Reviewing Demand Response for Energy Management with Consideration of Renewable Energy Sources and Electric Vehicles

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Review

Reviewing Demand Response for Energy Management with Consideration of Renewable Energy Sources and Electric Vehicles

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Abstract: This review paper critically examines the role of demand response (DR) in energy management, considering the increasing integration of renewable energy sources (RESs) and the rise in electric vehicle (EV) adoption. As the energy landscape shifts toward sustainability, recognizing the synergies and challenges offered by RESs and EVs becomes critical. The study begins by explaining the notion of demand response, emphasizing its importance in optimizing energy usage and grid stability. It then investigates the specific characteristics and possible benefits of incorporating RESs and EVs into DR schemes. This assessment evaluates the effectiveness of DR techniques in leveraging the variability of renewable energy generation and managing the charging patterns of electric vehicles. Furthermore, it outlines important technological, regulatory, and behavioral impediments to DR's mainstream adoption alongside RESs and EVs. By synthesizing current research findings, this paper provides insights into opportunities for enhancing energy efficiency, lowering greenhouse gas emissions, and advancing sustainable energy systems through the coordinated implementation of demand response, renewable energy sources, and electric vehicles.

Keywords: demand response; energy management system; renewable energy sources; electric vehicle

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1. Introduction

Energy management (EM) is the monitoring, planning, optimizing, planning, and energy conservation process used to build an energy-efficient system [1]. Global energy demand has increased as a result of population growth and increasing urbanization. In recent decades, numerous electromagnetic theories, including sustainable energy, renewable energy, and green energy, have emerged to address the challenges posed by increasing energy consumption. The primary goal of the green energy concept has been to minimize the negative environmental and economic impacts of using non-renewable energy sources [2]. It effectively fulfills the demand for clean energy while mitigating carbon emissions, greenhouse gas emissions, and adverse effects on human health [3]. The concept of sustainable energy was developed to preserve non-renewable energy resources for current and future generations. Sustainable energy is typically generated by combining energy efficiency with the use of renewable energy sources [4]. Renewable energy is an appealing concept that utilizes renewable energy sources (RESs) to meet global energy needs. Tidal, wind, and solar energy are among the most commonly used RESs [5]. The world's energy needs are currently largely satisfied by non-renewable resources like nuclear power, coal, oil, and natural gas. Despite considerable progress driven by experts to enhance the role of renewable energy sources (RESs) in meeting global energy demands, there is growing pressure on the traditional electromagnetic framework to adopt a hybrid model that integrates both renewable and non-renewable energy sources. While modernizing distribution systems into smart grids that efficiently monitor and manage interactions among consumers and utility companies [6], the shift to hybrid energy generation still demands additional enhancements. As a result, the smart grid concept accommodates distributed energy storage, renewable energy generation, and other related technologies [5].

A major challenge currently facing the electrical power system is integrating the unpredictable nature of renewable energy sources (RESs) while maintaining system reliability amidst rapid and widespread electrification. Demand response (DR) has garnered significant attention as a potential solution to these challenges. DR programs seek to encourage customers to adjust their energy consumption in response to factors such as changing prices or incentives. Over the past decade, demand-side management (DSM) solutions have been developed to promote energy-saving behaviors and reduce customer energy costs [7]. The majority of electricity users are used to paying flat rates that do not account for the varying expenses associated with producing and distributing electricity. Demand response (DR) tariffs or programs offer incentives to encourage reduced electricity consumption during peak pricing periods or when system stability is at risk due to these fluctuations [8]. These programs aim to encourage end users to decrease their energy consumption when market prices increase or grid reliability is threatened. The two categories of DR techniques are comprised of both price-based and incentive-based strategies.

- Real-time pricing (RTP) gives clients time-varying rates that illustrate the value and cost of power over various time periods, TOU tariffs, and critical-peak pricing (CPP) periods. When electricity rates are high, customers who are aware of this tendency consume less of it.
- Participating clients are rewarded via incentive-based DR systems for reducing their loads during certain times when the program sponsor requests it, which is usually when there is a grid reliability issue or when power prices are high.

RESs have a high penetration in the scenario of today's power system; utilizing the available energy is necessary to uplift the insufficient power requirement in the system. The RES is disclosed for its authenticity, sustainability, and reliability; having these features, the incorporation of renewable resources has sparked widespread interest. The gap between supply and demand should be as small as is practical, though. DR involves bridging the gap between electricity supply and demand. In a system with dynamic pricing, the ability of utilities and customers to manage their energy consumption is essential. The DR procedure can be finished while the loads are being managed at the distribution end [9].

Current discussions among relevant authorities encompass various concepts associated with demand response (DR) programs, renewable energy sources (RESs), and electric vehicles (EVs), focusing on electrical sourcing, storage mechanisms, and the development of efficient planning to achieve a diverse and optimal electromagnetic (EM) approach [10]. Table 1 outlines the advantages of DR programs.

Table 1. The benefits of DR implementation.

Environment	Utilities	Consumers
Decreased greenhouse gas emissions.	Improvement of system reliability.	Improvement of lifestyle.
Protection of the environment.	Reducing the cost of electricity production.	Improvement of service quality.
Reduction in resource consumption.	Increasing system efficiency.	Reduction in electricity bills.
Reduction in environmental degradation.	Reduction of operational expenses.	Enhancement of electricity supply to meet demand.

Impact statement: Energy management through DR has been widely studied, including the influence of renewable energy sources on energy management. This approach has emerged as a viable strategy for improving efficiency and reducing pollution. Many different DR approaches have been used in the literatures for energy management. RTP-based DR approaches in VPP are not often utilized in such studies. As a result, the used of RTP-based DR for EM provides a broad potential for future study. In addition, electric vehicles as an electrical storage system or source have become a hot topic. On the other side, VPP and MG have extensive research development with demand response.

Contribution: In order to pique readers' interest, this study reviews the use of the DR approach for EM on most of the recent works. Additionally shown is the system's integration of RESs and EVs as well as the use of DR in VPP, MG, and other areas. Utilization of MILP and MINLP, a stochastic programming technique, is also shown in one section.

2. Demand Response

2.1. Price-Based DR

A. Time of Use

TOU pricing's major objective is to retain distinct fixed charges for the consumption of power at different times during the day or week [11]. The typical energy market scenario may be enhanced with TOU pricing, social welfare, or imbalance cost considerations as a price-changing rate system based on daily energy use that is unaffected by daily variations in supplier costs [12,13]. The peak rate, off-peak, and, possibly, shoulder-peak rates for TOU schemes can be separated across a utility-defined time period. Clients are urged to lower their load during peak demand hours by means of TOU pricing plans, which charge very expensive fees during peak demand hours and offer customers inexpensive charges during off-peak demand periods. However, the effectiveness of such a tariff is limited because consumers do not receive incentives in response to a decrease in load. Figure 1 shows the different types of DR programs.

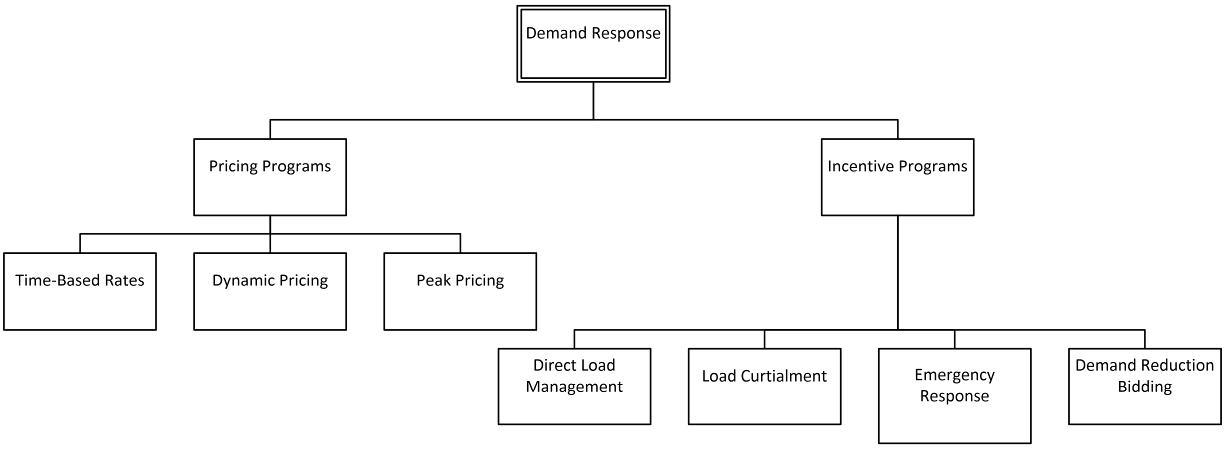

Figure 1. Different types of demand-response programs.

