Energy user benchmarking using clustering approach

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***Abstract*—Achieving energy efficiency is crucial in order to improve environment and life quality. Therefore, within the residential sector, research efforts on advanced approaches to steer end users to save the energy and adapt their consumption are widely spread. One of recent approaches being used is creating a competitive environment which would stimulate the users to improve their habits. The main idea of this paper is proposing a data-driven machine learning clustering approach for ranking users depending on their consumption measurements and other relevant data collected from a real-world pilot in France. Within this paper, exploited data, implementation details and results will be presented.**

I. Introduction

Within recent years, environmental protection has occupied an important place in the research scope. Therefore, saving electrical energy was recognized as an important issue with a huge impact on saving the environment. Depending on the type of users, numerous approaches were proposed. In the industrial domain, the potential of electrical energy savings by rescheduling the load turned out to be significant. On the other hand, residential users tend to be much less flexible in adjusting their consumption through load rescheduling and in turn increasing savings.

With the number of people adopting new concepts such as smart homes, the amount of IoT connected devices is growing rapidly [1], [2], [3]. This transition in the residential sector opens numerous possibilities for novel energy-related services aimed at improving the quality of life for residents, as well as having positive effects on the environment. These range from algorithms that determine the activation of different devices (also known as Non-Intrusive Load Monitoring) [4] in order to give feedback to users when each appliance is consuming, Optimization algorithms that align the user demand with intermittent renewable energy production and make best use of variable pricing tariffs [5], [6] and [7] as well as other analytical services that have the ability of condensing the vast amount of data collected and transforming it into useful information for the end user [8] and [9]. Some of these services are analyzed in specifically in terms of energy applications of IoT in [10]. However, motivation presents a key prerequisite for the users to adopt these new concepts.

Therefore, various approaches were proposed in the literature in order to steer the end users to change their habits, and, consequently reduce environmental pollution by saving on electrical energy. One of the aforementioned ideas was to create a competitive environment which would encourage users to improve their habits and became more energy efficient. In other words, the idea is to benchmark the users with a score (e.g. from 0 to 100%) between themselves in accordance with their energy efficiency. Furthermore, the ranking is also supposed to motivate the users to either strive to achieve a leading position in the ranking or to try and advance on the list if their ranking is not so good. In essence, this approach is motivated by the fact that it will be easier for the users to accept the changes and to adapt if they can observe someone else's (better) example, but the proposed system also has a side effect of creating a unique environment with social pressure to be more efficient.

II. Brief State of the Art Analysis

The energy-use performance benchmarking (ranking) and user behavior assessment methodologies appear to be a relatively unexplored topic in the relevant literature of this domain, especially when compared with other energy related topics like demand side management or demand response optimizations, which is why the author found this topic challenging and worth exploring. Conventional approaches, as reviewed in [11], can be classified as normalization, Ordinary Least Square, Stochastic Frontier Analysis and Data Envelopment Analysis. Additionally, fuzzy logic is present in energy benchmarking, as well, in [12], but for residential building only. In [13, p. 1], artificial intelligence has been used, or precisely, Artificial Neural Networks.

Within this paper, the focus will be placed on an exploitation of widely spread clustering approaches, whose use in the energy efficiency domain has been reviewed in [14]. The application of the clustering methodology in this paper will be focused on the specific novel user benchmarking approach for increasing the energy savings. The results will be showcased on real-world data collected from a residential pilot in France.

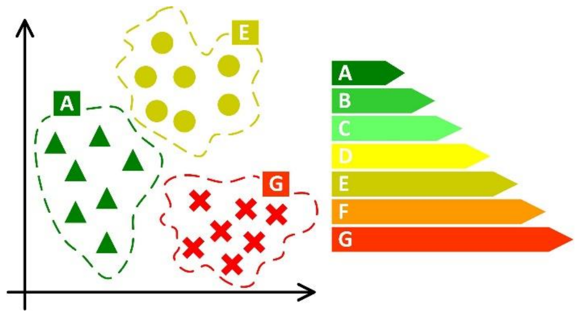

Figure 1. Illustration of a clustering-based ranking system in two dimensions

III. Methodology

The main problem regarding user benchmarking is the definition of a criterion which would rank different users and defining the relevant features which are supposed to be taken into consideration in order to influence the provided ranking. Defining the criterion is a rather delicate question as it can be subjective. For example, if energy consumption depending in relation with the occupancy and a building characteristic (wall material conductivity, window area, etc.) are taken as two terms within the criterion function, the respective weigh factors associated with these contributions in the criterion can take any of an infinite number of values depending on the decision maker preferences, general knowledge and prior experience.

