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Demand response performance and uncertainty: A systematic literature review

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ABSTRACT

The present review has been carried out, resorting to the PRISMA methodology, analyzing 218 published articles. A comprehensive analysis has been conducted regarding the consumer's role in the energy market. Moreover, the methods used to address demand response uncertainty and the strategies used to enhance performance and motivate participation have been reviewed. The authors find that participants will be willing to change their consumption pattern and behavior given that they have a complete awareness of the market environment, seeking the optimal decision. The authors also find that a contextual solution, giving the right signals according to the different behaviors and to the different types of participants in the DR event, can improve the performance of consumers' participation, providing a reliable response. DR is a mean of demand-side management, so both these concepts are addressed in the present paper. Finally, the pathways for future research are discussed.

1. Introduction

In the local electricity markets, bottom-up approaches have been proposed to boost the involvement of local grid operators and encourage the active participation of small consumers [1]. These tactics are crucial to successfully penetrate Distributed Generation (DG) technologies in the current network, avoiding the use of fossil fuels. So, by focusing on the empowerment of the local resources, namely active consumers' flexibility, the potential of renewable energy resources can be explored without jeopardizing the system's reliability and security.

Progressing towards a future where the demand side has greater importance in the system, consumers should follow the signals from network or utility companies. To achieve system balance, their response is crucial [2]. Many advantages come from this approach, such as real choices to end-users, new opportunities and challenges, more competitive prices; effective investments; higher service standards; security of supply, sustainability; and the decarbonization of the electrical system [2,3]. The Demand Response (DR) concept and the respective programs were then defined [4]. Nevertheless, it is important to enabling technologies such as the Internet of Things (IoT) to be used to raise the consumers' awareness and their contribution to market transactions [5].

1.1. Contextualization and background

In the former paradigm, the system operator considered the load from electricity consumers in power and energy systems as rigid. However, each consumer has a set of appliances that do not have a fixed schedule and can be used flexibly by introducing the DR definition [6]. This concept means that following the different signals, the consumer uses them at different times or does not use them. In recent years, numerous definitions of DR have been proposed. A commonly used definition says [7]: "*… tariff or program … to motivate changes in electric use by end-use customers … changes in the price of electricity over time, … incentive payments … high market prices … grid reliability …*". A more recent one, published in European Directive 2019/944, says [8]: "*… change of electricity load by final customers … market signals … time-variable electricity prices or incentive payments, …final customer's bid to sell demand reduction or increase … market … alone or through aggregation*".

Until introducing the smart grid concept and DR, the consumer had no direct information regarding the market transactions. With the growing concern regarding climate change, the role of this new player must be empowered. Due to the volatile behavior of DG, it is crucial to make the consumers the center of the business model and consider their flexibility as fundamental to achieve the system balance. A consumer-centric approach has countless advantages, for example, for flexibility

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Abbreviations

AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive integrated moving average
BRPs	Balance Responsible Parties
CBL	Consumer Baseline Load
CC	Capacity Credit
CDR	Correlated Demand Response
CVaR	Conditional Value at Risk
DG	Distributed Generation
DLC	Direct Load Control
DNN	Deep Neural Network
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EMS	Energy Management Scheme
EU	European Union
FIS	Fuzzy Inference System
HVAC	Heating, Ventilating, and Air Conditioning
IoT	Internet of Things
ISO	Independent System Operator
kNN	K-Nearest Neighbor Method
LEC	Local Energy Community
MCS	Monte Carlo Simulation
MF	Membership Function
MPC	Model Predictive Control
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PV	Photovoltaic Systems
RE	Roth-Erev
RF	Response Frequency
RI	Response Intensity
RL	Reinforcement Learning
RTO	Regional Transmission Organization
TLP	Typical Load Pattern
TOU	Time of Use
TSO	Transmission System Operator
VaR	Value at Risk

markets, where the main players are [1]: Transmission System Operators (TSO), Distribution System Operators (DSO), Balance Responsible Parties (BRPs), aggregators, and retailers. The TSO is responsible for the service and stability of the transmission system, while the DSO is the entity responsible for the distribution system's operation. TSO/DSO collaboration is crucial to unleashing the potential of flexibility [9,10]. The retailer is a commercial entity selling electricity to consumers. The aggregator gathers flexibility through renewable-based and active consumers [11].

In this way, the DR definition must also comply with time flexibility. Thus, DR programs have different timescales, as presented in Fig. 1, and range from several years (on the left) to real-time (on the right). Year-long timescales are usually applied to improve long-term planning. Shorter timescales are more devoted to incentive-based DR programs, e.

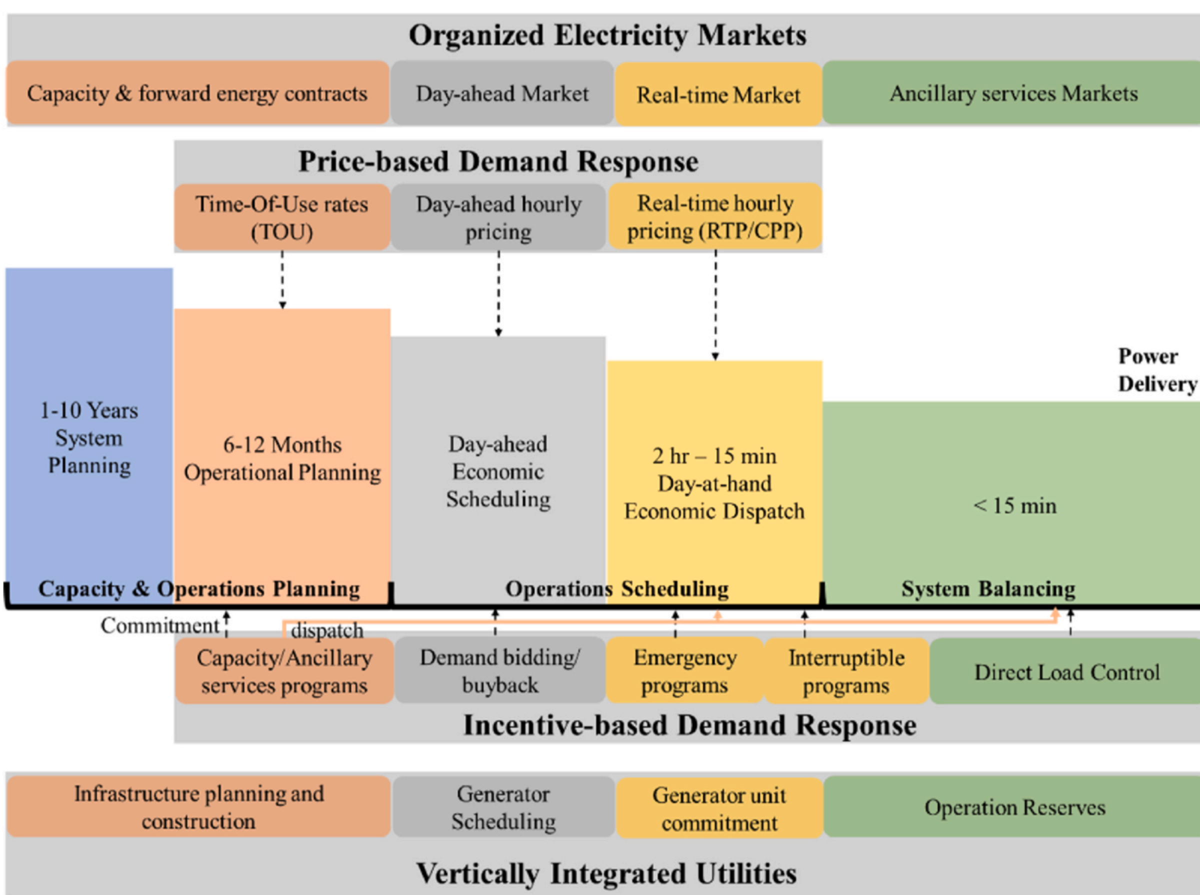

Fig. 1. Electric Power System and Demand Response implementation timescales.

g., applying Direct Load Control (DLC).

The performance from consumers' participation and how they react to a given signal are critical topics to successfully implement DR programs [6]. From the perspective of the entity requesting DR, gathering this type of information to give the right signals to the right consumers and the proper remuneration that will fit their needs is the right path to reduce the response uncertainty and maintain the system reliable and secure [6]. From the active consumers' perspective, the type of consumer participating in this type of event matters. The residential consumer's response is highly affected by the level of discomfort caused during a DR event [12]. However, industrial consumers' goal is to maximize their profits when participating in these programs and while managing any discomfort [13].

For this reason, different objectives require different approaches. Thus, it is necessary to respond to the consumers by adopting different approaches and contexts. Although approaches in the literature encourage consumer participation, most of them are profit-driven [14–16].

1.2. Motivation and contributions

The main motivation of the present literature review is to understand the current state-of-art of approaches to the uncertainty, performance, and reliability of consumer participation in DR programs. Some of the questions are: Is it important to deliberate methods to reduce uncertainty and enhance consumers' participation in DR programs? Should the distinct types of active consumers be treated differently? Should the individual behavior be analyzed to find proper methods of incentivizing each consumer's response? The authors have found interest in these questions after analyzing the related literature, as explained from now on, and finding the need for it doing their research.

