The European Electricity Demand, Generation & Power sector emissions

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Plan

- Obtaining Data
- Data preprocessing
- Exploratory Data Analysis
- Demand Forecast (Annual/ Monthly)
  - Just forecasting
- CO2 forecast (Annual/Monthly)
  - Just forecasting
- Electricity generation
  - Forecast
  - Bass model for types of fuels
- Prices(2015-2024)
  - Gradient Boosting for prices

The European Electricity analyses

Analyzing electricity demand, CO_2 emissions, and prices in the European Union (EU) is crucial for several reasons. Firstly, it helps policymakers understand the dynamics of energy consumption, facilitating the development of sustainable energy policies to meet environmental goals. Secondly, insights into CO_2 emissions are vital for tracking progress towards climate targets and identifying areas for improvement in the transition to cleaner energy sources. Lastly, analyzing electricity prices aids in ensuring energy affordability and competitiveness, providing valuable information for businesses and consumers in planning and decision-making. In summary, this analysis is essential for informed decision-making, policy formulation, and promoting a sustainable and resilient energy future for the EU.

The Goal of the Project

1) What will be the future electricity demand for Europe?
2) What will be future CO_2 emissions for Europe?
3) How does alternative types of generation influence the electricity demand and electricity prices?

Data

Datasets:

- Annual dataset (from 2000 to 2022)
- Monthly dataset (from 2015-01 to 2022-10)

Our core data covers the following subjects:

- Electricity generation (TWh), provided both by fuel type and aggregated
- Electricity demand (TWh), calculated as the sum of power production and net imports - Installed power generation capacity (GW), broken down by fuel type
- Emissions from electricity generation (Mt CO_2e)

Fuel Types:

- In our global dataset, fuel data is mapped into nine generation types:
  Bioenergy, Coal, Gas, Hydro, Nuclear, Solar, Wind Other Fossil and Other Renewables,.

Electricity Prices:

- Electricity prices monthly dataset

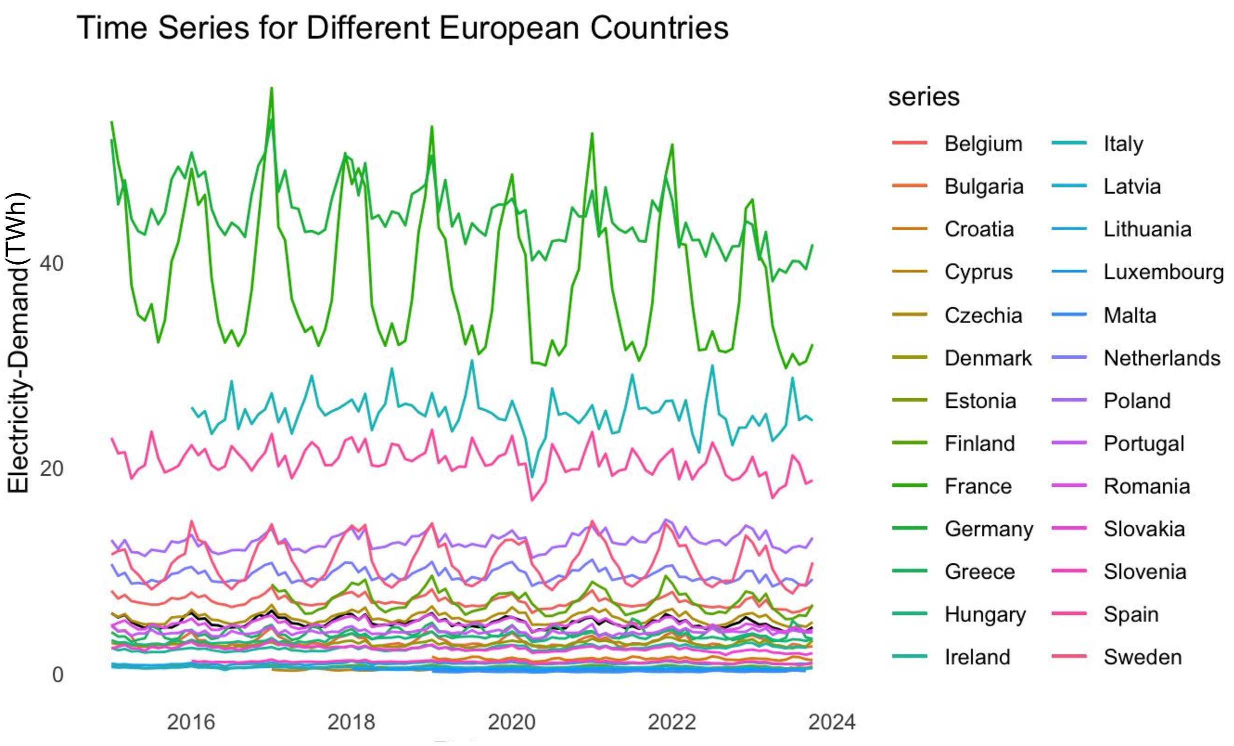
Key sources

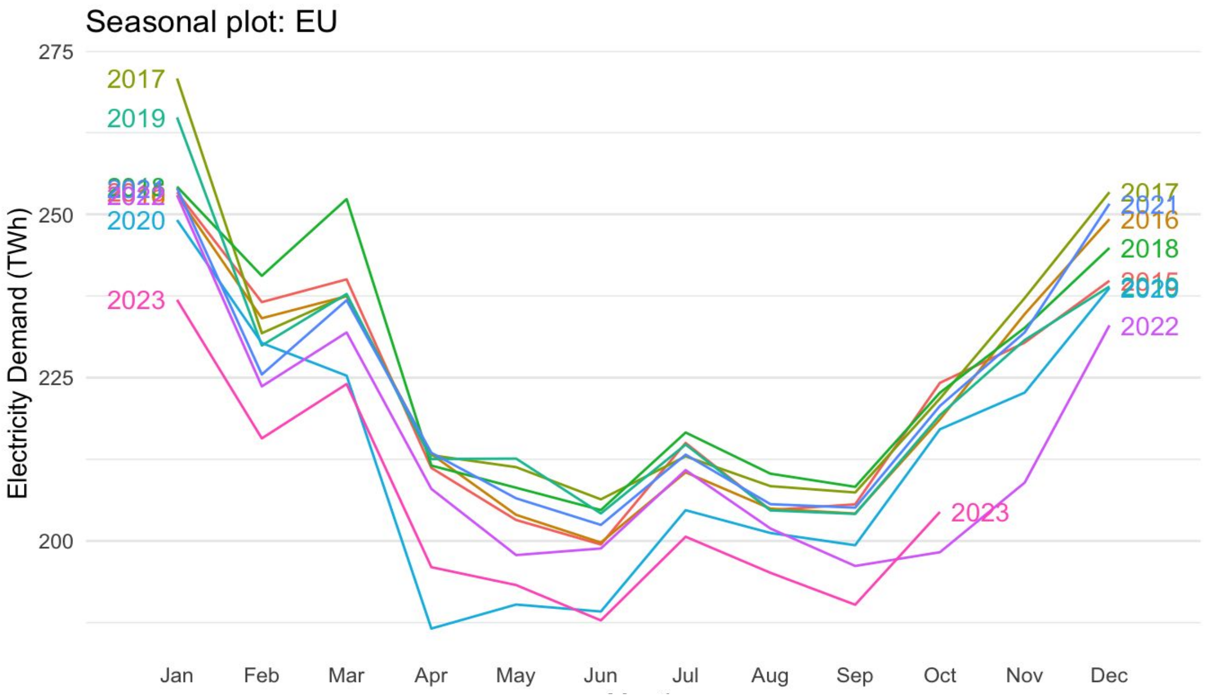
Exploratory Data Analysis (EU Electricity Demand)

The EU represents **10%** of global electricity demand.

Germany has the highest electricity demand **(556 TWh)**, accounting for almost 20% of total EU demand.

Germany is followed by **France (484 TWh)**, **Italy (322 TWh)** and **Spain (265 TWh)**. The Nordic countries of **Finland (15 MWh)** and **Sweden (13 MWh)** have the highest demand per capita, while **Romania (3 MWh)** has the lowest.

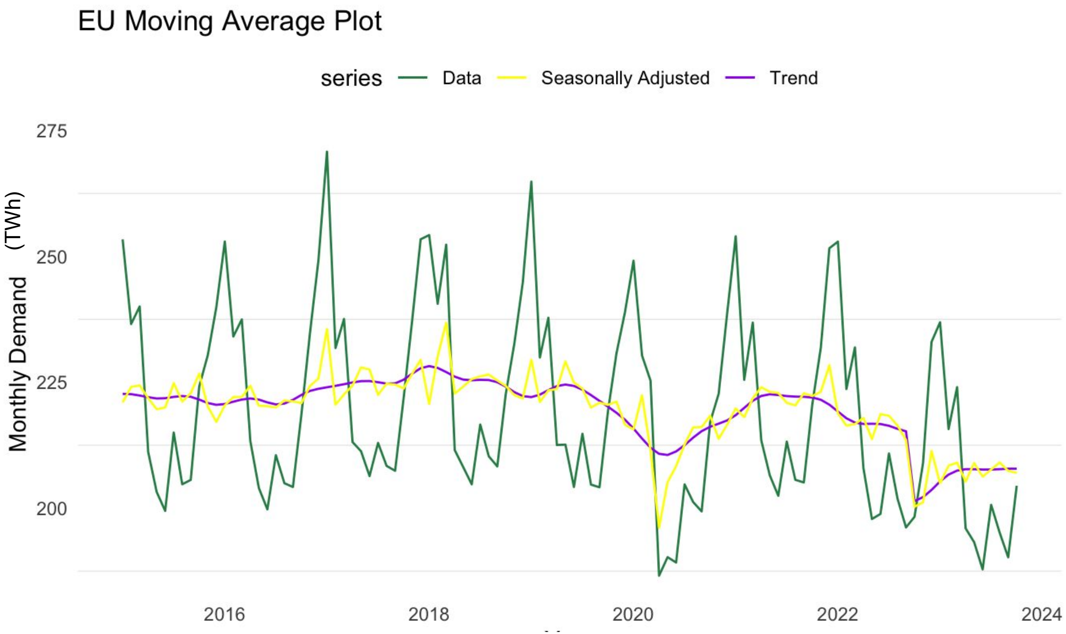


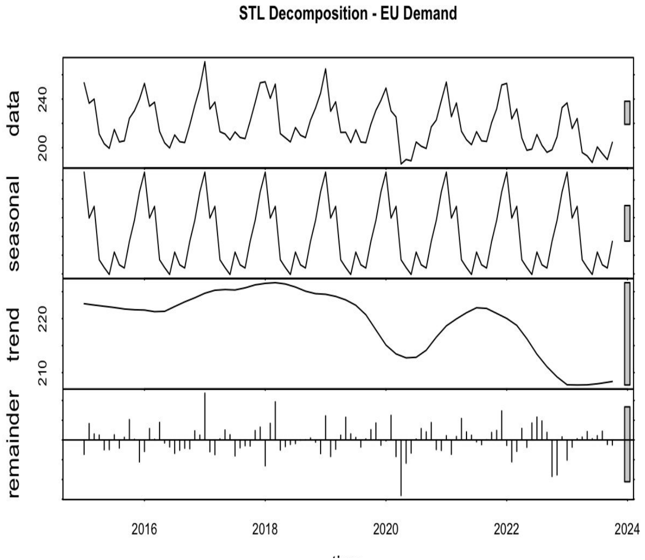


In late 2022, the European Union experienced a notable 7.9% decline in electricity demand, comparable to the most severe Covid-19 lockdowns.

The duration and permanence of this decline remain uncertain, posing challenges for future demand forecasting. Despite the current dip in demand, there is a crucial need to sustain efforts in transitioning to clean energy.

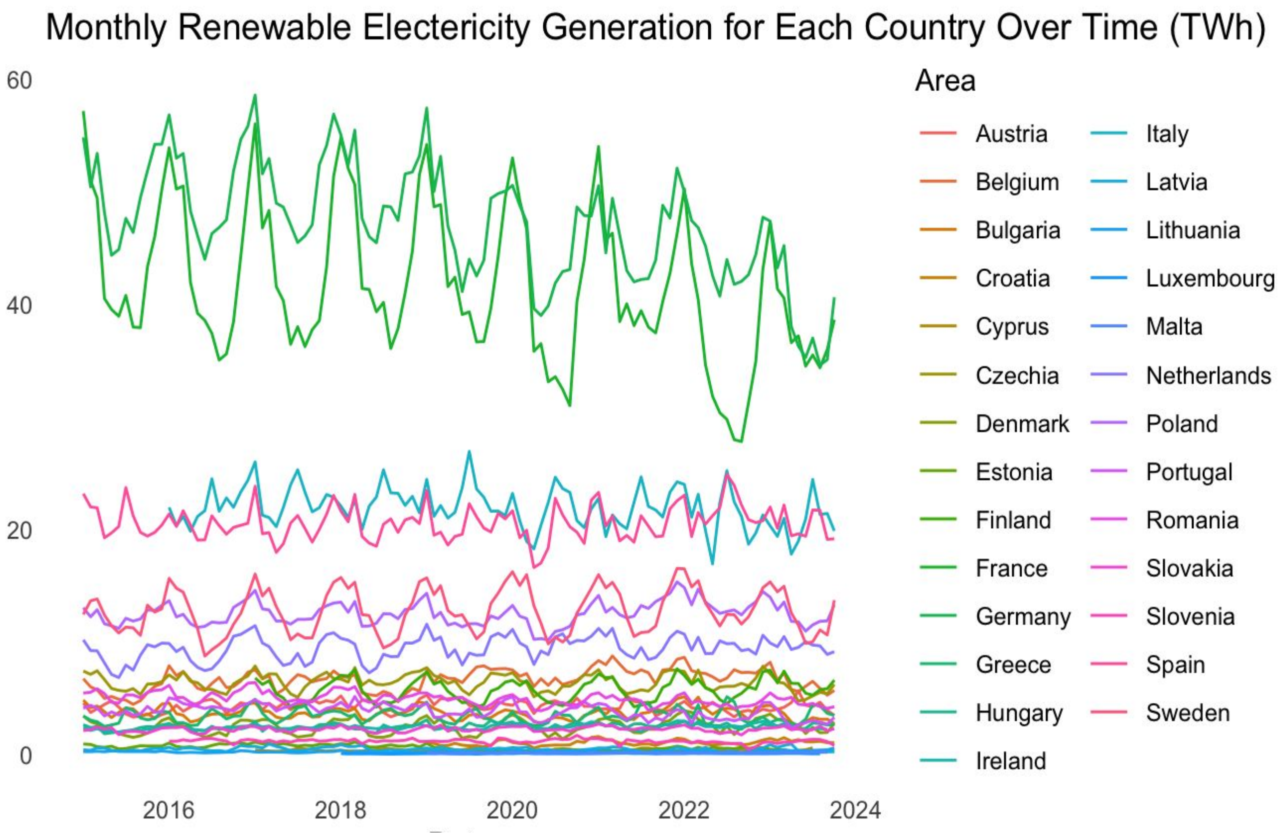
The significant drop in electricity demand at the close of 2022 stems from various factors, including efficiency improvements, altered industrial practices, mild temperatures and shifts in consumer behavior due to rising electricity costs and reactions in solidarity against Russia's invasion.



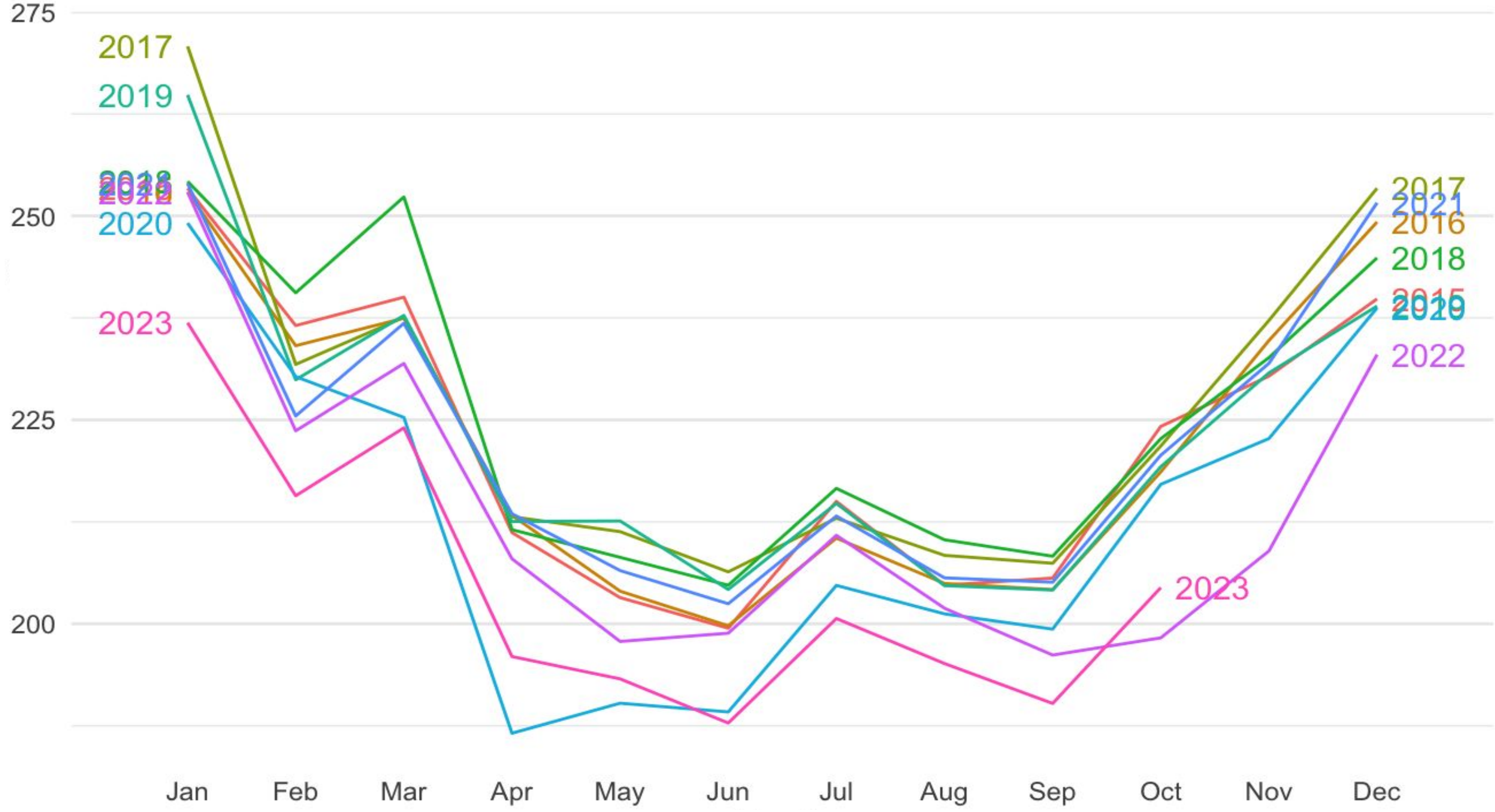


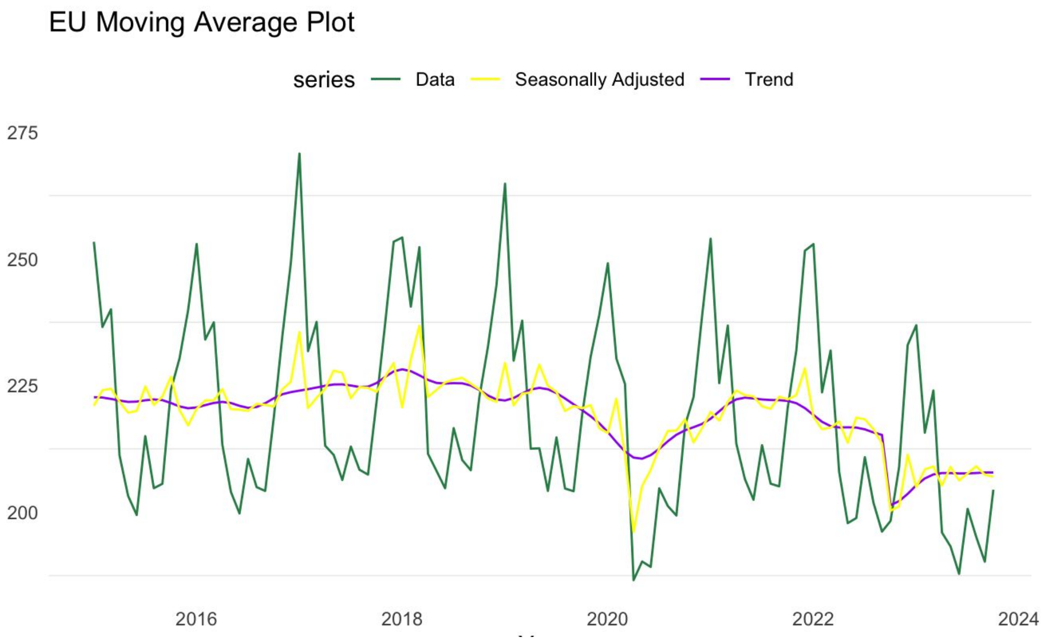
The application of Moving Average proves valuable in revealing the underlying trends in electricity demand for each country. This technique aids in understanding the overall trajectory of demand, especially when faced with noisy or fluctuating data.

