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Research paper

A data-driven methodology for deriving electricity consumption typologies from smart meters

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ABSTRACT

We present a data-driven methodology to identify residential electricity consumption typologies from large-scale smart meter data. The proposed approach combines seasonal feature extraction, clustering via Self-Organizing Maps (SOMs), and expert-in-the-loop validation to ensure both statistical robustness and operational relevance.

Although the methodology is tailored to residential consumption, it also captures other non-residential load patterns – such as commercial, industrial, and public-sector profiles – present in the analyzed data.

The methodology was applied to more than 23,000 time series from five international datasets, resulting in 40 distinct consumption patterns. These clusters were grouped into five behavioral categories – primary residences, holiday homes, equipment-intensive households, offices, and public lighting – each capturing characteristic daily and seasonal load signatures.

The resulting typology enables a more realistic and interpretable representation of household electricity use, improving the design of demand-side strategies, tariff schemes, and forecasting models. In particular, it offers a practical foundation for energy planning and policy targeting across diverse regions, and can inform real-time classification tools or adaptive services under conditions of data scarcity or external disruptions.

1. Introduction

Understanding residential electricity consumption is essential for the planning, operation, and sustainability of modern energy systems. Household load profiles are used across the energy value chain to guide decisions on technology deployment, infrastructure sizing, tariff design, and demand response strategies. From evaluating the viability of PV systems, EV charging, or battery storage, to developing building energy management systems or performing long-term infrastructure planning, a realistic representation of household demand is critical (Proedrou, 2021; Kewo et al., 2023).

However, access to detailed and representative consumption data at the household level remains limited. In many real-world scenarios – such as planning for new developments or assessing the impact of energy policies – measured load profiles are either unavailable or incomplete. As a result, practitioners often resort to standardized or synthetic profiles (Fünfgeld and Tiedemann, 2000; El Kababji and Srikantha, 2020). Standardized profiles, derived from aggregated averages, overlook the behavioral diversity and temporal variability of individual households (Kwac et al., 2013). Synthetic models, such as *SynPro*, *LoadProfileGenerator.de*, and *CREST* (Fischer et al., 2015; Pflugradt et al., 2022; Richardson et al., 2010), attempt to simulate demand patterns but rely on fixed assumptions and manual configuration, which can lead to inaccuracies. Some studies report sizing errors of up to 15% when inappropriate profiles are used (Jurasz et al., 2022).

The widespread deployment of smart meters opens new opportunities to derive consumption typologies directly from observed data. A comprehensive, data-driven typology can better capture the full spectrum of household behaviors – including those of shift workers, high-consuming appliances, or second homes – thus enhancing the realism of simulations and enabling more targeted interventions in planning, tariff design, and policy development.

Despite growing research in this area, existing clustering approaches frequently fall short of operational needs. Many methods rely on daily

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average profiles, ignoring seasonal dynamics (Beckel et al., 2012), or apply dimensionality reduction techniques that obscure critical behavioral features (Yildiz et al., 2018; Ryu et al., 2020). Scalability to large, heterogeneous datasets remains a challenge, and validation is often limited to internal metrics such as silhouette score (Beckel et al., 2013; Kell et al., 2018; Satre-Meloy et al., 2020), with little attention paid to interpretability, usability, or alignment with stakeholder needs.

This paper addresses these limitations by proposing a **methodology** to derive operationally meaningful **typologies** of residential electricity consumption from large-scale smart meter data. The approach combines seasonal feature extraction, clustering via Self-Organizing Maps (SOMs), and an experts-in-the-loop validation process to ensure that resulting profiles are both statistically robust and relevant for practical applications. These typologies are intended to support decision-making by utilities, regulators, and energy cooperatives, helping them design better infrastructure, tariffs, and demand-side strategies.

While the methodology is primarily designed to characterize residential consumption, its application to real-world smart metering datasets also reveals other non-residential patterns – such as those associated with commercial, industrial, or public-sector users – when these are present in the data.

To our knowledge, no prior work has combined these components in a unified framework tailored to the operational needs of the energy sector. In contrast to existing studies, our method prioritizes interpretability, scalability, and alignment with real-world applications.

In parallel, the energy landscape is evolving with the rise of domestic prosumers — households that both consume and generate electricity, typically through PV and battery systems (Heinisch et al., 2019; Hu and Chuang, 2023; Šriupša et al., 2023). While most existing studies focus on economic incentives or technology adoption, the behavioral dimension of prosumption remains underexplored. Our approach complements this body of work by providing a typology rooted in observed consumption patterns, independent of specific technologies.

The main contributions of this work are:

- A scalable clustering methodology based on seasonal time series features and Self-Organizing Maps (SOMs), tailored to capture realistic residential consumption behaviors.
- An expert-in-the-loop validation process that enhances the interpretability and practical relevance of the resulting clusters.
- An initial typology of consumption patterns organized into five broad categories, offering a structured basis for operational applications in planning, tariffs, and demand-side strategies.

By bridging the gap between statistical modeling and operational needs, our framework contributes to more accurate simulations, fairer access to renewable energy solutions, and user-centered energy policies. It also supports the goals of Sustainable Development Goal 7 (Affordable and Clean Energy) (United Nations, 2015).

The remainder of the paper is structured as follows: Section 2 reviews existing approaches and their limitations; Section 3 details the datasets, features, clustering method, and validation process; Section 4 presents the typology and discusses its implications; and Section 5 concludes and outlines directions for future work.

2. Related work and key challenges

Clustering of residential electricity load profiles has been widely explored in the literature, particularly since the first public datasets became available (Beckel et al., 2013, 2012; Satre-Meloy et al., 2020; Kell et al., 2018; Liu et al., 2021). Most existing methodologies follow a common pipeline: data cleaning, feature extraction, dimensionality reduction, and clustering. While this approach has produced valuable insights, several critical limitations persist when it comes to operational use.

First, many studies focus on clustering typical daily load patterns, often by averaging across days (Beckel et al., 2012). While this simplifies analysis, it misses important seasonal shifts and long-term behavioral patterns (Kewo et al., 2023). Methods based solely on daily profiles are unable to capture key differences between summer and winter behavior, or weekday and weekend routines, limiting their applicability for system design and tariff optimization. In our methodology, these effects are captured through a diverse feature set spanning multiple temporal scales, ensuring that intra-annual variations and long-term behaviors are reflected in the clustering.

Second, dimensionality reduction techniques such as Principal Component Analysis (PCA) are commonly used to manage the complexity of time series data (Yildiz et al., 2018). However, PCA and similar methods may distort critical features, as they prioritize variance preservation over the retention of application-relevant patterns. For instance, PCA can introduce artificial consumption where none existed originally, particularly affecting day-specific structures such as weekend or holiday behavior (see Fig. 1). Our approach avoids this risk by working directly on interpretable features derived from the original series without applying PCA or other opaque transformations.

Third, time series clustering often relies on similarity measures such as Euclidean distance or Dynamic Time Warping (DTW) (Montero and Vilar, 2015). While DTW can align similar patterns with phase shifts (Zhang et al., 2022; Gullo et al., 2009), it may also obscure critical information about peak demand timing, which is essential for tariff design and energy planning. In our approach, load profiles are first transformed into a feature space designed to retain when consumption typically occurs within the day and across seasons, allowing this temporal information to be preserved in the clustering process.

Fourth, normalization techniques intended to improve clustering performance by removing scale differences often discard valuable information about absolute energy consumption levels (Liu et al., 2022; Nweye and Nagy, 2022). For practical applications such as system sizing or demand response, this magnitude information is critical and must be preserved. In our case, magnitude-sensitive features (e.g., total consumption, peak load, seasonal aggregates) are kept in their original scale for clustering. Normalization is applied only after clustering, as a visual aid to enhance the interpretability of the resulting patterns without affecting the grouping itself.

Fifth, most published works operate on relatively small or homogeneous datasets, such as the British *Low Carbon London* project (London Datastore, 2013) or the Irish *ISSDA* dataset (Commission for Energy Regulation (CER), 2012). Consequently, the developed methods may not generalize well to more diverse populations with varying lifestyles, time zones, and climatic conditions. In contrast, we train and validate our methodology on more than 23,000 load profiles from five countries spanning different climates, tariff regimes, and socio-economic contexts, which increases its robustness and transferability.

Finally, clustering validation is often performed using internal metrics like silhouette width or Dunn index (Brock et al., 2008), which provide statistical coherence but not necessarily operational usefulness. Very few works involve domain experts in evaluating cluster interpretability and application relevance, leading to groupings that may be mathematically sound but practically meaningless. We combine internal validation metrics with an experts-in-the-loop process, where domain specialists review and refine the clustering outputs, ensuring that the resulting typology is both statistically robust and operationally relevant.

Overall, despite significant research efforts, current clustering approaches often fall short of producing typologies that are both interpretable and scalable for real-world energy applications. Our methodology was specifically designed to overcome these shortcomings by combining seasonally-aware, magnitude-preserving, and interpretable features with a clustering approach suitable for large, heterogeneous datasets, and expert-driven validation.

