UMEÅ UNIVERSITY

Monthly Electricity Consumption Forecasting Using an Explainable AI Framework

Tyra Wodén

Tyra Wodén
Spring 2026
Degree Project in Interaction Technology and Design, 30 credits
Supervisor: Esteban Guerrero Rosero
External Supervisor: Elin Eriksson
Examiner: Ola Ringdahl
Master of Science Programme in Interaction Technology and Design, 300 credits

Abstract

Acknowledgements

Contents

1 Introduction

In recent years, the Swedish electricity market has been affected by large variations in price and periodically high electricity costs[1][2]. This has increased the need for customers to understand and influence their electricity consumption and future electricity costs.

With the emergence of environmental problems due to climate change, sustainable energy management is becoming increasingly important [1, 2]. The ability for customers to understand and influence their household energy consumption is significant for sustainable energy use. Household energy consumption makes up a considerable part of the total energy consumption, approximately 30% in some European and American countries. Managing household energy more efficiently has large potential in saving energy, since it is estimated that 27% of energy used by households can be saved through more efficient use [3].

[Something about how the energy demand in the world is increasing]

[Something about how forecasting electricity consumption can help users make smart decisions about their consumption, both saving money and benefitting the environment.]

[Something about monthly forecasting and why that is useful]

For users, the ability to have confidence in the forecast is important. Users may, for example, question how the forecasting mechanism makes decisions, or question what factor is the most determining in the forecast. A system that can explain such things to the user is able to increase its reliability with users. Handling users' data in a safe and transparent manner is also important when implementing Artificial Intelligence (AI) based systems. Citizens of the European Union have a right to transparency and information about the decision-making of AI models that have a direct link to them, as outlined in the General Data Protection Regulation [4]. [Something about how XAI helps with these things]

Previous research has identified various models for predicting electricity consumption, both statistical and AI based [5, 6]. In recent years, increasing interest has been shown for AI solutions to energy consumption forecasting, due to their strength in handling nonlinear problems [4, 5]. Forecasts are often based on several factors such as weather conditions and building conditions, causing nonlinear patterns that statistical methods struggle with [5]. However, one disadvantage with AI methods is the black-box nature of the models which causes a lack of transparency and interpretability in the decision-making process. To solve the problem of elucidating the internal process and decision-making of AI algorithms, the field of explainable AI (XAI) has emerged within recent years. XAI methods are able to open up the black box, and provide explanations for why a model predicts a certain way [7].

[1] Allhorn, J., Tidningen Näringslivet: Chockvändningen: Nu har norra Sverige högst elpriser - "Har förändrats ganska snabbt" (January 2026). https://www.tn.se/inrikes/46369/chockvandningen-nu-har-norra-sverige-hogst-elpriser-har-forandrats-ganska-snabbt/

[2] Rydegran, E., Energiföretagen: Dramatik och rekord sammanfattar Elåret 2022 (December 2022). https://www.energiforetagen.se/pressrum/pressmeddelanden/2022/Dramatik-och-rekord-sammanfattar-Elaret-2022/

[To address this need, Umeå Energi has worked on developing and improving their interfaces for customers, for example by developing an application for private customers. According to customer analytics from Umeå Energi, a highly requested feature is to receive an estimation of both the electricity consumption and the electricity cost before the invoice arrives. Currently, Umeå Energi has developed a linear regression model to forecast the consumption for the current month. The model is based on historical consumption and temperature, aggregated by month. For certain customer groups, Umeå Energi has access to high definition measurement data where customer electricity consumption is registered on a 15-minute level, which creates opportunities for more advanced modeling. There may also be other factors, apart from historical consumption, that affect the electricity consumption, for example weather data, calendar information (holidays etc.), and energy prices.]

