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Review

Integrated Demand Response Programs in Energy Hubs: A Review of Applications, Classifications, Models and Future Directions

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Abstract: In the traditional power system, customers respond to their primary electricity consumption pattern based on price or incentive to take additional advantages. By developing energy hubs (EHs) where electricity, heat, natural gas and other forms of energy are coupled together, all types of energy customers, even the inelastic loads, can participate in the demand response (DR) program. This novel vision has led to the concept of "integrated demand response (IDR)". IDR programs (IDRPs) in EHs involve coordinating multiple DR activities across different energy systems, such as buildings, industrial complexes and transportation networks. The main purpose of IDR is so that multi-energy users can respond not only by shifting or reducing their energy consumption from the demand side, but also by changing the type of energy consumed in response to the dispatching center. The integration of IDRPs in EHs can help to reduce energy costs, improve grid stability and increase the penetration of renewable energy sources (RES) in the power system. Moreover, by synchronizing DR activities across different energy systems, IDRPs can provide additional benefits, such as improved energy efficiency, reduced greenhouse gas emissions and increased resilience to power outages and other disruptions. In this paper, we provide an overview of the IDRP across EH areas, encompassing different aspects of it. First, the nature behind IDRP and its basic concept is introduced. Then, a categorization of fundamental principles within the IDRP is undertaken. Furthermore, modelling formulation and optimization techniques of IDRP in EHs are conducted. In addition to the IDRP content and model, this article deals with the research performed in this field from different perspectives. Finally, the advantages and prospect challenges of IDRPs are discussed.

Keywords: multi-energy systems (MESs); renewable energy; energy hubs (EHs); demand-side management; integrated demand response (IDR) program

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1. Introduction

In recent years, the rapid growth of energy demands, the lack of fossil resources and most crucially, environmental problems have persuaded countries worldwide to control their energy generation and consumption patterns in an optimal manner [1–3]. Undeniably, meeting thermal and electrical energy demands as primary loads is essential. Moreover, following the government's net-zero target by 2050, it is imperative to reduce carbon emissions and promote integrated energy systems (IESs) based on RESs [4,5]. It has been proposed in various studies that an integrated framework such as EHs will enhance RES functionality.

The "A vision of future energy networks" (VOFEN) project introduced the notion of an EH within its structure [6]. This project leveraged the benefits offered by diverse energy carriers through the transition towards integrated multi-energy systems (IMES) over an extended time horizon of 20 to 30 years [7]. In this project, the emergence of EHs has sparked significant interest and attention [8]. In general, an EH can be characterized as a framework in which the generation, consumption, conversion and storage of various energy carriers are carried out [9]. The terms "integrated", "hybrid" and "multi" are occasionally employed to denote an EH. This underscores the interconnectedness of multiple energy sources within its structure [10–12].

As stated in [13], the coordination of power sources, energy storage and responsive loads within an EH demonstrates superior economic outcomes and efficiency compared to the separate management of each element. Given that an EH encompasses a diverse array of features including resources, converters, transmitters, energy storage systems and demand, it can be evaluated for emerging advanced technologies as an efficient framework. Flexibility, reliability, efficiency and optimal operation are the main achievements of the EH framework. However, EH impacts should be examined precisely in transmission and distribution networks for different purposes.

Compared with the traditional method of energy generation, an IES can improve energy supply by using energy conversion equipment, storage and flexible management of distributed resources such as electricity, gas, heating and cooling. However, achieving high energy efficiency requires both the demand and supply side. Due to the recent advances in smart grid technologies, demand side management (DSM) activities such as valley filling, peak clipping and flexible load shaping are now regarded as essential strategies. The DR program, which is in the last category, has been considered as the point of a decisive solution in this respect [14,15].

Meanwhile, complex load characteristics, various energy sources coupling, large load demand and a lack of reliability in power supply pose new challenges for DR programs on the dispatch side [16]. The fundamental challenge of future energy systems is how to minimize the effects of DR implementation on the consumer. Therefore, multi-energy systems (MES), due to the presence of a diverse range of consumers with different types of loads, can lead to a reduction in the impact of consumer participation in DR programs. The original concept of MESs has brought a new perspective to the DR program. The integration of different energy carriers enables customers to play an active role in the DR program not only by changing their consumption patterns but also through switching their source of consumption. This modified innovation of the DR program, called IDR [15], strengthens the balance between supply and demand while decongesting the power system [17,18]. IDR programs are essential components for the effective and efficient management of modern power systems. Their integration into EHs provides greater flexibility to networks, and their use by TSOs and DSOs can help them manage systems with more precision. Therefore, an in-depth understanding of IDR programs is crucial for all stakeholders involved in the energy industry.

To date, the research on IDR analysis in MESs including EHs has attracted the attention of many researchers. In this paper, the review and perspective of IDR in EHs are covered to provide a reference for succeeding studies.

To arrange an outline of the present EH research, bibliometric scanning has been performed using the certified Web of Science (WoS) databases. The data used in this article were gathered on 6 November 2022.

Figure 1a indicates how many EH-based publications have been included in the WoS Core Collection over the past fifteen years [19]. It is estimated that approximately 1074 documents have been published in the aforementioned databases during these years. As it turns out, despite some variations in the content and focus, the number of EH-based publications annually is on the rise. From 2008 to 2013, the number of EH-based publications is comparatively low. However, it doubled in 2014 compared to 2013 and started to increase rapidly in the following years, reaching 198 in 2022, which demonstrates the prominence of EH implementations.

