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On the assessment and control optimisation of demand response programs in residential buildings

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Abstract

The ability to control and optimise energy consumption at end-user level is of increasing interest as a means to achieve a balance between supply and demand, particularly when large penetration of distributed renewable energy sources is being considered. Demand Response programs consist of a series of externally-driven control strategies aimed at adapting consumer end-use load to specific grid requirements. In a demand response scenario, a network of connected systems can be exploited to activate balancing strategies, to provide demand flexibility during periods of high stress for the grid. However, the widespread deployment of demand response programs in the building sector still faces significant challenges. Smart technology deployment, the lack of common standardised assessment procedures and metrics, the absence of established regulatory frameworks are among the main obstacles limiting the development of portfolios of competitive flexibility assets. The residential sector is even more affected by these challenges due to a marginal economic case, the issue of long term harmonisation of hardware and software infrastructure and the influence of the end-user behaviour and preferences on energy consumption. The present paper provides a review on the current developments of the Demand Response programs, with specific reference to the residential building sector. Methodologies and procedures for assessing building energy flexibility and Demand Response programs are described with a special focus on numerical models and available control algorithms. Moreover, markets schemes and social aspects - such as technology acceptance and awareness - and their influence on smart control technologies and algorithms are discussed. Current research gaps and challenges are identified and analysed to provide guidance for future research activities.

Keywords: demand response, energy flexibility, residential building, smart grids, smart buildings, optimisation algorithms

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1. Introduction

Over the past decade, the European Union (EU) has established ambitious targets for increasing the penetration of renewable energies into the power system with the aims of reducing fossil fuel dependency as well as mitigating the impact of climate change. The consequent large-scale penetration of renewable energy resources envisioned by the current policies presents major issues for Transmission System Operators (TSO) since it poses new challenges on the balance between supply and demand. Traditionally, supply-demand balance has been achieved by controlling the output of conventional generation systems in response to changes in the demand in a sort of *demand-driven* control. However, the increase of distributed renewable energy systems can lead to greater fluctuations on the supply side, due to the higher aleatory of their generation, with a consequent requirement of faster-balancing responses from grid operators. Conventional generation units may not have sufficient ramping capabilities to counter these rapid fluctuations McKenna and Keane [1], which might affect grid reliability and wholesale electricity prices [2]. Without sufficient forward planning to include other flexibility sources, high penetration levels of renewable generation and high demand peaks may lead to system contingencies, or in extreme cases, system blackouts [3, 4].

In this scenario, a network of connected buildings could be capable of activating balancing strategies, triggered by external network signals, providing the demand flexibility required to manage fluctuations of distributed generation systems. The building sector is considered one of the biggest energy end-users, accounting for about 39% of the overall primary energy consumption [5]. In Ireland and the UK, the domestic sector accounts for more than 26% of the total end-use electricity consumption [6, 7]. Proposals for new buildings, equipped with connected sensors and smart controllers responsive to smart grid signals [4] have been put forward to achieve flexibility at the end-user side. This leads to the so-called Demand Side Management (DSM), which can be defined as a portfolio of measures aimed at optimising the energy consumption at the building level. Among the different DSM measures, the term Demand Response (DR) indicates all those strategies implemented by consumers to adapt their load profiles to specific external requirements (i.e., grid), by shifting, reducing or increasing the energy consumption [8].

Implementing DR programs in buildings requires the deployment of smart optimisation controllers, which can lead to a more rational use of energy in the building stock, while enabling the exploitation of the user flexibility from a grid perspective to improve the reliability and the efficiency of the power system as a whole [9]. In addition, DR measures could reduce energy market prices and harmful emissions during peak load periods, since they may be more efficient and cost effective than the generation systems which typically provide these high peak demands [10]. Even if DR is not a novel concept, being developed and used in industry for load shedding/shifting [9], currently DR programs are mainly utilised to provide emergency support and ancillary services [11], while limited participation in the planning stage. Very little efforts at implementing such programs in a more pervasive manner has been undertaken so far.

The development of a widespread usage of DR programs for residential (and commercial) buildings still faces several challenges, mainly related to the lack of experience in developing fully tested and certified tools implementing common and standardised assessment procedures, as well as uncertain market regulations and policies [9] (see section 2.3 for more details). The realisation of advanced smart grid features requires rapid prototyping and validation of building models and control algorithms to allow detailed techno-economic assessments of DR programs. Building simulation software can be utilised to assess the value and the risks associated with the adoption of new technologies which provide electricity demand flexibility. However, as equipment and algorithms are typically not analysed in detail, it is challenging for utilities and regulators to install, operate and exploit these new resources at a highly distributed level such as the residential sector [12].

Despite the large amount of research carried out over the last decades to understand and characterise potential building energy flexibility markets, substantial work is still required to achieve common assessment and regulation frameworks to generate portfolios of *flexibility assets* (i.e., valuable sources of energy flexibility for demand response applications), capable of playing a role in the energy market. This research gap is particularly important for the residential sector, which presents specific and unique challenges associated with its small and highly distributed dimension [13].

Therefore, the present review paper is aimed at providing an overview of the current state of development of DR technologies and markets, describing the results achieved and the challenges still open, as well as providing recommendations for future research directions. The first part of the paper provides a general overview of demand response programs for building applications (section 2), to describe the main benefits and outstanding challenges still in place, together with a description of the main classification and market schemes. Then, section 3 describes the implementation of DR programs in different residential systems and it discuss the role of social aspects, such as acceptance and awareness, in achieving a successful participation in DR programs. Finally, section 4 describes different methodologies and metrics commonly available in the literature for assessing energy flexibility in residential buildings to provide insights on how a common rational and structured set of indexes to evaluate demand response programs can be developed.

The second part of the paper focuses on modelling and control of DR programs in buildings. Section 5 introduces the building modelling aspects, by providing a description of the main numerical tools and simulation software currently available (white-box, grey-box and data-driven models, reduced-order models and calibration techniques). Then, section 6 describes control algorithms for energy management systems to enable DR programs in residential buildings with the aim of providing some insights on general approaches for their development and optimisation. Several optimisation problems and solution methods for DR programs are discussed, such as rule-based, heuristic and homeostatic control systems, integer linear programming methods and load forecasting methods.

Finally, Section 7 summarises the present paper and outlines the main research gaps and outstanding challenges of DR programs for residential buildings, while it provides some suggestions on future research directions.

2. Demand response programs for building applications

2.1. General overview

DR is one of the DSM measures that has been promoted since the 1970's in the UK and other countries, so as to reduce high winter peaks as well as avoiding associated grid upgrade costs [14]. DR has been defined as "*changes in electricity use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised*" [15]. Therefore, the objective of DR is to intentionally reshape the electricity demand in response to a signal sent by an aggregator or TSO. The changes can be quantified in terms of the level of instantaneous building demand or total electricity consumption and different approaches can be used, as described in Section 4. A broad range of possible measures to affect energy consumption patterns and magnitude aiming at reducing (energy efficiency measures, peak shaving, demand limiting), increasing (load growth, valley filling) or rescheduling energy demands (load shifting) at the building level can be adopted at building level [16].

Since DR programs modifies the energy consumption on a short-term horizon, the most common DR actions are based on specific time-constrained load modifications. As for instance, load shifting can be made at the building level by exploiting building thermal inertia (e.g., pre-cooling, pre-heating) or at the system level by using intermediate storage (e.g., batteries and thermal storage). While in the first one, the charging/discharging phases are interconnected (i.e., one follows the other) and they characteristic curves depend on the building characteristics and occupancy profile, the latter allows the load shifting to a different time-slot of the day, thus providing greater flexibility and relevant cost savings. On the other hand, energy losses and charging/discharging phase efficiencies can limit the utilisation of these storage and, in turn, lead to greater primary energy consumption and environmental impacts [9]. Therefore, controls algorithms and automation techniques become paramount to achieve optimised schedule of the energy supply, especially under a DR framework. DR measures can have different levels of automation [17, 18]:

- Manual DR: it requires human intervention to reduce, shift or force loads or to change the demand pattern. This human intervention can be made at user level (e.g., building occupants) or at central level (e.g., building manager or aggregator).

- Semi-automated DR measures: a person operates a centralised system to initialise the demand response strategy for a set of buildings. Then, control algorithms optimise the DR schedule for a single or group of targeted buildings.

- Automated DR strategies: external communication signals trigger a pre-programmed algorithm to activate, optimise and manage the DR action. No human interaction is required, although responsible subjects can be able to override the event at any time.

Despite the type of approach followed, detailed knowledge on the specific building characteristics and their energy performance is required when DR programs are implemented.

In fact, one of the main pillar of DR programs is that any modification of the standard consumption pattern must not compromise the user services and comfort. Therefore, linking control and optimisation algorithms with building numerical models, capable of forecasting building load profiles and to perform detailed comfort assessment [19], is a paramount task to achieve a fully developed DR framework in buildings. At this regard, Section 5 provides a detailed review of the common methodologies and simulation software developed over the last years.

2.2. Benefits from DR programs

The increase of interest in DR schemes is associated with several benefits at both end-user and grid perspectives. Figure 1 illustrates the impact of DR program benefits on different actors involved.

At generation level, DR programs can be a more efficient and cost-effective way to manage peak load periods, limiting the use of expensive peak generators [14, 20]. This could produce an overall reduction of the carbon footprint of the power grid and lead to a reduction of electricity price [21, 22]. DR programs also enhance the reliability of the power grid due to the dynamic demand curtailment, reducing the risk of outages and transmission strains. Since DR is a distributed resource located at the end of the distribution system, environmental benefit coming from a reduction of electricity losses in the transmission and distribution lines can be also obtained [23]. Moreover, DR programs can mitigate the fluctuations of renewable energy generations, leading to a higher penetration of such systems at large scales. The peak reductions achieved by a smart management at the demand side can reduce the need for infrastructure upgrade, decreasing the overall investment and operating costs and consequently increasing the overall market efficiency [24, 25].

At the user level, the access to DR schemes can rely on a more optimised and cost-effective energy consumption, thanks to smart control systems required to activate a manage DR programs. These advanced systems can also introduce user-adapted thermal comfort and cost control by providing real-time direct feedback to users and occupants on the building energy (and cost). This will eventually increase the user knowledge on their own energy consumption, providing also awareness on related environmental issues, as explained in Section 3.2. Moreover, business opportunities could arise from bill savings and revenues generated by the energy flexibility assets sold as a service to the whole energy system through DR schemes.