B. Critical Peak Pricing

Critical peak pricing (CPP) and time-of-use (TOU) methods are similar in their approach to setting prices for different times of the day. However, CPP introduces a dynamic rate that allows for short-term, event-based pricing during periods of high demand or other costly system conditions [14]. Unexpected demand shifts brought on by systemic factors such as reserve shortages and bad weather are addressed by the CPP tariff. When applied to flat rates or time-of-use (TOU) rates, the result is a high rate [15]. Both the total number of required days annually and the number of time periods that the CPP rate is in effect are specified in the pertinent contracts. Alternatively, the tool starts a few minutes or hours prior to the CPP rate being implemented and notifies users in real time of a CPP occurrence. There are two more CPP categories: extreme-day CPP and extreme-day price. The CPP rates for peak and off-peak days are exclusive to the most extreme day [16]. The extreme day CPP uses flat rates on all other days. Extreme-day rates, on the other hand, charge hefty fees for energy use that is active around-the-clock.

C. Real-time pricing

Real-time pricing (RTP) enables energy providers to dynamically adjust energy consumption prices, with users receiving advance notifications before each pricing interval [17–19]. In

RTP schemes, fluctuations in energy market pricing, zonal costs, or locational costs directly impact end users [20–22]. Effective transmission of information between energy suppliers and users is essential for the successful operation of RTP systems. The necessity for real-time communication capabilities within energy management systems (EMSs) at user sites poses a significant challenge during RTP scheme implementation [23]. The majority of the information flow between energy sources and EMSs involves high computational complexity, necessitating substantial bandwidth requirements, which can impede system efficiency. In day-ahead RTP (DA-RTP) schemes, users receive advance notifications of predicted real-time prices for the following day and are billed accordingly for their consumption [24].

2.2. Incentive-Based DR

A. Direct Load Control (DLC)

Different types of loads such as lighting, electrical pumps, air conditioners, electrical heaters etc., which are a common residential load, can be directly regulated with a DLC technique, which is preferable to the utilities [25]. Knowing this, the DLC schemes are typically favored for large numbers of residential subscribers [26]. Economic benefit and dependability being the top priorities for every operation, the DLC events might also be triggered [27]. Typically, these systems outline the quantity and duration of interruptions to fulfill end-user expectations adequately and maintain customer satisfaction without compromise [28]. The end user receives rewards or reductions on their electricity bill in exchange for signing up for the DLC system, as well as receiving some reimbursement for additional costs [29]. Because the utility manages these services, the end user is not informed in advance of any problems.

B. Curtailable Load Programs

During peak hours, consumers are often requested to turn off some of their loads according to system requirement and they are given incentives for their load reduction or even for interrupting their normal power-consumption pattern [30]. Curtailable load schemes benefit both medium and large consumers. These schemes are designed for such consumers, and, similar to the DLC program, curtailable load contracts should specify the maximum number and duration of calls. Given that these initiatives are required, consumers who fail to react to DR occurrences risk penalties. In reaction to problems with reliability, utilities may contact customers, but load reductions may also be sold on the market [31].

C. Emergency DR Program

Market-based emergency demand response (DR) programs can be seen as a combination of curtailable load and direct load control (DLC) programs, as they incentivize consumers to decrease energy consumption during peak periods. Customers have the option to decrease their loads to avoid predetermined penalties. In [32], the authors proposed an event-driven DR program scheme, assessing the advantages of adjusting set-points for home electric water heaters. By implementing DR based on a pre-defined table of operations specifying locations and required electricity amounts, potential critical incidents are averted. However, real-world instances have revealed that excessive shedding under emergency DR programs may lead to unforeseen power oscillations, complicating sequential generation control [33].

D. Capacity Market Programs

The capacity market program (CMP) is open to consumers who can reduce the load on alternative generation or distribution resources by a predetermined amount [34]. Customers that take part in a CMP often receive a day's notice to cut back on their energy use, and they get punished if they do not significantly contribute to the load reduction [35]. It is imperative for participants to exhibit that they are able to attain minimal load reduction with assured rewards, regardless of the necessity of limiting their usage.

E. Demand Bidding Programs

Users can actively participate in the energy market by posting load-reduction bids using demand-side bidding [36]. Small customers can take part in the bidding process indirectly through a third party, while large consumers can participate in direct bidding and utilize cutting-edge load management strategies to buy and sell products on the market directly [37]. Demand-side participants are also permitted to participate in the markets for capacity and auxiliary services, providing a range of system solutions services over a range of time periods, as mentioned in [38,39].

F. Day-Ahead Demand Response

This involves planning and scheduling demand-response events a day in advance based on predictions of grid conditions, weather, and electricity prices. Consumers or automated systems receive signals or prices a day before the event, allowing them to plan and adjust their consumption accordingly. The paper [40] explores combining RESs and coal-fired power units with carbon capture schemes. Various DR programs and hydropower plants are used strategically to enhance power system flexibility. The day-ahead (DA) operation planning uses a market-clearing framework, modeled as a risk-constrained, two-objective, stochastic mixed-integer linear programming problem.

Overall, integrating DR options improves performance by cutting costs, emissions, and boosting revenue. This framework addresses RES and demand uncertainties using a hidden Markovian process (HMP) technique. An enhanced augmented ε-constraint method aims to minimize operational costs and CO_2 emissions. In [41], the manuscript introduces the GOA-SNN strategy for day-ahead energy management of hybrid renewable energy systems with DR. Combining PV, diesel generator, and battery systems, the strategy leverages the Gazelle Optimization Algorithm (GOA) and Spiking Neural Network (SNN) to enhance outcomes for consumers and utility providers. It minimizes human intervention and uses bi-directional communication, focusing on off-grid systems. The strategy optimizes scheduling and incentives to maximize HRES operation over 24 h, using GOA for resource scheduling and SNN for demand prediction. Lower electricity prices are used to influence consumer behavior, identifying optimal discount times to improve energy management.

G. Load Side Management

This refers to the techniques and strategies employed to control and manage the consumption of electricity at the consumer side (i.e., homes, businesses, industries). Load side management aims to optimize energy usage, reduce costs, and shift loads to off-peak times to alleviate stress on the grid. Energy communities are vital for the sustainable energy transition by engaging end users actively. Many trials falter due to unrealistic expectations and unpredictable energy-demand behaviors. In [42], the paper analyzes residential load profiles and consumer surveys to refine DSM strategies. It validates appliance behavior for high and flexible loads in three scenarios and uses a genetic algorithm to optimize demand and load profiles with time-variable tariffs. The findings reveal that shiftable appliances can reduce peak load by up to 29%, increase renewable self-consumption, and cut energy bills by 9%. In [43], the study tackles the increasing cost of grid electricity caused by the widening demand-supply gap by creating a hybrid ant colony optimization and genetic algorithm. The algorithm improves demand-side management and supports sustainable energy use. It cuts community peak load demand by 35.4% and reduces costs by 33.67%, outperforming traditional and mutated ACO methods in peak load, total cost, peak-to-average ratio, and waiting time.

H. Load Shifting

Load shifting is a demand response strategy where electricity usage is shifted from peak periods (when demand is high and electricity is expensive) to off-peak periods (when demand is low and electricity is cheaper). This helps in flattening the demand curve and reducing peak loads on the grid. In [44], the research introduces a hybrid DSM technique for managing generation costs and emissions in a low-voltage MG system, using TOU pricing. In Table 2, the author compares the proposed optimization technique with various algorithms recently used in the literature to evaluate ECD and $CEED_{PPF}$ for the test system and finds that the proposed CSAJAYA algorithm delivers the best results with superior solution quality. Here, the author compares the proposed optimization technique with various algorithms recently used in the literature to evaluate ECD and

CEEDPPF for the test system and finds that the proposed CSAJAYA algorithm delivers the best results with superior solution quality. Table 2 highlights the effectiveness of various optimization algorithms in managing economic and environmental costs in a power system with renewable energy integration. The CSAJAYA with DSM algorithm emerges as the most efficient, offering the lowest costs in both ECD and CEED metrics.

Table 2. Comparison of ECD and CEEDPPF metrics for a 5-unit test system across different algorithms [44].