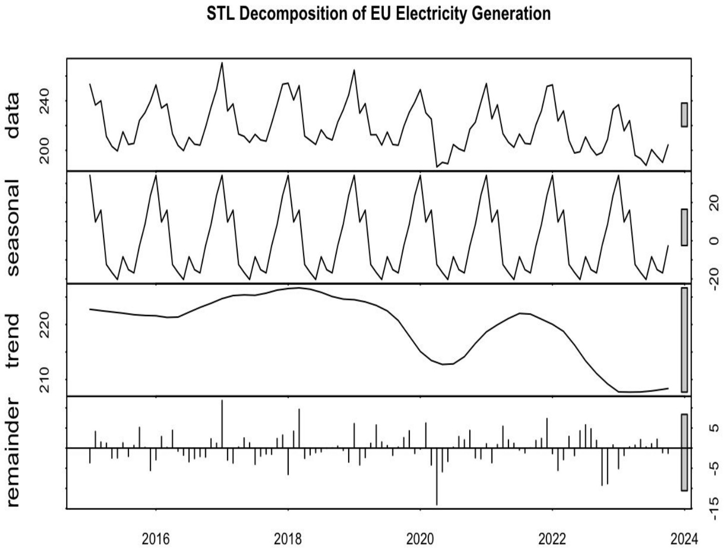
Exploratory Data Analysis (EU Electricity Generation)

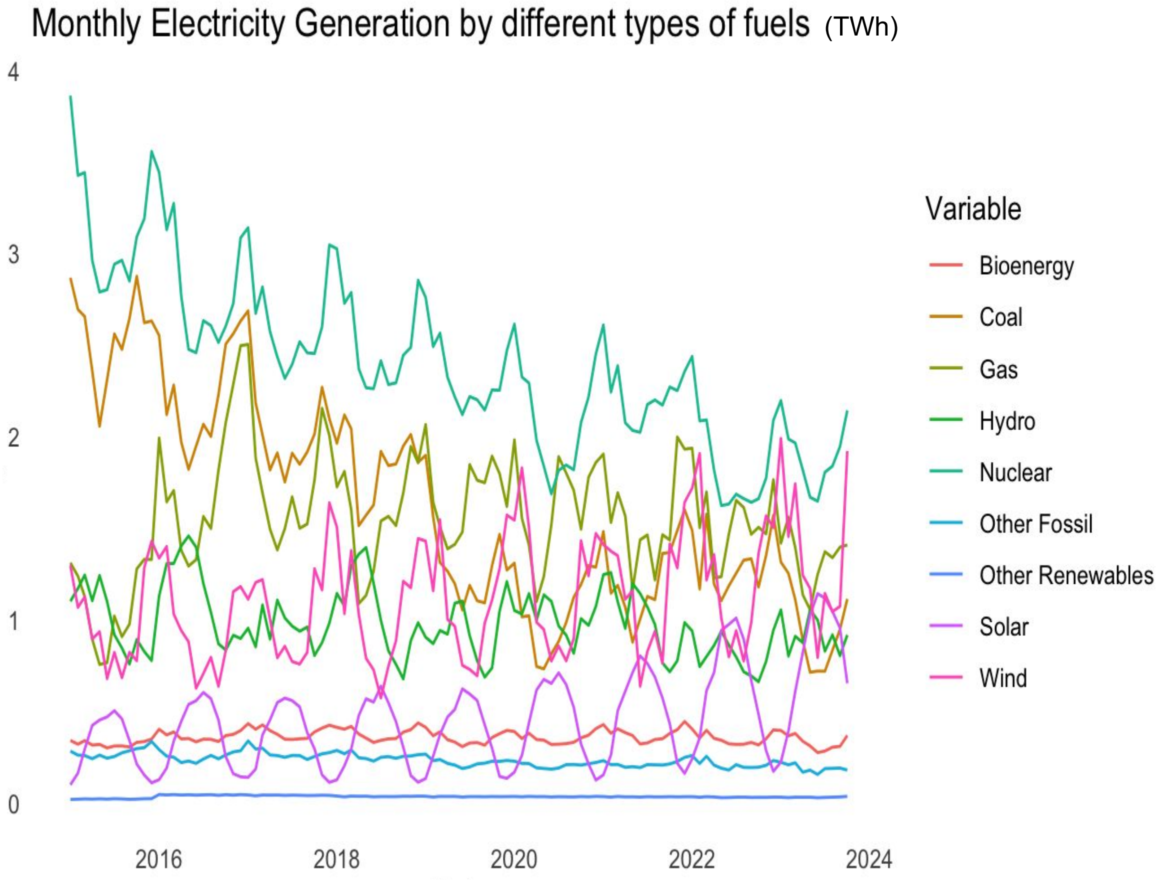


EU Electricity Generation Seasonal plot: (TWh)



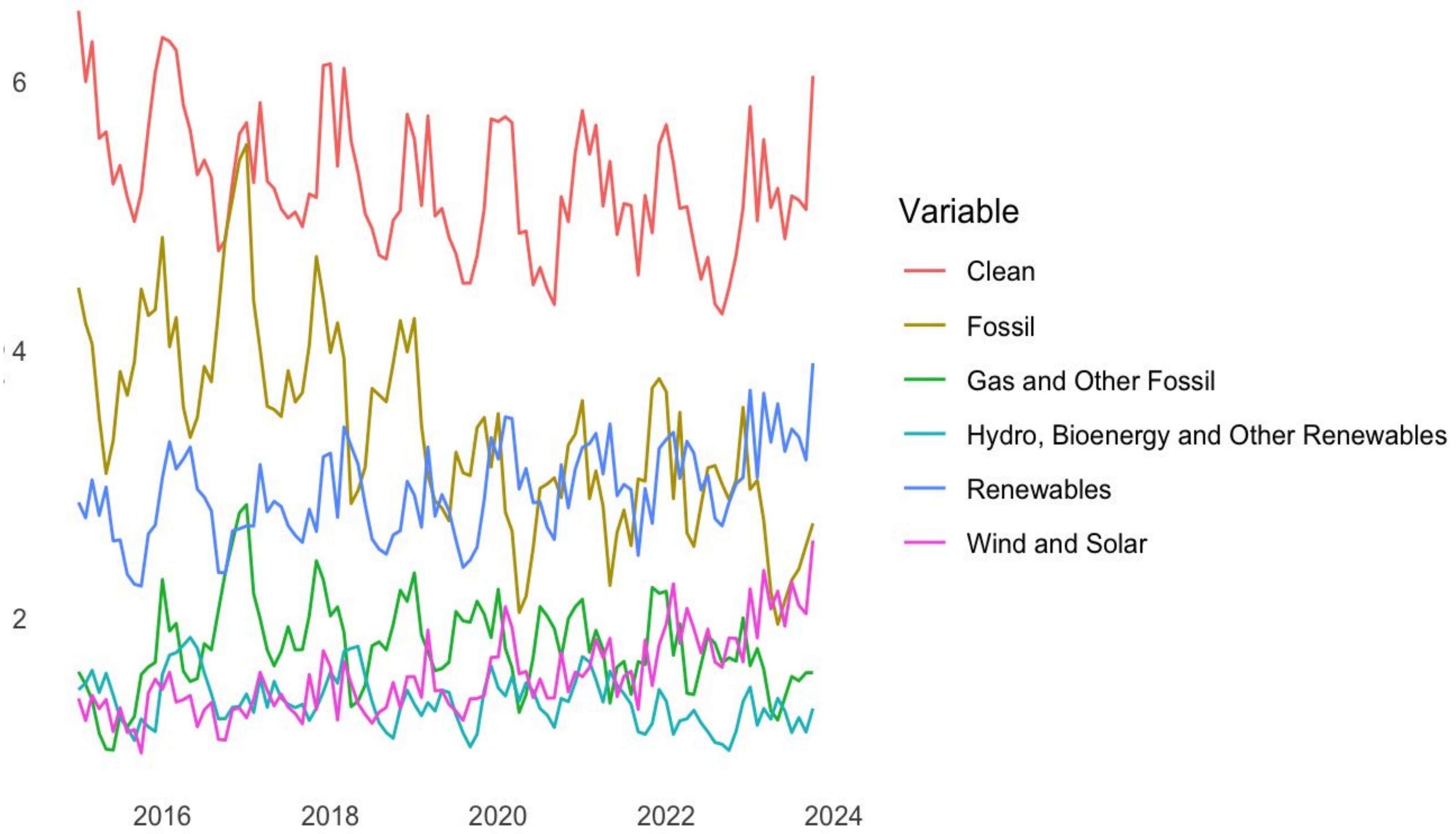

EU Moving Average Plot
series
Data
Seasonally Adjusted
Trend
275
250
225
200
2016
2018
2020
2022
2024


STL Decomposition of EU Electricity Generation
data
seasonal
trend
remainder
240
200
20
0
-20
220
210
5
-5
-15
2016
2018
2020
2022
2024

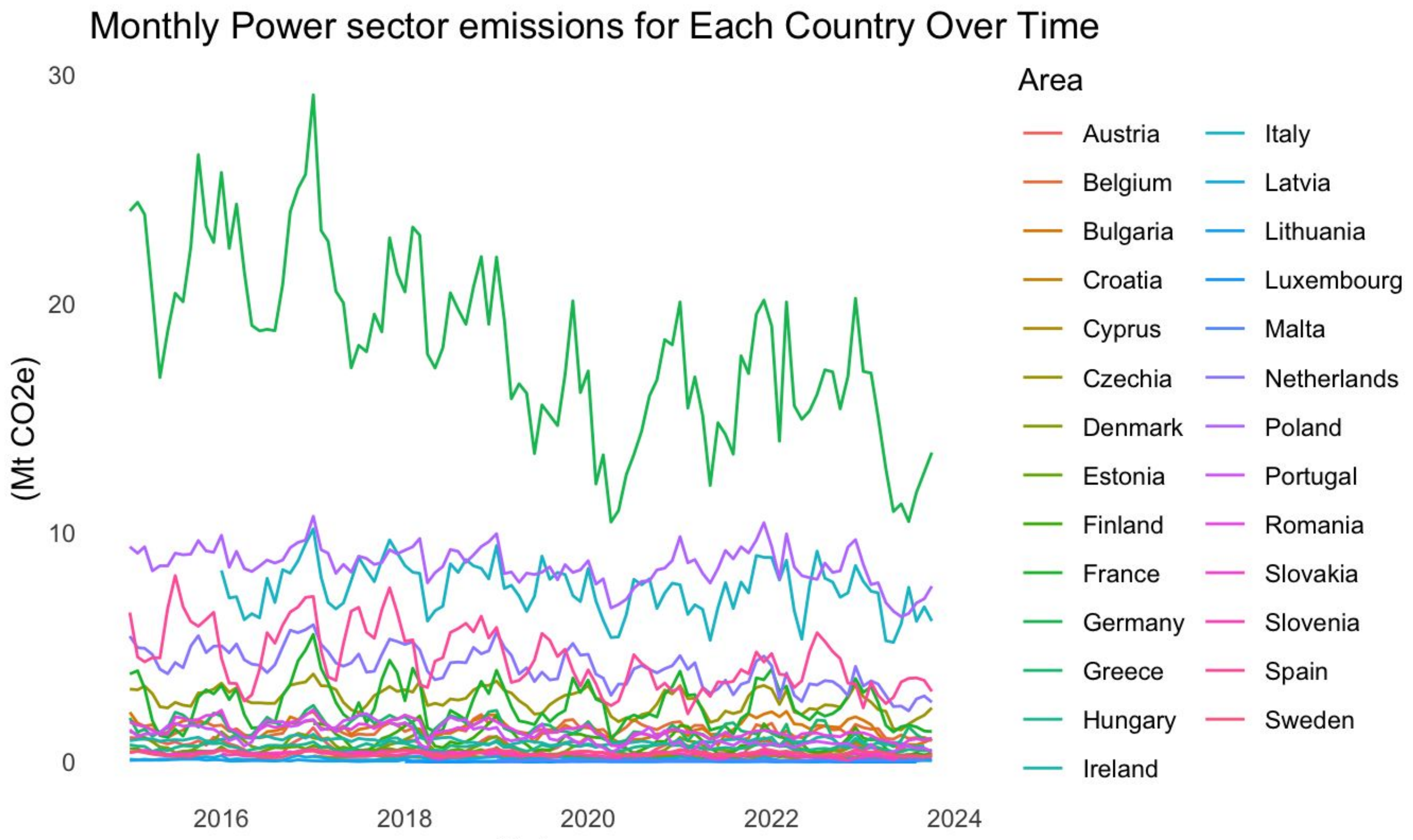


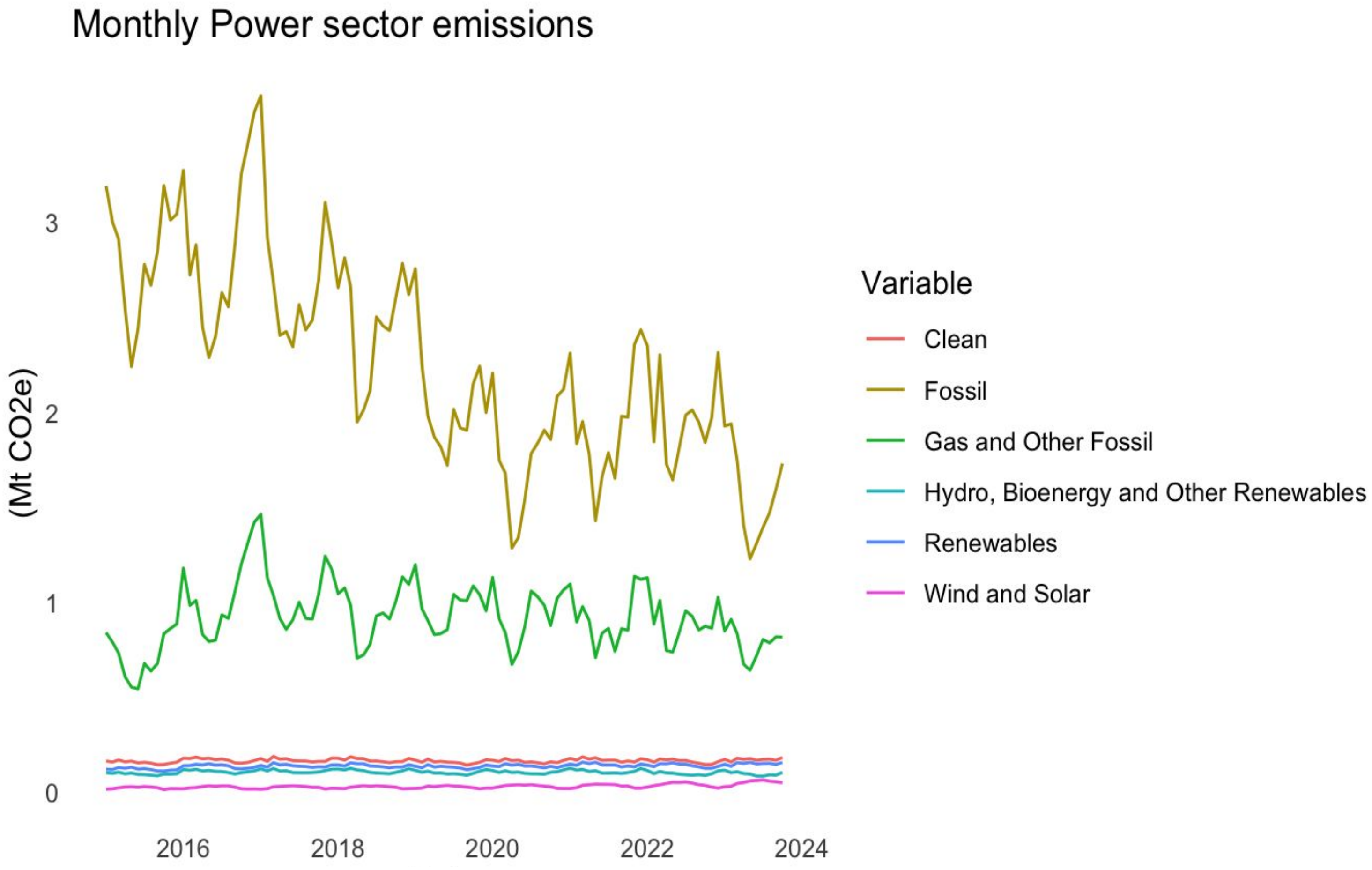
The EU, an early adopter of renewable energy, is striving to achieve a 45% renewable energy target by 2030, aiming for 69% of its electricity to be generated from renewables. Currently, fossil fuels still account for a significant portion, with 39% (1,104 TWh) of electricity coming from coal, gas, and other fossil sources. Coal contributes 16% (447 TWh), gas 20% (557 TWh), and other fossil fuels 3.6% (100 TWh). Nuclear remains the largest single contributor at 22% (613 TWh), while wind (15%, 420 TWh) and solar (7.3%, 203 TWh) together surpass all other sources, totaling 22% (623 TWh). Hydro contributes 10% (283 TWh), bioenergy 6% (167 TWh), and other renewables 0.2% (6.7 TWh).

Monthly Electricity Generation by different types of aggregated fuels (TWh)



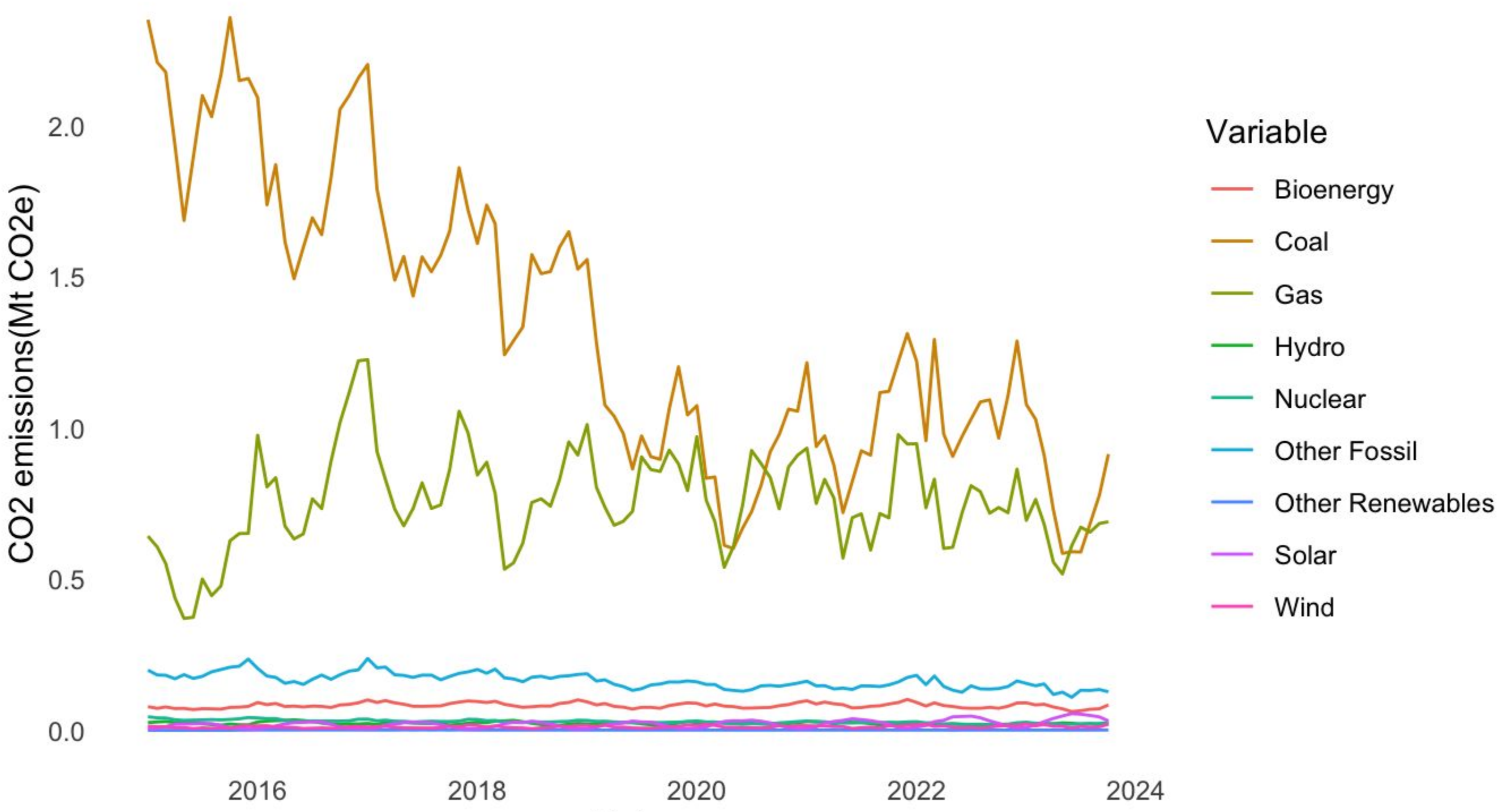
Exploratory Data Analysis (EU power sector emissions)



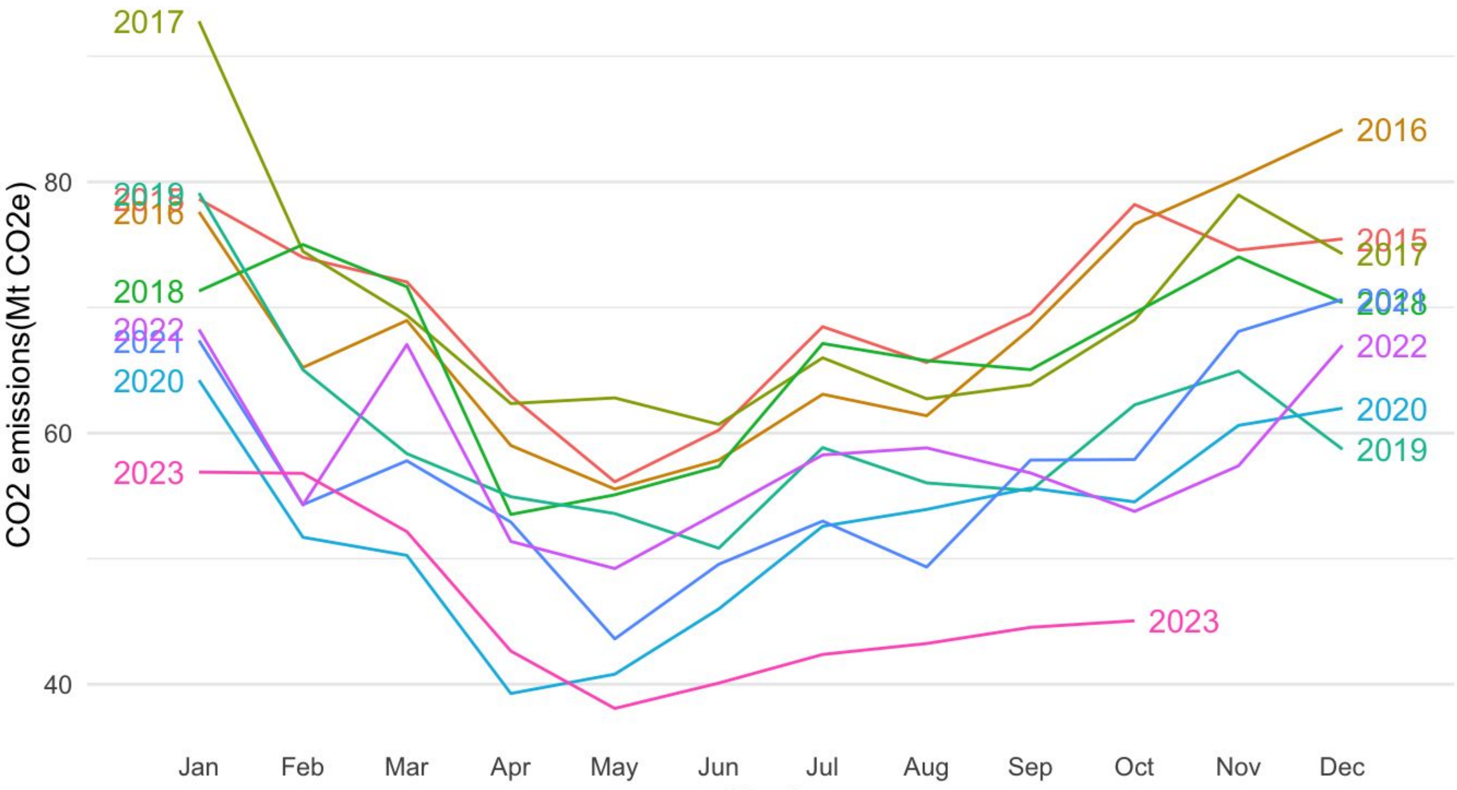


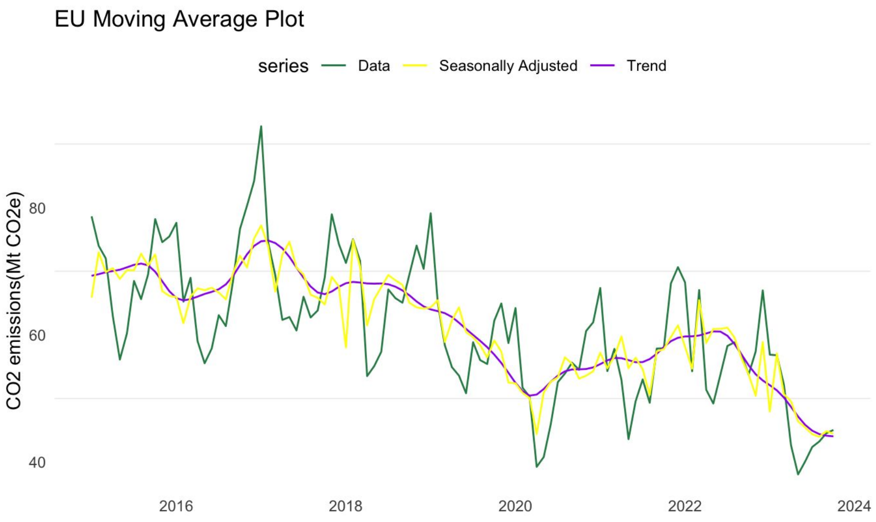
Monthly Power sector emissions
(Mt CO2e)
3
2
1
0
2016
2018
2020
2022
2024
Variable
Clean
Fossil
Gas and Other Fossil
Hydro, Bioenergy and Other Renewables
Renewables
Wind and Solar

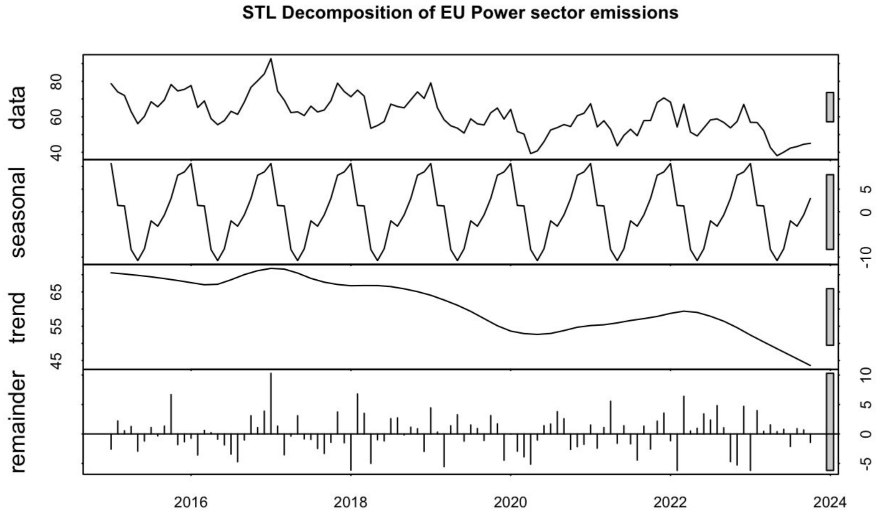
Power sector emissions



EU Power sector emissions Seasonal plot:




EU Moving Average Plot
series
Data
Seasonally Adjusted
Trend
CO2 emissions(Mt CO2e)
80
60
40
2016
2018
2020
2022
2024


STL Decomposition of EU Power sector emissions
data
seasonal
trend
remainder
2016
2018
2020
2022
2024

Data Modeling

- Electricity Demand Forecasting(TWh)
- Electricity Generation Forecasting(TWh)
- Electricity CO2 Emissions Forecasting
- Electricity Price Forecasting

Data clusterization

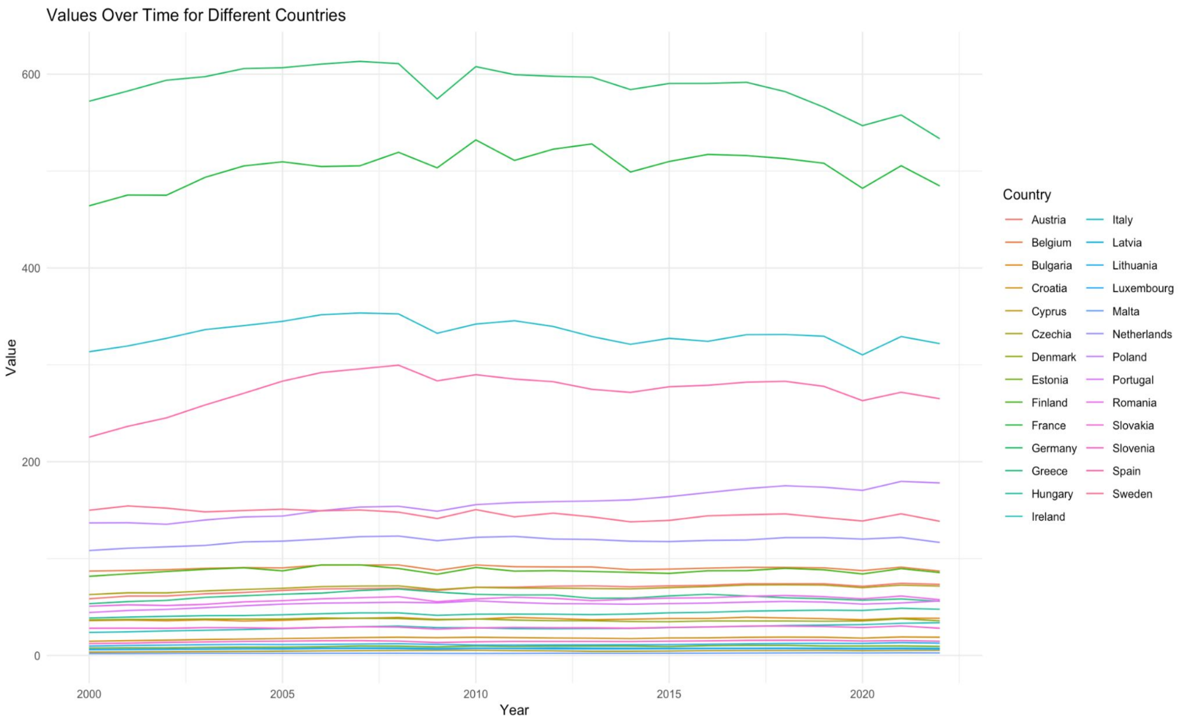
We approach our dataset from two perspectives. First, we categorize the data based on countries and perform clustering analysis. In the second aspect, we classify the dataset according to different types of fuels. Through this approach, we conduct a thorough analysis and forecasting for electricity demand and generation, exploring diverse angles to gain comprehensive insights.

