

Explainable AI for In-depth Benchmarking of Domestic Electricity Consumption

Summary Master Thesis

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ABSTRACT

Machine learning (ML) models can provide precise predictions, but are usually—compared to more traditional statistical methods such as linear regression—non-interpretable to humans. Research has put forth Explainable Artificial Intelligence (XAI) techniques that represent patterns discovered by ML in a human-readable way. One application area that can benefit from high predictive performance and the explanation of patterns in data is energy benchmarking. In the field, feedback of energy benchmarks has so far often been limited to a single performance score. Thus, it remains unclear to benchmark recipients which characteristics affect their specific consumption. Taking a linear regression model as baseline, this thesis tests the applicability of XAI for energy benchmarking in the context of domestic electricity use. The results of this work show that XAI is able to identify building and household characteristics that are, according to an ML model, relevant for electricity consumption, while offering higher predictive performance than a statistical approach.

1 INTRODUCTION

Reducing electricity demand is one of the key challenges for the future [6]. An element that has already proven to be effective in motivating savings is benchmarking [9, 12]. However, for energy benchmarks, it is often not clear which factors influence a specific performance [2]. Recipients are therefore left with insufficient information to decide which efficiency measures should be implemented.

Statistical approaches such as linear regression have long been used to explain factors that influence electricity consumption [7, 8]. Though beneficial, linear approaches suffer from poor modeling capabilities. Recently, ML has made progress in improving methods [4]. Although the predictive power of ML is high, such models come with a lack of transparency. The field of research dealing with this problem is called XAI [3]. XAI aims to improve the transparency of complex machine learning models that offer high prediction quality but are difficult for humans to interpret [1]. However, the potential of such methods to improve benchmarks through explanations in domestic electricity consumption has not yet been fully exploited.

2 RESEARCH QUESTIONS AND APPROACH

This thesis examines two research questions using data from 1,262 Irish households [5]. First, the explainability of electricity consumption based on building and household characteristics (e.g., floor area, number of residents) using a linear approach. In doing so, a multiple linear regression (MLR) model is applied to determine the explanatory power of the regressors and the extent to which an

MLR can explain the variance in energy use intensity (EUI), a performance measure often used in energy benchmarking to compare energy consumption. Hence, the first research question (RQ) is:

RQ₁: *To what extent can the domestic electricity consumption be explained by linear regression using building and household characteristics?*

Second, building on RQ₁, this work explores the differences between the explanations of an MLR model and an XAI method. Thus, the second RQ is:

RQ₂: *How does the explanation of an XAI approach for a domestic electricity consumption based on non-linear machine learning differ from the explanation of a linear regression model?*

To answer RQ₂, I apply non-linear ML in combination with the XAI method Shapley Additive Explanations (SHAP) [10]. For the comparison of the explanations of both methods, this work relies on the properties *predictive accuracy*, *consistency*, and *fidelity* described by [13].

3 RESULTS

Concerning RQ₁, the analysis shows that an MLR model without feature interactions explains 54.1% of the variance (Adjusted R²) in the EUI and the model with hand-crafted second-order interactions explains 55.9%. When comparing the explanations of both methods within RQ₂, I find in terms of *predictive accuracy* that XAI combined with ML offers up to 8.69% lower Mean Absolute Error (MAE) than MLR when estimating the EUI (XGBoost by [4] provides the best results). The *consistency* analysis reveals that both methods explain overall similarly and thus estimate similar contributions for a given prediction. High *consistency* is desirable, as consistent explanations are considered more robust and meaningful [11]. The measurement of *faithfulness* uses the perturbation of feature values in order to blur the influence of important features and, thus, to test to what extent the prediction shifts in the opposite direction. The analysis of *faithfulness* shows that for both methods the prediction shifts in the opposite direction after the feature values have been perturbed—the statistical MLR model and XAI approach can therefore be said to be *faithful*.

4 CONCLUSION

The results of this work show that non-linear ML combined with SHAP is a suitable approach to explain domestic electricity consumption and offers higher predictive performance compared to a linear model, while maintaining explainability. This may lead to new insights on the consumer side, promotes the adoption of energy efficiency measures, and thus fosters resource conservation in the long term. Furthermore, this work demonstrates the power of XAI methods to provide explanations for energy consumption and offers several areas for future research.

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