International Journal of Advanced and Applied Sciences, 11(5) 2024, Pages: 230-248

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Enhancing smart grid electricity prediction with the fusion of intelligent modeling and XAI integration

Jamshaid Iqbal Janjua [1, 2], Reyaz Ahmad [3], Sagheer Abbas [4], Abdul Salam Mohammed [3], Muhammad Saleem Khan [1], Ali Daud [5], Tahir Abbas [6], Muhammad Adnan Khan [7, 8, 9, *]

[1]*School of Computer Science, National College of Business Administration and Economics, Lahore, Pakistan*
[2]*Al-Khawarizmi Institute of Computer Science (KICS), University of Engineering and Technology, Lahore, Pakistan*
[3]*Department of General Education, Skyline University College, University City Sharjah, Sharjah, United Arab Emirates*
[4]*Department of Computer Science, Bahria University, Lahore, Pakistan*
[5]*Faculty of Resilience, Rabdan Academy, Abu Dhabi, United Arab Emirates*
[6]*Department of Computer Science, TIMES Institute, Multan, Pakistan*
[7]*School of Computing, Skyline University College, University City Sharjah, Sharjah, United Arab Emirates*
[8]*Riphah School of Computing and Innovation, Faculty of Computing, Riphah International University, Lahore, Pakistan*
[9]*Department of Software, Faculty of Artificial Intelligence and Software, Gachon University, Seongnam, South Korea*

A R T I C L E I N F O

Article history:
Received 4 January 2024
Received in revised form
13 May 2024
Accepted 16 May 2024

Keywords:
Smart cities
Machine learning
Energy forecasting
Explainable artificial intelligence
Residential energy conservation

A B S T R A C T

This study examines the vital role of accurate load forecasting in the energy planning of smart cities. It introduces a hybrid approach that uses machine learning (ML) to forecast electricity usage in homes, improving accuracy through the extraction of correlated features. The accuracy of predictions is assessed using loss functions and the root mean square error (RMSE). In response to increasing interest in explainable artificial intelligence (XAI), this paper proposes a framework for predicting energy consumption in smart homes. This user-friendly approach helps users understand their energy consumption patterns by employing shapley additive explanations (SHAP) techniques to provide clear explanations. The research uses gradient boosting and long short-term memory neural networks to forecast energy usage. In the context of sustainable urban development, it emphasizes the importance of conserving energy in homes. The paper explores AI and ML methods for predicting residential energy use, aiming to make socially meaningful impacts. It highlights the need to understand the factors affecting predictions to improve the accountability, reliability, and justification of decisions in energy optimization. Explainable AI techniques are used to gain insights into the prediction models and identify factors influencing household energy consumption. This research aids in decision-making processes related to electricity forecasting, advancing discussions on intelligent decision-making in power management, especially in smart grids and sustainable urban development.

1. Introduction

In recent years, there has been a visible surge in the degree of attention surrounding the application of machine learning (ML) models in the domain of energy consumption prediction. The primary goal of this study is to enhance the level of awareness among smart home users regarding their prospective energy use (Kim and Cho, 2021; Zhang et al., 2021). Furthermore, these systems can predict the energy consumption of individual apparatuses. Nevertheless, the operational mechanisms of these prediction systems may appear enigmatic to consumers, who may possess limited comprehension of the fundamental decision-making processes at play. Consequently, individuals may exhibit a preference for objective justifications elucidating the rationale behind a certain decision implemented on their behalf by the system (Ehsan et al., 2021). Users may pose inquiries such as "What is the fundamental rationale behind the projected energy quantity?" or "What was the primary determinant taken into account when formulating this forecast?" What

* Corresponding Author.
Email Address: adnan@gachon.ac.kr (M. A. Khan)
https://doi.org/10.21833/ijaas.2024.05.025
Corresponding author's ORCID profile:
https://orcid.org/0000-0003-4854-9935

strategies can be employed to enhance energy efficiency?

The capacity of the system to offer detailed responses to such inquiries has the capacity to improve the confidence and transparency of AI models among end-users. Furthermore, in accordance with the provisions outlined in the General Data Protection Regulation, individuals who are citizens of the European Union have an inherent entitlement to receive appropriate notification regarding the decision-making processes employed by artificial intelligence (AI) models that are directly linked to them. In recent times, there has been a significant surge in focus on the examination and elucidation of intricate ML models (Crabbé and Van Der Schaar, 2021; Lundberg and Lee, 2017). The aforementioned motivation stems from the desire of AI practitioners and developers to enhance the effectiveness of these models. However, additional investigation is required to explore the methodologies by which explanations focused on human-centered perspectives might be developed in a manner that is comprehensible to those lacking expertise in AI theory and development. It is imperative to take into account the incorporation of varied user requirements across multiple domains in research related to user-centered design, given its inherent contextual nature. For instance, this study aims to investigate the strategies that can be employed to boost the clarity of explanations for users within a certain pragmatic framework and subsequently put these strategies into practice. In addition, the task of elucidating the prediction generated by a time series forecasting model presents difficulties due to the intricate interaction between the explanations and the corresponding temporal attributes and components (Crabbé and Van Der Schaar, 2021).

The active involvement of households in the development of sustainable smart cities holds paramount significance, given their substantial contributions to overall energy consumption within urban areas. The urban landscape grapples with the imperative task of efficiently addressing the energy needs of residences and diverse industries, all while navigating the constraints imposed by finite energy resources. Governments worldwide are proactively addressing these challenges by consistently working towards implementing legislation aimed at enhancing energy efficiency and promoting conservation in residential settings. Consequently, there arises a critical need to forecast the daily energy consumption patterns of households, facilitating the anticipation of energy requirements for the entire city. Although various ML models exist to forecast energy consumption, their inherent complexity often poses challenges in comprehension. The intricacies of these models, along with the rationale behind their specific predictions, remain elusive, contributing to a lack of transparency. Additionally, there is an ongoing struggle to fully comprehend how these models behave when employed in real-world data. The insufficient understanding of ML models among citizens may lead to skepticism regarding the credibility of the generated projections. Recognizing the pivotal role citizens play in energy optimization, it becomes imperative for them to possess a comprehensive understanding of the factors influencing domestic energy consumption. Recent trends reflect a growing inclination towards innovative approaches aimed at addressing these challenges. The overarching goal is to enhance model understandability and reduce complexity, with the primary objective being to improve comprehension of expected outcomes, benefiting homeowners, researchers, model developers, and professionals involved in the realm of smart cities (Masood et al., 2018; Badshah et al., 2023), ultimately striving for a thorough understanding of the internal dynamics of ML models while ensuring their integrity.

The utilization of AI has led to the advancement of improved methodology for ML algorithms and the incorporation of innovative ways for assessing Deep Learning (DL) in various sustainable smart city applications. In numerous instances, these methodologies have the potential to confer a competitive advantage by enhancing efficiency and accuracy while simultaneously reducing the occurrence of errors. In contemporary times, the conservation of energy for household purposes has emerged as a prominent subject of attention.

Accurately predicting power system load holds significant strategic value in efficiently managing the operational aspects of power systems within deregulated economies (Feinberg and Genethliou, 2005). This resource provides essential contextual information that is vital for making educated decisions in the management of electricity networks, particularly in the strategic planning of operational activities during normal electrical conditions. The capacity to produce resources in both low-demand and high-demand modes is contingent upon the dimensions and makeup of technical apparatus, which is determined by load forecasts. The anticipation of load power consumption is presently a noteworthy field of research within the electric power sector (Lin et al., 2021; Quan et al., 2014; Zueva et al., 2015). The main object of this work revolves around the analysis of short-term and operational graphs.

The aim of power consumption prediction involves analyzing many elements that influence variations in load, as well as forecasting future load patterns for power consumption. The primary components implicated in anticipation of electricity consumption by consumers encompass several factors: Active and reactive load schedules across various temporal intervals, encompassing daily, seasonal, and annual cycles; electricity usage as a time-varying variable; and the fundamental attributes of load curves during specific forthcoming periods.

The academic literature has extensively examined and analyzed the topic of Explainable Artificial Intelligence (XAI) (Gunning et al., 2019). Numerous techniques have been developed in the existing corpus of research to address the concept of XAI, particularly in relation to DL models (Adadi and Berrada, 2018; Das and Rad, 2020). However, the adoption of XAI techniques for forecasting daily household energy consumption and offering explanations regarding the factors influencing energy usage is not extensively widespread. The constrained availability of resources poses a challenge for individuals in their ability to identify and address these factors in order to optimize energy efficiency. The present work assembles a dataset that is primarily centered on the urban area of French households, encompassing many factors that can impact the energy consumption patterns of residential dwellings. Obtaining all attributes inside a single dataset may not be feasible in practice. However, the process of gathering relevant characteristics can be achieved by the integration of many interrelated databases. The prediction of daily energy consumption in residential buildings can be achieved by the application of several ML algorithms often used in this context. The utilization of various methodologies in the domain of XAI enables the examination of the inherent lack of transparency in a black-box model and facilitates the generation of coherent explanations. This elucidation facilitates the discernment of reasons accountable for energy consumption and enables the execution of viable remedies. The present study presents a novel approach utilizing a Gradient Boosting and Long Short-Term Memory (LSTM) model for the purpose of predicting home energy usage. Moreover, a strategic approach has been created to offer elucidations by integrating the LIME and SHAP (Lundberg and Lee, 2017) methodologies to enhance the comprehensibility of the forecasting process. The methodology used in this study clarifies the decision-making process by establishing a correlation between the time taken and the contributions of the features. The primary aims of our research are centered on delivering explanations that prioritize the human perspective, hence improving users' comprehension of the rationale behind certain choices connected to energy.

Smart cities utilize advanced technologies to amend the superiority of life for their residents through the promotion of sustainability, facilitation of economic growth, and enhancement of productivity. The aforementioned objectives are achieved through the utilization of intelligent technologies, which facilitate seamless movement, effective economic management, and enhanced quality of life. The proactive utilization of Information and Communication Technologies (ICTs) is implemented to gather data in order to monitor, assist, and improve various aspects of urban infrastructures. These domains comprise a wide range of areas, including, but not limited to, energy consumption, transportation networks, healthcare services, educational institutions, and environmental activities, specifically waste management.

Accurately predicting and effectively managing electricity use in residential areas are major challenges in smart urban environments. Efficiently controlling the power consumption of households can help in several ways, such as providing energy, managing power, and predicting electricity demand and load (Khemakhem et al., 2019).

The energy sector is currently engaged in the promotion and integration of Information and Communication Technologies (ICT) and ML techniques. This integration aims to develop intelligent urban grids that offer enhanced benefits in terms of electrical reliability, power delivery, communication security, efficient energy generation, and optimized energy usage. Our main focus revolves around the utilization of these methodologies within the context of power load forecasting regulations, which are relevant to communities involved in both energy generation and consumption.

The construction of prediction models in contemporary times is significantly dependent on the usage of statistical analysis and time series modeling (Lin et al., 2021; Quan et al., 2014; Firsova et al., 2019). The electricity consumption of a specific system can be characterized by a time series, which denotes the instantaneous power consumption at discrete time intervals. These models exhibit a significant level of efficacy in addressing various challenges related to forecasting techniques within the electric power sector.

