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Review

Theoretical Analysis of Integrated Community Energy Systems (ICES) Considering Integrated Demand Response (IDR): A Review of the System Modelling and Optimization

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Abstract: The transition of the energy model dominated by centralized fossil energy use and the emergence of the Energy Internet and the Integrated Community Energy System (ICES) has gained attention. ICES involved the connection of electricity, heat, gas, and other kinds of energy, and was a significant form of the targeted transformation of conventional single energy networks. Within this system, the traditional demand response (DR) was transformed into an integrated demand response (IDR) in which all energy consumers could participate. The purpose of this study is to discuss the important technologies and models along with assessment and optimization strategies for the implementation of ICES and IDR, based on an extensive literature review. The analysis results show the "IDR + ICES" ecosystem proved to hold great potential for achieving renewable energy penetration, energy efficiency, and climate change control goals, while there are still many limitations in the coordination and reliability of the model and the design of the market mechanism. To conclude, the challenges and opportunities that ICES and IDR face were summarized, and future avenues for research are outlined.

Keywords: integrated demand response; integrated community energy systems; energy storage system; renewable energy; electric vehicle charging

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1. Introduction

1.1. Motivation

In recent decades, as a result of fast population expansion, economic development, and urbanization, worldwide energy consumption has expanded dramatically [1], resulting in a substantial increase in carbon dioxide emissions and a worsened global warming. A total of 195 countries to the United Nations Framework Convention on Climate Change signed the Paris Agreement in December 2015, which aimed to keep global warming below 1.5 °C relative to pre-industrial levels [2]. The issue of environmental pollution has become more apparent with the exhaustion of fossil fuel resources. However, the rapid growth of renewable energy technologies had been transforming the energy business everyday. To achieve the goals of the Paris Agreement, creating a clean, safe, and low-carbon energy system by increasing renewable energy consumption, reducing greenhouse gas emissions, and improving the comprehensive utilization rate of all energy forms have become the priorities for those countries with intensive energy usage [3].

International studies have demonstrated that renewable energy technologies and increased energy efficiency might considerably contribute to emissions reductions [4], and the transformation of energy systems was acknowledged as a means to use energy more effectively [5]. Each energy component in the conventional energy system has been individually planned, developed, and operated. This way of construction severed the connection between various forms of energy, severely limiting the flexibility and efficiency of energy system functioning [6]. The rapid growth of information and communication technology (ICT) and Internet technology made integrated energy system (IES) information transfer more efficient, accurate both inside and across energy systems of the development of multi-energy system foundation, and so it is attracting increasing interests. However, there has been no uniform definition for the notion of IES, which has been around for a long time. The energy systems in the aggregation of multiple energy systems can take into account different types of energy differences and diversity (such as energy and capacity limits of space and time, conversion, and storage and expenses to the difficulty of the characteristics, the energy, energy density, etc.), thereby optimizing the allocation of more space for a variety of energy coupling systems. Therefore, compared to the conventional energy system, the integrated energy system's interaction between its multiple energy subsystems was more diverse [7], and the system's energy utilization efficiency had greater potential.

For traditional energy systems, demand response (DR) as the main solution for demand-side management was one of the basic strategies to make full use of demand-side flexibility [8]. It provided greater grid flexibility via price and incentives [9], such as energy bill relief that enabled consumers to shift energy consumption from periods of high demand to periods of low demand by adjusting loads or producing and storing energy at certain times. DR was also an excellent technique for renewable energy to overcome its fluctuation, uncertainty [10], and promote its further integration with the grid. However, with the transformation of the energy system, the technology and market environment for implementing demand response had changed significantly, and just considering the demand response of the power system could not effectively achieve the optimal coordination of supply and demand for the energy Internet [11]. In this context, Integrated Demand Response (IDR) was offered, which claimed that according to the complementarity of the Multi-Energy System (MES), even inelastic loads might actively participate in the DR process, maximizing the interactivity of DR resources while ensuring user comfort [12]. Thus, the transformation of the conventional energy system could be seen as the optimization of a distinct operating and management model. Consequently, the original supply and demand balance system, market, and pricing mechanism were no longer applicable, prompting the DR to ultimately initiate the transition to the IDR.

The IES could be subdivided into user level, regional level, and trans-regional level. This was carried out according to the spatial distribution and size division of the energy system's power generation, transmission, distribution, and consumption functions [13]. Currently, the majority of multi-energy systems consist of regional IES with centralized distributed energy stations. As one regional IES, ICES terminals consist mostly of dispersed multiple energy units that are physically connected via energy supply networks (such as electricity, heat, and gas networks), energy storage connections (energy storage), and energy conversion links (air conditioning, heat pump, etc.). In accordance with the real nature of most multi-energy systems, the scheduled optimization of large-scale energy systems seeks to link one or more communities. In addition, unlike other kinds of energy integration, ICES was the outcome of an integrated strategy that delivers systems functions such as balancing and ancillary services to neighboring systems [14]. Both ICES and IDR were hot topics at the time; however, current research rarely considers both of them, although the full implementation of IDR in ICES is necessary. This integrated strategy would realize the potential of need response, improving the economics and safety of the system.

1.2. Contribution to Knowledge

In this paper, VOS viewer was used to conduct a scientometric analysis in order to acquire a more comprehensive understanding of the interrelationships and underlying patterns of major components in the present research literature. 'Integrated Community Energy System' and 'Integrated Demand Response' were selected as keywords, 132 relevant research publications were assessed, and 32 core keywords were determined. As presented in Figure 1, new papers were shown in yellow, whereas older articles were shown in purple, indicating that integrated demand response and IES were now more attractive study subjects. Bigger circles within the figure indicated the main keyword. However, there was no clear major keyword, indicating that the distribution of relevant research was scattered and systematic study focusing on IDR and ICES is still in its infancy. Specifically, modelling and optimization, two of the most important parts of the ICES + IDR ecosystem, were not thoroughly discussed.

