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Behavioural patterns in aggregated demand response developments for communities targeting renewables☆

Carlos Cruz [a,*], Esther Palomar [a], Ignacio Bravo [a], Manuel Aleixandre [b]

[a] Department of Electronics, University of Alcala, Alcala de Henares, 28871, Madrid, Spain
[b] Institute of Innovative Research, Tokyo Institute of Technology, Yokohama 226-8503, Japan

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ABSTRACT

Encouraging consumers to embrace renewable energies and energy-efficient technologies is at stake, and so the energy players such as utilities and policy-makers are opening up a range of new value propositions towards more sustainable communities. For instance, developments of turn-key demand response aggregation and optimisation of distributed loads are rapidly emerging across the globe in a variety of business models focused on maximising the inherent flexibility and diversity of the behind-the-meter assets. However, even though these developments' added value is understood and of wide interest, measurement of the desired levels of consumer engagement is still on demonstration stages and assessment of technology readiness. In this paper, we analyse the characteristics of the loads, the behaviour of parameters, and in a final extent, the behaviour of each kind of consumer participating in aggregated demand scheduling. We apply both non-automatic and machine learning methods to extract the relevant factors and to recognise the potential consumer behaviour on a series of scenarios that are drawn using both synthetic data and living labs datasets. Our experimentation showcases a number of three patterns in which factors like the community's demand volume and the consumer's flexibility dominate and impact the performance of the tested development. The experimentation also makes current limitations arise within the existing electricity consumption datasets and their potential for inference and forecasting demand flexibility analytics.

1. Introduction

The Demand Response (DR) market is still encountering some barriers throughout the world with some exceptions in the United States, Australia and selected European markets (Munuera, 2020). Regulatory uncertainty and strategic shifts on the part of the relevant market players that reduce their investment activity, have dampened a coordinated and collective introduction of the DR outlook. For instance, less than 2% of the global potential for demand-side flexibility is currently being utilised (Gianfrate, Piccardo, Longo, & Giachetta, 2017). Furthermore, despite being numerous and varied, the benefits of DR have not reached yet to the consumers' awareness. In US, for example, it has been estimated that a 5% load reduction during the top 1% of peak hours would bring about a net present value of $3 billion a year in benefits (Bayer, 2015; Zhou, Balandat, & Tomlin, 2018). Electricity pricing and financial incentives are the current strategy to encourage consumers to shift or reduce their electricity use (Soares, Gomes, & Antunes, 2014). Time of Use (TOU) electricity tariffs are evolving towards more sustainable behaviours by encouraging electricity use when there is an abundance of supply from solar photovoltaic (PV) cells in the middle of the day (Venizelou, Makrides, Efthymiou, & Georghiou, 2020). However, many consumers today simply do not know what hours of the day are the most CO2 intensive, nor the times when variable renewables are generating the most, or when prices are low (and sometimes negative) in electricity wholesale markets (Qureshi, Girault, Mauger, & Grijalva, 2017). To encounter these challenges, utilities, authorities and policy-makers as well as the Internet-of-Things (IoT) industry increasingly try to consolidate their service and product offerings that focus on integrating and exploiting consumers' flexibility and consumption awareness (Afzalan & Jazizadeh, 2019). Demand side flexibility can be scheduled as an energy resource, and can greatly have an impact on the electricity system balancing and reliability.

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* Corresponding author.
E-mail addresses: carlos.cruzt@uah.es (C. Cruz), esther.palomar@uah.es (E. Palomar), ignacio.bravo@uah.es (I. Bravo), aleixandre.m.aa@m.titech.ac.jp (M. Aleixandre).
URL: https://eneffpilot.web.uah.es (E. Palomar).

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Nomenclature

$\mathcal{L}$	Duration in hours of appliance operation
$\mathcal{N}$	Number of consumers
ANN	Artificial Neural Network
DR	Demand Response
DSM	Demand Side Management
fD	Fixed demand
HC	Hierarchical Clustering
HC	Hierarchical clustering
ICT	Information and Communication Technologies
IoT	Internet of Things
KNN	K-Nearest Neighbours
LDA	Linear Discriminant Analysis
LG	Linear Regression
MAE	Mean Absolute Error
$MAPE$	Mean Absolute Percentage Error
MSE	Mean Square Error
PCA	Principal Component Analysis
RF	Random Forest
rw	Twenty four hour supply vector from renewables
SVR	Support vector machine regression
t_{beg}	Earliest start time appliance
t_{end}	Latest final time appliance
t_{sched}	Scheduled start time of appliance
vD	Variable demand

Connected appliances such as heaters, air conditioners, washers or electric vehicles can be aggregated together and their electricity use controlled remotely to shift demand over time, for example, when prices are lower and variable renewables are generating (D'hulst et al., 2015). Consumers offering their flexibility by expressing and rescheduling their processes are rewarded in exchange e.g. for lower prices or other value added services such as points that can be cashed out via Paypal (e.g. OhmConnect, 2020). Moreover, prosumers, i.e., producers of their own (and other's) energy, for example by using a rooftop solar panel, storing energy in household or electric car batteries, and/or selling the produced energy on their own premises, play an important role for the success of local stakeholder interactions and local energy balance (Gercek, Schram, Lampropoulos, van Sark, & Reinders, 2019; Santiago, Lopez-Rodriguez, Trillo-Montero, Torriti, & Moreno-Munoz, 2014).

1.1. Engaging with demand response

Research and development of DR technology is being reactivated on these days that prosumers at all levels, residential and tertiary buildings, individually or through a demand aggregator, are able to participate in energy system balancing and flexibility markets (Gelazanskas & Gamage, 2014; Hakimi et al., 2020). Developments of turn-key aggregation and optimisation of distributed loads are rapidly emerging across the globe on a variety of business models (Correa-Florez et al., 2019). These are currently focused on the remote monitoring of individual customer loads, generation and storage, managing and optimising the aggregated portfolio and maximising the inherent flexibility and diversity of the behind-the-meter assets. Some aggregators develop the same strategy of sending signals to their consumers to modify their demand as a response to the System Operator requirements and/or market price signal (– real-time locational pricing interface with a distribution system operator – DSO). Ghorashi et al. (2020) add a penalisation component in their DR proposal that can mitigate the peak rebound and decrease the load deviation on a 13%, and throw a 106% increase of revenue at the utilities' side. Other business models of electricity aggregation support consumer partnerships by creating a platform for consumers to subscribe to distributed power plants (Awad & Gül, 2018).

Consumer engagement in DR programmes and awareness of their benefits have been promoted mostly on an individualised way (Abapour et al., 2020; Ming et al., 2020). Electricity retailers' messaging emphasises individual preferences, which consist of individual action and choice. Moreover, the reward scheme is commonly monetary, individual and based on attributable performance rather than contribution. A research survey to residential DR programme participants in Australia (Arena, 2018) captured how an individualistic design of the programme, specially the design of the rewarding scheme, might cause people rationalise their participation as contributing to broader goals (Guo et al., 2018). The survey also revealed that there were several factors that limited or favoured household participation in a RD event, i.e., the insulative quality of the house, efficient and smart technologies, relationships of people in the house, and the desire to act to shift a routine or comfort level. We believe that a critical missing piece for understanding and optimising DR is the recognition of the social and behavioural factors and their impact on the consumer engagement as well as on the final aggregation service's performance. For example, Mamounakis et al. (2019) propose a real-time pricing scheme for DR based on a clustering algorithm that allocates the gains fairly (according to the algorithm's reaction to the participants' flexibility) among consumers; it also promotes behavioural change towards energy efficiency by achieving 30% of reduction in the cost of system energy (in scenarios of highly flexible consumers) and greater welfare of aggregated users. In addition, Moroni et al. (2019) enumerate a set of four valuable instrumental advantages from organising energy communities, i.e., direct investment and operation and maintenance cost reduction, transaction cost reduction, risk reduction and electricity self-consumption maximisation from the use of smart microgrids.

Fig. 1 illustrates the five main areas of actuation to which aggregation contributes when building DR capacity. We also include the main machine learning (ML) techniques applied to these actuation areas, and analyse the existing literature that addresses each of them in Table 1. Being optimisation the most explored area, in this paper we analyse the behavioural patterns that may arise out of the consumers/prosumers' interaction and participation in day-ahead aggregation services, which in turn empower energy forecasting, consumer segmentation and demand optimisation of the community (neighbourhoods/districts) load and its balance. Deployed on our laboratory, the ENEFF aggregator (Cruz et al., 2019) implements a day-ahead optimisation scheduler that develops and integrates the ability of electricity consumers to jointly change their pattern of demand in response to the available renewable supply. The ENEFF aggregator is both efficient ($<$ 20 seconds for 8 households) and cost-effective ($<$ 100 euros in hardware components, no need of appliance renovation nor additional network infrastructure) in scheduling the joint demand of a coalition of consumers/prosumers which put their demand flexibility at its disposal. It is also turn-key, controlling the functioning of the participants' appliances and domestic network-enabled devices according to the allocated supply for each participating household. Our analysis covers the five actuation areas by applying the most powerful ML techniques to the problem domain and aiming at exploring the impact of adding the consumer flexibility into the demand aggregation process. We describe the methodology of our analysis and the main goals in Section 1.3.

1.2. Measuring demand response capacity

During its evaluation in controlled scenarios, the ENEFF demand aggregator performs more efficiently in the presence of certain factors. Recognition of these factors, on one hand, and the analysis of the dominance of each factor on the generation of community patterns, on

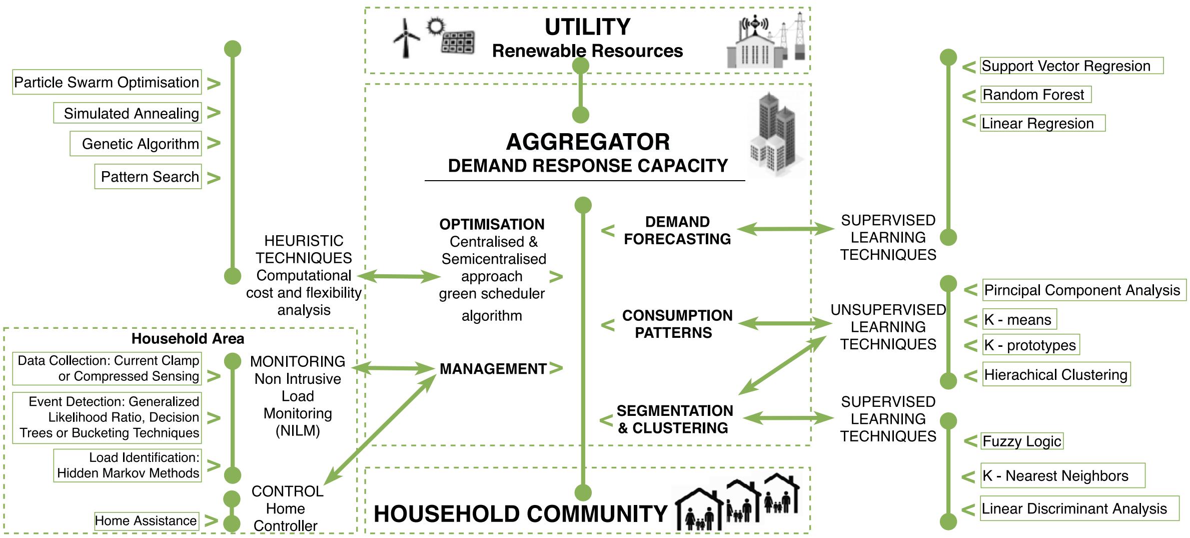
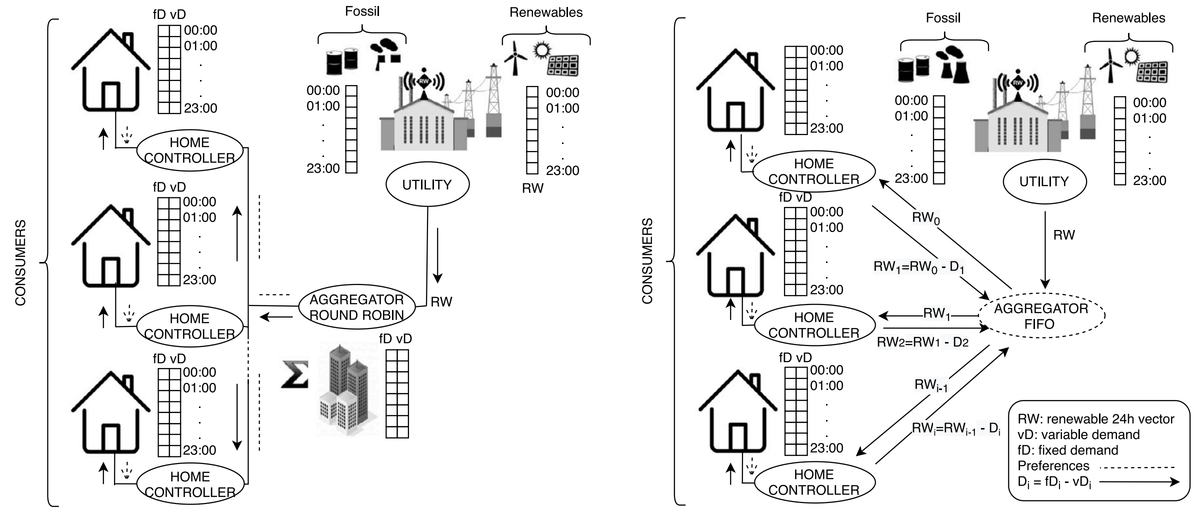


Fig. 1. Areas of actuation studied on our aggregated DR development and main machine learning techniques.