The integration of smart grid technologies (Amjad et al., 2012) is a crucial component in the deployment of smart cities. The utilization of this technical implementation facilitates the collection and analysis of large quantities of data obtained from the field. The proliferation and advancement of smart meters in smart urban settings have led to the implementation of several advanced metering techniques. The efficacy of these approaches relies on the utilization of mechanisms that facilitate the collection and transmission of data to centralized systems through residential gateways. The primary goal is to enhance the efficiency of power system management. This encompasses both the elements of power generation and power consumption. The assessment of economic benefits is based on an examination of the relationship between environmental limitations and relevant data. The progress of decision-making systems forms the fundamental basis for accurately predicting load demand in power markets and effectively managing power resources.

In the domain of electrical load forecasting, a considerable number of prediction algorithms integrate time series analysis with statistical approaches. There exist various forecasting approaches that place emphasis on the crucial aspect known as load variations. Furthermore, methodologies exist that take load variations into account as a stochastic phenomenon. However, effectively replicating the operation is a considerable problem owing to the intricate and non-linear correlation between the load and its various dependent components. Furthermore, it is imperative to acknowledge that current approaches to forecasting electrical load are inadequate in effectively handling data that is characterized by noise or incompleteness despite the frequent need to work with such data in real-world scenarios. Hence, the enhancement of electrical load prediction efficacy can be achieved through the incorporation of novel concepts and methodologies that combine many data sources, hence improving the handling of imprecise and incomplete input data.

In the field of time series analysis, the subsequent elements are commonly utilized:

- A trend is a phenomenon characterized by a gradual and continuous change, which reflects the impact of persistent variables over an extended duration.
- The seasonal component refers to the recurring patterns observed in the analyzed phenomenon.
- The random component refers to a constituent that demonstrates the impact of stochastic factors.

The characterization of the variability in the behavior of electrical loads often involves the identification of repetitive patterns. This enables the development and use of physical and mathematical models that effectively characterize the electrical load of different types of electrical equipment. The classification of load prediction can be categorized into three unique classes based on the time period, as mentioned by Yildiz et al. (2017). Durations can be classified into three discrete temporal intervals: Short-term, medium-term, and long-term. The temporal range of short-term duration spans from a few seconds to a few days, whereas the temporal range of medium-term length encompasses a period extending from a few days to a few months. Ultimately, the extended temporal span varies from a few months to many years.

The term "short-term load forecast" refers to the estimation of the anticipated electrical demand in the near future for specific sections or the entire network within the domain of electricity demand (Firsova et al., 2019; Ma, 2022). Within a limited time frame, often ranging from 1 to 24 hours, it is widely recognized that durations falling within this range are classified as short-term. However, there exist certain instances when a time span of 48 hours may also be categorized as short-term. Short-term load forecasting is a frequently employed method for forecasting network demand in a practical setting. The utilization of short-term load forecast can be employed to address the subsequent tasks (Quan et al., 2014; Firsova et al., 2019):

- There is an imperative to augment the level of support for energy trading.
- Market activity refers to the process of determining the price of electricity within a particular market.
- The present goal is to optimize a network.
- The topic under investigation concerns demand regulation.
- The task at hand pertains to the prediction of the maximum level of demand.
- Demand management is a strategic approach employed by businesses to effectively manage and govern the demand for their products or services.
- The areas of concentration involve load balancing and overload protection.
- The procedure of discerning defects and irregularities.
- The phenomenon of peak reduction, also known as alignment, is observed.

Short-term projection models predominantly depend on recent data pertaining to energy use, typically including the most recent day or week. The projected temperature serves as the primary forecasting factor. Currently, the process of obtaining precise temperature predictions for both short-term (i.e., hourly) and medium-term (i.e., daily) intervals does not pose significant challenges. The observed patterns exhibit a reduced level of responsiveness to both seasonal fluctuations and long-term consumption trends.

In the context of short-term forecasts, it is common practice to generate a substantial number of prediction calls, referred to as service requests, at regular intervals, typically on an hourly basis or even more frequently in certain instances. Furthermore, it is well acknowledged that implementing methods often include representing specific families or transformers as autonomous models. Subsequently, there has been a substantial rise in the quantity of requests for forecasts.

The prediction of electricity consumption often entails the application of established statistical methodologies, including auto-regression, seasonal curves, component analysis, and other relevant approaches (Quan et al., 2014; Zueva et al., 2015; Firsova et al., 2019; Ma, 2022).

When utilizing statistical approaches, it is possible to identify multiple stages within the process of prediction. The procedure has a series of distinct stages that encompass a number of crucial steps. The initial step in obtaining statistical information involves the collection of data from a dataset via a sampling methodology. Subsequently, the data undergoes standardization in order to guarantee uniformity and facilitate comparability. Subsequently, the data is categorized according to its structural characteristics. The subsequent examination of the dynamics of the process is conducted in order to acquire valuable insights and enhance comprehension. A suitable period of retrospection is chosen in order to enhance the precision of the study. The data is further processed to minimize interference and improve comprehensibility. Ultimately, additional data is integrated to enhance the dependability and resilience of the model. The construction of the Residential Power Load Prediction Machine (RPLPM) model involves the utilization of ML methodologies, namely the implementation of the gradient boosting regressor, multivariate linear regression (MLR), and LSTM techniques. The proposed predictive model objectives are to improve prediction accuracy through the use of training data.

2. Literature survey

The discipline of assessing data to enhance comprehension of energy usage in residential constructions has been increasingly embraced by academicians. In recent years, there has been a notable enhance in the utilization of regressive models for the goal of predicting short-term residential load consumption. This is accomplished by utilizing the available data.

The purpose of this section is also to provide a comprehensive review of the remaining literature on the topic at hand. By examining and analyzing previous research, this review aims to identify gaps in knowledge and highlight key findings, and considerable scholarly focus has been devoted to the prediction of home energy consumption, mostly driven by the rapid advancements in sustainable smart city technology and the related services it provides. A considerable number of recent academic publications have focused on ML techniques aimed at estimating energy use and offering opportunities for improvement. The study's authors utilized data pertaining to the structural attributes and technological elements of buildings. The researchers successfully trained multilayer perceptron (MLP) and support vector regression (SVR) models to estimate the cooling and heating requirements in residential buildings. This accomplishment was attained within the context of the fourth experiment, as evidenced by Moradzadeh et al. (2020). The essay presented a forecasting technique consisting of two stages (Wang et al., 2010). In the initial phase, conventional methods of time forecasting were employed to generate day-ahead load forecasts. Subsequently, support vector machines (SVM), linear regression, and quadratic models were employed to enhance the precision of the predictions. The mathematical models for backpropagation neural networks and Elman neural networks were created by Zheng et al. (2020) to address the time-dependent characteristics of energy consumption data. The implemented models utilized reduced learning rates, decreased number of layers, and internal state storage. Nonetheless, an important constraint of ML models lies in their inherent lack of transparency.

Currently, a range of approaches are employed to determine the correlation between input factors and their respective output projections. There are four primary group classifications that can be distinguished (Yildiz et al., 2017). The study will utilize statistical approaches, including Auto Regressive Integrated Moving Average (ARIMA), k-nearest neighbor models (KNM), and Multiple linear regression (MLR). There are several ML approaches available for the purpose of regression tasks. The technique of SVR has been proposed in previous studies (Jain et al., 2014; Paudel et al., 2015). Another technique that can be employed is the Decision Tree (DT) (Yu et al., 2010). The algorithm described can be further developed to construct the Random Forest (RF), which is a compilation of decision trees that can be utilized for both classification and regression tasks (Westphal and Lamberts, 2007). In addition, Artificial Neural Networks (ANN) (Karatasou et al., 2006; Tso and Yau, 2007; Westphal and Lamberts, 2007) constitute a set of strategies that can be utilized. Various ANN architectures have been developed, such as feed-forward neural networks (FFNN), multilayer perceptron (MLP), and LSTM.

LSTM is utilized in many applications, such as smart grids, industrial environments, and home energy management systems. LSTMs have demonstrated their capacity to capture both diurnal and seasonal patterns, rendering them versatile for various load forecasting scenarios. Although LSTM models have achieved notable success in Short-Term Load Forecasting (STLF), there are still existing difficulties that need to be addressed. The issue of model interpretability continues to be a concern, particularly in situations where transparency is essential for making informed decisions. Furthermore, the optimal performance of the LSTM model necessitates meticulous consideration of hyperparameter selection, input feature choice, and outlier handling.

The research reviewed suggests an increasing inclination toward employing LSTM for short-term load prediction in the power industry. LSTMs provide the capability to effectively capture complex temporal relationships, handle nonlinearity, and may be combined with other techniques (Yang et al., 2024; Lotfipoor et al., 2024), making them a highly promising option for addressing the issues in STLF. As progress continues, additional investigation is required to enhance techniques, tackle difficulties in interpretability, and investigate innovative methods to enhance the precision and dependability of short-term load projections utilizing LSTM networks.

Presently, researchers are devoting their attention to examining several approaches to XAI that demonstrate extensive applicability in the domain of intelligent urban environments. The utilization of XAI methodologies, such as Shapley Additive Explanations (SHAP), enables the examination of long-term prediction models to assess the potential impacts of climate change on the energy consumption associated with building cooling (Chakraborty et al., 2021). Wenninger et al. (2022) investigated the yearly projections of building energy efficiency using a predictive model that operates over an extended period. In this study, the authors employ an additional methodology based on XAI, as described by Fan et al. (2019), to estimate the energy efficiency of a building. This is achieved by implementing a short-term predictive model. However, the system's performance is subpar in the presence of trust matrices. The study conducted by Yoo and Ko (2020) employed a recurrent neural network (RNN) model that incorporated feature importance and an attention mechanism to forecast residential energy consumption. Prior studies have utilized an encoder-decoder architecture comprising an LSTM sequence and a self-attention mechanism to make short-term forecasts regarding the energy usage of buildings (Gao and Ruan, 2021; Li et al., 2021; Miller, 2019). The model description provided by Tiwari et al. (2022) also includes the prediction of load demand for households. The categorization of buildings based on their usage patterns is achieved through the utilization of ML classifiers and the examination of correlations among their attributes, as outlined by Pandey et al. (2022). Many research studies often overlook the potential impact of several factors, such as weather conditions, social dynamics, and environmental components, on energy use. The ability to interpret these variables presents homeowners with the potential to enhance energy optimization by employing appropriate procedures grounded in valid criteria. In the present setting, it is crucial to possess a thorough comprehension of several XAI methodologies that can potentially enable the provision of explanations in predicting residential energy usage.

2.1. XAI methods

This paper aims to discuss several methodologies employed in the field of XAI as they offer a framework for effectively conveying the connections within a model and discerning the fundamental components that contribute to the generated outcomes. Further investigation is required in the field of residential energy usage in order to enhance transparency and provide a more thorough assessment of efficiency. There are multiple approaches within the domain of XAI that can be utilized to identify the fundamental input properties. In the field of methods, it is noteworthy to emphasize two significant approaches referred to as LIME and SHAP. The utilization of the Local Interpretable Model-agnostic Explanations (LIME) method is prevalent in the field of ML to provide explanations for the predictions made by complex models.