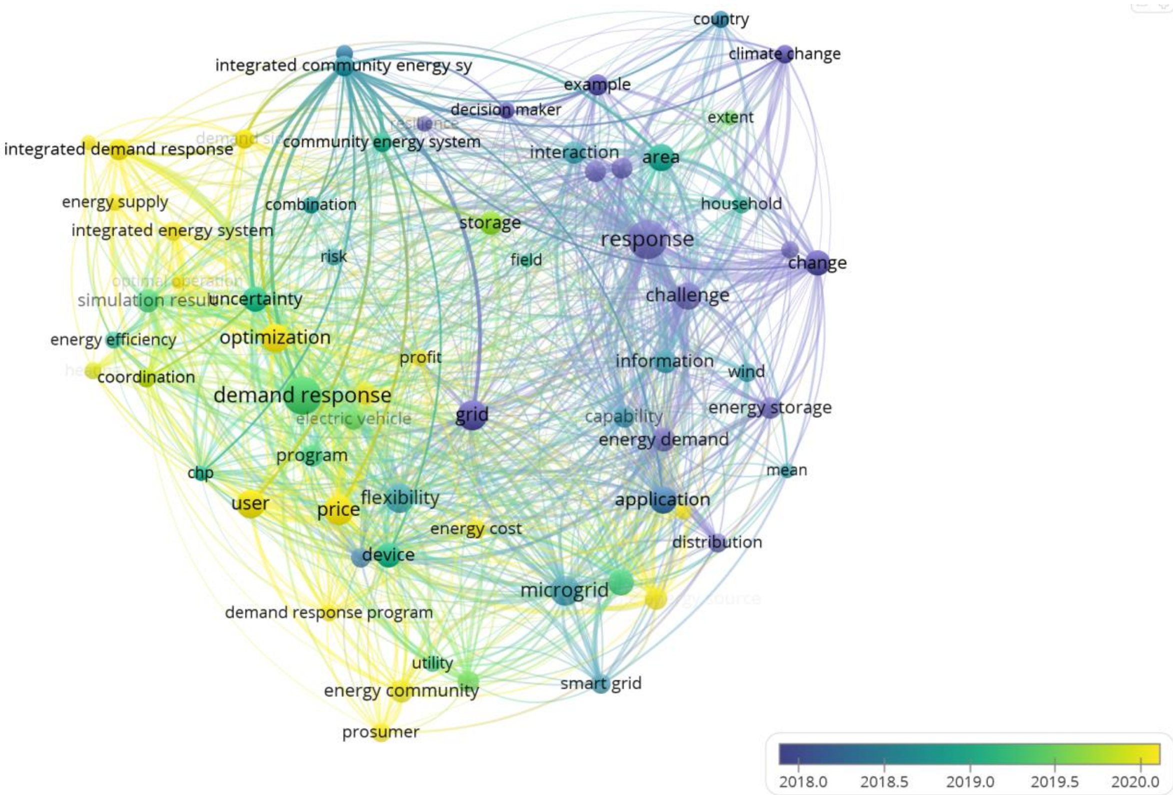

Figure 1. ICES + IDR publications' co-citation network and the overall temporal relationship (Source: Using VOSviewer tool [15]).

Additionally, an exhaustive search was performed for review papers that are highly relevant to the topics reviewed in this paper, and what they have reviewed is summarized in Table 1 below.

Specifically, despite the fact that the available literature covered essentially every aspect of independent DR and ICES, each has a different focus. Their investigation of the two core components of RES and ESS is generally weak when analyzing the modeling and optimization methods for ICES, including the evaluation of DR projects. Few research articles had focused on the use of DR/IDR from the perspective of ICES, and none had comprehensively covered the most crucial features of the key subdivision of the "IDR + ICES" ecosystem. In order to cover gaps in the literature, this study presents a holistically detailed analysis of the modelling, evaluation, and optimization of the "IDR + ICES" ecosystem, which are the most critical issues. This paper also analyzed obstacles and potential prospects for future research, which would hopefully inspire scholars in this field to continue exploring and establishing a more scientific IDR analysis methodology and implementation mechanism.

Table 1. Review papers highly relevant to the ICES and IDR in recent years.

Ref.	Title	Modelling and Optimization			DR Program Evaluation	
		IES	RES	ESS	User-Side Capacity/Potential	Cost/Pricing/Benefit
Abeysekera et al., 2016 [16]	Integrated energy systems: An overview of benefits, analysis, research gaps and opportunities	√	×	×	×	×
Wang et al., 2017 [12]	Review and prospect of integrated demand response in the multi-energy system	√	×	×	√	√
Huang et al., 2019 [11]	From demand response to integrated demand response: Review and prospect of research and application	√	×	×	×	√
Vahid-Ghavidel et al., 2020 [17]	Demand response programs in multi-energy systems: A review	√	×	×	×	×
Zhao et al., 2021 [18]	A review of system modeling, assessment and operational optimization for integrated energy systems	√	×	√	×	×
Li et al., 2021 [19]	Operation optimization of integrated energy system under a renewable energy dominated future scene considering both independence and benefit: A review	√	√	×	×	×
Mohseni et al., 2022 [20]	Demand response-integrated investment and operational planning of renewable and sustainable energy systems considering forecast uncertainties: A systematic review	√	×	×	×	√
Alabi et al., 2022 [21]	A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems	√	√	×	×	×
Song et al., 2022 [22]	A critical survey of integrated energy system: Summaries, methodologies and analysis	√	×	×	×	×
Oskouei et al., 2022 [23]	A Critical Review on the Impacts of Energy Storage Systems and Demand-Side Management Strategies in the Economic Operation of Renewable-Based Distribution Network	×	√	√	×	√
Liu et al., 2023 [24]	Key technologies and developments of multi-energy system: Three-layer framework, modelling and optimisation	√	×	√	×	×

√: detailed review; ×: no review or only mention.

1.3. Paper Organization

The remaining sections are organized as follows. Section 2 presents the review methodology, followed by the conceptual framework and fundamental theory of demand response in an integrated community energy system. Section 3 elaborates the review results and analysis, including basic modeling and simulation method of ICES that take DR into account, and control optimization methods for related IDR strategies. Section 4 provides a critical analysis of this review paper, proposes future research directions, and concludes with a summary.

2. Methodology and Definitions

2.1. Review Methodology

The review approach applied in this paper was based on a scientific foundation. To begin, a comprehensive conceptual framework for the ICES + IDR ecosystem was derived from international/national standards (ISO/IEC Series Standard, OpenADR), representative reports (IEA Series Report), and significantly relevant papers/books (see Figure 2).

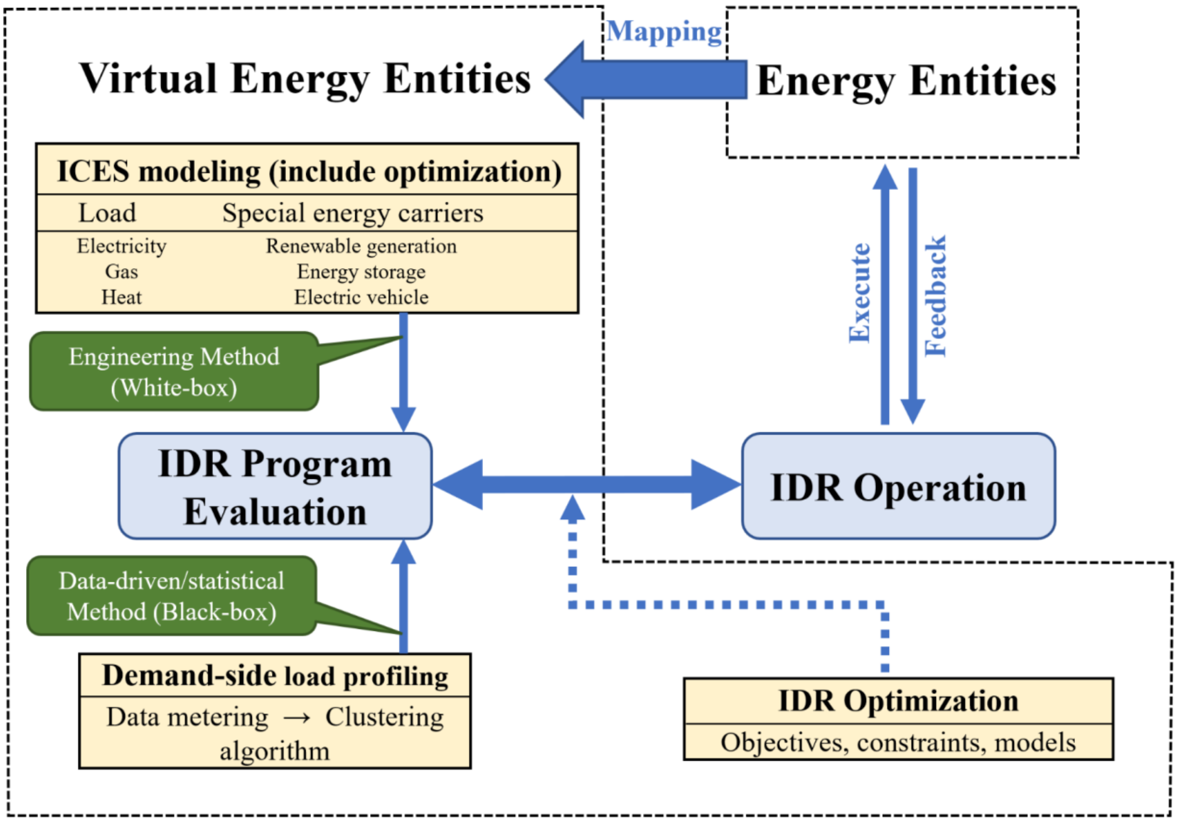

Figure 2. The conceptual framework of ICES + IDR ecosystem (source: authors' edition).

