Demand-Side Flexibility in Power Systems, Structure, Opportunities, and Objectives

A Review for Residential Sector

Golmohamadi, Hessam; Golestan, Saeed; Sinha, Rakesh; Bak-Jensen, Birgitte

Published in:
Energies

DOI (link to publication from Publisher):
10.3390/en17184670

Publication date:
2024

Document Version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Golmohamadi, H., Golestan, S., Sinha, R., & Bak-Jensen, B. (2024). Demand-Side Flexibility in Power Systems, Structure, Opportunities, and Objectives: A Review for Residential Sector. *Energies*, *17*(18), Article 4670. https://doi.org/10.3390/en17184670

energies

IMPACT FACTOR 3.0

CITESCORE 6.2

Review

Demand-Side Flexibility in Power Systems, Structure, Opportunities, and Objectives: A Review for Residential Sector

Hessam Golmohamadi, Saeed Golestan, Rakesh Sinha and Birgitte Bak-Jensen

Special Issue

Renewable Energy Power Generation and Power Demand Side Management

Edited by

Prof. Dr. Bingtuan Gao, Dr. Xiaofeng Liu and Dr. Lixia Sun

MDPI

https://doi.org/10.3390/en17184670

energies

Review

Demand-Side Flexibility in Power Systems, Structure, Opportunities, and Objectives: A Review for Residential Sector

Hessam Golmohamadi *, Saeed Golestan, Rakesh Sinha and Birgitte Bak-Jensen *

Department of Energy, Aalborg University, 9220 Aalborg, Denmark; sgd@energy.aau.dk (S.G.); rsi@energy.aau.dk (R.S.)
* Correspondence: hessamgolmoh@energy.aau.dk (H.G.); bbj@energy.aau.dk (B.B.-J.)

Abstract: The integration of renewable energy sources (RESs) is rapidly increasing within energy systems worldwide. However, this shift introduces intermittency and uncertainty on the supply side. To hedge against RES intermittency, demand-side flexibility introduces a practical solution. Therefore, further studies are required to unleash demand-side flexibility in power systems. This flexibility is relevant across various sectors of power systems, including residential, industrial, commercial, and agricultural sectors. This paper reviews the key aspects of demand-side flexibility within the residential sector. To achieve this objective, a general introduction to demand flexibility across the four sectors is provided. As a contribution of this paper, and in comparison with previous studies, household appliances are classified based on their flexibility and controllability. The flexibility potential of key residential demands, including heat pumps, district heating, electric vehicles, and battery systems, is then reviewed. Another contribution of this paper is the exploration of demand-side flexibility scheduling under uncertainty, examining three approaches: stochastic programming, robust optimization, and information-gap decision theory. Additionally, the integration of demand flexibility into short-term electricity markets with high-RES penetration is discussed. Finally, the key objective functions and simulation software used in the study of demand-side flexibility are reviewed.

Keywords: battery storage; demand flexibility; electric vehicle; heat pump; residential; uncertainty

check for updates

Citation: Golmohamadi, H.; Golestan, S.; Sinha, R.; Bak-Jensen, B. Demand-Side Flexibility in Power Systems, Structure, Opportunities, and Objectives: A Review for Residential Sector. *Energies* **2024**, *17*, 4670. https://doi.org/10.3390/en17184670

Academic Editor: Adrian Ilinca

Received: 29 August 2024
Revised: 10 September 2024
Accepted: 15 September 2024
Published: 19 September 2024

1. Introduction

1.1. Why Demand Flexibility?

In the last decade, the penetration of renewable power, including wind and solar, has been increasing in power systems worldwide. Some countries have scheduled plans to increase the penetration of renewable energy sources (RESs) up to 100%. For example, Denmark has committed to a 100% renewable power supply by 2050 [1]. In this way, many fossil fuel power plants are retired and replaced with renewable ones. Increasing RES penetration, the intermittency and volatility of the supply side increase noticeably. In addition to the phase-out of fossil fuel power plants, due to growing concerns about environmental problems, the use of fossil fuel vehicles is decreasing in the world. Instead, the penetration of electric vehicles (EVs) is increasing gradually. EVs are highly mobile electrical demands with variable connection points to power grids [2]. Therefore, the imperfect data of the connection points introduces significant uncertainty in power systems. As a result, future power systems will encounter considerable uncertain data not only on the supply side but also on the demand side. To hedge against intermittent generation and consumption, future power systems need demand-side flexibility in power system management.

Based on the above-mentioned facts, there are two main reasons to emphasize demand-side flexibility in power systems. The reasons can be summarized as follows:

1. The phase-out of fossil fuel power plants and vehicles.
2. The phase-in of RESs and EVs with intermittent power generation and consumption.

1.2. Flexibility in Demand Sectors

Demand-side flexibility is the portion of demand that can be changed, i.e., reduced, increased, shifted, or curtailed, in response to external stimuli. The stimuli can be price-based or incentive-based demand response programs (DRPs) [3] to encourage consumers to change their electricity consumption. In power systems, there is a wide variety of electricity consumption on the demand side. To unlock power flexibility, the demand side should first be split into different sectors, including residential, commercial, industrial, and agricultural. This classification makes it possible to schedule DRPs for each sector based on its electricity consumption characteristics. Expert knowledge is therefore required to understand the key characteristics of electricity consumption. Flexibility studies should be conducted for each sector individually because demand profiles, load patterns, and flexibility potentials exhibit significant variability across the different sectors. Moreover, each sector has different operational constraints, energy consumption behaviors, and regulatory frameworks, which impact their response to demand-side management strategies. It is worth mentioning that multi-carrier energy systems, e.g., integrated gas and electricity [4] and hydrogen systems [5], exhibit significant flexibility potentials.

In the residential sector, there is significant flexibility potential in the electricity consumption of Heat, Ventilation, and Air Conditioning (HVAC). Additionally, in recent years, electrically operated heat pumps (HPs) have been replacing conventional fossil fuel heating systems. HPs are an economical alternative, not only reducing energy consumption costs but also facilitating the integration of renewables into power systems [6]. Therefore, much more flexibility potential can be extracted from residential buildings. In addition, by increasing the use of smart household appliances, the electricity consumption of shiftable devices, such as washing machines, can be scheduled to align with the flexibility requirements of the supply side [7]. Moreover, heating and cooling systems [8], water heaters [9], EVs, household appliances, and home batteries [10] are introduced as the main sources of demand flexibility in the residential sector. Furthermore, small renewable self-generation facilities, such as photovoltaic panels [11] and micro wind turbines can facilitate demand flexibility in the residential sector.

In the industrial sector, many processes in both light and heavy industries can offer considerable demand flexibility to the grid. Generally, industrial plants consist of energy-intensive processes. By unlocking power flexibility in these processes, significant demand response (DR) can be injected into the supply side. Some heavy industries, such as cement manufacturing plants, include interruptible processes [12]. Therefore, these processes can be interrupted in response to the flexibility requirements of the power system. In this way, uninterruptible processes can be supplied by feedstock from storage. Storage facilities can increase the flexibility of such industries. In the case of light industries, there is significant flexibility potential in food industries, such as dairy processing plants, which consume both power and heat in their internal processes [13]. Recently, cement manufacturing plants [14], metal and aluminum smelting [15], pulp and paper milling [16], and oil refineries [17] have been extensively discussed in the literature for their potential demand flexibility. In addition, many industries are equipped with Combined Heat and Power (CHP) units that can be scheduled to provide heat-to-power flexibility for both industrial operations and the upstream power grid [18].

In the agricultural sector, there are many flexibility opportunities in open-air farms, such as water irrigation systems and poultry farms. On farms and in greenhouses, water irrigation pumps can be operated based on the flexibility requirements of the supply side. Energy-intensive groundwater pumps can be turned off or down during renewable power shortages. Water booster pumps with Variable Frequency Drives (VFDs) can adjust water pressure to provide up/down-regulation for the power system during surpluses or shortages of renewable power [19]. In poultry farms, electrically operated HPs can be installed to adjust electricity consumption in response to renewable power availability on the supply side. In these farms, heat controllers play a key role in flexible power consumption. To integrate the flexibility potential of the agricultural sector into power systems, a major restructuring is required in this sector [20].

Related to the commercial sector, recently, the use of EVs has increased considerably. EVs are mobile electrical storages that can act as prosumers in power systems. Since EVs are parked for long hours during the day, the electrical storage capacity of their batteries can be used to provide power flexibility. The charging and discharging capacity of EVs can be used for the up- and down-regulation of the power system during their dwell time [21]. Smart charging stations, including those in private and public parking lots, can optimize the charging and discharging strategies of EVs, not only to provide flexibility to the power system but also to generate profit for EV owners [22]. Many parking lots in commercial shopping centers and airports now accommodate EVs for extended periods. When equipped with smart charging stations, these parked EVs can serve as a reliable flexibility resource for power systems with high-RES penetration [23]. In a recent study, public parking lots were considered virtual power plants supplying the commercial sector and shopping malls [24]. Furthermore, hypermarket refrigerators [25] can provide demand flexibility to local grids in the commercial sector.

Based on the abovementioned facts, power flexibility in demand sectors requires expert knowledge. Therefore, flexibility opportunities should be aggregated separately in each demand sector. Segregated flexibilities may not meet power system requirements. To address this, a Demand Response Aggregator (DRA) is introduced to coordinate demand-side flexibilities based on the technical requirements of the supply side. The DRA is defined as a marketer, broker, public agency, city, county, or special district that combines loads of multiple end-use customers to facilitate the sale and purchase of electrical energy, transmission, and other services on their behalf [26].

The DRA provides contracted consumers with opportunities to understand their demand flexibility on one side and integrate the aggregated flexibility potentials into power systems on the other side. Based on expert knowledge, residential, commercial, industrial, and agricultural DRAs, i.e., RDRA, CDRA, IDRA, and ADRA, are identified. Additionally, Parking Lot Aggregators (PLAs) are introduced to coordinate the charging and discharging strategies of EV fleets in response to power system requirements. Figure 1 depicts a schematic diagram showing the role of DRAs as intermediary agents in power systems. This figure illustrates how flexibility potentials are aggregated on the demand side and integrated into the supply side.

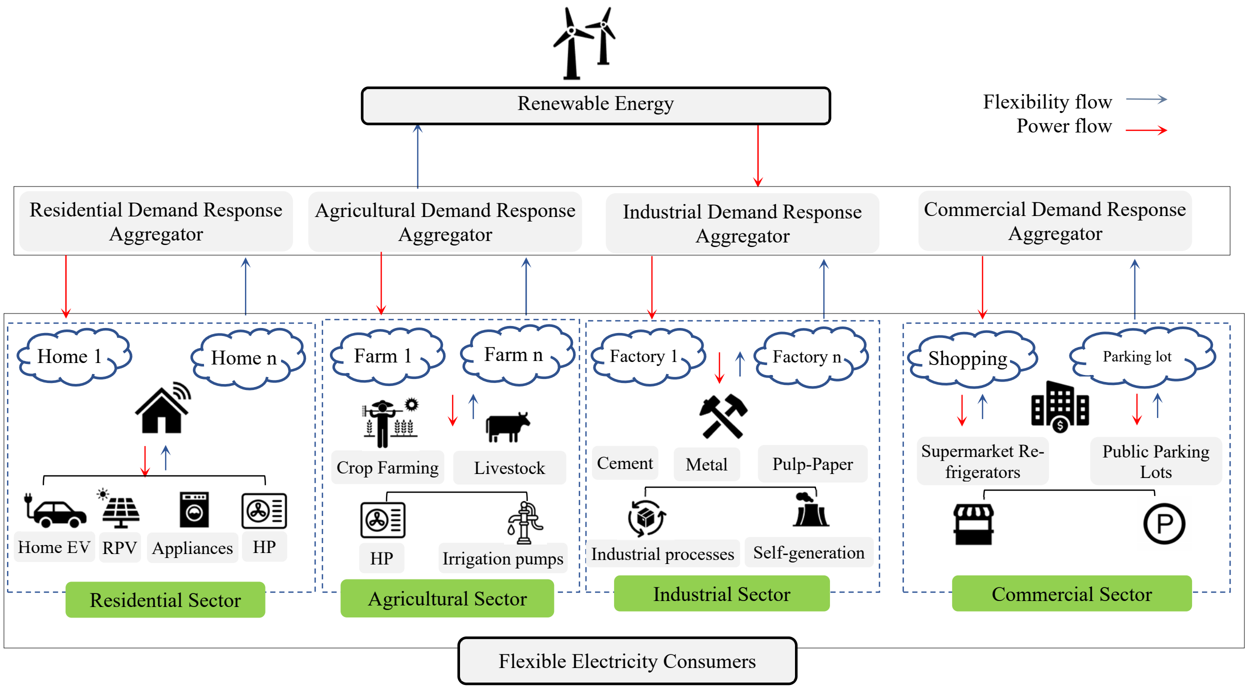

Figure 1. General overview of flexibility in four demand sectors [27].

