The Role of Local Aggregator in Delivering Energy Savings to Household Consumers

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Abstract: Energy communities, also known as renewable or citizen energy communities, can be a source of innovative aggregation solutions at the local level. The unleashed flexibility potential of households could provide self-balancing services for local energy communities or create new revenue streams for local flexibility aggregators. This paper proposes a methodology for the assessment of the energy savings potential of residential customers, factoring in local climatological conditions, energy consumption patterns, and building energy performance when the available input data are scarce. For baseline consumption modelling, the correlation between historical energy consumption data collected from a survey, building energy performance parameters, and the availability of flexibility assets was determined, taking into account the inconsistency between the quantity and quality of collected data from various consumers. For this purpose, a modelling approach using calculations for “Agent” buildings was used. In this way, each building user was assigned to a specific “Agent” with dedicated consumption characteristics for a flexibility asset. The capacities engaged in a flexibility programme were modelled according to the available flexibility assets, whilst the duration of a flexibility demand response (DR) event was considered a function of building energy performance characteristics, and consequently, activation strategies were applied. Additionally, several energy savings activation scenarios were modelled to interlink technical and behavioural constraints of household consumers. These constraints restrict the available flexibility, thus influencing the possibility of daily repetitions of a DR event and increasing savings with flexibility event activation. This model is intended to optimise flexibility assets provided by the end-users and, in this manner, deliver permanent energy savings, offering new business opportunities for aggregators or local energy communities. The novelty of this research is the recognition of an aggregator as a permanent energy savings provider, even if the obtained savings are very conservative per individual flexibility asset. Nevertheless, if properly aggregated and identified, the obtained savings could create novel business opportunities for a local aggregator.

Keywords: energy community; flexibility assessment; residential buildings; baseline analysis; consumption categorisation; heating degree days (HDD); cooling degree days (CDD); energy savings; load reduction; novel business models; aggregation of energy savings

1. Introduction

In a conventional power system, electrical energy is produced in large power plants and transmitted through transmission and distribution networks to its end-consumers. During energy system transition, the high proliferation of solar and wind power plants forces transmission and distribution network operators to procure additional balancing solutions to ensure the security and quality of supply. Another driver of the energy transition is the energy consumers, who are increasing their level of awareness and shifting from passive to active participants in the electricity system. In addition to network operators
who seek to solve balancing or network congestion problems, a very important role in the energy transition will also be assigned to energy communities and citizen co-ownership in renewable energy [1]. The transition to a more dynamic and variable power system opens the possibility to incorporate novel solutions for real-time and long-term demand and supply balancing. Besides posing new technical challenges, the massive integration of renewable energy sources and new technologies on the demand side (e.g., electric vehicles and heat pumps) are changing the landscape of energy systems by creating new possibilities to produce, use, and store energy [2].

Technological changes are occurring rapidly, and new solutions that allow consumers to become active participants in the energy transition are becoming more affordable. Changes in national regulatory frameworks that are crucial for the integration of new market actors, such as aggregators or energy communities, are happening, though at a slower pace.

In the Clean Energy for all Europeans package [3], the European Union (EU) has set ambitious energy and climate targets for 2030 to boost long-term neutrality by 2050. The new rulebook places the “energy efficiency first” principle as a priority and sets a target to increase the efficiency of EU energy use by almost one-third—at least 32.5%—by 2030. Moreover, a particular emphasis in [3] is placed on the improvement of energy performance in the building sector, which is highlighted as crucial for the clean energy transition. Buildings are the largest energy consumers and account for 40% of the final energy consumption and 36% of greenhouse gas emissions in Europe. The key priorities for the package are thus energy efficiency first, the EU’s global leadership in renewables, and a fair deal for energy consumers.

Consistent with empowering the activation of final consumers, in the framework of the Clean Energy package, an important boost is expected to be realised by the establishment of energy communities. Citizen energy communities’ rights and obligations are described in Article 16 of EU Directive 2019/944 for common rules for the internal market for electricity [4]. As set in the directive [4], citizen energy communities are entitled to arrange, within the community, the electricity that is produced by the production units owned by the community and are financially responsible for any resulting imbalances in the electricity system. In a broader frame, this means that energy communities are capable of aggregating consumer assets (both production units and flexibility assets) and dispatching this energy.

Moreover, energy communities, also known as renewable energy communities, are also an integral part of EU Directive 2018/2001 on the promotion of the use of energy from renewable sources [5], where a particular focus is given to household consumers. According to [5], consumers are entitled to participate in a renewable energy community and are able to produce, consume, store, and sell renewable energy that is produced by production units, maintaining the rights and obligations of the renewable energy community members as customers who have access to all suitable energy markets. Additionally, the enabling framework indicated by the directive [5] shall ensure that renewable energy communities that supply energy or provide aggregation or other commercial energy services are subject to the provisions relevant for such activities. The citizen energy communities and renewable energy communities recognised in directives [4,5] are also expected to have a crucial role in promoting energy efficiency and energy poverty alleviation.

Energy communities, whether they are called renewable or citizen energy communities, should be able to deliver innovative aggregation solutions at the local level. The unleashed flexibility potential of households could provide ancillary services to grid operators and self-balancing services for energy communities, or it could be directed towards achieving energy savings obligations (set by the Energy Efficiency Directive [6]) and energy efficiency objectives.

In 2018, households, or the residential sector, represented 26.1% of final energy consumption or 16.6% of gross inland energy consumption in the EU. Most of the EU’s final energy consumption in the residential sector is covered by natural gas (32.1%) and electricity (24.7%) [7]. The electricity consumption trends in the EU indicate that, whilst electricity
consumption in the services sector increased by more than a third in the period from 2000 to 2018 (+35.4%), an increasing trend of 16.5% was registered in the household sector during the same period [8]. Even if such indicators suggest the considerable potential for activating flexibility derived from electricity consumption in households, a more thorough analysis of the eligible loads, which could be involved in such flexibility provision, should be made.

Although the directives legitimise household asset aggregation through energy communities and aggregators at the EU level, the flexibility potential of households is still significantly unexplored at the global level for a variety of reasons: (i) the scarcity and frequent absence of historical data with the desired resolution for load profiles; (ii) absence of information on installed equipment in consumer households; (iii) diverse consumer behaviour; (iv) socio-economic background and resulting investment for state-of-the-art equipment; (v) availability of energy infrastructure mostly related to heating, i.e., district heating; (vi) diverse building energy efficiency performance; (vii) differing climatological conditions, etc.

Various works have been carried out to assess local market flexibility potential to procure ancillary services in local markets [9] as a response to distribution system operator (DSO) requests [10] for capacity market purposes [11] or to solve local grid congestion [12]. In the listed works, the delivered flexibility was obtained by shaping, shifting, shedding, or arbitraging (over time) the engaged load profiles. By means of a local aggregator, household demand response flexibility could also be triggered to achieve permanent energy savings as a reduction from the baseline load. This paper intends to study the possibility of delivering cumulative energy savings, obtained by individual demand reduction in season- and weather-sensitive loads, to a local energy community by means of an aggregator in an environment where historical smart metering data are scarcely available or not available at all. This type of flexibility activation is not envisioned as a response to a third-party (i.e., DSO) request but, on the contrary, addresses the possibility of delivering an energy savings programme to its users in a framework of a business model based on cumulative energy savings settlement. This type of flexibility activation programme does not need to consider simultaneous activation benefits and constraints. On the contrary, it relies on the possibility of aggregating energy savings obtained by each user through flexibility activation, thereby establishing a novel programme for local aggregators.

This paper proposes a methodology for the assessment of the energy savings flexibility potential of residential consumers, which considers scarcely available historical consumption data, surveyed data, climatological conditions, usual consumption patterns, and building energy performance.