In order to better comprehend this conceptual framework, a new definition of Virtual Energy Entities as a mapping of real energy entities was proposed. IDR program assessment was supported by ICES modelling (white-box approach) and demand-side load analysis (black-box method) in this conceptual framework. Then, based on these assessments, the IDR operations would be executed on the energy entities while feedback information would be gathered to determine if optimization was necessary, as well as the identification of important optimization parameters. Once the optimization had been completed, the IDR operation would be executed again.

On the basis of the conceptual framework, relevant keyword and phrase combinations were selected under the following themes: ICES modelling/optimization, demand response load profiling, and IDR optimization. An exhaustive search of all highly relevant articles was conducted using Web of Science, which in turn led to the construction of a detailed literature review.

2.2. Definition of ICES + DR Ecosystem

2.2.1. Demand Response (DR)

Clark W. Gellings introduced the idea of demand-side management (DSM) for the first time in 1985 [25]. The concept of demand-side management had developed from the deployment of managerial techniques to create demand-side resources by influencing load demand [26]. Generalized demand response, defined by the U.S. Department of Energy as one of the most comprehensive DSM solutions (DR) [27], is described as follows:

> *"A tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized."* (*p. V*)

According to the above definition, the objective of DR was the traditional electric power grid, which was intended to accommodate generation uncertainty and load demand fluctuations. Demand Response was specifically divided into price-based Demand Response (PBDR) and incentive-based Demand Response (IBDR) [28]. Although the types of user engagement vary, the user comfort restrictions for flexible load scheduling were identical. PBDR gave time-varying pricing signals to power users, helping them select timings for power consumption amidst increased prices during periods of peak demand and emergencies, demotivating customers. IBDR acquired the control right of user-side flexible load through a program to carry out centralized optimal load scheduling. Figure 3 below shows the overall DSM categorization as well as the individual subcategories included in DR.

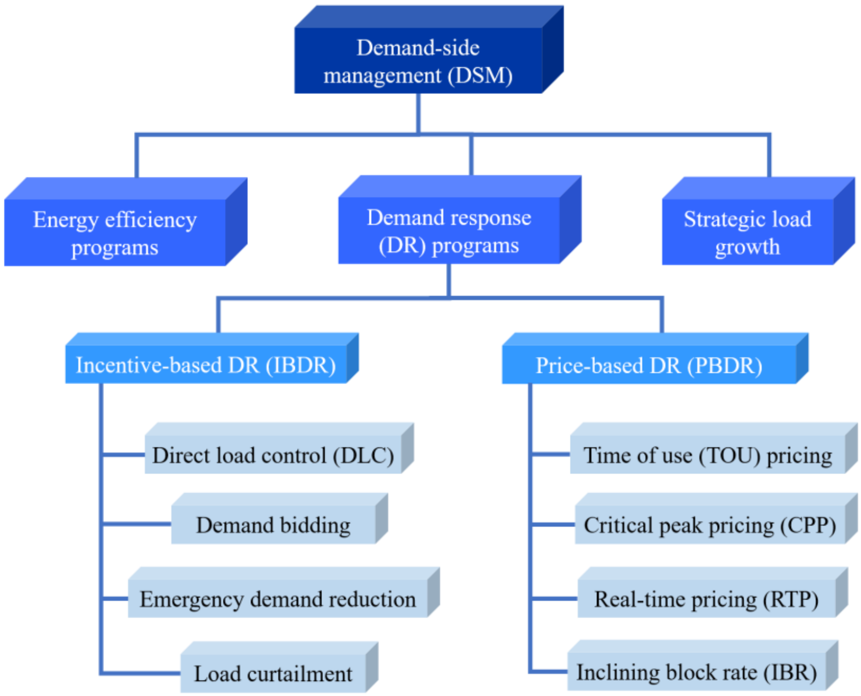

Figure 3. The classification of the DSM (source: [29,30]).

In fact, DR provided significant economic improvements to the management and regulation of the traditional electric power grid [31]. Nonetheless, as alternative energy sources were pursued, a better integration of energy systems was essential. At the time, the traditional energy supply systems for transportation, heating, and electrical usage were essentially independent. The future trend, however, would be the transition from the conventional electric power grid to the smart grid and IES as a whole. Its interior would become more interconnected [32]. This resulted in a shift of focus to converting traditional DR to IDR and continuing to generate the maximum advantages.

2.2.2. Integrated Community Energy Systems (ICES)

To guarantee the application of DR schemes and associated technologies, classifying ICES was essential. As shown in Figure 4, this paper classified the IES into two categories based on the existence of specific energy carriers, namely conventional and non-conventional. A conventional IES excluded renewable power sources and other distinct energy carriers. From the perspective of energy network type, typical IESs could be divided into electric–thermal, electric–gas, CHP, and CCHP systems. On the basis of the conventional IES, the non-conventional IES considered special energy carriers, such as renewable power generation, electric vehicle charging and discharging, energy storage system, fuel cell, ground source heat pump, etc. This paper focuses on the first three special energy carriers.

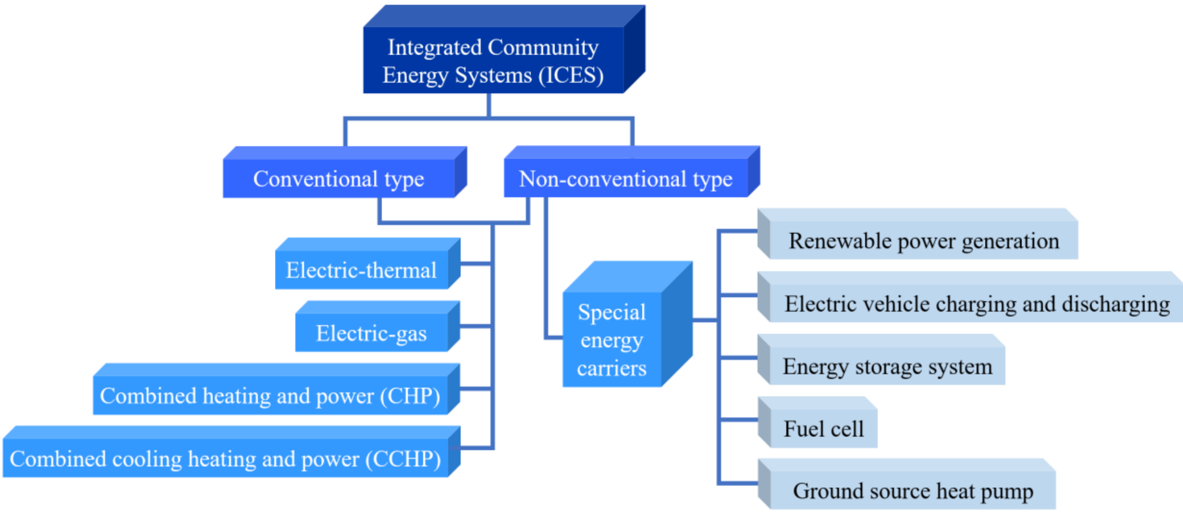

Figure 4. The taxonomy of the ICES in this review (source: authors' edition).