The authors want to understand the implications of adding such an uncertain player into the current system. In the previous paradigm, consumer contributions were indirect, having little or no knowledge regarding this matter. Gathering different algorithms, solutions, and conclusions into a single document summarizing the current state of the art regarding this topic can be useful to create better-quality models. As far as the authors' knowledge, the DR concept has already been applied in some real markets but is still fresh in others. These new players should be further studied and understood to achieve a successfully implemented solution throughout the system. Their response is uncertain and could impact the performance of the remaining players in the market, jeopardizing the security and reliability of the system. For instance, in the review carried out by *Ivana Dusparic* et al. [17], whose focus was the residential DR, several algorithm characteristics have been discussed, concluding that performance concerning the algorithm for a particular DR implementation has been discussed energy use should be considered. The conclusion of this study emphasizes that a DR approach may use more than one algorithm that can be combined to meet the implementation requirements. Each solution must be tailored to a particular context.

Thus, context is also an important topic addressing DR programs that need to be customized. For instance, the type of consumer, their energy patterns be influenced by climate, and many more in the review published by *Miadreza Shafie-khah* et al. [13] where the recent advances in DR for industrial and commercial sectors were studied, as well as the benefits and barriers associated with their role. The authors categorized the different business models and objective functions. Consumer behavior was mentioned referring to trust level among parties – high trust levels should be sufficient to prevent any barriers to viewing DR as a reliable source, and widespread adoption of DR programs – lack of understanding of the benefits of DR can cause less investment by different parties.

A broader review of the barriers and enablers of DR in the Smart Grid was conducted by *Nicholas Good, Keith Ellis, and Pierluigi Mancarella* [18]. The barriers were categorized into fundamental and secondary, producing a comprehensive and discrete classification. The first ones include challenges related to intrinsic human nature, namely social/-economic barriers and enabling essential technology. The second type of barrier is related to anthropogenic institutions, such as regulations entities or markets, or even the resulting behaviors from feedback in response to DR participation, known as physical constraints. One of the study's important highlights is behavioral economics, which indicates that individual factors play a critical role in shaping consumers' decisions. In the paper, these authors refer to those behavioral aspects attracting more interest more recently. The focus is especially for residential and small commercial consumers, where the uncertainty has been emphasized as a particularly inflexible barrier to the exploitation of DR.

Furthermore, with an emphasis in terms of social welfare losses, *Marilena Minou, George D. Stamoulis, and Thanasis G. Papaioannou* [15] study considers that appropriate policies and demand reduction strategies exploiting altruism can benefit consumers (mainly in contracted-based Automated DR (ADR) programs and considering the consumers' preferences external contexts). Regarding the ADR provider perspective, the benefits will come in terms of incentive costs. However, the leveraging of altruists should be performed carefully. They are saddle with high energy reductions. Moreover, although yielding in small values of total incentives, they can yet prove inefficient for the social welfare of the system.

Consequently, with introducing these new concepts, the policies must be updated. Policymakers are making advances to create common rules for the new paradigm. In Europe, the Directive (EU) 2019/944 [11] recasts Directive 2012/27/EU on common rules used in the internal electricity market. It puts citizens at the center as they take ownership of energy transition and take advantage of innovative technologies to decrease costs by actively participating in the market, with the most vulnerable consumers being protected. Also, it was mentioned that the retail market should serve consumers better, notably by improving the links between the wholesale and retail markets, allowing all consumers to participate in the transition of energy and contribute to the overall reduction of energy consumption by providing efficient solutions. This results in more flexible markets and fully integrates all market players, including renewable energy producers, new energy service providers, energy storage, and flexible demand.

The present literature review discusses the uncertainty, performance, and reliability of consumer participation in DR programs. An innovative exploration is made into the behavior of active consumers and the aspects that may impact their response – which is highly uncertain and difficult to predict – and, consequently, impacts their performance and energy management reliability. Thus, the authors consider as a hypothesis, that the need for a more in-depth study of the influence of the context on the response should be explored and the different compensation techniques for the distinct types of active participants. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology is used.

The present paper is then organized into seven sections. An introduction is provided in section 1. Then, in section 2, the methodology followed to carry out this research review is described. Section 3 and Section 4 show, respectively, mechanisms to control DR and techniques and methods applied to DR. This is followed by Section 5, where consumer response uncertainty, performance, and reliability for DR are presented. Section 6 discusses the findings. Final remarks are presented in section 7.

2. Methodology

A systematic literature review has been performed considering the PRISMA methodology [19]. The present literature review started with formulating the research questions in the first phase: Should the distinct types of active consumers be treated differently? Should the authors analyze individual behavior in-depth to find proper methods for incentivizing their response? How the consumers' performance can be improved in DR programs? The current study focuses on finding answers to these questions in the reviewed literature.

The second phase of a systematic review involves the inclusion and exclusion criteria. The research results were obtained considering the following:

1. Include
   a. Describe any Demand Response tactics and other related consumer concepts (namely Demand Side Management or Consumer Flexibility).
   b. Consumer Behavior analysis considering their performance or response uncertainties.
   c. Document related to the Demand Response topic or similar, referring to the keywords considered as important by the authors (refer to Table 1).
2. Exclude
   a. No access to the full paper.
   b. Written in a language other than English or Portuguese.

The authors selected the online research tools and the multiple databases in the third phase. The five chosen databases were Web of Science, Science Direct, SciELO, IEEEX, and ACM. Table 1 presents the definition of the keywords and expressions that have been used.

Clarification of definition comparison for "performance" and "behavior" should be done. When the authors refer to consumer behavior, it means the players' actions to respond to a DR event in a certain context. Performance is related to the actual consumer response quantification, i.e., how much KW or KWh of reduction was provided.

A research equation must be formulated according to the language of each tool. For instance, Science Direct does not support the substitution symbol, also known as wildcard, represented by a "?" or truncation symbol represented by a "*." Both symbols are useful for substituting letters within a word or retrieving words with the same origin. However, all the remaining research tools supported the utilization of Boolean operators for the formulation of research equations, for instance ("Demand Response" AND Uncertainty* AND Real-time). The quotation marks mean that the word must be contained within the resulting document.

Several levels, resulting in different combinations of keywords or expressions, have been applied and are presented in Fig. 2.

In this way, the keywords in the first three levels must exist within the full paper searching these fields: title, abstract, keywords, or 'all fields' (search simultaneously in all record fields). The research finished in May 2021, so the listed references are published until this date. Therefore, the studies considered in this literature review have been published no farther than five years before this research. This assures that only the most recent studies have been considered.

Level 4 was considered for online research tools such as Science Direct, which does not support wildcards, for instance, when there were important related words within level 3, in plural form, or varying in spelling (American English vs. the United Kingdom English) like behavior and behavior.

Moving on to evaluating the obtained results, Fig. 3 represents a systematic review of the information flow. In the Identification stage, the agglomerated number of the identified records is too high (3,148,838 records). Still, it must be highlighted that there were five databases, several combinations of keywords, and the number also includes duplicate material and papers from different languages and areas. However, after analyzing the results, the research equations where most of the non-related documents were found included the keyword "flexibility" – should be reformulated as "load flexibility" or "consumer flexibility" to avoid an excessive number of references from other areas.

During the screening stage, the duplicates, non-related references, and documents in languages other than Portuguese and English were excluded reducing the total to 6,784 records. After that, to filter the

Table 1
Keywords and expressions (ordered by relevance).

Keyword	Definition
Demand Response (Flexibility, Program, Participation, Performance, Uncertainty, Reliability)	According to the Directive 2019/944 (EU), the definition of Demand Response is "*the change of electricity load by final customers from their normal or current consumption patterns in response to market signals, including in response to time-variable electricity prices or incentive payments, or in response to the acceptance of the final customer's bid to sell demand reduction or increase at a price in an organized market* "[11]. Thanks to real-time information exchange, active consumers can schedule their appliances according to signals designed to induce lower consumption, for instance, when system reliability is jeopardized. Their performance in these events will define the success of the DR implementation in real markets. So, the response uncertainty must be mitigated to increase reliability from the systems perspective [15,20–25].
Demand Side Management (DSM)	Demand-side management is a portfolio of procedures to enhance energy systems' utilization on the demand-side to meet several goals. These measures may include the management of consumption patterns of smart appliances, renewable energy systems, and home energy management systems to improve energy utilization efficiency [26–28].
Compensation (Remuneration, Incentive, Payment, reward)	Benefits are given to a person to reward participation in a DR event to motivate continuous participation. Several types can be used, such as economic remuneration, for instance, discounts on the energy bill or shopping vouchers to be used in stores of the consumer's choice, etc. This benefit should be fair and consider the remaining participants [29].
Penalty (Penalties)	Punishment for not fulfilling the agreement on a DR program, where penalty policies may also exist for violating contract obligation [30,31].
Behavior (Behavior, Behavior, Behaviours)	A set of reactions in response to the stimulus provided in a DR event. These can be signals sent to the active consumer to change the consumption in response to variations in the electricity price, incentives applied in high market prices, or when system reliability needs improvement [32].
Real-time	According to the Directive 2019/944 (EU), in the DR area and the context of smart metering: "*a short time period, usually down 2 s or up to the imbalance settlement period in the national market*" [11].
Community (Communities, Local Community, Local Communities)	In a DR context, an active community is a group of individuals working together for the same goal. In this way, distributed generation and consumer empowerment have made local energy communities effective and cost-efficient to meet consumers' needs and expectations regarding energy sources, services, and local participation. In addition, these communities offer inclusive options for all consumers to directly produce, consume, or share energy [8].
Electricity Market	Unlike other markets, electricity markets involve trading a service that cannot be easily stored and produced using a large variety of generating installations. Therefore, incorporating electricity markets requires a high level of collaboration among system operators, market participants, and regulatory authorities, particularly where electricity is traded via market coupling in the DR context [11].
Local Electricity Market	Considering the electricity market definition, the local electricity market can be defined for a particular region. So, it can be thought of as a sub-market for a commodity that serves a specific purpose for that local community, including in DR programs [33].