1.3. Paper Structure and Contributions

This paper reviews the key concepts of demand-side flexibility with an emphasis on the residential sector. The main contributions of the paper are as follows:

(1) Classification of household appliances: a classification of household appliances from the perspectives of flexibility and controllability is provided, along with a comprehensive review of the most important residential demands, including HPs, district heating, EVs, and PV-battery systems.
(2) Survey of demand flexibility under uncertainty: a survey of demand flexibility under uncertainty is conducted, focusing on three recent models, including stochastic programming, robust optimization, and information-gap decision theory.
(3) Review of objectives and simulation software: a comprehensive review of the main objectives of demand flexibility and the software tools used for scheduling demand flexibility is carried out.

The rest of the paper is organized as follows: Section 2 reviews demand flexibility in the residential sector and home energy management systems. Section 3 addresses demand flexibility under uncertainty. Section 4 discusses the integration of demand flexibility into short-term electricity markets. Section 5 reviews the key objective functions, communication and data exchange, and software simulations. The challenges and limitations of current technologies for demand-side flexibility, as well as future works, are discussed in Section 6. Finally, Section 7 concludes this study. Figure 2 shows the main contents of the paper.

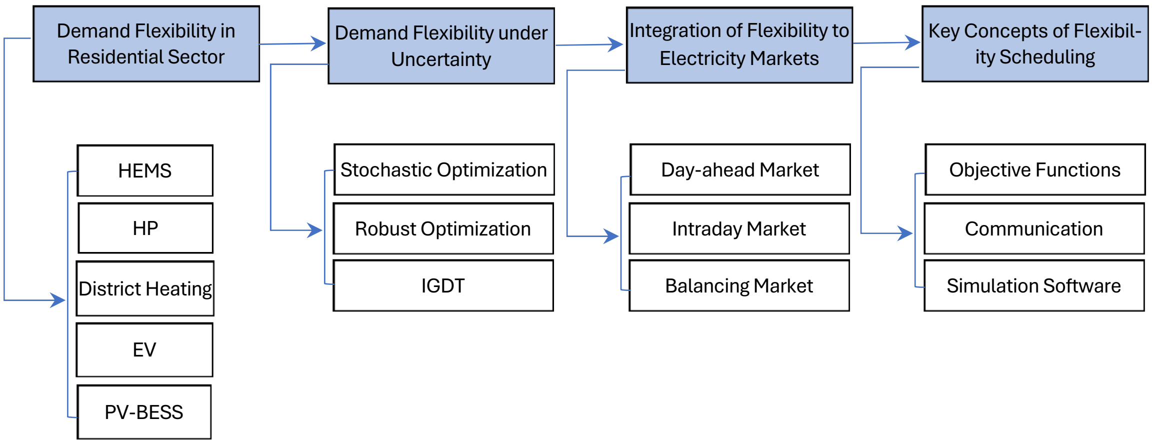

Figure 2. The main contents of the paper.

2. Demand Flexibility in Residential Sector

From 1974 until now, electricity consumption has been increasing across demand sectors worldwide. In 2018, the residential sector consumed 6008 TWh of electrical energy [28]. In comparison with other sectors, this represents 27% of the total electricity consumption. The high share of power consumption in the residential sector is a key factor contributing to power system flexibility.

To fully harness the flexibility potential of residential demand, it is first necessary to identify and classify flexible demand based on its controllability. In the following subsections, after providing a general classification, the flexibility potential of the most important residential demands is reviewed.

2.1. Classification of Household Appliances

In residential buildings, electricity consumption varies widely from energy-intensive appliances, such as HVAC systems, to low-power devices, such as LED lamps. Some household appliances, such as HVAC systems, can store energy during daily operations. This energy storage capability is reflected in the building's thermal dynamics [29]. The operation of certain appliances can be shifted to specific times without causing inconvenience. For example, washing machines and tumble dryers are shiftable appliances [30]. To investigate the flexibility potential of residential buildings, household appliances can be classified into three distinct categories, as follows:

(1) Thermostatically controllable appliances (TCAs)
(2) Controllable non-thermal appliances (CNTAs)
(3) Uncontrollable appliances (UAs)

TCAs are appliances whose energy consumption follows thermal dynamics. Examples include HVAC systems, electric water heaters (EWHs), HPs, and refrigerators. The flexibility potential of TCAs is reflected in their thermal dynamics, which are described by Differential Equations (DEs) [31]. Therefore, to unlock the power flexibility of TCAs, sophisticated controllers are needed to optimize these DEs [32]. The power consumption of HPs can be optimized to unlock the flexibility of both space heating and domestic hot water consumption [33]. In addition, the power consumption of household refrigerators can be optimized by addressing door-opening patterns to provide peak shaving for power grids [34].

CNTAs are electrical appliances whose operational flexibility is independent of thermal dynamics. Examples include lighting systems, dishwashers, and washing machines. This group can be divided into two subgroups: (1) deferrable CNTAs and (2) curtailable CNTAs. Deferrable CNTAs, such as washing machines and dishwashers, are devices whose operations can be shifted to times outside of DR events, such as during low-price hours. In this case, the CNTA operation is deferred to off-peak hours without changing the total electricity consumption [35]. In contrast, curtailable CNTAs include appliances whose power consumption can be adjusted (increased or decreased) in response to DR requests. In this situation, the power consumption changes, but there is no expectation to shift the remaining consumption to other times. For example, when the power consumption of a lighting system is adjusted in response to DR requests, there is no expectation to shift the power consumption to other hours to compensate for reduced lighting [36].

In contrast to the aforementioned appliances, UAs are inflexible devices, such as TVs, ovens, and computers. This group of appliances barely responds to DR plans because their daily operation is closely related to residents' comfort. Therefore, unlocking the flexibility of UAs without compromising occupants' comfort is challenging. To summarize, Figure 3 illustrates household appliances from the perspective of power flexibility.

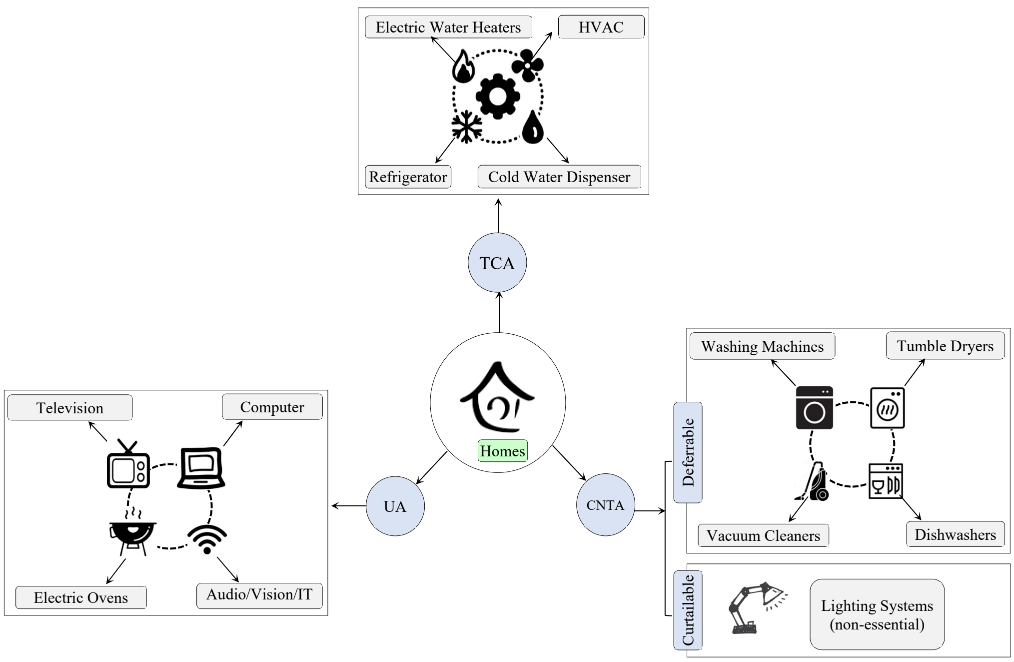

Figure 3. Classification of household appliances from the flexibility point of view.

2.2. Home Energy Management System

The home energy management system (HEMS) is an advanced framework designed to monitor, control, and optimize the operation of household appliances, including TCAs and CNTAs. The system aims to balance two competing objectives: (1) meeting flexibility requirements on the supply side and (2) ensuring residents' comfort on the demand side [37]. The HEMS features a communication system with the grid system operator, such as the Distribution System Operator (DSO). However, this setup varies by country, as different entities may be responsible for data exchange in some regions. The DSO informs the HEMS of DR events, which may include peak hours, off-peak hours, price-based, and incentive-based DR plans. Conversely, the HEMS receives comfort parameters from home residents, such as reference indoor temperature, hot water temperature, and laundry time. Thus, the main duty of the HEMS is to provide power flexibility for the supply side while maintaining the comfort conditions for the occupants.

Regarding the communication system, the HEMS typically uses a Power Line Carrier (PLC) or standard communication networks [38]. The PLC allows communication with the DSO in remote areas, where conventional networks are unavailable.

Smart controllers are the core components of the HEMS. These controllers, equipped with computer processors, optimize the operation of household appliances. Their primary function is to balance the flexibility requirements of the supply side with the comfort conditions of the demand side. Residents set their comfort preferences through a user-friendly interface. In this panel, occupants can specify their preferences for appliance operation, such as indoor temperature. Flexibility requirements, including price signals and critical hours, are received from the DSO. In [39], a smart HEMS is suggested to unlock the flexibility potentials of BESS, photovoltaic systems, and EVs. To provide a general overview of the HEMS, Figure 4 depicts a schematic diagram of a module-based HEMS.