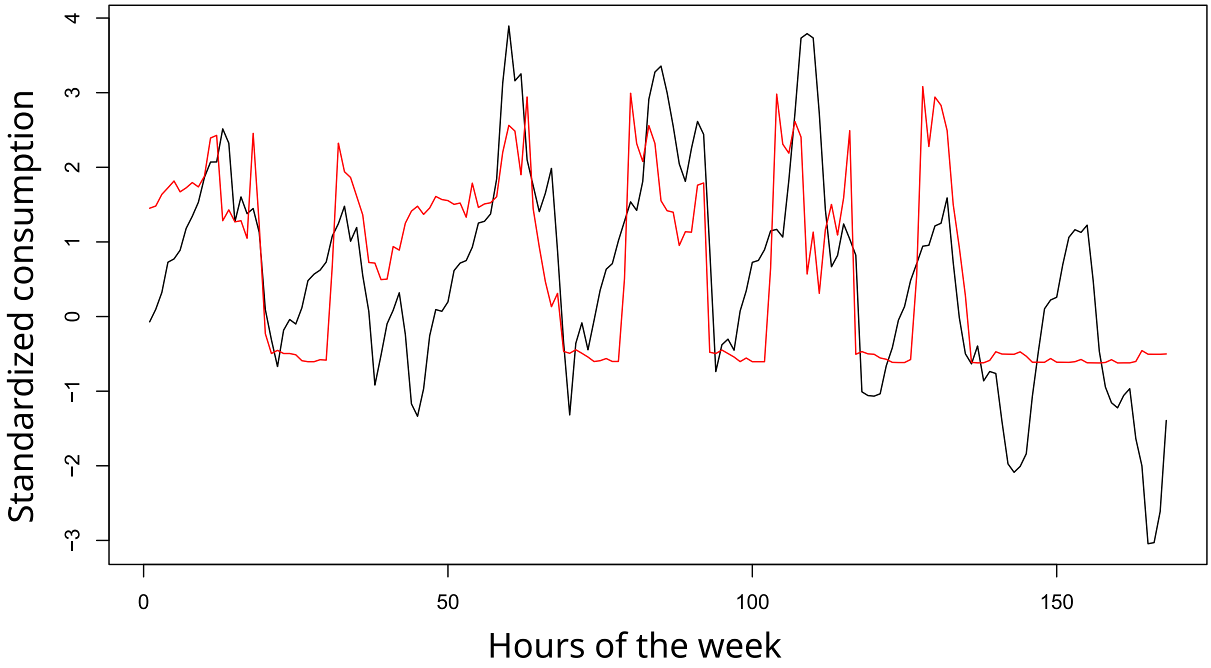


Fig. 1. A comparison between a household electricity load profile (red) and its PCA reconstruction using 250 principal components, based on the dataset described in Section 3.2. The PCA reconstruction introduces spurious energy consumption on Sundays, where the original data show none.

3. Materials and methods

3.1. Overview of the methodology

To address the challenges identified in Section 2, we developed a methodology based on three pillars: (i) careful feature design to retain application-relevant information, (ii) scalable and interpretable clustering techniques, and (iii) an experts-in-the-loop validation process to ensure practical relevance.

Fig. 2 summarizes the overall workflow. Residential load profiles are first preprocessed and standardized. Key features capturing seasonal patterns and magnitudes are then extracted. Clustering is performed on these features, and results are validated both statistically and with domain experts. Finally, a taxonomy of consumption patterns is constructed.

3.2. Datasets and preprocessing

3.2.1. Dataset selection

To ensure the representativeness and robustness of our clustering approach, we initially screened 25 datasets from both open-access repositories and utility companies (full list provided in Appendix). Datasets were selected based on the following criteria:

- **Data quality:** Minimum series length of one year and minimal missing values.
- **Site type:** Preference for residential households; datasets containing commercial, industrial, or aggregated profiles were filtered out whenever possible.
- **Geographic diversity:** Inclusion of datasets from different climatic zones, regulatory frameworks, and socio-economic contexts to increase generalizability.
- **Data accessibility:** Publicly available or sharable under research agreements.

Following this selection process, five datasets were retained: Goiener (Quesada et al., 2024), ISSDA (Commission for Energy Regulation (CER), 2012), Low Carbon London (London Datastore, 2013), Elergone (UCI Machine Learning Repository, 2015), and NEEA (Northwest Energy Efficiency Alliance, 2022). Together, they provided 35,286 raw time series spanning multiple years, seasons, and usage profiles.

3.2.2. Eligibility and scope

The unit of analysis in our methodology is the yearly consumption pattern. Therefore, we require a minimum series length of one full year. Time series shorter than one year are excluded *a priori* and are neither imputed nor artificially extended. Time series covering multiple years are retained in full, and subsequent processing operates over the entire available span.

3.2.3. Time alignment and harmonization

Given the differences in metering practices, sampling rates, and time conventions across datasets, a harmonization process was necessary before analysis:

- **Sampling Frequency:** Time series were resampled to a common 1-hour interval by averaging sub-hourly data when necessary.
- **Time Zones and DST Adjustments:** All timestamps were converted to local standard time. Daylight Saving Time (DST) transitions were corrected to avoid artificial jumps or duplicated hours, which could otherwise distort daily and weekly patterns.

3.2.4. Handling missing data

Incomplete or inconsistent readings are common in real-world datasets. To address this, we applied a two-tier imputation strategy designed to preserve both local continuity and weekly seasonality:

- For **short gaps** (of at most 8 consecutive samples), we used seasonally split linear interpolation, implemented in R via `imputeTS::na_seasplit()` with `algorithm="interpolation"` (Moritz and Bartz-Beielstein, 2017). The time series was segmented by weekly seasonality, and interpolation was performed within each seasonal subseries. This way, missing values were inferred only from neighboring weeks at the same weekday and hour.

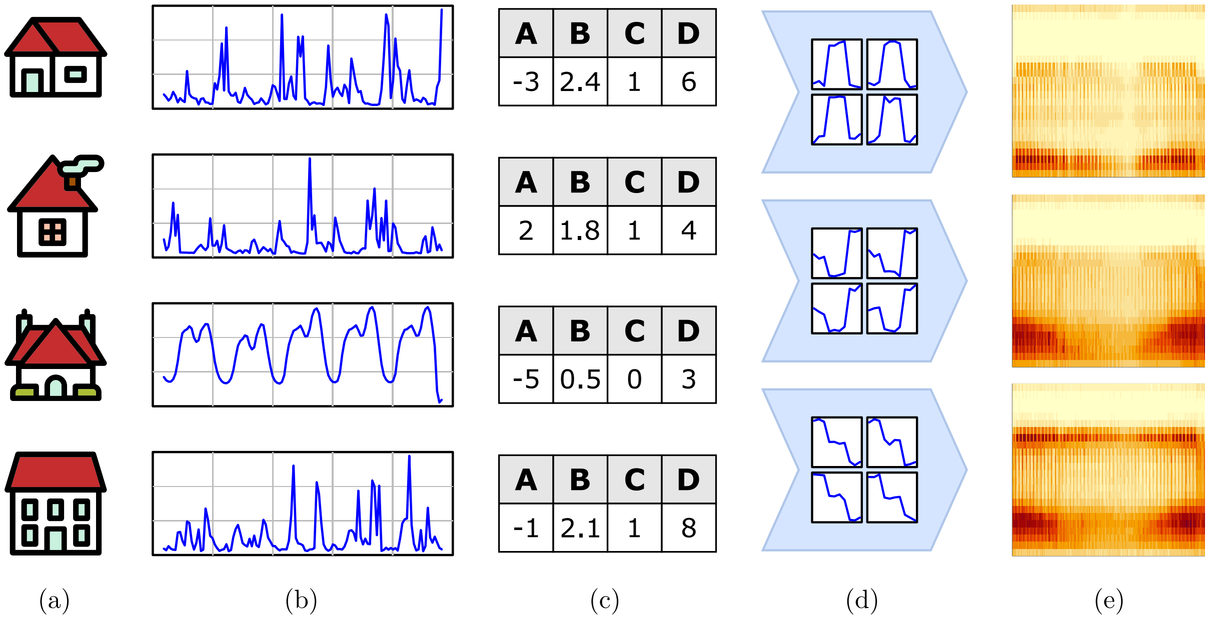


Fig. 2. General overview of the proposed methodology. The complexity of the residential sector stems from the heterogeneity of households (a), which is reflected in the load profiles they generate (b). Prior to analysis, load profiles undergo data cleaning and feature extraction, resulting in a reduced set of numeric descriptors, i. e., features (c). All load profiles, represented by their features, are then clustered based on common electricity consumption patterns (d). Finally, clusters are visualized as heatmaps (e) to support identification and taxonomic analysis.

- For **longer gaps** (over 8 consecutive samples), we used seasonally split Last Observation Carried Forward (LOCF) with a 7-day seasonality window, implemented in R via `imputeTS::na_seasplit()` with `algorithm="locf"` (Moritz and Bartz-Beielstein, 2017). Missing values were filled with the most recent observation from the same weekday–hour slot in previous weeks.

The two methods serve different purposes: interpolation ensures local continuity, while seasonal LOCF captures broader structural patterns, preserving the weekly cycle even across extended gaps. Time series with more than 5% missing samples or containing all-zero values were discarded, with the proportion of imputed samples and the effect of this rule reported in Table 2. All preprocessing scripts, including seasonal interpolation and LOCF, are available at Quesada et al. (2022) for full reproducibility.