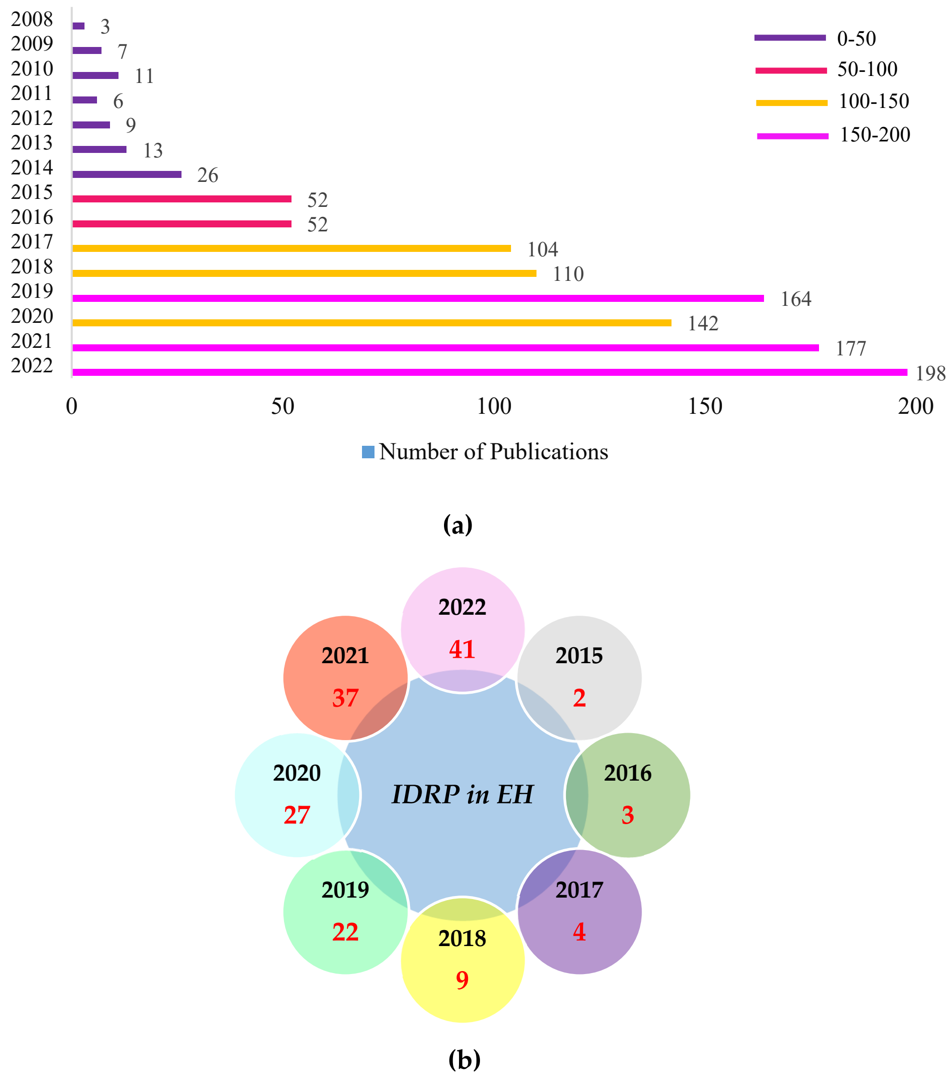

Figure 1. A bibliometric analysis of EH publications: (**a**) count of WoS's indexed publications; (**b**) count of WoS's indexed publications with the IDRP keyword from 2015 to 2022.

Moreover, examining the emergence of IDRPs in the field of EH research and highlighting the direction in which research is moving should not be underestimated. In this regard, Figure 1b displays the results of the keyword searched under the theme "integrated demand response program" in the periods of 2015 to 2022. It is readily apparent that the number of EH-based publications incorporated into the IDR program has been expanded significantly year by year.

This research focuses on analyzing IDRP characteristics in EHs from a variety of viewpoints. The dominant contributions of this study can be summarized as follows:

- Examining emerging trends and the importance of IDRPs in the EHS area using bibliometrics.
- An analysis of the current IDRP models and their optimization approaches.
- Comparing recent EH-based articles integrating the IDRP from various points of view.
- Revealing challenges and future directions in IDRPs from a mathematical optimization standpoint.

Section 2, after introducing the IDRP concept, outlines its detailed classification and formulation modelling. Section 3 describes EH optimization approaches under IDRP uncertainty. In Section 4, the general formulation of the IDRP optimization strategy based on EHs is briefly demonstrated. In Section 5, IDRP-based research in the EH area is reviewed and compared in different outlooks. In Section 6, some key advantages of

IDRP are explained. Section 7 presents the prospective challenges and trends of IDRP for improving its modelling and coupling with other efficient technologies. Lastly, Section 8 concludes the theoretical findings of the present study.

2. Integrated Demand Response Program

2.1. Concept of IDRP

The idea of the IDR program was first introduced in 2015 through the investigation of DR programs in smart EHs [17,18]. This research marked a turning point as it proposed a non-cooperative game to model the interaction between smart EHs and extended traditional DR to IDR in order to effectively modify electricity and gas consumption patterns. The term "integrated" refers to a DR program implemented within an IES, emphasizing the interaction between multiple energy sources for optimal energy management.

Many definitions have been proposed for IDR in the literature. According to [20], IDR is an advanced form of DR that manages both electrical and thermal energy in Multi-Energy Systems (MESs) concurrently. [21] defines IDR as a fundamental approach to increase the consumption of renewable energy and improve energy efficiency in IESs. [22] provides a more precise definition, stating that IDR is a strategy that breaks down the barriers between various energy sectors by enabling conversion between them. Therefore, in general, IDR can be described as a program that facilitates the participation of multiple types of energy sources in optimizing the demand response, resulting in a wider optimization space and greater benefits for customers.

2.2. IDRP Classification

Because IDR integrates multiple sources of energy, it is capable of responding to market price changes and incentive signals on multiple timescales.

The two primary classifications of IDR that are critically important in the operational strategy are the perspectives of timescales and types, which are illustrated in Figures 2 and 3, respectively [15,22–30]. Additionally, Table 1 summarizes the model categorization and provides a brief description of the advantages and disadvantages of each model. This information is essential for understanding the benefits and drawbacks of each IDR model, and it helps guide decision-making in selecting the optimal model for a given situation.

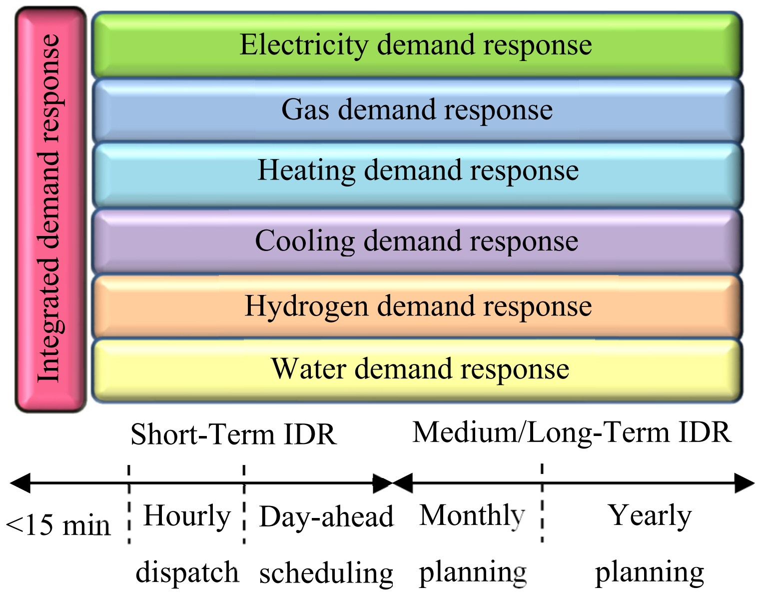

Figure 2. The characteristics of the IDR program based on timeframes [14].

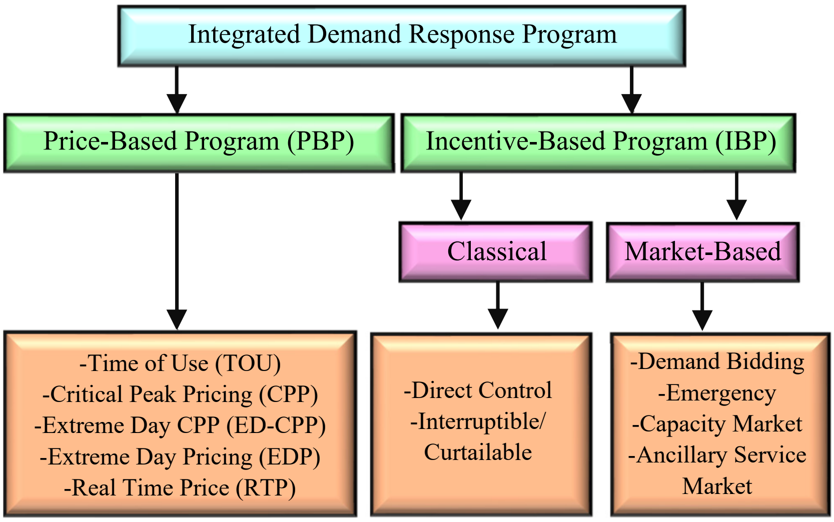

Figure 3. The characteristics of the IDR program based on types [22].

