# Energy Efficiency Benchmarking for Smart Homes*

Marko Jelić[1] [0000−0002−0220−1688], Dea Pujić[1] [0000−0002−3934−6346], and Marko Batić[1] [0000−0002−8443−3932]

Institute Mihajlo Pupin, University of Belgrade
{marko.jelic, dea.pujic, marko.batic}@pupin.rs

**Abstract.** Numerous strategies were developed over the years in order to encourage users to reduce energy consumption and bolster energy efficiency. However, with increasing levels of efficiency achieved by most household appliances, one of the most impactful approaches that remains as a means to further increase energy efficiency is attempting to encourage users to behave in an energy efficient manner. More precisely, positive behavior change can be motivated through the creation of unique social pressure and competition. Namely, the idea of the methodology presented in this paper is providing a fair, normalized, comparable ranking (benchmark) between different energy consumptions of different users. Therefore, the ranking is supposed to motivate them to either retain a leading position in the ranking or to attempt to improve their behavior and advance within the ranking.

**Keywords:** Energy efficiency · User benchmarking · Smart homes · Data envelopment analysis · Machine learning.

## 1 Introduction

The energy-use performance benchmarking 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. Review papers [3] and [13] predominantly analyze non-residential building benchmarking solutions, while a recent survey [5] focuses on demand forecasting in the residential sector and states that *"Residential energy performance prediction has historically received less attention, as compared to commercial buildings."* and that there is a *"need for the availability of more residential building data sources to be able to assess*

* The research presented in this paper is partly financed by the European Union (Horizon 2020 SINERGY project GA #952140) and partly by the Ministry of Education, Science and Technological Development and the Science Fund of the Republic of Serbia (AI-ARTEMIS project, #6527051).

*and improve models, and further testing is needed including those models that have not yet been significantly used for residential buildings"*.

With regards to specific methodologies, [3] separates the applied methodologies into: Simple normalization, Ordinary least squares (OLS) and its modifications, Stochastic frontier analysis (SFA), Data envelopment analysis (DEA), simulations (model-based) and Artificial neural networks (ANN). As was previously mentioned, most of the included use cases are exclusively related to the non-residential domain. Schools are chosen as the main building type of interest by [12] and [14] that apply OLS while [2] and [6] use a model-based approach to efficiency estimation. A school is also used for benchmarking in [7] with descriptive statistics and ANNs. Others focus on office buildings with [9] performing benchmarking through simple normalization, [16], [1] and [4] through OLS, [11] and [10] using DEA and finally [8] and [11] employing simulations.

Given findings in the aforementioned analysis regarding relevant papers that are dedicated to the subject of energy-use efficiency benchmarking, it can be deduced that the current state-of-the-art solutions appear to be ill-equipped to deal with an IoT future in which individual homes will be outfitted with a vast number of sensors. Therefore, this paper aims to introduce a flexible methodology that can be utilized for smart homes and that incorporates various factors pertaining to the energy consumption of the analyzed households. Furthermore, the same methodology could even be extended towards commercial objects that are sufficiently covered with smart sensors.

## 2 Methodology

With the main goal of the presented methodology being the holistic and comprehensive assessment of user behavior through multiple energy usage indicators, the user benchmarking methodology is based on four different elements denoted $r_i$ where each one of them depicts a different aspect of energy efficiency (normalized comparison with others, normalized comparison to oneself, alignment with intermittent renewable generation and engagement), as will be described in greater detail in the following sections. With respect to the weights $w_i$ of each of these criteria, the final unscaled score (rating) can be obtained as a linear combination of these factors

$$R_{\text{unscaled}} = \sum_{k=1}^{4} w_k r_k = w_1 r_1 + w_2 r_2 + w_3 r_3 + w_4 r_4.$$

However, these raw results are further processed before being presented to end users. Namely, linear scaling is applied to convert the obtained interval of values into the range of [40, 95]%, as specified in accordance with expert inputs, so that less efficient users are not demotivated and so that the most efficient users get the impression that there is still room for improvement.

### 2.1 Data envelopment analysis

According to [15], DEA represents a quantitative, nonparametric technique which is used in operational research and most commonly economics to establish a best practice group of decision making units (DMUs) (the so-called efficiency frontier) and to determine which units are less efficient when compared to the best practice groups and at what the magnitude of inefficiencies are.

