Residential Demand Response Strategies and Applications in Active Distribution Network Management

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ABSTRACT

Electricity distribution is moving towards active, more flexible, smarter and decentralized energy systems. This transition requires System Operators (SO) to dynamically monitor and control the power flow across the network. Demand Response (DR) can be considered as an alternative solution to the costly investment of upgrading conventional Distribution Networks (DN). Hence, the role of DR as a considerable potential of elastic demands in the Active Distribution Network Management (ADNM) is vital. The aim of this paper is to review the recent literature and pilot implementations towards residential DR activation and applications at the electricity distribution level. Background concepts, DR programmes and key participants in ADNM are explained. DR activation strategies for residential demand responsiveness at the network level are categorized and discussed together with the challenges and future directions of this technology. The most relevant DR innovation trials in Great Britain (GB) and their outcomes are also discussed.

HIGHLIGHTS

- Review of residential Demand Response for distribution network management
- Classification based on strategies, applications and network constraints
- Analysis of the most relevant innovation trials in Great Britain
- Discussion of barriers, challenges and future direction in the implementation of residential Demand Response

Word count: 11530

KEYWORDS

Residential demand response, distribution network, flexible demand, active distribution network management.

ABBREVIATIONS

ADNM	Active Distribution Network Management	FES	Flexibility Energy Scheme
DER	Distributed Energy Resource	HEMS	Home Energy Management System
DR	Demand Response	LV	Low Voltage
DLC	Direct Load Control	MV	Medium Voltage
DN	Distribution Network	RTP	Real-Time Pricing
DNO	Distribution Network Operator	RDRA	Residential Demand Response Aggregator
DSO	Distribution System Operator	SO	System Operator
dToU	Dynamic Time-of-Use	ToU	Time-of-Use

1. Introduction

The Climate Change Act (CCA) 2008 made the United Kingdom (UK) the first country to introduce long-term, legally-binding targets to mitigate climate change [1]. The CCA also prompted many countries thereafter to review their environmental policies and this resulted in the creation of worldwide legally binding 'carbon budgets'. By 2016, 189 countries had become a party of the United Nations Framework Convention on Climate Change (UNFCCC) to adopt strategies and regulations for achieving net-zero emission target. To date, five more countries, Sweden, France, Denmark, Hungry and New Zealand have also set carbon-budgets into law, while others, Spain, Chile and Fiji have proposed legislations [2].

In GB, the target of this proposed legislation was the reduction of carbon dioxide emission by a minimum of 27% by 2020, a reduction of 90% in the carbon intensity from energy generation by 2030 [3] as well as final target of 80% for 2050 [4]. Along with deploying clean energy technologies, there is also a great requirement for improving the energy usage efficiency [5], i.e., using less energy to deliver the same service. On the other hand, the change in the load shapes due to the introduction and growth of new loads in the network introduced a new challenge faced by the future networks. DR can provide an intelligent way of managing efficiently electricity demand and supply from decentralized energy sources [6].

An analysis from Guidehouse Insights (former Navigant) predicted triple growth in the global residential DR capacity from 2019 baseline to reach to 47.4 GW by the end of 2028 [7]. After North America, where DR has been implemented widely for decades, Europe is next in line with GB being the first country to open various DR markets to consumers [8]. A UK energy consumption analysis [9] reported that the 46% increase in the number of households and the 17% population growth since 1970 have drastically changed the total domestic electricity consumption. Therefore in spite of improvement in the efficiency of home appliances, their frequency usage, cyclic length as well as energy consumption are still rising [10]. With expected dramatic rise in Heat Pumps (HP) and Electric Vehicles (EV) by 2050 [11-12], the load demand as well as the number of voltage violations will also rise [13], thus causing concerns for Distribution Network Operators (DNO). The adverse effects of integrating these new loads can be alleviated through DR by optimizing their operation time [14].

Advancements in automated infrastructure and technology in DN have enabled residential consumers to participate in demand curtailment plans as reviewed by Haider et al [15]. Optimization-based home energy management algorithms have recently been developed for DR activation of prosumers. The objective of these systems is to find the optimal consumption schedule for consumers considering various factors such as their consumption profiles, energy cost and environmental concerns. Comprehensive literature reviews have been conducted in this area where factors such as DR programmes, optimization techniques and smart technologies have been considered [16-23]. In a more advanced approach, Antonopoulos et al. [24] have provided a comprehensive systematic review on applying Artificial Intelligence (AI) and Machine Learning (ML) techniques to Home Energy Management Systems (HEMS) and network optimization by predicting the available DR capacity and price adjustment. Their analysis shows that after game theory and mechanism design techniques, the majority of researches applied AI at residential level.

There is a need for smart solutions to minimize the cost of the DN to accommodate the previously mentioned changes in the electricity consumption pattern and integration of more decentralized flexible generators. This has driven the typical managing functionalities of DNOs to now shift to Distribution System Operators (DSOs) with a view to ensuring a smarter and active network [25-26]. This transformation is also aligned with net-zero decarbonization policies [27]. The characteristics and challenges in this transition to DSO are depicted in Figure 1. The future role of a DSO should consider improving the engagement of electricity users to provide real-time flexibilities in support of local demand-supply balancing and system optimization. DR as an alternative and innovative solution necessitates customers' awareness of opportunities to participate in available programmes [28].

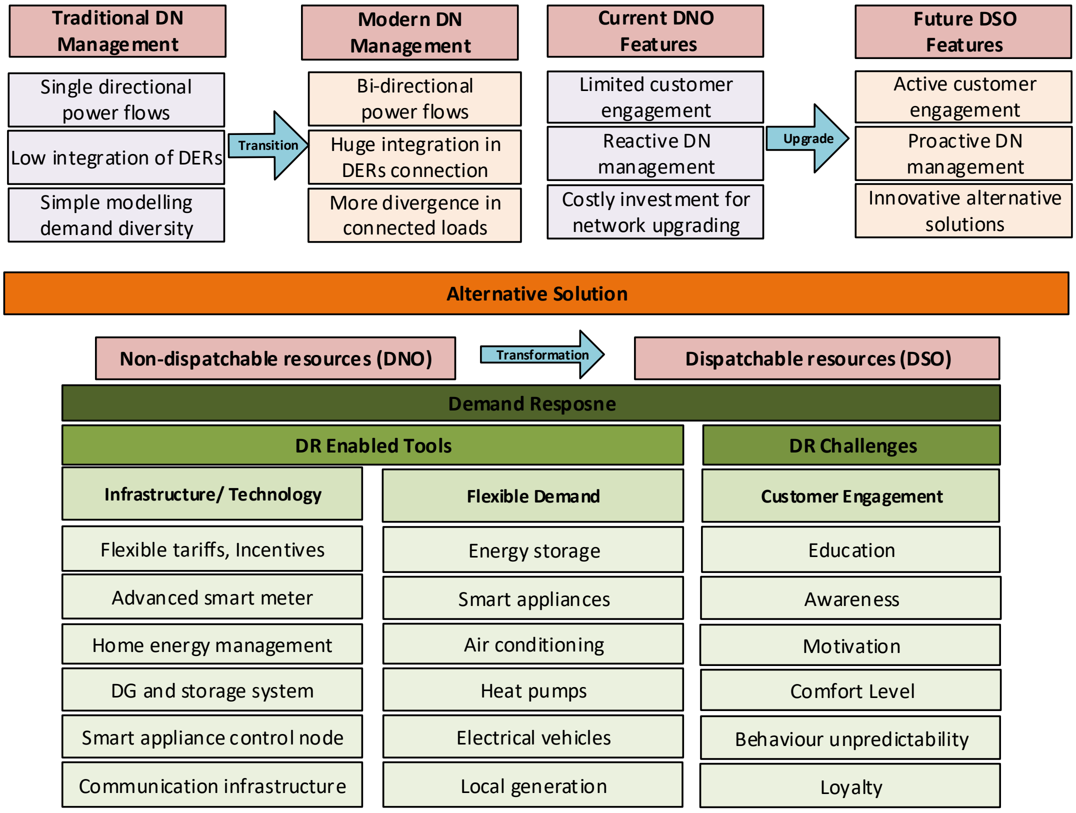

Figure 1. DNO to DSO transformation – features, challenges and the DR as an alternative solution [29]

Many approaches have been used in reviewing DR, using various categorization strategies. A thorough review of DR in smart grid in [30] shows the advantages of DR in reducing peak load and in enhancing reliability. Kang et al [31] confirmed the same benefits of DR but using an economic approach and with the use of energy storage. The application of DR has also been extended to microgrids and this has been extensively reviewed in [32]. They concluded that the simulation results may not be practical due to the simplicity of modeling the microgrids parameters as well as the assumptions of customers' willingness towards participating in DR. However, these findings could be used as the baseline for further work for real implementation.

A meta-analysis of 32 residential DR programmes by Srivasta et al [33] concluded that there is a direct correlation between the success of the programmes with geography of urbanization, the energy policies and regulations, and the economic development. A review of international DR implementation [34] shows the adoption of DR programmes are being pursued globally due to their advantages to all participants especially with the increase in the use of renewable sources. Other studies [35-36] identified and analyzed the DR barriers for price-base DR and direct load control. The main barriers for both consumers and DSOs are uncertainties in benefits and limited deployment of appliance control technologies such as HEMS.