Additionally, several scenarios for flexibility activation were modelled to interlink the technical and occupancy constraints of household consumers. This model is intended to optimise flexibility assets offered by end-users, deliver energy savings to their portfolio of consumers, and create new revenue for local aggregators.

2. Literature Review

The sources of input data for assessing flexibility are various, as are the methods. This section aims to study diverse concepts, methods, and lessons learned for assessing both load modelling and flexibility. Although numerous studies have analysed the opportunities for procuring flexibility services from low- and medium-voltage grid consumers, there is a considerable dearth of studies related to appliance usage patterns to enable demand response programmes and the interrelated behavioural components for household consumers. This review particularly focuses on load reduction opportunities, thus eliminating shiftable load, which is not relevant for the purpose of reducing the overall electricity consumption. The primary focus of the analysis is permanent savings instead of peak shaving or arbitraging within the day.
2.1. Analysis of Research of Demand-Side Consumption Modelling from Metered Data

To perform a flexibility analysis of appliance assets where smart meters are present, a commonly used method for studying the consumption of electric appliances in a household environment is non-intrusive load monitoring (NILM) or non-intrusive appliance load monitoring (NALM). Even if smart meters measure the overall power consumption of the entire household, they allow supplier companies and system operators to access information on active and reactive power [13].

The power consumption of individual appliances can be estimated using several machine learning techniques to investigate characteristic frequency contents from the load curve of the household [14]; thus, signal analysis algorithms that can be disaggregated can be used in order to extract information on each appliance [15].

Martinez-Pabon et al. [16] proposed a methodology to predict customer eligibility to participate in demand response (DR) programmes by using agglomerative hierarchical clustering of smart meter datasets, thus defining an optimal number of clusters. Every household is placed in a cluster to determine the accessibility to demand response programmes, and appropriate candidates for joining DR programmes are selected based on the pertinent clusters, which combine electricity consumption and lifestyle (i.e., leaving home in the morning and returning in the afternoon). It should be noted that this paper takes into consideration the overall electricity consumption and therefore assesses the overall flexibility of the selected sample without focussing on the flexibility potential of certain appliances within the household and the actual interest in changing the usage patterns of certain appliances.

Klein et al. in [17] also worked on disaggregation, breaking down the aggregated power consumption provided by smart meters into individual appliances in order to achieve a new level of understanding of the actual consumer load. The goal of this paper was to group electrical appliances into classes based on their time-series signature “fingerprints”. Fingerprints can be very important when selecting devices that can easily respond to demand response signals. Klein et al. analysed household appliances, such as cooling devices, space heaters, refrigerators, and washing machines, which are usually taken into consideration for flexibility programmes.

The behavioural patterns of aggregated demand response flexibility were analysed in [18]. Heuristic optimisation techniques were used in addition to NILM and load control to recognise the potential consumer behaviour through a series of scenarios. The results provide valuable outcomes of consumer profiles and consumption drivers within a community, which could impact the acceptance of such services (available flexible kW, number of active consumers, and the decrease in energy consumption).

Data retrieved from smart meters are important in the assessment of flexibility from household consumers. However, smart meters are currently insufficiently present in households, and the rollout of smart meters is happening at a remarkably slow pace [19], as was initially expected, especially within the EU. Furthermore, it is clear that not all appliances that define the total household load are eligible as flexible loads. For flexibility assessment purposes, these data should be further elaborated and disaggregated. Additionally, retrieving data from smart meters by a utility, such as DSO, requires consumer consent. The European data protection regulations also firmly stipulate that the user has to provide explicit consent to any use of such personal data.

2.2. Analysis of Demand-Side Consumption Modelling Research from Surveyed Data

In the absence of metered energy consumption, specific usage patterns can be estimated using surveys. Several studies have researched the correlation between household income and electricity consumption [20–22]. An econometric analysis of electricity consumption in residential homes [23] in Portugal pointed out that income is the key driver. However, its impact is reduced once variables such as house type, occupancy, appliances, and size are taken into consideration. A study [24] covering 45 consumer types in the mainland of Spain showed that households with lower income or located in regions with
lower flexibility potential could be excluded from the provision of flexibility, raising inequities in the energy transition, which is strongly flexibility-oriented. This should be especially considered when coupling flexibility assets with building energy performance, as higher-income householders tend to have more opportunities for building refurbishment. In the UK [25] and US [26], a positive correlation has been observed between electricity consumption and the floor area of the dwelling. Young Yun and Stemmers [27] analysed the interrelationship between behavioural, physical, and socio-economic parameters for household cooling energy consumption, which revealed that occupant behaviour (related to choices) is the most significant issue. However, this suggests that occupants use air conditioning as a function of exterior conditions (climate and weather), as opposed to the interior temperature.

2.3. Estimation of Energy Consumed for Heating and Cooling and Thermal Inertia of Buildings

The increased share of electricity demand in buildings can be attributed to heating, ventilation, and air-conditioning systems (HVAC) [28], which are responsible for thermal comfort within buildings. When considering households, even though the automation of households is far less complex than that of commercial buildings, home automation rollout is happening at a slower pace. With smart home functionalities becoming more affordable and accessible, it is reasonable to expect home automation to be more intensive in the years to come.

By increasing the thermal resistance of buildings with the application of thermal insulation materials, thus improving the building envelope, total building energy demand will be reduced [29]. Such an approach is particularly interesting when comparing heating and cooling demands with the demand-side flexibility potential of residential buildings. Thermal resistance (R-value) and thermal transmittance (U-value) are simplified representations of the heat transfer of a building envelope component. Nevertheless, these indicators do not consider dynamic behaviour. As pointed out in [30], the latter is introduced by exposing a building to variations in usage and environmental conditions such as time-varying outdoor temperature and solar irradiation. In [30], buildings are presented as thermal storage assets that are capable of absorbing, storing, and progressively releasing heat depending on the temperature difference from the immediate surroundings. This principle is indeed very interesting when introducing demand response schemes in buildings in which the primary source for heating and cooling is represented by electrical energy. Although the thermal inertia of buildings is a complex subject involving building usage factors, this may allow different responses to external stimuli depending on the thermal insulation characteristics of the building.

A previous study [31] coupled the thermal inertia of building mass and air-conditioning systems in commercial buildings and especially focussed on the positive effects of DR strategies to reduce peak load consumption. It is important to point out that models developed for assessing the DR flexibility potential of commercial buildings could fail in application for residential buildings or homes due to occupancy and behaviour-related factors determined by the unpredictability of occupant behaviour.

A battery equivalent model to characterise and quantify the aggregate flexibility of residential consumers from thermostatically controlled building loads was proposed in [32]. The model uses a simplified representation of building thermal dynamics but focusses more on its validation to estimate aggregated flexibility from AC systems. From the simulation, a positive correlation between AC units in the “off” state and decreased outdoor temperature was registered. Flexibility assessment methods for integrated electricity and district heating systems utilising the thermal inertia of both district heating networks and aggregated buildings were analysed in [33]. The results show that the model that considers the thermal inertia of district heating systems and the building side produced better results in terms of flexibility and reduced the operating costs of the district heating system. This case, although it considers an aggregated building, requires a considerable number of parameters for building energy performance calculations and fails in application when such data are scarce.
2.4. Load Reduction Flexibility Assessment

Though the impact of flexibility sourced from flexible loads at low voltage levels to higher voltage levels has not been thoroughly investigated, a bottom-up approach from LV to transmission nodes was proposed in [34]. This related work is particularly interesting because, in the first stage, it estimated the daily consumption loads of various appliances existing in both commercial and residential buildings in a Portuguese case study. The characteristics of residential load consumption profiles and time-varying loads are significantly applicable to the case of Croatia as well. Consistent with the Portuguese case study, in this work, it was assumed that indoor heating represents +50% of the average load profile from November to April, while in the periods 1–21 December and 22–31 March, −25% of the average was considered. Indoor cooling was presumed to cover −50% of the average load profile in May, while in June, July, and August, +50% was expected. This work was used as a benchmark for assuming flexibility profiles in the case study reported in this paper. The consumption of thermostatically controlled loads was reduced by 10% in the peak periods, corresponding to a 1–2 °C change in temperature set points.

