Energy & Buildings 308 (2024) 113988

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enbuild

Pattern-driven behaviour for demand-side management: An analysis of appliance use

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ARTICLE INFO

Keywords:
Energy and behaviour
Energy modelling
Demand profiling
Demand-side management
Load patterns
Controllable appliances

ABSTRACT

Energy communities play a key role in the transition to sustainable energy, helping to inform and engage end-users so that they can become active energy consumers. In practice, trials and pilots often risk failure due to misplaced expectations and unforeseen behaviours when it comes to achieving flexible energy demand resources. In order to tackle these challenges, residential electricity load profile datasets and consumer survey results emerge as powerful tools for identifying controllable loads, energy consumption models, and tailored understanding of communities' energy contexts. This paper first outlines and analyses these datasets' capabilities to leverage data-driven decision-making for more efficient deployments of demand-side management (DSM) systems. A number of appliance behaviour patterns are extracted, based on high and flexible loads for shifting, being validated over three different use cases to support turn-key DSM in the presence and absence of renewable supply and bill saving. A genetic algorithm optimization is applied to underpin flexible demand reallocation and optimal community load profiles by combining time-variable tariff of use. Experiments demonstrate that controllable and shiftable appliances can reduce average peak load by up to 29% by increasing renewable self-consumption, leading to a valuable energy bill saving of 9%. Our findings also point to the current limitations of existing load/consumption datasets, which are hindering more efficient DSM design of flexibility and demand response programmes in energy communities.

1. Introduction

Smart energy communities have attracted considerable attention, with new options and services available for consumers, such as renewable energy self-consumption, Demand-Side Management (DSM) and energy efficiency [1,2]. They open up new frontiers in energy market decentralization and modifies the role that individuals, communities and stakeholders will play in the new societal energy landscape. Their development has widespread social implications due to new trends in people-centred energy production and distribution, with the successful and innovative combination of new technologies representing a new cooperation-based paradigm [3]. The challenge is to adopt a multi-directional process that seeks to modify people's behaviour with a view to boosting sustainability.

However, sustainable practices and community-based models have not yet been widely implemented, with current DSM systems being deployed to improve energy efficiency based mainly on smart metering [4] or novel non-invasive technologies to control smart home devices automatically [5]. DSM can be defined as an optimal model providing energy management services to efficiently monitor and manage electricity generation, storage, and consumption in smart households [6]. Some of these energy models are characterized by a strong emphasis on participation and awareness [7], encouraging community energy consumers to play a more active role, for example by installing micro-generation, battery storage energy resources, or automatic appliances [8]. Furthermore, specific factors, such as socio-economic aspects, the ecological footprint, use of natural resources, and information and communication development, should be emphasized when evaluating the impact of policies on diverse resources. For instance, uncovering typical energy consumption patterns through empirical case studies or making decisions on incentives may hold the potential to foster advancements in DSM systems [9]. Existing studies rarely touch upon the optimal scheduling patterns mainly based on flexible controllable loads, and targeted analysis and optimization methods in this regard are still lacking.

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https://doi.org/10.1016/j.enbuild.2024.113988
Received 5 December 2023; Received in revised form 29 January 2024; Accepted 7 February 2024
Available online 15 February 2024

Nomenclature

$\bar{u_i}/u_i$	Switch on/off mark transition of a controllable appliance i (1 = off-on/on-off).
μ_i	Operation time slots of the controllable appliance i
π	Cost of energy (€/kWh)
abbreviation	explanation for the abbreviation
at	Time slot of automatic appliance operation
BTU	Unit of heat energy
D^{AHUCOL}	Air handlers for cooling
$D^{AHUHEAT}$	Air handlers for heating
D^{CDR}	Clothes dryers
D^{COK}	Stoves, cook-tops, and ovens
D^{COL}	Air conditioning
D^{CW}	Clothes washers
D^{DHUM}	Dehumidifiers
D^{DWH}	Dishwashers
$D^{EVAPCOL}$	Evaporative coolers
D^{FANS}	Fans
D^{FRZ}	Freezers
$D^{HTBHEAT}$	Hot tub heaters
D^{HTBPMP}	Hot tub pumps
D^{HUM}	Humidifiers
D^{KWH}	Total site electricity usage
D^{LGT}	Lighting
D^{MICRO}	Microwaves
D^{PLHEAT}	Pool heaters
D^{PLPMP}	Pool pumps
D^{RFG}	Refrigerators
D^{SCHED}	Appliance demand scheduling
D^{SPH}	Space heating
D^{TVREL}	Television
D^{WTH}	Water heating
D_i^{CA}	Controllable appliances
D_i^{MISC}	Non-controllable appliances
EIA	Energy Information Administration
LB_i	Lower band of allowable operation time slot of the controllable $appliance_i$
$RECS$	Residential Energy Consumption Survey
S_{PV}	Storage Photovoltaic system
u_i	Commitment status of an appliance i (1 = on, 0 = off).
UB_i	Upper band of allowable operation time slot of the controllable $appliance_i$
CUFEETNG	Natural gas usage non clfd loads
DOEID	Identification number
KWHAHUCOL	Electricity usage for air handlers used for cooling
KWHAHUHEAT	Electricity usage for air handlers and boiler pumps used for heating
KWHCDR	Electricity usage for clothes dryers
KWHCFAN	Electricity usage for ceiling fans
KWHCOK	Electricity usage for cooking (stoves, cook-tops, and ovens)
KWHCOL	Electricity usage for air conditioning
KWHCW	Electricity usage for clothes washers
KWHDHUM	Electricity usage for dehumidifiers
KWHDWH	Electricity usage for dishwashers
KWHFRZ	Electricity usage for freezers
KWHHUM	Electricity usage for humidifiers
KWHMICRO	Electricity usage for microwaves
KWHNEC	Electricity usage for other devices and purposes not elsewhere classified
KWHPLPMP	Electricity usage for pool pumps
KWHRFG	Electricity usage for refrigerators
KWHRFG2	Electricity usage for second refrigerators
KWHSPH	Electricity usage for space heating
KWHTBHEAT	Electricity usage for hot tub heaters
KWHTBPMP	Electricity usage for hot tub pumps
KWHTVREL	Electricity usage for all televisions and related peripherals
KWHWTH	Electricity usage for water heating
MILP	Mixed-Integer Linear Programming
R^2	Coefficient of determination
RMSE	Root Mean Square Error
XGB	Xtreme Gradient Boosting

1.1. Demand-side management context

The future deployment of DSM systems will allow consumers to participate in the energy market individually or collectively [10]. From the consumer–household point of view, research is focused mainly on DSM, based on controlling appliances to minimize energy costs (see Fig. 1a). DSM development is based on smart meters, whether distributed or centralized smart appliances, providing scheduling and optimizing energy decisions [11]. The presence of sensors or a metering infrastructure is also a valuable component of the latest energy communities, as it gives the controller access to information and it enables real-time monitoring of energy supplies. A wide variety of techniques is deployed aimed at adapting consumption profiles [12] or setting energy demand preferences according to specific priorities and time intervals [13]. Many companies involved in management and efficiency (e.g. Belkin, GE, IBM, Intel, Siemens) are making progress in developing smart sensors and algorithms in order to make decisions about consumers' energy use. However, the platforms that are used do not really facilitate accessibility for control and development.

From the community perspective, an important role is played by cooperative systems, which ensure sustainable energy through residential consumers and systems based on demand aggregation [15]. A sustainable community energy system is an integrated approach to meeting the energy requirements of a local community from renewable energy sources [16,17]. In practice, smart energy communities provide expertise in promoting renewable energy and managing energy consumption, while empowering end-users and increasing their energy awareness. The microgrid context and smart grid mechanisms also improve energy efficiency and reduce costs through renewable energy technologies [18,19].

Table 1 lists key projects focusing on DSM for consumer communities and smart device use. These pilot projects and test beds are helpful tools to validate and encourage the introduction and acceptance of DSM technology at European Union (EU) level. Furthermore, a new interactive map has been launched by the European Commission's energy communities repository [20], where the number of communities and additional information is provided via web (type of community, number of members, energy production, etc.).