Accessing the right data to accurately model the demand profile is a key enabler in order to manage the DR effectively. Consequently the European Union's Third Energy Package legislation proposed in 2007 required European states to rollout, where economically viable, electricity smart meters to 80% of households by 2020 [37]. Smart meters provide a two-way communication interface between customers, DSOs and suppliers [38]. This will enable the introduction and employment of more dynamic electricity tariffs and improve low voltage (LV) networks monitoring, thus leading future DSOs to gain additional roles [39]. A comprehensive review on smart meter data analytics [40] specified three key applications of these data on DR programmes: load analysis, load forecasting and load management.

The importance of such data has triggered a significant interest in recent researches to employ data-driven approaches, AI and machine-learning enabled analysis to evaluate DR capacity. Numerous literature focus on applying these techniques to extract and analyze the information from real-time smart meter readings, historical data, weather forecasting, etc. The typical applications of these techniques consist of generating a bunch of clusters of households with homogeneous characteristics patterns using supervised machine learning techniques [41-43]. For extracting consumption patterns, unsupervised learning techniques [44-45] have been a preferred approach while for efficiency ranking, non-parametric data-driven method [46-48] have been utilized. Other applications model the end-users energy load profile using data-driven approach [49-53] and AI/machine learning techniques [54-60] to predict the potential quantity of available flexibility from end-users under various DR schemes and price variations. In advanced and smart grid systems, these techniques merge the data into the network or price optimization models to adjust the network control policy or market strategies with the aim of balancing constraints management and demand-supply [61-66].

These new technologies together with advancements in infrastructure such as Internet of Things (IoT) [67] and local generations, have enabled the emergence of a new energy platform, Peer to Peer (P2P) energy. A report by Sia Partners [68] states that peer to peer energy trading community can result in reduction of up to 11% in consumers energy bill and nearly 2% profit from their Photovoltaic (PV) generation. Recent studies [69-72] proposed a P2P energy market platform to coordinate DR in a decentralized way with some focus on LV grid connected Microgrids [73-77] and Nanogrids [78]. An evaluation of P2P mechanisms in the GB electricity network by Zhou et. al. [79] concluded a potential economic and technical benefit for consumers. In a proposed P2P energy sharing framework [80], three different models are introduced: bill sharing (BS), mid-market rate (MMR) and auction-based pricing strategy (APS). In the former, the trading price among participants is calculated based on the consumption and production of each consumer within the community, while the price is set by the retailer in MMR based on community's demand and generation. On the other hand, in APS energy trading is done through an auction-based system.

1.1 Scope of the paper

Based on the technical review papers studied, DR implementation has either been investigated on its general effect in reducing peak demand or improving the system reliability. However, there are no in-depth analyses of what constraints can be managed across different levels of the DN through residential DR. Hence, the purpose of this paper is to investigate and review the activation strategies and resources, development and performance of the residential DR from the network's perspective. The main contributions of this review compared to the existing ones are that it:

- Discusses the existing DR applications and solutions from network perspective as a direction for DSOs to maximize the usage of available flexibility in the network.
- Investigates and categorizes the applications and impact of residential DR in managing different constraints in the DN at different voltage levels considering different solution designs and frameworks as a guideline for researches and industry practitioners in the field
- Provides a state-of the art review and categorization of the residential DR innovation pilots in GB projects as a beneficial guideline for future network planning studies
- Identifies the processes, requirements, capabilities and challenges involved in the effective and widely utilization of flexible low-voltage loads in optimizing the DN as a path to future research direction

1.2. Literature Search Strategy

The methodology adopted for searching for relevant materials for this review paper is depicted in Figure 2. A combination of two of the largest databases of peer reviewed publications, Scopus and IEEE Explore, was the main tools utilized. These were the most relevant search engines on DR and related topics, with materials published in an array of different journals. The main keywords used were:

- ‘Demand Response’ AND ‘Active Distribution Network Management'
- ‘Flexible Demand’ AND ‘Distribution Network’
- ‘Optimization’ AND ‘Distribution Network’
- ‘Demand Response AND ‘Aggregators’

The broad number of results returned from these queries were scrutinized and filtered. All papers cited in this work are related to residential DR and network management.

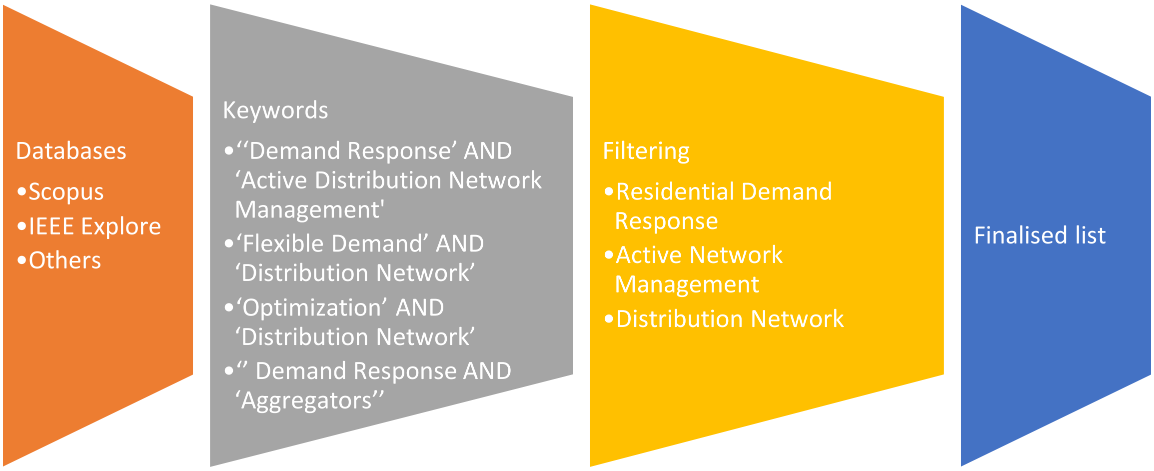

Figure 2. Literature search strategy

A total of 226 publications were reviewed for this paper, mostly from 2010 onwards. While there has been a low number of publications prior to 2011, a rapid increase is observed from 2012 to 2020. This result is very much in line with the increase in worldwide activity in DR around that period.

1.3. Structure of the paper

We identified the processes involved in the implementation of DR for DN constraints management. A breakdown of this hierarchical structure is shown in Figure 3 and this paper is developed around this structure. For clarification, it is worth mentioning that this categorization started as a basic outline for the paper but was later developed fully with progress in reviewing and analyzing the literature. Chapter 2 gives a classification of DR mechanisms. Key participants and their interactions in the energy network are explained in chapter 3. The objectives of the DR controllers are reviewed in terms of both economic and technical targets in chapter 4. DR frameworks and applications in managing various constraints in the DN are presented in the chapter 5 and 6 respectively. Chapter 7 provides a brief overview of the DR strategies in microgrids. Chapter 8 summarizes the most relevant pilots implemented in GB. Chapter 9 tackles the main challenges and future directions in DR implementation at residential level and is followed by a conclusion.

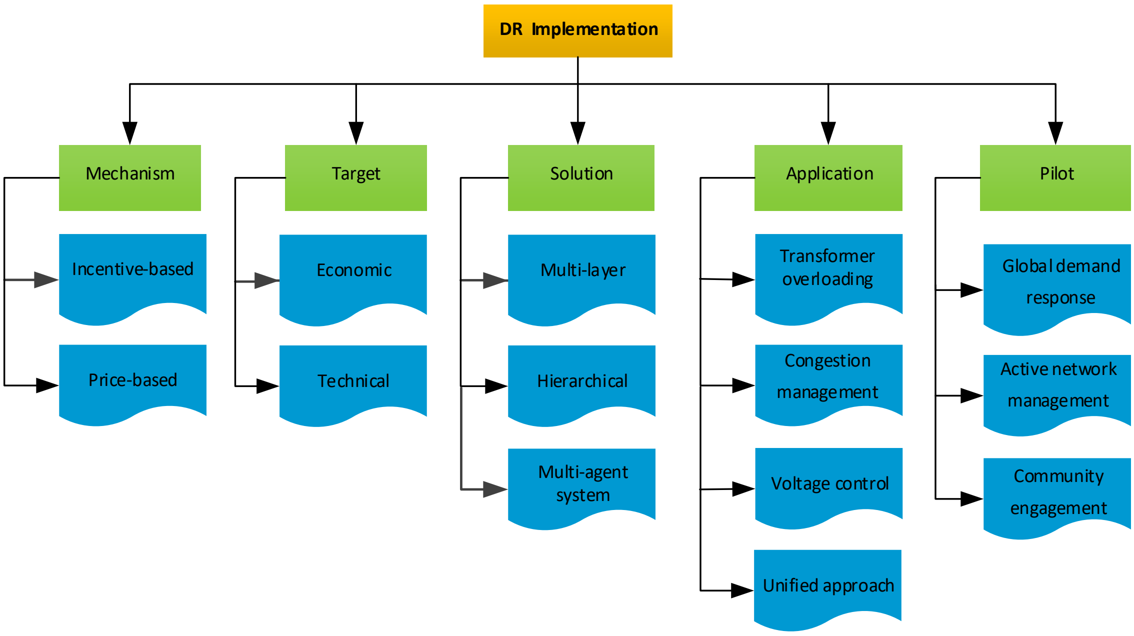

Figure 3. Classification of DR implementation reviewed

2. Classification of Demand Response Mechanisms

The two main categories of DR programmes are incentive-based and price-based. The former provides consumers with predefined incentives for their participation in DR schemes, especially during system stress conditions. In price-based DR, tariffs offered to consumers vary at different times during the day. This type of scheme is usually more suitable for the residential market while the incentive-based ones are more appropriate for larger customers or aggregated demands [81]. Figure 4 shows the classification and differentiation of various DR programmes which are discussed in the next sub-section. The concept behind this classification is further developed in the following section.

