applied sciences

MDPI

Review

Demand Flexibility: A Review of Quantification Methods, Models, and Required Data

Morgan M. Shepherd [1,*] and Salman Mohagheghi [2]

[1] Advanced Energy Systems Program, Colorado School of Mines, Golden, CO 80401, USA
[2] Electrical Engineering Department, Colorado School of Mines, Golden, CO 80401, USA; smohaghe@mines.edu
* Correspondence: mmshepherd@mines.edu

Abstract: As renewable energy is increasingly integrated into our electricity supply, it becomes more challenging to ensure reliability and security due to the intermittent nature of these resources. With the electrification of buildings and technological advancements across various aspects of their operations, the building sector is expected to play a key role in reducing emissions while supporting the needs of the grid. Buildings and the loads they house can provide grid resources via demand flexibility, shifting, and shedding electric load, as necessary. This key resource has received increased attention from researchers, building operators, electric utilities, policymakers, and system operators as a tool to improve power grid reliability and reduce system costs. Before increasing reliance on demand flexibility, however, a better understanding of its availability is needed to inform planning efforts. This paper includes a review of the literature on current methods and data used to model the available flexibility of power delivered to customers. This review also summarizes how demand flexibility is defined and quantified to help inform future studies in this field. The results of this review illustrate the diversity found within this field of research and the innovation that researchers are employing to solve this complex problem.

Keywords: commercial demand; demand flexibility; demand response; demand side management; distribution grid; energy flexibility; industrial demand; residential demand; power grid operation

check for updates

Citation: Shepherd , M.M.; Mohagheghi, S. Demand Flexibility: A Review of Quantification Methods, Models, and Required Data. *Appl. Sci.* **2024**, *14*, 11276. https://doi.org/10.3390/app142311276

Academic Editor: Rodolfo Dufo-López

Received: 20 October 2024
Revised: 26 November 2024
Accepted: 27 November 2024
Published: 3 December 2024

1. Introduction

1.1. Background

With increased action toward climate change mitigation, the power grid is shifting away from polluting, traditional power generation technologies and toward renewable energy resources. Renewable technologies are intermittent and stochastic, relying on the availability of the resources on which they depend [1]. Unfortunately, these resources do not always align with demand. This mismatch can lead to operational challenges for the grid and perpetuates society's dependence on fossil fuels as a safety measure during times when renewable generation is unavailable.

The electrification of buildings and technological advances across various aspects of energy systems have positioned the building sector to play a significant role in reducing emissions while supporting the power grid. While energy storage has been proposed as a solution to supply and demand misalignment, these systems are still relatively expensive and have environmental impacts throughout their life cycle [2]. Alternatively, buildings can provide grid resources through demand flexibility or demand response (DR) by shifting or shedding electric load in response to grid conditions and/or the availability of renewable energy, often requiring minimal retrofits, with little inconvenience to customers. Demand flexibility can provide benefits to the electric grid, including voltage support, peak demand reduction, and reliability support. This flexibility can reduce costs for the overall power system and individual customers [3]. In the context of this work, the term "demand flexibility" will be used to refer to customers of all sectors responding to grid conditions in the form of demand-side management of energy use. Throughout this paper, the term "demand" is used to denote energy demand via consumers connected to the power grid. Definitions of the various terms used across the studies analyzed are discussed further in Section 3.1.

Historically, studies have focused on the operational viability of this resource for various applications or end-uses. More recently, stakeholders such as building managers, electric utilities, policymakers, and system operators have become more interested in quantifying the availability of demand flexibility for various planning activities [4]. Through an increased understanding of the availability of demand flexibility across the grid, operators can improve DR dispatch, streamline planning practices, and reduce the operational costs of the grid. This interest has led to an emerging field of research focused on quantifying the flexibility potential of buildings. As illustrated by this review, these studies have employed a variety of techniques across different sectors, with little standardization and consistency. These techniques will be summarized here.

1.2. Goals and Methods of This Review

The goal of this paper is to present and summarize common trends among previously published research studies on the topic of energy demand flexibility. To achieve this, a database query was conducted on the Web of Science platform using terms described further in the Methods Section. The results were included in the review if the title, abstract, and contents represented the topics of this review. Methods, definitions of key terms, and data inputs are reviewed thoroughly in addition to the granularity of studies, appliances included in analyses, metrics employed to quantify flexibility, sectors studied, use cases considered, and research gaps. These topics were chosen to inform future quantification studies, contributing to increased standardization and informing the direction of future work.

The rest of this paper is organized as follows: first, the approach followed to conduct this literature review is discussed in Section 2. The results of the review are presented in Section 3, focusing on the review of the definitions, metrics, methods, data inputs, and the types of end uses analyzed across studies. Section 4 discusses the applications and gaps in this field of research. Finally, concluding remarks appear in Section 5 of the paper.

2. Methods

This section summarizes the approach adopted to collect and review sources as part of this review of the literature. In summary, a list of key terms was developed and searched on the Web of Science. Once the results were recovered from the database, the titles and abstracts were reviewed according to the inclusion criteria. If a result met the inclusion criteria, it was included in the review.

The first step in this review was to define a list of key terms found in Table 1. This list was cross-referenced with reviews regarding similar topics and expanded based on the specific goals of this work [4,5]. The terms were separated into four sets, each defining various aspects of the search scope. The first set defined which sectors were to be reviewed. In this review, all sectors were considered within scope, i.e., residential, commercial, and industrial. Set two defines the level of aggregation of the buildings under consideration. This review includes studies at all levels, including individual buildings, districts, communities, the entire grid, and microgrids. Set three specifies various terms that could be used to refer to flexibility. Finally, set four includes terms that could be used to refer to estimation studies. Each set is combined through the "AND" operator.

Filters were used to limit the search to the title, abstract, and author keywords. The search was applied to years after 1990 and excluded meetings, dissertations, editorial materials, and clinical trials. The database search was performed on 2 April 2024, on the Web of Science platform; 1402 results were retrieved, which were refined to 64 studies after a review of the titles and abstracts of each search result. A paper was included in the review when it was clear (through the title and abstract) that the goal of the paper was to quantify the demand-side flexibility of electricity resources within buildings. After flagging applicable papers based on these criteria, they were read and reviewed to track the chosen categories of information. In addition to those collected through this process, other known and relevant sources were included. Trends are presented in the Results Section, while takeaways are presented in the Discussion and Conclusion Sections.

Table 1. Table describing each set of key terms included in the database search. An asterisk (*) allows for variability at the end of the term. For example "energy flexib*" allows the search to include "energy flexible" and "energy flexibility".

Key Terms	Purpose
Set 1: "residential" OR "home" OR "house*" OR "indust*" OR "commercial"	Define sector scope
Set 2: "building" OR "district" OR "community" OR "grid" OR "microgrids"	Define aggregation level
Set 3: "energy flexib*" OR "demand flexib*" OR "load flexib*" OR "operat* flexib*" OR "demand response" OR "DR" OR "load shift*" OR "load shed*" OR "load shav*" OR "load reduc*" OR "demand-side management" OR "demand side management" OR "DSM" OR "load modulat*" OR "load curtailment" OR "demand curtailment" OR "direct load control" OR "peak shav*"	Specify demand-side flexibility
Set 4: "measure*" OR "quanti*" OR "potential" OR "estimate*" OR "calculate*" OR "evaluat*" OR "defin*"	Specify quantification studies

3. Results

This section summarizes the trends observed across the studies included in this literature review. Topics discussed are based on issues and questions that might be of interest to relevant stakeholders such as researchers, electric utilities, policymakers, and grid operators. Trends among the following topics will be discussed further in the subsections below: definitions of demand flexibility, metrics used to quantify flexibility, methods employed among studies, granularity of analyses, appliances analyzed, data inputs, and sectors analyzed in each study.

3.1. Definitions of Key Terms

Throughout the literature, various terms have been cited and defined when referencing topics related to demand-side management (DSM). This section will analyze the terms defined by the authors in this field.

DSM was defined by [1,6–11] as encompassing any changes to customer electricity usage in response to the needs of the power grid. Across all studies reviewed, 12 different terms were used to refer to DSM or a subset of DSM, such as DR or demand flexibility. When reviewing the literature, many of the studies either defined DR [6,12–27] or a term related to demand flexibility [1,3,22,28–40] when referring to how customers can manage demand. These terms, DR and flexibility, seem to be used interchangeably throughout the literature, with DR frequently used to refer to programs implemented by utilities to manage and incentivize customer demand variations. Conversely, terms, including the word "flexibility" are used to broadly define any modification to power on the supply- or demand-side.

Although there was no variation in terms referring to DR, terms defined by authors when referring to flexibility range significantly and include: "flexibility" [1,22,28,30–32], "demand flexibility" [33], "load flexibility" [3], "building energy flexibility" [29,34–36], "energy flexibility" [35,37,38], "EV flexibility services" [39], and "planning flexibility" [40]. Each of these terms can be used to describe a particular process or type of flexibility. For example, demand flexibility would be different from supply flexibility. Notably, energy flexibility could encompass either supply- or demand-side flexibility.

While some authors employ their own definitions of these terms, many cite standardized definitions. For example, the International Energy Agency (IEA) Energy in Buildings and Communities Programme (EBC) Annex 67 definition for "building energy flexibility" [41] was commonly cited [29,34–36]. Both DR and flexibility are cited as being broad categorizations of activities in which customers can match their demand with grid resources to support activities such as grid planning or decreasing emissions.

