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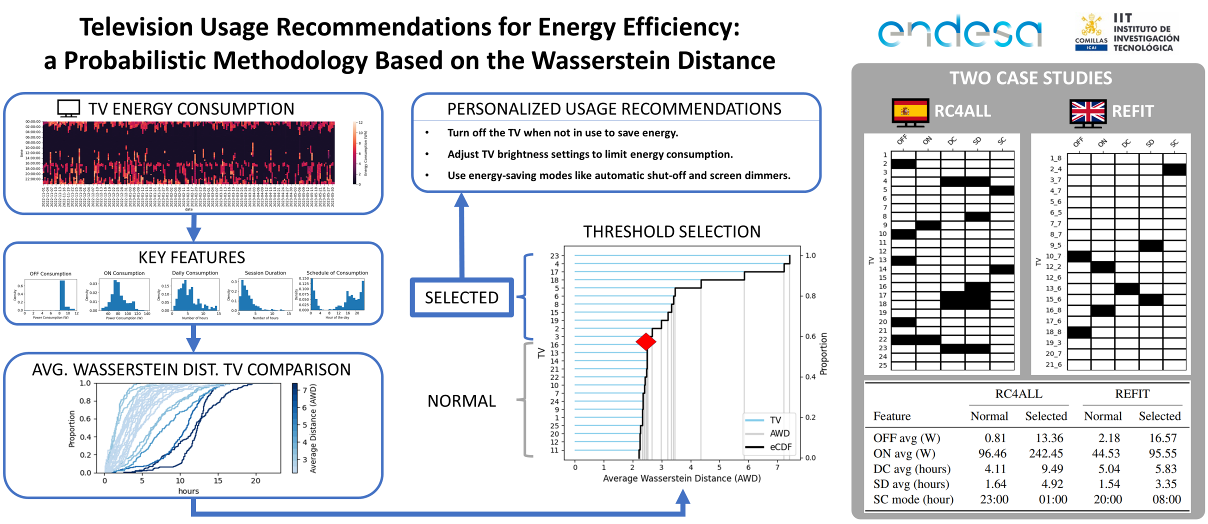
Graphical Abstract

Television Usage Recommendations for Energy Efficiency: A Probabilistic Methodology Based on the Wasserstein Distance

Francisco Rodríguez-Cuenca, Eugenio Francisco Sánchez-Úbeda, José Portela, Antonio Muñoz, Víctor Guizien, Andrea Veiga Santiago, Alicia Mateo González



	RC4ALL		REFIT	
Feature	Normal	Selected	Normal	Selected
OFF avg (W)	0.81	13.36	2.18	16.57
ON avg (W)	96.46	242.45	44.53	95.55
DC avg (hours)	4.11	9.49	5.04	5.83
SD avg (hours)	1.64	4.92	1.54	3.35
SC mode (hour)	23:00	01:00	20:00	08:00

Highlights

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- TVs impact homes significantly, with large energy consumption and health risks.
- Five easy-to-understand features are extracted from TV energy consumption.
- Average Wasserstein Distance is used to measure feature-based TV proximity.
- Two methods select TVs with significant deviations for energy usage recommendations.
- Spanish and UK case studies show differing usage patterns and unhealthy practices.

Television Usage Recommendations for Energy Efficiency: A Probabilistic Methodology Based on the Wasserstein Distance

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Abstract

This paper presents a general and interpretable methodology for delivering personalized energy-saving recommendations to household televisions. TVs, though often overlooked, account for 7% of household energy consumption, ranking as the fourth most costly category. The methodology extracts five easy-to-understand scalar features from historical TV energy consumption data, each representing a key usage aspect: OFF consumption, ON consumption, Daily Consumption, Session Duration, and Schedule of Consumption. It then employs a probabilistic approach based on the Wasserstein Distance to compare these features across TVs. Based on this comparison, two methods—percentage and elbow— are introduced for identifying TVs with significant deviations by feature, accompanied by tailored recommendations.

The methodology is applied to case studies in Spain (RC4ALL project) and the UK (REFIT dataset), with results compared. The percentage method flags 60% of TVs (15 in RC4ALL, 12 in REFIT), while the elbow method flags 56% (14 TVs) in RC4ALL and 40% (8 TVs) in REFIT. Selected TVs in RC4ALL show greater deviations, with ON power 2.5 times and OFF power 16 times above normal, compared to 2 and 7 times in REFIT. TVs' extended daily usage and long sessions raise health concerns. This methodology can also be applied to devices beyond TVs.

Keywords:
Recommender system, Energy saving, Occupant behavior, Household appliances, Wasserstein distance, Data-driven

1. Introduction

The 2.7% increase in global electricity demand in 2022 [1] and its impact on carbon dioxide emissions [2] is currently raising significant environmental concerns. Notably, the residential sector, which accounts for 30-40% of total electricity consumption in OECD countries, is a major contributor to this issue [3]. However, adopting household energy-efficient behaviors holds the potential for a substantial 25% reduction in the EU's CO_2 footprint [4].

These energy-saving behaviors fall into two categories: *curtailment*, routine actions like turning off lights, and *efficiency*, less frequent structural changes such as investing in energy-efficient products [5]. Certain energy-saving behaviors pose greater challenges; for instance, reducing energy consumption in heating is more achievable than addressing lighting and electric appliances [6].

Governments can boost the adoption of energy-efficient appliances and behaviors through strategies like propaganda [7], energy labels [8], and financial incentives [9]. However, these measures face the challenge that households often find it more difficult to save electricity than initially expected [10].

Alternative approaches utilize smart meters and smart plugs. Smart meters, which measure overall energy usage, generate comprehensive monitoring data for various applications, such as analyzing customer electricity consumption behavior, segmentation, load forecasting, and demand response [11]. Non-Intrusive Load Monitoring (NILM) enhances these applications by dissecting smart meter data, even at low sampling rates, to identify individual household appliances [12] and other household characteristics [13]. Conversely, smart plugs provide a practical solution by directly controlling individual devices, eliminating the need for complex disaggregation methods.

Public datasets are important since they can boost research by offering access to data collected by smart meters and plugs. The Pecan Street Dataport dataset provides detailed information with minute-to-second resolution from hundreds of homes, although it lacks specific TV data [14]. In contrast, the REFIT dataset focuses on measurements from only 20 houses at 8-second intervals but includes data for 21 television site appliances [15]. Other significant datasets, including REDD, Tracebase, DRED, BLUED, ECO, and UK-Dale, also contribute measurements for appliance energy usage (see [16, 17, 18, 19, 20], respectively). These datasets collectively enhance research by allowing the extraction of knowledge from consumer behavior in order to influence it through feedback, appliance scheduling, or recommendations.

Energy usage feedback has proven highly effective in promoting energy-saving behaviors [21]. For optimal efficacy, feedback should be frequent, extended in duration, provide appliance-specific breakdowns, present information clearly, and utilize interactive tools to enhance success [22].

Home Energy Management Systems (HEMS) also strive to enhance energy efficiency, as well as reduce costs, and improve user comfort [23] by analyzing and managing appliance schedules [24]. However, experiences in Sweden uncovered challenges in changing practices, citing inflexibility, dwelling constraints, insufficient incentives, lack of guidance, and limited device control [25].

Recommender systems in the energy domain serve diverse purposes: some focus on recommending electricity plans [26], while others induce behavior change by suggesting energy-saving activities and appliances [27]. For example, some recommender systems aim to discover knowledge from grid data and recommend energy-efficient appliances to participants [28]. Another approach leverages "micro-moments," targeting specific moments with recommendations and potentially offering small, instant rewards to shape improved energy-efficient profiles [29].