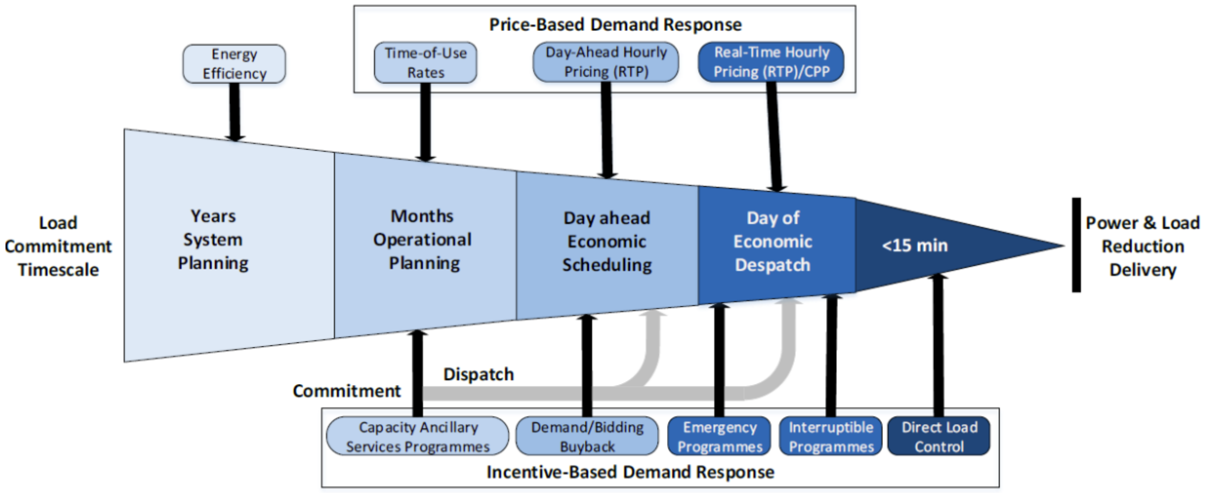

Figure 4. Classification of demand response programmes [82]

2.1 Incentive-Based Programmes

Direct Load Control (DLC) is a programme where SOs are given remote access to customers' equipment to control systems or local reliability contingencies. One example is the "Shetland Northern Isles New Energy Solutions (NINES)" project which was trialed in GB to control electric storage heaters during network emergency conditions or peak load periods [83].

Interruptible/Curtailed (I/C) Load programmes consist of operators requesting customers for pre-defined load curtailment and where non-responders are penalized [84]. Since the residential loads are normally considered as aggregated loads, this facilitates the operator's communication and management.

Demand Bidding/Buyback (DB) programmes give consumers the opportunity to participate in the electricity market by bidding for specific load curtailment [85]. They are run in short periods such as hour or day ahead and are seen as low risk for consumers.

Capacity Markets (CM) programmes involve participants pledging to provide defined load curtailment and they may get penalties for non-compliance. These programmes normally run over medium to long time periods. This scheme was recently implemented in GB where bids are made from the combination of DR (including embedded generation and storage) and existing generation capacity [86].

Ancillary Service Markets (ASM) programmes provide reserve services based on the extent and timeliness of consumers' responses [87]. Their participants are predominantly large and regular energy consumers.

Emergency Demand Response (EDR) programmes are voluntary schemes where pre-defined incentives are offered to customers for their demand curtailment during reliability events [88]. Non-compliance does not result in penalties.

2.2 Price-Based Programmes

Fixed pricing is the traditional pricing system with constant price over specific periods e.g., season or year. Electricity bill reduction in this case is only possible by lower consumption.

Time-of-Use (ToU) are pre-determined rates for specific time periods during the day or week. Customers are informed of these tariffs days or even months ahead. Generally, ToU tariffs are higher during peak times as they reflect the mean price of wholesale market. For instance, the ToU tariff known as the Economy 7, was introduced to residential customers in GB in 1978 with different pricing bands for day and night [89].

Dynamic Time-of-Use (dToU) rates have a shorter notification period for prices, typically one hour ahead or less. However, although prices can be closer to the actual tariff, there is the possibility of delayed responses due to customers losing foresight. The potential of this kind of tariff in providing DR was investigated in the Low Carbon London (LCL) trial [90]. This pilot resulted in bill reduction in 85% of households.

Critical Peak Pricing (CPP) consists of rates during critical peaks and these are normally higher than average ToU rates. Since more customers are engaged, the reliability of the system is enhanced thus leading to higher demand curtailment [91].

Real-Time Pricing (RTP) offers a dynamically changing tariff reflecting the real price of wholesale market. This is based on uniform time steps, e.g. hourly or day ahead, thus allowing customers to alter their consumption to their benefit. A Day-Ahead RTP (DA-RTP) [92] is an alternative RTP where the electricity price is predicated and announced to the customers in a day-ahead basis.

*Vickrey-Clarke-Groves (VCG***)** is a centralized mechanism, based on voluntarily provided load information by consumers, utilized to determine the price for specific periods [93]. Incentives are also offered to customers in a bid to encourage them to provide correct information. This pricing scheme is also useful in lowering electricity consumption as well as load shifting.

3. Players and Interactions in GB Flexibility Market

Developments in the power network have created new roles and relationships for all interacting players within the electricity system [94]. In fact, the modern electricity systems can now be modeled as a networked environment where duplex communication exists between participants. A report published by Origami in 2019 [95] indicated that although a majority of countries are moving towards a DSO flexibility markets using more decentralized and distributed energy usage using DR as a grid security support, they are still in at a trial stage. GB, Australia and North America are the only countries that have a roadmap and plan to turn this to a business as usual solutions.

Since the focus of the trials and innovation pilots categorized and analyzed in this paper are focused on GB network, this section provides useful definitions of the key players in the flexibility market of the future DSO in GB. Figure 5 shows a block diagram illustrating the communication between various players within the GB energy network [96]. As can be seen, the key participants are consumers, electricity suppliers, DSOs, aggregators and data sharing platforms with Office of Gas and Electricity Markets (Ofgem) as the regulatory body. However, the actual model can vary according to network structures of each country.

The role of DSO is to provide a secure network with services including voltage control and network restoration. DSOs do not generate or sell energy as this is the responsibility of energy suppliers. The cost of DSO services, also known as Distribution Use of System (DUoS), is normally added to consumer’s bill which is regulated by Ofgem. Usually residential consumers pay a fixed rate of DUoS and the electricity price are limited to certain ToU tariffs. Incentives are offered to DSOs to investigate innovations for efficiency and power quality improvement. As discussed previously, the current GB distribution network is operated by DNOs whose roles are now changing to DSOs. The current GB network is serviced by six different DNOs that are responsible for specific regional areas [97]. Energy Suppliers acquire electricity from either wholesale markets or directly from generators, which is then sold to individual customers. There are currently six main suppliers in GB [98] and their primary focus is to provide a competitive tariff to maximize their market share. This has been the driving force behind the move towards dynamic tariffs.

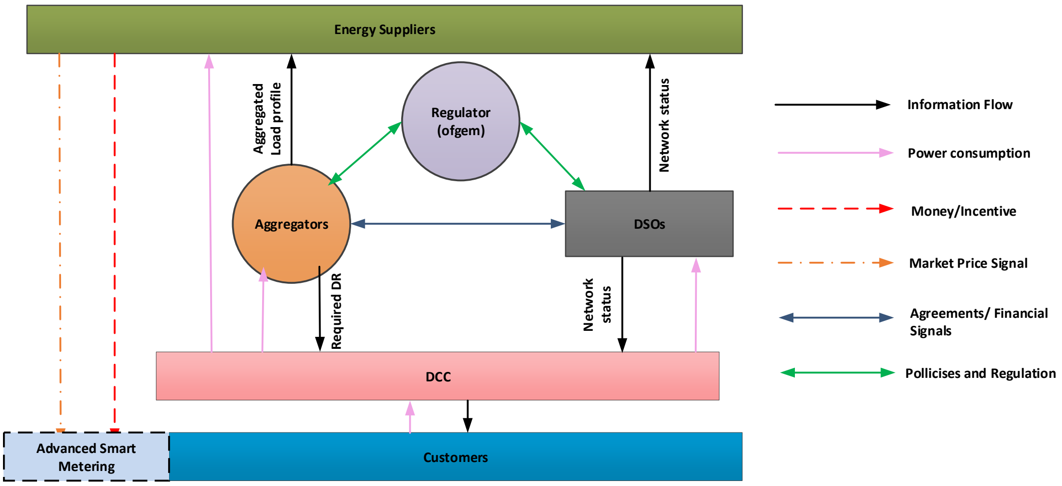

Figure 5. Block diagram of DR participants' interaction in future GB DSO network [96]

Consumers are now able to take an active role in the network and this has created new sources of flexibility. One in four households are now equipped with smart meters that can provide accurate and real time energy consumption data profiles. Besides relaying their demand information, they can also monitor and control their consumption. Ofgem reported a total customer savings of £6.43 billion in 2010, with 34% attributed to load shifting/ToU tariffs [99].