Based on this review, Figure 1 displays the relationship between DSM and DR including examples of the different types of DR defined and studied in various papers. Specifically, Ref. [22] defines two types of DR, incentive-based and price-based. Incentive-based DR refers to programs that offer an incentive, oftentimes monetary, to decrease customer demand during times of grid stress. On the other hand, price-based DR refers to electricity prices that influence customer demand on a continual basis. This definition is similar to the Federal Energy Regulatory Commission (FERC) definition of DR [42] cited by [16,19], which generally defines two DR categories. Examples of incentive-based programs may include direct load control (DLC) and interruptible programs that allow a utility to control customer demand or limit access to electricity during periods of high grid stress (e.g., heat waves). Examples of price-based DR include time-of-use (TOU) pricing, critical peak pricing (CPP), or real-time pricing (RTP), which are utility tariffs that encourage customers to voluntarily decrease demand during high energy prices that are typically associated with peak hours. The key difference between the two types of DR programs is that incentive-based programs involve infrequent service interruptions, while price-based programs enable voluntary, ongoing load shaping to support the grid.

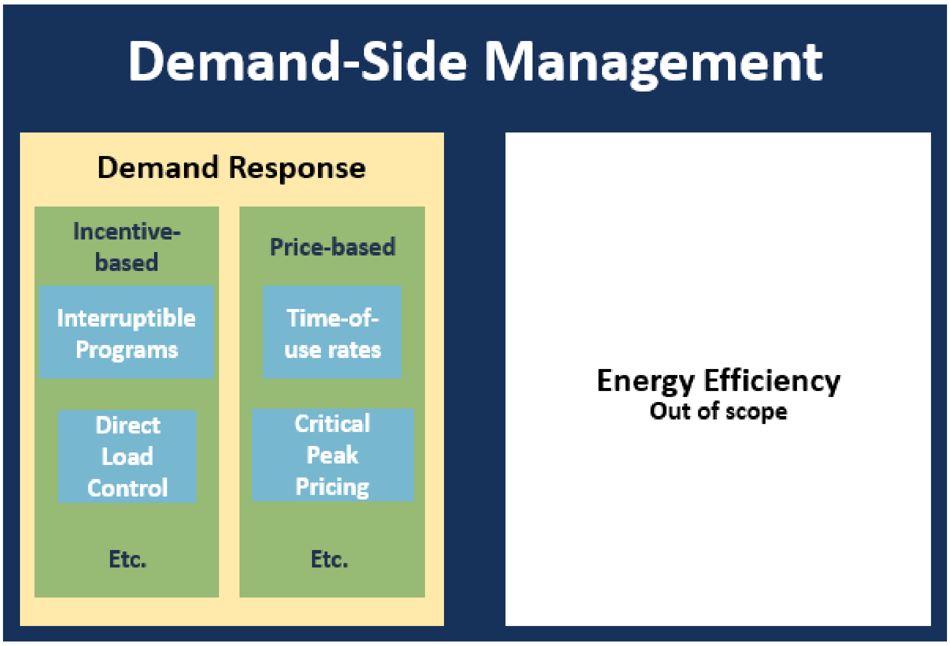

Figure 1. Schematic of DSM with DR and energy efficiency as two sub-categories. While energy efficiency is out of scope in this work, DR includes two sub-categories of incentive-based and price-based programs. DLC and interruptible programs are both types of incentive-based DR. TOU and CPP are both types of price-based DR.

Other notable terms defined throughout the literature include flexible loads [43], flexumer [44], building clusters [35], demand-side services [43], and drivers of price responsiveness [45]. These are not broadly used terms and have been used in specific applications. It should be noted that many papers did not define any terms and instead, cited the benefits of and applications for DR or other forms of DSM without presenting any definitions.

3.2. Metrics Used to Quantify Flexibility Potential

A common source of diversity among the studies reviewed was how authors quantified flexibility potential estimations. In this context, flexibility potential refers to the estimated demand reduction or temporal shift achievable by a single or group of customers over a defined time period. More than 20 metrics were used to quantify flexibility potential. There is no clear standardization of metrics authors used as most studies defined their own terms with little overlap among studies.

Although most authors used units of power [3,7,10,11,16,18,21,23,25,31–35,38–40,43,46–58], other authors used units of energy [9,11,12,15,19,28,29,31,33,35,40,45,53,59–61], emissions [8,9,59], economic measurements [8,9,11,26,53,62], or ramping capacity [31,33,40,56]. Examples of other less commonly used units are temperature [30] and area [24] with [22,27] developing specialized indices. For example, [27] quantified DR potential as a measure between 0 and 1 with 1 referring to high potential.

With such a diverse set of terms and units used to measure flexibility potential, it is difficult to objectively compare studies and understand how flexibility potential varies across sectors and end-uses. It is also difficult to quantify the total availability of this resource over a region when authors employ different quantification metrics that cannot be easily converted into a common quantity.

3.3. Methods Deployed Across Studies

This section includes a summary of the methods employed by authors across the studies reviewed. As illustrated in this section, there is a wide variety of methods employed throughout the literature with little standardization or consistency. This could be due to the diversity of end-uses analyzed and/or the relative novelty of this field of study.

Of the studies reviewed, authors either quantified flexibility potential for individual buildings, aggregated buildings, or aggregated loads. Methods frequently employed by the authors included clustering [25–27,53,63], optimization [6–9,11,15,17,23,28,35,44,47,55,59,64], regression [16,19,24,25,27,46,52,53,58], and simulation [7,11,15,17,22,24,28,31,33,34,37,38,40,50,51,54,58,59,62,65,66], with many researchers employing multiple techniques and methods in one study. Clustering methods generally tend to group buildings into subsets that have similar characteristics in terms of electricity consumption, load shape, or demand flexibility. Regression models often try to estimate the amount of flexibility based on various building or user characteristics. These can then be employed as models in system-wide analyses or might be used for prediction purposes. Optimization-based approaches, on the other hand, typically incorporate user and/or load characteristics into a building-level or system-level optimization model, to reduce demand, reduce costs, or meet a certain operational target. However, many authors developed novel models to illustrate the flexibility of loads and building types.

3.3.1. Clustering

Clustering techniques were used to group buildings together based on various attributes affecting their flexibility potential. Most studies employing clustering techniques did so based on consumption patterns [26,27,53,63], while [25] used clustering to determine day-types. By grouping buildings into clusters, their potential flexibility levels can be estimated as an aggregate value. These clusters could also be targeted by DR providers and utilities to achieve desirable load reductions or shifts.

3.3.2. Regression

Regression models were used to predict various changes in the system under study. Specifically, [16,30] designed regression models to estimate the temperature response of buildings during a DR event. For example, [30] estimated the temperature drop when heating was turned off. Moreover, [19,46,53,58] designed regression models to estimate the amount of expected load reduction during a DR event. Moreover, [25,27,52] used regression to identify indicators of flexibility potential, which can be applied in the flexibility quantification process or used to inform other techniques within the methodology.

3.3.3. Optimization

Many studies employed optimization models to minimize costs [6,8,11,13,35,44,47,59,62,64]. These included electricity demand costs, generation costs for the system, and the total system costs in general. Other optimization models optimized (minimized) values such as power demand [7,23,35,36]. An interesting technique employed by researchers involved minimizing variations in demand from the system mean value to flatten the load curve [13,28,36]. The authors of [55] included various measures in their cost considerations. They maximized overall profits, which were functions of feed-ins from the grid, energy costs, and electricity usage. Finally, the authors of [44] optimized costs but also minimized carbon emissions [28], maximized social welfare, and [6] maximized production of the facility under study.

In terms of the constraints employed for optimization models, researchers have included constraints that represented system limits [7,8,11,13,35,36,59,62,64] and technology limits [6–8,13,28,35,36,44,47,56,64]. System constraints include the supply–demand balance [11,59,64], building temperature requirements [35], power flow equations and grid infrastructure limits [8,64], minimum lighting requirements [36], industrial process flows [7,56,67], and ramping constraints [8,47].

3.3.4. Simulation

Studies that included simulations utilized software, such as EnergyPlus [24,33,34,38,51,58], Comstock [68], Modelica [17,31] and Dymola [37], among others. Simulations were often paired with other methods to compare demand under normal conditions with demand and system behaviors during a DR event.

3.3.5. Novel Methods

As mentioned previously, a significant number of papers included novel modeling techniques that could not be grouped into any standardized techniques mentioned earlier. Specifically, [10,18,28,49] developed flexibility models for individual loads, [1,39,40,47] developed statistical models for individual loads, and [3,61,68] developed statistical models for building demand. These authors developed their own equations that modeled the behaviors of buildings and applicable energy demands to evaluate changes in demand or load shape in response to DR events.

There is notable diversity among the methods presented in the current literature. Quantifying load flexibility is a complex task and requires various considerations that cannot always be modeled via existing methods, hence requiring creativity to develop methods that can do so accurately.

3.4. Sectors of Focus

The sectors included in this review include residential, commercial, and industrial. The residential sector was the focus of 28 studies [1,3,10,11,13,16,22,23,25,27,28,30,32,34,35,38,39,45,47,48,50,52,54,55,57,59,63,65], the commercial sector was the focus of 13 studies [14,17,19,20,24,33,36,37,44,46,51,53,62], and 9 studies focused specifically on industrial applications [6–9,26,56,61,66,67]. Although some studies focused on a single sector, others analyzed two or all three. For instance, [15,29,40,58,60,64,69] focused on the flexibility potential of residential and commercial buildings or end-uses that are present in each building type. For example, the authors of [40] studied the flexibility potential of electric vehicles (EVs) that could charge and discharge at home or at the workplace. The authors of [31,46] included analyses of the commercial and industrial sectors. The focus of [31] was thermal energy storage (TES), which can be present in both building types. Finally, [12,18,21,43,49] quantified the potential flexibility of all three sectors. Figure 2 illustrates the number of studies focusing on each sector, including the overlap between studies of each sector.