3. Case Study

The case study in this paper involves 20 residential buildings (mainly detached family houses) that are situated on the island of Krk, Croatia, and are thus subjected to similar climate and weather conditions. The island, situated in the Northern Adriatic, has a moderate and mild Mediterranean climate with average temperatures of around 24 °C in summer and 9 °C in winter. Krk is particularly interesting, as the island municipalities are working towards net-zero greenhouse gas emissions and sustainable development growth [35], whilst a district heating or thermal network grid is not present on the island. This leads to the fact that electrical energy is a popular source for heating and dominant for cooling, which makes residential householders suitable candidates for participation in demand-side flexibility programmes. However, these types of loads, when compared to other typical household loads, are highly dependent on the season, which should be considered when assessing their availability over the year. Table 1 lists the various sources that were used for flexibility modelling purposes, while survey results are presented in Appendix A.

Table 1. Summary of the case study data sources.

| Type of Data                              | Source                                                                 | Unit or Type                                                                 |
|-------------------------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Data categorisation about heating and cooling | Survey                                                                 | Heat pump (HP), air conditioning system (AC) or other                       |
| Centralised or decentralised cooling system | Survey                                                                 | Centralised, decentralised                                                   |
| Agents’ buildings’ historical consumption data | Billing and real-time data provided                                      | kWh                                                                         |
| Annual electricity consumption             | Survey                                                                 | kWh                                                                         |
| Building energy performance self-assessment | Survey                                                                 | Type of façade, shadings, windows                                           |
| Square area of the household cooled and heated areas | Survey                                                                 | m²                                                                           |
| Occupant type                             | Survey                                                                 | All-year resident, holiday user                                              |
| Average temperature, heating and cooling degree days | meteo.hr [36], timeanddate.com [37], degreedays.net [38] | °C, CDD, HDD                                                                |
Table 1. Cont.

| Type of Data                                           | Source               | Unit or Type       |
|--------------------------------------------------------|----------------------|--------------------|
| Set indoor temperature for heating and cooling months  | Survey               | °C                 |
| Monthly energy consumption                             | Agent users          | kWh                |
| Heating energy demand $Q_{H,nd}$ categorisation        | Ordinance [39]       | kWh/m$^2$ annually |
| Presence of PV                                         | Survey               | Yes, no            |

4. Methodology

This paper firstly proposes a methodology for weather- and season-sensitive flexibility asset modelling based on surveyed data collected directly from consumers interlinked with outdoor temperature data, occupational constraints, and building energy performance. In order to simulate a real environment when load profile historical data are difficult to retrieve, this study relies solely on data collected from the surveyed consumers and does not use historical load profile data. Methods used for load disaggregation to obtain certain flexibility profiles are not applied in this case study due to their unavailability. Furthermore, considering different resolutions of energy consumption data collected from various consumers, this study proposes a methodology for mapping typical consumption patterns of flexible loads and thus modelling consumption baselines where needed.

Secondly, to obtain cumulative energy savings at the local level based on modelled and collected data, activation strategies and criteria for flexibility activation are proposed. The sequence diagram developed for the process of assessing, modelling, and activating flexibility to obtain energy savings proposed in this paper is shown in Figure 1.

Figure 1. Sequence diagram.

The first step is to assess the availability of flexibility assets as suitable candidates for load reduction. These are controllable loads whose operating point can be adjusted to decrease consumption by a certain percentage (i.e., thermostatically). Taking into account the absence of electric vehicle charging points (EV) in the case study, heat pumps (HPs)
and air-conditioning (AC) units are the most suitable assets qualified for load reduction and, consequently, energy savings.

As potential candidates for flexibility procurement, users were divided into three main categories: those that use the heat pump solely for heating, those that use it for both heating and cooling, and finally, those that use air-conditioning units for cooling in the summer months. Consumers for whom electrical energy is not the primary source of heating, whose air-conditioning systems are used for reheating and increasing thermal comfort, were not considered eligible for flexibility programmes, as they directly influence the user’s comfort. Besides flexibility assets, in the data collection process, each user was surveyed about the building envelope, occupancy, and energy consumption.

Following the data collection process, methodologies for flexibility modelling are described in the following subsections, along with the simulated activation strategies.

4.1. Baseline Analysis and Assessment of Monthly Flexible Load Consumption for “Agent” Households

Since monthly historical consumption data were solely available for a small number of buildings, the first step of the modelling process is to select “agent” end-users with available monthly data to determine specific electrical energy consumption for heating, cooling, and/or both. The overall goal of this exercise is to extrapolate the consumption patterns from the “agent” households to the remaining ones based on selected criteria and, in this way, achieve a sort of mapping that requires proper end-user categorisation considering their technical and behavioural constraints.

Three household buildings were selected as agent buildings to represent three types of heating and cooling modalities: “Agent 1” uses a heat pump just for heating; “Agent 2” uses a heat pump for both heating and cooling; and finally, “Agent 3” uses a heat pump or air-conditioning (AC) unit for cooling in the summer months.

Eligible loads for obtaining energy savings in this exercise are highly season- and weather-sensitive. A linear regression analysis of monthly consumption variations in relation to the outside temperature was performed using monthly energy consumption data. A negative relationship between overall monthly energy consumption (as a dependent variable) for a building that is occupied on a full-time basis and uses a heat pump solely for heating purposes and average outdoor monthly temperatures (as an independent variable) is shown in Figure 2. The coefficient of determination (or R-squared) was 0.89, indicating a significant causality between outside temperature and heating energy consumption, which was further considered in the baseline modelling process.

![Figure 2. Linear regression analysis between monthly energy consumption and outdoor average.](image)

Once the dependencies between outdoor conditions and energy consumption were determined, the next step was to analyse the energy performance of different buildings in correlation with the mentioned variables. A commonly used variable to calculate building energy consumption and building energy performance is the degree day. Heating
degree days (HDDs) are a measure of how much (in degrees) and for how long (in days) the outside air temperature was lower than a set indoor temperature. Using the pre-set constant temperature of the observed users and their location, HDDs were calculated. Bearing in mind that this exercise step analyses the causality between monthly energy consumption and outdoor conditions, the share of electricity used for heating purposes was estimated from the colder months ($E_{heating, HP \, monthly}$), i.e., October (32%), November (50), December (59%), January (73%), February (59%), March (55%), April (45%), and May (18%), based on the difference between the pre-set indoor temperatures and heating degree days (HDDS), whose values are comparable to the shares in [34]. The values were applied for both Agent 1 and Agent 2, since they both use HP for heating purposes.

Figure 3 depicts a notable deviation in energy consumption between the two buildings during heating months, especially with increasing differences between indoor and outdoor temperatures. This discrepancy indicates that energy consumption is highly affected by building energy performance, since both examined end-users use specific setpoints of constant indoor temperature in the heating months and are all-year residents in their related households.

![Figure 3. Monthly consumption of electricity per square metre between two agent buildings for heating.](image)

Once monthly energy consumption engaged for heating was calculated based on the performance analysis of agent buildings, specific monthly electrical energy engaged for heating $E_{heating, HP \, spec}$ (kWh/m²) was calculated for both buildings. Once monthly consumption used specifically for heating was obtained, indicating that energy consumption is directly affected by building energy performance, a building classification of different energy consumption in relation to its performance was needed.

