Evaluation of Variable Renewable Energy Source's contribution to cost of control energy

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Contents

1 Introduction

Governments and scientists around the world largely agree on the need for a low-carbon electricity production. In the Sustainable Development Goal 7 (affordable and clean energy)[1]. A step in this direction is the construction, installation and connection of Renewable Energy Sources (RES) such as Hydropower, Wind and Solar to the electricity grid. These produce little to no direct emissions while supplying electricity and have life cycle carbon costs far lower than fossil fuels (Laboratory (2021)). A substrate of RES are so called Variable-RES (VRES), which are electricity sources whose production cannot easily be increased or decreased by the operator. Wind and Solar both rely on meteorological conditions, if these are not right, nothing is produced. This is contrary to most other sources whose production can be increased or decreased according to market needs. Although the time it takes to ramp production up or down can still present a challenge.

The lack of direct control over production with VRES presents a huge challenge to the adoption of such sources, since there is no large scale energy storage available. Battery Storage, Pumped Hydro and Heat Pumps do store energy, but currently these forms of power would not be able to power a country for even a couple of hours.

The addition of electricity from VRES has the possibility to:

1. Drastically lower electricity prices.
2. Increase price volatility.
3. Rapidly change the quantity of electricity available on the grid in either direction.

The reason for the first claim is that VRES has practically no marginal costs. No fuel rods, pumping, gas or other notable inputs are required to produce solar and wind energy. This means producers of VRES will bid their energy at almost any price. If they cannot profit - maximize, they will loss - minimize.

The second claim is the case because meteorological events tend to be fairly consistent across an area. When one wind / solar farm is producing, so are the ones around it. This means there is huge downward pressure on prices during periods of favorable VRES production and none at all during unfavorable conditions.

The third claim is particularly relevant for control energy's price. The reason for this is described in the next two points.

1.1 Control Energy

One aspect of electricity prices is the price paid for control energy. This is the short term (up to 15 min) electricity supply used to keep the grid at a constant frequency, due to unforeseen changes in supply and demand. It is necessary since the amount of energy consumed and produced must always be identical. The increased penetration of VRES, which cannot be steered by operators means that the purchase of such energy should be increasing with more VRES installed on the grid in recent years.

1.2 Relevance

If the amount of control electricity purchased by Transmission System Operators increases then this means costs will be passed down to consumers. Since electricity is a primary input in the economy, higher prices will be reflected across the vast majority of goods and services. This is an undesirable outcome. It is therefore important for policymakers, stakeholder and the public to understand the drivers of increased prices of control energy. This is particularly important in the context of the SDG 7, which stresses the need for clean energy. Policymakers must understand the impact of increasing the share of VRES on the grid to be aware of potential economic and political backlash of their decisions.

[1] https://sdgs.un.org/goals

1.3 Literature Review

The academic literature on VRES's effect on control energy is fairly sparse. Using the search terms "control energy" and "(variable) renewable energy", only one relevant paper was found. Hirth and Ziegenhagen (2013) have found that the inclusion of VRES from 2008-2013 decreases procurement cost of control power by 50%, presumably permitting lower prices for end consumers. The broader literature on the effect of VRES on electricity supply is broader.

These areas generally focus on both variability of supply and prices. Amongst them: Pereira da Silva and Horta (2019) who use EGARCH time series and regression while studying the Iberian power market; Frauendorfer, Paraschiv, and Schürle (2018) who find that the Swiss are "importing" lower German power prices during peak solar production, as Germany has much more solar energy sources than the Swiss. Finally, the authors Dong et al. (2019) find that the Swedish have more stable prices due to the relativley high proportion of non variable fossil and hydropower than the Danes, who are more reliant on VRES in the form of wind and solar. Other studies in the area are more conflicted, such as Rintamäki, S. Siddiqui, and Salo (2017) who compare Germany and Danish prices and wind that the effect of increasing wind production on day ahead prices is not constant. The point is that increasing VRES leads to variability in supply, which presumably means more cost for balancing out an unpredictable supply when the predictions are wrong.

It is the purpose of this study to see whether and if so, to what extent renewable energy sources are related to increasing costs of control energy.

2 Data Sources

2.1 Data provided by Swissgrid

Swissgrid provides a variety of data about electricity in Switzerland, which they make publicly available.[2] They provide the data in intervals of 15 minutes. They provide data about the production, consumption for Switzerland and for the individual cantons. Additionally, they also provide the information of amount used and the cost of control energy, split up in positive and negative as well as secondary and tertiary. There is no data provided about primary control energy. They state that "The data are reliable from 6 months onwards, until then the partners from the electricity sector who provide Swissgrid with the data can still claim changes."[3]. The data of the year 2024 will not be used for the Swissgrid data to account for this uncertainty.

Table 1: Data provided from Swissgrid

column name	type	example value
Timestamp	-	02.01.2023 05:00
Total energy consumed by end users in the Swiss controlblock	kWh	1176761.8330000001
Total energy production Swiss controlblock	kWh	1232928.746
Total energy consumption Swiss controlblock	kWh	1803182.031
Net outflow of the Swiss transmission grid	kWh	541518.00467000005
Grid feed-in Swiss transmission grid	kWh	845526.21799999999
Positive secundary control energy	kWh	258
Negative secundary control energy	kWh	-278
Positive tertiary control energy	kWh	0
Negative tertiary control energy	kWh	-71000
Cross Border Exchange CH->AT	kWh	124899
Cross Border Exchange AT->CH	kWh	8008
Cross Border Exchange CH->DE	kWh	128505
Cross Border Exchange DE->CH	kWh	250292
Cross Border Exchange CH->FR	kWh	0
Cross Border Exchange FR->CH	kWh	612336
Cross Border Exchange CH->IT	kWh	78706
Cross Border Exchange IT->CH	kWh	32540
Transit	kWh	332110
Import	kWh	903176
Export	kWh	332110
Average positive secondary control energy prices	Euro/MWh	34.93
Average negative secondary control energy prices	Euro/MWh	7.41
Average positive tertiary control energy prices	Euro/MWh	0
Average negative tertiary control energy prices	Euro/MWh	6.5250000000000004
Production Canton AG	kWh	510773.69900000002
Consumption Canton AG	kWh	104738.518
Production Canton FR	kWh	19952.938999999998
Consumption Canton FR	kWh	56305.006999999998
Production Canton GL	kWh	16679.557000000001
Consumption Canton GL	kWh	244909.27600000001
Production Canton GR	kWh	34253.826999999997
Consumption Canton GR	kWh	81946.960999999996
Production Canton LU	kWh	8576.5930000000008
Consumption Canton LU	kWh	77246.048999999999

[2]https://www.swissgrid.ch/en/home/operation/grid-data/generation.html
[3]https://www.swissgrid.ch/en/home/operation/grid-data/generation.html

column name	type	example value
Production Canton NE	kWh	905.01
Consumption Canton NE	kWh	10088.959999999999
Production Canton SO	kWh	270425.989
Consumption Canton SO	kWh	27886.216
Production Canton SG	kWh	13832.652599999999
Consumption Canton SG	kWh	86254.721999999994
Production Canton TI	kWh	11064.049000000001
Consumption Canton TI	kWh	83456.611000000004
Production Canton TG	kWh	5529.7420000000002
Consumption Canton TG	kWh	34471.962
Production Canton VS	kWh	52431.171999999999
Consumption Canton VS	kWh	202387.43367
Production Cantons AI, AR	kWh	1633.5984000000001
Consumption Cantons AI, AR	kWh	10056.028
Production Cantons BL, BS	kWh	23711.212
Consumption Cantons BL, BS	kWh	69410.312999999995
Production Cantons BE, JU	kWh	69187.933000000005
Consumption Cantons BE, JU	kWh	263829.79499999998
Production Cantons SZ, ZG	kWh	8785.4750000000004
Consumption Cantons SZ, ZG	kWh	37257.983
Production Cantons OW, NW, UR	kWh	11381.2
Consumption Cantons OW, NW, UR	kWh	19331.675999999999
Production Cantons GE, VD	kWh	42499.368000000002
Consumption Cantons GE, VD	kWh	151965.99400000001
Production Cantons SH, ZH	kWh	19551.166000000001
Consumption Cantons SH, ZH	kWh	193779.315
Production across Cantons	kWh	108920.65
Consumption across Cantons	kWh	36087.513330000002
Production control area CH - foreign territories	kWh	2832.9140000000002
Consumption control area CH - foreign territories	kWh	11771.698

