# Advanced Energy Management Systems and Demand-Side Measures for Buildings towards the Decarbonisation of Our Society

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## 1. Introduction

The synchronised power system is one of the top human engineering achievements of the twentieth century (Almassalkhi and Hiskens 2015). Throughout the early part of the twentieth century, the number of electrified cities increased, leading to a connected system identified as the synchronised power grid (Hughes 1993). Since then, the power system has evolved, presenting new hurdles for system operators, both at transmission (TSO) and distribution (DNO) level. Environmental impact, increased penetration of renewable energies, the continued growth in demand, and the uncertainty of fuel reserves are just a tiny part of a set of new challenges that the power systems research community is addressing (Nolan and O'Malley 2015). Grid reinforcement can be part of the solution to these challenges; however, it is costly and does not always improve the system's robustness. Recent blackouts in Germany, Texas and Italy caused by a domino effect of small evaluation mistakes are the empirical evidence of a more significant research problem (Boemer et al. 2011; Gimon and Fellow 2021). Assessing these issues requires complex modelling and extensive computational capabilities and can lead to counterintuitive results.

In 2012, researchers at the Max Planck Institute for Dynamics and Self Organisation in Göttingen, discovered that the power grid is affected by Braess' paradox. This phenomenon was discovered by the German mathematician Dietrich Braess in 1968 while undertaking studies on road network models (Pas and Principio 1997). The definition of the paradox as stated in Braess (1968, p. 1) is as follows:

> "For each point of a road network, let there be given the number of cars starting from it and the destination of the cars. Under these conditions, one wishes to estimate the distribution of traffic flow. Whether one street is preferable to another depends not only on the quality of the road but also on the density of the flow. If every driver takes the path that looks

most favourable to him, the resultant running times need not be minimal. Furthermore, it is indicated by an example that an extension of the road network may cause a redistribution of the traffic that results in longer individual running times."

The same principle applies to the power grid, where adding one or more links to the power grid could degrade the overall efficiency of the system (Witthaut and Timme 2012). The increasing energy demand, environmental concerns and the installation of interconnected Renewable Energy Systems (RES) add to the underlying complexity of the problem. RESs are associated with low carbon emissions; however, for the general public, the threats caused by their intermittent nature are underrated and not well understood (Vargas et al. 2015). Despite these technical challenges, post-Kyoto regulations endorsed by the European Union have established the target of full decarbonisation by 2050 (International Energy Agency 2016).

Historically, system operators owned most of the system, and they planned the generation mix a day-ahead while tuning the daily electricity production to compensate for unplanned generator outages or unexpected load oscillations. High penetration of renewable energy increases the complexity of this process to an unexplored level (Bozalakov et al. 2014). Furthermore, the increasing electricity consumption caused by a larger adoption of low-carbon technologies in end-use sectors represents another influencing factor on the demand side of the network. The increasing percentage of electric vehicles and heat pumps can strain the network capacity and ultimately lead to blackouts (Veldman et al. 2011).

Extending the control to the demand-side of the system can become part of the solution (Cecati et al. 2011; Fuller et al. 2011; McKenna and Keane 2016; Nolan and O'Malley 2015; Torriti et al. 2010). The adaptability of demand is not new to the dynamics of the power grid infrastructure. These measures have been promoted in various countries across the world to clip winter or summer peaks and defer grid reinforcement (Paterakis et al. 2017).

Following these measures, power grids have gradually adapted to the increased demand and are adopting a higher percentage of new renewable energy generators such as photovoltaics and wind turbines. System operators did not embrace the penetration of RES until it started to affect the supply/demand balance of the whole system, altering the system frequency beyond safety thresholds (Ulbig et al. 2014). At that point, system operators had to take into account not only the unscheduled load demand but also the variability of power generation caused by weather conditions (Bozalakov et al. 2014). These open challenges cannot be addressed within the boundaries of the existing power system (Farhangi 2010). The integration of information technology, communications, and circuit infrastructure could lead to disruptive technological innovations for the integration of higher penetration of RES, increasing assets efficiency and reducing overall carbon emissions (Yan et al. 2013).

In this chapter, relevant research on the topic of the built environment, Demand Response (DR) and optimisation algorithms for DR are critically reviewed, and the key results and advancements in the area are contextualised. Section 2 assesses the impact of buildings on the energy system while Section 3 introduces the concept of demand-side management and DR, assessing the advantages and disadvantages of automatic versus manual DR. Section 4 assesses how an energy management systems (EMS) can be used to implement demand response strategies. Section 4.1 examines the idea of home area network (HAN) or local area network (LAN) and how technological innovation. is changing the interaction between users and buildings. This part discusses the effect of technological advancements in developing interconnected appliances and communication protocols. It also focuses on the definition and characterisation of EMS in a smart-grid scenario. This section discloses several research gaps on the communication infrastructure between buildings and the power grid. In this part, an extensive analysis of optimisation algorithms for DR is presented. Section 5 analyses how advanced controllers can foster the transition to a lower-carbon economy, reducing the energy costs and facilitating the integration of renewable in the system. In Section 6, an overall contribution of buildings towards the full decarbonisation is analysed. The chapter concludes with Section 7 by identifying a path towards the decarbonisation of our society through advanced energy management systems.

## 2. Buildings as a Fundamental Asset for the Decarbonisation

Generally, the building stock can be divided into residential and commercial buildings. Census data or building surveys can be used to collect relevant information to characterise the building stock at the country level (Mata et al. 2014). In recent years, building energy certificates and other geographical information systems have enriched existing databases and increased data accuracy (Võsa et al. 2021). Moreover, some European and national projects have compiled available information for a country or group of countries or new methodologies to certify energy rating for buildings such as Active Building Research Programme (2013); ePANACEA (2020); Episcope EU (2013); U-CERT (2019).

The built environment accounts at least for 40% of the total electricity consumption (Pérez-Lombard et al. 2008). Seasonal peaks are caused by increased lighting, cooling or heating demands, and such profiles are also peaking wholesale electricity prices and reduced reliability due to tight generation reserve margins. Higher penetration of electric vehicles and heat pumps have caused an increased demand which is being modulated by RES and the smart grid rollout (Arteconi et al. 2013; Smith 2010). In these transitional circumstances, where the global target of 2050 is looming closer, the motivations of massively employing demand response programs using buildings have never been so compelling.

As illustrated in Figure 1, the European Union has a large and old building stock that requires retrofitting and upgrading. Despite a significant variation in the EU members' built environment, full decarbonisation would not be possible without a massive retrofitting plan across the EU. Furthermore, within the EU, there is a large variance in the energy consumption required to heat or cool the buildings. Figure 2 illustrates how more than half of the European countries have an average consumption per square meter above the average and far from NZEB or passive building standards.

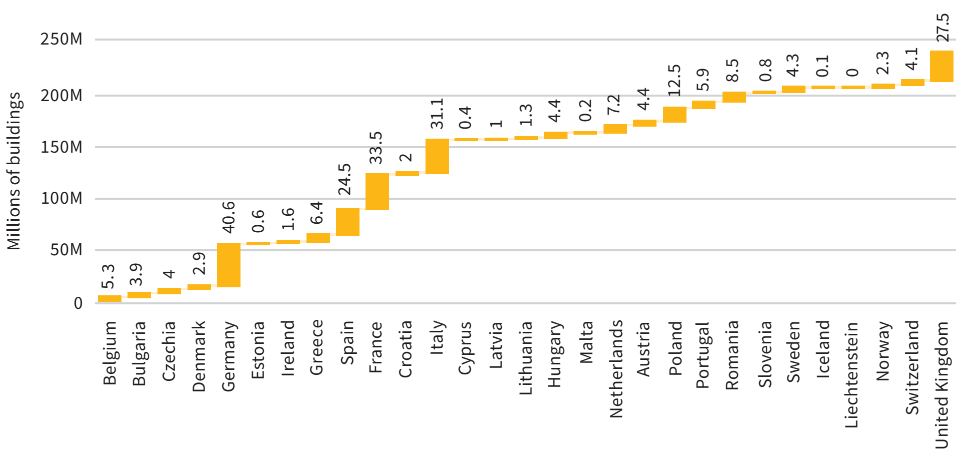


**Figure 1.** Building older than 15 years old of retrofit potential for Europe. Source: Graphic by author, adapted from Pallonetto et al. (2022).