The benefits of using smart meter can go far beyond price-based DR. In practice, a successful DR model at low-voltage level is only feasible if considered in an aggregated level. Aggregators collect the demand flexibility and local generation across their domain regardless of energy supplier or DSO and this increases the network reliability. They act as an interface between energy consumers and other stockholders [100]. This third party entity's role is to enable the active participation of small responsiveness demand in DR programmes. They are also more knowledgeable of market rules compared to individual households and their responsibilities include satisfying all participants' interests.

An Energy management system, comprising energy monitoring, control, and optimization, requires a dynamic data exchange between DSOs, energy suppliers and individual or aggregated end users. For security and privacy reason, home energy consumption data will be available through a centralized and single point thus requiring a data access & data sharing framework. The Data Communication Company (DCC) [101] is responsible for data communication establishment and management in GB. This network entity acts as an interface between smart meters and other authorized entities in the network. Smart meters can thus preserve their smart functionality regardless of consumer's energy supplier. However, the optimal platform for data exchange interaction between aggregators and DSOs as well the communication standard needs to be defined by DSOs.

It is worth mentioning that a survey by KPMG5 in 2020 [102] reported that the key challenges that the DSOs in Europe are facing is the lack of comprehensive understanding and definition of market rules and regulations. This slows down the development of the required tools and infrastructures of enablers for DSO model implementation and the usage of DR. A framework and the role of independent aggregators need to be defined in order to allow their maximum participation s into the energy markets [2].

4. Demand Response Targets

The strategies adopted when designing and implementing DR control mechanisms can be based on economic and technical aspects. The literature reviewed has been classified according to these two aspects.

4.1 Economic Targets

The economic target of DR control schemes refers to the consideration of electricity cost and incentives in the objective function of Residential Demand Response Aggregators (RDRA). The algorithms and control mechanisms for DR reviewed in this paper are considered from the network point of view, with RDRAs as the studied targets. These aggregators interact with their associated households in order to implement DR services, taking into account their own profit. Their strategy is based on either minimizing cost or maximizing profits/incentives. Several attempts have been made in studying the roles and advantages of RDRA [103-105]. Applying RDRA to provide an active energy management environment has also been considered in a diverse range of studies [106-108].

Based on their objectives, DR aggregators have been grouped into three categories applying various price-based tariffs including ToU, Day-Ahead (DA) and RTP as presented in Table 1. Profit and social welfare maximization focus on single RDRAs serving multiple households. On the other hand, for the electricity market category, several aggregators are considered.

Table 1. Classification of papers based on RDRAs' objectives

DR Tariff ***Objective***	***ToU***	***DA***	***RTP***
Profit Maximization	[109, 110]	[111, 112, 113]	[109, 112, 114, 115]
Social Welfare Maximization	[116, 117, 118, 119, 120]	[119, 121, 122, 123, 124, 125, 126, 127, 128]	[110, 116, 117, 119, 120, 123, 125, 127, 129, 130, 131, 132,133]
Electricity Market	[134]	[122, 135, 136, 137, 138, 139]	[139, 140, 141, 142, 143]

In the first category, the aim of each RDRA is to provide and sell the DR services to the SOs. This is done through compensation payment to consumers for the changes in their energy usage.

Generally, the DR objective function can be defined as [96]:

$$max\{R - \sum_{h\in H} C_h(P_h)\} \tag{1}$$

where the proceeds of the RDRA and the consumers‘ incentives are represented by R, C_h is the cost and P_h is power consumption of end user per hour.

RDRAs have modeled various dynamic tariffs to improve the market decision-making and pricing scheme designs. For instance, the RDRA's objective function proposed in [110] was to maximize the end-user's surplus which was calculated by the differentiation between the total agreement and the actual payment of households. The simulation results indicated an approximate 20% reduction in consumer bills as well as flatter load profiles over time.

In the second category, each entity at the network, seeks to enhance its own profit. This implies that the goal of energy consumers may not necessarily be in line with the RDRA's one. A unified approach was used in [133] to reduce consumers' electricity cost as well as flattening the average load profile. This study was developed based on the proposed framework on [144] to solve its communication problems and shorten processing time by using a parallel architecture. In a different approach, RTP and ToU were combined to mitigate DN overloading [117].

Similar to profit maximization, in the electricity market category the aim is to maximize the DR availability for sale. However, the role of SOs and the contributions of other aggregators in the network are also considered. In other words, the electricity market is modeled with all network entities having a self-interested and non-cooperative nature. In this model, SOs aim to minimize the cost of network operation by providing rewards to RDRAs.

4.2 Technical Targets

The residential responsive demand can contribute in the management of the DN at two levels: *local* DR, where the focus of the implementation is on the low voltage networks, and *wide-area* DR management, which analyzes the application of DR at Medium Voltage/Low Voltage (MV/LV) network levels. Table 2 presents an overview of recently published literature in this area. In local DR, the system model comprises one SO that serves a secondary substation which plays the role of an aggregator connected to several domestic loads. However, detail about the DR request and control strategies from the SO is [145] not a requisite and is assumed to be known. At MV/LV network level, the SO interacts with RDRAs in LV feeders to improve the reliability and security of the DN.

Table 2. Technical DR targets classification.

Network Level	Local DR (LV)	Wide-area DR (MV/LV)
Ref	[146, 147, 148, 149,150, 151,152, 153, 154, 155, 56, 157, 158, 159, 160, 161,162, 163, 164, 165, 166, 167]	[153, 168, 169, 170, 171, 172, 173, 174, 175, 176]

Generally, consumers can contribute towards solving operational issues in the network through DR events. In the case of a DR event, the required demand limit is either allocated to each consumer/feeder or the required load curtailment is automatically applied. The former action refers to EDR programmes where contribution in the DR scheme is voluntary whereas the latter relates to DLC programmes.

The strategies to define the allowable demand for each household/feeder can be categorized into: Curtailment Potential Scheme (CPS), Flexibility Energy Scheme (FES) and a combination of both. A categorized list of research work is shown in Table 3. In CPS, individual available DR is considered for determining the total required curtailment. In FES, the objective function of the feeder controller also takes into account the household's characteristics. Therefore, the DR mechanism seeks to maximize the consumer's comfort while also maintaining the network constraint within limits. However, this increases the complexity of the computational process and necessitates the use of more advanced optimization techniques.

Table 3. Categorization of methodologies for calculating the allowable demand of households.

Methodology	Curtailment Potential Scheme (CPS)	Flexibility Energy Scheme (FES)	CPS/FES
Ref	[117, 147, 151, 158, 159, 160, 162, 163, 165, 177]	[149, 152, 154, 155, 156, 166, 167, 178, 173, 174, 175]	[157]

5. Demand Response Solution

The interaction between DR participants in the network has been modelled through several frameworks in the literature. The overall goal of a DR framework is to determine an optimal load scheduling in order to manage the DN. The model consists of households connected to a Load Service Entity (LSE) such as a DSO. Upon receiving a DR event signal from the LSE, households adjust their controllable appliances' operations accordingly to:

- Maximize the social welfare
- Limit the overall household demand within thresholds during peak time
- Meet all household and network constraints

As an example, a residential DR was proposed in [64, 178] as a multi objective function to minimize power losses in the network while maximizing the use of flexible demand. It was concluded that the voltage sensitivity to changes in demand is greater at the buses located at the end of the feeder. It was also shown that the selection of setting parameters for DR objective is important to avoid rebound peaks.

A DR framework and structure should be able to provide an integrating environment for all entities, with specific attributes, in the network. Therefore DR can maintain network constraints within the boundary limits while meeting all DR participants' goals. Three framework models from the literature are discussed further.

A *multi-layer framework* comprises several layers where entities within the same layer have similar attributes or functionalities [179, 181]. For example, a two-layer framework proposed in [139], as shown in Figure 6, has all direct participants in electricity market in the first layer. The entities in the second layer, on the other hand, are consumers providing DR services.

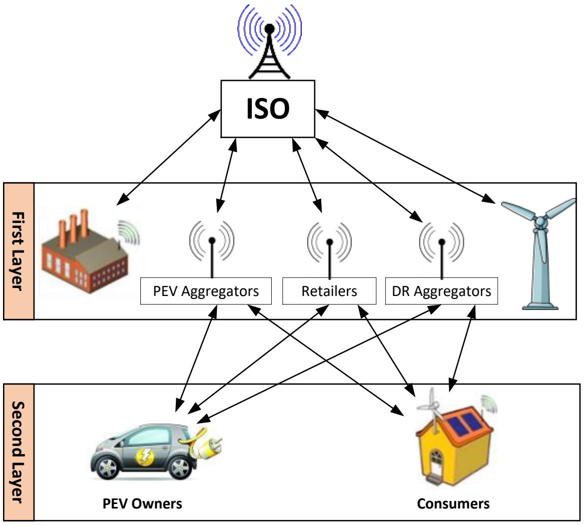

Figure 6. Multi-layer framework [139]

A Hierarchical Framework comprises entities in different levels where they are able to communicate with entities on their upper level. Typically DR controllers, e.g., LSE and DSO, are located at the top level whereas end users are in the lower levels. This structure is also known as supervisor-employee model. In the three-level structure [134] shown in Figure 7, aggregators are defined in the second level, acting as an interface between the first and third level.