Table 1. A comparison of the advantages and disadvantages of IDR models [14].

Model	Advantages	Disadvantages
Short-term IDR	- Short-term economic dispatch in the supply chain companies - Minimizing social costs - Enhancing flexibility	- Highly affected by holidays, meteorology conditions and maintenance - Requiring a higher level of communication and control
Medium/long-term IDR	- Improving reliability - Decreasing energy consumption - Long-term profits for investment companies	- More complexity due to more variables existing - Requiring more system flexibility - Lacking deep research
Priced-based IDR	- Offering advanced pricing mechanism - Scheduling the charging time more efficiently - Minimizing the total cost	- Neglecting the customer convenience level
Incentive-based IDR	- Load reduction - Minimizing the total cost	- Unreliable control strategy and compensation mechanism

2.2.1. Incentive-Based IDR Programs

Participants in these programs receive monetary compensation if they reduce their consumption during peak times or special events [15]. Various incentive-based IDR programs are introduced and discussed below.

Classical

- Direct Load Control (DLC) Programs

DLC programs typically involve enrolling specific consumers and appliances in the program, which enables the utility to turn them off or cycle their usage as needed. This is typically completed during periods of peak demand or events, to reduce overall energy consumption. By strategically managing energy usage in this way, DLC programs can help to prevent blackouts, improve grid reliability and reduce strain on the system during times of high demand [22–24].

- Interruptible/curtailment programs

These programs are designed to encourage consumers to reduce their energy usage by the utility's goals. Registered participants are offered incentives by the utility to reduce their consumption during times of high demand or other specified events [24,25].

Market-Based

- Demand bidding

The network operator reduces the loads according to the amount and price suggested by the consumers. Consumers can gain profit when the price is higher than the price they offered. Due to its ability to maintain a constant price, this method is appealing to consumers [26,27].

- Emergency

During emergencies such as tornadoes, earthquakes and floods, consumers are offered an incentive to curtail their consumption [28].

- Capacity market

Using this approach, the network operator pays consumers a cost before an event occurs to have them reduce their consumption during the event. Essentially, the operator is responsible for securing the network [29].

- Ancillary service market

With this method, consumers propose the amount of load curtailment or reduction to be performed, which is referred to as an "operating reserve" in the energy market. If approved, the consumers receive the market clearing price. These loads must respond quickly and curtail usage as needed during peak periods. By participating in this type of demand response program, consumers can help ensure grid reliability and potentially earn compensation [27].

2.2.2. Priced-Based IDR Programs

A price-based IDR program involves charging consumers different prices at different times depending on when they consume services. The consumers are thus charged according to the costs of energy supply. The following is a description of the main types of price-based IDR programs [30].

- Time of Use (TOU)

In terms of time-varying tariffs, this is one of the most common models. Using this method, the customers are encouraged to adjust their consumption patterns (e.g., reducing consumption during peak hours) by varying the price at different times. According to this method, the tariff is set at various prices during different periods within a day. In general, the tariff is determined for a given period and represents the average cost of energy production and transmission during that period [30].

- Critical Peak Pricing (CPP)

Critical peak pricing is an ideal solution to reduce energy consumption during periods of high demand, when the reliability of the system is at risk, or when the wholesale market price is excessively high. During these critical hours, Time-of-Use (TOU) pricing is updated with the Critical Peak Pricing (CPP) tariff [31].

- Extreme Day CPP (ED-CPP)

The tariff is similar to the CPP, however, in this tariff the energy price is extremely high during the critical hours and flat during the rest of the day [30].

- Extreme Day Pricing (EDP)

Unlike the CPP program, where the price of energy increases only during critical periods, the EDP method increases prices at all times when the system or market is in crisis. The same critical day is used to determine this price increase [32].

- Real-Time Price (RTP)

This method involves adjusting the price of energy according to the wholesale market price throughout the day. Unlike TOUs and CPPs, where the price is determined at the time of contract, RTP is a new development. Economists consider RTP to be the most appropriate and direct the IDR program for a competitive electricity market. The RTP technique is extensively utilized by end-users and consumers are informed of the current cost of electricity in real time [33].

2.3. Integrated Load Modelling

As expected, economic factors such as energy prices, rewards and incentives and punishment policies that depend on the adopted DR program can prompt energy users to alter their consumption patterns. Most articles focus on two types of loads: adjustable loads and uncontrollable loads.

Adjustable loads, which can be adjusted based on the consumption time, refer to elastic loads and include transferable load, curtailable load and substitutable load. On the other hand, uncontrollable loads, which have a constant power consumption time without delay, refer to the foundation load [3,22].

2.3.1. Uncontrollable Load

Uncontrollable loads, which usually comprise lighting installations, heating installations, etc., are loads that are not responsible for the price of electricity and cannot be reduced or cut off at will. The equation for this type of load is expressed as follows, with the variables defined at the end of the section:

$$P_t^{k,UL} = \Psi_t^{k,UL} P_t^{k,B} \tag{1}$$

2.3.2. Transferable Load

Transferable loads, such as electric vehicles (EVs) and water heaters, can be shifted to a different time while the consumption period remains fixed. This type of load demand should not be interrupted once initiated, which means that the daily load demand would remain unchanged. Equation (2) describes this type of load.

$$P_t^{k,TL} = \Psi_t^{k,TL} P_t^{k,B} [1 + \varepsilon_t^{k,TL} (\rho_t^k - \rho_t^{k,B}) / \rho_t^{k,B}] \tag{2}$$

2.3.3. Substitutable Load

Substitutable loads, which usually include gas-/electric-powered air conditioning units, water heaters, etc., have no restriction on energy consumption at any time provided they can meet the total load demand in a given period.

$$P_t^{k,SL} = \Psi_t^{k,SL} P_t^{k,B} [1 + \varepsilon_t^{k,SL} (\rho_t^k - \rho_t^{k,B}) / \rho_t^{k,B}] \tag{3}$$

2.3.4. Curtailable Load

In this type of load, which typically includes lighting loads and air conditioning, the decision-maker has the ability to curtail the load within a specific time. However, this action may result in a rebound effect on the load in subsequent periods. This behaviour can be expressed using Equations (4) and (5):

$$P_t^{k,CL} = \Psi_t^{k,CL} P_t^{k,B} [1 + \varepsilon_t^{k,CL} (\rho_t^k - \rho_t^{k,B}) / \rho_t^{k,B}] \tag{4}$$

$$0 \leq P_t^{k,CL} \leq P_{t,\max}^{k,CL} \tag{5}$$

2.3.5. Total System Load Demand with IDR

The total electrical, thermal and cooling loads of the EH in IDRP mode can be expressed as Equation (6):

$$P_t^{Load} = P_t^{k,UL} + P_t^{k,TL} + P_t^{k,SL} + P_t^{k,CL} + P_t^{Convertable} \tag{6}$$

where P_t^k refers to the various load demand, k = 1, 2, 3, 4 is the electric load, gas load, thermal load and cooling load; Ψ_t^k is the ratio of the load in total load demand; and $P_t^{k,B}$ is the load demand of the EH considering the benchmark electricity price. Moreover, ε_t^k is the price elasticity coefficient of load, and ρ_t^k and $\rho_t^{k,B}$ are the purchase price and benchmark electricity price of users at time t, respectively.