2.2 Generation Share Wind and Solar

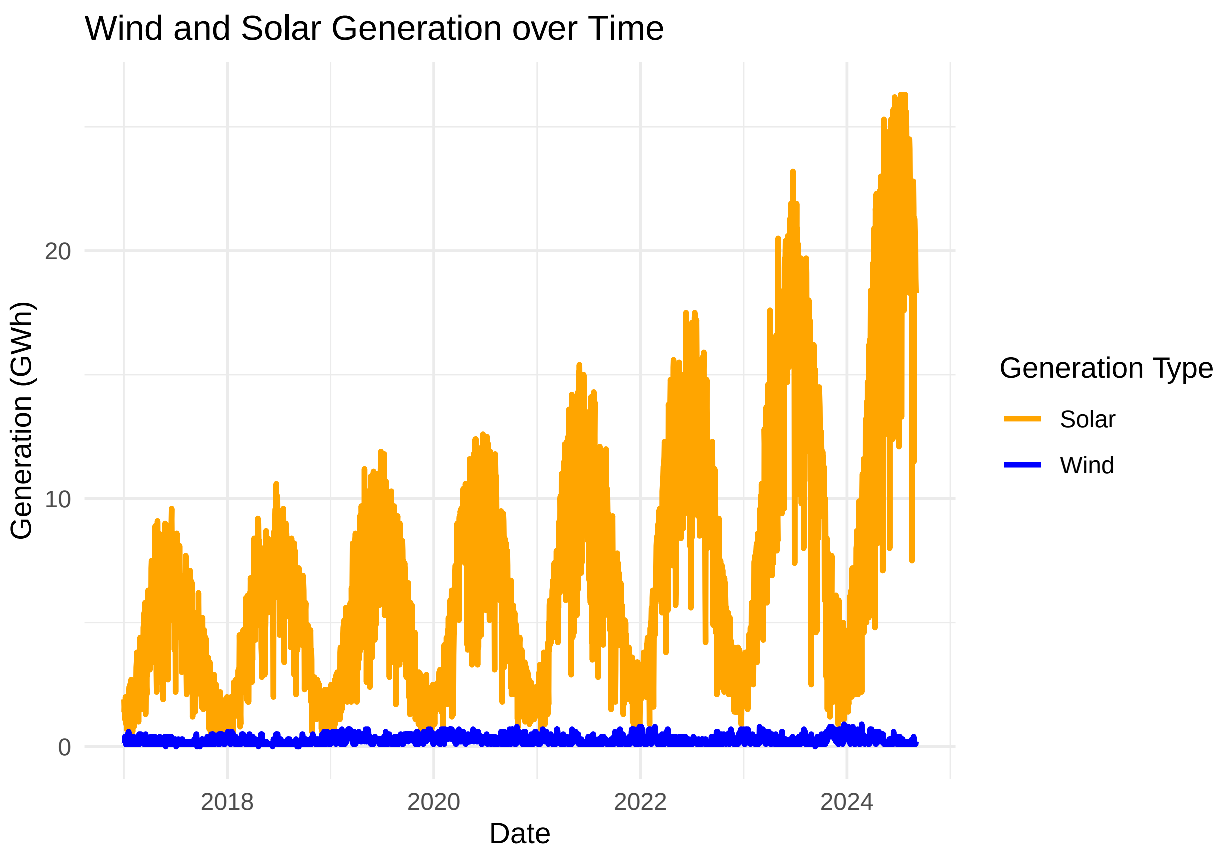
Open Data on VRES Production in Europe, including Switzerland.

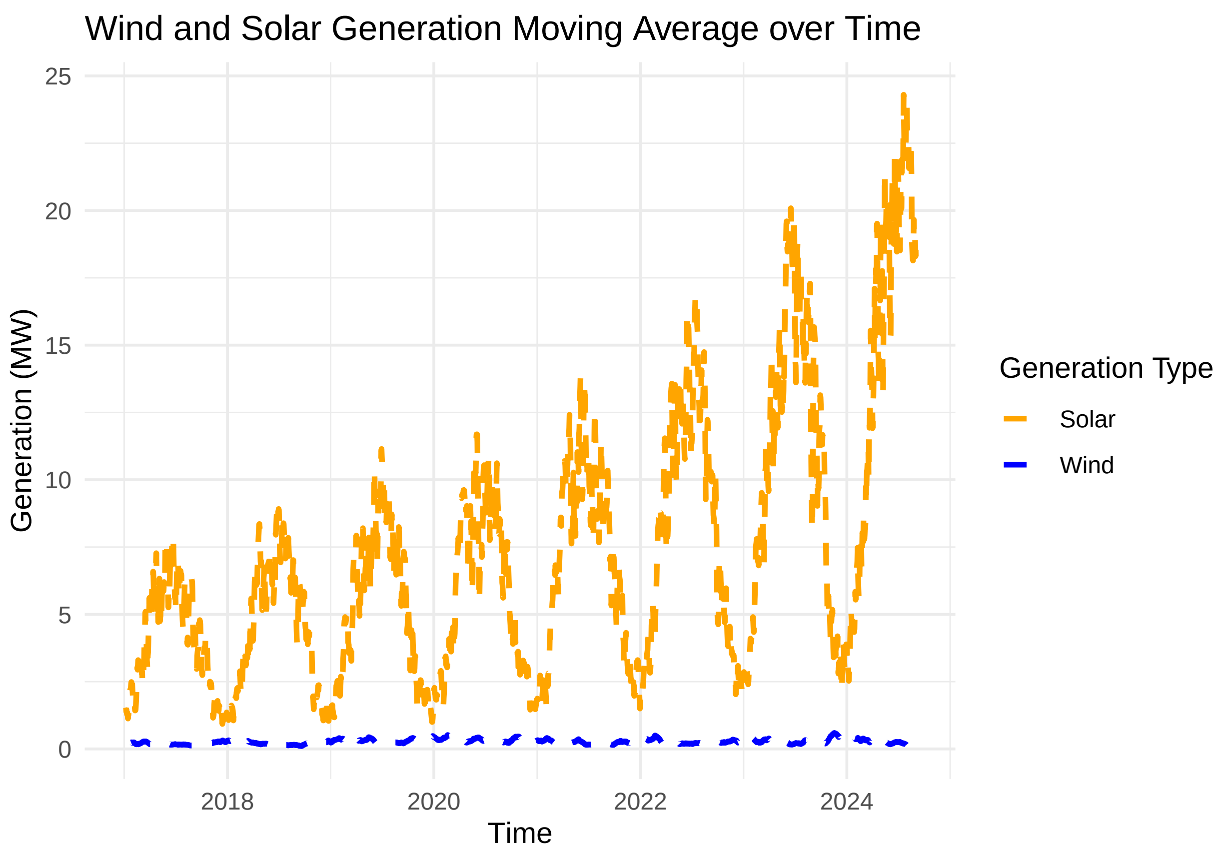
redo this part -> ENTSOE data - Actual load as csv + generation per type as csv - MW per blocks of 1 hour, eq. to MWh

Access: https://data.open-power-system-data.org/time_series

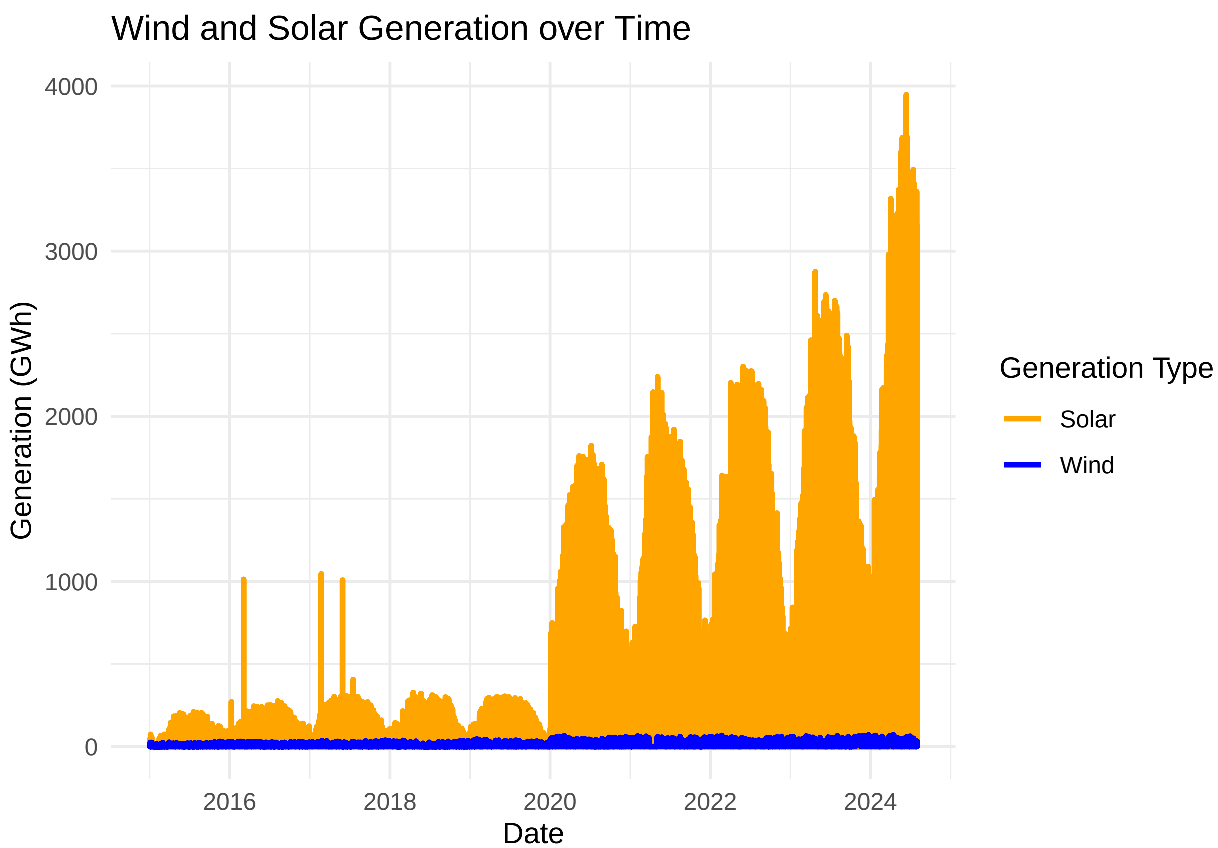
2.3 Overview Variable Renewable Energy Sources