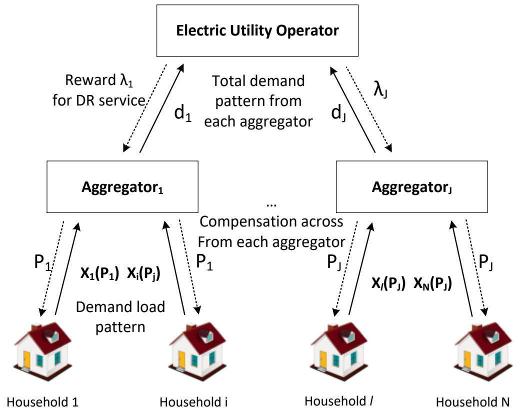

Figure 7. Hierarchical framework [134]

***A** Multi-Agent-System (MAS) framework* models network entities as agents with specific characteristics, functionalities and behaviors [157]. Although autonomous, they interact with each other to reach the overall system goals by splitting and sharing the tasks. In [182] four types of agents, as depicted in Figure 8, are introduced to represent generators, wholesale markets, retailers and households.

The main difference between the Hierarchical and Multi-layer frameworks is that in the former, each entity can only interact with another one in its upper level while in the latter there is no restriction in communications between layers.

The complex nature of the future electricity network makes MAS the most suitable model due to its decentralized structure where each intelligent agent can act independently and simultaneously [170]. This can also maximize the network stability in the occurrence of local fault or communication failure [94]. A comprehensive literature on DR implementation studies using MAS have been presented in [183]. A review of the applications of MAS in managing smart grids [184] showed the benefits of this decentralized approach in reducing cost, enhancing customer welfare and in providing a framework to maximize integration of low carbon technologies. However,

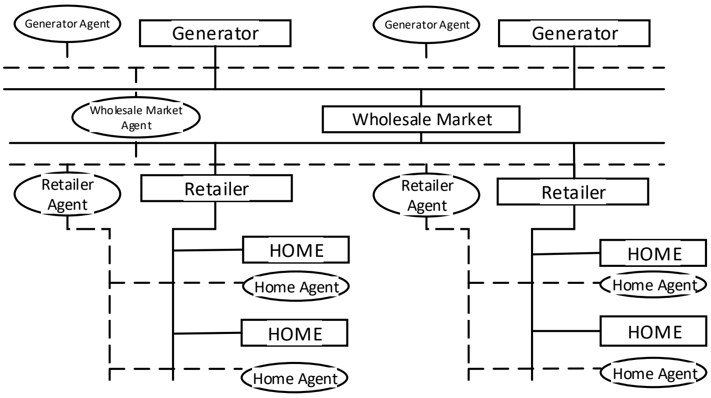

Figure 8. MAS framework [182]

the proposed MAS frameworks in the literature are limited in terms of scalability [139, 134], adoptability [185] , the number of manageable network constraints [153, 168, 186], DR scenarios [14, 35, 38] and types of agents [187, 188].

6. Demand Response Application for Distribution Network Management

The DNs mainly deal with three major operational issues: transformer overloading, voltage limits and network congestion. Generally, network congestion occurs at MV networks while transformer overloading is mostly at LV networks. A classification of these categories from the literature is provided in Table 4.

6.1 Transformer Overloading Management

Exceeding the maximum capacity of a MV substation or MV/LV transformer can be the cause of overloading issues at LV feeders. During such conditions, the duration of the DR event and the extent of load shedding are two parameters considered for maintaining the demand within acceptable limits.

Many approaches have been devised and studied with the aim of overcoming the overloading challenges in DNs. One such DR control strategy involved the integration of local generation to relieve congestion [151]. Another study [152] applied a direct load control approach based on a merit order and confirmed the achievability of a 100% PV penetration in the LV network. Similarly, [154] proposed an EDR mechanism aimed at lowering the transformer power demand. However, in these studies the demand allocation is assigned to consumers without considering their individual characteristics. These can increase the possibility of a power rebound. [155-156] addressed this issue using a MAS framework where households' atributes, including user constraints, satisfaction level and appliances, are also taken into account during a DR event. Hence, the drawbacks of having a new peak load after DR event duration can be lessened.

Table 4. Classification of DR application

Constraint	Reference
Voltage	[145, 147, 150, 155, 158, 159, 163, 165, 166, 167, 173, 174, 175, 189, 190]
Transformer Overloading	[151, 152, 154, 156, 160]
Congestion	[145, 147, 150, 155, 158, 159, 163, 165, 166, 167, 173, 174, 175, 189, 190]
Combination	[146, 149, 157, 168, 191]

6.2 Congestion Management

Price-based DR is the main mechanism proposed in the literature to manage the congestion at the DN. The methodology is split into four steps:

- DR Aggregators update their load profiles based on individual demand from their corresponding households.
- An initial demand bid is sent to the DSO in a day ahead or real time market.
- The DSO adds a supplementary cost to the existing tariff in case of any possible congestion.
- Accordingly, aggregators adjust their demands based on the updated price.

Several methods have been presented in order to determine the congestion price. In [153] a Locational Marginal Pricing (LMP) is applied and showed peak overloading of 1% and 2% during night and morning respectively. [169] used a dynamic thermal model of the transformer which also verified the effectiveness of such a price-adjustment programme as an economic tool to reduce peak demands.

In a different real-time pricing DR [172], the pricing tariffs and additional overloading costs are allocated distinctively to each zone (feeder) of the network. This can provide a more localized and distributed control of the network. However, the proposed pricing scheme faces many challenges. For instance, since the consumers have to pay the price of local problem at the network, their attitudes toward DR participation can decrease.

Consumers in RTP can decide about their consumption behavior at any given time. Therefore, a direct DR control mechanism is usually necessary along with price-based DR in order to guarantee the provision of adequate flexible demand. A combination of both DR types can ensure the generation-demand balancing in the DN [169]. An approach in [171] integrates both incentive and price-based DR schemes, based on the available DR size under normal conditions and during emergency conditions respectively.

6.3 Voltage control

The uncertainity in renewable energy generation and increase in demand can cause the voltage to exceed its allowable limits. Voltage violations, under-voltage and overvoltage, can occur at both LV and MV feeders. This can lead to voltage drops and consequently power cut. The literature mainly considered the incentive-based DR such as DLC or EDR where consumers in pre-agreed contracts can be involved in load reduction schemes if required.

At the LV network, this problem, in the case of solar energy, has been mainly addressed by controlling the active power through PV invertors. In order to alleviate the voltage constraint in the network, several methods of droop control, such as Active Power-Voltage (P-V) [157-159], Reactive Power–Voltage (Q-V) [148, 177] and Active Power-Frequency (P-f) [160], have been proposed and applied. The maximum output set point is determined for the PV invertor where it is decreased during voltage drop issues.

A distributed DR mechanism is applied in other studies to control the power usage of home appliances. In [155] the amount of load curtailment for each household is determined and allocated according to the size of their electrical panel. However, voltage problems at LV feeders are primarily studied in the form of a combined approach together with congestion management.

At MV feeders, to improve the voltage stability of the network, the identification of the buses characteristics regarding their voltage sensitivity is required. Many studies [150, 174, 189, 192] have shown that DR can be used as an effective tool to reduce the overall voltage drop across the network and to increase it at the end of the feeders. The main concerns in designing and applying DR mechanisms are the determination of the quantity and optimal load curtailment at each feeder. The former is mostly calculated using optimisation techniques which aim at determining the minimum required DR size [173] or maximum load capacity of each bus [174]. The latter is usually determined by voltage sensitivity analysis using several methods such as:

- Voltage Deviation Index (VDI) [193-196]
- Updated version of Jacobian matrix [197-198]
- Direct approach dependent on the network topology [199-200]

- Adjoint network model [201]
- Y-matrix model [202-203]
- Constant current model [204-205]
- Bus power flow model [175, 202-203]

After calculating the voltage senstivity of all buses in the network, two methodologies are utilized in the literature for shedding the required demand reduction:

Loop procedure [189, 192] is one in which the load shedding procedure initially begins at the buses with the biggest magnitude of voltage deviation. The process terminates when the voltage is back within the statutory limit. This method is applicable especially when the required amount of DR is not identified.

Distributed Curtailment [150, 208] is another methodology in which the total required load curtailment is distributed among buses based on their voltage sensitivity. This technique is mainly suitable where the total required DR size is known.

One important issue to consider in DR implementation is addressing Demand Response Mismatch (DRM) [209], which are inconsistencies between scheduled and actual DR. Inclusion of reactive power and voltage dependency in DR calculations can help to mitigate this problem and improve reliability of power systems [210-211].

6.4 Unified Approach

Due to the correlative nature of constraints at the DN, several studies have examined unified-based approaches where more than one constraint are considered. A hierarchical agent-based model is proposed in [157] that analyzed both voltage and thermal limits. The PV output and heat pump are controlled using CPS-DLC and FES methodologies respectively. In [149] a two-level hierarchical DR framework consisting of two DR controllers is presented: one for improving the voltage profile and the other for controlling the transformer overloading. The first target is achieved through incentives allocated to consumers for shifting their loads. In the latter, this is done through peak load shaving. A new approach is presented in [146] to mitigate the voltage and current constraints within the limits. Unlike other studies, where the DR objective function is to minimize the power losses and/or voltage deviation index, here the maximization of the allowable total demand is considered.