To enable this classification, based on available data in the absence of energy audits, an assumption for specific annual heating energy demand $Q_{H,nd \, annual}$ of agent buildings was made. The Algorithm for calculating the energy required for heating and cooling building space according to HRN EN ISO 13790 norm [40], among other things, defines the steps for calculating the specific heating energy demand for residential buildings under different climatological conditions in the Republic of Croatia. The norm specifies that when the calculation of the specific annual heating energy demand (kWh/m² a) for a building is completed, an energy class with the letter (A+, A, B, C, D, E, F, G) [39] is indicated on the energy certificate of the building. In this specific case, as the specific monthly and thereafter annual consumption of electrical energy dedicated to heating $E_{heating, HP \, annual}$ (kWh/m² a) was already calculated for agent buildings, these values needed to be converted into heating-specific energy demand $Q_{heating, HP \, annual}$ in order to obtain the classes and thus allow mappings.

The seasonal performance factor (SPF) is an indicator used to evaluate the efficiency of heat pumps. It is presented as a ratio between the total heat supplied by the heating system to a building and the electricity used by the heat pump and related devices of the heating system over the year [41]. The SPF value also depends on the efficiency of the heat pump (coefficient of performance, COP) and climatic conditions [42]. For the purpose of
this paper, a conservative average factor \[43\] of 2.5 for air-source heating pumps was used as the SPF, meaning that \( Q_{\text{heating,HP annual}} = \text{SPF} \times E_{\text{heating,HP annual}} \), classifying Agent 1 as class D and Agent 2 as class B. The authors considered this to be adequate on the basis of the envelope and insulation information collected by a survey.

The next step is dedicated to remodelling the specific consumption by agent buildings according to different levels of energy performance. Since the energy performance of buildings is particularly relevant for heating, and specific annual heating energy demands \( Q_{H,nd\text{annual}} \) are already prescribed in \[39\] according to specific climatic circumstances and building energy performance, the relations between different levels of \( Q_{H,nd} \) were used (i.e., 
\( D \) in \( A^+ \) is; \( E_{\text{heating,HP annual}}(A^+) = E_{\text{heating,HP annual}}(D)/10 \)).

For cooling, Agent 2 and Agent 3 were examined. Since the main source of cooling within the household premises is split units (the same one as a standard AC system), the specific results of Agent 3 could be applied to all case study households using an AC system. The main difference is in the fact that the heat pump provides a centralised cooling system for the entire building, while AC units are separate units (for example, one unit in the living room and the second in the bedroom). For cooling purposes, the share of engaged electricity \( (E_{\text{cooling,HP/AC monthly}}) \) was estimated based on the degree days for cooling (CDD) in May (3%), June (20%), July (49%), August (55%), and September (25%), which is also comparable to the assumptions in \[34\]. Cooling degree days (CDDs) are a measure of how much (in degrees) and for how long (in days) the outside air temperature was higher than a set indoor temperature. The monthly energy consumption engaged for cooling was therefore recalculated to specific monthly electrical energy engaged for cooling \( E_{\text{cooling spec}} \) (kWh/m²).

Dedicated formal energy performance grading does not exist for cooling, so classifying buildings according to cooling performance could lead to the wrong conclusion, as previously mentioned in the literature review. Occupants tend to activate and deactivate AC units as a function of weather conditions as opposed to the interior temperature. The steps of this procedure are graphically shown in Figure 4.

![Figure 4. Baseline analysis and modelling of monthly flexible load consumption.](image)

### 4.2. End-User Building and Consumption Categorisation

Once monthly consumption patterns had been defined for agent buildings with different energy performance characteristics, the following step was to remodel or map the results obtained in the previous step. Each building user was assigned to a specific “Agent” (Table 2) with specific monthly consumption dedicated to heating and cooling. Whilst the categorisation for heating is far more tailored to the different energy performance of
buildings, all buildings were categorised under the same $E_{cooling,HP/AC \ monthly}$ due to the lack of a correlation between their consumption and building performance.

Table 2. Summary of the case study data sources—example for specific heating and cooling electrical energy demands for two months.

| Building             | Assigned “Agent” | Specific Monthly Consumption Heating for January $E_{heating,HP \ spec}$ (kWh/m$^2$) | Specific Monthly Consumption Cooling for August $E_{cooling,HP/AC \ monthly}$ (kWh/m$^2$) |
|----------------------|-----------------|---------------------------------------------------------------------------------|---------------------------------------------------------------------------------|
| Building 1 with HP   | 2B, 1           | 3.11                                                                             | 1.20                                                                             |
| Building 2 with HP   | 1D, 1           | 9.34                                                                             | 1.20                                                                             |
| Building 3 with HP   | 2B, 1           | 3.11                                                                             | 1.20                                                                             |
| Building 4 with HP   | 2A, 1           | 1.56                                                                             | 1.20                                                                             |
| Building 5 with HP   | 2B, 1           | 3.11                                                                             | 1.20                                                                             |
| Building 6 with AC   | 1               | Not applicable (N.A.)                                                           | 1.20                                                                             |
| Building 7 with AC   | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 8 with AC   | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 9 with AC   | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 10 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 11 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 12 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 13 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 14 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 15 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 16 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 17 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 18 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 19 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |
| Building 20 with AC  | 1               | N.A.                                                                             | 1.20                                                                             |

4.3. Methodology for Aggregator Flexibility Asset Modelling and Activation Strategies

Figure 5 presents the steps for aggregator flexibility asset modelling developed for the analysed sample. Baseline monthly energy consumption per flexibility asset (kWh/m$^2$) was created in the previously described methodology for agent buildings. After each user was appointed to a specific “Agent” with the specific monthly consumption for heating ($E_{heating,HP \ spec}$ (kWh/m$^2$)) and cooling ($E_{cooling \ spec}$ (kWh/m$^2$)), using input parameters such as square metres of heated area and cooled area, baseline monthly energy consumption for flexibility assets for each month was obtained.

Figure 5. Methodology for aggregator flexibility asset modelling—monthly to daily baseline assessment and activation strategies.
Whilst specific energy consumption for heating considers the building energy performance (Figure 6), this is not the case for cooling for the previously mentioned reasons (Figure 7).

**Figure 6.** Baseline energy consumption for heating.

After monthly consumption profiles have been created, the next step is to model daily baseline consumption profiles of flexibility assets. This means that monthly flexibility consumption profiles need to be converted into daily consumption profiles. For this purpose, HDD and CDD parameters from [38] were used for the location of Krk (Omišalj). Indoor temperatures were set at 22.5 °C for heating and 21 °C for cooling (as an average obtained from the survey), while for days where HDD and CDD were below 2 and 1, respectively, they were not considered. The main purpose of HDD and CDD is to quantify the demand for energy needed to heat or cool a building. For the analysed period of one year, a total of 238 days for heating and 95 days for cooling were considered. Additionally, average daily HDD (Figure 8) and CDD (Figure 9) were considered for each month, meaning that daily energy consumption variations were calculated.

**Figure 7.** Baseline energy consumption for cooling.
With these normative active hours, a very conservative baseline was obtained, but the
was made.

Therefore, several scenarios were considered. Likewise, the presence of PV could lead to
positive impact is that flexibility activation would minimise the effect on user comfort.