2.4. IDRP Modelling

The operation of MESs involves numerous constraints, some of which interact with one another. Therefore, it is essential to avoid the coincidence of peak loads to ensure efficiency. IDR programs are applied to address various load demands simultaneously. An incentive-based IDR program is preferable to a price-based IDR program as the latter may cause difficulties. For instance, transferring all load demands to another time interval may result in an additional peak load. Therefore, it is appropriate to model incentive-based IDR programs as follows [3,21,22,34–36].

2.4.1. Transferable IDR

The transferrable IDR program is modelled based on the mathematical relationships proposed in Equations (7)–(10), defining the variables at the end of the section [22,34,35].

$$P_{n_i,t}^{(e,g,h,c),TL,do} = P_{n_i,t+N_x}^{(e,g,h,c),TL,up} \tag{7}$$

$$0 \le P_{n_i,t}^{(e,g,h,c),TL,up} \le LPF^{((e,g,h,c),TL,up} P_{n_i,t}^{(e,g,h,c)} I_{n_i,t}^{(e,g,h,c),TL,up} \tag{8}$$

$$0 \le P_{n_i,t}^{(e,g,h,c),TL,do} \le LPF^{((e,g,h,c),TL,do} P_{n_i,t}^{(e,g,h,c)} I_{n_i,t}^{(e,g,h,c),TL,do} \tag{9}$$

$$0 \le I_{n_i,t}^{(e,g,h,c),TL,do} + I_{n_i,t}^{(e,g,h,c),TL,up} \le 1 \tag{10}$$

2.4.2. Substitutable IDR

The substitutable IDR program is modelled using the mathematical formulations presented in Equations (11)–(14) [22,36].

$$\sum_{t=1}^{T} P_{n_i,t}^{(e,g,h,c),SL,up} = \sum_{t=1}^{T} P_{n_i,t}^{(e,g,h,c),SL,do} \tag{11}$$

$$0 \le P_{n_i,t}^{(e,g,h,c),SL,up} \le LPF^{((e,g,h,c),SL,up} P_{n_i,t}^{(e,g,h,c)} I_{n_i,t}^{(e,g,h,c),SL,up} \tag{12}$$

$$0 \le P_{n_i,t}^{(e,g,h,c),SL,do} \le LPF^{((e,g,h,c),SL,do} P_{n_i,t}^{(e,g,h,c)} I_{n_i,t}^{(e,g,h,c),SL,do} \tag{13}$$

$$0 \le I_{n_i,t}^{(e,g,h,c),SL,do} + I_{n_i,t}^{(e,g,h,c),SL,up} \le 1 \tag{14}$$

2.4.3. Curtailable IDR

In Equations (15)–(17), the mechanism for implementing curtailable IDR programs is outlined [22].

$$P_{n_i,t}^{(e,g,h,c),CL,do} = \sum_{m=1}^{4} \lambda_m P_{n_i,t+1}^{(e,g,h,c),CL,up} \tag{15}$$

$$0 \leq P_{n_i,t}^{(e,g,h,c),CL,up} \leq LPF^{(e,g,h,c),CL,up} P_{n_i,t}^{(e,g,h,c)} I_{n_i,t}^{(e,g,h,c),CL,up} \tag{16}$$

$$0 \leq P_{n_i,t}^{(e,g,h,c),CL,do} \leq LPF^{(e,g,h,c),CL,do} P_{n_i,t}^{(e,g,h,c)} I_{n_i,t}^{(e,g,h,c),CL,do} \tag{17}$$

where n and i are the indexes of the EH number and type. $P_{n_i,t}^{(e,g,h,c),up}$ and $P_{n_i,t}^{(e,g,h,c),do}$ indicate the shifted up and down power by the transferrable/substitutable/curtailable IDR program. $LPF^{(e,g,h,c),up}$ and $LPF^{(e,g,h,c),do}$ specify the load participation factor of shift up–down power by the transferrable/substitutable IDR program. Moreover, binary variables of shift up and down power by the transferrable/substitutable/curtailable IDR program are named with $I_{n_i,t}^{(e,g,h,c),up}$ and $I_{n_i,t}^{(e,g,h,c),do}$, respectively. In addition, λ refers to the rebounded load factors.

2.4.4. Convertible IDR

Generalized, convertible loads are a specific category within the IDR program, and they can be characterized as follows [21]:

$$\begin{bmatrix} P_t^g \\ P_t^e \\ P_t^h \\ P_t^c \end{bmatrix} = \begin{bmatrix} \alpha_g^t & \beta_{e-g}^t & 0 \\ \alpha_{g-e}^t & \beta_e^t & 0 \\ \alpha_{g-h}^t & \beta_{e-h}^t & \gamma_h^t \\ \alpha_{g-c}^t & \beta_{e-c}^t & \gamma_{h-c}^t \end{bmatrix} \begin{bmatrix} P_t^g(\text{sup}) \\ P_t^e(\text{sup}) \\ P_t^h(\text{sup}) \end{bmatrix} \tag{18}$$

$$\begin{aligned} &\alpha_g^t + \alpha_{g-e}^t + \alpha_{g-h}^t + \alpha_{g-c}^t = 1 \\ &\beta_{e-g}^t + \beta_e^t + \beta_{e-h}^t + \beta_{e-c}^t = 1 \\ &\gamma_h^t + \gamma_{h-c}^t = 1 \end{aligned} \tag{19}$$

where $P_t^g(sup)$, $P_t^e(sup)$ and $P_t^h(sup)$ are the total quantities of natural gas, electric and heating energies delivered at time t, respectively; the natural gas proportion coefficients at time t are represented by α_g^t, α_{g-e}^t, α_{g-h}^t and α_{g-c}^t. Moreover, β_{e-g}^t, β_e^t, β_{e-h}^t and β_{e-c}^t refer to the proportion coefficients of electric energy at time t; γ_h^t and γ_{h-c}^t are two proportional coefficients associated with heating energy at time t.

Curtailable IDRP is the simplest option, especially if it is a matter of urgency. However, it may be cost-intensive for system operators as well as eclipse customers' convenience. Furthermore, it has the potential to rebound the load during subsequent time intervals. Convertible IDR is the most beneficial program that can be applied to manage the various energy demands in a variety of targets. Nevertheless, due to the complexity of the energy-converting mechanism in the EH framework, this IDRP type requires more effort to support its content. In transferable and substitutable IDRP, although the total energy remains unchanged during the given period, if it is not controlled appropriately, it may cause extra peaks.

It seems that applying a hybrid IDRP technique can effectively take advantage of each type and neutralize critical challenges.

Figure 4 provides an overview of the IDR program in EHs. Compared to conventional electric DRs (CEDRs), the IDR in EHs can handle multiple energy loads, such as electrical loads (ELs), heating loads (HLs), cooling loads (CLs) and gas loads (GLs).