In fact, recommender systems have been proven to be significantly more effective than general savings tips and feedback [30], and personalized advice on electricity savings has gained prominence. Some research delves into the energy-saving potential of specific appliances, exemplified by the REFIT study on kettle usage [31]. Furthermore, personalized recommendations for fridges address factors such as the need for replacement [32] and provide tailored curtailment and efficiency measures [33]. This last paper links efficiency with a refrigerator's baseline consumption without human interaction while associating curtailment with relative consumption, a measure indicating the percentage influenced by human activities.

Largely inconspicuous, televisions represent a significant percentage of household consumption, the fourth most costly category at 7% of total consumption [34], and are also one of the longest-running appliances in households [35]. This viewing period often coincides with increased use of other appliances, such as air conditioning in the summer [36].

Notably, a substantial portion of TV consumption is associated with the TV set box operating even when the television is turned off [34]. TV energy consumption patterns are culturally shaped by factors like communal versus individual viewing, genre popularity, and peak viewing hours. Cultural preferences also influence the adoption of energy-efficient models; for instance, environmental consciousness may expedite the adoption of such technologies. Additionally, excessive TV usage poses health risks, including adolescent obesity [37], insomnia [38], and even depression [39].

Acknowledging these nuances is crucial, as individuals, despite being informed and willing, may encounter resistance due to cultural norms or structural barriers [40]. These barriers can substantially diminish potential energy and emission savings (63-80%) [41], underscoring the need for precisely tailored intervention strategies for specific target groups [42].

Existing research has largely overlooked the specific consumption patterns associated with televisions to make specific TV usage recommendations. This is the first study to address this significant gap by introducing a probabilistic methodology to deliver personalized and culturally sensitive energy-saving recommendations for TV usage.

Our approach is an improvement over previous recommendation methods, such as targeting micro-moments [29], focusing on energy-saving appliances [28], and comparing average baseload segments and daily load profiles [32, 33]. In contrast, we use disaggregated probability distributions of easy-to-understand features and apply the Wasserstein Distance to compare user behavior. This allows us to identify users with less efficient habits and offer them targeted recommendations. Furthermore, our methodology accounts for cultural resistance by comparing TV usage within culturally homogeneous contexts.

We apply this methodology to Spanish homes within the RC4ALL project and UK homes using the REFIT dataset and conduct a comparative analysis of the results. This study is a pivotal component of the RC4ALL project, committed to delivering energy-saving techniques through detailed monitoring of specific appliances in selected homes [43, 44].

The objective of this paper is to improve television energy usage through the automatic generation of personalized recommendations. Its contributions include the introduction of a novel probabilistic methodology that uses the Wasserstein Distance to offer personalized recommendations and its application to real-world TV energy consumption data from households in Spain and the UK.

The paper is structured as follows: Section 2 introduces the proposed methodology using examples from the RC4ALL project. Case studies are outlined in Section 3, with results and discussion in Section 4. Finally, Section 5 presents the conclusions.

2. Methodology

The proposed methodology follows different steps, as depicted in Figure 1. It is based on a historical dataset of TV energy consumption data. First, five distinct and interpretable features are extracted, each capturing an aspect of TV usage. Second, these features are then employed to compare the TVs amongst themselves. Third, those exhibiting potential improvement in each specific feature are selected for recommendation. Finally, personalized recommendations are provided based on the features identified with room for improvement.

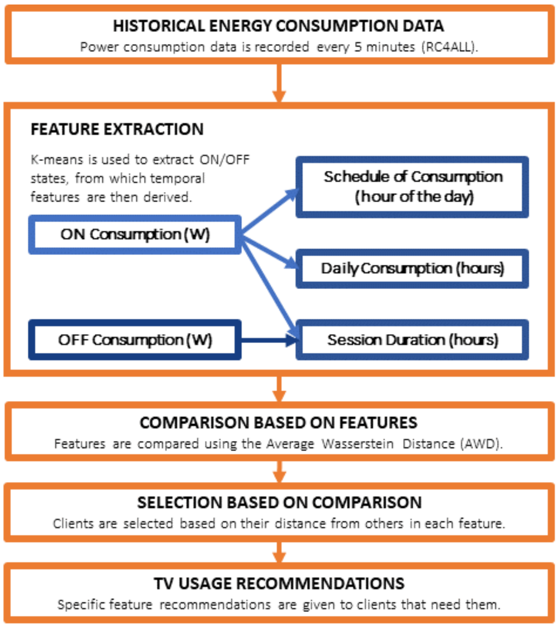

Figure 1: Methodology Schema.

2.1. Engineered Features

The extraction of relevant features starts with the historical energy consumption of each TV. Figure 2 illustrates the energy consumption pattern of a specific TV from the RC4ALL project (TV13-RC4ALL). In this project, energy consumption is measured in watt-hours (Wh) using a smart plug, with readings taken every 5 minutes.

These energy consumption records may exhibit some small data irregularities like surges or empty values. For instance, Figure 2 displays a small number of unusually high values. However, given the methodology's robust probabilistic approach and the infrequency of such occurrences, no additional treatment is necessary beyond the filtering of null values.

Five engineered features have been extracted from these energy records as scalar variables, representing a unique aspect of energy usage. These scalar variables are independent, complementary, and easy to interpret, providing a solid foundation for comparing users and making clear and actionable recommendations.

These features are ON Consumption (ON), OFF Consumption (OFF), Daily Consumption (DC), Session Duration (DC), and Schedule of Consumption (SC). Figure 3 shows an example of these features for TV13-RC4ALL. By examining the probability distribution of these variables, valuable insights into typical patterns in TV consumption can be gained.

The detailed calculation of these features is explained in the following sections.

2.1.1. ON/OFF Consumption

To comprehensively understand televisions' energy consumption, it is necessary to differentiate between their on and off-power consumption states, which can be challenging due to intermediary values across TVs.

Our study defines the off state to include complete power-off and standby modes, accounting for the range of power consumption levels during inactivity. This approach helps us tackle energy waste from all "off" consumption types, making it easier to spot efficient vs. inefficient usage. While separating these modes was considered, grouping them offered clearer insights into user behavior and targeted our recommendations more effectively. Conversely, the on state encompasses all instances of active operation.

To categorize power consumption values into ON and OFF consumption features based on these state definitions, we first calculate the average power consumption (in watts) for each interval using the energy consump-

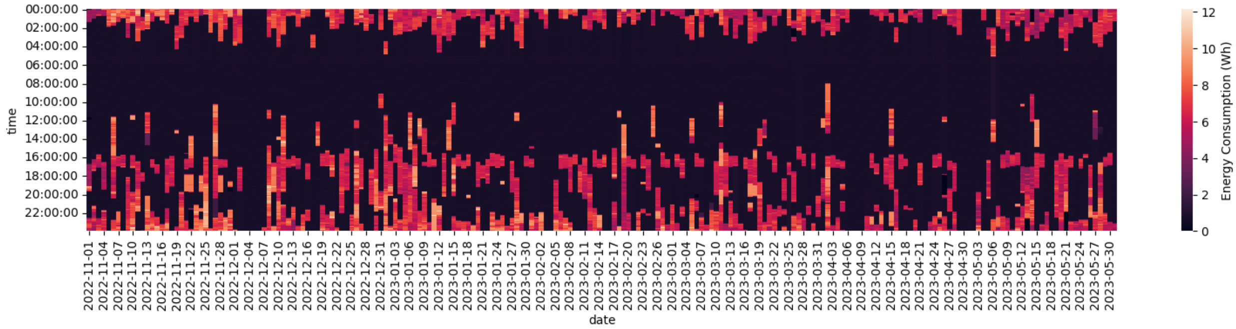

Figure 2: Energy Consumption of TV13 from the RC4ALL project in five-minute intervals.

