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Interactive Machine Learning-Powered Dashboard for Energy Analytics in Residential Buildings

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Abstract. Efforts to reduce energy consumption in buildings are crucial for climate change concerns. In this sense, energy monitoring increases energy awareness and mitigates energy wastes. This study integrates machine learning models, advanced visualisations, and interactive tools to create an insightful energy monitoring dashboard. Novel contributions include a 2D map of daily energy demand profiles combining spatial encodings based on t-SNE, fluid aggregation, and filter operations via a datacube framework, as well as visual encoding powered by morphing projections. This approach facilitates the decisions of end users regarding the optimisation of energy in residential facilities.

1 Introduction

Climate change, energy crises, and the quest for greater energy independence have recently prompted governmental organisations and companies to accelerate efforts to reduce energy consumption. In this challenge, *electric energy monitoring* plays an important role in commercial and residential buildings, which together account for 30% of global energy consumption [1].

Energy monitoring tools aim to improve the energy use of end users by providing intuitive representations of the energy demand, leading to a better *energy awareness* (i.e. understanding of energy demand) and avoiding energy waste [2]. In this context, *Machine Learning* (ML) techniques have been widely studied as powerful tools for disentangling energy demand time series. Particularly, non-intrusive load monitoring, energy consumption forecasting and anomaly detection models exemplify ML-based energy monitoring tools. Although ML-based models excel human beings on unveiling unknown knowledge from raw energy demand time series, their well-known lack of interpretability may be detrimental to energy awareness.

In this work, we bring the user into the loop of analysis by integrating ML-based models of energy demand time series, advanced data visualisation and fluid interaction tools into an insightful energy monitoring dashboard. Some authors have previously suggested data visualisation approaches for monitoring the energy demand of large buildings and households [3], however, most of these approaches focus on static visualisations that lack fluid interactive elements.

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Only a few *visual analytics* approaches have explored the potential synergies between ML, data visualisation, and fluid interaction [4].

Our approach revisits previous visual analytics methodologies for monitoring energy demand in residential facilities, presenting the following contributions: 1) a 2D map of daily energy demand profiles based on t-SNE; 2) fluid aggregation and filter operations enabled by a *data-cube framework* [5]; and 3) insightful visual encoding of the daily profiles using *sparklines* charts and *morphing projections* [6].

2 Data-Cube framework

Fluid aggregation and filter operations allow end users to decompose the energy demand analysis into meaningful sub-problems. For instance, users can refine their analysis by filtering based on different attributes (such as location, type of building, or time of day), or aggregating the energy demand by different time intervals (i.e. daily, weekly or monthly profiles).

The data cube model speeds up filter and aggregation operations by efficiently indexing data into a hypercube [5]. In a multidimensional table D containing all energy demand records, the sides of the data cube are defined by the *attributes*. Each attribute a_i represents a finite set of discrete values or *groups* obtained after applying a grouping operation to the records of the i-th column of D:

$$a_i = \{g_1^i, g_2^i, \dots, g_{|a_i|}^i\} \quad i = 1, 2, \dots, n$$

Here, g_1^i represents the first group for the i-th attribute, $|a_i|$ denotes the cardinality of attribute a_i, and n is the number of attributes defining the dimension of the resulting structure. The resulting data cube structure, denoted as $C(a_1, a_2, \dots, a_n)$, consists of cells with coordinates $\left(g^1, g^2, \dots, g^n\right)$, where all records in D are arranged. In this cell configuration, aggregation, filter, and projection operations can be applied to groups rather than individual records, thereby significantly reducing the number of elements involved.

Projection operation restricts the multivariate analysis to a few attributes selected by the users:

$$\Pi_{a_1, a_2, \dots, a_p} C(a_1, a_2, \dots, a_n) \rightarrow C(a_1, a_2, \dots, a_p) \tag{1}$$

It returns a contracted p-dimensional cube, being $p < n$ and $\{a_1, a_2, \dots, a_p\} \subset \{a_1, a_2, \dots, a_N\}$. In our approach, users select the *active attributes*[1] a_p by varying the *attribute importance coefficients* λ_p, so that the cube is projected onto the attributes a_p with $0 \leq \lambda_p \leq 1$.

Filter operation entails selecting specific groups in one or more attributes of the cube:

$$\sigma_{\substack{a_l=\{p,q\} \\ a_i=\{a,b,c\}}} C(a_1, a_2, \dots, a_n) \rightarrow C(a_1, a_2, \dots, \underbrace{\{a, b, c\}}_{a_i}, \dots, \underbrace{\{p, q\}}_{a_l}, \dots, a_n) \tag{2}$$

[1]For the sake of simplicity, the attributes involved in the data cube's projection are denoted as *active attributes*.

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where $\{p, q\}$ and $\{a, b, c\}$ represent the filtered groups for the attributes a_l and a_i, respectively. In our dashboard, users can simultaneously select contiguous range of groups across multiple attributes by means of a set of sliders.