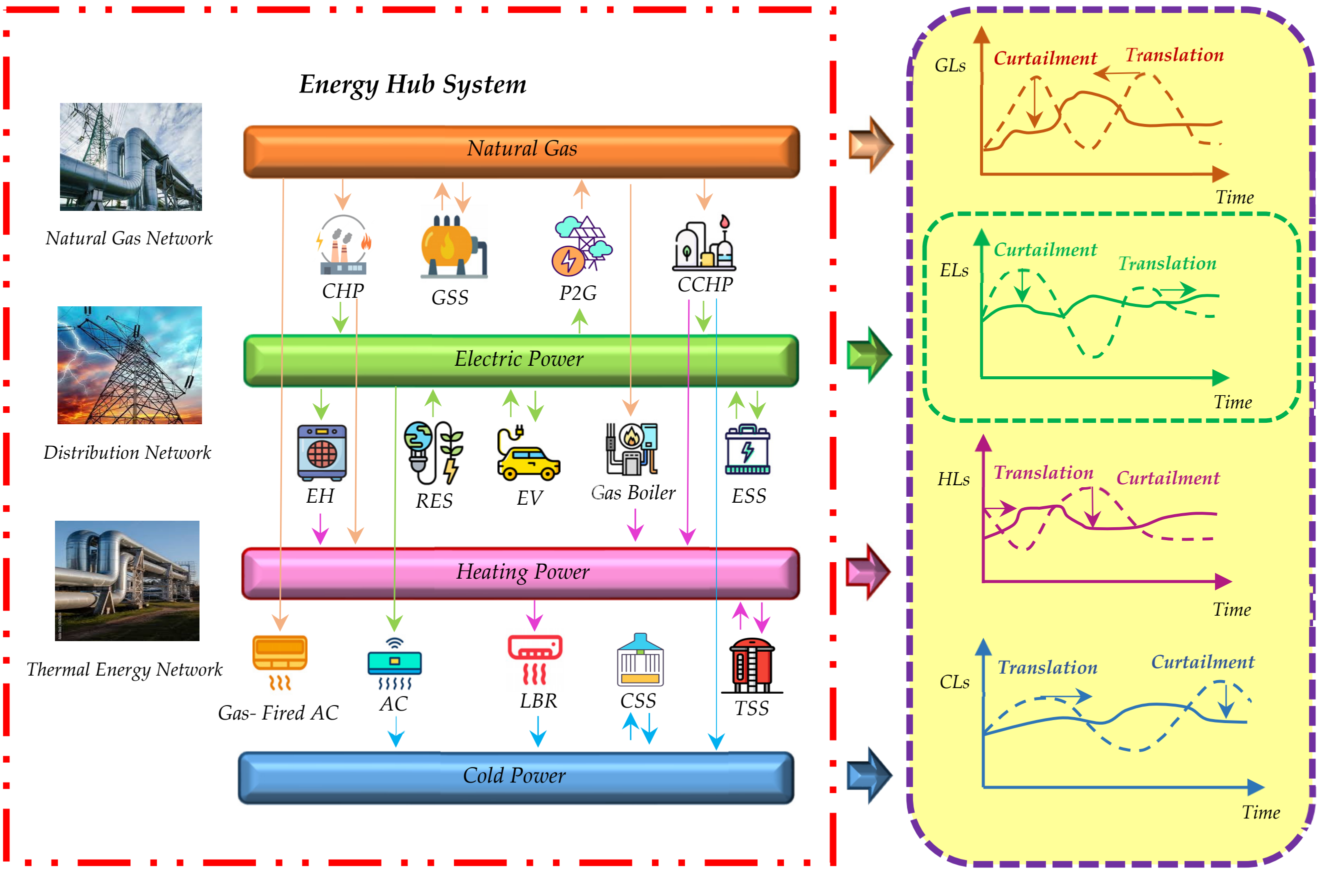

Figure 4. An overview of the IDR program in EHs. CCHP: Combined Cooling Heat and Power, CHP: Combined Heat and Power, EH: Electric Heater, AC: Air Conditioner, LBR: Lithium Bromide Refrigerator, ESS: Electrical Storage System, GSS: Gas Storage System, TSS: Thermal Storage System, CSS: Cooling Storage System, P2G: Power to Gas [21].

Furthermore, energy coupling devices are employed in EHs to provide multiple energy couplings. Hence, in terms of multiple energy supplies on the demand side, the IDR program has greater flexibility than the CEDR [21].

3. Uncertainty Consideration in IDRP

The random behaviour and fluctuating nature of variables such as demand and the price of energy contribute to uncertainty in the modelling process, and leaving out these uncertainties leads to inaccurate models with illusory results.

Various types of uncertainty can affect modelling and optimization processes, depending on the resources involved. Identifying the specific type of uncertainty is crucial in understanding its impact on system modelling and performance. In EH management, it is imperative to take into consideration uncertainties arising from consumer behaviour. Uncertainties in this regard include the percentage of consumers participating in DR programs, the percentage of consumers who are capable of switching between different energy carriers, as well as consumers who do not participate in DR programs and may control their energy consumption. Figure 5 illustrates the categories of IDR uncertainty modelling techniques in energy systems [37,38]. Additionally, the main features and drawbacks of each uncertainty modelling are summarized in Tables 2 and 3, respectively [39–46].

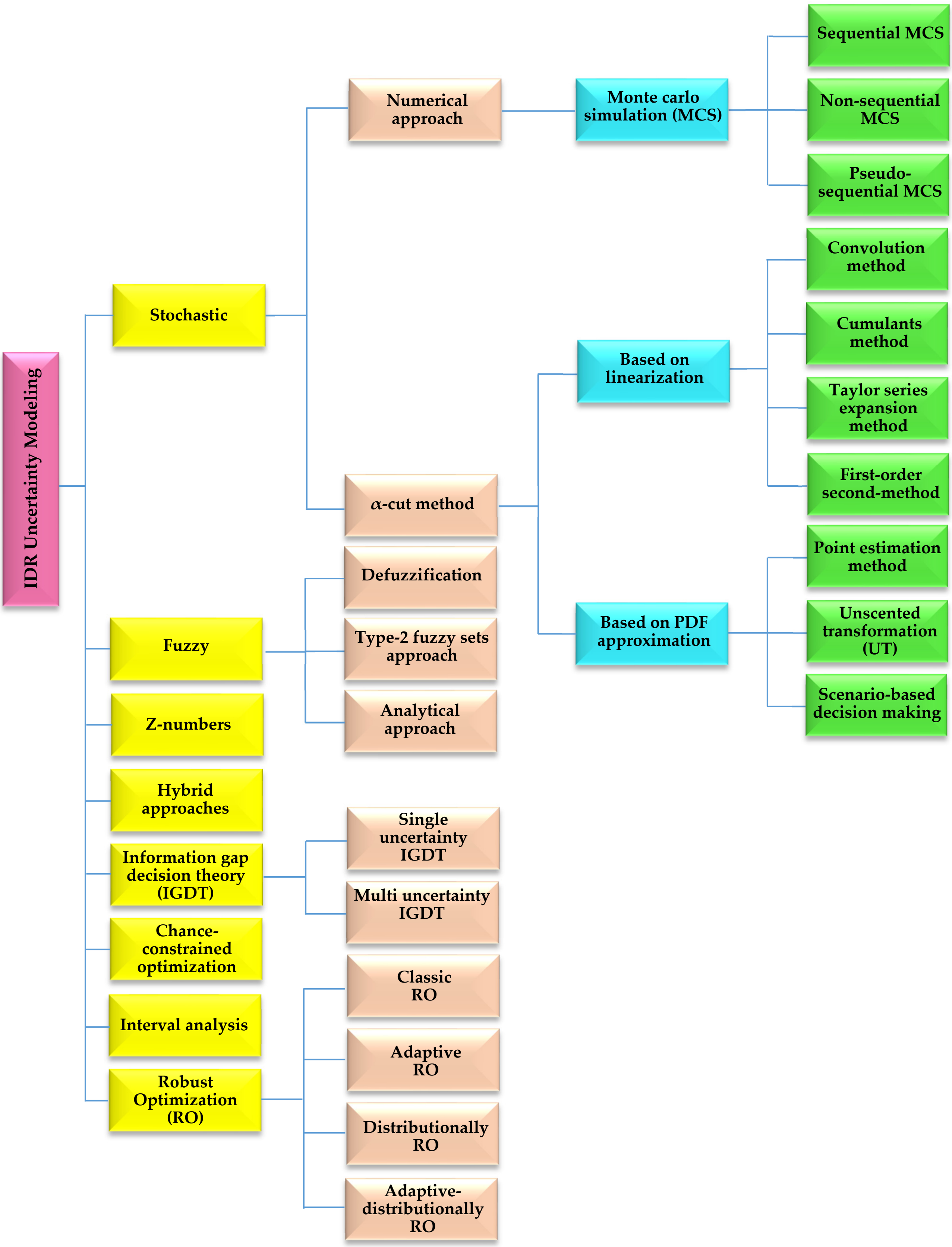

Figure 5. IDR uncertainty modelling techniques [37,38].

