DETERMINISTIC ANALYSIS OF SWEDISH ELECTRICITY SUPPLY FOR ITS INTERNAL MARKET

László Margitics

2025. OCTOBER 31.
CORVINUS UNIVERSITY OF BUDAPEST
Statistical Methods for Time Series

Table of Contents

Introduction

This analysis intends to evaluate potential deterministic models for understanding the Swedish internal electricity supply and demand changes over time.

Recently, energy prices have gone through the roof in the European Union due to the war in Ukraine, which erupted in February 2022. Not only that, but EU legislations also require member states to increase their energy efficiency while developing green solutions. Sweden, in particular, presents quite a unique case due to its high per capita electricity usage. As noted by Koreneff et al. (2009), this is driven by substantial use of electric heating due to the cold temperatures in the country and the extensive electricity-intensive industry.

To model how and why electricity demand in Sweden's internal market is changing over time, researchers emphasize the need for accurate forecasting methods and models. Campillo et al. (2012) highlight the fact that all modern models must incorporate physical parameters, such as temperature, to accurately simulate energy demand and supply. Additionally, the Swedish deregulated electricity market is not static at all. It is very much subject to both short- and long-term challenges. According to Holmberg & Tangerås (2023), there is an ongoing energy crisis and a huge green transition. The EU's three crises have hit harder than expected; the Russian invasion of Ukraine is "choking off" exports of electricity, Europe's nuclear reactors are reducing their output, and the fall of hydroelectric power production in Europe due to droughts in Norway.

While the aforementioned studies provide a broad overview of different challenges, a detailed statistical analysis of recent monthly electricity hours available to the internal market can help with the interpretation of certain factors. Therefore, the objective of this analysis is to create the most optimal deterministic model for Sweden's 'Available to internal market' electricity data. It will identify and explain the different parts of the model, such as trend, seasonality, temperature, and test for autocorrelation in the residuals. Additionally, it will use seasonally adjusted data to compile a structural break model with potential structural breaks in time series, while attempting to link it with an explanation.

The following chapters will delve into the methodology used to build and select the appropriate deterministic model, offer an analysis of important findings, answer whether the crises cause structural breaks in the time series, clearly speak about shortcomings and areas of improvement, and finish off with concluding remarks.

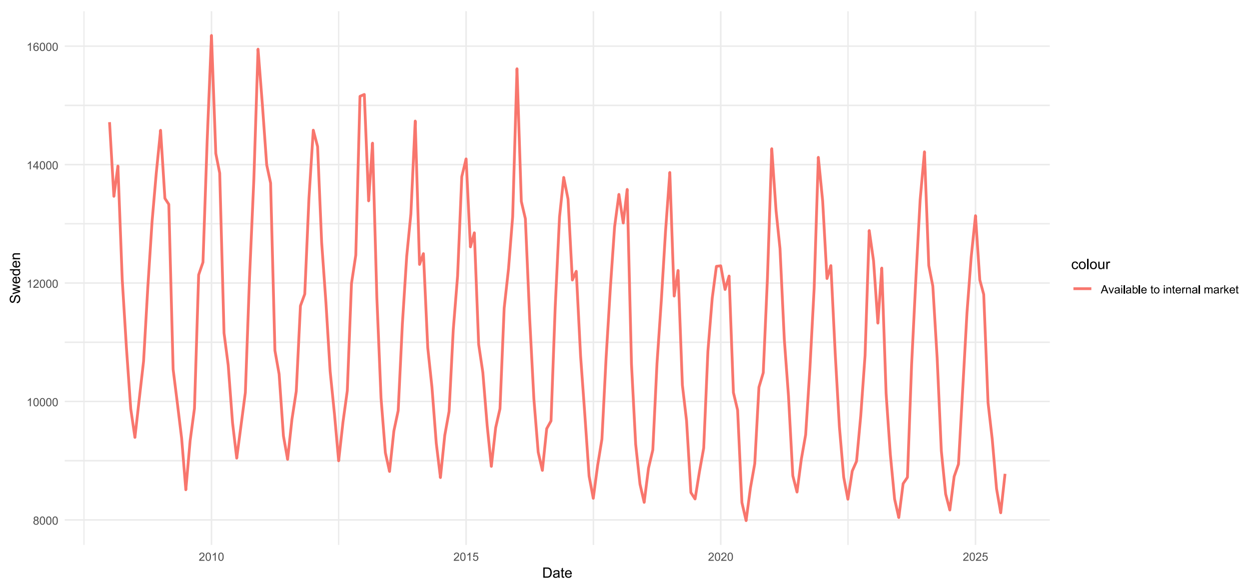
Data

Swedish electricity supply data for internal markets has been collected from the EUROSTAT database. The table queried is named “*Supply, transformation and consumption of electricity - monthly data*”, which can be found here. It was later specifically narrowed down to only Sweden’s data.