In consistence with the related literature, let the following symbols be

- $j$ the order number of DMU,
- $i$ the order number of input used by DMUs,
- $r$ the order number of output used by DMUs,
- $\theta$ the efficiency/inefficiency rating,
- $y_{rj}$ the amount of output $r$ by DMU $j$,
- $x_{ij}$ the amount of input $i$ by DMU $j$,
- $u_r$ the weight coefficient assigned to $r$-th output,
- $v_r$ the weight coefficient assigned to $i$-th input.

Now, the DEA problem is posed as determining the maximum objective function as defined by

$$\theta_j = \max\left\{\frac{u_1y_{1j} + u_2y_{2j} + \cdots + u_sy_{rj}}{v_1x_{1j} + v_2x_{2j} + \cdots + v_my_{mj}}\right\} = \max\left\{\frac{\sum_{r=1}^{s} u_ry_{rj}}{\sum_{i=1}^{m} v_ix_{ij}}\right\}$$

where $s$ is the total number of outputs and $m$ is the total number of inputs. The maximization is obtained under a set of constraints

$$(\forall j)\left(\frac{u_1y_{1j} + u_2y_{2j} + \cdots + u_sy_{rj}}{v_1x_{1j} + v_2x_{2j} + \cdots + v_my_{mj}}\right) = \left(\frac{\sum_{r=1}^{s} u_ry_{rj}}{\sum_{i=1}^{m} v_ix_{ij}}\right) \leq 1$$

and

$$u_1, u_2, \ldots, u_s > 0 \quad \text{and} \quad v_1, v_2, \ldots, v_m \geq 0.$$

However, DEA is most often implemented using linear programming, which cannot be performed with the given set of constraints and the objective function because the division between the numerator and denominator presents a non-linear operation. This issue is circumvented by modifying the given set of formulas through an additional constraint that specifies that all denominators must be equal to one. In this modified form, DEA is formulated as maximizing the objective function specified by

$$\theta_j = \max\left\{\sum_{r=1}^{s} u_ry_{rj}\right\}$$

subject to

$$(\forall j)\left(\sum_{r=1}^{s} u_ry_{rj} - \sum_{i=1}^{m} v_ix_{ij} \leq 0 \quad \wedge \quad \sum_{i=1}^{m} v_ix_{ij} = 1\right)$$

while the constraints

$$u_1, u_2, \ldots, u_s > 0 \quad \text{and} \quad v_1, v_2, \ldots, v_m \geq 0$$

still apply.

In general, DEA is capable of considering a wide variety of different input parameters. For energy efficiency applications specifically, these parameters can be grouped in two different categories

- Static parameters:
  - heated area,
  - heated volume,
  - outward wall (and window) area,
  - wall thickness,
  - wall material (conductivity),
  - number of reported tenants;
- Dynamic parameters:
  - total energy consumed,
  - avg. occupancy for the household/building,
  - cooling/heating degree days,
  - diff. between indoor and outdoor temperature.

However, having in mind that for the specific use cases that will be demonstrated in the following text, buildings from the same neighborhood were considered, with all of them sharing the same construction properties and microclimate, the number of considered parameters is limited to

- total energy consumed,
- average total occupancy,
- average absolute difference between indoor and outdoor temperature,
- total heated area,

as including others would add no additional information.

A resulting arrangement of users in this space with the total energy consumed as the primary output is illustrated in Figure 1 where those users on the inefficiency frontier are assigned the rating of 0 and others are given a rating $r_1 = \theta_i$ corresponding to their position between the origin and frontier, as dictated by the DEA approach.

### 2.2 ML-based consumption prediction

The main idea of this novel approach was to exploit machine learning through models like random forests, k nearest neighbors, support vector machines, linear regression and neural networks as the estimator of the user's expected energy usage in accordance with his previous behavior making the most of machine learning's (ML) extraordinary estimation potential. It is intended to be used in a way which would result in rewarding on penalizing the users depending on their change in behavior. In other words, given a similar set of inputs as the DEA

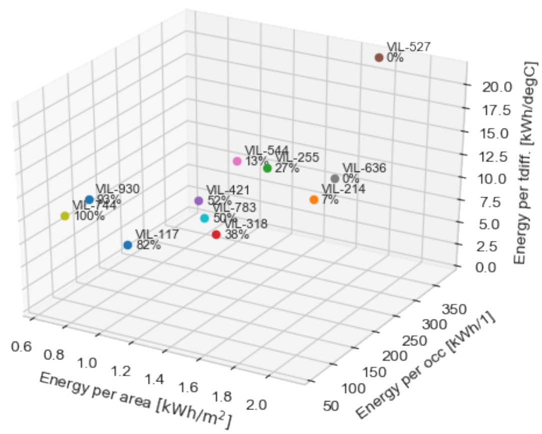


**Fig. 1.** An example of DEA spatial arrangement

approach uses, it is supposed to approximate what amount of energy a user is expected to consume. Therefore, the estimated value $\hat{E}$ can then be compared with measured (real) one $E_{\text{meas}}$, and reward or penalize the user proportional to the difference that would be assigned to that user, as illustrated in Figure 2. This concept could be considered as an example of the differential part in control theory, as it measures the difference from the previous behavior and proposes the "control" accordingly i.e., behavioral stimulus which is in form of positive or negative rating in this particular case. The output of the discussed ML-based part of the benchmarking methodology can therefore be defined as

