Review

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

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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 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 that multi-energy users can respond not only by shifting or reducing 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 a review, assessment, and classification of fundamental principles, modeling techniques and optimization methods for IDR programs in EHs.

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

1. Introduction

In recent years, the rapid growth of energy demand, 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]. Besides, following the Government's net-zero target by 2050, it is imperative to reduce carbon emissions and promote integrated energy systems (IESs) based on RES [4, 5].

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 [6, 7].

Meanwhile, complex load characteristics, various energy sources coupling, large load demand, and lack of reliability in power supply pose new challenges for DR programs on the dispatch side [8]. The fundamental challenge of future energy system 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

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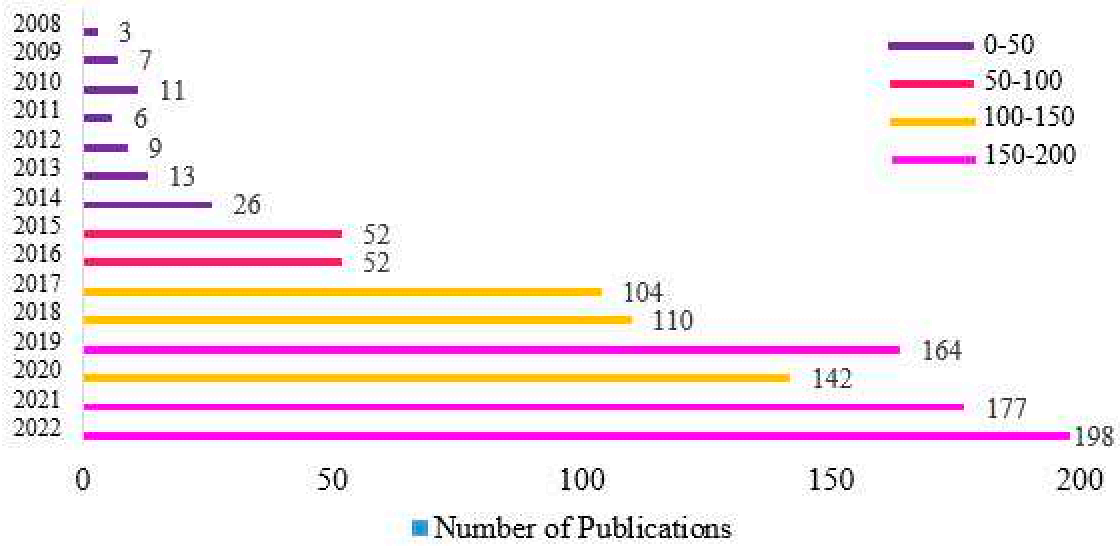
perspective to DR program. The integration of different energy carriers enables customers to play an active role in the DR program not only by changing their consumption pattern but also by means of switching their source of consumption. This modified innovation of DR program, called IDR [7], strengthens the balance between supply and demand while decongesting the power system [9, 10]. 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 is done to provide a reference for succeeding studies.

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

Figure 1(a) indicates how many EH-based publications have been included in the WoS Core Collection over the past fifteen years [11]. 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 are 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.

Moreover, examining the emergence of IDRP in the field of EH research and highlighting the direction in which research is moving toward should not be underestimated. In this regard, Figure 1(b) 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 number of EH-based publications incorporating to the IDR program has been expanded significantly year by year.



(a)

(b)

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

2. Integrated Demand Response Program

2.1. Concept of IDRP

The idea of IDR program was first introduced in 2015 through the investigation of DR programs in smart EH [9, 10]. 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 of multiple energy sources for optimal energy management.

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Many definitions have been proposed for IDR in the literature. According to [12], IDR is an advanced form of DR that manages both electrical and thermal energy in Multi-Energy Systems (MESs) concurrently. [13] defines IDR as a fundamental approach to increase the consumption of renewable energy and improve energy efficiency in IESs. [14] 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 demand response, resulting in a wider optimization space and greater benefits for customers.

2.2. IDRP Classification

Considering the fact that 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 operational strategy are the perspectives of timescales and types, which are illustrated in Figures 2 and 3, respectively [7, 14-22]. 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.

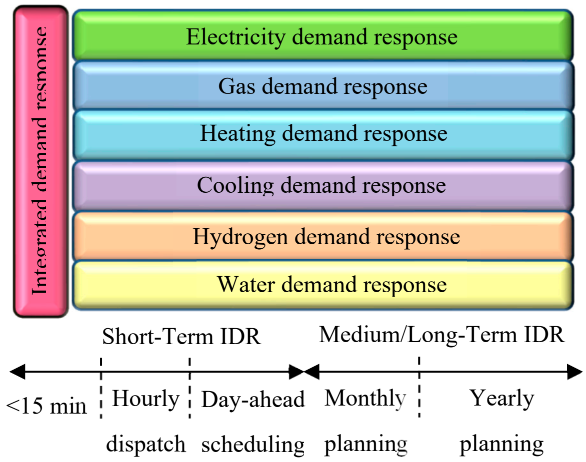

Figure 2. The characteristics of IDR program based on timeframes [6].