Open-Meteo was used to include crucial weather data on the mean daily temperatures in Sweden (Zippenfenig, 2024). It was later aggregated by month for each specific year, analyzed using Excel, and formatted in a way that is easy for use in RStudio.

Methodology

For all models covered in this analysis, the deterministic school was used. After initial data setup in RStudio, the time series for Sweden was checked using the *ggplot2* package. The plot (*1. Figure*) strongly suggested a linear trend; thus, it was fit using the *lm()* base R function, resulting in the first model, *linmodel*. As expected, it did not explain much of the variation in the time series, as the seasonality was not captured by this model.



1. Figure - Time series for Sweden's electricity available for internal markets

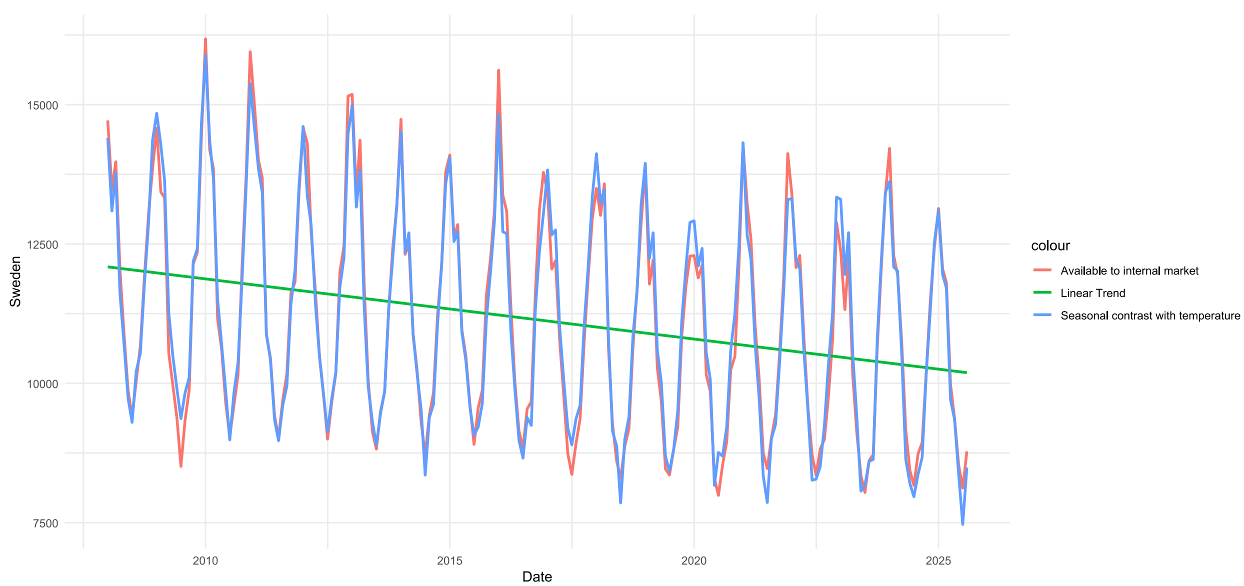
Logically, the next step involved introducing the seasonality into a new model via the *months* variable. A choice has arisen between using an additive or multiplicative approach. From the initial "eyeball test", the time series additive model seemed reasonable. Seasonal dummies were added to the existing simple linear trend component, jointly creating the seasonal *dummymodel*. The resulting model has significantly improved the explanatory power of the linear-only model. To analyze the seasonal effects in relation to the overall average, the dummy coding was switched to contrast coding, resulting in the *contrastmodel* that has an identical fit.

Effect coding the months variable was done manually using built-in functions such as *contrasts()* and *contr.sum()*. As expected, the very strong explanatory power achieved with the *dummymodel* also remained for the *contrastmodel* as well. Reaching this type of extraordinary explanatory power with a simple deterministic seasonal model seemed all well, but looking back at the initial graph, a new idea could come to mind; fitting a non-linear trend.