Reliable internal communications and proper smart appliance interoperability are key issues to be addressed in relation to future large-scale deployment. For instance, pilot implementations [21–23] have analysed smart meter flexibility, feedback on electricity consumption and price incentives, as well as implementing pattern recognition. The research work presented Karatasou and Santamouris [24] highlighted household size and number of appliances as positive associations with regard to residential energy consumption. Results for a Belgian study focused on 418 programmable appliances in 186 households, showing the positive impact of incentive payments for those participants who offer flexibility every 40 hours [25]; furthermore, great variation was observed amongst 240 Belgian families in terms of reducing energy

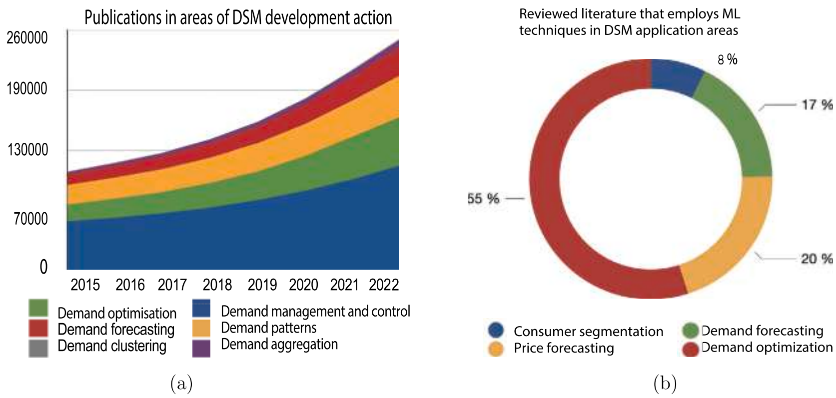


Fig. 1. Publications in areas of DSM development since 2015 (a); Machine Learning (ML) techniques deployed by DSM applications (b). *Source* Scopus search engine [14]. Results carefully filtered for specific energy sector applications. (For interpretation of the colours in the figure(s), the reader is referred to the web version of this article.)

Table 1
Main projects focusing on energy communities featuring residential consumers and/or prosumers. Key functionality of aggregating energy and flexibility, optimizing energy or managing storage systems, and smart devices use.

Project name	Country	Smart devices use	Project start year	Weblink (Last accessed: November 24, 2023)
Voltalis	France	✓	2019	https://corporate.voltalis.com
Viure de l'aire Cooperative	Spain	-	2017	https://www.viuredelaire.cat
Smart Åland Energy project	Finland	-	2022	https://smartenergy.ax
Bambooenergy	Spain	✓	2021	https://bambooenergy.tech/es
Som Energia Cooperative	Spain	-	2014	https://www.somenergia.coop
Schoonschip Energie Cooperatie Residential	Netherlands	-	2019	https://schoonschipamsterdam.org
EDEMA	Germany	✓	2022	https://openei.org/
Green Energy Cooperative	Croatia	-	2022	https://www.zez.coop/en/
Next Kraftwerke	Germany	-	2009	https://www.next-kraftwerke.com
Vibeco Energy production Aggregator	Finland	-	2020	https://vibeco.fi/en
Your Energy Moment	Netherlands	-	2019	https://www.rvo.nl
Energy Cooperative	Spain	-	2023	https://comunidadesenergeticas.org
Smartly Energy Solution Provider	Norway	✓	2022	https://www.smartly.no
Collective Energy Cooperative	Greece	✓	2021	https://coen.coop/en
LINEAL	Finland	-	2013	https://cordis.europa.eu/project/id/608860
EirGrid	Ireland	✓	2006	http://www.eirgridgroup.com
NCEI Cooperative	Ireland	✓	2012	https://www.ncei.ie
CommonEn/Electra Energy Cooperative	Greece	-	2020	http://electraenergy.coop
Rising.eco REC Facilitator	Hungary	✓	2022	https://rising.eco/en/home
EPV CEC Facilitator	France	✓	2019	https://www.enr-citoyennes.fr
EmasP S.Coopeative Urroz	Spain	-	2023	https://comunidadesenergeticas.org/urroz
Lasierra Cooperative	Spain	-	2023	https://comunidadesenergeticas.org/lasierra
Flexnet	Norway	-	2015	https://www.sintef.no/en/projects/flexnett
MegaWattPuur Cooperative	Belgium	-	2017	https://www.megawattpuur.be
Denderstroom Cooperative	Belgium	-	2016	https://denderstroom.be/projecten
DB Strom Retailer	Germany	✓	2018	https://www.dbstrom.de
Energie Steiermark Retailer	Austria	-	2020	https://www.e-steiermark.com
HEG Cooperative	Germany	-	2012	https://heg.solar/

consumption by offering flexibility [26]. More than three thousand Norwegian households also reduced their electricity demand by improving power system operation and planning through incentives for demand flexibility capabilities (e.g. variable electricity prices or grid tariffs) [27]. The introduction of electric vehicle charging or photovoltaic self-consumption entailed a significant impact on domestic load scheduling and can be performed by DSM in order to incentivize and/or increase self-consumption [28,29]. However, the heterogeneity of the household sector is not reflected in a single profile, and its use may lead to a misleading assessment of demand behaviour.

The policy implications of sustainable urban communities accessing markets varies across the European Union, this being another challenge to be faced for DSM benefits and regulation. For instance, the European Citizens' Energy Federation includes a wide community of 1,500 European energy cooperatives and approximately one million citizens active in the energy transition [30]. Portugal, Spain, Italy and Croatia

Table 2
Main datasets focusing on energy community featuring residential consumers. Key attributes centred on duration, number of appliances and households.

Dataset	Location	Duration (days)	Num. of households	Num. of smart sensors	Resolution	Weblink (Last accessed: December 2, 2023)
EMBED	California	27	3	-	2 Hz	http://embed-dataset.org
REDD	USA	19	6	10	15 kHz	http://redd.csail.mit.edu
BLUED	USA	8	1	43	12 kHz	https://tokhub.github.io/dbecd/links/Blued.html
Tracebase	Germany	1	-	122	1 Hz	https://github.com/areinhardt/tracebase
BERDS	USA	365	1	4	20 sec	https://tokhub.github.io/dbecd/links/berds.html
AMPds	Canada	365	1	19	60 sec	http://ampds.org
iAWE	India	73	1	33	60 sec	https://iawe.github.io
GREEND	Italy	365	9	-	1 Hz	http://www.andreatonello.com
PLAID	USA	-	-	1074	30 kHz	https://energy.duke.edu
COMBED	India	30	6	200	1 Hz	https://combed.github.io
DRED	Netherlands	180	1	12	1 Hz	https://www.st.ewi.tudelft.nl/~akshay/dred
Dataport	USA	1460	1200	84000	1 min	https://www.pecanstreet.org/dataport
UK-DALE	UK	912	5	25	16 kHz	https://paperswithcode.com/dataset/uk-dale
REFIT	UK	730	20	250	8 sec	https://paperswithcode.com/dataset/refit
ENERTALK	Korea	30	22	-	15 Hz	https://github.com/ch-shin/ENERTALK-dataset
RECS	USA	365	18500	-	-	https://www.eia.gov/consumption/residential
Smart*	USA	90	3	21	1 Hz	https://traces.cs.umass.edu/index.php/smart
Fresh Energy	Germany	365	200	-	60 sec	https://zenodo.org/record/3855575
CLNRPD	UK	365	12000	-	-	http://www.networkrevolution.co.uk
BLEM	Germany	365	200	-	3 min	https://github.com/QuantLet/BLEM
ECO	Switzerland	365	6	-	1 sec	http://www.vs.inf.ethz.ch
Borealis	Pakistan	426	365	-	1 sec	https://web.lums.edu.pk/~eig/index.html
Dataport	USA	-	365	-	1 sec	https://www.pecanstreet.org/dataport

have not, as yet, actively implemented policies to integrate demand-side resources in their energy markets, have not adapted their energy infrastructures to allow participation by unified communities, and have not defined the role to be played by independent DSM. Denmark, Finland and Sweden, in contrast, have enabled DSM systems through energy retailers, offering demand-side solutions as a package with electricity bills. As demonstrated by pilots in Norway and Denmark, economic incentives, under certain conditions, can influence the way energy is consumed [31]. In Germany, aggregators (mediating entities between the system operator and residential customer) currently require agreement with a supplier before they can access consumer flexibility, whilst grid services in the Netherlands are provided through a network of household meters. In contrast, default agreements in France allow aggregators to access all markets without negotiation. Active management through mechanisms aimed at increasing consumer participation has been most widely exploited in the UK. Companies aggregate the consumption of all their customers and operate as a single entity vis-à-vis the network operator. Consumers thus participate in markets where they can balance the system by instantaneous consumption management.