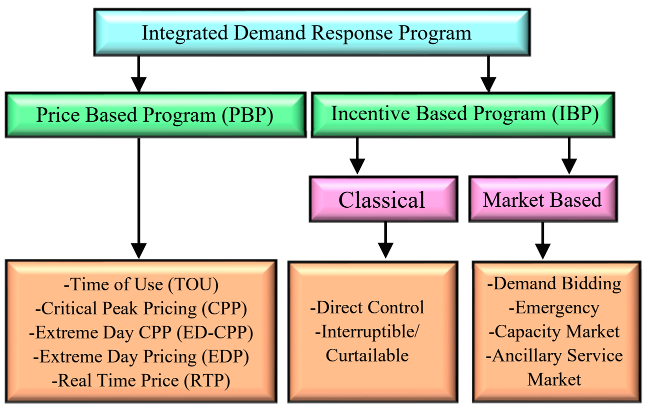

Figure 3. The characteristics of IDR program based on types [14].

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 [7]. Various incentive-based IDR programs are introduced and discussed below.

2.2.1.1. Classical

- *Direc 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 done during periods of peak demand or events, with the goal of reducing 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 electrical system during times of high demand [14-16].

- *Interruptible/ curtailment programs*

These programs are designed to encourage consumers to reduce their energy usage in accordance with 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 [16, 17].

2.2.1.2. Market-based

- *Demand bidding*

The network operator reduces the loads according to the amount and price suggested by the consumers. The 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 [18, 19].

- *Emergency*

During emergency situations such as tornadoes, earthquakes, and floods, consumers are offered an incentive to curtail their consumption [20].

- *Capacity market*

Using this approach, the network operator pays consumers a cost before an event occurs in order to have them reduce their consumption during the event. Essentially, the operator is responsible for securing the network [21].

- *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 [19].

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. Following is a description of the main types of price-based IDR programs [22].

- *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 of time within a day. In general, the tariff is determined for a given time period and represents the average cost of energy production and transmission during that period [22].

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- *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 [23].

- *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 [22].

- *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 [24].

- *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 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 [25].

Table 1. A comparison of the advantages and disadvantages of IDR models [6]

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 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 existing more variables -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

2.3. Integrated Load Modeling

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, 14].

2.3.1. Uncontrollable load

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

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

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

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 Eq 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 load in total load demand; $P_t^{k,B}$ is the load demand of EH considering the benchmark electricity price. Moreover, ε_t^k is the price elasticity coefficient of load, 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 Modeling

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, 13, 14, 26-28].

2.4.1. Transferable IDR

The transferrable IDR program is modeled based on the mathematical relationships proposed in (7)-(10), defining the variables at the end of the section [14, 26, 27].

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

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

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

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

2.4.2. Substitutable IDR

The substitutable IDR program is modeled using the mathematical formulations presented in equations (11)-(14), [14, 28].

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

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

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

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

2.4.3. Curtailable IDR

In equations (15)-(17), the mechanism for implementing curtailable IDR programs is outlined [14].

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

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

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

Where n and i are the indexes of EH number and type. $P_{n_{i},t}^{(e,g,h,c),up}$ and $P_{n_{i},t}^{(e,g,h,c),do}$ indicates the shifted up and down power by transferrable/ substitutable/ curtailable IDR program. $LPF^{(e,g,h,c),up}$ and $LPF^{(e,g,h,c),do}$ specifies load participation factor of shift up-down power by transferrable/ substitutable IDR program. Moreover, binary variables of shift up and down power by 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. Also, λ refers to the rebounded load factors.

2.4.4. Convertable IDR

Generalized, convertible loads are a specific category within the IDR program, and they can be characterized as follows [13]:

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

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

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*.

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

Furthermore, energy coupling devices are employed in EH to provide multiple energy couplings. Hence, in terms of multiple energy supply on the demand side, the IDR program has greater flexibility than the CEDR [13].