Engaged capacities were modelled according to the available flexibility assets, whilst
activation strategies, in terms of event duration and repetitions, were set as a function of
building energy performance characteristics and behavioural and occupancy limitations,
along with the presence of PV. The duration of a flexibility (DR) event was considered

For the purpose of converting the average daily consumption of flexibility assets into the
engaged power (kW), it is assumed that the heating system is active for $t_{d,heating} = 17$ (h/d),
mainly from 06:00 to 23:00, as a normative used for calculations in the HRN EN ISO 13790
norm for residential buildings with non-continuous operation. Although 17 daily active
hours for a heating system may seem to be a high number, it should be noted that normative
values for determining the annual heating energy demand $Q_{H,nd} annual$ of the building were
used to perform building energy performance categorisation. This part of the calculation
should therefore correspond to the previous steps. Moreover, building occupants were
consulted to estimate the active hours of heating, and it could be deduced that if occupants
are present on their premises, these hours correlate with the norm. Nevertheless, if heating
hours are reduced because of occupancy factors, users with heating pumps and thermostats
tend to pre-heat the building and consume more energy. These periods are not eligible
for flexibility activation to achieve energy savings, as they directly affect user comfort,
which should be a priority. For cooling, on the other hand, the norm imputes $t_{d,cooling} = 24$ h
for systems with continuous operation and $t_{d,cooling} = 17$ (h/per day) for systems with
non-continuous operation, where the latter was used for consumers with a cooling system.
With these normative active hours, a very conservative baseline was obtained, but the
positive impact is that flexibility activation would minimise the effect on user comfort.

A moderate decrease of 10% in power was used to define baseline flexibility. Obviously,
daily occupancy is an imperative factor for activating a DR event; thus, occupancy
constraints are presented here as a possibility to allow daily repetitions of a DR event.
Therefore, several scenarios were considered. Likewise, the presence of PV could lead to
self-consumption prioritisation and a higher level of awareness of building occupants in
terms of energy savings [44]. In this case, an associated correction for DR event activation
was made.

Engaged capacities were modelled according to the available flexibility assets, whilst
activation strategies, in terms of event duration and repetitions, were set as a function of
building energy performance characteristics and behavioural and occupancy limitations,
a function of building energy performance characteristics, and consequently, flexibility event activation strategies were applied. As shown in Figure 10, the y-axis represents the calculated baseline load, while the x-axis represents the time engaged in a DR event. The duration of a flexibility event is subject to strategies directed towards maximising the savings obtained from flexibility per calculated engaged capacity.

![Figure 10. DR event description: available load vs. event duration.](image)

The final part of activation strategies is related to occupancy and behavioural constraints, which are presented in the form of DR event repetitions. Once the DR event duration has been calculated (Figure 10), the next step is to assess its daily repetition possibilities (Figure 11) for achieving additional energy savings. As part of the activation strategies, it was considered that daily repetition activation scenarios are dependent on seasonal limitations, occupant presence, and behavioural factors related to the existence of PV. It is expected that PV owners tend to increase self-consumption when PV is producing energy, which was also considered in the applied activation scenarios.

![Figure 11. DR event description with repetitions.](image)

5. Results

The results obtained by using the methodology and the related discussions are subdivided into two main categories: flexibility earned from heat pumps for heating purposes and flexibility earned from cooling assets.

5.1. Flexibility Earned from Heat Pumps for Heating Purposes

Specific monthly heating consumption was mapped on the remaining samples based on the information provided from the survey; hence, a modelled flexibility consumption profile was assigned to each consumer. Daily engaged power (capacity) per flexibility asset was calculated according to the methodological steps, representing the baseline load available for flexibility programmes. The next step is to define proper DR strategies that are feasible for residential buildings, which are manifested in the DR event duration (Figure 8). Different DR event durations were assigned according to the criteria shown in Table 3.
Table 3. DR event duration rationale—heating.

| Building Energy Performance (BEP)/HDD | On Average (h) | Below 60% (h) | From 60% to 80% (h) | From 120% to 140% (h) | From 140% to 160% (h) | From 160% to 180% (h) | Above 200% (h) |
|--------------------------------------|----------------|---------------|---------------------|-----------------------|-----------------------|----------------------|----------------|
| Good                                 | 2              | 2.8           | 2.2                 | 1.7                   | 1.4                   | 1.2                  | 1              |
| Medium                               | 1              | 1.4           | 1.1                 | 0.9                   | 0.7                   | 0.6                  | 0.5            |
| Bad                                  | 0.3            | 0.5           | 0.5                 | 0.3                   | 0.2                   | 0.2                  | 0.2            |

The DR event is defined by capacity, duration, and ramp. For this exercise, considering that the DR event duration is significant, the ramp is of negligible value. When considering the values for DR event duration listed in Table 3, a very discrete amount of energy savings can be obtained if one DR event occurs per day, especially when considering HDD variations per day; thus, the engaged power is reduced (Figure 12). As can be seen from the illustrations in both figures, even if the average outside temperature was the same, the energy required for heating was more pronounced in February than in December, and this is a consequence of a higher energy demand registered in February (more HDD in February relative to December).

Figure 12. Daily energy savings on an average day for heating.

The previous calculation already foresees the building energy performance effect and scales the DR event duration based on the building energy performance characteristics and engaged power. To assess the possible daily repetitions of a DR event (Figure 13), thus increasing the savings, occupancy constraints and behavioural factors related to the presence of PV (it is expected that PV owners tend to prioritise self-consumption when PV is producing energy) need to be considered. Daily repetitions are shown in Table 4.
Figure 12. Daily energy savings on an average day for heating. The previous calculation already foresees the building energy performance effect and scales the DR event duration based on the building energy performance characteristics and engaged power. To assess the possible daily repetitions of a DR event (Figure 13), thus increasing the savings, occupancy constraints and behavioural factors related to the presence of PV (it is expected that PV owners tend to prioritise self-consumption when PV is producing energy) need to be considered. Daily repetitions are shown in Table 4.

Figure 13. Daily energy savings obtained with 50% decrease from average consumption without DR repetitions per building—months with more consistent average temperature over the analysed period are not considered (i.e., November, January).

Table 4. Daily repetitions of a DR event—heating.

| Number of Daily Repetitions of a DR Event | Occupancy Level | Winter | Mid-Season |
|-----------------------------------------|-----------------|--------|------------|
| No PV                                   | Low occupancy   | 2.0    | 2.0        |
|                                         | High occupancy  | 2.7    | 2.4        |
| PV                                      | Low occupancy   | 2.0    | 0.7        |
|                                         | High occupancy  | 2.7    | 1.4        |

Since the energy produced from PV is far lower in colder months, the number of possible repetitions in November, December, January, February, and March remains the same as in the case with no PV. The selected repetitions take into account weekends; e.g., during October, April, and May, people usually tend to spend more time outside on weekends. Worst-case and best-case activation scenarios after applying occupancy constraints are presented in Figure 14. For residents with PV, in mid-season months (October, April, and May), a significantly reduced number of repetitions is assigned, as PV should produce more energy during these months.

When DR strategies are applied, the results achieved by applying the methodology strongly indicate that buildings with better energy performance present a significantly higher potential in delivering flexibility programmes intended for energy savings because of their better thermal inertia. In the near future, it is reasonable to expect that buildings with low-end energy performance will be renovated and that more PVs will be installed for self-consumption purposes. This should be considered when designing longer-lasting terms governing flexibility programmes. Likewise, present and future trends lead to a higher share of buildings with better energy performance; thus, in line with long-term goals for 2030 and beyond [45], a significant amount of building stock will be renovated. Demand-side programmes for buildings exploiting the thermal inertia of residential buildings have a noteworthy potential for delivering benefits to both flexibility providers (consumers) and aggregators of flexibility.
Table 4. Daily repetitions of a DR event—heating.

| Occupancy Level | Winter | Mid-Season |
|-----------------|--------|------------|
| No PV           | 2.0    | 2.0        |
| PV              |        |            |
| Low occupancy   | 2.0    | 0.7        |
| High occupancy  | 2.7    | 1.4        |

Since the energy produced from PV is far lower in colder months, the number of possible repetitions in November, December, January, February, and March remains the same as in the case with no PV. The selected repetitions take into account weekends; e.g., during October, April, and May, people usually tend to spend more time outside on weekends. Worst-case and best-case activation scenarios after applying occupancy constraints are presented in Figure 14. For residents with PV, in mid-season months (October, April, and May), a significantly reduced number of repetitions is assigned, as PV should produce more energy during these months.