Table 1
Reviewed literature for specific DR application areas.

Research	Areas of competence					
	Optimisation	Control & monitoring	Demand forecasting	Consumption patterns	Segmentation & clustering	Renewables integration
Gianfrate et al. (2017), Li, Ma, Robinson, and Ma (2018), Piscitelli, Brandi, and Capozzoli (2019)				✓	✓	
Abapour, Mohammadi-Ivatloo, and Tarafdar Hagh (2020), Antonopoulos et al. (2020), Awad and Gül (2018), Bayer (2015), Correa-Florez, Michiorri, and Kariniotakis (2019), Cruz, Palomar, Bravo, and Gardel (2019), Gelazanskas and Gamage (2014), Gercek et al. (2019), Ghorashi, Rastegar, Senemmar, and Seifi (2020), Lucas, Jansen, Andreadou, Kotsakis, and Masera (2019), Mamounakis et al. (2019), Moroni, Antoniucci, and Bisello (2019), Usef Energy (2016), Venizelou et al. (2020), Wang et al. (2020, 2020), Zhou et al. (2018)	✓					
Afzalan and Jazizadeh (2019, 2019), Soares et al. (2014)	✓				✓	
D'hulst et al. (2015), Qureshi et al. (2017)	✓	✓				
Darby and McKenna (2012), Ghaemi and Brauner (2009), Guo et al. (2018), Santiago et al. (2014), Satre-Meloy, Diakonova, and Grünewald (2019), Sepehr, Eghtedaei, Toolabimoghadam, Noorollahi, and Mohammadi (2018), Vallés, Bello, Reneses, and Frías (2018),				✓		
Hakimi, Hasankhani, Shafie-khah, and Catalão (2020), Ming et al. (2020), Shi et al. (2019)	✓					✓
Gajowniczek and Zabkowski (2014), Ming et al. (2020)	✓		✓			
Li et al. (2018), Wen, Zhou, and Yang (2019)					✓	
Walker, Khan, Katic, Maassen, and Zeiler (2020), Wijaya, Vasirani, Humeau, and Aberer (2015)			✓			
ENEFF Aggregator (Cruz et al., 2019)	✓	✓	✓	✓	✓	✓

the other hand, are of utmost importance for the actual deployment of a DR programme on a particular community. In particular, the identification of consumer behaviours and community patterns could help to determine which platforms, market rules, or incentives are most effective in a certain community and how the community members could respond in the future (Antonopoulos et al., 2020; Piscitelli et al., 2019). Moreover, it can contribute to bridge both designed and actual performance features expected aggregation and scheduling algorithms for validation and refinement. To this regard, there are various methods for the classification of consumers and the construction of the typical daily load curves. The study in Ghaemi and Brauner (2009), for instance, analyses the electricity consumption for 51 households in Austria finding a correlation between average annual consumption and daily demand. Similarly, the method proposed in Sepehr et al. (2018) serves to model the load profile of 149 residential subscribers in Iran by classifying consumption profiles in terms of the number of household occupants and defining the probability density function for the starting time of each appliance. Households with kids and pets presented less predictable behaviour. In Afzalan and Jazizadeh's work (Afzalan & Jazizadeh, 2019), a classification metric sorts the users with flexible loads out in a community (300 households primarily located in Austin, TX) according to their load shifting flexibility for deferrable loads. The metric helps to identify suitable user segments with higher predictive potential for demand reduction finding predictable behaviours in the use of EV, AC and wet appliances. Authors defined temporal flexibility of loads as a function of the time of the day so finding opportunities for the integration of renewables, e.g., peaks around noon indicates opportunities for solar power integration. Demand flexibility is defined by Satre-Meloy et al. (2019) around the relationship between the type



(a) RR strategy under centralised aggregator approach (b) FIFO strategy under semi-decentralised approach

Fig. 2. Smart community: roles, structure, and communication flows.

of activity and its consumption at 1-minute timescale in the residential sector. A statistical analysis based on multiple linear regression shows how activity-related factors that influence electricity consumption vary from day to day. Their analytical results point to dwelling and appliance-related variables, especially EV ownership, number of power showers, living in a detached home, number of rooms, and number of TVs/computers as well as cat ownership and number of occupants as the strongest predictors of increased daily consumption. Furthermore, to support targeted demand-side management and efficient operation of smart grid, Wen et al. (2019) investigates the recognition of consumption behaviours or clusters within daily electricity consumption profiles (ECPs) from trials at Ireland and China using clustering methods such as k-means and Principal Component Analysis (PCA). Their experiments showed that similarities among ECPs in the same cluster in terms of the total electricity consumption and the volatility of ECPs. Authors made recommendation about the clusters and type of residents of more significance to implement DSM and develop personalised DR strategies. Their experimentation also showed that PCA almost has no influence on the clustering results while improving efficiency of the algorithm performance.

Utilities that understand communities' consumption and production patterns are leveraging their capacity and balancing services as well as reducing the cost of integrating renewable energy sources into existing energy systems (Li et al., 2018; Usef Energy, 2016). Shi et al. (2019) shows how scheduling methods that neglect user comfort levels may result in long load-shifting time periods for transferable loads and high interruption power for interruptible loads. Their experiments over a Particle Swam Optimisation algorithm also prove the inverse proportional relationship between user energy costs and the coefficients of comfort levels. Strategies for optimising renewable energy consumption rate are also discussed and their conclusions present some doubtful incompatibilities between renewable energy generation and community demands, and daily energy costs. Nevertheless, challenges remain in load flexibility estimation (Darby & McKenna, 2012). Lucas et al. (2019) present a structured way using Factorial Hidden Markov model to calculate flexibility that can be extracted by one house, which gives a valuable tool to aggregators as the first step to bring demand response to the residential sector. Support Vector Machines (SVM) and Multi-Layer Perceptrons (MLP) are the techniques applied in Gajowniczek and Zabkowski (2014) to the forecasting of the day-ahead consumption on an individual household in Poland. Predictions resulted within acceptable levels of accuracy, but authors realised the volatility of analysis on household level, as consumption habits can vary significantly due to the many variables such as climate, thermal system performance or occupancy patterns. Wang et al. (2020) remark the importance for aggregators to comprehend the available DR capacity of consumer participants before trading in the day-ahead market. To encounter this challenge, the aggregated DR capacity is estimated as the difference between the Customer Baseline Load (CBL) and the actual load whereas the consumer's responsiveness to the DR signals is modelled to minimise the individual daily cost of electricity consumption. The relevant factors which have significant impacts on the aggregated DR capacity are extracted by PCA and then applied to a SVM based forecasting model to predict the aggregated DR capacity (with 80% accuracy for over 70% of the testing dataset). Their results are, however, not exhaustive in analysing the impact of the behavioural features (e.g. the uncertainties associated to human behaviour) that may influence the large-scale implementation of their DR programme. In Vallés et al. (2018), a probabilistic characterisation of residential consumers flexibility based on Quantile Regression (QR) provides a parametric representation of consumers that allows minimisation of the uncertainty and variability of consumer responsiveness. The analysis of a case study in Spain distinguishes a number of influential factors, i.e., the number of occupants, the electricity consumption and the education level of consumers, that have effect on demand responsiveness. Results throw individual flexibility profiles that are not extrapolated easily to aggregated settings. In fact, the relatively small loads and numerous actors have hindered a more homogeneous introduction of residential DR schemes across the globe, and similarly a wider deployment of local micro generation of renewable energy.

As aforementioned, Table 1 compiles the relevant related work and its contribution to the actuation areas when developing aggregation and DR services. The suitability of different ML techniques has been tested and measured on controlled environments or simulations with datasets. Similarly, our study analyses the suitability of these techniques on controlled scenarios finding, in some cases, improvement of the technique accuracy in the automatic extraction of behavioural factors and/or patterns, and even, in other cases, identifying a precise number of patterns or clusters from real consumers' consumption data.[1] We also show how these clusters behave when being simulated as

[1] We configure real scenarios by using the electricity demand profiles for 200 households randomly selected among the ones available in the 2009 Residential Energy Consumption Survey (RECS) dataset for the Midwest region of US (Muratori, 2018).

consumer communities interacting in aggregated demand scheduling. Tested scenarios vary the aggregation setting (i.e., centralised, semi-decentralised), the scheduling algorithm (which is also being developed and validated on our laboratory) and the type of consumer data. For the latter, a preliminary non-automatic analysis of the factors governing the optimised scheduling of the community's demand identifies those that dominate and rule the algorithm performance and objective achievement. Our approach is novel and systematic (as explained in the methodology) and, we believe, could be also inspirational for the scientific community, utility companies and energy efficiency policy-makers to leverage aggregated DR technology and services at community level.

1.3. Methodology of this work

We estimate the DR capacity of a community participating in the demand aggregation and scheduling framework presented in our previous work[2] (Cruz et al., 2019) applying the methodology as follows:

1. We extract the determining factors and potential patterns of a community behaviour by analysing the algorithm performance and the influence of the factors on it. A number of three patterns are extracted from a series of different consumer community settings representing the user–appliance interactions and consumption and their flexibility pattern. We use synthetic data for this analysis.
2. We implement unsupervised ML methods, i.e., k-means, hierarchical clustering and PCA, to automatise the analysis on the same scenarios as well as on public datasets containing consumption records. Patterns automatically recognised lead to the same influential factors extracted on our previous analysis. Unfortunately, dataset could not provide insights into consumers' flexibility features.[3]
3. We also evaluate the scenarios on supervised ML methods such as linear discriminant analysis, k-nearest neighbours and fuzzy logic. Training and testing samples are extracted from the same datasets to validate previous results. Classification over the testing data threw accuracy scores greater than 90%.
4. We include the analysis of profiling or predicting community consumption to identify temporal variations of load-specific demands. Models such as random forest, support vector machines for regression and linear regression are evaluated and compared in terms of their accuracy over the same datasets. Community prediction scored 95% of accuracy.

We believe that the analysis and recognition of the behavioural patterns and factors pointed out in our work can help to achieve a better estimate of the potential of demand-side response from a consumer community, not only prior to the programme deployment but also along the programme execution at the community. In particular, it can serve (i) to estimate the level of engagement of the consumers in a DR event, (ii) to identify and target potential candidates for automated DR, (iii) to load targeting, (iv) to help the community predict its micro generation needs and also (v) customise the reward scheme according to the recognised community pattern.

The reminder of the article is organised as follows. Section 2 overviews the DR system model and presents the analysis of community behaviour based on the algorithm's performance cost. The automated analysis is fully described in Section 3. In Section 4, we explore the prediction accuracy of community profiles from a number of regression models. Finally, Section 5 concludes and presents the immediate research directions.