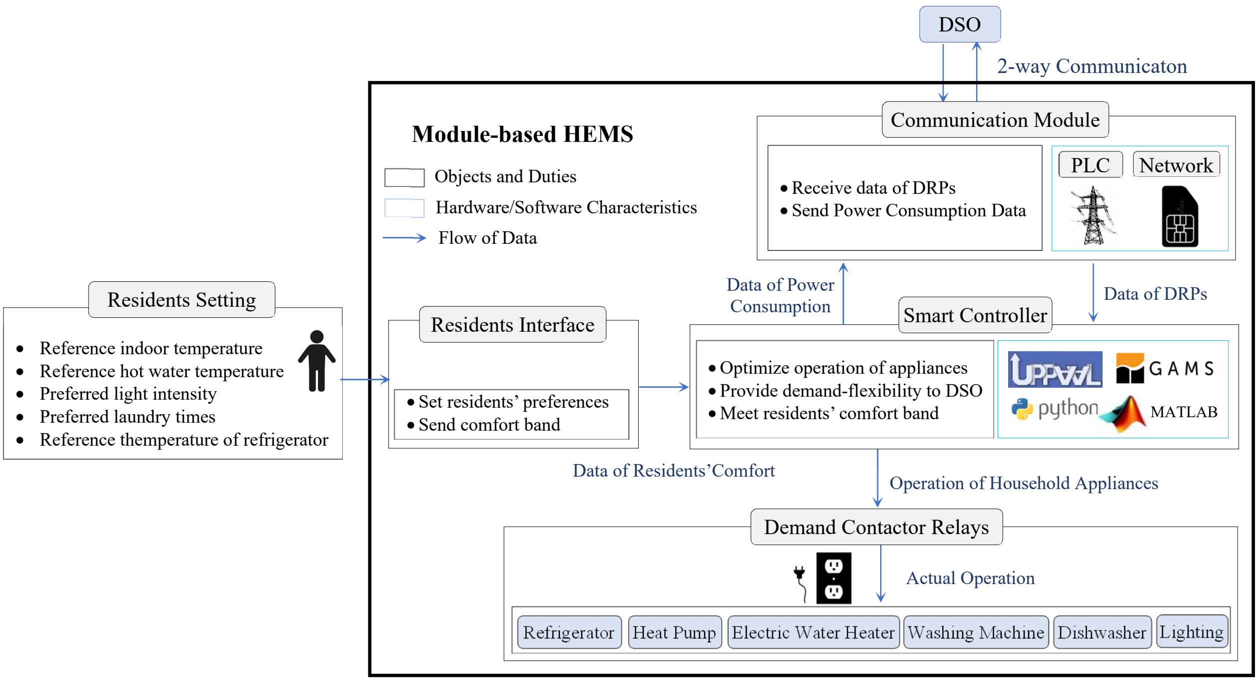

Figure 4. The module-based structure of the HEMS [40].

2.3. Heat Pumps

In recent years, HPs' popularity has increased due to their energy efficiency. They can typically produce 3–5 times more heat energy than the electricity they consume. Additionally, they can recover heat waste from the ground, outdoor environment, and sewage water [41]. The flexibility of HPs is addressed for both cooling and heating purposes [42].

The flexibility potential of HPs depends on the thermodynamic characteristics of buildings. Therefore, in many studies, the thermal dynamics of buildings are calculated to design an HP controller. Among them, the Continuous-Time Stochastic Model (CTSM) was developed by the DTU Compute [43] and was used in many studies to design HP controllers [44]. The HP controller aims to unlock HPs' flexibility in response to external signals, such as electricity prices, while maintaining the indoor air within the comfort range, e.g., between 20–25 °C. The controller receives the indoor air setpoint from the resident and communicates with the local DSO to obtain flexibility requirement data, electricity prices, and meteorological data such as the outdoor temperature and solar irradiation.

In many studies, model predictive control (MPC) is designed for HVAC, taking weather data forecasts into account to optimize future control actions [45]. Some studies suggest economic MPC (EMPC) for HPs to minimize household energy consumption costs [46].

HP compressors can be turned up or down in response to flexibility signals. Although the compressors can quickly respond to electricity price changes, the indoor temperature remains stable due to the longer time constant of thermal dynamics, compared to electrical dynamics. Many studies suggest using heat storage to increase the flexibility potential of HPs. Heat storage can be in the form of water tanks [47] or phase-change materials (PCMs) [48]. Regardless of the type, heat storage allows the HP to operate when electricity prices are low, i.e., down-regulation is required for power system imbalance, and then supply the heating system from the heat storage during high electricity prices when up-regulation is required for power system imbalance.

2.4. District Heating

District Heating (DH) consists of a distributed heat network where heat is generated at a central location and distributed to residential buildings through insulated pipes. The heat is used for space heating and hot water. Generally, DH heat sources can be classified into electricity, fossil fuels, solar-thermal, biomass, geothermal, and waste heat [49].

For electrically operated DH systems, HPs and electric boilers offer significant flexibility potential [50]. Fuel-based DH systems are divided into heat-only units and CHP units. Heat-only units, such as gas boilers, have no demand flexibility for power systems. In contrast, CHP units can provide power flexibility for the electricity grids [51]. Solar–thermal, biomass, and geothermal DH systems are non-electrical and thus offer limited power flexibility. In some cases, DH systems utilize waste heat from electrical consumers, such as industries and data centers [52]. Although this type of DH has no direct power flexibility, it may indirectly unlock power flexibility from the main heat source.

In DH systems with electricity-based heat sources, there are three types of heat flexibility:

(1) The flexibility of thermal inertia of buildings: This is reflected in the thermal dynamics of buildings. Buildings contain thermal mass, such as walls and windows, which can store heat energy [53]. Consequently, indoor temperatures can be adjusted in response to electricity price variations and/or renewable power availability on the supply side.
(2) The flexibility of thermal storage devices: These are specifically designed to store heat energy. Common storage devices in DH systems include water tanks, boreholes, chemical storage, and aquifers [54]. Heat energy can be stored during low-price hours (excess power) and used during high-price hours (power shortages).
(3) The flexibility of the heat network: This is reflected in the temperature of the heat carrier. Adjusting the heat carrier temperature can provide power flexibility. However, temperature variation can accelerate pipe aging and material fatigue, particularly at weak joints, which is a limiting factor [55].

To provide a general insight into the flexibility potential of DH systems, Figure 5 presents a schematic diagram from the flexibility perspective.

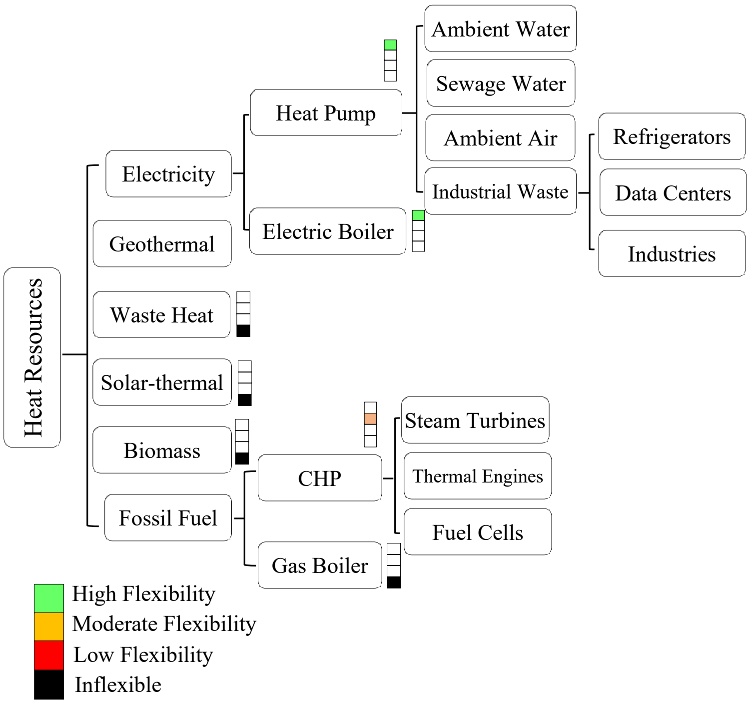

Figure 5. Qualification of flexibility potentials in a DH concerning the heat resources.

2.5. Electric Vehicles

EVs are mobile electric consumers and storage units which, unlike fixed demand, can be connected to different points of distribution grids. As the penetration of EVs increases and fossil fuel cars are retired, the distribution grid comes under pressure, causing transformer overload and congestion in power lines [56]. This can threaten the reliable operation of distribution grids. However, if the charging and discharging of EVs are coordinated, they will not compromise the reliability of the power system. Instead, they can enhance the system's reliability by providing a workable electrical storage backup for the power system.

To unlock EV flexibility, smart charging stations are required. These charging stations can work in both vehicle-to-grid (V2G) and grid-to-vehicle (G2V) modes. Common charging stations are G2V, while V2G is less common due to technical barriers. Smart G2V stations encourage charging during times when electricity prices are low, corresponding to an excess of renewable power availability. Therefore, charging tariffs are important signals to unleash EV flexibility. While G2V stations can provide down-regulation to the power network [57], V2G stations can provide up-regulation when the grid encounters a deficit of renewable energy or system reliability is jeopardized due to failure or unscheduled maintenance [58].

Nowadays, local DSOs/aggregators/retailers use mobile apps to inform EV owners of the charging and discharging prices for the next 24 h. Charging and discharging tariffs can be designed adaptively based on the flexibility requirements of the local grid. For example, during peak (off-peak) hours, charging tariffs are set high (low) to discourage (encourage) EV owners from charging, aiming to provide peak shaving (valley filling). Here, the IoT and communication play a key role in unlocking EV flexibility.

EV flexibility can be discussed for private [59] and public parking lots [60]. Private parking refers to residential parking where EVs are parked typically after working hours. Therefore, the dwell time is usually limited to nighttime hours, with capacities of 2.3, 7.4, 11, and even 22 kW. On the other hand, public parking lots serve a wide variety of EVs with different time characteristics, i.e., arrival time, dwell time, and departure time [61]. Among them, office parking lots typically see EVs arriving around 8 am, departing at 4 pm, and having an 8 h dwell time. Food court parking experiences two rush times, during lunch and dinner, with a one-hour dwell time. Entertainment complexes have arrival and departure times after working hours, for example, from 6 pm to 11 pm. Therefore, if the charging and discharging operations of public parking lots are coordinated, they can act as a virtual storage plant 24 h a day.

2.6. Photovoltaic and Battery Storage

Photovoltaic (PV) systems play a key role in enhancing power system flexibility. In residential areas, rooftop PV systems are practical solutions for decentralized power generation. They help reduce stress on the power system during peak demands and can supply local demands [62], preventing power line congestion in weak areas [63]. As a result, they can postpone power system reinforcement to increase the capacity of power transformers and line flows [64].

PV systems can operate alone or be integrated with battery energy storage systems (BESSs). In the former, PV power generation is injected into the grid or consumed by local demands directly. In the latter, the PV system is linked with a BESS and a smart energy management system (SEMS) [65]. This way, the PV-BESS can respond to real-time demand and supply conditions to either store solar power in the battery or inject it into the local grid. Therefore, the PV-BESS can provide peak shaving and valley filling [66]. Some studies suggest using the PV-BESS to provide frequency regulation [67] and voltage support [68].

3. Demand Flexibility under Uncertainty

The long-term aim of demand-side flexibility is to facilitate the integration of renewables into power systems. The intermittency and volatility of renewable power introduce significant uncertainty into power systems. In this context, deterministic approaches often fail to fully leverage demand-side flexibility. Therefore, to manage the uncertainties associated with renewable power, non-deterministic methodologies should be adopted. Stochastic programming, robust optimization, and information-gap decision theory (IGDT) are commonly used in such studies. These non-deterministic methodologies allow for the incorporation of imperfect data regarding uncertain variables into the flexibility problem.

To select an appropriate non-deterministic approach, two key questions should be addressed:

(1) How complete is our information about the uncertain variables?
(2) How precise do the strategies need to be for the final plan?

The first question pertains to the information available about uncertain variables, such as the availability of historical data, Probability Distribution Functions (PDFs), and possible scenarios. For instance, in power system studies, wind velocity regimes are typically described using the Weibull PDF [69]. Therefore, when definite PDFs are available, non-deterministic approaches that utilize these distributions can be applied. Conversely, in some studies, there is no perfect information about the probability distribution of certain uncertain variables, such as electricity prices. In these cases, non-probabilistic quantification of the uncertain variables is required. Thus, non-deterministic approaches that accommodate non-probabilistic models of uncertainties are adopted.

The second question addresses the main objective of the operator in studying the problem under uncertainty. In some studies, the operator aims to determine the optimal responses of the system to all possible realizations of uncertain variables. For these scenarios, non-deterministic approaches that optimize the problem across various possible trajectories of the uncertain variables are used. On the other hand, if the operator is not concerned with all realizations of the uncertain variables, the focus shifts to optimizing strategies under best-case and/or worst-case scenarios. In such cases, non-deterministic approaches that address the gaps between favorable and unfavorable aspects of uncertain variables, rather than considering the entire PDF, are employed.

Based on the above facts, three non-deterministic approaches—stochastic programming, robust optimization, and IGDT—are commonly used in power system studies under uncertainty. These approaches are elaborated on in the following subsections.