1.2. Energy demand behaviour and tools for data analysis

Understanding consumer behaviour, the energy capacity provided to participants and the necessary infrastructure that allows energy demand usage recording [32,33] are all areas of great interest for DSM advances. Several factors would affect residential energy consumption, which can be defined as variables including type of household, appliance use, degree of consumption and age of devices [34], or location, climatic characteristics, demographic factors, among others [35]. More specifically, smaller room sizes, older buildings without environmental efficiency measures, middle-income households, less educated heads of households, or households with older adults are some of the targets associated with significant demand patterns [36], [37]. In-depth analyses have been carried out on the behavioural and socioeconomic dimensions of energy consumption capacity [38,39]. Other proposals [40–44] posit efficient DSM based on smart appliances and Machine Learning (ML) models aimed at facilitating demand classification and forecasting according to groups of households, energy communities or similar energy-demand clusters. In this context, time-series or demand-quantity analyses determine patterns of energy consumption, such as time of use and duration, as well as appliance-appliance associations[1] in households, which are also key factors in analysing the energy consumption behaviour of consumers [45,46].

Analysis of surveys also helps to identify the characteristics and potential driving-forces behind residential energy consumption and to analyze residential demand response acceptance according to appliance use [47]. For instance, a survey was conducted to identify flexible load pattern in Luo et al. [48], and Foteinaki et al. [49] modelled household electricity load profiles based on Danish time-use survey data. This is a challenge, as it is no trivial matter to validate survey acceptance or to determine the multiple relationships between the use of different appliances from concurrent numerical data streams or categorical values.

Energy consumption datasets constitute another valuable instrument for energy demand behaviour analysis. Table 2 shows a series of available datasets focused on residential energy demand. While the majority of these datasets are open-access, certain sources require a provisional subscription (e.g., Dataport) or their availability is limited (e.g., EMBED). These datasets are not only based on the location and number of households, but also on the temporal resolution of detection, as well as the duration of the data collection. Electricity consumption is commonly provided at household level and the analysis is not usually focused on appliance disaggregation. In this respect, non-invasive

[1] Agreement on home appliance efficiency standards will preserve consumer features and deliver remarkable energy savings. IEEE plays a significant role in the development of standards and technologies related to electrical and electronic devices, including appliances.

Table 3
Detailed comparison of this study with related work.

Reference	Classification of energy use pattern	Objectives Cost/Comfort/ Efficient	Demand optimization	Survey	Dataset	Appliance type: Controllable/ Non-Controllable	Categorical variables	Pricing scheme
Zhang et al. [58]	✓	X / X / X	✓	X	X	X / X	✓	X
Luo et al. [48]	✓	✓/ ✓/ X	X	X	X	✓/ ✓	✓	✓
Wang et al. [23]	✓	✓/✓/ X	✓	X	✓	X / X	X	X
Thorve et al. [59]	✓	✓/ ✓/ X	✓	X	✓	✓/ ✓	X	X
Iraganaboina and Eluru [34]	✓	✓/✓/X	X	X	✓	X / X	X	X
Ghofrani et al. [39]	✓	✓/X /X	✓	✓	X	X / X	✓	✓
Al-Kababji et al. [38]	✓	X / X / X	X	✓	X	X / X	✓	X
Antonopoulos et al. [33]	✓	✓/ ✓/ X	✓	✓	✓	✓/ ✓	✓	✓
Rhodes et al. [43]	✓	✓/ ✓/ X	✓	X	✓	✓/ ✓	✓	X
Foteinaki et al. [49]	✓	✓/ ✓/ X	✓	X	✓	✓/ ✓	✓	X
Zhu et al. [36]	X	✓/ ✓/ X	✓	X	✓	X / X	X	X
Hao et al. [37]	✓	✓/ ✓/ X	✓	X	✓	✓/ ✓	X	✓
Cruz et al. [60]	✓	X / X / ✓	✓	✓	✓	✓/ ✓	✓	X
This study	✓	✓/ ✓/ ✓	✓	✓	✓	✓/ ✓	✓	✓

demand monitoring is a recognized demand tool that has been developed for non-intrusive demand visualization, monitoring or prediction. However, equipment cost, which hampers scalability and disaggregation accuracy, is the main challenge to be faced.

As stated in Fig. 1b, a fundamental aspect of DSM development is related to demand optimization. Appliance scheduling usually considers time intervals and consumer preferences, as well as types of consumption profile, aiming to minimize peak demand [50] or to reduce energy cost [51]. DSM formulation can be performed by heuristic [52] or deterministic algorithms [53]. Heuristic optimization is commonly based on nature-inspired [54], Mixed-Integer Linear Programming (MILP) [55,56], or linear/non-linear optimization [57].

The advantages of population-based and nature-inspired methods are the ability to efficiently modify appliance scheduling based on solution set. These algorithms find promising solutions due to their exploration capabilities based on a large number of decision variables (e.g. on/off transition of a controllable appliance, commitment status of an appliance, selection of specific tariff hour). For instance, Genetic Algorithm (GA) or Artificial Neural Network (ANN) heuristics are usually deployed to optimize consumption peaks, or to tariff-choosing decision process, helping users to minimize their demand costs [61–63]. However, certain algorithms do not offer the guarantee of finding an optimal solution when compared to deterministic programming methods [64] or unless problem-specific information is deployed.

1.3. Research gaps and motivations

Our study stems from the review of selected literature (projects, datasets and surveys) with a view to analysing and understanding the current limitations preventing DSM systems and developments from being more widely adopted. For instance, the added value of DSM strategies has been extensively simulated and studied in recent years and their implementation approached by a variety of models and constantly evolving rules. Table 3 summarizes the dimensions addressed by our study in comparison with the revised literature. Therefore, the following objectives are highlighted:

- To select the most critical appliances for electricity consumption from validated surveys
- To explore the set of appliances with strong statistical associations
- To study the impact of demand optimization on a building-wide scale.

Our analysis focuses on the extraction of consumption patterns at the appliance level, aiming to identify and evaluate the appliances with the greatest impact on energy demand and its aggregated scheduling. Our findings stress the inefficiency of applying common parameters such as electricity consumption profiles, social conditioning factors, or household size when it comes to measuring energy demand at the appliance level. Moreover, our experiments show that traditional energy consumption has a limited potential market for residential communities without an understanding of cooperation. Hence, strong statistical associations are sought amongst types of appliance loads in cooperative consumer settings and behavioural patterns. Additionally, forecasting applications are explored involving controllable loads to optimize their performance and impact at the community level. A data-driven time-of-use tariffs load model is proposed featuring the influence of the controllable appliances' patterns over the DSM performance, seeking its optimization through the integration of renewable energy supply. Our model is validated by means of a case study and benchmark.

The novelty lies in the following three aspects: 1) considering users' consumption behaviour, a correlation and forecast-based descriptive analysis is performed to determine the relationship between a building's electrical appliances and energy demand; 2) taking into account the operating load profiles and electricity consumption datasets, household appliances are classified into those with the greatest impact on energy consumption. This profile will allow us to perform an automatic scheduling procedure of the household appliances; and 3) taking into account their related activity, an optimization process is applied to continuously loaded appliances to enhance energy DSM programs, thus contributing to energy savings and peak load reduction.

The remainder of this paper is structured as follows: The methodology and the analysis of the data is included in Section 2. Section 3 shows the simulation results and the validation of the model with the optimized demand profiles. Finally, Section 4 draws the main conclusions and future research directions.

2. Methods

Household energy consumption attributed to the use of controllable appliance accounts is set up for approximately 70% of total consumption [65]. This consumption derives from household tasks, such as, running the dishwasher, charging electronic devices (e.g. electric cars) or any other appliance that consumes electricity without human control.

The flowchart of the study is presented in Fig. 2. First, the results of the survey analysis in terms of appliance behaviour are presented

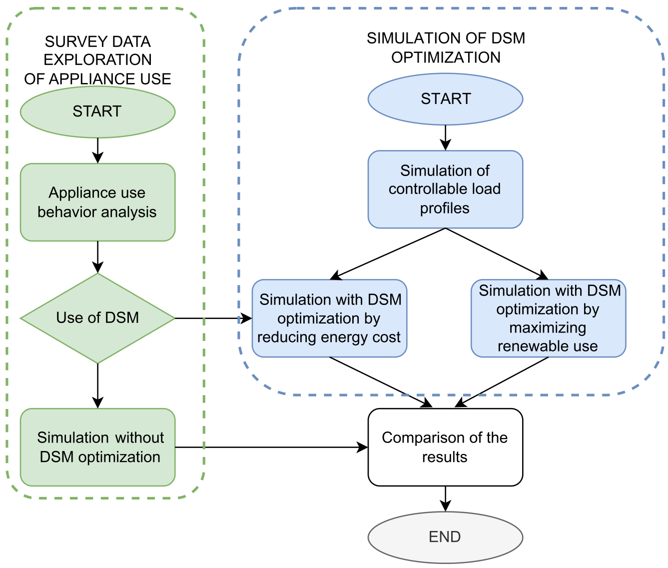


Fig. 2. Methodology and workstream.

and analyzed. Loads' correlation and frequency of use for appliances through numerical and categorical variables are applied. For instance, a standardized measure of linear association between sets of scores (e.g., Pearson correlation) provides insights regarding variables with a higher impact on total energy demand. Energy forecasting techniques (e.g., Gradient Boosting), which focused on the numerical relationships of controllable appliances, allow us to reduce numerical errors in the results. Second, a DSM simulation of an automatic scheduling of controllable appliances, based on both, the analyzed survey and the appliance pattern of the previous studies, is presented. More specifically, the participants' load profile survey is therefore simulated and then compared with a non-optimization-based DSM.