Further inspecting the initial time series plot, an extremely slight curvature could be observed in it, which may simply be a structural shift. This hunch was tested, and a new exponential model was built, where the dependent variable was log-transformed. After analyzing the resulting regression and comparing it with the simple linear trend, it was found that, based on the residual standard error (S_e), continuing with the linear trend and the *contrastmodel* was indeed justified.

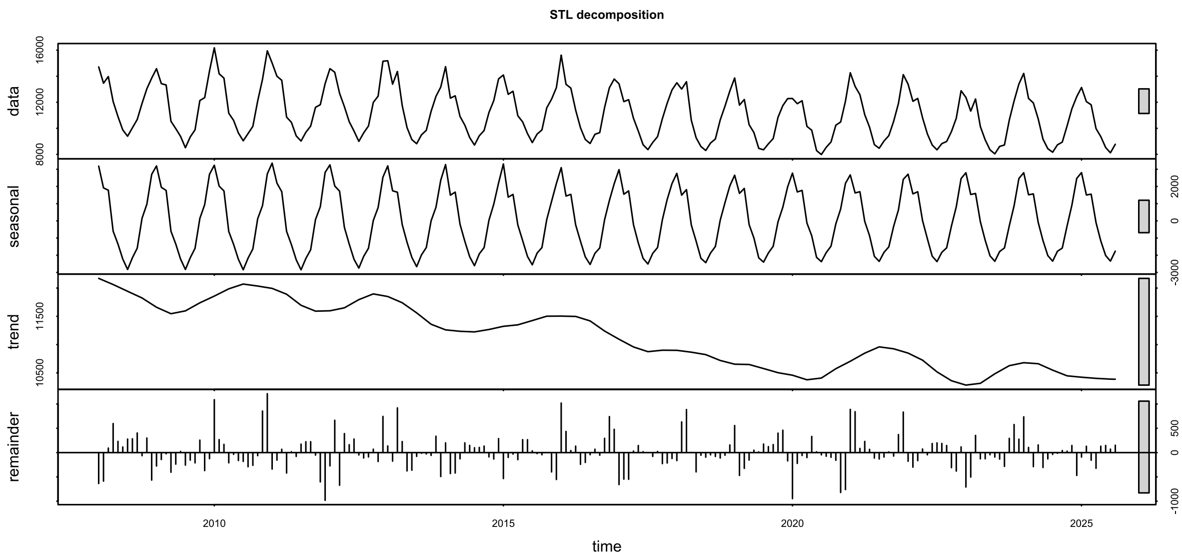
Another specification was tested, a quadratic trend possibility. Comparing the model to the contrast-coded one, it was discovered that in the population outside of the sample, the squared term was not significant based on the partial t-test, H_0 was failed to be rejected at any common significance levels. Additionally, both the Akaike and Bayes-Schwarz Information Criteria (IC) suggested retaining the *contrastmodel*.

A new variable was introduced. The variable captured the arithmetic mean of Sweden's daily temperatures averaged by the respective months. This addition increased the already staggering high explanatory power of the *contrastmodel* to 96.96%. After checking the ICs, specifically the AIC (Akaike) and BIC (Bayes-Schwarz), it was decided that the current best deterministic model is the temperature-added *tempmodel* (*2. Figure*).



