UMEÅ UNIVERSITY

Monthly Electricity Consumption Forecasting Using an Explainable AI Framework

Tyra Wodén

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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].

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 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 [4, 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 [6, 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) [6]. 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

[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/

customer-level data in this study also provides an aspect that is underrepresented in previous works [5, 7]. 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.

2 Previous Work

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 [4]. 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: [8].
- Monthly electricity consumption forecasting based on decomposition methods and ARIMA: [9].
- Forecasting cooling energy using ANN (for three university buildings, weekly/monthly): [10].
- SVR and fruit fly optimization with seasonal indexing to address the fact that electricity consumption has a seasonal component: [11]. Results show that the proposed model is a reliable forecasting tool.

Papers on ensemble learning for energy consumption forecasting:

- Forecasting high voltage consumers' monthly electricity consumption using an ensemble learning approach based on LSTM, GRU, TCN: [12].
- Ensemble learning for short-term electricity consumption forecasting: [13].
- Ensemble learning for short-term electricity consumption forecasting of office buildings: [14].
- Ensemble learning for annual electricity consumption forecasting: [15]. Predictions are made using numerous different variables, but not historical consumption. Identifies that there is a lack of household-level data for the task of prediction based on historical consumption data (time series).

Papers specifically on XAI and energy consumption forecasting:

- Forecasted hourly energy consumption for the steel sector using three different LSTM models [16]. 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 [17]. 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.
- Predicted electricity consumption for residential buildings based on hourly data with information about consumption for different household areas (such as kitchen and appliances) [6]. 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

2.1 Statistical Approaches

2.2 Machine Learning Approaches

3 Methodology

4 Results

5 Discussion

6 Conclusion

7 Some LaTeX tip and tricks

7.1 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
```

7.2 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.

7.3 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.

7.4 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.

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A First Appendix

If any.