2.1. Description of household appliances and their controllability

Fig. 3 shows the main elements and energy control flows of a DSM paradigm. As can be seen, it is considered that energy can be directly consumed by a set of smart sensors and/or load appliances. A smart appliance can be defined as a device providing information and communication capabilities through a controllable system. Appliance usage is characterized by the operating mode, the duration, the energy consumption and the limit of occurrence of daily events.

The operational mode of appliances describes the appliances' operation and the related behaviour, which can be classified into two categories according to their ability to be controlled: non-controllable and controllable loads. While the operation of non-controllable loads is governed by consumer decisions, controllable loads can be programmed automatically for different times of the day (independent appliance use irrespective of the consumer). Controllable loads can also be switched on by a household member, but are switched off automatically. For instance, manual loads include cooking or lighting, while controllable loads include the dishwasher or air conditioning. In this regard, demand optimization can be performed through an automatic scheduling of appliances, fossil-renewable sources and their cost as input variables.

2.2. Survey data exploration for appliance use

The 2015 and 2020 Residential Energy Consumption Surveys (RECS) provided by Energy Information Administrators (EIA) are explored [66]. The RECS collect data on energy-related characteristics and usage patterns from a representative sample of approximately 20,000 households. This dataset-survey was selected to provide reliable energy-use estimation from energy suppliers on how much site electricity is consumed during the reference year.[2] The analysis presented brings together energy characteristics data on the housing unit, appliance usage patterns and household demographics. One of the improvements to the end-use model for the RECS surveys was to allow energy to depend on the outside climate. More specifically, RECS provides energy-related data for housing units, consisting of 5,686 observations, 755 numerical features (i.e. electricity use of appliances, number of smart sensors, etc.) and four categorical features (i.e. climate, state name, etc.) for the RECS survey of 2015; and it presents 18,496 observations, 781 numerical features and seven categorical features for the RECS survey of 2020.

Household appliances vary according to end use, in general, as well as appliance and household age, equipment type and size of the appliances, which also correlate with the corresponding energy consumption. Different methods have been showcased to select the most critical appliances for electricity consumption. For instance, the Pearson correlation data selection/extraction method has been used as a bi-variate analysis for measuring the strength of the association between appliances' use and their relationship. It was conducted as a standardized measure of linear association between two sets of scores to select the variables with a higher impact on total energy demand. More specifically, a set of appliance features with strong statistical associations is compared with annual electricity usage (in kWh).[3] Fig. 4 shows the correlation between the total consumption target variable (D^{KWH}) and the most used appliances, indicating a lack of association between variables. Red and purple represent strong positive correlation, whereas grey represents very weak positive or negative correlation. Many appliances provide a high correlation with each other, such as clothes dryers and washing machines ($D_i^{DKWHCDR}$, D_i^{DKWHCW}), thus indicating the presence of multicollinearity among appliance features. D^{KWH} also shows moderate to strong positive correlation (>0.3) with all the top 32 most important appliances. Some variables belonging to non-controllable appliances presented correlation coefficients of over 0.2, as they are not able to explain the energy consumption for cook-tops.

Fig. 5a checks how different non-controllable appliances (i.e., microwaves, portable heating, ovens and televisions) relate to D^{KWH}. The scatter plots are quite informative and do not provide a clear fixed linear relationship, which are in line with the results obtained from correlation analysis. The lighting appliances cannot be disaggregated per individual appliance and this target presents a clear contribution to the overall consumption. Non-controllable loads such as air handlers for heating and cooling and evaporative coolers experience both, a soft lineal tendency and poor consumption when compared to the total energy demand. Fig. 5b shows the electricity usage of controllable loads when compared to total energy consumption. There is no fixed linear relationship across the controllable loads. For instance, refrigerators, heating, clothes washers, freezers and pool pumps have a great impact on overall consumption (up to 1000 kWh). On the contrary, air handlers, boiler pumps and dryers and dishwashers do not present a clear contribution.

The total number of household appliances, the frequency of use and age are all available variables of RECS surveys. Frequency use of controllable loads (i.e., clothes dryer use and dishwasher use) were also analyzed.[4] In general, the more these appliances are used, the older they are or the larger their size, the more energy they consume. For instance, Fig. 6 shows the analysis obtained for three types of non-controllable appliance usage pattern features relating to total D^{KWH}. The appliance frequency use of microwaves, oven and the cook-top part of stoves does not provide a clear tendency when compared with the total energy consumption. Most of the households also use controllable loads

[2] RECS surveys provide details on the consumption estimation of household end uses.

[3] The target variable D^{KWH} stands for kilowatt-hour throughout the corresponding year.

[4] All features falling under housing characteristic and usage patterns are discrete numerical variables (i.e., the variables whose values exist in a particular range or are countable in a finite amount of time).

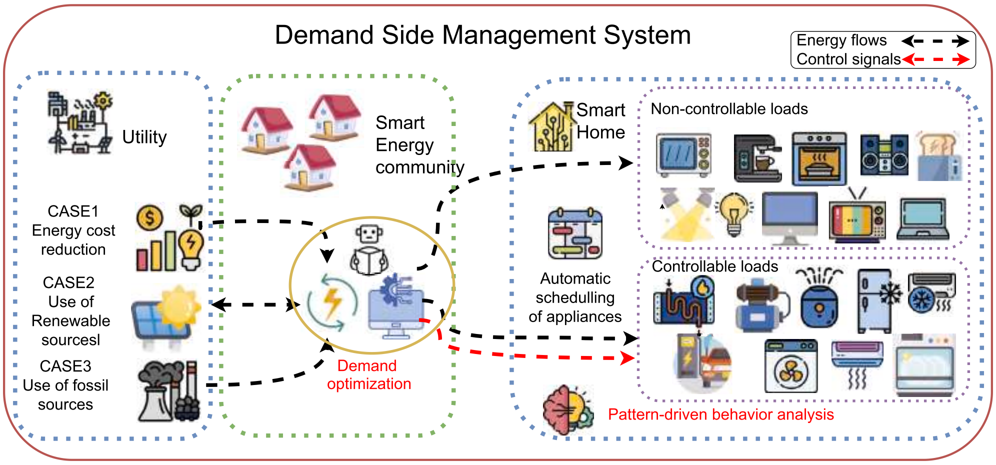


Fig. 3. Design representation of the main consumer elements and types of appliances.