3.2.5. *Exclusion of COVID-19 affected periods*

The COVID-19 lockdowns that began in early 2020 substantially altered household electricity consumption patterns (Flanagan et al., 2021). To ensure that the typology reflects standard behaviors, we applied the following filtering criteria:

- **Spain (Goiener):** A cutoff date of March 1, 2020, was established to exclude data potentially affected by the onset of the national lockdown on March 15, 2020.
- **United States (NEEA):** Given that data collection began in 2020, after the start of stay-at-home orders (around March 24, 2020), no pre-COVID-19 subset was available. While no filtering was applied, the potential influence of pandemic-related behavioral changes is considered when interpreting results.
- **Ireland (ISSDA), United Kingdom (LCL) and Portugal (Elergone):** These datasets do not extend into the lockdown period and thus required no filtering.

3.2.6. *Final dataset*

After preprocessing, the resulting dataset comprised 23,638 annual load profiles, representing a total of more than 20 million hourly measurements. Table 1 summarizes the filtering and cleaning results. The five datasets were harmonized to a common hourly resolution measured in kWh and analyzed jointly. This unified dataset includes a diverse mix of regions and user types, capturing a broad spectrum of real-world consumption behaviors. It serves as the foundation for the subsequent analysis.

Table 2 summarizes the outcomes of the complete selection pipeline. For each dataset, it reports the number of available time series at each stage of the process, their average duration, and the proportion of imputed values, ending with the final selection used for analysis.

3.3. *Feature extraction*

3.3.1. *Rationale for feature extraction*

Direct clustering of raw load profiles is hindered by practical issues: the time series in our dataset vary in length – with a minimum duration of one year – and begin and end on different calendar dates, making direct comparisons between them unreliable. These challenges motivate the transformation of each time series into a compact set of numerical features that standardizes their representation while preserving the most relevant information for clustering.

We evaluated both established time series feature sets and designed custom descriptors based on domain knowledge to better reflect the characteristics of residential electricity use.

3.3.2. *Feature sets*

A total of seven feature sets were considered during preliminary experiments:

1. **Basic statistical descriptors:** Mean, variance, skewness, kurtosis, quantiles, outlier measures, and total annual consumption.
2. **Seasonal aggregates:** Averages and variability over time bands reflecting intra-day, weekly, monthly, seasonal, and tariff-related patterns, including:
    - **Intra-day patterns:** Hourly averages and averages over 4- and 6-hour blocks.
    - **Weekly/monthly patterns:** Per weekday, weekend vs. weekday, and per calendar month.

Table 1
Characteristics of the datasets used in this study. *Short name* refers to the abbreviation used for each dataset. *No. of meters* is the total number of individual measurement points (i.e., smart meters). *Country* specifies where the data were collected. *Site types* include H (households), C (commercial sites such as businesses and offices), I (industrial sites), and F (public facilities), with bold text marking the predominant type. *Sampling interval* is the time between consecutive measurements. *Collection period* indicates the range of years over which the data were recorded. *TS length (days, mean ± sd)* reports the mean duration (in days) and standard deviation for the time series in the dataset.

Short name	No. of meters	Country	Sitetypes	Sampling interval	Collection period	TS length (days, mean ± sd)
Goiener	22 851	ES	H, C, I, F	1 h	2014–2021	951 ± 567
ISSDA	6 435	IE	H, C	30 min	2009–2010	513 ± 86
LCL	5 449	GB	H, C, F	30 min	2011–2014	630 ± 110
Elergone	370	PT	H, C, I, F	15 min	2011–2014	1 178 ± 313
NEEA	200	US	H	15 min	2018–2020	320 ± 143

Table 2
Results of the time series selection process for each dataset. *Raw TS* is the total number of original time series. *TS ≥ 1 year (pre-COVID)* indicates the number of series with at least one continuous year of data prior to COVID-19 lockdowns. *TS length (days, mean ± sd)* reports the mean duration (in days) and standard deviation for the series in the previous column. *Imputed samples (%)* shows the average proportion of imputed values within those series. *Selected TS* is the number of series that meet all selection criteria (e.g., imputed values < 5%, non-zero readings, COVID-19 filters). *Selected TS (%)* expresses this as a percentage of the total raw series.

Name	Raw TS	TS ≥ 1 year (pre-COVID)	TS length (days, mean ± sd)	Imputed samples (%)	Selected TS	Selected TS (%)
Goiener	22 851	12 189	847 ± 219	0.6 ± 6.2	11 943	52.3
ISSDA	6 435	6 084	532 ± 20	0.3 ± 3.6	6 043	93.9
LCL	5 449	5 270	642 ± 88	0.3 ± 1.2	5 238	96.1
Elergone	370	351	1 224 ± 249	0	351	94.9
NEEA	200	64	496 ± 31	2.0 ± 3.1	63	31.5
Total	35 305	23 958	727 ± 139	0.5 ± 4.3	23 638	67.0

- **Seasonal variation:** Aggregates by meteorological season, including combinations with intra-day time bands.
- **Tariff-based periods:** Time bands aligned with electricity pricing schemes.

3. **Peak and off-peak periods:** Time bands of highest and lowest consumption identified within the same temporal groupings used in the seasonal aggregates.
4. **Load factors:** Ratios of mean to peak load over daily, weekly, and annual periods.
5. **Autocorrelation features:** Autocorrelation at lags of 1, 7, and 28 days.
6. **`tsfeatures` features (R package)** (Hyndman et al., 2020): Measures of trend, seasonality, entropy, and stationarity.
7. **`catch22` features (R package)** (Lubba et al., 2019): A compact set of 22 general-purpose time series features.

Each feature set was evaluated based on its ability to generate coherent and interpretable clusters using standard algorithms. All feature extraction scripts are available at Quesada et al. (2022) for full reproducibility.

3.3.3. Standardization

To retain meaningful differences in energy usage, time series were not standardized before extracting amplitude-dependent features (e.g., total consumption, peak load, seasonal aggregates). In contrast, shape-based features (e.g., autocorrelation, entropy) were computed after standardizing each series to zero mean and unit variance. This selective approach preserves magnitude information while enabling meaningful comparisons of load profile shapes.

3.3.4. Final feature selection

To enhance clustering interpretability, we evaluated all feature sets – and selected combinations – derived from the extracted pool. Each was tested in preliminary experiments using multiple algorithms and varying numbers of clusters (see Section 3.4), and representative visualizations were reviewed by domain experts (see Section 3.5).

Experts unanimously favored the feature set based on **seasonal aggregates**, computed as average consumption over consecutive 4-hour intervals within each meteorological season. This set includes 24 features following the sequence: *12–3 am in spring*, *4–7 am in spring*, …, and *8–11 pm in winter*. The structure preserves intra-day and seasonal dynamics, offering a compact yet expressive representation of household routines. Experts found it especially helpful for identifying occupancy patterns, daily habits, and heating or cooling effects.

Other feature sets showed clear limitations. When fixing the analysis to SOM with 40 clusters, *peak and off-peak periods*, *tsfeatures*, and *autocorrelations* produced visually redundant clusters, with several heatmap patterns duplicated or entangled across groups — hindering interpretability. Particularly problematic were the *Catch22 features*, which, in addition to the above, resulted in sparsely populated clusters – some containing only very few time series – compromising robustness and practical utility. The remaining feature sets failed to produce meaningful clustering outcomes in the initial screenings and were thus discarded from further analysis.

Experts based their judgment on technical reports and independently reviewed heatmaps, boxplots, and distributional plots. Their consensus on the seasonal aggregates as the most interpretable and operationally relevant feature set held across experiments. All supporting reports and visualizations are publicly available at Quesada (2022).

3.4. Clustering method

3.4.1. Evaluation of clustering algorithms

To identify an appropriate clustering method for large-scale residential load profiles, we conducted a comparative evaluation of nine algorithms commonly used for time series or feature-based clustering (Brock et al., 2008). These included:

- **Hierarchical clustering:** UPGMA (Unweighted Pair Group Method with Arithmetic Mean) and DIANA (Divisive Analysis).
- **Partitional clustering:** k-means, PAM (Partitioning Around Medoids), and CLARA (Clustering Large Applications).
- **Unsupervised neural networks:** Self-Organizing Maps (SOM) and Self-Organizing Tree Algorithm (SOTA).
- **Fuzzy clustering:** FANNY.
- **Model-based clustering:** Finite Gaussian mixture models.

Each algorithm was tested on multiple datasets and feature sets under standardized conditions to assess clustering quality, scalability, and interpretability.

3.4.2. Selection criteria

The following criteria guided the selection of the final clustering algorithm:

- **Cluster quality:** Measured using internal validation metrics such as silhouette width, Dunn index, and connectivity (Brock et al., 2008).
- **Interpretability:** Ability to produce clusters with distinct and recognizable consumption patterns.
- **Scalability:** Computational feasibility when applied to tens of thousands of time series.
- **Expert feedback:** Practical relevance and clarity of cluster structures as assessed by domain experts.