2. System overview and preliminary analysis

In our development for DR, consumers (also producers) of electricity connect, form coalition, and collaborate pursuing common goals. The following sections overview the system model, roles and procedures, and identify a preliminary set of behavioural patterns within a simulated community.

2.1. Roles and main procedures

Our approach to DR tends to stimulate consumer collaboration supporting their energy behavioural change towards both, greater energy-efficient and greener habits. To this end, consumers are provided with an app for pre-allocating a 24 hour demand along with their time preferences that could be as much elastic as the consumer opts for every appliances to be scheduled. A home controller serves as a gateway between the consumer and aggregator and acts as the manager of the household's appliance. Fig. 2 depicts the system architecture's roles and two settings, whereas Table 2 further illustrates the communication flows and states terminology.

A new scheduling algorithm aggregates the electricity demand of the participating consumers' appliances. The scheduling optimises the aggregation of the appliances' time frame preferences in respect to an objective function that takes the available energy supply from renewables rw as parameter. The latter, i.e. a 24 hour vector containing the expected(/stored) supply from green sources, is issued by the local utility provider and received by the community aggregator for the daily reallocation.

2.2. Two settings for DR

The working methodology adopted in this work involves the comparison of two main settings or algorithms as follows:

- Centralised setting: Consumers share their information with the community aggregator for load reallocation (Fig. 2–a). This scenario assumes that consumers are not against of profiling at the aggregator, who implements a scheduling algorithm following a Round Robin (RR) method. Basically, the aggregator attempts to find in order or turns the optimised community allocation of demand according to the received time preferences and the available energy from renewables.
- Semi-Decentralised setting: For more privacy-aware scenarios, the aggregation logic runs individually at and for every consumer as a First In, First Out (FIFO) strategy, in which each participant earlier-arriving to the rw vector accesses it, blocks it and allocates his/her demand on the shared supply. For the sake of simplicity, the aggregator role could co-exist on this setting but as a common repository maintaining consistency on the shared copy of the supply vector (Fig. 2–b).

2.3. Preliminary analysis of behaviours

We posed the algorithm at the aggregator to deal with a series of scenarios and use cases in order to non-automatically extract and identify potential community behaviours and the influential factors on the aggregation and scheduling process and its performance. Table 3

[2] The ENEFF framework is briefly described in Section 2 for the present paper's self-containedness.

[3] An important limitation of the methodology is the difficulty of extracting consumer flexibility information from the dataset used for validation. The dataset comprises the hourly consumption of a consumer community during a year. Some of our scenarios for validation will try to build margins of flexibility as to simulate rigid/flexible demand behaviours. Pilot deployment in living lab is also a limitation of our analysis since we have not yet put the aggregator development ENEFF through real validation.

Table 2
Roles and exchanged messages' structure.

APP	→	$Controller$:	m1: $\{fD, vD, \mathcal{L}, t_{beg}, t_{end}, ID\}$ $\forall$ appliance to be scheduled $\in A_c$
$Controller$	→	$Aggregator$:	m1 $\times A_c$ appliances $\forall$ consumer $c \in C$ ($+B_c$ $\forall$ prosumer $c \in C$)
$Utility$	→	$Aggregator$:	$rw = [s_0, \ldots, s_{23}]$ (kW)
		$Aggregator$:	runs the scheduling for matrix $\mathcal{A}$
$Aggregator$	→	$Controller$:	$[d_0, \ldots, d_{23}]$ (kW) $\times A_c$ appls.
$Controller$	→	$Appliance$:	(ON/OFF) $\forall$ $[0, \ldots, 23]$ $\forall$ appliance to be scheduled
		where:	the consumer c introduces for his/her appliances $\in A_c$, identified by ID, its fixed and shiftable load variable demand vD (kWh when the appliance is on), fixed demand fD (kWh when the appliance is off), the duration of its shiftable consumption $\mathcal{L}$ (in number of hours of activation), and the preferred time period for this appliance's activation (t_{beg}, t_{end}), which represents the time frames of flexibility and has to be no less than L, for every smart appliance identified by IDi.; if c is prosumer, B_c is the accumulated power (e.g. battery); s_t is the supply (kW) expected in time slot t, whereas d_t is the demand (kW) scheduled in time t of the day.

Table 3
Factors for the different scenarios.

Factors	Value/Label	Description
Community size	< 5/Small, > 30/Big	The number of consumers is not a determining factor in the performance of the scheduling algorithm but the total number of their appliances. Experiments conducted for small scenarios with less than 5 consumers and big scenarios of 30 consumers or more.
N. of appliances	< 40/Small, > 1200/Big	The number of appliances to be scheduled by the aggregator directly affects the algorithm performance. Fig. 3 shows the linear tendency of the computational cost when the number of appliances increases. The algorithm runs very fast for communities with less than 40 appliances.
Demand volume	< 9 kWh/Low, > 18 kWh/High	The volume of shiftable demand could impact on the performance and it depends on the volume and flow of the renewable supply's availability. Data was extracted from real datasets.
Demand flow	$\sigma(load) < 20\%$/Flat, > 20%/Peak	Load is inherently variable; with this factor in Peak we represent the existence of 20% variability along the day.
Consumer flexibility	< 3 h/Rigid, 3 <> 6 h/Mixed, > 6 h/Flexible	The elasticity of the consumers' demand directly influences the efficiency of the scheduling computation. Three types of scenarios were identified, which depict different consumer behaviours on the establishment of their time preferences and flexibility of activation.
Supply rw flow	$\sigma() < 20\%$/Flat, $\sigma() > 20\%$/Peak	The availability of dispatchable and variable renewable power generators could affect the performance of the community scheduling (our experiments will show the opposite though).

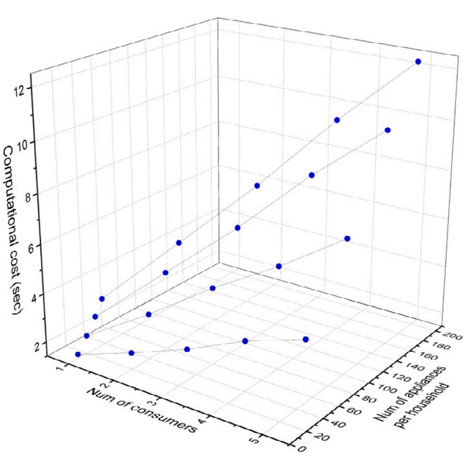


Fig. 3. Computing time relationship between the number of participants and appliances under a centralised setting.

compiles the factors that the algorithm is considering for the computation of the optimal[4] community schedule; this computation cost increases proportionally to the number of appliances and participants as shown in Fig. 3. In particular, use cases are established according to:

- Demand volume: We allocate two cases on this factor, i.e., case $\mathcal{A}$ for consumers that require high demand and case $\mathcal{B}$ for low demanding consumers.
- Demand flow: We also evaluate the algorithm's robustness against two types of baseload. Thus, case $\mathcal{C}$ represents a flat flow of demand along the day whereas case $\mathcal{D}$ illustrates demands concentrated on a specific time period of the day forming peaks of load.
- Consumer flexibility: We identify three cases of consumer in terms of the elasticity of his/her demand's time preferences. This elasticity depends on the duration of the appliances' load and the preferred time period set for all of them; hence, cases $\mathcal{E}$, $\mathcal{F}$, and $\mathcal{G}$ represent a rigid, mixed and flexible behaviour, respectively.
- Supply flow: We consider the supply flow as an important factor in scheduling the flexible assets based on current supply from renewables; case $\mathcal{X}$ is representing a supply that flows uniformly along the day, and case $\mathcal{Y}$ when peaks occur.

All scenarios possible combining the factors above are compiled in Table 7 in Appendix. We generated communities of 5 consumers and 48 appliances per household using synthetic data. Hence, to evaluate the impact of the demand volume and flow, we conducted experiments under the different scenarios of consumer flexibility. As depicted in Fig. 4, high and peak-based demand communities, and flexible ($\mathcal{GBD}-$) communities represent upper bounds on the aggregation algorithm. In particular, consumers' flexibility parameters such as the duration of appliances' operation ($\mathcal{L}$) can increase the difficulty of the optimisation search (finding the optimal shared resource allocation). Our experiments found that demand volume and consumer flexibility parameters, specially when the latter are short time values, impact negatively on the scheduling performance.

We now evaluate the impact of the consumer flexibility on the aggregation result over different community sizes following a centralised setting. The algorithm can reallocate 32.5% of the demand under a

[4] The optimisation function outputs an array of 24 slots with the definitive supply for every appliance given the operation time demanded $\mathcal{L}$, the preference interval $[t_{beg}, t_{end}]$ and the available supply rw. For instance, the function is responsible of searching the optimum time slot t_{sched} for every appliance's start. The optimisation will determine how appropriate an adjustment is by minimising the total overconsumption (in hours) of the community appliances against the available renewable supply at a certain time slot.

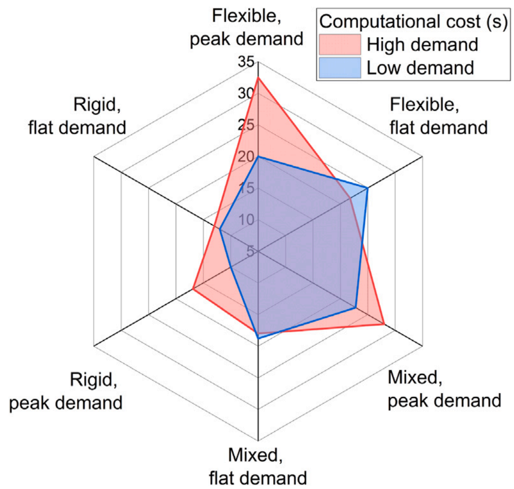


Fig. 4. Impact of the demand volume on the computational time in the different scenarios of consumer flexibility and demand flow.

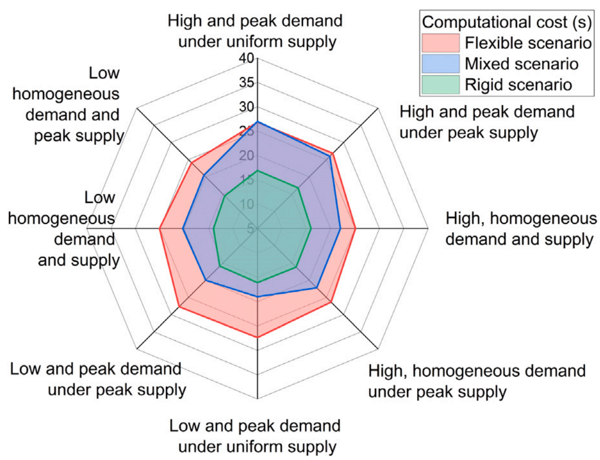


Fig. 5. Impact of the consumer flexibility on all combinations of factors, including the supply flow, in terms of the computational cost.

flexible scenario, encountering a lower bound of 0.8% when consumers cannot express flexibility (i.e., $\mathcal{EAC}-$ scenarios). Moreover, we conducted experiments combining all factors; finding are summarised in Fig. 5 where communities displaying rigid flexibility allocate faster the shared resource. High flexibility increases the search space of the residential appliances' load allocation, making the ENEFF aggregator model to consume much more time searching the optimal schedule.

Furthermore, we analyse the influence of the supply flow (including the case of insufficient supply) in Fig. 6, encountering peak-time demand and high demand communities ($-\mathcal{BD}-$) at the upper bounds of computational cost. Flat demand communities have a chance on absorbing any possible supply disruption or unbalance of (local) supply.