Sl. No	Algorithms	ECD with RES ($)	CEED with RES ($)
1	GA	103,625.2777	120,305.9871
2	PSO	103,474.3922	120,218.7259
3	DE	103,600.8322	120,293.9634
4	SCA	103,477.1104	120,224.3862
5	TLBO	103,478.823	120,254.9188
6	GWO	103,486.5133	120,225.3156
7	MGWO	103,482.164	120,221.5939
8	WOA	103,732.5368	120,600.9558
9	MWOA	103,662.4691	120,464.7106
10	CSA	103,469.3322	120,219.0719
11	MGWOSCACSA	103,468.5678	120,213.5
12	CSAJAYA	103,468	119,807
13	CSAJAYA with DSM	103,107	119,334

The approach reduces generation costs by 10–13% with 30–40% customer participation and balances cost and emissions more effectively than existing methods, as confirmed by statistical analysis and comparisons with prior studies. The paper [45] optimizes energy costs and resource use in home energy management by enhancing participation in DR programs and renewable electricity source, focusing on load shifting and scheduling constraints. Using a genetic algorithm, it reduces costs by up to 24.3% for individual households and 11.8% for a community of 20 homes, with savings of 12.67 EUR and 31.78 EUR, respectively. Community scheduling provides cost reductions of 1.5–26.8% compared to individual scheduling.

I. Peak Shaving

Peak shaving involves reducing electricity consumption during peak demand periods to lower the peak demand level. This can be done through energy storage, distributed generation, or adjusting the operation of certain appliances or industrial processes. Peak shaving helps utilities avoid the need for additional power generation and reduces the overall cost of electricity supply. In [46], the study aims to reduce peak grid demand while ensuring comfort by using an energy-efficient solar PV and battery storage system with a rule-based peak-shaving strategy. Optimized with a genetic algorithm, the strategy achieves energy consumption reductions of 19.02% to 20.9% and peak demand reductions of 33.1% to 49.82%. It also maintains the battery's state-of-charge at 50% by the end of each day, offering flexible daily management. Table 3 shows vademand response types.

Table 3. Types of demand response programs.

Type	Description	Example
Time-Based Rates	Consumers adjust their energy use based on price signals that vary by time.	Time-of-Use pricing, Real-Time Pricing
Incentive-Based Programs	Consumers receive financial incentives to reduce or shift their energy use during peak periods.	Direct Load Control, Demand Bidding
Ancillary Services	Demand response resources are used to provide grid support services, such as frequency regulation.	Frequency Regulation, Spinning Reserve
Behavioral Programs	Consumers receive feedback and insights on their energy consumption to encourage voluntary reductions.	Home Energy Reports, Energy Apps

3. Energy Management

As delineated in [47], the objective of an energy management system (EMS) is to integrate renewable energy sources and distribute diverse energy resources to users with optimal efficiency, thereby guaranteeing system reliability, security, and safety. According to [48], an EMS makes it possible to monitor, manage, optimize, and regulate every facility related to generation, distribution, transmission, and consumption. Thus, taking operational limits into account, the main goal of an EMS is to create a cost-effective and efficient balance between supply and demand.

Each residential client is considered as a smart home EMS in [49], where the author focuses on real-time two-way interactions between a utility provider and several customers. For home EMSs, in [50], the study proposes an hour-ahead DR algorithm. To address the uncertainty in future pricing, an artificial neural network-based steady price prediction model is offered. In [51] the study outlines a day-ahead EMS for reducing operation expenses and improving dependability of a MG while accounting for several difficulties for maintaining thermal and electrical. In order to establish an energy management (EM) technique with demand response (DR) program and hydrogen storage, researchers in [52] build a program logic controller (PLC). In [53], an intelligent park microgrid (MG) is modeled, which integrates solar power, a combined cooling, heating, and power system, energy storage system (ESS), and responsive loads to optimize planning utilizing price-based demand response (DR). Furthermore, in [54], the study investigates stochastic EM in a MG utilizing RESs (solar, wind, and tidal energy) with a disaster recovery plan and storage. In [55], an issue covered is the operation of networked MGs. In order to ensure cost-effective operation, an incremental DR program is taken into consideration in EM. An independence performance index (IPI) for networked MGs to help cooperative multi-objective optimization and reduce energy transfer to the primary grid is presented in [56]. In [57], a novel demand response (DR) strategy utilizing multi-agent deep reinforcement learning is put forward for managing the energy of discrete industrial systems. Meanwhile, [58] proposes a collaborative framework designed to incorporate a targeted DR program with an incentive-based model and a reconfiguration approach into the day-ahead energy management (EM) of microgrids (MGs).

In [59], the research focuses on integrating a HEMS with a smart thermostat, using a MILP model for day-ahead load scheduling. The goal is to improve photovoltaic (PV) self-consumption and achieve cost savings. To efficiently manage refrigerant air conditioning while ensuring thermal comfort, the thermostat is designed using fuzzy logic. For the DR of multi-thermal-zone constructions, [60] offers the ideal method for controlling building energy in connection to a smart electrical grid. The best energy hub (EH) scheduling is suggested in [61] using a multi-objective decision-making approach. Pollution, power outages, average EH reserve, and total EH cost is all considered in the proposed model. In [62], interruptible/curtailable service DR software is suggested to assist energy customers in reevaluating their patterns of energy usage based on incentive and punishment measures. To reduce energy consumption in IoT-enabled homes, the author developed a method utilizing the wind-driven bacterial foraging algorithm (WBFA) from [63]. This method helps lower the peak-to-average ratio (PAR), reduce electricity costs, and enhance user comfort. Taking on the issues of energy management (EM) for microgrids (MG), a three-layer multi-agent system model that incorporates demand response (DR) and energy storage systems (ESS) is adapted to actual Chinese circumstances in [64]. Furthermore, in [65], in order to provide more realistic rewards, an energy management system (EMS) is integrated with an incentive-based DR program and creates a consumer cost function. In order to represent MG scheduling and VPP EM issues simultaneously, a hierarchical model is given in [66]. In [67], the article offers a COVID-19 based optimization approach to manage energy in a power system to increase stability and renewable energy penetration. In [68], the paper aims to develop a strategy for managing distribution feeders to implement emergency demand response (EDR) during overload and contingency situations. The proposed approach in the paper focuses on managing smart home appliances and EVs, taking into account demand rebound and consumer convenience. The strategy is validated through simulations, showing its effectiveness in reducing network stress, minimizing congestion, and maintaining consumer comfort during demand-response events. In [69], the study included considerations for the energy market price, pricing offered by sources of distributed generation (DG), the presence of EVs on the grid, and responsive loads for EM. In [70], a method for regulating energy hubs in the commercial, industrial, and residential domains while taking demand response (DR) activities into account is presented. The model follows the limits of AC optimal power flow and integrates network design to prevent inappropriate power transactions. In [71], a home energy management system (HEMS) that balances distributed energy supplies and load demand while accounting for customer satisfaction, utility prices, and distribution transformer quality is recommended. In [72], a novel self-scheduling approach for HEMSs using a linear discomfort index (DI) that considers end-user preferences in scheduling home appliances is presented. In [73], a HEMS technique is recommended for coordinating household load demand, including electric vehicle (EV) battery activities, in residences without renewable energy source (RES) or energy storage system (ESS) integration. In [74], an integrated optimal energy management (EM) strategy for an AC microgrid (MG) connected to the grid is discussed, aiming to minimize operating costs and reduce emissions. A long-term MG planning optimization approach that considers consumer comfort is introduced in [75]. In two stages, the proposed model employs the endogenous Stackelberg leader–follower relationships; interactions between the MG operator and responsive load aggregators are handled first, followed by aggregator–customer exchanges. This gives a practical methodology for improving the precision of investment appraisals for DR-aided energy systems. The comparison of EMSs using different techniques is summarized in Table 4. Table 5 gives a comparison of literature on EMS.

Table 4. Key technologies in demand response.

Technology	Role in Demand Response
Smart Meters	Provide real-time data on energy consumption and enable dynamic pricing.
Advanced Metering Infrastructure (AMI)	Facilitates communication between utilities and consumers.
Home Energy Management Systems (HEMS)	Allow consumers to automate and optimize energy usage.
Distributed Energy Resources (DERs)	Enable consumers to produce and store energy locally.

Table 5. Comparison of the literature on EMS.