3.1. Stochastic Programming

Stochastic programming is a probabilistic approach that provides the system operator with detailed information about different realizations of uncertain variables [70]. In this approach, different sets of scenarios are generated to cover the uncertain range of the stochastic variable. These scenarios are typically based on historical data and selected using the best-fitted PDFs. Each scenario is characterized by a magnitude and a probability value. When the problem involves multiple uncertain variables, different permutations of scenarios create possible trajectories. The problem is then optimized across all these trajectories, providing decision-makers with optimized strategies for all potential scenarios. Although this approach offers detailed information about optimized strategies, it requires accurate data on the distribution of uncertain variables. Additionally, due to the large number of scenarios, stochastic programming can impose a heavy computational burden, making it less suitable for near real-time analysis. In recent studies, stochastic programming has been extensively utilized in two-stage [71], three-stage [72], and multi-stage approaches [73] to provide demand flexibility in power systems. In [74], multilayer iterative stochastic dynamic programming is introduced to optimize energy management in smart residential areas considering EV systems.

3.2. Robust Optimization

In robust optimization, the uncertain range of the uncertain variable is defined by lower and upper thresholds. The problem is then optimized for the worst-case realization within these bounds [75]. In this approach, no PDF or probability is defined for the uncertain variables. Due to the absence of scenarios, this approach is very efficient in terms of execution time. However, it fails to determine optimal strategies for different realizations of the uncertain variables. Unlike stochastic programming, which addresses various uncertain variables, robust optimization focuses on determining robust strategies against the worst-case realization of the key uncertain variable. Therefore, the most critical uncertain variable is used to develop these robust strategies. In [76], robust optimization is employed to aggregate substantial power flexibility from a large number of distributed energy resources. This approach is further applied to optimize the flexible operation of active distribution grids with bidirectional EV fleets [77]. Robust optimization is also used to model electricity price uncertainty in flexibility-constrained smart HEMSs with roof-top PV systems and BESSs [78]. In [79], robust optimization is applied to building heating systems and HPs for demand response control considering the uncertainty of building demand. In [80], robust optimization is discussed to optimize the HEMS's operation with EVs, addressing the uncertainties associated with real-time electricity prices.

3.3. Information-Gap Decision Theory

IGDT is a non-probabilistic approach that addresses both the adverse and favorable aspects of severe uncertain variables. To establish two threshold strategies, IGDT uses two immunity functions: the robustness function and the opportuneness function [81]. Similar to robust optimization, IGDT considers an uncertain range, known as the envelope bound, for the uncertain variable. IGDT aims to find robust strategies that can handle both catastrophic failures and windfall successes. The working points of the problem are located within the gap between the adverse and favorable states. This approach has recently been used in several studies to facilitate the integration of flexibility in power systems. In [82], IGDT is employed to manage the risk associated with uncertain wind power generation in flexible power system operation. This approach is further addressed to model strategic decisions of a price-maker virtual power plant considering demand flexibility [83]. In [84], the IGDT is applied to optimize the charging and discharging of EVs to cope with the uncertainty of distributed generation in active distribution grids.

Although this paper discussed only the three abovementioned non-deterministic models, but they are not limited to these. For example, interval optimization is addressed in power system studies to model uncertainties associated with renewable energy output [85] and load demands [86].

Figure 6 depicts a general overview of scenario characterization for the three non-deterministic approaches. In subfigure (a), it is shown how different trajectories are formed by different scenarios through a scenario graph in stochastic programming. In subfigure (b), the lower and upper bounds of the robust optimization are shown to determine the worst-case realization of the uncertain variable. In subfigure (c), the pernicious and propitious facets of the uncertain envelope are depicted in the IGDT.

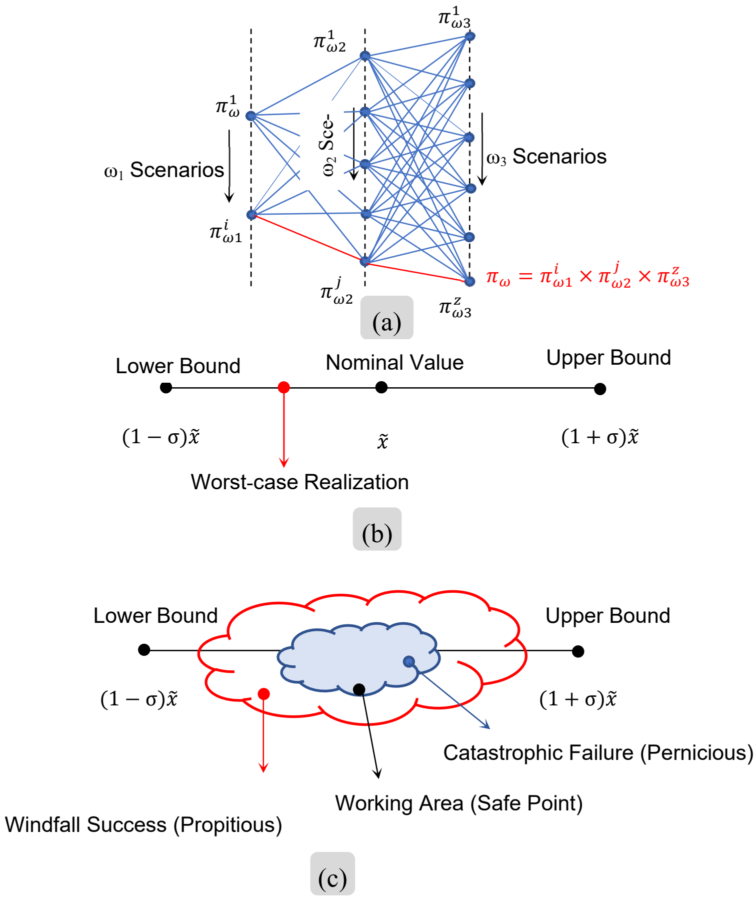

Figure 6. Uncertainty characterization in (**a**) stochastic programming (**b**) robust optimization (**c**) IGDT.

4. Integration of Demand Flexibility to Electricity Market

In power systems with high-RES penetration, the uncertainty of power generation decreases as the power delivery time approaches. As the delivery time nears, the supply-side uncertainty gradually diminishes. To address the intermittent nature of RES, power balancing between generation and consumption is managed hierarchically, from one day ahead to real-time. This approach allows for the unlocking of flexibility potentials in different time slots based on renewable power availability.

Typically, in short-term electricity markets, three trading periods are scheduled to manage RES intermittency over 24 h:

(1) Day-ahead market: conducted 24 h before the power delivery time, this market determines electricity prices based on the intersection of supply and demand curves [87].

(2) Intraday market: Held 60 to 10 min before the power delivery time, this market, also known as the adjustment market, allows participants to adjust their power procurement strategies based on updated flexibility requirements. Participants can buy or sell parts of their power portfolio, originally procured from the day-ahead market, in response to RES availability [88].

(3) Balancing market (real-time market): conducted a few seconds before the energy delivery time, this market provides final up-/down-regulation to the power system [89].

Demand-side flexibilities are integrated into these three trading periods. The challenge is to align the flexibility potentials of demand sectors with the timing of these market periods. The time response of different demand flexibilities varies: some can be unlocked on short notice and integrated into near real-time markets, while others may require longer notice and thus are suited for day-ahead markets. For example, in the metal smelting industry, the operation of smelting pots cannot be interrupted once the process has begun, making them unsuitable for short-notice flexibility; therefore, they are inappropriate for the intraday and balancing markets [90]. In contrast, crushers in cement manufacturing plants can be interrupted on short notice, allowing them to provide near real-time flexibility in balancing markets [91].

Based on these considerations, demand-side flexibilities should be categorized into different classes based on their response times to long, mid, and short advance notices. This categorization is fundamental to analyzing flexibility in demand sectors and determining which flexibility opportunities can be integrated into the hierarchical electricity market floors. Figure 7 illustrates the hierarchical integration of demand flexibilities into the three market floors according to long, mid, and short notice periods.

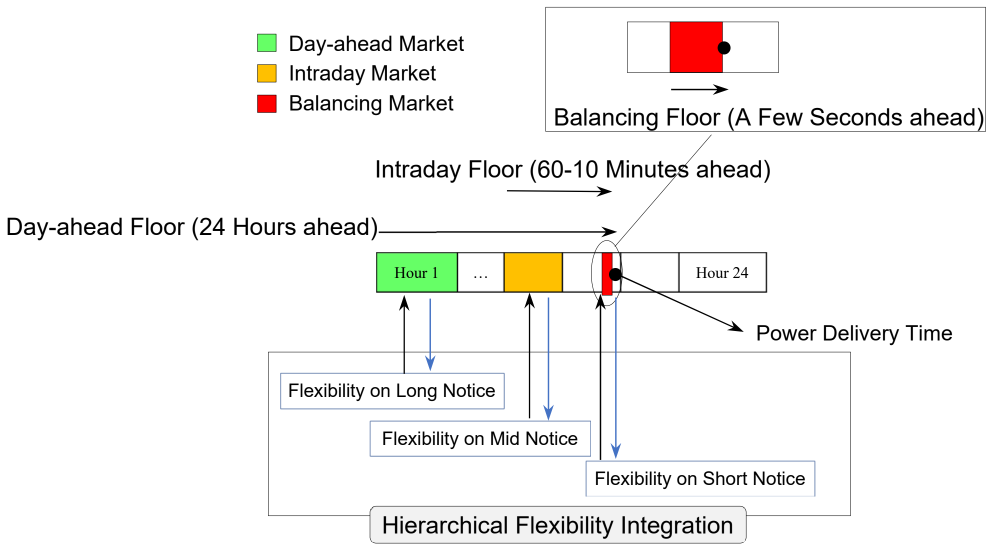

Figure 7. Hierarchical flexibility integration into three trading floors of short-term electricity markets [92].

5. Key Concepts of Flexibility Scheduling

In this section, some key concepts of demand flexibility scheduling are reviewed. They include objective functions of demand flexibility, communication and data exchange, and simulation software.

5.1. Objective Functions

The DR programs are designed to unleash the heat and power demand flexibility with the aim of achieving specific objectives. From a mathematical point of view, the objective function can be constructed in either a linear or non-linear function depending on the demand model and corresponding constraints. The linear functions can be optimized by mathematical approaches called linear programming (LP). The non-linear objective functions are optimized by non-linear programming (NLP) and metaheuristic algorithms, e.g., Genetic Algorithm.

In the demand response literature, more specific objective functions are discussed. Among them, the most important objectives include energy consumption cost minimization [93] and self-consumption maximization [94], maximization of renewable power penetration [95], minimization of greenhouse gas emissions [96] and carbon emission control [97], maximization of power system reliability [98], voltage regulation [99], frequency control [100], increasing power quality [101], congestion management [102], peak shaving and valley filling [103], and increasing energy efficiency [104].

In addition to the aforementioned objectives, some studies highlight grid balancing as the aim of demand flexibility. Demand flexibility primarily contributes to supply–demand balancing in power systems during periods of surplus and deficit of renewable energy [105]. This role becomes especially critical in power systems with high levels of RES penetration, where the supply side is subject to the intermittency of wind and solar power. Thus, demand flexibility is specifically coordinated to provide up- and down-regulation to counteract positive and negative imbalances in the power system.

In some studies, demand flexibility is designed to respond to operational needs within local distribution grids such as failures in power supply and equipment [106]. When anomalies such as equipment failures or operational abnormalities are detected in the local grid, the local DSO collaborates with the DRAs in different demand sectors to address the technical problems of the local grid. This involves responding to fault detection mechanisms with appropriate and timely actions aimed at restoring the distribution grid or preventing the spread of faults to other areas. These actions may include demand curtailment or adjustment, as well as maneuvers to reconfigure power flows within the distribution grid, thereby mitigating the risk of cascading failures. Thus, the MPC is extensively used to design a fault-tolerant energy management system (EMS) in power systems with high-RES penetration [107]. To sum up, Table 1 summarizes the main objective functions of demand-side flexibility in some recent studies.

Table 1. Some key objective functions of demand-side flexibility in recent studies.