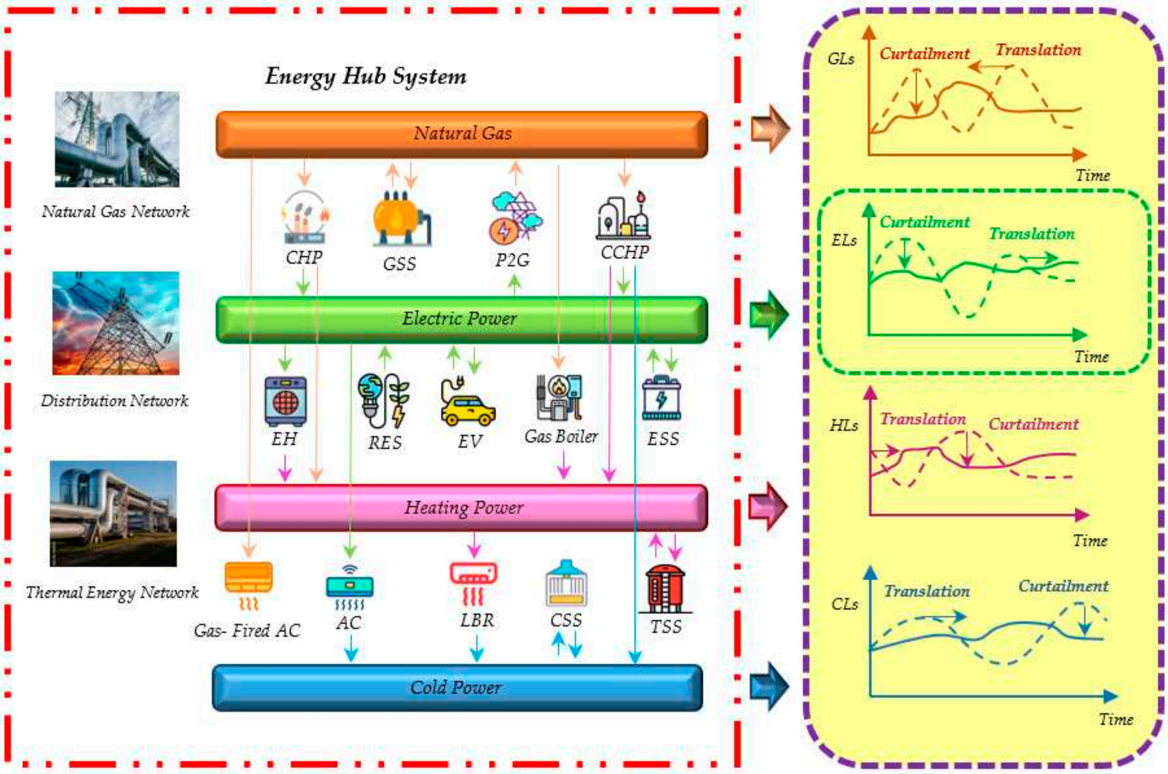

Figure 4. An overview of the IDR program in EH. CCHP: Combined Cooling Heat and Power, CHP: Combined Heat and Power, EH: Electric Heater, AC: Air Conditioner, LBR: Lithium Bromide Refrigerator, ESS: Electrical Storage System, GSS: Gas Storage System, TSS: Thermal Storage System, CSS: Cooling Storage System, P2G: Power to Gas [13].

3. Advantages of IDRP

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The IDRP concept brings the synergistic effects of MESs by thoroughly considering the critical complementarity of multi-energy consumption [29-31]. IDRP advantages are analyzed in terms of user benefits as well as system performance below.

1) 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.

2) 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.

3) 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.

4) Therefore, by transforming electricity to thermal and cooling energy, as well as gas, the penetration percentage of RES can be increased.

5) As a result, in addition to the total operational costs of the system, it has a significant promising effect on the decarbonization index.

6) 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.

7) By exploiting different energy complementarities, IDR is able to improve the reliability of MESs. In another word, various energy systems alongside IDR support each other to meet the load demands of energy consumers.

4. Uncertainty Consideration in IDRP

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

Various types of uncertainty can affect modeling and optimization processes, depending on the resources involved. Identifying the specific type of uncertainty is crucial in understanding its impact on system modeling and performance. In EHs management, it is imperative to take into consideration uncertainties arising from consumer behavior. 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 own energy consumption. Figure 5 illustrates the categories of IDR uncertainty modeling techniques in energy systems [32, 33]. Additionally, the main feature of each uncertainty modeling technique is summarized in Table 2.

Table 2. A comparison of the different approaches main feature.

Technique	Main feature
Stochastic optimization	A 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	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.

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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 the 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 take their advantages