Therefore, with the main goal of avoiding subjective rankings by predefining a ranking criterion, an unsupervised machine learning clustering approach has been chosen. In other words, as a part of this paper, a benchmarking clustering service, which categorizes the users in one out of k groups depending on their energy efficiency, was developed, as illustrated in Figure 1. This figure specifically illustrates how a clustering approach is applied in the case when two ranking contributions are considered, each one depicted on either the x or y axis. The unsupervised clustering algorithm, through its iterations, detects a predefined number of groups called clusters. Each one is defined using its center point and the maximum allowed distance from that center.

A. K-means clustering implementaton

Concretely, using real world-pilot data, a K-means clustering model has been trained for the purpose of calculating the necessary model parameters. Furthermore, depending of the previous users' energy efficiency which influenced the choice of the relevant parameters, future users' energy behavior is ranked, avoiding subjective criterion definition.

The K-means algorithm, in short, requires a predefined number of clusters and initializes their centers using one of several methods (e.g. randomly) somewhere in the region occupied by individual observations. Afterwards, through several interactions, the positions of the cluster centers are updated until the amount that they are shifted by is less than a predefined value signifying that they are not moving any more. This update process is conducted in order to minimize within-cluster sum of square distances between each observation and the center (also known as within-cluster variance) which is used as a criterion that influences how the centers are moved.

B. Feature selection

It has already been mentioned that the choice of the relevant features is one of the crucial steps for the development of the user benchmarking algorithm. The primary feature chosen in this paper was total energy consumption for a period of 24 hours. Furthermore, relevant literature suggests numerous weather parameters that should be included in order to able to perform normalization procedures that are necessary to fairly compare users which are located in different weather conditions. For example, different amounts of energy have to be used in a town where the temperature is often below zero and heating is required then in one where the temperature is usually around a moderate value like 20℃. Also, it should be kept in mind that heating and cooling appliances are often the largest consumers and, as such, have the greatest impact on the total consumption. Nonetheless, in the use case which was considered in this paper, all users are residents of the same building block, which is why none of the commonly utilized weather parameters differ between them, and so those features are irrelevant for the proposed benchmarking algorithm in this case. Additionally, building characteristics are frequently used, as different qualities of building insulation can dramatically affect energy efficiency. However, because of the previously mentioned reason of all users living in the same building block, these parameters were also removed from consideration.

Apart from the total energy consumption, average occupancy and indoor temperature were selected for input features as having greater occupancy is supposed to imply that the occupants will use more appliances and the temperature should reflect the usage of heating elements such as electric heaters. Although the presented methodology will be demonstrated as a 2D use case, it is flexible enough to support the introduction of any additional input features, depending on the practical use case, even though they have not been considered as a part of this work. Therefore, the K-means model has been designed to have two inputs: a ratio between the total user's energy consumption and the average occupancy and a ratio between the total user's energy consumption by the difference between the average indoor temperature and 30℃.

IV. Results and Discussion

A. Data preparation

All of the aforementioned data was collected from 9 apartments in France on a daily basis, for three months with different weather conditions: August, October and December of 2019. After removing the outliers from the data, the ranking system was designed with the aim of clustering the users in the one out of 3 energy efficiency groups: the efficient user, the moderately efficient user or the inefficient user.

Figure 2. An illustration of three different energy efficiency clusters with their respective cluster centers (each dot represents one household's measurement obtained for a predefined time range)

B. Clustering output

After normalizing the inputs, the model has been trained in Python, and the results for the training set and the obtained clusters centers are shown in Figure 2. This figure shows the output of the unsupervised training procedure where the three aforementioned clusters are illustrated in different colors along with their centers as their defining feature in the K-means algorithm. It is worth mentioning that the K-means algorithm does not have any beforehand knowledge of what each cluster represents. It only takes into account the spatial distribution of the data, the required number of clusters, and minimizes their within-cluster variance by adjusting the centers. Afterwards, when this procedure is completed, it is up to an expert to provide semantic meaning to each of the clusters in accordance with the assumptions that were made when the number of clusters was determined. In this case, it is obvious that the group of instances in the lower left of the diagram represents the most efficient one. However, there may be ambiguities when determining the labels of the other two clusters. Namely, due to the arrangement of the data, an implicit importance has to be assigned to each of the values depicted on the axes as contributors to the energy ranking. In this case, consuming a lot of energy per each occupant is deemed slightly less energy efficient that purely increasing the indoor temperature through the use of heating devices since reducing this factor can adversely affect user comfort. Therefore, the cluster with the center on the far right was labelled as inefficient while the one on the top as moderately efficient.

Due to the definition of the K-means algorithm and the fact that it is an unsupervised approach, the number of clusters which is defined prior to the training procedure has a noticeable effect on the results. Namely, specifying different numbers of clusters from the training procedure would results in different distributions of their limits. With initial setup presented in this paper utilizing only three groups of efficiencies, further development and testing should be conducted when more groups are introduced and the arrangement of output clusters should be analyzed.