Figure 5 below shows a THREE-energy (electricity, gas, and heat) ICES that takes renewable energy accessibility and energy storage into consideration. It should be emphasized, however, that the ICES in its practical application did not include all the components of this complex system, which were presented for ease of understanding.

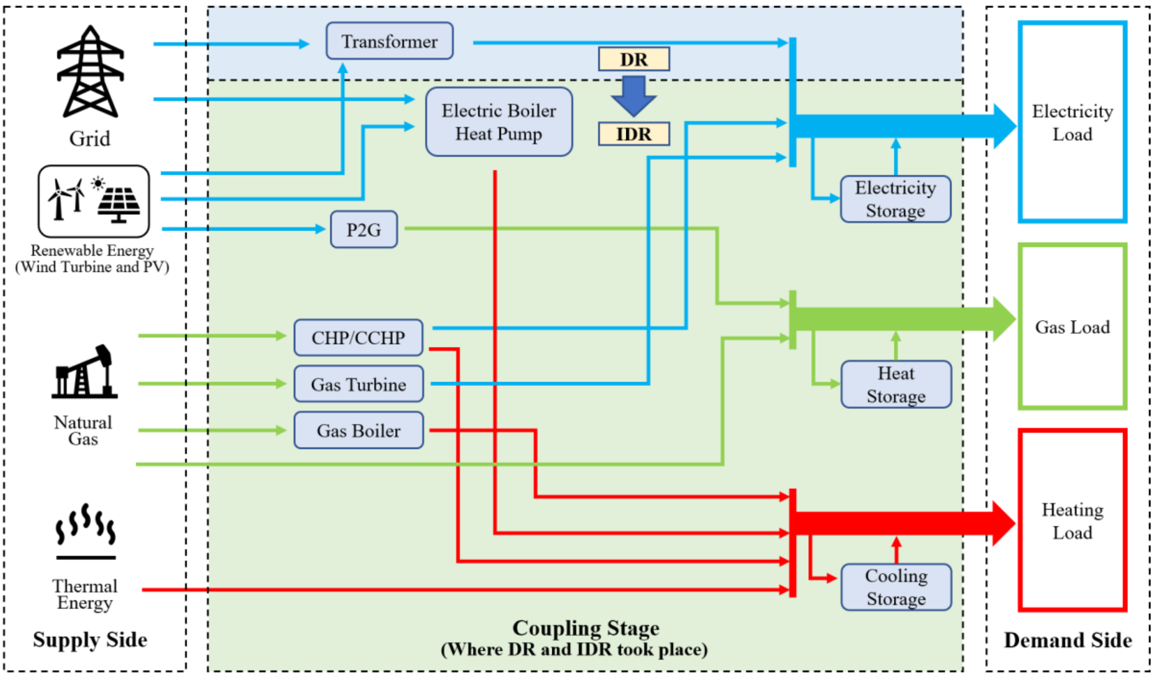

Figure 5. The schematic diagram of a typical integrated community energy system (source: authors' edition).

A complex and direct connection existed between the electrical system, natural gas system, and thermal system [14] in this system. The coupling equipment between the electric power system and the natural gas system consisted of a gas turbine, Power to Gas (P2G), combined heating and power (CHP) [33], and combined cooling heating and power (CCHP) [34]. Electric boilers and heat pumps combined electric and thermal systems. The CHP and the gas boiler were responsible for connecting the natural gas system to the thermal system. In ICES, the four components of source, network, charge, and storage had used a variety of strategies to raise the proportion of renewable energy consumption, but the potential was restricted. Notably, ICES eliminated the barriers between traditional isolated energy systems, resulting in increased flexibility of system operation. It also expanded the scenarios for renewable energy consumption, such as the conversion of failed renewable energy generation into heat supply to the thermal system using electrothermal coupling elements. Since access to renewable energy sources made for a cleaner energy supply, ICES could better integrate rapidly developing renewable energy technologies, accelerating their replacement of conventional energy sources and ultimately achieving sustainable energy development.

Theoretically, during ICES operation, the energy conversion between multiple energy systems could achieve multi-energy complementarity, which was beneficial to the power factor correction, valley filling of the power system, and the consumption of renewable energy. However, in the current environment of renewable energy grid connection, the critical problem was that wind- and solar-generated electricity could not be utilized instantly [35]. This had significantly inhibited the sustainable growth of renewable energy.

2.2.3. Integrated Demand Response (IDR)

The upper half of Figure 5 shows the conventional DR, which was based on the resource control of the generation side driven by the thermal power unit. Wind power and solar energy, as essential pillars of renewable energy supply, were impacted by random natural elements such as wind speed, light, and ambient temperature and were highly intermittent and variable. In addition, there were uncertainties in the power of various energy loads and internal parameters of the system, such as the equipment's energy conversion efficiency, etc. The operational security and stability of ICES after the access to renewable energy were significantly challenged by multiple influences. In this regard, Refs. [36,37] presented the concepts of Integrated Demand-Side Management (IDSM) and Integrated Demand Response (IDR). IDR could considerably reduce the impact of unpredictable renewable energy generation by promoting energy complementarity, activating the scheduling potential of temperature-controlled loads, and utilizing the inherent energy storage of cooling/heating systems to enhance operational flexibility. The object of the narrow definition of DR was only a single electricity system, while the broad definition of DR included IDR, i.e., the object also included other energy systems in addition to a single power system. The following sections of this paper use the broad definition of DR.

3. Results and Analysis

The review of the literature on all highly relevant topics was completed under the conceptual framework shown in Figure 2. The review result started from the modeling optimization of conventional and non-conventional IES, where the review results of non-conventional IES cover a variety of energy carriers. It was followed by the results of the review of demand-side load profiling, including the workflow, main algorithms, and analysis techniques. In conclusion, the reviewed results of the evaluation and optimization of IDR program were presented, and the reviewed papers were analyzed from the perspective of optimization objectives/constraints and optimization algorithms/models. The result of the review contains critical discussions to show the prevailing methods and possible shortcomings of current research, as well as possible future research opportunities.

3.1. ICES Modelling Optimization

The basis of demand response was to realize the coordinated development of energy users and suppliers. The premise for reaching this objective was the integration of business and information across all connections. Aggregators were IDR-implemented entities [38] that acted as an intermediary connecting ICES and users, creating beneficial energy and financial interactions between them. First, aggregators must conduct a thorough evaluation of the energy output of the supply side and ICES and offer accurate simulations and forecasting models to design the optimal dispatch as well as transaction strategies. However, as previously shown in Figure 5, the interaction and effect of many energy networks in

ICES make scheduling and operation of the system more challenging, posing additional modelling, analytical, and operational optimization difficulties. All ICES system functions are interconnected, meaning that the failure of any function would impact the entire system. Furthermore, regardless of the scale of the energy system considered, results at a larger scale could also be achieved by means of integration. It was therefore important to consider the integration of different energy subsystems, their contribution to the overall system efficiency, as well as the characteristics and optimization of IES itself [39]. In general, the simulation approach of demand response influences the amount of detail addressed in the network model of the subsystems in the IES.