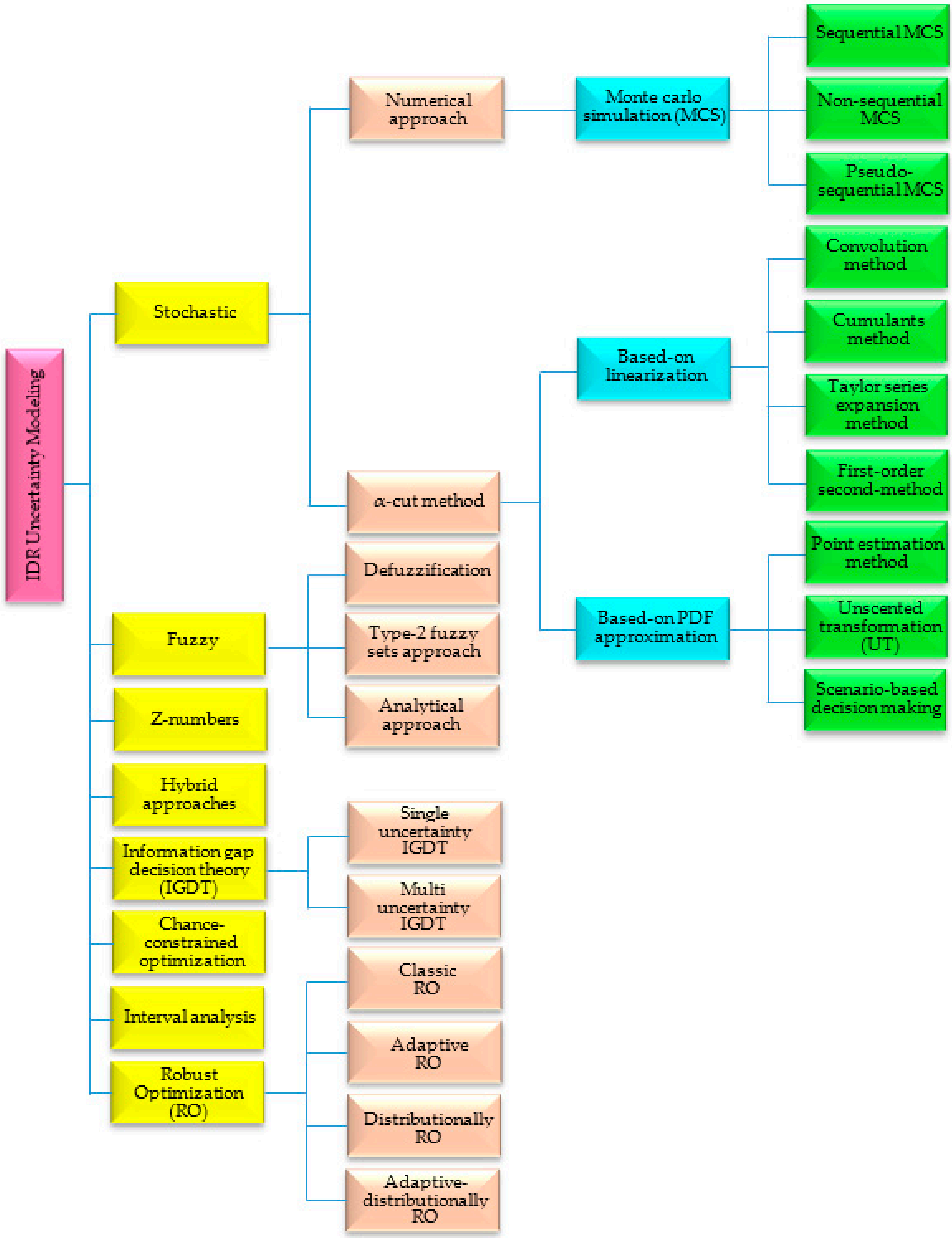

Figure 5. IDR uncertainty modeling techniques [32, 33].

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 energy demand and conversion mode without affecting overall energy demand, depending on price or other incentive factors.

The optimization model of EHs incorporating IDR can be expressed as follows [34]:

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

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 EH

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

[1] pertains to the notion of a smart micro-scale EH (SMEH) known as 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 to perform a dual role in not only converting power from RESs into hydrogen (P2H) during periods of low electricity prices and vice versa (H2P) 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, [8] proposes a novel optimal load dispatch for an EH that incorporates heat storage unit and EVs. The uncertainty of electricity price and EVs is also simulated to achieve a reliable energy management. In addition, the electrical and thermal demand response (DR) technologies are comprehensively reviewed in the proposed scheme to additional decrease the energy construction cost of users.

In [12], a stochastic approach is applied for optimal operation of an EH consists of wind farm, electrical and thermal storages which covers IDR program to participate in the electricity and thermal markets. An optimal scheduling of MEH based on cooperative game and virtual energy storage (VES) is developed in [13] to enhance scheduling flexibility of the MEH. In this model, IDR program is also assessed to respond potentially on the demand side. Ref [14] proposes a two-stage stochastic scheme for 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 algorithm, respectively. Moreover, DR and IDR programs have been incorporated in the model. A comparison of the proposed model with DICOPT

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solver in the GAMS software was substantiated through MATLAB and GAMS software interface to assess their efficiency and accuracy. Ref [27] 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 CO2, NO2, and SO2 emissions. Moreover, ACOPF constraints are imposed to avoid any non-physical power flow in the system.