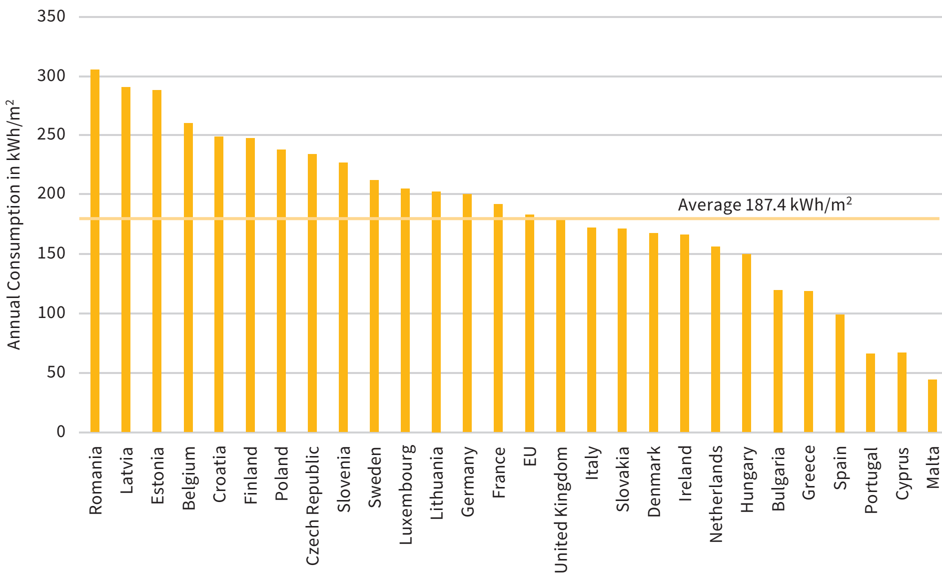


**Figure 2.** Average building consumption for square meter across Europe. Source: Graphic by author, data from Eurostat (2020).

Among low carbon technologies worth mentioning for the built environment, there is the heat pump. Heat pumps can reduce the energy consumption of the building and can be installed and used in tandem with renewable energy sources such as photovoltaic systems. Heat pumps deployment can also support the evolution of the power system and contribute to the high penetration of renewable sources through end-users participation in demand-response markets. Such a combination makes heat pumps more attractive. Such an advanced technology can meet the heat demand of the building while reducing carbon emissions by a factor of three (Boemer et al. 2011; Eriksen et al. 2005; Paterakis et al. 2017). From the power system perspective, innovations such as building home automation, smart grid rollout, diffusion of intelligent appliances and EMS integration are necessary prerequisites to boost the efficiency of the power system while increasing the RES penetration to meet the emissions target (European Commission 2010). These features will enable electricity end-users to modulate their electricity consumption by dynamically responding to fluctuations in the power generation caused by RES (Mohsenian-Rad et al. 2010b; Pedersen et al. 2017). End-users can manually or automatically alter their consumption patterns via home automation or EMS controllers in a smart built environment. Grid reliability and evolution in the regulations to enable DR in the electricity market are the primary reasons for the intense interest to develop intelligent EMS that can reduce energy costs and dynamically adapt to grid constraints (Conka et al. 2014; Pereira and da Silva 2017).

## 3. Demand-Side Measures towards the Full Decarbonisation of Our Society

DR is one of the Demand Side Measures (DSM) measures promoted as a mechanism to increase the percentage of renewable energies in the system (Albadi and El-Saadany 2008). It is 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" (Gils 2014, p. 1).

This measure is being implemented worldwide by various TSOs through the remuneration of DR aggregators in the electricity market. In some cases, the aggregators were the TSOs or a related entity. Aggregators can control the energy demand of residential and commercial buildings, representing 40% of the total primary energy consumption.

The widespread adoption of DR programs leads to a paradigm shift in how TSOs manage the grid. Such changes require a bi-directional communication link between buildings and operators occurring with the smart grid rollout (Silva et al. 2012).

### *3.1. DR Objective and Programs*

A DR signal by an aggregator or TSO, triggers the intentional reshape of the electricity demand profile. The variation can be measured as the level of instantaneous demand or total electricity consumption deferred. DR assets can dynamically change the electricity demand curve, providing peak shaving, frequency control, load shifting and forcing measures (Nolan and O'Malley 2015).

DR programs can be classified by financial schemes. DR aggregators can remunerate DR events to end-users with Incentive Based Programs (IBP) or Price Based Programs (PBP) (Aghamohamadi et al. 2018; Albadi and El-Saadany 2008). The difference between PBP and IBP is that in the latter one, end users get a financial benefit or a price reduction due to their affiliation to the scheme.

Among IBP programs, there are market-centred schemes. Market-centred DR is for medium size users or demand response aggregators. The schemer requires market access and equipment to connect to the TSOs communication infrastructure. In these cases, the financial benefit for the user is correlated with the flexibility provided. As described in Qdr (2006), the Market-centred DR programs include the following categories:

1. Emergency DR. These incentives are proportional to load reduction during emergency reserve shortfalls events. When utilised, a demand reduction signal is sent to all large users enrolled.
2. Capacity Market Program. This program is for users who can precisely estimate a determined load reduction when system contingencies happen. The users involved have a day-ahead notice, and if they do not answer, they are penalised. The payment is based on the declared peak load reduction achievable by the asset.
3. Ancillary Service Program. Operating reserve is bid in terms of curtailment capacity. If the bid is accepted after the measure is implemented, customers are paid the spot market price.
4. Demand Bidding (also called Buyback). In this program, consumers bid the load reduction in the wholesale market, where a bid is accepted if it is less than the market price.

In the PBP, the electricity price is directly correlated with the market price (Albadi and El-Saadany 2008). The objective of these schemes is to flatten the electricity profile to lower peak demand. Typical PBPs may encompass some or all of the following features:

1. Time of Use Tariffs (TOU) tariffs where there are two or more time blocks such as night, peak and off-peak electricity prices.
2. Critical Peak Price (CPP) is often utilised during high contingencies or higher electricity usage for a few days or hours or months.
3. Extreme Day Price (EDP) is a specific subset of the CPP program. In this case, the electricity tariff increases during a specific time of the day. During the rest of the day, a flat tariff is used. In this case, the DR event is set for one or more days.
4. Real Time Price (RTP), where the electricity tariff is synchronised to the market time resolution, which typically changes every hour.

#### 3.1.1. Lessons Learnt from DR Pilot Programs

The development and testing of demand response programs have shown benefits and challenges yet to be addressed. China started piloting DR programs in 1990, but energy shortages during 2003–2008 reinforced the implementation of DR pilot projects. Since then, the established DR programs were based on TOU rates, Curtailable/Interruptible loads, the use of off-peak storage devices such as heat storage boilers and ice-storage air conditioners. These programs highlighted challenges related to human behaviour, absence of competitive electricity markets, customers unawareness of prices and absence of recovery mechanism for users and utility investments (Tahir et al. 2020). It should be noted that shifting from manual load-shifting in response to network stress at predictable times of day to dynamic programs price- or quantity-based requires additional Information and Communication Technology (ICT) support. The uncertainties associated with human behaviour are the main challenges in the implementation of these programs. The RealValue project included a test bed of more than 800 households across three different EU nations (Darby et al. 2018). Customers who were used to paying for a service from the power system became prosumers through distributed generation, storage and demand response. As a consequence, the connections across the resources dynamically managed by users and the established actors such as utilities required innovative ideas and additional user and ICT support to provide a fraction of potential theoretical flexibility estimated (Darby 2020).

Table 1 summarises and compares the experience of different demand response trials deployed worldwide and highlights different types of barriers, benefits and technology enablers (Lu et al. 2020). The table shows how critical is the use and identification of shiftable/curtailable loads coupled with storage to enable the deployment of DR programs. Switching to automated direct load control is complex and requires a reliable and trustworthy IT infrastructure and data exchange mechanisms. Additional, similar works highlight the importance of user acceptance and how occupants behaviour is the primary barrier to the success of these programs (Anaya and Pollitt 2021).