7. DR Strategies in Microgrid

The need for implementing microgrids has been accentuated by the challenges to efficiently manage the integration of distributed energy resources (DER) with the view to decentralize, decarbonize and improve grid reliability and resilience at lower cost [212]. Microgrids have two operating capabilities: autonomous and on-grid. In on-grid mode, local power generation is the first choice for meeting demand of the microgrid, and any excess power required or generated are either imported from or supplied to the grid. In autonomous mode, it is vital for generation to match demand for stability of the microgrid [213]. Several approaches have been investigated to maintain this balance. One of the most efficient and reliable methods is through DR [214-215]. [216] proposed a flexible microgrid where boundaries can be adjusted based on factors such as DR levels and customer comfort amongst others. This method resulted in utilities cost reduction of up to 19% compared to static microgrid operation.

DR control mechanisms are either performed offline, e.g., incentive-based [214, 216] and day-ahead [215] , or, online, such as RTP [213]. Studies have shown that the latter is more reliable, efficient and practical when dealing with uncertainties in the microgrid [217]. However there are still serious concerns about the resilience, efficiency and stability of microgrids due to the dynamic nature of DERs [218-223]. Most research works have only studied microgrids under normal conditions or with minor faults [220-231]. Recent studies have proposed, developed and implemented various multi-objective optimization (MOO) methods to improve the reliability of microgrids under major network faults, system failures and load unbalance [232]. In this paper a new decentralized control strategy for microgrids in both offline and real-time environments have been performed using a combination of MOO and fuzzy decision making to improve the fault ride through capability. The disturbance in that microgrid has been modelled as non-linear constraints for MOO to guarantee the optimum power sharing. H.R. Baghahee et al. [233], have used multi objective particle swarm optimization to overcome the computational burden for optimum coordination of overcurrent relays in meshed and interconnected networks. It is to be noted that the application of MOO is not limited to the improvement of stability and resilience only. It can also be used in designing and optimizing hybrid energy systems [234-238], in cost minimization of the system over long operation periods [239], as well as in optimization of transmission system devices [240].

Detailed studies in the use of intelligent algorithms, such as evolution and metaheuristic, as solutions to multi-objective optimization have been performed in areas such as microgrids and renewable energy generations [153,187-190]. Results demonstrated the effectiveness of such techniques in achieving global optima. In [218, 241] a novel load flow methodology has been presented for radial and meshed networks, which can solve nonlinearities in the load flow. Using this method, [242] introduced a hierarchical 3-level control strategy to calculate the reactive set points of DR controllers in any type of microgrid. This control scheme can enhance the stability and ameliorate power sharing using more accurate power calculations. A similar approach [241, 243] was adopted to include nonlinear and sensitive loads.

Moreover, optimal sizing and optimal power management strategies are also integrated with modern DR schemes. In this kind of solution, the initial set points of the control system are determined by a robust power flow algorithm that can efficiently solve the load flow problem in the microgrid with high values and uncertainties in R/X ratio and load multiplier.

However, adopting an optimized and coordinated energy management system such as a multi-microgrid approach can be more efficient and cost effective. This strategy discourages individual microgrids from misusing common resources and instead acts towards the best interests of the whole system [215] .

8. Overview of GB Demand Response Innovation Pilots

Innovation pilots are projects that apply novel solutions as replacements for expensive upgrades of the network with a view to providing economic benefits to both consumers and the DNO [244]. This section briefly reviews the activities in terms of residential DR related pilot projects that have been trialed in GB. They are classified using the following categories: global demand response, active network management and community engagement.

8.1 Global Demand Response

The trials in this category have the aim of introducing various DR pricing schemes to financially encourage consumers to lower or shift their peak power consumption. ToU and dToU have been the only implemented tariffs so far in GB and their efficacy has been investigated through different pilots [245] as summarized in Table 5.

Table 5. Summary of relevant innovation pilots in GB network with the focus on global DR.

Category	**ToU**				**dToU**
Trial	Customer Lead Network Revolution	Ireland Electricity Smart Metering Behaviour Trials	Energy Demand Research Project	Northern Ireland Powershift	Low Carbon London
Organisation	Northern Powergrid	Commission for Energy Regulation within the Republic of Ireland	EDF, E.ON, Scottish Power and SSE	Northern Ireland Electricity.	EDF, UK Power Networks
Location	North of England	Ireland	London and the southeast of England	Northern Ireland	London
Time Period	2010-2015	2009-2010	2007-2010	2003- 2004	2010-2014
Innovation	Assess the impact of low carbon technologies including PVs, HPs and EVs and ToU for residential, industrial and commercial customers	Investigate the potential of smart meters, ToU tariffs and Demand Side Management (DSM) stimuli on load reduction/shifting	•Trials by four energy suppliers , •Investigate the effect of supplying information on long term consumption	Evaluating the potential of shifting peak demand through ToU tariff	Investigating the impact of dToU on demand-supply balancing and network constraint management
Scale	11,000 homes (2000 others)	5,028 homes	60,000 homes	200 homes	5,533 homes
Solutions and Technologies	ToU, Smart meters	5 ToU rates, bi-monthly billing with a demand reduction incentive	Financial incentives for consumption below target Smart meters	•3 ToU rates •Keypad meter with an IHD	dToU
Communication Strategies	Home display	bi-monthly billing, monthly billing, bi-monthly billing with an electronic energy monitor	•Real time display, •Letters, •Website		Text messaging
Investment	£31 million	-	£9.75 million	-	£28 million
Key Lessons Learned	Reduce residential peak demand by 6.39% between 4pm-8pm	Households on average saved 2.5% on bills	Results showed that overall there was no significant reduction in consumption	Annual bills decreased by 5.5%	8% reduction in demand

8.1.1 Time-of-Use Tariffs

The main finding of these trials verified that ToU tariffs can trigger a shift in the demand of households from peak to non-peak period, although there exists a high variation in the outcomes of the trials. It was also found that the effect on peak demand was more significant than that of overall energy consumption. Some projects adopted various ToU tariffs for better comparison. The Energy Demand Research Project (EDRP) [246-247], for instance, used two ToU tariffs from energy suppliers Électricité de France (EDF) and Scottish and Southern Energy (SSE). While EDF's tariff was daily-based, SSE's incorporated seasonal price as well. Peak demand reductions of 8% and 4% were observed for weekends and weekdays respectively for a total of 1936 participants [245]. The Ireland Electricity Smart

Metering Trials (IESMT) [248] adopted five different ToU tariffs and showed 2.5% - 9% demand reduction from approximately 5000 households [245]. Another pilot, the Customer Lead Network Revolution (CLNR) [249], resulted in a reduction of 6% in peak consumption for 600 households [250]. A decrease of 75W in peak load per household was obtained through the Energy Control for Household Optimization (ECHO) [251] pilot, which was developed to control shiftable appliances. The Sunshine Tariff [252] yielded a daily 13% demand reduction for consumers equipped with automated control technology. The outcome of these pilots also concluded that together with economic incentives, education is also a requisite for the successful introduction of ToU. Currently, the emphasis of implementing ToU tariffs is focused principally on awareness and energy engagement.

8.1.2 Dynamic Time-of-Use Tariffs

The Low Carbon London (LCL) [253] pilot was the first dToU scheme implemented in the UK. It was aimed to explore the DR potential in various trials run by suppliers or DNOs. The outcomes indicated an increase of up to 14% in consumption during low price periods and a reduction of 9% during high price ones. This resulted in bill reduction for 85% of households with a mean saving of 4.9%.

8.2 Active Network Management

ADNM with residential DR services was implemented by some trials. A summary of three major trials aiming to investigate the efficiency of DR in ADNM platforms for managing network constraints and increasing DERs' penetration is provided in this section and in Table 6.

Table 6. Summary of relevant innovation pilots in GB network with the focus on ADNM.

Trial	*Shetland Trial*	*Customer Load Active System Services*	*Accelerating Renewable Connections (ARC)*
Organisation	Scottish and Southern Electricity	Electricity North West	SP Energy Network
Location	Shetland islands	Clusters across GB	Scottish borders and East Lothian area
Time Period	2013-2017	2014-2016	2012-2014
Innovation	Evaluating the effectiveness of DSM on active network management	Evaluating the application of innovative voltage, management technologies to provide DR services	Combination of ADNM scheme and community engagement to manage the generation-supply by generators and locally-produced energy
Scale	234 homes	60 primary substations serving approximately 485,000, Domestic and industrial and commercial customers	Covers geographical area of 2700km^2
Solutions and Technologies	Battery and DSM enabled appliances, ADNM	Cash incentives Smart voltage control, advanced active network management system	PV, wind turbines, modification of network equipment, Incentive on connections engagements
Communication Strategies	Website, phone, home visit, local meeting	Leaflet, website	Workshop with local community, online tools,
Investment	£21 million	£8,084 million	£8.46 million

Trial	*Shetland Trial*	*Customer Load Active System Services*	*Accelerating Renewable Connections (ARC)*
Key Lessons Learned	DSM with ADNM platform can be an alternative for future DN, Learning and improving the relationship with customers in order to change their consumption behaviour	ADNM with DR can successfully provide voltage and frequency support without affecting power quality of network devices	Reduced infrastructure, Lower cost over traditional solution Save energy cost for local communities

The Customer Load Active System Services (CLASS) [254] project was a successful pilot that provided a good insight on the voltage/demand relationship for all participants. The use of smart voltage controllers in major substations demonstrated the application of innovative voltage management approaches to provide DR. Results showed that DR potential of up to 3.3GW was achieved.