Local interpretable model agnostic explanations (LIME), suggested by Ribeiro et al. (2016), is a technique that is not dependent on any specific model. In the current context, the term "local" is utilized to denote the specific extent or scale of the model being examined. This suggests that the Lime technique is employed to elucidate a particular instance or entry rather than providing an explanation for the entire dataset as a whole. The LIME algorithm generates interpretable representations that are comprehensible to human users. The incorporation of explanatory components within the model is essential for enhancing its interpretative capability. The methodology has the capability to operate on black box models, making it suitable for generating explanations that are independent of the specific model being used. The algorithm discussed above plays a vital role in elucidating the operational mechanics of many AI models. LIME is an abbreviation that represents a mathematical optimization problem. The aim of this technology is to provide a localized calculation of the complicated model (f) for a specific input (x).

SHAP is a method used in the field of ML to present explanations for distinctive estimates made by black-box models. The methodology proposed in the study conducted by Lundberg and Lee (2017) presents a framework that is not limited to any single model. Its primary objective is to provide visual explanations for ML algorithms. The conceptual basis of this notion is rooted in the fundamental principles of game theory. The Shapley value is utilized to ascertain and elucidate the incremental contribution of each participant within the system.

The variable f is employed as a representation of the black box model, which is utilized to generate predictions. Conversely, the variable x is employed as a symbol to represent the input data point. The symbol z' is employed to represent the collection of attributes, while x' is utilized to signify the simplified data points. In the particular context of evaluating forecasts for residential energy usage, the SHAP technique is regarded as more appropriate for discerning and comprehending the distinct contributions made by each constituent.

3. Proposed methodology

This section provides a description of the dataset, as well as the methodology that is proposed for the forecasting of electricity use.

3.1. Dataset description

The dataset comprises a wide range of variables and observations, providing a comprehensive collection of data. The document offers a comprehensive overview of the collected data, facilitating a comprehensive examination and understanding of the material. The current investigation entails the examination of the dataset titled "Household Electric Power Consumption" acquired from reliable sources, including Kaggle and UCI. The dataset consists of multivariable time series data, largely focusing on the electricity consumption of a single household. The dataset encompasses a time span of four years, commencing in December 2006 and concluding in November 2010. The dataset has a grand total of 2,075,259 data readings, which were gathered at a sampling rate of one minute. The data was gathered from a residential dwelling situated close to Paris, France. The data regarding electricity use was gathered from a wide variety of household electrical equipment. Each column inside the dataset represents a distinct component of electricity consumption. In addition to the variables of date and time, there exist seven additional variables within the context of a multivariate series, which can be characterized as follows: The variable "global_active_power" represents the total amount of active power consumed by residential units, measured in kilowatts. The variable referred to as "global_reactive_power" measures the aggregate amount of reactive power consumed by residential units, measured in kilowatts. Voltage is formally defined as the average electrical potential difference measured in units of volts. The concept of "global intensity" refers to the average current intensity measured in amperes (A).

Sub-metering_1 is employed to measure the active energy consumption, which is indicated in watt-hours, of the electrical equipment located within the kitchen area. The concept of "sub-metering_2" refers to the measurement and quantification of active energy use, expressed in watt-hours, primarily for electrical equipment used in washing facilities. The concept of "sub-metering_3" refers to the measurement and quantification of active energy consumption, expressed in watt-hours. This measurement primarily focuses on the electrical appliances that are employed within the temperature control system.

3.2. Pre-processing

The pre-processing stage is an essential step in the analysis of data. The process involves the initial preparation of raw data in order to facilitate further analysis through various techniques, including but not limited to cleaning, converting, and organizing. The primary aim of this stage is to make the data pre-processing procedure encompass a sequence of operations that are necessary for addressing particular facets of the dataset. The dataset underwent an initial processing stage wherein the date and time variables were combined, employing the Python programming language. The application of this technology resulted in a significant benefit in the conversion of measurements from minutes to hours during a future phase, hence enhancing effectiveness. Furthermore, it was noted that the utilization of wireless data collecting resulted in the identification of a total of 25,979 values that were deemed invalid or missing. In certain instances of data, the '?' symbol is seen instead of numerical values. The incorporation of absent values inside the dataset is deemed unacceptable and should not be disregarded. Furthermore, the non-numeric values were substituted with the mean of the corresponding variables for the power load measurement from the preceding day. Ultimately, the dataset underwent resampling at an hourly interval, wherein the meter readings recorded at minute intervals were aggregated to derive a single representative value for each hour. The “fillna()” Python method was employed to achieve this objective, resulting in the creation of a sanitized dataset. The dataset underwent subsequent cleaning, recording, and indexing procedures based on date-time values to enhance its usability for subsequent analysis and research purposes.

3.3. System design

The topic being discussed refers to the domain of system design. The technique encompasses a series of procedures, and the comprehensive procedure of system design is depicted in Fig. 1. The methodology involves the selection of time-series parameters or columns from the dataset, the use of data re-sampling techniques, and the training of a model. The subsequent section provides a comprehensive explanation of the dataset.

The initial dataset was imported, and parameters or features derived from time-series data were acquired. The assessment was undertaken in order to ascertain the relative importance of each attribute as indicated by the time-series data. The dataset was subjected to resampling using time-series features that demonstrate a significant level of statistical significance. Subsequently, the dataset that underwent rigorous data cleaning and resampling procedures was employed to train the data model using three distinct approaches: MLR, linear regression, and gradient boosting regressor.

The training dataset consisted of the initial 80% of the data, while the remaining 20% was designated as the test dataset. The selection of the loss function was made based on an evaluation of the methodologies utilizing performance indicators, including mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). The application of the root mean square error (RMSE) is utilized to quantify the disparities between each predicted value and its matching observed value. In the realm of time-series data analysis, it is feasible to develop models that encompass both dependent and independent variables. The main aim of these models is to generate a linear equation that accurately represents the fundamental connection between these variables. The hypothesis posits the presence of a linear correlation concerning the variables x and y, whereby the value of y is contingent upon the value of x. The mathematical description of the equation is as follows: the variable 'd' represents the y-intercept, while the variable 'e' represents the weight allocated to the parameter x.

The equation can be expressed in the form of $y = d_0 + (d_0 . x)$, where y represents the dependent variable, d_0 is the initial value, and x signifies the independent variable. In the training phase of a regression-based model, several values of independent variables are utilized to evaluate the predictive capacity of the dependent variable. The model under consideration is frequently known as the MLR model. The dataset utilized for predicting home energy usage comprises the data attributes of submetering_1, submetering_2, and submetering_3.

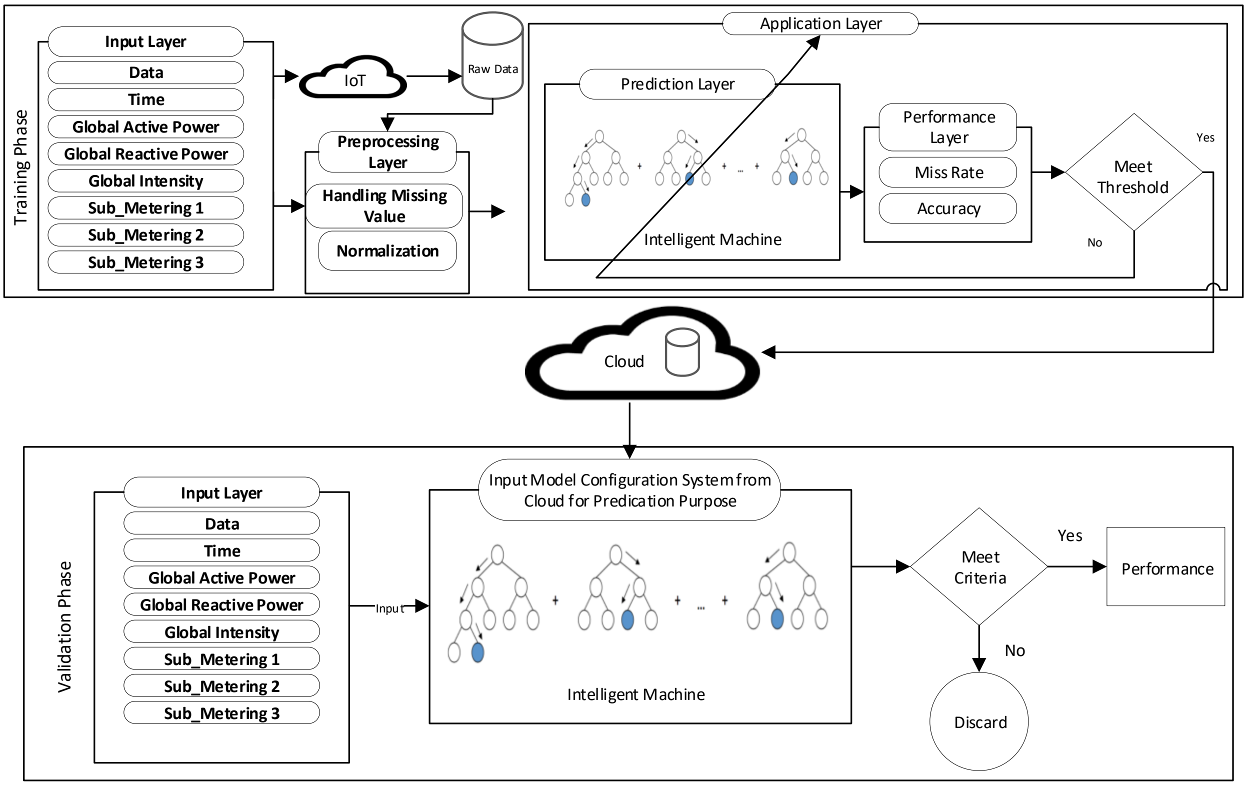


Fig. 1: Proposed model (RPLPM) of residential power consumption prediction in smart grids using gradient boosting, linear regression, and LSTM interchangeable machine

The equation governing MLR can be expressed in the following manner, and the equation can be expressed in the form of,

$$y = d_0 + e_1x_1 + e_2x_2 \dots + e_nx_n$$

The system configuration for electricity load forecasting can further be expressed as

$$E_{Load} = \beta_0 + \beta_1\lambda_1 + \beta_2\lambda_2 + \dots + \beta_n\lambda_n + \varepsilon$$

where, E_{Load} represents the electricity load, $\lambda_1, \lambda_2, \dots, \lambda_n$ are features, and $\beta_0, \beta_1, \beta_2, \dots, \beta_n$ are coefficients. During training, MLR aims to minimize the total sum of squared variances between predicted and actual values.

$$Minimize\ \sum_{i=1}^{N}\left(E_{Load_i} - (\beta_0 + \beta_1\lambda_{1i} + \beta_2\lambda_{2i} + \dots + \beta_n\lambda_{ni} + \varepsilon)\right)^2$$

where, ε is the error term. The coefficients are estimated using the least squares method.