**Table 1.** Demand response measures and limitations Legend: ✓ Support it, (✓) Partially supported.

| Type of Measure | Distributed Generation | Shiftable/Curtailable Load | Storage | Complexity | Signal Type | Signal Volatility | Privacy Risk | Price Risk | Human Behaviour Uncertainty Risk | Notes |
|---|---|---|---|---|---|---|---|---|---|---|
| TOU pricing | (✓) | ✓ | ✓ | Low | Price | Static | Low | Low | High | Distributed generation can support it if is controllable or synchronise with high prices periods |
| Dynamic pricing | (✓) | ✓ | ✓ | High | Price | Dynamic | Medium | High | High | It requires a complex IT infrastructure, high risk |
| Fixed load capping | ✓ | ✓ | ✓ | Low | Volume | Static | Low | None | Low | If hardware controlled is simple to deploy |
| Dynamic load capping | ✓ | ✓ | ✓ | High | Volume | Dynamic | Low | None | High | Can be complex and the signal can be hacked |
| Direct load control | (✓) | ✓ | ✓ | High | Control | Predefined | High | None | Low | Complex and high privacy risk, high potential, it requires detailed data |
| Critical Peak Price | (✓) | ✓ | ✓ | Low | Price | Static | Low | None | Low | Simple but limited benefits, depends on occupant behaviour |
| Extreme Day Price | (✓) | ✓ | ✓ | Low | Price | Static | Low | None | Low | Simple but limited benefits, depends on occupant behaviour |

Source: Table by author, data from Lu et al. (2020).

### 3.1.2. Summary of DR Benefits

Figure 3 shows the correlation between stakeholders and DR schemes. The benefit for end-users is typically a reduction in the electricity bill or financial remuneration. On the other side, operators such as TSOs can increase the efficiency of the market, reducing the volatility and the use of peak generators (Albadi and El-Saadany 2008). Moreover, from a broad market perspective, DR programs can reduce the electricity price increasing the capacity of the system (Aghamohamadi et al. 2018; Braithwait and Eakin 2002). Such benefits also defer grid reinforcement, reducing the running costs and improving the market efficiency (Paterakis et al. 2017;

Qdr 2006). The overall reliability of the grid increases thanks to the use of DR schemes because the dynamic demand curtailment reduces the outage and transmission strains risks. Furthermore, reducing the contribution of peak generators and reducing the curtailment operation caused by a surplus of RES generation (EDP Consortium 2016; Hamidi et al. 2009) reduces the carbon emission of the system.

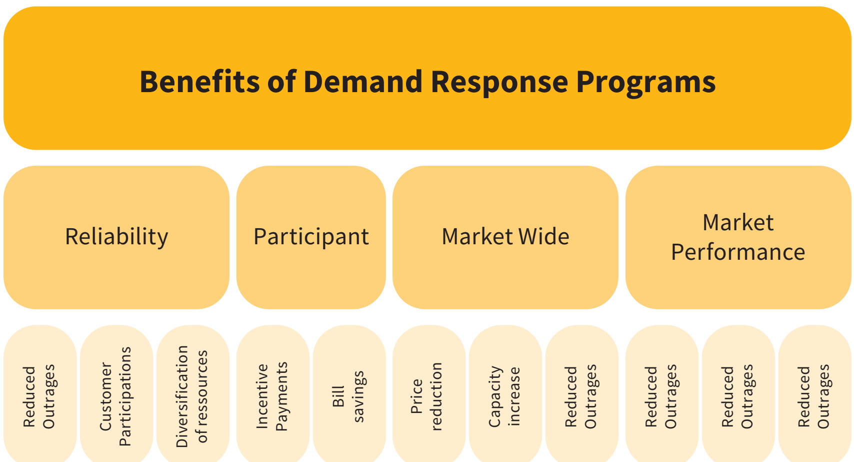


**Figure 3.** Overview of demand response schemes for different stakeholders and from the market perspective. Source: Graphic by author, data from Qdr (2006).

3.1.3. DR Operational Challenges

DR programs can also be classified by the level of automation. Manual DR measures rely on human actions to reduce or increase loads or alter the demand profile. For semi-automated DR measures, the user controls a digital system to trigger a demand response action. When using automated DR strategies, an external signal operates a programmed method and consequently does no human intervention is required. However, in this case, users must always be able to override the system (Piette et al. 2006; Rothleder and Loutan 2017).

Within the many challenges to DR schemes, a key factor is the availability of reliable resources. In some cases the system cannot respond to the DR signal; therefore capturing the available flexibility and capacity of the resources using flexibility metrics and metering equipment is a fundamental requirement to implement such programs. Additionally, the stochastic consumer behaviour could reduce the benefit of DR schemes if not considered. The high variability of the DR resources could be smoothed by aggregation. In fact, in Nolan and O'Malley (2015), when stochastic behaviour is accounted for, the aggregation of few thousand households represents a stable DR asset. Hence, the domestic sector electricity demand has the potential to provide services such as spinning reserves, frequency controls and Short Term Operating Reserve (STOR). In the building sector, STOR can be exploited using automation or increasing the energy awareness of the occupants.

## 4. The Role of Advanced Energy Management Systems

The smart grid is the next generation of the power system that enables a two-way communication channel from the end-user to the TSO, with the objective of monitoring and controlling end-user electricity demand in a power system with high RES penetration (Farhangi 2010).

The employment of smart grid technologies will support European countries to reach their $CO_2$ emissions reduction target and renewable generation increase (European Union 2017). In particular, the EU climate-neutral goal by 2050 is ambitious; increase penetration of RES to meet annual maximum generation. To reach the target, RES generators with their variable and uncertain electricity supply have been connected to the grid, thus increasing the operational challenges for system operators. The increasing wind and solar penetration impose significant technical difficulties such as large frequency variations, which require strict voltage control. These requirements have led to the utilisation of the smart grid for automatic DR projects in commercial, industrial and residential buildings (O'Sullivan et al. 2014).

Automatic DR control of heating, cooling and light systems requires the presence of one or more interconnected sensors and one or more corresponding controller devices. The sensors are usually connected to the cloud with a HAN or LAN. A DR controller device, called EMS, can read the sensor data and reshape the energy demand of the building according to a price or an interrupt signal from a TSO. Some of the systems are defined as intelligent. In this context, an intelligent appliance, algorithm or control indicates a system that uses various artificial intelligence computing approaches like neural networks, Bayesian network or optimisation techniques (Antsaklis and Passino 1993).

### *4.1. HAN/LAN, Definition and Developments*

A HAN is a dedicated data network infrastructure within buildings built for data transfer and device communication. In the late 1990s, HANs became the emerging gateway to connect devices to the Internet. The availability of Internet access in buildings has boosted the diffusion of HAN systems since the early 2000s (Clements et al. 2011).

The de facto standard for the first period of HAN development was the Ethernet and 802.11 Wi-Fi standard (Huq and Islam 2010).

In the coming decades, the rate of diffusion of HANs across buildings is set to increase exponentially. In fact, the total number of connected devices is expected to reach 50 billion by 2030 (Ahmed et al. 2016). A good percentage of such devices will exchange sensor data in real-time and require low bandwidth, meaning that there is less stress on the overall network infrastructure. The phenomenon of connecting any device to the Internet is covered by the all-encompassing phrase the IoT (Ahmed et al. 2016; Atzori et al. 2010).

The use IoT devices connected to the HAN to perform actions that could reduce carbon emissions or peak power consumption has different requirements than the standard use of HAN (Darby 2006). In fact, only a small percentage of HAN connected devices can be classified as smart-grid enabled.

A smart-grid enabled device provides a two-way communication system to utility companies and could be remotely controlled to increase the overall efficiency of the power grid (Balakrishnan 2012; Bazydło and Wermiński 2018). It is necessary with these devices to have a stable link and low bandwidth allocation (Gungor et al. 2011). The devices affected by these changes include thermostats, HVAC systems, major appliances, home automation systems, EMS, lighting, gas meters, water meters, and electricity meters.

In recent years, the increased installation of local renewable energy systems such as PV and solar panels has raised additional challenges for the HAN research community (Liserre et al. 2010). Controlling in real time a RES at the building level with smart-grid enabled devices increases the complexity of the problem.