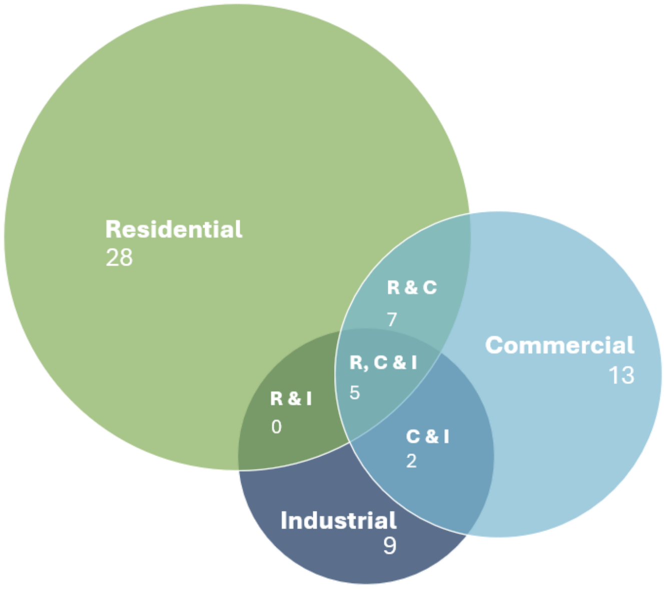

Figure 2. Venn diagram of sectors analyzed across studies reviewed, including residential, commercial, industrial, and studies that focused on more than one sector.

3.5. Data Inputs

Researchers considered various data sources to inform estimations of demand flexibility. The most common data sources include weather and climate data, technology characteristics, demand data, and building data, with demand data being the most prominent.

3.5.1. Demand Data

Demand data was used to inform methods employed by the authors 44 times among the studies reviewed in this paper [1,8,10–16,18,19,22–31,34,35,37,39,40,44–47,49,51–55,58,59,61,63,65,66,68,69]. Notably, [10,23,54,63] used demand data at the individual appliance- or plug-level. However, this level of granularity may not always be accessible due to the need for more granular metering and data collection behind the meter. Privacy concerns are a major obstacle when considering this type of measurement.

Data illustrating energy use was used in a variety of applications. Naturally, the data can be employed to develop load profiles and discern what end-uses are present. This allows researchers to understand where opportunities may exist for demand shifting or shedding. Data can also be used to understand occupant energy-use characteristics to inform flexibility potential estimations.

Demand data was frequently used in parallel with other data sources to inform model development and case studies. For example, in [35], demand measurements were paired with electricity prices, building stock data, weather data, and technology characteristics to project residential flexibility potential under various future scenarios and assess retrofit efforts in Italy.

3.5.2. Weather and Climate Data

In addition to other data sources, 25 studies incorporated weather or climate data into their calculations. Specific data inputs included outdoor air temperature [14,15,18,19,25,28,46,52], climate classifications [24], and weather trends [10,13,22,31,33,35,38,40,51,55,58,59,62,66] relevant to the area under study. These inputs were used to predict building loads specifically in relation to outdoor temperatures. This is not surprising because higher air conditioning (A/C) demand is expected during warmer months and heating demand is higher in winter months, contributing to increased flexibility potential at these times of the year.

3.5.3. Building Characteristics and Models

Researchers frequently included data regarding building characteristics such as heat capacity or square footage [3,14,15,17,24,28,31–33,36–38,51,60,62]. Building operating characteristics can be used to illustrate building responses to flexibility activities. For example, understanding the characteristics of building thermal capacity directly affects flexibility estimations related to heating, ventilation, and air conditioning (HVAC) operations.

Other commonly used types of data relate to building occupants. Naturally, the presence and number of occupants in a building determine how they may directly or indirectly interact with energy systems. Direct interaction could be conducted through appliance and lighting usage, whereas indirect interaction can be viewed in terms of body heat emissions that can increase the heat load within a confined space. Occupancy data was included in [32,36,59,69]. This can be collected using data from occupancy sensors, which may raise privacy concerns. Alternatively, occupancy can be estimated based on non-intrusive load monitoring and load disaggregation, where detecting the usage pattern of certain appliances can indicate the number and/or types of occupants present, e.g., different age groups. Other studies used regional population statistics [10,32,54], which may indicate certain trends or behavioral patterns in energy consumption.

A few studies informed their calculations through novel datasets similar to building characteristics, including benchmarking data [68], building locations [38], and regional building stock statistics [12,35,59,60]. Each dataset provided broad statistics regarding the building stock of a region under study.

3.5.4. Appliance and Technology Data

Data illustrating the characteristics of the technologies analyzed in each study were another major category of datasets seen throughout this review [3,6,7,10,12,14,15,21,28,31,32,34–37,39,44,54,59,60,64,65,69]. This includes characteristics of household appliances, EVs, commercial loads, and industrial units. Characteristics include general load profiles for certain technologies, storage capacities, or cycle characteristics for various residential appliances.

EVs are an increasingly important source of energy demand across various sectors, this requires special consideration in these models. Studies included datasets specific to EVs, aside from general characteristics of how they operate. Specifically, some included mobility data [40,50,55,56,64], EV charging data [39,50,55], and EV adoption data [21,56]. These datasets provided information on how many EVs are present per region and how they are used; factors that can affect the overall demand on the grid.

3.5.5. Grid Data

The last major category of data used in this field was grid-related data. These datasets include emissions, operations, and generation. The authors of [8,11,16,17,29,40,44,55,59,68] considered emissions or other generation characteristics in their analyses, which included the emission intensity of the grid, the availability of a renewable resource, and general characteristics of generation, such as the ramp rate. Moreover, [8,13,16,59,64,68] included grid infrastructure data or models that illustrated the overall topology and operational constraints of the system. These inputs were commonly used to illustrate the effects of demand flexibility on system performance, for instance, node voltages, line flows, and the operating conditions and health of assets.

Related to this category, some studies included temporal electricity prices, including tariffs and locational marginal prices (LMPs) [6,9,15,17,22,35,39,44,62,65] to inform savings calculations and optimal scheduling of end-uses.

Although the analysis above summarizes common data inputs, many studies included less common data types. Some examples are indoor air temperature [37] or occupant comfort measurements [29], socioeconomic or demographic data [12,45,54], and industrial production data [18,21,67]. Although directly related to flexibility estimations, these datasets are not as readily available publicly or require direct measurements during testing, which makes them harder to incorporate into analysis.

3.6. End-Uses Analyzed

The studies reviewed include a variety of end-uses and energy systems. Most consider multiple load types per building [3,9,10,13,16,17,22,23,29,34,37,38,44,45,53,54,56–62,64,69] while others narrow down their focus on a particular end-use [1,11,14,15,20,25,27,30–33,35,36,39,47,50,51].

There were clear trends regarding which end-uses were primarily focused on for each sector. For example, lighting [36,62] and space conditioning [5,14,15,17,20,29,31,33,35,37,44,51,53,59,60,62] were major foci for commercially focused research studies. Studies that either focused on residential research or included it in addition to the analysis of other sectors considered appliances that were commonly found in households. Figure 3 illustrates the major appliances of focus in residential studies. For instance, [3,10,13,23,54,69] included clothing washers and driers. Moreover, [3,10,13,23,45,54,64,69] included dishwashers in their analyses. Space and water conditioning was a major focus as well [1,3,4,10,11,13,15,16,22,23,25,27,30–32,34,38,45,52,57,59,60,62,63]. EVs and electric vehicle supply equipment (EVSE) [10,13,34,36,47,50,63,64] were a common focus for both commercial and residential studies; they are an emerging end-use with potentially high demand commonly found in either type of building. While residential and commercial sectors have broadly defined end-uses that are commonly found in buildings of each sector, industrial studies required more specialized approaches to characterize the processes present [6–9,26,46,61,67].

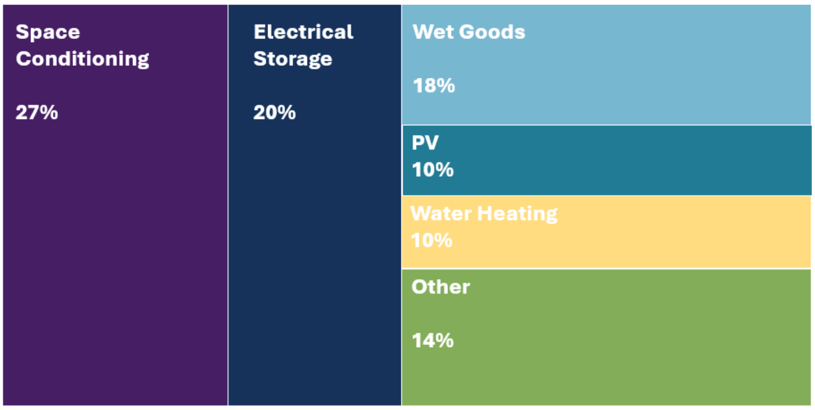

Figure 3. Visualization of the share of appliances included in studies quantifying residential flexibility potential. Adapted from [5].

Illustrated clearly by authors in this field, space and water conditioning were a major contribution to residential and commercial demand making them common inclusions in studies for these sectors. Specifically, [3,17,20,29,30,33,34,37,38,51,58–60] included HVAC systems in their work. Moreover, [10,14,16,23,25,27,48,52,53,62,63] included A/Cs, in particular. The authors of [3,11,22,45,58,59] included water heaters. [10,15,22,23] incorporated space heating into their estimations. More generally, [10,13,29,32,34,35,44,57,60] included heat pumps, [44,61] included thermostatically controlled loads (TCLs), and [29,31,34,37,44,57] included TES. TES could refer to either physical storage or thermal storage of a building. As noted by all authors of these studies, heating and cooling indoor air, as well as heating water, require significant amounts of energy, making them obvious inclusions in these studies.

Even though studies were not comprehensive of all end-uses that could be found in each building type, many authors focused on commonly found appliances and energy systems based on ownership trends for the regions under study as illustrated by Table 2.