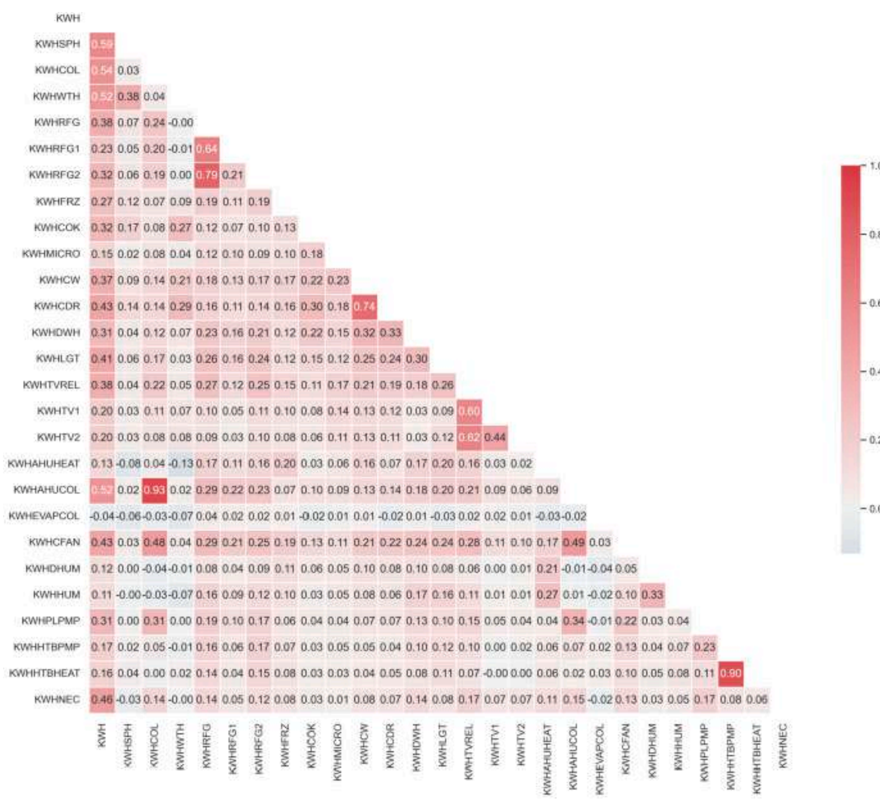
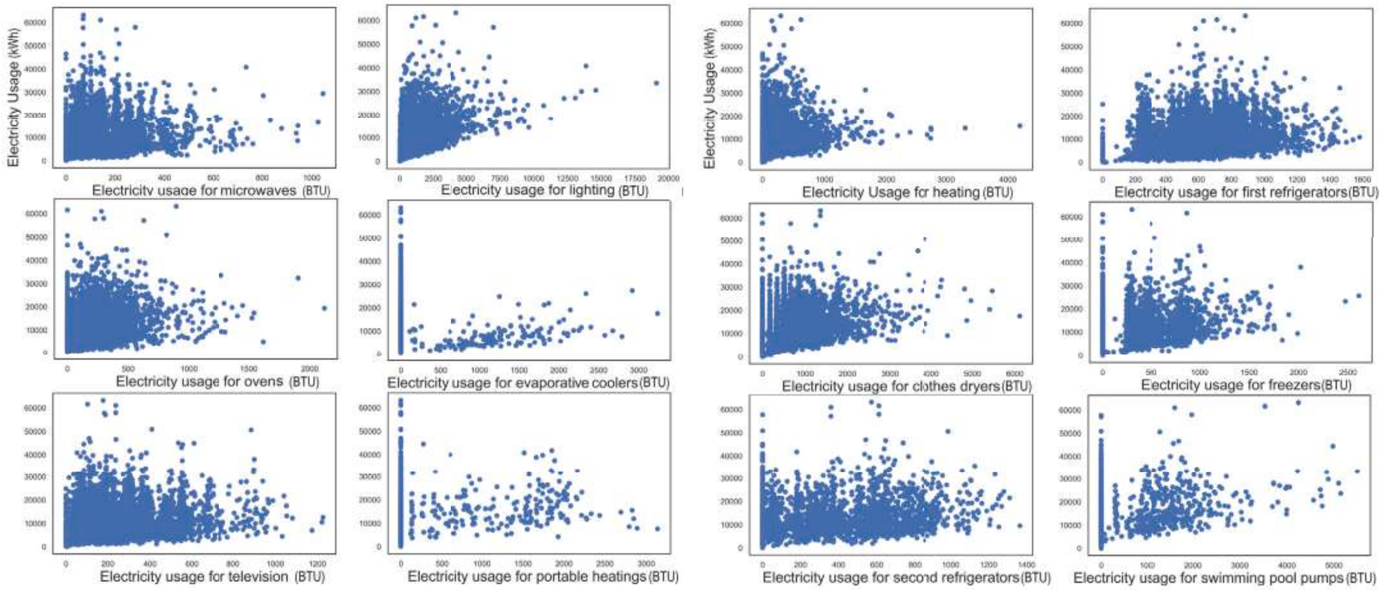


Fig. 4. Correlation values obtained between the total D^{KWH} energy use and the consumption of the most important appliances in RECS 2015 Survey.

every time, as exemplified in Fig. 7. For instance, dishwasher use is set at “2 or 3 times a week”. The median kWh outcomes are in line with boxplot results, indicating that the more frequent the household use of the controllable appliance (e.g., dishwasher), the greater the global energy consumption, which provides valuable information about the scheduling performance. Thus, feature pattern has a direct relationship with the D^{KWH} target variable. In general, the energy consumption of controllable loads for space heating or space cooling is affected most by housing characteristics, whereas appliance characteristics determine energy consumption. Fig. 8 compares the influence of end-appliance with regard to total consumption. As a result, 28 target variables were found to be of low importance. Electricity usage for space and water heating, central air conditioning, individual units, evaporative coolers, and other purposes not elsewhere classified, entailed a higher impact on appliance energy consumption.

From the correlation results, appliance variables are selected to train a preliminary energy consumption model. The result is recursively fitted by eliminating variables with a low significance in energy consumption. Therefore, a regression model was implemented aimed at upgrading the forecasting performance for the higher load importance of energy consumption. The analysis was carried out by reducing error between current and predicted values through the bias-variance trade-off (i.e., Gradient Boosting Regressor and Xtreme Gradient Boosting - XGB). The objective of the analysis was to find the non-controllable loads that provide a low importance when compared to the total consumption. Fig. 9a shows the main features obtained after averaging over 10 training sessions to reduce variance. The tree-based models provide an optimal Root Mean Square Error (RMSE) value. The XGB model has the lowest RMSE as XGB is a more regularized form of Gradient Boosting. XGB provides very fast training that can be parallelized across clus-



(a)

(b)

Fig. 5. Scatter plots of non-controllable (a); and controllable loads (b) and their comparison with total energy consumption D^{KWH} in RECS 2015 Survey.

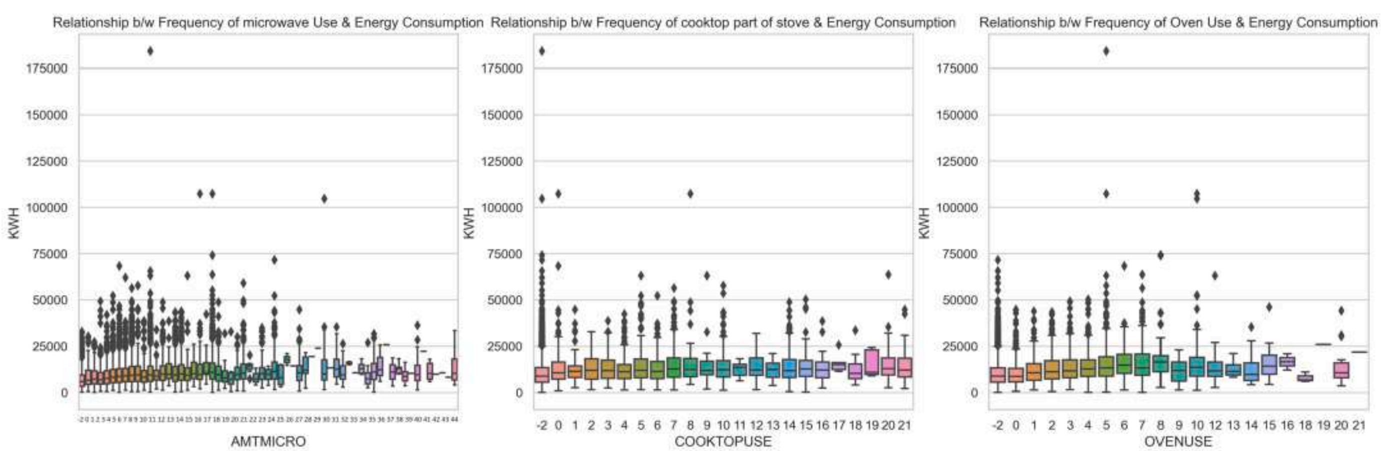


Fig. 6. Relationship between frequency of microwave use, cooktop use and oven use (number of uses) and energy consumption (kWh) in the RECS 2020 Survey.