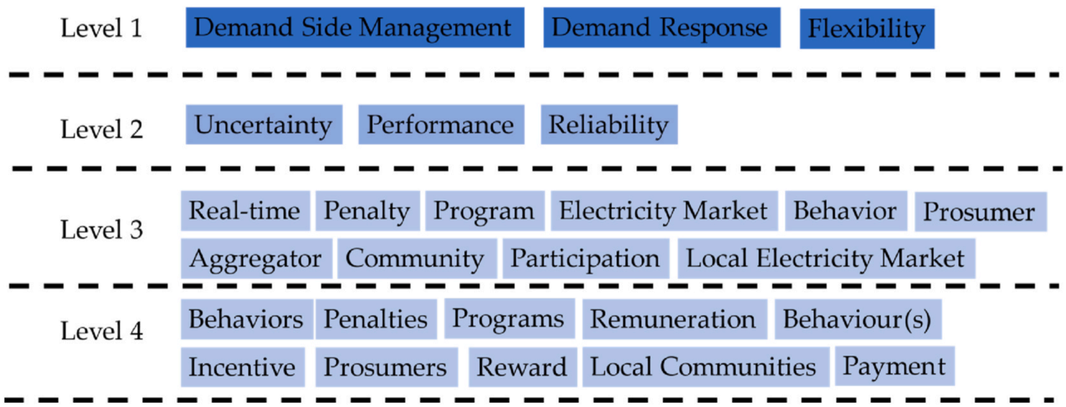

Fig. 2. Keywords combinations.

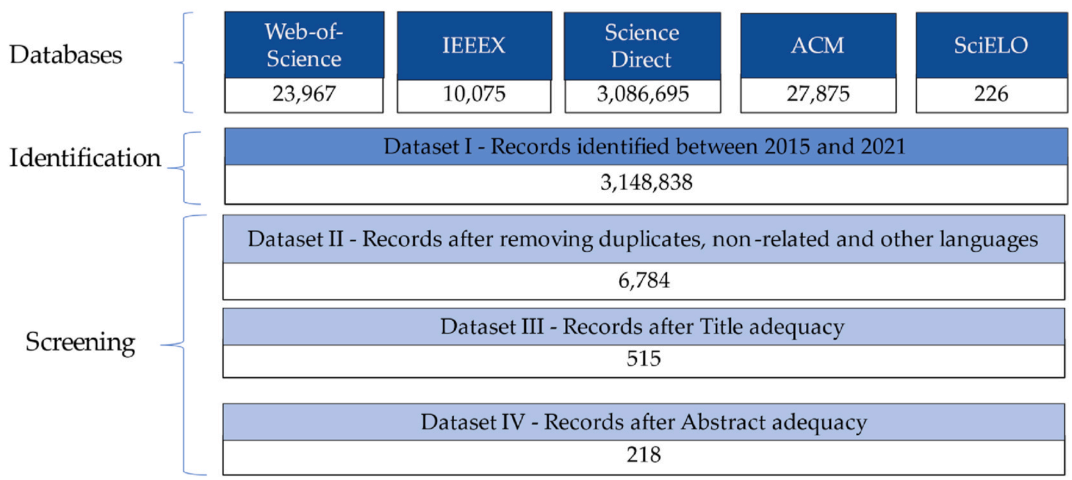

Fig. 3. A number of records in the dataset at each step.

articles that were not within the scope of this research, the title and abstract adequacy were verified. Finally, the records were subjected to a fluctuating reading guaranteeing their relationship with the study.

According to Fig. 4 and Dataset II in Fig. 3, "Demand Response" has the highest influence in the dataset of level 1 keywords, with an influence of more than 55%.

For level 2 keywords, "uncertainty" has the highest level of influence and exceeds "performance" by 4.5%. These two keywords have a higher level of influence than "reliability." Unfortunately, the trustworthiness of the active consumer's response to demand-side management methods is not yet addressed in the literature.

The resulting dataset, Dataset IV, as defined in Fig. 3, was analyzed, and nine factors were highlighted as important for the role of active consumers in the electricity market. The keywords were grouped and are

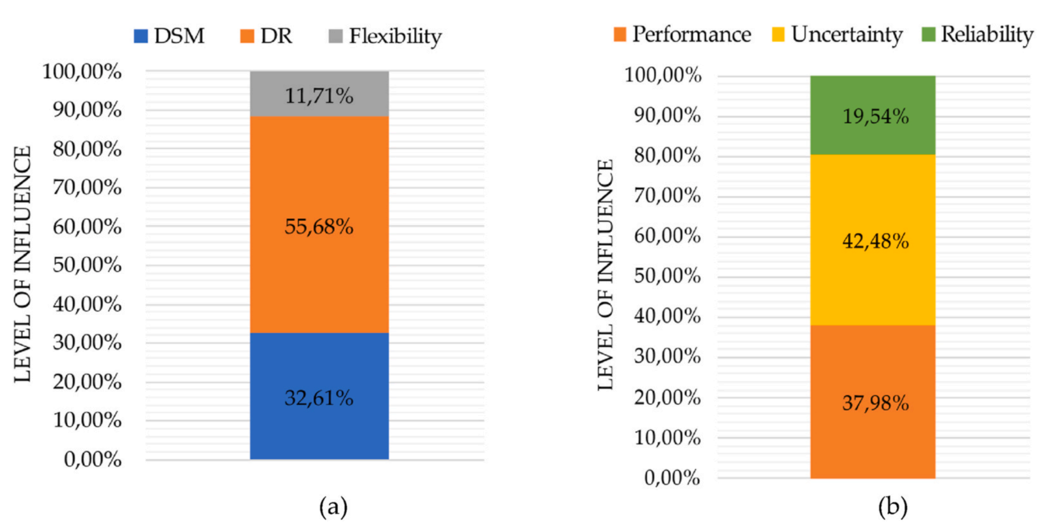

Fig. 4. Keywords in Dataset II: a) related to level 1; b) related to level 2.

listed in Table 2.

The following sections present the extraction, analysis, and interpretation of the information found, the discussion, and conclusions from this systematic review.

3. Mechanisms to control DR

The present section organizes the reviewed papers according to the type of DR they addressed, indicating the ones that contributed to DR Uncertainty, Performance, and Reliability research. The detailed exploration of the works gathered in the dataset will be further discussed in section 5. Although many other DR programs can be defined, the authors selected those with higher mentions in the publications from the resulting dataset. Price and Incentive-based are the types of DR with the most references in the resulting dataset. Demand Response Exchange (DRX) and Electric Vehicles (EV) were the least referenced types of DR in the dataset. However, as mentioned by Zhiwei Xu et al. [119], the flexible resources from the demand-side can play a critical role in balancing the supply and the demand in the future smart grid, namely providing various DR services. One of these resources is the EV. However, as Bhagya Nahali Silva, Murad Khan, and Kijun Han [223] emphasize, EV owners' security and privacy concerns is another challenge that limits the popularity of EV-based energy management because, although it is a hot topic, there are w low number of publications in the resulting dataset regarding uncertainty ([1,20,47,69,164,224–226]), performance ([59,104]) and reliability ([167]), as can be seen. Some of these works only refer to these resources, and it is not the focus of the study. Vehicle owners are hesitant to grant authority to control EVs to an Aggregator.

3.1. Incentive-based

Under incentive-type programs, consumers agree to participate according to rules by signing contracts. These usually determine that penalties are applied to the consumer in case of lack of response in the contractual terms. J. Meng et al. [213] consider an incentive-based DR in their study and used a multi-dimensional DR evaluation method considering the several affecting factors such as response speed and response duration that can comprehensively evaluate the response performance of users on the power demand side and effectively quantify the contribution of its response to grid load regulation. In work done by Ioannis Konstantakopoulos et al. [178], they created an adaptive model that learns active consumers' preferences and how they change over time to generate the appropriate incentives to ensure active participation. The uncertainty topic, regarding the incentive-based programs, were mentioned on [1,20,69,77,86,140,164,177,226]. The performance was an important topic in Refs. [14,21,84,115,125,140,144,146,147,195,213,215,227–229]. Lastly, fewer works mentioned reliability, namely [14,84,87,213,228].