Aggregation operation summarises the information within cells by applying an user-defined aggregation procedure $\mathcal{A}$ to the records contained in each cell. Mean, standard deviation, maximum, minimum or even more sophisticated user-defined functions are examples of aggregation procedures. In our approach, $\mathcal{A}$ is set to the average of the daily profiles (time series of 24 time-steps) within each cell. Note that if more than one electric variable is measured, users can select the variable by which the daily profiles are aggregated.

3 Visual encoding and morphing projections

The aggregated profiles are presented to end users in a 2D map as sparklines. Their position in the map is derived by the cells' index in the data cube, so that a set of coordinates or *spatial encoding* E_i is assigned to the groups of the attributes a_i by means of a lookup table:

a_i	g^i_1	g^i_2	$\cdots$	$g^i_{\lvert a_i \rvert}$
$\mathbf{P}^i$	$\mathbf{p}^i_1$	$\mathbf{p}^i_2$	$\cdots$	$\mathbf{p}^i_{\lvert a_i \rvert}$

where $\mathbf{p}^i_j \in \mathbb{R}^2$. A set of different *spatial encodings* $\mathbf{P}^1, \mathbf{P}^2, \ldots, \mathbf{P}^p$ can be created for the active attributes of the data cube. In order to provide the user with an interactive and fluid mechanism to mix the available spatial encodings and to transition progressively between them, the *morphing operation* maps $\mathbf{P}^1, \mathbf{P}^2, \ldots, \mathbf{P}^p$ into a final set of coordinates $P^{\boldsymbol{\lambda}} = \{\mathbf{p}^{\boldsymbol{\lambda}}_k\}_{k=1,2,\ldots,K}$ [2], setting a linear combination of the encodings:

$$\mathbf{p}^{\boldsymbol{\lambda}}_k = \sum_{i=1}^{p} \lambda_i \mathbf{p}^i_k \tag{3}$$

where λ_i are the attribute importance coefficients and typically $\sum_i^p \lambda_i = 1$. Importance coefficients are attached to sliders in the final dashboard by which the user can smoothly switch between views and modify the projection operation at the same time.

4 ML-based spatial encodings

The location of the sparklines in the 2D map plays an important role in our proposal, since it enables the spatial arrangement of the information by multiple attributes simultaneously, thus facilitating the multi-way analysis. Our dashboard offers both user-defined and ML-based encodings. User-defined encodings distribute the groups of the cube using basic layouts, such as vertical, horizontal or circular arrangements [6]. Meanwhile, coordinates in ML-based encodings are

[2]Here, K is the number of active cells $K = |a_1 \times a_2 \times \cdots \times a_p|$.

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computed by applying a dimensionality reduction model to the energy demand records. In our approach, the t-SNE model [7] is used to reduced daily energy demand profiles into 2D coordinates, providing the users with a spatial encoding that organizes energy consumptions patterns in terms of similarities.

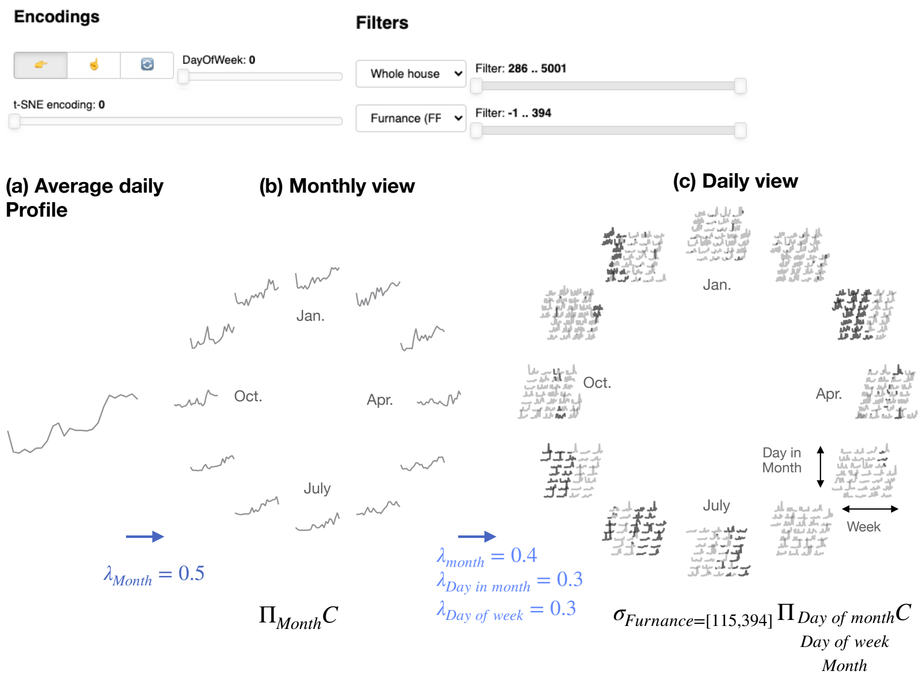

Fig. 1: Examples of the average energy demand profile (a), monthly view (b), and calendar view filtered by the `Furnance` appliance (c) are obtained by activating one attribute after another using the configuration sliders (top).

