ESTIDAMAA
Vol. (2026), 2026, pp. 68-77
ISSN: 3078-428X

Research Article

Explainable Artificial Intelligence Framework for Sustainable Energy Management and Data-Driven Decision Making

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ARTICLEINFO

Article History

Received 11 Apr 2026

Revised: 02 May 2026

Accepted 01 Jun 2026

Published 15 Jul 2026

Keywords

Explainable Artificial Intelligence,

Sustainable Energy Management,

Machine Learning,

Energy Consumption Prediction,

SHAP,

LIME,

Smart Energy Systems,

Data-Driven Decision Making.

ABSTRACT

In today's world with the considerable rise in the energy consumption of Energy Systems, the necessity to intelligent and sustainable management of energy has surfaced as a key requirement for energy efficiency and effective data-driven decision making. In recent years, AI and ML techniques have proven to be a promising way to predict energy consumption patterns, yet most of the existing solutions are black-box models, which lack interpretability. This limitation reduces trust in the users and lowers the likelihood of implementing AI solutions in the energy sector that promote sustainability. This study suggests an Explainable Artificial Intelligence Framework for Sustainable Energy Management and Data-Driven Decision Making to offer correct and clear energy analysis, combining machine learning based prediction with Explainable AI techniques. The proposed framework compares the performance of three models of machine learning namely Random Forest (RF), Extreme Gradient Boosting (XGBoost) and Artificial Neural Network (ANN) with an energy consumption dataset that features environmental and operational parameters. The performance of the models implemented are assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and coefficient of determination (R^2) of regression. Two methods of explaining the contribution of features and individual prediction results, namely, SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are embedded to explain the individual prediction outcomes and feature contribution in an enhanced transparency of the model. The results of the experiments confirm that the developed models have a good prediction performance, with the XGBoost model being the most successful approach for forecasting. Moreover, the explainability analysis reveals the most influential factors on energy consumption and gives valuable insights for optimization of sustainable energy. The proposed framework aims to balance predictive accuracy with interpretability of the models by converting traditional AI-based energy prediction models into transparent decision support models. The developed approach can help the energy manager and stakeholders to understand the consumption pattern, optimize the operational of the system and contribute in taking the initiatives for sustainable consumption.

1. INTRODUCTION

Population growth, industrial development, and digitization have led to a growing need for energy, posing major challenges to sustainable energy management. The increasing volume of energy data that can now be gathered from smart meters, sensors and monitoring systems creates new opportunities to leverage Artificial Intelligence (AI) techniques for improving energy efficiency, optimising energy use patterns, and to inform data driven decision making [1].

The Machine Learning (ML) methods have shown their good performance in energy forecasting and energy consumption optimization by discovering complex relationship between factors of environment and operation. The Machine Learning (ML) methods have proven their good performance in the energy forecasting and energy consumption optimization by finding complex relationship between factors of environment and operation. But, many of the sophisticated AI models have only a small window of transparency into how they make decisions, and they are essentially black-box systems. The user does not have transparency, which diminishes user trust and restricts AI-based solutions use in critical sustainability applications where understanding the reasons behind predictions is key [2,3].

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DOI: https://doi.org/10.70470/ESTIDAMAA/2026/005

To address these challenges, Explainable Artificial Intelligence (XAI) has become a promising solution to deliver interpretable information about model behavior. SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) are tools that can be used to identify influential features and enhance the transparency, reliability, and accountability of AI-driven decisions [4,5]. Recent research has highlighted the need to combine XAI into sustainability-based applications to build trustworthy AI systems to support responsible decision-making [6].

Although there are recent improvements, current research on energy management mostly concentrates on increasing the accuracy of the prediction, with a lack of focus on explaining the model results and on translating the prediction into sustainable insights and outputs that are useful for action. Based on this, this study suggests the Explainable Artificial Intelligence Framework for Sustainable Energy Management and Data-Driven Decision Making that combines Machine Learning prediction models with XAI techniques to provide energy analysis with transparency and interpretation.