2.3. Challenges

The importance of developing comprehensive and optimised techno-economic DR programs, but also capable of taking into account social, economic and geographic characteristics was already highlighted in Kim and Shcherbakova [26]. In order to exploit the benefits of DR programs outlined in Section 2.2, several challenges must be overcome. Generally, these challenges can be grouped into four categories:

- Markets and regulatory frameworks: the lack of appropriate market mechanisms for DR programs is one of the greatest barriers for their development [27]. It is important to consider that any modification to the market must not compromise the market

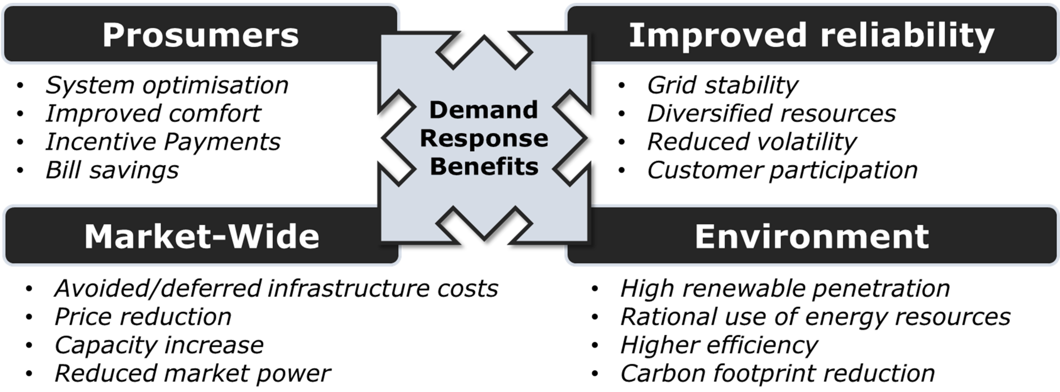

Figure 1: Recognised benefits from DR programs in buildings

stability itself. Current markets are designed as centralised systems, making their adaption to the highly distributed and diverse nature of end-user demand challenging. The restrictive nature of the electricity market, which typically requires stringent performance standards and substantial notice to plan DR actions (typically, many hours in advance), prevents demand from participating effectively in the power market by limiting the flexibility potentially exploitable [11]). Therefore, limited participation of DR programs in the day-ahead marked has been obtained, while they are mainly used to provide emergency support and ancillary services to the grid. A further challenge for DR programs is represented by the current regulatory and tariff structure. A lack of clarity in the current price structure still occurs, as well as uncertainties over regulatory frameworks - e.g., subsidies and aggregation procedure - are limiting the access of end-users (especially in the residential sector) to the energy markets [28].

- Definitions and assessment methodologies: the lack of common terminology, standards and quantification procedure to assess and optimise DR programs at both end-user and market levels is still a matter of concern. Being capable of assessing the energy flexibility available by capturing the technical, economic and environmental information, is a paramount aspect to characterise and offer the *flexibility assets* as a service to the energy markets. Over the last few years, research efforts have been put on overcoming this research gap, especially for building applications. The IEA EBC ANNE67 *Energy Flexible Buildings* [29] is an example of an international research consortium aimed at identifying the critical aspects and solutions on defining, assess and control the energy flexibility provided by buildings under a smart grid framework. More information on this research gap, including a literature review on the developed definitions and methodologies, are reported in Section 4.

- Controls algorithms: capturing the time-varying availability using advanced metering and tailored metrics is a necessity for the success of DR schemes. Numerical models capable of forecasting the building electric and thermal demand in a short-time period are paramount to provide comprehensive assessment of DR programs. Since these programs are activated and last for short periods of time (typically on hourly base) and considering the volume of end-users which, eventually, would constitute a *flexibility asset*, a trade off between the two conflicting goals of accuracy and computational cost must be found. Typically, building models must go under validation and calibration processes which require metered data not always available [30]. Moreover, establishing reliable and efficient optimisation algorithms and standardised aggregation techniques represents research gaps which is limiting the deployment of DR programs in buildings. Over the last few years, several attempts have been made in order to establish procedures to improve accuracy as well as reducing model complexity. An overview of the different modelling techniques is reported in Section 5.

- Social aspects: the impact of stochastic consumer behaviour strongly affects the benefit of DR programs. The uncertainties associated with the user behaviour could be smoothed by aggregating end-users flexibility profiles, as demonstrated by Nolan and OMalley [10]. However, the lack of information about user behaviour and operation patterns still represents a big challenge for the assessment of DR programs. Other social aspects - such as awareness, acceptance and perceived involvement by the end-user - are paramount to achieve high participation rates [31], which is in turn crucial for making of DR programs a successful business case [32]. These aspects are discussed in more details in Section 3.2.

2.4. Classification and schemes

The design of efficient DR programs is paramount for achieving high grades of customer participation. Generally, end users receive an incentive or a discount on electricity bills, while TSOs trade electricity in a more efficient market with a reduced price volatility and peak power requirements [33]. DR programs are classified in different categories which are usually based on an underlying financial scheme. In fact, DR events are remunerated to the end user by the TSO or DR aggregators based on Price Base Program (PBP) or Incentive Base Program (IBP) [21, 33]. In the IBP, end users receive a credit or a bill discount because of their participation in the program. A subcategory of IBP is the market-based programs, which is generally suitable for large customers or aggregators. These measures require market access and systems for TSOs to communicate directly to users and the monetary reward for their performance depends on the amount of load reduction. On the other hand, the PBP scheme is based on electricity tariffs following the real time price cost [33]. The goal of these programs is to reduce the electricity demand variance, increasing the price on high-peak demand and reducing at low peak.

Table 1 provides an overview on the DR program classification based on the type of economic scheme adopted [9, 24, 25, 34]. This classification reflects also the type of behavioural approach followed by the end-user, which can be either passive or active:

- Passive DR: the users adapt their load depending on external price patterns to minimise their operational costs. These optimised schedules tend to reduce the consump-

Table 1: Classification and development of DR program [9, 24]

DR programs	**IBS**	**PBS**	**Description**
Direct Load control	X		The system operator controls certain equipment of the participants and the participant receives payments in return.
Curtailable load	X		Incentives are provided to turn off specific loads or to adjust their energy demand.
Demand side bidding	X		Also called *Buyback*, consumers enters into the wholesale market, where a bid can placed and accepted depending on the competitive market price.
Capacity market	X		Participants bid into the capacity market to provide load reductions when required by the system. The payment is based on the declared peak load reduction achievable by the asset.
Ancillary services	X		Participants bid curtailment as an operating reserve, often for short periods of time. If the bid is accepted, customers will be paid the spot market price for the commitment and the curtailment.
Emergency services	X		The scheme incentives for measured load reduction during reserve shortfalls periods. In this case, enrolled large users receive a load reduction signal.
Time of use tariffs		X	Fixed set of electricity rates changing with the time of day the and day of week. Day to day market volatility of electricity is not captured.
Critical peak pricing		X	Significantly higher rates are charged when the power system is under high pressure. This can occur with very little notice and can be operational for several minutes to several hours.
Extreme Day Pricing		X	A specific subset of CPP program. The peak price is utilised within a daily time resolution. As a result, the DR events may last one or more days. A flat rate is used for the remaining period..
Real time pricing		X	The tariff is synchronised to the wholesale market price, marginal price or other pricing mechanism. Typically, it can be with hourly or 30 minutes resolution).

tion during high price periods (i.e., peak periods), leading to an indirect service to the grid operators. The action is driven by the potential cost savings associated with it, rather than direct request or interactions between the actors. Passive DR actions are typical of PBS schemes.

- Active DR: typical of IPBs, the users modify the consumption patterns following specific requests from the grid operator. These DR actions are characterised by sub-optimal economic operational conditions, leading to higher operational costs. The cost increment represents the monetary value (i.e., marginal cost) of the DR action implemented, which has to be claimed back from the grid in form of payment of incentives.

Eventually, the type of scheme adopted depends on the the ability of the end-users to control their consumption which, in turn, is influenced by the type and size of the end-user. The aggregation of multiple end-users into *smart energy island* can foster the access to DR market schemes for smaller prosumers like residential buildings. However, this aggregation requires a detailed knowledge of the specific details and requirements of each end-user, such as user behaviour patterns, building and energy system characteristics, etc. Software capable of forecasting and aggregating end-user energy consumption profiles are therefore essential to achieve high penetration of DR mechanisms at building level. More insights about this issue are given in Section 5.

3. Enabling Demand Response programs in residential buildings

R3-C2

As described in the previous section, DR programs encompasses changes in normal energy consumption patterns by end-users to alter their instantaneous demand. In this framework, the residential sector represents an interesting target for DR applications since it accounts for a significant share of overall primary consumption, with a strong impact on the electricity network [32]. However, DR on residential buildings has not been fully developed due to several challenges like low profit margins, long term amortisation of the hardware infrastructure and the high impact on customer behaviour [35, 36], as detailed in Section 2.3. The following sections outline the different aspects involved in the implementation of DR programs in buildings.

3.1. Systems

In residential buildings, DR events can activate the response of different equipment, lasting from 1 minute to 2 hours, to provide a response to the triggering signal within different time resolutions. Different residential systems can be exploited for activating DR programs [34]:

- Heating systems: within the EU residential sector, electric heating absorbs 22% of electricity consumption while water heating and air-conditioning are responsible for about 9% and 10% respectively [37]. Over the coming decades, it is expected that a higher penetration of electric heating coupled with Thermal Energy Storage (TES) will occur in the domestic sector [38, 39]. DR programs targeting residential heating systems can decrease load consumption during peak hours, by altering thermostatic set points of the heating or cooling equipment dynamically without significantly affecting occupant comfort. The connection between smart meters and thermostats with the grid network can lead to substantial electricity demand reduction and energy saving by adjusting occupants' preferences and consumption patterns [40]. As for instance, Chassin et al. [41] developed a new thermostat design aimed at controlling the load on the base of real-time prices or time of use tariffs. Elasticity in energy demand of about 10-25% were achieved at relatively low costs.

- On-site generation: the installation of residential on-site electricity generators has been a general priority in EU directives [37]. Examples include PhotoVoltaics (PV) systems, small wind turbines or Combined Heat and Power (CHP) machines. Cost optimisation algorithms can be implemented to achieve significant energy and cost savings, while providing load flexibility. As for instance, D'Ettorre et al. [42] investigated the use of predictive control algorithms for a residential heat pump system which led to a reduction up to 12% of the heating energy cost. Moreover, coupling generation systems with thermal or electric energy storage can increase the flexibility of the generation system, which becomes a controllable distributed DR asset for the Renewable Energy Systems (RES) integration at system level. However, greater installation costs and energy losses occurring during the system operation might lead to longer return of the investment, especially for electric storage. Therefore, detailed economic assessment should be carried out since the preliminary stage for the design [9].

- Household appliances: white goods (i.e., washing machine, dryer, dishwasher, etc.) are generally considered potential source of flexibility for user-led demand response programs [43]. According to Yao and Steemers [44], appliances can be divided into six categories: cold, wet, cooking, lighting, brown and miscellaneous. Infield et al. [45] noted that in the UK, a household can shift their peak consumption by up to 48% during a DR event. The study was conducted on a list of appliances controlled by end users: the occupant can defer an electricity intensive activity to other times when the electricity is less expensive. Instruments aimed at increasing the user awareness, - e.g. the deployment of information channels capable of informing the user about real time and scheduled consumption/costs - and the introduction of mechanism to reward the achieved energy savings, are paramount to obtain the behavioural change required for the activation of these DR programs [46].

3.2. Energy awareness to enable DR

As mentioned before, social aspects, such as acceptance and equality of new technologies and systems, are paramount to achieve a successful participation in DR programs for households. Most of electricity users are still unfamiliar with the opportunities associated with the new energy systems envisioned by policy makers and this represents one of the main challenge to the development of such systems.

Increasing awareness of energy consumption can help consumers to reduce their energy expenditure while enabling (and accepting) manual/automatic DR at residential level. As highlighted by Darby and McKenna [32], participant rate is a critical aspect in making a business case for DR programs and, therefore, a proper framework must be established. The authors identified some general principles: (i) the importance of simple and clear tariffs, (ii) reliable feedback systems to exchange information with the users, (iii) attention to data security and privacy and (iv) customer education and awareness. Therefore, communication channels must be set up to provide information and feedback to the end user. Different types of feedback can be provided Abrahamse et al. [47]:

- Tailored information: personalised data are collected about specific individuals (i.e., household occupants) to determine the most appropriate information required to meet their unique needs. Home energy audits can provide insights on the current energy consumption patterns of targeted end-users, giving advice on potential energy-saving measures and actions which may lead to substantial energy and cost savings.