Table 2
Main topics in the dataset IV.

Keywords	References
Aggregator	[13,34–67]
Behavior	[21–23,30,32,68–97]
Prosumer	[20,25,55],[98–138]
Community	[139–151]
Compensation/Penalty	[22,85–88,152]
Electricity Market/Local Electricity Market	[41–44,46,153]
Participation	[16,24,29,31,33,38,154–183]
Program	[14,16,26,43,48,184–215]
Real-time	[26,185,186,193,194,196,198–200,202–205,207,209,210,214,216–222]

3.2. Price-based

Moving to Price-based, these programs are based on the energy price change, looking for the consumers' response to those changes. This could lead to more randomness in consumer behavior when compared to incentive-based programs, for which the contractual rules determine predefined response behaviors. Still, there is always the freedom of choice from the perspective of the active consumer who has the power to disconnect the appliance.

Active consumers can receive discounts by reducing energy demand during critical peak periods, as in the work done by Gerardo Osorio et al. [135]. Namely, Real-time Pricing programs are deeply intertwined with the wholesale market price, varying in real-time throughout the day. In the straightforward approach used by Byung-Gook Kim et al. [20], with dynamic consider the decision from the active players in their environment and learn the dynamics of the entire system and find its optimal energy consumption scheduling based on the observations. Reliability was the keyword least mentioned for this type of DR program: [22,106,135,171,213,228,230]. The performance was started in 13 works: [40,117,158,186,192,195,202,205,213,228,231–233]. Finally, uncertainty was a mentioned in the following works: [[20,29,36,40,43,46,47,65,98,100,106,112,116,118,119,121,133,156,161,185,186,214,231,232].

3.3. Both incentive and price based

By analyzing the combination of these two types of DR programs in the resulting dataset can be concluded that performance and Reliability were mentioned in less than five works when combining these two types of DR programs: [195,213,228]. Two of them refer to these topics in their studies. The uncertainty was highlighted in Refs. [14,23,30,54,55,77,84,86,88,111,115,132,192].

3.4. Demand Side Management (DSM)

DSM can be defined as the modification of consumers' demand. As Julián Valbuena et al. [190] refer, DSM modeling at the building sector is challenging since the existing models are not flexible enough to incorporate a wide set of modeling features and guiding principles, while including all important aspects of end-use. The performance was the keyword with more mentions in the dataset gathered: [27,59,61,113,123,127,155,158,164,187,192,196,205,234–236]. Uncertainty was reported in Refs. [20,109,116,137,158,164,168,187,235] and the Reliability concept in Refs. [28,190,201,206].

3.5. Demand Response Exchange (DRX)

DRX refers to a new DR scheduling program. Derived from the market clearing mechanism, the motivation for change in load is dependent on a bidding entity and not price or incentive. Therefore, load profile attributes should be assessed carefully before submitting any bid to avoid losing load satisfaction, higher electricity bills, system stress, etc. [195]. With this, only a few works refer to this DR program and only consider uncertainty and performance topics: [31,149,195].

3.6. Load shifting

In this DR program, the Aggregator has permission to use consumers' loads for DR within pre-specified limits for internal balancing. So, it is defined as shifting electricity consumption to another period. Pedro Faria et al. [32] proposed scheduling load-shifting opportunities performed by a VPP. The main advantage is modeling the consumption shifting constraints (limits for each period/set of periods) from the VPP and the consumer standpoints.

Mellouk et al. [187] scheduled energy consumption profiles for each active consumer. They are treated independently to determine the optimal distribution of devices' operating time among different periods to avoid peak hours generally characterized by the highest values for the cost coefficient. Load shifting is one of the types of DR with more studies regarding the performance topic: [32]. The reliability was not mentioned, and uncertainty has a total of 6 publications in the resulting database: [58,120,122,136,163,207].

3.7. Others

Other less known DR types were found in the gathered publications. The keyword with more mentions was the uncertainty: [13,14,18,23,29,31,32,34,36,37,44,47,55,58,69,84,85,87,103,110,112,113,117–120,126,129,134,137,144–146,149,159,164,171,172,176,180,186,190,193,195,198,201,206,210,211,214,225,228,231,232,235,237–244]. For instance, Chen et al. [29] proposed a framework to encourage the new active players and their resources, such as parking lots with high penetration of electric vehicles, to participate directly in the real-time retail electricity market based on an integrated eVoucher program. As the authors mentioned, this program can work for various scenarios involving economic or physical extreme events.

To study and select the right participants for a DR event, Yingying Li, Qinran Hu, and Na Li [77] formulate the DR problem as a combinatorial multi-armed bandit (CMAB) problem with a reliability goal. These authors believe that the multi-armed bandit (MAB) method emerges as a natural framework to handle intrinsic and heterogeneous uncertainties associated with small consumers such as residential.

Reliability was the second one with more mentions: [13,14,22,30,38,77,83,84,87,100,106,109,111,112,121,167,171,173,197,201,213,228,230,241,243,245]. As can be seen, some of the references were mentioned in both keywords search. Shuai Fan et al. [144] focused on large-scale DR. These authors mention that current incentive-based DR schemes are unsuitable for large-scale DR due to their centralized formulation, jeopardizing the system reliability. With this, propose a consumer directrix load (CDL), which is a desired load profile, to replace the customer baseline load (CBL). The authors refer that the uniqueness of this solution makes it more suitable for distributed schemes, while numerous CBLs must be calculated in a centralized manner to ensure fairness.

The performance was the least mentioned keyword in the others point: [21,27,31,37,84,85,115,140,145,170,192,193,213,215,228,229]. One concern that has become major in the DR program design topic is resource privacy and preserving the managing entity. Amir Ghasemkhani et al. [246] affirm that active consumers' privacy protection is being ignored when designing DR programs since their behavior patterns can be easily recognized when interacting with the managing entity. The proposed and commonly used solution incorporates perturbations in users' load measurements. However, although it can protect the active consumers' privacy, this modification would reduce the managing tools' performance in achieving an optimal incentive strategy. Therefore, further studies should be developed to include privacy-preserving solutions.

4. Technics and methods applied to DR

Discussing the methods found in the resulting database, Artificial Intelligence (AI) methods were reviewed first and then non-AI methods. Although some methods can be converted into AI approaches, the presented studies used the method in their original form.

4.1. Artificial Neural Networks

Artificial Neural Networks (ANN) methods are the foundation of AI methods and are designed to simulate how the human brain analyzes and processes information. In the DR Uncertainty topic, as mentioned in Refs. [104,185] and for DR performance [77,180,196,209,215,247]. None of these works mentioned reliability. Renzhi Lu et al. [202] resort to both ANN and Reinforcement Learning (RL) to design an hour-ahead energy management scheme for different appliances within a HEMS, where ANN was used for price forecasting.

4.2. Reinforcement Learning

RL is characterized by Machine learning models trained to make a sequence of decisions to achieve a goal in an uncertain, potentially complex environment. All the keywords from level 2 were included in the RL works in the gathered dataset: uncertainty ([20,40,87,108,112,180,202]), performance ([20,77,87,180]) and reliability ([20,77]). For instance, Amir Ghasemkhani and Lei Yang [112] leverage RL to learn the users' response functions. In theory, AI models can be subjected to gamified interactions between participants.

4.3. Game theory

Game Theory is considered the most vital mathematical branch was exploring the conflicts, collaborations, and strategic interactions between rational players within a single system by several authors such as Haytham A. Mostafa, Ramadan El Shatshat, and M. M. A. Salama [175]. Their study considered a participant system to achieve rational and independent interaction with several players, improving the distribution system. The works using this algorithm mentioned uncertainty ([47,54,59,85,113,125,144]), performance ([20,158,164,178]) but not reliability.

4.4. Autoregressive Moving Average

The autoregressive integrated moving average (ARIMA) is one of the easiest and most effective Machine Learning algorithms for performing time series forecasting. It is a generalization of the Autoregressive Moving Average (ARMA) model. The study of Hamed Mortaji et al. [48] indicated that load shedding using the ARIMA time series prediction model and smart, direct load control could remarkably reduce consumers' power outage. In the resulting database from the present paper, the uncertainty keyword ([21,36,44,58,65,115,173,202,214]), the performance keyword ([21,58,87,115,124,202]) and the reliability keyword ([21,58,87,115,124,202]) were mentioned when using these algorithms.

4.5. Clustering methods

Researchers use Clustering Methods extensively in the power system, mainly to find patterns in electrical loads, as in the study conducted by Mansour Charwand et al. [91]. The cluster analysis was mentioned works where the uncertainty keyword ([115,143,150]), performance keyword ([73,215]) and the reliability ([26,126,137,139,146–148,151,214]) were referred. The last one has a higher number of publications.