A multi-objective dynamic model is developed in [35] to design a hub energy considering flexible efficiency of converters, equipment degradation rate and annual/yearly growth of load and energy prices. This problem is investigated the effects of P2G technology, energy storage system as well as IDR program on the operation. Moreover, it has tried to enhance the efficiency of boiler and CHP via hydrogen injection. Uncertainties attributed to the wind speed, demand and price are considered in the model. Authors of [36], proposes a shrinking-horizon optimization framework to solve the EH scheduling problem considering flexible loads, storage systems and wind turbines. In addition, wind turbine output power as well as electricity price are modelled as the uncertain parameters. In order to enhance system flexibility and modify the load demand curve, the EH users are able to cooperate in an IDR program which is applied to all three electrical, heating and cooling loads.

[37] has proposed an innovative scheduling of multi-carrier's 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 of EH owners would be decreased. Therefore, an effective Weymouth model is developed for simulating the gas network to assess the impact of P2G technologies and EHs on the congestion alleviation and cost reduction. In addition, an improved scenario reduction algorithm based on SCENRED has been utilized in this work to make the proposed model computationally efficient. The SCENRED includes three algorithms to reduce scenarios which in this research fast backward algorithm is used. Distributed generation, energy storage, as well as shiftable IDR program has been applied in this model to assist achieve the purposes of the operator. The scheme is linearized via the Taylor series and Cartesian method to make it computationally tractable.

Ref [38] has presented a developed optimization strategy of a hydrogen-based smart micro EH (SMEH) regarding the hydrogen storage system (HSS) and IDR program. Actually, IDR is utilized to control both electrical and heat demands. In addition, the uncertainty of the electricity price is considered in the modeling to increase the accuracy of the proposed problem. According to this model, the RESs is converted into hydrogen (P2H) by the HSS and, stored at low-power-price hours. Afterwards, the stored hydrogen can be conveyed to the hydrogen industry (H2P) at the high-power-price hours. A stochastic model is designed in [39] for unit commitment (UC) in EH which involves hydrogen vehicle (HV) parking lot, electric heat pump (EHP), absorption chiller (AC), photovoltaic (PV) unit, boiler, hydrogen electrolyzer (HE) and electric, thermal, cooling and HSS. In this research, the uncertainties of demands, PV power and initial energy of HVs are modeled and loss of storage systems and HV tanks are also taken into account. Moreover, the impacts of IDR program on EH operation are investigated.

[40] develops a novel Internet of Thing (IoT)-based strategy for optimal energy management of Multi Energy Hubs (MEH). Actually, the proposed IoT-enabled MEH system consists of three interconnected residential, commercial, and industrial EHs. Each EH consists of CHP, RESs, Plug-in-electric vehicle (PHEV), boiler, and heat storage (HS) systems, which is relied on electricity and natural gas as the main sources of power. An unscented transformation (UT) uncertainty method, which is such a stochastic strategy is used for modeling the uncertainty of RESs (PV, WT), and an IDR program is considered with MEH electrical and thermal demands. In [41], a novel water-based storage system called Pico hydel energy storage is analyzed for day-ahead scheduling of EH. The performance of the proposed EH is evaluated with the inclusion of demand response programs for electricity, gas, water, and thermal. Risk-averse approaches, such as conditional value-at-risk and second-order stochastic dominance (SSD) approach, are used. Additionally, [42] studies the risk-

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based scheduling of a more realistic EH scheme using the conditional value at risk (CVaR) method. IDR programs are applied to manage demand curve and costs.

Ref [43], presents a comprehensive framework based on IGDT-robust constrained unit commitment (SCUC) approach for optimal scheduling of the regional power system considering grid-connected EHs under 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 multi-energy DR program. Therefore, the essential focus is on the 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 [44] to establish an appropriate optimization model. This article connects energy storage equipment and a large number of integrated EVs to the grid in order to enhance 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 [45], the scenario-based framework is applied to design 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 the CO2 emissions in addition to improving the performance of boiler units and CHP via injecting hydrogen. A two-stage planning approach based on nodal energy prices strategy is presented in [46] to manage the integrated demands of the end users using an IDR program. In fact, the major purpose of this research is evaluating the impact of the nodal energy prices on the penetration of solar energy and especially the IDR program. A robust EH scheduling based on hybrid interval-stochastic framework was proposed in [47] for flexible energy management among RESs, considering IDR program and different energy storages such as ISC.

In [48], a risk-based optimal operation of EH with the presence of IDR program as well as multiple energy storage such as P2G and compressed air energy storage (CAES) are investigated. Investigations of IDR facilities are also taken into account in [49], for adopting a stochastic operation of EH which divided into three sub-hub (electric, thermal, and cooling hub).

The aim of research [50] is to introduce a model for effective management and distribution of an EH, which is based on the consideration of uncertainties pertaining to RESs, electrical loads, operating and maintenance costs, 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 [51], a model for 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 [52], an evaluation is conducted to compare the performance of EHP and P2G technologies in both electricity and gas systems, considering a price-based IDRP.

[53] represents the coordinated operation of an EH incorporating a diverse range of electrical, thermal, and cooling demands, with the aim of achieving 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 3 provides a comparison among recent studies.

Table 3. Comparison of the recent studies.