- Goal setting: information aimed to promoting energy conservation are provided on daily/hourly base to foster the user behavioural change. Savings between 5-10% can be achieved, especially if these information are combined with user commitments to achieve specified goals.

- Direct feedback: real-time information comes directly from smart meters or personal devices. These feedback allow the end-users to be aware of their consummations on a real-time base, leading to indirect behavioural changes and, thus, savings in the range of 5-15% percent.

Over the last few years, several projects have been carried out with the aim of increasing the user energy awareness. As for instance, Liu et al. [48] developed a domestic energy management software, called *DEHEMS*, to give direct feedback on energy consumption to persuade users for a behavioural change to achieve energy saving goals. Several data visualisation methods and interactive interfaces were used to allow the householders to explore their consumption patterns and gather information about potential energy-savings behaviour to be adopted. The software was tested on 250 UK and Bulgarian dwellings and the analysis of the data collected showed that the household energy consumption decreased during the experimental campaign. Moreover, the authors indicated that more than 90% of the occupants reported behavioural changes as a result of the software utilised. Another noteworthy project focused on the value of energy awareness is *beAware* [49]. During the timeline of the project, a device displaying a real-time countdown for each kilowatt hour consumed was designed and tested. The primary goal of this project was to increase the consumers perception of their energy use and to provide daily tips to save energy. The experimental campaigned showed a decreased consumption of about 5% overall the full trial period.

Another important concern on the load management is represented by the user acceptance and satisfaction when implementing energy saving actions and DSM programs. Starting from the assumption that *user satisfaction* is quantifiable, comparable and relative, Ogunjuyigbe et al. [50] developed an interesting DSM technique capable of controlling the load demand maximising the user satisfaction at the minimum cost. Generally, the *perceived control* is recognised as a fundamental psychological aspect influencing the user comfort, satisfaction and acceptance [31, 51].

The participation of DR programs typically require the implementation of smart control systems with different levels of user involvement. Manual controls requires the occupants in a dwelling to reduce/increase their energy consumption depending on the information/feedback received (i.e., peak electricity price). On the other hand, enabling automatic DR for residential building requires algorithms able to assess and forecast the building load, the available flexible demand [52], the associated cost and the environmental impact (see Section 6). Manual DR allows the end user to take control of their comfort and costs but with the negative effect of reducing the optimisation capability. On the other hand, automatic systems provide useful optimisation platforms in which the user involvement is typically limited, due to the complexity of these algorithms, with the reverse side of reducing their awareness and their eventual satisfaction. Therefore, a balance between manual and automatic DR control system should be pursued to achieve the best solution depending on the specific application planned.

4. Flexibility metrics for assessing DR

Thanks to the increasing availability of smart-metering and smart-management systems, control strategies capable to unlocking the building energy flexibility potential to activate DR programs have to be implemented. However, one of the main challenges (see 2.3) is represented by the lack of common and standardised assessment procedure to evaluate DR programs. This is a paramount aspect in order to formalise targets and metrics to identify the best option among all the possible DR measures. Moreover, the need to provide indicators which can be communicated and easily interpreted among different stakeholders makes the development of this common framework even more challenging [53].

Over the last decade, a lot of research has been done in order to develop suitable Key Performance Indicators (KPI) to deploy energy flexibility measures in buildings. Among others, IEA EBC Annex 67 [54] has worked to develop common methodologies and terminology to quantify and communicate energy flexibility of individual building and building clusters, through those that are considered its main dimensions, namely capacity, time and cost. The proposed approach is based on the capability of buildings and systems to change their energy demand profile with respect to a reference scenario, according to external penalty signals (e.g. energy prices, carbon dioxide emissions, RES exploitation, etc.) acting as additional boundary conditions [55]. Dynamic Flexibility Functions (DFF) capable to identify the dynamic response of a building (or cluster of buildings) to the penalty signal is identified first. Then, each dimension of the energy flexibility can be assessed based on a Flexibility Index (FI) measuring the deviation of the considered parameter from the reference value (e.g. relative amount of saved carbon dioxide emission).

Generally, three different dimensions need to be considered when assessing DR programs:

- *Economic dimension*: estimating the market price for flexibility assets and the risk associated with running DR programs represents a key information for a successful and competitive participation into the energy market. Metrics aimed at assessing operational (marginal) costs of DR programs, considering the market scheme adopted (see Section 2.4), are therefore required. Generally, the cost associated with a specific flexibility measure (ΔC_F) can be evaluated by comparing the operational costs resulting from the activation of a specific DR action, OC_{DR} with the ones of a baseline reference scenario OC_R:

$$\Delta C_F = \frac{OC_{DR} - OC_R}{OC_R} \cdot 100\% \tag{1}$$

It is important to highlight that proper optimised conditions should be considered as reference with respect the flexibility dimension under investigation, thus avoiding to include possible control inefficiencies into the flexibility metrics.

- *Technical dimension*: from a grid perspective, indicators aimed at identifying the capacity of the building to shift in time its electrical consumption, without compromising the thermal comfort, are paramount for a proper planning. The available electric energy flexibility ($AEEF$) measures the variation of the building electrical energy consumption over the period (τ) in which the flexibility measure is active. As for instance, by defining $P_{e,Dr}$ and $P_{e,R}$ as the electric power profiles resulting with and without flexibility measures, respectively and α their ratio ($\alpha = P_{e,DR}/P_{e,R}$), the $AEEF$ can be expressed as follows:

$$AEEF = \int_0^\tau |P_{e,DR} - P_{e,R}| \cdot dt = \int_0^\tau |\alpha - 1| \cdot P_{e,R} \cdot dt \tag{2}$$

It is interesting to note that this index naturally introduces two other parameters in describing the provided flexibility, namely its duration, τ and its intensity, α, with $\alpha > 1$ or $\alpha < 1$, according to whether up or down flexibility is considered.

- *Environmental dimension*: from a policy perspective, quantitative information about primary energy consumption and carbon dioxide emissions associated with the DR programs are essential. As for instance, a primary energy efficiency PEE can be defined as the ratio between the primary energy consumption achieved in the reference scenario (PE_R) and the one obtained when DR programs are implemented (PE_{DR}).

$$\eta_{PEE} = PEE_R/PE_{DR} \tag{3}$$

These indicators are functions of the flexibility measure adopted, which in turn depends on its intensity (α) and duration (τ) [53]. Therefore, the overall building response to different flexibility actions can be represented in key-decision maps to characterise the specific DR programs, as the one shown in Figure 2. This approach can provide a base-ground for the information exchange among different stakeholders. In fact, these maps can be used by aggregators to formulate bidding strategies exploiting all the flexibility potential offered by their flexibility assets. At the same time, these indicators can be used by legislative entities from a policy-making perspective, since they can identify the most environmentally sustainable DR actions based on primary energy consumption or the CO_2 emissions savings.

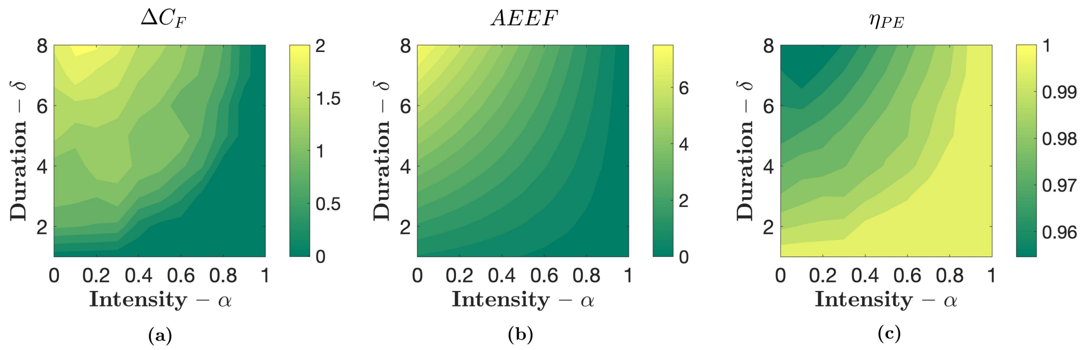

Figure 2: Example of the flexibility maps resulting from the indicators.

As discussed before, developing comprehensive metrics is challenging due to the complexity of the aspect involved. However, several attempts to achieve reliable and structured indexes has been made over the last few years. Table 2 provides an overview of some of the main KPI currently available, listed by literature source and classified depending on the dimension covered. This literature assessment clearly demonstrates the lack of common methodological framework as well as common definitions still in place [56]. While technical aspects, such as energy flexibility available and instantaneous capability for load reduction, are generally assessed by specific KPIs in all works analysed, little attention is generally given to economic and environment assessments. Filling these gaps is paramount since it is undoubted that a successful and competitive access into the energy market relies on proper methodology and metrics to assess costs and revenues obtained by DR programs. Moreover, also the environmental aspects are scarcely addressed despite several studies conclude that offering energy flexibility to the grid might increase the local energy use of a building [54].

One of the main limitation of the proposed KPIs relies on the arbitrary nature of the definition of flexibility considered by the respective researchers, as it was already highlighted by Lopes et al. [57]. The several stakeholders involved in DR markets may have different perspectives and targets depending on the specific services enabled. This make the research of common methodologies and KPIs even more challenging. At this regard, Zhang et al. [58] proposed a comprehensive set of metrics to quantify building-to-grid DR flexibility from different stakeholders perspectives (e.g., TSO, retailers, aggregators, etc.). As for instance, global assessment metrics for DR flexibility provided are required by TSO to prepare measures for energy and power payback following DR activation, thus avoiding network congestion and system imbalance. On the other hand, aggregators needs to take into account the impact of DR programs on end-users consumption patterns as well as the potential costs/revenue associated with them. From the end-user perspective, metrics aimed at identifying their comfort satisfaction under DR programs has to be introduced. A full description of the different stakeholders requirement and the associated evaluation methods refer to Zhang et al. [58].

Table 2: Overview of key performance indicators (KPIs).

Reference	Description	Key Performance indicators	Flexibility dimensions: *Economic*	*Technical*	*Environ.*
Masy et al. [59]	Flexibility (F) is quantified in terms of procurement costs (PC) savings and in terms of load volumes shifted (VS) obtained by the DR action compared to a reference scenario (R).	$\begin{cases} F_{PC} = \frac{PC_{max}-PC}{PC_{max}-PC_{min}} \\ F_{VS} = \frac{F_{PC}-F_{PC,R}}{F_{PC,R}} \end{cases}$	✓	✓	
Le Dréau and Heiselberg [60]	The flexibility factor (FF) is defined as the ability to shift the energy use from high to low price periods,τ_{hp} and τ_{lp}, respectively.	$FF = \frac{\int_0^{\tau_{lp}} P_e dt - \int_0^{\tau_{hp}} P_e dt}{\int_0^{\tau_{lp}} P_e dt + \int_0^{\tau_{hp}} P_e dt}$		✓	
Péan et al. [61]	Flexibility is assessed as the deviation from the reference energy consumption (ΔE_{DR}) caused by the DR event occurring over the period τ_{DR}. A DR efficiency (η_{DR}) is introduced to measure the additional energy required (rebound effect) and the offered energy flexibility capacity.	$\begin{cases} \Delta E_{DR} = \int_0^{\tau_{DR}} (P_{e,DR} - P_{e,R}) dt \\ \eta_{DR} = 1 - \frac{\int_0^{\infty} (P_{e,DR}-P_{e,R}) dt}{\left\lvert \int_0^{\tau_{DR}} (P_{e,DR}-P_{e,R}) dt \right\rvert} \end{cases}$		✓	
Zhan and Kummert [62]	The energy flexibility (EF) is identified as the difference between the power profiles resulting with and without DR ($P_{e,DR}$ and $P_{e,R}$). $P_{f,max}$ assesses the maximum power shifted obtained by a DR event, while η_{DR} quantifies the energy consumption change after the DR event.	$\begin{cases} EF = \int_0^{\tau_{DR}} (P_{e,DR} - P_{e,R}) dt \\ PF_{f,max} = max \lvert P_{e,DR} - P_{e,R} \rvert \\ \eta_{DR} = \frac{\int_0^{\tau_{DR}} (P_{e,DR}-P_{e,R}) dt}{\int_0^{\infty} (P_{e,DR}-P_{e,R}) dt} \end{cases}$		✓	

Table 2: Overview of key performance indicators (KPIs).