$$r_2 = \text{tansig}\left(\ln\left(\frac{\hat{E}}{E_{\text{meas}}}\right)\right) = \frac{2}{1 + e^{-\ln(\hat{E}/E_{\text{meas}})}} - 1.$$

Namely the idea of using the logarithm function was to obtain negative result when the real measured consumption is greater than the one based on previous behavior, as a negative penalty for inefficient behavior is supposed to be assigned,

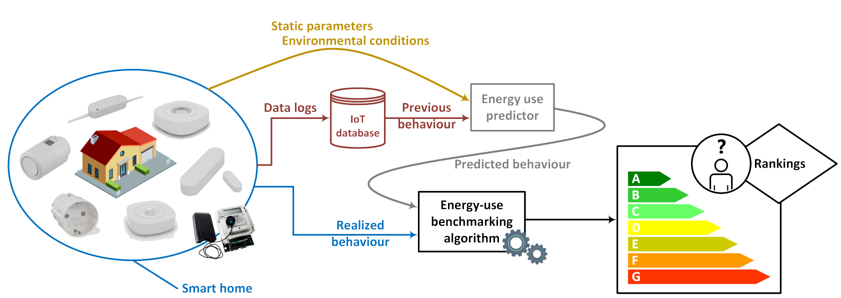


**Fig. 2.** ML-based consumption prediction illustration (with assets designed by Freepik)

and vice versa. Additionally, the tansig function has been chosen as it is an odd limited function, so for the same positive and negative behavior the same absolute penalty would be assigned and the output would be within the required limits.

### 2.3 Production and demand correlation

Having in mind the increasing penetration of RES installations with individual users, one of the key goals to their efficient usage is maximizing self-consumption, i.e., ensuring that as much of locally produced energy is also consumed locally. Achieving this objective entails that the demand profile should be well aligned with the generation profile meaning that peaks in the demand should follow the peaks for production and vice versa for valleys. However, the stiff character of users' daily habits can notably hinder this process as customs are not so easy to adapt to, for example, the production profile of PV modules which generally displays peak performance during the mid-day period when the sun is shining the brightest.

Therefore, in order to numerically quantify how well-aligned the consumption profile $X$ is to the renewable generation profile $Y$, their correlation coefficient $\sigma$ is calculated as

$$r_3 = \sigma\{X, Y\} = \frac{\mathrm{Cov}(X, Y)}{\sqrt{\mathrm{Cov}(X, X) \cdot \mathrm{Cov}(Y, Y)}}$$

and used as the third benchmarking contribution $r_3$.

### 2.4 Responsiveness

The final part of the proposed energy efficiency performance evaluation methodology considers user's responsiveness to notifications and suggestions delivered through a companion mobile application for their smart device management in form of a reward for users that show motivation for behavioral improvements. Namely, this part of the system is supposed to additionally encourage users willing to adapt their demands in order to save energy. For example, if the household/building owner promptly reacts to suggestions about energy conservation, such behavior should be rewarded. Additionally, this factor is not meant for any penalization if the suggestions are not considered because some of the events that are being checked may not imply that energy is being wasted.

The score rewarded in this category is obtained simply by ranking the users by three equally weighted and combined factors that are considered to contribute to the overall responsiveness: the percentage of the energy conservation notifications that they have responded to in due time (less than 30 minutes), the total number of controls actions sent using the app (turning appliances on or off) and total number of sessions (discreet log-ins separated by more than 30 minutes).

## 3 Conclusion

In summary, this paper provides an outline of a benchmarking methodology for smart homes of the future with a specific goal of further increasing energy efficiency. It takes into account a multitude of different factors relating to the collective energy consumption of a community as well as changes in individual behavior. It also considers other factors such as integration with renewable generation and interaction with installed smart devices through a provided platform. Planned future efforts include the evaluation of the methodology on a real set of users and illustrating the link between changes in the ranking and in energy consumption.

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