Additionally, inhibitors to the adoption of HAN as part of the smart-grid infrastructure are categorised in Eustis et al. (2007):

- Energy pricing that provides financial benefits to control energy use more efficiently and enable consumers to reduce their costs.
- Open, flexible, secure and efficient communication protocol established and accessible.
- Compliance of the services with consumer choice and privacy; wherein the consumer, ultimately, is the decision-maker.

Despite a general awareness that an interconnected system can enable utilities to more effectively balance energy demands and integrate with renewable energies systems, the above challenges raise additional questions about the architecture of HAN, different communication protocols (Huq and Islam 2010) and the strategy and algorithms that can be implemented by an EMS connected to HANs.

### *4.2. The Architecture of HAN in a Smart Grid Scenario*

As previously noted, there is a trade-off between keeping the HAN architecture simple and efficient versus safeguarding the privacy and security of the users. In a smart grid scenario, it is essential to guarantee the safety of the network against cyberattacks that could compromise the entire power grid.

The interconnection between the various devices and the HAN should consider the bandwidth allocation and the potential vulnerabilities that each device could expose. As illustrated in Figure 4, installing a Home Energy Gateway or EMS that can separate the smart-grid-enabled devices from other devices could increase the security of the system. This architecture design utilises a connected gateway as a demilitarised zone, enhancing the security of the data transfer and controls. The presence of an EMS or smart gateway is also mentioned in Clements et al. (2011), where they draw a clear distinction between the two different layouts.

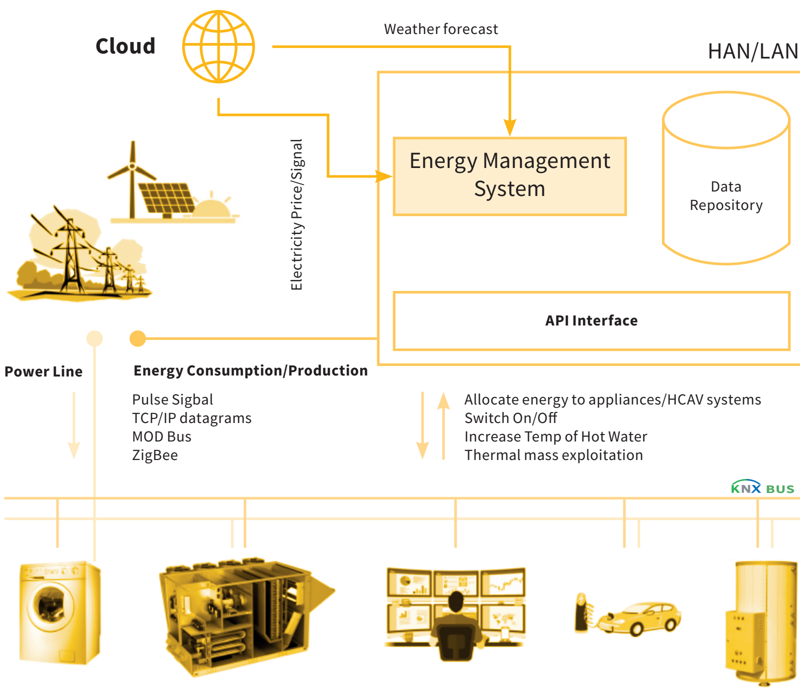


**Figure 4.** Overview of connected devices and local renewable energies systems to a HAN infrastructure via a home energy gateway devices. Source: Adapted from Pallonetto et al. (2021).

The layout in Figure 5 assumes the presence of a dedicated network with the TSO connected to the appliances. In this example, the home gateway is a proprietary stand-alone device. This layout keeps the data transmission physically separated through a virtual private network. The main advantage of this configuration is the increased data security and reliability. The dedicated network can also provide a minimum band allocation to ensure a sufficient data throughput. The main disadvantage of this layout is the high infrastructural cost. Hybrid designs require less network infrastructure because the appliances are connected to the utility using a shared network such as the Internet. In this scenario, the band allocation may represent a challenge, and several security risks have been identified (Huq and Islam 2010).

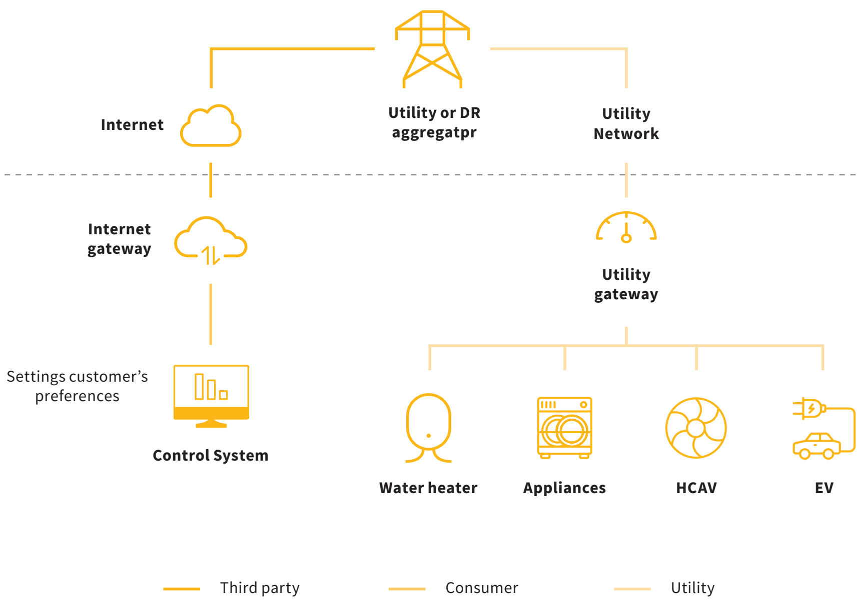


**Figure 5.** Overview of HAN infrastructure on a dedicated network. Source: Graphic by author, data from Pedreiras et al. (2002).

In contrast, in rural areas which lack sufficient network infrastructure, the layout in Figure 6 represents the only viable solution for data exchange between the HAN and TSO. Different communication protocols can also affect the layout of the interconnection between appliances and EMS or between the EMS and TSO. The following section examines the required band allocation, common communication protocols and their characteristics.

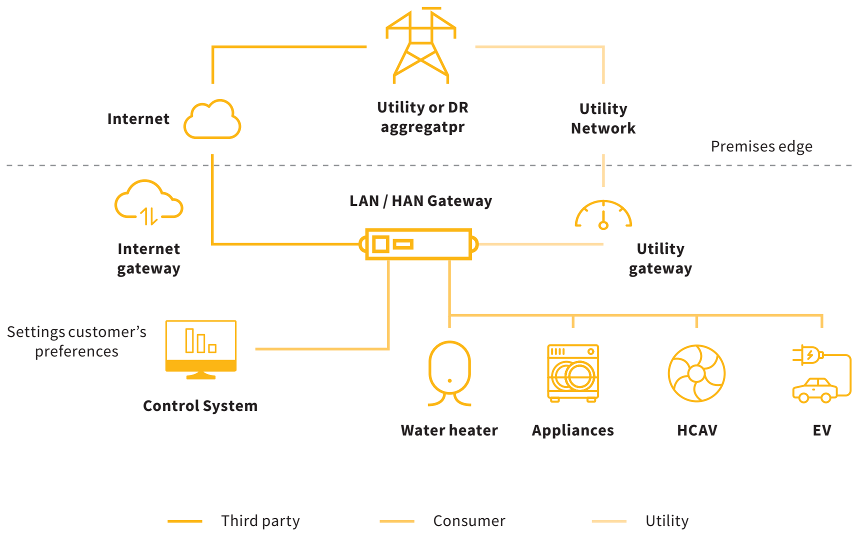


**Figure 6.** Overview of HAN infrastructure on a shared network. Source: Graphic by author, data from Pedreiras et al. (2002).

### *4.3. Communication Protocols for HAN*

Communication protocols are used for data transmission between sensors and the HAN. During the last decade, various attempts at protocol standardisation have been made, each with limited success (Eustis et al. 2007). Different protocols can be categorised into three broad categories: new wires, no new wires and wireless, as illustrated in Table 2.