Intelligent strategies include the amalgamation of multiple base classifiers in order to form a committee. The efficacy can be significantly enhanced in comparison to a classifier operating at its initial state (Bishop, 2006). The core principle underlying boosting is the iterative construction of new models, which are subsequently combined or ensemble. In a particular iteration, a recently produced and less powerful learner model is utilized for the purpose of training, taking into account the faults of all previously trained ensemble models. The procedure for generating a sequential model adheres to a methodology comparable to other boosting procedures and is also extended to facilitate the optimization of a differentiable loss technique (Bishop, 2006). The utilization gradient descent algorithm is employed to tackle the purpose of minimizing a specified objective function, leading to the development of a predictive model consisting of a set of weak predictive models represented by decision trees. Each successive forecast enhances the precision of its previous iteration by considering the residual error. The significance of the method lies in its usefulness for addressing issues in both the classification and regression domains (Bishop, 2006). Supervised learning methodologies are specifically designed to minimize a predetermined loss function by iteratively adjusting the parameters of the model. The MSE is commonly employed as a loss function in many applications. The fundamental goal of the model is to generate forecasts that minimize the MSE. The equation can be rephrased in a more scholarly manner as follows: The equation can be reformulated in a more scholarly fashion as follows:

$$y_i^p = y_i^p + a.\frac{\partial\sum(y_i - y_i^p)^2}{\partial y_i^p}$$

In the given framework, the symbol α is employed to denote the learning rate, whereas the term $\sum(y_i - y_i^p)$ signifies the summation of residuals. The model, denoted as RPLPM, is depicted in Fig. 1. The process is comprised of two distinct stages: The primary training stage and the subsequent validation stage. The methods described in this study report had three distinct tiers, specifically the input layer, the output layer, and a hidden layer. The utilization of extreme ML has facilitated the integration of backpropagation, a methodology that incorporates various techniques for error computation, including feedforward, weight initialization, and backpropagation itself. The subsequent step involves the adjustment of weight and bias settings. The hidden layer consists of multiple instances of regression trees, each equipped with an activation function denoted as $f(z)$, aiming to minimize the square loss. The incorporation of an extra regression tree model, denoted as "wl," into the existing model F results in an improved prediction, which may be expressed as the sum of $f(z)$ and $wl(z)$. The evaluation of model correctness is conducted using the "Miss rate" criterion and the RMSE statistic. The results imply that the gradient-boosting regressor reveals greater performance in contrast to the MLR model with regard to the training RMSE. The input layer and hidden layer of the proposed model can be characterized as having a gradient-based nature. Gradient Boosted Regression Trees (GBRT) regressors are a nonparametric regression method that employs input z_i to produce predictions y_i, according to the provided formulation.

The predicted value $\hat{y}_i$ can be represented as the multiplication of the function $F_M(z_i)$ with the sum of the weights $w_M(z_i)$ for m ranging from 1 to M. In the context of boosting frameworks, the term "wl_M" commonly represents weak learners, which are estimators. Gradient Boosting Regression Trees (GBRT) employ decision tree regressors as weak learners with a predetermined magnitude. The parameter "n-estimators" is associated with the constant "M." The refinement of system configuration utilizing Gradient Boosting optimizes electricity load forecasting by sequentially adding weak learners. The algorithm minimizes the negative gradient of a loss function, combining predictions of multiple decision trees. The iterative process updates the model:

$$E_{Load}F_m(X) = F_{m-1}(X) + \Upsilon_m h_m(X)$$

where, $E_{Load}F_m(X)$ is the final model, Υ_m is the optimal step size, and $h_m(X)$ is the weak learner. The goal is to minimize:

$$Minimize \sum_{i=1}^{N} L\left(y_i, E_{Load}F_{m-1}(X) + \Upsilon_m h_m(X_i)\right)$$

The final prediction is a weighted sum of individual tree predictions, ensuring accurate and robust electricity load forecasts.

LSTM networks, as part of recurrent neural networks (RNNs), capture temporal dependencies for electricity load forecasting. For each time step t, LSTM computes forget (G_t), input (I_t), and output (Y_t) gates, as well as cell states (S_t) and hidden states (H_t). The notations employed as A_t : Input at time t, D_t : Hidden state at time t, S_t: Cell state at time t, G_t, I_t, Y_t : Forget, input, and output gates at time t, W, U, B: Weight matrices and bias terms, ϕ: Sigmoid activation function and *tanh*: Hyperbolic tangent activation function. These are determined by the equations:

$$G_t = \emptyset(W_{forget} \cdot A_t + U_{forget} \cdot D_{t-1} + B_{forget})$$
$$I_t = \emptyset(W_{input} \cdot A_t + U_{input} \cdot D_{t-1} + B_{input})$$
$$\tilde{S}_t = tanh\,(W_{cell} \cdot A_t + U_{cell} \cdot D_{t-1} + B_{cell})$$
$$S_t = G_t \cdot S_{t-1} + I_t \cdot \tilde{S}_t$$
$$Y_t = \emptyset(W_{output} \cdot A_t + U_{output} \cdot D_{t-1} + B_{output})$$
$$D_t = O_t \cdot tanh\,(S_t)$$

LSTMs, trained using backpropagation through time, can capture sequential dependencies, enabling accurate and dynamic predictions of electricity consumption over time.

Blockchain technology is a method of storing data that makes it difficult to alter, hack, or cheat. When a transaction occurs on the blockchain, it is recorded in the ledgers of every participant in the network. Each device in the blockchain network has a copy of the blockchain's ledger.

In this research, blockchain technology over the cloud is integrated with intelligent machines to improve the accuracy of electricity prediction models. As shown in Fig. 1, the cloud is blockchain-enabled, and optimized model weights are stored in a secure environment.

Integrating ML models with blockchain technology involves using permissioned smart contracts to securely store and manage optimized weights of AI models used for electricity forecasting. This blockchain-based approach ensures reproducibility and technical rigor by providing a tamper-proof ledger of model configurations. The secure storage of weight configurations on the blockchain facilitates validation processes and allows seamless integration with other systems, enhancing the reliability of electricity forecasting in smart grids.

3.4. Co-relational analysis

Co-relational analysis is a statistical tool utilized to examine the relationship between two or more variables. The analysis of correlations between variables in the energy usage dataset was conducted using the Python Pandas package. The aforementioned strategy is widely acknowledged as a prominent methodology for assessing correlations. The methodology utilized in this study entails the computation of pair wise correlations among all factors or traits encompassed within the dataset. The process establishes a linear relationship between variables within a dataset and computes the correlation coefficient to quantify the degree of interaction between two columns or parameters. The coefficient demonstrates a range of values from 1 to -1 on a unitary scale. A value of 1 indicates a complete correlation between a parameter and itself, demonstrating a strong positive relationship. Conversely, a correlation value approaching zero suggests a diminished association.

However, the existence of a number representing unity, irrespective of its polarity, indicates a more pronounced positive or negative relationship between two columns or parameters within the dataset. Fig. 2 illustrates the relationship between energy use trends. The primary focus of prediction lies in the variable of global_active_power. The analysis of the correlation between these metrics and other variables enables the conclusion that a negative correlation is present with voltage. A significant correlation exists between the global active power and the individual sub-meters. Moreover, a study inquiry was undertaken utilizing a system of daily data re-sampling granularity, as depicted in Fig. 3. A negative correlation has been established between the unutilized energy, namely the global reactive power, and the global active power. In prospective studies, it is recommended to control for the variables of voltage and global reactive power while developing predictions for global active power. The input parameters will provide the current time in hours, but the output parameter will denote the global_active_power.

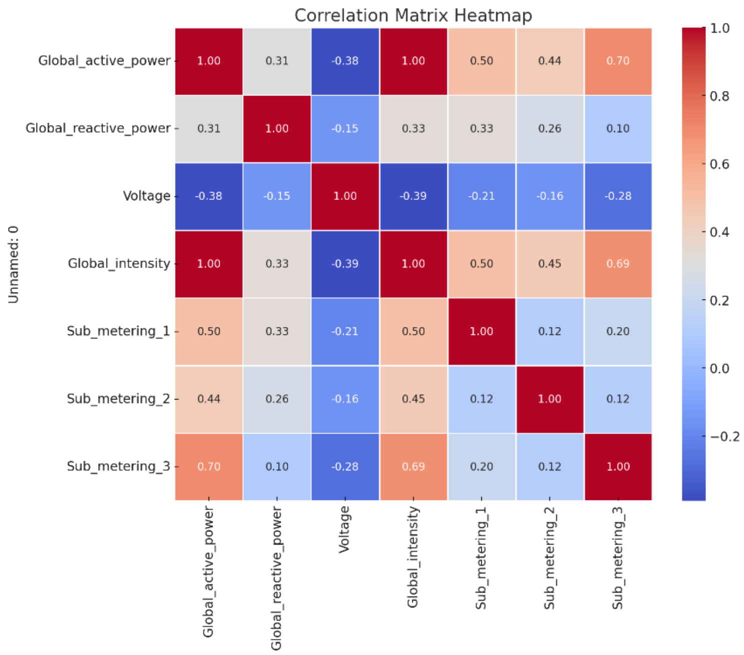


Fig. 2: Energy parameter correlation matrix at hourly intervals

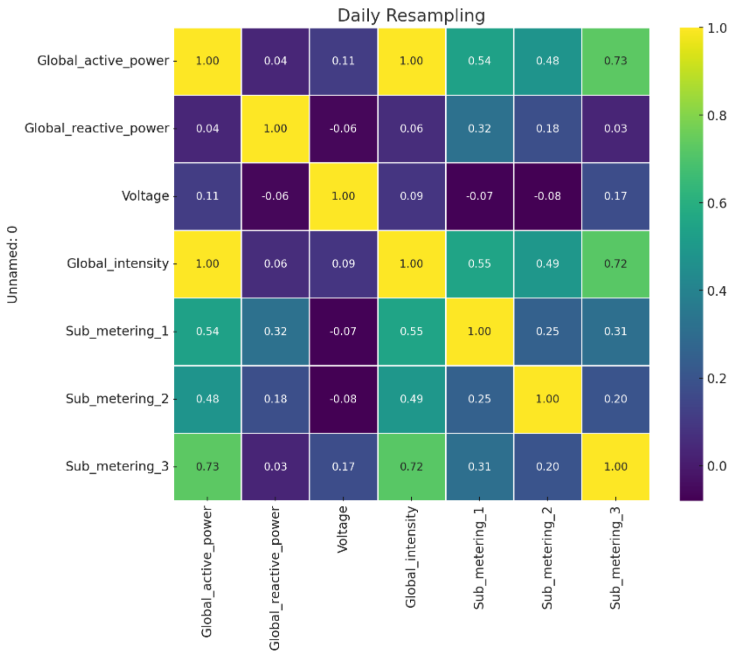


Fig. 3: Energy parameter correlation matrix at daily intervals

3.5. Exploratory data analysis

Exploratory data analysis (EDA) is a key methodology utilized in the fields of statistics and data science. The procedure involves performing an initial analysis and examination of a dataset to obtain insights and understand its fundamental characteristics.