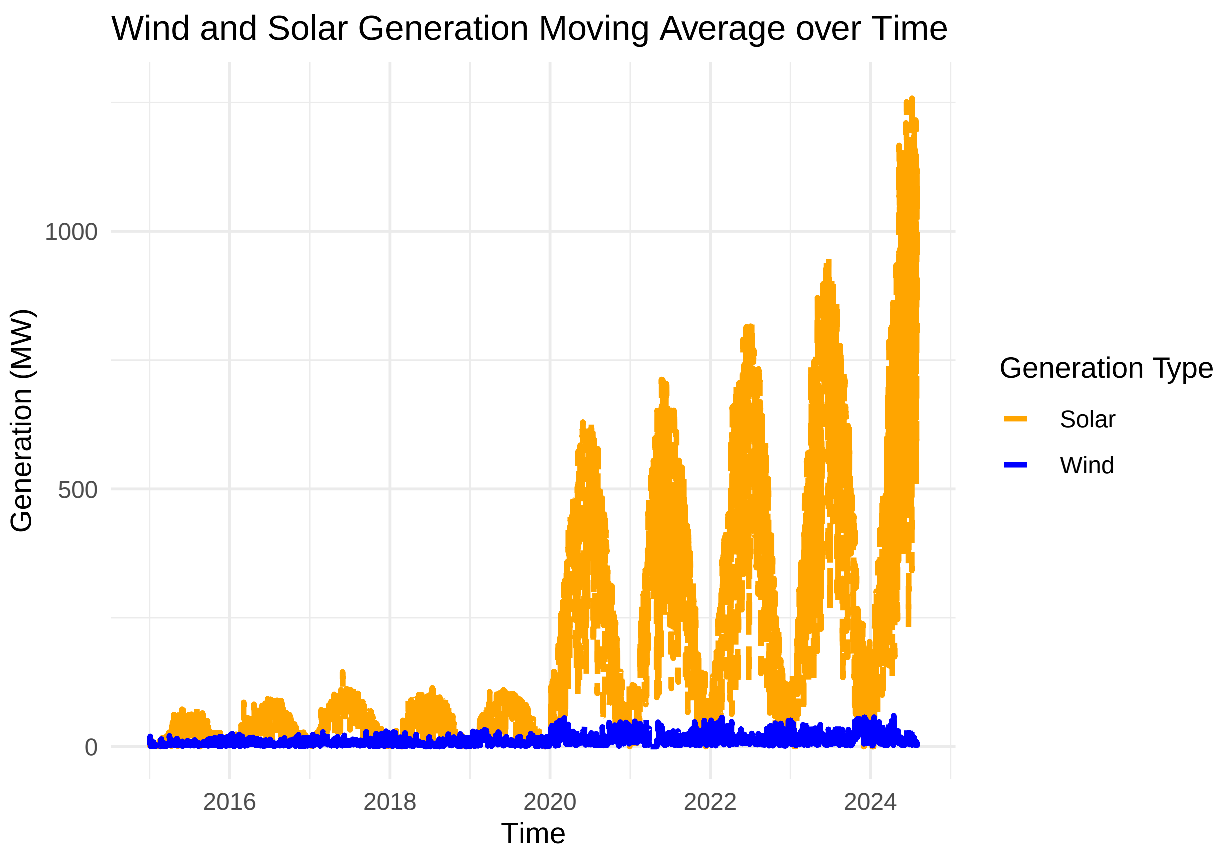
```
## Warning: Using ‘size‘ aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use ‘linewidth‘ instead.
## This warning is displayed once every 8 hours.
## Call ‘lifecycle::last_lifecycle_warnings()‘ to see where this warning was
## generated.
```


Wind and Solar Generation over Time
Generation (GWh)
0
10
20
2018
2020
2022
2024
Date
Generation Type
Solar
Wind



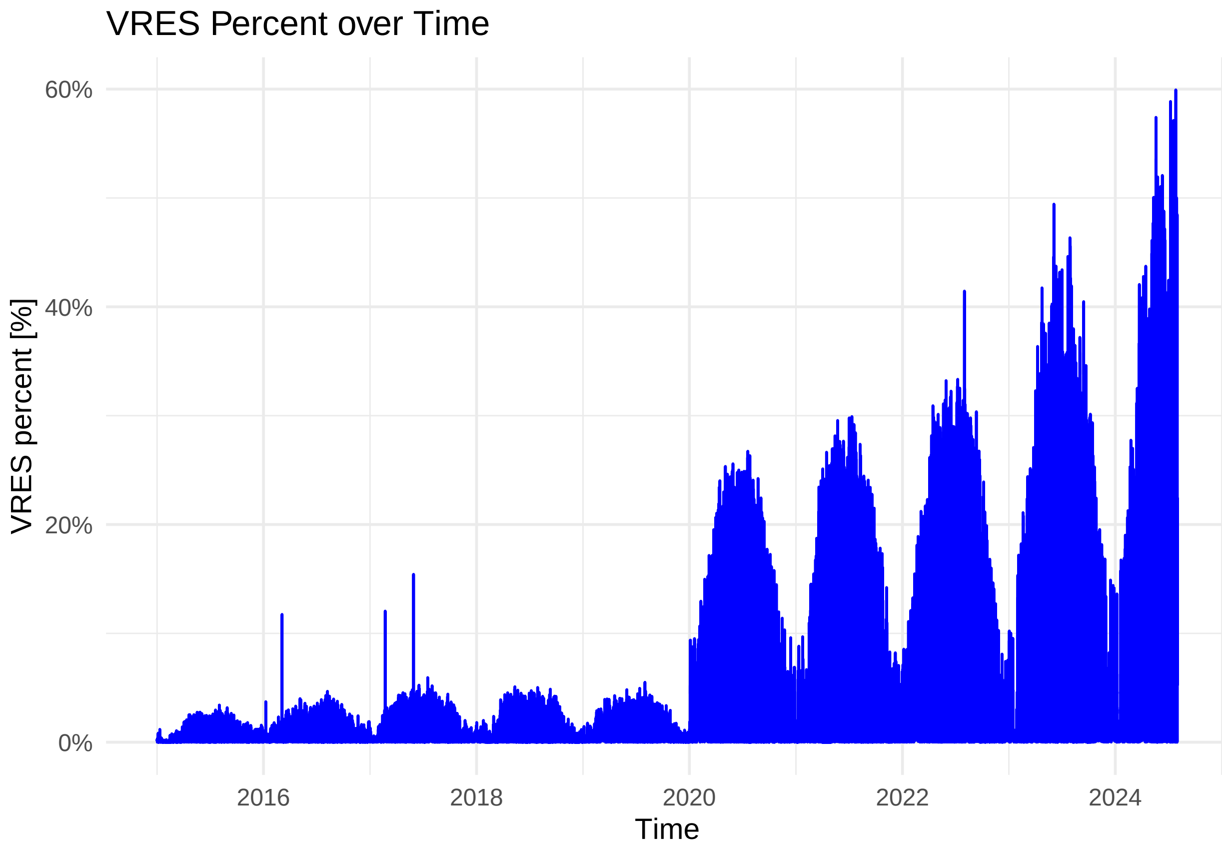
Wind and Solar Generation Moving Average over Time
Generation (MW)
25
20
15
10
5
0
2018
2020
2022
2024
Time
Generation Type
Solar
Wind