**Table 2.** Overview of different commercial communication protocols and evaluation of their suitability for smart grid applications.

| Technology | Category | Frequency | Data Rate | Range | Power Consumption | Application |
|---|---|---|---|---|---|---|
| Bluetooth | wireless | 2.4 GHz | 25 MB/s | 10 m | Low | Smart health devices, close range communication |
| DASH7 | wireless | 433 MHz | up to 200 KB/s | 1000 m wireless | Low | Smart cities, smart buildings, smart transport, smart health |
| ZigBee | wireless | 2.4 GHz, 0.915 GHz, 868 MHz | 250 KB/s | up to 100 m wireless | Low | Smart homes, smart health |
| WiFi | wireless | 2.4 GHz or 5 GHz | 6.75 Gb/s | up to 1 km wireless | Medium | Smart homes, smart health, smart buildings |
| 3G | wireless | 0.85 GHz | 24.8 Mb/s | 1–8 km | High | Smart cities, smart transport, smart industries, smart grid |
| 4G | wireless | up to 2.5 GHz | 800 Mb/s | 1–10 km | High | Smart homes, smart industry, smart grid |
| Ethernet | wired | up to 100 GHz | 100 Gb/s | up to 500 m | Medium | Smart homes, smart industry, smart grid |
| Power-line | no new wires | up to 250 MHz | 1.3 Gb/s | 300 m | Low | Smart homes, broadband, smart grid |

Source: Adapted from Ahmed et al. (2016).

In the new wires category, the de facto standard is ethernet (Pedreiras et al. 2002). The ethernet protocol is widely established and reliable. This protocol allows for greater integration with modern security mechanisms and procedures. The data transfer performance, from 10 Mb/s to more than 100 Gb/s, is sufficient for the throughput required. The main disadvantage of this technology is that the cable cannot be shared among different devices, so it requires a star design with one link for each device. Consequently, it is not extensively used in residential but mostly in commercial buildings (Ahmed et al. 2016).

In the wireless category, there are different protocols such as Bluetooth, ZigBee, Wifi and DASH7. A shared feature between the ZigBee, DASH7 and Bluetooth protocols are low energy consumption. However, Bluetooth has a lower communication range compared to ZigBee and DASH7 (Hayajneh et al. 2014). This limited range makes it suitable for smart health devices connected with phones or accessories paired to a central device. Although the hardware complexity of Bluetooth is lower than ZigBee or DASH7, it is not reliable for smart buildings or mobile devices that require longer ranges. Comparing DASH7 and ZigBee, the main differential is the trade-off between range and data rate transmission. ZigBee has a higher data transmission rate while it has a lower distance range.

In the no new wire category, one of the most common protocols is the powerline. Powerline protocols allow for communication via electricity sockets (Pavlidou et al. 2003). The disadvantages of this protocol are the limited distance range and the interference in the power supply, which can lead to fluctuations in the quality of the communication.

*4.4. Overview of EMS Features and Objectives*

During the last few years, the research and development on EMS have increased (Beaudin and Zareipour 2015). An EMS can be defined as a group of technologies used to manage the energy profile of a building, reducing the overall energy expenditure. Among these technologies, it is possible to include sensors, smart thermostats, electronic displays and smartphone apps that increase energy consumption awareness and offer remote or automatic control.

As suggested by Aman et al. (2013), an EMS should exhibit the following characteristics:

1. Monitor the energy consumption. The system provides energy consumption information at various time resolutions.
2. Disaggregation of the energy consumption. End-users can benefit from information about the real-time impact of appliances over a period of time.
3. Data availability and accessibility. The system makes the information available to the end-user via an interface. The interface is deployed as a physical device or through a web or mobile portal.
4. Appliances control. The EMS should provide programmable, remote and automatic control of devices
5. Data Integration. Integration of different types of information such as indoor temperature, humidity, acoustics, and light; and consumer historical data.
6. Ensuring cyber-security and data privacy. The system must restrict unauthorised access to third parties.
7. Intelligent controls and insights of data analytics. A requirement is to trigger smart actions that optimise energy consumption, maintaining consumer comfort.

As Paradiso et al. (2011) highlighted, EMS should perform intelligent actions that balance energy consumption and comfort. Specific algorithm techniques such as machine learning, data analysis or predictive control can be used. From the power system perspective, an EMS must be used more extensively for DR or to draw up a house profile o target energy improvement measures.

In Table 3, several studies have been examined based on some of features suggested by Aman et al. (2013) and Paradiso et al. (2011). All the EMSs have energy monitoring capabilities, and five have data disaggregation capabilities. The feature absent in the studies was the possibility to control load using intelligent algorithms.

In general, consumers are not aware of how an electrical system inside the building works, and, due to a low electricity price, they are not motivated to use their time to make energy-related decisions (Bartram et al. 2010). Therefore, to reach the objective of the EMS, the algorithm must perform intelligent actions to balance consumer comfort and energy consumption. Moreover, in a DR scenario, a smart EMS can adjust the power consumption to reduce the cost by exploiting the price signals, such as RTP, CPP or TOU. The action reduces the responsibility of the consumer to control and manipulate all their appliances all the time, while also providing flexibility to the power system for the integration of RES. The load controllability and the use of intelligent algorithms represent a research gap in the current literature that should be addressed.

**Table 3.** Features and characteristics of EMS technologies.

| Evaluation Criteria | Metering and Analytics | Dis-Aggregation | Availability | Interoperability | Scalability | Actuators | Cybersecurity | Smart Controls and Intelligence |
|---|---|---|---|---|---|---|---|---|
| Totu (Totu et al. 2013) | Yes | No | Not discussed | Yes for large scale infrastructures | Yes | Yes | No | Yes advanced algorithms |
| PERSON (Yang and Li 2010) | Yes (API) | Yes | Decentralised at user premise; no web or mobile interface | Not discussed | High scalability Low cost and low power consumption | Manual remote control of the switches and dimmers in the home. | No | Context-aware intelligent algorithm |
| Bess (Mahfuz-Ur-Rahman et al. 2021) | Yes | No | Not available | Yes | Not available | Yes | No | Yes, smart AI control |
| WattDepot (Brewer and Johnson 2010) | Yes | No | Web based interface | No | Open source; freely available not scalable as it is | No | Limited | No |
| Viridiskope (Kim et al. 2009) | Yes (discontinued) | Yes | Not discussed | No API present | Requires indirect sensors; no inline installation requires | No | No | No |
| Mobile feedback (Weiss et al. 2009) | Yes | Yes | Interactive; readily available feedback on smartphone | Not discussed | Low scalability because of the mobile app | No | No | No |
| DEHEMS (Liu et al. 2013) | Yes | Yes | Web based UI, real-time display unit | No API but possibility to have integrated sensors, electric supply, gas supply line | Medium, it requires third party sensors | No | No | No |
| EnergyWiz (Petkov and Foth 2011) | Yes | No | Mobile phone app | Integrated historical usage and user info from peers | Requires mobile app installation | No | No | No |
| Nobel (Karnouskos 2011) | Yes | Yes | Mobile phone app | No | Low, requires mobile app installation and sensor integration not present | No | No | Yes, smart algorithm but requires human interaction |
| Simapi (Pallonetto et al. 2021) | Yes | No | Web and mobile app | API | Yes, high scalability | Yes | No | Yes |
| Alis (Rodgers and Bartram 2010) | Yes | No | Web, smart phone app, touch panel | Integrated API, based on community usage | No, requires extensive installation; less affordable | Yes (limited) | No | No |

Source: Adapted from Aman et al. (2013).

*4.5. EMS in Smart and Active Buildings*

As illustrated in Figure 7, one of the key features of the smart grid is to enhance the communication capabilities between building systems and the power grid. Such communication includes a network infrastructure inside buildings that could monitor and control the electric systems connected to the HAN.