The practice of EDA is a fundamental methodology employed to conduct preliminary investigations on a given dataset. This facilitates the utilization of preliminary data analysis to ascertain the core attributes, detect patterns, or find deviations present within the data. The comprehension of dataset properties can be achieved by analyzing temporal data patterns. The components of the dataset that have been analyzed are as follows. The identification of patterns within datasets is a fundamental method within the framework of EDA. The aforementioned tool serves as a visual aid that aids in the identification of significant patterns and the highlighting of variable characteristics within a specific dataset. Line charts were developed with the purpose of visually representing the attributes of a given dataset. Multiple methodologies were employed to achieve the desired objective for the provided dataset. Fig. 4 illustrates the dataset that has been provided to represent the whole set of meter measurements, which have been subjected to resampling on a monthly basis. The graphical representation depicts the monthly energy use over a span of four years, where each data point corresponds to a 48-month timeframe. There is a notable discrepancy in energy consumption throughout several months. The analysis of energy consumption patterns across many months can provide useful insights into understanding external influences, such as temperature swings. The winter months are distinguished by lower temperatures relative to the summer months, leading to an increased need for and utilization of air-conditioning systems in the summer season. The data was visually represented through a graph to illustrate the measurements in meters. These measurements were obtained through the iterative process of daily re-sampling. The presented picture encompasses a temporal duration of 1442 days.

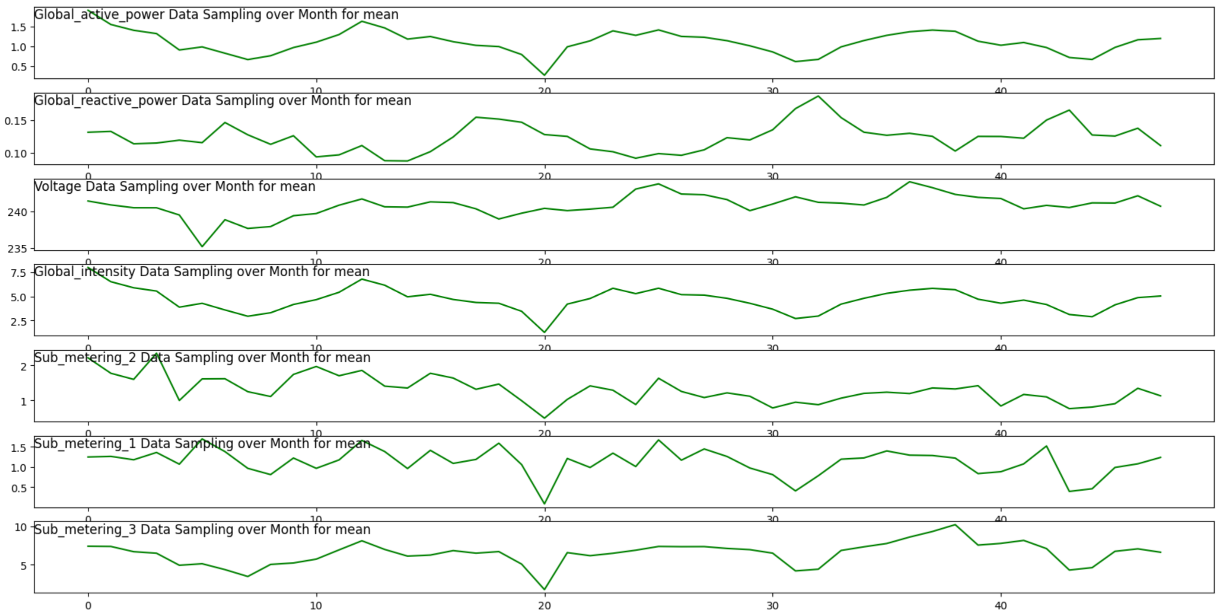


Fig. 4: Monthly-based data set features

Fig. 4 illustrates the fluctuation in energy consumption over a range of days during the month. The utilization of this visualization enables the analysis of trends within the characteristics of the dataset. Additional analysis can be conducted to examine the influence of both summer and winter seasons on the dataset. Moreover, it is noteworthy to notice that various variables present in the dataset have a less pronounced association with the primary variable of global active power. To accurately depict the measurements of meter data, the dataset illustrated in Fig. 5 was subjected to resampling at regular hourly intervals. The dataset, spanning the duration of four years, resulted in a cumulative total of 34,589 hours. The variable "sub_metering_3" exhibits a more pronounced correlation with "global_active_power," indicating its potential to effectively represent the energy consumption of climate control equipment used for air conditioning and heating during the documented period. The assessment of global reactive power involves the calculation of surplus power generated by a unused residential system. In order to enhance computational efficiency and expedite model testing, we implemented an hourly resampling technique, resulting in a reduction in the dataset size from 2,075,259 minutes to 34,589 hours.

A visual representation of the distribution of global active power consumption across distinct hours of the day is shown in Fig. 6. The horizontal axis (x-axis) is dedicated to the hours, delineating the various time intervals, while the vertical axis (y-axis) conveys the corresponding global active power consumption values. Through this visualization, we gain a comprehensive insight into the fluctuations and patterns in global active power consumption over the course of the day. Analyzing Fig. 7 allows for the identification of potential trends and variations in power usage, aiding in the interpretation of the underlying dataset and facilitating a more nuanced understanding of energy consumption patterns.

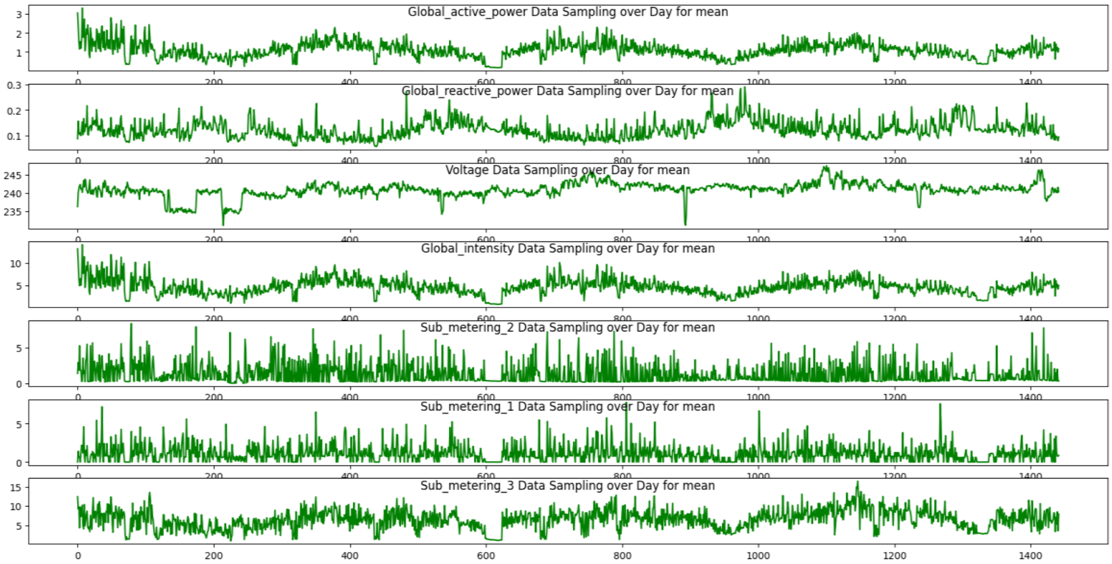


Fig. 5: Daily-based data set features

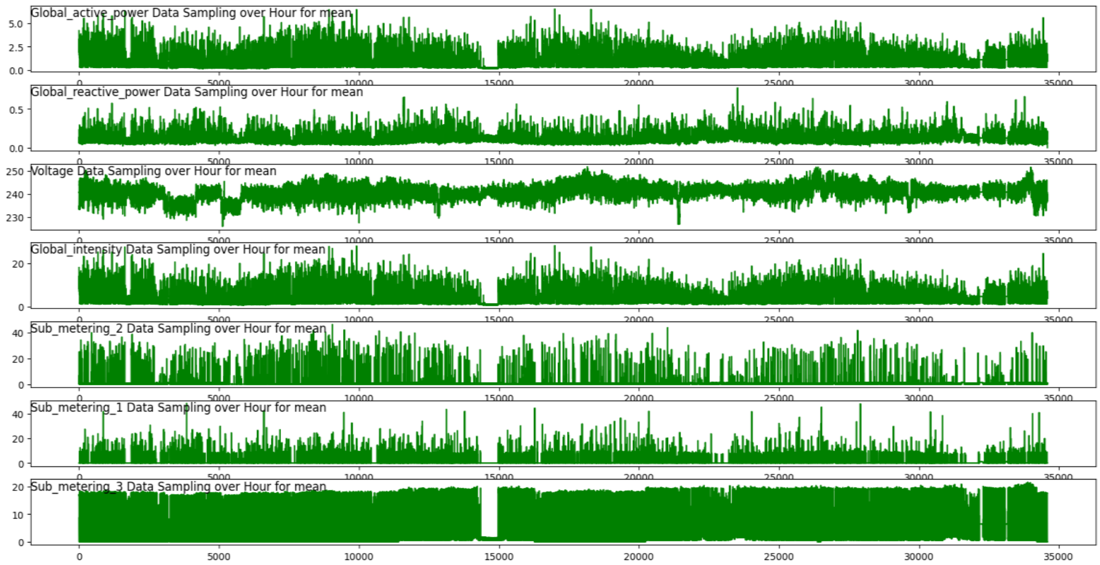


Fig. 6: Hourly-based data set features

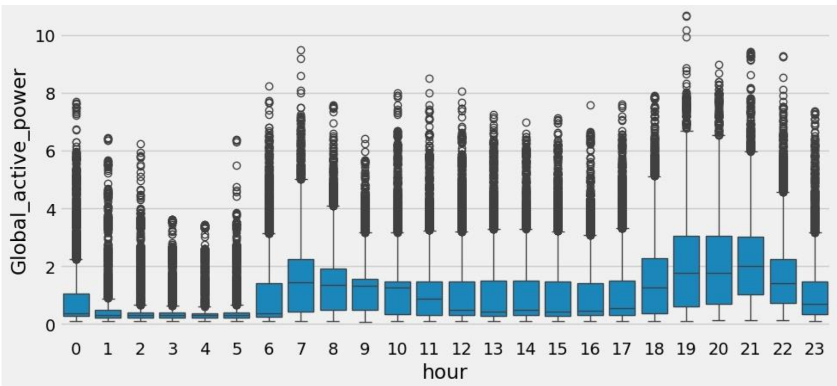


Fig. 7: Hourly power consumption

3.6. XAI integration

In order to offer a thorough comprehension of the decision-making mechanisms utilized by energy demand forecasting models for smart home users, our suggested methodology incorporates the integration of XAI and consists of three key components. The framework comprises three main components:

- A model for prediction and forecasting,
- A generator for reasoning and explanation, and
- An interface that facilitates collaboration and provides explanations to end-users in a manner that prioritizes human needs and preferences.

The fundamental components of the XAI integrated system are illustrated in Fig. 8. The primary component utilizes a pre-trained ML model to provide predictions and projections for forthcoming energy demands. The estimates presented in this study are derived from pre-processed measurements obtained from individual appliances. The following stage of the study involves an analysis of the underlying factors that influence the decision-making process and provides justifications for the anticipated conclusion, specifically about the forecasted energy consumption for the upcoming week. Moreover, our collaborative interface will offer and demonstrate explanations that prioritize human perspectives, aiming to enhance users' comprehension of the underlying rationales behind specific actions. The initial element of our system, referred to as the forecasting model, comprises a pair of LSTM layers or Gradient Boosting layers, for example, subsequently succeeded by a solitary completely linked layer.