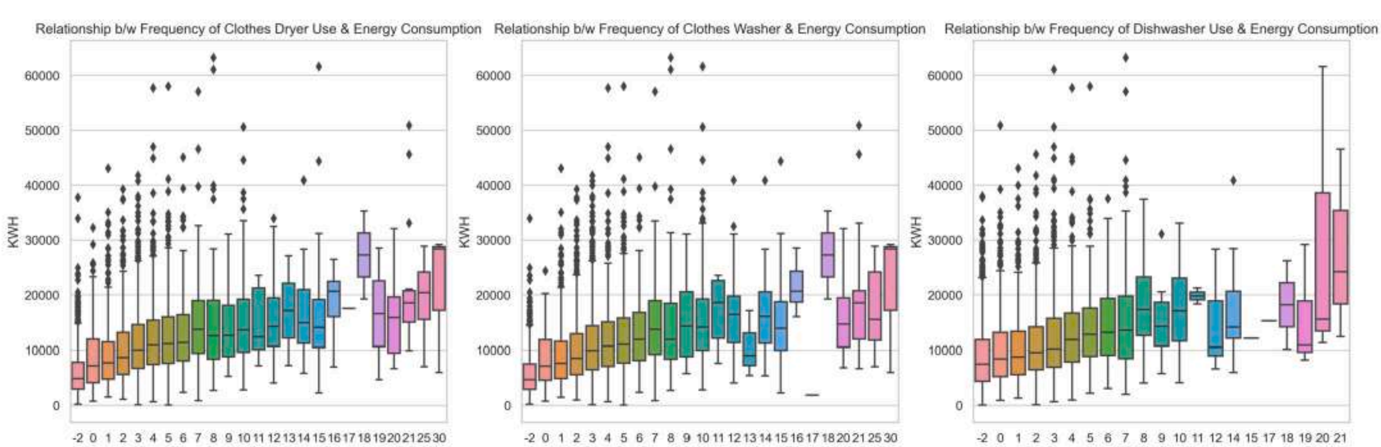


Fig. 7. Relationship between frequency of oven use, dry use and dwash use (number of uses) and energy consumption (kWh) in the RECS 2015 Survey.

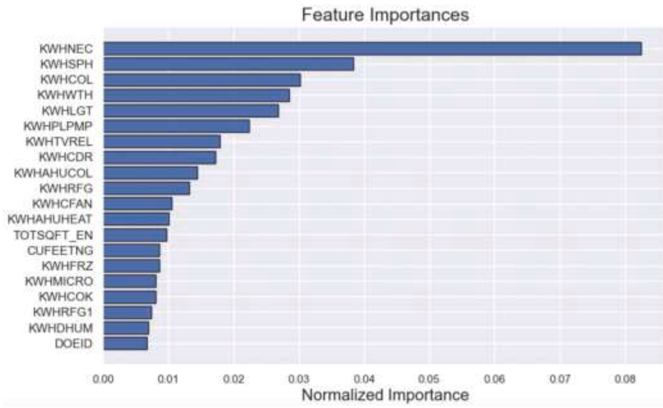


Fig. 8. Variable importance scores of appliance energy consumption.

ters and improves model generalization capabilities, delivering a high performance when compared to Gradient Boosting. The model is also evaluated based on unseen data with the appliance variables that contribute most to total energy consumption. Fig. 9b shows the energy consumption predictions by using the top cumulative features with an accuracy of R^2 score of 0.92. Here, the actual labels follow the selecting variable of most important features of appliance energy consumption as exemplified in Fig. 8.

2.3. Demand optimization

Demand optimization is simulated according to appliance operating patterns at pre-determined time periods in order to optimize energy demand while maintaining fundamental constraints (i.e., consumer decision, scheduling process). Several metaheuristic techniques can be deployed to find the optimal appliance scheduling. The function model is selected to balance between two objectives to be achieved, i.e., to reduce consumption peaks by taking advantage of available renewable sources or to reduce consumption peaks wherever possible at the minimum cost. The total appliance energy sum (D_i^{total}) of a household 'A_i' per appliance 'a_{ij}' is given by Eq. (1).

$$D_i^{total} = \sum_{t=0}^{23} \sum_{a_{ij}\in A_i} (D_i^{CA}) \tag{1}$$

$$D_i^{MISC} = D_i^{TVREL} + D_i^{LGT} + D_i^{FAM} + D_i^{WTH} + D_i^{COK} \tag{2}$$

$$\begin{aligned} D_i^{CA} = D_i^{FRZ} + D_i^{RFG} + D_i^{PLHEAT} + \\ D_i^{DHUM} + D_i^{HUM} + D_i^{PLPMP} + D_i^{DWH} + D_i^{CW} + \\ D_i^{CDR} + D_i^{EVAPCOL} + D_i^{AHUCOL} + D_i^{AHUHEAT} + \\ D_i^{COL} + D_i^{HTBPMP} + D_i^{HTBHEAT} + D_i^{SPH} \end{aligned} \tag{3}$$

D_i^{MISC} is denoted by miscellaneous plug load (Eq. (2)) that is attributed to cleaning activities (e.g. hoover), cooking (e.g. microwave), work appliances (e.g. computers), entertainment (e.g. television), and other smaller electronic devices that cannot be automatically controlled. D_i^{CA} corresponds to the sum of controllable loads (as stated in Eq. (3)) that is attributed to heating/cooling activities (e.g. water heating, air conditioning), cooling (e.g. refrigerator), cleaning (e.g. clothes dryers, washing machine) or entertainment activities (e.g. pool pumps).

The representation of the objective function can be denoted by Eq. (4)-(5)-(6). UB_i and LB_i are considered to be the upper and lower band of allowable operation time slot per controllable appliance 'a_{ij}'. D_i^{SCHED} is denoted as the scheduled operation time of the appliance 'a_{ij}' that should be within the $[LB^i, UB^i]$ interval. G_{RW}, G_{PV}, and π_{cost} are denoted as renewable base and cost variables, respectively.

$$min\{F(D_i^t, G_{RW}^t + G_{PV}^t, \pi_{cost}^t)\}; \tag{4}$$

$$\mathcal{F}(D_{CA}^t, G_{RW}^t + G_{PV}^t) = sum[rms(G_{RW} + G_{PV}) + max(D_{CA})] \tag{5}$$

$$\mathcal{F}(D_{CA}^t, \pi_{cost}^t) = rms[(D_{CA}) * \pi_{cost}] \tag{6}$$

subject to the following constraints:

$$UB_i \le D_i^{SCHED} \le LB_i, \forall i \in \left\{D_i^{SCHED}\right\} \tag{7}$$

$$\begin{aligned} \sum_{t=0}^{23} D_i^{SCHED} < \sum_{t=0}^{23} D_i^{UB}; \sum_{t=0}^{23} D_i^{SCHED} \\ \ge \sum_{t=0}^{23} D_i^{LB}, \forall i \in \left\{D_i^{SCHED}\right\}, \forall t \in T \end{aligned} \tag{8}$$

$$\sum_{a_{ij}\in A_i} (D_i^{MISC} + D_i^{CA}) \le G_{RW} + G_{PV}, \forall i \in \left\{D_i^{CA}\right\}, \forall t \in T \tag{9}$$

Appliances need to be switched off. Along the same lines, appliances also need to be switched on for a time between two predefined moments as stated by Eq. (7)-(8)-(9).

$$\sum_{t=LB_i}^{t=UB_i} u_i^{at} = \mu_i, \forall a_{ij} \in A_i, \forall i \in \left\{D_i^{CA}\right\}, \forall t \in T \tag{10}$$

$$\bar{u}_i^{at} - u_i^{-at} = u_i^{-at} - u_{i-1}^{-at}, \forall a_{ij} \in A_i, \forall i \in \left\{D_i^{CA}\right\} \tag{11}$$

$$\sum \bar{u}_i^{at} = 1, \forall a_{ij} \in A_i, \forall i \in \left\{D_i^{CA}\right\} \tag{12}$$

Controllable appliances need to be operated a predefined number of hours within an allowable time windows, as forced by the constraint (10). In addition, controllable appliances just can be activated just once in a continuously operation over a time interval, as imposed by the constraints (11) and (12).