[The main goal with this Master's thesis is to investigate and quantify the contributions of different variables to a monthly electricity consumption forecast. Previous research has identified several models that are able to accurately predict energy consumption for different time intervals, utilizing various combinations of data sources [6, 5]. In recent years, increasing interest has been shown for Machine Learning (ML) and AI solutions to energy consumption forecasting, due to their strength in handling nonlinear problems [4, 5]. However, the black-box property of many popular AI models has increased the demand of asserting confidence and transparency through means of Explainable Artificial Intelligence (XAI) [4]. This study will address this need by using XAI methods (SHAP, Feature Importance etc.) to evaluate how different variables such as weather data, holidays, and energy prices affect the accuracy of monthly household electricity consumption forecasts. The novelty in this research lies in explaining the variable contributions in the monthly scope. The access to customer-level data in this study also provides an aspect that is underrepresented in previous works [5, 8]. In addition to the XAI approach, efforts will be made to continuously update and improve the forecast during the month, as actual observed values of electricity consumption become available.]

For Umeå Energi, this research will add value by supporting customers in making informed decision about their energy consumption. According to internal customer analytics, a highly requested feature is to receive an estimation of both the electricity consumption and the electricity cost before the invoice arrives. Umeå Energi is currently in the process of launching an application for private customers. The ultimate goal is to include to monthly consumption forecasts in the application.

[Definition of short/mid/long-term forecasts]

[The contributions of this work can be summarized as follows:]

2 Theory

This chapter presents relevant theoretical background for the concepts and methodologies used in this research.

2.1 Time Series Forecasting

A time series is a set of chronologically arranged observations, generally under the assumption that time is a discrete variable [9]. In a time series with T real value samples $x_1, \ldots, x_T$, the value at time i is represented by x_i ($1 \leq i \leq T$). The problem of time series forecasting can be defined as predicting the values of $x_{w+1}, \ldots, x_{w+h}$, where w is the historical window, i.e., the number of values considered in order to produce the prediction, and h is the prediction horizon, i.e, the number of future values to be predicted. Prediction happens given the previous samples $x_1, \ldots, x_w$ ($w + h \leq T$), with the goal of minimizing the error between the predicted value $\hat{x}_{w+i}$ and the actual value x_{w+i} ($1 \leq i \leq h$) [10].

A time series may be univariate or multivariate, where univariate refers to a series with a single observation recorded over time, and multivariate refers to a series with a group of variables with interactions. Analysis of time series often begins with obtaining the underlying patterns of the observed data. The next step is fitting a model to represent the data for future predictions, which can be a complex task. The analysis of the time series is usually performed by decomposing it into three components [6, 11]:

1. *Trend* - The general movement of the variable during the observation period. Trend does not take irregularities and seasonality into account.

2. *Seasonality* - The periodic fluctuation of the variable. It includes stable effects, along with time, magnitude, and direction.

3. *Residual* - The remaining, largely unexplainable part of the time series. In some instances, this can be high enough to mask the trend and seasonality.

Both linear and nonlinear techniques may be used for solving time series problems. In linear methods, the idea is that strong correlations in the data allow for linear combinations to determine the next observation. However, the random component of the time series may prevent precise predictions. Nonlinear methods are applied in the machine learning domain to forecast future values based on a model describing the data. Machine learning solutions to forecasting problems have gained popularity, due to the fact that they are suitable both for linear and nonlinear problems [10]. Time series analysis has been extensively applied to the problem of energy consumption forecasting, especially since real-time monitoring of buildings has become more common, and the availability of recorded data has increased [6].

The scope of energy consumption forecasting problems can generally be divided into three categories; short-term forecasting (1 hour to 1 week), medium-term forecasting (1 month to 1 year), and long-term forecasting (1 year and above) [5]. [maybe move this to introduction for context]

2.2 Ensemble Learning

Ensemble learning is a family of methods that combine several machine learning algorithms to make decisions. It can be seen as the ML interpretation of “wisdom of the crowd”, that is, the idea that aggregating the opinions of several individuals is better than selecting the opinion of one individual. Multiple weak learners make predictive results that are fused together via voting mechanisms, in order to achieve better performance than from any single algorithm. Any type of machine learning algorithm, e.g. decision tree, neural network, or regression model, can be used as an ensemble learner [12, 13].