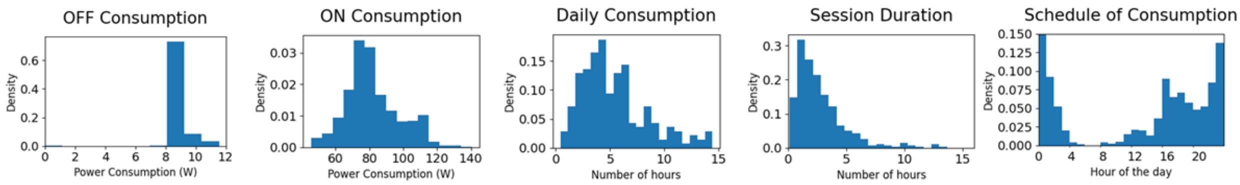

Figure 3: Histogram for each proposed feature of TV13 from the RC4ALL project.

tion records (measured in watt-hours every 5 minutes for RC4ALL). We then apply a k-means clustering algorithm with two centroids to distinguish between the two states.

In particular, we have used the greedy k-means++ algorithm with Euclidean Distance as metric. The choice of the k-means algorithm is deliberate due to the substantial disparity between TV's on and off states and has been done previously in similar studies [45, 46]. This approach is effective under the assumption that TVs undergo both turning on and off events throughout their consumption history, implying they do not remain in a single state throughout.

Figure 4 shows the power consumption decomposition in TV13-RC4ALL, employing histograms to display the historical consumption values. In this example, the analysis reveals that the OFF power consumption predominantly comprises standby mode, with minimal occurrences of consumption recorded at 0, averaging around 9 W. Moreover, the ON consumption is centered around 80 W, which aligns with the typical power consumption patterns seen in the dataset.

2.1.2. Daily Consumption

Daily Consumption (DC) refers to the total amount of time a TV is actively on during the course of a day. This metric is an important factor in understanding overall engagement and habits. Moreover, DC plays a significant role in assessing the impact of TV usage on energy consumption, health, and other related aspects.

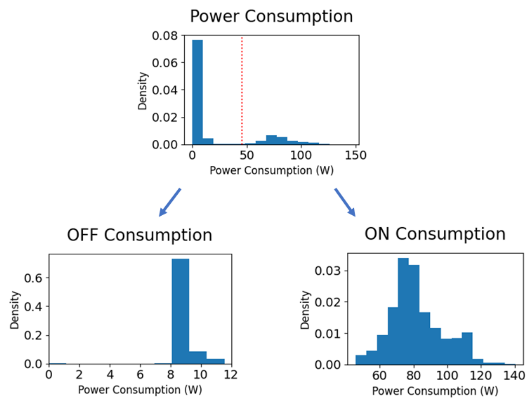

Figure 4: Estimation of ON and OFF states for TV13-RC4ALL.

For instance, excessive daily TV consumption has been linked to sedentary behavior and adverse health effects [39, 37].

Figure 3 presents a histogram illustrating the DC pattern of TV13-RC4ALL. The histogram reveals two distinct peaks at 4 and 6 hours, representing the primary periods of daily television usage. Additionally, a smaller peak can be observed at 14 hours, suggesting occasional instances when the television remains active for an extended duration during the daytime.

Note that measuring DC in time units instead of energy allows us to obtain a normalized feature and easily compare between different TVs.

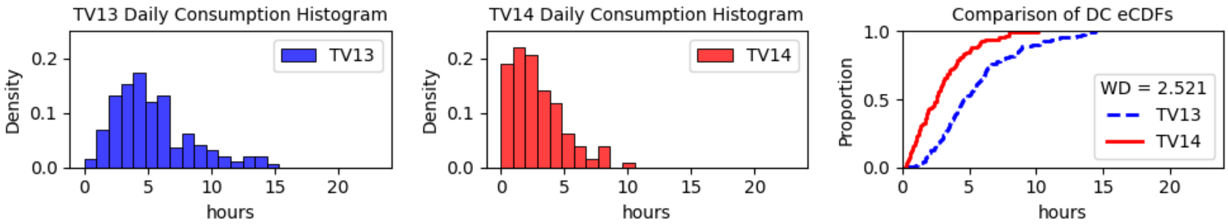

Figure 5: Comparison of the DC distribution of TV13 and TV14 from RC4ALL project.

2.1.3. *Session Duration*

Session Duration (SD) measures the duration of individual viewing sessions, from the moment the TV is turned on until it is turned off. This feature captures the specific time intervals users engage with their TVs. It provides insights into users' preferences for shorter or longer viewing sessions. Moreover, prolonged sitting or excessive screen time has implications for health-related considerations [47], which can inform recommendations to promote healthier TV viewing habits.

In Figure 3, a histogram visually represents the SD pattern of TV13-RC4ALL. The histogram demonstrates that, in this case, television viewing primarily occurs in 1 or 2-hour sessions, with a gradual frequency decrease as the session duration increases.

2.1.4. *Schedule of Consumption*

The Schedule of Consumption (SC) feature captures the hours of the day a TV is actively on. This is important for several reasons. Firstly, it provides insights into users' daily routines and lifestyle choices. For example, the prevalence of TV viewing during late-night hours may indicate a preference for nighttime entertainment or relaxation. Secondly, the SC feature has implications for health-related considerations. Research has shown that excessive TV viewing at night, particularly before bedtime, can affect overall sleep quality [38].

This feature allows for measuring how "normal" a household's TV consumption is within a population. Deviations from common consumption patterns may indicate unique preferences, irregular routines, or other factors.

Figure 3 shows a histogram depicting the SC distribution for TV13-RC4ALL. This histogram shows that television viewing in this specific case is primarily concentrated in the evening. Notably, the data reveals a significant surge in television usage after or during meals, around 16:00, and a subsequent increase in activity after or during dinner, after 21:00, extending as late as 03:00.

2.2. *Comparison based on the Wasserstein Distance*

The methodology integrates the Wasserstein Distance (WD) as a dissimilarity measure between probability distributions [48], enabling the comparison of consumption among different TVs for any given feature.

The WD, also known as the Kantorovich–Rubinstein or Earth Mover's distance, is a metric that quantifies the minimum cost of transforming one probability distribution into another [49]. It can provide a robust way to compare the differences between two probability distributions, taking into account the shape and magnitude of the distributions rather than just their means or variances [50].

Given two one-dimensional probability cumulative distribution functions (CDF), $U(x)$ and $V(x)$, the Wasserstein distance between the distributions equals to the area between both functions [49, 51]:

$$W = \int_{-\infty}^{+\infty} |U(x) - V(x)| \mathrm{d}x \tag{1}$$

The WD is extensively employed across various fields, including statistics [48], politics [52], and machine learning [53, 54]. Unlike Kullback–Leibler divergence (KL), a commonly used non-parametric method, the WD is symmetrical and considers the distance between data samples, accurately representing the disparity between two distributions. While a large WD signifies substantial differences in data samples, KL divergence can be great even with slight differences [55].

By computing the WD between any pair of televisions for a particular feature, we can evaluate the relative proximity of each television to the others on that feature, using only their empirical distributions.

For example, figure 5 juxtaposes the empirical cumulative distribution functions (eCDFs) of TV13 and TV14 from the RC4ALL project to compare their DC. TV13 demonstrates higher daily consumption than TV14, which is evident in the overlapping eCDFs. The curve for TV14 has a higher probability density for lower consumption values, whereas TV13 shows increased probability with larger values. The WD is then

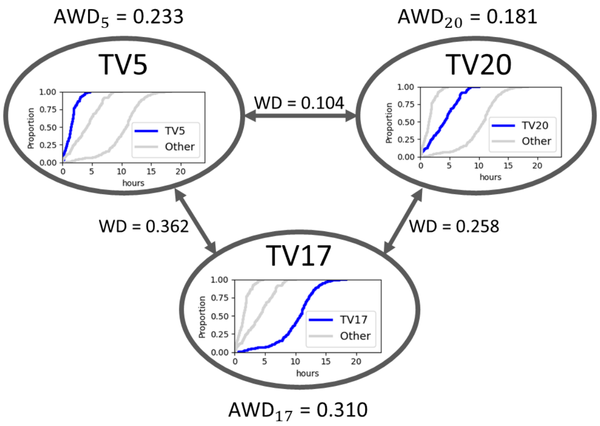

Figure 6: AWD example using three TVs from RC4ALL.

used to quantify the difference between these two distributions.