A dense layer is employed to obtain estimations pertaining to the aggregate energy consumption of residential units. The model is trained using the Mean-Squared-Error (MSE) as the selected cost function, and the Adam optimizer is employed for this purpose. The researchers performed tests utilizing a publicly accessible benchmark dataset that specifically centers on the consumption of electric energy within residential families. The dataset was gathered over a span of 47 months, specifically from December 2006 to November 2010. The dataset comprises the aggregated global active power consumption of a residential unit measured in kilowatts. It also includes sub-metering readings for specific areas like the kitchen and laundry room, recorded at one-minute intervals. The term "submetering_1 data" pertains to the quantification of active power usage, specifically in the context of several domestic devices like a dishwasher, an oven, and a microwave. The total power consumption of the laundry room is comprised of various appliances, specifically a washing machine, a tumble-dryer, a refrigerator, and a light source. The term "submetering_2" is used to refer to a group of appliances. Furthermore, the measurement of power usage for both an electric water heater and an air-conditioner is denoted as submetering_3. The values are denoted in kilowatts. In order to do data pre-processing, it is crucial to recognize the presence of missing values and null values. The minimax algorithm is a widely employed decision-making approach in the fields of game theory and AI.

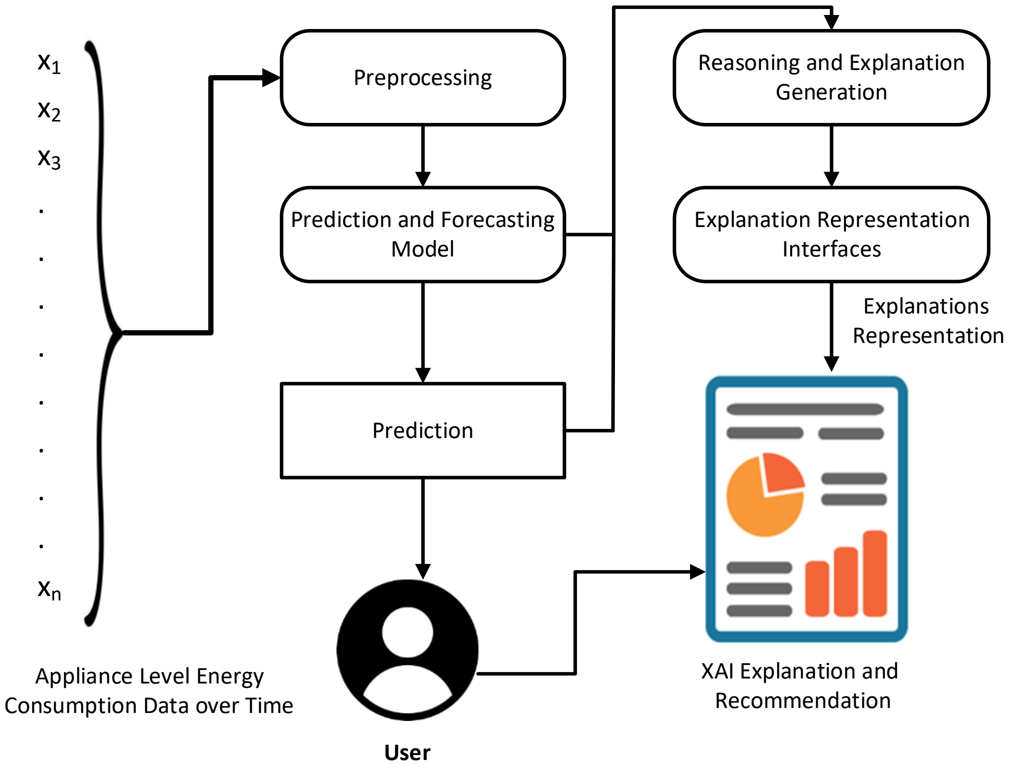
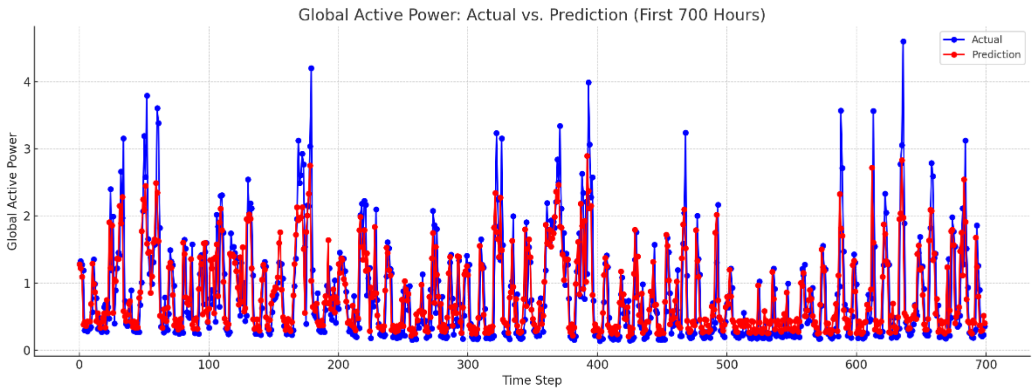


Fig. 8: Electricity load prediction system in smart grids integrated with XAI

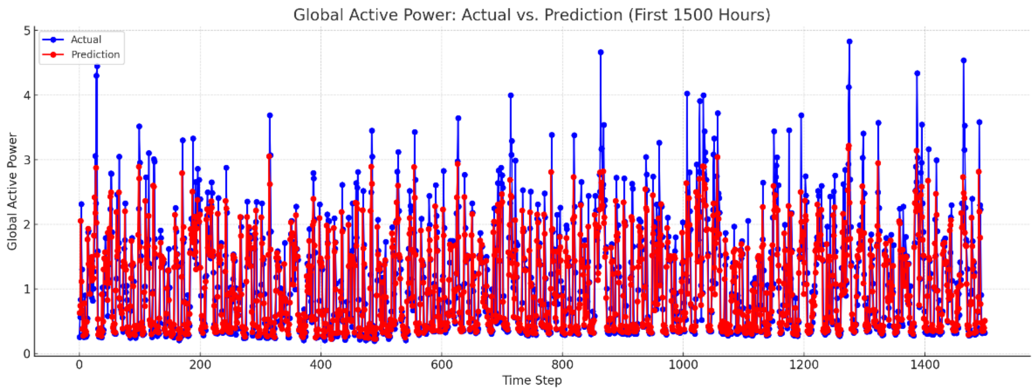
Normalization is a regularly employed data pre-processing technique that entails the adjustment of dataset values to conform to a specified range, typically [0, 4]. Subsequently, we modify the anticipated numerical value to a distinct magnitude in order to improve its visual depiction in its initial unit. In order to provide a clearer understanding of the projected energy usage, a combination of Local Interpretable Model Agnostic Explanations LIME and Shape Additive Explanation (SHAP) (Lundberg and Lee, 2017) methodologies was utilized. SHAP is a technique that is based on game-theoretic concepts. The LIME methodology is employed to estimate the SHAP values by dissecting the projected output of the model. The decomposition process is achieved through the back-propagation of the individual contributions of each neuron to all aspects. After doing a thorough examination of the data, it may be inferred that the acquired findings demonstrate statistical significance.

4. Results and discussion

This article presents a comprehensive analysis of the experimental findings, focusing on the evaluation of the efficacy of our prediction methodology in forecasting the performance of home load. The assessment is conducted using a dataset that has been expressly collected for the purpose of this research. The projected values for the dataset on residential power use are presented in Fig. 9(a). The prediction of global active power was conducted over the initial 700-hour period. The prediction was calculated for duration of 1500 hours, as depicted in Fig. 9(b), encompassing the time range from 22000 to 20500 hours. The data presented in Fig. 9(c) underwent a modification process, resulting in a revision of the initial estimate from 3000 hours to 7000 hours. The evident effectiveness of our prediction engine in producing high-quality forecast outcomes is notable.



(a)



(b)

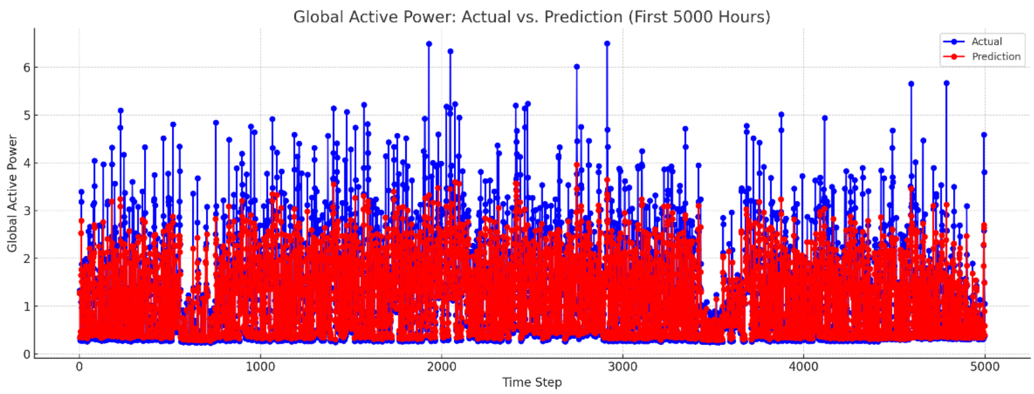


Fig. 9: Predictive results on household dataset with (a) 700 hours, (b) 1500 hours, and (c) 5000 hours

The anticipated values for global_active_power, which pertain to electricity consumption, are depicted in Fig. 10. These values have been derived using the MLR model. A discrepancy is evident between the anticipated values and the average of the linear graph.

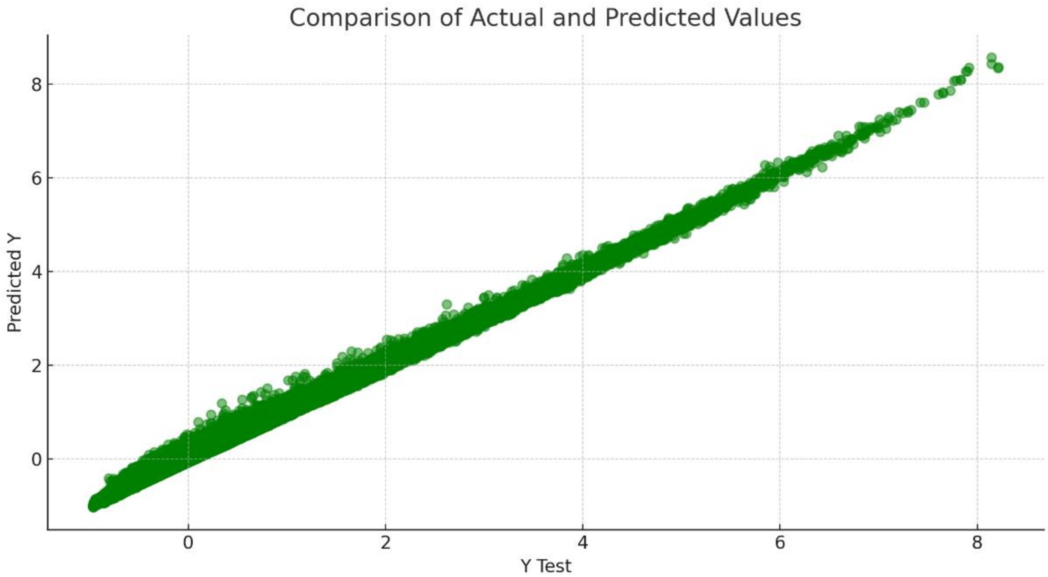


Fig. 10: Linear representation of GBR predictions on the dataset

Prediction outcomes are illustrated in Fig. 11 for global_active_power obtained by employing a gradient-boosting regressor. The extent to which the expected values align with the central axis of the linear line has a direct impact on the production of favorable outcomes by the proposed model. The accuracy of forecasting residential electricity usage is considered acceptable with respect to the amount of training data accessible.