4.6. Fuzzy theory

Fuzzy theory can also be applied, and the research approach can deal with ambiguous, subjective, and imprecise judgments. In the resulting dataset, when looking for fuzzy theory algorithms, uncertainty ([91,107,149,163,195]), performance ([83,91,124,149,163,186,195,248]), and reliability ([13,83,117,121,248]) keywords were found. For example, Fuzzy Inference System (FIS) was used and compared with other non-fuzzy approaches by Skrikanth Reddy K et al. [149], where the superior performance of FIS concludes the efficacy of this type of model for processing load profiles and behavior (willingness) in designing the DR bids for market participation.

4.7. Model-based predictive control

Model-based predictive control (MPC) has attracted the researchers' attention to this area due to its prediction abilities, quick processing capacity, and suitability for multivariable control operations. However, few works mentioned this algorithm, including only uncertainty ([86,122,123]) and performance ([86]). For instance, Farzad Arasteh and Gholam H. Riahy [123] developed a real-time algorithm to systematically coordinate the DR programs and ESS operation in market-based wind integrated power systems.

4.8. Conditional Value at risk

In the DR perspective, Conditional Value at Risk (CVaR) can be used for the stochastic program for decision making of DR aggregator considering various sources of uncertainty, as done by Homa Rashidizadeh-Kermani et al. [55]. Since CVaR as a risk measure was embedded in the problem to control different levels of risk associated with profit volatility. Works using this algorithm also mentioned DR uncertainty ([36,55,121,211]), DR performance ([86,119,121,131]) and DR reliability ([119,228]).

4.9. Monte Carlo Simulation

Probabilistic models incorporate random variables and probability distributions into the model. Confronting this stochastic solution with a deterministic model with only a single possible, a probabilistic model gives a probability distribution as a solution. Many works mentioned probabilistic models also including uncertainty ([65,98,110,120,133,136,191]), performance ([77,140]) and reliability ([47,154]). One of the best-known probabilistic methods is the Monte Carlo Simulation (MCS). Zvi Baum et al. [14] resort to MCS the of design a convenient framework to estimate Dynamic-Active DR's performance in which the stochastic characteristics of supply and demand can be reflected and the behavior of the system over time, in response to both external and internal influences, can be modeled. This algorithm was also mentioned in publications with uncertainty ([14,25,106,109,159,214]), performance ([38,41,56,98,119,180,190]) and reliability ([59,98,137,154,180]) were highlighted.

4.10. Markov Chain

Also, the Markov Chain (MC) follows probabilistic rules and is a common, relatively simple means of modeling statistically random processes. Yue Yang generates an MC model at an appliance level to capture temporal and inter-device correlations in power consumption. Further works with MC refer to uncertainty ([24,111,137]), performance ([86,137]) and reliability ([13,86,101,123]).

4.11. Others

Other algorithms were also found in the resulting database, however, they only refer to uncertainty keyword ([21,23,29,30,34,43,46,58,60,69,77,83,84,88,105,116–118,126,132,134,140,152,156,157,161,186,192,207,231,232]).

5. Uncertainty, performance, and reliability of the DR participants

The role of the consumer is changing. These new players are becoming more active participants with a great influence on system reliability, so their performance must be enhanced, and the response uncertainty dealt with. The focus of the present section is the main keywords found in the studies from the dataset obtained: uncertainty, performance, and reliability.

5.1. DR uncertainty

DR resources' load reduction process is stochastic, statistical, and stationary [169]. Many approaches are used in the literature, but many consider probabilistic distribution regarding the participation uncertainty dilemma and how it was dealt with. According to Bo Zeng and Xuan Wei [107] study, where the Capacity Credit (CC) from DR is assessed, which accommodates probabilistic and possibilistic uncertainties. The definition of CC was developed to quantify DG resources' capability to offer the capacity to power systems. However, the DR participants' flexibility could play a similar role in the Smart Grids concept, so the definition was extended. These authors resort to the fuzzy theory to express the uncertainty introduced by incomplete information and probabilistic propagation technique to describe the human-related uncertainties, standardizing them under the same framework. Consequently, the value of participation level changes with the decision-making during operation, making the formulation a time-dependent model. In the case of Smriti Singh and Ashwani Kumar [100], the MCS was used to model the uncertainty in consumers' participation, extracting samples that correspond to the most probable event. Since the active consumer often fails to reduce their load due to some external factors, the authors developed a probabilistic load model based on a normal distribution function according to the available historical load data. The uncertainties related to the stochastic variations of the variables involved in residential DR include load demand, user preferences, environmental conditions, house thermal behavior, and wholesale market trends. As Pierluigi Siano and Debora Sarno [214] believed, they can be modeled using the MCS method.

As mentioned earlier, besides MCS, MC is a stochastic process in which the present status is quite independent of past or future ones being suitable for modeling the uncertainty introduced by DR participants [123]. Abbas Tabandeh, Amir Abdollahi, and Masoud Rashidinejad [111] share this opinion and mention the importance of Advanced Metering Infrastructure (AMI) for this process. A failure from these technologies can influence the consumers' participation. In their study, the MC model is used for a DR resource to determine the consumers' participation by splitting the participation percentage into finite states – from 0 to 100% with a step of 25%. However, by distinguishing appliances and resorting to individual smart plugs, Zhai et al. [24] applied the same state logic with MC. These authors divided into two main types to define the corresponding flexibilities: appliances working in cycles and appliances working at fixed state. By understanding the habits and routines of this new player, starting with the appliances, the models can be more robust and capable of reducing the response uncertainty. In this way, Chia-Shing Tai, Jheng-Huang Hong, and Li-Chen Fu [108] develop a real-time multi-agent deep RL-based approach to solve the DSM problem and consider user behavior. Again, focusing on the state extraction part of the appliances, three different groups were created to understand the degree of influence of the state of the appliance on the user and the tolerance of frequent switching. First, the Heavy Conflict group includes appliances whose stat switching would lead to a less severe but still strong impact on the user experience. Finally, Less Conflict group, the operation time is less conflicting for the consumer and can be scheduled later - washing machine, dish dryer. The ability to adapt to and learn about user preferences and update the system repeatedly can improve one of the crucial characteristics of implementing DR in the real world: consumer comfort.

As mentioned earlier, for the residential type, comfort is crucial for their participation. This type of the participant is less willing to give up on certain equipment in a specific context just to participate in the market transactions. Nevertheless, the problem can be even more complex. In the study done by Liang et al. [211], the relationship between two pieces of equipment is a particular example of correlated DR (CDR). Gaming PCs and Heating, Ventilating, and Air Conditioning (HVAC) systems were presented. The authors believe these two appliances created a new factor in the management problem: CDR relationships considering heating and cooling demand. So, with the expected increase of power consumption from Gaming PCs, this appliance generates wasted heat along the DR process, requiring the Air Conditioner (AC) system to consume more power to maintain the indoor temperature in summer, which makes the original DR effect worse. However, in winter, the AC system consumes less power to maintain the indoor temperature when the gaming PC performs DR and generates waste heat, which improves the DR effect. In the presented model, the CDR unit consists of two parts: an uncertain and uncontrollable internal heat source – Gaming PC, and an HVAC system that provides DR independently. Considered a whole, the internal heating source brings uncertainty into the entity. Thus, the CDR decisions were operated properly by a risk management scheme considering a CVaR incorporated with a stochastic approach between many other uncertainties. The results confirm that the stochastic approach is more capable of handling uncertainties than the deterministic approach, reinforcing the approach of previous methods.

Still, the active consumers are responsible for the appliances. Participation is voluntary, and although penalties can be applied, they have total control to change their minds. In this way, the authors must focus on the active consumers' behavior. The assumption of DR participants as rational is widely accepted in many studies from the literature. The optimizations from many works look at active consumers as economic agents who always make the "right" decisions and understand the market transactions [109]. However, should the consumer be considered a rational agent who makes an optimal decision?

Bearing in mind, one of the main approaches to encourage others is Game Theory. Defined as the formal study of interdependence between adaptive agents and the dynamics of cooperation and competition that emerge from this [249]. In this case, the term agents refer to an entity with the capacity to make informed choices and act upon those choices autonomously to affect the state of the environment [237]. The interdependence between these adaptive agents means that the values associated with some property of one element become correlated with those of another. In other words, and for this context, the achievement of a goal of one agent becomes correlated with others. For instance, in this topic, game theory approaches can be categorized into two kinds, one is played between consumers, and the second is played between the utility and consumers. Also, two different levels can be defined for the interdependence between agents: the micro and the macro level.

5.1.1. Macro-level perspective

From a macro-level perspective, all the agents must work cooperatively to achieve an overall successful outcome at the macro level. Pondering the work from Akash Talwariya, Pushpendra Singh, and Mohan Kolhe [54], where these authors use the Monte Carlo Simulation (MCS) to consider uncertainty in both consumption and generation but also build a Stepwise Power Tariff model with Bayesian Game Theory to consider the active consumer's decisions. In this situation, it is expected that agents do not want to share their best strategy with other players, as happens in non-cooperative games. However, it can be drawn from the results that the best response is when consumers share full information about energy consumption with energy retailers and consumers.