Kathirgamanathan et al. [63]	Flexibility is quantified as the electric energy consumption deviation ($AEEF$) due to the DR event compared to a reference case without DR. The *downward* and *upward* efficiency (η_{AEEF}) is evaluated as the ratio between the rebound effect and the energy flexibility offered.	$\begin{cases} AEEF = \int_0^{\tau_{DR}} \lvert P_{e,DR} - P_{e,R} \rvert \, dt \\ \eta_{AEEF,down} = 1 - \frac{\int_0^{\tau_{DR}} \left(P_{e,DR} - P_{e,R}\right)^+ dt}{\lvert \int_0^{\tau_{DR}} \left(P_{e,DR} - P_{e,R}\right)^- dt \rvert} \\ \eta_{AEEF,up} = \frac{\lvert \int_0^{\tau_{DR}} \left(P_{e,DR} - P_{e,R}\right)^- dt \rvert}{\int_0^{\tau_{DR}} \left(P_{e,DR} - P_{e,R}\right)^+ dt} \end{cases}$		✓	
Reynders et al. [64]	Flexibility, defined as the amount of storable heat during a DR event (F_{DR}), is evaluated as the difference in the thermal energy provided with ($\dot{Q}_{DR}$) and without ($\dot{Q}_R$) DR. The efficiency η_{DR} is defined as the capability to exploit the stored heat to maintain the thermal comfort.	$\begin{cases} F_{DR} = \int_0^{\tau_{DR}} \left\lvert \dot{Q}_{DR} - \dot{Q}_R \right\rvert dt \\ \eta_{DR} = 1 - \frac{\int_0^{\infty} (\dot{Q}_{DR} - \dot{Q}_R) dt}{\int_0^{\tau_{DR}} (\dot{Q}_{DR} - \dot{Q}_R) dt} \end{cases}$		✓	
Favre and Peuportier [65]	Carbon emission (V_{CO_2}), evaluated as the electric power consumption P multiplied by its conversion factor f_{CO_2}, is considered as an additional objective function to be minimised.	$V_{CO_2} = \int_0^T \left(f_{CO_2} \cdot P_e(t)\right) dt$			✓
De Coninck and Helsen [66]	Flexibility is assessed by the energy consumption and cost deviations ($\Delta E, \Delta C$) resulting from DR measures with respect a reference scenario without DR.	$\begin{cases} \Delta C = \int_0^T \left(C_{DR} - C_R\right) dt \\ \Delta E = \int_0^T \left(P_{e,R} - P_{e,DR}\right) dt \\ c = \Delta C / \Delta E \end{cases}$	✓	✓	

5. Modelling techniques and simulation software

Over the last decade, the exponential grow of the computational power have affected the software development with huge impact on all sectors [67] since it allows simulation software models to be more detailed and accurate [68]. Creating an integrated model of the thermal behaviour of a building is a complex task, due to the huge amount of information which must be processed and analysed. New generations of building simulation software take into account weather data, building thermal features, occupancy profiles, solar irradiation and the electric and thermodynamic characteristics of all system components. The representation of a building is, therefore, composed by multiple physical models that, during the simulation, exchanges data and provides an estimate of the energy consumption for each time step.

Building simulation software can be used for long-term system planning, season scheduling, as well as short-term daily load operation [69]. As described in Zhao and Magoules [70], there are several different techniques for estimating of building energy consumption. Typically, building energy models can be divided into different typologies:

- *Detailed white box (DWB) models*: a detailed dynamic physical representation of the simulated building is adopted, allowing more accurate results despite a greater user effort in their implementation and higher computational costs while running [71]. Over the last few years, several commercial simulation tools, such as ESP-R [72], TRNSYS [73] and EnergyPlus [74], have been developed and extensively used to model the energy consumption in buildings. An overview of their main characteristics is reported in Section 5.1.

- *Simplified white-box (SWB) models*: these models implement a simplified representation of the building physics (i.e., by using the thermo-electric analogy [75]) to reduce the model complexity and, thus, the computational cost. However, physical-based information of the modelled building (e.g., building thermal and geometrical properties) are used to determine the model parameters and no tuning or optimisation algorithms are used.

- *Reduced-order (RO) models*: a simplified building description is used to model the building physics, as for the SWB models, while data-driven calibration algorithms are used to reduce the model complexity and the number of parameter required based on accuracy metrics. The resulting building model keeps the original physically-based structure, but the calibrated parameter does not reflect the actual building properties. Consequently, these calibrated models can be considered as *Grey-box (GB) models*, since the real physical characteristic of the building will be lost. Example of these models can be found in [76] and [77].

- *Black-box (BB) models*: these models does not require any physical information but they are based on the implementation of functions which are calibrated on a specific set of training data describing the dynamic behaviour of a system (i.e., building) [78]. While these methods can lead to fast and reasonably accurate models, their nonphysical structure makes the interpretation of the results provided challenging.

Moreover, their accuracy depends on the training procedure, which must be repeated anytime a physical change of the system occurs (i.e., building retrofitting). Different techniques can be used, such as Multiple Linear Regression (MLR), Genetic Algorithms (GA), Artificial Neural Networks (ANN), Support Vector Machines (SVM), etc. A full review of these system can be found in Foucquier et al. [78].

5.1. Overview of white-box software

The white-box methodology requires a detailed modelling of the system physics equations and, unlike other approaches, can reach higher levels of accuracy when modelling energy consumption [70, 71]. A detailed white-box model takes into account the building dynamics and the physical equations of each sub-system. The simulation core is represented by a list of physics based equations which are solved to compute temperature estimation and energy consumption [30]. The thermal and geographic characteristics, the orientation and elevation of the building model, are used to simulate the building energy load [19].

Different software platforms have been developed and extensively used to model the energy consumption in buildings. Table 3 describes the features of the most popular packages. It can be noted that the feature mostly implemented by all the software packages examined is the building thermal mass which is used to describe the dynamic variation of the internal temperature. Similarly, the building geometric description of the building is fully implemented by almost all packages. One exception is represented by Energy Plus, a building simulation software developed from earlier simulation software supported by the US Government in 1980s [74]. Despite it was recently completed refactored from Fortran to C++, the geometric description feature has been delegated to third party software. Other software, such as ESP-R [72] and TRNSYS [73] have an integrated environment with a Computer Aided Design (CAD) application and automatic report generation tools.

As illustrated in Table 3, EnergyPlus and ESP-R are the only packages with a fully implemented time step simulation approach. In ESP-R, a set of conservation equations are solved for each sub-problem within the simulation time step and the results are combined with occupancy profiles, control system, and weather inputs. The core procedure uses a database to store the status information and allow the plug-in of different modules for energy performance assessment. EnergyPlus manages the time-step approach via the simulation manager, which coordinates the communication between the simulation engines and the system components, providing the thermal and electrical output at each time step. Moreover, both ESP-R and EnergyPlus also output a detailed calculation of combined heat and mass transfer. EnergyPlus has main building component that handles the heat and mass balance calculations, while ESP-R uses a subset of equations to model the solution.

Another commercial software that computes the combined heat and mass transfer calculations is TRNSYS. TRNSYS has a different approach compared to ESP-R and EnergyPlus, since it implements a component based simulation in which the main building/system components - such as valves, heat pump, pipes, boilers, etc. - are physically modelled and connect with each other [73]. The components are designed and connected using the available user interface while the building inputs are configured with a different interface called

TransysBuild interface. One interesting feature not present in EnergyPlus but that characterises TRNSYS is the modularity. TRNSYS includes libraries for different components, such as thermal and photovoltaic solar systems, HVAC and renewable energy systems, cogeneration, fuel cells, etc. This component-based design allows for the addition of numerous different model components.

Both TRNSYS and EnergyPlus are able to be coupled in co-simulation environments using a time step approach. The co-simulation capabilities of EneryPlus have been used by researcher to develop testing framework for control algorithms [79]. On the other hand, the absence of native co-simulation tool to interact with the control application is one of the main weakness of ESP-r. Therefore, as illustrated in Table 3, ESP-R supports the majority of the modern features of Building Energy Simulation (BES) and, generally, is primarily used for design decision support rather than for testing control systems [80].

A different approach is used by Modelica [81, 82]. Modelica is an object-oriented modelling language designed for modelling dynamic systems. The design of each component is described by a set of equations while the model interface exposes only the input and the output of the mathematical description. The Modelica environment has a graphical and textual editor which is used to generate the Modelica source code and links to the libraries. Objects for thermal systems, electrical systems, and mechanical systems are aggregated within libraries. These objects define standard interfaces to access the component methods. An interesting feature of Modelica is the possibility to select a time integrator library. The library contains several standard integration elements that can be used to develop sophisticated algorithms and control designs. The separation between the control elements and the equation systems allows for the possibility to restart the integrator, as in the case of model predictive controllers, or to connect the system to other developing environments such as MATLAB \Simulink for control design [83]. In comparison to TRNSYS or other building simulation software, Modelica has numerous libraries available and it has a faster solver, while the main disadvantage is represented by its modular nature [82]. In Modelica, the selected building templates are used to model a building and have an important role in the output of the final simulation.

5.1.1. Calibration procedure

After the completion of the building model using a selected BES, the model needs to be calibrated to produce an accurate output. The objective of the calibration is to minimise the differences between the simulated and reference (measured) data. The research framework outlined by [86] describes the most common uses of a calibrated building model:

- Decompose the thermal or electricity consumption patterns for each system;
- Support recommendations for an equipment change, schedule or control setting change;
- Monitor and verification purposes especially pre or post-retrofit or when the retrofit is complex;
- Fault detection or identification of malfunctioning systems;

Table 3: Comparison of different building energy system programs based on common features [84, 85]

Features vs Software Package	BLAST	BSim	DeST	DOE	ECOTect	Energy+	eQuest	ESP-r	Trnsys
Simulation solution	PI	CI	PI	NI	NI	CI	CI	CI	CI
Time step approach	PI	PI	OI	NI	NI	CI	PI	CI	PI
Geometric description	CI	CI	CI	CI	CI	PI	CI	CI	CI
Simultaneous radiation and convection	CI	CI	CI	CI	NI	CI	CI	CI	CI
Combined envelope heat and mass transfer	CI	CI	NI	NI	NI	CI	NI	CI	CI
Solution method for conduction heat transfer	TFM	NI	TFM	TFM	FDM	TFM	TFM	FiDM	TFM
Internal mass considerations	CI	CI	CI	CI	CI	CI	CI	CI	CI
Occupant comfort	CI	NI	NI	NI	PI	CI	NI	PI	PI
Solar gains shading and sky considerations	NI	NI	PI	NI	CI	CI	PI	PI	CI
Variable construction element properties	NI	NI	NI	NI	CI	NI	NI	NI	NI
PCMs	NI	NI	OI	NI	NI	NI	NI	OI	OI
EIA	PI	NI	NI	PI	NI	CI	PI	PI	OI

CI: Completely/wholly implemented (well addressed and backed by supportive documentation).