The Shetland Trial [255] provided DR services to 234 participants by replacing their old storage and water heaters with modern smart storage heaters, which were selected for their demand shifting potential. The ADNM computes next day schedules based on requirements obtained daily from devices, before updating them with instructions. The potential for a flexible framework for future changes to the network was clearly demonstrated by this pilot. The Accelerating Renewable Connections (ARC) [256] trialed a combination of ADNM and local community engagement schemes to manage locally generated sources and supply through community engagement. Connections of 49.5MW from wind farms and 2.2MW from PV panels were successfully deployed to local households. Through this project, consumers could potentially save around £1.9 million over the lifetime of the systems. More recently Smart Energy Isles pilot [257] aimed to increase penetration of renewable energies in a microgrid by improving the existing ADNM. This on-going trial allows local communities to benefit from the maximized local generation.

8.3 Community Engagement

These trials were designed to investigate the potential of local communities to engage in DR programmes. The aim was for DNOs to collaborate with consumers to lower demand and maximize the local available DR with a view to deferring network reinforcement investment. Several pilots [239] were implemented to change the customers' behaviors, and avoid peak demands by shifting consumption to non-peak periods. An overview of recent community-related pilot projects, categorized according to their focus, is provided in the following sub-section and summarized in Table 7.

8.3.1 Integrating Low-Carbon Technologies

This category aims at assessing the efficiency of incorporating renewable energy resources into the DN. The Sola Bristol project [258] for example, equipped participating households with PV panels, energy storage units and operated under ToU pricing. Although the results confirmed the benefits of integrating storage and ToU tariffs, the project could only be economically viable with higher integration of DERs. It was found that a significant effect on DR would be possible with PV installed in no less than 60% of households. Customer awareness of these energy schemes is instrumental in improving engagement. My Electric Avenue [259] was another such trial and it investigated the effect of charging clusters of EVs on the networks during peak periods. The results from analyzing various LV networks across Britain indicated that with an EV penetration of 40%-70%, 32% of LV feeders would necessitate intervention. A recently started trial, Multi Asset Demand Execution (MADE), is assessing the potential flexible DR from multiple energy assets including EVs, HPs and PVs under fixed and dToU tariffs. Conflicts of interest in the provided DR methodology between local community and network operator, technical and environmental impact on the whole network and possible energy consumers' saving are the expected key learnings.

8.3.2 Customer Awareness

In this category, the objective of trials is to raise awareness and to educate customers about the energy schemes. Consumers are kept up-to-date with the development of the trial and their benefits in order to encourage them and maintain their interests in the schemes. The Energywise [260] project was developed to focus on fuel poor consumers to provide them with the prospect of taking part in DR opportunities. The motivations for customers to engage with this project included energy cost reduction, better knowledge of energy consumption and provision of complementary energy devices. The Solent Achieving Value from Efficiency (SAVE) [261], was another such project, which aimed at evaluating the viability of energy efficiency schemes and engagement in order to alleviate network constraints. This trial involved the use of energy coaches working at local community level to improve awareness of responsible energy usage and sustainability. People were encouraged towards sustained behavior change through the use of drivers such as community engagement events.

8.3.3 Incentives

These pilots aimed at maximizing customer engagement by providing attractive incentives. The Activating Community Engagement (ACE) [262] trial developed and run an online game where customers earned credits for reducing their consumption during specific periods. Prizes were awarded to winning communities as well as individual participants. In a different community engagement trial, the Power Savers Challenge [263], customers whose demands were less than the previous year were rewarded. 251 households took part in this trial and a total demand reduction of 201MW was achieved. 70% of participating communities reached their targets, achieving a reduction of 4% as compared to 2013. Another such pilot, Energy Action [264], implemented a reward scheme for 10 communities to maintain their consumption under the transformer maximum capacity. The study concluded that financial community incentives were not enough to guarantee a high level of response due to the unpredictability of community demands.

9. Discussion of Key Challenges and Future Directions

The DR researches and trials reviewed in this paper show that utilization of flexibility provided from residential loads or local generations can be beneficial for DSOs and end-users in several means. An incremental interest in innovation projects trialed in GB proves the potential of this solution in managing the networks' constraints. However, in reality, the wider DR implementation for residential energy users faces several challenges and limitations. This has restrained the projects' scopes and scales and concealed the actual value hidden in the back of these available energy resources. This section classifies the key challenges according to technical, social and financial perspectives and provide some recommendations as a future direction for researchers in this field and industry practitioners.

Table 7. Summary of relevant innovation pilots in GB network with the focus on community engagement

Category	Trial	Organisation	Location	Time Period	Innovation	Scale	Solutions and Technologies	Communication Strategies	Investment	Key Lessons Learned
Education	Solent Achieving Value from Efficiency	Scottish and Southern Electricity	Solent	2014-2019	Testing cost effectiveness of energy efficiency measurements and engagement	4,600 homes	•Financial incentive, •Community energy coaches •Deploying LED lighting	•Personalized data-driven messaging, •One-by-one written contact, •Community engagement	£7 million	Consumers engaged better with local community than DNOs
	Energywise	UK Power Networks	Tower Hamlets, East London	2014 – 2017	Testing the effects of demand reduction techniques for fuel poor customers	538 homes	•ToU, incentives (vouchers, etc.) •Smart meters, smart energy monitor and devices, •Temperature monitoring equipment	•Face-to-face communication, •Dedicated support line, •Community engagement, •Engagement strategy and materials	£5.49 million	Successful engagement due to tailored approach
Incentives	Activating Community Engagement	Northern Powergrid	County Durham	2015 – 2017	Community engagement through online gaming to achieve demand reduction	-	•Incentives based on demand reduction, •Smart plugs	•Online game, •Posters and flyers, •Educational programme, •Council website, •Community engagement	£1.1 million	•Complete understanding at a participant level is crucial •Importance of providing adequate and not overwhelming information to participants
	Power Savers Challenge	Electricity North West	Stockport	2013 - 2015	Increasing capacity for renewable energy generation on the DN	251 homes	•Incentives based on the consumption of previous year •LED light bulbs, shower timers, Plug-in timers	•Newsletter, online, •Events and advice, •Home display, •Community engagement	-	•Participants well supported and engaged •Importance of providing adequate and not overwhelming information to participants
	Community Energy Action	Western Power Distribution	10 locations from central to south west England	2012-2013	Assessing the feasibility of reducing peak demand by DSM in predictable and reliable	834 homes	Cash incentives for each peak and overall consumption reductions targets for each community	•Newsletter, online, •Leaflet, •Door knocking	-	Methodology was not successful and not recommended as a way to reduce demand

Category	Trial	Organisation	Location	Time Period	Innovation	Scale	Solutions and Technologies	Communication Strategies	Investment	Key Lessons Learned
Integrating low-carbon tech.	Sola Bristol	Western Power Distribution	Bristol	2011-2016	Assessing feasibility of integrating low-carbon tech. using new technologies and storage management	61 homes	•Sunshine tariff (ToU) •PV, energy storage, DC circuits	Home display, community engagement, website	£2.8 million	•Understanding of customers'' use of energy to maximise and tune energy management •Possible savings for customers •Demonstrate the benefits of deploying DR aggregation through in-home Multi energy asset
	My Electric Avenue	Scottish and Southern Energy	Across UK	2013-2015	Directly control EVs to manage local LV network	-	Lease on EV at a reduced rate, free/minimal cost charging point installation, Esprit (innovative piece of technology for directly controlling EV charging)	Local community event and engagement, newsletter, social media	£9 million	•Need of intervention with increase in the penetration of Evs •Forecast of around £2.2 billion savings by 2050
	Multi asset demand execution (MADE)	Western Power Distribution	South West, South Wales,West midlands, East Midlands	2019-2020	Providing higher DR services through multiple energy assets at household level	5 homes	•EVs, •Hybrid heating systems • Solar PV	Website, Direct communication	£1.655 million	•Possible savings for customers •Demonstrate the benefits of deploying DR aggregation through in-home Multi energy asset

DR Infrastructures refer to initial requirements and advanced technologies for enabling DR services for households. In order to efficiently utilize the smart and postponable appliances and local energy generations, which are consider as flexibility resources, end-users need to be equipped with energy consumption monitoring and control devices. One of the key prerequisites is smart metering devices that increase LV visibility by enabling a dynamic and bi-directional data communication in near real-time between consumers and network entities [265]. However, the installation of these devices has faced several economical and technical challenges.