Active consumers are selfish, so their behavior should be further studied in this situation [172]. Maximizing the individual consumer welfare DR programs by building an approach that considered the utility function and studying the consumer risk aversion behavior was the goal of Amir Niromandfam, Ahmad Sadeghi Yasdankhah, and Rasool Kazemzadeh [110] work. The utility function measures consumers' preferences. This is an important concept in microeconomics since it can understand how rational consumers make consumption decisions. Again, a central assumption in classical game theory is that players are always rational and strive to maximize their hyper–rationality payoffs [144]. However, the rules and dynamics may not be aligned with this assumption because what is rational for the whole is irrational for the individual. These agents, assumed to be rational, consistently act to improve their payoff without the possibility of making mistakes. They also fully know other players' interactions and have an infinite capacity to calculate all possibilities beforehand [250]. So, agents have accurate information, and any uncertainty is reduced to a probability distribution. However, this prediction may not be applied in certain situations as humans' behavior differs dramatically.

With this, numerous reasons may impact the active consumer actions: cultural, financial, natural, or social capital (that is, the relationships with other people and their roles within a social group) [251]. From this perspective, it is not the concept that players are trying to optimize. Their payoff needs to be adjusted for the different market options. Instead, the narrow definition of rationality as optimization according to a single metric needs to be expanded within several contexts involving social interaction.

Many examples can support this view of "perfect" agents in many other methods. Homa Rashidizadeh-Kermani et al. [55] created an interface between the market and the active consumers in a competitive environment. These authors designed a decision-making model for the DR aggregator. In day-ahead energy and balancing markets, the aggregators offer selling prices to the active consumers to maximize their expected profit, considering consumers' reactions to the rivals' prices. From the utility perspective, the risk aversion was modeled using CVaR. As in game theory, the players also have their agendas in this work, and two different levels are considered. First, the competition between the aggregator and the rivals offers a better price at the upper level. After, the active consumers act out of self-interest in the lower level and choose the most competitive aggregator to minimize their payments. At this level, it is considered that decisions are made with perfectly accurate information regarding the price offered by the aggregators.

Participants were deemed to react optimally to the utility prices for the profit maximization problem. This assumption will impact the utility's profit since, instead of providing to their active consumers, in a competitive environment, the players are expected to move to lower prices, which consider only a single metric (the pursuit of profit) without context awareness from each participant. For instance, in the study conducted by Billing Zhang et al. [172], a contract-based incentive scheme was proposed to encourage consumers and small-scale suppliers to participate in direct energy trading. Based on their achievements, consumers', and suppliers' behaviors, affect each other, and their strategies are highly coupled. Therefore, there is a need for a model where the utilities are defined, the interactions are analyzed, and the Nash Equilibrium is found. However, under asymmetric information, the problem becomes more complex. Jianwei Gao, Zeyang Ma, and Fengjia Guo [109] wanted to define risk-behavior awareness to focus on the risk from the demand side when participating in DR programs. Both organizations and individuals have different attitudes toward risk-taking. A utility function can be considered feasible to illustrate consumer risk attitudes toward gain or loss, focusing mainly on power, exponential, and logarithmic models. However, the authors pointed out that classical utility functions do not consider consumers' psychological factors.

5.1.2. Micro-level perspective

At the micro-level, individual agents pursue their agendas according to their cost-benefit analysis. Again, it should be highlighted that the standard economic theory assumes that all individuals act solely out of self-interest. As an illustration of this point of view, the study presented by Shuai Fan et al. [144] designed a model for DR consumers to choose an ideal rebate ratio to maximize their welfare. The process is designed as a non-cooperative game in which the Nash Equilibrium exists. The so-called Gossip algorithm used in this study was improved for a socially connected network. In this way, consumers can exchange information with familiar DR participants to estimate global information. In the end, it impacts as individuals and as a group but always finds the best option. For instance, to deal with energy retail market price and develop a win-win situation between consumers from several sectors and the utility, Akash Talwariya et al. [54] designed a stepwise power tariff using a game theory model for DR. The results showed that when consumers shared full information on energy consumption with energy retailers and other consumers, the best response was found. Perhaps, some information can be useful to share instead of a non-cooperative approach.

Still, besides the energy price, many other factors can also influence the participation decision, and, again, the context is crucial to understanding their actions. Özge Okur et al. [122] introduce a comprehensive MPC to update and reduce individual imbalances based on input data. From the utility perspective, the results found considerable season discrepancies – the influence of the context in which the event is triggered. June and December were the months with a higher and lower total amount of imbalances, respectively. These authors intend to explain this difference resorting to the absolute solar generation forecast errors: smaller due to lower solar generation. Besides this conclusion, Özge Okur et al. [122] found that the type of consumers can impact the imbalance. So, while demand profiles from residential consumers peak in the early morning and evening hours, the commercial sector peak occurs during daytime hours, coinciding with the highest fundamental imbalances. Nevertheless, the authors also prove that, although this is beneficial for the power system, reducing those imbalances may not benefit financially from the aggregator's point of view. However, these conclusions can help understand and build a model to reduce the response uncertainty.

The complexity of defining and understanding the active consumers is not just related to the amount of load they reduce – which is quite difficult to predict, mainly due to sparse data and each consumer's characteristics. Since it is still in development, their empowerment also includes the prosumer concept – where a consumer can also produce their energy and sell to the market. In work developed in Ref. [115], the authors proposed a data-driven methodology considering the k-nearest neighbor method (kNN) and a weighted ensemble model to deal with the load prediction problem. First, kNN requires small amounts of data, and considering that each consumer may receive a request for load curtailment only a few times a year, the method is adequate. Regarding the disparity between consumers, a single prediction method may not cover all the consumers – it provides a remarkable prediction operation for one consumer but is poor for the remainder. The authors used a weighted ensemble model to apply distinct models for different consumers. Following the same line of thought, Wang et al. [143] focused on the uncertainty related now to the prosumers, the increasing installation of photovoltaic systems (PV), how load patterns become more random, and the consumer baseline load (CBL) difficult to estimate. Especially hard to distinguish between increased PV output power and decreased actual load power. However, in this case, the k-means algorithm was used to divide the consumers into control groups, after calculating a curve similarity index where each DR participant was matched with the most similar cluster based on the similarity between its load curve and cluster centroids during periods when the distributed photovoltaic output power was equal to zero.

Several issues were addressed throughout the uncertainty topic, and the models were used to provide suitable solutions in each authors' opinion. The topic is highly complex. The active consumers' participation is very hard to predict since it depends on several factors. Some authors tried to predict their contribution and deal with uncertainty using probabilistic models [100,107,123,214] since the process is stochastic, statistical, and stationary. However, both AMI failures and appliances participation context impact the response [24,108,111,211]. A focus on ways to incentive their participation and anticipate their schedule to avoid discomfort or losses must be included in the final solution to implement DR. Still, the active consumers have control over these appliances, and some consider that they act as rational and economic agents, always to achieve their individual goal [110,172,250]. However, some studies found that sharing the information may benefit individual and group perspectives [54,144]. Nevertheless, including the prosumer definition may also be valuable since the definition of active consumer is changing [143].

5.2. DR performance

The performance definition throughout the present paper refers to the level of success of the consumers regarding their participation in DR events. In other words, when the managing entity sends a signal to change its load consumption, it is expected to comply and participate in the event, considering this active consumer as a trustworthy player. Even though the participation is voluntary, some DR programs require participation in a certain context, agreed by both parties. And although in the previous section, the active consumer is considered a rational and economic agent, always striving to achieve their goals in a "perfect" way, the reality may be different. As new players, they have low information regarding the market transactions and often do not have the availability to decide the proper approach. Aid, understanding, and enhancing their performance in DR events are goals.

5.2.1. Impact of the consumer behavior

The following works consider the complex non-deterministic nature of consumer behavior regarding performance in DR events. For instance, Konda et al. [195] proposed an adaptive fuzzy inference system (FIS) strategy to improve the performance of DR schedules. The fuzzy method is not new for analyzing consumer behavior in responsive loads – regarding load type, sectoral and seasonal variation. However, in the actual scheduling implementations, the inappropriate strategies may lead to consumer dissatisfaction and the consequent decrease of their participation in DR events. These authors bet on FIS for DR scheduling considering this key aspect: rule-based development and membership function (MF) parameter setting/adjustment. However, the idea that MF parameters must be tuned using expert knowledge or intelligent computational approaches should be reinforced. Thus, the results demonstrated improved convergence and performance compared to the traditional random willingness assignment methodology regarding consumer availability for market participation.

Still focusing on the importance of FIS in the investigation of the impact of consumer behavior, impact of load profile, and temporal characteristics of load profile by load sector and load type, the same author published another research [149] contemplating the utilization factor and availability factors for modeling consumer behavior using linear, non-linear, and exponential functions. Firstly, in the Linear Response Behavior, the relation of the utilization factor and cost factor is linearly proportionate. The Non-linear Response Behavior approach is represented as the product between the utilization and availability factors. The results revealed the non-linearity/non-smooth nature of load profile attributes combined with consumers' willingness.

Hence, due to the unclear response characteristics, it would be beneficial for the profit-oriented managing entity to employ non-linear tools instead of a linear method. Dehghanpour et al. [185] presented an Artificial Neural Network (ANN) approach to capture the loads' behavior using a non-linear ANN-based model to capture the non-linearities from loads' aggregate behavior. Based on the study results, these authors believe that as the penetration level of price-sensitive appliances increases in the system, the higher the improbability. Their methodology was based on a multiagent framework with machine learning that allows these authors to address interoperability and decision-making under incomplete information in a system that maintains data privacy, which can be crucial for active consumers to participate in DR programs.

