energy trading between hubs. Besides, in the case without any renewable energies, all the three hubs tolerated the highest cost compared to other cases. This is due to the fact that a significant fraction of their load demand during the initial and final hours of the day is supplied by the industrial hub. Moreover, after renewable energies, the DR programs have the highest impact on the operating cost of the industrial hub. It was also noted that the residential and commercial hubs had to pay more for the emission costs compared to the industrial hub in the absence of transactive energy trading. With respect to the fact that the industrial hub could have supplied a substantial amount of the energy demand of the other two hubs, the residential and commercial hubs have to transact power with the upstream grid and pay for the emission costs. The absence of wind turbine caused the industrial hub to pay the highest amount for the emission as the capacity of the wind turbine was considerable. Five DR programs were tested, besides the energy management program, showing that the best one was the shiftable IDR program. This efficacy was due to the opportunities provided by impacting the heating and cooling load demand as well, particularly in summer and winter. It is also noteworthy that the residential hub is more affected by the DR programs in comparison with the other two hubs which is due to the higher flexibility of residential loads compared to industrial and commercial loads.

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