Clustering data before forecasting can be useful for several reasons:

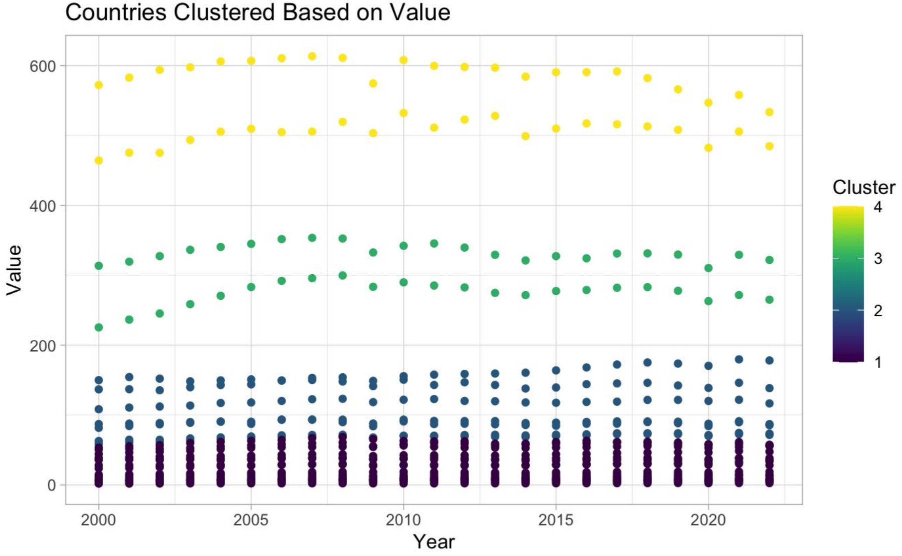
- Handle similar behaviour between some countries
- Require different forecasting models for different clusters
- Manage the complexity of forecasting models
- Leverage the similarities within clusters to enhance forecast accuracy
- Make forecasting more scalable

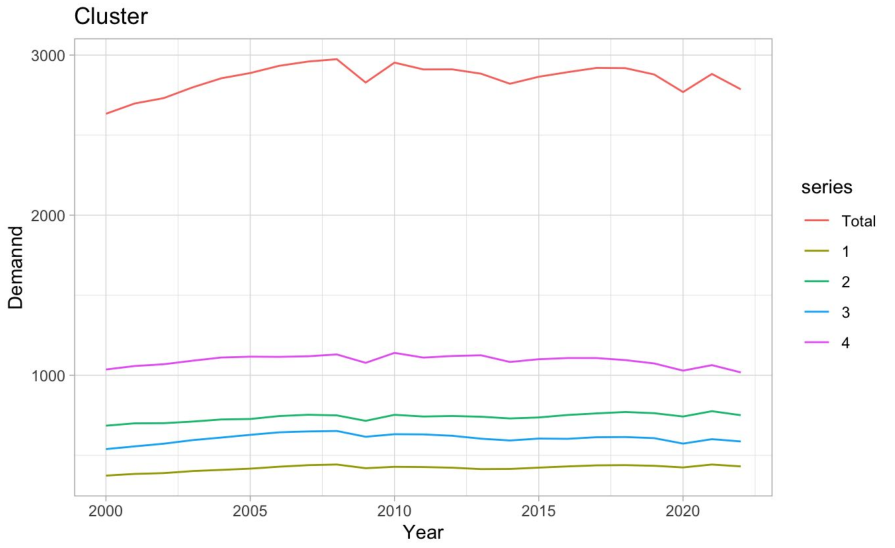
Demand Forecasting (annual)

1) Clusterization
2) Transforming data into hierarchical time-series, which should help for forecasting data on different levels(Total, Clusters and also different countries)
3) Splitting our data into train and test split
4) Applying combination of different methods for distributing forecasts within the hierarchy and different methods for forecasting method to use for each series.
5) Comparing final metrics



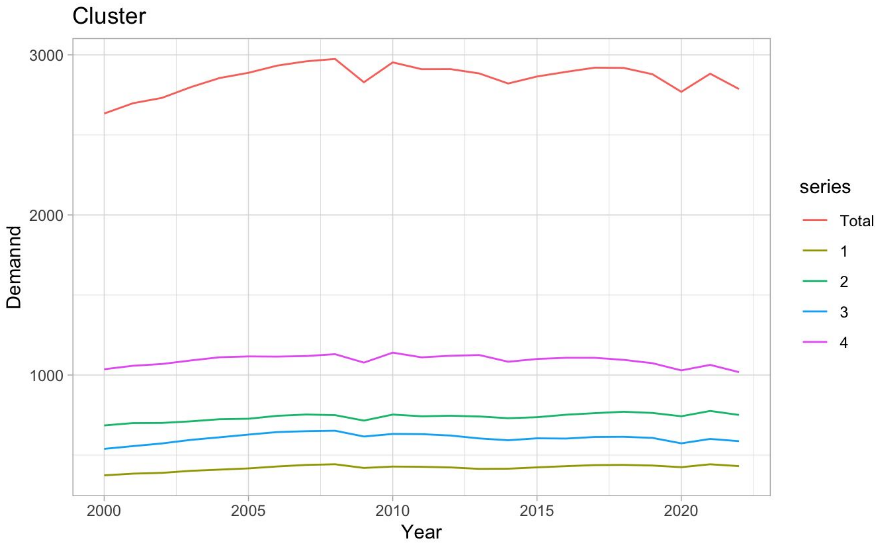
1) Clusterization

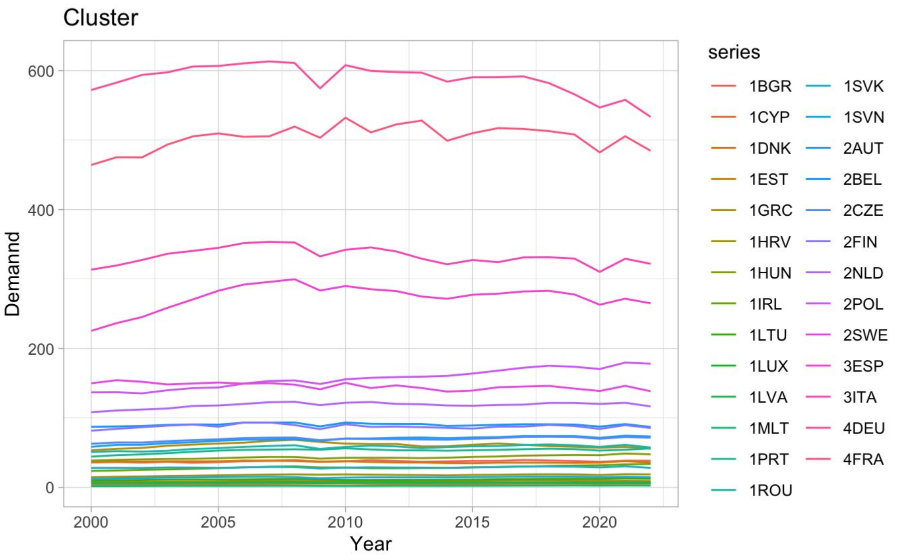




1	1BGR, 1HRV, 1CYP, 1DNK, 1EST, 1GRC, 1HUN, 1IRL, 1LVA, 1LTU, 1LUX, 1MLT, 1PRT, 1ROU, 1SVK, 1SVN
2	2AUT, 2BEL, 2CZE, 2FIN, 2NLD, 2POL, 2SWE
3	3ITA, 3ESP
4	4FRA, 4DEU

2) Hierarchical time series





1	1BGR, 1HRV, 1CYP, 1DNK, 1EST, 1GRC, 1HUN, 1IRL, 1LVA, 1LTU, 1LUX, 1MLT, 1PRT, 1ROU, 1SVK, 1SVN
2	2AUT, 2BEL, 2CZE, 2FIN, 2NLD, 2POL, 2SWE
3	3ITA, 3ESP
4	4FRA, 4DEU

3) Forecasting methods

Method for distributing forecasts within the hierarchy:

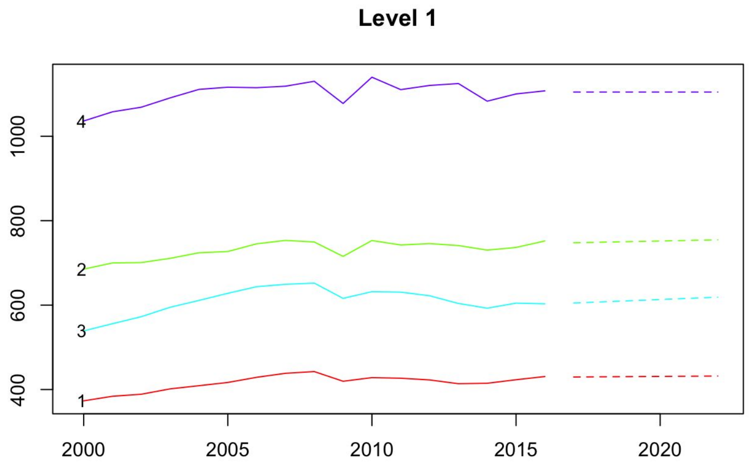
- "comb" (Optimal Combination)
- "bu" (Bottom-Up)
- "mo" (Top-Down using Historical Proportions)
- "tdgsa" (Temporal Disaggregation using Generalized Structural Models)
- "tdfp" (Temporal Disaggregation using Functional Predictors)

Forecasting methods:

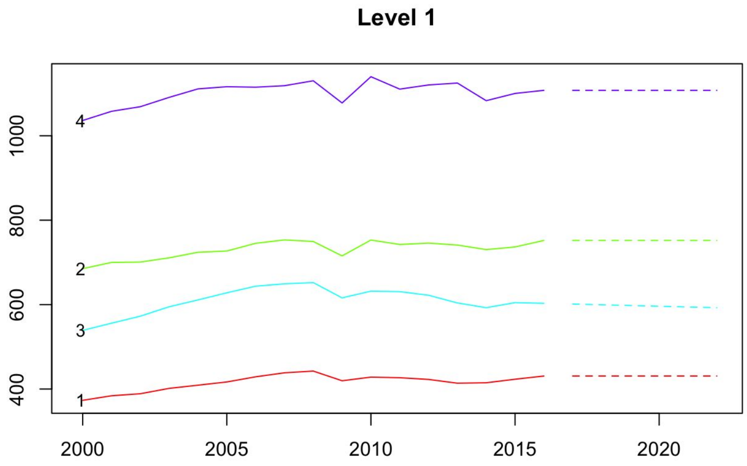
- "ets" (Error, Trend, Seasonality)
- "arima" (AutoRegressive Integrated Moving Average)
- "rw" (Random Walk)

In our analysis we used all possible combinations of this parameters.

3) Forecasting



ETS + bu



ARIMA + mo

3) Evaluation metrics

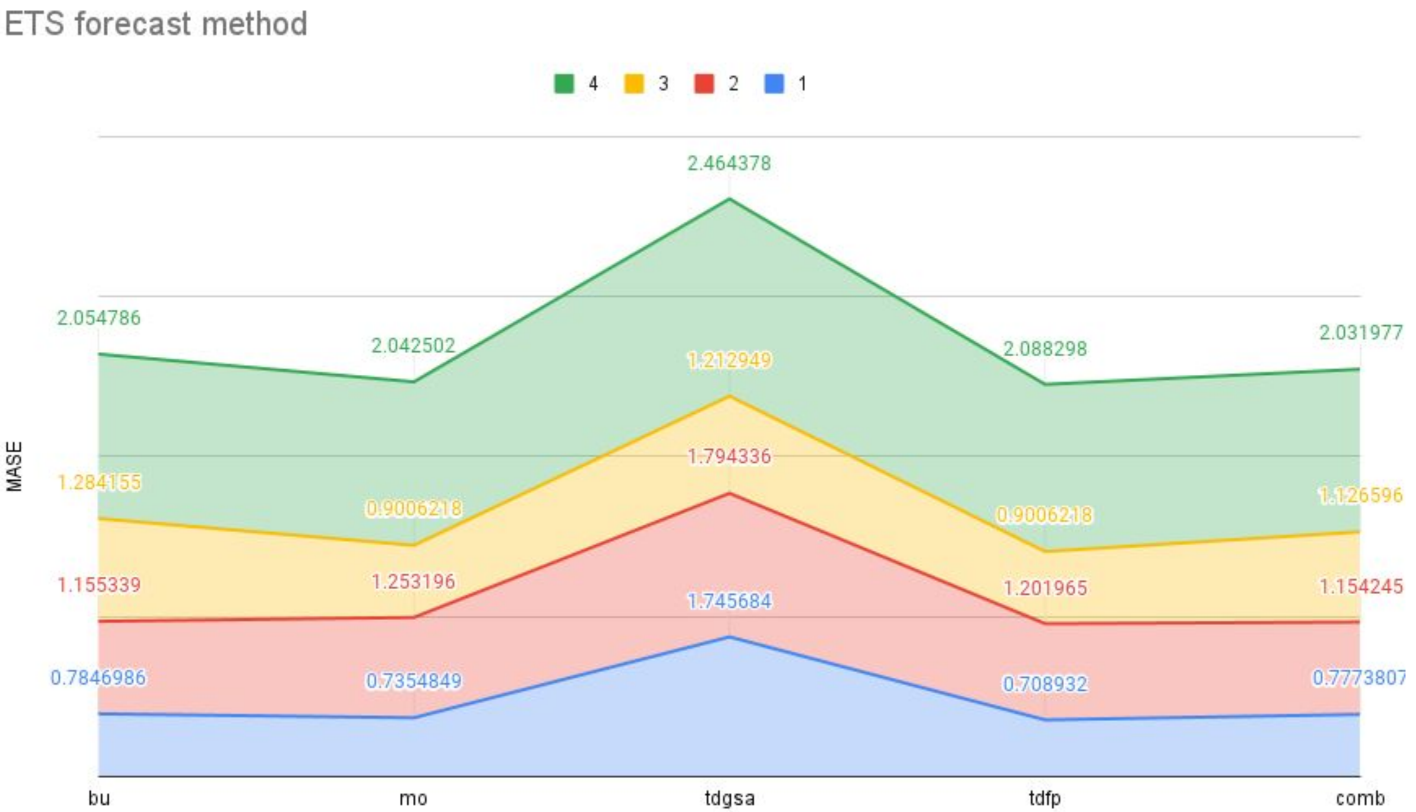
To be able estimate which combination of methods worked better we calculated man values for metrics such as:

- ME (Mean Error): Measures the average difference between predicted and observed values; a good model has ME close to zero.
- RMSE (Root Mean Squared Error): Measures the square root of the average squared differences between predicted and observed values; a good model has lower RMSE values.
- MAE (Mean Absolute Error): Measures the average absolute differences between predicted and observed values; a good model has lower MAE values.
- MAPE (Mean Absolute Percentage Error): Measures the average percentage difference between predicted and observed values; a good model has lower MAPE values, and it's often expressed as a percentage.
- MPE (Mean Percentage Error): Measures the average percentage difference between predicted and observed values, similar to MAPE; a good model has MPE close to zero.
- MASE (Mean Absolute Scaled Error): Compares the performance of the forecast model to a naive model (e.g., mean or random walk); a good model has MASE values close to 1, indicating it is as accurate as the naive model.

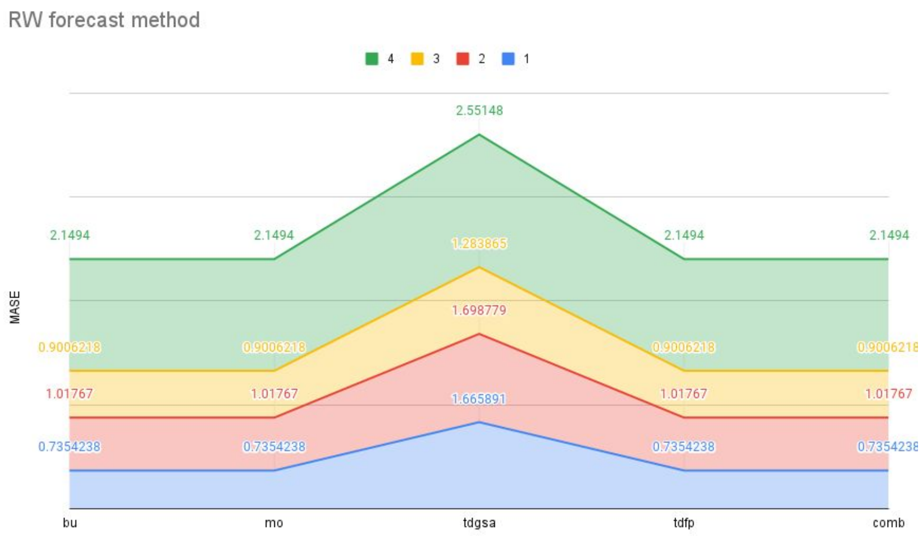
3) Metrics result

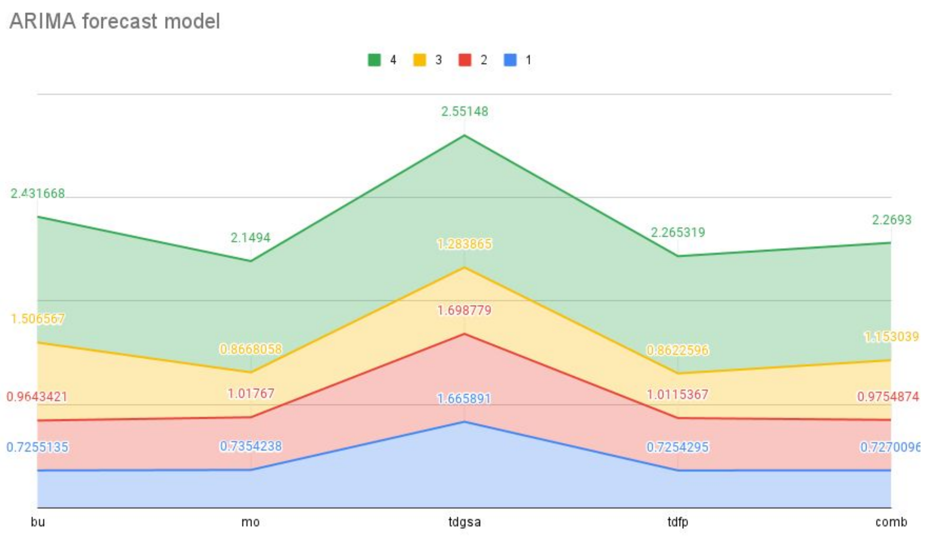
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1			"------ETS---------"						"------RW---------"						"------ARIMA---------"			
2	Clusters		1	2	3	4			1	2	3	4			1	2	3	4
3		ME	3.8997774	9.56227	-12.594498	-40.351444			3.9233333	8.718333	-3.815	-43.166667			0.924245	-1.7013542	-17.977326	-48.83549
4		RMSE	7.2360972	15.453838	22.240753	51.731606			7.0393039	14.264162	15.2792414	53.956289			6.5274676	13.5135301	26.568656	58.590316
5		MAE	6.4909288	14.03015	17.511861	41.266518			6.0833333	12.358333	12.2816667	43.166667			6.001357	11.7107292	20.54486	48.83549
6		MAPE	1.4877317	1.833717	2.979468	3.970164			1.3934278	1.613795	2.0809538	4.152268			1.3832019	1.548835	3.499617	4.685331
7		MPE	0.8783384	1.233862	-2.178141	-3.887541			0.884402	1.124164	-0.6990276	-4.152268			0.1931002	-0.2484063	-3.081144	-4.685331
8	bu	MASE	0.7846986	1.155339	1.284155	2.054786			0.7354238	1.01767	0.9006218	2.1494			0.7255135	0.9643421	1.506567	2.431668
9			1	2	3	4			1	2	3	4			1	2	3	4
10		ME	3.9240924	13.673585	-3.8151592	-39.981391			3.9233333	8.718333	-3.815	-43.166667			3.9233333	8.718333	2.25097	-43.166667
11		RMSE	7.039727	17.732002	15.2792811	51.44348			7.0393039	14.264162	15.2792414	53.956289			7.0393039	14.264162	13.1642222	53.956289
12		MAE	6.0838394	15.218501	12.2816667	41.019816			6.0833333	12.358333	12.2816667	43.166667			6.0833333	12.358333	11.8205224	43.166667
13		MAPE	1.3935428	1.983783	2.0809543	3.946504			1.3934278	1.613795	2.0809538	4.152268			1.3934278	1.613795	1.9834995	4.152268
14		MPE	0.8845767	1.775691	-0.6990541	-3.852743			0.884402	1.124164	-0.6990276	-4.152268			0.884402	1.124164	0.322082	-4.152268
15	mo	MASE	0.7354849	1.253196	0.9006218	2.042502			0.7354238	1.01767	0.9006218	2.1494			0.7354238	1.01767	0.8668058	2.1494
16			1	2	3	4			1	2	3	4			1	2	3	4
17		ME	14.440077	21.789962	-16.54084	-49.492417			13.780044	20.629553	-17.507901	-51.241696			13.780044	20.629553	-17.507901	-51.241696
18		RMSE	15.578032	24.540974	22.19235	59.138983			14.968262	23.516705	22.922207	60.610489			14.968262	23.516705	22.922207	60.610489
19		MAE	14.440077	21.789962	16.54084	49.492417			13.780044	20.629553	17.507901	51.241696			13.780044	20.629553	17.507901	51.241696
20		MAPE	3.303912	2.842849	2.823884	4.747105			3.152063	2.690276	2.985356	4.911597			3.152063	2.690276	2.985356	4.911597
21		MPE	3.303912	2.842849	-2.823884	-4.747105			3.152063	2.690276	-2.985356	-4.911597			3.152063	2.690276	-2.985356	-4.911597
22	tdgsa	MASE	1.745684	1.794336	1.212949	2.464378			1.665891	1.698779	1.283865	2.55148			1.665891	1.698779	1.283865	2.55148
23			1	2	3	4			1	2	3	4			1	2	3	4
24		ME	3.3859234	12.740382	-4.5685249	-41.360999			3.9233333	8.718333	-3.815	-43.166667			3.017812	7.1377171	0.9991524	-45.494682
25		RMSE	6.7545343	17.022759	15.4845862	52.522874			7.0393039	14.264162	15.2792414	53.956289			6.69324	13.5513731	13.3493046	56.428695
26		MAE	5.8641967	14.596366	12.2816667	41.939555			6.0833333	12.358333	12.2816667	43.166667			6.000662	12.2838491	11.7585266	45.494682
27		MAPE	1.344292	1.902982	2.0835538	4.034712			1.3934278	1.613795	2.0809538	4.152268			1.3769279	1.6070895	1.9774548	4.374063
28		MPE	0.7607641	1.652991	-0.824845	-3.982474			0.884402	1.124164	-0.6990276	-4.152268			0.6757143	0.9159301	0.1113672	-4.374063
29	tdfp	MASE	0.708932	1.201965	0.9006218	2.088298			0.7354238	1.01767	0.9006218	2.1494			0.7254295	1.0115367	0.8622596	2.265319
30			1	2	3	4			1	2	3	4			1	2	3	4
31		ME	3.9207948	10.165275	-9.794267	-39.89075			3.9233333	8.718333	-3.815	-43.166667			1.3764107	0.30604225	-10.970104	-45.574637
32		RMSE	7.2114683	15.713326	19.708613	51.201943			7.0393039	14.264162	15.2792414	53.956289			6.4974742	12.89836865	20.258636	55.649179
33		MAE	6.4303956	14.016862	15.363255	40.80845			6.0833333	12.358333	12.2816667	43.166667			6.0137327	11.8460752	15.72385	45.574637
34		MAPE	1.4736705	1.830746	2.613696	3.9263			1.3934278	1.613795	2.0809538	4.152268			1.3847423	1.56275261	2.676931	4.377446
35		MPE	0.8832691	1.313341	-1.706236	-3.84344			0.884402	1.124164	-0.6990276	-4.152268			0.2973181	0.01601573	-1.902318	-4.377446
36	comb	MASE	0.7773807	1.154245	1.126596	2.031977			0.7354238	1.01767	0.9006218	2.1494			0.7270096	0.97548741	1.153039	2.2693

3) Metrics result



3) Metrics result





3) Metrics result

Interpretation:

1) For each cluster(CLusters 1, 2, 3 and 4) separately and for each method(Error-Time-Series, Random Walk or ARIMA) we choose the best hierarchical method which represent the best MASE.
2) Select only one combination of hierarchical and forecasting method for each cluster separately.