Figure 14. Energy savings obtained based on modelled data (top, worst-case estimation; bottom, best-case estimation).

5.2. Flexibility Earned from Cooling Assets

The same modelling approach applies to cooling, meaning that specific monthly cooling consumption profiles obtained from the agent were mapped on the remaining samples based on the information provided from the survey; hence, a modelled flexibility consumption profile was assigned to each consumer for cooling. Daily engaged power per cooling asset was calculated based on the steps defined in the methodology, adopting the corresponding \( t_{d,\text{cooling}} \). Different DR event durations, depending on the CDD, were assigned according to the criteria shown in Table 5.

Table 5. DR event duration rationale—cooling.

| CDD (Variations from Average) | On Average (h) | Below 60% to 80% (h) | From 60% to 140% (h) | From 140% to 160% (h) | From 160% to 180% (h) | Above 200% (h) |
|-------------------------------|----------------|----------------------|----------------------|----------------------|----------------------|----------------|
| Duration                      | 1.0            | 1.5                  | 1.2                  | 0.8                  | 0.6                  | 0.4            | 0.2            |

As shown by the results obtained with the applied values in Figures 15 and 16 (PO indicating permanent occupant and SO seasonal occupant), a similar conclusion to the case of heating can be applied here. Even if the same cooling consumption is applied to all of the observed buildings, outstanding values for buildings 1, 3, 4, and 5 indicate higher energy consumption for cooling, since these buildings have a centralised cooling system, and therefore, a larger area is cooled. Without the application of DR strategies that encompass DR event repetitions over a day, energy savings would be minuscule.
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Figure 15. Energy savings obtained on an average day for cooling.

For achieving acceptable energy savings in such programmes, strategies involving daily repetitions of a DR event need to be considered. On the other hand, occupancy constraints are of fundamental importance when assessing the availability of cooling assets for flexibility programmes. This case study encompasses various types of residents, such as permanent building occupants and holiday (seasonal) users. Furthermore, centralised cooling systems imply an automated system: when the temperature reaches a certain set point, the system is activated, while decentralized AC units are more dependent on the consumer's will. All of those aspects encompass personalised DR strategies, which consider working days, weekends, holidays, etc., as shown in Table 6.

Table 6. Daily repetitions of a DR event—cooling.

| Number of Repetitions of a DR Event | Permanent User with Centralised Cooling System | Permanent User with Decentralised Cooling System | Seasonal/Holiday User |
|-------------------------------------|-------------------------------------------------|--------------------------------------------------|------------------------|
| High occupancy                      | 3.0                                              | 2.0                                              | 0.3                    |
| Low occupancy                       | 2.0                                              | 1.3                                              | 0.2                    |

From the experimental observation of consumers, it can be deduced that when PV is present, such a "correction" has not been made as in the case of heating. Cooling units are usually active during daylight when PV produces energy; hence, self-consumption can be increased, which is usually a priority. The achieved savings obtained from the described DR strategies are shown in Figure 17. The presented savings do not indicate the overall energy savings per household but energy savings achieved by engaging cooling assets. Such energy consumption is much more volatile when comparing it to consumption for heating, especially for decentralized AC cooling units. Additionally, cooling energy consumption patterns are more stochastic and difficult to assess if dedicated metering data...
constraints are of fundamental importance when assessing the availability of cooling assets for flexibility programmes. This case study encompasses various types of residents, such as permanent building occupants and holiday (seasonal) users. Furthermore, centralised cooling systems imply an automated system: when the temperature reaches a certain set point, the system is activated, while decentralized AC units are more dependent on the consumer’s will. All of those aspects encompass personalised DR strategies, which consider working days, weekends, holidays, etc., as shown in Table 6.

### Table 6. Daily repetitions of a DR event—cooling.

| Number of Repetitions of a DR Event | Permanent User with Centralised Cooling System | Permanent User with Decentralised Cooling System | Seasonal/Holiday User |
|------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------|
| High occupancy                     | 3.0                                           | 2.0                                           | 0.3                   |
| Low occupancy                      | 2.0                                           | 1.3                                           | 0.2                   |

From the experimental observation of consumers, it can be deduced that when PV is present, such a “correction” has not been made as in the case of heating. Cooling units are usually active during daylight when PV produces energy; hence, self-consumption can be increased, which is usually a priority. The achieved savings obtained from the described DR strategies are shown in Figure 17. The presented savings do not indicate the overall energy savings per household but energy savings achieved by engaging cooling assets. Such energy consumption is much more volatile when comparing it to consumption for heating, especially for decentralized AC cooling units. Additionally, cooling energy consumption patterns are more stochastic and difficult to assess if dedicated metering data are absent. Thus, these results should be interpreted with caution, especially in relation to decentralized AC units.

![Figure 17. Daily savings obtained with application of DR strategies—best-case vs. worst-case scenario (PO, permanent occupancy; SO, seasonal occupancy).](image-url)
6. Discussion

This work involves two different levels of assessments. The first assessment is related to the definition of baseline consumption for heating and cooling, which entails the mapping of existent energy consumption data to households with limited data. The second assessment considers aggregator flexibility based on the existing portfolio of users. Different energy consumption patterns for heating and cooling were assessed. When making this assumption, HDD and CDD are used, allowing a more accurate assumption of the heating and cooling demand to be made compared to a simple average daily or monthly temperature. This is particularly evident in the months of December and February, where the average temperature is the same, but heating energy demand is more prominent in February due to more temperature variations. Whilst automated heating systems powered by heat pumps provide more consistent consumption, the system usually activates as the room temperature drops below a selected setpoint. Cooling is much more inconsistent, especially when considering decentralised air-conditioning units and lower occupancy of household premises during summer months. Building and user classification is more accurate when analysing heating flexibility performance, since the correlation between building performance and heating consumption is obvious. On the contrary, the uncertainty of the assessment is more prevalent during cooling months, especially when considering solely decentralised AC units as the flexibility provider.

This exercise mostly relies on baseline energy modelling and energy demand parameters that are usually used for building energy demand calculations. Probabilistic load models commonly applied for households, such as a Monte Carlo simulation [46], are useful to determine the outcome and the likelihood of certain events when aggregated or certain load profile data exist, and hence, variables and constraints can be directly set.

The modelling proposed in this paper is not aimed at a more precise extrapolation of a single load profile. On the contrary, the principal goal of the proposed method is to utilise a limited dataset to extract a conservative estimate of average power engaged by flexibility assets. The estimated value of the power engaged for cooling on a specific day is shown in Figure 18, where the estimate from the proposed method is compared with the actual values in a house recorded with real-time measurement equipment. In the depicted case, the heat pump operates continuously, and the impact on user comfort should remain minimal if flexibility activation is applied.

![Figure 18. Fifteen-minute measurements on a summer day vs. linear estimated power value for cooling.](image-url)
Recent work in [47] explored the uncertainty in aggregated energy flexibility in high-rise residential building clusters using a data-driven stochastic model. This captures the stochasticity of occupancy patterns using the Markov chain Monte Carlo occupancy model combined with the TRNSYS simulation tool building thermal model. Such data-driven building energy performance modelling requires the existence of detailed data on the building envelope and installed systems (HVAC, AC, etc.). Even if this approach is not applicable to numerous single-family detached buildings because of the lack of such data, the results from [47] positively demonstrate that energy flexibility estimates for a cluster of buildings are more reliable than those for a single building, which is in line with the main postulates of this paper. However, the model in [47] does not consider the behavioural parameters related to the presence of PV, which could implicitly put some constraints on flexibility asset activation, as shown in this paper.