Subsequently, the aggregated distance of each TV to all others can be estimated by summing its distances to the rest. This calculation treats the televisions as interconnected nodes in an undirected complete weighted graph, where every node is linked to every other node, and the edge weights represent the distances between them [56]. To aid comparability, this sum of distances is then averaged by the number of edges.

This concept can be encapsulated in the definition of the Average Wasserstein Distance (AWD):

$$A_k = \frac{1}{N-1} \sum_{\substack{i=1,N \\ i \neq k}} W_{i,k}, \tag{2}$$

where N is the total number of compared TVs and $W_{i,j}$ is the WD between TVs i and j.

Figure 6 presents an example where the AWD is calculated using a subset of only three TVs from RC4ALL, represented as nodes (limited to these three TVs, results differ from the full dataset). The AWD effectively synthesizes WDs between TVs into a single, coherent value per TV. This establishes a distance-based ranking system for televisions, where lower values mean closeness to the rest and higher values denote greater distances. In this example, TV17 exhibits a larger AWD, indicating that it is the most distant TV among the three.

Figure 7 employs an eCDF to portray the DC patterns of all RC4ALL TVs, with a color gradient illustrating their AWD. In this graphic, lighter hues correspond to more prevalent consumption patterns that group closer together, while darker shades accentuate the less common and distinctive consumption patterns.

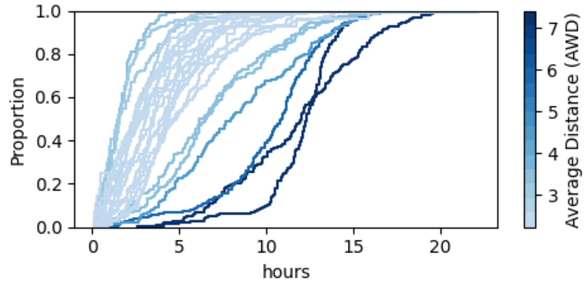

Figure 7: DC comparison in RC4ALL using TVs' eCDFs and AWD.

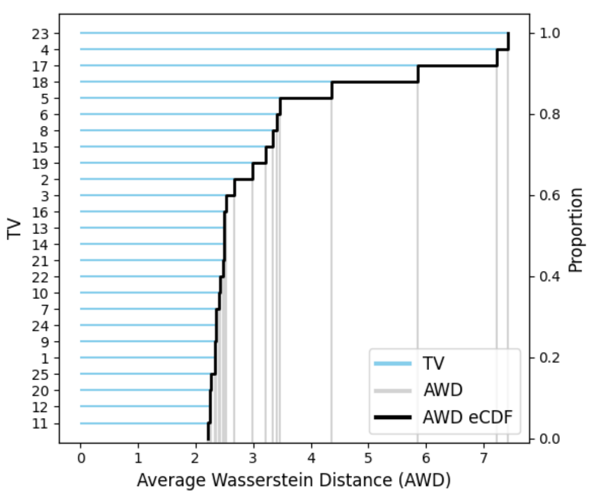

Figure 8: RC4ALL's DC AWD eCDF with each TV's contribution.

2.3. Selection based on Comparison

This section defines the criteria for selecting eligible televisions for personalized recommendations by feature. We present two distinct but complementary methods based on the AWD eCDF, each showing specific advantages.

The proposed methods use the distances of all TVs using the AWD eCDF per feature. Each TV contributes a single value to the AWD eCDF, resembling the sorted TV's AWDs stacked on top of each other. Figure 8 illustrates this concept, presenting individual AWDs and the AWD eCDF for the DC feature in the RC4ALL project.

Both methods function similarly, setting a threshold over the AWD eCDF to partition the original set into two new sets of TVs, with the set requiring recommendations consisting of those with larger AWDs.

Regardless of the chosen method, an additional filter is applied when comparing selected TVs based on their ON, OFF, DC, or SD features. This filter requires a selected TV to exhibit consumption levels at the median that surpasses the global median. This is necessary because the AWD solely serves in this methodology as a measure of proximity, and the undesirable consumption of these features is distinguished by consumption levels exceeding those of other TVs.

However, since higher consumption later in the day doesn't imply unfavorable habits, the SC feature is excluded from the second filter.

2.3.1. Selection by Percentage

The most straightforward method for selecting televisions for recommendations involves initially establishing a specific threshold as a percentage and subsequently choosing that percentage of televisions that demonstrates the most significant deviation from the rest.

Figure 9 illustrates the results of applying this strategy using the DC feature from the RC4ALL project. The initial graph visually represents the AWD eCDF and two thresholds at 20% and 30% selection, effectively segregating the TVs into distinct groups below and above the threshold values. The subsequent two graphs depict the TVs falling above the designated threshold. Notably, the non-selected TVs exhibit a relatively consistent pattern on their eCDFs, while those chosen for recommendation display varying degrees of deviation from the established norm.

Note that the percentages may vary based on the specific requirements of each application of the methodology, showcasing the adaptability of the approach.

2.3.2. Selection by elbow

Another heuristic approach involves the selection of an AWD threshold by identifying the "elbow" or "knee" point on the AWD eCDF. This method is commonly employed to determine the optimal complexity in many well-known methods, for example, to estimate the correct number of clusters in K-Means [57]. In our case, it serves as a heuristic strategy to identify the optimal point at which TVs become noticeably sparser. It also improves upon the previous method by utilizing the AWD eCDF itself for the threshold selection.

For instance, we observe two distinct elbow points on the DC eCDF from the RC4ALL project, as shown in Figure 10. These points represent more or less stringent thresholds, as seen in the resulting TV selection. As explained before, in the case of the DC feature, a second filter is applied, choosing the TVs with a median consumption that surpasses the global median. Figure 11 shows the final set of TVs selected using the first elbow of Figure 10 after applying this second filter.

2.4. Recommendations based on Comparison

Once TVs exhibiting abnormal consumption patterns and behaviors are selected, specific recommendations can be provided to those clients. This section focuses on the assignment of recommendations for each proposed feature. These recommendations are classified into two primary categories: power consumption and time-related recommendations.

2.4.1. Power Consumption Recommendations

Efficient power consumption is essential for optimizing TV usage. With this objective in mind, two types of recommendations are offered: ON Consumption and OFF Consumption recommendations.

The ultimate aim is to minimize energy usage and maximize efficiency. To achieve this goal, energy-saving recommendations have been gathered from reputable institutions such as Energy Guide UK [58], the Sustainability Victoria project from the Victoria State Government [59], and the Eco Cost Savings and Constellation companies [60, 61, 62]. These trusted sources provide valuable insights and strategies for reducing energy consumption while using TVs. Table 1 contains the proposed recommendations.

2.4.2. Time-Related Recommendations

Practical recommendations on managing television time are provided to prevent excessive viewing. These guidelines aim to assist individuals in maintaining a balanced lifestyle and making conscious choices regarding their TV usage. They serve as helpful suggestions and raise awareness about the potential negative effects of prolonged or excessive television sessions.

The recommendations are sourced from reputable organizations such as the American Academy of Pediatrics [65], the Mayo Clinic [64], the Minnesota Department of Health [63], and the most up-to-date scientific studies available [39, 66, 38, 47, 37].