C. Temporal aspects of the ranking

Furthermore, in Figures 3, 4 and 5 the rankings for three different households are illustrated. It is important to point out that for the individual household rankings vary through time depending on their current performance, implying that the users have the potential to adjust their habits and improve energy efficiency in time. Additionally, the idea was to present the information for the whole neighborhood (i.e. to include other users living in the nearby area) to each user, so that the influence of social pressure can be utilized to improve their habits and facilitate the transition towards more energy efficient behavior.

The presented results in Figures 3, 4 and 5 illustrate a distinction between the three groups of users with different levels of efficiency. For example, H1 and H3 tends to be classified as efficient most of the time with only a few instances when its score is inefficient and H3 having noticeably more moderate instances. On the other hand, H2 has significantly more instances when it behaves inefficiently. At least according to the chosen

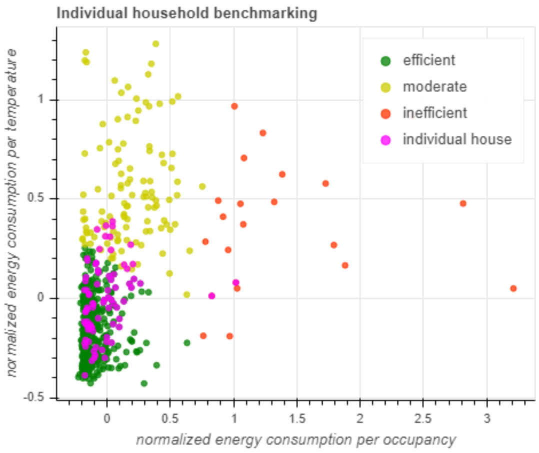

Figure 3. An illustration of different ranking in time for a single household (anonymized codename “H1”) shown in magenta, overlaid on top of the clusters determined previously

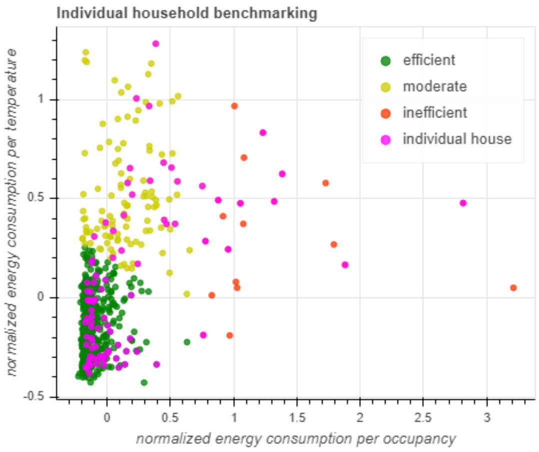

Figure 4. An illustration of different ranking in time for a single household (anonymized codename “H2”) shown in magenta, overlaid on top of the clusters determined previously

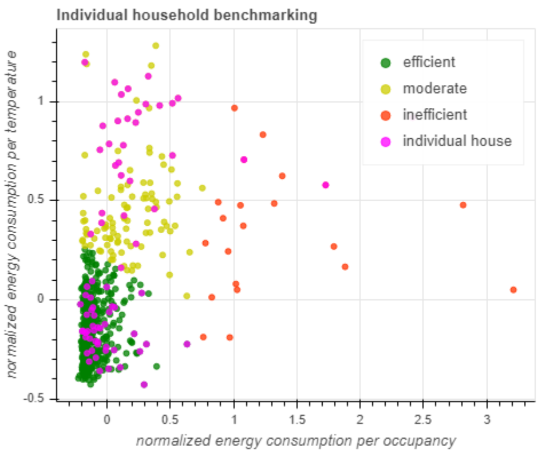

Figure 5. An illustration of different ranking in time for a single household (anonymized codename “H3”) shown in magenta, overlaid on top of the clusters determined previously