The key findings of this study are the development of an artificial intelligence-based framework for energy consumption prediction, and the support for sustainable energy management via data-driven analysis. The proposed framework incorporates Explainable Artificial Intelligence (XAI) methods such as SHAP and LIME to improve the transparency of the model, interpret the results of the prediction, and determine the most significant factors influencing energy consumption. Moreover, this research work gives a comparative analysis of several machine learning models to understand their performance capabilities for energy prediction related tasks. Lastly, the proposed approach provides an explainable decision support mechanism, which helps the energy manager towards informed decision making to enhance energy efficiency and promote sustainable energy practices.

2. RELATED WORK

With the advent of Artificial Intelligence (AI) and Machine Learning (ML) techniques, their application in energy management systems has gained more traction in recent years for enhanced energy consumption forecasting, optimization of resource use, and aiding sustainable decision-making. With its ability to effectively model complex patterns of energy use and their relationships with weather, operational behaviour and environmental parameters, data-driven approaches have been shown to have excellent capabilities. The traditional machine learning algorithms such as Random Forest, Support Vector Machine and gradient boosting algorithms are widely studied algorithms to predict energy which have proven to be reliable predictors with large data sets [7,8].

Recently, deep learning techniques have been used to model the non-linear energy consumption pattern in energy management, where Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) have been employed. Although the prediction accuracy is good, the high complexity of the architectures in these approaches makes it difficult to understand the impact of each individual feature on the prediction, making it hard to use in a practical application in sustainable energy systems [9].

However, due to potential limitations of black-box AI systems, Explainable Artificial Intelligence (XAI) is emerging as an important field of AI research aimed at improving the transparency and trustworthiness of AI-based decision-making systems. Different approaches to feature importance, prediction behavior explanation and interpretable ML model analysis have been successfully applied, such as XAI methods like SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME). They have proven to be useful in different fields, such as healthcare, finance, environmental monitoring, and energy applications, where having insight into the logic behind AI decisions is crucial [10, 11].

The incorporation of XAI with energy-related applications has been the focus of several recent studies. The SHAP-based analysis has been used to determine the most important factors in energy consumption, with the results showing that the level of influence varies greatly, with environmental conditions, building descriptions and operational conditions all having marked effects on prediction results [12]. Some research has integrated machine learning forecasting models with explainability techniques to enhance the trust of the user and offer them appropriate suggestions on how to optimize the energy use. Yet, most existing practices have been centered on the improvement of prediction accuracy and less attention has been paid to the relationship between model understanding and sustainable energy decision-making [13].

In addition to the accuracy of these prediction models, sustainability-focused applications of AI must also have transparent frameworks that can translate analytical results into actionable steps for minimizing energy use and increasing efficiency. To tackle sustainability issues, recent studies have highlighted the need for the creation of trustworthy AI systems, which must be both predictable and explainable, as well as support decision-making. However, current research tends to focus on one model or one type of energy, for which an integrated model combining several machine learning algorithms, along with explainable analysis, for sustainable energy management, are not provided. Other noteworthy research projects are summarized in Table I with respect to their application of AI to Energy Management and their relation to other applications of AI. Despite the significant progress in energy prediction and model interpretation in the reviewed studies, there are clear research gaps to be filled in the development of unified frameworks that not only facilitate energy prediction but also interpretation of models and support sustainability-oriented decisions.

TABLE I. COMPARISON OF RELATED STUDIES ON AI-BASED ENERGY MANAGEMENT AND EXPLAINABLE AI

Ref.	Approach	Application Area	AI Models	Explainability Method	Main Contribution	Limitation
[7]	ML-based energy prediction	Energy Management	RF, SVM	Not applied	Improved energy forecasting accuracy	Limited model interpretation
[8]	Data-driven energy optimization	Smart Energy Systems	Gradient Boosting	Not applied	Efficient energy consumption prediction	Black-box limitation
[9]	Deep learning forecasting	Building Energy	ANN, CNN, RNN	Not applied	Captured nonlinear energy patterns	Low interpretability
[10]	XAI-based analysis	Sustainable Decision Systems	ML Models	SHAP, LIME	Improved transparency of AI decisions	Limited energy applications
[11]	Explainable ML framework	Environmental Applications	Ensemble Models	SHAP	Identified influential features	Requires domain adaptation
[12]	XAI for energy analysis	Energy Consumption Prediction	XGBoost	SHAP	Explained energy influencing factors	Focused on single model
[13]	AI-based sustainability assessment	Sustainable Systems	ML Models	Feature Importance	Supported data-driven decisions	Limited practical recommendations