MASE		
Cluster 1	bu + ETS	0.7846986
Cluster 2	tdfp + ARIMA	1.0115367
Cluster 3	tdfp + RW	0.9006218
Cluster 4	mo + ARIMA	2.031977

Additional forecasting models

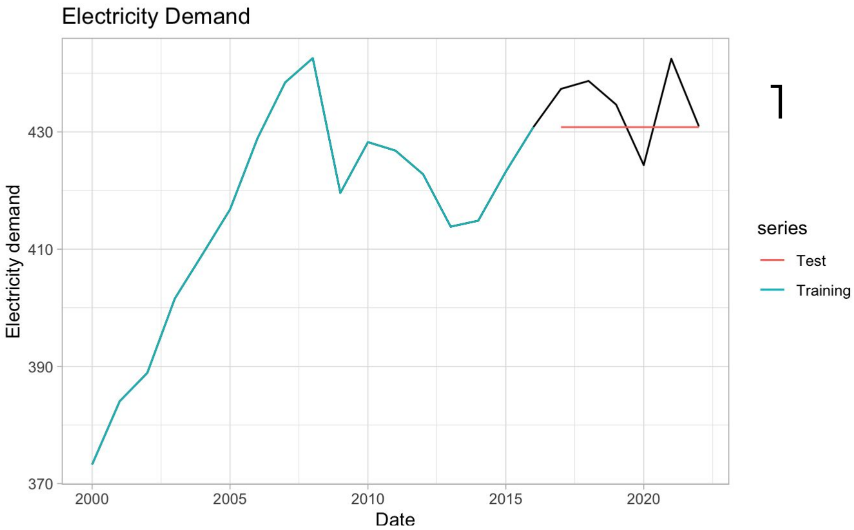
Additionally for each cluster separately we applied some forecasting models that weren't included in hts() package:

- Mean
- Random walk with a drift
- Differences
- Auto Arima
- Holt's

For each one of them data was splitted into train and test split (80% and 20% accordingly) and calculated metrics.

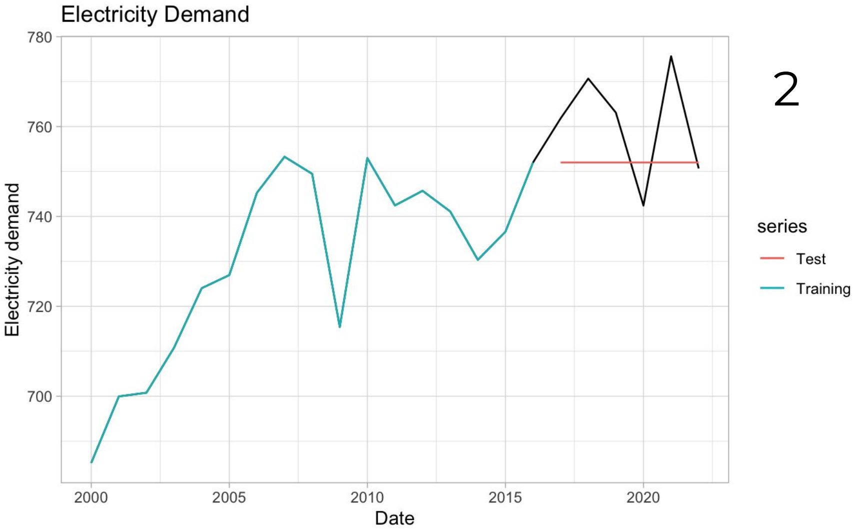
MASE		
Cluster 1	bu + ETS	0.7846986
Cluster 2	tdfp + ARIMA	1.0115367
Cluster 3	tdfp + RW	0.9006218
Cluster 4	mo + ARIMA	2.031977

MASE							
	Diff	AutoArima	Holts	Holt's damped	Mean	RWF	RWF+drift
Cluster1	706.1578979	1.762494	758.5089064	747.1059037	2.29017	2.945886	4.8686437
Cluster2	2280.36343	1.6124594	2390.249858	2358.542656	1.69171	2.564694	4.4358003
Cluster3	7769.67788	2.614147	8198.354679	8241.544652	2.345992	2.431495	1.9782254
Cluster4	9041.870326	1.3328949	9194.52827	9270.359442	1.292478	1.292478	1.9860548



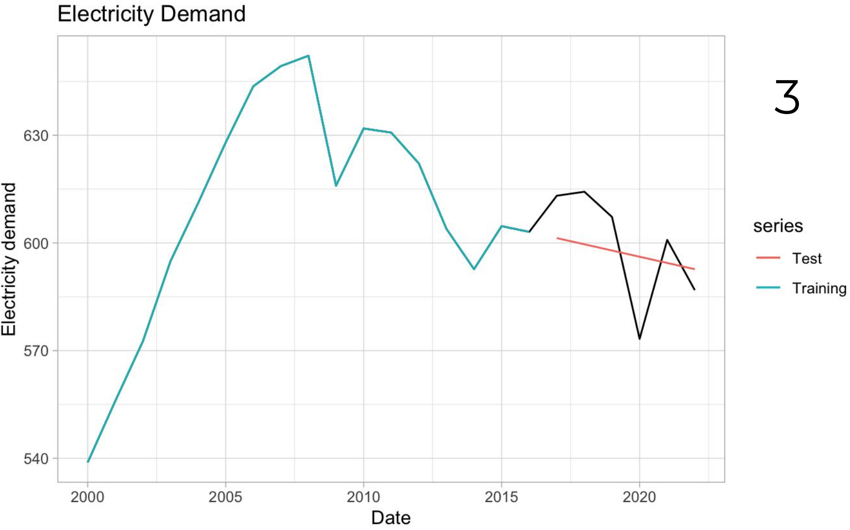
Electricity Demand
Electricity demand
Date
series
Test
Training

1



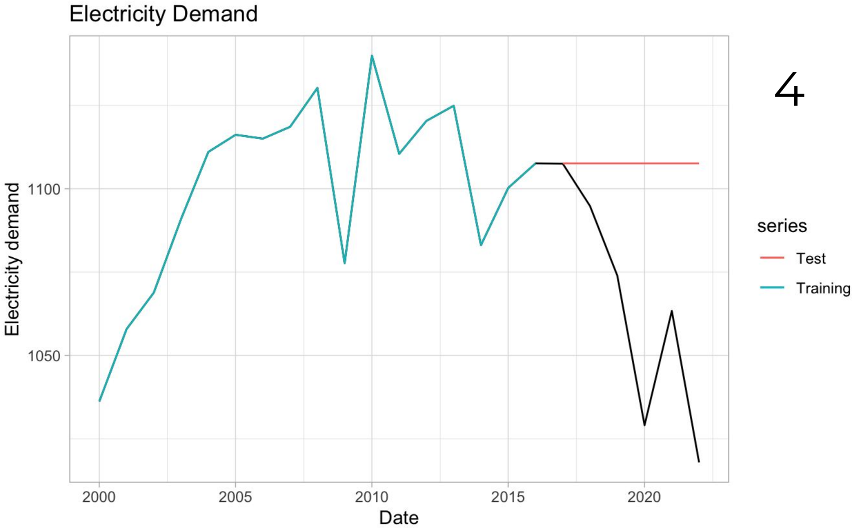
Electricity Demand
Electricity demand
Date
series
Test
Training

2



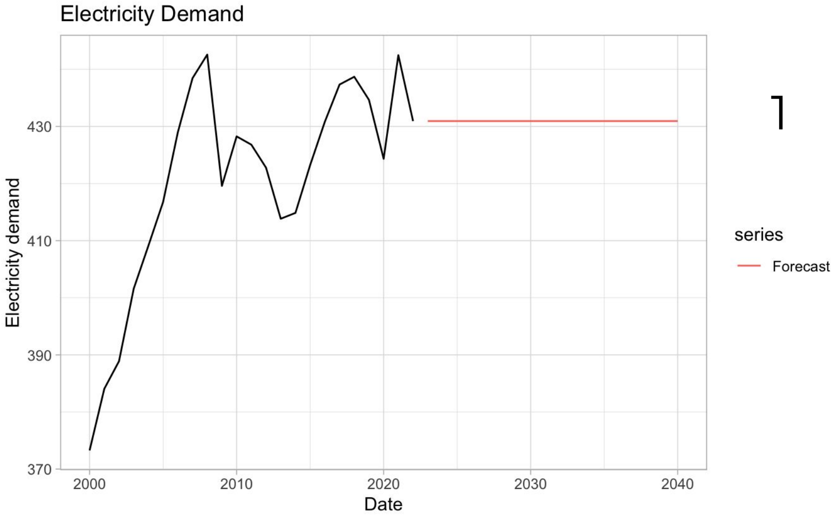
Electricity Demand
Electricity demand
Date
series
Test
Training

3

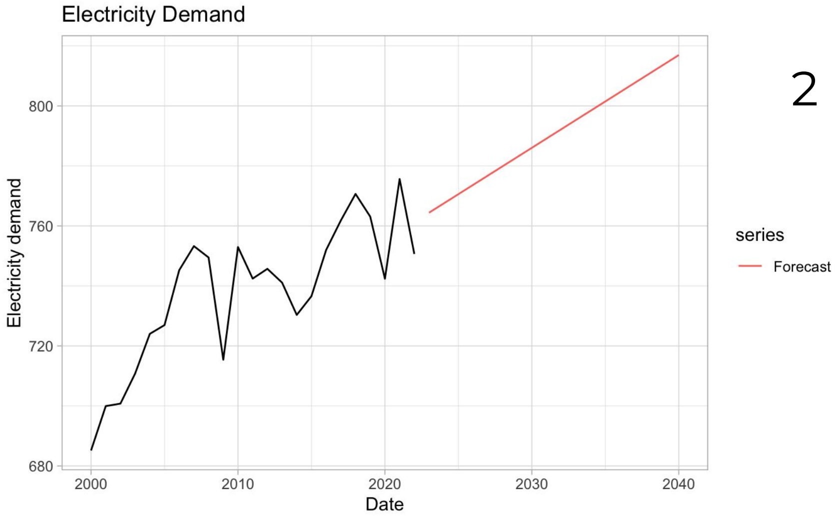


Electricity Demand
Electricity demand
Date
series
Test
Training

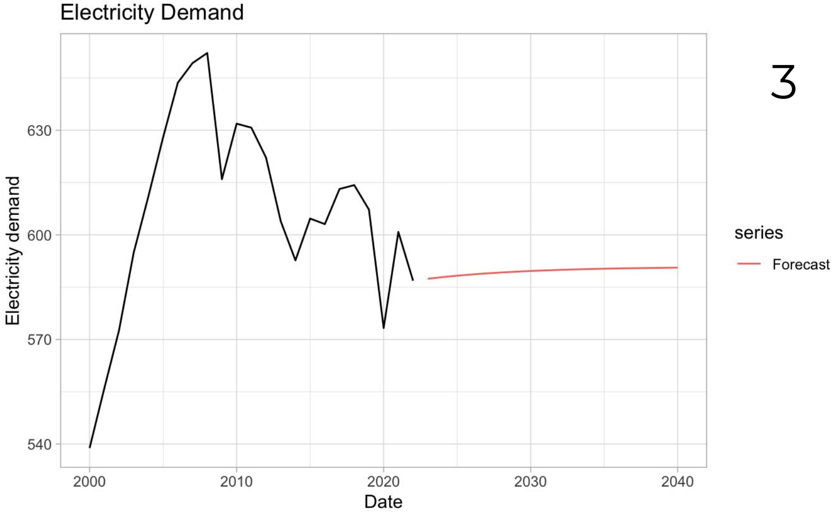
4


Electricity Demand
Electricity demand
370
390
410
430
2000
2010
2020
2030
2040
Date
series
Forecast

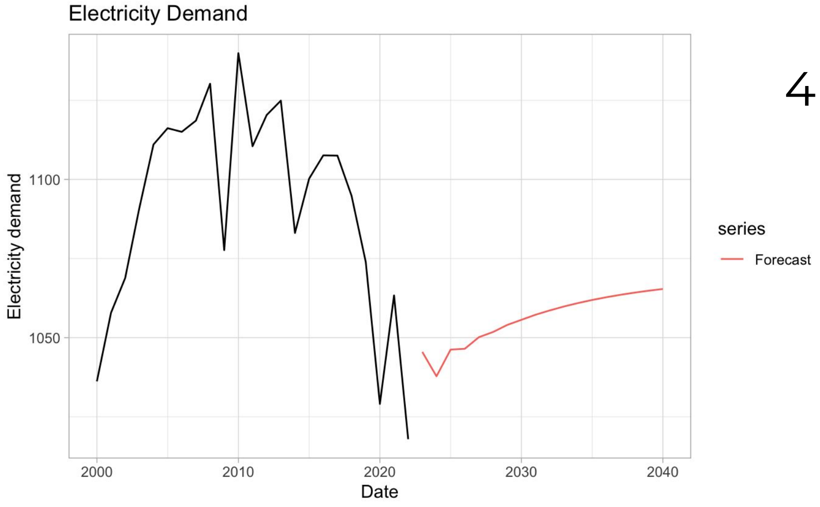
1


Electricity Demand
Electricity demand
680
720
760
800
2000
2010
2020
2030
2040
Date
series
Forecast

2

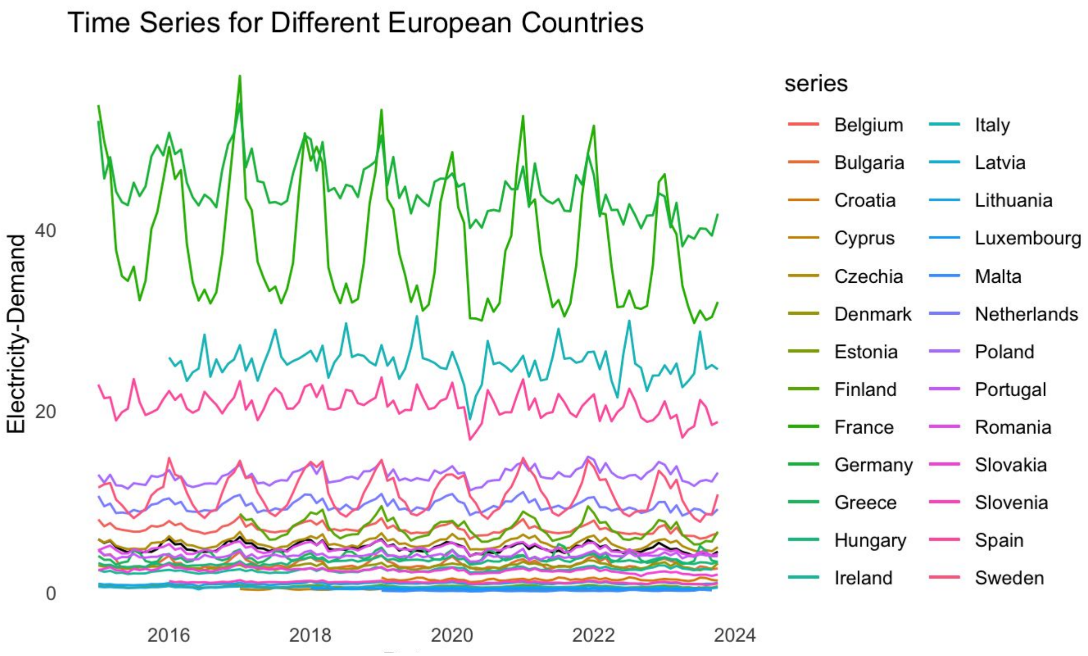

Electricity Demand
Electricity demand
540
570
600
630
2000
2010
2020
2030
2040
Date
series
Forecast

3


Electricity Demand
Electricity demand
1050
1100
2000
2010
2020
2030
2040
Date
series
Forecast

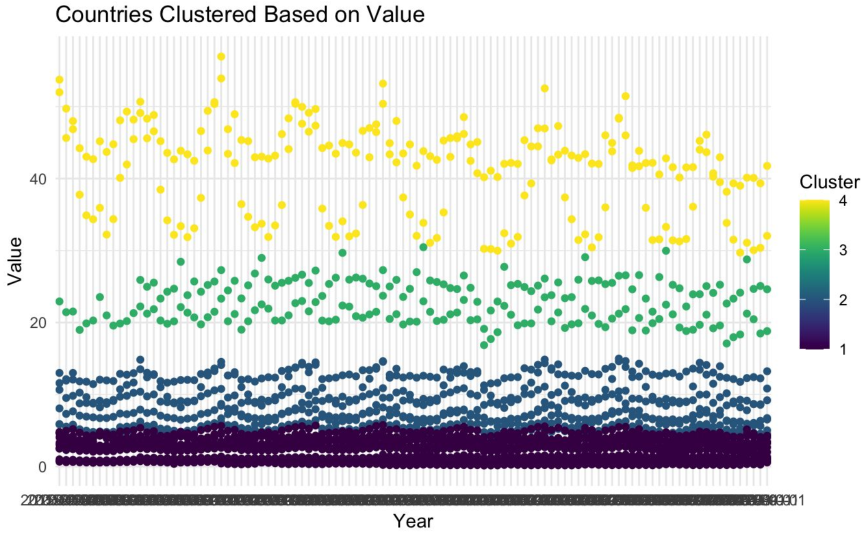
4

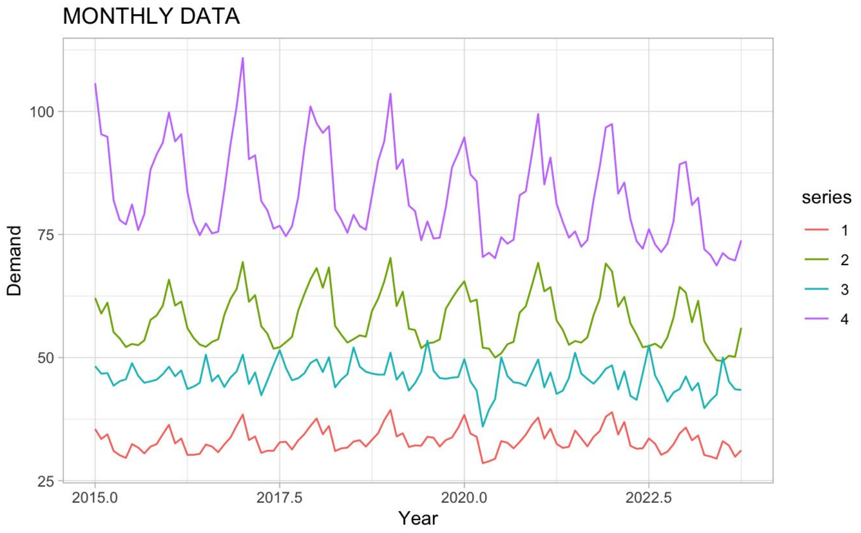
Demand Forecasting (monthly)



1) Clusterization
2) Transforming data into hierarchical time-series, which should help for forecasting data on different levels(Total, Clusters and also different countries)
3) Splitting our data into train and test split
4) Applying combination of different methods for distributing forecasts within the hierarchy and different methods for forecasting method to use for each series.
5) Comparing final metrics

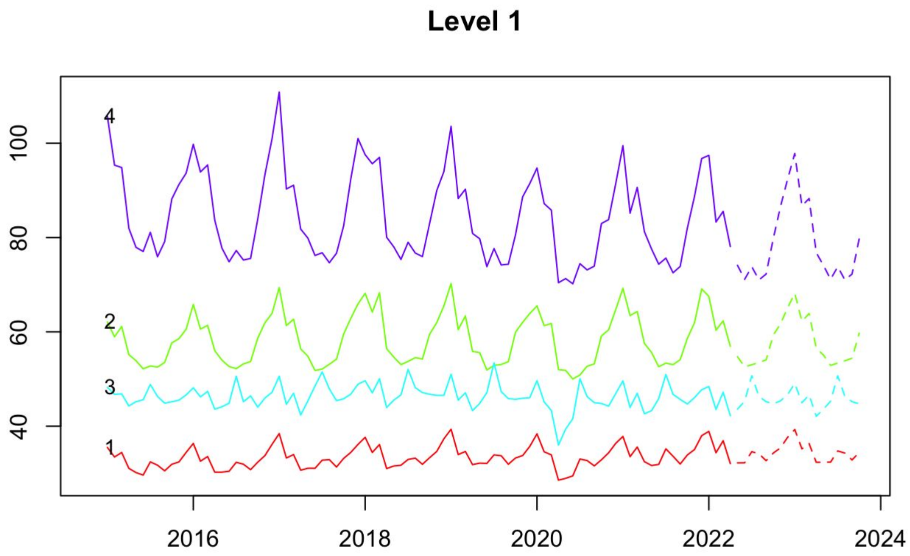
1) Clusterization





1	1BGR, 1HRV, 1CYP, 1DNK, 1EST, 1GRC, 1HUN, 1IRL, 1LVA, 1LTU, 1LUX, 1MLT, 1PRT, 1ROU, 1SVK, 1SVN
2	2AUT, 2BEL, 2CZE, 2FIN, 2NLD, 2POL, 2SWE
3	3ITA, 3ESP
4	4FRA, 4DEU