We also include comparison of all factors under the two settings in Fig. 7 in terms of the computational cost of the relevant scenarios. Flexible communities are costly in computation compared to more rigid communities under the two settings. Counting on a centralised processing algorithm that allocates the shared resource is generally more efficient, with a few exceptions, e.g., in peak-time demanding communities. In general terms, semi-centralised demand (aggregation and) scheduling models run less efficiently and provoke ineffective use of the shared resource as shown in Fig. 8. The semi-decentralised setting generate a 46% waste of the available supply in flexible communities. Note that, in this setting, demand is managed and reallocated

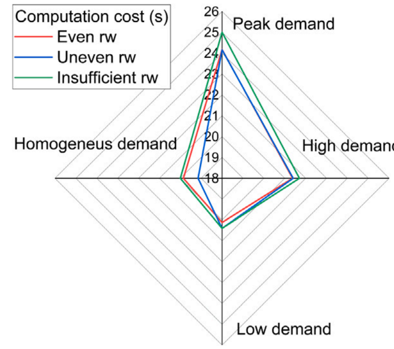


Fig. 6. Impact of the supply flow on the computational time in the different scenarios of demand volume and flow.

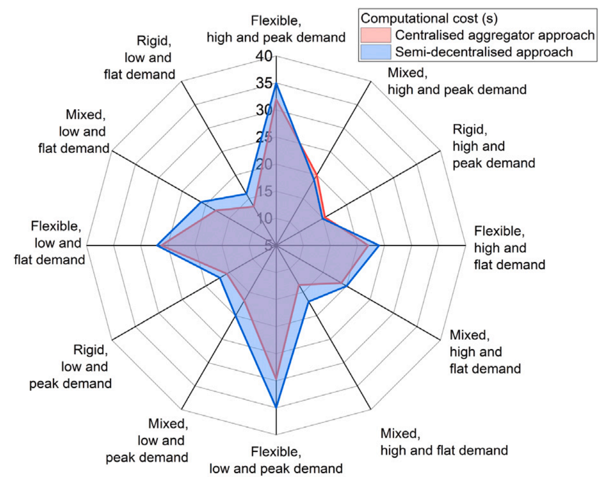


Fig. 7. Computational time comparison between centralised and semi-decentralised settings under most relevant scenarios and factors.

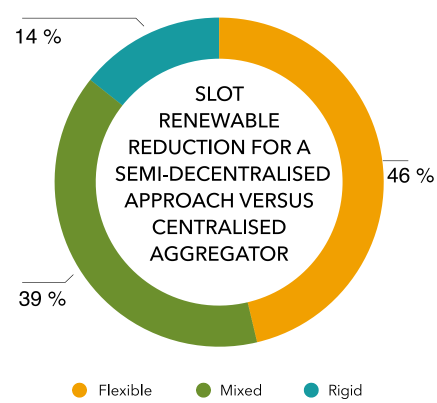


Fig. 8. Use/Waste of the available supply in the semi-centralised setting and under different communities' flexibility scenarios.

individually without taking into account the preferences of the whole community.

Hence, both, the performance cost and the degree of balancing between demand and supply, distinguish a number of 6 main scenarios, whose behaviours and influence on the community aggregation algorithm are illustrated in Figs. 9–11. Graphs on the top plot the aggregated demand prior to (in blue) and after (in red) running the optimisation algorithm in response to the renewable supply that is plotted at the bottom showing the available supply prior to (in green)

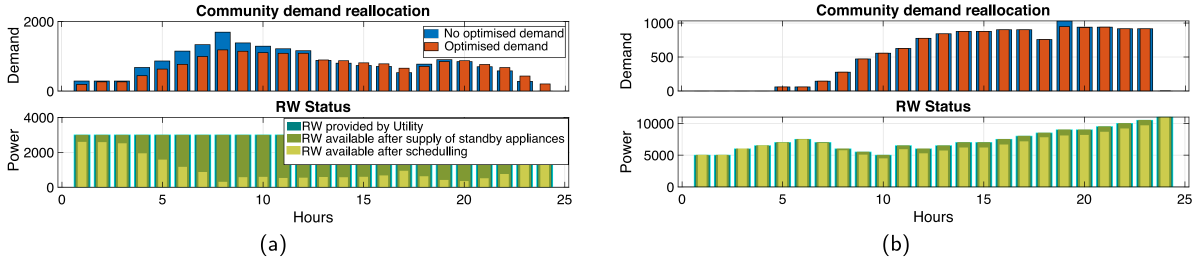


Fig. 9. Busy communities demand high under rigid scenarios of flexibility, on a peak-time basis ($\mathcal{EADX}$) and counting on a flat supply from renewables as in (a); or counting on flat demand and sufficient renewable energy supply ($\mathcal{EACY}$) as shown in (b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

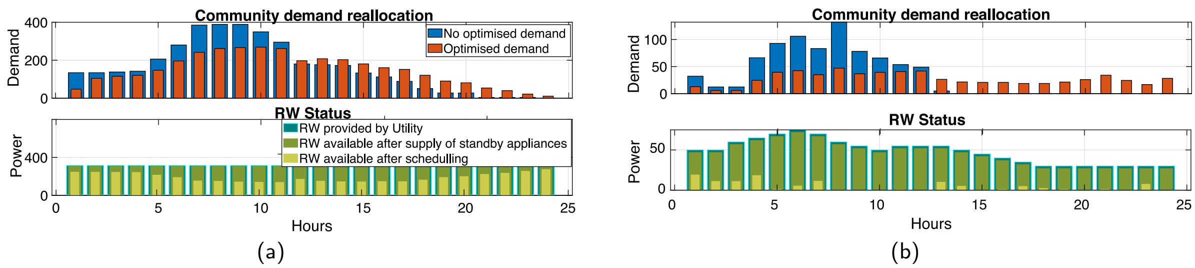


Fig. 10. Concerned communities comprise flexible consumers, that may demand medium-low volume, on a peak-time basis ($\mathcal{GBDX}$) as in the scenario displayed in (a) with a flat supply from renewables. Concerned behaviour is also distinguished in flexible, flat, low-demanding communities ($\mathcal{GBCY}$) where the supply from renewable is insufficient sometime along the day as in (b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

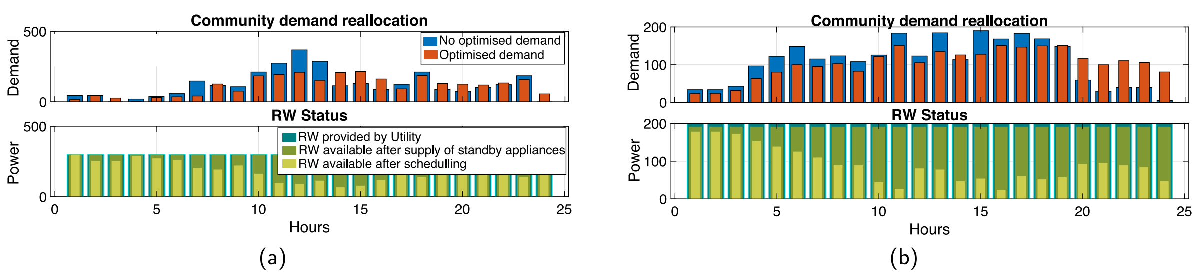


Fig. 11. Demanding behaviours perform over mixed-flexible communities consuming mostly under a peak-time basis such as in (a) with high demanding consumers ($\mathcal{FADX}$); and (b) with consumers demanding lower throughout the entire day ($\mathcal{FBDX}$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and after (in yellow) the allocation to consumer fixed and shiftable demand. The identified behaviours can be described as follows:

Busy behaviour: Busy consumers demand high and create an scenario difficult to adjust when their flexibility is rigid and concentrated on same time periods. Our aggregator has low margin to flatten the demand along the day and barely manages to allocate the available supply as depicted in Fig. 9. It is however the fastest scenario counting on sufficient supply. Communities displaying this pattern can unlock up to 3% of flexible demand volume.

Concerned behaviour: Communities displaying an energy-saving behaviour are defined by low demanding consumers that demonstrate high demand flexibility through long preferences' time periods. We tested our aggregation algorithm against concerned communities consuming on a peak-time basis and considering different scenarios of supply volume. For instance, Fig. 10 shows how our aggregator flattens the peak demand and matches electricity demand to periods when intermittent renewable energy is available. Because of the participants' flexibility, operation time of variable loads can be shifted between periods of the day. Note however that the aggregated scheduling takes longer (increasing up to 2%). Communities displaying this pattern make available up to 30% of flexibility in demand volume.

Demanding behaviour: Demanding communities display an heterogeneous dynamism of consumer flexibility as illustrated in Fig. 11 for different supply scenarios. Our aggregator manages to flatten peak-time consumption on an efficient way, even counting on insufficient supply in some slots. Communities displaying this pattern transform up to 15% of flexible demand volume.

Taking into account our aggregator's DR features, Concerned consumers who demonstrate great flexibility through long preference periods can present high responsiveness to DR signals. As a result, renewable resources are efficiently managed with 30% of margin for reallocation if compared to the 15% obtained for demanding communities or the 1% for Busy behaviours. Moreover, our results emphasise the importance of defining the temporal flexibility of loads as a function of

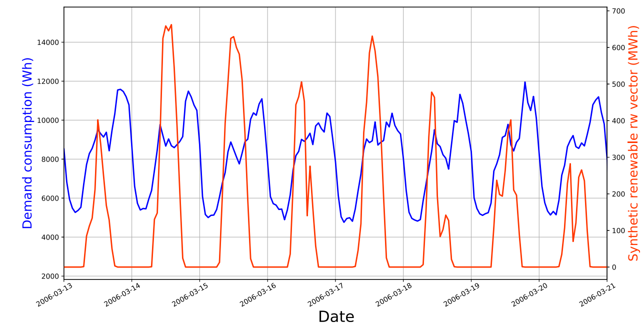


Fig. 12. Time series of the of energy consumption (blue curve) and rw vector provided by the Utility (red curve) in the aggregated model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the time of the day to provide opportunities for maintaining the power balance, for peak demand reduction as well as for the integration of renewables.

3. Automated analysis

We now configure a series of ML methods for pattern recognition that can help to identify new behaviours within our dataset as well as to validate the ones established in previous section. We first describe the methodology applied to this analysis.

3.1. Data/feature processing and methodology

We prepare the data at the aggregator's side; in particular, we use the NREL[5] dataset (NREL, 2020) that consists of the electricity demand profiles (residential power consumption, validated using metered data, with a resolution of 10 min (Muratori, Roberts, Sioshansi, Marano, & Rizzoni, 2013)) for 200 households randomly selected from the US Midwest region. Households vary in size and number of occupants and the profiles represent total electricity use, in watts. This dataset also compiles synthetic solar PV power plant data points for the US representing the year 2006. Fig. 12 depicts a partial time series of these data for a household and the available renewables provisions.

We use the Scikit learning module (Pedregosa et al., 2011) to process the dataset and analyse the extracted features. The process of preparing the data for analysis comprises several steps, i.e., (i) checking and handling of missing values; (ii) evaluation of data quality; (iii) checking and handling of outliers and scaling. Hence, the final dataframe is a "CSV" type file with two data types, namely, the timestamp and the energy consumption value (in watts) at that moment. It is however not possible to identify consumer flexibility profiles.

We will first experiment with unsupervised learning methods, whose main objective is to infer natural structures presented in a set of training samples (extracted from the NREL database). Afterwards we will apply previous analysis to supervised classification methods as to compute accuracy of the estimations.

3.2. Unsupervised analysis

Our analysis with unsupervised methods opts for (i) k-means clustering, which is very suitable for analysing large scale data sets, and its indices, including Elbow and Silhouette Index, support the determination of a suitable cluster number; (ii) k-prototypes, an extension of the k-means algorithm to categorical domains, allows clustering objects to be described by mixed numeric and categorical attributes; (iii) hierarchical clustering, though being a time-consuming algorithm, it has been frequently employed to identify typical energy usage profiles of buildings, to understand building energy consumption characteristics so helping the development of effective strategies to improve building energy efficiency; it provides a highly detailed separation of clusters; and (iv) PCA helps us investigate data dimensionality reduction, which is a very advantageous method when there is a lack of labelled data, or when dealing with large scale smart meter data, thereby improving the data mining efficiency.