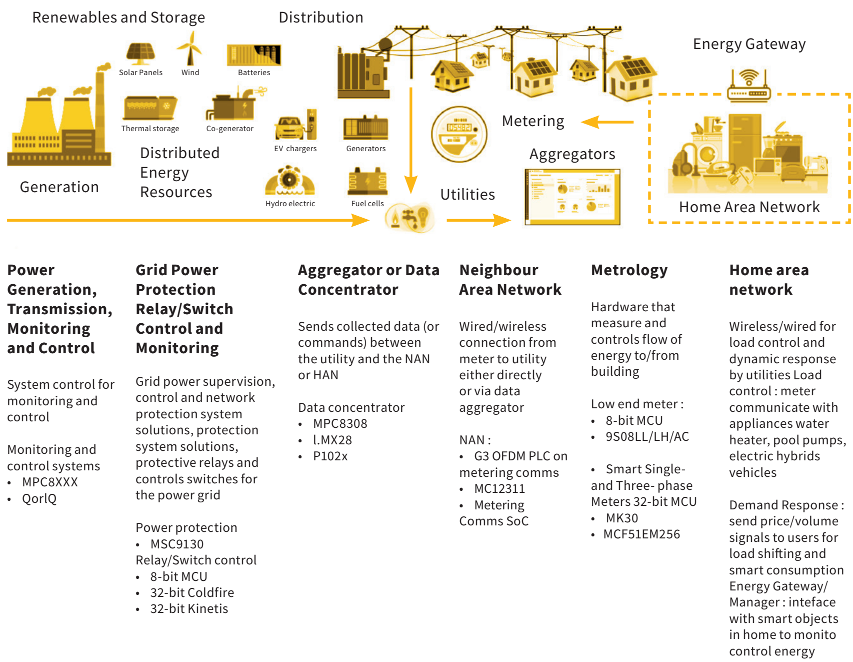


**Figure 7.** Example of a HAN/LAN and EMS communication in a smart grid context. Source: Adapted from Balakrishnan (2012).

Alam et al. (2012) define a smart dwelling as the end node of the smart grid that provides services in ambient intelligence, remote home control or home automation. Furthermore, each dwelling or node of the smart grid has the possibility to broadcast information about its electricity consumption profile and status. In a smart house, the EMS adapts the house energy consumption to the overall grid requirements without affecting the comfort of the occupants. However, to provide flexibility to the grid and reduce carbon emissions, buildings require communication capabilities (smart buildings) and advanced energy features. Therefore, in the last few years, researchers have pushed for a standardisation effort to formally define and categorise buildings with the capability of being integrated into the power system as active buildings. An active building is a building that can generate, store and modulate energy to adapt to their own demand or to the needs of the local grid (Fosas et al. 2021). The massive deployment of EMS in active and smart buildings could boost the decarbonisation both at the end-user and system level.

## 5. Control Algorithms for Implementing Demand Response in EMS

An EMS is defined as a system that can access information on energy consumption and generation at the building level and can implement DR measures to control heating and cooling systems, appliances or other devices connected to optimise the power usage and respond to grid signals. As illustrated in Pallonetto et al. (2020), the EMS in a DR scheme aims to different objectives:

- Reducing the overall energy consumption by increasing awareness providing data analytics and decomposition of energy use. Additionally, the EMS can control systems and appliances i.e., operating an HP at maximum COP, or optimising the inverter efficiency in a PV system with an MPPT algorithm.
- Shifting energy demand. Reducing peak consumption by exploiting TES or electric storage is a common DR measure. A signal can also trigger the measure and so that the control can shift the load to off-peak hours.
- Forcing loads. Forcing the use of high-load systems can be facilitated by storage and can be triggered by a DR signal during high penetration of RES in the system or locally generated electricity/energy.

The consumption reduction method is implementable in many different ways, whereas, the implementations for shifting and forcing is challenging. The main issue is the lack of standard flexibility metrics and the slow adoption of domotics systems. Additionally, time-dependent electricity tariffs provided by utilities or the market are not necessarily aligned to end-user demand profiles, hence storage is required to implement DR measures (Gottwalt et al. 2017).

Encoding a smart algorithm in the EMS can potentially minimise the overall energy consumption and cost while ensuring the expected service level and thermal comfort.

### *Optimisation Problems and Solution Methods*

The use of control algorithms for building management systems is a recurrent theme in the literature. (Gatsis and Giannakis 2011b; Mariano-Hernández et al. 2021; McKenna and Keane 2016; Yoon et al. 2014). The control algorithms are characterised by a specific objective function and a set of constraints. In a DR program, the objective function aims to cost or energy minimisation or welfare maximisation. Welfare is defined as the utility profit minus the generation cost and system losses (Dong et al. 2012).

As described in Pallonetto et al. (2020), Table 4 summarised an extensive literature on DR optimisation algorithms. Optimisation methods are reported on the columns while rows indicate the objective functions. The control algorithms assessed in this table have been tested to enable buildings to participate in DR programs. Nevertheless, other perspectives for intelligent EMS can include the market, the distribution grid and the buildings. Thus, 4 of the 38 papers assessed (3L, 7U, 20W, 36B) embed multiple optimisation strategies, such as mixed linear integer, continuous integer and quadratic programming, to reduce power flow overloads caused by variable renewable energy generation or load variations. In 7U and 36B, the EMS use electric storage to provide flexibility to the power system. The paper 20W illustrates a distributed algorithm with a minimal communication overhead. The system force loading in proportion to high uncertainty loads or generation such as renewable. The paper 3L include specialised constraints for balancing the distribution network. These two papers, despite the different approaches, top-down and bottom-up, respectively, aim to maximise the welfare in a smart grid system. One of the limitations of the control systems analysed is that none of these papers provides a comparable optimal solution.

**Table 4.** Optimisation problems and solution methods in for DR in the literature (see Table 5 for legend).

| Objective Function \ Optimisation Method | Linear Integer Programming | Mixed Integer Programming | Mixed Integer Linear Programming | Mixed Integer Non-Linear Programming | Mixed Discrete/Continuous Programming | Convex Optimisation Problem | Non Convex Optimisation Problem | Non Linear Programming | Heuristics | Particle Swarm Optimisation | Binary Partical Swarm Optimisation | Stochastic Optimisation | Markov Decision Problem | Robust Optimisation | Other Methods | Game Theory |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Min. Cost | 23*U*<br>38*U* | 1*U* | 22*B* | 24*B* | | 36*U* | 13*Y* | | 21*D*<br>28*E*<br>35*U* | 14*U*<br>13*B* | 14*U* | 15*F* | | | 31*T*<br>32*T*<br>33*T* | 28*A* |
| Min. Consumption | 29*Q* | 7*U* | 22*T*<br>9*B* | 8*B* | | 19*U*<br>23*U* | 26*U* | | | 16*B* | | 11*U* | 26*U* | 34*T* | 23*U* | |
| Max. Welfare | | | | 25*B* | 3*L* | 2*U*<br>18*U* | | 10*M* | | | | | | | 8*E*<br>8*O* | 24*O*<br>6*U* |
| Min. Cost and Min. Consumption | | 30*T* | 27*B* | | | | | | 39U | | | | | | 4*U*<br>17*B* | 5*U* |
| Max. Welfare Min. Consumption | | | | | 20*W* | | | | | | | | | 12*A*<br>37*U* | | |

Source: Reused from Pallonetto et al. (2020).