3) Metrics result

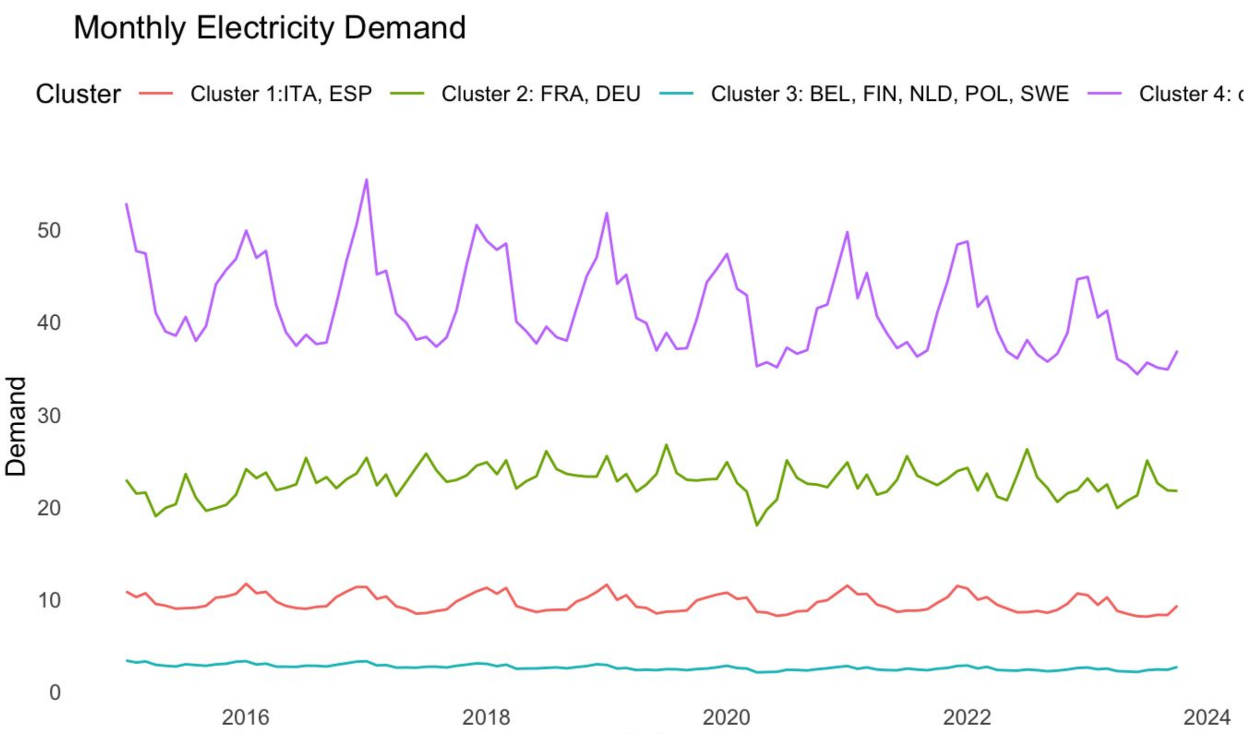


Cluster 1	mo + ETS	1.120319
Cluster 2	bu + ETS	1.407586
Cluster 3	mo + ARIMA	1.383699
Cluster 4	mo + ARIMA	0.906393

MASE

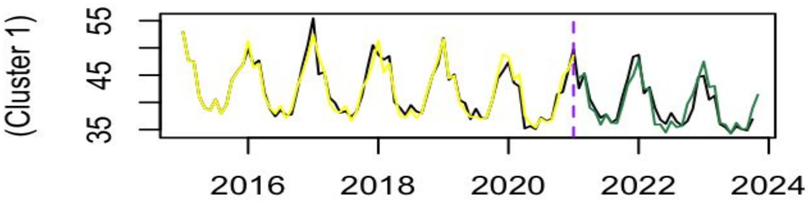
	Diff	AutoArima	Holts	Holt's damped	Mean	RWF	RWF+drift
Cluster1	65.0070396	3.1664336	69.49724	79.967492	2.63301	5.343455	5.861082
Cluster2	198.1578491	4.9862094	217.098148	221.369405	2.512771	2.287691	2.167538
Cluster3	380.4985345	2.056831	420.027086	428.409238	0.9685603	3.611542	3.91553
Cluster4	574.3565311	4.0577794	645.944708	690.373044	2.439981	2.532825	2.85815

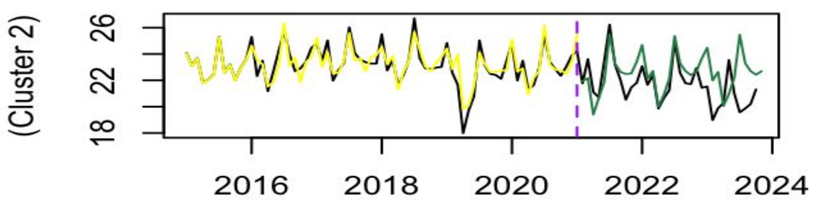
K Means clustering based on different countries



Demand Forecasting: auto.arima model (monthly)

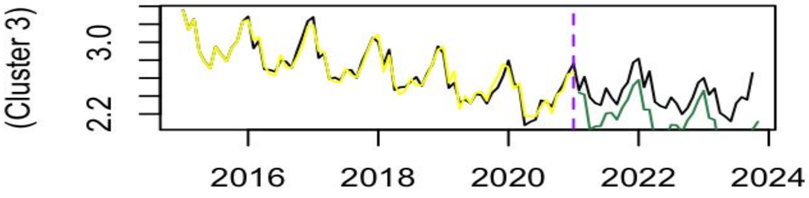
Electricity Demand Forecasting

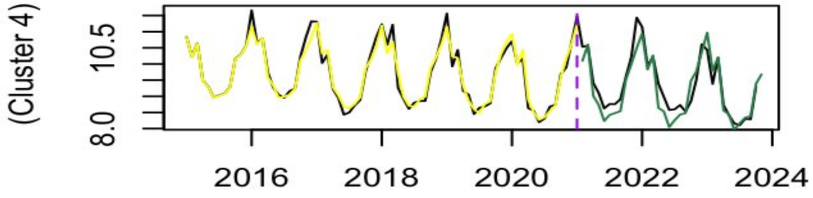




	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.027	1.22	0.85	0.016	1.95	0.529	0.005
Test set	0.037	1.55	1.18	0.052	2.95	0.737	0.476

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
-0.039	0.645	0.48	-0.25	2.09	0.54	-0.086
-0.858	1.859	1.37	-4.29	6.53	1.56	0.5437

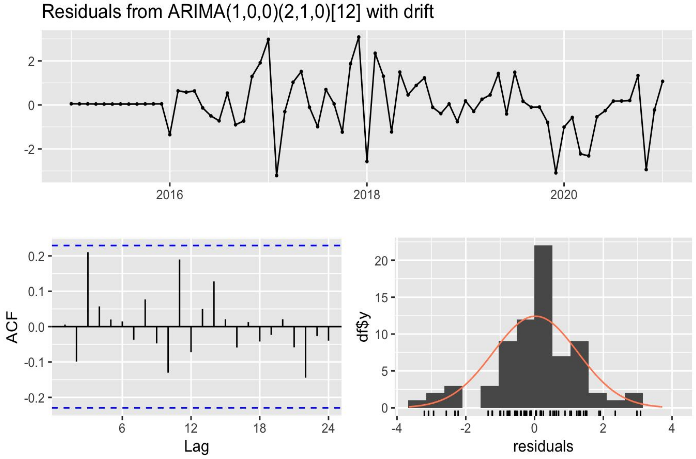




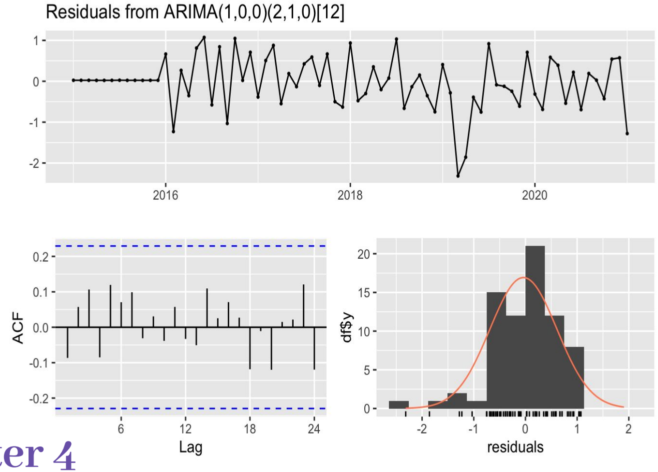
	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.0022	0.0564	0.044	0.029	1.673	0.350	0.104
Test set	0.284	0.308	0.284	11.85	11.85	2.26	0.566

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
0.013	0.188	0.134	0.054	1.353	0.438	0.065
0.149	0.360	0.284	1.586	3.030	0.926	0.375

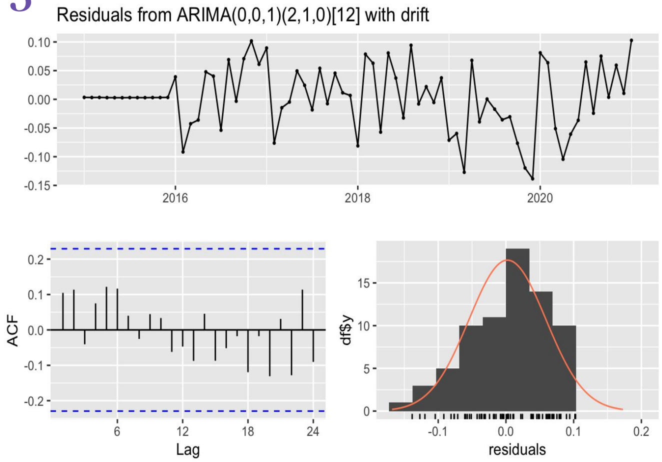
Cluster1



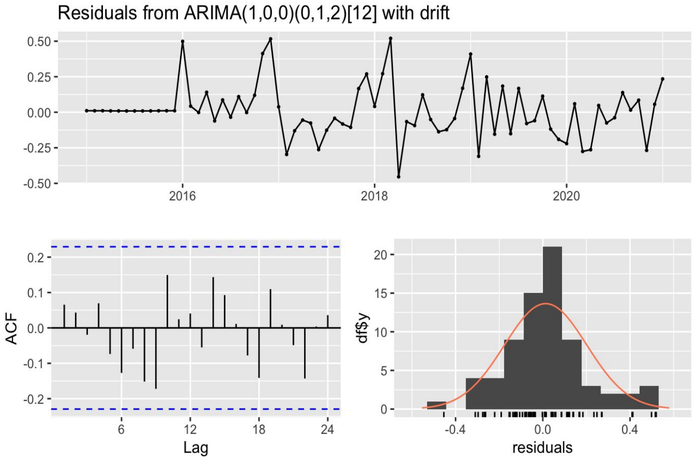
Cluster 2

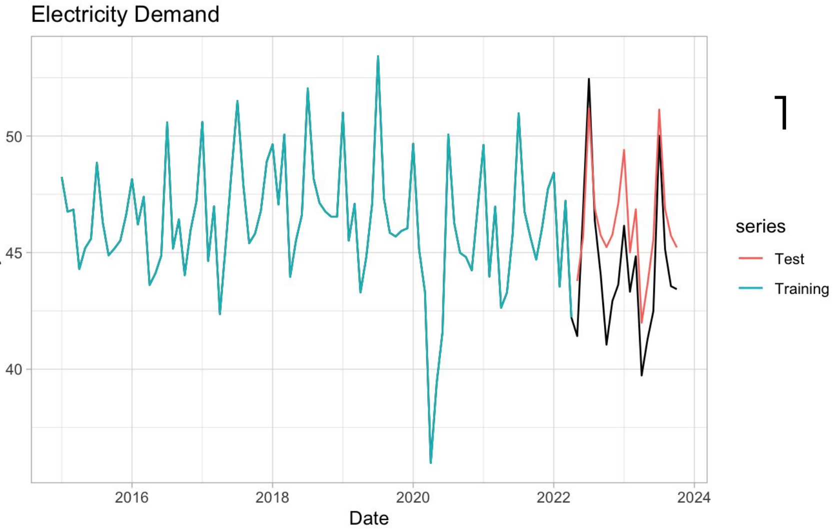


Cluster 3



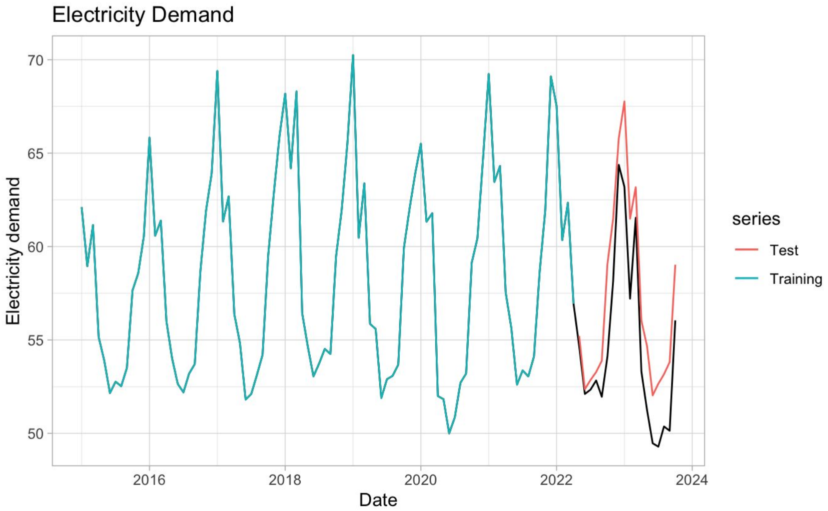
Cluster 4





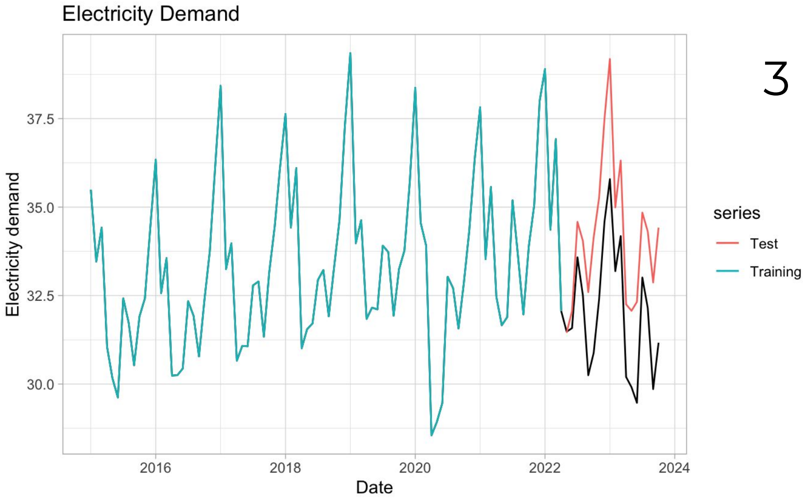
Electricity Demand
50
45
40
2016
2018
2020
2022
2024
Date
series
Test
Training

1



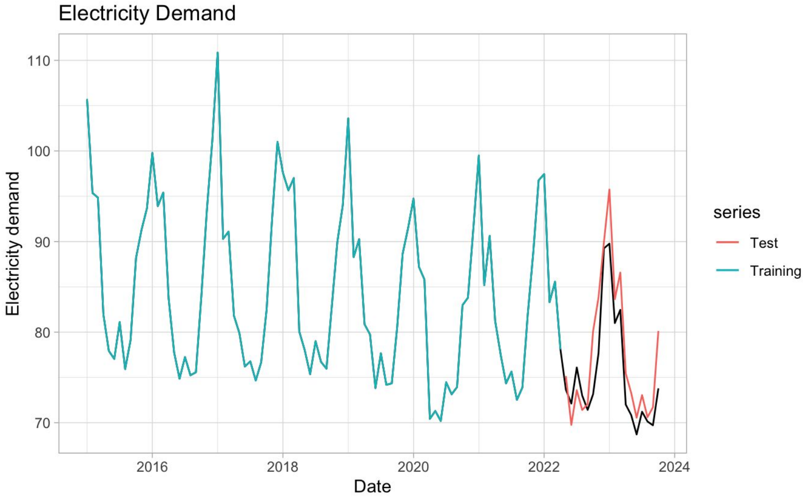
Electricity Demand
70
65
60
55
50
Electricity demand
2016
2018
2020
2022
2024
Date
series
Test
Training

2



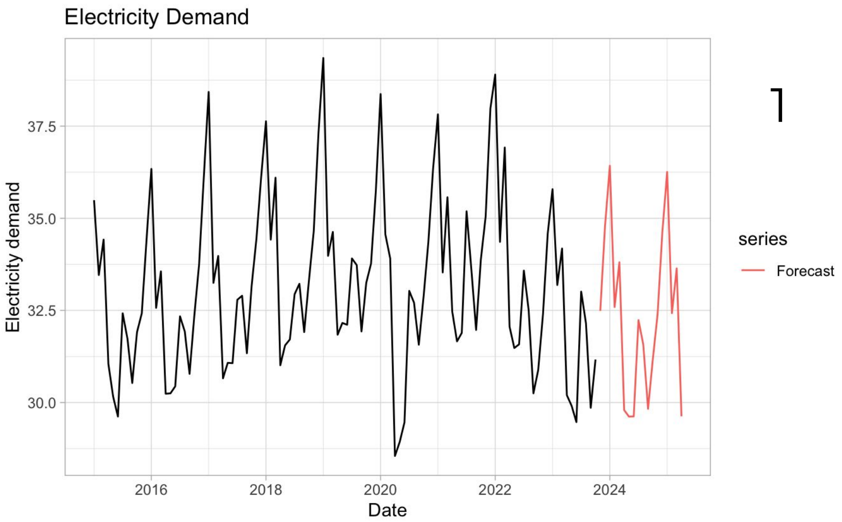
Electricity Demand
37.5
35.0
32.5
30.0
Electricity demand
2016
2018
2020
2022
2024
Date
series
Test
Training

3

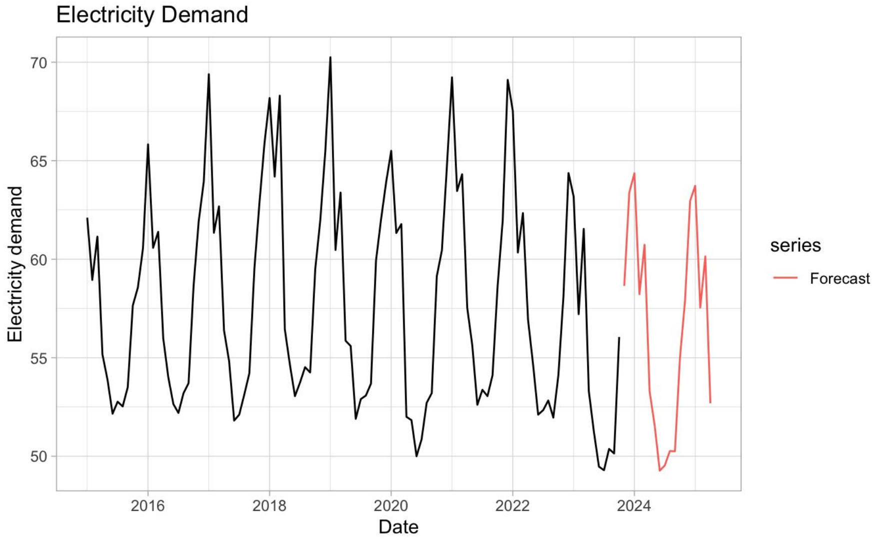


Electricity Demand
110
100
90
80
70
Electricity demand
2016
2018
2020
2022
2024
Date
series
Test
Training

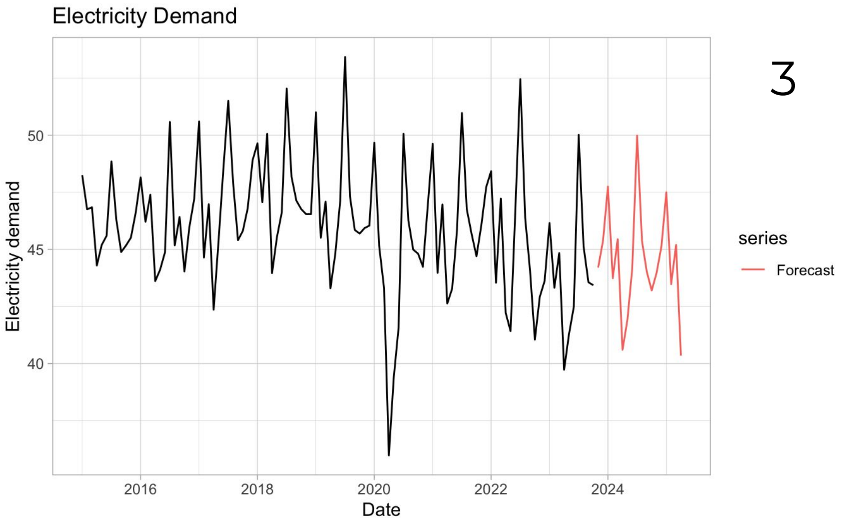
4


Electricity Demand
Electricity demand
37.5
35.0
32.5
30.0
2016
2018
2020
2022
2024
Date
series
Forecast

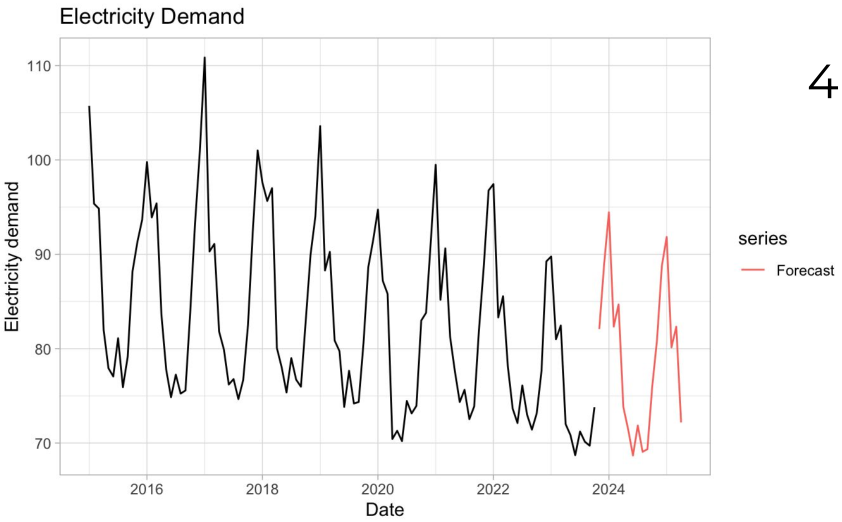
1


Electricity Demand
Electricity demand
70
65
60
55
50
2016
2018
2020
2022
2024
Date
series
Forecast

2

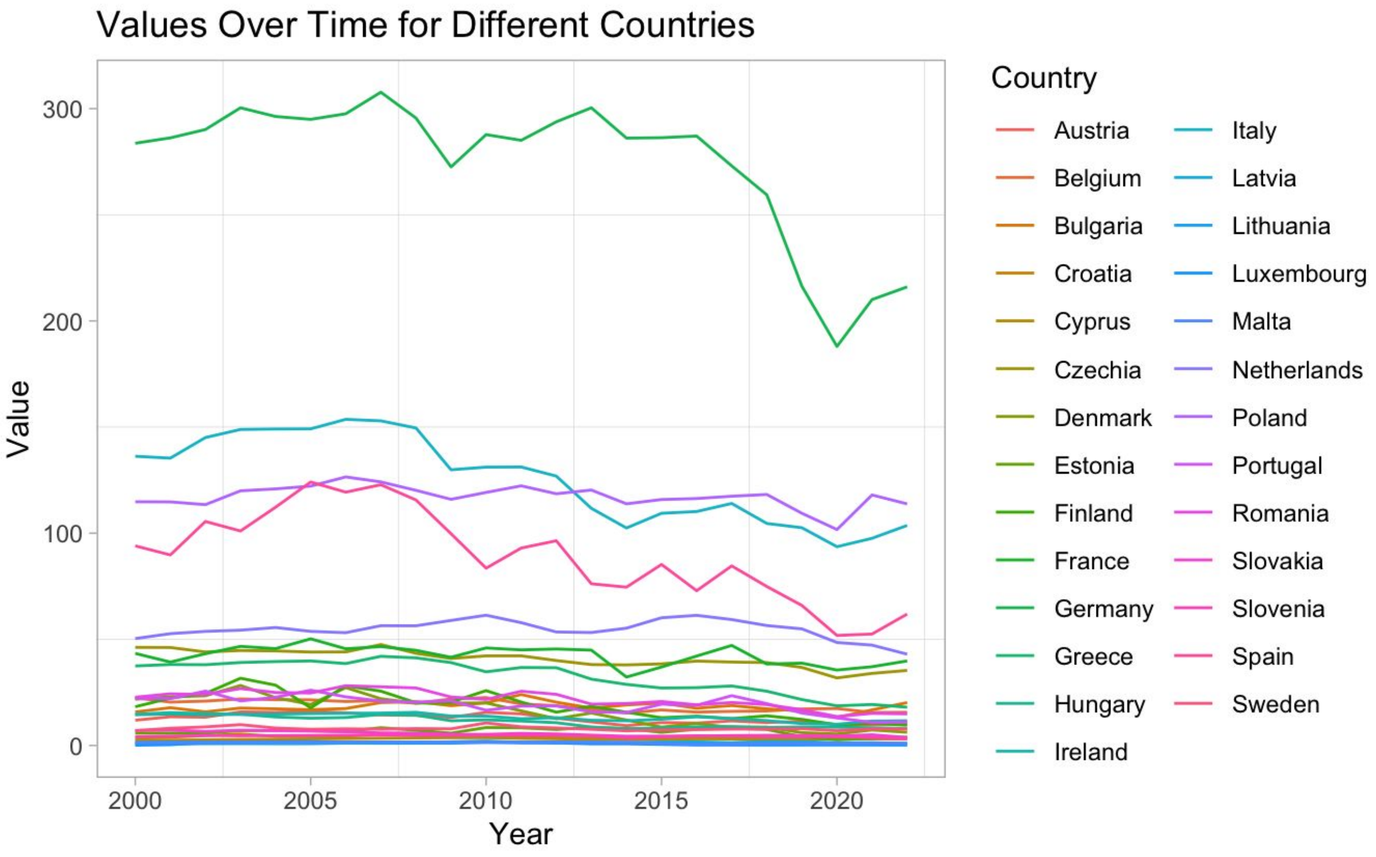

Electricity Demand
Electricity demand
50
45
40
2016
2018
2020
2022
2024
Date
series
Forecast