Table 2. Summary of methods, granularity, end-uses, metrics, data inputs, and sectors considered in the literature. An "X" in the "Case Study" column signifies that the study included a case study to validate the developed methods. Letters R, C, and I in the "Sector" column indicate residential, commercial, and industrial sectors, respectively.

Author	Methods	Case Study	Granularity	End-Uses	Metric(s)	Data Inputs	Sector
Gasca et al. [1]	Statistical models for loads	X	Aggregate	TCL	Power flexibility (p.u.)	Demand, temperature	R
Munankarmi et al. [3]	MPC, flexibility model of building	X	Single	PV, HVAC, battery, water heater, dishwasher, clothes drier	Forward flexibility operation (kW)	Power estimations, building characteristics, technology characteristics	R
Röben et al. [6]	Optimization (production and cost)		Single	Copper production	Annual electricity cost reduction (%), specific revenue per ton Cu (EUR/tCu), shifted electricity demand (%, MWh, and GWh), electricity costs per ton Cu (EUR/tCu)	Production characteristics, time-varying electricity prices	I
Sun and Li [7]	MPD, optimization (capacity), simulation	X	Single		Power consumption reduction (kW)	Technology characteristics, production characteristics	I
Rövekamp et al. [8]	Optimization	X	Aggregate		Economic value (euro and tCO2)	Grid emissions, demand, grid operations	I
Summerbell et al. [9]	Optimization (cost)	X	Single	Stone crusher, raw mill, kiln, cement mill	Reduction in electricity costs (%), reduction in electricity (%), CO_2 emissions (t/year)	Technology characteristics, temporal electricity prices, grid emissions	I
O'Reilly et al. [10]	Flexibility models for individual loads	X	Aggregate	EV, AC, dishwasher, clothes washer, clothes drier, electric heater, heat pump, heat circulation pump, refrigerator, freezer	Reduction potential (MW)	Population, appliance ownership, demand, technology characteristics, weather	R
Hungerford et al. [11]	Optimization (cost), simulation	X	Aggregate	Water heaters	Peak reduction (MW), capacity saving (AUD), renewable curtailment (GWh)	Demand, generation	R
Aryandoust and Lilliestam [12]	Load profile models per sector, simulation	X	Aggregate		Spinning reserve (GWh), primary, secondary, and tertiary reserve (GWh)	Demand, demographic, DR acceptance survey, building stock, technology characteristics	R, C, I
Klaassen et al. [13]	Optimization (capacity and cost)	X	Aggregate	Dishwasher, clothes washer and drier, heat pump, CHP, EV	Costs flexibility	Grid operations, weather, generation characteristics, demand, energy market	R
Li et al. [14]	Thermal model of building, field test		Single	AC	DR potential (%)	Building characteristics, technology characteristics, temperature, demand	C
Romanchenko et al. [15]	Optimization, simulation	X	Aggregate	Space heating	Shifted space heating demand (GWh)	Building characteristics, temperature, solar irradiation, technology characteristics, demand, district heating characteristics, temporal electricity prices, fuel prices	R, C
Dyson et al. [16]	Regression, classification	X	Single	PV, AC	DR potential (MW)	Demand, weather, grid operations, solar resource	R
Gehbauer et al. [17]	MPC, optimization, simulation	X	Single	Dynamic window, HVAC	Demand savings (kW, W/m^2), resource adequacy ($/kW), peak demand savings (kW, W/m^2), energy cost savings ($\$/m^2$), electricity savings (MWh, kWh/m^2), emissions savings (tCO_2)	Temporal electricity prices, building characteristics, occupant comfort, weather, dynamic facade, technology characteristics	C

Table 2. *Cont.*

Author	Methods	Case Study	Granularity	End-Uses	Metric(s)	Data Inputs	Sector
Gils [18]	Flexibility models for individual loads		Aggregate		Load reduction or increase (GW)	Industrial production, demand, outdoor air temperature	R, C, I
Granderson et al. [19]	Regression		Aggregate		DR load reduction benefits (%)	Demand, temperature	C
Härkönen et al. [20]	Classification, load profile models for commercial building types		Aggregate	HVAC	Gross yearly revenue (euro), gross ancillary market revenue (euro)	Building stock, technology characteristics, historical DR market prices	C
Heitkoetter et al. [21]	Optimization	X	Aggregate		Load reduction or increase potential (MW)	Demand, appliance ownership, building characteristics, industrial location and production, EV adoption, technology characteristics	R, C, I
Homaei and Hamdy [22]	Optimization, simulation	X	Single	Space and water heating	Cost effective flexibility index	Temporal electricity prices, demand, weather	R
Lucas et al. [23]	Optimization, factorial hidden Markov model, machine-learning		Aggregate	AC, dishwasher, clothes washer, clothes drier, fridge, heating, lighting, microwave, freezer, pool pump/dehumidifier	Flexibility power (W)	Demand	R
Luo et al. [24]	Simulation, regression, bayesian framework		Single	HVAC, lighting, plug loads	Demand increase intensity (W/sqft)	Building characteristics, demand, climate	C
Qi et al. [25]	Clustering, correlation analysis, regression	X	Aggregate	AC	DR potential (kW)	Demand, temperature	R
Rodriquez-Garcia et al. [26]	Clustering	X	Single		Economic profitability ($)	Demand, temporal electricity prices (historic)	I
Toosty et al. [27]	Clustering, regression	X	Aggregate	Heat pump AC	DR potential	Demand	R
Ostovar et al. [28]	Optimization (social welfare), flexibility models for individual loads, simulation	X	Single		Potential flexibility (kWh)	Demand, building characteristics, appliance characteristics, temperature, solar irradiance	R
Awan et al. [29]	Fuzzy analytic hierarchy and multi-criteria decision analysis	X	Single	PV, TES, HVAC, heat pump	Aggregated energy flexibility potential (AEFP) (%)	Demand, Grid emissions, temporal electricity prices, occupant comfort	R, C
Crawley et al. [30]	Regression		Aggregate	Electric heating	Temperature drop (Celsius)	Indoor temperature, demand	R
Stinner et al. [31]	Flexibility models for building types, simulation	X	Aggregate	TES	Ramp-up capacity (MW/min), power capacity (MW), energy (MWh)	Demand, weather, building characteristics, occupancy, technology characteristics	C, I
Wang et al. [32]	Occupancy model, thermal model of building		Aggregate	Heat pump	Energy flexibility potential (W)	Building characteristics, population, occupancy	R
Hurtado et al. [33]	Statistical models for building demand, simulation	X	Aggregate	HVAC	Ramping rate (kW/min), power capacity (kW), energy capacity (kWh), comfort capacity (min), comfort recovery (min)	Building characteristics, technology characteristics, weather	C
Bampoulas et al. [34]	Simulation	X	Single	PV, EV, TES, HVAC, battery, heat pump	DR potential (kW)	Demand, technology characteristics	R
Mugnini et al. [35]	Thermal model of building, optimization	X	Aggregate	Heat pump	Electrical power-shiftable (MW_e), average daily shiftable energies (GWh_e)	Demand, temporal electricity prices, building stock, weather, technology characteristics	R
Yu et al. [36]	Optimization	X	Single	Lighting		Weather, technology characteristics, building characteristics, occupancy	C
Chen et al. [37]	Flexibility models for individual loads, simulation	X	Single	HVAC, Thermal mass, lighting	Electricity flexibility (W, kW, or J)	Indoor temperature, building characteristics, demand, occupancy, technology characteristics	C

Table 2. *Cont.*

Author	Methods	Case Study	Granularity	End-Uses	Metric(s)	Data Inputs	Sector
Majdalani et al. [38]	Genetic algorithm, simulation	X	Single	PV, HVAC	Expected flexibility savings index (% of dwelling load)	Weather, building characteristics, building location	R
Sorenson et al. [39]	Statistical models for EV demand	X	aggregate	EV	Energy flexibility potential (kW)	Demand, temporal electricity prices, local traffic, EV charging	R
Yu et al. [40]	Statistical models for EV demand, simulation	X	Aggregate	PV, EV, wind turbine	Flexibility indices: energy, power, and ramp capacity (% reduction)	Mobility, demand, appliance usage, technology characteristics, generation characteristics	R, C
O'Shaugh-nessy et al. [43]	Literature review	X	Aggregate		Load flexibility (GW)		R, C, I
Fleschutz et al. [44]	Optimization	X	Single	PV, EV, TES, wind turbine, battery, CHP, cooling machine, H2 storage, electrolyzer, DAC, power-to-heat, heat pump	Energy-weighted: average price and carbon emission factor, time-weighted: average price, average carbon emission factor, and cost-emissions ratio, energy-based cost-emission ratio	Temporal electricity prices (historic), grid emissions, generation characteristics (PV), demand, historic natural gas prices, technology characteristics	C
Guo et al. [45]	Neural network, integrated machine learning	X	Aggregate	Water heater, dishwasher	Peak demand reduction (kWh)	Demand, demographic, socioeconomic	R
Mathieu [46]	Load profile models for buildings, regression	X	Single		Average demand shed (kW)	Demand, outdoor air temperature	C, I
Zhao et al. [47]	Statistical models for EV demand, disaggregation algorithm, optimization (cost)	X	Aggregate	EV	Flexibility (kW)	Demand	R
Chen et al. [48]	Thermal model of building	X	Aggregate	AC	DR potential (MW)		R
Dranka and Ferreira [49]	Flexibility models for individual loads		Aggregate		DR potential (GW)	Demand	R, C, I
Ding et al. [50]	Statistical models for EV demand, simulation	X	Aggregate	EV	Peak shaving potential (MW), valley filling potential (MW), V2G discharge DR potential (MW)	Mobility, technology characteristics, EV charging	R
Sehar et al. [51]	Simulation, occupant comfort model	X	Single	HVAC	Peak load savings (kW)	Building characteristics, weather, demand	C
Song et al. [52]	Regression, neural network, thermal model of building	X	Aggregate	AC	DR potential (kW)	Demand, temperature	R
Triolo et al. [53]	Clustering, regression	X	Aggregate	AC, Cold water chillers, hot water generators, heat recovery chillers, hot and cold water storage	Demand reduction (% of current demand), cost savings ($)	Building characteristics, demand, daily system load served by central energy facility (CEF)	C
Vellei et al. [54]	Agent-based model, simulation	X	Aggregate	Dishwashers, clothes washers	Mean hourly load reduction (GW)	Technology characteristics, population, appliance usage, socioeconomic	R
von Bonin et al. [55]	Optimization	X	Aggregate	PV, EV	Shifting potential (kW)	Weather, generation (PV), technology characteristics, mobility data, EV charging, demand, electricity price forecast	R
Wang et al. [56]	Backward powertrain model, optimization	X	Aggregate	FCEV, centralized electrolytic hydrogen production	Peak shaving (GW), valley filling (GW), ramp mitigation (MW/min)	SERA model, EV adoption and usage, EV characteristics, mobility, EPA driving characteristics	I
Wolisz et al. [57]	Literature review	X	Aggregate	Heat pump, CHP, TES, battery	Installed capacity (GW)		R
Yin et al. [58]	Regression, simulation	X	Aggregate	HVAC, refrigerator, water heater	DR potential (%), peak load reduction (kW)	Demand, weather	R, C
Cruickshank et al. [59]	Optimization, simulation, flexibility models of individual loads	X	Aggregate	Hot water heater, battery, HVAC, PV	Production cost ($/MWh), CO^2 emissions (lb)	Weather, building stock, demand, technology characteristics, fuel costs, generation characteristics, time-of-use of appliances, occupancy, grid emissions, network	R