**Table 5.** Legend for Table 4.

| Position | Reference | Reference | Algorithm |
|---|---|---|---|
| 1 | Behrangrad et al. (2010) | A | Interior point method |
| 2 | Cao et al. (2012) | B | Commercial software |
| 3 | Cecati et al. (2011) | C | Multiple-looping algorithm |
| 4 | Chang et al. (2012) | D | Evolutionary algorithm |
| 5 | Chen et al. (2011) | E | Greedy search algorithm |
| 6 | Chen et al. (2012) | F | Lyapunov optimisation technique |
| 7 | Choi et al. (2011) | G | Relaxed convex programming |
| 8 | Cui et al. (2012) | H | Simulated annealing |
| 9 | Zhang et al. (2011) | I | Lagrange–Newton method |
| 10 | Doostizadeh and Ghasemi (2012) | L | Sequential Quadratic Programming |
| 11 | Ferreira et al. (2012) | M | Benders decomposition |
| 12 | Gatsis and Giannakis (2011a) | N | Q-Learning algorithm |
| 13 | Gatsis and Giannakis (2011b) | O | Filling method |
| 14 | Gudi et al. (2012) | P | Co-Evolutionary PSO algorithm |
| 15 | Guo et al. (2012) | Q | Branch and bound method |
| 16 | Jiang and Fei (2011) | R | Parallel distribution computation |
| 17 | Hedegaard et al. (2017) | S | Signaled particle swarm optimisation |
| 18 | Alibabaei et al. (2016) | T | MPC (Model Predictive Control) |
| 19 | Joe-Wong et al. (2012) | U | Author's software |
| 20 | Kallitsis et al. (2012) | V | Distributed subgradient algorithm |
| 21 | Logenthiran et al. (2012) | W | Iterative decentralised algorithm |
| 22 | Mohsenian-Rad et al. (2010a) | Y | Lagrangian dual algorithm |
| 23 | Molderink et al. (2009) | | |
| 24 | Soares et al. (2011) | | |
| 25 | Sortomme and El-Sharkawi (2012) | | |
| 26 | Totu et al. (2013) | | |
| 27 | Wang et al. (2012) | | |
| 28 | Xiao et al. (2010) | | |

**Table 5.** *Cont.*

| Position | Reference | Reference | Algorithm |
|---|---|---|---|
| 29 | Zhu et al. (2012) | | |
| 30 | Yoon et al. (2014) | | |
| 31 | Ma et al. (2011) | | |
| 32 | Cole et al. (2014) | | |
| 33 | Bianchini et al. (2016) | | |
| 34 | Kircher and Zhang (2015) | | |
| 35 | Schibuola et al. (2015) | | |
| 36 | Knudsen and Petersen (2016) | | |
| 37 | Park et al. (2017) | | |
| 38 | Alimohammadisagvand et al. (2016) | | |
| 39 | Pallonetto et al. (2019) | | |

Furthermore, the analysis elicits a trade-off between optimisation at a 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 two-way communication to aggregators or TSOs.

This double aim can be reached if the optimisation algorithm objective function minimises both cost and consumption. As also demonstrated (Cole et al. 2014; Hedegaard et al. 2017) (32T, 17T), in the case of merely cost minimisation, the energy consumption and associated emissions can increase.

As illustrated in Figure 9, the majority of the optimisation algorithms which were analysed have a single objective function that minimises costs. Nevertheless, various studies used a double objective function (4U, 5U, 27B, 30T). In this category, different techniques were utilised such as heuristics, analytical solutions and game theory. Only the heuristic controller (30T) 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.

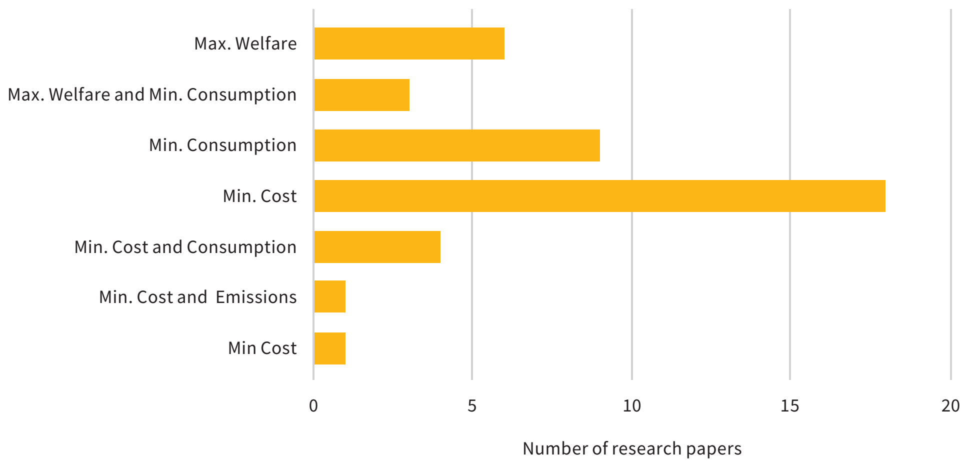


**Figure 8.** Classification of the most common algorithm objective functions in the literature. Source: Graphic by author, data from Pallonetto et al. (2020).

Two works (4U, 5U) used a cluster of residential buildings (10 and 60, respectively) to assess the results of the algorithm. When tested on the test load profiles, 5U showed a demand reduction of 13.5% and cost savings of 3.6%, while 4U used a randomly generated problem, and the approach cannot be compared with equivalent works. The remaining two works (27B, 30T) utilised a model of a single building to assess the benefits of the double objective function algorithm. Wang et al. (2012) (27B) reached an overall cost savings of 9% and a load reduction of 6%.

Although these results were significant, the MPC approach outperformed the others. Among the literature examined which aimed to minimise the cost of the energy expenditure, the MPC systems (17T, 18T, 31T, 32T, 33T, 38U) reached savings up to 28%. Above all, the papers analysed used a white box model such as EnergyPlus. The literature includes both residential (17T, 18T, 31T, 32T, 38U) and commercial buildings (33T). The predictive models used for the forecast were linear models (38U), autoregressive statistical models (31T, 33T), reduced-order model (32T) or grey-box model (17T) while other used machine learning algorithms (39U). It should be also noted that none of the MPC systems used a white box as a predictive model but as a testbed.

In Knudsen and Petersen (2016) (38U), the authors developed an MPC with two objective functions (emissions and electricity price). The MPC was a state-space model which is similar to a reduced-order model (Dehkordi and Candanedo 2016). Such an EMS reduced the carbon footprint by 5 to 10 per cent.

Moreover, as illustrated in Figure 10, of all the works analysed, the majority of them was tested on a single residential building. However, none of the papers mentioned any calibration of the building model despite, as illustrated in Figure 8, the majority of the works used a BES model for testing.

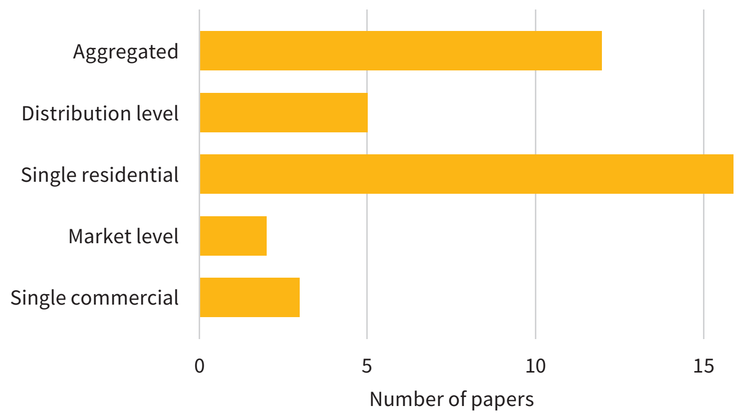


**Figure 9.** Classification of testing methodology in the literature. Source: Graphic by author, data from Pallonetto et al. (2020).

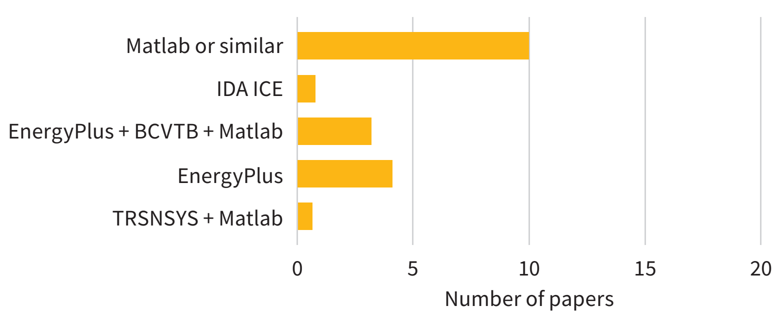


**Figure 10.** Software platform utilised for control algorithm. Source: Graphic by author, data from Pallonetto et al. (2020).

Figure 11 shows that the RTP price was used in the majority of the assessments. The RTP price is proportional to the market price but requires a fully automated EMS and could incur in low acceptance among end-users. Moreover, using RTP price, the assessment of control algorithms is more complex from considering the electricity profile perspective.