5 Results

Experimental set-up. The proposed method is tested using one year of electric energy demand data from the publicly available dataset, the *Almanac of Minutely Power dataset* (AMPd) [8]. The dataset contains records of the total energy consumption of a house and 22 appliances, collected with a sampling period of one minute. Before computing the data cube and the t-SNE, the energy records are subsampled to a ten-minute sampling period. The ML-based encoding is computed using the t-SNE method applied to the daily profiles of the total energy demand of the house[3]. All the details and source code of the

[3]The hyperparameters for t-SNE are manually set to: perplexity = 15; epochs = 2000, early exaggeration = 12.

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application are available in our public repository[4], and the application itself is accessible in the following link: `https://gsdpi.edv.uniovi.es/apps/energy_dcMP/energy_dcMP.html`.

Dashboard. Fig. 1 exemplifies a multi-way analysis, where a transition from a general perspective to a detailed analysis of the energy demand in the house is facilitated by the data cube operations and morphing projections. The user starts from an aggregated perspective of all daily profiles (Fig. 1a). Then, the cube is projected into the `month` attribute by increasing λ_{Month}, using its corresponding encoding slider and selecting a circular encoding. This provides the user with a circular view where monthly energy consumptions can be insightfully compared (Fig. 1b). The user can dive into the monthly profiles by increasing $\lambda_{Day\ of\ Week}$ and $\lambda_{Day\ of\ Month}$ with horizontal and vertical encodings, respectively, resulting in a calendar view where all daily profiles are displayed (Fig. 1c). The analysis can be further detailed by adding filters. In Fig. 1, the calendar view includes a filter on `Furnance` attribute, intuitively highlighting the days when the house's furnace was in use.

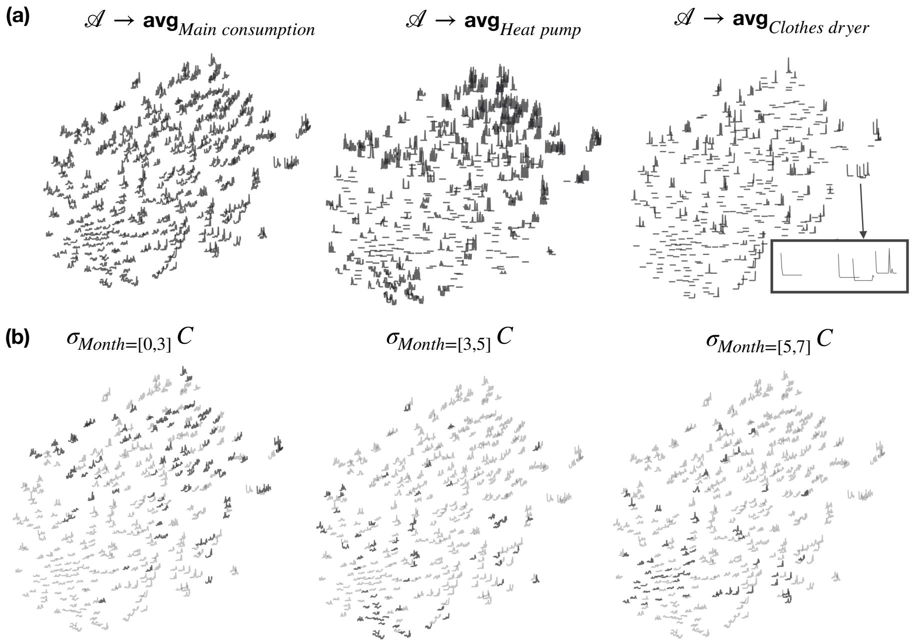

Fig. 2: (a) Analysis of t-SNE view by different aggregations. (b) Analysis of t-SNE view aggregated by the `Main consumption` attribute using different filters.

In Fig. 2, several views of the t-SNE encoding are shown. In Fig. 2(a), the t-SNE projection is illustrated using the average of the `Main consumption`, `Heat`

[4] `https://github.com/gsdpi/energy_monitoring_esann24`

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`pump`, and `Clothes dryer` daily profiles as aggregation procedures $\mathcal{A}$. Aggregation by `heat pump` suggests that the winter profiles are grouped at top, while summer profiles at the bottom of the t-SNE view. Furthermore, aggregation by `Clothes dryer` shows that some clusters are related to midnight consumptions of the clothes dryer (see framed detail in Fig. 2). In Fig. 2(b), the areas of the t-SNE related to winter, spring, and summer are revealed by filtering the data cube by `Month`.

6 Conclusions

The proposed interactive approach exhibits preliminary, though encouraging, results on the analysis of energy demand patterns in residential facilities. Morphing projections along with the aggregation, projection and filter data cube operations facilitate the generalised analysis, but also detailed energy demand exploration, allowing end users to better understand their consumption from various perspectives. In addition, the integration of ML-based spatial encodings into the analysis helps users to correlate ML-based maps with specific appliance usage patterns through filtering and aggregation operations. This approach not only enhances comprehension but also facilitates informed decision-making regarding energy usage optimisation and efficiency improvements.

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