Table 2. *Cont.*

Author	Methods	Case Study	Granularity	End-Uses	Metric(s)	Data Inputs	Sector
Kohlhepp and Hagenmeyer [60]	Thermal model of buildings	X	Aggregate	HVAC, heat pumps, cold storage	Storage capacity (J)	Technology characteristics, building characteristics, building stock	R, C
Strobel et al. [61]	Flexibility models for building types		Single	TCLs	Shifted energy amount (kWh)	Demand, SOC	I
Cai and Braun [62]	Simulation, optimization (indoor air temperature)		Single	AC, lighting	Cost savings ($), peak demand reduction (W/ft^2), percentage people satisfied (%)	Building characteristics, weather, temporal electricity prices	C
Afzalan and Jazizadeh [63]	Clustering	X	Aggregate	EV, clothes washer and drier, dishwasher, and AC	Demand reduction projection (MWh)	Demand	R
Babrowski [64]	Optimization		Aggregate	PV, EV, EVSE	Load shift potential (GW)	Mobility data, grid operations	R, C
Schram et al. [65]	Simulation, flexibility and NPV model of batteries	X	Aggregate	Battery, PV	Peak shaving potential (%)	Technology characteristics, demand, temporal electricity prices	R
Zhu et al. [66]	Simulation, neural network, Bayesian framework	X	Single	AC	Maximum power shedding point, maximum power shedding, mean power shedding, maximum power rebound, maximum DR rebound	Weather, internal disturbances, demand	I
Mohagheghi and Raji [67]	Optimization	X	Single	Manufacturing workstations	DR potential (kW)	Demand, factory layout, crew availability	I
Andrews and Jain [68]	Simulation, flexibility model of building		Aggregate		Emissions reduction (%)	Grid emissions, demand, grid operations, benchmarking data	C
Peacock and Owens [69]	Export and import flexibility models		Aggregate	Wind, dishwasher, clothes washer	Maximum addressable opportunity (%)	Electricity export and import, demand, occupant behavior, technology characteristics, participation rates	R, C

MPC: Model predictive control (MPC); MPD: Markov Decision Process (MDP).

4. Discussion

4.1. Applications of Flexibility Quantification

Flexibility quantification can be used to inform the integration of renewable energy resources, enhance power grid stability and security, support DR program development, and guide policy development.

4.1.1. Integration of Renewable Energy Resources

Renewable energy technologies are reliant on energy resources, such as wind and solar irradiance, which are intermittent and somewhat stochastic [1]. Although there has recently been significant progress in developing more accurate predictive models for these resources, forecast uncertainties can still introduce challenges for power grid operation and security [70]. This is especially problematic at high penetration levels of renewable resources. Traditionally, one solution has been to over-design wind and solar power plants to allow for some level of operational flexibility when the available energy is less than expected or desired. In fact, early efforts in replacing fossil fuel-based power plants with renewable counterparts relied on increasing the new plant's rated capacity compared to the decommissioned one in order to compensate for any drop in available generation. With the drop in price of utility-scale batteries in conjunction with more efficient chemistries, the focus has shifted toward combining renewable resources with energy storage [71]. While both approaches are effective in turning renewable generation into a dispatchable resource, they incur additional costs and can lead to negative environmental impacts. Demand flexibility is a relatively inexpensive, environmentally friendly, and readily available resource that can be combined with renewable generation to reduce its operational uncertainties [72].

Quantifying the availability of demand-side flexibility can assist electric utilities in multiple ways. First, the knowledge of the locations and levels of flexibility available across the grid can inform grid planners regarding the most appropriate locations and/or penetration levels for renewable generation as well as what energy storage resources are needed and where. Furthermore, information on when demand flexibility might be available can be used in power grid energy dispatch, especially in allocating reserves. The general idea that demand flexibility can play a major role in facilitating renewable energy integration and system planning was cited across studies [1,8–11,16–18,20–22,26,27,31,32,34,38,40,43,49,50,55,56,58,61,64]. Accurate flexibility models can help turn demand into a semi-dispatchable resource that can alleviate some of the operational uncertainties of renewable resources. This can in turn help improve the seamless integration of these resources with the grid, hence, facilitating decarbonization efforts at all levels [43,68]. In terms of smart buildings, understanding flexibility potential and cost savings when pairing electrification with flexibility can provide valuable insights to guide the electrification of buildings [30].

4.1.2. Power Grid Stability and Security

The stable and secure operation of the electric power grid relies on the availability of adequate and efficient ancillary services. These are typically provided in the form of frequency and voltage control at different timescales. They may consist of frequency regulation, load following, capacity reserves, and voltage support. While generation sources have traditionally been considered providers of ancillary services, demand flexibility can be viewed as virtual power generation, offering similar support. Different DR programs can offer demand reduction at various timescales ranging from a few seconds (for instance, in DLC-type programs and emergency DR) to a few minutes (for instance, in interruptible DR). Not only can this reduce overall operational costs, but it may also lower the stress on generation resources that would otherwise have to go through ramp-up and ramp-down cycles. In fact, demand flexibility has been proposed by researchers for capacity reserves, frequency support, ease of ramping for generation resources, load shaping, peak demand reduction, and improved utilization of generation capacities [1,10,11,18,32,34,40,43,64]. Some have also proposed integrating DR and demand flexibility with generation planning.

However, the criticality of ancillary services in ensuring power grid stability and security necessitates an accurate assessment of the amount of energy or demand curtailment available, the timing, the duration, and the associated probabilities. This requires a precise model for quantifying demand flexibility potential subject to all associated uncertainties. Higher accuracy levels can result in improved performance efficiency and lower operational costs across the grid.

4.1.3. DR Program Development and Implementation

One of the key challenges associated with integrating DR with distribution grid operation is estimating the level of flexibility accurately [72]. Although one of the key goals of quantifying demand flexibility is to reduce system and customer costs [8–11,34,38,43–45,51,54,58], inaccurate estimations can lead to increased costs at various levels. Overestimating potential demand reduction could result in a mismatch between load and generation, leading to higher operational costs as the utility would be forced to revert to more expensive generation resources to meet demand. On the other hand, underestimating potential demand reduction may result in curtailing more demand than necessary, which results in financial losses for the electric utility and inconvenience for end users.

Most current DR programs implemented for residential customers are of the DLC type, where, during times of need, the electric utility remotely and directly turns off certain loads—often A/C units—typically with little to no coordination with the customer. The benefit of DLC is that the amount of demand reduction can be predicted with high accuracy, making it a reliable and dispatchable resource. However, many building appliances are not compatible with DLC due to technical limitations, privacy concerns, or user convenience issues [5]. This introduces a missed opportunity for both the utility and the customers. As modern buildings continue to be equipped with advanced home energy management systems (HEMS), opportunities are emerging for utilities to implement more advanced DR programs in which customers (or their HEMS units) decide to comply with a DR event or conversely, to opt out. While this creates possibilities to include a more diverse set of appliances and, hence, more potential for flexibility, it introduces unique challenges related to predicting what households will comply with the DR event and by how much.

Demand flexibility models can inform the development and implementation of DR programs in various ways. As noted in the papers reviewed, by providing more accurate forecasts, DR events can be rolled out in a more targeted and localized fashion, with higher reliability. These forecasts can be used to determine optimal incentive structures that maximize customer participation while minimizing the financial burden on the utility [25,48]. Lastly, these models can be used by electric utilities in customer targeting [1,24,25,27,31,34,45,50,51,63]. Flexibility analysis can indicate which users are generally more flexible than others, what appliances are more reliable for achieving the targeted demand reduction, and what times are best to dispatch DR in which parts of the grid. This information can assist DR program managers in targeting customers more efficiently and in a more localized fashion.