References	The Key Objective Function
[93]	Energy consumption cost minimization
[94]	Self-consumption maximization
[95]	Maximization of renewable power penetration
[96,97]	Minimization of greenhouse gas emissions and carbon emission control
[98]	Maximization of power system reliability
[99]	Voltage regulation
[100]	Frequency control
[101]	Increasing power quality
[102]	Congestion management
[103]	Peak shaving and valley filling
[104]	Increasing energy efficiency

5.2. Communication and Data Exchange

To optimize the operation of local energy communities, the objective function may require real-time data from various sources. These include electricity market data such as electricity prices [108], meteorological data [109] such as forecasts of wind speed and outdoor temperature, and grid operator data such as voltage magnitude and line power flows. Additionally, data from measurement sensors, such as domestic hot water and indoor air temperatures in residential buildings, are essential for a HEMS [110]. Therefore, to unlock demand flexibility, either one-way or two-way communication units are required [111].

To provide a general overview of the communication and data exchange, Figure 8 depicts a schematic diagram of a smart irrigation system designed for agricultural farms. The predictive controller within this system gathers data and information from multiple sources, including the local grid operator, meteorological office, as well as local measurement sensors and setpoints provided by farmers. The objective function of the controller is to run the water pumps when the electricity price is low and the surplus of renewable power is available and to turn down the water pumps during the high electricity prices corresponding to the deficit of renewable power availability.

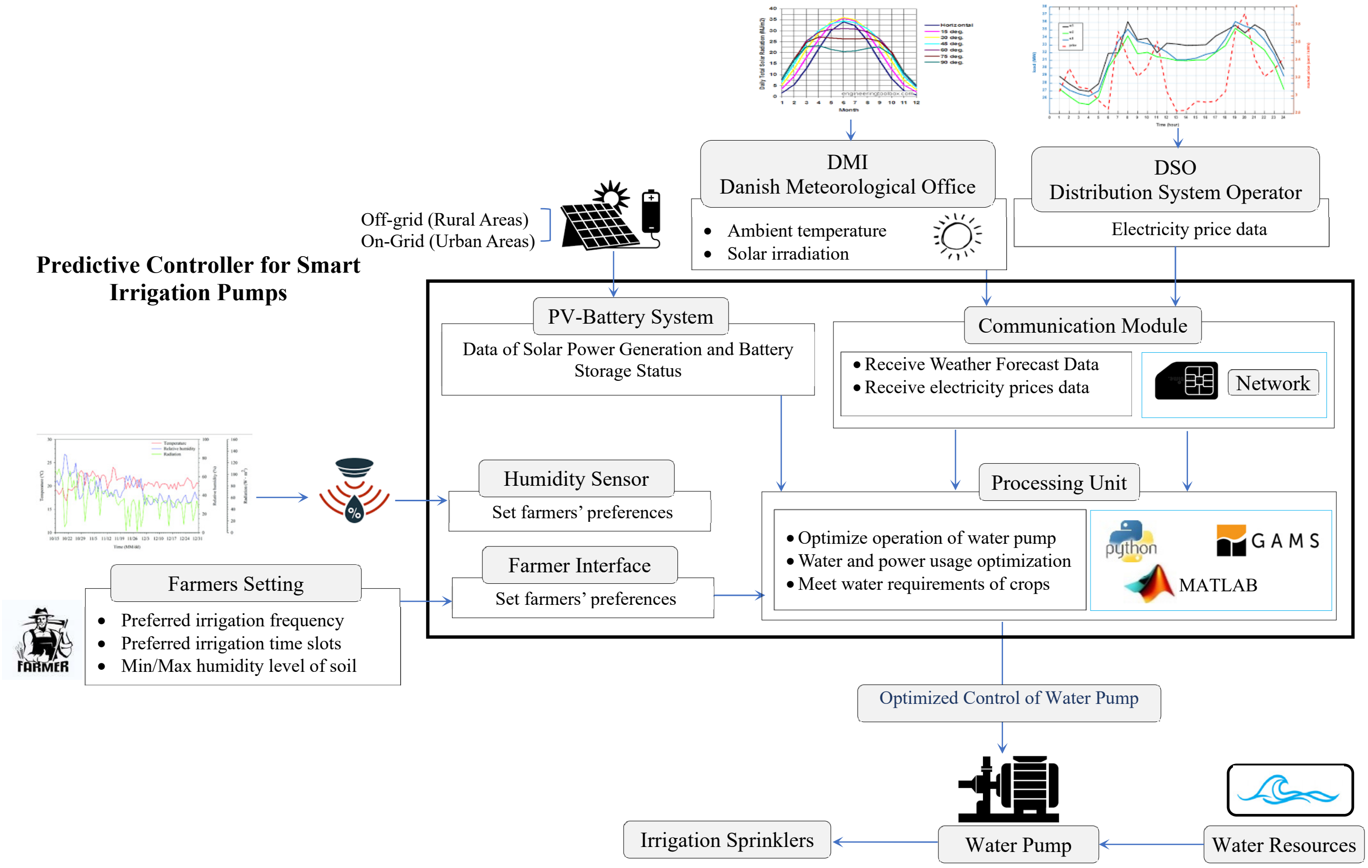

Figure 8. Schematic diagram of a controller for the smart irrigation of farms, with communication and data exchange units.

5.3. Simulation Software

In order to model demand flexibility, simulation software is used. On these software platforms, various energy sources and demands can be modeled. For example, to unlock demand flexibility in a smart building, a smart HEMS can be modeled in a simulation. This model can simulate the electric demand of HPs, EVs, and household appliances, including controllable ones, such as washing machines and tumble dryers, and non-controllable ones, such as audio systems, TVs, and lighting systems. In [112], to unlock the heat-to-power flexibility of a residential HP, sensor measurements are first exported to R software to simulate the building's thermal dynamics. These thermal dynamics are then exported to a model-checking software, UPPAAL-STRATEGO [112] and MATLAB [113], to simulate the HP controller and unleash the heat demand flexibility. "UPPAAL is an integrated tool environment for modeling, validation, and verification of real-time systems modeled as networks of timed automata and was developed in collaboration between the Uppsala University, Sweden, and the Aalborg University, Denmark" [114]. Recently, it was used at Aalborg University to design HP controllers.

In addition to demand, the model can include self-generation facilities, such as PV systems and BESSs. The simulation software can also simulate the comfort needs of residents. For example, for the HP controller, the simulation software can translate the preferred indoor air temperature into a range with lower and upper thresholds. For EVs, it can obtain the preferred departure time and minimum departure state of charge (SoC) from the PDF of in-driving and out-driving EV fleets. The software can then optimize the charging and discharging of the EVs during dwell time to minimize power costs and provide flexibility to power grids.

Various software tools are suggested in studies for simulating demand flexibility. Among them are MATLAB, Simulink [115], MATPOWER [116], GAMS [117], DIgSI-

LENT [118], GridLAB-D [119], OpenDSS [120], EnergyPlus [121], and EnergyPro [122]. Among them, MATPOWER and DIgSILENT can be used to model active distribution grids with the aim of congestion management and voltage regulation. GAMS is a general-purpose software for mathematical modeling and optimization, enabling the implementation of stochastic programming and robust optimization.

After simulation, the demand flexibility is tested in real-time simulators for real-world validation. This process allows for the flexibility potentials to be evaluated in a controlled and realistic environment to ensure their effectiveness. Subsequently, this demand flexibility undergoes limited real-world field tests to further confirm its performance and reliability in practical applications. In the literature, different real-time simulators are discussed to test the demand flexibility, including OPAL-RT [123], RTDS [124], Typhoon HIL [125], PLECS RT Box [126], dSPACE [127], and xPC [128].

To sum up, Table 2 compares the main features of some scoping studies in recent years in comparison to the current study.

Table 2. The main features of some recent scoping studies for demand-side flexibility.

Reference	Addressed Demand Flexibility and Related Concepts
[129]	- Building flexibility - HVAC - EWH - Refrigerators - Wet appliances - Lighting
[130]	Flexibility potentials for industrial, residential, agricultural and commercial sectors
[131]	- Demand flexibility in northern Europe, Sweden, Denmark, Norway, Finland, Estonia, Lativia, Lithuania - Flexibility of industrial, residential, commercial sectors - Flexibility of heating system, shopping centers, office buildings
[132]	- District heating - Heat resources - Control methods of flexible heat demands - Integration of heat flexibility into electricity markets
[133]	- Energy efficiency - Price-based and incentive-based demand response programs - Hardware and communication technology for demand flexibility - Soft computing such as neural network and fuzzy logic - Optimization approaches for scheduling demand flexibility

6. Limitations and Future Works

Although demand-side flexibility is discussed for the residential sector, there are some limitations and challenges for the actual implementation associated with current technologies. Among them, the most important limitations can be stated as follows:

(1) Consumer awareness and engagement in demand response programs;
(2) Lack of standardizations for smart HEMSs;
(3) Insufficient grid infrastructures for communication and data exchange;
(4) Lack of market and regulatory mechanisms;
(5) Vulnerability to cybersecurity attacks.

Although a comprehensive review is conducted for the residential demand flexibility, future directions can involve enhancing digitalization and smart technologies to overcome the current technological barrier. Among them, artificial intelligence and machine learning, as well as automated demand response, can be integrated to the future demand response technologies.

7. Conclusions

This paper reviewed demand-side flexibility in power systems, with a particular emphasis on the residential sector. To highlight the importance of demand flexibility in power systems, flexibility potentials were examined across four sectors: residential, industrial, commercial, and agricultural. It was concluded that harnessing sector-specific flexibility potential requires expert knowledge. Moreover, for demand flexibility to be effective in bulk power systems, sectoral demand flexibility should be aggregated through demand response aggregators.

The focus then shifted to demand flexibility within the residential sector. Household appliances were categorized into three groups based on flexibility and controllability: thermostatically controllable appliances, controllable non-thermal appliances, and uncontrollable appliances. The role of home energy management systems in enhancing building demand flexibility was also discussed. Heat pumps were identified as significant sources of flexibility in residential buildings, with their potential being controllable through thermal dynamics and model predictive controls. The district heating system was highlighted as a key factor in increasing renewable energy integration into the residential sector, particularly through the application of central and booster heat pumps. Additionally, the flexibility potential of EVs in residential and parking lots was examined, noting how EVs can address local distribution grid issues through smart charging and discharging schedules. The roles of PV systems and battery energy management systems were also reviewed, demonstrating how these technologies can facilitate demand flexibility and postpone the need for local distribution grid reinforcement.

The discussion then turned to demand flexibility scheduling under uncertainty, covering three common non-deterministic approaches: stochastic programming, robust optimization, and information-gap decision theory. The integration of demand flexibility into short-term electricity markets was also reviewed, with flexibility potentials classified into short-, mid-, and long-term advance notices for participation in day-ahead, adjustment, and balancing markets.

Finally, three key concepts of flexibility scheduling were examined: objective functions, communication and data exchange, and simulation software. It was concluded that communication systems are critical for unlocking demand flexibility, as they enable the necessary real-time or short-notice data exchange before integrating flexibility into upstream power grids.

Author Contributions: Conceptualization, H.G. and S.G.; methodology, H.G.; validation, H.G.; formal analysis, H.G.; investigation, H.G., S.G.; resources, H.G., S.G., R.S. and B.B.-J.; data curation, S.G., H.G., R.S. and B.B.-J.; writing—original draft preparation, S.G. and H.G.; writing—review and editing, H.G., S.G., R.S. and B.B.-J.; visualization, H.G. and S.G.; supervision, B.B.-J.; project administration, B.B.-J.; funding acquisition, B.B.-J. All authors have read and agreed to the published version of the manuscript.