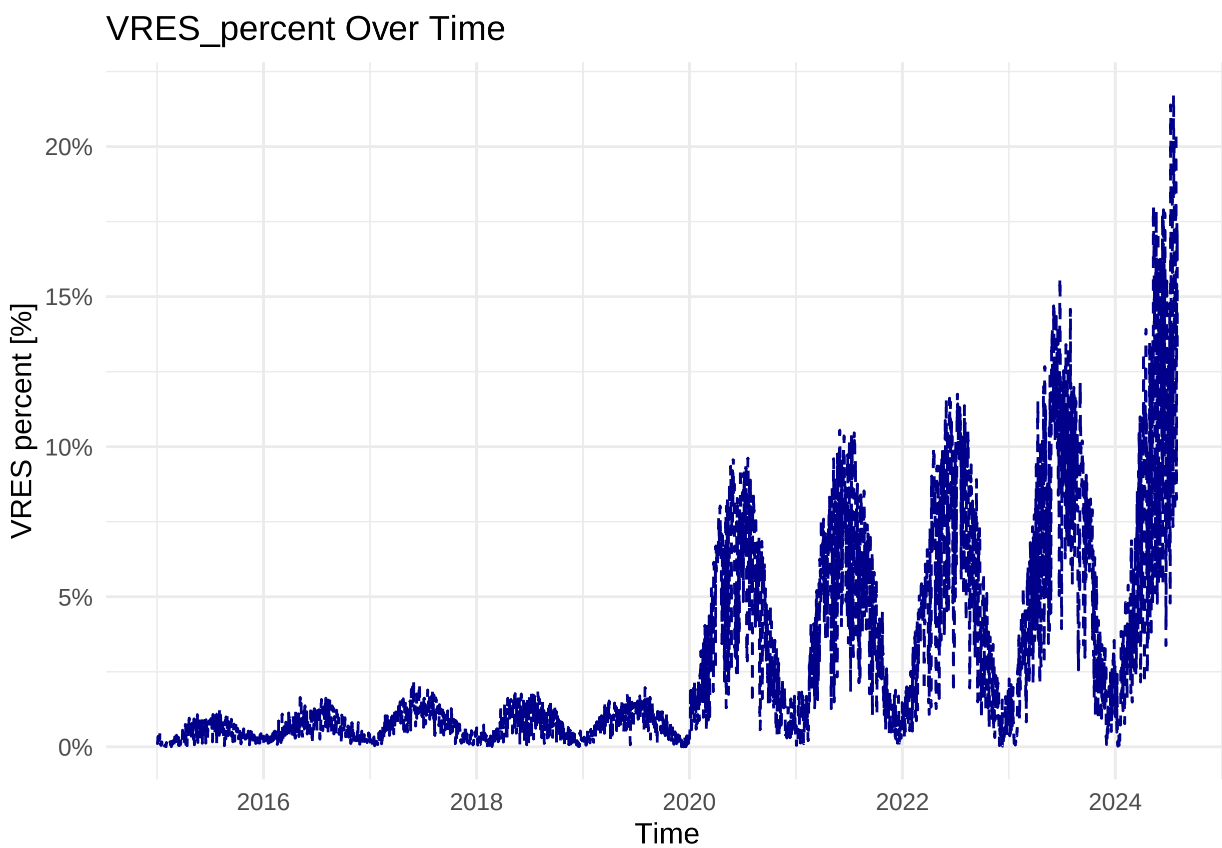

Wind and Solar Generation over Time
Generation (GWh)
4000
3000
2000
1000
0
2016
2018
2020
2022
2024
Date
Generation Type
Solar
Wind




```
## [1] 0
```

```
## [1] 0.5992799
```


VRES Percent over Time
60%
40%
20%
0%
VRES percent [%]
2016
2018
2020
2022
2024
Time



The above graph displays VRES_percent (Variable Renewable Energy Sources as a percentage of total energy demand) over time. A clearly cyclical wave pattern can be identified, indicating the presence of seasonality, which is expected due to the seasonal nature of wind and solar energy production. This seasonality reflects the fluctuations in renewable energy availability throughout the year.

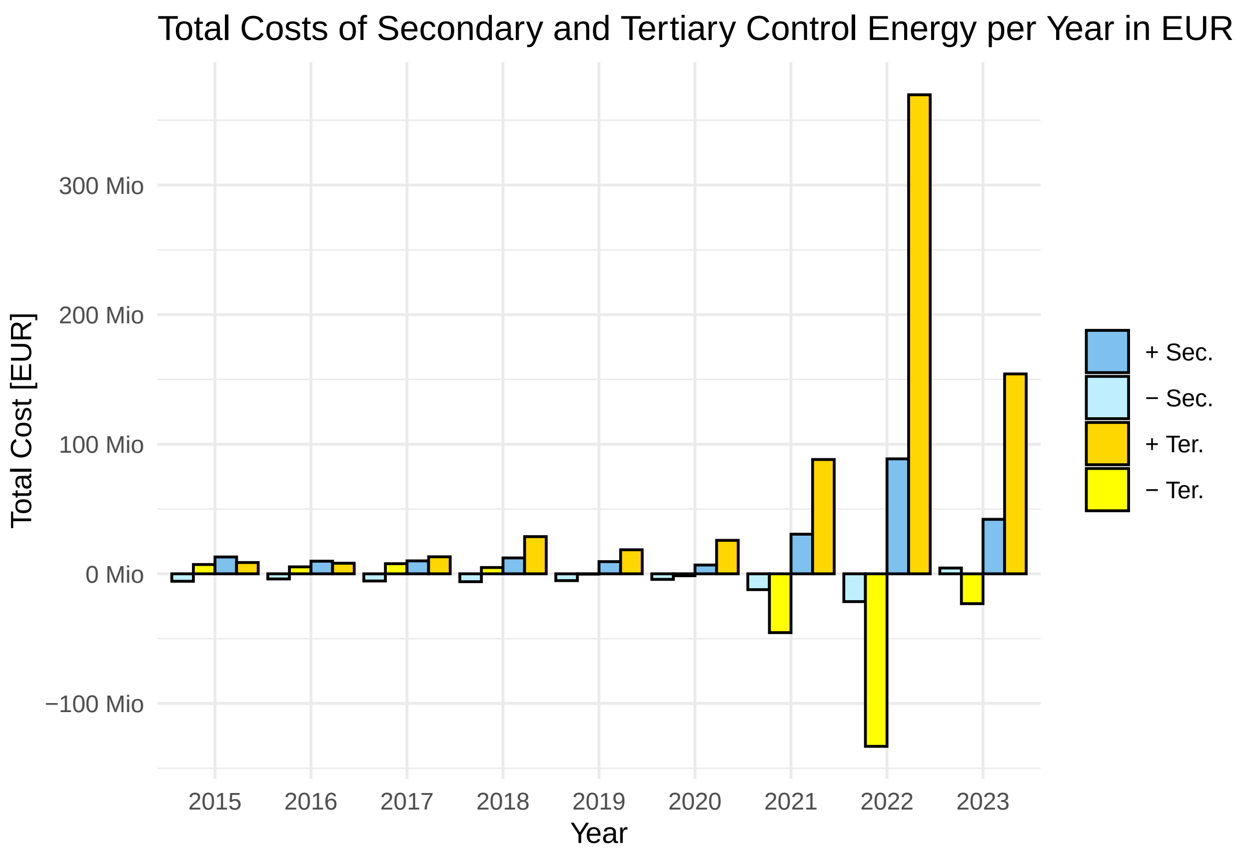
the maximum value has been pushed up noticeably every year since 2020 and almost reached 60%. When looking at the moving average, where each dot represents the average contribution over a 24 hour period, this share is lowered significantly, still reaching a contribution of 20% to the daily production in the last recorded summer of 2024.

```
# Cost aggregated by Year

# Convert the 'Timestamp' column to POSIXct format
d.h$Timestamp <- as.POSIXct(d.h$Timestamp, format = "%Y-%m-%d %H:%M:%S")

# Extract the year from the 'Timestamp' column
d.h$year <- year(d.h$Timestamp)

# Group by 'year' and summarize the total cost for each year
df_yearly_cost <- d.h %>%
  group_by(year) %>%
  summarise(total_cost = sum(cost_neg_sec_EUR, na.rm = TRUE))


# Filter out the year 2024 and group by 'year', then summarize the total cost for each year
df_yearly_cost <- d.h %>%
  filter(year != 2024) %>%  # Exclude the year 2024
```

```r
  group_by(year) %>%
  summarise(total_cost = sum(cost_neg_sec_EUR, na.rm = TRUE)) #y-axis with 'Mio' and commas

# Reshape the data into long format, selecting all four relevant columns
d.h_long <- d.h %>%
  filter(year != 2024) %>%  # Exclude the year 2024
  pivot_longer(cols = c(cost_pos_sec_EUR, cost_neg_sec_EUR, cost_pos_ter_EUR, cost_neg_ter_EUR),
               names_to = "cost_type", values_to = "cost_value")

# Group by 'year' and 'cost_type', then summarize the total cost for each
df_yearly_cost <- d.h_long %>%
  group_by(year, cost_type) %>%
  summarise(total_cost = sum(cost_value, na.rm = TRUE)) %>%
  ungroup()
```

```
## `summarise()` has grouped output by 'year'. You can override using the
## `.groups` argument.
```

```r
# Create a bar plot for the sum of costs per year, with different colors for each 'cost_type'
ggplot(df_yearly_cost, aes(x = as.factor(year), y = total_cost / 1e6, fill = cost_type)) +  # Y-axis in
  geom_bar(stat = "identity", position = "dodge", color = "black") +  # Dodge to separate the bars
  ggtitle("Total Costs of Secondary and Tertiary Control Energy per Year in EUR") +
  xlab("Year") +
  ylab("Total Cost [EUR]") +
  scale_y_continuous(labels = label_number(suffix = " Mio", big.mark = ",")) +  # Format y-axis

  # Use the correct order of colors and labels according to the levels of cost_type
  scale_fill_manual(values = c("skyblue2", "lightblue1", "gold", "yellow"),
  breaks = c("cost_pos_sec_EUR", "cost_neg_sec_EUR", "cost_pos_ter_EUR", "cost_neg_ter_EUR"),
  labels = c("+ Sec.", "- Sec.", "+ Ter.", "- Ter.")) +  # Custom colors and labels

  theme_minimal() +
  theme(legend.title = element_blank())  # Hide the legend title
```




```
# Identify exact duplicate rows
duplicate_rows <- d.h[duplicated(d.h) | duplicated(d.h, fromLast = TRUE), ]
duplicate_rows
```