K-means Algorithm: Fig. 13-a depicts the exploration conducted over the NREL dataset with the electricity load profiles and averaged by hour. A number of three groups or clusters were obtained by applying the Elbow and average silhouette methods.[6] Clusters show a common dynamics in consumption but we can distinguish groups of consumers demanding higher and more prominent peak-time load whereas others displaying a flatter and lower consumption profile along the day. For instance, Cluster 1 (in Fig. 13-red curve) presents similarities with the Busy pattern ($\mathcal{EBD}-$) extracted from the non-automatic analysis in terms of demand volume and flow. Cluster 2 (in blue) curve clearly corresponds to the Concerned consumption scenario (i.e., $\mathcal{FA}--$ combinations), whereas Cluster 3 (in green) displays a consumption behaviour fitting the Demanding pattern, i.e., it shows an heterogeneous demand volume and flow ($\mathcal{G}-\mathcal{D}-$).

K-prototypes Algorithm: Configured with the same number of clusters, Fig. 13-b shows the consumption patterns extracted from the same NREL dataset, in which we have included categorical features stating the three types of behaviours identified in Section 2.3. To this regard, demand volume and flow are the two factors analysed as to pair each household's dynamics with one of the behaviours. Though similarities with k-means are visible in Fig. 13 and so both clustering methods produce three clusters that are easily distinguishable, the classification of the samples varies between the two algorithms, e.g. our categorisation of samples into the Cluster 3 deviates in 20 households that are classified into Cluster 2, and 4 households considered as Busy behaviours are classified into Cluster 3. We can see that k-prototypes clusters are more equally distributed, though boundaries are difficult to distinguish from this dataset.

Hierarchical Clustering (HC): This method computes a hierarchical representation or dendrogram of the data structures found within the NREL dataset, which are organised into a tree for a meaningful classification. The horizontal position of each branch relates to the distance (dissimilarity) among clusters. Fig. 14 illustrates a number of 3 sub-clusters of similar data that can be interpreted as follows: cluster 1 (in red) with 52 points (households), cluster 2 (in blue) comprises 58 points, and cluster 3 (in green) groups 90 points. This algorithm searches factors of similarity/dissimilarity within the dataset; two clusters namely Cluster 1 and 3 present more similarities (in both dimensions demand volume and flow) since they belong to the same branch. These sample populations lie within the scenario $\mathcal{FBDX}$. Data in Cluster 2 also shares common dynamics with Cluster 3, which is the most populated cluster compiling heterogeneous behaviours. Data and dendrogram correlation let us infer that the patterns extracted in our non-automatic analysis fit well the current HC clustering.

Principal Component Analysis (PCA): Aiming at minimising redundant data and optimising the cluster centroids, we apply PCA to the NREL dataset obtaining a visualisation (as in Fig. 15) of three different

[5] The National Residential Efficiency Measures Database https://data.nrel.gov/system/files/69/Residential-Profiles.xlsx is a publicly available, centralised resource of residential building retrofit measures and costs for the U.S. building industry.

[6] The difficulty of determining the cluster number is due to the variability of the data which is unknown. The optimal number of clusters is somehow subjective and depends on the method used for measuring similarities and, the parameters used for partitioning: Elbow distortion is the sum of squared distances from each point to its assigned centre, and the average silhouette approach measures the quality of a clustering.

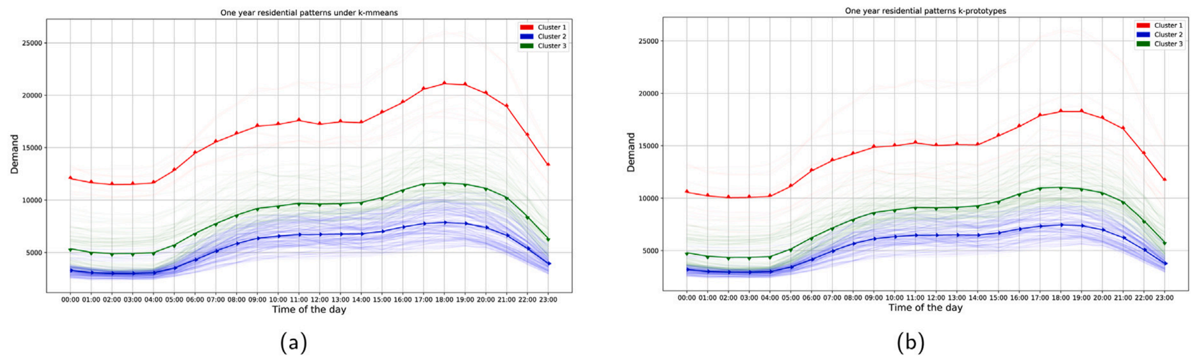


Fig. 13. K-means (a) and K-prototypes (b) analysis throw a number of three consumption patterns over a year: Cluster 1 displaying a similar pattern than the Busy behaviour (red curve), Cluster 2 showing a flat and low-demand Concerned behaviour (blue curve) and Cluster 3 for a more heterogeneous Demanding consumer (green curve). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

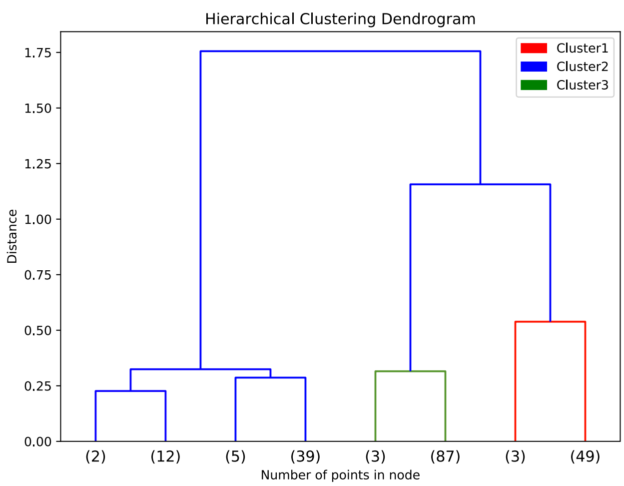


Fig. 14. The HC dendrogram computed over the dataset shows a number of 3 clusters; the graph also indicates the quantity of points/individuals found in each branch. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

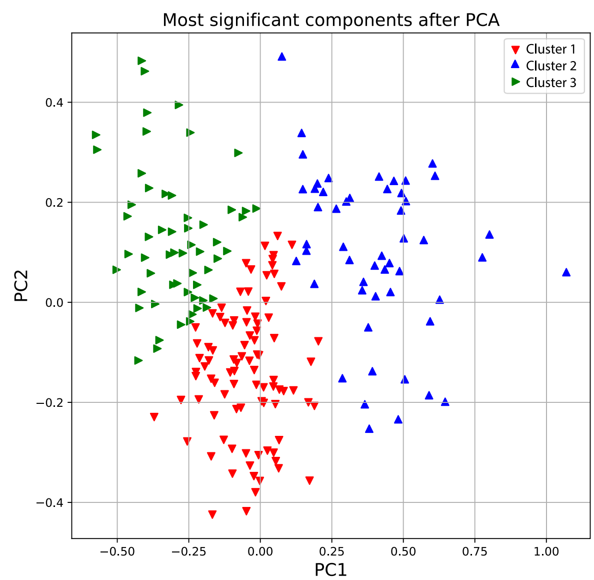


Fig. 15. Principal Component Analysis results in three classified patterns through a number of 2 principal components (PC) that explain the 87% of the cumulative variance.

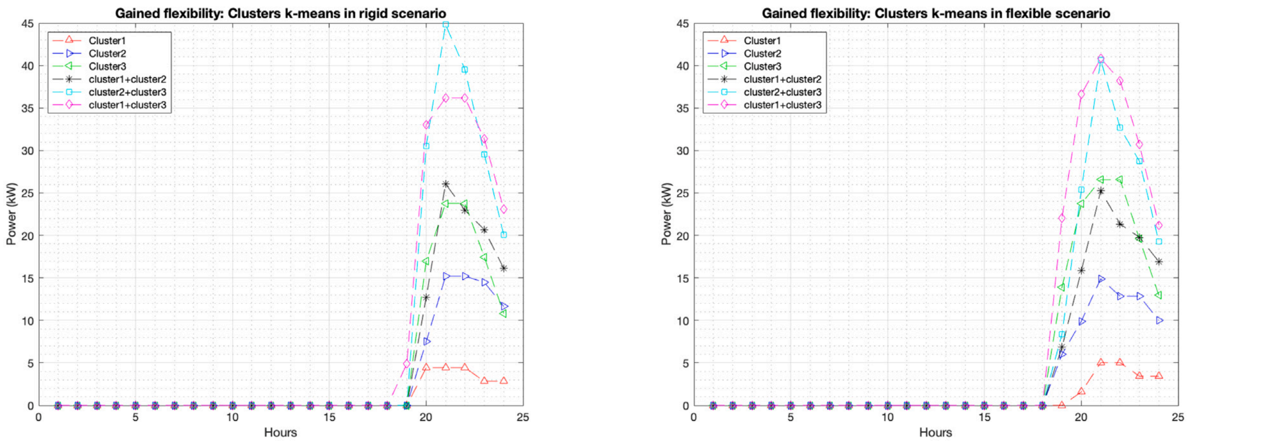
clusters on two principal components which make the cumulative contribution rate reach 87%. The first and second components explain the highest possible variation (62% and 25% respectively). The components obtained from PCA reveal the consumption behaviours of different connection point types. Cluster 1 and 2 present a wider dispersion with reference to their centroid; this is mainly due to the different consumption trends among households in cluster. Note that the NREL dataset is processed reserving a number of 24 principal components (every hour of the day) and data were grouped into 3 clusters according to previous experiments and our experience.

On the ENEFF aggregator: We have considered the resultant clusters as scenarios for new experiments on the ENEFF aggregation and scheduling algorithm. The NREL dataset's households' consumption data is configured as parameters on the algorithm over different hypothesis of flexibility preference[7] and renewable supply. Fig. 16-a depicts the gained flexibility on a rigid scenario, in which the aggregator has little margin to shift households' load. On this setting, the coalition of clusters works well, being Clusters 2 and 3 (which could represent the Concerned and Demanding behaviour respectively) the coalition flexibilising the most, though it represents less than the 28% of their total load. For instance, Cluster 2 manages to shift 41% of its load to less busy slots, whereas Cluster 3 best performs individually in terms of flexibility volume. The aggregated demand scheduler is remarkably working well on peak-time and rigid demand settings.

Similar results appear on more flexible communities as depicted in Fig. 16-b that displays greater volume of shiftable demand over coalitions between Clusters 1 with 3, and Cluster 2 with 3 as well as in Cluster 3 independently, shifting the 36%, 26% and 34% of their respective loads. Moreover, Cluster 2 is again the community flexibilising the most (42% of its demand). Busy communities like in Cluster 1 (demanding high and peak-based) are, however, only performing efficiently in conjunction with a different cluster type.

We have also conducted experiments with the resultant clusters over the semi-decentralised framework setting in which the algorithm assigns the renewable supply available upon consumer request. In our experiments, supply is allocated in order by households' enumerator on the NREL dataset; the algorithm does not execute household preference optimisation on this setting but it does shift the start point of the

[7] The NREL samples are clustered according to the ML method and manually configured to generate scenarios of flexibility as follows: Household's minimum annual consumption sets the fixed demand whereas its difference with the slot of maximum consumption sets the shiftable demand; we also extract consumption peak's period manually and its duration. Rigid scenarios of flexibility stretch the start of the period a third of the peak duration; same period on flexible scenarios adds half of the duration. Different supply scenarios are tested being flat-based.



(a) (b)

Fig. 16. Gained flexibility (kW) of the clusters extracted by k-means on the ENEFF aggregator: (a) on a rigid scenario of household flexibility, and (b) on a more flexible scenario.

allocation within each cluster to evaluate best and worst cases. For instance, Clusters 2 and 3 get between the 32%–11% and the 33%–16% of flexible demand from their respective load, though in coalitions they do not perform as efficiently as in centralised settings. Cluster 1 improves its volume of flexible demand by joining Cluster 2; by contrast it makes the coalition with Cluster 3 saturate the renewable supply during the peak of load.