According to Dietterich [14], there are three reasons why ensemble learning methods achieve good performance in machine learning. The first reason is statistical. Models can be seen as searching for the best hypothesis within a hypothesis space H. When data is limited, which it often is, the models can find several hypotheses in H that give the same accuracy on the training data. This makes it hard to choose between hypotheses, since it is unknown which one will generalize better for unseen data. Ensemble learning can help with avoiding this problem of overfitting. Secondly, ensemble learning provides computational benefits. Many models function via performing some type of local search, which may be prone to getting stuck in a local optima. A better approximation of the unknown true function may be obtained from an ensemble constructed by the local search started from many different points. The third reason is representational. In most situations, the unknown true function may not be included in H. Combining several hypotheses from H, the space of representable functions can be expanded to possibly include the true function.

Three common strategies for constructing ensembles are bagging, boosting, and stacking [15]. Bagging, or bootstrap aggregating, proposed by Breiman [16] is a method for obtaining an aggregated prediction by building multiple versions of a predictor. Bootstrapping is used to generate multiple samples of data from the original dataset, which are then used to independently train the different predictors. Majority voting is used to aggregate the final prediction [12]. The main objective of the bagging technique is to reduce the variance of a prediction model. A common example of the bagging technique is the random forest (RF) algorithm [15, 17].

In boosting, several models with individually weak predictions are aggregated to obtain a model with high accuracy. Models are trained sequentially to correct the errors of previous models. The main objective with this technique is reducing model bias [15, 17, 18]. Two examples of boosting algorithms are Gradient Boosting Machines (GBM), which uses gradient descent to minimize the loss function, and XGBoost, which is an extension of GBM focused on resource optimization and prevention of overfitting [17].

Stacking utilizes different learning algorithms called base learners to make initial predictions. These outputs are then combined via a meta-learner to make the ultimate predictions. The goal is to capture a wider range of patterns using the strength of different models, while minimizing the generalization errors [15, 17, 10]. Accuracy improvements mainly happen when there is diversity among the individual models, since differences in generalization principles generally lead to different results [17].

2.3 Explainable Artificial Intelligence

According to Saarela and Jauhiainen [19], there are two main objectives with classifiers; they should be able to make accurate predictions for new given input features, and they should be interpretable (i.e., provide explanations for how a given input relates to the output). Usually, models have a trade-off between accuracy and interpretability. Linear regression models are generally transparent and easy to understand, but their performance is often worse than more complex nonlinear models. On the other hand, the nonlinear models perform well but lack in interpretability.

In recent years, artificial intelligence has been widely adopted in society, and humans increasingly rely on AI as part of decision-making. Research in the field of AI has for many years focused on improving the predictive accuracy. However, the black-box nature of many AI systems creates a lack of transparency, and explaining to users how the AI systems work is highly problematic. Pressure from society, ethics, and legislation has created a demand of a new type of AI that is interpretable to users and can explain its inner functions. To address these issues, explainable AI methods that elucidate the decision-making process have been developed [7, 20].

XAI methods can be applied at different levels of the AI modelling. Firstly, explainability can be applied pre-modelling through means of data pre-processing and data analysis. This approach gives insights into the datasets used for training the ML models, and it can expose imbalances in the data. Secondly, the model itself can be inherently interpretable. This refers to models that have a simple structure, such as linear regression and k-Nearest Neighbors. Models like these are understandable by design, and users are able to interpret the model based on the model summary or parameters. Thirdly, explainability can be applied post-modelling to deal with the black-box problem of more complex ML models. Post-modelling methods include textual and visual justifications, simplification of the model, and feature relevance. These methods can explain how an algorithm performs during training, and how predictions are generated given a certain input. XAI approaches may be model-specific, meaning they are applied to a specific type of model, or model-agnostic, meaning they are not dependent on model architecture and can be applied for any model [7, 20].

[Ensemble models are based on the aggregation of several models, which makes it more complex to interpret the results. Post-modeling XAI methods such as simplification and feature relevance can be implemented to explain the ensemble [7].]

[Maybe have a section for local/global explanations. And model agnostic/model specific explanations.]

Feature importance is the most common explanation tool for classification models [19]. Feature importance describes how important a variable was for the model output, that is, the individual contribution of a feature, regardless of the shape or direction of the feature's effect, dependent on a particular classifier. These descriptions may be local or global, where local importance describes the feature's contribution to a specific prediction, and global importance describes the feature's contribution for the entire model [19, 20].