4.1.4. Policy Development

Finally, flexibility quantification can be used for policy development [8,10,22,38,39,68]. By informing policymakers of the opportunities available through demand-side flexibility and benefits gained by the grid, more effective policies can be proposed to support or require the integration of flexibility into all demand sectors. Similar to the development of building performance standards (BPSs) and other decarbonization initiatives, scientific research can be used to inform the development of policies that can require and incentivize certain actions by building owners and operators [68]. Flexibility provides alternative pathways to DSM than efficiency measures that may not be suitable for all applications. Similar to informing statutory decisions, stakeholders such as grid operators could implement flexibility quantification techniques to inform the integration of flexibility into energy markets [10,22,23,25,37,49,50,58]. By illustrating the value of this resource and understanding its availability, system operators can work with policymakers to develop technical and policy practices to support this integration. However, this requires a deep understanding of the spatiotemporal variability and availability of the resource. If developed properly, demand flexibility can be a major component for day-ahead and balancing markets as well as ancillary service markets where various services such as frequency regulation, load following, and voltage control are offered. Policy and system support for this resource can help ensure ease of implementation at all levels, from individual building operations to the entire energy market.

4.2. Research Gaps and Future Directions

Some of the major gaps and opportunities seen across this review include possibilities for more advanced data-driven methods, a lack of research into industrial flexibility potential, issues with the availability and accessibility of data, and minimal consideration of human behavior or equity in demand flexibility models.

4.2.1. Advanced Analytical Methods

A large portion of the studies reviewed in this paper employ conventional data analytics techniques such as regression and clustering for either modeling or predicting demand flexibility. These techniques are very effective in lower-dimensional settings with less complex dynamics. We saw a few examples of neural networks used in studies within this field [45,52,66]. However, as the diversity and breadth of the available data increases, more advanced data-driven models might be needed. For instance, non-intrusive load monitoring used for indirect occupancy detection in a building may require the adoption of deep learning techniques to detect and distinguish nuanced usage patterns and signatures of various appliances in the household. This is especially true if those patterns are investigated across multiple buildings and users. Another complexity arises if the dimensions of a demand flexibility model increase by considering not just building characteristics and outdoor environmental factors but also indoor variables such as temperature, airflow, occupancy, body heat, and/or user convenience models. This can turn the problem into a complex multilayered model in which conventional techniques and algorithms may fail to fully identify and represent the complexity of demand flexibility. Deep learning models such as autoencoders or recurrent neural networks may prove to be more efficient in those situations. However, when adopting more advanced machine learning models, their superior modeling capabilities must be balanced against their interpretability (or lack thereof).

4.2.2. Industrial Flexibility Potential

Compared to the residential and commercial sectors, demand flexibility potential for the industrial sector has been relatively unexplored and few researchers have focused on quantifying the flexibility potential of industrial activities [18,21,26,31,43,49,67]. In fact, of the studies reviewed, only nine papers quantified industrial flexibility potential on its own.

Often, researchers presented methods designed to evaluate the flexibility potential of a particular industrial activity or employed simplifying assumptions to use regional statistics of industrial production [18]. This is in part due to the significant differences like industrial demand compared to that of residential and/or commercial sectors. Demand reduction in an industrial facility may impact the plant's production levels, pre- and post-process inventory buildup, and the work schedule of the crew, to name a few. These factors complicate the analysis and limit the generalizability of different solutions since each industrial process is different, not just in characteristics but also in terms of operation, objectives, and requirements. There have only been a few examples focused on the detailed flexibility potential of the industrial sector. For example, [26] provided a tool for industrial process operators to evaluate the costs and benefits of participating in DR; the tool analyzes the facility to determine how an industrial customer should proceed before a DR event. In [67], the authors developed an optimization model to maximize demand reduction potential subject to various operational constraints such as inventory constraints, cost constraints, crew constraints, and workstation interdependencies.

The oversimplified analysis of industrial activities leads to inaccurate estimations of the sector's flexibility potential. It also ignores the inherent variability in energy use and operation characteristics of this sector, which could otherwise be used to improve the reliability and security of the power grid. There is both a need and an opportunity for developing generalized demand flexibility models for various industrial facilities or sectors where common themes and patterns are identified, characterized, and modeled without overlooking unique features and operation aspects.

4.2.3. Data Availability

There are common types of data used by authors in this field. Many studies focus on a single or a limited number of end-uses for analysis, which narrows the data required to inform their methodology. For example, studies that analyzed A/C flexibility potential often used historical demand data, temperature data, building characteristics, and technology characteristics. Although these might be suitable for A/C-specific studies, they do not provide a complete picture of the building response to a DR event and the effects on occupants; increased diversity of data is required to account for all contributors to flexibility variations. An accurate demand flexibility model needs input data that are comprehensive and granular.

As illustrated in Section 3.5, common datasets seen across studies include demand, weather/climate, building characteristics, appliance characteristics, and grid data. These all focus on the technical characteristics and factors driving flexibility, and as such, may not account for all variables contributing to flexibility potential estimations. For example, the authors of [45] identified various drivers of price responsiveness that are not reflected in the data evaluated in Section 3.5. Among other factors, they identified income status, the number of occupants, and perceived behavioral control as being contributors to price responsiveness. However, these factors were not seen frequently—if at all—in flexibility studies. References [12,54] included a subset of those drivers but were not comprehensive. Determining which attributes contribute to flexibility potential may require direct engagement with customers and stakeholders to gain a deeper understanding of the drivers of flexibility and identify the data needed to enhance confidence in estimations.

Another limitation involves the accessibility of data. While building characteristics, technology characteristics, and historical demand may generally be accessible, other useful (and at times necessary) data, such as indoor temperature data and occupancy data, are often unavailable due to privacy concerns, lack of granular measurements, or both. This can negatively impact the accuracy of the developed model by ignoring variables that have a direct impact on demand and its flexibility potential. The issue can be partially addressed by either estimating the unavailable data or including surrogate data. For instance, indoor temperatures can be estimated using physics-based models and occupancy can be estimated based on non-intrusive load monitoring methods. However, this approach can cause cumulative errors in the model. A more severe challenge occurs when modeling user behavioral patterns with respect to DR and demand flexibility. User behavior data cannot be easily measured or estimated. In fact, large-scale, longitudinal surveys might be the only viable option to collect meaningful data to develop models. But even those models may not be easily generalizable. An opportunity exists for multidisciplinary sociotechnical analyses spanning engineering, economics, and social sciences to develop models that reflect how users interact with energy systems and DR programs.

Even when the required data are available, they may not have the necessary granularity levels. For instance, an accurate demand flexibility model of a building would need usage data from individual appliances. Such data are difficult to obtain for an individual building, but almost infeasible to collect for a cluster of buildings or a region. Advanced deep learning techniques, as described above, might be used to detect consumption patterns and signatures of various appliances from aggregate meter data. Another example is related to occupancy detection. While general occupancy can be determined easily from meter data, determining the number and age of individuals in the building, without direct measurement, is far more complicated. At the same time, the demand profile and response to DR events might be directly impacted by which occupants are inside the building. Statistical models can be developed using historical data to assign temporal probabilities to the number and types of occupants in the building at any given point in time. The associated probabilities will then need to be incorporated into the models to provide estimations under uncertainties.

4.2.4. Human Behavior in Flexibility Quantification Studies

A key missing feature in previous work is the inclusion of complex human behavior and how it affects flexibility potential estimations. Although automated load flexibility is the goal, occupant preferences play a major role in the availability of this resource. Although acknowledged throughout the literature as a driving factor in quantifying demand flexibility potential, previous studies do not account for residents' variable interactions with the energy systems around them. The authors tend to account for variability among customers by simplifying user preferences to a range of indoor temperatures [3,17,29,33] or by simply attributing household variability to differences in load profiles. These methods do not account for the immense diversity of needs among electricity customers and oversimplify their actions based on minimal datasets. Although there are a few authors who have incorporated data such as demographic [45], census [32], or survey data [12,32,40,54–56], this may not be comprehensive of attributes that affect individual flexibility potential.

There is a need for the development of human behavior models that reflect the general ways in which individuals interact with energy systems without becoming too narrowly focused on random patterns. This is of course a challenging task, mainly due to the lack of granular and comprehensive user data. Advanced machine learning models can be used to extract consumption patterns from raw data and convert them into meaningful and generalizable information to be used in flexibility models. Not only can this be used to improve the forecast accuracy of demand flexibility, but it can also be used to develop more customized DR programs.

4.2.5. Equity

DR is a power grid application that is most closely related to and impacts customers. Yet, how its implementation affects individuals and households is not yet properly explored in the literature.

Demand flexibility touches on two tenets of energy justice, namely distributional justice and recognition justice. Distributional justice refers to the fair distribution of harms and benefits across a community [73]. This is an important consideration, particularly for DR, because the benefits of DR actions are realized by everyone connected to the grid. However, the burden is only seen by those who choose to participate which could lead to ongoing inequity. Measures to ensure that demand from a specific group or 'class' of customers is not overly utilized during DR events and is a welcome first step to ensure distributional justice. This can, for instance, be achieved by limiting the number of times—either consecutively or in total—that each customer or household can be targeted for demand reduction. Furthermore, metrics to reflect DR benefits can be developed. For instance, improvement in reliability or resilience can be compared across various customer groups to ensure benefits are well distributed across all customers of the power grid. Recognition justice, on the other hand, acknowledges and focuses on the differences in capabilities and limitations of individual customers when it comes to adapting and responding to the undesired side-effects of DR participation [73]. Perhaps the most commonly acknowledged factor is related to the impact of excess indoor temperatures. For example, the effects of increased indoor air temperature due to A/C DR on various age groups. Research shows that those over the age of 65 or under the age of 5 are on average less tolerant of temperature extremes and as such, should be deprioritized for DR participation during extreme weather events [74]. Perhaps less understood is how appliance DR and load shifting can affect customer convenience, depending on user demographics and the types of appliances.

Such equity considerations are a major gap in research across studies seen in the literature. Equity and energy justice, from distributional and recognition angles, need to be properly integrated with and incorporated into demand flexibility models. Equity-focused methods can then be used to target customers with high DR potential and/or to implement targeted and localized DR events.