5.2.2. Consumer behavior learning and prediction

ANN and ARMA prediction techniques to identify unclear load profiles. In work done by Mahmud et al. [104] and according to the results, day-ahead energy management mitigates indecision by implementing preventive measures. So, by considering a "learning" approach, the DR could be defined as automated as in the Aras Sheikhi, Mohammad Rayati, and Ali Mohammad Ranjbar [180] study. These authors consider the participant a price taker consumer with a fully automated energy management scheme (EMS) based on Reinforcement Learning (RL) to minimize their energy bills simultaneously. The EMS learns behaviors over time, the insecurity of energy prices, and appliance efficiency into making optimal decisions in a stochastic environment. The extracted information from AMI technologies can be used in a panoply of situations, namely, DR programs, load profiling, consumer consumption prediction, or even theft detection. Thus, the effects of the imprecise and incomplete information from failures in AMI technologies may condition outcomes from an approach, namely clustering algorithms.

However, many DR implementation solutions include consumer clustering to process consumer input data for possible flexibility such as occupancy, temperature, humidity, bidding strategy design, etc. Focusing on the AMI from the perspective of the residential consumer, Table 3 organizes studies that used clustering methods to analyze information from smart metering data. The table contains the number of participants, the data source, the location of the study, the clustering method, and the data size.

Some of the studies have a big dataset. However, as already mentioned, clustering is sensible to the input information, and errors from smart equipment may result in erroneous outputs. Thus, the a priori processing of the dataset with adequate data mining tools is crucial. This enables the aggregator to access meaningful information that helps deal with active consumers properly and enhance their performance. The incorporation of fuzzy variables to mitigate impact was suitable in the study conducted by Mansour Charwadn et al. [91]. This study aimed to represent the consumer load pattern, modeling the indecision and non-determinacy (hesitation) using the intuitionistic fuzzy divergence technique, which contains the membership, non-membership, and hesitancy function. Hence, this thresholding method considers each consumer's load pattern as an image, and each load value is assigned as a pixel. A minimization procedure is required to guarantee high separation accuracy for indecision in the consumer's pattern. Each consumer's Typical Load Pattern (TLP) is extracted using neighbor information (2-dimensional daily load values). The results evidenced that, with fewer thresholds, the simulation time is reduced and TLP accuracy.

5.2.3. Economic influence in the DR events

Employing a Deep Neural Network (DNN) to predict the unknown prices and energy demands can be useful to overcome future uncertainties and enhance performance, according to the Renzhi LU and Seung Ho Hong [87] work. In cooperation with DNN, RL is adopted to obtain the optimal incentives for different consumers considering both service providers and consumers' profits. RL is model-free, adaptive, and concise. Contrarily to the previous methods, the service provider does not need prior knowledge. Instead, it discovers the optimal incentive rates by "learning" from direct interaction with each active consumer.

Table 3
Clustering methods applied to residential consumers' smart metering data.

Ref.	#	Location	Method	Data size
[53]	197	UK, Bulgaria	Bayesian non-parametric	9 months
[50]	1.057	US	Dynamic Time wrapping	1 month
[219]	1.200	China	FCM clustering	1 Month
[252]	3.622	Ireland	Finite mixture model	1 year
[221]	300	–	Hierarchical clustering	104 days
[222]	265	Portugal	Hierarchical clustering	2 months
[51]	656	Switzerland	k-means	1 year
[52]	197	UK, Bulgaria	k-means	1 year
[218]	4.181	China	k-means and spectral clustering	1 Month
[217]	218.090	–	K-Means, Hierarchical Clustering	3 years
[220]	4.232	Portugal	k-means, Logistic Regression, Decision trees	1 year and 6 months

Moreover, the incentive rates are acquired and adapted autonomously, considering the uncertainties and flexibilities of the system. Finally, it is based on a look-up table, its implementation in the real world becomes much easier. As mentioned earlier, consumers are finitely rational as agents. However, due to psychological factors, such as cognitive or experimental judgment biases, consumers' positive outlook on participating in a DR program (viewing it as either loss or gain) depends on the reference point. So, their risk attitudes – risk-seeking, risk-averse, or risk-neutral, will shift. Remani T., E. A. Jasmin, and T. P. Imthias Ahamed [40] also consider RL an efficient tool for solving the decision-making problem under doubt. Their study intends to solve a load commitment problem considering consumer comfort, stochastic renewable power, and tariff. The problem was modeled as a Markov decision process. To use RL, state, state space, transition function, action, and reward function were identified.

Furthermore, other algorithms were also used to overcome this problem. Nsilulu Mbungu et al. [131] used an adaptive Time of Use (TOU) Model Predictive Control (MPC) approach to create a managing system for a real-time electricity pricing environment, integrating both solar energy generation and an energy storage system in an isolated power grid. The authors achieved good results in managing energy consumption by prioritizing some loads while centralizing the power supply as a demand function. In this approach, the consumer had the opportunity to keep track of their fee and decide on the use of the energy.

The Nash bargaining theory can be used to achieve the overall system's maximum social welfare when studying the economic interaction between the DSO and microgrids. In work performed by Hung Khanh Nguyen et al. [125], the authors concluded that when the system's social welfare is positive – the saving cost from the peak ramp reduction of the DSO is greater than the total cost of microgrids – the bargaining problem is feasible. Mosaddek Hossain Kamal Tushar et al. [59] created an energy planning noncooperative game for residential consumers with at least a Nash Equilibrium in the prediction phase. It was considered that, according to the Nash theorem, every noncooperation game with a finite number of players and action profile has at least one mixed strategy with a Nash equilibrium. So, the game ends when the equilibrium state is achieved, and no consumers are willing to change their strategy, reducing their payoff.

A fuzzy stochastic CVaR can be used to manage the risk associated with doubt, mainly focusing on price-based DR. The study done by Jiafu Yin and Dongmei Zhao [121] established that the price elastic response curve is inaccurate, the fuzzy characteristics of consumer behaviors are visible. Hence, to mathematically characterize the indecision of DR, the authors introduced the concept of self–elastic to formulate the response behavior-changing percentage of demand reduction concerning the changing percentage in incentive price during the same time interval. To assess the probabilistic risk, the authors pointed to the popularity of the stochastic CVaR criterion and the necessity to design a coherent risk measure in this fuzzy environment. Furthermore, the evidence that compared with the Value at Risk (VaR) method, the unit commitment model based on the CVaR expands the required reserves to minimize the complexity of indecision, protect against the operational risk and meet the system trustworthiness requirement.

Although several methods are used to improve the performance of DR schedules, namely fuzzy methods [149,195], it is important to deliberate those inappropriate strategies that may lead to consumer dissatisfaction and the consequent decrease of their participation in DR events. So, the managing entity of these new players must "learn" and capture their behavior to be able to provide the correct assistance in all situations [104,180,185]. Another approach considered in the former works was the clustering method, that although it has input problems, is widely used in the literature, as can be seen in Table 3. It was also noticed that the economic incentives could be useful for enhancing DR performances [40,59,125]. So, learning and understanding consumer behavior is a step forward to improving the contribution of these new players in the power and energy market.

5.3. DR reliability

In the literature, reliability is defined by the system being in a certain operating state and measured through indicators such as discontinuity duration, interruptions frequency, or not supplied energy [190]. The present paper is described from the system operator perspective regarding the DR events and all the intervenient. The previous two keywords mainly focus on active consumers, empowerment, and ways to enhance their role in the energy market. But the introduction of these new players will impact the system operation. In this way, the authors intend to understand the influence of DR on system security and reliability. Reliability will refer to the quality of being trustworthy or performing consistently well in such events, avoiding further problems.

Focusing on the perspective service provider, the randomness of DR responses caused by the consumers' volatile behavior when achieving a DR target can impact the system's reliability. Amir Ghasemkhani and Lei Yang [112] approach involve incurring a penalty on the participants. The authors mentioned that current research on pricing-based DR assumes that consumers' response functions are available to this player or maybe predicted by it. The RL-based algorithm was then used to aid the serving entity in learning the customers' aggregated behaviors to determine an optimal pricing strategy instead of using pre-defined response functions.

The non-necessity of gathering a priori information to allow each service provider and consumer to understand their position in the grid is supported by Byoung-Gook Kim et al. [20] when developing an RL to overcome the challenges of implementing dynamic pricing and energy consumption schedule. The authors compared two distinct scenarios in their study: the consumers with learning capability and the second involves myopic consumers. Not all consumers in the microgrid are not necessarily strategic. For them, it is more important to learn the dynamics of the entire system and find its optimal energy consumption scheduling based on the observations. However, Byoung-Gook Kim et al. [20] did not discard studying the strategic behaviors of the rational agents and their impact on system operation. Xiaodong Yang et al. [103] designed an adaptive MPC scheduling strategy to dynamically deal with predicted errors and update decision strategies according to the system's latest status and short-term predicted values. Three objectives were set: finding an optimal trajectory for power trade between the cooperating microgrids system and the main grid, addressing supply and demand uncertainties, and operating with outage events during emergency conditions. After several attempts, it was proven that supply-demand balance could be enhanced by implementing shift loads in each microgrid and can be adjusted by exchanging power with the adjacent microgrids.