Ref	Types	Solar	Wind	ESS	EV	DR	Uncertainty	MG	Approach
49	EMS	No	No	Yes	No	Yes	No	No	Distributed Real Time Algorithm
50	HEMS	No	No	No	No	Yes	No	No	ANN
51	EMS	Yes	Yes	Yes	No	Yes	Yes	Yes	PSO and MOPSO
52	EMS	Yes	Yes	Yes		Yes	Assumed	No	FLC and PLC Controller
53	EMS	Yes	No	Yes	Yes	Yes	No	Yes	GA
54	EMS	Yes	Yes	Yes	No	Yes	Yes	Yes	Augmented ε-constraint
55	EMS	Yes	No	Yes	No	Yes	Yes	Yes	MILP
56	EMS	Yes	Yes	No	No	Yes	Yes	Yes	Compromised Program
57	EMS	No	No	No	No	Yes	No	No	MADDPG
58	EMS	Yes	Yes	No	No	Yes	Yes	Yes	PSO
59	HEMS	Yes	No	Yes	Yes	Yes	No	No	MILP
60	EMS	No	No	No	No	Yes	No	No	PSO
61	EMS	Yes	Yes	Yes	No	Yes	Yes	No	Lexicography Optimization
62	EMS	Yes	No	Yes	No	Yes	Yes	No	DDFR
63	EMS	No	No	No	No	Yes	No	No	WBFA
64	EMS	Yes	Yes	Yes	No	Yes	No	Yes	ACPSO
65	EMS	Yes	Yes	Yes	No	Yes	No	Yes	EMS-WOA
66	EMS	Yes	Yes	Yes	Yes	Yes	Yes	No	MILP
67	EMS	Yes	Yes	Yes	Yes	Yes	No	Yes	MIQCP
68	EMS	Yes	Yes	No	Yes	Yes	Yes	No	MIP

Table 5. *Cont.*

Ref	Types	Solar	Wind	ESS	EV	DR	Uncertainty	MG	Approach
69	EMS	Yes	Yes	Yes	Yes	Yes	Yes	No	MILP
70	HEMS	Yes	No	Yes	Yes	Yes	No	No	DR Optimization
71	EMS	Yes	Yes	Yes	Yes	Yes	No	Yes	ICDSMMCM
72	HEMS	No	No	Yes	Yes	Yes	No	No	MILP
73	HEMS	No	No	Yes	Yes	No	No	No	HEMS
74	EMS	Yes	Yes	Yes	No	Yes	Yes	Yes	PSO

3.1. Centralized EMS

The centralized energy management system (EMS) comprises a singular central controller, a robust computer system, and a secure communication network. This architecture oversees energy consumption regulation. The central controller, serving as either a utility or aggregator, collects data from all nodes, including distributed energy resource (DER) energy generation, load and consumer energy consumption patterns, meteorological data, and relevant market participant information. These data are utilized to execute an optimization program, ensuring goal achievement and efficient system operation. This centralized control system offers the best overall performance, but it also has significant drawbacks. This control system is less suitable for real-time communication requirements because all information is received and managed in one location, especially if a sizable amount of assets need to be managed [76].

3.2. Decentralized EMS

Peer-to-peer communication and autonomous control abilities are features of the distributed processing system of the decentralized EMS design. By enhancing expandability, permitting greater operational flexibility, and preventing single-point failure, the decentralized EMS architecture thereby overcomes the shortcomings of the centralized architecture by preventing single-point failure in [76].

3.3. Hierarchical EMS

A hierarchical architecture divides the system into several levels of control, each with a unique set of control objectives as mentioned in [77]. The norm calls for two- or three-level systems. Information is exclusively transferred between units at nearby levels; there is no information exchange between units at the same level. Supervisory control, optimization control, and execution control are the three basic EMS hierarchy levels. Sublevels at each level are also a possibility, depending on how the system is described.

4. EV Charging Scheme

The charging behavior of EVs is optimized by optimizing the overall grid stability and renewable energy availability, mentioned in [78]. To combat the possibility of not charging to the specified SOC as well as the percentage of interruption, a scheduling-driven algorithm is used to determine the chargeability of EVs with DR in [79]. To give EV customers advice on how to charge with the least amount of volatility and expense, an extensive communication framework is presented in [80]. In [81], a dynamic differential game model is formulated, utilizing time-of-use (TOU) pricing from the power grid and electric vehicle (EV) charging capacity. The objective is to mitigate peak-to-valley differences in the power grid and reduce EV charging costs. In [82], an application of real-time pricing for demand response (DR), aiming to increase EV charging participation while minimizing electricity expenditures, is introduced. In [83], the maximum increment in locational marginal price for two demand-side management (DSM) programs, load shifting, and demand bid price responsiveness, during evening charging scenarios, is reduced from 9% to 5% compared to the base-case scenario. In [84], it discusses the development of price-based and incentive-based DR scenarios for corporate EV fleets, along with optimization methods to improve EV charging schedules. Table 6 presents details on various types of plug-in electric vehicles (PEVs), while Figure 2 illustrates the state-of-charge (SOC) and demand characteristics of PEVs over time. Figure 3 depicts EV charging scheme.

Table 6. Popular PEV brands [23].

Brand	Capacity (kWh)	Percentage (%)	Pch-Max (KW)
Nissan Leaf	40	25.52	11.5
Tesla Model S	100	21.81	17.2
Tesla Model X	100	18.64	17.2
Renault Zoe	41	15.00	20
Alliance other PEV	25	19.03	12.5

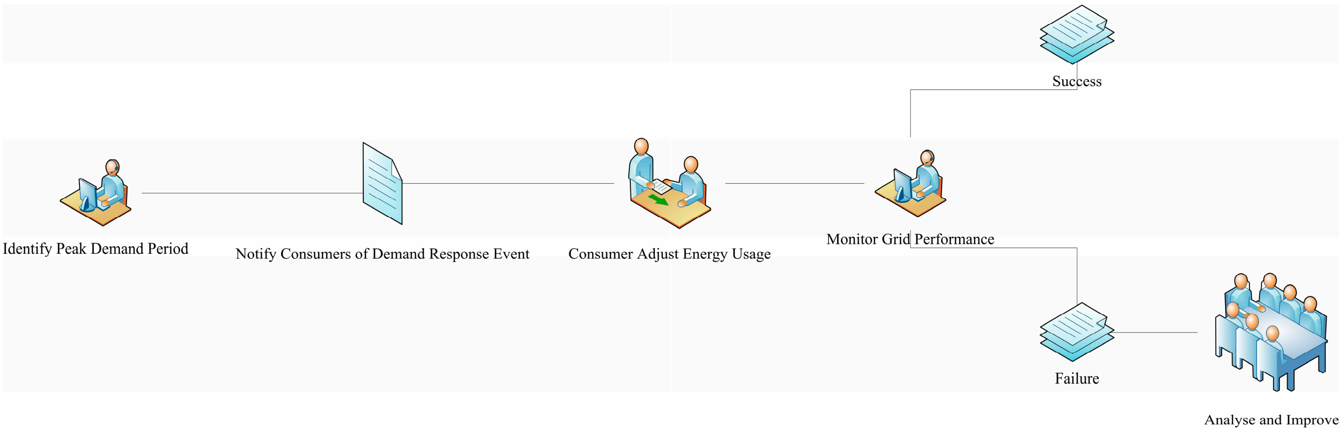

Figure 2. Demand Response Process.

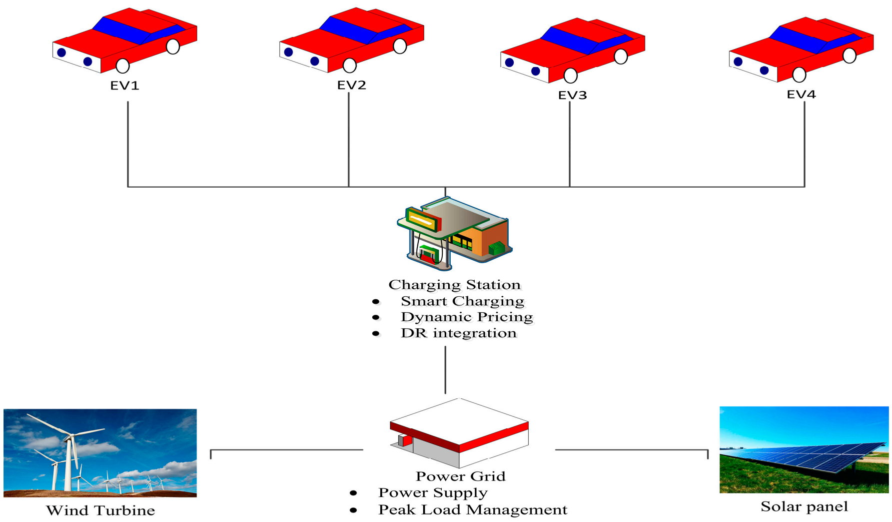

Figure 3. EV charging scheme.

The DR-based EV charging optimization approach is also used in [85], where a multi-objective charge-discharge model of EVs is built and real-time energy pricing is studied. In [86], the paper proposes an ideal EV control model with DR that takes into consideration the current price of power. The active demand program management and EV charging control are handled by a multi-agent system that is intelligent and decentralized, and the EV charging system is properly regulated to support system voltage stability [87]. In [88], the study presents algorithms that anticipate the aggregation of EV charging and an EV model considering EV charging characteristics. These algorithms are then integrated into the multi-agent system.