5. Conclusions

This literature review presents trends among previously published research pertaining to demand flexibility modeling and quantification. Within the context of this paper, the term 'demand' refers to energy demand associated with consumers connected to the electric power grid. Trends analyzed across studies included definitions of key terms, metrics, and units used to quantify demand flexibility potential, methods deployed by authors in this field, data inputs used to inform studies, and end-uses included in analyses. Little standardization was observed across studies with authors frequently developing their own methods and metrics to quantify and describe demand flexibility. Applications of flexibility quantification were also discussed to illustrate the opportunities for studies in this field. Research gaps were identified to inform the direction of future studies and research. The material presented in this paper is highly beneficial for researchers who are interested in advancing this field of study. It can also inform actions by policymakers, electric utilities, and grid operators who plan to utilize demand flexibility as a resource to improve power grid operational efficiency, lower operational costs, and integrate renewable energy resources with the power grid.

Author Contributions: Conceptualization, M.M.S. and S.M.; methodology, M.M.S.; investigation, M.M.S.; writing—original draft preparation, M.M.S. and S.M.; writing—review and editing, S.M.; visualization, M.M.S.; supervision, S.M.; funding acquisition, M.M.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Advanced Energy Systems (AES) Graduate Program at the Colorado School of Mines and the National Renewable Energy Laboratory.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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

References

1. Gasca, M.V.; Ibáñez, F.; Pozo, D. Flexibility quantification of thermostatically controlled loads for demand response applications. *Electr. Power Syst. Res.* **2022**, *202*, 107592. [CrossRef]
2. Dehghani-Sanij, A.R.; Tharumalingam, E.; Dusseault, M.B.; Fraser, R. Study of energy storage systems and environmental challenges of batteries. *Renew. Sustain. Energy Rev.* **2019**, *104*, 192–208. [CrossRef]
3. Munankarmi, P.; Jin, X.; Ding, F.; Zhao, C. Quantification of Load Flexibility in Residential Buildings Using Home Energy Management Systems. In Proceedings of the 2020 American Control Conference (ACC), Denver, CO, USA, 1–3 July 2020; pp. 1311–1316. [CrossRef]
4. Li, H.; Johra, H.; de Andrade Pereira, F.; Hong, T.; Le Dréau, J.; Maturo, A.; Wei, M.; Liu, Y.; Saberi-Derakhtenjani, A.; Nagy, Z.; et al. Data-driven key performance indicators and datasets for building energy flexibility: A review and perspectives. *Appl. Energy* **2023**, *343*, 121217. [CrossRef]
5. 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]
6. Röben, F.T.C.; Liu, D.; Reuter, M.A.; Dahmen, M.; Bardow, A. The demand response potential in copper production. *J. Clean. Prod.* **2022**, *362*, 132221. [CrossRef]
7. Sun, Z.; Li, L. Potential capability estimation for real time electricity demand response of sustainable manufacturing systems using Markov Decision Process. *J. Clean. Prod.* **2014**, *65*, 184–193. [CrossRef]
8. Rövekamp, P.; Schöpf, M.; Wagon, F.; Weibelzahl, M. For better or for worse? On the economic and ecologic value of industrial demand side management in constrained electricity grids. *Energy Policy* **2023**, *183*, 113781. [CrossRef]
9. Summerbell, D.L.; Khripko, D.; Barlow, C.; Hesselbach, J. Cost and carbon reductions from industrial demand-side management: Study of potential savings at a cement plant. *Appl. Energy* **2017**, *197*, 100–113. [CrossRef]
10. O'Reilly, R.; Cohen, J.; Reichl, J. Achievable load shifting potentials for the European residential sector from 2022–2050—ScienceDirect. *Renew. Sustain. Energy Rev.* **2024**, *189*, 113959. [CrossRef]
11. Hungerford, Z.; Bruce, A.; MacGill, I. The value of flexible load in power systems with high renewable energy penetration. *Energy* **2019**, *188*, 115960. [CrossRef]
12. Aryandoust, A.; Lilliestam, J. The potential and usefulness of demand response to provide electricity system services. *Appl. Energy* **2017**, *204*, 749–766. [CrossRef]
13. Klaassen, E.A.M.; van Gerwen, R.J.F.; Frunt, J.; Slootweg, J.G. A methodology to assess demand response benefits from a system perspective: A Dutch case study. *Util. Policy* **2017**, *44*, 25–37. [CrossRef]
14. Li, W.; Yang, L.; Ji, Y.; Xu, P. Estimating demand response potential under coupled thermal inertia of building and air-conditioning system. *Energy Build.* **2019**, *182*, 19–29. [CrossRef]
15. Romanchenko, D.; Nyholm, E.; Odenberger, M.; Johnsson, F. Flexibility Potential of Space Heating Demand Response in Buildings for District Heating Systems. *Energies* **2019**, *12*, 2874. [CrossRef]
16. Dyson, M.E.H.; Borgeson, S.D.; Tabone, M.D.; Callaway, D.S. Using smart meter data to estimate demand response potential, with application to solar energy integration. *Energy Policy* **2014**, *73*, 607–619. [CrossRef]
17. Gehbauer, C.; Lee, E.S.; Wang, T. An evaluation of the demand response potential of integrated dynamic window and HVAC systems. *Energy Build.* **2023**, *298*, 113481. [CrossRef]
18. Gils, H.C. Assessment of the theoretical demand response potential in Europe. *Energy* **2014**, *67*, 1–18. [CrossRef]
19. Granderson, J.; Sharma, M.; Crowe, E.; Jump, D.; Fernandes, S.; Touzani, S.; Johnson, D. Assessment of Model-Based peak electric consumption prediction for commercial buildings. *Energy Build.* **2021**, *245*, 111031. [CrossRef]

20. Härkönen, K.; Hannola, L.; Lassila, J.; Luoranen, M. Assessing the electric demand-side management potential of Helsinki's public service building stock in ancillary markets. *Sustain. Cities Soc.* **2022**, *76*, 103460. [CrossRef]
21. Heitkoetter, W.; Schyska, B.U.; Schmidt, D.; Medjroubi, W.; Vogt, T.; Agert, C. Assessment of the regionalised demand response potential in Germany using an open source tool and dataset. *Adv. Appl. Energy* **2021**, *1*, 100001. [CrossRef]
22. Homaei, S.; Hamdy, M. Quantification of Energy Flexibility and Survivability of All-Electric Buildings with Cost-Effective Battery Size: Methodology and Indexes. *Energies* **2021**, *14*, 2787. [CrossRef]
23. Lucas, A.; Jansen, L.; Andreadou, N.; Kotsakis, E.; Masera, M. Load Flexibility Forecast for DR Using Non-Intrusive Load Monitoring in the Residential Sector. *Energies* **2019**, *12*, 2725. [CrossRef]
24. Luo, N.; Langevin, J.; Chandra-Putra, H.; Lee, S.H. Quantifying the effect of multiple load flexibility strategies on commercial building electricity demand and services via surrogate modeling. *Appl. Energy* **2022**, *309*, 118372. [CrossRef]
25. Qi, N.; Cheng, L.; Xu, H.; Wu, K.; Li, X.; Wang, Y.; Liu, R. Smart meter data-driven evaluation of operational demand response potential of residential air conditioning loads. *Appl. Energy* **2020**, *279*, 115708. [CrossRef]
26. Rodríguez-García, J.; Álvarez Bel, C.; Carbonell-Carretero, J.F.; Alcázar-Ortega, M.; Peñalvo-López, E. A novel tool for the evaluation and assessment of demand response activities in the industrial sector. *Energy* **2016**, *113*, 1136–1146. [CrossRef]
27. Toosty, N.T.; Shimoda, S.; Hagishima, A. Aggregated peak-load analysis and demand response potential of a residential building in Osaka, Japan. *Environ. Dev. Sustain.* **2023** , 1–18. [CrossRef]
28. Ostovar, S.; Moeini-Aghtaie, M.; Hadi, M.B. Flexibility provision of residential energy hubs with demand response applications. *IET Gener. Transm. Distrib.* **2022**, *16*, 1668–1679. [CrossRef]
29. Awan, M.B.; Sun, Y.; Lin, W.; Ma, Z. A framework to formulate and aggregate performance indicators to quantify building energy flexibility. *Appl. Energy* **2023**, *349*, 121590. [CrossRef]
30. Crawley, J.; Manouseli, D.; Mallaburn, P.; Elwell, C. An Empirical Energy Demand Flexibility Metric for Residential Properties. *Energies* **2022**, *15*, 5304. [CrossRef]
31. Stinner, S.; Huchtemann, K.; Müller, D. Quantifying the operational flexibility of building energy systems with thermal energy storages. *Appl. Energy* **2016**, *181*, 140–154. [CrossRef]
32. Wang, A.; Li, R.; You, S. Development of a data driven approach to explore the energy flexibility potential of building clusters—ScienceDirect. *Appl. Energy* **2018**, *232*, 89–100. [CrossRef]
33. Hurtado, L.A.; Rhodes, J.D.; Nguyen, P.H.; Kamphuis, I.G.; Webber, M.E. Quantifying demand flexibility based on structural thermal storage and comfort management of non-residential buildings: A comparison between hot and cold climate zones. *Appl. Energy* **2017**, *195*, 1047–1054. [CrossRef]
34. Bampoulas, A.; Saffari, M.; Pallonetto, F.; Mangina, E.; Finn, D.P. A fundamental unified framework to quantify and characterise energy flexibility of residential buildings with multiple electrical and thermal energy systems. *Appl. Energy* **2021**, *282*, 116096. [CrossRef]
35. Mugnini, A.; Polonara, F.; Arteconi, A. Quantification of the energy flexibility of residential building clusters: Impact of long-term refurbishment strategies of the italian building stock—ScienceDirect. *Energy Build.* **2023**, *296*, 113416. [CrossRef]
36. Yu, Z.; Lu, F.; Zou, Y.; Yang, X. Quantifying the flexibility of lighting systems by optimal control in commercial buildings: Insight from a case study. *Energy Build.* **2020**, *225*, 110310. [CrossRef]
37. Chen, Y.; Chen, Z.; Xu, P.; Li, W.; Sha, H.; Yang, Z.; Li, G.; Hu, C. Quantification of electricity flexibility in demand response: Office building case study. *Energy* **2019**, *188*, 116054. [CrossRef]
38. Majdalani, N.; Aelenei, D.; Lopes, R.A.; Silva, C.A.S. The potential of energy flexibility of space heating and cooling in Portugal. *Util. Policy* **2020**, *66*, 101086. [CrossRef]
39. Sorensen, A.; Lindberg, K.; Sartori.; Andersen, I. Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data. *Energy Build.* **2021**, *241*, 110923. [CrossRef]
40. Yu, Z.; Lu, F.; Zou, Y.; Yang, X. Quantifying energy flexibility of commuter plug-in electric vehicles within a residence–office coupling virtual microgrid. Part II: Case study setup for scenario and sensitivity analysis. *Energy Build.* **2022**, *254*, 111552. [CrossRef]
41. Jensen, S.O.; Marszal-Pomianowska, A.; Lollini, R.; Pasut, W.; Knotzer, A.; Engelmann, P.; Stafford, A.; Reynders, G. IEA EBC Annex 67 Energy Flexible Buildings. *Energy Build.* **2017**, *155*, 25–34. [CrossRef]
42. National Assessment and Action Plan on Demand Response | Federal Energy Regulatory Commission. Available online: https://www.ferc.gov/electric/industry-activity/demand-response/national-assessment-and-action-plan-demand-response (accessed on 10 December 2023).
43. O'Shaughnessy, E.; Shah, M.; Parra, D.; Ardani, K. The demand-side resource opportunity for deep grid decarbonization. *Joule* **2022**, *6*, 972–983. [CrossRef]
44. Fleschutz, M.; Bohlayer, M.; Braun, M.; Murphy, M.D. From prosumer to flexumer: Case study on the value of flexibility in decarbonizing the multi-energy system of a manufacturing company. *Appl. Energy* **2023**, *347*, 121430. [CrossRef]
45. Guo, P.; Lam, J.C.K.; Li, V.O.K. Drivers of domestic electricity users' price responsiveness: A novel machine learning approach. *Appl. Energy* **2019**, *235*, 900–913. [CrossRef]
46. Mathieu, J.L.; Price, P.N.; Kiliccote, S.; Piette, M.A. Quantifying Changes in Building Electricity Use, with Application to Demand Response. *IEEE Trans. Smart Grid* **2011**, *2*, 507–518. [CrossRef]