3.4.3. Final clustering method selection

In initial screenings, the algorithms that yielded the most meaningful and visually coherent clusters were k-means, PAM, and SOM. These were examined in more detail, while the remaining methods were discarded due to structural issues. FANNY produced fuzzy (soft) assignments, which are unsuitable for typology generation. DIANA and SOTA led to unbalanced results dominated by one or two large clusters, with the rest sparsely populated. Hierarchical clustering tended to merge distinct patterns too early. Model-based clustering occasionally failed to converge or produced empty clusters.

The shortlisted methods were applied to the same feature set, using $k = 40$ clusters. Interpretability was assessed based on: (i) the visual distinctiveness of the resulting patterns; (ii) their correspondence to recognizable household routines; (iii) the balance of cluster sizes; and (iv) the preservation of seasonal and intra-daily structure.

While k-means and PAM performed reasonably well, SOM outperformed them by capturing non-linear relationships, yielding more balanced clusters, and offering a topology-preserving layout that supported the taxonomy developed in Section 4. These advantages were confirmed during the expert review process: panel members independently examined the cluster outputs and later discussed them collectively. SOM was the method that most consistently enabled the clear and unambiguous assignment of narrative labels to each cluster. Comparative reports and visualizations are available at Quesada (2022).

3.4.4. Determination of the number of clusters

The choice of the number of clusters was informed by statistical validation and domain-driven interpretability. We evaluated three internal clustering metrics – connectivity, Dunn index, and silhouette width – using SOM on the full dataset with seasonal aggregate features. Metrics were computed for selected values of k from 5 to 70 (in steps of 5), with finer resolution (steps of 2) between $k = 20$ and $k = 40$ (see Fig. 3).

- **Connectivity** increased steadily with k, but the growth rate became more gradual beyond $k = 30$, suggesting that increasing the number of clusters had a diminishing effect on local structure degradation.
- **Dunn index** showed several local maxima – especially around $k =$ 20, 24, 36, and 40 – indicating that well-separated and compact solutions may exist at multiple granularities.
- **Silhouette width** dropped sharply from $k = 5$ to $k = 10$ and continued to decline irregularly, stabilizing after $k = 30$, which suggests limited benefits in compactness and separation beyond that point.

These trends pointed to the range $k = 30$–45 as statistically reasonable. We selected $k = 40$ as a balanced compromise: large enough to reflect the diversity expected by domain experts – some of whom suggested that up to 90 distinct patterns could be meaningful – while maintaining interpretability and operational usability.

The convergence between internal metrics and expert feedback (Section 3.5) provides strong support for the 40-cluster solution.

3.5. Experts-in-the-loop validation

Expert feedback played a central role in shaping the final clustering solution, supporting key design choices and validating the practical relevance of the resulting typology. To ensure interpretability and real-world applicability, we implemented a structured Experts-in-the-Loop (EITL) validation process.

The panel comprised six specialists with complementary backgrounds: two academic researchers in machine learning and load forecasting, two professionals from a cooperative utility with expertise in energy systems and electricity markets, one developer of synthetic load profile generators, and one statistical advisor. Their involvement focused on: (i) evaluating the interpretability of clusters, (ii) supporting key methodological decisions, and (iii) co-developing a taxonomy of consumption patterns and associated personae.

The evaluation procedure focused on a set of 40 heatmaps representing the median annual load profiles of each cluster (Section 3.6). These were printed as individual cards and visually inspected by experts, who collaboratively sorted them into broader consumption groups based on shared temporal and seasonal patterns (Fig. 4). Through open discussion and successive refinements, the panel reached consensus on a five-class behavioral taxonomy.

To assess the robustness of this expert-derived structure, we compared it with a data-driven taxonomy generated by hierarchical clustering. The strong alignment between both approaches reinforced the semantic coherence of the proposed classification (Section 4.1).

3.6. Visualization of consumption patterns

3.6.1. Annual heatmaps of load profiles

To facilitate the interpretation of residential load profiles and their clustering, we developed a visualization strategy based on annual heatmaps. Each full year of a time series (from January 1 to December 31) was reshaped into a 24 × 371 matrix (see Fig. 5). Incomplete fragments at the beginning or end of the series were discarded. In these matrices:

- **Rows** correspond to the 24 h of the day.
- **Columns** correspond to the days of the ISO year (53 weeks × 7 days), following the ISO 8601 calendar standard (International Organization for Standardization, 2019).

This structure preserved daily and weekly cycles without overlapping weekdays and weekends, enabling clear visualization of seasonal and behavioral patterns.

3.6.2. Aggregation of cluster profiles

For each cluster, the annual matrices of its member time series were aggregated by computing the element-wise median. This approach:

- Reduced the influence of outliers.
- Preserved key structural patterns.
- Provided a representative visualization of each cluster.

The resulting heatmaps visually summarized the typical consumption behavior of each cluster and were used during the Experts-in-the-Loop validation process.

3.6.3. Normalization for visual consistency

To ensure comparability across different clusters, each time series was scaled individually by its *upper whisker* value, computed as:

$$Q_3 + 1.5 \times \mathrm{IQR}$$

where Q_3 is the third quartile and IQR is the interquartile range of the original series.

This scaling was applied solely for **visualization purposes** and does not affect clustering or feature extraction. It rescales each series

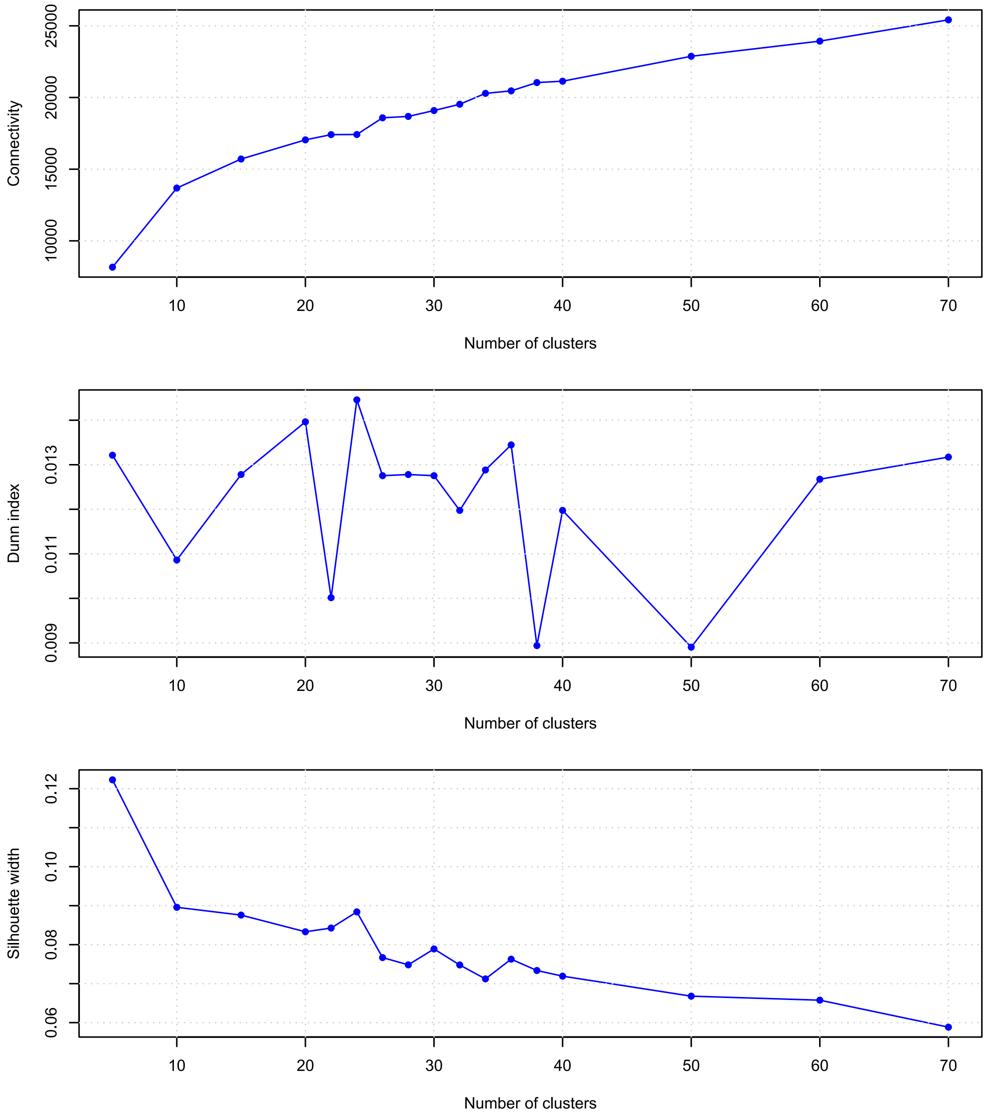


Fig. 3. Internal clustering validation metrics (Connectivity, Dunn index, and Silhouette width) for SOM clustering on the full dataset with seasonal feature aggregates. These indicators supported the choice of $k = 40$ clusters.

between 0 and 1 to emphasize the relative temporal patterns within each household. By doing so, it avoids color saturation due to outliers and allows meaningful comparison of profiles regardless of absolute consumption level.

3.6.4. Dendrogram of cluster similarities

To support interpretation beyond the 40-cluster solution, we performed a hierarchical clustering of cluster medians to explore broader behavioral categories.