PI: Partially implemented (implementation limited to some features and/or no supportive documentation provided).

OI: Optionally implemented (addressed for research but not included in the standard feature).

NI: Not/Negligibly implemented (not included / simplified features implemented only).

TFM: Transfer Function Method

FDM: Frequency Domain Method.

FiDM: Finite Difference Method.

- Installation and tuning of control systems for DR or under normal operation;

There are five main categories of calibration methodologies: manual, iterative, graphical, statistical and automated [87]. The manual approach requires the intervention of the modeller who interactively tunes the output to the measured data, while the automated method involves the use of statistical or mathematical models to assist or complete the calibration. In either case, the calibration employs analytic tools to improve the accuracy up to an established acceptance criteria [88]. The utilisation of one or more methodologies mainly depends on the model purpose. Other influencing factors for a calibration methodology selection are: data availability and resolution, the complexity of the building systems (such as the type of heating system), the thermal envelope performance and the occupancy patterns [89]. Different data sources supply a different level of insight of the construction, contributing to the calibration process [90]. Typical data providers for a calibration process are:

A) Direct interview with building stakeholders;
B) Data sensor logging;
C) Technical documentation;
D) Project plans;
E) Benchmark case studies;
F) Spot or short-time measurements;
G) Policy and regulation.

Therefore, the application of these methodologies to calibrate a simulation model over a full year and using different time resolutions, is dependent on the final application of the model. Testing control algorithms using building simulation models to assess DR measures requires the fine calibration of the internal heat gains, the behaviour of the thermal envelope and the modelled zones during the demand response events [91]. Using a Short-Term Energy Monitor test (STEM) to adjust the primary heat flows rather than individual parameters could improve the model accuracy during demand response events [86]. The lack of standards for sub-hourly resolutions and the use of over-simplified guidelines, means these calibration techniques are limited by the number and the accuracy of measured data points in the building compared to the various input supported by the modelling software. Furthermore, many of the current approaches still rely on the expertise and the knowledge of the modeller [90, 92].

5.2. Thermal network models

Over the last decades, a lot of effort has been put in the simplification of building numerical models as alternative to more complex approaches. Simplified building energy models, if properly calibrated, are capable of forecasting building thermal and electrical low with reasonable accuracy while reducing the computation time required for energy simulations. Moreover, simplified models generally needs less detailed building information which, in turn, reduces the human effort in collecting and processing data Heidarinejad et al. [93]. All

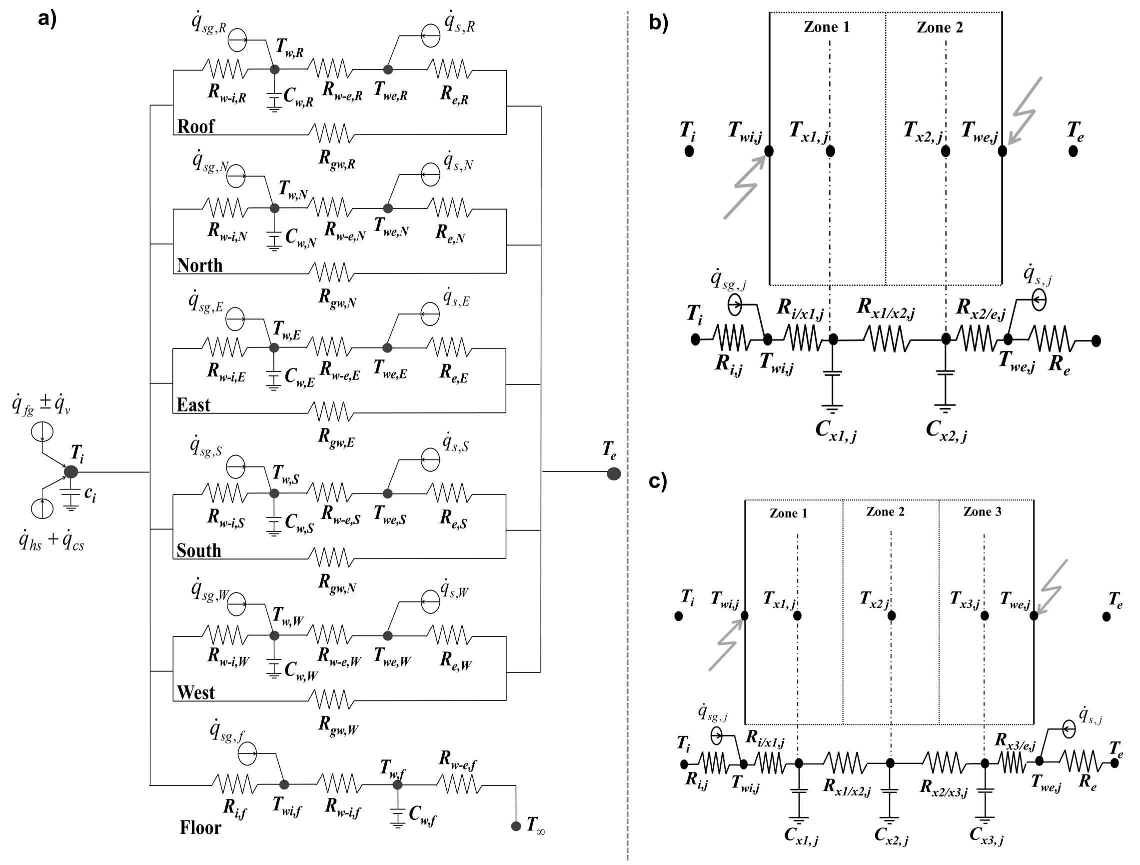

Figure 3: (a) Example of RC network for a single-zone building with 1C wall-mode. Different wall discretisation orders: (b) 2C wall mode, (c) 3C wall mode. Adapted from [75] and [96]

these characteristics make these models suitable for building aggregation applications [94] - e.g., smart grid - in which tools for building stock has to be developed and run in short time frameworks [95].

Among the different methods developed, the lumped parameter approach is one of the recognised techniques capable of meeting the target of reducing the computational cost while achieving a good grade of accuracy, as demonstrated by [70, 97]. These tools model the thermal interaction between the building envelope components and energy systems by adopting the thermo-electric network analogy (RC). Each component (or sub-component) is represented by a lumped thermal capacitance node with a potential which represents its temperature. Thermal resistances are introduced to model the heat transfer between adjacent nodes, while heat sources (e.g., internal gains) are represented as current sources directly connected with the correspondent node. The resulting thermo-electrical network leads to a set of partial differential equations, each of them describing the energy balance at each thermal node, taking the following form [75]:

$$C_n \frac{dT_n}{d\tau} = \sum_{\forall i \in N} \frac{T_i - T_n}{R_i} + \Phi_n \tag{4}$$

where C and T_n are the thermal capacitance of the component n, R_i is the thermal resistance between elements i and n, and Φ_n is the sum of all the heat fluxes applied to the node n. The number of nodes (i.e., equations) determines the order of the model and the number of parameters required, and it can consider a measure of the model complexity. Therefore, different level of complexity can be obtained, as shown in Figure 3 [75, 96]. As for instance, Zhou et al. [98] developed a simplified RC model to predict the next day hourly building load for control purposes, which consists on two parts: (i) the building envelope (external walls, including roof and floor), modelled as two isothermal layers, and (ii) the internal zone, represented by two thermal capacitances. The final model (8 thermal resistances and 7 thermal capacitances, i.e., 8R7C) showed a good performance in predicting the energy consumption, with percentage error below to 8%.

Similarly, Bacher and Madsen [99] proposed a bottom-up procedure in which the simplest feasible model is iteratively improved to select more complex ones. The procedure was tested for a building in Denmark and the results showed that the procedure is capable of providing detailed knowledge of the heat dynamics of the building. Berthou et al. [100] developed four different models (4R3C, 6R2C, 6R3C and 7R3C) to predict heating and cooling demands as well as the indoor air temperature of a ten-storey office building in Paris. Estimation errors below 15% were shown by all model considered. A 23R7C model to predict the building energy consumption for heating and cooling was developed in [75]. The model implemented a single node capacitance for the building envelope and it took into account different wall orientations to compute the absorbed solar radiations (direct, diffuse and reflected). The comparison with synthetic data from commercial software (i.e., TRNSYS and Energy Plus) showed deviations below 9%. The model was then extended in [96] by increasing the model order to investigate the influence of the wall discretisation on the model accuracy (Figure 3). Another detailed model, based on the lumped capacitance approach, to estimate the building energy performance was developed by [101]. The model implements detailed physical description of the heat transfer phenomena for the building energy systems and was used to test the performance prediction for several standards.

5.3. Data-driven models

Data-driven models utilises building monitoring data (e.g., temperatures, thermal and electric profiles, energy system performances, etc.) to generate and optimise models capable to forecast the building energy consumption. Over the last few years, data-driven models gained a lot of attention since they allow good predicting performances, without the necessity to performing detailed analyses on the specific building physical characteristics [102]. Instead, historical data are used for model optimisation and training purposes. Despite their promising performance, the need of wide-ranging and representative historical data for the training procedure, together with the model validity constrained into specific training ranges, represent the main limitations of this approach [103]. Data driven models can be divided into two main categories: (i) grey-box and (ii) black-box models. The following sections will provide some insights and further readings about these two approaches.

5.3.1. Grey box models

Grey-box modelling is a hybrid approach, where physics and data driven components coexist [104]. Generally, a grey-box model keeps the physical-based structure to model the system dynamic while statistical and/or optimisation techniques are used to estimate the unknown parameters basing on the experimental dataset [105]. Even if these unknown parameters may be linked with the physical properties of the building, the use of stochastic models and optimisation algorithms, to achieve good prediction accuracy, could make this link challenging to be formulated [106].

Despite the extensive research carried out over the last decades, the identification of proper methodologies capable of detecting a trade-off between accuracy and computational cost, which depends on the specific application the model is intended for, is still an open challenge. As for instance, De Rosa et al. [107] introduced a top-down methodology to detect a reduced-order model capable of simulating the building energy consumption in a short-term horizon, compatible with the implementation of demand response measures, and with a reasonable computational cost. The methodology is based on the progressively reduction of the complexity of building models, calibrated against experimental data, while retaining the model structure. Similarly, Dqu et al. [108] investigated a set of models to describe the envelope of a multi-zone residential building. Starting from a physical model based on experimental data, the authors reduced the physical model separating the building static and the dynamic characteristics. The procedure validation demonstrated that the models were able to predict the building energy consumption within 5% accuracy. In order to characterise the thermal behaviour of an entire residential district, Nielsen and Madsen [109] developed a simplified grey-box model, showing how these methods can be used for aggregating purposes. Reynders et al. [105] proposed a methodology to detect suitable building reduced-order models based on statistical methods and experimental measurements. The approach was tested on different dwellings, demonstrating that only few model structures are required to represent the majority of buildings.

Therefore, the identification of the model structure is paramount for a correct development of grey-box models, especially when occupied buildings are considered. Harb et al. [110] presented a methodology to forecast the thermal response of occupied buildings by calibrating the parameters of four RC models with different levels of complexity (i.e., order: 1R1C, 3R2C, 4R2C and 8R3C; refer to Section 5.2 for more details). The calibration was carried out by using an optimisation algorithm to determine the parameter set which gives the best accuracy in predicting the internal air temperature. The models were tested with experimental data from different buildings (both residential and commercial) and the results showed that a good prediction accuracy can be obtained, with discrepancies lower than 0.3K.