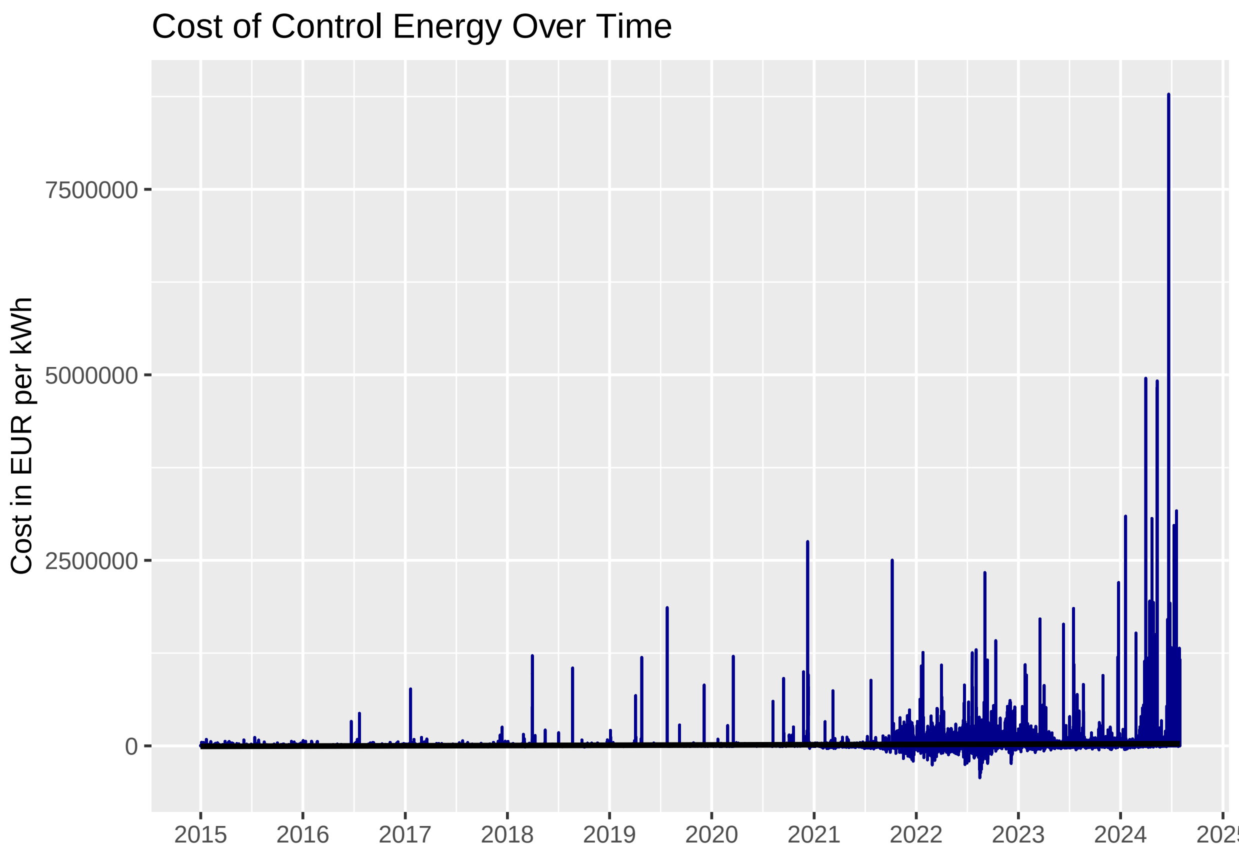
```
## # A tibble: 0 x 25
## # i 25 variables: Timestamp <dttm>, VRES_percent <dbl>, total_cost_EUR <dbl>,
## #   total_load_MW <dbl>, cost_pos_sec_EUR <dbl>, cost_neg_sec_EUR <dbl>,
## #   cost_pos_ter_EUR <dbl>, cost_neg_ter_EUR <dbl>, pos_sec_amount_kwh <dbl>,
## #   neg_sec_amount_kwh <dbl>, pos_ter_amount_kwh <dbl>,
## #   neg_ter_amount_kwh <dbl>, avg_price_pos_sec_EUR_MWh <dbl>,
## #   avg_price_neg_sec_EUR_MWh <dbl>, avg_price_pos_ter_EUR_MWh <dbl>,
## #   avg_price_neg_ter_EUR_MWh <dbl>, CH_solar_generation_actual_MW <dbl>, ...
```

This plot visualizes the total yearly "costs" (gain in the case of negative values) in Euro of secondary and tertiary control energy (positive and negative) from 2015 to 2023. The plot highlights trends in the costs associated with these control energy types, it is clearly visible that these total costs have risen in the last years, seemingly coinciding with the rise of solar energy production seen in our Data. To further analyze this relationship the next chapter will dive deeper into the Analysis using Time series.

3 Time Series of Hourly Data

3.1 Control Costs

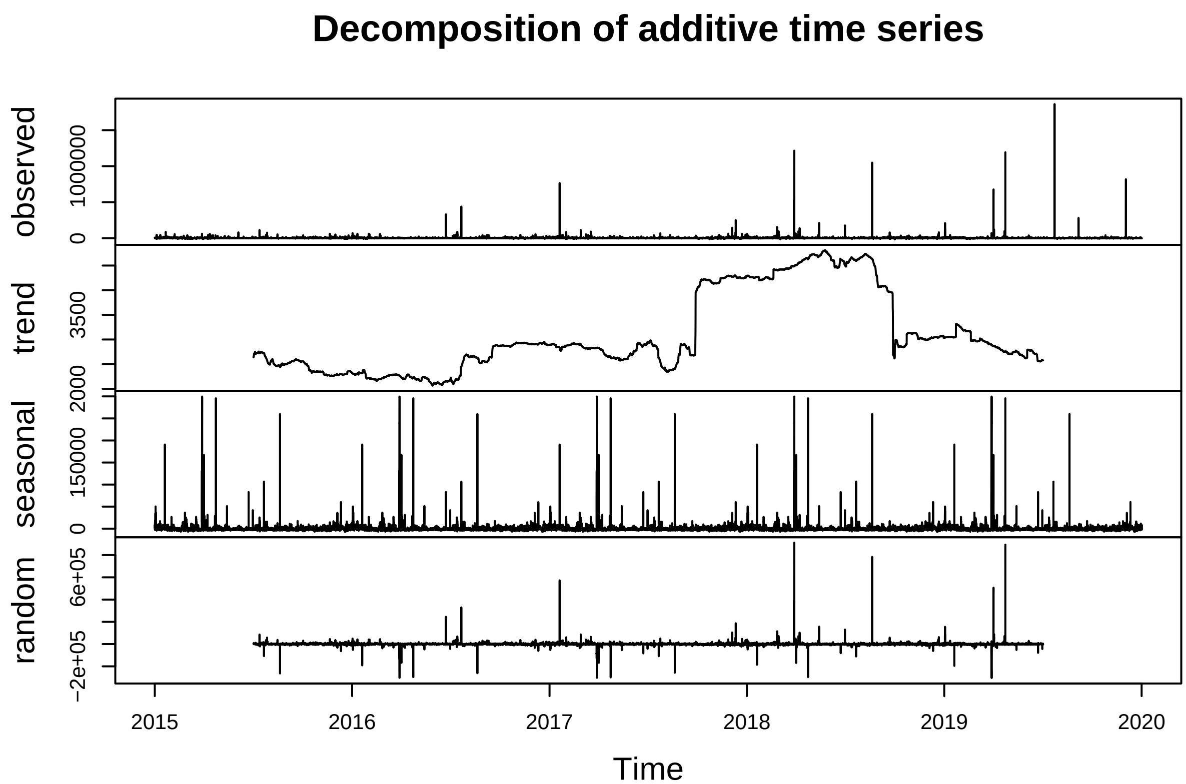
3.1.1 1. Visualization of Control Costs



The time series plot illustrates the cost of control energy over time, measured in EUR per kWh, from 2015 through 2024. The x-axis represents the time period, while the y-axis reflects the control energy costs in EUR. The graph reveals an overall increasing trend in control costs as time progresses, with periods of volatility that become more pronounced starting in early 2021. Although the costs were relatively stable from 2015 until 2020, with only minor spikes, a noticeable rise in both the frequency and magnitude of cost fluctuations is observed from 2021 onwards. This suggests that control energy costs became more volatile, with significant spikes emerging around 2022 and peaking in late 2023 and early 2024.

One notable aspect of the data is the presence of multiple sharp peaks, indicating sudden surges in costs, which likely correspond to times of increased demand for control energy or variability in renewable energy generation. These peaks, reaching as high as EUR 7,500,000 per kWh, imply high operational costs during these periods. Additionally, there are moments where the costs drop to zero or even become negative. Negative costs could imply that Swissgrid occasionally earns money, likely through balancing mechanisms when energy supply exceeds demand, thus allowing the sale of excess energy. These patterns highlight the importance of understanding the underlying drivers, such as increased integration of variable renewable energy sources (VRES) into the grid, which may contribute to such fluctuations.