47. Zhao, H.; Yan, X.; Ren, H. Quantifying flexibility of residential electric vehicle charging loads using non-intrusive load extracting algorithm in demand response. *Sustain. Cities Soc.* **2019**, *50*, 101664. [CrossRef]
48. Chen, X.; Wang, J.; Xie, J.; Xu, S.; Yu, K.; Gan, L. Demand response potential evaluation for residential air conditioning loads. *IET Gener. Transm. Distrib.* **2018**, *12*, 4260–4268. [CrossRef]
49. Dranka, G.G.; Ferreira, P. Load flexibility potential across residential, commercial and industrial sectors in Brazil. *Energy* **2020**, *201*, 117483. [CrossRef]
50. Ding, S.; Xu, C.; Rao, Y.; Song, Z.; Yang, W.; Chen, Z.; Zhang, Z. A Time-Varying Potential Evaluation Method for Electric Vehicle Group Demand Response Driven by Small Sample Data. *Sustainability* **2022**, *14*, 5281. [CrossRef]
51. Sehar, F.; Pipattanasomporn, M.; Rahman, S. A peak-load reduction computing tool sensitive to commercial building environmental preferences. *Appl. Energy* **2016**, *161*, 279–289. [CrossRef]
52. Song, Z.; Shi, J.; Li, S.; Chen, Z.; Jiao, F.; Yang, W.; Zhang, Z. Data-driven and physical model-based evaluation method for the achievable demand response potential of residential consumers' air conditioning loads. *Appl. Energy* **2022**, *307*, 118017. [CrossRef]
53. Triolo, R.C.; Rajagopal, R.; Wolak, F.A.; de Chalendar, J.A. Estimating cooling demand flexibility in a district energy system using temperature set point changes from selected buildings. *Appl. Energy* **2023**, *336*, 120816. [CrossRef]
54. 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]
55. von Bonin, M.; Dörre, E.; Al-Khzouz, H.; Braun, M.; Zhou, X. Impact of Dynamic Electricity Tariff and Home PV System Incentives on Electric Vehicle Charging Behavior: Study on Potential Grid Implications and Economic Effects for Households. *Energies* **2022**, *15*, 1079. [CrossRef]
56. Wang, D.; Muratori, M.; Eichman, J.; Wei, M.; Saxena, S.; Zhang, C. Quantifying the flexibility of hydrogen production systems to support large-scale renewable energy integration. *J. Power Sources* **2018**, *399*, 383–391. [CrossRef]
57. Wolisz, H.; Punkenburg, C.; Streblow, R.; Müller, D. Feasibility and potential of thermal demand side management in residential buildings considering different developments in the German energy market. *Energy Convers. Manag.* **2016**, *107*, 86–95. [CrossRef]
58. Yin, R.; Kara, E.C.; Li, Y.; DeForest, N.; Wang, K.; Yong, T.; Stadler, M. Quantifying flexibility of commercial and residential loads for demand response using setpoint changes. *Appl. Energy* **2016**, *177*, 149–164. [CrossRef]
59. Cruickshank, R.; Henze, G.; Florita, A.; Corbin, C.; Stone, K. Estimating the value of jointly optimized electric power generation and end use: a study of ISO-scale load shaping applied to the residential building stock. *J. Build. Perform. Simul.* **2022**, *15*, 507–535. [CrossRef]
60. Kohlhepp, P.; Hagenmeyer, V. Technical Potential of Buildings in Germany as Flexible Power-to-Heat Storage for Smart-Grid Operation. *Energy Technol.* **2017**, *5*, 1084–1104. [CrossRef]
61. Strobel, N.; Fuhrländer-Völker, D.; Weigold, M.; Abele, E. Quantifying the Demand Response Potential of Inherent Energy Storages in Production Systems. *Energies* **2020**, *13*, 4161. [CrossRef]
62. Cai, J.; Braun, J.E. Assessments of demand response potential in small commercial buildings across the United States. *Sci. Technol. Built Environ.* **2019**, *25*, 1437–1455. [CrossRef]
63. Afzalan, M.; Jazizadeh, F. Residential loads flexibility potential for demand response using energy consumption patterns and user segments. *Appl. Energy* **2019**, *254*, 113693. [CrossRef]
64. Babrowski, S.; Heinrichs, H.; Jochem, P.; Fichtner, W. Load shift potential of electric vehicles in Europe. *J. Power Sources* **2014**, *255*, 283–293. [CrossRef]
65. Schram, W.L.; Lampropoulas, I.; van Sark, W.G. Photovoltaic systems coupled with batteries that are optimally sized for household self-consumption: Assessment of peak shaving potential. *Appl. Energy* **2018**, *223*, 69–81. [CrossRef]
66. Zhu, J.; Niu, J.; Tian, Z.; Zhou, R.; Ye, C. Rapid quantification of demand response potential of building HAVC system via data-driven model. *Appl. Energy* **2022**, *325*, 119796. [CrossRef]
67. Mohagheghi, S.; Raji, N. Dynamic Demand Response: A Solution for Improved Energy Efficiency for Industrial Customers. *IEEE Ind. Appl. Mag.* **2015**, *21*, 54–62. [CrossRef]
68. Andrews, A.; Jain, R.K. Evaluating building decarbonization potential in U.S. cities under emissions based building performance standards and load flexibility requirements—ScienceDirect. *J. Build. Eng.* **2023**, *76*, 107375. [CrossRef]
69. Peacock, A.D.; Owens, E.H. Assessing the potential of residential demand response systems to assist in the integration of local renewable energy generation. *Energy Effic.* **2014**, *7*, 547–558. [CrossRef]
70. Srinivasan, A.; Wu, R.; Heer, P.; Sansavini, G. Impact of forecast uncertainty and electricity markets on the flexibility provision and economic performance of highly-decarbonized multi-energy systems. *Appl. Energy* **2023**, *338*, 120825. [CrossRef]
71. Hassan, Q.; Algburi, S.; Zuhair Sameen, A.; Salman, H.M.; Jaszczur, M. A review of hybrid renewable energy systems: Solar and wind-powered solutions: Challenges, opportunities, and policy implications. *Results Eng.* **2023**, *20*, 101621. [CrossRef]
72. O'Connell, N.; Pinson, P.; Madsen, H.; O'Malley, M. Benefits and challenges of electrical demand response: A critical review. *Renew. Sustain. Energy Rev.* **2014**, *39*, 686–699. [CrossRef]

73. Chadwick, R. *Encyclopedia of Applied Ethics*, 2nd ed.; Elsevier Inc.: Amsterdam, The Netherlands, 2011; ISBN: 9780123739322.
74. Arsad, F.S.; Hod, R.; Ahmad, N.; Ismail, R.; Mohamed, N.; Baharom, M.; Osman, Y.; Radi, M.F.M.; Tangang, F. The Impact of Heatwaves on Mortality and Morbidity and the Associated Vulnerability Factors: A Systematic Review. *Int. J. Environ. Res. Public Health* **2022**, *19*, 16356. [CrossRef] [PubMed]