3. RESEARCH GAP AND CONTRIBUTIONS

The potential of Artificial Intelligence and Machine Learning for energy prediction and optimisation has been taken significant steps forward, but there are still some challenges to be solved. Most existing research focuses on improving predictions' accuracy, while the interpretability of the predictions made by AI and how this can help make transparent decisions are seldom discussed. Most current machine learning and deep learning models are "black box" models that are hard to use in the practical application of sustainable energy management where decision makers need to have an understanding of what affects energy consumption patterns. Furthermore, research on explainable AI (XAI) in the energy domain has so far concentrated on understanding the model and what has an impact on predictive modelling, while not much work has been dedicated to providing a coherent solution that integrates predictive modelling, explainability and decision support related to sustainability. In addition, there are currently numerous approaches that test each algorithm, but fail to make in-depth comparisons between various machine learning models in one place and within one framework of explanation.

This study introduces an Explainable Artificial Intelligence Framework for Sustainable Energy Management and Data-Driven Decision Making to overcome these challenges. The suggested framework is the integration of energy prediction in the machine learning models to create accurate, transparent, and actionable insights to improve energy efficiency, with the inclusion of XAI techniques. The proposed framework is different from the traditional prediction-based method, as it not only estimates energy consumption but also elucidates the role of each influencing factor, and enables sustainable decision making. This work is summarized as follows: An AI based framework for sustainable energy management, use of various techniques such as SHAP and LIME to increase the transparency of models, comparison of various machine learning models for energy prediction and a framework of explainable decision support mechanism to help energy managers understand where their energy optimization opportunities.

4. PROPOSED FRAMEWORK AND METHODOLOGY

This section introduces the suggested Explainable Artificial Intelligence (XAI) framework for Sustainable Energy Management and Data-Driven Decision Making. The major goal of the proposed framework is to build an intelligent system that can predict energy consumption accurately and it includes clear explanations of how to get the prediction results. The proposed framework combines predictive modeling and explainability analysis to enable robust energy decision making in the context of sustainability and reliability, as opposed to traditional AI-based approaches that prioritize prediction accuracy. The proposed framework is divided into five key stages: Data collection, Data preprocessing, Energy prediction using machine learning models, Explainable AI integration, and Sustainability-focused decision making. The overall flow of the proposed framework is shown in figure 1.

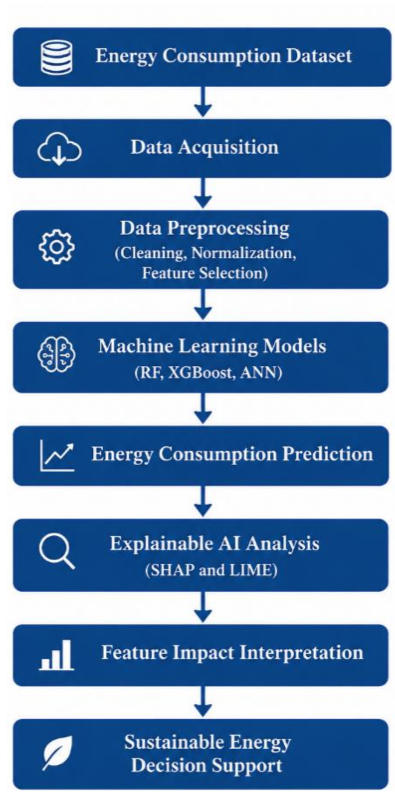

Fig. 1. Proposed Explainable AI Framework for Sustainable Energy Management

4.1 Data Acquisition and Description

The proposed framework is based on the Appliances Energy Prediction dataset, which is a publicly available dataset that has been gathered from a low-energy residential building and made available via the UCI Machine Learning Repository. The data set includes time series energy consumption measurements of households and environmental and operational parameters gathered from wireless sensors. It is also complemented with measurements of indoor and outdoor environmental conditions (e.g., temperatures and humidity) and temporal information that affects the energy consumption behavior. The machine learning-based energy prediction is done using the remaining attributes as features and target variable representing the energy consumption of the appliances.