Funding: This project received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No. 957682 for SERENE and No.101022587 for the SUSTENANCE projects.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author/s.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

Battery energy storage systems	BESS
Combined Heat and Power	CHP
Continuous-Time Stochastic Model	CTSM
Controllable non-thermal appliances	CNTA
Demand response	DR
Demand Response Aggregator	DRA
Demand response program	DRP
Differential Equations	DE
Distribution System Operator	DSO
District heating	DH
Electric vehicle	EV
Electric water heaters	EWH
Energy management system	EMS
Grid-to-vehicle	G2V
Heat pump	HP
Heat, ventilation, and air conditioning	HVAC
Home energy management system	HEMS
Information-gap decision theory	IGDT
Model predictive control	MPC
Phase-change Materials	PCM
Photovoltaic	PV
Power Line Carrier	PLC
Probability Distribution Function	PDF
Renewable Energy Source	RES
Thermostatically controllable appliances	TCA
Uncontrollable appliances	UA
Variable Frequency Drives	VFD
Vehicle-to-grid	V2G

References

1. Lund, H.; Mathiesen, B. Energy system analysis of 100% renewable energy systems—The case of Denmark in years 2030 and 2050. *Energy* **2009**, *34*, 524–531. [CrossRef]
2. Dumlao, S.M.G.; Ishihara, K.N. Impact assessment of electric vehicles as curtailment mitigating mobile storage in high PV penetration grid. *Energy Rep.* **2022**, *8*, 736–744. [CrossRef]
3. Pourramezan, A.; Samadi, M. A novel approach for incorporating incentive-based and price-based demand response programs in long-term generation investment planning. *Int. J. Electr. Power Energy Syst.* **2022**, *142*, 108315. [CrossRef]
4. Zhang, S.; Chen, S.; Gu, W.; Lu, S.; Chung, C.Y. Dynamic optimal energy flow of integrated electricity and gas systems in continuous space. *Appl. Energy* **2024**, *375*, 124052. [CrossRef]
5. Saedi, I.; Mhanna, S.; Mancarella, P. Integrated electricity and gas system modelling with hydrogen injections and gas composition tracking. *Appl. Energy* **2021**, *303*, 117598. [CrossRef]
6. Klyapovskiy, S.; You, S.; Cai, H.; Bindner, H.W. Integrated Planning of a Large-Scale Heat Pump in View of Heat and Power Networks. *IEEE Trans. Ind. Appl.* **2019**, *55*, 5–15. [CrossRef]
7. Lezama, F.; Soares, J.; Canizes, B.; Vale, Z. Flexibility management model of home appliances to support DSO requests in smart grids. *Sustain. Cities Soc.* **2020**, *55*, 102048. [CrossRef]
8. Finck, C.; Li, R.; Kramer, R.; Zeiler, W. Quantifying demand flexibility of power-to-heat and thermal energy storage in the control of building heating systems. *Appl. Energy* **2018**, *209*, 409–425. [CrossRef]
9. Lakshmanan, V.; Sæle, H.; Degefa, M.Z. Electric water heater flexibility potential and activation impact in system operator perspective–Norwegian scenario case study. *Energy* **2021**, *236*, 121490. [CrossRef]
10. Luo, Z.; Peng, J.; Tan, Y.; Yin, R.; Zou, B.; Hu, M.; Yan, J. A novel forecast-based operation strategy for residential PV-battery-flexible loads systems considering the flexibility of battery and loads. *Energy Convers. Manag.* **2023**, *278*, 116705. [CrossRef]
11. Yang, S.; Gao, H.O.; You, F. Demand flexibility and cost-saving potentials via smart building energy management: Opportunities in residential space heating across the US. *Adv. Appl. Energy* **2024**, *14*, 100171. [CrossRef]
12. Golmohamadi, H.; Keypour, R.; Bak-Jensen, B.; Pillai, J.R.; Khooban, M.H. Robust Self-Scheduling of Operational Processes for Industrial Demand Response Aggregators. *IEEE Trans. Ind. Electron.* **2020**, *67*, 1387–1395. [CrossRef]
13. Gregory, A.T.M.; Homan, K.; Aghajanzadeh, A. *Opportunities for Automated Demand Response in California's Dairy Processing Industry*; Lawrence Berkeley National Laboratory: Berkeley, CA, USA, 2015.

14. Olsen, A.; Goli, D.; Faulkner, S.; McKane, D. *Opportunities for Energy Efficiency and Demand Response in the California Cement Industry*; Lawrence Berkeley National Laboratory: Berkeley, CA, USA, 2010.
15. Bao, P.; Zhang, W.; Cheng, D.; Liu, M. Hierarchical control of aluminum smelter loads for primary frequency support considering control cost. *Int. J. Electr. Power Energy Syst.* **2020**, *122*, 106202. [CrossRef]
16. Helin, K.; Käki, A.; Zakeri, B.; Lahdelma, R.; Syri, S. Economic potential of industrial demand side management in pulp and paper industry. *Energy* **2017**, *141*, 1681–1694. [CrossRef]
17. Alarfaj, O.; Bhattacharya, K. Material Flow Based Power Demand Modeling of an Oil Refinery Process for Optimal Energy Management. *IEEE Trans. Power Syst.* **2019**, *34*, 2312–2321. [CrossRef]
18. Wang, J.; You, S.; Zong, Y.; Træholt, C.; Dong, Z.Y.; Zhou, Y. Flexibility of combined heat and power plants: A review of technologies and operation strategies. *Appl. Energy* **2019**, *252*, 113445. [CrossRef]
19. Golmohamadi, H.; Asadi, A. A multi-stage stochastic energy management of responsive irrigation pumps in dynamic electricity markets. *Appl. Energy* **2020**, *265*, 114804. [CrossRef]
20. Aghajanzadeh, A.; Therkelsen, P. Agricultural demand response for decarbonizing the electricity grid. *J. Clean. Prod.* **2019**, *220*, 827–835. [CrossRef]
21. Loschan, C.; Schwabeneder, D.; Lettner, G.; Auer, H. Flexibility potential of aggregated electric vehicle fleets to reduce transmission congestions and redispatch needs: A case study in Austria. *Int. J. Electr. Power Energy Syst.* **2023**, *146*, 108802. [CrossRef]
22. Li, Z.; Lei, X.; Shang, Y.; Jia, Y.; Jian, L. A genuine V2V market mechanism aiming for maximum revenue of each EV owner based on non-cooperative game model. *J. Clean. Prod.* **2023**, *414*, 137586. [CrossRef]
23. Heydarian-Forushani, E.; Golshan, M.; Shafie-Khah, M. Flexible interaction of plug-in electric vehicle parking lots for efficient wind integration. *Appl. Energy* **2016**, *179*, 338–349. [CrossRef]
24. Daryabari, M.K.; Keypour, R.; Golmohamadi, H. Stochastic energy management of responsive plug-in electric vehicles characterizing parking lot aggregators. *Appl. Energy* **2020**, *279*, 115751. [CrossRef]
25. Maouris, G.; Escriva, E.J.S.; Acha, S.; Shah, N.; Markides, C.N. CO_2 refrigeration system heat recovery and thermal storage modelling for space heating provision in supermarkets: An integrated approach. *Appl. Energy* **2020**, *264*, 114722. [CrossRef]
26. U.S. Energy Information Administration (EIA). Available online: https://www.eia.gov/tools/glossary/?id=electricity (accessed on 12 June 2024).
27. Golmohamadi, H. Flexible Operation of Power-To-X Energy Systems in Transportation Networks. In *Interconnected Modern Multi-Energy Networks and Intelligent Transportation Systems*; John Wiley & Sons: Hoboken, NJ, USA, 2024; pp. 117–164. [CrossRef]
28. IEA. World Electricity Final Consumption by Sector, 1974–2019. Available online: https://www.iea.org/data-and-statistics/charts/world-electricity-final-consumption-by-sector-1974-2018 (accessed on 10 June 2024).
29. Mugnini, A.; Ramallo-González, A.P.; Parreño, A.; Molina-Garcia, A.; Skarmeta, A.F.; Arteconi, A. Dynamic building thermal mass clustering for energy flexibility assessment: An application to demand response events. *Energy Build.* **2024**, *308*, 114011. [CrossRef]
30. Sadeghianpourhamami, N.; Demeester, T.; Benoit, D.; Strobbe, M.; Develder, C. Modeling and analysis of residential flexibility: Timing of white good usage. *Appl. Energy* **2016**, *179*, 790–805. [CrossRef]
31. Cibin, N.; Tibo, A.; Golmohamadi, H.; Skou, A.; Albano, M. Machine learning-based algorithms to estimate thermal dynamics of residential buildings with energy flexibility. *J. Build. Eng.* **2023**, *65*, 105683. [CrossRef]
32. Hasrat, I.R.; Jensen, P.G.; Larsen, K.G.; Srba, J. End-to-End Heat-Pump Control Using Continuous Time Stochastic Modelling and Uppaal Stratego. In *Theoretical Aspects of Software Engineering*; Aït-Ameur, Y., Crăciun, F., Eds.; Springer International Publishing: Cham, Switzerland, 2022; pp. 363–380.
33. Evens, M.; Arteconi, A. Design energy flexibility within a comfort and climate box–An experimental evaluation of the internal heat pump control effects. *Appl. Therm. Eng.* **2024**, *254*, 123842. [CrossRef]
34. Farzamkia, S.; Ranjbar, H.; Hatami, A.; Iman-Eini, H. A novel PSO (Particle Swarm Optimization)-based approach for optimal schedule of refrigerators using experimental models. *Energy* **2016**, *107*, 707–715. [CrossRef]
35. Vellei, M.; Le Dréau, J.; Abdelouadoud, S.Y. Predicting the demand flexibility of wet appliances at national level: The case of France. *Energy Build.* **2020**, *214*, 109900. [CrossRef]
36. Golmohamadi, H.; Keypour, R.; Bak-Jensen, B.; Pillai, J.R. Optimization of household energy consumption towards day-ahead retail electricity price in home energy management systems. *Sustain. Cities Soc.* **2019**, *47*, 101468. [CrossRef]
37. Tuomela, S.; Tomé, M.d.C.; Iivari, N.; Svento, R. Impacts of home energy management systems on electricity consumption. *Appl. Energy* **2021**, *299*, 117310. [CrossRef]
38. Khan, A.A.; Razzaq, S.; Khan, A.; Khursheed, F. Owais HEMSs and enabled demand response in electricity market: An overview. *Renew. Sustain. Energy Rev.* **2015**, *42*, 773–785. [CrossRef]
39. Prum, P.; Charoen, P.; Khan, M.A.; Bayati, N.; Charoenlarpnopparut, C. Energy Management Scheme for Optimizing Multiple Smart Homes Equipped with Electric Vehicles. *Energies* **2024**, *17*, 254. [CrossRef]
40. Golmohamadi, H. Stochastic energy optimization of residential heat pumps in uncertain electricity markets. *Appl. Energy* **2021**, *303*, 117629. [CrossRef]
41. Wang, Q.; Zhang, X.; Geng, X.; Chen, X.; Xing, M. Experiments on the characteristics of a sewage water source heat pump system for heat recovery from bath waste. *Appl. Therm. Eng.* **2022**, *204*, 117956. [CrossRef]