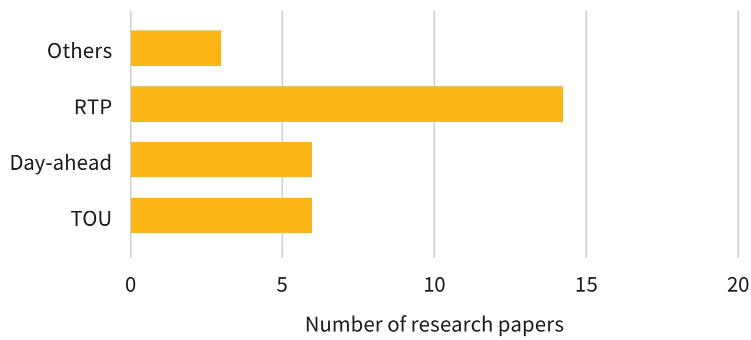


**Figure 11.** Most common electricity price schemes for algorithm testing. Source: Graphic by author, data from Pallonetto et al. (2020).

## 6. A Path towards the Full Decarbonisation

In the past decade, the distinction between energy efficiency measures and DR has become less stratified (Goldman et al. 2010). High penetration of variable RES generation and storage has widened the use of DR beyond peak hours to be applicable throughout the day (Calvillo et al. 2017; Jiang and Low 2011). From an end-user perspective, energy efficiency measures have been enhanced by controlling technologies in buildings (EDP Consortium 2016) that allow the exploitation of thermal storage and local renewable energy system as dynamic controllable load.

The effectiveness of full decarbonisation of our building stock using advanced energy management systems is dependable on energy efficiency regulations and policies that generally target the national building stock from an isolated (or single) building point of view. The building retrofit measures are designed to reduce energy consumption by deploying energy-efficient and low-carbon building technologies as illustrated by the IEA (2013) roadmap towards 2050. These methodologies do not take into account that the building, as a responsive leaf element of a smart grid system, could dynamically provide flexibility, both at distribution and transmission level, exploiting thermal and electric storage as well as deferrable loads within end-user thermal comfort constraints. Therefore, there is a need to deploy a more holistic approach to designing energy efficiency regulations that recognise the building as a dynamic energy asset. The implications of evaluating deferrable loads, storage and end-user comfort and constraints, can provide a comprehensive assessment of the impact of these new technologies and the influence of human behaviour on the energy profiles of residential buildings.

Additionally, the assessment of a DR resource must be calculated based on the quantity of energy that could be altered compared to a baseline use. The identification of a baseline and the quantification of the flexibility as a deviation from a baseline consumption are still open challenges in the research community (Jazaeri et al. 2016; Mathieu et al. 2011; Wijaya et al. 2014). The temporal quantification of available DR resources is a critical research need to enable DR at a household level (Gils 2014; Herter et al. 2007; Hurtado et al. 2017; McKenna and Keane 2016). The use of high-resolution simulation models defined as digital twins for commercial and residential buildings, embedding occupancy, consumer behaviour profiles and comfort constraints, is a new research frontier that could lead to a better understanding of the benefit of DR measures and the impact of large scale trials on the power system.

From an integration perspective, the implementation process of control algorithms that ensure occupant thermal comfort while increasing the energy flexibility of the system by providing DR capabilities is a critical research need for the smart grid rollout (CER 2011; Farhangi 2010; Gottwalt et al. 2017; Nolan and O'Malley 2015). Although in the research community, the design of new algorithms for DR optimisation is a subject undergoing intense study, new machine learning techniques and technology advancements need to be assessed as suitable for the development of intelligent residential controllers.

The contribution of the built environment is paramount for the full decarbonisation of our society. Five different perspectives have been the narrative threads of this chapter:

- Energy perspective: the implications of evaluating retrofit measures, load shifting, storage and end-user comfort and constraints provided a comprehensive assessment of the impact of new technologies as well as the influence of human behaviour on the energy profiles for buildings. The methodology for an energy perspective assessment was further applied to the evaluation of control algorithms for estimating the impact of EMS and RES at a building level upon the energy consumption and profiles.
- End-user perspective: evaluating the research findings for the benefit of end-users in terms of reduction of energy expenditure, adherence to thermal

comfort constraints and accessibility to energy data is an essential instrument for new technology adoption. The end-user perspective also concerns the transferability of the technology benefit across all the building categories.

- Utility perspective: where the evaluation of the results of the research benefits the utility in terms of reducing the system contingencies caused by the penetration of RES via demand-side measures and improving the predictability of building electricity demand is a fundamental criterion for the deployment of these new technologies. The utility perspective concerns the reliability, resilience and stability of the power grid with the objective of improving the overall efficiency hence leading to a generation cost reduction.
- Integration perspective: where the interaction between buildings, electromobility and their control system, the end-user, utilities and a bi-directional communication infrastructure defined within the smart grid needs to be evaluated from the point of view of the accessibility, interoperability, availability and controllability of the assets. The integration side of the research also allows the convergence of objectives for both the utility and the end-user.
- Environmental perspective: through an online data-driven assessment of the carbon emissions associated with the electricity consumption of the building at system and building level can increase awareness and drive the change. The implications of the retrofit measures and the use of control algorithms on the carbon footprint of the building are of interest to policy-makers and local government authorities.

## 7. Conclusions

Besides demand-side management and the installation of advanced energy management systems, several future lines of intervention are critical towards the full decarbonisation of the built environment: monitoring equipment, IoT data collection infrastructures, user engagement, distributed energy generation, storage and energy efficiency management measures. Data gathering and sensors installation can provide useful insights into the occupancy profile patterns of the building. They could also help to locate areas where the temperature constraints need to be precisely defined because of ongoing activities at low metabolic rates or areas where the setpoints can be dynamic. Sensor installations and data collection can also support a more accurate calibration of digital twins and therefore provide insight even on fine-tuned energy efficiency measures such as detailed multi-zone air ventilation rate and thermostatic set points. Occupants and buildings users are at the core of the transition to a low carbon economy. They can be empowered as smart energy users of the building. A smart energy user should not only consume energy but also be a conscious actor in energy savings, building energy policy and even in future energy measures either as an individual or as part of an energy community. Smart energy users are well aware of the consequences of their choices and way of life for energy consumption and the environment. Smart energy users are also actors in climate policy not only with their individual and collective decisions but also by creating awareness among fellow users and organising community events and movements to accelerate the transition to a post-carbon world. To facilitate user empowerment, the energy manager could support the engagement with screens and dynamic visualisation of the building energy consumption. Interactive screens with carbon emissions, zone energy performances, temperature and weather indicators can also facilitate gamification among users and promote a virtuous cycle where individuals gain awareness and lead energy efficiency measures. Another line of action is the installation of renewable energy generators and storage. Different technologies such as photovoltaic, solar thermal systems, heat pumps or biomass cogenerator (CHP) can represent viable solutions for further reducing the emissions of buildings. A biomass cogenerator can provide both electricity and thermal energy, making buildings a central element of a green circular ecosystem. Additionally, a CHP can contribute to heating and cooling loads through a trigeneration system. Other options to consider are power purchase agreements with wind and solar farms or heat recovery systems from nearby processing plants. Electric and thermal storage are the main enabler of all these technologies and can support the mass deployment of advanced DR programs. It should also be noted that the electrification of the mobility sector will allow a capillary diffusion of EVs. The latest charging technologies for EV batteries support a bidirectional electricity transfer with the grid (V2G). Therefore, EVs batteries can also provide distributed electricity storage to further support the increased penetration of renewable energies in the power system if the flexibility of these devices can be dynamically controlled and dispatched. Energy efficiency and management are at the heart of the decarbonisation process. The current work has highlighted several measures for reducing the energy consumption of the building and the provision of energy system services. However, the suggested line of actions can be further developed to depict a comprehensive roadmap for the full decarbonisation of the built environment. For instance, multi-zone thermostatic set points or zone air ventilation controllers can contribute to adapting the energy demand to the current occupancy profile of the building. Areas of the building that are not used or with a reduced occupancy profile can have a dynamic schedule. Additionally, a digital twin can be used to further design an innovative insulation layer with advanced materials such as phase change materials and similar. These lines of intervention coupled with advanced energy management systems and demand-side measures will allow reaching the ambitious emission target for 2050 and beyond reducing the overall impact of climate changes.

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