3.1.1. Conventional Integrated Energy Systems and Demand Response

For conventional IES, demand response simulation was typically represented as a virtual Power plant (VPP)/Virtual Generation Unit (VGU) or by means of peak shift restriction. There was usually a certain amount of distributed energy resources (DERs) in IES, which refers to smaller generation units located on the customer's side of the electricity meter. The aggregator integrates all DERs into a single power generation system, which was accomplished by VPP, so the essence of VPP was like an aggregator. The advantage of VPP was that, through DR, it could aggregate flexible capacity to solve peak power demand [40]. In a broad sense, the concept of VGU was like VPP. Ref. [41] considered a gas–electric virtual power plant (GVPP) and introduced PBDR and IBDR to regulate user behavior. Based on the robust stochastic optimization theory, a GVPP stochastic scheduling optimization model was established considering the uncertainties of wind and solar. The results showed that under the objective of maximizing economic benefits, the load curve became smooth, the consumption of renewable energy was strengthened, and the operation risk of the system was reduced. In [42], based on a two-stage optimization model of VPP, a new optimization scheduling method for a power–thermal interconnection virtual power plant considering a market transaction mechanism was established. Ref. [43] modelled DR as a VGU and verified a distributed energy management method for interconnected operation of cogeneration units based on DR through a sub-gradient-based dynamic search direction distributed iterative algorithm.

IDR typically considered the thermal inertia of buildings and thermal loads as schedulable resources for electro-thermal systems and was restricted by the thermal comfort of users. Despite the fact that the CHP system also comprised the thermal system, thermal inertia was typically disregarded in favor of peak shift. Ref. [44] took ice-storage air conditioners as the main optimization equipment, established a multi-energy collaborative optimization model aiming at the lowest comprehensive operating cost according to different working modes, and determined the optimal operation strategy. Ref. [45] considered the scenario of replacing condensing gas boilers with heat pumps, and the results showed that demand response based on active and passive thermal storage could significantly reduce peak electricity demand with the right level of building retrofit and type of heat pump installation.

As mentioned above, a regional or community-level integrated energy system is a dynamic and complex information physical system, and the entities that comprise them may cooperate, not cooperate, or even conflict [46]. In this context, demand-side flexibility management plays a key role. Generally, the demand response plan in the traditional power grid was implemented individually and randomly for entities in the region, which might have had negative effects such as peak rebound [47], affecting the security and stability of the integrated energy system. Coordination and negotiation among various entities within integrated energy systems were seen as an essential strategy for resolving these entities' competing objectives and optimizing demand-side flexible resource allocation.

There was a lot of literature on the coordination and negotiating strategies of various ICES target bodies. These strategies were fundamentally based on the Multi-Agents System (MAS) concept, which typically employed a two-layer coordinated control model. In the prevalent two-layer paradigm, the upper layer typically symbolized the maximizing of economic benefits for stakeholders, whereas the lower layer's target process was typically different. Ref. [48] took the integrated energy system of electricity, grid, and natural gas as an example, and established a two-layer programming optimization model. The model considered two DR procedures by introducing the concept of VPP, namely coupon-based DR and interruptible-load-based DR, and performed optimal scheduling analysis for the integrated energy system with the overall profit maximization of the system as the objective function. Ref. [49] established a two-layer optimization strategy under the peak shifting constraint and tested it in a cold–heat–electric–gas integrated energy system in a park. Under this strategy, IDR regulated more resource types, flexibility, and lower interactive compensation. It resulted in maximizing the benefits of users and multi-energy operators. Ref. [50] established a two-layer operation optimization model for small- and medium-sized regional integrated energy systems with time-varying electricity prices and flexible operation methods, aimed at lower comprehensive energy consumption costs and higher energy efficiency. The target KKT condition was solved as the feasibility measure of the upper-level optimization to obtain the optimal distribution scheme of the output of the renewable energy unit.

The characteristics of various load types, large user groups, and strong randomness of the ICES [51] make the IDR more uncertain, and many simulation methods have been proposed for this. Ref. [52] proposed a short-term stochastic model of EGTran combined with hourly demand response. The model applied the Monte Carlo simulation method to build multiple scenarios to represent the uncertainties of the coordinated power system and natural gas system. The research results showed that the addition of natural gas system constraints greatly increased the amount of calculation. Yet, the case study proved that hourly demand response could provide stable load distribution and was an effective strategy to reduce operating costs. Ref. [53] used Monte Carlo simulations and mixed-integer linear programming (MILP) models to evaluate distributed energy resource wind, price, and demand uncertainty. Furthermore, its impact on the total cost of energy hub operation and reliability was determined.

3.1.2. Non-Conventional Integrated Energy Systems and Demand Response

Scenario 1—Renewable Generation Integrated

The improved economic and environmental advantages of renewable energy sources make them more accessible, with photovoltaics and wind turbines serving as the primary renewable energy inputs for urban-level integrated energy systems. Demand response was seen as an essential method for facilitating the interaction between demand-side resources and renewable energy [54]. The instability and limited predictability of renewable energy output and the energy system presented significant operational issues for ICES. Dealing with the uncertainties associated with IES scheduling was the focus of the current related research, which primarily employs three techniques: resilient optimization, scenario-based approaches, and chance-constrained programming (CPP).

Ref. [55] proposed a two-layer robust optimization model including demand response and thermal comfort, with internal and external levels of optimization to minimize economic investment and reduce the dissatisfaction of residents participating in demand response, respectively. The model considered the uncertainties of multi-energy load and renewable energy forecasting in the integrated energy system, while its effectiveness was proved by simulation comparison. Ref. [56] presented a multi-objective optimization model for integrated energy systems in the context of biogas–solar–wind renewable power generation. A multi-tasking algorithm to optimize the operating cost, carbon emissions, and energy losses of the integrated energy system was designed. Ref. [57] proposed an original bi-level economic–environmental equilibrium model to optimize dispatch strategies for integrated energy systems that included renewable energy generation. The results enabled economic–environmental tradeoffs and addressed stratified interactions. Ref. [58] proposed a scenario-based robust energy management approach through optimizing the worst-case scenarios for renewable energy generation (RG) and loads. It was robust against most implementations of modeling uncertainty sets by Monte Carlo verification. Ref. [59] proposed an optimization framework based on scenario/interval/information gap mixed-decision theory to model the uncertainty of renewable generating units, local energy demand, and solve the optimal access problem under load response as well as electricity price response schemes. Ref. [60] constructed an electrical energy storage device (ESD) model in the form of CCP, which strengthens the coordination of IDR and renewable energy uncertainty, verifying the effective improvement of the final operating economy through a real ICES case. Ref. [61] proposed an optimal regulation model based on CCP, testing the potential of IDR in the context of renewable energy uncertainty. The results showed clear advantages both in terms of system operating costs and carbon emissions. Ref. [62] proposed an interval-based robust chance-constrained optimization model for configuring a demand response program that considered wind power uncertainties and equipment failures. The literature is summarized in Table 2 below.

Table 2. Summary of selected literature about IES scheduling optimization.

<table>
<tr><th>Technical Type</th><th>Ref.</th><th>Algorithm Mainly Used</th><th>Objective Function</th></tr>
<tr><td rowspan="3">Resilient optimization</td><td>[55]</td><td>NSGA-II; Gurobi solver</td><td>Economic; social</td></tr>
<tr><td>[56]</td><td>MO-MFEA-II</td><td>Economic; social; environmental</td></tr>
<tr><td>[57]</td><td>NSGA-II and GA iteration</td><td>Economic; environmental</td></tr>
<tr><td rowspan="2">Scenario-based approaches</td><td>[58]</td><td>Self-built mathematical model; Monte Carlo verification</td><td>Economic; environmental</td></tr>
<tr><td>[59]</td><td>IGDT-based robust model; Fuzzy decision-making algorithm;</td><td>Economic</td></tr>
<tr><td rowspan="3">Chance-constrained programming (CPP)</td><td>[60]</td><td>Mixed-integer linear programming (MILP) model; CPLEX solver</td><td>Economic</td></tr>
<tr><td>[61]</td><td>Mixed-integer linear programming (MILP) model; CPLEX solver</td><td>Economic; environmental</td></tr>
<tr><td>[62]</td><td>Self-built interval based robust CCP</td><td>Economic</td></tr>
</table>

As could be observed from the above literature review, robust optimization was a hedge against the worst-case implementation, making it typically more useful in the study of worst-case uncertainty situations [63]. Nonetheless, conservative solutions restricted its extensive application. Relatively speaking, the scenario-based method has more application, but its optimization outcomes are highly dependent on the quality of scenario development and reduction techniques. The CCP approach coordinates the system's security, dependability, and economic value by establishing an optimum amount of opportunity constraint confidence.