The semi-physical interpretation of lumped parameter (RC) approach can be exploited to calibrate a cluster of retrofitted building models simultaneously [76]. Therefore, a procedure for performing a model order reduction to increase the model performance without compromising its accuracy must be found. This trade off between accuracy and computational cost can be obtained by both automated and user-led procedures. The first approach is based on independent algorithms - such as balance truncation [111] - to optimise model structure and parameters on the basis of performance indicators (e.g., RSME, running time, etc.) without the user interaction, while latter requires professional judgements when trimming choices are taken. Despite the undoubted economic convenience of avoiding human interaction with the algorithm, the automated procedure may lead to a loss of model structure and, in turn, to a reduction of prediction accuracy, as demonstrated in [112].

Generally, the calibration of a lumped-capacitance (RC) model is carried out by searching for a set of optimal parameter p_0, Eq. 5, which provides the best thermal response of the system, as for instance, measured by the room temperature $T_{r,0}$. Calibration procedures correlate the variation in thermal performance (i.e., ΔT_r) with the variation in parameters (Δ_p), which can be inferred from the semi-physical modelling [113].

$$p_0^* = [R_0^*, C_0^*] \tag{5}$$

Different metrics can be used for assessing the model predictive performance. As for instance, the Root Mean Square Error (RMSE) is typically used to determine the error between simulation results and experimental dataset. Taking as target variable the internal temperature (as in [110]), the RMSE takes the form shown in Eq. 6, where $T_{r,e}$ and $T_{r,s}$ are the experimental and simulated values of the room temperature respectively, while τ is the time interval over the time horizon TH.

$$RMSE = \frac{1}{TH}\sqrt{\sum_{\tau=1}^{TH}\left(T_{r,e}^{\tau} - T_{r,s}^{\tau}\right)^2} \tag{6}$$

However, the small magnitude of the internal temperature variations, which is typical of temperature-controlled rooms as in the residential/commercial building sector, can affect the calibration procedure due to the small differences in the metrics obtained, as demonstrated in De Rosa et al. [113]. To overcome this problem, the authors suggested the use of the building energy consumption as target variable to assess the model predictive performance. The reasoning behind this choice came from considering that the accuracy in estimating the building energy consumption is the main decision key for modellers and building managers in most applications (e.g., retrofitting, energy flexibility assessment, etc.), since it is directly linked with operational costs and environmental issues.

5.3.2. Black box models

The black-box approach is based on statistical analysis or machine learning techniques such as SVM or ANN. The main difficulty in implementing these models lies in the need of large dataset of historical data and in the complexity associated with the tuning procedure [69, 85]. A lot of works has been done to train black-box models for forecasting building energy consumption. Among all techniques adopted, regression methods, SVM, decision trees and ANN and deep learning are the most common.

A regression method is a technique aimed to identify a mathematical relationship between one or more independent variables and a dependent variable using measured data [114]. In energy related applications, the dependent variable can be heating or cooling loads, power consumption or internal temperature, while the independent variables can span from weather data to occupancy activities, solar exposure or building element characteristics such as U-value, window to floor area ratio, etc. As for instance, Catalina et al. [115] developed and validate a multiple regression model for residential buildings in warm climates. The target variable was the monthly heating demand, while the selected features for the regression model were: building U-value, window to floor area ratio, time of the day and a thermostatic set point function defined as building time constant and climate. After several regression models were tested, a second order polynomial model was selected as the best fit regression model. The model validation included 270 scenarios, which resulted in an average error of 2% between the prediction and the reference data. An update to their work was subsequently published in [116], where the heat consumption was introduced as independent variable. A building heat loss coefficient and the difference between indoor set point temperature and air temperature were added to the regression model. The updated model was tested and validated against reference data, showing a relatively good accuracy considering its generality.

Despite the use of SVM is relatively new, they have been effectively employed to predict building heating or cooling load [117], especially with non linear problems and with limited data available. These models can be trained with several type of data and various time resolution. Li et al. [118] developed a SVM model using the dry-bulb temperature and the solar radiation as predictor variables, which achieved a mean relative error of 1% in predicting the building cooling load. Similarly, Jung et al. [119] used a genetic algorithms with an SVM model to forecast daily building energy consumption using historical data as input for the previous four weekdays. The average RMSE of the developed model varied from 7.59 to 11.13. A comparison between SVM and ANN was performed by Li et al. [120] in three different settings: traditional back propagation, radial basis function and general ANN regression. The study concluded that the SVM and the general regression ANN models achieved better accuracy and generalisation than the back propagation neural network and radial basis function ANN methods.

Over the last years, ANN have been used widely to predict the building energy consumption and load profiles. One common result obtained from testing these models was that the results are accurate if the training dataset includes all independent variables required and covers a large period of time [117]. Dombayci [121] developed an ANN model aimed to forecast hourly heating energy consumption of a single-storey building in Turkey. The model was trained with heating energy consumption values covering 4 years (2004-2007) and, then, tested with the values recorded in 2008, showing good accuracy (RMSE equal to 0.988).

Further techniques to predict energy building loads include Deep Learning Neural Networks (DLNN) and Stacked Ensemble Models (SEM), Generalised Additive Models (GAM) with Auto Regressive (AR) cRandom Forest (RF) models. DLNN is based on a multi-layer feed-forward ANN trained with stochastic gradient descent using back-propagation [122]. The network can contain a large number of hidden layers, consisting of neurons with tanh, rectifier, and maximum output activation functions. Advanced features such as adaptive learning rate, rate annealing, momentum training, dropout, L1 or L2 regularization, checkpointing, and grid search can enable high predictive accuracy [123].

Ensemble machine learning methods use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms [124]. Many of the popular modern machine learning algorithms are actually ensembles. For example, RF and Gradient Boosting Machine (GBM) are both ensemble learners. Both bagging (e.g. Random Forest) and boosting (e.g. GBM) are ensembling methods which take a collection of weak learners (e.g. decision tree) and form a single, strong learner. Stacked Ensemble method is supervised ensemble machine learning algorithm that finds the optimal combination of a collection of prediction algorithms using a process called stacking. This algorithm category have been extensively used over the last years to predict energy profiles [125] or internal temperature [13].

GAM with auto-regressive linear components is a different technique that has been extensively developed recently. Although attractively simple, the traditional linear model often fails in many situations due to non-linear phenomena. GAM are flexible statistical methods that can be used to identify and characterise nonlinear regression effects. In the regression setting, a generalised additive model has the following form:

$$y = \beta_0 + f_1(X_1) + f_2(X_2) + ... + f_p(X_p) + \epsilon \tag{7}$$

where $X_1, X, ..., X_p$ represent the predictors and y is the outcome. The f parameters may be functions with a specified parametric form (e.g., polynomial or un-penalized regression spline), or unspecified *smooth* functions to be estimated by non-parametric means.

RF (strong learner) is built as an ensemble of Decision Trees (weak learners) to perform different tasks such as regression and classification. The idea behind a decision tree is to search for a pair of variable-value within the training set and split it in such a way that it will generate the "best" two child subsets. The goal is to create branches and leaves based on an optimal splitting criterion, a process called tree growing [126]. Specifically, at every branch or node, a conditional statement classifies the data point based on a fixed threshold in a specific variable, therefore splitting the data. To make predictions, every new instance starts in the root node (top of the tree) and moves along the branches until it reaches a leaf node where no further branching is possible. Using random forest models for predicting the building energy consumption, Wang et al. [127] reached average RMSE values below 2%.

6. Control algorithms for DR

An Energy Management System (EMS) can give easy to access information to home electricity consumption patterns to control appliances in real time and optimise power usage in a building. The objectives of an EMS in a DR scenario are the following:

- *Consumption reduction*: this can be achieved by raising awareness of more careful utilisation patterns as well as more efficient usage of the dwelling systems, i.e., operating a Heat Pump (HP) at maximum Coefficient Of Performance (COP), or executing a Maximum Power Point Tracking (MPPT) algorithm in a PV system;

- *Consumption shifting*: This can be done by shifting high-load household appliances or electric load to off hours or in response to a signal to decrease the peak load demand;
- *Consumption forcing*: This can be done by forcing the use of high-load household appliances or electric load to off hours or in response to a signal to increase the instantaneous demand, for storing energy in a TES or a battery.

Different techniques can be used to implement consumption reduction methods. On the other hand, as previously mentioned, obstacles in the implementations of the methods for load shifting and forcing still occur. Lack of standards and the slow diffusion of building automation systems represents the first inhibitor. Secondly, the time-varying prices provided by utility companies or the electricity market do not necessary match the customer consumption patterns, thereby a form of storage is likely to be required [39]. This is the reason why it is necessary to embed EMS system with optimisation algorithms that have the potential to minimise the consumption and the associated energy expenditure, whilst maintaining the thermal comfort and the service level expected by the end users.

6.1. Optimisation problems and solution methods

In recent years, various studies have been published discussing the use of control algorithms to enable DR programs in the residential sector [128–130]. The aims of DR optimisation algorithms are to enable DR programs and to widen diffusion of DR programs in the power system. Therefore, parts of the research community have been focused on three distinct perspectives: the market, the distribution grid and the buildings. Although the current paper is focused on the residential building implications of the optimisation algorithms embedded in the EMS, analysing the techniques adopted in the other two perspectives contributed to the development of a holistic approach to the problem. Generally, the common element in each algorithm is an objective function and a set of constraints. This objective function can target the costs, the energy consumption or the welfare (defined as the utility profit minus the generation cost and system losses [131]). When the objective function targets the energy cost and the consumption, a minimisation problem is implemented as a benefit for end users. On the other hand, if the objective function targets the welfare, a maximisation problem will be solved.

Table 4 illustrates an extensive literature analysis on DR optimisation algorithms. Each column refers to an optimisation method while each row represents one of the five most common objective functions elicited from the current literature. It can be noted that only few of the paper assessed assessed [138, 149, 169, 170] use a mix of techniques, such as mixed linear integer, continuous integer and quadratic programming, with the aim of reducing power flow overloads caused by variable renewable energy generation or load variations. In [138] and [170], the optimal controller exploited the capacity of electric batteries at distribution and power system level, to compensate for any imbalances. While Kallitsis et al. [149] is focused on a distributed algorithm that reduces the messaging bandwidth to allocate power in proportion to high uncertainty loads or generation such as renewable, Cecati et al. [169] is concerned on how to implement an optimisation algorithm for the benefit of the distribution network. Despite the different approaches, both papers aim to

Table 4: Optimisation problems and solution methods in for DR in the literature

	Min Cost	Min Consumption	Max Welfare	Min Cost and Min Consumption	Max Welfare and Min Consumption
Game Theory	28.A		24.O - 6.U	5.U	
Robust Optimisation		34.T			12.A - 37.U
Markov Decision Problem	41.Z	26.U			
Stochastic Optimisation	15.F - 3.O	11.U - 42.T			
Binary Particle Swarm Optimisation	14.U				
Particle Swarm Optimisation	14.U - 13. B				
Heuristic	21.D - 28.E - 35.U			2.E - 39.U	
Non-Linear Programming			10.M		
Non-convex Optimisation Problem	13.Y	26.U			
Convex Optimisation Problem	36.U	19.U - 23.U	2.U - 18.U	40.E	
Mixed Discrete/Continuous Programming			3.L		20.W
Mixed Integer Non-Linear Programming	24.B	8.B	25.B		
Mixed Integer Linear Programming	22.B	22.T-9.B		27.B	
Mixed Integer Programming	1U	7.U		30.T	
Linear Integer Programming	23U,38U	4.U - 29.Q		1B	
Other methods					