Remarks. Note that, even though the consumer flexibility could not be analysed from the NREL dataset in our analysis using unsupervised ML methods, the patterns automatically recognised fit our previous analytical hypothesis. Besides, we calculated the standard deviation (SD) and the average consumption for the three clusters identified by k-means, k-prototypes and HC (shown in Table 4). The results obtained differ form the initial centroids (k-means) and the categorical households selected (k-prototypes). These values determine the degree of homogeneity and volume of consumption throughout the year on each cluster. For instance, on k-means, Cluster 1 (Busy pattern/scenario $\mathcal{EA}--$) represents the upper bound in both factors throwing fluctuating and high demands. On HC, Cluster 2 (Concerned behaviour $\mathcal{GB}--$) throws the most uniform and lowest consumption. Moreover, PCA revealed the low variability of the dataset.

3.3. Supervised analysis

We now implement and use supervised ML methods to validate the clustering analysis and to determine most efficient classification methods that can help assigning the profiles to a particular group of consumers over the NREL dataset and our own dataset of synthetic data. We have conducted (i) fuzzy logic analysis for studying fuzzy similarity and fuzzy relations to increase the efficiency of consumer classification into community patterns, (ii) linear discriminant analysis, that has a good performance in classification of electricity consumption behaviour and load forecasting, and (iii) k-nearest neighbours classification, which is recently applied to daily energy consumption prediction based on classification throwing high accuracy results.

Fuzzy logic: We now apply fuzzy logic to the dataset generated with synthetic data in Section 2.3 for the computation of the algorithm's performance cost. Our dataset (populated with synthetic data) is structured into a 24 fuzzy-variable set comprising all factors' combinations as shown in Table 7 and their computational time normalised as in Fig. 17. For instance, the visualisation of all factors' combination in terms of the normalised cost throws an interesting result of the factor impact on consumer coalitions and their behaviour, e.g., rigid communities ($\mathcal{E}---$) run fast when scheduling. We then classify (to some degree)

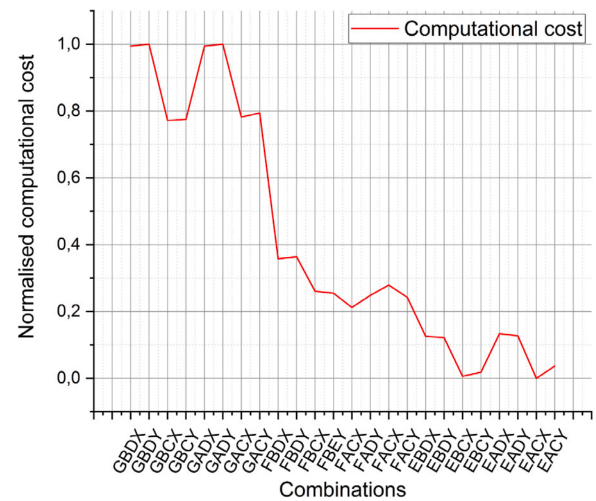


Fig. 17. Data preparation for fuzzy analysis: Normalised average values of the computational cost for the 24 combinations regulated in Table 7.

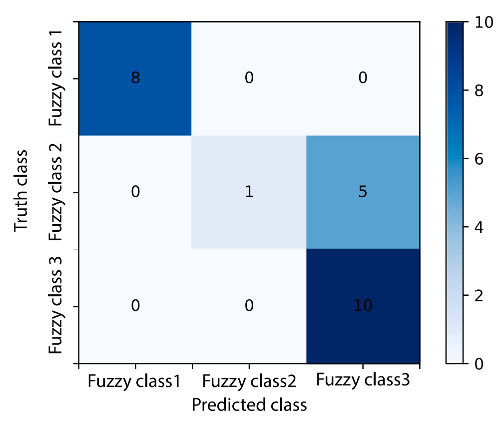


Fig. 18. Matrix confusion for the fuzzy classification on our dataset with synthetic data. A number of 3 classes are set as fuzzy rules; only 8 combinations (rule corresponding to Busy pattern) and 10 (matching with Demanding pattern) have been classified with 0.79 of accuracy. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the input data into one of the following three fuzzy rules or classes: (1) rigid demand, peak-based, (2) flexible demand, low volume, and (3)

Table 4
Mean consumption and standard deviation (in watts) along the year for each of the identified patterns.

	K-means		HC		K-prototypes	
	Mean	SD	Mean	SD	Mean	SD
Cluster1	16265	3237	12506	2733	14180	2810
Cluster2	5640	1799	5054	1532	5402	1677
Cluster3	8481	2445	7368	2328	7916	2433

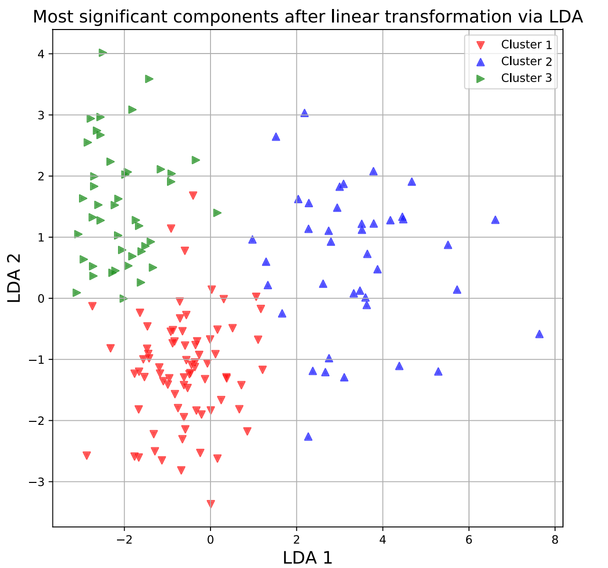


Fig. 19. Linear Discriminant Analysis classification on our dataset for the three classes throws an accuracy of 90%.

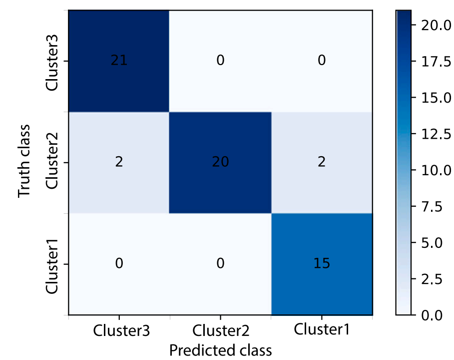


Fig. 20. Matrix confusion of the KNN classification of 60 samples from the NREL dataset considering the clusters identified in Section 3.2.

mixed and flat demand. Fig. 18 depicts the confusion matrix achieved for fuzzy logic classification into these three classes with an accuracy[8] of 0.79. We can see that Class 1, which matches the Busy pattern, classify correctly the 33.3% of the combinations, whereas the 42% of the cases lies within Class 3 that represents the Demanding pattern (the mixed behaviour scenario). Class 3 also throws several false positives classifying combinations that belong to Class 2, which correlates to the Concerned behaviour. The classification is not good and barely discriminates the flexible behaviour. Thus, we add the fuzzy classifier as input to an evolutionary method to refine the membership functions. We introduce our dataset containing the 24-factor combinations classified as described above to a Genetic Algorithm (GA) and a Particle Swarm Optimisation (PSO) algorithm (Mälardalen, 2011). Each algorithm is executed 30 times and the implementation of fuzzy classifier achieves an accuracy of 0.93 under both experiments. Both evolutionary algorithms manage to minimise the classification error, and notify the percentage of the number of samples that were misclassified.

Linear Discriminant Analysis (LDA): Fig. 19 plots[9] the results of an LDA classifier generated by fitting the class-conditional probability density function to the NREL dataset using Bayesian rule. Feature set is defined by the 200 households' hourly consumption. The classifier looks for the linear separability of the classes. The accuracy value obtained (testing over a 20% out of the 200-samples training set) from the LDA classifier is 0.9. As to reduce dimensionality, LDA has thrown similar results than PCA.

K-Nearest Neighbours (KNN): Fig. 20 depicts the confusion matrix of the KNN classification over a number of 60 samples/households from the NREL dataset. Despite a few false positives, samples on dataset are correctly classified with accuracy of 94%. For instance, Table 5 compiles true-quality classification indices, obtaining a macro average of 0.94 for the three patterns and 0.93 on both F1 Score and recall parameters; support is the number of samples true positives that lie within each class. In particular, the KNN classifier is 100% precise identifying Cluster 2 (Concerned) behaviours as well as being the most exhaustive. Cluster 3, the one compiling mixed and heterogeneous behaviours, throws lower values for these indices, though the number samples for training/learning is the lowest. Cluster 1's rule, however, incorrectly classifies a few samples from Cluster 2, throwing some doubts around the suitability of the dataset used for our analysis.

On the ENEFF aggregator: We have considered the classification of KNN over the NREL dataset's households' consumption data to configure new scenarios for the ENEFF aggregation and scheduling algorithm. We establish two different scenarios of flexibility preference, i.e., rigid and flexible, and renewable supply. Fig. 21-a depicts the gained flexibility on a rigid scenario, and shows similar results than the experiments with the unsupervised ML methods in terms of flexibility volume gained. In fact, coalitions of clusters gain bigger volume of flexible demand, e.g., 34% of the load between clusters 2 and 3. Behaviour of clusters is remarkably flattened by the KNN classification, though Cluster 1's ratio of flexibility remains the poorest (23%). Flexible scenarios depicted in Fig. 21-b show a more balanced dynamics of clusters, that flexibilise around the 30% of their total load; cluster 2 reaches a 38% of flexible demand.

KNN clusters were also applied to the semi-decentralised version of the aggregated demand scheduler. Findings on the gained flexibility in the different scenarios[10] emphasise the need of more heterogeneous samples of consumer behaviours. Classifications established over the NREL samples by KNN present a similar ratio of both the volume of flexible demand gained after the cluster scheduling as well as its ratio over the total volume of demand. The best scenarios performing flexibility are Cluster 3 (between 32% and 26% of best and worst

[8] Colour intensity reflects the classification accuracy for the combinations on each class.

[9] LDA reduces the number of dimension from original to $c-1$ number of features where c is the number of classes. In our experiment, we have 3 classes and 24 features; LDA then reduces from 24 features to only 2 features, so letting us plot over these most significant components after the linear transformation.

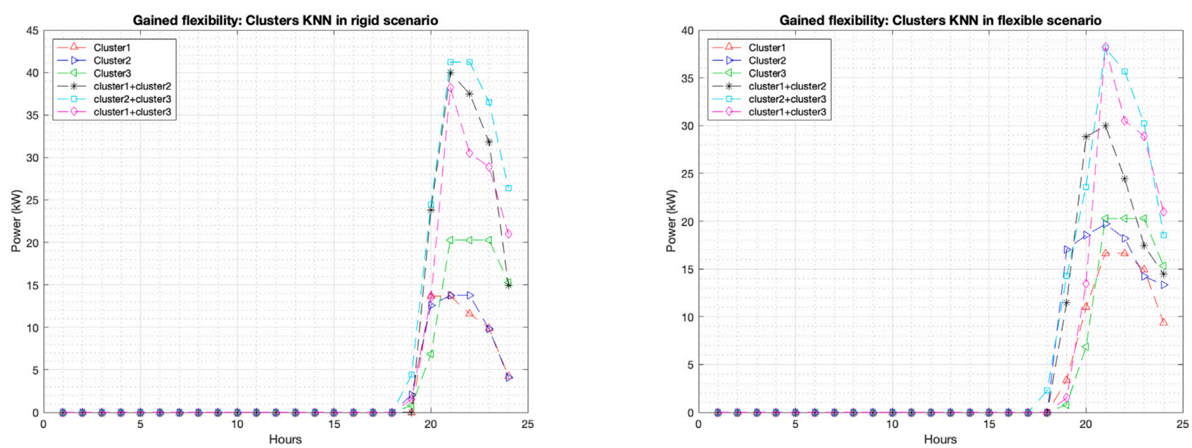
[10] We configured new scenarios of flexibility over the NREL samples as described in Section 3.2.

Table 5
Quality and precision parameters for KNN classification over 60/140-sample dataset tested.