2. Figure - Goodness of Fit for tempmodel on the original time series

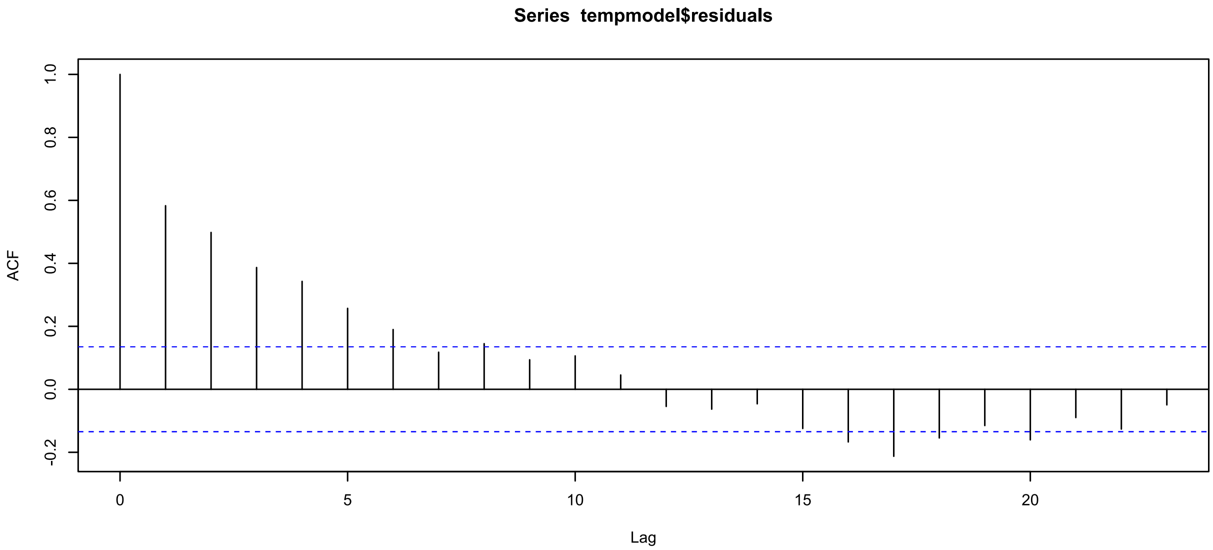
To quickly assess whether the additive approach initially considered was indeed correct, STL decomposition was employed (*3. Figure*). Fortunately, the plot's seasonal component suggested seasonal differences, implying an additive approach for STL. The following question could arise: why not use the STL decomposition to create a final, much better model?



3. Figure - STL decomposition of time series

STL decomposition is a smoothing method, just as are different types of moving averages (MAs). For the trend part, it uses LOESS, which generates a much better fit for the overall time series than any other previously defined model specification, as the trend is very much non-linear. Within the sample, smoothing techniques yield a more accurate estimation and follow structural breaks more effectively. The problem with the smoothing methods is that they cannot be used for forecasting, whereas the previous best *tempmodel* definitely can. For this particular task, where fitting a best deterministic model is of paramount importance, sticking with a well-defined, clearly and easily interpretable model is sensible.

Not only are the previously mentioned points limitations of deterministic approaches. The biggest fallback is the role of the residual. Testing for autocorrelation in the error term using the Breusch-Godfrey (BG) hypothesis test, it became evident that there is serial autocorrelation. This alone indicated that the residual is not a White Noise (WN) process, which, in the stochastic school, would sign further modelling, as there is still some information left in the residual that can be captured and explained. In other words, it is not entirely random. The Autocorrelation Function (ACF) also confirmed this by not being equal to zero (4. Figure).