References

1	Arabzadeh et al. [132]	8	Cui et al. [139]	15	Guo et al. [145]	22	Mohsenian-Rad and Leon-Garcia [151]	29	Zhu et al. [158]	36	Knudsen and Petersen [164]
2	Behrens et al. [133]	9	Di Zhanga et al. [140]	16	Jiang and Fei [2]	23	Molderink et al. [152]	30	Yoon et al. [129]	37	Park et al. [4]
3	Bahrami et al. [134]	10	Doostizadeh and Ghasemi [141]	17	Hedegaard et al. [146]	24	Soares et al. [153]	31	Ma et al. [159]	38	Alimohammadisagvand et al. [165]
4	Chang et al. [135]	11	Ferreira et al. [142]	18	Alibabaei et al. [147]	25	[154]	32	Cole et al. [160]	39	Pallonetto et al. [13]
5	Chen et al. [136]	12	Gatsis and Giannakis [143]	19	Joe-Wong et al. [148]	26	Totu et al. [155]	33	Bianchini et al. [161]	40	Adhikari et al. [166]
6	Chen et al. [137]	13	Gatsis and Giannakis [128]	20	Kallitsis et al. [149]	27	Wang et al. [156]	34	Kircher and Zhang [162]	41	Ruelens et al. [167]
7	Choi et al. [138]	14	Gudi et al. [144]	21	Logenthiran et al. [150]	28	Xiao et al. [157]	35	Schibuola et al. [163]	42	Garifi et al. [168]

Algorithms

A	Interior point method	E	Greedy search algorithm	I	Lagrange-Newton method	O	Filling method	S	Signaled particle swarm	W	Iterative decentralised
B	Commercial software	F	Lyapunov optimisation	L	Sequential Quadratic	P	Co-Evolutionary PSO	T	MPC(Model Predictive Control)	Y	Lagrangian algorithm
C	Multiple-looping	G	Relaxed convex	M	Benders decomposition	Q	Branch and bound method	U	Author's software	Z	AI Neural Network
D	Evolutionary algorithm	H	Simulated annealing	N	Q-Learning algorithm	R	Parallel distribution	V	Distributed subgradient		

maximise the welfare in a smart grid system. However, none of these papers provides a comparable optimal solution, while the analysis elicits a trade-off between optimisation at single building and power grid level.

It is a requirement for a smart grid DR algorithm to ensure the optimisation of the resources at an isolated building level, while contributing to the power grid stability and reduction of the environmental impact via a two-way communication to aggregators or TSO. This double aim could be reached only if the objective function of the optimisation algorithm minimises both cost and consumption, which are two conflicting goals, since the results obtained by a cost minimisation can lead to an increase of the energy consumption and associated emissions.

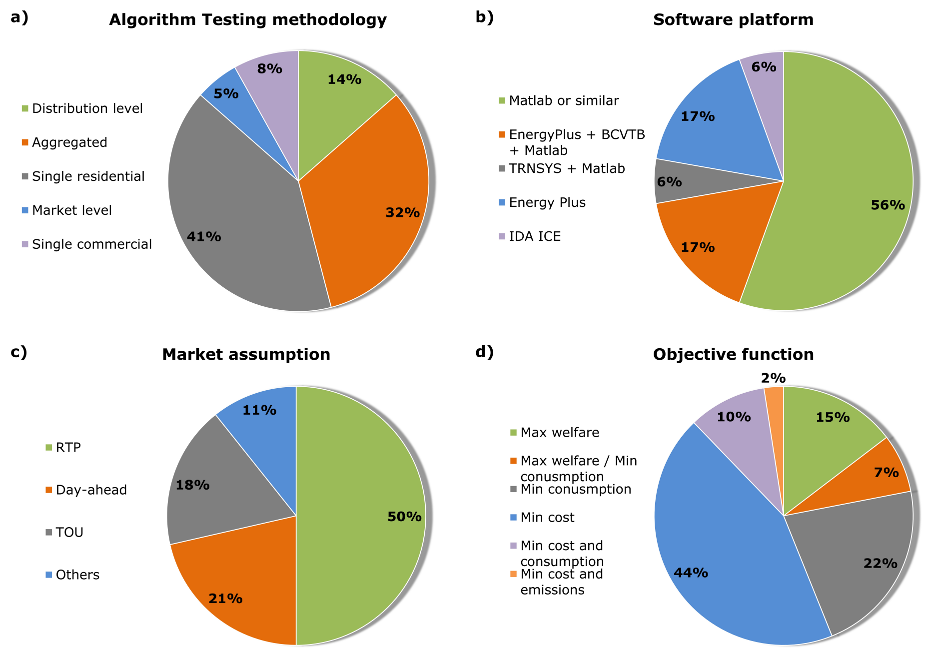

Figure 4: Publication frequency in the period 2010-2018 depending on: (a) testing methodology, (b) software platform, (c) electricity market price, (d) objective function.

In order to provide a picture of the research efforts carried out over the last few years, Figure 4 reports the publication frequency on different aspects of building control algorithms for DR. As illustrated in Figure 4a, the majority of the works analysed was tested on single residential buildings. Only 14% and 5% of them were focused on distribution and market levels respectively. However, none of the papers mentioned any calibration of the building model despite, as illustrated in Figure 4b, the most of them used a BES model for testing. Concerning the electricity price, Figure 4c shows that Real Time Price (RTP) price was the most utilised market framework compared to other price schemes. It is however important to highlight that it is not realistic for the residential sector to assume the adoption of RTP price to end users in the short term, due to the current market limitations.

The majority of the optimisation algorithms (Figure 4d) were based on a single objective function aimed at minimising the costs. Nevertheless, various studies used a double objective function [135, 136, 156, 171]. In this category, different techniques were utilised such as heuristics, analytical solutions and game theory. Only the heuristic controller [171] was able to reduce the consumption by 9.2% and the costs by 14.4%, using a threshold limit to operate the controllable loads under RTP prices. Two works [135, 136] used a cluster of residential buildings (10 and 60 respectively) to assess the results of the algorithm. When tested on the test load profiles, Chen et al. [136] showed a demand reduction of 13.5% and cost savings for 3.6%, while [135] used a randomly generated problem, and the approach cannot be compared with equivalent works. The remaining two works [156, 171] utilised a model of a single residential building to assess the benefits of the double objective function algorithm. Wang et al. [156] reached an overall cost savings of 9% and a load reduction of 6%.

The research papers which included the cost minimisation using an Model Predictive Control (MPC) approach [146, 147, 159–161, 165] were capable to output savings up to 28%. Four of the papers used EnergyPlus as a test bed and two of them the combination of EnergyPlus and Building Controls Virtual Test Bed (BCVTB). In the majority of the cases selected the algorithm was embedded in a residential EMS, while only a few cases were concerned with commercial buildings [161]. The predictive models used for the forecast were linear models [165], auto-regressive statistical models [160, 161], reduced order model [160] or grey-box model [146]. None of the analysed works used a machine learning algorithm as a predictive model. It should be also noted that none of the MPC systems used EnergyPlus as a predictive model but as a test bed. EnergyPlus suffers from high computational time and long-running cycles as confirmed by Cole et al. [160]. A relevant work in the field was Knudsen and Petersen [164] where the authors used an MPC with a double objective function (emissions and electricity price). The chosen predictive model was a state-space model which is equivalent to a reduced-order model [172]. The results showed a cost and emissions reductions in the range of 5-10%. None of the works selected from the current literature showed an MPC with a double objective function for minimising energy expenditure and consumption.

In the next sections, rule-based and heuristic approaches and a linear integer programming algorithm are reviewed. The assessment aims to describe general approaches for the development of control algorithms to enable DR in the residential sector.

6.2. Rule-based control algorithms

Yoon et al. [129] proposed a Dynamic Demand Response Controller (DDRC) designed to reduce peak electricity usage for Heating Ventilation and Air Conditioning system (HVAC) of homes in response to the change of retail electricity price by considering customer preferences in both set-point temperature and price tolerance. The system implements a rule-based algorithm: the controller changes the set-point temperature to control HVAC loads depending on electricity retail price published every 15 minutes. The objective is to partially shift some of the electricity demand away from the peak periods. The rule-based controller adjusts the set-point temperature by 1 degree Celsius, when the retail electricity price is higher than an established threshold price. The threshold is calculated using the average historical price for each month and the associated average variance: if the absolute value of the inside temperature minus the thermostatic set point is higher than 1 degree Celsius the rule-based controller activates the heat pump to restore the comfort settings. The system was able to reduce the electricity consumption by 12% and 21% during a winter and summer month period, demonstrating that a DDRC could significantly contribute to reducing both electricity consumption and its associated cost with an acceptable level of discomfort (+/- 1 degree Celsius). However, the calculation of the thermal comfort is based on the internal temperature while, in the current literature, more advanced models are available.

Generally, DDRC acts as a thermostatic set point controller without performing any optimisation. This may lead to an increment of building power consumption when long periods of prices above the threshold. Moreover, the oscillations of the price close to the threshold and the associated intermittent activation of the HP can also cause mechanical problems. A more suitable price scheme for peak load shifting can be represented by a Time of Use (TOU) price. Although the results of the presented system are significant, the aforementioned issues could be a challenge in countries with a colder climate and a different price variance. In addition, occupant thermal comfort can be affected by price oscillations making the algorithm unlikely to be adopted by end users.

6.3. Heuristic control algorithms

The greedy algorithm developed by [173] provides a useful software infrastructure. The researchers proposed a home energy management system EMS for the residential load and control, based on price prediction. The main aim of the EMS system is: (i) to meter the electricity use, (ii) reading the sensors connected to the Home Area Network (HAN), (iii) to increase the awareness of the occupants, (iv) to identify consumption patterns and (v) to control household appliances. The main components are a price forecast module, a load scheduler and an energy consumption monitor.

The structure of a proposed EMS is shown in Figure 5. A control panel represents the main part of the EMS, which integrates three major functions of the system. Under the control panel, basic smart metering infrastructure, and several dashed lines symbolising the relationship between the three major functions, are installed. The first element of the control panel, the so-called *predictor*, is used to forecast real-time prices with the support of the utility via cloud. A price prediction unit estimates future expenses by applying a weighted averaging filter to past prices. In detail, an efficient prediction is based on prices from yesterday, the day before yesterday and the same day last week. A price parameter prediction model is given as follows:

$$X_h = (W_h X_h)^{d-1} + (W_h X_h)^{d-2} + (W_h X_h)^{d-7} \tag{8}$$

where X_h and W_h are the target variable (e.g., price) and the weighting factors respectively. The terms $(d-1)$, $(d-2)$ and $(d-7)$ represent yesterday, the day before yesterday and the same day the week before. Therefore, Eq. 8 formulates a weighted average price