2.3.1 SHAP

SHapley Additive exPlanations (SHAP) is a popular method for model explainability. It is model-agnostic, meaning that it can be used for any ML model. The SHAP method has its foundation in game theory, where the contribution of each player to the total payoff is calculated. In the case of machine learning, the players are represented by features (variables) and the payoff is the model output. To calculate the contribution score for each feature, all different combinations of features (i.e., coalitions in game theory) are evaluated. SHAP can be used to explain model outputs both locally and globally, i.e., both for specific instances and for all instances [21].

When using SHAP for model explanations, it is important that the users are aware of some important considerations of the method. Firstly, the SHAP method is model-dependent, meaning it can produce different explanations for the same task when different models are applied. Secondly, the explainability scores assigned to features do not represent the weights of the features. Rather, the explainability lies in the ranking of the features, meaning that feature importance is deduced from the ordering. Thirdly, it is assumed that the features are independent of each other. Therefore, some features that are correlated with other features may receive low scores even though they contribute significantly to the output. This is because the correlated features have already accounted for the impact of the low-scoring feature. [There is another point about bias in this paper] Because of these points, it is crucial to present SHAP results in an informative way by including corresponding output plots and assumptions behind the method [21].

[is it okay to use the same reference for all this?]

[write mathematical notation of SHAP [22]]

3 Previous Work

Research in the field of electricity consumption forecasting has established many methods for producing forecasts. These methods can roughly be divided into two categories; conventional methods and AI-based methods. Conventional methods such as time series analysis and regression methods have previously been widely applied to solve the problem of electricity consumption forecasting. Nowadays, AI-based methods are more popular due to their strength in solving nonlinear problems, something that the conventional methods struggle with [5].

Two comprehensive reviews on electricity consumption forecasting have been identified:

- An extensive review and comparison of both statistical and ML/DL techniques for forecasting is found in [6]. They also review combinations of different techniques, i.e. hybrid models. Claims that ANN has more advantages than statistical models, and has better performance for nonlinear problems. Highlights that hybrid models can be beneficial to capture complexities in building energy and operational data.
- Another review of statistical, AI, and hybrid methods for forecasting is found in [5]. They also highlight the strength in AI models for dealing with nonlinear patterns. Claims that hybrids between AI and Swarm Intelligence (SI) methods show potential for increased accuracy. Provides a clear overview of different studies regarding prediction time intervals, included features, building types etc.

Papers where experiments have been performed:

- Support Vector Machine (SVM) for forecasting energy consumption: [23].
- Monthly electricity consumption forecasting based on decomposition methods and ARIMA: [24].
- Forecasting cooling energy using ANN (for three university buildings, weekly /monthly): [25].
- SVR and fruit fly optimization with seasonal indexing to address the fact that electricity consumption has a seasonal component: [26]. Results show that the proposed model is a reliable forecasting tool.

3.1 Machine Learning Approaches

3.2 Ensemble Learning Approaches

Ensemble learning has previously been applied for the task of electricity consumption forecasting, mostly in the short-term scope. Divina et al. [10] proposed a stacking ensemble learning approach for short-term forecasting of Spain's general electricity consumption. They used a two-layer approach based on a bottom and a top layer. The bottom layer consisted of three base learning methods; regression trees based on evolutionary algorithms, Artificial Neural Network (ANN), and Random Forest (RF). The top layer used Generalized Boosted Regression Models (GBM) to combine the predictions of the base learners, and produce the final predictions. They found that the combination of weaker learning methods was able to produce superior results compared to several baselines, showing that ensemble learning is suitable for short-term electricity consumption forecasting. Neural networks were able to predict with high accuracy in the very near future, but accuracy declined when predicting further in the future. The ensemble method also showed significantly better performance compared to baselines when the amount of historical data was small, indicating that ensemble methods may be more flexible for different quantities of data.

Pinto et al. [27] also utilized ensemble learning for forecasting electricity consumption in the short-term. Using a consumption data from an office building, along with other variables such as temperature and humidity, they predicted hour-ahead consumption with three different ensemble methods. These methods were random forests, gradient boosted regression trees (GBR), and AdaBoost. They found that ensemble learning methods, especially AdaBoost, outperformed benchmark models such as support vector regression and fuzzy rule-based methods. They highlight including temperature and humidity information as advantageous to the forecasts, and they suggest that future work should consider additional external variables such as solar irradiation and thermal sensation.