3

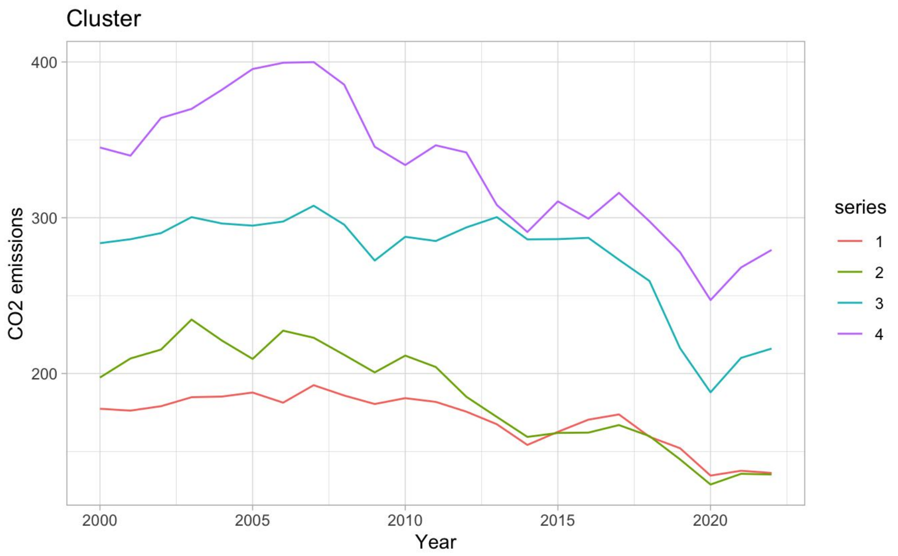

Electricity Demand
Electricity demand
110
100
90
80
70
2016
2018
2020
2022
2024
Date
series
Forecast

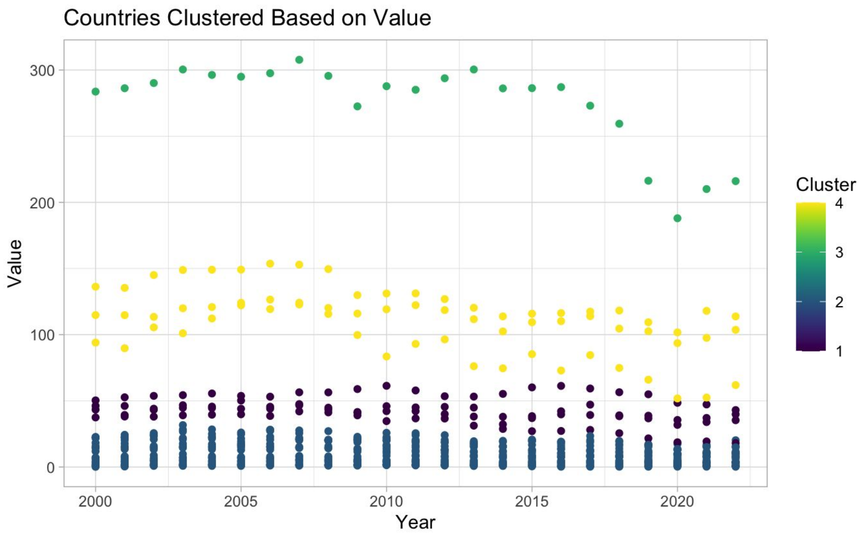
4

CO2 emissions (annual)



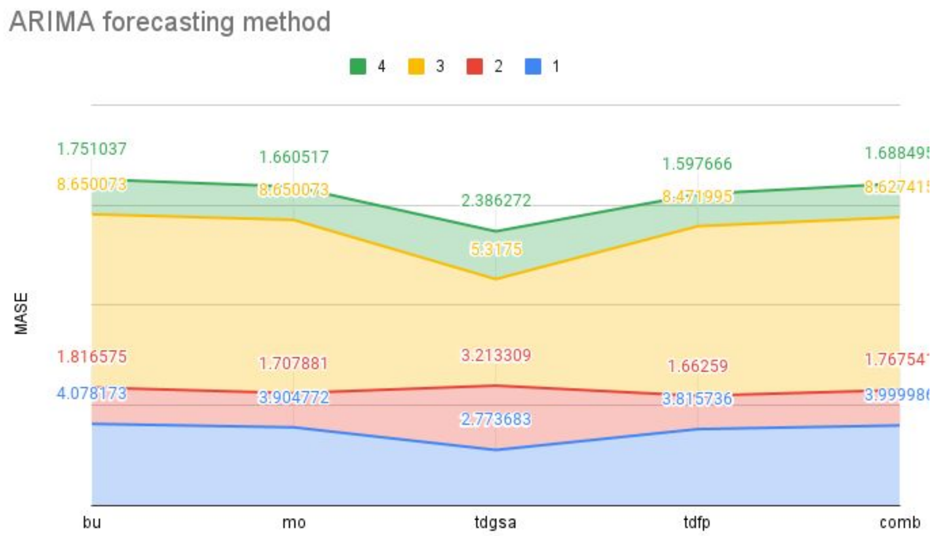
CO2 emissions





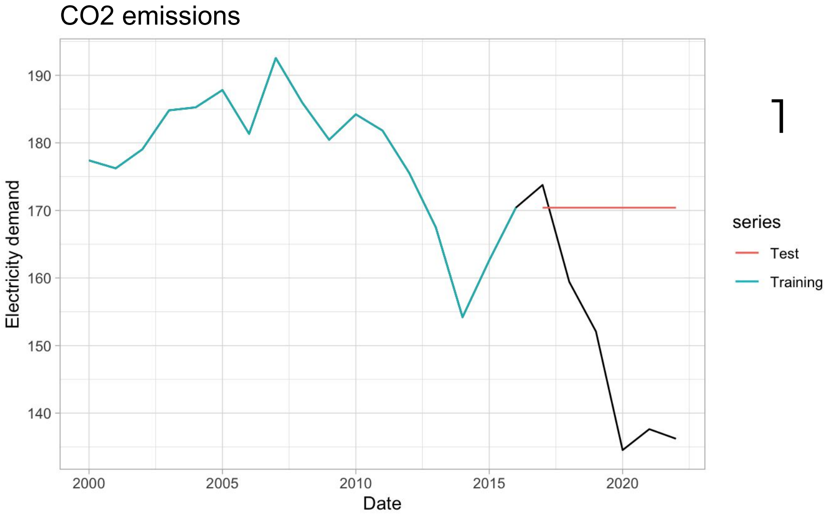
1	1CZE, 1FRA, 1GRC, 1NLD
2	2AUT, 2BEL, 2BGR, 2HRV, 2CYP, 2DNK, 2EST, 2FIN, 2HUN, 2IRL, 2LVA, 2LTU, 2LUX, 2MLT, 2PRT, 2ROU, 2SVK, 2SVN, 2SWE
3	3DEU
4	4ITA, 4POL, 4ESP

CO2 emissions metric results

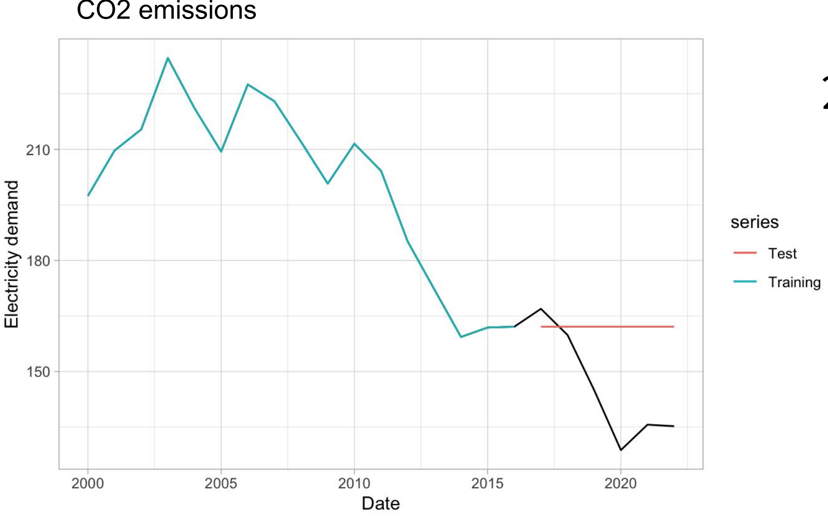


MASE		
Cluster 1	tdgsa+ARIMA	2.773688
Cluster 2	tdfp+ARIMA	1.66259
Cluster 3	tdgsa+ARIMA	5.3175
Cluster 4	tdfp+ARIMA	1.597666

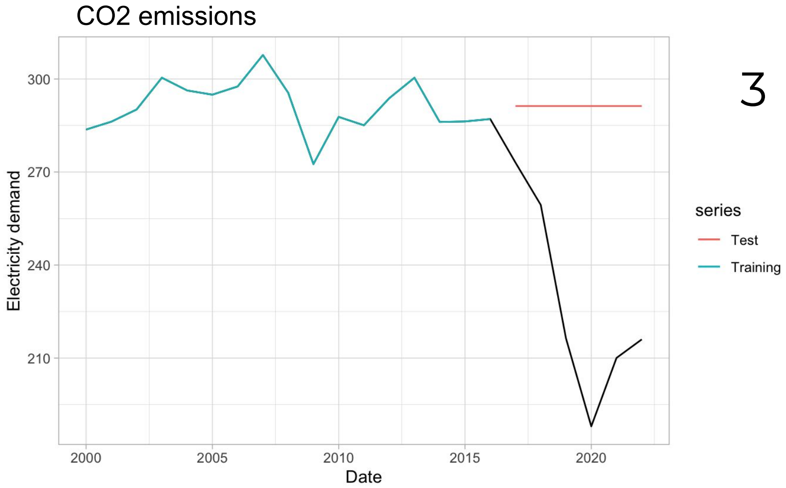
MASE							
	Diff	AutoArima	Holts	Holt's damped	Mean	RWF	RWF+drift
Cluster1	587.6696467	2.4018979	554.785257	0.4777357	1.9536848	2.190729	2.606126
Cluster2	100.8678949	3.0880719	86.7906476	0.6118198	2.410742	4.898359	6.0213658
Cluster3	3895.411246	2.919095	3670.632672	0.2378216	2.0431478	1.23884	1.1557316
Cluster4	1561.661974	3.1053258	1440.803403	0.6998133	1.833233	5.087676	6.177554


CO2 emissions
Electricity demand
190
180
170
160
150
140
2000
2005
2010
2015
2020
Date
series
Test
Training

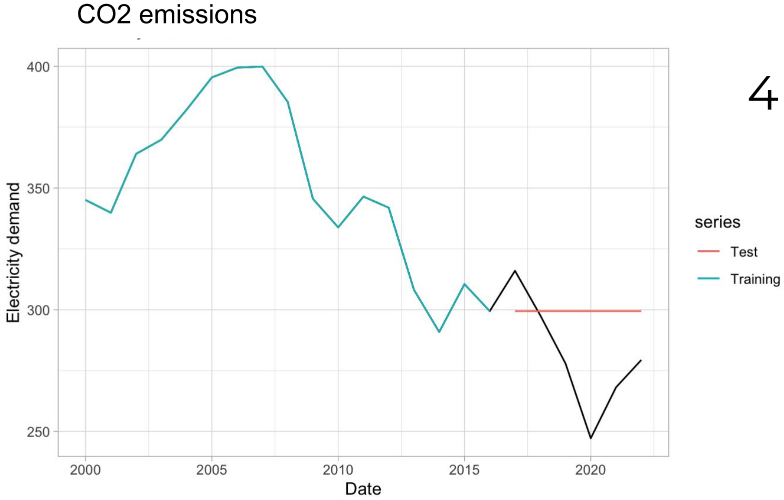
1


CO2 emissions
Electricity demand
210
180
150
2000
2005
2010
2015
2020
Date
series
Test
Training

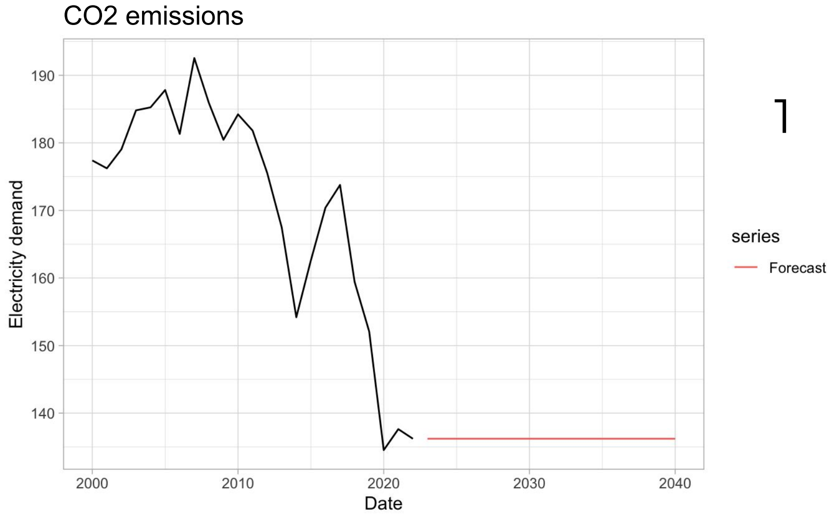
2


CO2 emissions
Electricity demand
300
270
240
210
2000
2005
2010
2015
2020
Date
series
Test
Training

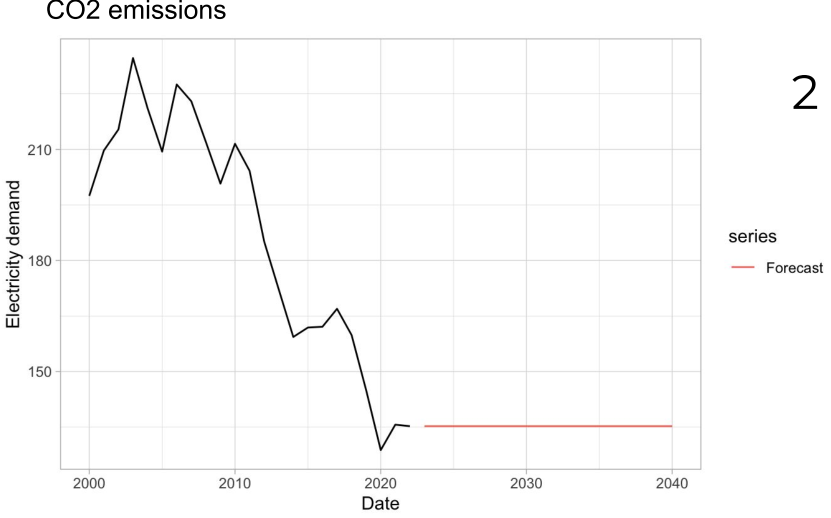
3


CO2 emissions
Electricity demand
400
350
300
250
2000
2005
2010
2015
2020
Date
series
Test
Training

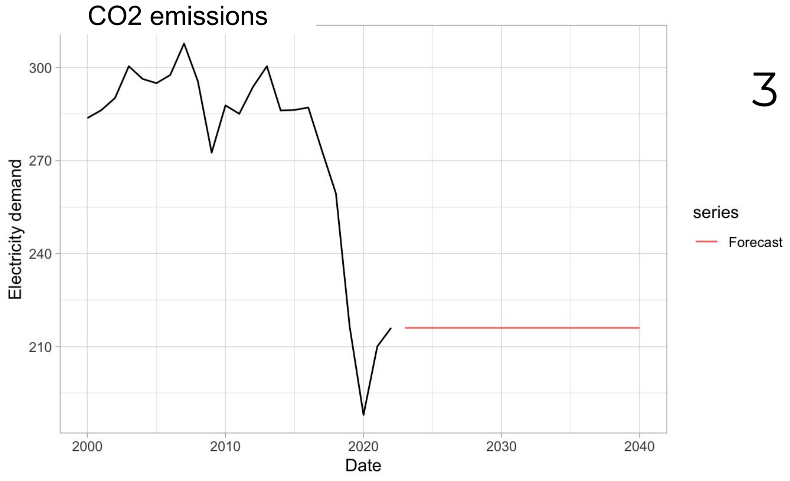
4


CO2 emissions
Electricity demand
Date
series
Forecast

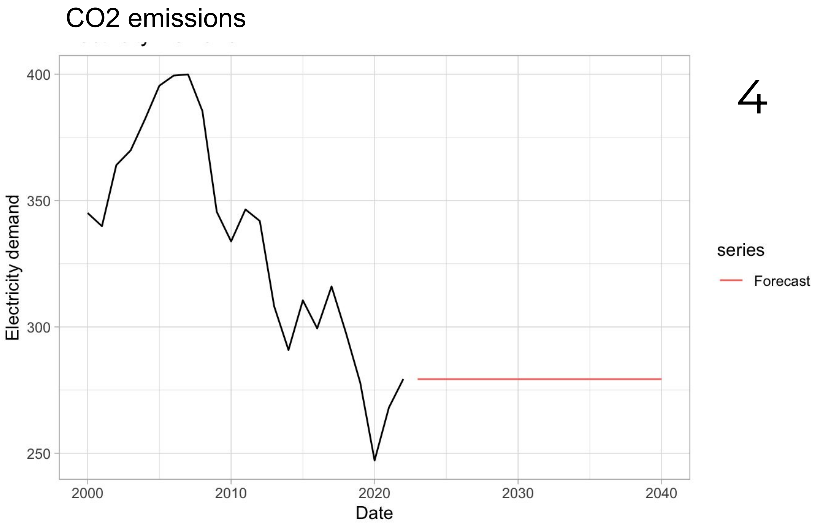
1


CO2 emissions
Electricity demand
Date
series
Forecast

2

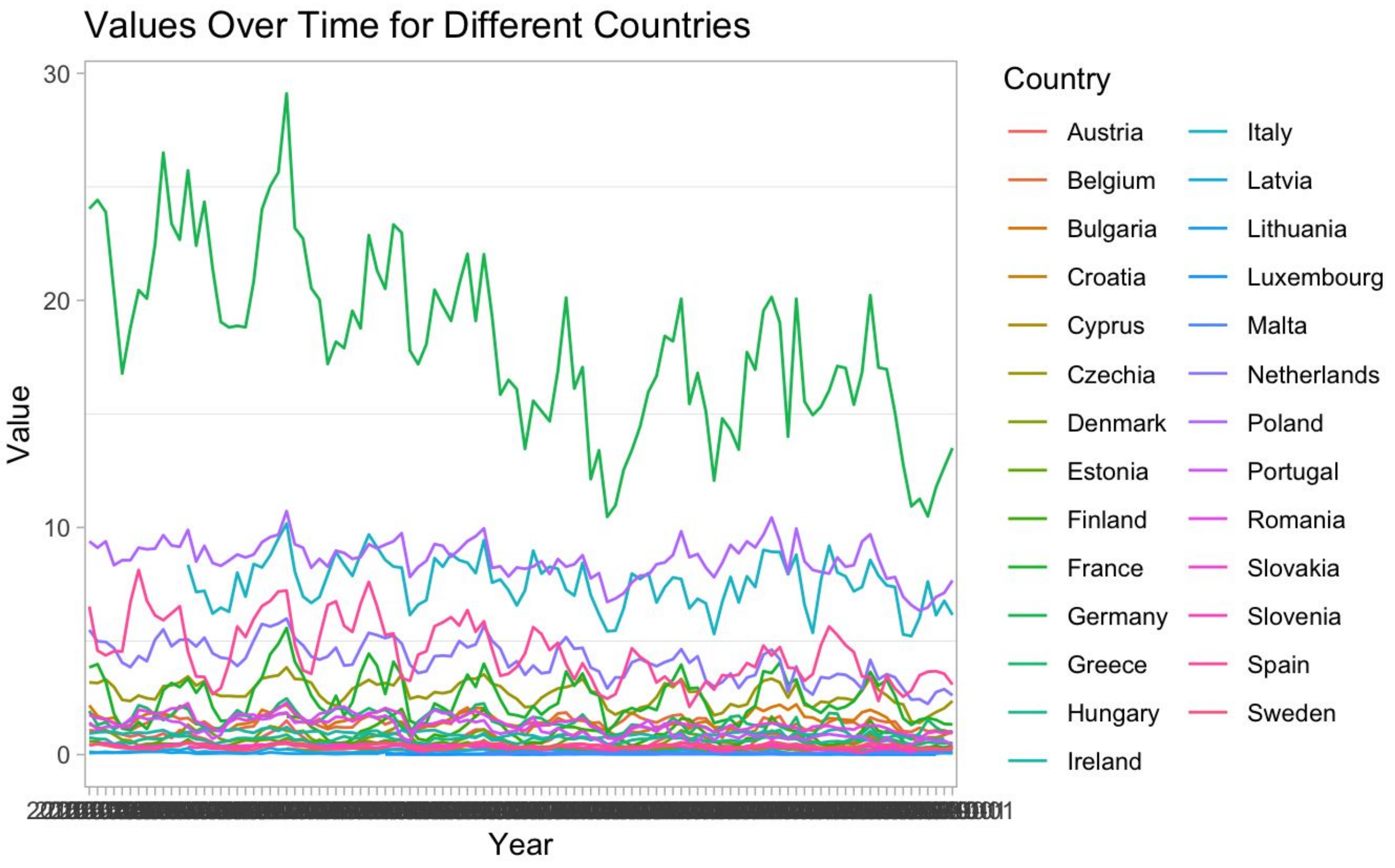

CO2 emissions
Electricity demand
Date
series
Forecast

3

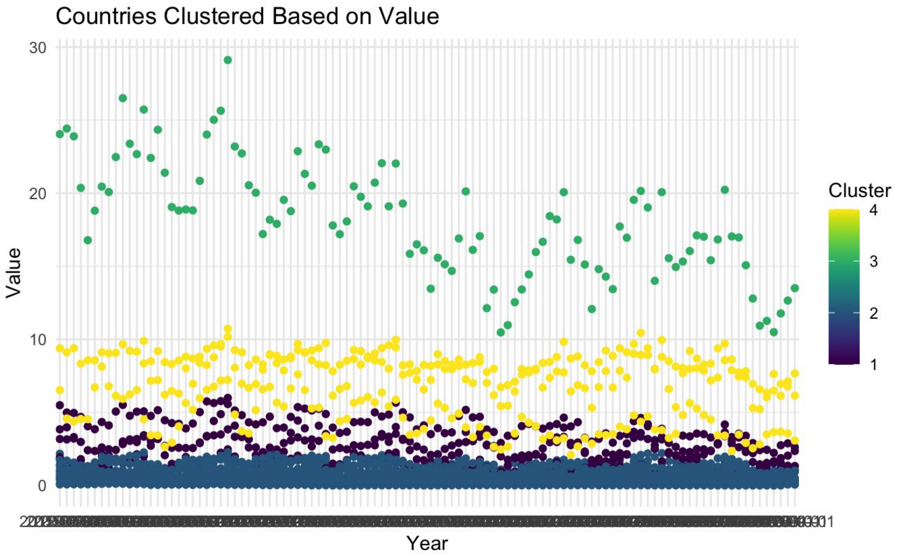

CO2 emissions
Electricity demand
Date
series
Forecast

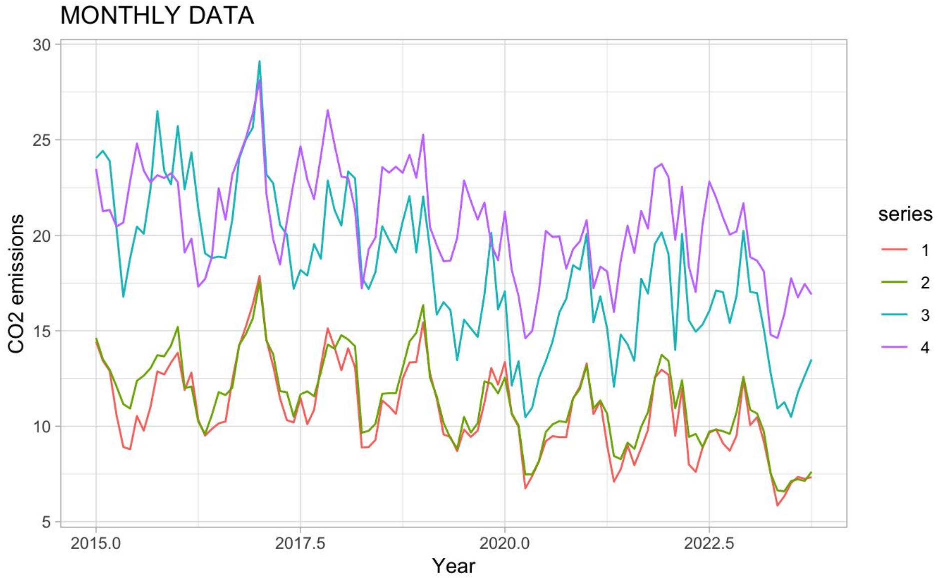
4

CO2 emissions (monthly)