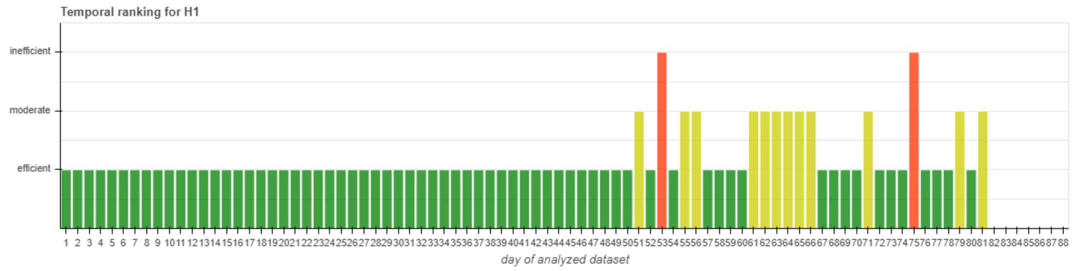

Figure 6. Temporal rank of “H1” illustrating how the score varies in time

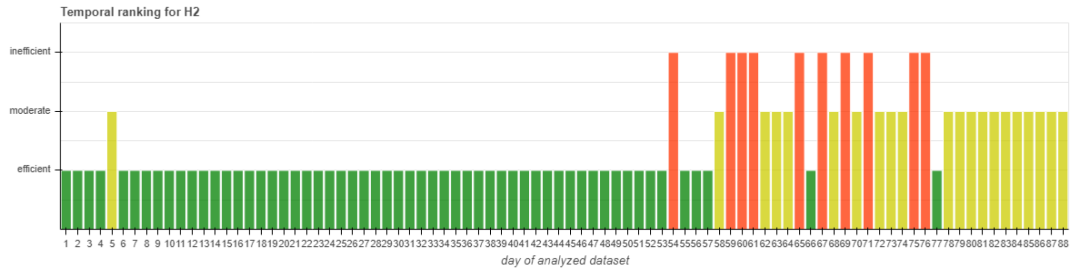

Figure 7. Temporal rank of “H2” illustrating how the score varies in time

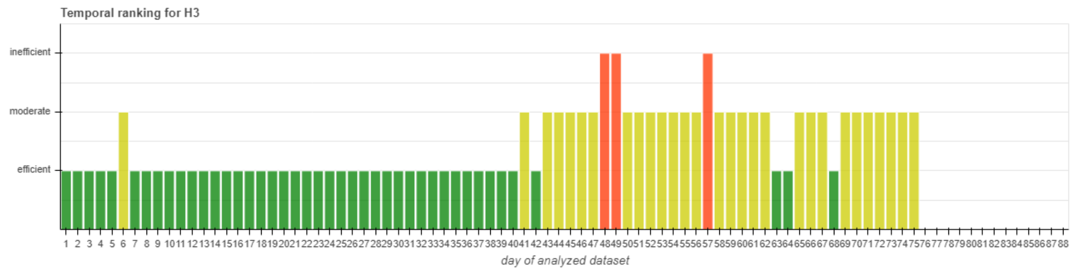

Figure 8. Temporal rank of “H3” illustrating how the score varies in time

normalization parameters, the results show that different efficiencies in similar circumstances are indeed possible to achieve, and this, in turn, provides substantiation for the development of an energy efficiency ranking which was implemented in this paper using a clustering approach. Further elaborating on this point, Figures 6, 7 and 8 show how the achieved ranking of the same three households analyzed previously varies through time, illustrating how the same users can be ranked differently in accordance with their respective current behavior. Due to the dataset being organized as first listing values from the summer period, then fall and winter, the results show that seasonality plays a key role in determining the output cluster. Therefore, once enough data is obtained, the methodology can be further improved by individually training on data from the considered seasons so that the total consumption does not so significantly impact the ranking.

D. User feedback

As previously mentioned, utilizing a benchmarking system is a unique multidisciplinary problem that involves different aspects that goes beyond just its technical implementations and includes social aspects as well. Since the social pressure is a key feature of the proposed system, the feedback loop requires user feedback. Therefore, preliminary interviews were conducted with end users (residents) in order to gauge their interest in this specific service and get an understanding of what features may be beneficial from their perspective. The response towards the system was overwhelmingly positive with most of the users expressing interest in having more information than just an aggregated rank. Namely, when the initial concept was conceived, a simplified approach in form of an aggregate presentation of the ranking (group in which the users belong) was thought to be the best for the sake of simplicity. However, the users have expressed interest in discovering the sources of their inefficiencies which provides encouragement of further research into energy use disaggregation and analyzing factors contributing to energy consumption as well as conveying them to end users.

V. Conclusion and Future Work

This paper presents a methodology that utilizes IoT measurements from smart sensors in smart homes that depict several factors that are supposed to affect the total energy consumption with the goal of determining several energy-efficiency groups of different users. By utilizing such an approach, a ranking system is derived in order to provide feedback to end users through an illustration of their efficiency as well as to create a unique environment using social pressure in which the end users would compete to obtain the title of the most efficient household in their neighborhood.

In the context of planned future work, it is crucial to point out that this is a data-driven approach. If it were to be implemented in real-world practice, it would require additional training after a certain amount of time with the new sets of data. Hopefully, after some time, most of the users would adjust and so they might be clustered as efficient ones more often, due to the improvement in their behavior. Therefore, in order to maintain the impact of the benchmarking algorithm ranking through social pressure, it would be necessary to retrain the model. Additionally, more energy efficiency groups could be proposed, as well. Finally, the research that would specifically focus on the effects that this approach has produced when the users are informed about their ranking would be the valuable.

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