Online MPC can be suitable for high indecision regarding the renewable generation and consumer responses. In the study performed by Farzad Arasteh and Gholam Riahy [123], this method was used for optimal real-time operation of wind integrated power systems, including coordinating energy storage systems and DR programs. In addition, these authors believed that the possibility of shifting load to off-peak hours makes the controller more flexible, resulting in a lower amount of load shedding and improvement of supply management. In the Prajwal Khadgi and Lihui Bai [86] case, MPC was interested in consumer response to DR events when applied to control the new active players. In this case, the consumers determined their optimal consumption by maximizing a multi-attribute utility function based on changing electricity prices, temperature, and thermal comfort. The results obtained by the authors indicate that among various static variable pricing schemes, the TOU rate is the most robust in achieving a higher Coincident Load Factor – the ratio of average load over a household's contribution to the system peak load in a daily cycle and reducing the costs from the perspective of the consumer.

Regarding the distinct dynamic variable pricing schemes, the former improves when comparing Demand Charge with Flat Rate. At the same time, Sudip Misra et al. [47] used a robust game theory to account for energy management constraints associated with indecision since it generally impacts the algorithms in this area. In this way, imperfect information was considered regarding all the indecision issues to optimize energy trading in the smart grid. Although, as a result, the consumers and the network act as players and the payoff values are optimized, the results showed an improvement compared to the existing energy management models.

However, although some appliances may belong to the same category, they can belong to different consumers, so flexibility is quite different because of power consumption and the owners' habits. Therefore, the authors determined that analyzing the DR potential by only considering appliance type and power consumption is irrational because consumer behavior strongly affects consumption, leading to big variations in the energy consumed by the same type of appliance. Therefore, the human factor cannot be discarded. To prove this view, a more specific study was presented by Maomao Hu and Fu Xiao [137] using the Markov Chain Monte Carlo model to quantify indecision in the aggregate energy flexibility considering stochastic occupancy and occupant behavior which characterizes the randomness of people entering or leaving a specified space at a particular time – influencing the appliances. As affirmed by these authors, the Markov-chain technique is widely used to simulate this process and generate stochastic occupancy patterns.

A negative impact of the active consumers in the network can lead to loss of security and jeopardize the system's reliability. So, many authors opt for economic strategies to test the trustworthiness of the participants in DR events using penalties [112] or distinct DR programs [20,86,103], some in real-time [123]. The game theory approach was still mentioned but explored imperfect information [47]. Again, the human factor cannot be discarded, and the different factors that may impact their decisions must be widely studied.

6. Discussion of the identified challenges and future Research

The active consumers that emerge in power systems are complex, and their actions rarely follow the traditional theory of decision-making, which makes their behavior hard to predict from this standpoint. Instead, psychology and behavioral economics must be employed for greater prediction accuracy. Contrasting both theories, traditional economic models expect consumers to make optimal decisions that result in optimal outcomes. On the other hand, behavioral economics considers that consumer choices can be improved by providing more information and other options to influence the consumers' behavioral patterns.

A growing number of scientific research intends to demystify traditional economic theory and point to the importance of understanding the context in which the consumer operates so that solutions can be found to influence their behavior, to make the desired decision easier, quicker, and more convenient from their perspective, minimizing the physical and psychological effort and reducing the perceived doubt. This can be achieved by, for instance, providing the consumer with comparisons between themselves and the other players' performances, possessions, and wellbeing. By demonstrating that consumers with a profile like theirs (the same power contract, the same consumer type, etc.) are using less energy and taking energy-saving actions that are beneficial, the consumer will be more encouraged to follow these positive energy-saving norms and reduce their consumption accordingly.

Moreover, implementing fair rewards and monetary incentives can motivate the DR event participation regarding intrinsic and extrinsic compensation. Finally, the trust factor is important to give the right message for the demand side to make the right decisions – if they seem skeptical can either disengage or react defensively to the information. Using simple and easy-to-understand messages to communicate with consumers who have limited knowledge of the energy market can help increase confidence in the solution. If there is doubt around the electricity supply, market prices, government policies, and long-term financial payoffs, investment in this approach may seem risky for many consumers.

Furthermore, there is a need to upgrade to smart equipment to enable communication between the active consumer and the energy market. The active consumers must improve and integrate technologies capable of, for instance, being controlled by the local community manager or equipment to simply receive the proper signals to participate in the market transactions. Focusing on each appliance instead of considering the whole building may reduce doubt in DR events. Thanks to advances in AMI technologies and the extracted information, the managing entity can delineate and understand its strategy to succeed in the energy market by persuading active consumers to opt for cooperation instead of rivalry.

The above discussion evidence that context-awareness approaches are necessary to handle consumer participation more accurately [1]. Activating consumers according to the context and providing adequate performance evaluation, for example, through key performance indicators [253], makes the consumer better integrated into the process, increasing their motivation and understanding of the rewards process. Moreover, contracts between consumers and entities requesting DR should be drawn up according to the preferences and interests of each player [254]. Aggregators will play a key role in collecting the available DR from small consumers and establishing contracts using the potential of DR to the fullest [122]. Moreover, Artificial Intelligence methods help support decisions on DR management, namely load forecasting [255, 256]. This method helps understand future consumption, which is crucial when estimating potential flexibility in managing a DR event.

Moreover, learning approaches can be used to learn about consumer behaviors. These approaches learn from events and apply them to similar future events. This enables them to make more accurate decisions in the future [257].

In summary, with all the information studied through the present paper, the authors believe that future lines of research should focus on the consumer side, emphasizing comfort and behavioral aspects, privacy-awareness in the DR programs definition, and the contextual management of the resources to implement DR solution in the future smart grid successfully.

7. Final remarks

The role of the end-user is changing together with the gradual implementation of the Smart Grid concept. This concept urges for greater consumer flexibility: consumers who can control and change their consumption according to signals given by the energy market. However, this new paradigm also enables on-site production for small entities. The new active consumer will have more power over the transactions on the market, and thus, understanding and dealing with their decisions will be crucial to a successful implementation. Consumer empowerment will have an impact on the operation of the grid. If the right solution were designed to include all the necessary features to deal with the uncertainty introduced by new players, a huge step would be taken towards developing a smarter grid. However, when empowering the consumers' many factors should be considered:

- Consumers should not be considered agents that have access to perfectly accurate information – the behavior of real people tends to differ dramatically. Although, after the discussion, the authors believe that participants will always be active and willing to change their strategy and consider them as “perfect” economic and rational agents with complete awareness of the market environment, seeking the optimal decision may be a faulty assumption. To solve this problem and reduce the response uncertainty, the authors suggest a contextual solution: giving the right signals according to the different behaviors and the different types of participants in the DR event.
- The DR participants' actions in the energy market will be complex and rarely follow the traditional economic decision-making theory. So, they are considered hard to predict from this standpoint but are rather predictable from psychology and behavioral economics. In the authors' opinion, implementing DR in the market should discover what influences the participants: the social influence, intrinsic and extrinsic rewards, and trust may play a key role.
- Sharing the full information between players, retailers, and other consumers leads to better results. However, privacy concerns can be raised. The authors believe that trust should be crucial and instigated from both sides. Therefore, define limits and boundaries regarding which information should or not be shared.
- Approaches must consider non-linear tools regarding load profiles' uncertain nature combined with consumers' willingness to participate. Several study results prove that a stochastic approach can handle more uncertainties than a deterministic approach. In this case, the authors believe that each type of active consumer has its characteristics and should be treated accordingly.
- Focus on the appliances for DR, through Advanced Metering Infrastructures, instead of solutions where all the consumers' flexibility is considered. By understanding the functioning of the appliance and the impact of the consumer comfort, since it has freedom of choice to disconnect any time, the uncertainty of the response can be reduced. However, another problem derived from this perspective is the correlated DR relationships. For instance, in a load shifting approach, an appliance that generates heat may require other cooling equipment to maintain the consumers' comfort. For this case, the authors believe that all the appliances should be listed in the DR contract and further define their relationship and consequences.
- Despite several existing approaches in DR and DSM field, it has been found that the consumers deserve more knowledge to support their decisions in DR participation instead of reacting to incentives and prices. Given that the knowledge is self-reported, there may be a considerable divergence between attitudes and observable behaviors, for example, the consumers who still depend on non-renewable resources, do not rely on public transport, and make heavy use of their vehicles, neglect recycling, and any other actions that harm the environment. The authors believe that more information should be shared on social media, new policies including and giving more awareness on the impacts of this concept.

Thus, influencing the behaviors of active consumers and their decisions to reduce uncertainty and enhance their performance on DR events can bring several advantages for all the players involved in market transactions and facilitate the penetration of renewable resources in the system. Therefore, more projects should focus on understanding how to influence and reduce uncertainty on the consumer side.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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