In addition, it was essential to note that, even though ostensibly renewable generation reduces overall generation costs, suboptimal scheduling may increase the final generation cost of thermal units by increasing cycling and decreasing fuel efficiency, hence further increasing the final generation cost. Several adjustments of the ICES electrothermal system were demonstrated to further improve this issue. Ref. [64] explored the opportunity to use electric boilers and thermal storage tanks to improve the flexibility of cogeneration units through a test system, and it turns out that this strategy was more effective in reducing wind curtailment, resulting in better integration of wind power generation. Ref. [65] proposed that the traditional DR has no obvious effect on solving the pressure of wind turbines. Considering the coordinated deployment of thermal energy and electric energy, IDR could improve the flexibility of the complementary coupling of energy flow in the regionally integrated energy system and the utilization efficiency of wind power generation equipment.

Scenario 2—Energy storage systems (ESSs) and electric vehicles (EVs) Integrated

The intermittency of renewable energy supply makes generation less predictable and could lead to incompatibility of ICES with the grid. In this context, the energy storage system (ESS) allows the conversion of electrical energy in the power system into a form that could be stored and then converted back into electrical energy when required (see Figure 6). ESSs are an opportunity to increase the flexibility and resilience of ICES, while also potentially reducing total energy prices [66]. Currently, batteries are still the main energy carrier for ESS in most research. Although biomass energy storage and gas energy storage (such as hydrogen) are still in an immature stage, their huge application potential could already be foreseen, especially for hydrogen storage systems [67].

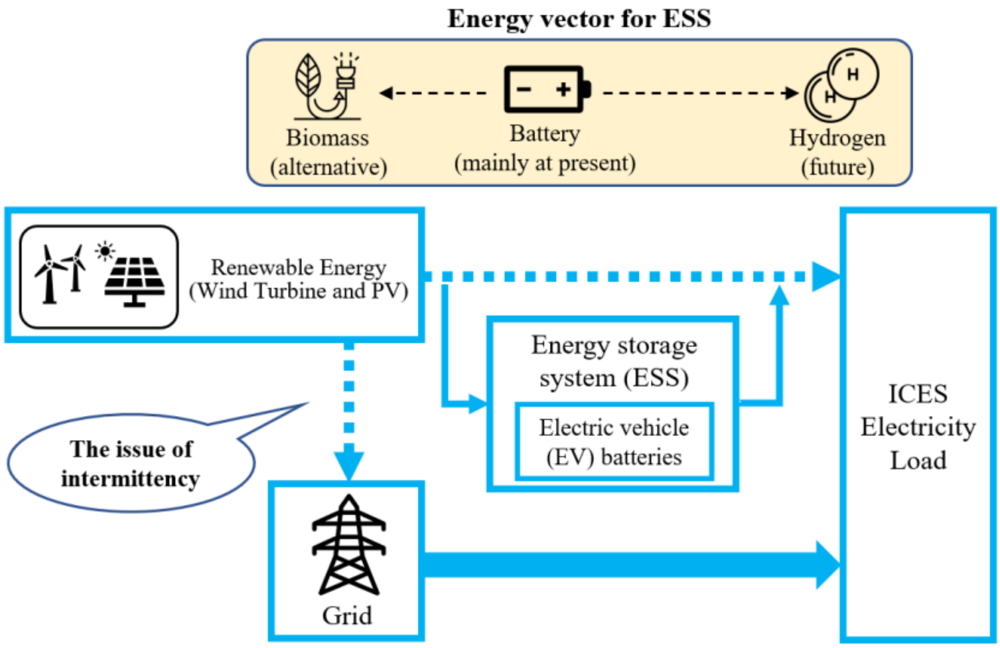

Figure 6. Schematic diagram of the role of ESS and EV in ICES electric system (source: authors' edition).

Specifically, hydrogen has a lower volumetric energy content due to its lower density at room temperature. If various advanced storage and production technologies could be used to achieve higher target energy densities [68], hydrogen, as a perfect ingredient for energy storage or delivery [69], would easily replace the dominant position of batteries, which was very suitable as the main energy vector for ESS in ICES.

ESS could be deployed in ICES and, combined with demand-side management (DSM), it could improve the self-consumption of photovoltaic power generation and reduce the imbalance of supply and demand in the grid [70]. On the other hand, ESS could also be used to react to price signals. When the price of electricity is low, the battery starts charging immediately. When electricity prices are high, the batteries could be discharged, making a profit by selling the electricity back to the grid [71]. The application of ESS at the community scale was also called Community Energy Storage (CES), as opposed to Household Energy Storage (HES) at the single scale. Refs. [72,73] state that CESs may offer additional benefits compared to HESs in terms of economies of scale, energy trading, and enhanced grid balancing capabilities.

There were many advanced algorithms used for scheduling and optimization of ESS and ICES subsystems. Ref. [74] proposed an integrated genetic algorithm and two-point estimation method to calculate the maximum capacity and the remaining energy of the storage system through stochastic modeling. The results demonstrated that this strategy could minimize the total cost of a battery–energy storage hybrid system based on renewable energy generation. Ref. [75] investigated optimal component sizes for each configuration of an integrated energy system by using particle swarm optimization (PSO). A systematic approach to optimal allocation of resources including diesel, photovoltaic, wind, and battery energy storage was identified. Due to the relatively expensive unit energy storage provided by batteries, as well as the routine maintenance cost and unavoidable decay of batteries, the application of ESS in ICES faces numerous constraints in the form of investment cost. Electrochemical energy storage (EES) technology [76], which has become popular in recent years, was also slowly penetrating the market due to its current high capital costs, although prices are expected to drop significantly due to large-scale deployments.

In the context of low-carbon transportation, the rapid increase in the number of electric vehicles (EVs) was an additional alternative with great potential. EVs have numerous qualities, not only the type of load, but also scheduling potential [77]. Nevertheless, this came with a range of complications resulting from the high-power charging of EVs. In contrast, given the comparable unpredictability and uncertainty of renewable power generation, a study into their coordination and scheduling would be appealing. Ref. [78] considered demand response multi-energy system smart community decisions and found that the total operating cost of smart communities decreased when renewable energy and electric vehicles penetrate simultaneously. In addition, EVs could also be regarded as a low-flexibility ESS to some extent but could be enhanced by appropriate IDR strategies. Ref. [79] pointed out that EVs facilitate the integration of variable renewable energy (VRE) and proposed a scheduling strategy that utilized EV charging flexibility to integrate stochastic outputs from renewable energy production. Ref. [80] used a Mixed-Integer Linear Programming (MILP) model based on the Chance-Constrained Programming (CCP) model to build a two-layer optimal scheduling model for a multi-stakeholder scenario with Electric Vehicle Charging Station (EVCS). A balance of interests between ICES and EVCS was achieved through the coordination of flexible demand response with uncertain renewable generation. The ITM project at KEMA Labs in the Netherlands used time allocation techniques and corresponding incentives to coordinate V2G and mitigate the impact of electric vehicles on the grid [81].