Ref	Time-Horizon	IDRP	Storage systems	OF Modeling		Objective Function	Emission
				Multi	Single		
[1]	Short-Term	E, H	ESS, TSS, GSS, H_2SS	×	✓	Cost	×
[8]	Short-Term	E, H	TSS, WSS, EV	×	✓	Cost	✓
[12]	Short-Term	E, H	ESS, TSS	×	✓	Cost	×
[13]	Short-Term	E, H, C, G	ESS, GSS	×	✓	Profit	×

[14]	Short-Term	E, H, C	ESS, TSS	×	✓	Cost	✓
[27]	Short-Term	E, H, C	ESS, TSS, EV	×	✓	Cost	×
[35]	Long-Term	E, H	ESS	✓	×	Cost	✓
[36]	Short-Term	E, H	ESS, TSS, CSS, EV	×	✓	Cost	✓
[37]	Short-Term	E, H	ESS, TSS, HSS	×	✓	Cost	×
[38]	Short-Term	E, H	ESS, TSS, HSS, GSS	×	✓	Cost	×
[39]	Short-Term	E, H, C, H_2	ESS, TSS, CSS, HSS, HV	×	✓	Cost	×
[40]	Short-Term	E, H	ESS, TSS, EV	×	✓	Cost	×
[41]	Short-Term	E, H, W, G	ESS, TSS, WSS	✓	×	Economic, Technical, Environmental	✓
[42]	Short-Term	E, H, C	TSS, CSS, HSS, PHEV	×	✓	Cost	✓
[43]	Short-Term	E, H	ESS, TSS	×	✓	Cost	✓
[44]	Short-Term	E, H, C	ESS, TSS, WSS, EV	✓	×	Cost	✓
[45]	Short-Term	E, H, C	ESS	×	✓	Cost	✓
[46]	Short-Term	E, H, C	ESS, TSS	✓	×	Cost	×
[47]	Short-Term	E, H	ESS, TSS	×	✓	Cost	×
[48]	Short-Term	E, H, G	ESS, TSS	×	✓	Cost	×
[49]	Short-Term	E, C	ESS, TSS, CSS	×	✓	Profit	×
[50]	Short-Term	E, H	ESS, TSS	×	✓	Cost	✓
[51]	Short-Term	E, H	TSS	×	✓	Cost	✓
[52]	Short-Term	E, H	ESS, WSS	×	✓	Cost	×
[53]	Short-Term	E, H	ESS, TSS	✓	×	Economic, Environmental	✓

In terms of temporal scale, almost all studies have taken a short-term view. Most of the articles have studied the effect of DR program on electricity, gas, heat and cold energy carriers, except for refs [39] and [41] 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 EH. EVs, which are employed as a type of storage in Vehicle-to-Grid (V2G) mode [54], have attracted a lot of attention in IES in recent years. In this regard, several studies have considered EVs as a mobile energy storage, including refs [8], [27], [36], [40], and [44]. Additionally, ref [42] has employed PHEV, while ref [39] has used Hydrogen vehicle (HV). Gas and water storage systems have been employed in three and four studies, respectively. Moreover, just [1] 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 [41], has modeled 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 references [41] and [53]. [41] examined technical (voltage profile) and environmental (CO2, NO2, and SO2 emissions) objectives in addition to the economic objective and [53] minimized CO2 emissions along with total operation cost.

6. Prospect Challenges of IDRP

In EH optimization models, IDR is typically modeled 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 [55]. Therefore, developing a specialized and accurate model for IDR program 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 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 [56]. 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 demand while ensuring the stability and reliability of EHs.

7. Conclusion

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 IDR program and reviews the current studies on EH optimization in relation to the planning, operation, and business of EH. 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.

References

1. Mansour-Saatloo, A., et al., *Robust scheduling of hydrogen based smart micro energy hub with integrated demand response.* Journal of Cleaner Production, 2020. **267**: p. 122041.
2. Bagherzadeh, L., et al., *A short-term energy management of microgrids considering renewable energy resources, micro-compressed air energy storage and DRPs.* International Journal of Renewable Energy Research, 2019. **9**(4): p. 1712-1723.
3. Zhang, L., et al., *Research on the optimal allocation method of source and storage capacity of integrated energy system considering integrated demand response.* Energy Reports, 2022. **8**: p. 10434-10448.
4. Falkner, R., *The Paris Agreement and the new logic of international climate politics.* International Affairs, 2016. **92**(5): p. 1107-1125.
5. Moghaddam, A.M., et al. *Assessing the Role of Wind Turbine in Residential Energy Hubs*. in *2020 28th Iranian Conference on Electrical Engineering (ICEE)*. 2020. IEEE.
6. Chen, Z., et al., *Integrated demand response characteristics of industrial park: a review.* Journal of Modern Power Systems and Clean Energy, 2019. **8**(1): p. 15-26.
7. Wang, J., et al., *Review and prospect of integrated demand response in the multi-energy system.* Applied Energy, 2017. **202**: p. 772-782.
8. Li, R. and S. SaeidNahaei, *Optimal operation of energy hubs integrated with electric vehicles, load management, combined heat and power unit and renewable energy sources.* Journal of Energy Storage, 2022. **48**: p. 103822.
9. Sheikhi, A., et al., *Integrated demand side management game in smart energy hubs.* IEEE Transactions on Smart Grid, 2015. **6**(2): p. 675-683.