5. DR in the Presence of Renewable Energy Source

Renewable energy sources (RESs) have been increasingly integrated into the power grid, achieving substantial penetration levels in [89]. Large-scale electricity generation from various RESs, including hydroelectric, solar, wind, tidal, geothermal, and biomass energy, is pivotal in diminishing the dependency on traditional fossil fuels for energy production in [90].

Solar energy is currently the top source for an environmentally clean, secure, and reliable power source in [91]. A small portion of this enormous source is what they are using. Wind energy is a viable form of renewable energy in [92]. The key advantage is that this energy usage works even when the weather is unfavorable. The position of the wind turbine is critical for achieving maximum efficiency because it boosts the system's effectiveness. Rapid water flow is used to generate hydropower. Any other traditional sources of energy can be replaced by it. Its application is limited due to its availability in various places. There exist various opportunities for harnessing the potential of water flow. Tidal energy is derived from the conversion of water movement into electrical energy. Geothermal energy exploits the heat stored beneath the Earth's surface, providing a renewable and environmentally clean energy source. Energy from living organisms is used to produce biomass. The sun's energy is stored as a chemical molecule in biomass. This energy is released during a chemical process.

However, the continuous growth of power also leads to the requirement of developing these technologies. RES has a huge impact in the upstream as well as in individual residential homes. End users not only buy power from the grid but also have the potential of selling their power produced to the grid through smart grid technology. Renewable resources are also termed as DGs. Several DGs are combined and are capable of forming a MG as well as a VPP [93]. Proper planning of DGs is an important aspect for the power provider company and reducing the planning cost might also be done using DR. There are a number of uncertainties to be considered for the renewable resources due to the varying random input parameters. A power smoothing service must be provided to challenge the stochastic nature, which can be performed using DR and EV in [94].

DR in Virtual Power Plant

A new approach to industrial virtual power plants (IVPP) programming considers the coexistence of EVs and DR initiatives. In order to increase system profitability, improve grid dependability during peak load periods, and lessen load shedding in industrial clusters, an innovative solution is offered for industrial virtual power plants (IVPPs) to optimize energy management [95]. Figure 4 shows a simple representation of VPP.

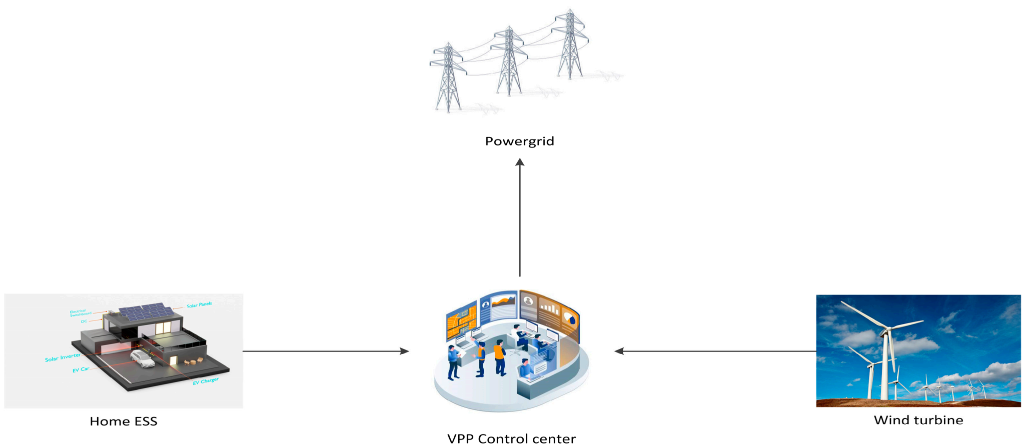

Figure 4. Simple representation of VPP.

Electric vehicles (EVs) that are available in parking lots are used in tandem with demand response (DR) loads in this optimization. With the aim of optimizing IVPP revenue, the objective function is developed for DER short-term production planning in conjunction with EV integration and DR projects. The impact of a VPP that integrates resources from EVs, DR, and WPPs on the energy market is assessed. The stochastic multi-period game models for day-ahead (DA) power markets and the concept of oligopolistic competition are described [96]. These models employ techniques for generating and reducing scenarios to handle uncertainties in wind speeds and incorporate a penalty system for any discrepancies between the WPP's actual output and the agreed-upon quantities. In [97], a stochastic chance-constrained planning approach is employed to create a multi-objective optimization model for scheduling VPPs. This model evaluates the cost of implementing demand response (DR) by analyzing the variation in system revenue. It integrates conventional power plants with a VPP composed of a fleet of electric vehicles (EVs), a wind power plant, and a solar power plant. The VPP's operations are guided by a stochastic scheduling model that accounts for uncertainty through three objective functions. Furthermore, a three-stage hybrid intelligent solution is proposed, integrating the entropy weight method, fuzzy satisfaction theory, and particle swarm optimization algorithm to tackle the problem. Given an example from Table 7, in a VPP with RESs, the following scenario illustrates DR throughout the day:

- 00:00: Total demand is 50 MW (30 MW renewable, 20 MW non-renewable). No DR adjustment, net demand is 50 MW.
- 06:00: Demand rises to 70 MW (40 MW renewable, 30 MW non-renewable). DR reduces demand by 10 MW, net demand is 60 MW.
- 12:00: Peak demand is 120 MW (80 MW renewable, 40 MW non-renewable). DR reduces demand by 30 MW, net demand is 90 MW.
- 18:00: Demand drops to 90 MW (60 MW renewable, 30 MW non-renewable). DR reduces demand by 10 MW, net demand is 80 MW.
- 24:00: Demand is 60 MW (35 MW renewable, 25 MW non-renewable). No DR adjustment, net demand is 60 MW.

Table 7. DR interacts with renewable energy sources within a VPP example.

Time	Total Demand (MW)	Renewable Generation (MW)	Non-Renewable Generation (MW)	Demand Response (MW)	Net Demand (MW)
00:00	50	30	20	0	50
06:00	70	40	30	−10	60
12:00	120	80	40	−30	90
18:00	90	60	30	−10	80
24:00	60	35	25	0	60

DR adjustments help optimize renewable energy use and maintain grid stability.

As detailed in [98], the virtual power plant (VPP) concept is introduced to streamline the integration and use of distributed energy resources (DERs). The demand response (DR) model applied focuses on price-based DR for common loads and incentives. To improve the VPP's profitability, the issue is tackled using a mixed-integer linear programming (MILP) approach. In [99], risks associated with such integration are investigated and an integrated approach is proposed to mitigate them by making use of FACTS devices. In [100], the presented work tackles the same issue, but develops a different approach to mitigate the risk, i.e., by developing financial instruments as incentives and punishment.

6. DR with Mixed-Integer Programming

To investigate the effects of DR on shared EV planning operations, a mixed-integer programming model including DR operations has been proposed in [101]. The model comprises two stages, the first of which involves setting up the charging station and the second of which involves transporting the car. In order to explore and approximate supply-side and demand-side uncertainty into manageable forms, additional techniques are used, including entropy knowledge, distributional robust set, sample average approximation, and multi-level charging times for EVs. Optimizing the risk analysis of a microgrid (MG) connected to an electric vehicle parking facility and a disaster recovery plan—two more flexible resources—is the main focus of study as mentioned in [102]. More precisely, better financial and environmental goals are to be achieved through a major integration of renewable energy sources (RESs) including solar and wind energy. Under this scenario, the system operator is in charge of figuring out the best ways to react to changes in the load, the real-time power market, variations in the output of PV and wind power, and the actions of drivers of electric cars. In this decision-making process, the risk is measured using the conditional value-at-risk criterion.

The topic of SCUC when a DR program and merged PEV fleets are present is covered in [103]. Reduced operational expenses are the goal, provided that all constraints are followed. In addition to security requirements, a variety of limitations are taken into account, including those for the system, units, transmission system, DR program, and PEVs. A suitable PEV model is created to allow for their integration into the grid while taking into account efficiency, charging and discharging characteristics, and the SCUC as a two-stage stochastic MIP issue. Additionally, this paper presents a workable model of DR program based on the idea of demand elasticity at a given price.

In [104], it is suggested to use a hierarchical model to simultaneously represent the MG scheduling and VPP EM problems. Since the scheduling inputs are stochastic, a scenarios-based approach is used to model the uncertainty in power generation and load demand. A stochastic MILP model is the result, which is the final model. The fluctuations can be covered at the lowest feasible cost by utilizing DR program and EVs.