In GB, the initial rollout plan of smart meters by 2020 has now been re-scoped to 2024. Customers widely experienced functionality failures in the original smart meters (first generation) particularly when switching between energy suppliers [266]. Moreover this version of smart meter is not compatible with all types of PV cells. These issues were resolved in the second generation meters [267], first introduced in 2018. The old-type meters have to be upgraded, and this can be done remotely [268]. In addition, smart meters cannot be connected to about 30% of households due to poor internet connectivity causing communication difficulties between in home-display and smart meters. Therefore, further investigation is warranted to come up with alternative solutions to overcome these communication issues. Nevertheless, it is predicted that 4.5% of households may not been able to access smart meters due to the solutions being extremely expensive [267]. A report by trade body Energy UK warns the Department for Business, Energy and Industrial Strategy (BEIS) that despite the 2024 extension, in the best case scenario, only 68% of the targeted 85% can be achieved [269]. The amount and accuracy of data that is needed to achieve an acceptable level of profile estimation is yet to be determined.

Despite the challenges, the rollout of smart meters can facilitate innovative and new ways of active engagement of consumers in the energy market. The participation of consumers in DR programmes can be done manually through e.g. in-home display or automatically through HEMS. However, moving towards a smart and digital future, energy providers are seeking to model dynamic electricity tariffs to mitigate network constraints in real time. This requires a fast and dynamic response of consumers using HEMS.

On the other hand, the literature undertaken in recent years shows the significant role of aggregators in enabling extensive DR market from local load/generation at LV level that are individually too small for playing an active role in the markets. Aggregators can enhance the network reliability by providing aggregated loads independent from energy suppliers or geographical area that are run by various DSOs. However, the integration of smart assets with customer’s ownership to the grid requires a standardized “physical” connection to maintain network stability and reliability. It also requires monitoring and control functionalities at network’s level.

Implementation of energy management system and demand side response can be delayed or paused if suitable infrastructure and communication protocols and transmission are not put in place. Inevitably, energy providers, market and SOs need to facilitate appropriate gateway and interfaces to be integrated to flexibility providers at low-voltage level. The focus of most of the research studies and innovation pilots are on commercial framework for aggregators and flexibility providers. There is less investigation on enabling the market, digitalization platforms and coordination between DSO, transmission SOs and independent aggregators.

A comprehensive review by M. Andoni et. al. [270] shows a considerable interest in literature on using recent technologies such as Blockchain and IoT platforms for digitalization. Blockchain can provide a secure and standardize data communication platform for the interaction of intelligent and smart devices at both network and customers levels. They can also be used in P2P and local energy trading. However, these findings are still in a very early stage and further investigations along with practical case studies are needed to prove that the model can be used in a decentralized, scalable, secure and economically viable way.

However, several factors still need to be addressed by SOs and energy regulators and these include the modeling of aggregators by DSOs, the suitability of industry standard and the role of aggregators in the energy markets. In addition, the market model should ensure a level playing field for all network entities with defined and clear role/responsibilities. This includes a solution design architecture with end to end data exchange model in a multi-agent system which can model the interaction of all entities. Despite significant recent studies on providing DR models through a MAS framework, there are still limitations in terms of scalability, adoptability, network constraints, DR scenarios and types of agents. Hence, there is a need to develop a coordinated model that considers the interest and objective of each individual type of network entity (agent) in a decentralized platform. In order to enhance the reliability of the network, a combination of incentive-based and price-based DR is also desired to be included in the DR model [171].

However to accommodate these new innovations and technologies, the required infrastructural changes in the conventional electricity network will necessitate a considerable financial investment [271]. This creates the issue of where the responsibility lies for setting up these arrangements [272]. Authors in [273] have referred to this concern as an incentive-problem and suggested that the cost of installations should be shared among network entities so that all DR participants can benefit from this service. What is clear is that a harmonized partnership between public and private sectors is needed to enable the research work in a real-environment.

Consumer Engagement is the key to success for DR implementation. Lack of adequate awareness about the advantages of these programmes as well as inexperience in using these new technologies are the main issues. Some projects have been trialed on a small scale of energy consumers aiming to encourage them to change their sustained behaviour. Moreover, low amount of incentives are offered to households with small DR capacity. Customers should be equipped with PV and plug-in EV (PEV) that provide more flexibility and hence fair economic benefit. More focus is recommended on localized approaches to consider DR within a local community through the use of user-friendly software applications and tools to raise customer awareness. Market rules and competitive rewards schemes can be extended to local communities where each community can get incentives for the reduction within that community.

However, some studies [274] show that even if consumers have high attitudes towards participating in DR programmes, they can still encounter some challenges. For instance, controlling the energy usage all day long is not practically possible for end-users even though home energy displays can make them aware of their electricity consumption and price. HEMS can solve this problem to a certain extent. The load scheduling can be programmed automatically taking into account network constraints and users' comfort level.

Besides education, awareness and incentives, data privacy and security are also major challenges. In GB the smart meter data is available to energy providers, SO and third parties through a central database, DCC. This requires policies and regulations that guarantee safety, security and liability of data exchange.

Technical Concerns are more significant for residential consumers due to the complexity of determining the accurate amount of available DR. This is because of the sporadic and unpredictable nature of domestic loads. Some external factors such as social events and weather conditions can also affect the consumption behavior of users [275].

To mitigate these issues, uncertainties in demand and generation should be considered in improving forecasting techniques at distribution level. This will help DR service providers to plan more accurately their actions [274].

Another concern is the peak rebound where a new peak can occur due the high number of demands shifting from peak to non-peak time. A coordinated DR algorithm and control mechanism is required to prevent such issues and thus enhance the network reliability [87]. In addition, the complexity issues arising from the huge data interaction in the network along with characteristics such as types of information and data transfer rate are among the key challenges faced by DSOs and energy providers.

Most of the proposed DR strategies relies on the implementation of HEMS to optimize home energy consumption. HEMS can schedule appliances that consume power in adjustable timeslots where their operations can be stopped, adjusted, or shifted to other timeslots. Based on such an energy management mechanism, HEMS proposed in studies can be categorized as conventional, advanced and smart. The optimization algorithm of the former is based on exclusively load management in response to a price signal e.g. [276-279] whereas the second group considers the price prediction e.g. [182, 280-281]. The latter applies Machine Learning techniques, AI and data-driven algorithms to DR strategies [282-283]. The principles of DR mechanisms in advanced and smart HEMS are fundamentally similar to the conventional HEMS, but are embedded with some sort of intelligence to improve the DR optimisation performance. The recent studies in this field show a considerable interest on the last category by applying AI solutions. AI is the preferred choice for residential level as it can provide an automated decision-making mechanism considering various customers' characteristics, energy usage, preferences and comfort level.

AI can also address the various challenges introduced so far in this paper, related to complexity of LV network, by improving the forecasting of demand, generation and electricity price, big data management, and performance and accuracy of optimisation algorithms at both customer and network levels. However most of the studies on AI applications are limited to a small scale data and simulation environment. Hence, further investigations and real-case scenarios need to be conducted in order to determine the most appropriate techniques in AI for different optimisation purposes.

10. Conclusion

The traditional role of DNOs' are now transforming to a DSO one due to changes and challenges within the modern electricity network. This provides facilities for wider implementation of DR to manage network constraints as a less-costly alternative solution to upgrading the network infrastructure. This paper provides a comprehensive review of the relevant researches and trials in GB on the residential DR mechanisms, targets, solutions and applications in managing DNs.

The DR objective function is investigated in terms of both economic and technical targets for both LV and MV feeders. Hence, the focus of this work is on the network level where the main stakeholders are consumers, DSOs, energy suppliers and aggregators. The DR applications and control strategies in microgrids are also reviewed. The outcomes of both literature and pilots demonstrated that DR can be an effective, reliable and economic alternative solution to network upgrading.

The challenges and obstacles faced by DR implementation are also explored from financial, social and technical perspectives. It is also shown that consumer engagement is one of the most important requirements for the success of implementing DR. Considering the various individual characteristics of consumers in algorithms and methodologies, can provide the DSOs with a better understanding of available flexibility demands for future planning.

In this work the authors reviewed 226 papers and have identified limitations in the proposed DR implementations. There is still a need for comprehensive frameworks in wide-area networks to model the interaction among participants under real time environments. Most proposed platforms focused solely on one aspect of the DR targets, either the technical target where the aim of DR algorithms is to manage the power flow across the network, or the economic target intended at minimizing electricity cost. This gap can be addressed by including both the technical and economic aspects in DR control schemes.

It has been discussed in the paper that residential consumers have intermittent energy consumption characteristics. This requires the consideration of a more direct approach in peak demand curtailment along with price-based DR as a means of demand-supply support. Very few studies have so far explored the combination of both incentive-based and price-based DR mechanisms in their algorithms and implementations. A distributed intelligent platform can activate the opportunities for residential flexible loads shifting and shedding that include both DR mechanisms.

Our review also presented the relevant innovative pilots in residential DR implementation trialed in GB network. One of the key findings is that the role of local community in providing flexible demand and network support is getting more prominent. Due to the individual low flexible load at residential level, flexibility services provided through DR aggregators seems to be more practical to provide technical support to the network. However, the thorough quantification of potential and available responsive demands and their effectiveness in managing the network under real time is still needs further investigation.

Our work has shown that the future of DR implementation is trending towards the use of new data driven technologies such as AI and Blockchain and P2P energy transaction. Although these are slowly becoming well established, there is still the need for more in-depth research to find optimal solutions for the challenges discussed in this paper. Researches and pilot projects are inexorably paving the way for these techniques to play a leading role in the future of DR implementation.

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