The procedure involved:

1. Vectorizing each cluster's median heatmap into a one-dimensional vector of 8904 elements (24 h × 371 days).
2. Computing pairwise Euclidean distances between vectors.
3. Applying agglomerative hierarchical clustering using Ward's method (Ward, 1963).

This approach yielded a dendrogram structure revealing similarities among clusters based on their annual consumption patterns. A division into five groups was explored to enhance interpretability, aligning with the expert-driven classification presented in Section 3.5.

4. Results and discussion

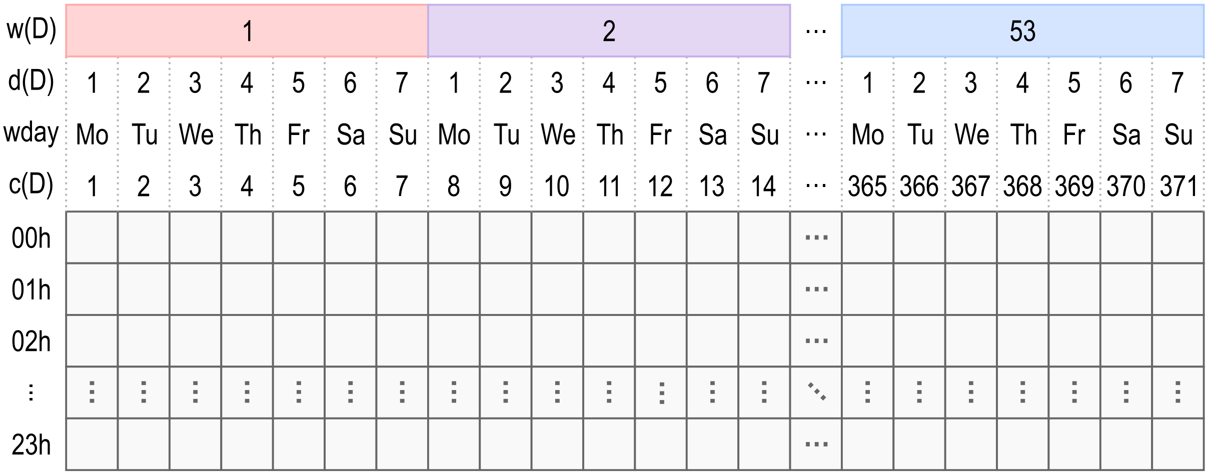
4.1. Overview of clustering results

Applying the methodology described in Section 3, we identified 40 distinct residential electricity consumption patterns from a diverse dataset of 23,638 households, spanning multiple climates, household types, and socioeconomic contexts.

To facilitate interpretation, these clusters were grouped into five major categories, drawing on expert-driven visual inspection of their annual heatmap representations and on the hierarchical clustering results (Fig. 6).

1. **Primary Residences** (74%): households occupied year-round, with distinct weekday/weekend patterns.
2. **Holiday Homes** (5%): properties mainly used on weekends, holidays, or during summer.
3. **High-Consumption Equipment Residences** (13%): profiles influenced by devices such as electric heaters or battery chargers.
4. **Offices and Small Businesses** (7%): sites with typical commercial load profiles.

Fig. 4. Electric consumption patterns represented as color-printed heatmap cards, manually grouped by domain experts.



w(D)	1							2							⋯	53						
d(D)	1	2	3	4	5	6	7	1	2	3	4	5	6	7	⋯	1	2	3	4	5	6	7
wday	Mo	Tu	We	Th	Fr	Sa	Su	Mo	Tu	We	Th	Fr	Sa	Su	⋯	Mo	Tu	We	Th	Fr	Sa	Su
c(D)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	⋯	365	366	367	368	369	370	371
00h															⋯							
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⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋱	⋮	⋮	⋮	⋮	⋮	⋮	⋮
23h															⋯							

Fig. 5. Structure of the annual heatmaps: each time series is reshaped into a 24 × 371 matrix, with rows corresponding to hours of the day and columns to days of the ISO year. Each date D is placed at column index $c(D) = 7 \cdot (w(D) - 1) + d(D)$, computed from its ISO week $w(D)$ and weekday $d(D)$, also labeled as $wday$.

5. **Public Lighting** (1%): patterns consistent with automated street lighting systems.

The five-category structure, highlighted with different colors in the hierarchical clustering of Fig. 6, reflects the convergence of expert knowledge and data-driven similarity analysis. Although these categories do not fully coincide with complete branches, they align with sub-branches – sometimes non-contiguous – revealing differences in how humans and algorithms assess similarity (e.g., visual semantics vs. numerical distance). This interplay underscores the value of combining both perspectives when analyzing behavioral diversity.

This taxonomy provides a practical framework for interpreting large-scale residential electricity load profiles. In the following subsections, each behavioral category is illustrated with a selected cluster that highlights typical features found within the group. These examples serve to ground the typology in real consumption patterns and support the subsequent discussion of planning, tariff design, and demand-side strategies.

4.2. Load profile typology and representative personae

To illustrate the five-category typology, we present one example from each group that captures visually salient and behaviorally meaningful features. These are not statistical representatives but have been selected for their clarity and interpretability. For readers interested in exploring the complete taxonomy, the full set of clusters is available at Quesada (2022).

To complement the technical description of each load pattern, we introduce a narrative *persona* for each group. These personae reflect the lifestyles and routines typically associated with the observed consumption patterns, helping to connect data-driven results with relatable, human-centered scenarios.

4.2.1. Primary residences

Primary residences constitute the largest group in the typology, encompassing approximately 74% of the analyzed time series. These

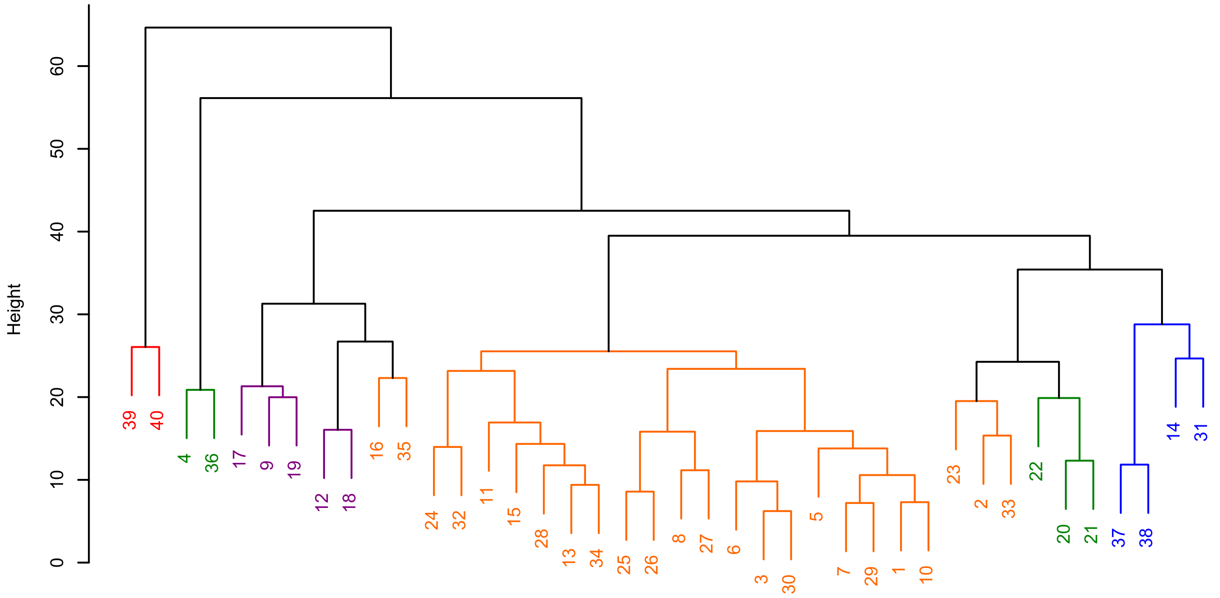

Fig. 6. Dendrogram illustrating the main groups of residential electricity consumption patterns. Primary residences (orange, 74%), secondary residences (blue, 5%), high-consumption equipment households (purple, 13%), offices and businesses (green, 7%), and street lighting (red, 1%) are identified. *Height* represents the distance between cluster medians according to *Ward's method* (Ward, 1963).

households are continuously occupied throughout the year and exhibit distinct weekly and seasonal electricity usage patterns. Cluster 13 (see Fig. 7) is shown here as an illustrative example, characterized by differentiated weekday and weekend behavior, strong evening activity, and moderate midday usage. Seasonal variation is also evident, with extended evening loads during winter and flatter daily profiles in summer. Other clusters in this group reflect variations in household routines, such as meal times, sleep schedules, and time spent at home during the day. Primary residence patterns are critical for system planning and demand-side strategies, as they capture the everyday rhythms of many residential consumers.

Cluster 13 representative persona: *The Busy Family* — A household with working adults and school-age children, active in the evenings and consistently present on weekends.

4.2.2. Holiday homes

Holiday homes represent approximately 5% of the dataset and are characterized by highly seasonal and irregular electricity usage patterns. Cluster 37 (see Fig. 8) is shown here as an illustrative example, with minimal consumption during most of the year and intense but concentrated activity during the summer months. Peaks are centered around midday and evening hours, reflecting typical occupancy patterns during vacations and weekends. Other clusters in this group differ in both the timing and duration of their active consumption periods. These profiles are particularly relevant for forecasting challenges in touristic areas and for designing dynamic seasonal tariffs.