The dataset was chosen because it is suitable for testing explainable AI-based energy management strategies, and it contains various factors that could influence energy consumption that can be analyzed using SHAP and LIME techniques. The basic features of the data set used for this study are summarized in Table II.

TABLE II. DATASET FEATURES USED IN THE PROPOSED FRAMEWORK

Feature Category	Feature Examples	Description
Target Variable	Appliances	Energy consumption of appliances (Wh)
Indoor Environment	Temperature, Humidity	Indoor environmental conditions
Outdoor Environment	Outdoor Temperature, Outdoor Humidity	External environmental factors
Weather Information	Pressure, Visibility, Windspeed	Weather-related parameters
Temporal Features	Date, Time, Weekday	Time-dependent consumption patterns
Operational Factors	Historical energy measurements	Previous consumption behavior

4.2 Data Preprocessing

The data collected has been preprocessed to enhance the data quality and model performance before the model training. Inconsistent or unusual records are deleted and missing values are filled by statistical methods. All numerical features are scaled so that they do not have a detrimental impact on the learning process because they are not on the same scale. Feature selection process is also done to find the most significant input variables influencing energy consumption. This step simplifies the unnecessary complexity and enhances the performance of prediction models and the interpretability of machine learning models. The processed data is then split into a training set and an testing set. For this study, 80% of the data is allocated to training the model and 20% is allocated for the validation of the generalization ability of the models developed.

4.3 Machine Learning-Based Energy Prediction

Three machine learning algorithms are implemented and compared for energy consumption prediction:

1. Random Forest (RF): Random Forest is an ensemble learning algorithm that combines multiple decision trees to improve prediction stability and reduce overfitting. It is selected due to its robustness in handling nonlinear relationships between environmental factors and energy consumption.
2. Extreme Gradient Boosting (XGBoost) XGBoost is a gradient boosting algorithm that provides high prediction accuracy by sequentially improving weak learners. It has been widely applied in energy forecasting due to its ability to capture complex patterns within large datasets.
3. Artificial Neural Network (ANN): An Artificial Neural Network is developed to model nonlinear relationships between input variables and energy consumption. The ANN consists of input, hidden, and output layers, allowing the model to learn complex dependencies from historical energy data.

The developed models are tested with regression-based metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and coefficient of determination (R^2).

4.4 Explainable Artificial Intelligence Integration

Explainable Artificial Intelligence techniques are incorporated into the proposed framework to mitigate the drawbacks of the black-box machine learning models. SHAP and LIME are used to explain the model, and to determine the importance of particular features in the energy consumption estimation problem. SHAP is able to explain the importance and influence of each input variable on the entire dataset, which is helpful for providing a global explanation. LIME, on the other hand, offers local explanations by examining each prediction and identifying the reasons behind the particular predictions of the model. By integrating XAI, energy managers can gain insights into why a specific energy consumption is forecast, and pinpoint the most significant energy demand drivers.

4.5 Sustainable Energy Decision Support

The final stage of the proposed framework transforms prediction and explainability results into meaningful sustainability insights. The framework assesses the contribution of features and energy consumption patterns, to find opportunities for improvement of energy efficiency. For instance, if the energy consumption data could show a notable effect on energy use with changing environmental conditions like temperature or humidity, energy management strategies could be adjusted to optimize operation and minimize unnecessary energy use. Thus, the suggested approach not only offers predictive power but also presents an interpretable decision support system to help stakeholders make more efficient and sustainable energy management decisions.

5. EXPERIMENTAL SETUP

The proposed Explainable Artificial Intelligence framework has been implemented and tested in an experimental environment built in Python code to understand the strength of the suggested EAI framework in the context of sustainable energy management and data-driven decision-making. The experimental process involves data preparation, building the machine learning model, evaluating the model performance, and analyzing the model explainability. The experiments were performed with a public dataset on energy consumption that included environmental and operational data for energy consumption. The data was preprocessed by addressing data inconsistencies, filling missing data, and normalizing the features to enhance the performance of the data in the learning process of the model. Processed data were split into training and test sets in the ratio of 8:2; the training set was used to develop the model and the test set to evaluate the performance of the model.