	Precision	Recall	F1-score	Support
Cluster 1	0.91/0.89	1/0.93	0.95/0.91	21/60
Cluster 2	1/1	0.91/0.97	0.91/0.99	20/35
Cluster 3	0.88/0.91	0.91/0.87	0.94/0.89	15/45
Accuracy				
macro avg	0.93/0.93	0.94/0.92	0.93/0.93	60/140
weighted avg	0.94/0.92	0.93/0.92	0.93/0.92	60/140

Table 6
Accuracy and computational time of the classification techniques used on our automated analysis.

Dataset	ML method	Score	Time (ms)
	Supervised algorithms		
NREL	K-nearest neighbours	0.93	4.25
	Linear discriminant analysis	0.9	5.10
Synthetic	Fuzzy logic	0.79	134.2
	Fuzzy logic with PSO	0.9	26300
	Unsupervised algorithms		
NREL	Principal component analysis	0.87	6.0
	K-means	Elbow: K = 3/Distortion = 0.29	750
		Silhouette: K = 3/Average = 0.22	1070
	K-prototypes	Elbow: K = 3/Cost = 20.5	493
	Hierarchical clustering	Threshold: 1	2.09



(a) (b)

Fig. 21. Gained flexibility (kW) of the clusters extracted by KNN on the ENEFF aggregator: (a) in a rigid scenario of household flexibility, and (b) in a more flexible scenario.

scheduling respectively) and the coalition between clusters 2 and 3 (31% on average). Moreover, Cluster 1 improves its ratio of flexible demand gained in the KNN semi-decentralised scenario with a best case of 22%; the mixed of behavioural patterns within the KNN classification provokes this increasing.

3.4. Discussion

Electricity suppliers, market regulators, and the consumers themselves, all need to understand how consumer communities respond to the aggregated version of DR developments. Our results of analysing the patterns that may emerged from a community of consumers cooperating towards a better use of both, their flexibility and the renewable sources (locally generated or not) have significant implications for those market players.

The electricity supplier can improve the decision making at different levels by the application of ML methods to an aggregated DR development like ENEFF. Unsupervised methods such as k-means can assist in the extraction of not only demand/load profiles (and the appropriate number of them) but also the variability and flexibility dynamics within a community. Moreover, as showed by the supervised methods, the analysis of patterns and their responsiveness to the scheduling algorithm in terms of the computational cost can help to classify the consumption behaviour, and this, in turn, enhances the shared resource (the available renewable supply) allocation and the community (joint) demand. For instance, the experiments shown how the ENEFF aggregator is able to classify different behavioural patterns with an accuracy up to 90% by supervised or unsupervised ML techniques. We compare the accuracy score and the computational cost for each experiment on the aggregator extracting patterns from a 200-household dataset. Table 6 compiles these measures for each technique showing best performance on KNN method and the worst on fuzzy Logic. Unsupervised algorithms perform faster achieving the same accuracy scores, what is making them very suitable for real-time classification of demand/load profiles. There are, however, some difficulties for the automatic analysis such as the measurement of accuracy in k-means, k-prototypes or HC techniques or the computational needs of the fuzzy classifiers. Also, when in conjunction with k-means or HC, PCA can improve consistency of clustering, so more accurate electricity consumption forecasting can be made. Our implementation of k-means is very efficient if compared to HC's results and the related work such as Wen et al. (2019). Our computational time is 78% faster with a similar silhouette value. Their experiments with PCA and 38 components reach a cumulative percentage of 99%, whereas we obtain a correlation of 87% with only two components due to a smaller disparity of consumption profiles. Experiments in Piscitelli et al. (2019) compare HC with an evolutionary learning algorithm and 17 consumption categories. Their analysis computed an 80% of accuracy rate and requires a large customer database to adequately represent each cluster. Li et al. (2018) experimentation also requires high machine resources (1367s) to classify 40 buildings in 9 clusters; their dataset was complex. Nevertheless, their findings on these experiments are close to our results: HC generally doubles the computational cost of k-means. Mälardalen (2011) offers a supervised fuzzy classification up to 90% accuracy in a different context. Our study also provides a high precision under a larger database by using the same technique.

Our experiments also show how flexible consumers could be motivated by the benefits from deploying DR technology at their households as, for example, how a joint turn-key scheduler would empowers the whole community of consumers coordinately target energy renewable sources. In fact, our development enhances 46% the management of the shared sources within a flexible community. Besides, note that all methods used for our analysis have been implemented on the aggregator hardware itself, running on the same Raspberry board, so assuring the realisation of pattern extraction and regression with the same machine resources than the aggregation and scheduling processes.

The system is also able to define consumer's responsiveness to DR signals. With the analysis of mean and SD of the hourly (or any other scale) electricity consumption, we can group and supply consumers displaying a similar pattern and accordingly. Cluster 1 (the Busy pattern) may display the worse reaction capability if compared to Cluster 3 as it has a higher and fluctuating consumption that make our aggregator DR has a difficult management of renewable resources. Global projections suggest that it will take time for consumers to fully respond, which implies that consumer behaviour may depend upon a suitable, friendly and cost-efficient implantation of the DR technology, comprising aggregated demand schedulers and turn-key community controllers.

4. Added value of demand forecasting

In this section, we discuss the inclusion of prediction models within the logic of our ENEFF aggregator of demand with the aim at minimising the impact of non-cooperative consumers on the DR framework. We address this challenge with Random Forest (RF), Support Vector Machines for Regression (SVR), and Linear Regression (LG) as follows. The former has gained enormous popularity within the techniques for predictive modelling and behaviour analysis due to its scalability and ease of use. The best solution takes the shape of a set of decision trees that is selected by means of a voting procedure. SVR displays excellent performance in the nonlinear regression estimation problems of small sample size; whereas LR, the most commonly used predictive modelling technique. We therefore apply these techniques to find an optimal path that characterises the trend or dynamics (forecast for the next hour load demand) of a community consumption within a tolerance.

Methodology. We define training and testing periods rather than random sporadic data points. Any given *X vector*/*Y target* pair in the training data (1151 points) should provide the current hour's electricity consumption (Y value, or target) with the previous hour's. We take a number of 1151/456 h observations per household for training/testing out of a dataset with 2470 h observations. The *aggregator* first cleans the data of irregularities, by averaging the data that is available. It then undergoes a normalisation phase, which will ensure that a convergence problem does not have a large variation, and making optimisation feasible. SVR and RF techniques depend on several hyper parameters (C, γ and n_{trees} $n_{estimators}$) and their configuration is an important task, as it will result in a more robust model.[11] In addition, we explore three settings in which to model a consumer community prediction, as follows:

(1) The aggregator models **individual** households. It requires one model for each household (200 households in our dataset). This approach enables a better understanding of the demand accuracy for individual predictions.

(2) The aggregator gathers energy demand within the three **clusters**/groups by looking at the average hourly demand.

(3) The aggregator aggregates the households' consumption before developing a unique **aggregated** prediction model of the community behaviour. Utilities would benefit from this approach improving their balancing services as well as the reliability of renewable estimation and provision for the community.

Evaluation. We subject these techniques to a scoring mechanism to evaluate their performance and accuracy on a series of metrics. For instance, the determination coefficient (R^2) (as depicted in Fig. 22-a) is an assessment metric for training and test accuracy that gives a statistical measure of the accuracy of the data given by the actual adjusted regression curve. The Mean Absolute Percentage Error (MAPE) throws the prediction accuracy of a forecasting method. The Mean Absolute Error (MAE) is an useful metric when large errors could cause consequences; whereas the Mean Square Error (MSE) computes the mean of the difference between the actual demand value and the expected demand value. The latter is used as the loss function during the training phase to minimise errors.

Fig. 22 shows the evaluation results of the three techniques on the aforementioned scoring criteria and for each of the settings. On one hand, the ENEFF aggregator dedicates more computational time in the individual setting for all techniques, due to the need of resources to extrapolate data in an individualised study. On the other hand, the aggregated setting threw greater precision in the prediction according to the R^2 factor (i.e. LR scored 0.41/0.92 at the household/aggregated level respectively). SVR, LG and RF provide successful forecasts in all cluster settings. The application of RF to prediction shows impressive results and stable performance in all the different approaches adopted, specially in the aggregated setting (R^2 0,93; MAE 0.2e−3; MSE 0,8e−6; MAPE 3.6%). SVR accuracy is surprisingly low (R^2 0,3 in the individual setting); however, this could be due to the omission of a comprehensive hyper-parametric search. The aggregated setting displays a tiny improvement if compared to the cluster-based settings. Similar tendencies are shown for all metrics within the three established clusters, except for the SVR regression within cluster 2.

The achievable accuracy in terms of MAPE indicator is surprisingly low, ranging between 16 and 105% for the individual setting, and between 2 and 41% for the aggregated settings. More specifically, MAPE presents poor accuracy in SVR technique as predicted demand high errors are likely to have a significant impact in prediction accuracy. MSE score also shows the same tendency, which gives a worse performance for individual case. Therefore, the choice of the DR model with forecasting at cluster level provides an increase of 57%, in terms of demand prediction accuracy.

[11] Using the same hyper parameters values for all different households might not be optimal. We have optimised the selection of the hyper parameters values by a cross-validated grid-search as in Wijaya et al. (2015) to compare the results obtained for both, the computation time and the SVR accuracy. We select [C, γ] = [1e6, 0.001] for SVM and $n_{estimators}$ = 1e3 for RF. C values < 1e-3 reduce accuracy 50%; and higher values for γ and C increase computation time by 28% percentage. We have also implemented the LR algorithm as it is rather independent of the choice of hyper parameters; therefore the computational time is significantly reduced.

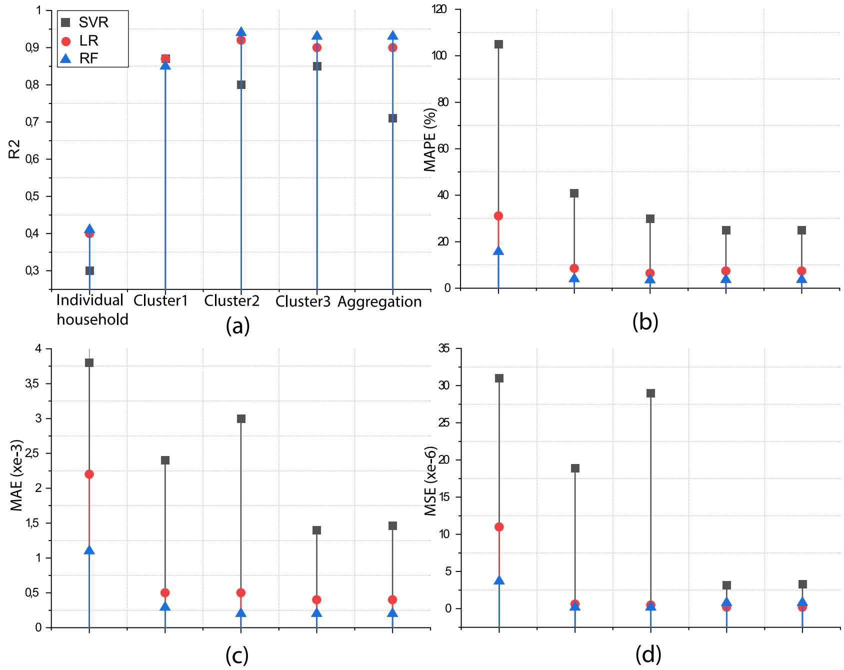


Fig. 22. Scoring metrics for SVR, LR and RF models: (a) R^2; (b) MAPE; (c) MAE; and (d) MSE under the three different settings: individual, clusters and the aggregated prediction model.