42. Kheiri, S.Z.; Mirzaei, M.A.; Parvania, M. Integrating the Energy Flexibility of Cold Climate Air Source Heat Pump in Home Energy Management Systems. In Proceedings of the 2024 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 19–22 February 2024; pp. 1–5. [CrossRef]
43. Juhl, R.; Kristensen, N.R.; Bacher, P.; Kloppenborg, J.; Madsen, H. Grey-box Modeling of the Heat Dynamics of a Building with CTSM-R. 2020. Available online: http://ctsm.info/building2.pdf (accessed on 15 June 2024).
44. Hasrat, I.R.; Jensen, P.G.; Larsen, K.G.; Srba, J. A toolchain for domestic heat-pump control using Uppaal Stratego. *Sci. Comput. Program.* **2023**, *230*, 102987. [CrossRef]
45. Hou, J.; Li, H.; Nord, N.; Huang, G. Model predictive control under weather forecast uncertainty for HVAC systems in university buildings. *Energy Build.* **2022**, *257*, 111793. [CrossRef]
46. Sawant, P.; Mier, O.V.; Schmidt, M.; Pfafferott, J. Demonstration of Optimal Scheduling for a Building Heat Pump System Using Economic-MPC. *Energies* **2021**, *14*, 7953. [CrossRef]
47. Vivian, J.; Prataviera, E.; Cunsolo, F.; Pau, M. Demand Side Management of a pool of air source heat pumps for space heating and domestic hot water production in a residential district. *Energy Convers. Manag.* **2020**, *225*, 113457. [CrossRef]
48. Nunna, A.C.; Zong, Y.; Georges, L.; You, S. Demand response with active phase change material based thermal energy storage in buildings. *Energy Rep.* **2023**, *9*, 227–235. [CrossRef]
49. Pakere, I.; Feofilovs, M.; Lepiksaar, K.; Vītoliņš, V.; Blumberga, D. Multi-source district heating system full decarbonization strategies: Technical, economic, and environmental assessment. *Energy* **2023**, *285*, 129296. [CrossRef]
50. Sorknæs, P. Hybrid energy networks and electrification of district heating under different energy system conditions. *Energy Rep.* **2021**, *7*, 222–236. [CrossRef]
51. Korpela, T.; Kaivosoja, J.; Majanne, Y.; Laakkonen, L.; Nurmoranta, M.; Vilkko, M. Utilization of District Heating Networks to Provide Flexibility in CHP Production. *Energy Procedia* **2017**, *116*, 310–319. [CrossRef]
52. Wahlroos, M.; Pärssinen, M.; Manner, J.; Syri, S. Utilizing data center waste heat in district heating–Impacts on energy efficiency and prospects for low-temperature district heating networks. *Energy* **2017**, *140*, 1228–1238. [CrossRef]
53. Fambri, G.; Marocco, P.; Badami, M.; Tsagkrasoulis, D. The flexibility of virtual energy storage based on the thermal inertia of buildings in renewable energy communities: A techno-economic analysis and comparison with the electric battery solution. *J. Energy Storage* **2023**, *73*, 109083. [CrossRef]
54. Todorov, O.; Alanne, K.; Virtanen, M.; Kosonen, R. A method and analysis of aquifer thermal energy storage (ATES) system for district heating and cooling: A case study in Finland. *Sustain. Cities Soc.* **2020**, *53*, 101977. [CrossRef]
55. Vandermeulen, A.; Van Der Heijde, B.; Helsen, L. Controlling district heating and cooling networks to unlock flexibility: A review. *Energy* **2018**, *151*, 103–115. [CrossRef]
56. Visakh, A.; Selvan, M.P. Analysis and mitigation of the impact of electric vehicle charging on service disruption of distribution transformers. *Sustain. Energy Grids Netw.* **2023**, *35*, 101096. [CrossRef]
57. Sharma, S.; Jain, P. Risk-averse integrated demand response and dynamic G2V charge scheduling of an electric vehicle aggregator to support grid stability. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e12867. [CrossRef]
58. Alfaverh, F.; Denaï, M.; Sun, Y. Optimal vehicle-to-grid control for supplementary frequency regulation using deep reinforcement learning. *Electr. Power Syst. Res.* **2023**, *214*, 108949. [CrossRef]
59. Sørensen, Å.L.; Lindberg, K.B.; Sartori, I.; Andresen, I. Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data. *Energy Build.* **2021**, *241*, 110923. [CrossRef]
60. Karimi-Arpanahi, S.; Jooshaki, M.; Pourmousavi, S.A.; Lehtonen, M. Leveraging the flexibility of electric vehicle parking lots in distribution networks with high renewable penetration. *Int. J. Electr. Power Energy Syst.* **2022**, *142*, 108366. [CrossRef]
61. Daryabari, M.K.; Keypour, R.; Golmohamadi, H. Robust self-scheduling of parking lot microgrids leveraging responsive electric vehicles. *Appl. Energy* **2021**, *290*, 116802. [CrossRef]
62. Moshövel, J.; Kairies, K.-P.; Magnor, D.; Leuthold, M.; Bost, M.; Gährs, S.; Szczechowicz, E.; Cramer, M.; Sauer, D.U. Analysis of the maximal possible grid relief from PV-peak-power impacts by using storage systems for increased self-consumption. *Appl. Energy* **2015**, *137*, 567–575. [CrossRef]
63. Cerna, F.V. A hybrid PV scheme as support to relieve congestion in the domestic supply network. *Int. J. Electr. Power Energy Syst.* **2022**, *134*, 107413. [CrossRef]
64. Holweger, J.; Pena-Bello, A.; Jeannin, N.; Ballif, C.; Wyrsch, N. Distributed flexibility as a cost-effective alternative to grid reinforcement. *Sustain. Energy Grids Netw.* **2023**, *34*, 101041. [CrossRef]
65. Ali, A.O.; Hamed, A.M.; Abdelsalam, M.M.; Sabry, M.N.; Elmarghany, M.R. Energy management of photovoltaic-battery system connected with the grid. *J. Energy Storage* **2022**, *55*, 105865. [CrossRef]
66. Wang, Y.; Liu, L.; Wennersten, R.; Sun, Q. Peak shaving and valley filling potential of energy management system in high-rise residential building. *Energy Procedia* **2019**, *158*, 6201–6207. [CrossRef]
67. Li, Z.; Cheng, Z.; Si, J.; Zhang, S.; Dong, L.; Li, S.; Gao, Y. Adaptive Power Point Tracking Control of PV System for Primary Frequency Regulation of AC Microgrid With High PV Integration. *IEEE Trans. Power Syst.* **2021**, *36*, 3129–3141. [CrossRef]
68. Chaudhary, P.; Rizwan, M. Voltage regulation mitigation techniques in distribution system with high PV penetration: A review. *Renew. Sustain. Energy Rev.* **2018**, *82*, 3279–3287. [CrossRef]
69. Salim, O.M.; Dorrah, H.T.; Hassan, M.A. Wind speed estimation based on a novel multivariate Weibull distribution. *IET Renew. Power Gener.* **2019**, *13*, 2762–2773. [CrossRef]

70. Birge, J.R.; Louveaux, F. *Introduction to Stochastic Programming*, 2nd ed.; Springer Series in Operations Research and Financial Engineering; Springer: New York, NY, USA, 2011; Volume 31. [CrossRef]
71. Jordehi, A.R.; Tabar, V.S.; Mansouri, S.; Sheidaei, F.; Ahmarinejad, A.; Pirouzi, S. Two-stage stochastic programming for scheduling microgrids with high wind penetration including fast demand response providers and fast-start generators. *Sustain. Energy, Grids Netw.* **2022**, *31*, 100694. [CrossRef]
72. Zatti, M.; Martelli, E.; Amaldi, E. A three-stage stochastic optimization model for the design of smart energy districts under uncertainty. In *Computer Aided Chemical Engineering*; Espuña, A., Graells, M., Puigjaner, L., Eds.; Elsevier: Amsterdam, The Netherlands, 2017; Volume 40, pp. 2389–2394. [CrossRef]
73. Flores-Quiroz, A.; Strunz, K. A distributed computing framework for multi-stage stochastic planning of renewable power systems with energy storage as flexibility option. *Appl. Energy* **2021**, *291*, 116736. [CrossRef]
74. Aljohani, T.M. Multilayer Iterative Stochastic Dynamic Programming for Optimal Energy Management of Residential Loads with Electric Vehicles. *Int. J. Energy Res.* **2024**, *2024*, 6842580. [CrossRef]
75. Ben-Tal, A.; Nemirovski, A.; El Ghaoui, L. *Robust Optimization*; Princeton University Press: Princeton, NJ, USA, 2009.
76. Chen, X.; Li, N. Leveraging Two-Stage Adaptive Robust Optimization for Power Flexibility Aggregation. *IEEE Trans. Smart Grid* **2021**, *12*, 3954–3965. [CrossRef]
77. Pirouzi, S.; Aghaei, J.; Niknam, T.; Shafie-Khah, M.; Vahidinasab, V.; Catalão, J.P. Two alternative robust optimization models for flexible power management of electric vehicles in distribution networks. *Energy* **2017**, *141*, 635–651. [CrossRef]
78. Bahramara, S. Robust Optimization of the Flexibility-constrained Energy Management Problem for a Smart Home with Rooftop Photovoltaic and an Energy Storage. *J. Energy Storage* **2021**, *36*, 102358. [CrossRef]
79. Ding, Y.; Bai, Y.; Tian, Z.; Wang, Q.; Su, H. Coordinated optimization of robustness and flexibility of building heating systems for demand response control considering prediction uncertainty. *Appl. Therm. Eng.* **2023**, *223*, 120024. [CrossRef]
80. Tostado-Véliz, M.; Hasanien, H.M.; Turky, R.A.; Jordehi, A.R.; Mansouri, S.A.; Jurado, F. A fully robust home energy management model considering real time price and on-board vehicle batteries. *J. Energy Storage* **2023**, *72*, 108531. [CrossRef]
81. Ben-Haim, Y. Chapter 3-Robustness and Opportuneness. In *Info-Gap Decision Theory*, 2nd ed.; Ben-Haim, Y., Ed.; Academic Press: Oxford, UK, 2006; pp. 37–114. [CrossRef]
82. Nikoobakht, A.; Aghaei, J.; Mardaneh, M. Managing the risk of uncertain wind power generation in flexible power systems using information gap decision theory. *Energy* **2016**, *114*, 846–861. [CrossRef]
83. Gazijahani, F.S.; Salehi, J. IGDT-Based Complementarity Approach for Dealing With Strategic Decision Making of Price-Maker VPP Considering Demand Flexibility. *IEEE Trans. Ind. Inform.* **2020**, *16*, 2212–2220. [CrossRef]
84. Chen, Q.; Wang, W.; Wang, H.; Dong, Y.; He, S. Information gap-based coordination scheme for active distribution network considering charging/discharging optimization for electric vehicles and demand response. *Int. J. Electr. Power Energy Syst.* **2023**, *145*, 108652. [CrossRef]
85. Zeng, L.; Xu, J.; Wang, Y.; Liu, Y.; Tang, J.; Wen, M.; Chen, Z. Day-ahead interval scheduling strategy of power systems based on improved adaptive diffusion kernel density estimation. *Int. J. Electr. Power Energy Syst.* **2023**, *147*, 108850. [CrossRef]
86. Wang, D.; Zhang, C.; Jia, W.; Liu, Q.; Cheng, L.; Yang, H.; Luo, Y.; Kuang, N. A Novel Interval Programming Method and Its Application in Power System Optimization Considering Uncertainties in Load Demands and Renewable Power Generation. *Energies* **2022**, *15*, 7565. [CrossRef]
87. Morales, J.M.; Conejo, A.J.; Madsen, H.; Pinson, P.; Zugno, M. Clearing the Day-Ahead Market with a High Penetration of Stochastic Production. In *Integrating Renewables in Electricity Markets: Operational Problems*; Morales, J.M., Conejo, A.J., Madsen, H., Pinson, P., Zugno, M., Eds.; Springer: Boston, MA, USA, 2014; pp. 57–100. [CrossRef]
88. Conejo, A.J.; Carrión, M.; Morales, J.M. Pool Trading for Wind Power Producers. In *Decision Making Under Uncertainty in Electricity Markets*; Conejo, A.J., Carrión, M.J., Morales, M., Eds.; Springer: Boston, MA, USA, 2010; pp. 195–251. [CrossRef]
89. Morales, J.M.; Conejo, A.J.; Madsen, H.; Pinson, P.; Zugno, M. Balancing Markets. In *Integrating Renewables in Electricity Markets: Operational Problems*; Morales, J.M., Conejo, A.J., Madsen, H., Pinson, P., Zugno, M., Eds.; Springer: Boston, MA, USA, 2014; pp. 101–136. [CrossRef]
90. Yao, M.; Hu, Z.; Zhang, N.; Duan, W.; Zhang, J. Low-carbon benefits analysis of energy-intensive industrial demand response resources for ancillary services. *J. Mod. Power Syst. Clean Energy* **2015**, *3*, 131–138. [CrossRef]
91. Golmohamadi, H. Demand-side management in industrial sector: A review of heavy industries. *Renew. Sustain. Energy Rev.* **2022**, *156*, 111963. [CrossRef]
92. Golmohamadi, H.; Larsen, K.G.; Jensen, P.G.; Hasrat, I.R. Hierarchical flexibility potentials of residential buildings with responsive heat pumps: A case study of Denmark. *J. Build. Eng.* **2021**, *41*, 102425. [CrossRef]
93. Bahlawan, H.; Castorino, G.A.M.; Losi, E.; Manservigi, L.; Spina, P.R.; Venturini, M. Optimal management with demand response program for a multi-generation energy system. *Energy Convers. Manag. X* **2022**, *16*, 100311. [CrossRef]
94. Rana, A.; Gróf, G. Assessment of local energy trading in a residential energy hub with demand management. *Energy Rep.* **2024**, *11*, 1642–1658. [CrossRef]
95. Al Hadi, A.; Silva, C.A.S.; Hossain, E.; Challoo, R. Algorithm for Demand Response to Maximize the Penetration of Renewable Energy. *IEEE Access* **2020**, *8*, 55279–55288. [CrossRef]
96. Zeng, H.; Shao, B.; Dai, H.; Tian, N.; Zhao, W. Incentive-based demand response strategies for natural gas considering carbon emissions and load volatility. *Appl. Energy* **2023**, *348*, 121541. [CrossRef]