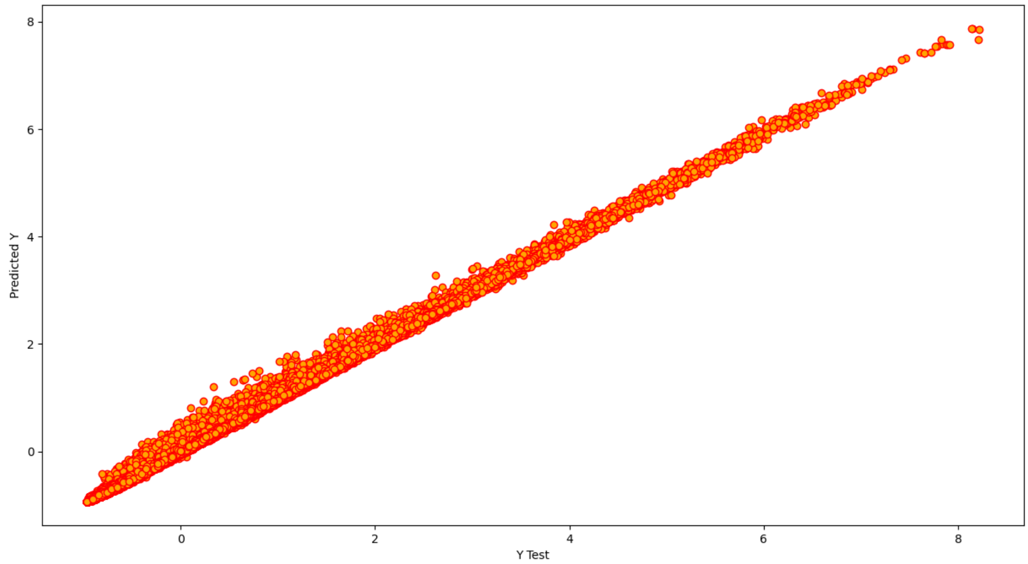


Fig. 11: Linear representation of LSTM predictions on the dataset

Table 1 presents all the results obtained from the experiment. The computations for the MAE, MSE, and RMSE were executed. The generated prediction values from models utilizing MLR and gradient boosting regressor were subjected to computational analysis. In order to enhance computational efficiency and expedite the generation of results, the dataset underwent resampling to a temporal resolution of one hour. When both models are applied to the same dataset, it can be observed that the gradient-boosting regressor model demonstrates superior accuracy compared to MLR.

Table 1: Performance metrics for implemented prediction methods

	RPLPM (MLR)	RPLPM (GBX)	RPLPM (LSTM)
MAE	0.0244	0.0222	0.0054
MSE	0.0015	0.0012	0.0020
RMSE	0.0386	0.0350	0.0079

Table 2 provides a comparison of performance metrics for electricity load prediction among different predictive models. The Root MSE is used as the evaluation metric. The RPLPM (GBX) model, implemented with a gradient boosting regressor, demonstrates superior performance with an MSE of 0.0012. In contrast, other models, including the CNN-LSTM Model, Conditional RBM Model, and LSTM

Model, exhibit higher MSE values of 0.2762, 0.7211, and 0.5420, respectively. A lower MSE indicates better predictive accuracy, highlighting the effectiveness of the RPLPM (GBX) model in comparison to the referenced predictive models.

Table 2: Performance metrics comparison with other predictive models

	RPLPM (GBX)	CNN-LSTM model (Hardas et al., 2024)	Cond. RBM model (Mocanu et al., 2016)	LSTM model (Wang et al., 2019)
MSE	0.0012	0.2762	0.7211	0.5420

To accurately forecast and assess patterns of household energy use and ascertain the determinants of such consumption, it is important to initially gather comprehensive data from multiple sources that possess the ability to impact a residence's energy utilization. The datasets have been subjected to pre-processing and structuring to enhance the efficacy of ML model training. The project involves the implementation of a training procedure utilizing specialized black box models. In order to enhance comprehension of the elements that influence energy consumption in residential environments, an interpretable AI method known as SHAP is employed. This methodology facilitates the identification of the fundamental factors contributing to energy consumption. In light of the aforementioned concerns, it is imperative to facilitate the empowerment of diverse stakeholders to foster the formulation of policies that prioritize the optimization of energy utilization.

The process of calculating the contribution importance score for each feature entails evaluating the disparity between the activation level of each neuron and its associated reference activation level. Following this, visualization techniques are employed to portray the unique contributions of individual attributes across a specified timeframe for a particular projected choice. This study examined a range of sub-metering data as potential variables.

The assessment of the model's predictive performance is carried out by employing two measures, namely Root-Mean-Squared Error (RMSE) and Mean Absolute Error (MAE), which yield values of 0.07 and 0.05, respectively. The evaluation of the performance's effectiveness is conducted through a comparative analysis with the performance achieved by Kim and Cho (2021) on the identical dataset. The primary objective of this study is to elucidate the anticipated outcomes pertaining to energy usage. The visual representation of the explanation can be observed in Fig. 12 and Fig. 13, which employs an area plot. The graphic clearly illustrates the relative impacts of multiple variables, particularly the energy use in different areas of the household. The main aim of our graphic is to illustrate the relative contributions made by various regions of the house in terms of historical energy use. The analysis of the visual depiction suggests that the Sub_metering_3 variable exerted a significant influence on the total calculation of energy use. The concept of "Sub_metering_3" refers to the practise of quantifying and monitoring the energy consumption of individual entities inside a larger system.

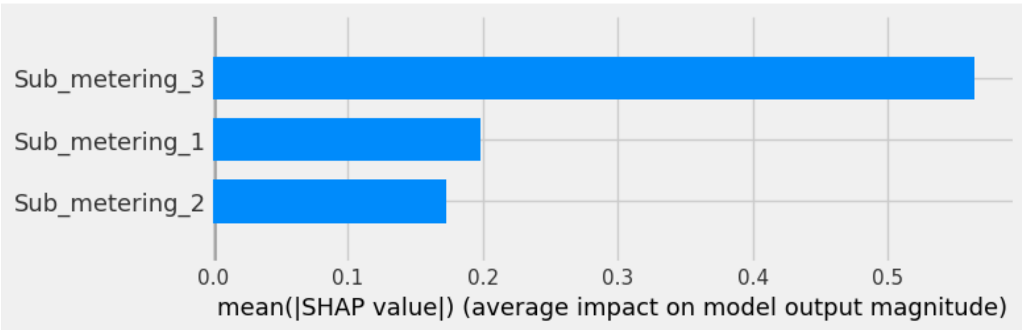


Fig. 12: EAI explanations bar plot electricity utilization by a different area to overall load prediction system integrated with XAI

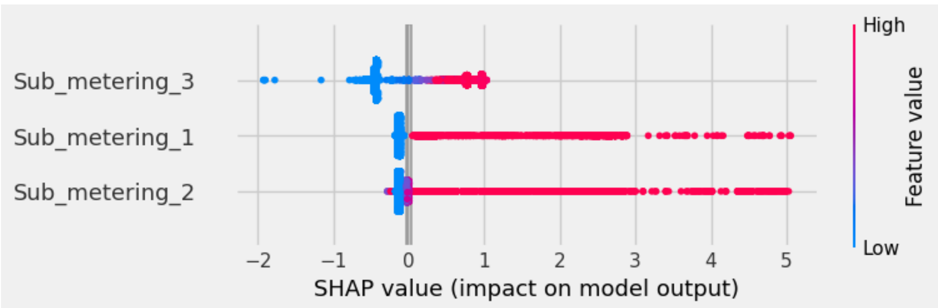


Fig. 13: EAI explanations beeswarm plot for importance score of electricity utilization by different areas to overall load prediction system in smart grids integrated with XAI

The air conditioner and water heater are regarded as essential household appliances. The effects of the Sub_metering_3 contribution commenced with the highest impact. The provided image also depicts the impact of supplementary characteristics over a span of time. The purpose of these explanations is to increase household members' awareness of their energy use patterns. Furthermore, the achievement of trust and transparency in AI models can be accomplished by the usage of the aforementioned reasoning processes.

Replacing internal factors such as Sub_metering_1, Sub_metering_2, and Sub_metering_3 with external factors like weather conditions, pressure, cloud cover, and user behavior, or vice versa, enables a more comprehensive analysis of the variables impacting global active power consumption. By treating both internal and external factors uniformly in the technological treatment, the goal is to reveal meaningful insights into their correlations and relative importance. This approach, whether it involves replacing internal factors with external ones or vice versa, not only enhances the transparency of predictions but also contributes to responsible AI modeling. Understanding the intricate interplay between both sets of variables can lead to more accurate and interpretable predictions, fostering trust in the model's outcomes. Adopting a unified methodology for analyzing and incorporating these factors, the research creates a more holistic and reliable framework for forecasting electricity usage in smart grids.