To guide managing television time, the recommendations are categorized into time-related features (see Table 2): daily consumption, session duration, and consumption schedule. It is important to note that some recommendations may overlap across these categories, as they address multiple aspects of time management. This classification empowers individuals to pinpoint and address specific areas of their TV viewing habits that may require attention and adjustment.

3. Case Studies

To validate the proposed methodology's effectiveness, we conducted case studies using monitored TVs

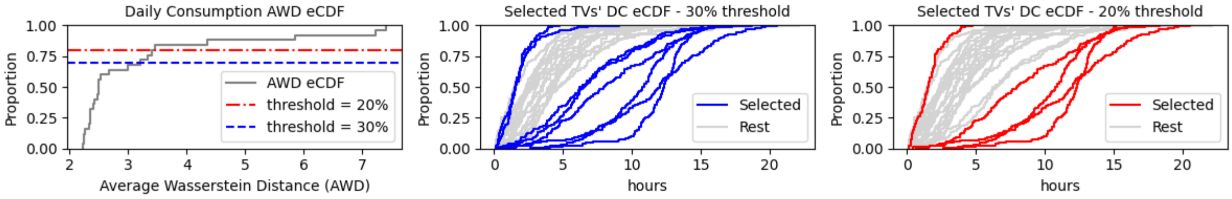

Figure 9: Selected TVs based on their DC feature with a percentage threshold (RC4ALL project).

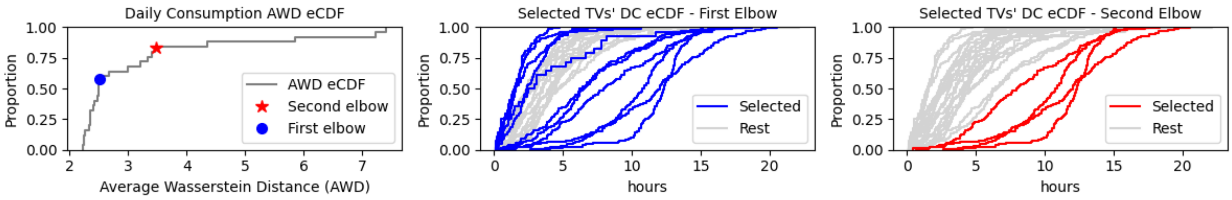

Figure 10: Selected TVs based on their DC feature with the elbow method (RC4ALL project).

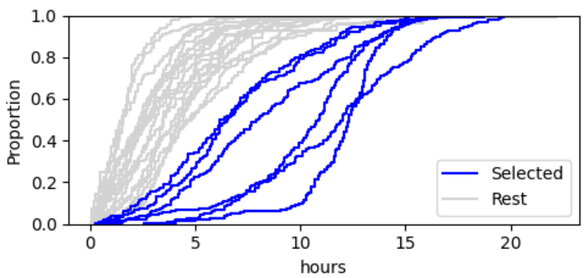

Figure 11: Potential candidates for DC recommendations.

on the RC4ALL project and the REFIT dataset. These case studies allowed us to evaluate the methodology's performance and assess its applicability in real-world scenarios. Our implementation made use of Python libraries, particularly relying on Scikit-learn for KMeans [51] and Scipy Stats for the Wasserstein Distance [67].

3.1. RC4ALL Project

The RC4ALL project is pivotal in advancing household energy-saving techniques by closely monitoring specific appliances in more than 50 homes. By analyzing the energy consumption patterns of these appliances, the project aims to gather valuable insights and knowledge that can be used to provide personalized recommendations to households across Spain. This collaborative effort, funded by the Ministry of Science and Innovation (MCI) and the State Research Agency (AEI), involves Comillas University and Endesa [43, 44].

This study focuses on measurements from 25 TVs. In particular, data were taken at five-minute intervals over a duration of seven months, starting on November 1, 2022, and concluding on May 31, 2023. This information was then preprocessed by filtering out null values. The 25 TVs within RC4ALL were assigned integers from 1 to 25 for practical identification.

3.2. REFIT Dataset

The REFIT Electrical Load Measurements dataset is the result of a valuable collaboration between the UK's Household Electricity Survey (HES), conducted by the Department of Environment and Climate Change (DECC), and the University of Strathclyde [15]. This extensive dataset, collected over approximately two years, consists of continuous monitoring data from 20 homes from the Loughborough area from 2013 to 2015, providing overall household power measurements and individual readings for common household appliances. The dataset captures detailed measurements at 8-second intervals, enabling comprehensive analysis of long-term TV energy consumption during typical domestic activities.

Currently, this is the only public data collection encompassing observations of over 10 TVs with 20 functional televisions.

The methodology was applied to the televisions within the REFIT dataset, which had undergone rigorous preprocessing before publication. To ensure uniformity across the television data, the dataset was constrained to 13 months, starting on March 20, 2014, and concluding on May 9, 2015. In accordance with the RC4ALL approach, consumption values were subsequently aggregated into five-minute intervals.

OFF Consumption	ON Consumption
• Choose an energy-efficient TV size that meets your needs [60]. • Upgrade to an Energy Star certified model [62]. • Choose LED TVs for higher energy efficiency [58]. • Look for Energy Star presets [62]. • Unplug the TV when not in use or use a smart plug for automation [62].	• Choose an energy-efficient TV size that meets your needs [60]. • Upgrade to an Energy Star certified model [62]. • Choose LED or LCD TVs for higher energy efficiency [58]. • Look for Energy Star presets or energy-efficient viewing presets [62]. • Turn off TVs when not in use to save energy [59]. • Reduce screen resolution to save power [62]. • Adjust TV brightness settings to limit energy consumption [59]. • Use energy-saving modes and features like automatic shut-off and screen dimmers [60].

Table 1: Power consumption recommendations for OFF/ON features.

We have used the notation "{home}_{appliance}" (as in "10_7") to label each of the televisions in the REFIT dataset, with the first number corresponding to the house identifier, and the second number corresponding to the appliance identifier within that home.

4. Results and Discussion

To assess the methodology's effectiveness, it was applied to RC4ALL and REFIT datasets, employing both the fixed percentage method (20% TV selection) and the elbow method. The secondary filtering step (excluding SC) narrowed the recommended TVs further to those surpassing the median value.

4.1. Feature Engineering

Firstly, the methodology employs K-Means with two centroids to distinguish between ON and OFF. Figure 12 shows the results as boxplots, with well-consolidated OFF and ON values. Comparing case studies reveals that RC4ALL TVs consume more ON power than REFIT, despite similar OFF consumption.

After categorizing consumption values into ON and OFF, the subsequent features, DC, SD, and SC, are generated, compared with the WD, and then aggregated into the AWD per TV.

4.2. Threshold Selection

Once the features are generated, and the TVs' AWD are calculated, the thresholds for selecting TVs requiring recommendations are determined.

Figure 13 depicts the resulting selection of AWD thresholds in three graphs for each feature and dataset. The first graph shows the elbow and percentage thresholds over the AWD eCDF, while the next two display the feature eCDFs for all TVs. The second graph highlights those chosen by the fixed 20% threshold, while the third highlights TVs selected by the elbow method.

The features exhibit a diverse range of distances, influenced by the dependency of the AWD on unit magnitude. As shown in the first column of figure 13, suitable selection thresholds can be identified using the elbow method. In cases where multiple elbows exist, the best one has been selected to provide a reasonable amount of recommendations. For instance, in REFIT's ON Consumption, selecting a lower AWD elbow would select over 40% of TVs, which might be undesirable.

The thresholds for the percentage and elbow methods, along with the final number of selected TVs, are available in Table 3. The elbow method typically selects approximately 17% of TVs per feature in RC4ALL, whereas REFIT's selection is approximately 9%, significantly lower than the fixed 20%. This difference might indicate a higher cohesion among TVs in the REFIT dataset.