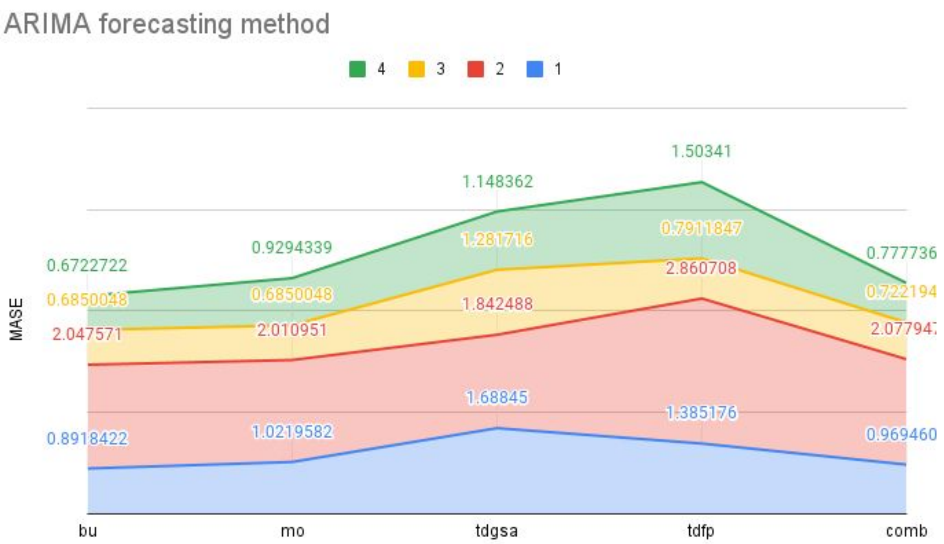
CO2 emissions





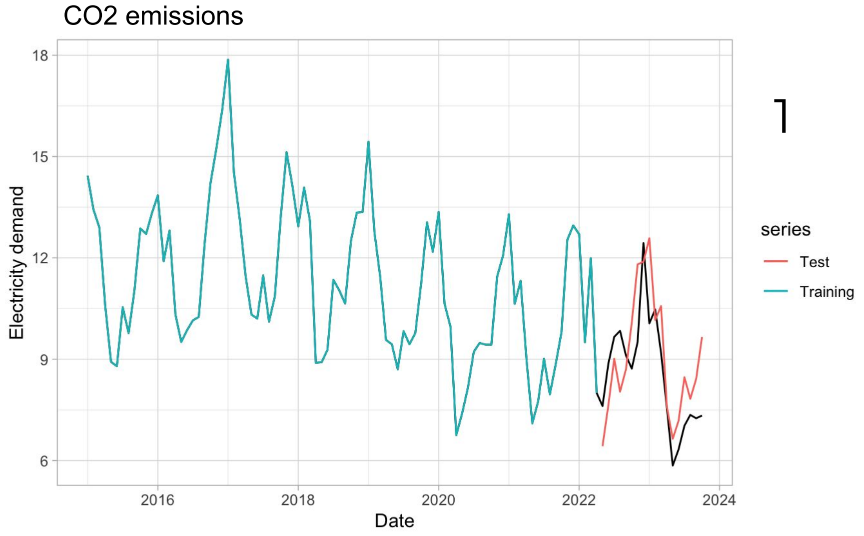
1	1CZE, 1FRA, 1GRC, 1NLD
2	2AUT, 2BEL, 2BGR, 2HRV, 2CYP, 2DNK, 2EST, 2FIN, 2HUN, 2IRL, 2LVA, 2LTU, 2LUX, 2MLT, 2PRT, 2ROU, 2SVK, 2SVN, 2SWE
3	3DEU
4	4ITA, 4POL, 4ESP

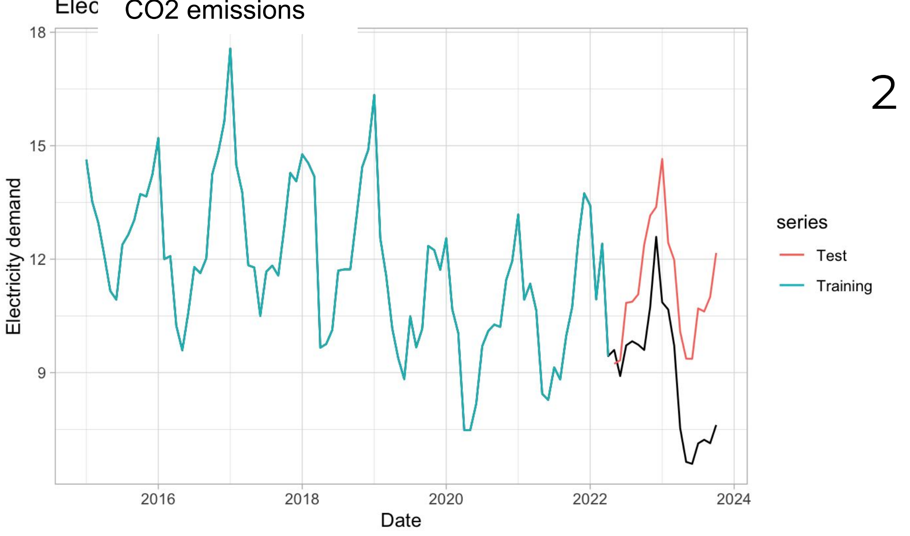
CO2 emissions metric results

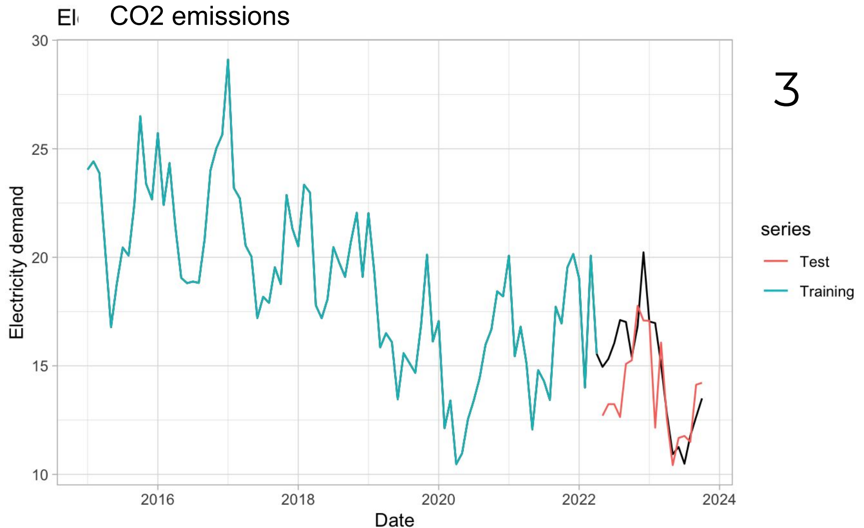


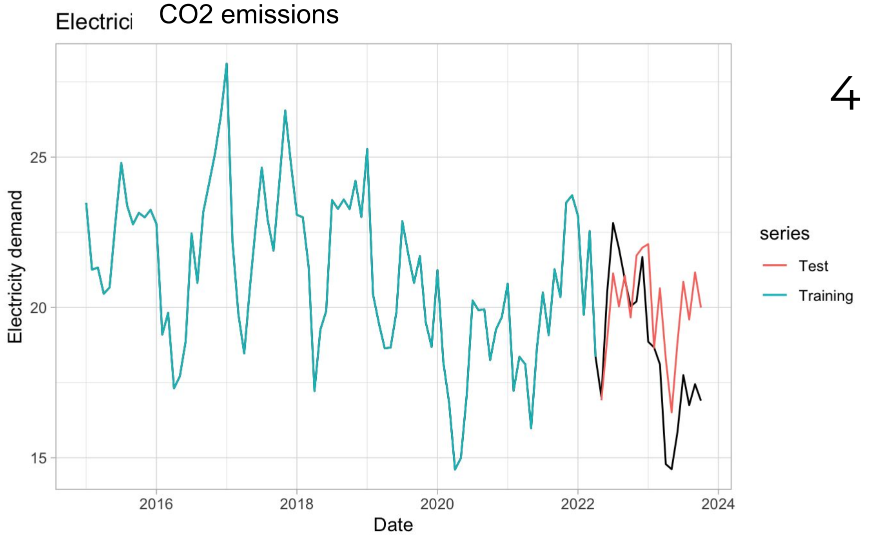
MASE		
Cluster 1	mo+ARIMA	1.0219582
Cluster 2	tdgsa+ARIMA	1.2167985
Cluster 3	mo+ARIMA	0.9428566
Cluster 4	m+ARIMA	0.9798756

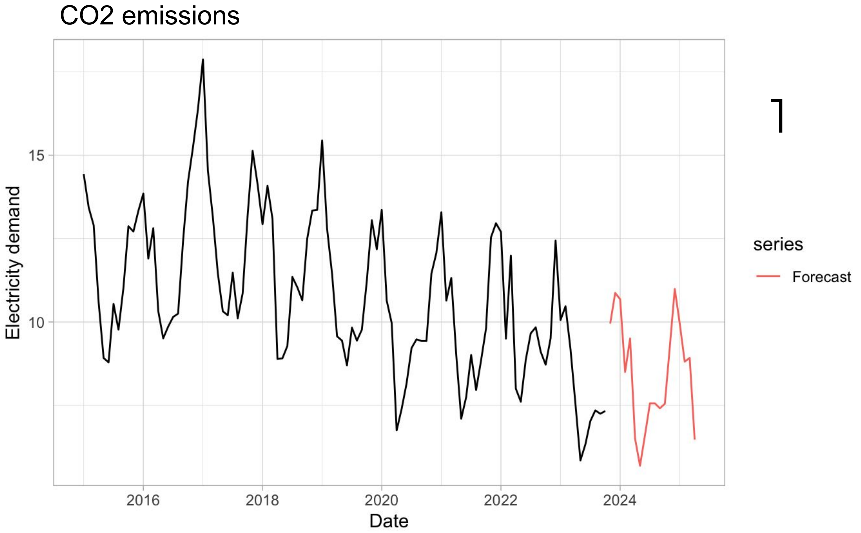
MASE							
	Diff	AutoArima	Holts	Holt's damped	Mean	RWF	RWF+drift
Cluster1	18.1057947	2.8163676	15.8659093	17.3987719	1.46046	2.943562	3.303208
Cluster2	6.1993152	4.2209246	4.2016429	5.4701881	1.898164	4.2690645	4.655625
Cluster3	118.8468767	3.2726499	98.4055115	121.4859469	1.439489	2.6899483	2.9217287
Cluster4	46.7846926	1.4447459	50.6552584	52.6576632	0.9853184	2.795733	3.0380404

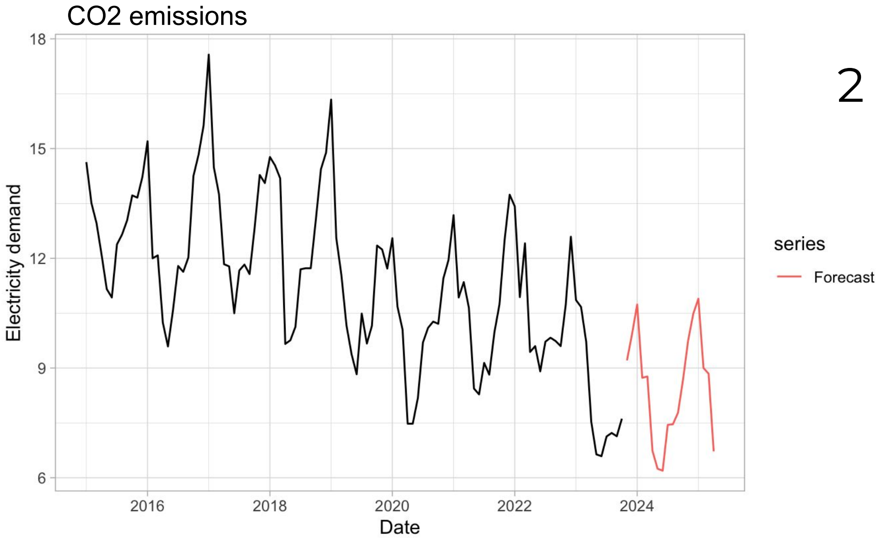

CO2 emissions
Electricity demand
Date
series
Test
Training
1

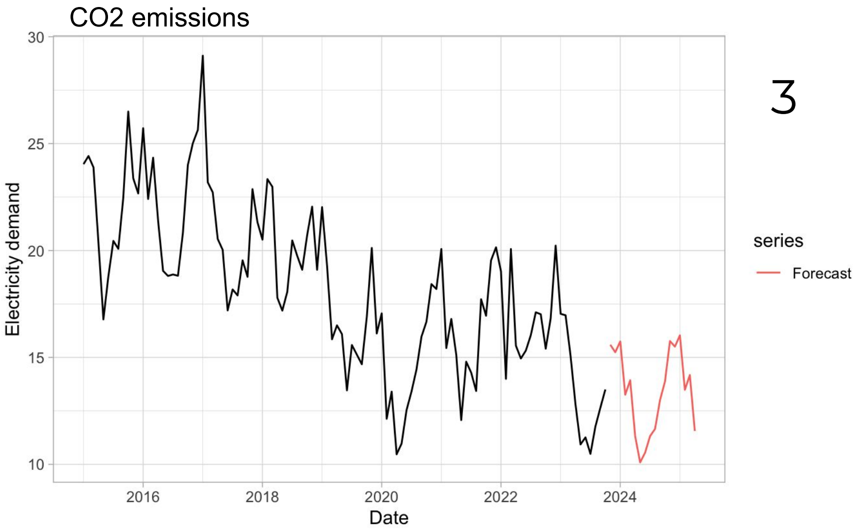

CO2 emissions
Electricity demand
Date
series
Test
Training
2

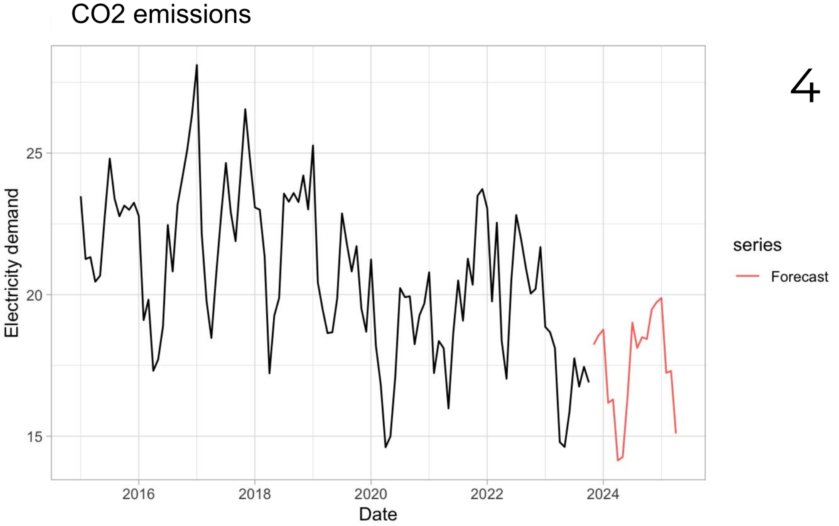

CO2 emissions
Electricity demand
Date
series
Test
Training
3


CO2 emissions
Electricity demand
Date
series
Test
Training
4


CO2 emissions
Electricity demand
Date
series
Forecast
1


CO2 emissions
Electricity demand
Date
series
Forecast
2


CO2 emissions
Electricity demand
Date
series
Forecast
3

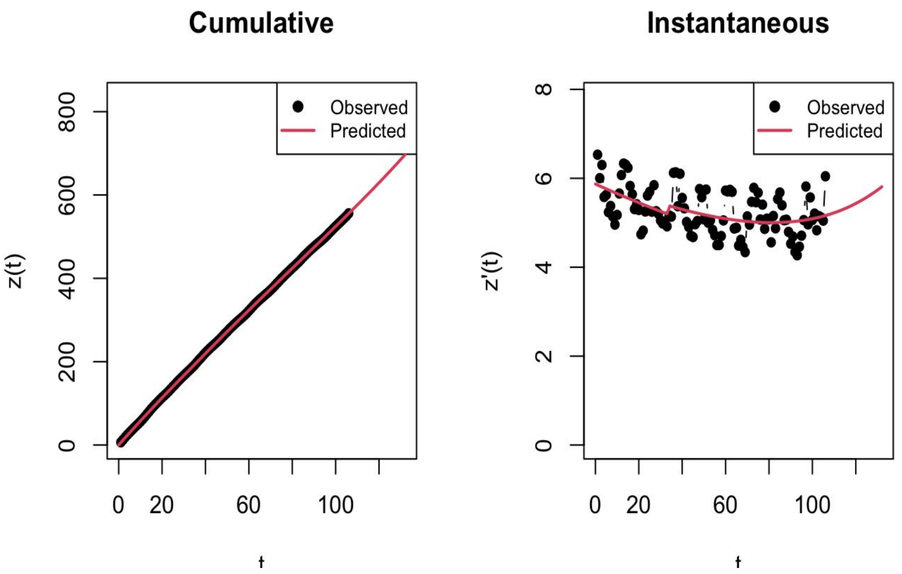

CO2 emissions
Electricity demand
Date
series
Forecast
4

Electricity Generation Forecasting (Bass Models)

- Renewable energies behave like commercial products seeking acceptance within specific market niches.
- These sources follow a finite life cycle influenced by competition and substitution dynamics.
- Similar to other markets, the energy landscape witnesses the rise of new technologies for both production and consumption, gradually replacing older counterparts that experience a natural decline before ultimately exiting the market.
- This analysis employs generative Bass models and UCRCD models to delve into the intricate interplay between various fuel types.
- The investigation seeks to understand how different fuels interact and forecast their future growth or decline in the competitive environment shaped by substitution dynamics.
- Leveraging the parameters of the Bass models, we aim to make predictions in this context.

Clean Sources

m: 2.233656e+02, p: 2.628156e-03, q:-1.136553e-03

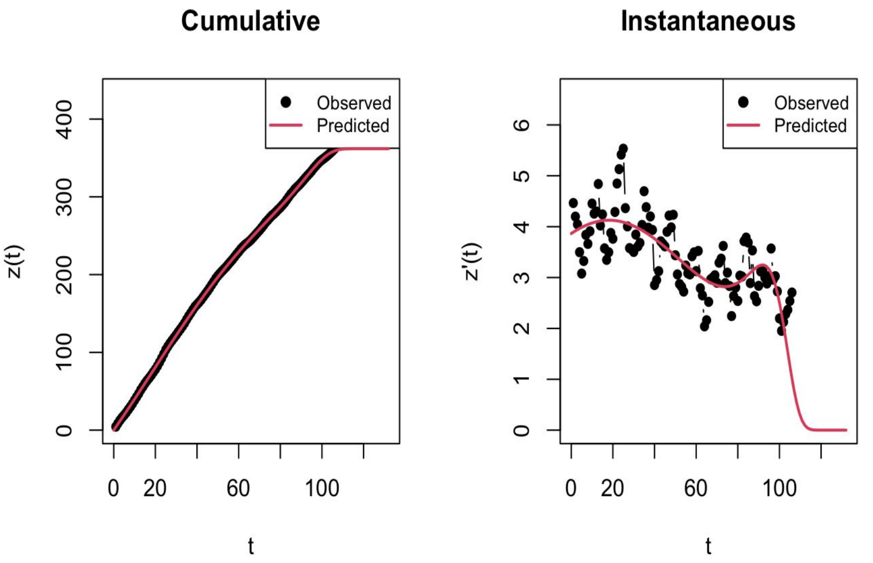


Residual standard error 0.993635 on 100 degrees of freedom

Multiple R-squared:0.999963 Residual sum of squares:98.73114

Fossil

m: 3.619061e+03, p: 1.067853e-02, q:1.784372e-02



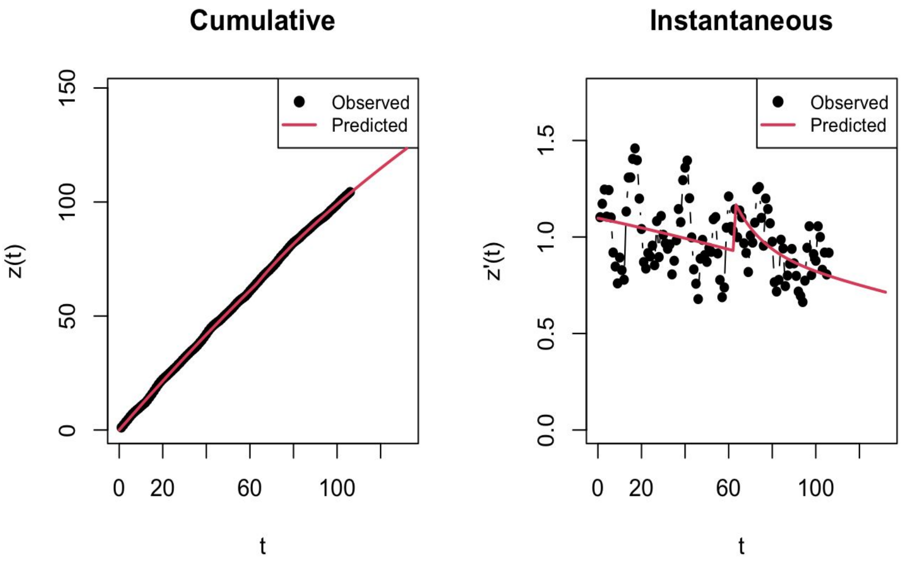
Residual standard error 1.173153 on 100 degrees of freedom

Multiple R-squared: 0.999881 Residual sum of squares:137.6289

The Generalized Bass Model

Nuclear

m: 263.029443105, p: 0.004172105, q:0.001995520

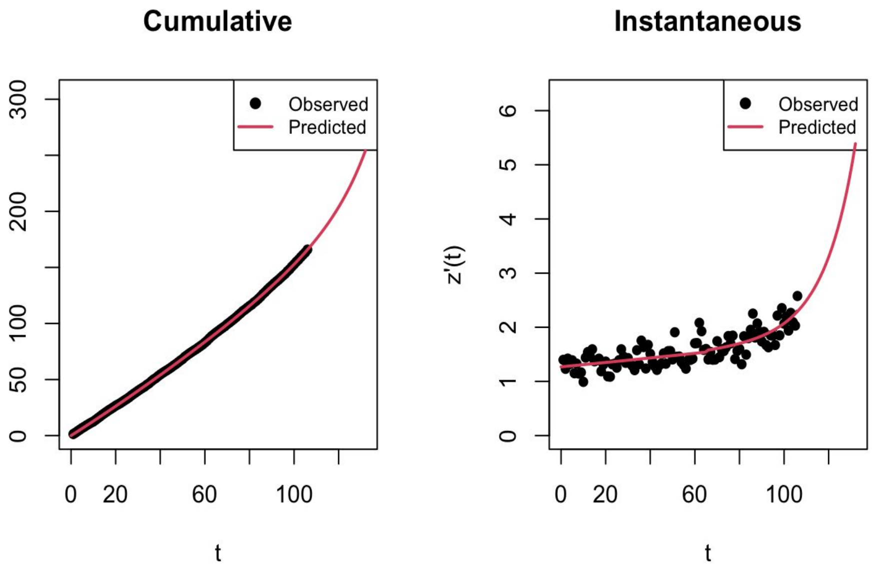


Residual standard error 0.625391 on 100 degrees of freedom
Multiple R-squared: 0.99993