Cluster 37 representative persona: *The Weekend Escape* — A second home used mainly during summer holidays and occasional weekends, with long idle periods during the rest of the year.

4.2.3. High-consumption equipment residences

This category, comprising around 13% of the dataset, includes households with load profiles dominated by the operation of high-consumption devices. Cluster 18 is shown here as an illustrative example (see Fig. 9), with elevated and highly regular night-time usage concentrated in the colder months. Activity peaks between midnight and early morning hours, followed by minimal daytime consumption, suggesting the presence of electric storage heating systems. Other clusters in this group differ in their intensity and the exact timing of night-time activity. These profiles are crucial for infrastructure planning and for designing off-peak incentive programs.

Cluster 18 representative persona: *The Night Storage User* — A winter-heated household with automatic systems operating at night, largely inactive during the day.

4.2.4. Offices and small businesses

This segment includes users with highly regular and temporally concentrated consumption patterns that align with standard business hours. Representing approximately 10% of the dataset, these users exhibit consistent weekday activity, with sharply reduced or null demand during nights and weekends. Cluster 22 is shown here as an illustrative example (see Fig. 10), where load peaks between 9:00 AM and 6:00 PM, with negligible consumption outside those hours, and reduced activity during summer and holidays. Other clusters in this group differ in opening hours and in whether activity is continuous or split across the day. These profiles are particularly relevant for demand aggregation and targeted efficiency programs.

Cluster 22 representative persona: *The Weekday Operator* — A small business or office with regular weekday activity, inactive during evenings and weekends.

4.2.5. Street lighting

Street lighting loads are characterized by their seasonal inversion with respect to solar radiation. These profiles are highly predictable and synchronized with astronomical dusk and dawn. They show a reversed U-shape pattern: elevated consumption throughout the night during winter months and shorter activation periods in summer, resulting in a distinct *light envelope*.' Cluster no.,40 is shown here as an illustrative example (see Fig. 11), displaying high nighttime consumption that narrows significantly during midsummer. The other member of this group also includes moderate daytime activity on weekends.

Cluster 40 representative persona: *The Municipal Lights* — An automated lighting system operating from dusk to dawn, with longer cycles in winter and shorter ones in summer.

4.3. Implications for energy planning and policy

The typology developed through clustering residential electricity load profiles provides a valuable framework for enhancing demand-side strategies, tariff structures, and infrastructure planning. By aligning

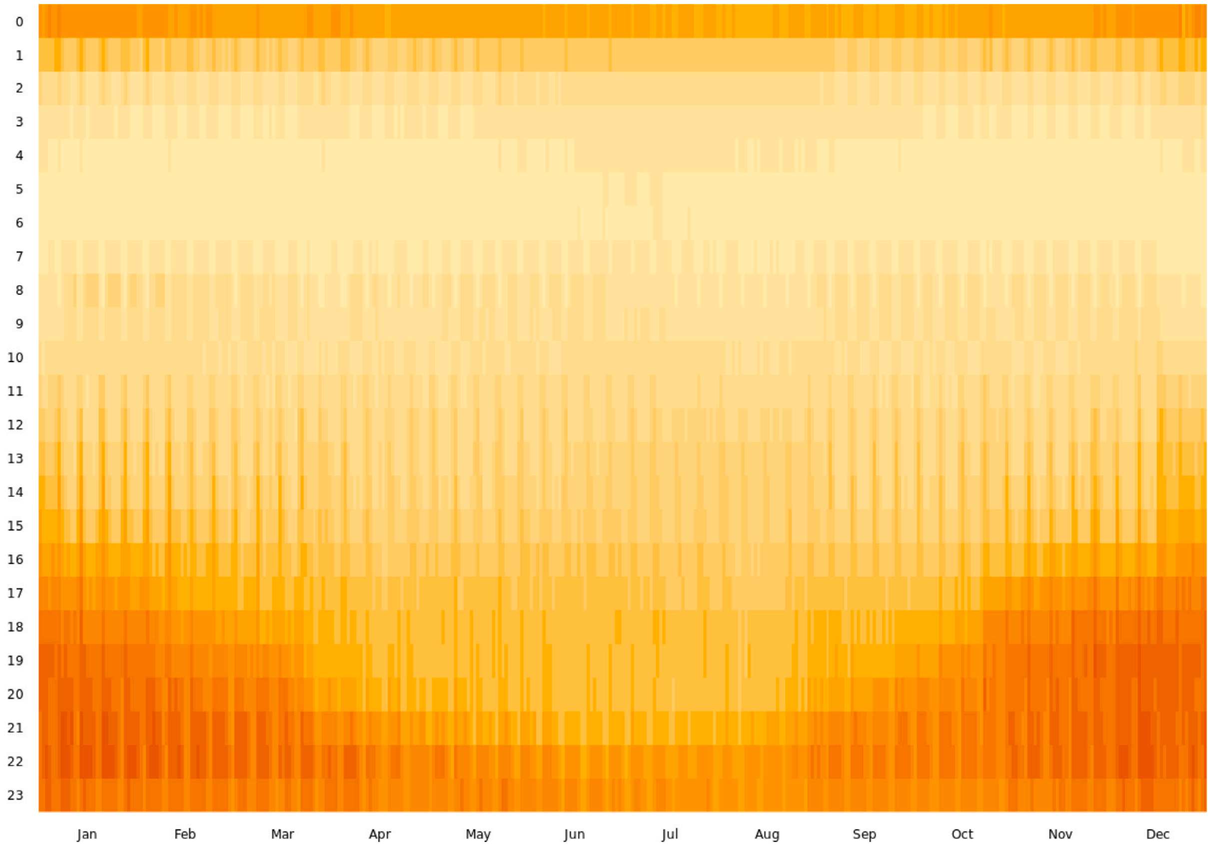

Fig. 7. Heatmap of a Primary Residence (cluster 13), illustrating differentiated weekday/weekend consumption and seasonal evening peaks.

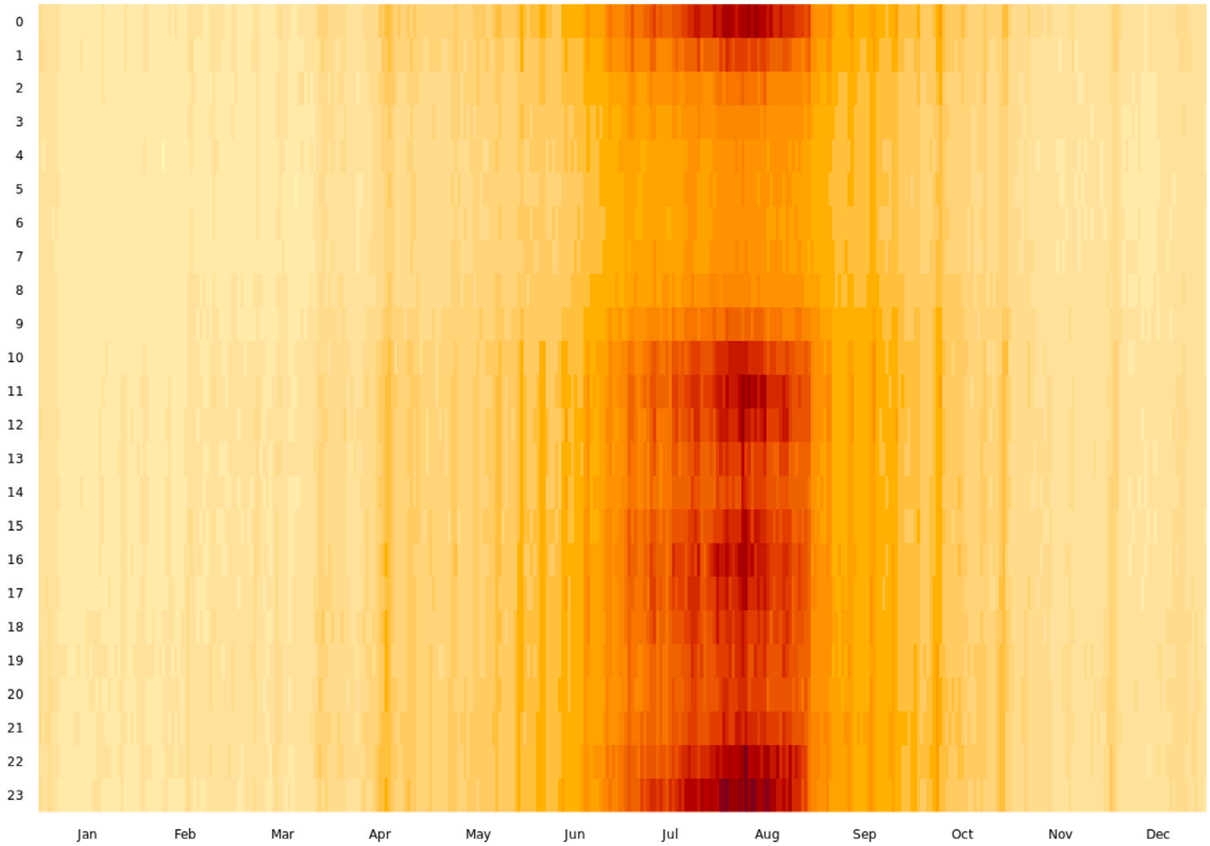

Fig. 8. Heatmap of a Holiday Home (cluster 37), highlighting seasonal occupancy with summer and weekend activity peaks.