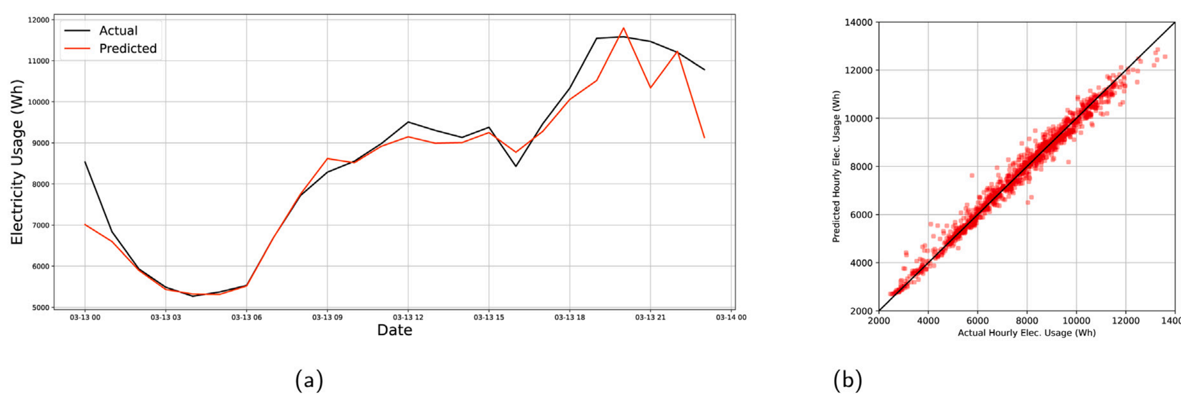


Fig. 23. (a) Time series of the current and predicted level of energy consumption in the aggregated setting. (b) Scatter plot of expected energy consumption in the test suite.

Individualised demand forecasting presents greater instability and the existing variability of electricity consumption complicates the establishment of higher levels of accuracy in this setting. SVR emphasises this drawback, which is shown by the MAPE factor with higher percentage of error in the individual setting (up to 105%) compared to the aggregated setting (26%). Furthermore, Fig. 23-a illustrates the time series of the actual and predicted electricity demand over the testing period in the aggregated SVR model, whereas Fig. 23-b presents its scatter plot. Overall, the RF model appears as the technique that better predicts within the aggregated setting (with an R^2 of 0.94), though it needs more computational time. The technique that performs worst in terms of accuracy is SVR at the individual setting with an R^2 of 0.3. Besides, the MSE value is calculated high by all the techniques in the training of individual setting.

Remarks. The effectiveness of demand forecasting relies on the number of customers at the aggregator. Predictions based on disaggregated consumption data could improve our analysis as well as the inclusion of different datasets for training. Our aggregator can be used for generating accurate consumption profiles and demand forecasts but require good parametric adjustment when applying SVM or RF. From our experiments, SVR is accurate and fast profiling consumer behaviours collectively. LR and RF performs well in all scenarios. Moreover, our aggregator system can predict future demand with 94% accuracy if compared to a single household residence, which provides a 40% of accuracy for energy demand forecast (with RF model). Structural impact decision from the utilities' side would be further founded.

Our results when compared to related work throw interesting findings; Walker et al. (2020) proposed an individual and cluster-based aggregate residential demand forecasting, being the latter 74% accurate using LR in a single cluster. They also applied SVR to the aggregated model enhancing the efficiency for 1000 customers grouped in clusters. On other hand, our model is based in a unique cluster without modifying hyper-parameter values for 200 households, which does not offer the best accuracy using SVR. However, we improve up to 82% the forecast in the aggregated model (LR) due to the fact that the effect of unpredictable individually patterns were alleviated considering them as a single group. Wijaya et al. (2015) also performed a prediction analysis at both, aggregated and individual level, in commercial buildings by applying techniques such as SVM or RF, among others. In particular, and as a consequence of he inconsistency of the collected data patterns of some buildings, their findings with RF presented lower error accuracy. Walker et al. (2020) observed that individual prediction models

Table 7
Simulation assumptions: Scenarios from combining the different factors values.

Demand volume	Consumer flexibility	Demand flow	Description	Supply flow	Scenario	Cluster	Graph
Rigid $\mathcal{L} = t_{end} - t_{beg}$	High (> 5 h)	Flat	House members with a high activity and occupancy. Loads are distributed along the day in a random way.	Flat Peak	$\mathcal{EBCX}$ $\mathcal{EBCY}$	Cluster 1	Fig. 9a
		Peak 8 a.m.–11 p.m.	Loads are distributed along the day, specially focused from early time in advance.	Flat Peak	$\mathcal{EBDX}$ $\mathcal{EBDY}$		
	Low (< 5 h)	Flat	House members with a low activity and occupancy. Loads are distributed during spare time.	Flat Peak	$\mathcal{EACX}$ $\mathcal{EACY}$	Cluster 1	Fig. 9b
		Peaks 8 a.m.–11 p.m. 10 a.m., 14 p.m., 22 p.m.	Loads are distributed at early hours and spare time.	Flat Peak	$\mathcal{EADX}$ $\mathcal{EADY}$		
Mixed $\mathcal{L} > t_{end} - t_{beg}$	High	Flat	House members with a high activity and occupancy. Loads are distributed throughout the day.	Flat Peak	$\mathcal{FBCX}$ $\mathcal{FBCY}$	Cluster 3	Fig. 11a
		Peak 10 a.m.–11 p.m.	Loads are distributed throughout the day.	Flat Peak	$\mathcal{FBDX}$ $\mathcal{FBDY}$		
	Low	Flat	House members with a low activity and occupancy. Activities focuses in the morning and in the afternoon.	Flat Peak	$\mathcal{FACX}$ $\mathcal{FACY}$	Cluster 3	Fig. 11b
		Peaks 10 a.m.–11 a.m. 15 p.m., 18 p.m.	Activities focuses in the afternoon. Loads are also distributed throughout spare time.	Flat Peak	$\mathcal{FADX}$ $\mathcal{FADY}$		
Flexible $\mathcal{L} = 24$	High	Flat	House members with a high activity and occupancy.	Flat Peak	$\mathcal{GBCX}$ $\mathcal{GBCY}$	Cluster 2	Fig. 10a
		Peak 6 a.m.–10 a.m.	House members whose average daily energy consumption is distributed at noon.	Flat Peak	$\mathcal{GBDX}$ $\mathcal{GBDY}$		
	Low	Flat	House members with a low activity and occupancy. Loads are distributed in the morning.	Flat Peak	$\mathcal{GACX}$ $\mathcal{GACY}$	Cluster 2	Fig. 10b
		Peak 5 a.m.-11 a.m.	Loads are distributed throughout the day and demand peak at early time.	Flat Peak	$\mathcal{GADX}$ $\mathcal{GADY}$		

are not satisfactory (R^2 0.45; MAPE 28%). These findings are similar to those we have obtained on the individual model using RF, but we have improved the error (R^2 0.41; MAPE 15.72%). Their prediction in aggregated settings improved notably (R^2 0.96; MAPE 2.5%), which is similar to our results under RF (R^2 0.94%; MAPE 3.6%). On the whole, we can state that this is due to the selection of trained-models for demand prediction. All these studies found that the prediction accuracy depends on the number of clusters and the cluster size.

5. Conclusions

This paper contributes to the analysis of the consumers' consumption patterns participating in electricity demand response and aggregation services and how the consumer profiles and consumption drivers within a community could impact the acceptance (in terms of volume of flexible kW, number of consumers enrolled and % decrease of fossil energy consumption) of such services. The analysis assumes a cooperative demand response programme in place, which, centralised on an aggregation player, aggregates all the participants' (day-ahead) demand and schedules it according to the available supply from the local renewable sources.

The performance of the proposed scheduling algorithm under different scenarios threw interesting results of its efficiency in the presence of certain factors such as the volume of demand and the flexibility of the consumer participants. Hence, we first conducted a non-automated analysis of all the factors, their impact on the allocation optimisation provided by real datasets as to extract a preliminary battery of potential behavioural patterns. The flexibility factor (how much flexible a consumer is when defining time ranges for his/her day-ahead demand) dominates the algorithm performance; though highly flexible communities are computationally more costly (less than 35 s for 5-consumers with 48 appliances each), the allocation of the community load much better optimises the available green supply. Moreover, the peak load and peak–valley difference of the community load profile can be reduced without altering participants' routines. The algorithm efficiently recognises inelastic communities where non-flexible consumers in busy communities makes the supply allocation more rigid among them. We have identified three consumption patterns governed by the discussed factors at this preliminary analysis.

To validate the analysed patterns, we applied most commonly used supervised and unsupervised machine learning techniques for pattern recognition such as k-nearest neighbour, discriminant analysis, k-means, hierarchical clustering and fuzzy modelling, amongst others, to the same datasets. Clustering performs fast recognising 3 clusters out of the datasets that group consumers according to the demand volume and flow. Flexibility features could not be recognised from the dataset though. Supervised classifications with k-nearest neighbours and LDA are also fast and accurate (>0.9 precision score). The former algorithm can distinguish a series of three behaviours over a total of 140 households on the NREL dataset with 93% of accuracy; in particular, a Busy pattern is recognised in 49% of the samples, 25% corresponds to the Concerned pattern and 32% to Demanding behaviours. Similarly, the application of fuzzy logic over the analysis of the factors with impact on the scheduling process is able to identify the same patterns with an accuracy of 79%. Scenarios with Busy behaviours compile the 33%, whereas the other two patterns in coalition make 45% of demand flexible for reallocation with only 47% of participation (i.e., 42% corresponds to Demanding consumers and 5% from Concerned behaviours).

The ENEFF aggregation and scheduling algorithm reaches an upper bound of flexibility (i.e., 42% out of the community demand) within coalitions of clusters (or consumer patterns) that display concerned and low-middle demanding behaviours. Indeed, the inclusion of flexible preferences implies a high responsiveness of the whole community to DR signals even under peak-demand conditions. Demanding behaviours get 15% of the whole demand flexible for reallocation. By contrast, we can find the lower bound on more busy scenarios where the volume of demand is high, and peak-based; communities under rigid conditions barely reallocate 1% of shiftable demand, even on flat-demand flow. The centralised framework, in which the aggregator makes arrangements for the community scheduling, gains 20% of additional flexibility when compared to the semi-decentralised version of the algorithm, that manages households' demand on a more individualised way.

Furthermore, we have included discussion on the suitability of regression techniques such as Support Vector Regression, Random Forest and Linear Regression to forecast consumption behaviour at the aggregator. We found high accuracy (>0.94) in the estimations and fast profiling of consumer behaviours at community and cluster approximations. Immediate future work focuses on the industry validation of the algorithm and the estimations on living labs; for instance to measure system's scalability we will include the local prosumers' sources. Moreover, a survey benchmark is being published online for measuring potential consumers' response to the programme and its capability for refinement.

CRediT authorship contribution statement

Carlos Cruz: Conceptualization, Methodology, Editing and visualisation, Software, Validation, Resources, Formal analysis, Investigation, Writing- original draft. **Esther Palomar:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Ignacio Bravo:** Supervision, Writing - review & editing. **Manuel Aleixandre:** Methodology.

Declaration of competing interest

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

Appendix

We include as an Appendix a more detailed explanation of the simulation assumptions of the scheduling process. Table 7 shows for the factors defined all the possible combinations or scenarios.

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Carlos Cruz holds an M.Sc. in Electronics engineering at the University of Granada. He is an experienced engineer with extensive background in detectors evaluation, software simulation and hardware design. He has worked on different research centres (ESRF and ALBA Synchrotrons, ESSBilbao, CSIC or CIEMAT) and has participated in several research projects, whose main results have been published in different high quality journals.

Esther Palomar is Ph.D. in Computer Science, Principal Investigator of the ENEFF-PILOT Project at University of Alcala, and, prior to this, she worked at Birmingham City University in the role of Reader. She also worked in the Department of Computer Science (COSEC - Computer Security Group) at Carlos III University of Madrid (Spain) as Assistant Professor (full-time) for 9 years, teaching computing, cryptography and network security.

Ignacio Bravo received the B.Sc. degree in telecommunications engineering, the M.Sc. degree in Electronics engineering, and the PhD degree in electronics from the University of Alcala, Spain. Since 2002, he has been is a Lecturer with the Electronics Department, University of Alcala, where he is currently Full Professor and Director of Internalisation. His areas of research are reconfigurable hardware, vision architectures based on FPGAs, and Electronic Design.

Manuel Aleixandre received the B.Sc./M.Sc. degree in Physics from the Universidad Autonoma of Madrid (Spain) and a PhD degree. His research interests include neural networks, statistics and multivariate data analysis. At present, he is scientific researcher at Tokyo Institute of Technology and his work focuses on neural networks and multivariate data analysis.