5. Conclusions

The present investigation encompassed the creation and execution of a residential power load prediction system. The introduction of the RPLPM model was aimed at achieving this objective by employing ML approaches. The application of feature extraction and associated feature selection techniques in predictive modeling has demonstrated a significant decrease in computing time. The utilization of training data greatly improves the accuracy of predictions and significantly raises the efficiency of the system, hence facilitating the development of a high-quality predictive model. The most favorable outcomes are observed when the data is resampled at an hourly frequency. The superior performance of the gradient-boosting regressor over MLR is evidenced by the lower RMSE attained during the training phase. Nevertheless, our contention is that GBR should not be considered a viable option for MLR. However, it is crucial to recognize that the simultaneous utilization of GBR, LSTM, and MLR can be employed to attain a harmonious equilibrium between time and accuracy. The research further investigates the concept of sustainable smart cities and its relationship with ML and XAI. Our main focus revolves around the application of SHAP approaches to enhance the interpretability of ML models in the context of sustainable smart cities. This paper presents a comprehensive examination of current research endeavors focused on exploring the difficulties associated with developing a transparent and human-centered system that can predict and forecast energy consumption in smart homes. The ultimate goal of this research is to bring advantages to the broader user community. A novel methodology has been suggested for the production of explanations, which combines the methodologies of LIME and Shapely Additive Explanations. The aim of this technique is to offer coherent and comprehensible explanations that enhance the comprehension of predictions produced by a forecasting model employing LSTM. There is a theory suggesting that the incorporation of a user-centered prototyping technique, along with a variety of explanatory visualizations, could potentially improve the understanding of the distinct user requirements within the energy sector. The interchangeability of internal and external factors is pivotal for gaining an understanding of the dynamics affecting energy consumption, ultimately contributing to the development of more robust and insightful predictive models for smart grid environments. The primary aim of this methodology is to extract essential insights and gather necessary specifications for the development of a collaborative and human-centric system designed to forecast energy consumption. The system places significant importance on its ability to offer justifications for its forecasts. As a result, implementation of the system will enhance transparency, fairness, and responsibility for the individuals utilizing it. This research places significant importance on its ability to offer justifications for its forecasts, thereby enhancing transparency, fairness, and responsibility for the individuals utilizing it. The article aims to contribute to recent advances in multiple criteria decision-making problems, including electricity prediction, and foster discussions on intelligent decision-making within the realm of sustainable smart cities.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Adadi A and Berrada M (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). IEEE Access, 6: 52138-52160. https://doi.org/10.1109/ACCESS.2018.2870052

Amjad T, Sher M, and Daud A (2012). A survey of dynamic replication strategies for improving data availability in data grids. Future Generation Computer Systems, 28(2): 337-349. https://doi.org/10.1016/j.future.2011.06.009

Badshah A, Ghani A, Daud A, Jalal A, Bilal M, and Crowcroft J (2023). Towards smart education through Internet of Things: A survey. ACM Computing Surveys, 56(2): 26. https://doi.org/10.1145/3610401

Bishop CM (2006). Pattern recognition and machine learning. Springer-Verlag, New York, USA.

Chakraborty D, Alam A, Chaudhuri S, Başağaoğlu H, Sulbaran T, and Langar S (2021). Scenario-based prediction of climate change impacts on building cooling energy consumption with explainable artificial intelligence. Applied Energy, 291: 116807. https://doi.org/10.1016/j.apenergy.2021.116807

Crabbé J and Van Der Schaar M (2021). Explaining time series predictions with dynamic masks. In the Proceedings of 38th International Conference on Machine Learning, PMLR: 2166-2177.

Das A and Rad P (2020). Opportunities and challenges in explainable artificial intelligence (XAI): A survey. ArXiv Preprint ArXiv:2006.11371. https://doi.org/10.48550/arXiv.2006.11371

Ehsan U, Wintersberger P, Liao QV, Mara M, Streit M, Wachter S, and Riedl MO (2021). Operationalizing human-centered perspectives in explainable AI. In the Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, Yokohama, Japan: 1-6. https://doi.org/10.1145/3411763.3441342

Fan C, Xiao F, Yan C, Liu C, Li Z, and Wang J (2019). A novel methodology to explain and evaluate data-driven building energy performance models based on interpretable machine learning. Applied Energy, 235: 1551-1560. https://doi.org/10.1016/j.apenergy.2018.11.081

Feinberg EA and Genethliou D (2005). Load forecasting. In: Chow J H, Wu FF, and Momoh J (Eds.), Applied mathematics for restructured electric power systems: Power electronics and power systems: 269-285. Springer, Boston, USA. https://doi.org/10.1007/0-387-23471-3_12

Firsova IA, Vasbieva DG, Kosarenko NN, Khvatova MA, and Klebanov LR (2019). Energy consumption forecasting for power supply companies. International Journal of Energy Economics and Policy, 9(1): 1-6. https://doi.org/10.32479/ijeep.7728

Gao Y and Ruan Y (2021). Interpretable deep learning model for building energy consumption prediction based on attention mechanism. Energy and Buildings, 252: 111379. https://doi.org/10.1016/j.enbuild.2021.111379

Gunning D, Stefik M, Choi J, Miller T, Stumpf S, and Yang GZ (2019). XAI—Explainable artificial intelligence. Science Robotics, 4(37): eaay7120. https://doi.org/10.1126/scirobotics.aay7120 **PMid:33137719**

Hardas BM, Kaushik S, Goyal A, Dongare Y, Aush MG, and Chiwhane S (2024). Deep learning with multi-headed attention for forecasting residential energy consumption. International Journal of Intelligent Systems and Applications in Engineering, 12(2s): 109-119.

Jain RK, Smith KM, Culligan PJ, and Taylor JE (2014). Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy. Applied Energy, 123: 168-178. https://doi.org/10.1016/j.apenergy.2014.02.057

Karatasou S, Santamouris M, and Geros V (2006). Modeling and predicting building's energy use with artificial neural networks: Methods and results. Energy and Buildings, 38(8): 949-958. https://doi.org/10.1016/j.enbuild.2005.11.005

Khemakhem S, Rekik M, and Krichen L (2019). Double layer home energy supervision strategies based on demand response and plug-in electric vehicle control for flattening power load curves in a smart grid. Energy, 167: 312-324. https://doi.org/10.1016/j.energy.2018.10.187

Kim JY and Cho SB (2021). Explainable prediction of electric energy demand using a deep autoencoder with interpretable latent space. Expert Systems with Applications, 186: 115842. https://doi.org/10.1016/j.eswa.2021.115842

Li A, Xiao F, Zhang C, and Fan C (2021). Attention-based interpretable neural network for building cooling load prediction. Applied Energy, 299: 117238. https://doi.org/10.1016/j.apenergy.2021.117238

Lin W, Wu D, and Boulet B (2021). Spatial-temporal residential short-term load forecasting via graph neural networks. IEEE Transactions on Smart Grid, 12(6): 5373-5384. https://doi.org/10.1109/TSG.2021.3093515

Lotfipoor A, Patidar S, and Jenkins DP (2024). Deep neural network with empirical mode decomposition and Bayesian optimisation for residential load forecasting. Expert Systems with Applications, 237: 121355. https://doi.org/10.1016/j.eswa.2023.121355

Lundberg SM and Lee SI (2017). A unified approach to interpreting model predictions. In the 31st Conference on Neural Information Processing Systems, Long Beach, USA: 1-10.

Ma H (2022). Prediction of industrial power consumption in Jiangsu Province by regression model of time variable. Energy, 239: 122093. https://doi.org/10.1016/j.energy.2021.122093

Masood I, Wang Y, Daud A, Aljohani NR, and Dawood H (2018). Towards smart healthcare: Patient data privacy and security in sensor-cloud infrastructure. Wireless Communications and Mobile Computing, 2018: 2143897. https://doi.org/10.1155/2018/2143897

Miller C (2019). What's in the box?! Towards explainable machine learning applied to non-residential building smart meter classification. Energy and Buildings, 199: 523-536. https://doi.org/10.1016/j.enbuild.2019.07.019

Mocanu E, Nguyen PH, Gibescu M, and Kling WL (2016). Deep learning for estimating building energy consumption. Sustainable Energy, Grids and Networks, 6: 91-99. https://doi.org/10.1016/j.segan.2016.02.005

Moradzadeh A, Mansour-Saatloo A, Mohammadi-Ivatloo B, and Anvari-Moghaddam A (2020). Performance evaluation of two machine learning techniques in heating and cooling loads forecasting of residential buildings. Applied Sciences, 10(11): 3829. https://doi.org/10.3390/app10113829

Pandey C, Roy DS, Poonia RC, Altameem A, Nayak SR, Verma A, and Saudagar AKJ (2022). GaitRec-Net: A deep neural network for gait disorder detection using ground reaction force. PPAR Research, 2022: 9355015. https://doi.org/10.1155/2022/9355015 **PMid:36046063 PMCid:PMC9424014**

Paudel S, Nguyen PH, Kling WL, Elmitri M, Lacarrière B, and Corre OL (2015). Support vector machine in prediction of building energy demand using pseudo dynamic approach. In the 28th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, Pau, France: 1-13.

Quan H, Srinivasan D, and Khosravi A (2014). Short-term load and wind power forecasting using neural network-based prediction intervals. IEEE Transactions on Neural Networks and Learning Systems, 25(2): 303-315. https://doi.org/10.1109/TNNLS.2013.2276053 **PMid:24807030**

Ribeiro MT, Singh S, and Guestrin C (2016). "Why should i trust you?" Explaining the predictions of any classifier. In the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Association for Computing Machinery, San Francisco, USA: 1135-1144. https://doi.org/10.1145/2939672.2939778

Tiwari V, Joshi RC, and Dutta MK (2022). Deep neural network for multi-class classification of medicinal plant leaves. Expert Systems, 39(8): e13041. https://doi.org/10.1111/exsy.13041

Tso GK and Yau KK (2007). Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. Energy, 32(9): 1761-1768. https://doi.org/10.1016/j.energy.2006.11.010

Wang Y, Gan D, Sun M, Zhang N, Lu Z, and Kang C (2019). Probabilistic individual load forecasting using pinball loss guided LSTM. Applied Energy, 235: 10-20. https://doi.org/10.1016/j.apenergy.2018.10.078

Wang Y, Xia Q, and Kang C (2010). Secondary forecasting based on deviation analysis for short-term load forecasting. IEEE Transactions on Power Systems, 26(2): 500-507. https://doi.org/10.1109/TPWRS.2010.2052638

Wenninger S, Kaymakci C, and Wiethe C (2022). Explainable long-term building energy consumption prediction using QLattice. Applied Energy, 308: 118300. https://doi.org/10.1016/j.apenergy.2021.118300

Westphal FS and Lamberts R (2007). Regression analysis of electric energy consumption of commercial buildings in Brazil. In the 10th Conference of the International Building Performance Simulation Association, Beijing, China: 1543-1550.

Yang F, Fu X, Yang Q, and Chu Z (2024). Decomposition strategy and attention-based long short-term memory network for multi-step ultra-short-term agricultural power load forecasting. Expert Systems with Applications, 238: 122226. https://doi.org/10.1016/j.eswa.2023.122226

Yildiz B, Bilbao JI, and Sproul AB (2017). A review and analysis of regression and machine learning models on commercial building electricity load forecasting. Renewable and Sustainable Energy Reviews, 73: 1104-1122. https://doi.org/10.1016/j.rser.2017.02.023

Yoo H and Ko N (2020). Blockchain based data marketplace system. In the International Conference on Information and Communication Technology Convergence, IEEE, Jeju, Korea: 1255-1257. https://doi.org/10.1109/ICTC49870.2020.9289087

Yu Z, Haghighat F, Fung BC, and Yoshino H (2010). A decision tree method for building energy demand modeling. Energy and Buildings, 42(10): 1637-1646. https://doi.org/10.1016/j.enbuild.2010.04.006

Zhang W, Liu F, Wen Y, and Nee B (2021). Toward explainable and interpretable building energy modelling: An explainable artificial intelligence approach. In the 8th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, Association for Computing Machinery, Coimbra, Portugal: 255-258. https://doi.org/10.1145/3486611.3491127

Zheng X, Ran X, and Cai M (2020). Short-term load forecasting of power system based on neural network intelligent algorithm. IEEE Access. https://doi.org/10.1109/ACCESS.2020.3021064

Zueva VN, Belozerskaya TY, Zueva VN, and Belozerskaya TY (2015). Calculation of electricity losses in the power transformer. Scientific-Methodical Electronic Magazine Concept, 8: 116-120.