In general, ESSs, including EVs, need to continue to strengthen their coupling to renewable generation, including optimization of local systems and flexible IDR programs. Finally, the true prosperity of ESS in ICES would also require policy support at the government level. In this regard, the United States [82] and China [83] have issued some laws and policies, such as encouraging non-utility-scale energy storage systems along with reduction in taxes and fees associated with renewable generation.

3.2. Demand-Side Load Profiling

Quantitative load profiling on the user end which could participate in demand response was the primary method for determining the demand end's potential response. For the traditional single electricity system, the main profiling method was to professionally evaluate the user's demand response potential through the installation of automatic control and communication equipment on the user side by the load aggregator. Aggregators provide economic incentives to consumers based on assessment results, integrate distributed resources into the operation of the power system, and thoroughly investigate load resources to fulfill market requirements. For ICES, the fast implementation of Advanced Metering Infrastructure (AMI) [84] enabled energy system stakeholders to conduct a deeper analysis of user-side energy consumption behavior to evaluate their future participation in IDR.

In the evaluation of demand response potential, Ref. [85] believed that it was necessary to study multiple types of loads and their demand response potential to understand the load elasticity of different types of electrical equipment, the conditions and other parameters supporting the demand response. There was not much research conducted on demand response potential assessment methods, but there was a certain research basis, using the multi-objective programming model (MOP) [86–88] and the computable general equilibrium model (CGE) [89,90].

Researchers have begun investigating a variety of data mining techniques for energy system loads that provide rapid and accurate assessment of demand-side potential. The prevalent load profiling approach was a clustering algorithm, which was an unsupervised, experimental learning technique with no defined result. A considerable amount of high-dimensional and high-volume energy consumption data collected by energy system metering equipment made data dimension reduction a prominent subcategory of cluster analysis. Ref. [91] divided the clustering technology into direct clustering and indirect clustering. The difference between them was whether the clustering technology needed to be implemented after dimensionality reduction rather than on pure original data. Data dimension reduction techniques include linear dimension reduction methods such as Principal Component Analysis (PCA) [92] and nonlinear dimension reduction methods such as Sammon Mapping and Curvilinear Component Analysis (CCA) [93]. On the other hand, clustering algorithms are divided into partitional clustering and hierarchical clustering [94] in related studies of DR. They had key differences in running time, assumptions, input parameters, and result clustering. Partitional clustering included k-means, self-organizing mapping (SOM), and other methods. Among them, the derivative algorithms of the k-means algorithm included K-means++, fuzzy K-means, K-medoids, etc. Hierarchical clustering included density-based and grid-based clustering.

At present, the mainstream load profiling technology is based on a partitional clustering algorithm. Ref. [95] took the load curve recognition of 27 buildings on a university campus as an example and tested the main clustering algorithms, including minimum variance criterion (MVM), Fuzzy C-means (FCM), K-means, and SOM. The superiority of K-means and the SOM algorithm in clustering error along with dimension reduction efficiency compared with other algorithms was proved. Ref. [96] evaluated the performance of several clustering algorithms for evaluating load pattern grouping and pointed out that these clustering methods had different applicability to different representative load patterns (RLP) and a number of customer classes. The K-means method was more suitable for the segmentation of customer groups. Due to its advantages in scalability and time complexity [97], the K-means algorithm had become the most widely used partitional clustering algorithm.

3.3. Evaluation and Optimization of IDR Program

Energy system stakeholders wanted to know the amount of energy saved during peak hours through demand response programs. By comparing this with the cost of the demand response process, the net benefit of these efforts, as well as the optimization methods, objectives, and constraints, could be estimated. Although metering equipment could be used to measure energy use at any given time, to measure peak reductions, the level of energy consumption without DR items must be estimated and then compared to the actual level of energy consumption. In addition, assessing the energy consumption of specific energy equipment might be expensive. Typically, scientific frameworks and mathematical modelling techniques were necessary to evaluate demand response systems and energy system use. Much recent research has modelled and evaluated DR programs in order to determine the effect of DR on the load profile features of energy systems. Various energy stakeholders were involved in the creation and execution of the DR plan; thus, optimization objectives and optimization constraints must be specified, followed by the selection of an effective optimization algorithm/model.

The main objectives of electricity power system DR optimization are usually minimizing total power consumption/total operating costs/carbon emissions or maximizing social welfare [98], while current IDR-related research is usually oriented toward minimizing the total cost. It is worth noting that some application scenarios might have more than one optimization objective, and the game theory method of the multi-objective optimal solution was usually applied. Ref. [99] applied a game theory framework to model competition among demand response aggregators to sell the aggregated energy stored in storage devices directly to other aggregators in the market. Another important concept that extensively uses game theory for IDR optimization was the energy hub (EH), first proposed in 2006 [100], which was defined as the place where different energy carriers are produced, converted, stored, and consumed [101]. The Energy Hub provided the basis for the inclusion of energy modelling, energy planning, energy operations, and energy markets in IES + DR. Much of the literature has dealt with the modelling of IES by introducing EH, and on this basis, researchers studied the game and cooperative operation between EH and IDR. Ref. [102] extended the existing DR program to the IDR program and described the interaction between the intelligent EH and the IDR as a non-cooperative game, using a unique Nash equilibrium sequential game model. Tests were carried out on an integrated energy system of electricity and natural gas, proving the benefits of the IDR scheme to both customers and suppliers. Ref. [37] developed an IDR scheme to connect multiple energy carriers to the smart grid, forming a smart energy hub model based on electricity and natural gas networks. Subsequently, the interaction between EHs was modelled as an ordinal game with a unique Nash equilibrium, which could optimize the developed IDR scheme.

In existing research, the main constraints included power and flow constraints of systems and lines (security constraints). In Ref. [103], for the mixed-integer linear programming model, the minimum annual total cost of the electric–gas coupling IES, the sales capacity of the grid, and the physical constraints of the natural gas grid and the district heating grid are used as optimization constraints. Ref. [104] established an IDR-based IES operation optimization model, which considered the operation constraints of multi-energy equipment and the transmission constraints of multi-energy transmission networks. Based on the safe operation constraints of the power grid and the natural gas network, Ref. [105] proposed an interval-optimized gas–electricity integrated energy system cooperative operation strategy considering IDR.

In terms of model classification, the DR model included dynamic programming and multi-stage stochastic programming. Ref. [106] modelled a DR scheme for power loads based on mixed-integer non-linear programming (MINLP) and solved the optimal probabilistic operation scheduling problem using a single-stage energy hub of 2 m + 1 PEM. Ref. [107] proposed a two-stage stochastic framework, where the first and second stages were the optimal design and optimal operation of the energy hub, respectively. The effectiveness of the DR scheme in energy hubs was assessed under this framework. Ref. [108] proposed a two-stage co-optimization framework that considered the integration of multiple customer types, demand scenarios, and battery energy storage systems (BESSs), which facilitated the most beneficial DR planning decision guidance. Ref. [109] proposed an optimal coordinated investment method for distributed generators and demand response facilities based on a linearized price-elastic demand response model.

Meanwhile, some practical DR evaluation index systems were also established. Ref. [110] established a three-level analytic hierarchy process (AHP) index system to determine the reduction priority and reduction allocation of each demand response. Ref. [111] built a load pattern prediction and evaluation index system based on demand response. To determine the demand response energy conversion potential of different buildings at a given time of day, Ref. [112] proposed a standardized evaluation procedure and evaluation index based on model-predictive control and predetermined price signals to enable aggregators to better select buildings combined to serve the grid more cost-effectively. In terms of DR technology development, the Lawrence Berkeley National Laboratory in the United States successfully developed the Open Automatic Demand Response Communication Protocol (OpenADR) [113] to support the operating model. Subsequently, the OpenADR2.0 specification was divided into OpenADR2.0a [114] and OpenADR2.0b [115]. The former uses low-end equipment to simply implement demand response and price information transmission, while the latter uses higher-end equipment to increase complex scenarios, price-dynamic processes, which could provide feedback and more services.