Table 2. A comparison of the different approaches' main features.

Technique	Main Features
Stochastic optimization	An SP approach utilizes probability distributions to represent uncertainties. It aims to optimize the anticipated value of an objective across multiple decision stages.
Fuzzy	The fuzzy technique uses fuzzy membership functions, including triangular and trapezoidal membership functions, as well as Gaussian fuzzy sets, to model uncertainty.
Z-numbers	A binary pair model is used for this method, where one component is a restriction on the value of an uncertain parameter, and the other shows its reliability.
Information gap decision theory	This method is a non-probabilistic decision-making approach and is usually used when there is insufficient information regarding uncertain parameters to ensure the robustness of the system.
Chance-constrained	The CC method is only applied to the constraints and allows for a probability to violate the constraints in the presence of uncertainties.
Interval analysis	It is usually employed when the interval of uncertain parameters varies and upper and lower boundaries are defined to obtain the outputs.
Robust optimization	This method utilizes interval values instead of PDF to display uncertainty and solves the problem for the worst-case scenario at any interval.
Hybrid approaches	A hybrid method integrates two or more methods for dealing with uncertainties and takes their advantages.

Table 3. A comparison of the main drawbacks of uncertainty modelling approaches.

Technique	Challenges
Stochastic optimization	Dealing with numerous decision stages and scenarios leads to a high computational burden.
Fuzzy	There is an obvious lack of precision and specificity in this approach.
Z-numbers	It deals with complexity in both formulation and calculation.
Information gap decision theory	Due to its inability to manage multiple uncertain parameters, it is not a particularly appropriate method.
Chance-constrained	Implementing this class of optimization problem requires a great deal of effort since it is limited to constraints.
Interval analysis	Interval analysis has the main disadvantage of dependency problems when the same variable occurs more than once.
Robust optimization	Nonlinear problems can be difficult to solve using this method in addition to being unable to consider correlation between random variables.
Hybrid approaches	Hybridizing several methods is not an easy process, and it needs to be scrutinized more closely to ensure a reliable result.

4. IDRP Optimization Strategy Based on EH

A preliminary requirement for executing the IDRP project is the framework analysis of the coupling link and the supplementary features in terms of energy. EH models this integration link using more than one individual power demand elasticity in the IDRP project. A load-side integrated energy demand allows agents to control both the energy demand and conversion mode without affecting the overall energy demand, depending on the price or other incentive factors.

The optimization model of EHs incorporating IDR can be expressed as follows [47]:

$$\begin{aligned}
&min\ f(E_{s,t}, G_{s,t}, H_{s,t}, C_{s,t}, P_t) \\
&subject\ \text{to}: \\
&E_{s,t} + E_{e,t} + E_t = D_{e,t} + \Delta D_{e,t} \\
&G_{s,t} + G_{e,t} = D_{g,t} + \Delta D_{g,t} \\
&H_{s,t} + H_{e,t} = D_{h,t} + \Delta D_{h,t} \\
&C_{s,t} + C_{e,t} = D_{c,t} + \Delta D_{c,t} \\
&g(E_{e,t}, G_{e,t}, H_{e,t}, C_{e,t}) \le 0 \\
&h(\Delta D_{e,t}, \Delta D_{g,t}, \Delta D_{h,t}, \Delta D_{c,t}) \le 0
\end{aligned} \tag{20}$$

where $E_{s,t}$, $G_{s,t}$, $H_{s,t}$ and $C_{s,t}$ specify the electric power, gas volume, heating power and cooling power flow to the system, respectively. Energy conversions within a system are represented by $E_{e,t}$, $G_{e,t}$, $H_{e,t}$ and $C_{e,t}$. P_t is the output of new energy generation. $D_{*,t}$ refers to the origin demand for three different types of energy, and $\Delta D_{*,t}$ refers to the size of the demand involved in the IDR. A characteristic operating under IDRP upper and lower constraints can be represented by inequalities g and h.

5. IDRP-Based Research in EHs

Various recent studies have analyzed DR programs in EHs and optimization operations to deal with the RESs volatility or to minimize energy purchase costs.

Ref. [1] pertains to the notion of a smart micro-scale EH (SMEH) known as a hydrogen-based SMEH, which considers the principles of IDRP and a hydrogen storage system (H_2SS) based on fuel cells. Moreover, the H_2SS has the capability of performing a dual role in not only converting power from RESs into hydrogen (P2H_2) during periods of low electricity prices and vice versa ($H_2$2P) during times of high electricity prices, but also in providing a reliable supply of hydrogen for use in industries dependent on this resource.

Obviously, optimal load dispatch is one of the main optimization concerns to support the efficient performance of the EH models. Accordingly, [16] proposes a novel optimal load dispatch for an EH that incorporates heat storage units and EVs. The uncertainty of electricity prices and EVs is also simulated to achieve reliable energy management. In addition, the electrical and thermal DR technologies are comprehensively reviewed in the proposed scheme to additionally decrease the energy construction cost of users.

In [20], a stochastic approach is applied for the optimal operation of an EH consisting of a wind farm and electrical and thermal storage, which covers the IDR program to participate in the electricity and thermal markets. Optimal scheduling of MEH based on the cooperative game and virtual energy storage (VES) is developed in [21] to enhance the scheduling flexibility of the MEH. In this model, the IDR program is also assessed to respond potentially on the demand side. Ref. [22] proposes a two-stage stochastic scheme for the planning and operation of an integrated EH considering electrical and thermal storage systems. This problem has considered various uncertainties such as wind turbine output power as well as electrical, heating and cooling loads. Both continuous and discrete methods are used to solve the problem by employing real and binary-coded genetic algorithms, respectively. Moreover, DR and IDR programs have been incorporated into the model. A comparison of the proposed model with the DICOPT solver in the GAMS software was substantiated through MATLAB and GAMS software interfaces to assess their efficiency and accuracy. Ref. [35] examines optimal models for coordinated and uncoordinated operations of MEHs connected to a radial distribution system. This study considers renewable power generation from wind and solar sources, as well as an IDR program. Environmental concerns are also addressed by considering CO_2, NO_2 and SO_2 emissions. Moreover, ACOPF constraints are imposed to avoid any non-physical power flow in the system.