[Maybe give some more examples of short-term studies]

Hadjout et al. [28] used an ensemble deep learning approach to forecast monthly electricity consumption for high voltage customers in the Algerian economic sector. They utilized three different deep learning models - Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU), and Temporal Convolutional Networks (TCN) - and grid search to find optimal weights for each model in the final ensemble prediction. Compared to the individual models separately, the ensemble approach performed significantly better using MAE and MAPE metrics.

Long-term forecasting using ensemble learning has been researched by Chen et al. [29]. They predicted the annual electricity consumption for American households using extreme gradient boosting forests and deep networks as base learners, and ridge regression as a combiner method. The data included variables pertaining to household demographics, household type, appliances, and geographical data, providing a wide range of information. The ensemble framework was able to reduce errors by 30% compared to classical regression models such as linear regression and support vector machines. Investigation into the importance of input features using principal component analysis showed that electricity price, number of rooms, natural gas usage, and temperature during summer were among the variables that contributed the most information. They also note that some features, like number of rooms, number of bedrooms, and total square footage, have a strong correlation and have potential to be represented more efficiently. They argue that feature selection is necessary, since discarding of unimportant features can enhance model performance.

3.3 Monthly Forecasting?

3.4 Explainable AI Approaches

Explainable AI methods have previously been applied for the task of short-term electricity consumption forecasting. Sim et al. [2] proposed a novel XAI approach for variable selection in energy consumption forecasting. They analyzed the influence of 15 different input variables pertaining to time information, climate data, and past energy consumption data. LSTM was selected as prediction model and SHAP was used to interpret the variables. The findings showed that time data such as year and hour had a strong influence on the prediction results, along with temperature, surface temperature, and energy-consumption-difference. Variables with a weak or ambiguous influence included humidity, wind speed, and sunshine amount. They concluded that forecasting performance can be significantly improved by selecting high-impact variables based on XAI analysis.

Maarif et al. [22] investigated the effect of 9 different features on energy consumption forecasting for a South Korean steel company. The features provided information about historical consumption, lagging and leading current power, carbon dioxide emissions, and load type. They utilized various LSTM models for the predictions, and used SHAP for the XAI analysis. It was found that leading current reactive power and seconds from midnight strongly influenced the model output, while CO_2 and load type had no effect on the forecast. They note that it is important to consider interpretability and performance trade-offs when developing XAI forecasting models, and that further research into this topic is needed for understanding the applicability of these models in the energy sector.

Januja et al. [4] maybe, but not reputable journal.

Moon et al. [15] utilized ensemble learning and XAI methods for short-term residential building electricity consumption forecasting. They performed an extensive comparison between five ensemble learning models and ten deep learning models. It was found that the decision tree-based ensemble methods were superior in handling diverse and noisy data, rendering them useful for electricity consumption forecasting. They highlight robustness, interpretability, and efficiency as advantageous characteristics in ensemble models. They argue that ensemble models can handle data that is not extensively preprocessed and that they require less data than deep learning models. A feature importance and SHAP analysis was performed on several ensemble models, revealing that temperature-humidity index and wind chill temperature had significant importance for the forecasting. The SHAP analysis combined with the decision tree-based models provided interpretive insights about complex interactions in the data.

XAI approaches have also been applied to long-term forecasting [30]. Chakraborty et al. [31] predicted long-term cooling energy consumption for residential and commercial buildings under different climate change scenarios. They used SHAP to explain the results and concluded that the XAI method increased the interpretability of the XGBoost prediction model. Another long-term study was conducted by Wenninger et al. [32], who predicted the annual energy consumption for German households, and proposed a novel QLattice model for enhanced explainability. They found that the QLattice model was appropriate for the task of energy consumption forecasting, even though XGBoost achieved slightly better predictive performance. However, a significant strength with the QLattice algorithm is its transparent design, which was found to greatly increase the model explainability compared to established models such as ANN, XGBoost, and Support Vector Regression (SVR).