According to base load and plug-in electric car loads, a nonconvex MIP model of household load is described in [105]. This idea's main objective is to lower power costs for home customers by altering PEV charging and discharging strategies depending on current price information (RTP). An inertial neural subnetwork and a feedback neural network are utilized in conjunction with a neurodynamic method to address this problem.

An innovative approach to day-ahead optimization for an integrated water–heat-electricity system is provided with the aim of achieving the reduction of fuel costs associated with purification, heat treatment, and power production units [106]. This strategy involves pure electric vehicle aggregators actively participating in bulk energy management (EM). These aggregators use cheaper, off-peak hours to charge their cars and charge them during the more expensive, peak hours. The optimizer of the generalized algebraic quantitative modeling approach produces a mixed-integer non-linear program, which is solved through the use of the branch-and-reduce optimization navigator (BARON) tool. To assess the water–heat–power hub system's viability and economics is the aim.

In [107], the study leverages mixed-integer linear programming (MILP) to evaluate the operations of a smart home. This smart home framework encompasses several key elements: a small-scale distributed generation (DG) unit that supports grid energy, energy storage systems (ESSs) with capabilities for peak clipping and valley filling, electric vehicles (EVs), and another small-scale DG unit used for charging and vehicle-to-home (V2H) operations. Various case studies are conducted to explore different demand response (DR) strategies, taking into account dynamic pricing and peak power limitations. These analyses aim to assess the technical and economic impacts of integrating ESS and DG units into smart home environments [108].

7. Energy Hub

An energy hub is a centralized facility designed to unify various energy conversion, storage, and distribution processes within a single system. These hubs are essential for enhancing the efficiency, reliability, and sustainability of energy supply networks. They make use of energy routers for electrical energy routing [109]. This section delves into the concept of energy hubs and their practical applications, highlighting their critical function in merging different energy sources to optimize the distribution and utilization of energy. We will also explore how energy hubs can incorporate demand response (DR) strategies to enhance the efficiency and sustainability of energy management systems (EMS). This analysis will underscore the potential advantages and challenges of using energy hubs to balance energy supply and demand, lower energy costs and emissions, and boost the reliability of energy networks. Figure 5 shows the conceptual flowchart of an energy hub.

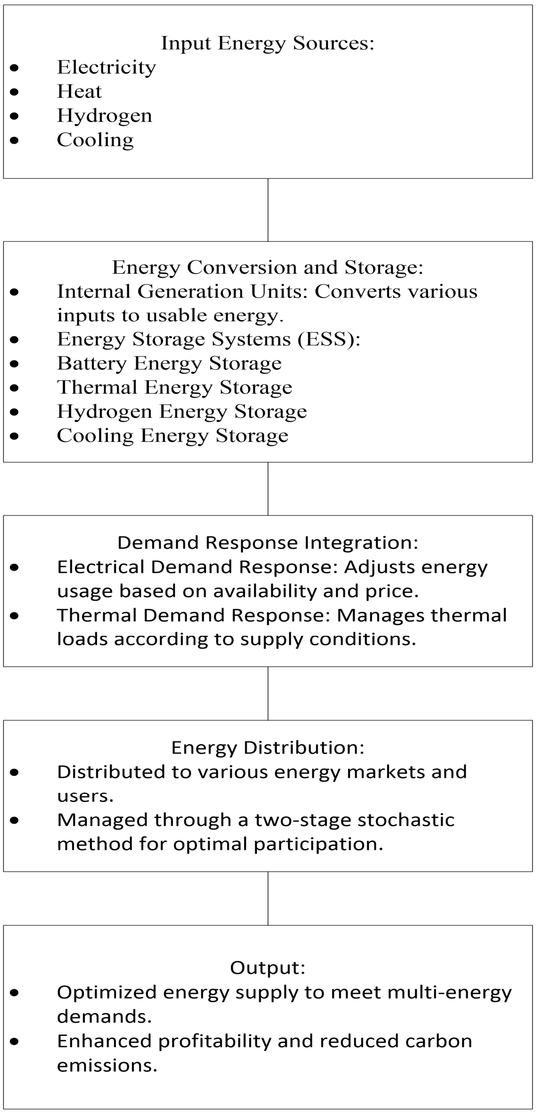

Figure 5. Conceptual flowchart of an energy hub.

In [110], the research focuses on tackling the self-scheduling challenge encountered by a virtual energy hub, which must contend with diverse uncertainties while engaging in multiple energy markets. The virtual energy hub manages multi-energy demands encompassing electricity, heat, hydrogen, and cooling by utilizing internal generation units and participating in various energy markets. It integrates critical elements such as cooling energy storage, thermal energy storage, and hydrogen energy storage systems. This paper aims to propose a robust strategy for optimizing a virtual energy hub's participation in various energy markets. It introduces a risk-averse management approach, employing a two-stage stochastic method to manage uncertainties. The approach also incorporates demand-side management through both electrical and thermal demand response programs. The study demonstrates that incorporating different types of energy storage systems into a virtual energy hub significantly boosts its profitability. Specifically, adding a battery energy storage system increases profits by 0.88%, thermal energy storage by 0.62%, cooling energy storage by 0.7%, and hydrogen energy storage by 1.5%. Moreover, implementing electrical demand response programs raises profits by 1.02%, while thermal demand response programs contribute an additional 0.25%.

In [111], an energy hub based on hydrogen is proposed for day-ahead scheduling through the implementation of a robust algorithm. The hydrogen storage system stores hydrogen, which can be converted into electricity during peak hours or supplied to the hydrogen industry for use during off-peak times. Additionally, a transferable integrated demand response system is provided to control the load pattern of consumers within the energy hub. In the proposed scheme, EV parking is also incorporated in the integrated demand response program, with EVs providing flexibility to the energy hub by adjusting their charging patterns according to the supply and demand of electricity. The integrated demand response system can help balance the grid, reduce carbon emissions, and lower electricity costs for EV owners and other consumers.

In [112], a distributed, two-sided multi-energy coordination framework is suggested in order to optimize energy supply from energy hubs (EHs) and user energy consumption, hence minimizing overall system costs. The approach successfully strikes a balance between user pleasure and EH fuel costs. The framework effectively handles many energy forms through the use of a standardized matrix modeling technique, enabling energy hubs (EHs) to handle a variety of energy kinds beyond just a few specific ones. Customers can also control energy- and time-shifting loads using this way. Customers can optimize their energy use by varying their use at different times and moving between energy sources, such as from gas to electricity, with integrated demand response (IDR). Through a dynamic network, EHs and consumers exchange information with only their close neighbors. A completely distributed sub-gradient averaging consensus algorithm that balances energy supply and demand at each time interval is presented in the paper. Numerical simulations show the algorithm's practical efficacy, while theoretical validation verifies its convergence and optimality.

The study in [113] aims to model an advanced energy hub that is fitted with a range of storage systems, including electrical and thermal storage, conventional energy sources like gas and electricity, renewable energy sources like wind, and a boiler for heat generation in addition to a combined heat and power unit. The hub operator improved the energy hub's concept and associated costs to ensure optimal simultaneous production of heat and electricity. The performance of the energy hub was to be evaluated in the following phase in relation to a load response program. According to the results, system expenses were reduced by 4.66% when the demand response software was optimized as opposed to running as normal. Additionally, the application greatly raised the battery's charge levels. Peak load was effectively lowered during peak times by moving peak load from periods of high demand and high prices to periods of lower demand and cost. As a result, the demand response program seems to be a very useful instrument for energy hub systems load management.

In [114], a novel IoT-based model covering the residential, commercial, and industrial sectors is presented. It investigates the relationships between different energy carriers across networked energy hubs. These hubs integrate a variety of technologies, such as boilers, heat storage units, plug-in hybrid electric vehicles (PHEVs), renewable energy sources, and combined heat and power (CHP) units. In order to reduce uncertainty related to renewable resources, researchers developed a stochastic framework that makes use of the unscented transformation technique. The results of the simulation show that trading heat and power amongst energy hubs significantly lowers reliance on natural gas and electricity, which lowers total network costs. Because they provide necessary loads during hours of peak demand, energy storage devices are very helpful at off-peak times. Moreover, network running costs are greatly reduced and the load demand curve is smoothed by including demand response (DR) programs and encouraging optimal energy use. This significantly affects the energy markets.