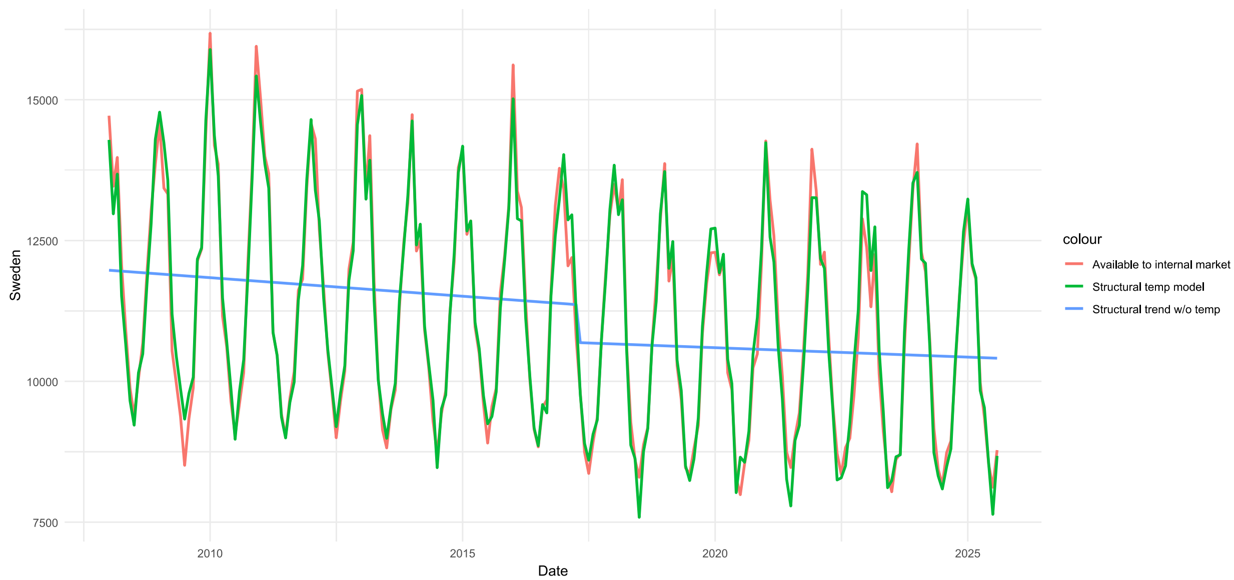


4. Figure - ACF of tempmodel's residuals, showcasing that it is not a WN process

After coming to terms with the limitations of the current best deterministic model, the objective was to test for the presence of structural breaks in the deseasonalized data. This was accomplished using the *breakpoints()* function from the *strucchange* package. For this purpose, a manual seasonal adjustment commenced. One structural break was found in the deseasonalized time series, occurring in April 2017. Furthermore, to test whether some major global events, such as the COVID-19 pandemic breakout (March 2020) and the start of the war in Ukraine (February 2022), had caused breaks, Chow tests were performed.

Following the identification of the aforementioned structural break, it was added to the final model's trend component. The procedure included adding a dummy variable (*sections*) to account for the two distinct periods (before and after April 2017), as well as an interaction term to allow for a change in the trend's slope. This led to the final model specification, the *strucmodel*. Based on the model comparison statistics (AIC, BIC, Adjusted R^2), this is the best fitting deterministic model that could be accomplished for the specific task of modeling Sweden's electricity demand in its internal markets (5. Figure). The final model can be expressed as an equation, of which the contents will be analyzed further:

$$\widehat{Sweden} = 12453.05 - 4.6 * t + 2.28 * t * section_{part2} - 803.55 * section_{part2} - 161.92 * mean\_temp - 542.14 * monthsApr - 342.02 * monthAug + 902.13 * monthDec + 161.7 * monthsFeb + 1343.48 * monthsJan - 700.1 * monthsJul - 627.97 * monthsJun + 723.24 * monthsMar - 419.92 * monthsMay + 163.15 * monthsNov - 47.09 * monthsOct$$



5. Figure - Goodness of Fit of the final, structural break model. Linear trend was added for each section without temperature.

Results & Analysis

Model Results

	Dependent variable:
	Sweden
t	-4.596***
	(0.968)
monthsApril	-542.141***
	(75.811)
monthsAugust	-342.020***
	(128.561)
monthsDecember	902.129***
	(123.689)
monthsFebruary	161.703
	(123.156)
monthsJanuary	1,343.481***
	(132.264)
monthsJuly	-700.099***
	(143.205)
monthsJune	-627.968***

	(123.634)
monthsMarch	723.239***
	(97.522)
monthsMay	-419.921***
	(89.387)
monthsNovember	163.151*
	(91.912)
monthsOctober	-47.085
	(75.770)
mean_temp	-161.919***
	(10.755)
sectionspart2	-803.554***
	(197.122)
t:sectionspart2	2.276
	(1.484)
Constant	12,453.060***
	(68.960)
Observations	212
R^2	0.974

Adjusted R^2	0.972
Residual Std. Error	326.743 (df = 196)
F Statistic	498.362*** (df = 15; 196)
Note:	*p<0.1; **p<0.05; ***p<0.01

To obtain the marginal effect of the *t* variable on electricity demand, one has to do some adjustments to the original model equation, specifically by differentiating. Doing this will result in the following equation:

$$\frac{\delta \widehat{Sweden}}{\delta t} = -4.596 + 2.276 * section_{part2}$$

This means that for interpreting the effect that the *t* has on electricity usage, the section must also be taken into consideration. Here, it can be stated that if time, specifically months, increase by 1, ceteris paribus, then it is expected that the electricity consumption in the segments after April 2017 will decrease by 2.32 gigawatt-hours. In the first section, before the structural break that was identified, this decrease is even more drastic after accounting for temperature and seasonality, as it is -4.596. However, it is important to note that the trend's slope change of +2.276 is not considered statistically significant. This finding will be further analyzed and explained. Additionally, this observation can be potentially justified by the slow but steady compliance of the EU regulation for increasing energy efficiency (Koreneff et al., 2009).