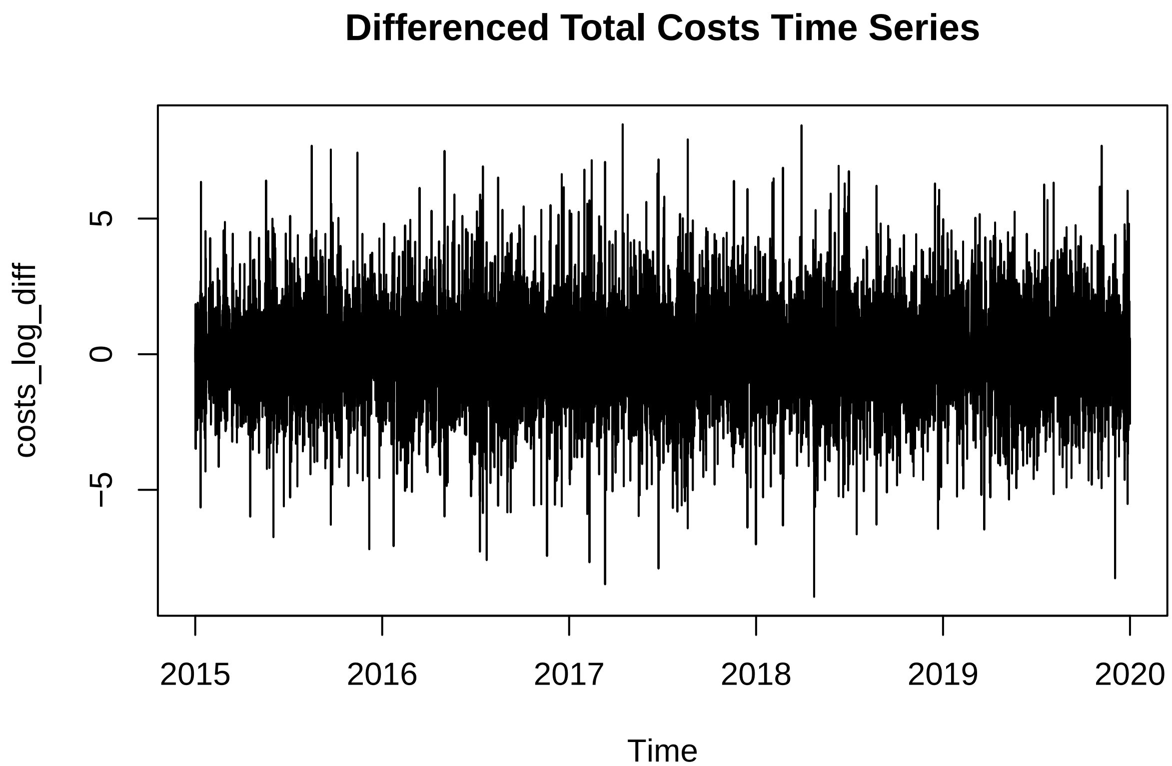
3.1.2 2. Decomposition of Control Costs

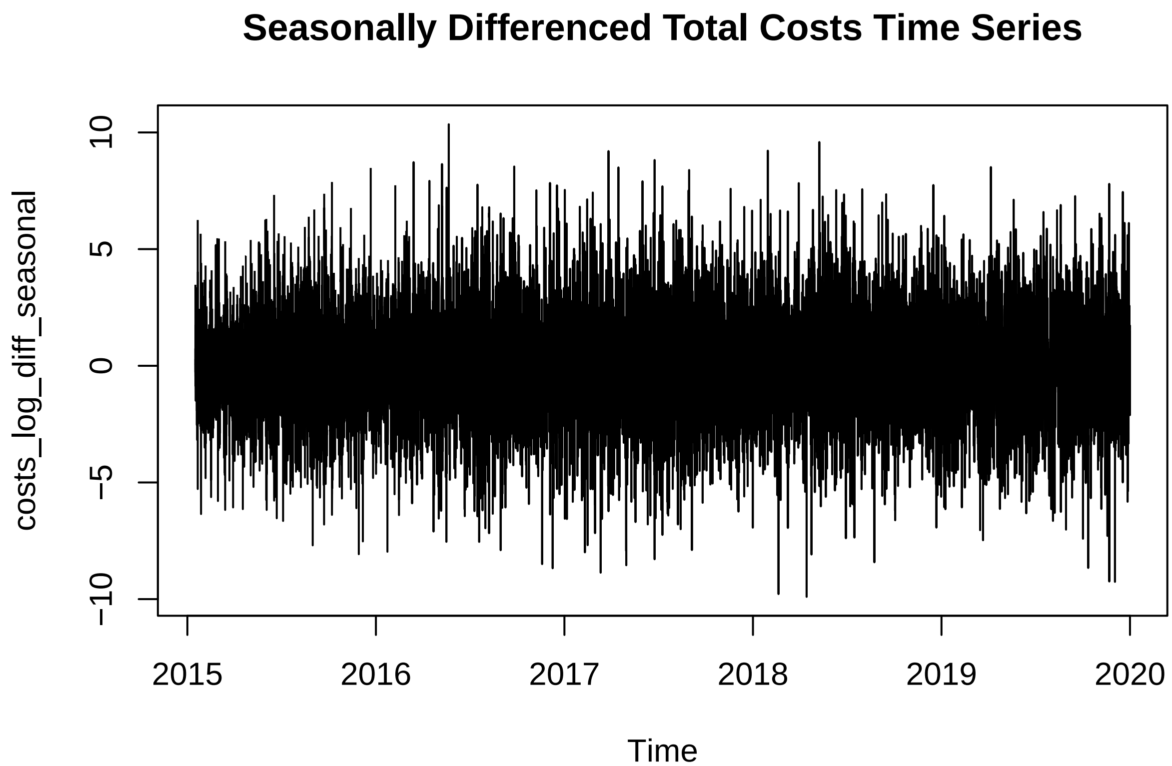


3.1.3 3. Stationarity of Control Costs

```
## [1] 20438
```

```
## [1] 0
```

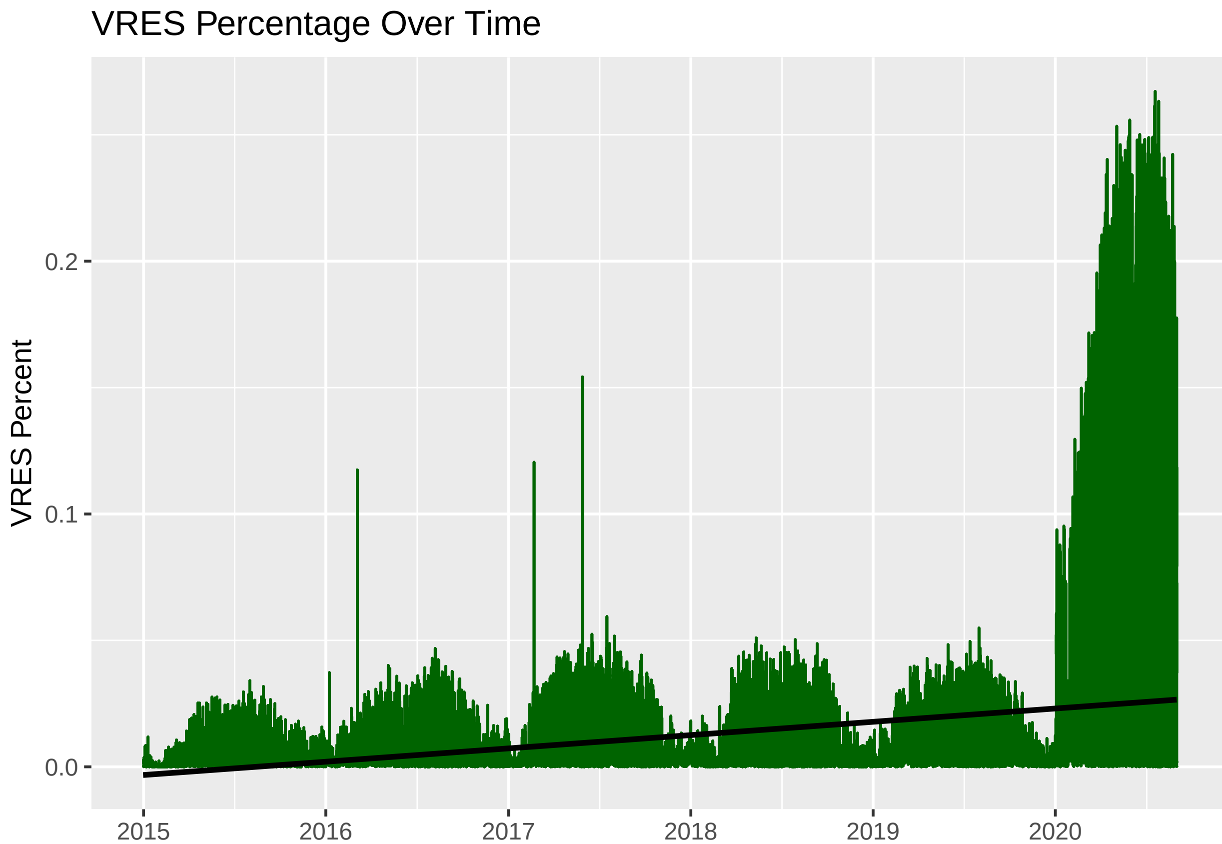

Differenced Total Costs Time Series
costs_log_diff
5
0
−5
2015
2016
2017
2018
2019
2020
Time