[With this, it is clear that there is a gap in research on XAI for medium-term forecasting. And in general, the consensus is that more research in the XAI field in the energy sector is needed (?)]

4 Methodology

4.1 Project Plan

To answer the research questions, a methodology established by Moon et al. [15] will be used. Some modifications to their method will be made in order for it to be tailored to this study's data and the monthly forecasting scope, e.g. adjusting the time ranges for which training and testing data is collected.

4.1.1 Data and tools

Forecasts will be based on historical consumption data from Umeå Energi and external variables. The consumption data is in form of time series data from 16000 customers over roughly three years on a 15-minute level. Some customers may not have data for all three years. Other variables such as weather data, calendar information, and electricity prices will be retrieved from Open APIs.

4.1.2 ML methods

To solve the research questions, state-of-the-art ensemble learning models previously used for short-term (hourly - daily) forecasting will be explored. Moon et al.'s work [15] will be an important reference for selecting models. The XAI method SHAP will be used explain variable contributions to the forecast. The monthly scope may have different importance for certain variables compared to the short-term forecasts.

4.1.3 Main methodological steps

- **Literature study**: Review existing work in the field of electricity consumption forecasting, in order to gain valuable theoretical background and insights on ensemble learning and XAI techniques for electricity consumption forecasting.
- **Data preparation**: Retrieve 15-minute level electricity consumption data, as well as relevant external data sources (such as weather data, calendar data, and electricity prices). Perform data analysis and pre-processing. Pre-processing includes transforming one-dimensional variables such as weekdays/holidays to two dimensions, assigning numerical values to string parameters, and calculating weather indices [15].
- **Model implementation**: Implement ensemble learning forecasting models based on the consumption data and the external sources. Optimize hyperparameters.
- **Model evaluation**: Use MAPE, CVRMSE, and NMAE metrics to evaluate the performance of ensemble learning models [15].

- **Evaluation of data sources**: Analyze and evaluate how the different data sources contribute to the accuracy of the forecasts using the Explainable AI method SHAP. This will enhance model interpretability [15].

4.1.4 Evaluation Methods

Evaluation will, as mentioned above, be performed for the models' performance and the variables' contributions. As a baseline comparison, an existing linear regression electricity consumption model (based on Umeå Energi historical monthly consumption and temperature data) will be utilized. Further comparisons will be made to previous works, particularly Moon et al.'s [15] work.

4.2 Actual

- Make correlation maps for the features.
- It is also possible to make diagrams for the decomposition of the time series [31].

4.3 Data Preparation and Analysis

This study utilizes a dataset of 15-minute level electricity consumption from x Swedish households, containing Y years of measurements retrieved from 20YY-MM-DD to 20YY-MM-DD. This data is provided by Swedish electricity company Umeå Energi. As part of enhancing the explainability of the forecasts, the data is analyzed initially to gain statistical insights.

[Plot showing consumption, discuss seasonality]

External variables are retrieved from. . . data finns fram till 2025-10-31, 16 variabler

[Table with all variables]

Finns även byvind, men från Holmön, vet inte om det är relevant

In [15], they calculated sine/cosine values for timestamps, maybe I should do the same.

4.4 Application of Ensemble Learning

4.5 Application of Explainable AI

Table 1 Selected input variables.

Variable	**Description**	**Data Type**
$Month$	Month of the year	Timestamp (numeric)
$Holidays$	Number of holidays during month	Numeric
$Temp_h$	Hourly air temperature (°C)	Weather condition (numeric)
$DewPT_h$	Hourly dew point temperature (°C)	Weather condition (numeric)
$Precip_h$	Hourly precipitation (mm)	Weather condition (numeric)
$PrecipInt_{15}$	15-minute precipitation intensity, max of average (mm/s)	Weather condition (numeric)
$Snow_d$	Daily snow depth (m)	Weather condition (numeric)
$Surface_d$	Daily surface condition	Weather condition (status?)
$DewP_h$	Hourly relative dew point (%)	Weather condition (numeric)
$WindD_h$	Hourly wind direction (°C)	Weather condition (numeric)
$WindS_h$	Hourly wind speed (m/s)	Weather condition (numeric)
$Cloud_h$	Hourly total cloud amount (%)	Weather condition (numeric)
$CloudB_h$	Hourly lowest cloud base (m)	Weather condition (numeric)
$SolarI_h$	Hourly long wave irradiance (W/m^2)	Weather condition (numeric)
$SunT_h$	Hourly sunshine amount (s)	Weather condition (numeric)
$AirP_h$	Hourly air pressure (hPa)	Weather condition (numeric)
$Visibility_h$	Hourly visibility (m)	Weather condition (numeric)
$Weather_h$	Hourly weather status	Weather condition (status?)
$Cons$	a	Historical consumption (numeric)
$Cons$	b	Historical consumption (numeric)
$Cons$	c	Historical consumption (numeric)