The effect of the mean temperature per month is both highly significant and negative, as expected. It can be said that a one-degree Celsius increase in average temperature results in an expected decrease in electricity available for the internal market of 161.9 gigawatt-hours, ceteris paribus, based on the model. This can be explained fairly easily, as in the warmer months, such as July, with an average temperature of 15 °C, there is absolutely no need for electric heating. The use of air conditioners for cooling is significantly more energy-efficient than electric heating during the winter season. This finding is consistent with Koreneff et al. (2009), who identified that the high per capita use of electricity in Sweden is linked to cold temperatures and, as a result, the use of electric heating.

Continuing the interpretations with the *sections*, it is important to note that it will be referenced to the period before the structural break, April 2017. This means that when the coefficient is -803.6, it can be stated that in the period after the break, at *t* level zero, the electricity demand in internal markets is lower by 803.6 gigawatt-hours than in the period before the break. This is also what can be seen at *5. Figure*, as the structural break lowers the trend's level.

An interesting observation can be made when looking at the significance of *t:sectionpart2*. In this model, the p-value suggests that the result is not statistically significant. It does not have an impact on predicting electricity supply in gigawatt-hours in the population outside of this sample. In other words, while the *strucmodel* estimates that the trend flattened a bit after the breakpoint, it cannot be concluded that this change in the slope is statistically different from zero.

Lastly, it could provide an interesting thought if one were to explore the significance and meaning of the coldest and warmest months on the dependent variable. Both *monthsJuly* and *monthsJanuary* are statistically significant (p-values < 0.001). Starting with the warmer one, the coefficient value is -700.099. Since effect coding was used, the interpretation is as follows: In July, the electricity supply available for the internal Swedish market is lower by 700.1 gigawatt-hours on average compared to the trend or mean. Following the same logic for interpreting the coefficient of January, it can be stated that the electricity supply available for the internal market of Sweden is higher by 1,343.5 gigawatt-hours on average compared to the trend. No surprises here, as Campillo et al. (2012) suggested in a more complex model, temperature plays a critical role in why the electricity consumption per capita is high in Sweden during cold seasons.

Analysis of Potential Breaks

What could have caused the structural break in April 2017? While there is no definitive answer to be found in the research papers, still, reading the paper by Holmberg & Tangerås (2023) can provide some ideas. They argue that some nuclear power has been phased out in Europe, and Sweden is also affected by it. According to the World Nuclear Association, Sweden's electricity is 30% powered by nuclear power reactors. This is a substantial amount, meaning if a major power plant were to be closed down, it could potentially affect the electricity that Sweden can provide to its internal market. This is exactly what happened in June 2017, when one of the biggest Swedish nuclear power plants was shut down, the Oskarshamn unit 1. Unit 2 was previously closed, so this meant total closure. This could have an impact big enough for it to show on the time series in April

2017, as preparations likely began for the shutdown around the spring season. This is not a definite explanation for the structural break; however, it provides a possible solution to it.

Two other potential structural break dates have been tested: the global COVID-19 pandemic breakout (March 2019) and the start of the Russian invasion of Ukraine (February 2022). The Chow test was utilized, showing p-values high enough to result in a failed rejection of H_0 for both cases. Thus, none of the mentioned events had structure-breaking effects on Sweden's electricity supply for internal markets; the tendency remained the same before and after the events. This might come as a surprise, as energy prices have been rising since the war in Ukraine erupted, prompting Sweden and the EU to focus more on their electricity supply (Holmberg & Tangerås, 2023).

Model Limitations & Diagnostics

Three main issues will be discussed in this chapter, which are completely justified critiques of the final model. These are the autocorrelation of the error term, the multicollinearity of mean temperatures and months, and heteroscedasticity.

Starting with heteroscedasticity, it was soon found, using the White test, that the model's error is homoscedastic; thus, the inference from the model is possible, and the parameter estimations are unbiased.

As stated in the Methodology, autocorrelation was tested using the Breusch-Godfrey test, which indicated that the residual term was not a WN process. In the stochastic approach, this would be a sign for further modeling, specifically the field of ARMA modeling. From this, it is obvious that there is still some information that can be extracted and later implemented from the error term. As the title suggests, the goal was to try to find the best deterministic model for the available electricity data in Sweden; it does not claim that this is the best model overall. A stochastic model was considered beyond the scope of this analysis. Further investigation can be done on this dataset and the final model, upgrading it to satisfy the stochastic school as well, thereby making it even greater for forecasting purposes.