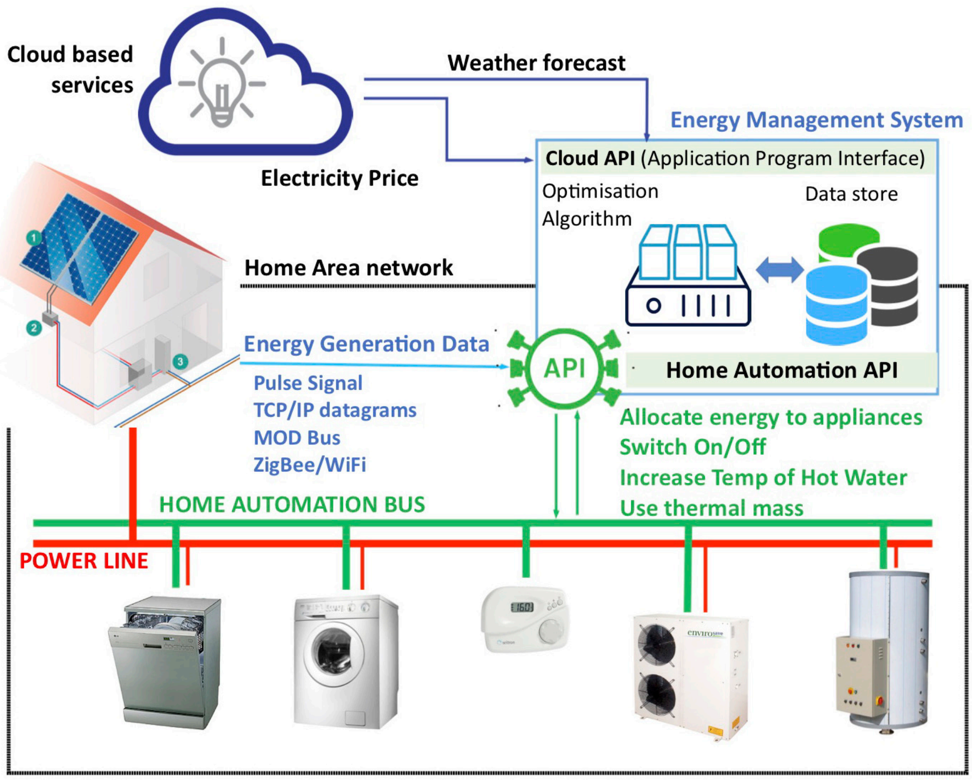

Figure 5: Design example of an Energy Management System for residential.

predictor filtered with coefficients. It was demonstrated that efficient price predictors for residential control can be obtained by the price parameter prediction model with optimal coefficients, based on prices from the Illinois Power Company (IPC) and two different ratio selection approaches namely, all-days-same and each-day-different coefficients. The first selection method, as its name suggests, assumes that all coefficients are the same every day, whereas the second approach separately selects different coefficients for each day of the week. In addition, the coefficients for both procedures can be obtained by calculating the prediction error resulting from Eq. 8.

The second element, the *Monitor*, provides measurements of different indicators such as current, voltage and power by using the smart meter. The *Scheduler* periodically collects reports from the other two elements, analyses all received data and decides a strategy for energy consumption scheduling. The strategy is then applied to all household appliances in the form of ON/OFF commands with specified power levels over either wired or wireless HAN. The *Scheduler* is a core module of the implementation, and it analyses all data reported by the *Monitor* and the *Predictor* as well as planning a strategy to control electronic devices in response to time-varying prices. In scheduling loads, two objectives are considered: (i) energy expenditure reduction for end-users and (ii) the minimisation of the waiting time before an appliance can be used. It is evident that in some cases, these two objectives may conflict and a resolution strategy is balancing the trade-off between objective functions must be pursued.

6.4. Homeostatic controls

Another interesting methodology for controlling energy systems is the homeostatic approach. Homeostatic control theory is based on the idea that homeostasis regulation and compensatory control mechanisms, which are typical of living organisms, can be applied to electric power systems [174]. Generally, homeostasis can be defined as the state of chemical and physical equilibrium maintained by living systems [175]. The homeostasis balance is maintained through a continuous feedback loop and adjustment of the nodes to reach a global equilibrium state. The main characteristics of homeostatic control are connectivity, co-evolution, emergence and self-organisation, as outlined in Yanine et al. [175].

Generally, homeostatic utility control mechanisms exploit distributed control systems which aim to maintain the supply-demand balance in the power grid. Homeostatic control can be used to balance microgrids equipped with renewable energy systems, such as small wind turbines and photovoltaics [174], and several homeostatic controls were designed both for energy and exergy management of microgrids [176]. In such systems, human interaction may also be considered and analysed as subsystems (Yanine et al. [175] refer to them as "*socio-technical systems, equally complex in nature as other living systems*"), which interact continuously with the other sub-systems and the environment, in order to control and regulate. These models regulate the energy intake and expenditure from a power generation and supply standpoint by using a set of rules and measuring the amount of power drawn from the grid versus the renewable energy generation. In more recent work, homeostatic controllers have been enhanced to become predictive and resilient to unexpected events and disruptive climate change scenarios [177].

Homeostatic control has been applied to building energy management systems by introducing the concept of architectural homeostatic buildings (AHBs), defined by as optimally-designed "*buildings with the architectural elements of high performance envelope and sufficient thermal mass*" [178], to increase the capability of the building to maintain a specific temperature passively [179]. Starting from this precondition, a mathematical link with the external environment is therefore necessary in order to provide the controller with the relevant heat extraction/injection equipment, in order to maintain the building thermal homeostasis in a comfortable range [179]. Because of this large thermal mass, homeostatic buildings are particularly suitable for implementing demand-response programs.

More general details about homeostatic control systems can be found in Yanine et al. [175] and Wang and Ma [178].

6.5. Load Forecasting to enable DR strategies in EMS

As an important part of smart grid infrastructure, time dependent electricity prices can improve the efficiency of power utilisation in comparison with ordinary flat rates. However, the average price currently charged to consumers does not reflect an actual wholesale price at the time of consumption, leading to higher Peak to average ratio (PAR) and energy costs occurs. As shown in section 2.4, different time-based schemes have been developed to overcome this limitation, such as real-time pricing RTP, day-ahead pricing, time of use TOU and critical peak pricing CPP. RTP in addition to a drop in electricity expenses can potentially reduce the emission levels which is correlated to the operation of peak generators [180].

Over the last decade, new machine learning algorithms and techniques have been developed and refined. Notwithstanding, a still undergoing research gap to address is represented by finding the most suitable machine learning method to forecast the energy consumption at residential buildings level. Most of the reviewed research implements residential load controls, where a low computational linear algorithm minimises the hourly load. As for instance, Zhu et al. [158] developed a test-bed simulation to analyse the efficiency of EMS based on the linear integer programming. The results showed the capability of the algorithm to reduce the PAR of 19% in the load demand. Moreover, the authors highlighted how the use of custom built model and forecast techniques could lead to significant cost minimisation under DR price signal. However, the scheduling system developed is suitable only for a fixed price scenario, it does not control the loads directly but provides a load schedule only. As stated by the authors, to implement the same controller in a real DR scenario, the provision of communication system to facilitate the exchange of information would be required.

Humeau et al. [181] explained the relationship between the effectiveness of EMS in leading to cost savings and the accuracy of the load forecast. The study also pointed out how machine learning techniques can contribute to the accuracy of the load and wholesale electricity price predictions. Modern smart meter technologies allow the analysis of household electricity expenditure in real time. As mentioned in Section 5, forecasting the energy consumption pattern at a residential building scale can help to improve the efficiency of distribution networks. The same research [181] also investigated the prediction discrepancies for electricity usage by using statistical relations between consumption series both at household and district scales and by applying different machine learning techniques, such as SVM or Support Vector Regression (SVR) and Multilayer Perceptron (MLP). SVR is a classifier that uses models to represent the training data as points mapped in space so that the training data of the classes are divided by a clear gap that is large enough. By contrast, MLP is a classifier that uses a feed forward artificial neural network model which maps sets of inputs onto a set of corresponding outputs.

Generally, there are two main types of forecasting: long-term (1-10 years ahead) and short-term (hours-weeks ahead) [182, 183]. The former is important for planning both transmission and distribution networks, whereas the latter is crucial for online scheduling and demand side management [184, 185]. Prediction capabilities have been inspired by machine learning research and have improved from linear regression and autoregressive moving average models to neural networks, boosting methods and support vector machines, which nowadays is considered to be state of the art [186]. Moreover, all these techniques were successfully used for prediction at a country level. The experiments described in Giannakis et al. [187] proved that SVR is the best method among the tested ones for load forecasting at a district level. At a single household level, linear regression showed the lowest error rate: only when 32 houses or more were studied, SVR outperformed linear regression methods.

This means that SVR predictions can show the best results only at large scale [188].

7. Discussion and conclusions

In recent years, there have been significant research efforts to develop, analyse and test DR optimisation algorithms. Different approaches have been considered, from the implementation of mathematical optimisation models to heuristic-based systems. The present paper presented an extensive literature review on the current state of development of DR programs, with a special focus on optimisation algorithms for residential buildings. The review covers different aspects on DR programs in building - such as technology, markets, tariff schemes, control and optimisation - in order to give a comprehensive picture of the current research and to highlight research gaps, challenges and potential future developments. The main outcomes of the literature review carried out can be summarised as follows:

- Generally, several benefits from the implementation for DR programs in residential buildings are evident. From a generation level perspective, aggregating multiple building DR programs can be an efficient and cost-effective way (i) for managing peak load periods by limiting expensive and environmentally damaging generation systems and (ii) to mitigate the fluctuation of renewable energy generation allowing their higher penetration at a large or distributed scale. At a user level, more optimised and cost effective usage of energy can be obtained by control algorithms enabled for DR programs for single end-users.

- A lack of appropriate market mechanisms and tariff structures for DR in residential buildings represents one of the main barriers to establish developed flexibility markets. The type of scheme adopted depends on the ability of end-users to control their own consumption. This, in turn, leads to the need of appropriately developed control algorithms and methodologies for the assessment of DR programs. Future work should be dedicated to extending the analyses on different market schemes to experimental test cases.

- The development of control and optimisation algorithms linked with building numerical models, capable of forecasting building load profiles and to perform detailed comfort assessment, is central to achieve a fully developed DR framework in buildings. Several techniques - i.e., white box reduced order models, calibration methods, data driven grey-box and black-box models - can be used as platform for implementing optimised control algorithms for DR programs. A trade off between two conflicting goals, accuracy and computational costs, must be found for building simulation tools. This is essential in order to develop simulation tools capable of predicting load patterns at aggregated building level. Therefore, special efforts must be dedicated in developing standardised tools capable of predicting the short term building energy consumption with low computational cost.

- EMS can be a useful tool to make all the information about households' real time energy consumption and expenditure available to the main stakeholders. Different techniques can be used to implement consumption reduction methods. However a lack of standards and the slow diffusion of building automation system represent some of the main inhibitors and obstacles to the implementation of DR programs.

- Obtaining optimal solutions for each specific case requires capabilities beyond current technological developments. Heuristic approaches can, however, provide approximations with acceptable accuracy in relative short time frames. When using heuristic techniques, special attention should be given to formulating stop criteria and objective functions to avoid misleading results. Assessing the results versus a baseline scenario is highly recommended.

- If a heuristic approach cannot provide significant results, then a more mathematical approach should be evaluated. Formulating the problem as a linear integer programming and developing an optimisation algorithm that uses the combination of MPC and machine learning algorithms for forecast embedded in an EMS which can control thermal loads has been identified as an outstanding research gap in the literature. Moreover, further research is required in order to test experimentally the capabilities and performance of these algorithms for DR applications.

- Developing comprehensive metrics to assess DR programs in buildings is challenging due to the complexity of the aspect involved. Currently, a lack of commonly accepted and standardised still occurs, representing one of the main obstacle to achieving a widespread distribution of DR programs in residential buildings. While technical aspects, such as energy flexibility available and instantaneous capability for load reduction, are generally assessed by specific KPIs in all works analysed, little attention is generally given to economic and environment assessments. Future research efforts would be dedicated to the development of more comprehensive metrics as the basis of establishing a standardised methodological framework.

- Finally, social and behavioural aspects - such as technology acceptance, awareness and integration - are critical to achieve high level of user satisfaction which, in turn, is essential successful participation of residential end-users into DR markets. To achieve this target, communication channels between operators and end-user, as well as, smart technology to provide feedback to the end-users, must be established.

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