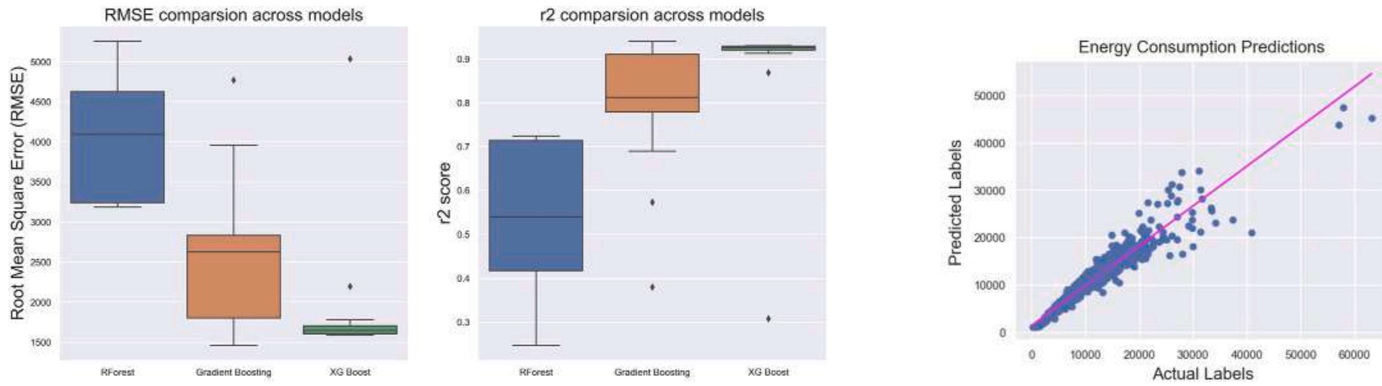
The optimization process follows a GA algorithm technique, allowing us to find an optimal operating time per appliance. Each appliance comprises a set of features called chromosomes that can be mutated to reallocate better features than the initial features. GA[5] finds a solution by starting with a random initial D^{SCHED} population. The number of evaluations is increased when the method finishes by calculating a P generation with feasible solutions for appliance scheduling (D^{SCHED} per appliance). The best D^{SCHED} solution is inserted into the best solution and the other solutions are discarded. Mutation or crossover operators can be used to generate the next evaluation of the current generation crossover-fraction = 0.9, and gaussian-mutation by default value). In this case, a mutation operator randomly modifies the scheduled start times (D^{SCHED}) of some appliances to generate new solutions with a better outcome.

2.4. Input data analysis

In order to show the capabilities of the DSM, an automatic demand scheduling of the most influenced controllable loads has been selected from Table 4. The customized benchmark highlights the usage behaviour per appliance in terms of mode and operation type, power and number of uses, among others. In addition, a case study based on the power company information has been used by providing three different tariffs from the Endesa Power Company [69]: 1) off-peak hours are the cheapest hours; 2) off-peak hours are the moderately priced hours in two hourly time intervals; and 3) peak hours are the most expensive hours and high electricity consumption should be avoided. Table 5 summarizes the energy price and the time interval considered according to the proposed tariffs.

The simulations were run over a one-week time horizon with a time step per appliance of one hour. To build scenarios based on energy efficiency, PV provision was taken from the figure [70] corresponding to an example of the daily load profile for solar PV production (G_{PV}). The

[5] The algorithm creates a set of possible optimal solutions and a starting value is not required.



(a) (b)

Fig. 9. Tuned mode RMSE and R^2 comparison across three model for controllable loads (a); and predicted loads with higher importance in energy consumption (b).

Table 4
Appliance usage behaviour and related activity ([56,59,67,68]; This study).

Activity	Appliance D^i	Mode	Max occ. per household	D_i^{SCHED}	Power (kW)	LB^i	UB^i	Weekly use of appliance
D^{FRZ}	Freezers	Controllable	2	10	2	3	23	110
D^{RFG}	Refrigerators	Controllable	2	13	2	3	23	110
D^{PLHEAT}	Pool heater	Controllable	2	3	2	3	23	20
D^{DHUM}	Dehumidifiers	Controllable	1	5	2	3	23	90
D^{HUM}	Humidifiers	Controllable	1	5	2.5	15	23	90
D^{PLPMP}	Pool pumps	Controllable	1	3	3	10	23	21
D^{DWH}	Dishwasher	Controllable	1	2.5	4	8	23	12
D^{CW}	Clothes washers	Controllable	1	4	2	3	23	15
D^{CDR}	Clothes dryers	Controllable	1	4	2,5	15	23	15
$D^{EVAPCOL}$	Evaporative coolers	Controllable	2	3,5	2	10	20	20
D^{AHUCOL}	Air handlers for cooling	Controllable	2	3	2,5	11	20	40
$D^{AHUHEAT}$	Air handlers for heating	Controllable	3	6	2,5	11	20	40
D^{COL}	Air conditioning	Controllable	3	6	2	10	21	80
D^{HTBPMP}	Hot tub pumps	Controllable	1	4	1	10	21	40
$D^{HTBHEAT}$	Hot tub heaters	Controllable	1	5	2	10	21	40
D^{SPH}	Space heating	Controllable	1	2	2	10	21	80
D^{WTH}	Water heating	Controllable	2	1	4	10	21	80
D^{COK}	Stoves, cook-tops, ovens	Non-controllable	10	12	1	6-24	6-24	
D^{TVREL}	Television	Non-controllable	2	14	0.5	6-24	6-24	
D^{LGT}	Misc. lighting	Non-controllable	20	24	1	6-24	6-24	
D^{FAN}	Fans	Non-controllable	3	6	2,5	6-24	6-24	

Table 5
Characteristics of the different tariffs considered in simulations.

Tariff	Energy price (π_{cost})	
1	0.10 €/kWh	
2	0.13 €/kWh (8:00 – 10:00 h)	(14:00 – 18:00 h)
3	0.18 €/kWh (10:00 – 14:00 h)	(18:00 – 22:00 h)

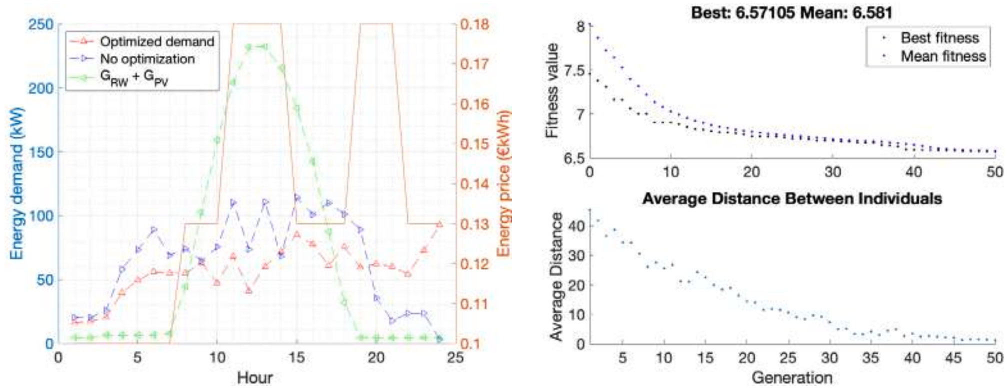
renewable base values within a non-PV provision context are denoted by (G_{RW}) and set to approximately 11 kWh. The hourly power according to fossil-fuel resources was selected from the daily scope dated 06/09/2023 and provided by the Omie Company [71]. Some 10% of the total MWh hourly values were selected from coal, nuclear, hydroelectric, combined cycle or co-generation/waste/mini-hydraulic sources.

3. Results and discussion

3.1. Optimization analysis results

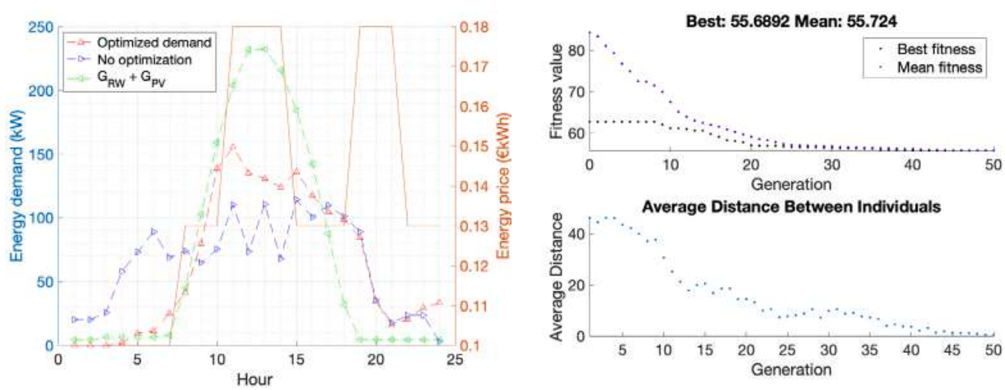
At each stage of the optimization process, the operation time of appliances will be modified within a certain predefined range. The aim of the proposed models is to reduce or otherwise minimize the maximum stress of the proposed variables. More specifically, experimentation aims to automatically optimize energy peak consumption in three cases: 1) reducing the daily bill of the end-user; 2) maximizing the use of renewable sources in order to achieve an efficient environment; and 3) optimizing the use of the non-renewable sources available. The evaluation is performed by an Intel® Apple M1 8.00 GB RAM personal computer under a Matlab R2023a environment.