A multi-objective dynamic model is developed in [48] to design an EH considering the flexible efficiency of converters, equipment degradation rate and annual/yearly growth of load and energy prices. This problem has investigated the effects of P2G technology, energy storage systems as well as IDR programs on the operation. Moreover, it has tried to enhance the efficiency of the boiler and CHP via hydrogen injection. Uncertainties attributed to the wind speed, demand and price are considered in the model. Authors of [49] propose a shrinking-horizon optimization framework to solve the EH scheduling problem considering flexible loads, storage systems and wind turbines. In addition, the wind turbine output power, as well as electricity price, are modelled as uncertain parameters. To enhance the system flexibility and modify the load demand curve, the EH users are able to cooperate in an IDR program that is applied to all three electrical, heating and cooling loads.

Ref. [50] has proposed innovative scheduling of multi-carrier EHs for managing the natural gas grids and electricity in an economic technique. In this model, P2G technology is employed for producing natural gas and selling it to the gas grid. In this way, the congestion in the gas pipelines and the costs of the EH owners would be decreased.

Therefore, an effective Weymouth model is developed for simulating the gas network to evaluate how P2G technologies can alleviate congestion and reduce costs. Moreover, in this study, a SCENRED-based scenario reduction algorithm has been employed to improve the computational efficiency of the proposed model. The SCENRED methodology is composed of three algorithms designed to reduce the number of scenarios. One of these, the fast-backward algorithm has been used in this research. Distributed generation, energy storage and a shiftable IDRP have been implemented to assist the operator in achieving its objectives. For computational tractability, the scheme has been linearized via the Cartesian technique and Taylor series.

Ref. [51] has presented a developed optimization strategy of a hydrogen-based smart micro EH (SMEH) regarding the H_2SS and IDR program. IDR is utilized to control both electrical and heat demands. In addition, the uncertainty of the electricity price is considered in the modelling to increase the accuracy of the proposed problem. According to this model, the RESs are converted into hydrogen (P2H_2) and stored by the H_2SS at low-power-price hours. Afterward, the stored hydrogen can be conveyed to the hydrogen industry ($H_2$2P) at high-power-price hours. In [52], a stochastic technique is formulated to address the unit commitment (UC) problem in the context of EHs. This comprehensive model encompasses various components, including a parking lot for hydrogen vehicles (HV), hydrogen electrolyzers (HE) and an electric heat pump (EHP). This study incorporates an approach that accounts for uncertainties in demand, PV power generation and the HV's initial energy levels. Furthermore, the analysis also includes considerations of storage system losses and HV tank performance. Moreover, the impacts of the IDR program on EH operations are investigated.

Ref. [53] develops a novel Internet of Things (IoT)-based strategy for optimal energy management of Multi Energy Hubs (MEH). The proposed IoT-enabled MEH system consists of three interconnected residential, commercial and industrial EHs. Each EH consists of a CHP, RESs, a Plug-in-electric vehicle (PHEV), boiler and thermal storage system (TSS), which rely on electricity and natural gas as the main sources of power. An unscented transformation (UT) uncertainty method, which is a stochastic strategy used for modelling the uncertainty of RESs (PV, WT), and an IDR program is considered with MEH electrical and thermal demands. In [54], a novel water-based storage system called Pico hydel energy storage is analyzed for the day-ahead scheduling of EHs. The performance of the proposed EH is evaluated with the inclusion of DR programs for electricity, gas, water and thermal. Risk-averse approaches, such as conditional value-at-risk (CVaR) and second-order stochastic dominance (SSD) approaches, are used. Additionally, [55] studies the risk-based scheduling of a more realistic EH scheme using the CVaR method. IDR programs are applied to manage demand curves and costs.

Ref. [56] presents a comprehensive framework based on the security constrained unit commitment (SCUC) approach for optimal scheduling of the regional power system considering grid-connected EHs under the high penetration of wind power units. The major contribution of this article is minimizing the wind power curtailment, and carbon emissions in addition to the operation cost considering the multi-energy DR program. Therefore, the essential focus is on establishing a suitable link between EHs and power systems to fulfill its commitment at the lowest operation cost.

A district energy system in the presence of multiple flexible loads and energy supplies is studied in [57] to establish an appropriate optimization model. This article connects energy storage equipment and a large number of integrated EVs into the grid in order to enhance the system flexibility; however, it restricts some of the energy flow in the IES to lessen the line reconstruction cost as well as the impact of the bidirectional energy flow on the power system. In [58], the scenario-based framework is applied to design an EH considering the varying regulation of gas converters and IDR as the innovations of the optimization problem. Furthermore, the EH is equipped with a P2G system in order to reduce CO_2 emissions in addition to improving the performance of boiler units and CHP via injecting hydrogen. A two-stage planning approach based on a nodal energy prices strategy is presented in [59] to manage the integrated demands of the end users using an IDR program. In fact, the major purpose of this research is to evaluate the impact of the nodal energy prices on the penetration of solar energy and especially the IDR program. A robust EH scheduling based on a hybrid interval-stochastic framework was proposed in [60] for flexible energy management among RESs, considering the IDR program and different energy storages such as ISC.

In [61], a risk-based optimal operation of EHs with the presence of an IDR program as well as multiple energy storage systems such as P2G and compressed air energy storage (CAES) is investigated. Investigations of IDR facilities are also taken into account in [62], for adopting a stochastic operation of EHs, which is divided into three sub-hubs (electric, thermal and cooling hub).

The aim of the research in [63] is to introduce a model for the effective management and distribution of an EH, which is based on the consideration of uncertainties pertaining to RESs, electrical loads, operating and maintenance costs, a cost analysis of greenhouse gas emissions and IDRP. To achieve this goal, the uncertainties associated with the EH have been classified into two categories, namely technical and economic. In [64], a model for the optimal operation of MEHs that caters to both electrical and heat energy requirements is suggested. The principal innovation of this research is the utilization of IDRP considering uncertainties associated with RESs and electricity prices to minimize the overall cost. In [65], an evaluation is conducted to compare the performance of EHP and P2G technologies in both electricity and gas systems, considering a price-based IDRP.

Ref. [66] represents the coordinated operation of an EH incorporating a diverse range of electrical, thermal and cooling demands, intending to achieve both environmental and economic benefits. The proposed EH includes a range of energy conversion systems and multi-energy storage systems. Additionally, the IDRP provides the flexibility necessary to meet energy demands, while the hub's ability to exchange power and heat with corresponding markets further enhances its efficiency.

Analyzing EH issues involves examining the type of storage devices, objective function, etc., which play a significant role in the results. Consequently, we will scan these themes in the articles under review. Table 4 provides a comparison among recent studies.

Table 4. A comparison of the recent studies.