Daily Consumption	Session Duration	Schedule of Consumption
• Completely restrict screen time for children under 18 months [63]. • Limit screen time for children aged 2-5 to one hour per day [63]. • To reduce adverse health events, limit TV time to less than 2 hours per day [47]. • Increased screen time, especially TV viewing, is associated with an increased risk of adolescent obesity [37]. • High levels of sedentary behavior and prolonged television viewing are linked to an increased risk of depression in adults [39].	• Completely restrict screen time for children under 18 months [63]. • Limit screen time for children aged 2-5 to one hour per day [63]. • To reduce adverse health events, limit TV time to less than 2 hours per day [47]. • High levels of sedentary behavior and prolonged television viewing are linked to an increased risk of depression in adults [39]. • Binge viewing, especially at a high frequency, is associated with poorer sleep quality, increased fatigue, and symptoms of insomnia [38].	• Keep screens out of the bedroom [63]. • Use no screens during meals and 1 hour before bedtime [64]. • Establish screen-free times and areas, such as bedrooms, mealtimes, and parent-child playtime [65]. • Distraction during consumption, such as watching TV, can affect taste processing and contribute to individual differences in overeating susceptibility [66]. • Binge viewing, especially at a high frequency, is associated with poorer sleep quality, increased fatigue, and symptoms of insomnia [38].

Table 2: Time-related recommendations for DC, SD, and SC features.

	RC4ALL					REFIT				
	20%		Elbow			20%		Elbow		
Feature	AWD thresh.	N	%	AWD thresh.	N	AWD thresh.	N	%	AWD thresh.	N
OFF	9.10	5	0.25	4.74	5	5.11	4	0.1	5.63	2
ON	79.58	3	0.08	86.50	2	33.84	2	0.1	35.00	2
DC	3.47	4	0.17	3.46	4	3.21	3	0.1	3.26	1
SD	2.08	5	0.25	1.50	6	1.06	3	0.1	1.12	2
SC	4.03	5	0.08	4.27	2	2.38	4	0.05	2.74	1

Table 3: AWD thresholds and the corresponding number of selected TVs in the case studies.

4.3. Selected TVs for Recommendation

The final TVs selected for recommendation by feature and method are shown in Figure 14. This figure illustrates that elbow and percentage methods often favor similar TVs.

In RC4ALL, the percentage method selects 60% (15 TVs), while the elbow method chooses 56% (14 TVs). For REFIT, the percentage method chooses 60% (12 TVs), whereas the elbow method settles for 40% (8 TVs). Notably, both RC4ALL and REFIT show similar percentage patterns.

In the RC4ALL dataset, the percentage and elbow methods lead to 7 and 5 TVs receiving two recommendations, respectively, with none receiving more than two. The most closely related recommendations are DC and SD, given to 4 TVs. This aligns with the notion that longer sessions may correspond to extended daily TV watching. TV23-RC4ALL shows the need for both recommendations, as depicted in Figure 14. Figure 15 showcases its historical energy consumption, revealing a distinctive daily pattern from 13:00 to 02:00. Additionally, evening consumption seems to increase with longer and sunnier days, an intriguing observation.

In the REFIT dataset, the percentage method yields three TVs receiving more than one recommendation, while the elbow method does not result in any. An illustrative case for recommendations is TV13_6-REFIT, receiving DC and SC recommendations through the per-

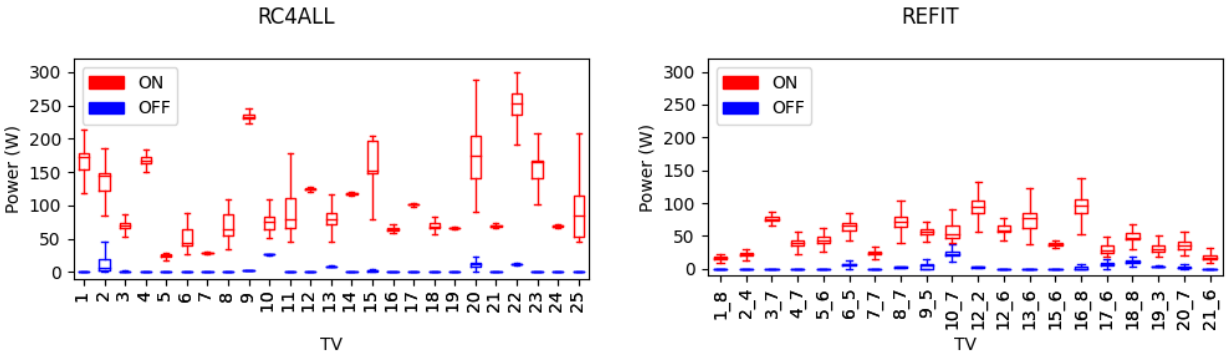

Figure 12: ON and OFF consumption after applying K-means on the case studies.

centage method and DC recommendations via the elbow method. As depicted in Figure 16, it demonstrates a regular daily consumption pattern from 6 to 7 (breakfast?) and evenings from 16 to 21, with heightened consumption during weekends and holidays such as summer and Christmas. Other TVs receiving multiple recommendations through the percentage method include TV18_8-REFIT (OFF and DC recommendations) and TV6_5-REFIT (OFF, SD, and SC recommendations). Remarkably, TV6_5-REFIT, despite receiving three recommendations via the percentage method, obtains none from the elbow method.

	RC4ALL		REFIT	
Feature	Normal	Selec.	Normal	Selec.
OFF avg (W)	0.81	13.36	2.18	16.57
ON avg (W)	96.46	242.45	44.53	95.55
DC avg (hours)	4.11	9.49	5.04	5.83
SD avg (hours)	1.64	4.92	1.54	3.35
SC mode (hour)	23:00	01:00	20:00	08:00

Table 4: Normal and selected central values by the elbow method.

To compare RC4ALL and REFIT TVs, feature averages were computed using the TVs selected by the elbow method, except for SC, for which the mode was determined. These resulting values are classified under selected and normal (non-selected) TVs in Table 4.

When comparing normal power consumption values, RC4ALL TVs, recorded in 2022-2023, exhibit higher ON consumption than REFIT TVs from 2014-2015. However, RC4ALL TVs show lower OFF consumption, possibly due to improved energy efficiency during standby mode despite larger screen sizes and increased capabilities, which is expected in the possibly newer TVs of the RC4ALL project.

Power consumption significantly increases when shifting from normal to selected TVs. ON consumption more than doubles in both cases, and OFF consumption increases more than seven times for REFIT and over 16 times for RC4ALL. This is expected to significantly impact home energy consumption, emphasizing the necessity of the recommendations outlined in Table 1.

When examining DC, typical TVs from RC4ALL watch daily about an hour less than in REFIT. However, selected RC4ALL TVs exhibit significantly higher DC, possibly due to some keeping the TV running in the background throughout the day, as shown in Figure 15.

Significantly, according to the proposed methodology, selected and non-selected TVs in REFIT and RC4ALL exceed the recommendations for DC detailed in Table 2, with the most substantial deviations found in the selected TVs.

In this context, it's vital to understand that TV selection is based on deviations from the norm, ensuring recommendations align with cultural preferences. If the selection were solely based on good habits, nearly all TVs would qualify, but instead, recommendations are offered to clients who need them most.

Regarding SD, while RC4ALL and REFIT TVs typically average less than two hours per session, RC4ALL TVs selected for recommendations spend an hour and a half more per session than their REFIT counterparts.

Figure 17 displays the SC histograms of the selected TVs by the elbow method (Figure 14), with the combined histogram of all other TVs ("Rest"). The "Rest" histogram serves as a reference for comparing typical TV consumption patterns with selected TVs.