Households that use centralised heat pumps for cooling are considered to be a more adequate and reliable provider for delivering flexibility. On the other hand, the assessment of baseline consumption for households with decentralised AC systems is more susceptible to uncertainties [32]; thus, their performance in delivering flexibility is more inconsistent. To assess cooling patterns in households, more research is needed to properly assess their flexibility potential, and building up an aggregator use case for these could be questionable. The work in [48] demonstrated the capability of AC and hot water heaters to ensure community-level control strategies for distribution voltage regulations dedicated to residential consumers. Obviously, this is not in conflict with the results reported in this paper and could lead to the conclusion that thermostatically controllable loads of residential consumers can offer both energy savings and flexibility services to distribution system operators.

Since this paper proposes a novel business model for a local aggregator or an energy community, a fair system of rewards achieved in such an energy savings programme could be the focus of future research. It should be noted that the peer-to-peer (P2P) trading mechanism [49], usually applied for renewable energy trading within a community, is not applicable in the particular case of energy savings. The results obtained using the methodology proposed in this research could open a path for future works to develop performance indicators (KPIs) for dedicated energy savings remuneration. These KPIs should be based on mappings to define the baseline flexibility of a given portfolio of household consumers and therefore quantify savings, flexibility, or both. This could facilitate novel energy performance contract (EPC) savings calculations [50], as measurement and verification techniques usually imply programme settlement as well as impact estimates.

7. Conclusions

As the unavailability of historical consumption data and the absence of real-time data are common issues when assessing the flexibility potential of household consumers, holistic methods that combine surveyed data and publicly available data are often a priority. From an aggregator perspective, the availability of data for defining flexibility profiles of amalgamated assets is an initial step for analysing its portfolio. Moreover, as consumers are becoming much more aware of data privacy and ownership issues, data availability could be a critical problem. Based on the experiences from this case study, when performing a survey, a specific set of questions needs to be directed towards obtaining the desired information—e.g., it is not sufficient to ask whether a surveyed user has a heat pump: the question should ask if it is the primary source of heating or if another source is usually used for that purpose; otherwise, wrong conclusions can be made. For this reason, mapping methods capable of assessing residential energy consumers' flexibility potential using surveyed and historical (at least monthly) energy consumption data could be very important for aspirational flexibility aggregators.

This paper primarily focuses on the aggregator as a provider of energy savings services, which is still an unexplored approach, unlike the use of an aggregator as an ancillary service provider or energy market participant. From the illustrated results, it
can be deduced that energy savings can be achieved from such programmes with a very conservative load reduction of 10% per specific flexibility asset. The proposed savings consider only the flexibility potential of heating and cooling systems in residential buildings and respect the additional limits coming from the building energy performance tied with occupancy and behavioural constraints. With such an approach, individual flexibility activation may not yield significant savings. However, if such granular permanent savings are aggregated and properly identified, this could create novel business opportunities for a local energy savings aggregator.

Moreover, the novelty of this approach is that with limited data available on building energy performance, the proposed method takes into account the thermal inertia of buildings in flexibility calculations by properly combining qualitative and quantitative data retrieved from the survey.

Energy efficiency obligation schemes in Europe, reported in Article 7 of the EED [6], set an obligation for energy companies (such as suppliers/retailers) to achieve energy savings targets [51]. Obliged parties and modalities for energy savings purchasing from third parties are defined in national regulations. If savings obtained from flexibility activation can be aggregated and properly verified, monitored, and purchased, this could create new business opportunities for a local permanent savings aggregator. This would be additionally facilitated by explicit demand response and information communication technologies that are able to support the verification of curtailment and signal identification, extending the possible scope of aggregation business.

Nevertheless, it needs to be considered that offering energy savings programmes through local aggregators, as part of a flexibility service, creates more awareness of their benefits as consumers become more aware of the energy costs and impacts of energy use. Accordingly, participation in such energy savings programmes offered by local aggregators could create implicit energy savings for local communities by virtue of behavioural changes with regard to energy consumption.

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**Data Availability Statement:** The data that support the findings of this study are available from the corresponding author, L.L.M., upon reasonable request.

**Conflicts of Interest:** The authors declare no conflict of interest.
### Appendix A

**Table A1. Input data collected from the survey.**

| Building 1 with HP | Building 2 with HP | Building 3 with HP | Building 4 with HP | Building 5 with HP | Building 6 with AC | Building 7 with AC | Building 8 with AC | Building 9 with AC | Building 10 with AC | Building 11 with AC | Building 12 with AC | Building 13 with AC | Building 14 with AC | Building 15 with AC | Building 16 with AC | Building 17 with AC | Building 18 with AC | Building 19 with AC | Building 20 with AC |
|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Level of usage    |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |
| Full-time house   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |
| Holiday house     |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |
| Average yearly consumption of electrical energy (kWh) | 7000  | 17,800 | 8000 | 3000 | 8700 | 3400 | 2000 | 2000 | 1600 | 4000 | 17,000 | 5000 | 4000 | 2000 | 2000 | 1600 | 1600 | 900 | 3000 | 800 | 900 | 1000 |
| Cooling device (split system) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cooling system (centralised) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Automatic or manual | A | M | A | A | A | M | M | M | M | M | A | M | M | M | M | M | M | M | M | M | M |
| Air conditioning (heating) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Heat pump | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other source of heat, non-electrical | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Heating system used for HW | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Heating system (centralised) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Thermostat | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| PV | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sq. metres | 250 | 200 | 160 | 200 | 350 | 110 | 120 | 120 | 140 | 120 | 480 | 270 | 171 | 140 | 110 | 100 | 600 | 130 | 90 | 70 |
| Non-heated area/sq. metres | 50 | 5 | 20 | 20 | 150 | 100 | 40 | 30 | 30 | 90 | 60 | 60 | 35 | NA | NA | NA | NA | NA | NA | NA |
| Heated area | 200 | 195 | 120 | 180 | 200 | 100 | 80 | 90 | 110 | 30 | 420 | 210 | 136 | NA | NA | NA | NA | NA | NA | NA |
| Cooled area | 200 | 60 | 120 | 180 | 190 | 44 | 24 | 40 | 52 | 24 | 96 | 54 | 40 | 30 | 44 | 24 | 120 | 41 | 28 | 13 |
| Floor height | 2.5 | 4 | 2.5 | 2.6 | 2.6 | 2.5 | 2.6 | 2.6 | 2.6 | 2.5 | 2.6 | 2.5 | 2.6 | 2.6 | 2.9 | 2.6 | 2.5 | 2.5 | 2.5 | 2.6 | 2.6 |
Table A1. Cont.

| Building with HP | Building 1 with HP | Building 2 with HP | Building 3 with HP | Building 4 with HP | Building 5 with HP | Building 6 with AC | Building 7 with AC | Building 8 with AC | Building 9 with AC | Building 10 with AC | Building 11 with AC | Building 12 with AC | Building 13 with AC | Building 14 with AC | Building 15 with AC | Building 16 with AC | Building 17 with AC | Building 18 with AC | Building 19 with AC | Building 20 with AC |
|------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Floor (n)        | 2                 | 1                 | 2                 | 2                 | 3                 | 1                 | 2                 | 2                 | 2                 | 2                 | 2                 | 3                 | 2                 | 2                 | 2                 | 1                 | 5                 | 1                 | 1                 |
| Family ≥4        | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 |               |
| Family <4 and ≥2 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 |               |
| Less than <2     | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                | NA                |               |
| **Building envelope** | Brick + thermo Styrofoam | Brick + plaster | Stone wood insulated + recent renovation | Brick + thermo Styrofoam | Stone + plaster | Lime-cement facade + Styrofoam | Stone wool insulation | Stone wool insulation | Brick + thermo Styrofoam | Brick + plaster | Lime-cement facade | Brick + thermo Styrofoam | Brick + plaster | Lime-cement facade | Brick + thermo Styrofoam | Brick + plaster | Lime-cement facade | Brick + thermo Styrofoam | Brick + plaster | Lime-cement facade | Brick + thermo Styrofoam |
| Shadings         | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 | ✓                 |               |
| Desired indoor temperature for heating (°C) | 22 | 23 | 22 | 21 | 23 | 23 | 22 | 21 | 24 | 22 | 21 | 23 | 22 | NA | NA | NA | NA | NA | NA | NA | NA |
| Desired indoor temperature for cooling (°C) | 20 | 25 | 23 | 25 | 23 | 22 | 23 | 21 | 23 | 22 | 25 | 20 | 23 | 20 | 21 | 25 | 23 | 24 | 22 | 20 |
| Windows thermal insulation performance (3—good; 2—average; 1—bad) | 2 | 1 | 2 | 3 | 2 | 3 | 2 | 3 | 2 | 2 | 1 | 2 | 2 | NA | NA | NA | NA | NA | NA | NA |