97. Hua, H.; Chen, X.; Gan, L.; Sun, J.; Dong, N.; Liu, D.; Qin, Z.; Li, K.; Hu, S. Demand-Side Joint Electricity and Carbon Trading Mechanism. *IEEE Trans. Ind. Cyber-Physical Syst.* **2024**, *2*, 14–25. [CrossRef]
98. Yang, H.; Zhang, X.; Chu, Y.; Ma, Y.; Zhang, D.; Guerrero, J.M. Multi-objective based demand response strategy optimization considering differential demand on reliability of power system. *Int. J. Electr. Power Energy Syst.* **2023**, *152*, 109202. [CrossRef]
99. Chandran, C.V.; Basu, M.; Sunderland, K.; Pukhrem, S.; Catalão, J.P. Application of demand response to improve voltage regulation with high DG penetration. *Electr. Power Syst. Res.* **2020**, *189*, 106722. [CrossRef]
100. Miow, X.C.; Lim, Y.S.; Hau, L.C.; Wong, J.; Patsios, H. Demand response for frequency regulation with neural network load controller under high intermittency photovoltaic systems. *Energy Rep.* **2023**, *9*, 2869–2880. [CrossRef]
101. Devarapalli, H.P.; Dhanikonda, V.S.S.S.S.; Gunturi, S.B. Demand-Side Management for Improvement of the Power Quality in Smart Homes Using Non-Intrusive Identification of Appliance Usage Patterns with the True Power Factor. *Energies* **2021**, *14*, 4837. [CrossRef]
102. Stawska, A.; Romero, N.; de Weerdt, M.; Verzijlbergh, R. Demand response: For congestion management or for grid balancing? *Energy Policy* **2021**, *148*, 111920. [CrossRef]
103. Golmohamadi, H. Operational scheduling of responsive prosumer farms for day-ahead peak shaving by agricultural demand response aggregators. *Int. J. Energy Res.* **2021**, *45*, 938–960. [CrossRef]
104. Wohlfarth, K.; Worrell, E.; Eichhammer, W. Energy efficiency and demand response–Two sides of the same coin? *Energy Policy* **2020**, *137*, 111070. [CrossRef]
105. Morales, J.M.; Conejo, A.J.; Madsen, H.; Pinson, P.; Zugno, M. Facilitating Renewable Integration by Demand Re-sponseDemand response. In *Integrating Renewables in Electricity Markets: Operational Problems*; Morales, J.M., Conejo, A.J., Madsen, H., Pinson, P., Zugno, M., Eds.; Springer: Boston, MA, USA, 2014; pp. 289–329. [CrossRef]
106. Freire, V.A.; Marquez, J.J.; Bordons, C.; Zafra-Cabeza, A.; de Arruda, L.V.R. Energy Management System for Microgrid Considering Operational Faults in Power Supply. In Proceedings of the 2020 International Conference on Smart Energy Systems and Technologies (SEST), Istanbul, Turkey, 7–9 September 2020; pp. 1–6. [CrossRef]
107. Morato, M.M.; Mendes, P.R.; Normey-Rico, J.E.; Bordons, C. LPV-MPC fault-tolerant energy management strategy for renewable microgrids. *Int. J. Electr. Power Energy Syst.* **2020**, *117*, 105644. [CrossRef]
108. Lu, R.; Bai, R.; Huang, Y.; Li, Y.; Jiang, J.; Ding, Y. Data-driven real-time price-based demand response for industrial facilities energy management. *Appl. Energy* **2021**, *283*, 116291. [CrossRef]
109. Kadlec, M.; Buhnova, B.; Tomsik, J.; Herman, J.; Druzbikova, K. Weather Forecast Based Scheduling for Demand Response Optimization in Smart Grids. In Proceedings of the 2017 Smart City Symposium Prague (SCSP), Prague, Czech Republic, 25–26 May 2017; pp. 1–6. [CrossRef]
110. Golmohamadi, H.; Larsen, K.G. Economic heat control of mixing loop for residential buildings supplied by low-temperature district heating. *J. Build. Eng.* **2021**, *46*, 103286. [CrossRef]
111. Ebeid, E.; Rotger-Griful, S.; Mikkelsen, S.A.; Jacobsen, R.H. A methodology to evaluate demand response communication protocols for the Smart Grid. In Proceedings of the 2015 IEEE International Conference on Communications Workshops (ICCW), London, UK, 8–12 June 2015; pp. 2012–2017. [CrossRef]
112. Hasrat, I.R.; Jensen, P.G.; Larsen, K.G.; Srba, J. Modelling of Hot Water Buffer Tank and Mixing Loop for an Intelligent Heat Pump Control. In *Formal Methods for Industrial Critical Systems*; Cimatti, A., Titolo, L., Eds.; Springer Nature: Cham, Switzerland, 2023; pp. 113–130.
113. Golmohamadi, H.; Larsen, K.G.; Jensen, P.G.; Hasrat, I.R. Optimization of power-to-heat flexibility for residential buildings in response to day-ahead electricity price. *Energy Build.* **2021**, *232*, 110665. [CrossRef]
114. UPPAAL Real Time Simulator. Available online: http://www.uppaal.org/ (accessed on 11 June 2024).
115. EL Zerk, A.; Ouassaid, M.; Zidani, Y. Development of a real-time framework between MATLAB and PLC through OPC-UA: A case study of a microgrid energy management system. *Sci. Afr.* **2023**, *21*, e01846. [CrossRef]
116. Suresh, V.; Janik, P.; Guerrero, J.M.; Leonowicz, Z.; Sikorski, T. Microgrid Energy Management System With Embedded Deep Learning Forecaster and Combined Optimizer. *IEEE Access* **2020**, *8*, 202225–202239. [CrossRef]
117. Akbari, E.; Shabestari, S.F.M.; Pirouzi, S.; Jadidoleslam, M. Network flexibility regulation by renewable energy hubs using flexibility pricing-based energy management. *Renew. Energy* **2023**, *206*, 295–308. [CrossRef]
118. Bhattarai, B.P.; Myers, K.S.; Turk, R.J.; Bak-Jensen, B. 21-Multi-time-scale energy management of distributed energy resources in active distribution grids. In *Smart Power Distribution Systems*; Yang, Q., Yang, T., Li, W., Eds.; Academic Press: Cambridge, MA, USA, 2019; pp. 503–528. [CrossRef]
119. Al Faruque, M.A.; Ahourai, F. GridMat: Matlab toolbox for GridLAB-D to analyze grid impact and validate residential micro-grid level energy management algorithms. In Proceedings of the 2014 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 19–22 February 2014; pp. 1–5. [CrossRef]
120. Subramanya, S.A.; Parathodiyil, M.; Nagashree, A. Implementation of Peak Demand Reduction on a Distribution Feeder Using Python-OpenDSS Co-Simulation. In Proceedings of the 2021 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, 9–11 July 2021; pp. 1–6. [CrossRef]
121. Elhefny, A.; Jiang, Z.; Cai, J. Co-simulation and energy management of photovoltaic-rich residential communities for improved distribution voltage support with flexible loads. *Sol. Energy* **2022**, *231*, 516–526. [CrossRef]

122. Andersen, A.N.; Østergaard, P.A. A method for assessing support schemes promoting flexibility at district energy plants. *Appl. Energy* **2018**, *225*, 448–459. [CrossRef]
123. Wang, J.; Blonsky, M.; Ding, F.; Drew, S.C.; Padullaparti, H.; Ghosh, S.; Mendoza, I.; Tiwari, S.; Martinez, J.E.; Dahdah, J.J.D.; et al. Performance Evaluation of Distributed Energy Resource Management via Advanced Hardware-in-the-Loop Simulation. In Proceedings of the 2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 17–20 February 2020; pp. 1–5. [CrossRef]
124. Lipari, G.; Del Rosario, G.; Corchero, C.; Ponci, F.; Monti, A. A real-time commercial aggregator for distributed energy resources flexibility management. *Sustain. Energy, Grids Netw.* **2018**, *15*, 63–75. [CrossRef]
125. Rodriguez, M.; Arcos-Aviles, D.; Martinez, W. Fuzzy logic-based energy management for isolated microgrid using meta-heuristic optimization algorithms. *Appl. Energy* **2023**, *335*, 120771. [CrossRef]
126. Aguilar, M.; Riffo, S.; Veliz, A.; González-Castaño, C.; Restrepo, C. RT Box card for studying the control communication impacts on microgrid performance and stability. *HardwareX* **2022**, *12*, e00322. [CrossRef] [PubMed]
127. Harmouch, F.Z.; Ebrahim, A.F.; Esfahani, M.M.; Krami, N.; Hmina, N.; Mohammed, O.A. An Optimal Energy Management System for Real-Time Operation of Multiagent-Based Microgrids Using a T-Cell Algorithm. *Energies* **2019**, *12*, 3004. [CrossRef]
128. Maturana, F.; Staron, R.; Loparo, K.; Ambre, R.; Carnahan, D. Simulation-Based Environment for Modeling Distributed Agents for Smart Grid Energy Management. In Proceedings of the Factory Automation (ETFA 2011), Toulouse, France, 5–9 September 2011; pp. 1–7. [CrossRef]
129. Luo, Z.; Peng, J.; Cao, J.; Yin, R.; Zou, B.; Tan, Y.; Yan, J. Demand Flexibility of Residential Buildings: Definitions, Flexible Loads, and Quantification Methods. *Engineering* **2022**, *16*, 123–140. [CrossRef]
130. Golmohamadi, H. Demand-Side Flexibility in Power Systems: A Survey of Residential, Industrial, Commercial, and Agricultural Sectors. *Sustainability* **2022**, *14*, 7916. [CrossRef]
131. Söder, L.; Lund, P.D.; Koduvere, H.; Bolkesjø, T.F.; Rossebø, G.H.; Rosenlund-Soysal, E.; Skytte, K.; Katz, J.; Blumberga, D. A review of demand side flexibility potential in Northern Europe. *Renew. Sustain. Energy Rev.* **2018**, *91*, 654–664. [CrossRef]
132. Golmohamadi, H.; Larsen, K.G.; Jensen, P.G.; Hasrat, I.R. Integration of flexibility potentials of district heating systems into electricity markets: A review. *Renew. Sustain. Energy Rev.* **2022**, *159*, 112200. [CrossRef]
133. Iqbal, S.; Sarfraz, M.; Ayyub, M.; Tariq, M.; Chakrabortty, R.K.; Ryan, M.J.; Alamri, B. A Comprehensive Review on Residential Demand Side Management Strategies in Smart Grid Environment. *Sustainability* **2021**, *13*, 7170. [CrossRef]