10. Bahrami, S. and A. Sheikhi, *From demand response in smart grid toward integrated demand response in smart energy hub.* IEEE Transactions on Smart Grid, 2015. **7**(2): p. 650-658.
11. Ding, T., et al., *Review of Optimization Methods for Energy Hub Planning, Operation, Trading, and Control.* IEEE Transactions on Sustainable Energy, 2022. **13**(3): p. 1802-1818.
12. Vahid-Pakdel, M., et al., *Stochastic optimization of energy hub operation with consideration of thermal energy market and demand response.* energy Conversion and Management, 2017. **145**: p. 117-128.
13. Chen, C., et al., *Optimal day‐ahead scheduling of multiple integrated energy systems considering integrated demand response, cooperative game and virtual energy storage.* IET generation, transmission & distribution, 2021. **15**(11): p. 1657-1673.
14. Mansouri, S.A., et al., *A multi-stage joint planning and operation model for energy hubs considering integrated demand response programs.* International Journal of Electrical Power & Energy Systems, 2022. **140**: p. 108103.
15. Silva, C., et al., *Demand response performance and uncertainty: A systematic literature review.* Energy Strategy Reviews, 2022. **41**: p. 100857.
16. Aljabery, A.A.M., et al., *Multi carrier energy systems and energy hubs: Comprehensive review, survey and recommendations.* International Journal of Hydrogen Energy, 2021. **46**(46): p. 23795-23814.
17. Albadi, M.H. and E.F. El-Saadany. *Demand response in electricity markets: An overview*. in *2007 IEEE power engineering society general meeting*. 2007. IEEE.
18. Lopes, F. and H. Algarvio, *Demand response in electricity markets: an overview and a study of the price-effect on the Iberian daily market.* Electricity markets with increasing levels of renewable generation: Structure, operation, agent-based simulation, and emerging designs, 2018: p. 265-303.
19. Albadi, M.H. and E.F. El-Saadany, *A summary of demand response in electricity markets.* Electric power systems research, 2008. **78**(11): p. 1989-1996.
20. Qdr, Q., *Benefits of demand response in electricity markets and recommendations for achieving them.* US Dept. Energy, Washington, DC, USA, Tech. Rep, 2006. **2006**.
21. Ma, T., J. Wu, and L. Hao, *Energy flow modeling and optimal operation analysis of the micro energy grid based on energy hub.* Energy conversion and management, 2017. **133**: p. 292-306.
22. Balijepalli, V.M., et al. *Review of demand response under smart grid paradigm*. in *ISGT2011-India*. 2011. IEEE.
23. Faria, P. and Z. Vale, *Demand response in electrical energy supply: An optimal real time pricing approach.* Energy, 2011. **36**(8): p. 5374-5384.
24. Herter, K. and S. Wayland, *Residential response to critical-peak pricing of electricity: California evidence.* Energy, 2010. **35**(4): p. 1561-1567.
25. Mancarella, P. and G. Chicco, *Real-time demand response from energy shifting in distributed multi-generation.* IEEE Transactions on Smart Grid, 2013. **4**(4): p. 1928-1938.
26. Mansouri, S.A., et al., *Demand response role for enhancing the flexibility of local energy systems.* Distributed energy resources in local integrated energy systems, 2021: p. 279-313.
27. Mansouri, S.A., et al., *A coordinated energy management framework for industrial, residential and commercial energy hubs considering demand response programs.* Sustainable Energy Technologies and Assessments, 2021. **47**: p. 101376.
28. Wang, B., et al., *Chance constrained unit commitment considering comprehensive modelling of demand response resources.* IET Renewable Power Generation, 2017. **11**(4): p. 490-500.
29. Geidl, M. and G. Andersson. *Optimal coupling of energy infrastructures*. in *2007 IEEE Lausanne Power Tech*. 2007. IEEE.
30. Behboodi, S., et al., *Renewable resources portfolio optimization in the presence of demand response.* Applied Energy, 2016. **162**: p. 139-148.
31. Mazidi, M., H. Monsef, and P. Siano, *Robust day-ahead scheduling of smart distribution networks considering demand response programs.* Applied energy, 2016. **178**: p. 929-942.
32. Jasinski, M., et al., *Operation and Planning of Energy Hubs Under Uncertainty-a Review of Mathematical Optimization Approaches.* IEEE Access, 2023.
33. Mohammadi, M., et al., *Optimal scheduling of energy hubs in the presence of uncertainty-a review.* Journal of energy management and technology, 2017. **1**(1): p. 1-17.
34. Cheng, L., et al. *Integrated Demand Response Under the Backgroud of Energy Internet: A Review and Outlook*. in *2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2)*. 2018. IEEE.
35. Mansouri, S.A., et al., *A Multi-objective dynamic framework for design of energy hub by considering energy storage system, power-to-gas technology and integrated demand response program.* Journal of Energy Storage, 2022. **50**: p. 104206.
36. Salehimaleh, M., A. Akbarimajd, and A. Dejamkhooy, *A shrinking-horizon optimization framework for energy hub scheduling in the presence of wind turbine and integrated demand response program.* Sustainable Cities and Society, 2022. **79**: p. 103689.
37. Salehi, J., et al., *Effect of power-to-gas technology in energy hub optimal operation and gas network congestion reduction.* Energy, 2022. **240**: p. 122835.