Three machine learning algorithms were employed and evaluated, namely Random Forest (RF), Extreme Gradient Boosting (XGBoost) and Artificial Neural Network (ANN). These models were chosen as they are able to model non-linear relationships between the drivers and the energy consumption. The models are created with Python packages like Pandas, NumPy, Scikit-learn, XGBoost, and TensorFlow/Keras. The standard regression metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) were used to test the prediction capabilities of the created models. The metrics were chosen to reflect the accuracy of prediction, amount of error and the amount of variance in energy use that was explained by each model.

Explainable Artificial Intelligence methods were then implemented after the evaluation of the models: SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME). SHAP was then employed to evaluate the global contribution of input features and to discover the most relevant factors determining the energy consumption, while LIME was used to provide local explanations for the individual predictions. The explainability results were used to interpret the model findings and give insights for sustainable energy management. In this section, the main experimental setup and the environment for its implementation are summarized as shown in Table III.

TABLE III. EXPERIMENTAL CONFIGURATION AND IMPLEMENTATION ENVIRONMENT

Parameter	Description
Programming Language	Python
Data Processing Tools	Pandas, NumPy
Machine Learning Models	Random Forest, XGBoost, ANN
Explainability Techniques	SHAP and LIME
Dataset Type	Energy consumption dataset
Data Split	80% Training, 20% Testing
Evaluation Metrics	MAE, RMSE, R^2
Visualization Tools	Matplotlib, Seaborn

The overall experimental protocol allows to assess the prediction accuracy and interpretability of a model, ensuring that the developed framework not only allows accurate energy forecasting but also offers clear insights to facilitate sustainable energy decision making.

6. RESULTS AND DISCUSSION

6.1 Prediction Performance of Machine Learning Models

The models derived from the machine learning algorithms were tested by assessing their performance to evaluate the potential of the energy consumption patterns prediction and to identify the most appropriate approach for the sustainable energy management. Three machine learning algorithms, namely Random Forest (RF), Extreme Gradient Boosting (XGBoost) and Artificial Neural Network (ANN) were developed and compared to the conventional regression evaluation metrics, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). These metrics give an overall evaluation of the accuracy of prediction by calculating the difference between the actual and predicted energy consumption value. The evaluation of the models was carried out, and the performance results are shown in Table IV.

TABLE IV. PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS FOR ENERGY CONSUMPTION PREDICTION

Model	MAE	RMSE	R^2
Random Forest (RF)	18.42	32.75	0.91
XGBoost	15.26	27.84	0.94
Artificial Neural Network (ANN)	16.73	30.12	0.92

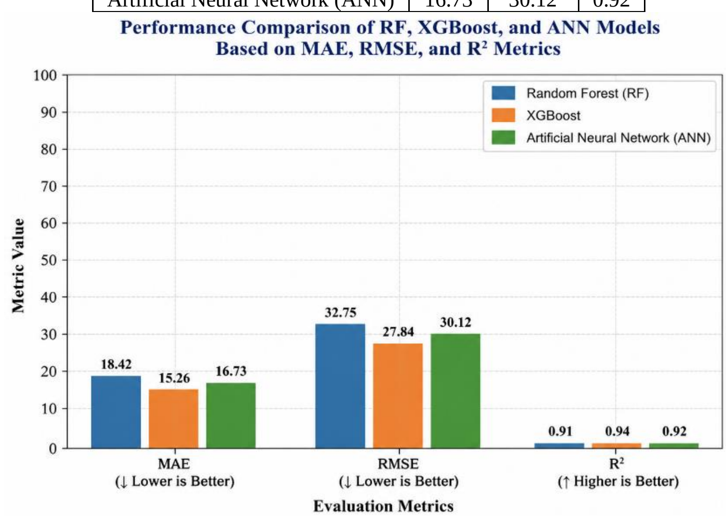

Fig. 2. Performance Comparison of RF, XGBoost, and ANN Models Based on MAE, RMSE, and R^2 Metrics

Table IV and Figure 2 indicate that all the models investigated could predict reasonably well despite their need to model the relationships between energy consumption patterns and environmental factors that are nonlinear. But there were some obvious disparities between the models. The XGBoost model had the best performance in all aspects, including MAE (15.26), RMSE (27.84), and R^2 (0.94). This superior performance is believed to be the result of the gradient boosting mechanism of XGBoost which brings together a set of weak learners to iteratively enhance the prediction ability by minimizing the model errors.