Multicollinearity is a valid concern here. It is evident that it persists between *mean_temp* and *months*, even without testing it. However, checking the Variance Inflation Factor (VIF), the resulting values make it even clearer, yielding 14.3 for the *mean_temp* variable, indicating high multicollinearity. This should signal the alarm, and one should address this situation if they do not want to have inflated standard errors, making the p-values unreliable for the partial t-tests of the coefficients. In this case, the high multicollinearity does not alter the result by much, as clearly the coefficient of *mean_temp* remains highly statistically significant (p-value < 0.001). Additionally, the overall explanatory power of the model, measured by the Adjusted R^2, remains robust. The only issue is that the parameter estimation is not efficient. With regard to the aforementioned points, no action was taken, such as the removal of variables or the use of Principal Component Analysis (PCA) to combine them, as both mean temperature and seasonality are critical in explaining the variation of electricity supply.

Conclusion

The main objective of this analysis was to build the best deterministic model possible for Sweden's 'Available to internal market' electricity usage data. Through a very thorough process of model specifications and selections, a final one was made. It is a multiple linear regression having a trend, effect-coded seasonality (*months* variable), mean monthly temperature in ℃, and one structural break component. The resulting model explains 97% of the variance in the dependent variable, providing several key findings and ideas on what drives the Swedish electricity supply in its internal market.

The analysis proved that temperature is a highly statistically significant predictor, and seasonality is a dominant factor. The initial huge jump in explanatory power of the model from the linear trend-only model to the seasonal one explains the latter part. The negative coefficient of temperature signifies the critical role of electric heating in a cold climate, being consistent with the literature on Swedish and Nordic electricity consumption in general.

Underneath the strong seasonality effect, a significant negative long-term linear trend was identified. This suggests a slow but steady decrease in electricity supplied to the internal Swedish market over the past 17 years, most probably showing the gains that Sweden has made in energy efficiency, driven by regulatory policies and some technical advancements.

Critically, the analysis tried to give a possible solution to the structural break occurring in April 2017. The event had caused a sharp downward shift in the trend of the time series, marking it as a grand moment in the fairly recent history of Sweden's electricity market. As also mentioned by researchers, it shows that the system is not static and it can be affected by structural breaks, potentially being linked to several changes in the nation's energy portfolio, such as the phasing out of nuclear power plants.

Undoubtedly, there is room for improvement when it comes to the final deterministic model. Starting with the obvious fact that further modelling is possible with the stochastic school for time series analysis. The Breusch-Godfrey test revealed that there is serial autocorrelation in the residuals that needs to be taken care of. This can be accomplished by further modelling with ARMA models. Additionally, the multicollinearity issue can also be taken care of meaningfully, such as adding new variables and then using PCA to filter out its effect. Implementing these ideas of improvement can potentially lead to an even more accurate and powerful model for forecasting and inferring the Swedish electricity supply for its internal market.

Table of Figures

References

Campillo, J., Wallin, F., Torstensson, D., & Vassileva, I. (2012). Energy demand model design for forecasting electricity consumption and simulating demand response scenarios in Sweden. *International Conference on Applied Energy*. https://urn.kb.se/resolve?urn=urn:nbn:se:mdh:diva-17525

Holmberg, P., & Tangerås, T. P. (2023). The Swedish electricity market – today and in the future. *Sveriges Riksbank Economic Review*, *1*, 5–36.

Home—Eurostat. (n.d.). Retrieved October 27, 2025, from https://ec.europa.eu/eurostat/web/main/home

Koreneff, G., Ruska, M., Kiviluoma, J., Shemeikka, J., Lemström, B., Alanen, R., & Koljonen, T. (2009). *Future development trends in electricity demand*. VTT Technical Research Centre of Finland. VTT Tiedotteita - Research Notes No. 2470 https://publications.vtt.fi/pdf/tiedotteet/2009/T2470.pdf

Nuclear Power in Sweden—World Nuclear Association. (n.d.). Retrieved October 28, 2025, from https://world-nuclear.org/information-library/country-profiles/countries-o-s/sweden

R Core Team. (2025). *R: A Language and Environment for Statistical Computing* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Zippenfenig, P. (2024). *Open-Meteo.com Weather API* (Version 1.4.0) [Computer software]. Zenodo. https://zenodo.org/doi/10.5281/zenodo.7970649