In [115], an energy hub is presented with an integrated residential demand response (DR) model, enabling consumers to actively engage in the energy system. Through a demand response program, the system can adjust load demands, empowering residential users to flexibly increase or decrease their energy consumption. This is achieved by adjusting the timing of electrical appliance usage or switching energy types, facilitated through IoT integration. IoT devices are pivotal in managing household appliances, allowing them to align with the demand response program. This flexibility implies that demand response capabilities within the energy hub can vary dynamically over time. The research findings highlight substantial cost savings, indicating that optimizing residential appliance usage via IoT can achieve more than a 70% reduction in total operating costs over a day with flexible demand response limits. Furthermore, the study reveals that for every 1% increase in demand response tolerance, there is a two-fold increase in the percentage of operational cost savings. Table 8 shows key components.

Table 8. Key components.

Component	Function
Internal Generation Units	Generate energy from various sources.
Energy Storage Systems	Store energy in various forms for later use.
Demand Response Programs	Optimize energy consumption patterns.
Energy Distribution Network	Distribute energy to different users and markets.

A demand-side management (DSM) approach for integrated community energy systems is presented in [116]. Using a dynamic energy router model, the study first evaluates energy conversion efficiency under various load scenarios. The energy hub model takes into account the availability of various energy sources as well as the demand for energy. Next, a demand response (DR) strategy that incorporates renewable energy generation is shown. Real-time pricing is used in the method to adapt to changes in renewable energy supply and load demand. To improve operational efficiency, a multi-objective optimization method is also designed with an emphasis on maintaining economic sustainability and decreasing carbon emissions. This approach takes device limitations into account when producing and transmitting energy. The suggested paradigm lessens the burden on the infrastructure supporting the energy supply, lowers carbon emissions, and dramatically enhances the financial performance of integrated community energy systems.

An improved load dispatch model for multi-carrier energy systems is presented in [117], taking into account the interplay between thermal and electrical energy components. The model's main objective is to reduce overall costs in the energy hub system, including resource costs, the effect of carbon emissions, and demand response (DR) initiative costs. The work presents a flexible robust optimization strategy to address uncertainties related to renewable energy sources and demand response (DR) programs. Three scenarios, each with a different level of energy storage integration and DR program implementation, were the subjects of simulation studies carried out by the researchers. The simulations show that the overall operating expenses of the energy hub system can be significantly reduced by incorporating energy storage systems with DR programs.

The functioning of an energy hub intended to satisfy thermal, electrical, and gas demands is examined in [118]. Electric vehicles (EVs), a boiler, a heat storage unit, a combined heat and power system, a wind turbine, and a power-to-gas (P2G) storage system are some of the components that this energy center incorporates. An emphasis on load-shifting is placed on a demand response (DR) program in order to boost the hub's operational flexibility. The study also looks at how three different electric vehicle (EV) charging scenarios—scheduled charging, uncontrolled charging, and vehicle-to-grid (V2G) charging—affect the energy hub's efficiency. The findings suggest that implementing V2G charging for EVs and combining P2G technology with DR can result in significant operational cost savings.

In [119], the study presents a new method designed to maximize gas and energy consumption in smart homes that are part of domestic energy hubs. The model includes several energy conversion technologies, including heat and energy storage systems, combined heat and power (CHP) units, and effective management of both electrical and thermal demands, with an emphasis on balancing cost-effectiveness and environmental sustainability. The goal of the technique is to minimize tenants' overall energy consumption and expenses by scheduling household duties as efficiently as possible. It looks into how merging micro energy communities (MEC) and time-of-use (TOU) demand-side management (DSM) might improve residential energy hubs (REH). The outcomes of the simulation show a decrease in emissions and energy expenses. Optimized energy storage reduces operating expenses, while heat storage devices assist balance natural gas consumption. This method not only guarantees effective scheduling and improves resident comfort, but it also makes it possible to sell excess electricity back to the grid, which lowers procurement costs even further. Table 9 highlights the effectiveness of different algorithms in achieving cost minimization in various energy system optimization scenarios.

Table 9. Comparison of numerical results for various algorithms applied to system optimization.

Ref. No	Algorithm	Objective	Formulation	Obtained Numerical Result ($)
[111]	Robust Optimization	Minimize system costs	$Cost = \min(\alpha_E P_{E,imp} + \alpha_G P_{G,imp} - \alpha_{hyd,\exp} + C_{store,hyd} P_{store,hyd} + C_{store,EV} P_{store,EV} + C_{E,up} + C_{E,down} + C_{T,up} T_{up} + C_{T,down} T_{down})$	36,886.1
[112]	Distributed sub-gradient averaging consensus algorithm	Minimize system cost by balancing EH fuel expenses with consumer benefits	$Obj = \min\left(\sum_{t\in P}\sum_{i\in I} C_{i,t} X_{i,t} - \sum_{j\in J}\sum_{\sigma\in S_{aux}} B_j R_{j,\sigma} Z_{j,\sigma}\right)$	2957.89
[113]	MILP	Minimize cost of EH	$\min Cost = \sum_{t\epsilon T}\left(\begin{array}{l}\alpha_{em} E_t + \beta_{chp} C_{chp,t} + \\ \gamma_{boil} C_{boil,t} + \varsigma_{end,t} + \varepsilon_p P_t\end{array}\right)$	1609.601
[116]	Interior Point Method	Minimize 24 h operating cost of ICES	$Obj = \min(C_{es} + C_{er})$	6163.66
[117]	MILP	Minimize total operating cost	$OF = \min(C_{elec} + C_{gas} + C_{em} + C_{edr} + C_{hdr})$	383.58
[118]	MILP	The EH evaluated components like boilers, wind turbines, P2G, EVs, and CHP, optimizing their schedules to minimize total operating costs	$Fobj = \min\left\{\sum_{t=1}^{T}(\alpha_e E_t + \alpha_g G_t + C_{eind} P_{wind,t}) + \sum_{t=1}^{T}[C_{DR}(DR_{up,t} + DR_{dn,t}) - C_{HS} H_{HS,t}] + \sum_{t=1}^{T} C_{GS} S_t - \sum_{t=1}^{T}\sum_{n=1}^{N_{EV}} C_{EV} P_{D,ev,n,t}\right\}$	42,531.80 (30% DR participation)

A novel scenario-based stochastic programming technique is presented to control wind velocity unpredictability when arranging an energy hub's daily operations in [120]. In order to meet demand for hydrogen and transfer it via a hydrogen network, this hub combines equipment for power conversion to hydrogen and storage tanks. In addition, a demand response (DR) program is presented in order to align supply and demand for energy. In order to evaluate the suggested strategy and look into the impacts of electrical and thermal DR programs, the research performs three case studies. Investigating hydrogen's function as the main energy carrier is the main focus. The findings indicate that the multi-energy system performs noticeably better when hydrogen is prioritized as the primary energy source rather than a secondary one, especially in terms of emissions reduction.

In [121], the study proposes an improved concept for an optimal load distribution system that aims to maximize price effectiveness and reduce CO2 emissions. The model combines various energy generation components such as combined heat and power (CHP) units, gas boilers, water pumps, heat storage units, hydrogen storage systems (HSS), photovoltaic (PV) arrays, and wind turbines (WT), establishing a comprehensive analytical structure. A thorough assessment of probable future swings in energy prices is made possible by the study's handling of uncertainties related to the output of renewable energy and the inconsistent charging habits of electric vehicles (EVs). A demand response (DR) program is integrated into the model to assess the impacts of water pumps and hydrogen storage systems while analyzing thermal and electrical systems. An improved particle swarm optimization (PSO) method is applied to address the optimization problem. The outcomes demonstrate the method's efficacy, especially in supporting EVs' synchronized charge/discharge strategy to reduce total expenses.

8. Discussion

In exploring the future landscape of demand response for energy management, it becomes evident that strategic integration of real-time pricing with virtual power plants, enhanced utilization of electric vehicles through vehicle-to-grid capabilities, and the development of hybrid energy systems comprising renewable and storage technologies present significant opportunities for innovation. Furthermore, the adoption of advanced optimization techniques and stochastic modeling can address the inherent uncertainties in energy supply and demand, paving the way for more resilient and efficient energy systems. By combining these strategies with smart grid technologies and hybrid incentive-based and price-based DR programs, the potential for transforming energy management practices is substantial, offering a pathway towards achieving sustainability, reliability, and economic viability in modern energy networks.

The following Table 10 shows a critical analysis of the strategies with their respective advantages and disadvantages.

Table 10. Analysis of the strategies with their respective advantages and disadvantages.