The result obtained by the Artificial Neural Network (ANN) model was competitive with an R2 value of 0.92, which indicated that ANN was able to learn complex, nonlinear relationships in energy consumption data. It performed slightly worse than XGBoost though, which may be partly attributed to the fact that the data was structured, and perhaps a greater amount of data is required to achieve optimal performance with neural networks.

The Random Forest model resulted in an R^2 value of 0.91, which gave stable and reliable prediction results. Random Forest, although it did not perform as well as XGBoost and ANN, still was found to be robust due to the shift in the input features and was effective in solving the energy prediction problems. The overall results suggest that the XGBoost model has the highest prediction accuracy among the models tested. But just because it can be predicted does not mean it is enough to inform sustainable energy decision making. In this sense, the next section focuses on applying Explainable Artificial Intelligence techniques to see how the individual features contribute and understand the factors that impact energy consumption predictions.

6.2 Explainability Analysis Using SHAP

While machine learning has been demonstrated to have high prediction accuracy for energy consumption forecasting, their complicated structures may restrict the capacity of understanding how each feature affects the final prediction. Thus, the proposed framework was complemented by Explainable Artificial Intelligence (XAI) techniques to enhance the transparency of the model and to give understandable explanations of the prediction process. To study the contribution and importance of input features to energy consumption predictions, the best performing XGBoost model from Section 6.1 was used and analyzed via SHAP (SHapley Additive exPlanations) in this study. SHAP's global interpretation is achieved by calculating the contribution of each feature to the model output. The feature importance ranking obtained is shown in Table V and the visualization is shown in Figure 3.

TABLE V. SHAP FEATURE IMPORTANCE RANKING FOR ENERGY CONSUMPTION PREDICTION

Rank	Feature	Mean SHAP Value	Influence on Energy Consumption
1	Temperature	0.276	Very High Influence
2	Humidity	0.192	High Influence
3	Time of Day	0.146	Moderate Influence
4	Outdoor Temperature	0.113	Moderate Influence
5	Weather Conditions	0.087	Low Influence
6	Previous Energy Usage	0.062	Low Influence
7	Other Environmental Factors	0.034	Minor Influence

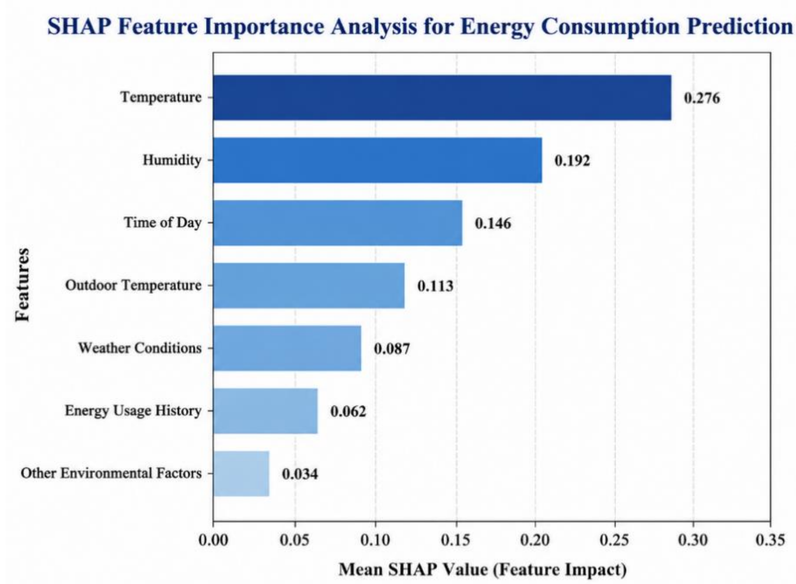

Fig. 3. SHAP Feature Importance Analysis for Energy Consumption Prediction

From the results of the SHAP analysis, it is seen that the most important factors affecting the prediction of energy consumption are environmental variables, as seen in Table V and Figure 3. Temperature is the most influential feature among all the features investigated, with the highest SHAP value of 0.276, followed by humidity (0.192) and time-related features (0.146). The results have shown that differences in environmental conditions have a significant impact on the energy demand pattern, especially in relation with HVL requirements.