Analyzing typical TV consumption, both case studies reveal a continuous six-hour period of minimal TV consumption, from 04:00 to 10:00 in RC4ALL and from 00:00 to 06:00 in REFIT. This pattern mirrors Spain's (RC4ALL) and Great Britain's (REFIT) distinct sleep schedules, with Spaniards typically starting and ending

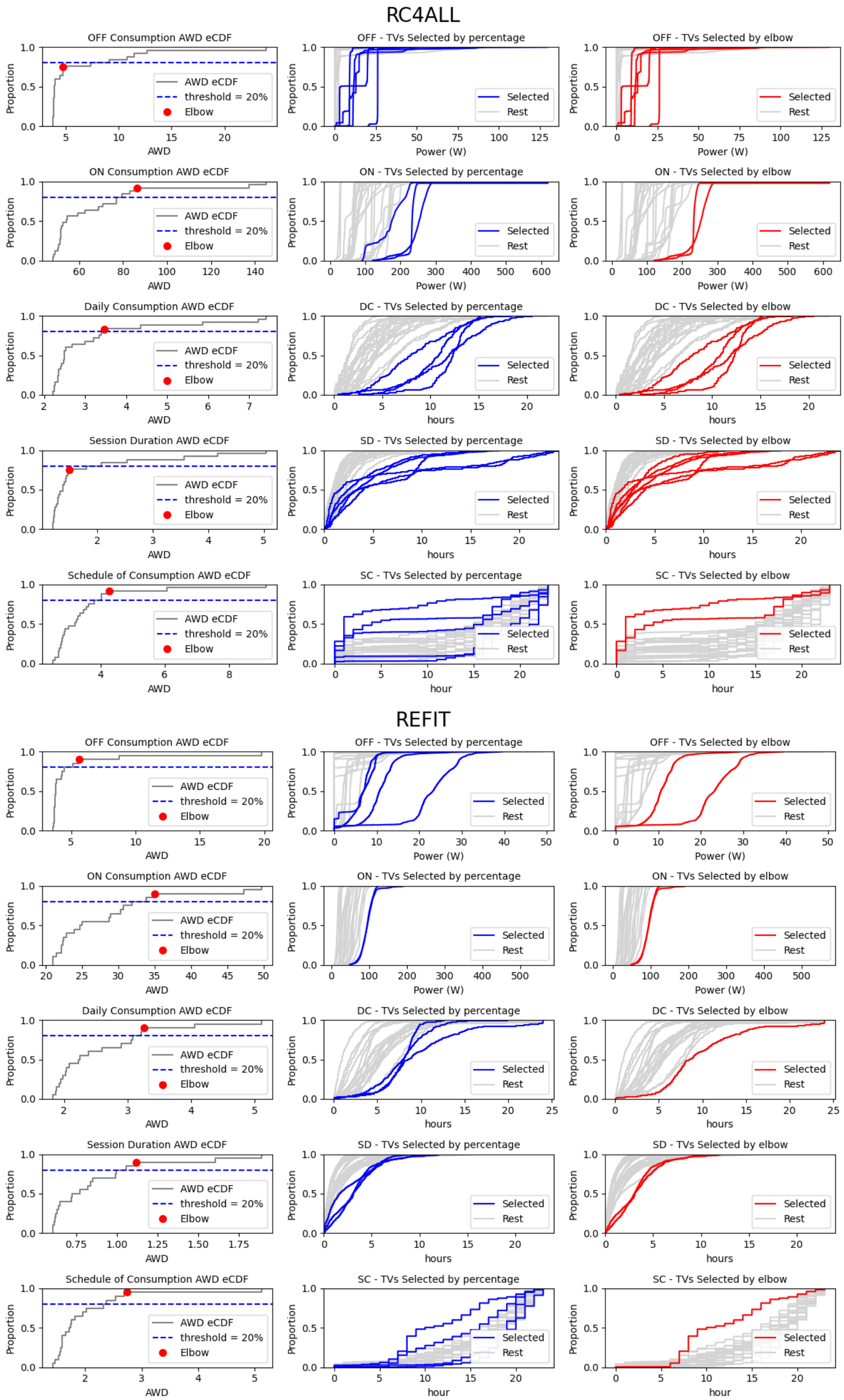

Figure 13: Comparing TV selection methods: AWD thresholds using elbow and percentage approaches.

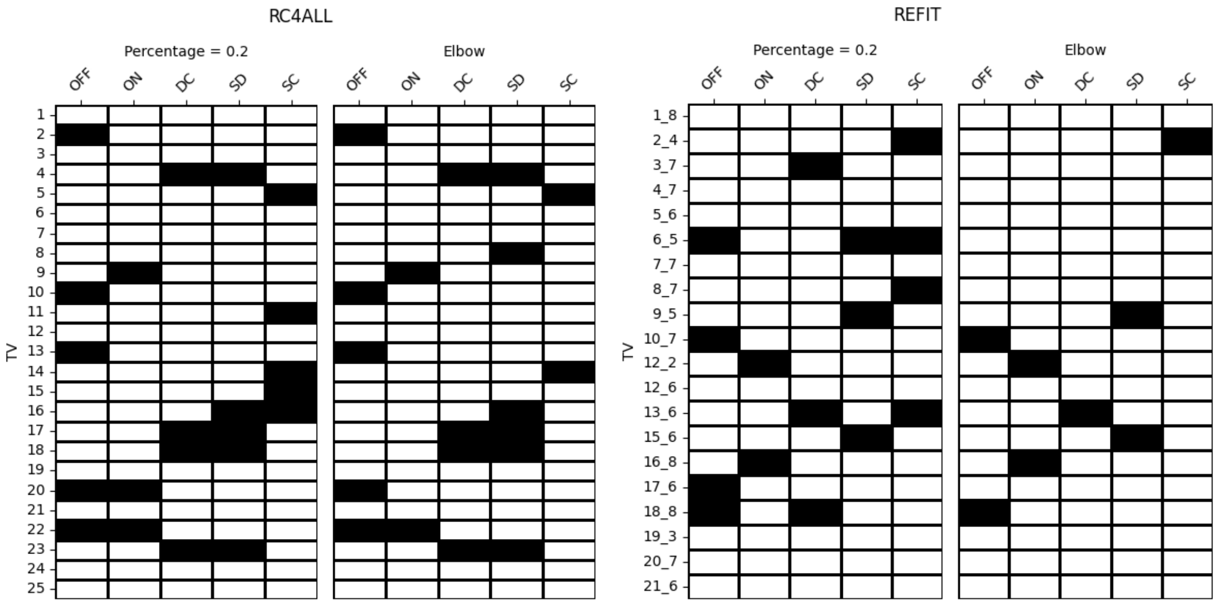

Figure 14: TVs selected for recommendation according to each proposed feature in each case study.

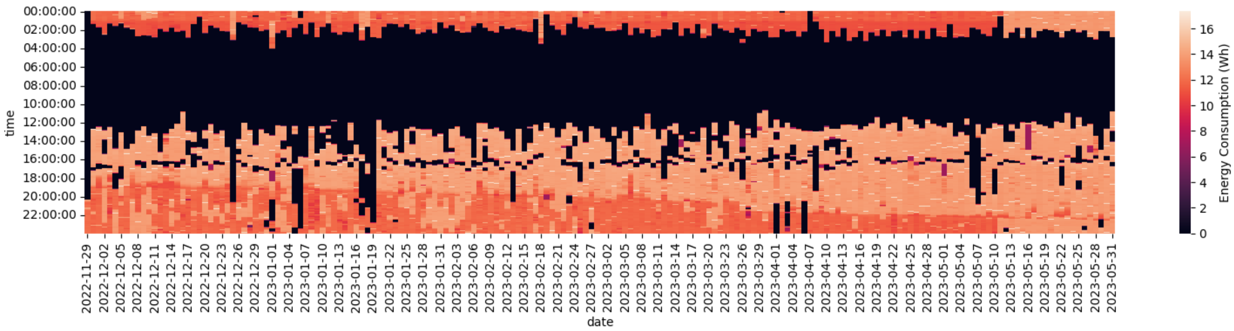

Figure 15: Energy Consumption of TV23-RC4ALL in five-minute intervals. TV23 is assigned DC and SD recommendations (Figure 14).