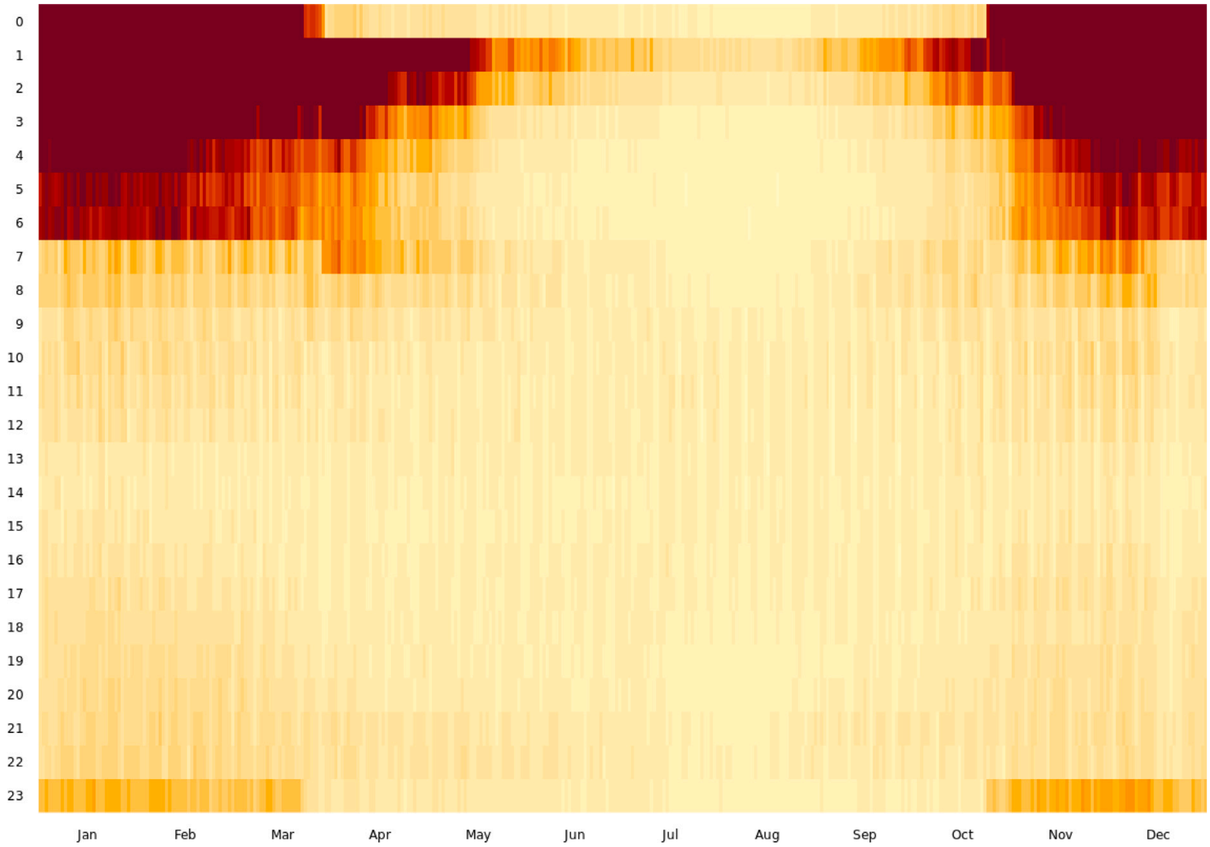

Fig. 9. Heatmap of a High-Consumption Equipment Residence (cluster 18), showing night-time electricity use concentrated in winter.

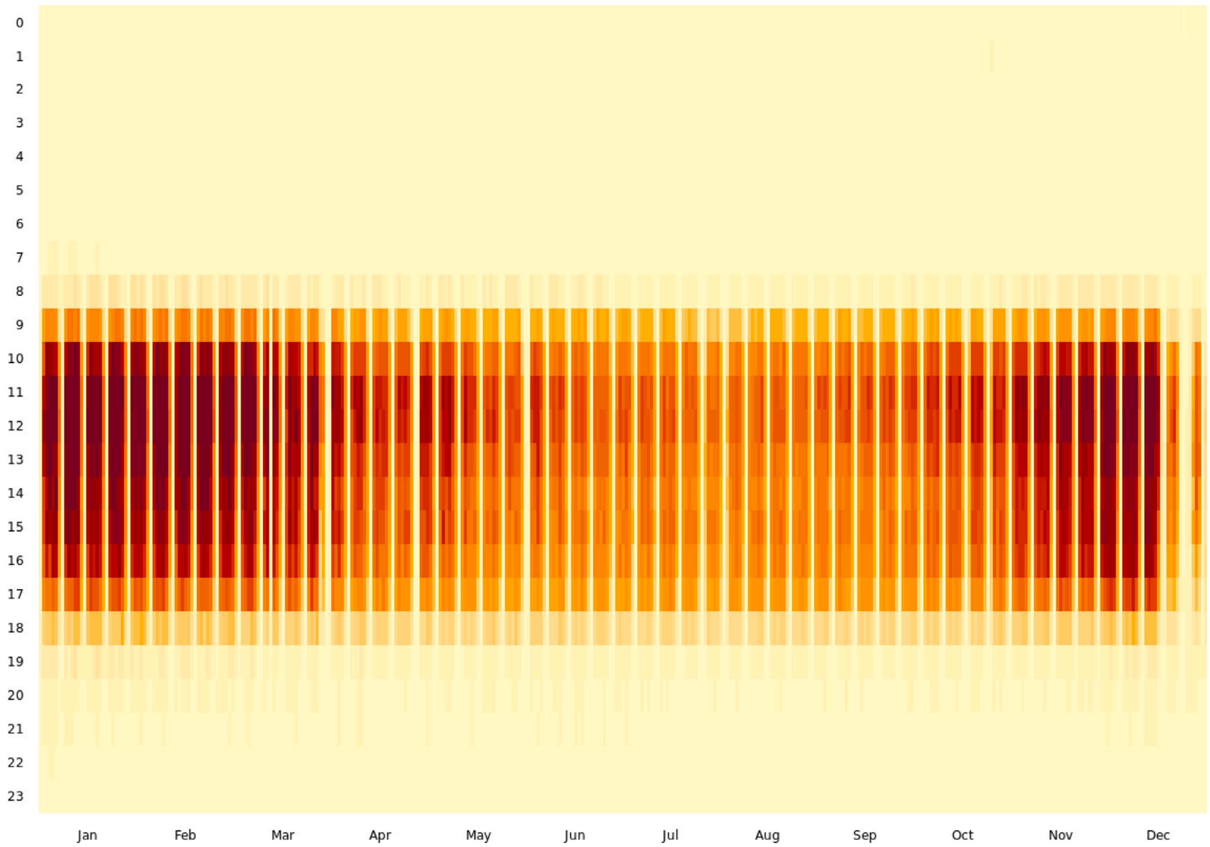

Fig. 10. Heatmap of an Office or Small Business (cluster 22), with daytime activity and minimal night/weekend consumption.