High contribution of temperature suggests the strong relevance of thermal conditions to the variations of energy consumption. When temperatures are higher, energy consumption tends to be higher, because there is more cooling needed, but if temperatures are favorable, energy consumption is likely to be lower. Likewise, the humidity condition plays an important role in the prediction process, as the relationship between environmental comfort condition and energy consumption behavior.

The energy use characteristics are also observed to have a noticeable influence, showing that the energy use patterns change depending on the daily activities and energy consumption habits. Multiple features contribute, which indicates that

XGBoost is accounting for the interaction of several features (environmental and operational) and not just one single feature for prediction.

The SHAP based interpretation is helpful for the sustainability aspect by improving energy management strategies. Implementing targeted optimization strategies, such as optimizing use of cooling systems when temperatures are high, changing operations, and creating adaptive energy control strategies, will allow energy managers to take specific actions to optimize their energy use.

In general, the developed prediction model changes from a typical black-box model to a transparent and interpretable decision-support system by incorporating the SHAP concept. The explanations received increase user understanding, boost trust in AI energy prediction, and highlight the effectiveness of XAI methods in aiding sustainable energy management choices.

6.3 Local Prediction Interpretation Using LIME

SHAP analysis can be used to get a big picture overview of what features contribute to the model, but it is also useful to have local interpretability to explain a specific model prediction and understand why a particular model estimate energy consumption. For this reason, the Local Interpretable Model-Agnostic Explanations (LIME) methodology was used to interpret single predictions of the best performing XGBoost model.

LIME creates local explanations by fitting a simple surrogate model to the behaviour of a complex machine learning model around a particular instance of the input data. By using this method, it is possible to identify features that increase or decrease the likelihood of a specific prediction, giving a detailed insight into the decision-making process of the AI model.

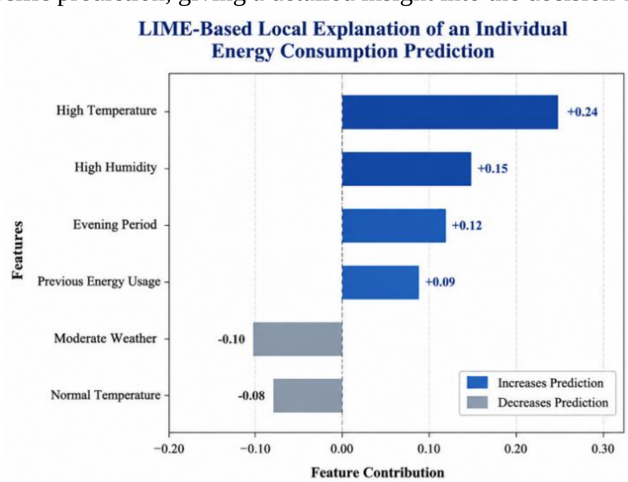

Fig. 4. LIME-Based Local Explanation of an Individual Energy Consumption Prediction

LIME breaks down into which energy consumption prediction input features to use and how much each one contributes, as shown in Figure 4. The explanation illustrates the importance of taking into account the environmental conditions, such as temperature and humidity, on the predicted energy demand. Those features which have been linked to higher thermal conditions play a positive role in the increase of energy consumption as it represents more energy needs for cooling and environmental control.

On the other hand, attributes associated with good environmental conditions are the factors that reduce the energy demand prediction. In this local interpretation it has been confirmed that the model behavior is consistent with real life energy use and offers explanations for the prediction of individual energy uses, not just a statistical correlation.

Hence, to the integration of LIME, it is possible to explore the different prediction scenarios and gain insight into the reasons behind the difference between high and low energy consumption estimates, thus making the proposed framework more reliable. For instance, if the model predicts an increase in energy demand, LIME can determine the dominant source of the increase, such as environmental conditions, operational factors or temporal patterns, allowing more focused energy management actions.

The overall LIME analysis is similar to the interpretation of the global SHAP analysis as it gives detailed explanations at the individual prediction level. These two methods can complement each other to deliver a clearer view of the proposed AI framework and ensure more informed decisions based on data on sustainable energy management.