5 Results

6 Discussion

7 Conclusion

7.1 Future Work

References

[1] Chu, S., Majumdar, A.: Opportunities and challenges for a sustainable energy future. Nature **488**(7411) (August 2012) 294–303

[2] Sim, T., Choi, S., Kim, Y., Youn, S.H., Jang, D.J., Lee, S., Chun, C.J.: eXplainable AI (XAI)-Based Input Variable Selection Methodology for Forecasting Energy Consumption. Electronics **11**(18) (September 2022) Multidisciplinary Digital Publishing Institute.

[3] Zhou, K., Yang, S.: Understanding household energy consumption behavior: The contribution of energy big data analytics. Renewable and Sustainable Energy Reviews **56** (April 2016) 810–819

[4] Janjua, J.I., Ahmad, R., Abbas, S., Mohammed, A.S., Khan, M.S., Daud, A., Abbas, T., Khan, M.A.: Enhancing smart grid electricity prediction with the fusion of intelligent modeling and XAI integration. International Journal of Advanced and Applied Sciences **11**(5) (May 2024) 230–248

[5] Mat Daut, M.A., Hassan, M.Y., Abdullah, H., Rahman, H.A., Abdullah, M.P., Hussin, F.: Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: A review. Renewable and Sustainable Energy Reviews **70** (April 2017) 1108–1118

[6] Deb, C., Zhang, F., Yang, J., Lee, S.E., Shah, K.W.: A review on time series forecasting techniques for building energy consumption. Renewable and Sustainable Energy Reviews **74** (July 2017) 902–924

[7] Minh, D., Wang, H.X., Li, Y.F., Nguyen, T.N.: Explainable artificial intelligence: a comprehensive review. Artificial Intelligence Review **55**(5) (June 2022) 3503–3568

[8] Lazzari, F., Mor, G., Cipriano, J., Gabaldon, E., Grillone, B., Chemisana, D., Solsona, F.: User behaviour models to forecast electricity consumption of residential customers based on smart metering data. Energy Reports **8** (November 2022) 3680–3691

[9] Kirchgässner, G., Wolters, J., Hassler, U.: Introduction to Modern Time Series Analysis. Springer Science & Business Media (October 2012) Google-Books-ID: o7jWV67165QC.

[10] Divina, F., Gilson, A., Goméz-Vela, F., Torres, M.G., Torres, J.F.: Stacking Ensemble Learning for Short-Term Electricity Consumption Forecasting. Energies **11**(4) (April 2018) Company: Multidisciplinary Digital Publishing Institute Distributor: Multidisciplinary Digital Publishing Institute Institution: Multidisciplinary Digital Publishing Institute Label: Multidisciplinary Digital Publishing Institute Publisher: publisher.

[11] Brockwell, P.J., Davis, R.A., eds.: Introduction to Time Series and Forecasting. Springer Texts in Statistics. Springer, New York, NY (2002)

[12] Sagi, O., Rokach, L.: Ensemble learning: A survey. WIREs Data Mining and Knowledge Discovery **8**(4) (2018) e1249

[13] Dong, X., Yu, Z., Cao, W., Shi, Y., Ma, Q.: A survey on ensemble learning. Frontiers of Computer Science **14**(2) (April 2020) 241–258

[14] Dietterich, T.G.: Ensemble Methods in Machine Learning. In: Multiple Classifier Systems, Berlin, Heidelberg, Springer (2000) 1–15

[15] Moon, J., Maqsood, M., So, D., Baik, S.W., Rho, S., Nam, Y.: Advancing ensemble learning techniques for residential building electricity consumption forecasting: Insight from explainable artificial intelligence. PLOS ONE **19**(11) (November 2024) e0307654 Publisher: Public Library of Science.