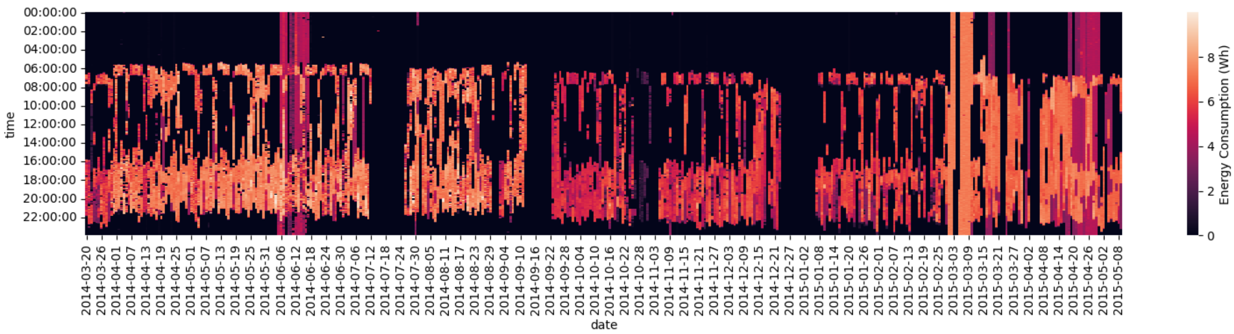

Figure 16: Energy Consumption of TV13_6-REFIT in five-minute intervals. TV13_6 is assigned DC and SD recommendations (Figure 14).

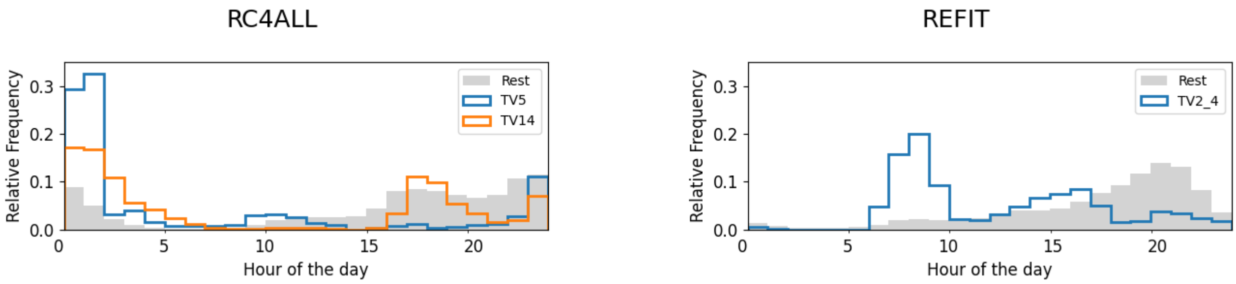

Figure 17: Histograms comparing the Schedule of Consumption for selected TVs against the rest in each case study.

their day at later hours.

Moreover, Figure 17 provides a deeper insight into the observations presented in Table 4. The peaks in the histogram align with the modes identified in the table. Also, in RC4ALL, TV usage is more evenly distributed throughout the day than in REFIT, which tends to concentrate after dinnertime.

In RC4ALL, selected TVs show more early morning activity than typical TVs. However, they differ in specific periods: TV5-RC4ALL displays increased activity between 09:00 and 12:00, while TV14-RC4ALL shows a rise in usage from 16:00 to 20:00.

The selected TV2_4-REFIT follows the usual pattern of minimal nighttime activity. Still, it notably deviates from normal behavior, with a substantial increase in activity from 06:00 to 09:00.

Assessing the relationship of the selected TVs with the potential recommendations described in Table 2, we can see that in RC4ALL, early morning usage aligns with the recommendations to keep screens out of the bedroom and one hour before bedtime. In REFIT, however, the selected TV has extensive activity from 06:00 to 10:00, indicating that users might watch TV while having breakfast, which coincides with the recommendation to avoid screens during mealtimes.

The methodology developed in this study is highly effective for TV datasets with substantial energy consumption records. While originally designed for televisions, it can be adapted to other intermittent-use appliances, such as personal computers, washing machines, dishwashers, and microwaves. This might entail incorporating features like weekly usage frequency, peak usage times, and energy consumption per use to better capture appliance-specific consumption behaviors.

However, it has limitations when applied to continuous-operation appliances, such as refrigerators or heaters, which require specialized features to account for energy efficiency and the influence of user behavior. Furthermore, the current approach does not account for seasonal variations, which could offer deeper insights into weekly or yearly patterns.

5. Conclusions

Embracing energy-efficient behaviors in households has significant potential for addressing environmental problems. Smart meters and plugs can aid this by providing detailed measurements of appliances' energy consumption, which can be used to generate specific usage recommendations.

This paper introduces the first methodology for delivering personalized, culturally sensitive recommendations for better TV energy usage. The approach involves extracting easy-to-understand scalar features from historical energy consumption, including OFF power consumption, ON power consumption, Daily Consumption, Session Duration, and Schedule of Consumption. Utilizing the Wasserstein Distance through a probabilistic approach, these features are compared across TVs. Two methods are proposed to select TVs that show significant deviations from normality for recommendations, along with suggested improvements on each feature.

The methodology is applied to TVs monitored in the UK's REFIT dataset and the RC4ALL project in Spain. The results demonstrate its effectiveness in selecting TVs for targeted recommendations across the five key features. The percentage method identifies 60% of the TVs in both datasets as needing recommendations—15 in RC4ALL and 12 in REFIT. Meanwhile, the elbow method selects 56% of TVs in RC4ALL (14 TVs) and 40% in REFIT (8 TVs).

Notably, deviation levels are significantly higher in RC4ALL, where selected TVs have ON power consumption 2.5 times and OFF power 16 times greater than normal. In contrast, selected TVs in REFIT have ON power 2 times and OFF power 7 times greater than normal. Furthermore, RC4ALL TVs average 9.49 hours of usage daily, with 4.92 hours per session, compared to

REFIT's 5.83 hours daily and 3.35 hours per session, highlighting the longer usage time in Spain.

The selected TVs also reflect cultural differences, with the TV schedules in RC4ALL aligning with later Spanish viewing habits, while REFIT's schedule matches earlier UK routines.

Regarding health, most TVs surpass the recommended two hours of daily consumption, averaging 4 to 5 hours. Recommendations for healthier usage, starting with the most deviating TVs, are therefore essential.

The proposed methodology shows promise as a universal approach for comparing and selecting TVs for usage recommendations. Future efforts could explore the impact of these recommendations.

An enhancement to the methodology could involve incorporating features that consider both weekly and yearly seasonality. Given that TV usage varies throughout the week, exploring additional features accounting for such patterns could provide a more nuanced understanding of TV usage. This, in turn, could contribute to more effective health and energy recommendations.

Moreover, this methodology can extend beyond TVs and be applied to other appliances, including personal computers, washing machines, dishwashers, and microwaves. This adaptation could add features like weekly appliance usage frequency, peak usage months, and energy consumption per use. Continuous-operation appliances, like refrigerators or heaters, may require specific features tailored to both appliance efficiency and the influence of users' living patterns.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT 3.5 in order to improve the readability and language of the manuscript. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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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.

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Data Availability

The processed data from the REFIT dataset required to reproduce the above findings is available to download from `https://pureportal.strath.ac.uk/en/datasets/refit-electrical-load-measurements-cleaned`.

The data obtained from households participating in the RC4ALL project (Agencia Estatal de Investigación, RTC2019-007380-3) cannot be shared at this time due to legal/ethical reasons.