✓—Existing; M—Manual; A—Automatic (centralized); NA—Not applicable.
References

1. Lowitzsch, J.; Hoicka, C.E.; van Tuilder, F.J. Renewable energy communities under the 2019 European Clean Energy Package–Governance model for the energy clusters of the future? Renew. Sustain. Energy Rev. 2020, 122, 109489. [CrossRef]

2. Torbaghan, S.S.; Blauuwbroek, N.; Nguyen, P.; Gibescu, M. Local market framework for exploiting flexibility from the end users. In Proceedings of the 2016 13th International Conference on the European Energy Market (EEM), Porto, Portugal, 6–9 June 2016; pp. 1–6. [CrossRef]

3. Directorate-General for Energy (European Commission). Clean Energy for All Europeans; Publications Office of the European Union: Brussels, Belgium, 2019. Available online: https://data.europa.eu/eli/dir/2018/2001/oj/eng (accessed on 1 March 2022).

4. Directive (EU) 2018/944 of the European Parliament and of the Council of 5 June 2019 on Common Rules for the Internal Market for Electricity and Amending Directive 2012/27/EU (Text with EEA Relevance); European Union: Brussels, Belgium, 2019; Volume 158. Available online: http://data.europa.eu/eli/dir/2019/944/oj/eng (accessed on 1 March 2022).

5. Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the Promotion of the Use of Energy from Renewable Sources (Text with EEA Relevance); European Union: Brussels, Belgium, 2018; Volume 328. Available online: http://data.europa.eu/eli/dir/2018/2001/oj/eng (accessed on 1 March 2022).

6. Directive (EU) 2019/944 of the European Parliament and of the Council of 11 December 2018 Amending Directive 2012/27/EU on Energy Efficiency (Text with EEA Relevance); European Union: Brussels, Belgium, 2018; Volume 328. Available online: http://data.europa.eu/eli/dir/2018/2002/oj/eng (accessed on 1 March 2022).

7. Energy Consumption in Households. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_consumption_in_households (accessed on 1 March 2022).

8. Electricity and Heat Statistics. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Electricity_and_heat_statistics (accessed on 1 March 2022).

9. Faia, R.; Pinto, T.; Vale, Z.; Corchado, J.M. A Local Electricity Market Model for DSO Flexibility Trading. In Proceedings of the 16th International Conference on the European Energy Market (EEM), Ljubljana, Slovenia, 18–20 September 2019. [CrossRef]

10. Lezama, F.; Soares, J.; Canizes, B.; Vale, Z. Flexibility management model of home appliances to support DSO requests in smart grids. Sustain. Cities Soc. 2020, 55, 102048. [CrossRef]

11. Khajeh, H.; Firoozi, H.; Hesamzadeh, M.R.; Laaksonen, H.; Shafe-Khah, M. A Local Capacity Market Providing Local and System-Wide Flexibility Services. IEEE Access 2021, 9, 52336–52351. [CrossRef]

12. Agbonaye, O.; Keatley, P.; Huang, Y.; Ademulegun, O.O.; Hewitt, N. Mapping demand flexibility: A spatio-temporal assessment of flexibility needs, opportunities and response potential. Appl. Energy 2021, 295, 117015. [CrossRef]

13. Zheng, J.; Gao, D.W.; Li, L. Smart Meters in Smart Grid: An Overview. In Proceedings of the 2013 IEEE Green Technologies Conference (GreenTech), Denver, CO, USA, 4–5 April 2013; pp. 57–64.

14. Murata, H.; Onoda, T. Estimation of power consumption for household electric appliances. In Proceedings of the 9th International Conference on Neural Information Processing (ICONIP ’02), Singapore, 18–22 November 2002; Volume 5, pp. 2299–2303. [CrossRef]

15. Benyoucef, D.; Klein, P.; Bier, T. Smart Meter with non-intrusive load monitoring for use in Smart Homes. In Proceedings of the 2010 IEEE International Energy Conference, Manama, Bahrain, 18–22 December 2010; pp. 96–101. [CrossRef]

16. Martinez-Pabon, M.; Eyeleveigh, T.; Tanju, B. Smart Meter Data Analytics for Optimal Customer Selection in Demand Response Programs. Energy Procedia 2017, 107, 49–59. [CrossRef]

17. Klein, P.; Benyoucef, D.; Mercikle, J.; Abdeslam, D.O. Analysis of fingerprints of electric appliances as starting point for an appliance characteristics catalog. In Proceedings of the IECON 2014-40th Annual Conference of the IEEE Industrial Electronics Society, Dallas, TX, USA, 29 October–1 November 2014; pp. 3517–3521. [CrossRef]

18. Cruz, C.; Palomar, E.; Bravo, I.; Alexandre, M. Behavioural patterns in aggregated demand response developments for communities targeting renewables. Sustain. Cities Soc. 2021, 72, 103801. [CrossRef]

19. Smart Metering deployment in the European Union | JRC Smart Electricity Systems and Interoperability. Available online: https://ses.jrc.ec.europa.eu/smart-metering-deployment-european-union (accessed on 1 March 2022).

20. Druckman, A.; Jackson, T. Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. Energy Policy 2008, 36, 3177–3192. [CrossRef]

21. Awad, U.; Knight, I. Domestic sector energy demand and prediction models for Punjab Pakistan. J. Build. Eng. 2020, 32, 101790. [CrossRef]

22. Yalcintas, M.; Kaya, A. Roles of income, price and household size on residential electricity consumption: Comparison of Hawaii with similar climate zone states. Energy Rep. 2017, 3, 109–118. [CrossRef]

23. Wiesmann, C.; Azeevedo, L.L.; Ferrao, P.; Fernández, J.E. Residential electricity consumption in Portugal: Findings from top-down and bottom-up models. Energy Policy 2011, 39, 2772–2779. [CrossRef]

24. Rubi-Pérez, D.; Heleno, M.; Alvarez-Bel, C. The flexibility gap: Socioeconomic and geographical factors driving residential flexibility. Energy Policy 2021, 153, 112282. [CrossRef]

25. Wyatt, P. A dwelling-level investigation into the physical and socio-economic drivers of domestic energy consumption in England. Energy Policy 2013, 60, 540–549. [CrossRef]

26. Sanquist, T.F.; Orr, H.; Shui, B.; Bittner, A.C. Lifestyle factors in U.S. residential electricity consumption. Energy Policy 2012, 42, 354–364. [CrossRef]
50. Agenis-Nevers, M.; Wang, Y.; Dugachard, M.; Salvazet, R.; Becker, G.; Chenu, D. Measurement and Verification for multiple buildings: An innovative baseline model selection framework applied to real energy performance contracts. *Energy Build.* 2021, 249, 111183. [CrossRef]

51. Bertoldi, P.; Rezessy, S. Energy Saving Obligations and Tradable White Certificates. JRC Science and Policy Reports, Text. December 2020. Available online: https://e3p.jrc.ec.europa.eu/publications/energy-saving-obligations-and-tradable-white-certificates (accessed on 2 March 2022).