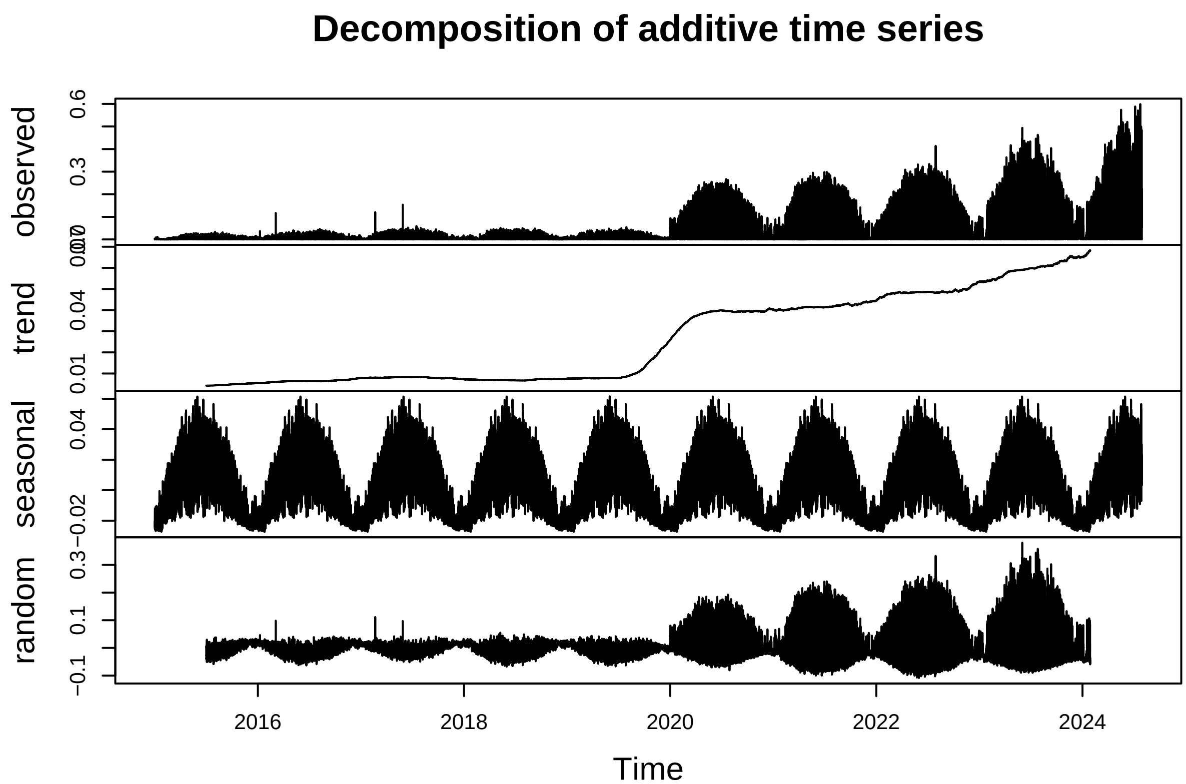
3.2 VRES of Control Energy

3.2.1 1. Visualization of VRES Control Energy

```
## 'geom_smooth()' using formula = 'y ~ x'
```


VRES Percentage Over Time
VRES Percent
0.2
0.1
0.0
2015
2016
2017
2018
2019
2020

3.2.2 2. Decomposition of VRES Control Energy

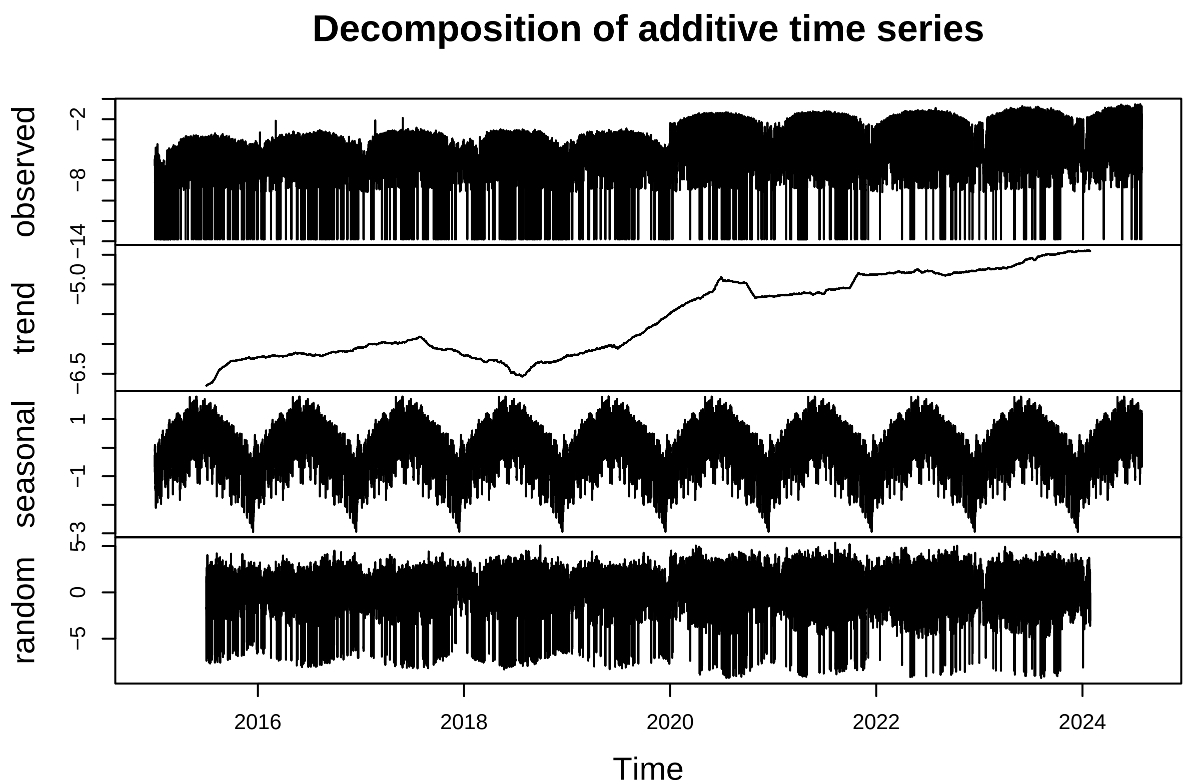


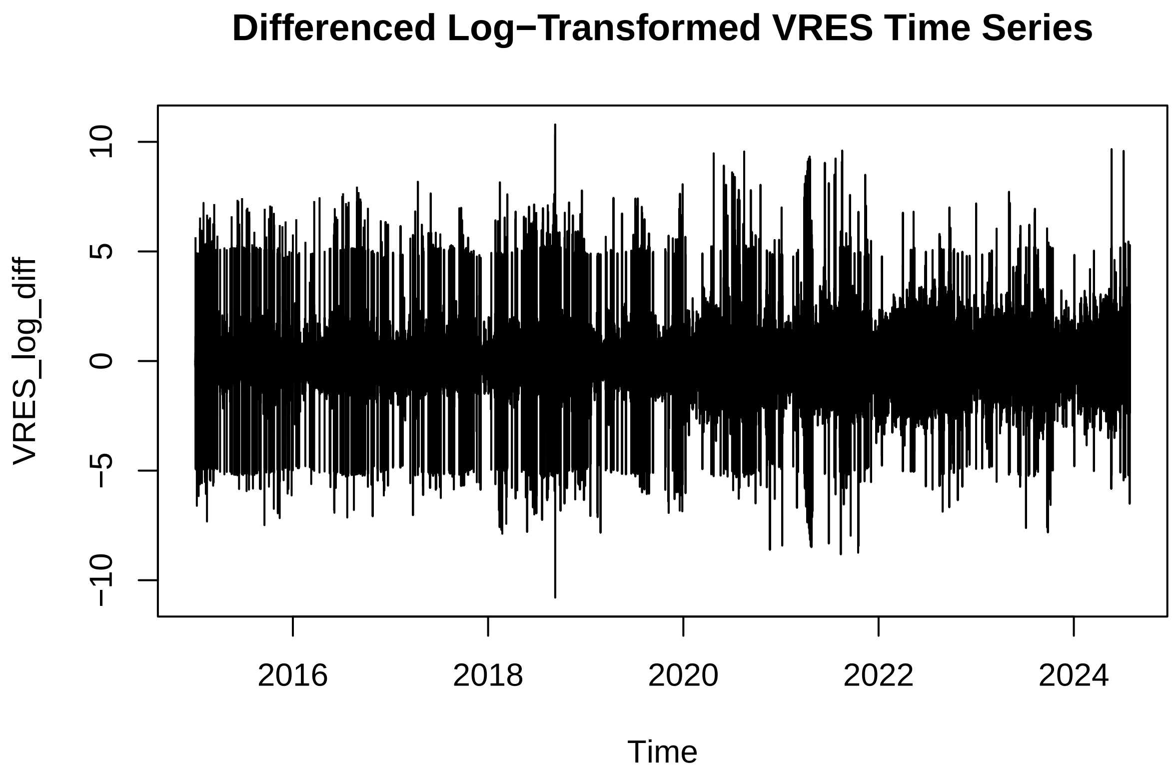
3.2.3 3. Stationarity of VRES Control Energy

```
##
##  Augmented Dickey-Fuller Test
##
## data:  VRES_ts
## Dickey-Fuller = -15.675, Lag order = 43, p-value = 0.01
## alternative hypothesis: stationary
```