38. Zhang, H., et al., *A novel power system scheduling based on hydrogen-based micro energy hub.* Energy, 2022. **251**: p. 123623.
39. Nasir, M., et al., *Optimal operation of energy hubs including parking lots for hydrogen vehicles and responsive demands.* Journal of Energy Storage, 2022. **50**: p. 104630.
40. Kazemi, B., et al., *IoT-enabled operation of multi energy hubs considering electric vehicles and demand response.* IEEE Transactions on Intelligent Transportation Systems, 2022.
41. Mokaramian, E., et al., *Four-objective optimal scheduling of energy hub using a novel energy storage, considering reliability and risk indices.* Journal of Energy Storage, 2021. **40**: p. 102731.
42. Allahvirdizadeh, Y., S. Galvani, and H. Shayanfar, *Data clustering based probabilistic optimal scheduling of an energy hub considering risk-averse.* International Journal of Electrical Power & Energy Systems, 2021. **128**: p. 106774.
43. Oskouei, M.Z., et al., *Techno-economic and environmental assessment of the coordinated operation of regional grid-connected energy hubs considering high penetration of wind power.* Journal of Cleaner Production, 2021. **280**: p. 124275.
44. Luo, Y., et al., *Emission trading based optimal scheduling strategy of energy hub with energy storage and integrated electric vehicles.* Journal of Modern Power Systems and Clean Energy, 2020. **8**(2): p. 267-275.
45. Mansouri, S.A., et al. *Energy hub design in the presence of P2G system considering the variable efficiencies of gas-fired converters*. in *2021 International Conference on Smart Energy Systems and Technologies (SEST)*. 2021. IEEE.
46. Pan, G., et al., *Optimal design and operation of multi-energy system with load aggregator considering nodal energy prices.* Applied Energy, 2019. **239**: p. 280-295.
47. Jamalzadeh, F., et al., *Optimal operation of energy hub system using hybrid stochastic-interval optimization approach.* Sustainable Cities and Society, 2020. **54**: p. 101998.
48. Mirzaei, M.A., et al., *Integrated energy hub system based on power‐to‐gas and compressed air energy storage technologies in the presence of multiple shiftable loads.* IET Generation, Transmission & Distribution, 2020. **14**(13): p. 2510-2519.
49. Rakipour, D. and H. Barati, *Probabilistic optimization in operation of energy hub with participation of renewable energy resources and demand response.* Energy, 2019. **173**: p. 384-399.
50. Iranpour Mobarakeh, S., et al., *Robust management and optimization strategy of energy hub based on uncertainties probability modelling in the presence of demand response programs.* IET Generation, Transmission & Distribution, 2022. **16**(6): p. 1166-1188.
51. Lu, X., et al., *A robust optimization approach for coordinated operation of multiple energy hubs.* Energy, 2020. **197**: p. 117171.
52. Zhu, F., et al., *Robust energy hub optimization with cross‐vector demand response.* International Transactions on Electrical Energy Systems, 2020. **30**(10): p. e12559.
53. Guo, Q., et al., *Economic-environmental evaluation of industrial energy parks integrated with CCHP units under a hybrid IGDT-stochastic optimization approach.* Journal of Cleaner Production, 2021. **317**: p. 128364.
54. Bagherzadeh, L. and H. Shayeghi. *Optimal allocation of electric vehicle parking lots and renewable energy sources simultaneously for improving the performance of distribution system*. in *2019 24th Electrical Power Distribution Conference (EPDC)*. 2019. IEEE.
55. Kojonsaari, A.-R. and J. Palm, *The development of social science research on smart grids: a semi-structured literature review.* Energy, Sustainability and Society, 2023. **13**(1): p. 1.
56. Huang, W., et al., *From demand response to integrated demand response: Review and prospect of research and application.* Protection and Control of Modern Power Systems, 2019. **4**: p. 1-13.