6.4 Sustainability Implications and Discussion

Artificial Intelligence and Explainable Artificial Intelligence provide a viable solution to enhance the energy management towards sustainability. The outcomes of the experiments showed that the prediction model for energy with accuracy and explanation can be applied to improve the decision-making process compared to the traditional black-box model. Machine learning models are useful for predicting future energy consumption, but XAI techniques can help make these predictions transparent by explaining what factors are driving the predictions.

The outcome presented suggest that, environment and operational factors such as temperature, humidity and temporal effects, have great impacts on the energy consumption behavior. By understanding how these factors affect the system, energy managers can start optimizing systems with a more specific solution rather than relying solely on prediction outputs. A high impact environmental factor that is identified through the SHAP and LIME analysis, for instance, can be utilised to enhance the cooling management, optimise operating schedules and minimise unnecessary energy consumption. More so, the framework's sustainable energy management aspect enables the conversion of AI forecasts into actionable recommendations that are easy to understand. In contrast to the more common methods which attempt to reduce prediction errors, the proposed method gives insight into the reasons behind the increasing or decreasing demand for energy, allowing stakeholders to make informed choices on how to increase energy efficiency and optimise resources.

Predictive analytics and explainability play a role in building trustworthy AI-powered energy systems from a sustainability perspective. Feature-level explanations enhance user trust and enable the implementation of AI solutions in practical energy management scenarios, whereas accurate forecasting can aid in proactive energy planning. In the context of smart buildings and energy-intensive systems, this is especially crucial since actions taken can directly impact on energy efficiency and environmental effects. Overall, the results support the applicability of XAI as a linkage between the performance of machine learning and the sustainable decision-making process. The proposed framework is transparent, flexible and will assist energy managers in understanding the drivers of energy consumption, improving the efficiency of their energy use, and moving toward more sustainable energy use.

7. CONCLUSION

There are some limitations in the traditional energy management methods based on Artificial Intelligence (AI). In this regard this study proposed an Explainable Artificial Intelligence Framework for Sustainable Energy Management and Data-Driven Decision Making to address these challenges. Machine learning models have demonstrated to be effective in predicting energy consumption patterns, but this effectiveness comes with a trade-off: the models are not very interpretable, particularly in the context of sustainability-related applications where decision makers demand clear understanding and justification of the outputs generated by AI. Therefore, the aim of this study was to develop an integrated framework combining energy insights from predictive analytics with energy insights from explainable AI techniques that are accurate and transparent and can be executed. The proposed framework has been designed in the experimental environment that would be used in Python and validated using 3 machine learning models: Random Forest, XGBoost, Artificial Neural Network. A dataset of energy consumption was used to train and test the models, which included energy consumption parameters such as environmental and operational parameters. From the experimental results, it can be concluded that the models investigated achieved a good level of prediction performance, with XGBoost achieving the highest overall prediction performance, due to its capacity to model more complex nonlinear relationships found in energy data. However, the study highlights that accuracy in predicting energy consumption is not enough in order to manage sustainable energy; there is a need to understand the factors influencing the energy management decisions in practical applications. To overcome this drawback, Explainable Artificial Intelligence (XAI) methods were incorporated into the proposed framework, such as SHAP and LIME. The explainability analysis provided information to the importance of different features in predicting energy consumption. The results highlighted the importance of the environment and the operation for the energy demand profile, making it possible to look for opportunities of optimization and plan more efficient energy efficiency strategies. The novelty of this work is in developing a single approach that integrates energy consumption forecasting, model interpretation, and sustainable decision support with AI-XAI. The proposed framework is different from the common black-box prediction model, because besides giving a better transparency of the model it would also boost the trust of the users and help in decision making for optimizing the energy. The framework will be further developed in future research, with the inclusion of real-time energy monitoring systems, renewable input data, advanced deep learning architectures, and adaptive optimization strategies. These enhancements can increase the capacity of explainable AI systems to aid in large-scale smart energy management and sustainable development goals.

Funding:

The authors did not receive any financial support, grants, or sponsorships from public, private, or not-for-profit sectors. This study was self-financed.

Conflicts of Interest:

The authors declare no conflicts of interest with the research presented.

Acknowledgment:

The authors appreciate their institutions' encouragement, advice, and provision of essential resources to facilitate this study.

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