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

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, 19].

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 [7].

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].

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 [20].

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 [20].

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

[write mathematical notation of SHAP [21]]

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: [22].
- Monthly electricity consumption forecasting based on decomposition methods and ARIMA: [23].
- Forecasting cooling energy using ANN (for three university buildings, weekly /monthly): [24].
- SVR and fruit fly optimization with seasonal indexing to address the fact that electricity consumption has a seasonal component: [25]. Results show that the proposed model is a reliable forecasting tool.

Papers specifically on XAI and energy consumption forecasting:

- Forecasted hourly energy consumption for the steel sector using three different LSTM models [21]. Used SHAP to interpret the decision-making, and found that leading current reactive power and the number of seconds from midnight contributed significantly to the model output.

- Ensemble learning for electricity consumption forecasting. Evaluated several decision tree-based ensemble learning techniques using SHAP [15]. Found that ensemble learning models outperform deep learning models. Also found that temperature-humidity index and wind chill temperature has a greater impact on short-term forecasts than more traditional parameters such as temperature. Released the code at https://github.com/sodayeong/PLOS-ONE_Github. Predictions are made in a daily scope. Data is from university dormitory buildings in South Korea (i.e. probably very low diversity in buildings) with hourly measurements.

- Predicted electricity consumption for residential buildings based on hourly data with information about consumption for different household areas (such as kitchen and appliances) [4]. Used LSTM as prediction model, and LIME and SHAP to provide comprehensible explanations of the predictions.

- Proposed a methodology for selecting input variables for energy consumption prediction using XAI (SHAP) [2]. Used Extreme Gradient Boosting (XGBoost), Support Vector Regression (SVR), Light Gradient Boosting Model (LightGBM), and LSTM for prediction. Found that variables with strong impact on the forecast include year, hour, energy consumption difference, temperature, and surface-temperature.

Overfitting can be a problem with ML/DL models

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. [26] 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. [27] 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. [28]. 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. [21] 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.

4 Methodology

5 Results

6 Discussion

7 Conclusion

7.1 Future Work

8 Some LaTeX tip and tricks

8.1 Producing PDF-documents

In some LaTeX distributions there exist a program called `pdflatex`. This program makes the production of good looking PDF documents easy. Use it like you use `latex`. The difference is that this program does not produce a dvi-file, but instead makes a PDF-document directly. You should be careful with graphics, avoid using the pstricks package if you like to use `pdflatex` and also read the following section about image inclusion.

If `pdflatex` of some reason does not work for you, you could use ps2pdf instead. It does not do as good job as pdflatex, and you have to be careful with the input flags, otherwise the PDF-document will look horrible, but you might have less trouble getting your latex documents though the compiler.

`ps2pdf`, as the name says, converts PS-files to PDF-documents. So, first run latex, then dvips, and finaly ps2pdf. Notice the flags used below, they makes sure, the correct fonts are used.

```
> latex thesis.tex
> dvips -D 600 -Z -G0 -Ppdf thesis.dvi | thesis.ps
> ps2pdf thesis.ps
```

8.2 Including pictures

One of the pros of LaTeX is that it produces very good looking documents, and therefore you also want the graphics to look nice. If you have found a program that can produce vector graphics, use it. It can often convert the pictures to the desired formats.

However, graphics can be a mess. Graphics and LaTeX is no exception. In this package, the `graphicx` package is used as it provides some good functionality. Unfortunately LaTeX is a bit tricky about which graphics formats to use. If you use `pdflatex` PDF-files and PNG-files can be used but with standard `latex` only EPS-files works (EPS stands for Encapsulated PostScript). Both EPS and PDF are a good format for vector graphics but not so good for bitmaps.

So, if you both like to produce PS as well as PDF documents, you often need two versions of the pictures. This is probably not a problem when they are easily exported to the desired format in the image-software used (Illustrator, XFig etc.).

But how to make LaTeX understand which picture to use? Well, LaTeX does this automagicaly. First we can tell LaTeX where to find our pictures,

```
\graphicspath{{pictures/}}
```

This makes LaTeX search the subfolder `./pictures/` for pictures to include as well as the current folder.

Secondly, use the `\includegraphics` command to include your pictures.

```
\includegraphics[width=70mm]{complicated}
```

Notice, that there are NO extension used on the name of the picture. This makes LaTeX search for the right one, e.g., a PNG- file if it is a PDF document, otherwise an EPS-file.

You can do all sorts of tricks with the include pictures, where scaling is the most common. Use 'scale', 'width', height' as in the example above.

Also notice how the graphics package are included below if you are not using this package.

8.3 References

There is a lot to be said about references. However. I recommend that you find some information on how to use bibtex. It can be a bit tricky at first but worth it any time in the long run. However, a few things can be useful to notice.

Authors should always be given with their full names, with the sir name last, e.g., Jan Pedher Johansson. If there are more then one author they should ALL be separated with an 'and', regardless if there are two, three or ten. This is all handeld and made correct by bibtex.

```
Bo Andersson and Anders Eriksson and Erik Bosson
```

Company names, abbreviations etc. can look funny using bibtex. Use { } if there are something you like to force.

{`Umeå Universitet`}	(so it does not become U. Universitet)
{`HTML`}	(so it does not become html or Html)

In the report document class references are not included in the table of contents. If you like it to be, use the trick described in the previous section.

Remember to cite the literature and web-papers in an appropriate way. There are many ways to do that, such as the following where you can read about how to create a reference list in a LaTeXreport using BibTex.

8.4 Other tricks

Notice the `tabular*` and the `tabularx` (requires the tabularx package) environments. With these enviroments you can have tables with a fixed width:

```
\begin{tabular*}{0.8\linewidth}{rll}
\end{tabular*}
```

The `tabularx` has a great feature if you like a column that works like a p¡width¿-column but with a variable width. In this example the first column will stretch to use the full width of the table depending on the with of the two last columns.

```
\begin{tabularx}{0.8\linewidth}{Xll}
\end{tabularx}
```

Notice that `tabularx` can not be used in your own defined environments.

In some large documents, it can look nice if the first pages, with the abstract, possible acknowledgment, table of contents, list of figures etc are numbered differently then the rest of the document, usually with roman numbers. Then the numbering restarts with the first chapter using normal numbers. To achieve this, put

```
\pagenumbering{roman}
```

before the first page, then

```
\cleardoublepage
\setcounter{page}{1}
\pagenumbering{arabic}
\chapter{Introduction}
```

before the first chapter.

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] 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.

[20] 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.

[21] 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.

[22] 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

[23] 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

[24] 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

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

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

[27] 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

[28] 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

A First Appendix

If any.