The results of the demand optimization process are shown in Figs. 10 - 11 - 12 by comparing optimized (red) and non-optimized demand (blue), taking into account energy price (red) and renewable or fossil re-



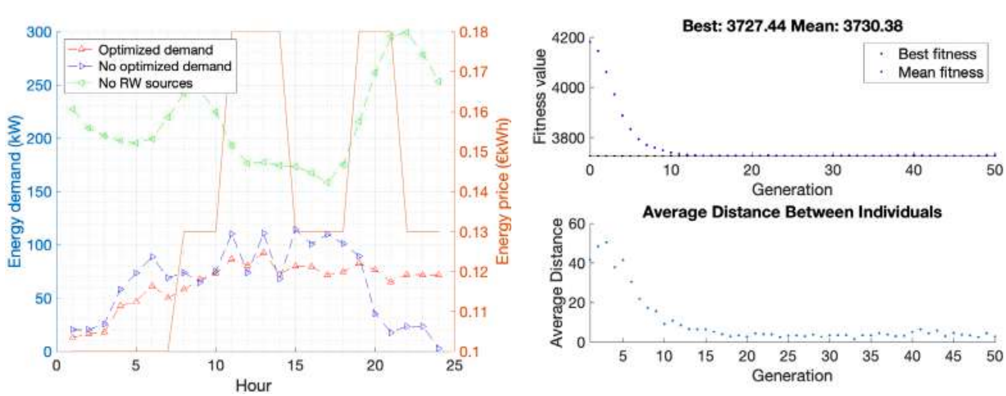
(a) (b)

Fig. 10. CASE1. Results obtained for the optimization of controllable appliances by reducing energy cost and reducing consumption peaks (a); number of needed iterations for the best mean optimized solution and population diversity (b).



(a) (b)

Fig. 11. CASE2. Results obtained for the optimization of controllable appliances by maximizing the renewable sources and reducing consumption peaks (a); number of needed iterations for the best mean optimized solution and population diversity (b).



(a) (b)

Fig. 12. CASE3. Results obtained for the optimization of controllable appliances by maximizing the non renewable sources and reducing consumption peaks (a); number of needed iterations for the best mean optimized solution and population diversity (b).

sources (green) as target variables. Non-optimized demand (blue) is the resulted appliances' reallocation without consideration of variables in demand optimization. Because of the participants' flexibility, operation time of controllable loads in all cases can be shifted between the 8 am to 12 pm interval of the day. Demand optimization provides a low margin to flatten demand throughout the entire day and barely manages to allocate the available supply despite the lowest energy cost during the early hours of 1 am - 7 am (see Fig. 10a). However, the daily bill can be reduced by up to 9% by rescheduling the controllable loads at affordable intervals in Case 1. Fig. 11a shows how demand optimization maximizes the use of renewable sources by generating a demand peak within a period of maximum available PV energy (9 am - 4 pm). The optimization can unlock up to 29% of the scheduled demand volume, this being considered the most efficient scenario of Case 2. Finally, Case 3 optimizes demand for a heterogeneous available energy source. Here, the possibility to demand optimization of the non-renewable sources available can reallocate up to 10% of total energy demand (see Fig. 12a).

Table 6
Results provided by the developed GA optimization process for the three cases.

CASE	Num. evaluations for fitness soln.	Num. evaluations for optimal distance between soln.	Solution time (s)
Case 1 - Energy cost reduction	48	45	12.02
Case 2 - Use of G_{RW} & G_{PV} sources	25	40	11.10
Case 3 - Use of non RW sources	12	20	10.49

Table 6 summarizes the results obtained for the three cases considered besides the total solution time, the required number of evaluations for fitness solution, and the diversity of population.[6] Decay trends of cost function by GA optimization are depicted by reducing the energy cost or maximizing the renewable resources. The Case 1 - Cost Model requires 48 evaluations (see Fig. 10b). The peaks volume of the cost target variable increases the search space for residential appliances' load allocation, which means it must search for a longer time in order to find the optimal schedule. The best solutions are achieved after 30 evaluations in Case 2 - Efficient Model (see Fig. 11b) and 10 interactions are required in Case 3 - Use of Fossil-Fuel Resources Model (see Fig. 12b). The results also imply that load shifting optimization can be achieved by the evaluation of the average distance between defined operating times of appliances at each generation. In this regard, the optimal value of demand allocation diversity is achieved in the fossil supply scenario (12 iterations). Communities with micro-generation capabilities are also considered efficient scenarios (25 iterations for fitness solution).

3.2. Discussion

The energy sector has lagged behind regarding publicly available demand datasets and surveys. The high upfront costs of gathering and processing data can hold back DSM development. Therefore, synthetic data are commonly used to generate energy consumption profiles according to appliance use, and to model, optimize and predict customer response to variables from DSM [59]. This fact is due to real data values only becoming visible once they have been gathered and analyzed. In addition, it is difficult to operate with highly accurate results based on synthetic data or even if consumption habits vary significantly due to a large number of variables such as weather, activity or occupancy patterns, household size, heterogeneous consumer behaviour, etc. Other factors include privacy concerns or the implementation cost of reading devices. Recorded data often leads to a lack of privacy and can leave customers vulnerable to security attacks. Data collection relies on direct user participation in DSM environments or automation processes, which requires potentially costly instrumentation to enable remote sensors and control platforms. User participation also entails convincing consumers to install more energy-efficient appliance technologies, and surveys can play an important role here [72].

The inclusion of categorical demand variables, in addition to accessible consumption data and available survey analysis of appliance patterns, would allow a more in depth behaviour pattern to emerge for demand optimization purposes. Some of the limitations of the analyzed RECS surveys relate to the lack of integration of both controllable consumption by electric vehicles and the diversity of renewable energy generation provided by prosumers at the household level (e.g. PV panel, renewable storage systems). Our collected data may not be able to adequately capture the variation in daily activity (e.g. observed in real-time smart metering, adverse weather, consumer engagement concerns, etc.). This can be challenging to address, especially when performing DSM in demand response scenarios. A significant challenge in developing realistic synthetic residential load profiles is to find appropriate datasets to represent different types of climates, social variables, demographics and types of non-controllable appliances, since the activity patterns of different countries and DSM regulation are not fully implemented [73]. The accessibility and availability of all the above-mentioned information from legitimate, open and up-to-date sources is crucial to check the validation and maintain the reliability of the resulting DSM models.

[6] The optimal distance between solutions determines the quality of the GA performance.

4. Conclusions

The accessible datasets of electricity consumption and load profiles based on time series are valuable instruments when it comes to better understanding demand dynamics and its fluctuations for Demand-Side Management (DSM) system design and real deployment. For instance, publicly available or available-at-request residential load profile datasets can play a powerful role in the implementation of new technologies in household appliances such as washing machines, dryers or room heaters that can be pre-programmed or controlled to switch on at specific times. Pearson correlation analysis is applied to the relevant datasets, such as the Residential Energy Consumption Survey (RECS) administered by the U.S. Energy Information Administration (EIA), in order to assess a linear relationship among the collected variables. Measured consumption and time-of-use of washing machines and dryers are found to be strongly associated (>0.7 correlation coefficient). Genetic optimization is generated considering the time-of-use tariffs and load to quantitatively capture the influence of the controllable appliances' patterns over the DSM performance and its optimization towards the integration of renewable energy supply. Experimentation demonstrated the impact of the controllable loads on the optimization of a community demand scheduling DSM over three different real scenarios, considering supply from renewables, supply from fossil sources and/or electricity bill. Optimization reaches the best case fastest (in terms of time spent in demand reallocation) in the fossil supply scenarios, with the scenarios based on bill being the least efficient. Community demand reallocation takes place, nonetheless, with viable time and resource expenditure. Additional findings showed an average peak load reduction of up to 29% by increasing renewable self-consumption, and electricity bill saving of 9%. Future research directions shall concentrate on integrating new variables into the data-driven model, such as battery charging loads, electric vehicles and micro-generation, as well as varying objective functions for different energy models.

Funding

Spanish Ministry of Science and Innovation, NextGenerationEU funding 2021-2024 for green and digital transition projects: Project title: "Demand Response to the test: Living lab demonstration of aggregated demand response scheduling that optimizes renewable energy use (PUT-DR-2TEST)", Ref.: TED2021-132700B-I00).

CRediT authorship contribution statement

Carlos Cruz: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Marcos Tostado-Véliz:** Writing – review & editing, Investigation. **Esther**

Palomar: Writing – review & editing, Investigation, Funding acquisition. **Ignacio Bravo:** Writing – review & editing, Investigation, Funding acquisition.

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.

Data availability

No data was used for the research described in the article.

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