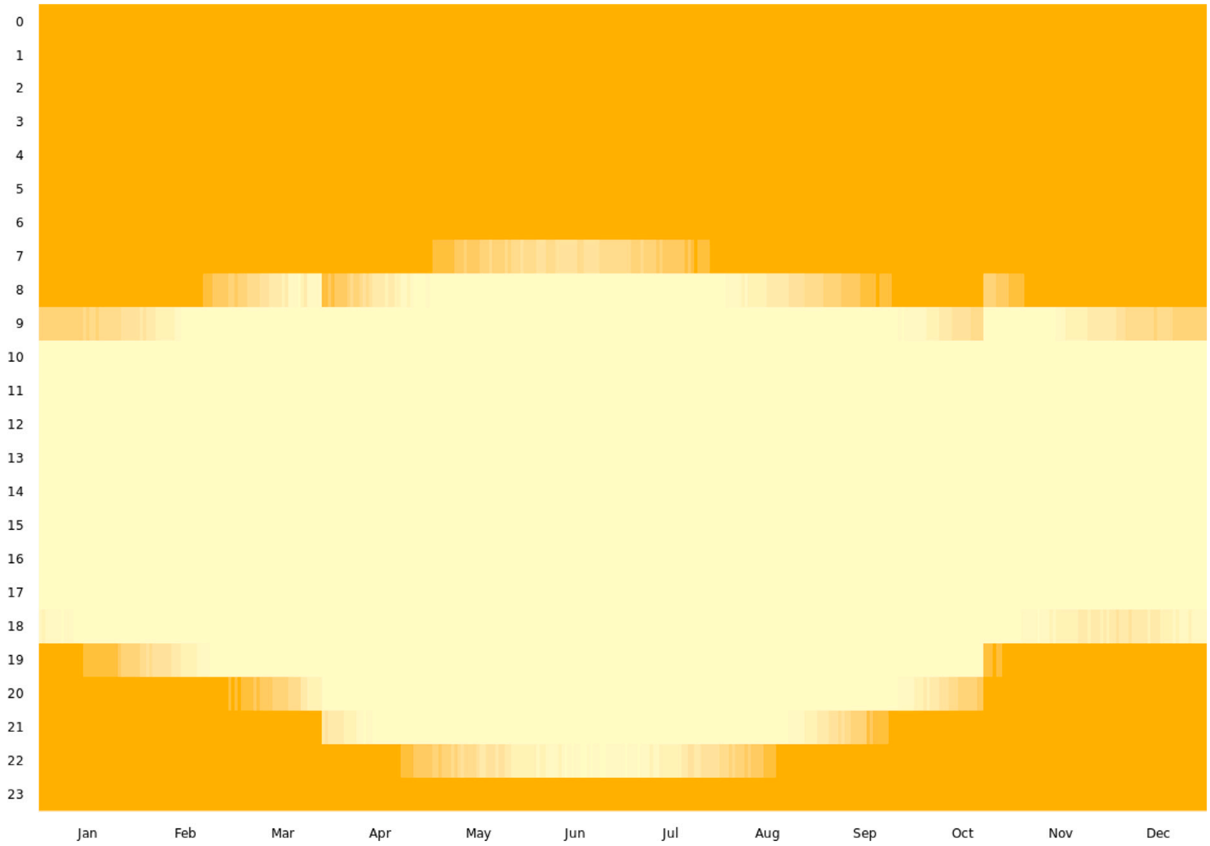

Fig. 11. Heatmap of Street Lighting (cluster 40), displaying night-time operation with seasonal adjustment to daylight hours.

interventions with behavioral archetypes, energy policies can become more effective, equitable, and adaptive.

Households with pronounced evening peaks, such as *The Busy Family*, are ideal candidates for targeted peak shaving programs. Incentives focused on early evening hours have proven successful in initiatives like the UK's Smart Energy GB campaigns (Smart Energy GB, 2025) and Italy's *Bioraria* time-of-use scheme (Torriti, 2013). Similarly, users with strong night-time loads, such as *The Night Storage User*, are well suited for off-peak incentive programs aimed at shifting demand outside critical hours.

Highly seasonal consumers, exemplified by *The Weekend Escape*, can benefit from dynamic or seasonal tariff schemes, as demonstrated by France's *Tempo* tariff (Électricité de France (EDF), 2025) or the Dutch dynamic network tariff pilots (Berenschot and Nederland, 2021). Identifying these users can help mitigate seasonal infrastructure stress in touristic regions.

From a grid planning perspective, understanding the spatial distribution of load typologies supports more accurate forecasting and flexible infrastructure development. For example, Spain's transmission system operator, Red Eléctrica, has incorporated smart meter data into its national grid expansion strategy, as outlined in its *2021–2026 Energy Transmission Network Development Plan* (Red Eléctrica de España, 2022). Areas with high concentrations of holiday homes or commercial activity may require adaptive capacity margins and dynamic network management strategies.

At the policy level, this typology supports more inclusive and sustainable energy strategies. Vulnerable users, such as elderly residents or telecommuters with rigid load requirements, can be targeted through social tariff programs. Meanwhile, flexible consumers can be prioritized for efficiency upgrades and self-consumption schemes. Such differentiation contributes directly to achieving Sustainable Development Goal 7 (Affordable and Clean Energy) (United Nations, 2015).

4.4. *Geographic and temporal variation in load profiles*

While the main goal of this study is to develop a methodology for deriving meaningful consumption typologies, we also performed exploratory analyses on geographic and temporal variation. These reveal regional differences and behavioral shifts following the COVID-19 pandemic, suggesting directions for future work.

4.4.1. *Regional differences in cluster distribution*

Cluster composition varies by country, reflecting regional lifestyles and tariff structures. While some patterns (e.g., clusters 15 and 28) are common across countries, others are more localized. For instance, Ireland and the US show a strong presence of business-oriented profiles (e.g., cluster 36), while Portugal and the US concentrate over 90% of time series in just five clusters. These patterns suggest national differences worth exploring in future studies.

4.4.2. *Pre- and post-COVID-19 comparison*

Spanish load profiles before and after March 2020 reveal shifts linked to the pandemic. Clusters associated with daytime absence (e.g., 9, 14, 26) declined, while profiles reflecting all-day occupancy and stable weekday/weekend behavior (e.g., 15, 25) increased. These changes align with increased teleworking and mobility restrictions, illustrating the sensitivity of residential demand to external disruptions.

5. Conclusions and future work

We proposed a data-driven methodology for identifying operationally meaningful residential electricity consumption typologies from smart meter data. By combining seasonal feature extraction, Self-Organizing Maps, and expert validation, we produced 40 distinct load profiles grouped into five behavioral categories. This typology supports demand-side planning, tariff design, and energy policy development.

Future work will focus on several directions:

- **Integration of climate variables:** Incorporating temperature, solar radiation, and weather events to better understand their influence on consumption patterns.
- **Detection of irregular working schedules:** Identifying shift workers and telecommuters to refine household classifications.
- **Real-time classification tools:** Developing algorithms to classify new users into clusters based on limited consumption data, enabling adaptive services.
- **Survey-based cluster assignment:** Designing simple questionnaire-based tools to assign households to behavioral clusters without requiring smart meter data.
- **Deepening regional analysis:** Building on initial findings to study how cluster compositions relate to geographic, socio-economic, and regulatory factors.
- **Extension to non-residential sectors:** Applying similar techniques to commercial and industrial profiles and studying mixed-use areas.
- **Longitudinal studies of behavioral change:** Expanding the exploratory COVID-19 analysis to broader timeframes and events to assess long-term demand shifts and resilience.

In addition, integrating real-time classification capabilities with contextual data – such as building characteristics, occupancy levels, or income indicators – could further enrich the typology and support the development of more resilient, efficient, and user-centric energy systems.

CRediT authorship contribution statement

Carlos Quesada: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pablo Montero-Manso:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Noah Pflugradt:** Writing – review & editing, Investigation, Conceptualization. **Leire Astigarraga:** Writing – review & editing, Validation, Resources, Investigation. **Chris Merveille:** Writing – review & editing, Validation, Resources, Investigation. **Diego Casado-Mansilla:** Writing – review & editing, Investigation, Conceptualization. **Cruz E. Borges:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

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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Appendix. Initial dataset screening

This appendix provides an overview of the **datasets initially screened** for inclusion in this study. These datasets, sourced from both literature and utility companies, comprise a wide range of residential electricity consumption data. Selection criteria focused on data quality, geographic and climatic diversity, household representativeness, and accessibility, as described in Section 3.2.1.

The datasets are grouped according to the approximate number of available time series:

- **Large datasets (more than 1000 time series):**

  1. *GoiEner dataset* (Quesada et al., 2024).
  2. *Energy Demand Research Project (EDRP)* (AECOM Building Engineering, 2018).
  3. *Smart-Grid Smart-City (SGSC)* (data.gov.au, 2015).
  4. *Electricity Customer Behavior Trial (ISSDA)* (Commission for Energy Regulation (CER), 2012).
  5. *Solent Achieving Value from Efficiency (SAVE)* (Rushby et al., 2020).
  6. *Low Carbon London (LCL)* (London Datastore, 2013).
  7. *ASHRAE Great Energy Predictor III (Kaggle)* (Kaggle, 2020).

- **Medium-sized datasets (100–1000 time series):**

  8. *Electricity Load Diagrams 20112014 (Elergone Energia)* (UCI Machine Learning Repository, 2015).
  9. *Measuring and Evaluating Time-Use and Electricity-Use Relationships (METER)* (Grunewald and Diakonova, 2020).
  10. *North East Scotland Energy Monitoring Project (NESEMP)* (Craig and Dent, 2017).
  11. *End Use Load Research (EULR), Northwest Energy Efficiency Alliance (NEEA)* (Northwest Energy Efficiency Alliance, 2022).

- **Small datasets (fewer than 100 time series):**

  14. *HTW Berlin synthetic dataset* (Tjaden et al., 2015).
  15. *Energy Literacy Through an Intelligent Home Energy Advisor (ENLITEN)* (Lovett et al., 2013).
  16. *Household Electricity Demand Study, GREEN Grid project* (University of Otago, 2018).
  17. *Wind–Solar–Heat Pump District (WPuQ)* (Schlemminger et al., 2022).
  18. *Autonomous Decentralized Regenerative Energy Systems (ADRES)* (Energy Economics Group, T.U. Wien, 2011).
  19. *Loughborough Energy Study (LES)* (Richardson and Thomson, 2010).
  20. *Personalized Retrofit Decision Support Tools for UK Homes (REFIT)* (Murray et al., 2015).
  21. *Open Power System Data (OPSD)* (Open Power System Data, 2020).
  22. *GREEND Electrical Energy Dataset* (Monacchi et al., 2014).
  23. *Individual Household Electric Power Consumption* (UCI Machine Learning Repository, 2012).
  24. *Almanac of Minutely Power dataset Version 2 (AMPds2)* (Makonin et al., 2016).

Data availability

The data used is public.

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