Topics	Advantages	Disadvantages
Energy Management	- Facilitates efficient energy use and management. - Supports integration of renewable energy sources (RES) with conventional grids. - Reduces carbon footprint by promoting green energy practices.	- Requires significant initial investment in technology and infrastructure. - Complex integration with existing systems, potentially leading to operational disruptions during transition phases.
EV Charging Scheme	- Reduces EV charging costs through optimization techniques like time-of-use (TOU) pricing. - Enhances grid stability by mitigating peak demand using dynamic pricing strategies. - Provides flexibility to EV owners through smart charging options.	- Uncertainty in charging due to reliance on real-time pricing and DR strategies. - Possible inconvenience to users due to variable charging schedules.
DR in the presence of Renewable Energy Source	- Promotes the use of RES by balancing supply-demand gaps through DR. - Enhances grid reliability by integrating distributed generation (DG) and virtual power plants (VPPs). - Supports end users' active participation in energy markets, potentially lowering energy costs.	- High variability and uncertainty in renewable energy output require sophisticated management strategies. - Potential for reduced energy reliability if not managed correctly, especially during peak periods or low renewable output.
DR with Mixed Integer Programming	- Provides optimized solutions for energy management considering both supply and demand uncertainties. - Enables integration of EVs and DR programs in energy markets, enhancing overall system efficiency.	- Computationally intensive and complex, requiring significant resources and expertise to implement effectively. - May require simplifications that could impact the accuracy of solutions in real-world applications.

Table 10. *Cont.*

Topics	Advantages	Disadvantages
Energy Hub	- Integrates multiple energy sources (e.g., electricity, heat, gas) to optimize energy flow and reduce costs. - Enhances resilience by diversifying energy supply and storage options. - Supports sustainable energy management by utilizing renewable and non-renewable resources efficiently.	- Complex system design and operation, requiring advanced control systems and algorithms. - High capital costs and potential regulatory challenges in implementation.

8.1. Main Findings

Integration with RES:

DR plays a crucial role in managing the fluctuations and unpredictability of renewable energy sources like solar and wind. By synchronizing energy usage with energy production, DR enhances the efficiency of clean energy utilization and minimizes dependence on fossil fuels.

Role of EVs:

The growing use of electric vehicles brings both challenges and opportunities for demand response. EVs can act as adaptable loads, and by leveraging DR programs, their charging times can be optimized to alleviate grid congestion and support the integration of renewable energy.

Technological Advancements:

Advancements in smart meters, energy storage systems, and data analytics are improving the accuracy and effectiveness of DR strategies. These technologies facilitate the real-time monitoring and management of energy usage, resulting in more efficient implementation of DR initiatives.

Economic and Environmental Benefits:

DR programs play a key role in lowering greenhouse gas emissions and reducing operational costs. By shifting energy use away from peak times and optimizing overall consumption, both utilities and consumers can realize considerable cost savings while also gaining environmental advantages.

8.2. Future Trends

Enhanced Interoperability:

Future research should focus on developing standards and protocols to improve interoperability between DR technologies and energy systems. This will enable seamless integration and communication between different components of the energy system.

Advanced DR Solutions:

The development of more dynamic and responsive DR strategies that leverage real-time data and analytics will be a key area of focus. These solutions should be adaptable to changing energy demands and market conditions.

Consumer Behavior Studies:

Understanding consumer behavior and preferences is crucial for designing effective DR programs. Research should explore methods to increase consumer engagement and participation, such as personalized incentives and feedback mechanisms.

8.3. Potential Areas for Research

Energy Hubs:

Investigating the use of energy hubs, which integrate various energy conversion, storage, and distribution processes, can enhance the efficiency and sustainability of energy management systems. Research can explore the potential advantages and challenges of using energy hubs to balance energy supply and demand.

Impact of EV Adoption:

With the ongoing increase in EV adoption, research should prioritize understanding the effects of EVs on DR programs and the energy grid. This includes investigating strategies for managing EV charging and incorporating EVs into the larger energy management framework.

Integration with Smart Grids:

The integration of DR with smart grid technologies offers opportunities for enhanced energy management and optimization. Research should investigate the potential synergies and challenges associated with this integration.

Integration of Machine Learning and AI:

Integrating machine learning and artificial intelligence into demand response frameworks presents another promising area. Research could focus on predictive modeling and data analysis techniques that facilitate real-time adjustments in energy usage based on consumer behavior patterns and environmental data. For instance, utilizing physics-informed neural networks could enable more adaptive control strategies.

Long-Term Sustainability Studies:

Long-term studies examining the sustainability and resilience of demand response strategies in the context of climate change and energy supply volatility are necessary. Research could focus on how demand response can be used to support grid stability during extreme weather events or crises, which has not been sufficiently addressed.

9. Conclusions

In summary, this review underscores the significant potential of demand response (DR) when integrated with renewable energy sources (RESs) and electric vehicles (EVs) to revolutionize energy management and promote a sustainable future. Through an extensive synthesis and analysis of the literature, this paper highlights the various benefits and challenges associated with incorporating DR, RESs, and EVs into modern energy systems. The review begins by elucidating the critical role of demand response in optimizing energy consumption, enhancing grid flexibility, and addressing the intermittency issues of renewable energy generation. DR programs encourage consumers to modify their electricity usage in response to price signals or grid conditions, providing a crucial mechanism for balancing supply and demand, lowering peak loads, and improving overall grid stability. Moreover, the integration of advanced technologies like smart meters, energy storage systems, and data analytics facilitates the implementation of more sophisticated DR strategies. These technologies enhance the precision and efficiency of energy demand management, paving the way for more dynamic and responsive energy systems.

Additionally, the review underscores the significant potential of integrating renewable energy sources (RESs) and electric vehicles (EVs) within demand response (DR) frameworks. With solar and wind energy increasingly prominent in the energy landscape, DR mechanisms can effectively manage the variability inherent in these sources. This integration promotes the optimal utilization of clean energy resources while reducing reliance on fossil fuels. Moreover, the widespread adoption of electric vehicles presents both opportunities and challenges for DR. EVs serve as flexible loads that can be managed through DR programs to optimize charging schedules, alleviate grid congestion, and facilitate the integration of RESs. However, their extensive adoption necessitates careful planning and coordination to ensure alignment with existing DR mechanisms and mitigate potential strain on electricity infrastructure.

In conclusion, while the synergies between DR, RESs, and EVs hold promise for advancing energy sustainability, several barriers must be addressed to realize their full potential. Regulatory frameworks must evolve to incentivize the deployment of DR and support the integration of renewable energy and electric vehicles into the grid. Moreover, technological advancements and innovation are essential to enhance the interoperability and scalability of DR solutions, enabling seamless integration with evolving energy systems. Additionally, education and outreach efforts are needed to raise awareness and encourage consumer participation in DR programs, fostering a culture of energy conservation and resilience. Overall, by capitalizing on the complementary strengths of demand response, renewable energy sources, and electric vehicles, stakeholders can unlock new opportunities for achieving a more resilient, efficient, and sustainable energy future.

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Abbreviations

EM	Energy management	WBFA	Wind-Driven Bacterial Foraging Algorithm
RESs	Renewable Energy Sources	PAR	Peak-to-Average ratio
DR	Demand response	DFR	Distribution Feeder Reconfiguration
DSM	Demand-side management	DG	Distributed Generation
RTP	Real-time pricing	DER	Distributed Energy Resource
EVs	Electric vehicles	MADDPG	Multi-Agent Deep Deterministic Policy Gradient
VPP	Virtual Power Plant	PSO	Particle Swarm Optimization
MG	Micro Grid	DDFR	Dynamic Distribution Feeder Reconfiguration
MILP	Mixed Integer Linear Programming	ACPSO	Adaptive Weight and Chaotic search Particle Swarm Optimization
MINLP	Mixed Integer Non Linear Programming	WOA	Whale Optimization Algorithm
TOU	Time of Use	MIQCP	Mixed-Integer Quadratic Constrained Programming
CPP	Critical Peak Pricing	MIP	Mixed-Integer Programming
DLC	Direct Load Control	ICDSMMCM	Incentive-Compatible Demand-Side Management Market-Clearing Mechanism
CMP	Capacity Market Program	PEVs	Plug-in Electric Vehicles
PLC	Program Logic Controller	IVPP	Industrial Virtual Power Plants
ESS	Energy Storage System	WPP	Wind Power Plants
IPI	Independence Performance Index	DA	Day-ahead
PV	Photovoltaic	SCUC	Security Constrained Unit Commitment
HEMS	Home Energy Management System	EH	Energy Hub
CEED	Combined Economic Emission Dispatch	SR	Spinning Reserve
CSA	Crow Search Algorithm	DE	Differential evolution
ECD	Economic Cost Dispatch	GWO	Gray Wolf Optimisation
MGWO	Modified Grey Wolf Optimisation	MGWOSCACSA	Modified Grey Wolf Optimisation Sine Cosine Algorithm Crow Search Algorithm
TLBO	Teaching Learning Based Optimisation		

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