[16] Breiman, L.: Bagging predictors. Machine Learning **24**(2) (August 1996) 123–140

[17] Ribeiro, M.H.D.M., Dos Santos Coelho, L.: Ensemble approach based on bagging, boosting and stacking for short-term prediction in agribusiness time series. Applied Soft Computing **86** (January 2020) 105837

[18] Schapire, R.E.: The strength of weak learnability. Machine Learning **5**(2) (June 1990) 197–227

[19] Saarela, M., Jauhiainen, S.: Comparison of feature importance measures as explanations for classification models. SN Applied Sciences **3**(2) (February 2021) 272

[20] Angelov, P.P., Soares, E.A., Jiang, R., Arnold, N.I., Atkinson, P.M.: Explainable artificial intelligence: an analytical review. WIREs Data Mining and Knowledge Discovery **11**(5) (2021) e1424 _eprint: https://wires.onlinelibrary.wiley.com/doi/pdf/10.1002/widm.1424.

[21] Salih, A.M., Raisi-Estabragh, Z., Galazzo, I.B., Radeva, P., Petersen, S.E., Lekadir, K., Menegaz, G.: A Perspective on Explainable Artificial Intelligence Methods: SHAP and LIME. Advanced Intelligent Systems **7**(1) (2025) 2400304 _eprint: https://advanced.onlinelibrary.wiley.com/doi/pdf/10.1002/aisy.202400304.

[22] Maarif, M.R., Saleh, A.R., Habibi, M., Fitriyani, N.L., Syafrudin, M.: Energy Usage Forecasting Model Based on Long Short-Term Memory (LSTM) and eXplainable Artificial Intelligence (XAI). Information **14**(5) (April 2023) Multidisciplinary Digital Publishing Institute.

[23] Dong, B., Cao, C., Lee, S.E.: Applying support vector machines to predict building energy consumption in tropical region. Energy and Buildings **37**(5) (May 2005) 545–553

[24] Sun, T., Zhang, T., Teng, Y., Chen, Z., Fang, J.: Monthly Electricity Consumption Forecasting Method Based on X12 and STL Decomposition Model in an Integrated Energy System. Mathematical Problems in Engineering **2019**(1) (2019) 9012543

[25] Deb, C., Eang, L.S., Yang, J., Santamouris, M.: Forecasting diurnal cooling energy load for institutional buildings using Artificial Neural Networks. Energy and Buildings **121** (June 2016) 284–297

[26] Cao, G., Wu, L.: Support vector regression with fruit fly optimization algorithm for seasonal electricity consumption forecasting. Energy **115** (November 2016) 734–745

[27] Pinto, T., Praça, I., Vale, Z., Silva, J.: Ensemble learning for electricity consumption forecasting in office buildings. Neurocomputing **423** (January 2021) 747–755

[28] Hadjout, D., Torres, J., Troncoso, A., Sebaa, A., Martínez-Álvarez, F.: Electricity consumption forecasting based on ensemble deep learning with application to the Algerian market. Energy **243** (March 2022) 123060

[29] Chen, K., Jiang, J., Zheng, F., Chen, K.: A novel data-driven approach for residential electricity consumption prediction based on ensemble learning. Energy **150** (May 2018) 49–60

[30] Machlev, R., Heistrene, L., Perl, M., Levy, K.Y., Belikov, J., Mannor, S., Levron, Y.: Explainable Artificial Intelligence (XAI) techniques for energy and power systems: Review, challenges and opportunities. Energy and AI **9** (August 2022) 100169

[31] Chakraborty, D., Alam, A., Chaudhuri, S., Başağaoğlu, H., Sulbaran, T., Langar, S.: Scenario-based prediction of climate change impacts on building cooling energy consumption with explainable artificial intelligence. Applied Energy **291** (June 2021) 116807

[32] Wenninger, S., Kaymakci, C., Wiethe, C.: Explainable long-term building energy consumption prediction using QLattice. Applied Energy **308** (February 2022) 118300

A First Appendix

If any.