4. Discussion and Conclusions

Existing studies demonstrated that the combination of ICES and IDR significantly enhanced the performance of local energy systems while contributing to the goals of renewable energy penetration, energy efficiency improvements, and climate change control. Nonetheless, a comprehensive literature assessment has also shown several current obstacles and possibilities in ICES and IDR research. Despite ongoing efforts by a considerable number of research groups, extensive empirical studies of customized or different scales of IES were still lacking and models that completely incorporate the coordination of components in ICES failed to acknowledge a number of potential external influences. Moreover, the integrated community energy system (ICES) had not yet built a comprehensive multi-energy management system and accountability mechanism. Numerous optimal and coordinated control approaches for diverse energy sources were presented in the literature; however, they are frequently case-specific rather than general. In terms of the used models themselves, most two-layer models in ICES research were oriented toward optimal economy; study on the system's reliability restrictions was relatively inadequate, and the system's safety under extreme conditions needed sufficient validation. Little research addresses the critical issue of model convergence speed, which may affect the timeliness of optimal decisions in extreme cases. In addition, as the geographical unit of analysis of the most research interest (community-level), when ICES scales up to the urban level, the rules and mechanisms for energy transactions between different ICESs themselves and the upper layer of the energy network are not yet perfect.

In related research on IDR assessment and control optimization, existing DR models cannot reflect all the essential characteristics of IDR; thus, a more complete coupled IDR model was required. There have been many studies on the provision of auxiliary services such as peak control and frequency modulation for users, but almost all of them were aimed at specific scenarios and IES configurations, often not universal. The design of the current IDR mechanism was fundamentally based on DR, and most of them only evaluate the user's response to the time-of-use electricity pricing. The existing ICES + IDR framework's optimal scheduling mainly aimed to maximize personal gains, which was inconsistent with reality. In addition, most research focused on the optimal dispatch of the integrated energy system, but the research and design of ICES's market mechanism remained in its infancy. The market penetration of the IDR approach was low, and the number of participants restricted its progression. Therefore, it was urgent to develop a practical real-time energy price clearing system and a flexible price incentive mechanism for IDR.

With the rapid development of Advanced Metering Infrastructure (AMI), it was possible to gather and store enormous amounts of high-resolution, actual energy usage data. In this context, the emerging subject of Urban Building Energy Modelling (UBEM) has numerous prospects for the future development of IDR. UBEM could be divided into top-down models based on statistical/data-driven methodologies and bottom-up models based on engineering, which have diverse utility in various situations. In terms of optimizing the IDR approach, the data-driven top-down model has the most potential applications. It could more accurately reflect the energy consumption behavior of consumers than the conventional analytical model, while the design of the IDR strategy would be more effective and adaptive. As shown in Figure 7, UBEM's data-driven model would be able to assist the further refining of the IDR strategy and incorporate the functioning of multiple levels of integrated energy systems in the future. IDR would serve as a vital interface between energy modelling and energy entities under this framework.

Utilizing the integrated benefits and information control capabilities of ICES, IDR would be integrated with ICESs of diverse sizes in the future to actively investigate the application mode and implementation mechanism of demand response. In the context of a large number of installed and distributed grid-connected renewable energy sources and numerous complementary energy sources in the region, further decreasing the implementation cost of IDR would improve the confidence of energy suppliers and consumers. Under the reasonable coordination structure, the economic gains provided by the IDR could be shared with all stakeholders, therefore enhancing the security of the integrated energy system.

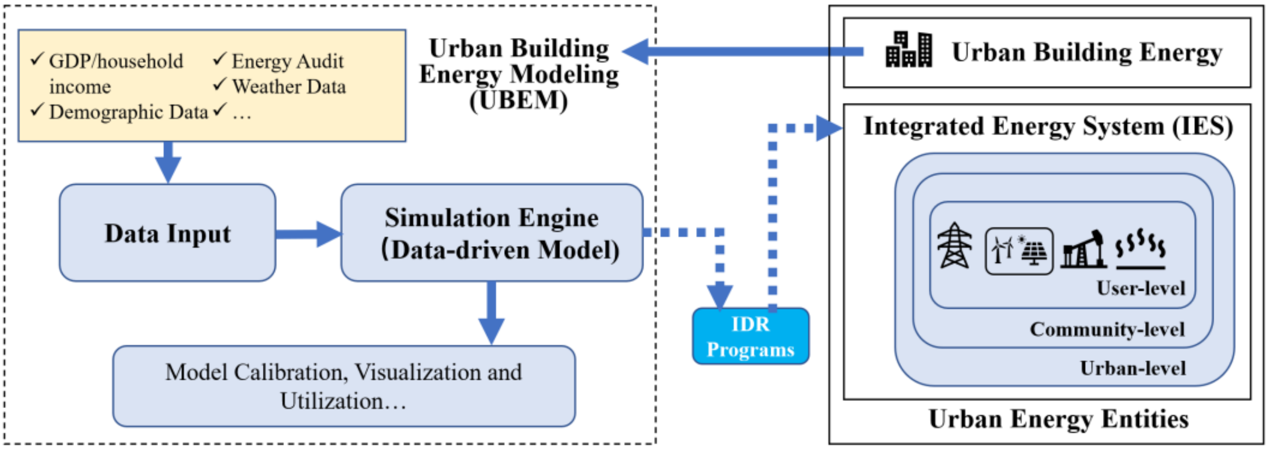

Figure 7. Schematic diagram of IES scheduling using IDR optimized by the UBEM model (source: authors' edition).

Moreover, several advanced technologies are significant contributors to IDR applications. Blockchain technology was crucial for distributing energy transactions [116]. Blockchain would become the fundamental application technology for demand response business models, especially as 5G communications become more prevalent and implemented. Continued improvement of demand response would be steadily automated through plenty of technologies, such as communication technology, and interface standards. Based on artificial intelligence algorithms, it was anticipated that the exact detection and control of user energy consumption characteristics would be accomplished; meanwhile, the quality of multi-energy comprehensive demand response would be enhanced.

Overall, ICES, as a theoretically developable sub-unit of the present energy system transition, stimulated the development of multi-energy system technology as well as the transformation of traditional power systems from DR to IDR. This paper described the advances made in the modelling, coordination, and deployment of integrated demand response in integrated community energy systems. The identification of critical procedures and methodologies for existing ICES and IDR implementations was offered, while the study findings could serve as an effective reference for future efforts to develop a comprehensive operational framework and implementation mechanism for ICES + IDR.

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Abbreviations

AHP	Analytic hierarchy process
AMI	Advanced metering infrastructure
AMI	Advanced metering infrastructure
BESS	Battery energy storage system
CCA	Curvilinear component analysis
CCHP	Combined cooling heating and power
CCP	Chance constrained programming
CES	Community energy storage
CGE	Computable general equilibrium model
CHP	Combined heating and power
CPP	Chance-constrained programming
DER	Distributed energy resource
DR	Demand response
DSM	Demand side management
EES	Electrochemical energy storage
ESD	Energy storage device
ESS	Energy storage systems
EVCS	Electric vehicle charging station
EVs	Electric vehicles
FCM	Fuzzy c-means
GVPP	Gas-electric virtual power plant
HES	Household energy storage
IBDR	Incentive-based demand response
ICES	Integrated community energy system
ICT	Information and communication technology
IDR	Integrated demand response
IDSM	Integrated demand side management
IES	Integrated energy system
MES	Multi-energy system
MILP	Mixed-integer linear programming

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