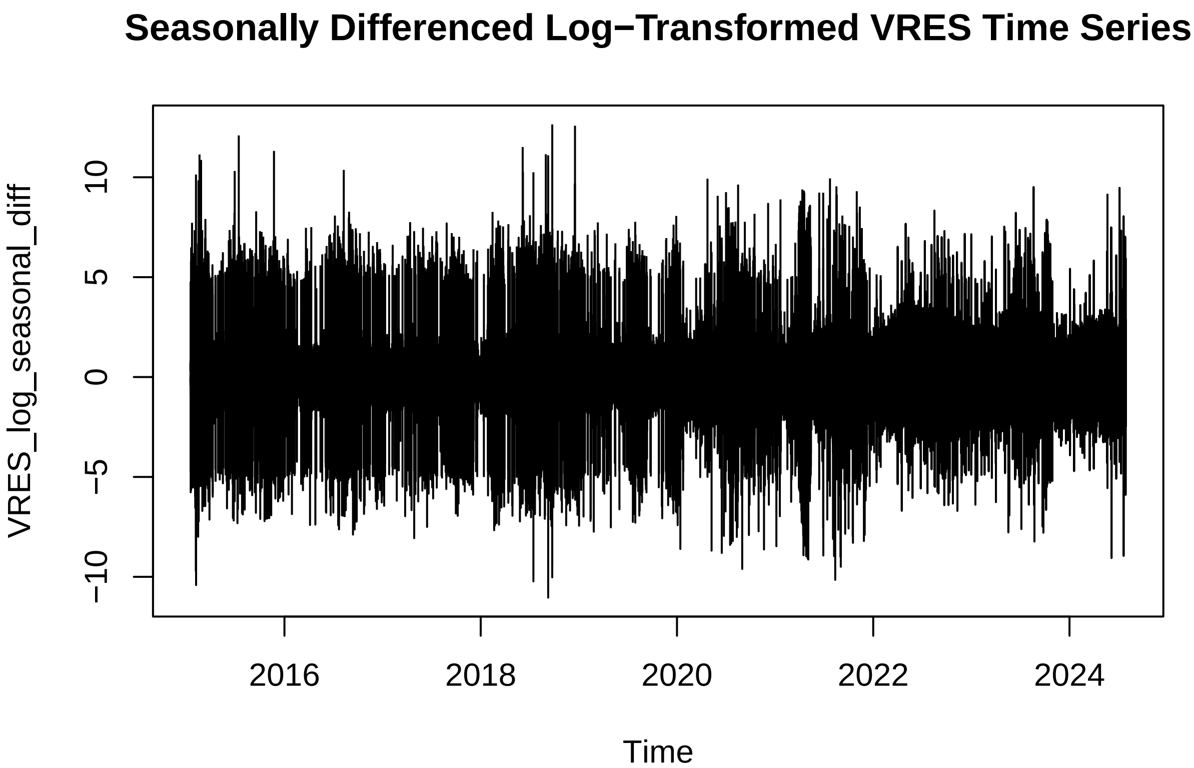
The Augmented Dickey-Fuller test has a p-value of 0.01 although the decomposition clearly shows a trend, seasonality and also a change in randomness. We suspect a decomposition of a multiplicative time series might help. A multiplicative decomposition assumes that the components (trend, seasonality, and noise) interact in a multiplicative manner. This is often suitable when the variability of the series increases as the level of the series increases, which might be indicated by the trend and seasonal patterns scaling with the overall level.

Applying a log transformation to the data can stabilize the variance, which often makes the series more amenable to decomposition or modeling. The log transformation essentially converts a multiplicative relationship into an additive one.


Decomposition of additive time series
observed
trend
seasonal
random
−2
−8
−14
−5.0
−6.5
1
−1
−3
5
0
−5
2016
2018
2020
2022
2024
Time


Differenced Log−Transformed VRES Time Series
VRES_log_diff
10
5
0
−5
−10
2016
2018
2020
2022
2024
Time

```
## [1] 0
```



3.2.4 4. Vector Autoregression of VRES Impact on Total Control Costs

```
##
##  Augmented Dickey-Fuller Test
##
## data:  costs_log_diff_seasonal
## Dickey-Fuller = -29.965, Lag order = 35, p-value = 0.01
## alternative hypothesis: stationary
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  VRES_log_seasonal_diff
## Dickey-Fuller = -72.56, Lag order = 43, p-value = 0.01
## alternative hypothesis: stationary
```

Determine the optimal lag length

4 Time Series of Daily Benchmark Data

4.1 Daily VRES and non-VRES Production

4.1.1 1. Visualization

The first graph illustrates the evolution of photovoltaic and wind energy production over time. Photovoltaic production (in orange) exhibits a clear seasonal pattern, with higher output during the summer months and lower production in winter, reflecting the natural variation in solar energy availability. In contrast, Wind production (in grey) remains consistently low throughout the year with some fluctuations but no clear trend, indicating that wind energy may play a relatively small role in the overall energy production mix compared to photovoltaic energy.

The second graph compares VRES (Variable Renewable Energy Sources, including Photovoltaic and Wind) with Non-VRES (comprising Hydro, Nuclear, Storage, and Thermal energy). The Non-VRES sources (in black) dominate total energy production and display significant variability over time, driven by factors such as fluctuating demand and adjustments in non-renewable energy generation. VRES production (in green), while much lower in magnitude, shows a clear seasonal trend, largely driven by photovoltaic energy, with peaks in the summer months.

4.1.2 2. Decomposition of Daily VRES Production

The decomposition reveals a clear linear trend and strong seasonal patterns, with some variability in both the seasonal component and residuals. While the seasonal noise is expected due to the nature of renewable energy sources like photovoltaic and wind, it does not obscure the overall pattern. The fluctuations in the residuals suggest potential volatility of variance, but this can be addressed by examining the residuals further after modeling.

4.1.3 3. Stationarity of Daily VRES Production

First, we apply regular differencing to remove the linear trend and since there is seasonality, we also apply seasonal differencing.

The first plot (Differenced VRES Time Series) shows the series after first-order differencing. While the trend is largely removed, there still appears to be seasonal fluctuations in the data, suggesting that seasonal differencing may be necessary.The variance seems somewhat stable, but there is some volatility toward the latter half of the series.

The second plot (Seasonally Differenced VRES Time Series) shows the data after applying both first-order and seasonal differencing. The seasonality appears to be removed successfully. The variance still shows some volatility, particularly in the later years, but the overall pattern is more stable than the first-differenced series.

The log-transformation and seasonal differencing have not sufficiently stabilized the variance, this indicates that the series may still exhibit heteroscedasticity (i.e., non-constant variance) which is why we consider a GARCH model.

4.1.4 4. Forecast of Daily VRES Production

Let's resume with the ACF and PACF since the GARCH model does not yield the desired result.

4.2 Daily Data of Day-Ahead Prices of Baseload

4.2.1 1. Visualization of Day-Ahead Prices

4.2.2 2. Decomposition of Day-Ahead Prices

4.2.3 3. Stationarity of Day-Ahead Prices

4.2.4 4. Forecast of Day-Ahead Prices

5 Time Series of Electricity Price Ranges (OLD - TO BE DELETED)

Plot: Time series plot showing the average secondary electricity price ranges over time. Purpose: To visualize how the secondary price ranges fluctuate over time.

Plot: Time series plot showing the average tertiary electricity price ranges over time. Purpose: To visualize how the tertiary price ranges fluctuate over time.

6 Time Series of VRES Percent

Plot: Time series plot showing the percentage of Variable Renewable Energy Sources over time. Purpose: To analyze the penetration of VRES in the energy grid over time.

7 Time Series of Actual vs Forecasted Load

Plot: Time series plot comparing the actual and forecasted electricity load in Switzerland. Purpose: To evaluate the accuracy of load forecasting and identify discrepancies.

Suggest 2-3 models, done well. This means verifying the assumptions and making neccesary transformation. I suggest doing the results in a seperate section

8 Results

8.1 Limitations

-cover general limitations

9 Conclusion

What did we learn, what did we not learn, how does this relate to policymakers.

Biblioghraphy

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