Ref	Time-Horizon	IDRP	Storage Systems	OF Modelling		Objective Function	Emission
				Multi	Single		
[1]	Short-Term	E, H	ESS, TSS, GSS, H_2SS	×	✓	Cost	×
[16]	Short-Term	E, H	TSS, WSS, EV	×	✓	Cost	✓
[20]	Short-Term	E, H	ESS, TSS	×	✓	Cost	×
[21]	Short-Term	E, H, C, G	ESS, GSS	×	✓	Profit	×
[22]	Short-Term	E, H, C	ESS, TSS	×	✓	Cost	✓
[35]	Short-Term	E, H, C	ESS, TSS, EV	×	✓	Cost	×
[48]	Long-Term	E, H	ESS	✓	×	Cost	✓
[49]	Short-Term	E, H	ESS, TSS, CSS, EV	×	✓	Cost	✓
[50]	Short-Term	E, H	ESS, TSS, H_2SS	×	✓	Cost	×
[51]	Short-Term	E, H	ESS, TSS, GSS, H_2SS	×	✓	Cost	×
[52]	Short-Term	E, H, C, H_2	ESS, TSS, CSS, H_2SS, HV	×	✓	Cost	×
[53]	Short-Term	E, H	ESS, TSS, EV	×	✓	Cost	×
[54]	Short-Term	E, H, W, G	ESS, TSS, WSS	✓	×	Economic, Technical, Environmental	✓

Table 4. *Cont.*

Ref	Time-Horizon	IDRP	Storage Systems	OF Modelling		Objective Function	Emission
				Multi	Single		
[55]	Short-Term	E, H, C	TSS, CSS, H_2SS, PHEV	×	✓	Cost	✓
[56]	Short-Term	E, H	ESS, TSS	×	✓	Cost	✓
[57]	Short-Term	E, H, C	ESS, TSS, WSS, EV	✓	×	Cost	✓
[58]	Short-Term	E, H, C	ESS	×	✓	Cost	✓
[59]	Short-Term	E, H, C	ESS, TSS	✓	×	Cost	×
[60]	Short-Term	E, H	ESS, TSS	×	✓	Cost	×
[61]	Short-Term	E, H, G	ESS, TSS	×	✓	Cost	×
[62]	Short-Term	E, C	ESS, TSS, CSS	×	✓	Profit	×
[63]	Short-Term	E, H	ESS, TSS	×	✓	Cost	✓
[64]	Short-Term	E, H	TSS	×	✓	Cost	✓
[65]	Short-Term	E, H	ESS, WSS	×	✓	Cost	×
[66]	Short-Term	E, H	ESS, TSS	✓	×	Economic, Environmental	✓

In terms of the temporal scale, almost all studies have taken a short-term view. Most of the articles have studied the effect of a DR program on electricity, gas, heat and cold energy carriers, except for refs. [52] and [54], which have also investigated its effect on the energy carrier hydrogen (H_2) and water (W), respectively. According to the literature, electric and heating storage devices are among the popular storage devices in EHs. EVs, which are employed as a type of storage in Vehicle-to-Grid (V2G) mode [67], have attracted a lot of attention in IES in recent years. In this regard, several studies have considered EVs as mobile energy storage, including refs. [16,35,49,53,57]. Additionally, ref. [55] has employed PHEV, while ref. [52] has used hydrogen vehicles (HV). Gas and water storage systems have been employed in 12% and 16% of studies, respectively. Moreover, refs. [1,50–52,55] used hydrogen energy storage.

Regarding the objective function, it is worth noting that about 20% of the reviewed articles have used a multi-objective approach. While 48% of the studies have considered emissions in their objective function, only one study, ref. [54], has modelled it as a pollution index, whereas the others have included emissions costs in the overall cost function. In all of the articles, the primary objective has been economic, except for refs. [54,66]. Ref. [54] examined technical (voltage profile) and environmental (CO_2, NO_2 and SO_2 emissions) objectives in addition to the economic objective, and [66] minimized the CO_2 emissions along with total operation cost.

6. Advantages of IDRP

The IDRP concept brings the synergistic effects of MESs by thoroughly considering the critical complementarity of multi-energy consumption [68–70]. IDRP advantages are analyzed in terms of the user benefits as well as system performance below.

By integrating various forms of energy, such as electricity, thermal energy and natural gas, IDR facilitates the system operator in providing maximum social welfare within a better efficiency scope.

IDR also minimizes the barriers among various types of energy and consequently makes it possible for energy users to consume energy in an adaptable manner and fully utilize the DR resources efficiently.

(1) With the integration of various forms of energy along with IDR, EHs enable energy users to flexibly switch their energy inputs in response to power system requirements or the prices of different energy sources.
(2) Therefore, by transforming electricity into thermal and cooling energy, as well as gas, the penetration percentage of RESs can be increased.

(3) As a result, in addition to the total operational costs of the system, it has a significant promising effect on the decarbonization index.
(4) With the innate storage efficiency of thermal and gas systems, the efficiency of demand-side resources can be fully exploited. The surplus of renewable energy can be economically stored in thermal and gas systems so that it can be used to reduce peak loads and smooth out fluctuations in electric power.
(5) By exploiting different energy complementarities, IDR is able to improve the reliability of MESs. In other words, various energy systems alongside IDR support each other to meet the load demands of energy consumers.

7. Prospect Challenges of IDRP

In EH optimization models, IDR is typically modelled through a few plain constraints that are based on traditional power system DR techniques. However, these constraints may not fully capture the coupling and energy conversion attributes of IDR. Additionally, motivating customers to actively participate in the DR program remains a major challenge for service companies [71]. Therefore, developing a specialized and accurate model for IDR programs in EHs is crucial for future research. Furthermore, while most studies have focused on the economic optimization of EH planning with IDR, there is a significant research gap in analyzing EH technical indicators, particularly in terms of reliability in the presence of IDR. To ensure that the IDR profits or benefits are distributed equitably among consumers and multi-energy suppliers, it is essential to design and implement an optimal pricing mechanism for IDR programs.

The implementation of IDR programs can stimulate multi-energy suppliers to organize and contribute technical support, while also motivating customers to adjust their energy consumption patterns through load shedding and load shaving. This can lead to improvements in the profitability and safety of EHs. However, despite the potential benefits, the development of multi-energy systems with IDR is still in its early stages and requires further investigation. Therefore, obtaining a flexible demand response model for the heating and cooling sectors is a promising objective that has not yet been achieved. The terminals designated for IDR programs should possess a broad range of functionalities that encompass data acquisition, data processing and storage, interactive terminal capabilities', input/output management, self-healing and self-maintenance, and the ability to simulate user actions [72]. In this sense, utilizing machine and reinforcement learning, data science, IoT, cloud computing and fog platforms and fifth-generation (5G) technology considering information privacy and cyber security, the IDR model can be controlled efficiently. Moreover, additional efforts must be undertaken to enhance hardware connectivity modalities, minimize power consumption, optimize peak and frequency modulation capacities, ensure compatibility with power grids, improve economic efficiency and enhance accessibility to IDR terminals.

Such a model would enable the efficient management of energy demands while ensuring the stability and reliability of EHs.

Therefore, the major future directions of IDRP can be categorized and summarized as follows:

✓ Originating an appropriate IDRP model capturing the coupling and energy conversion attributes.
✓ Assessing IDRP impacts on EH flexibility and reliability.
✓ Equipping infrastructure and designing technologies to enhance the IDRP efficiency and simulate user actions.
✓ Controlling IDRP more efficiently utilizing machine and reinforcement learning, data science, IoT, cloud computing and fog platforms and fifth-generation (5G) technology.

8. Conclusions

This paper provides a comprehensive overview of IDRP-based EH research and highlights the potential challenges associated with IDR programs. Through a bibliometric analysis, the paper offers valuable insights to other researchers in this field. The study introduces the basic concept and formulation of the IDR program and reviews the current studies on EH optimization concerning the planning, operation and business of EHs. The paper identifies the key prospective challenges of IDR and emphasizes the importance of adopting flexible models such as DRP in multi-energy systems, particularly in the heating sector. While existing literature highlights the reliance of current IDR models on generalized DR program models designed for electrical loads, the review section provides insights into problem-solving methods and technological advancements that can facilitate future research in this area. Overall, the study provides a comprehensive understanding of the challenges associated with implementing IDR programs and aims to contribute to the development of more effective and efficient IDR programs for modern power systems.

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