Residual sum of squares: 39.11143

Wind and Solar

m: 2.481858e+03, p: 5.116010e-04, q:3.621990e-02



Residual standard error 0.325253 on 100 degrees of freedom

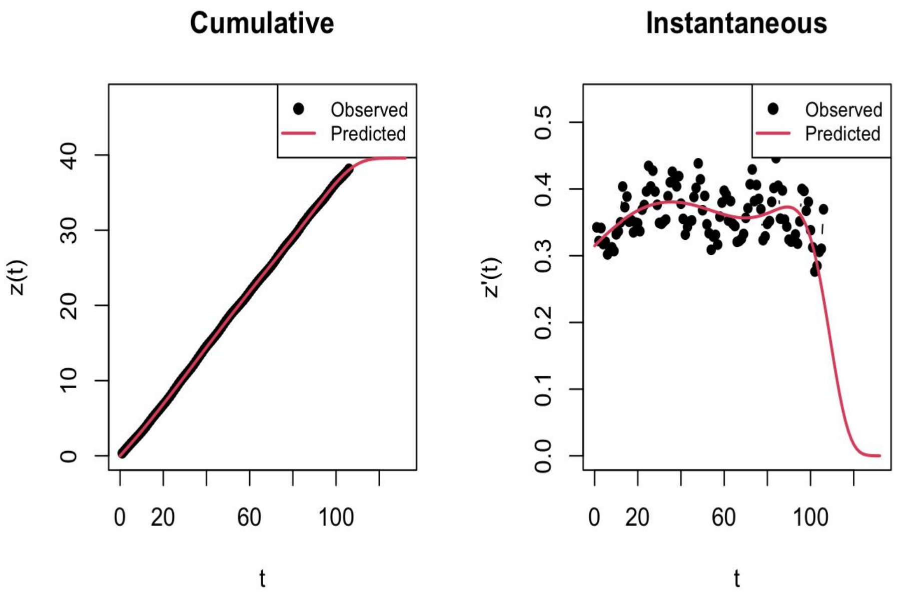
Multiple R-squared: 0.999955

Residual sum of squares: 10.57895

The Generalized Bass Model

Coal

m: 39.588633, p: 0.007950267, q:0.018620944

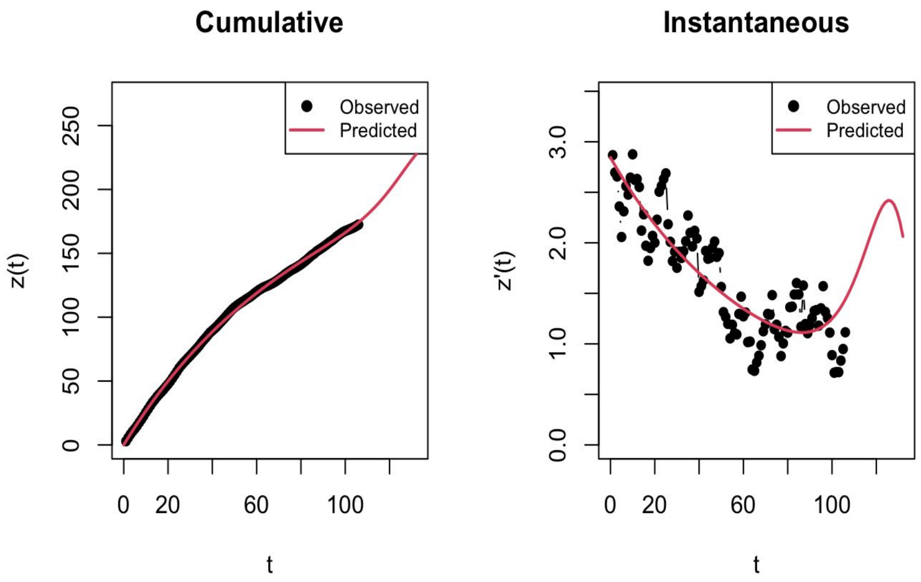


Residual standard error 1.439404 on 100 degrees of freedom
Multiple R-squared: 0.999162

Residual sum of squares: 207.1884

Gas

m: 1.543094e+03, p:1.843485e-03, q:-1.178371e-0



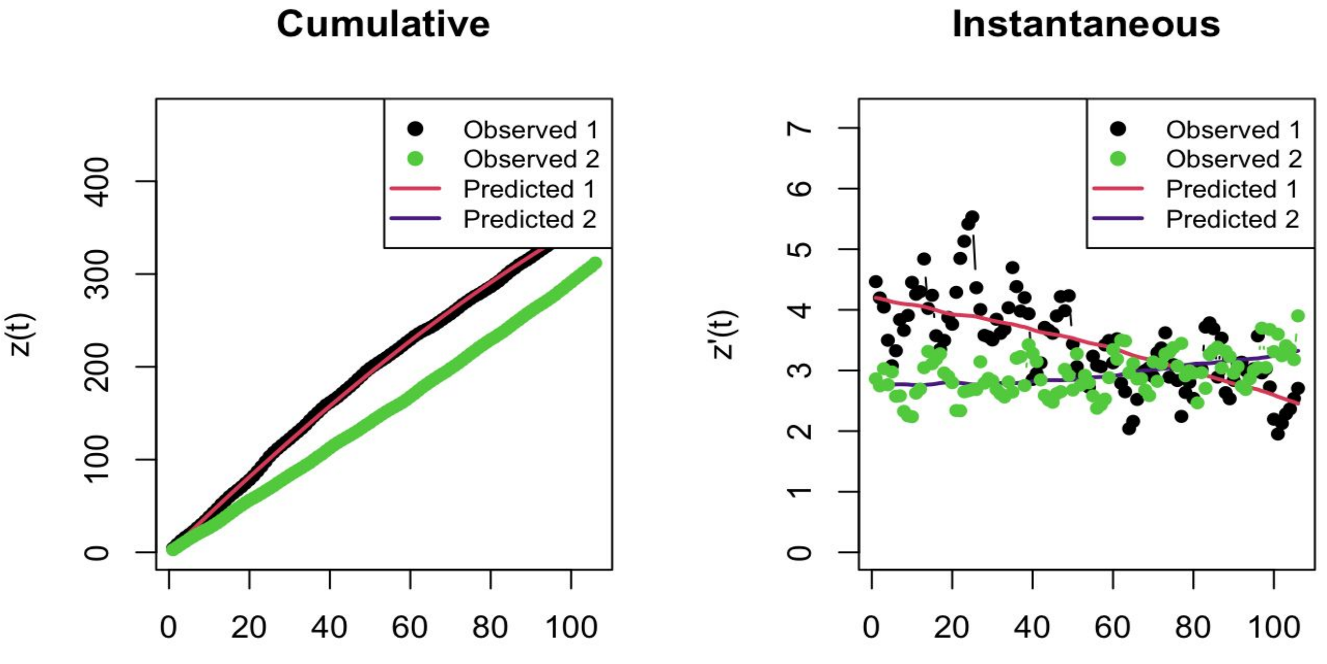
Residual standard error 0.971406 on 100 degrees of freedom
Multiple R-squared: 0.999636

Residual sum of squares: 94.36303

Innovation Diffusion in Competition(UCRCD Models)

UCRCD Models considers the competition between two products, that enter the market at different time

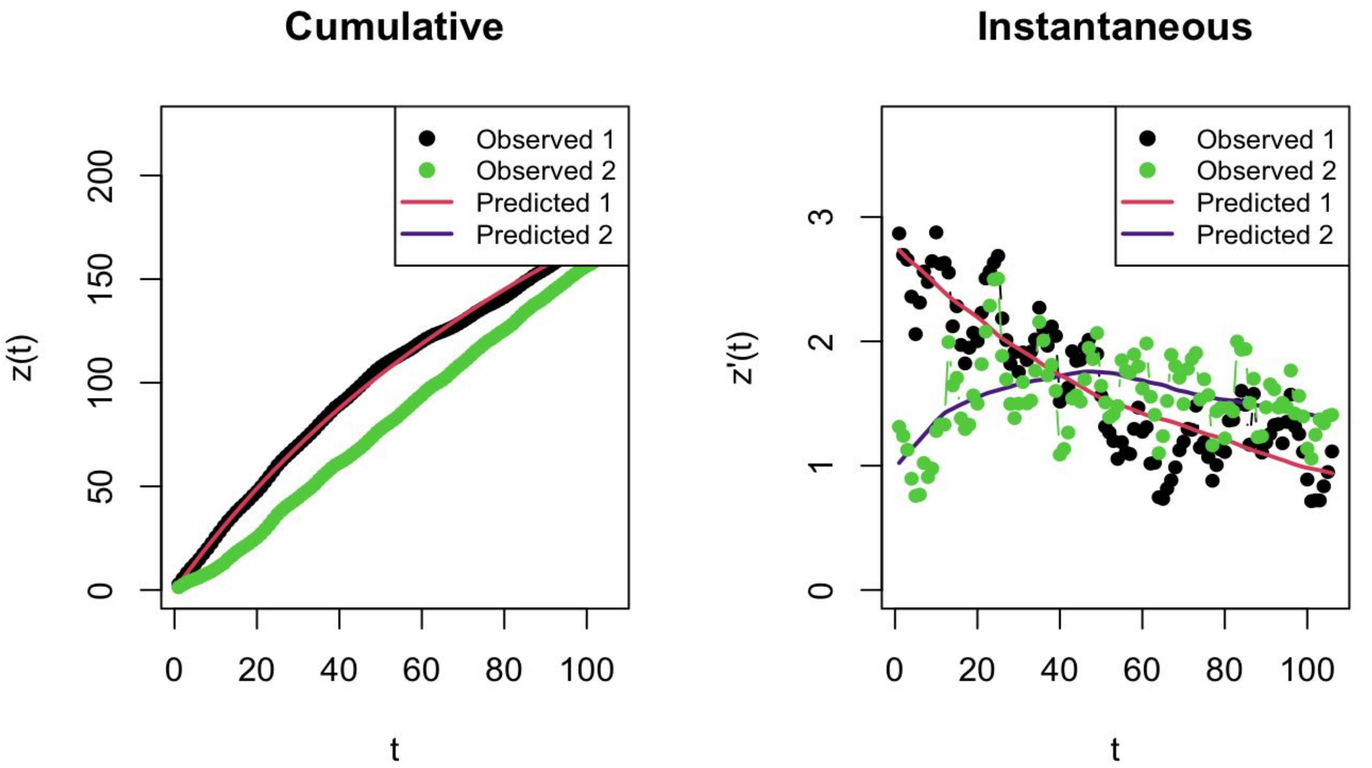
Fossil and Renewables




```
mc: 2.927348e+03,
p1c: 1.438503e-03,
p2:  9.364377e-04,
q1c: -1.107138e-02,
q2: 1.243688e-02,
delta: 1.778608e-02,
gamma: 1.880531e-02
```

```
Residual standard error Series 1: 0.541173  on  99  degrees of freedom
Residual standard error Series 2: 0.303644  on  99  degrees of freedom
Multiple R-squared:   0.523894  Residual sum of squares:  38.12171
```

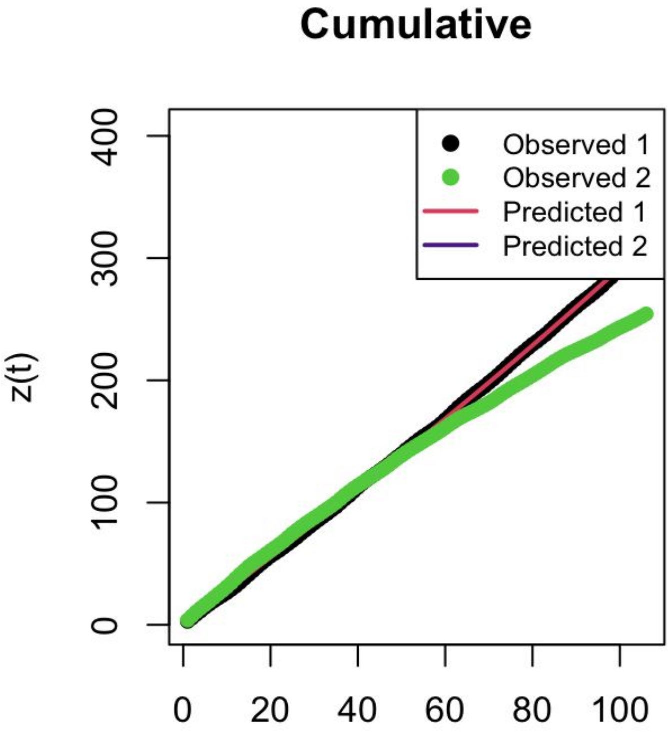
Coal and Gas

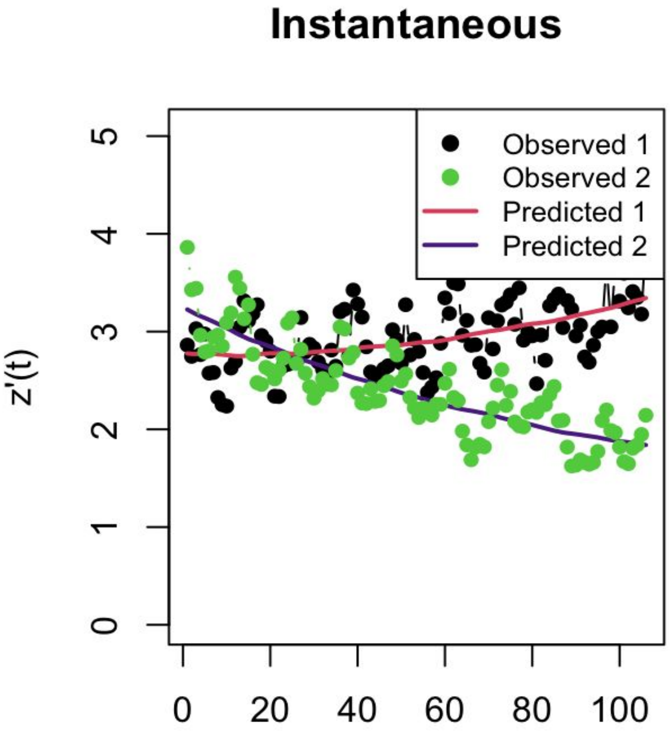


mc: 700.153769813,
p1c: 0.003956520,
p2: 0.001399701,
q1c: 0.002789573,
q2: -0.01489899,
delta: -0.01101655,
gamma:-0.03866909

Residual standard error Series 1: 0.289565 on 99 degrees of freedom
Residual standard error Series 2: 0.293921 on 99 degrees of freedom
Multiple R-squared: 0.641417 Residual sum of squares: 16.85348

Nuclear,Wind and Solar

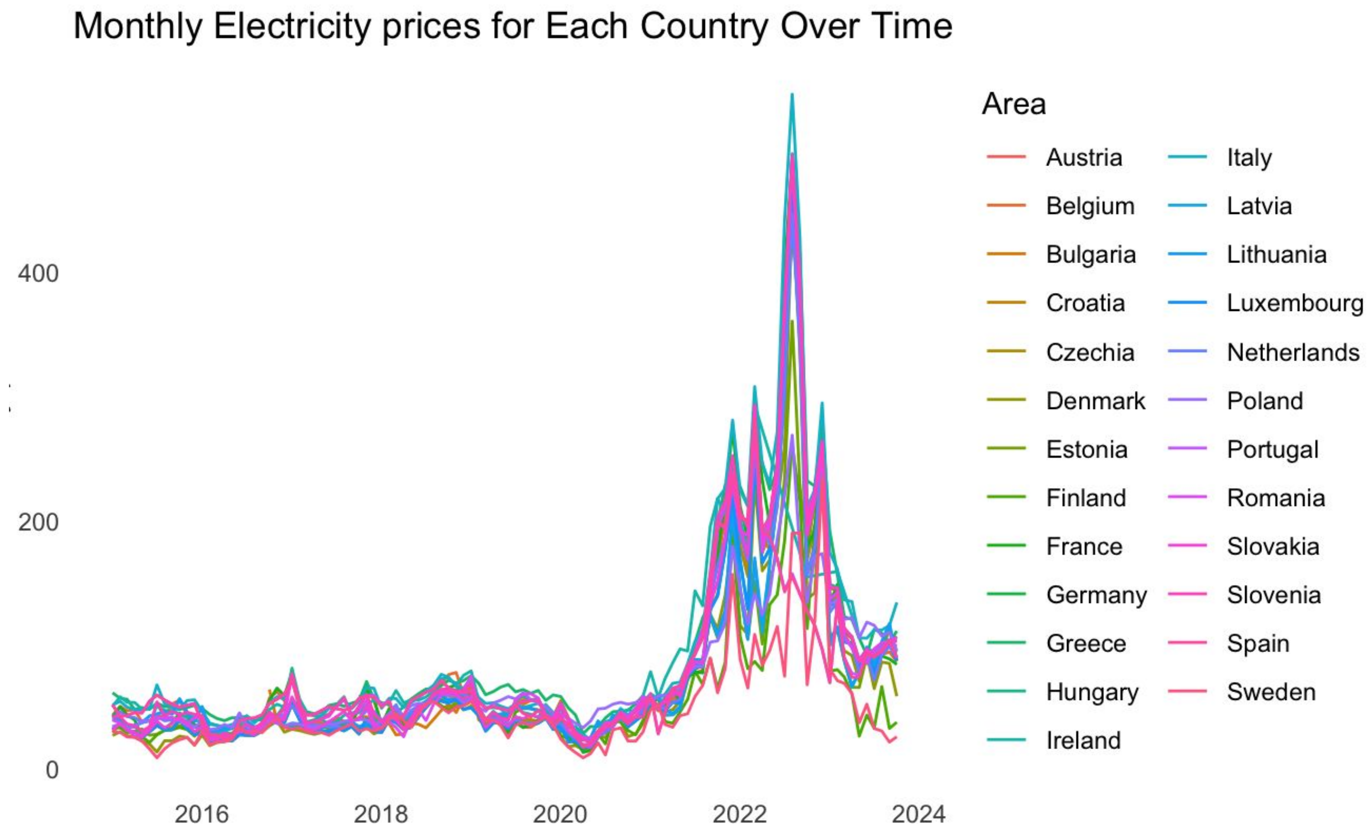


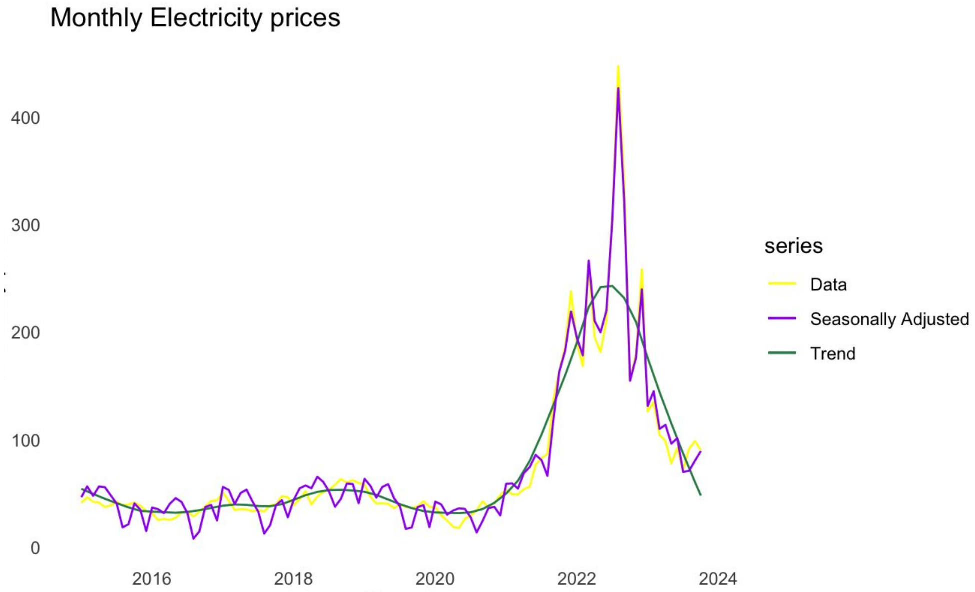


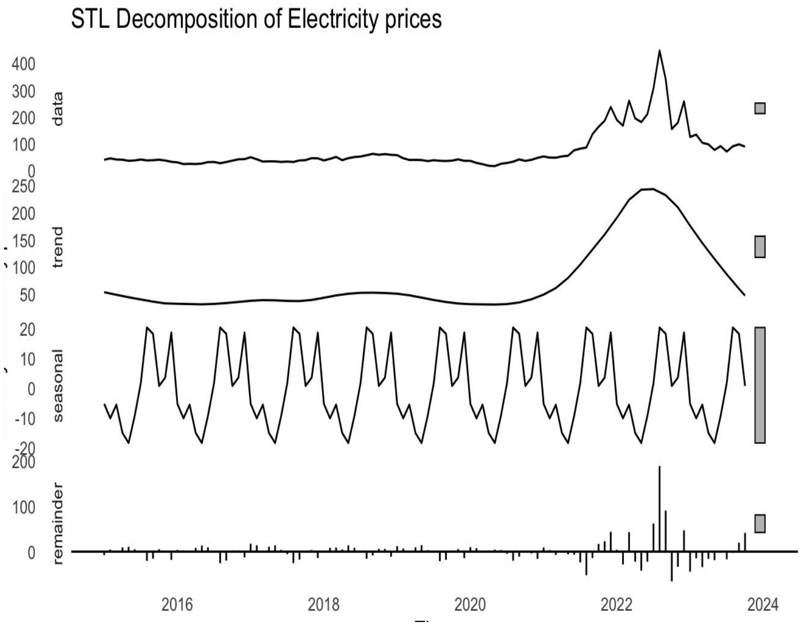

```
mc: 6.422842e+03,
p1c: 4.332360e-04,
p2:  5.066905e-04,
q1c: -7.622766e-0,
q2: -8.912983e-0,
delta:1.667155e-02,
gamma:-1.221487e-0
```

```
Residual standard error Series 1: 0.302724  on  99  degrees of freedom
Residual standard error Series 2: 0.265134  on  99  degrees of freedom
Multiple R-squared:   0.691886  Residual sum of squares:  16.03184
```

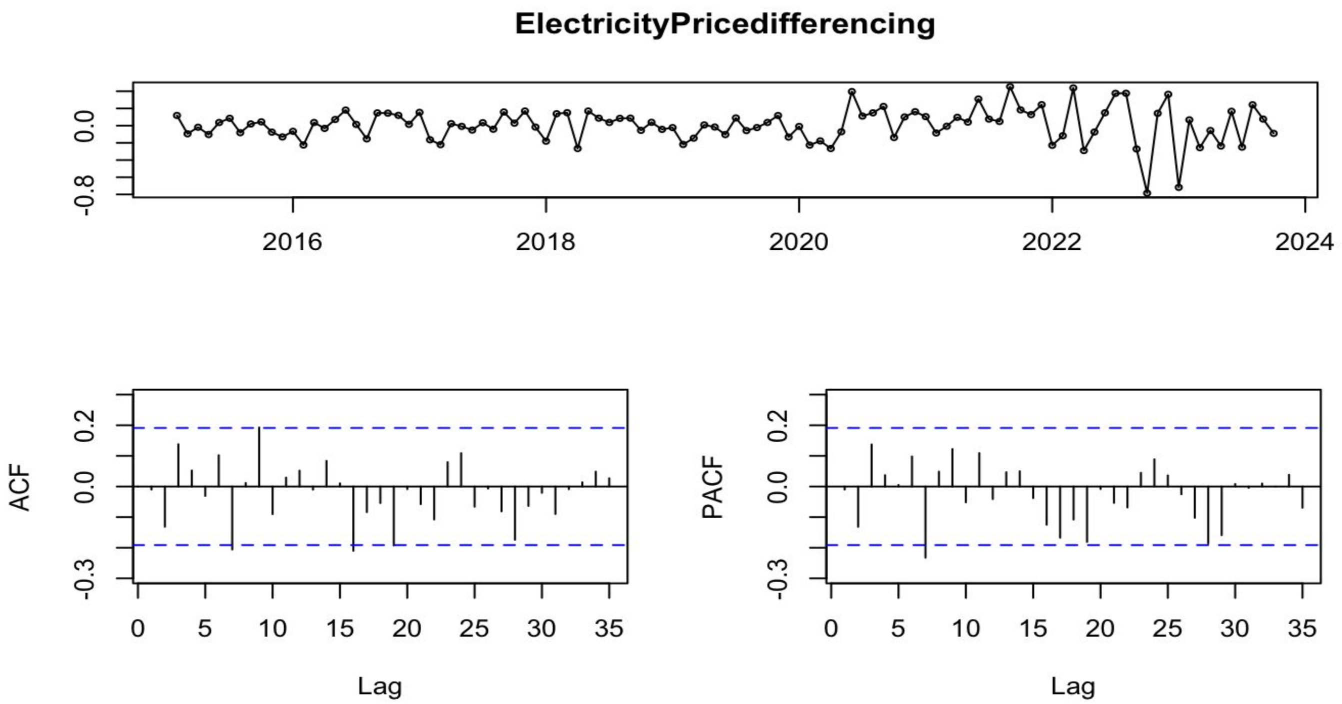
Electricity Price Forecasting:



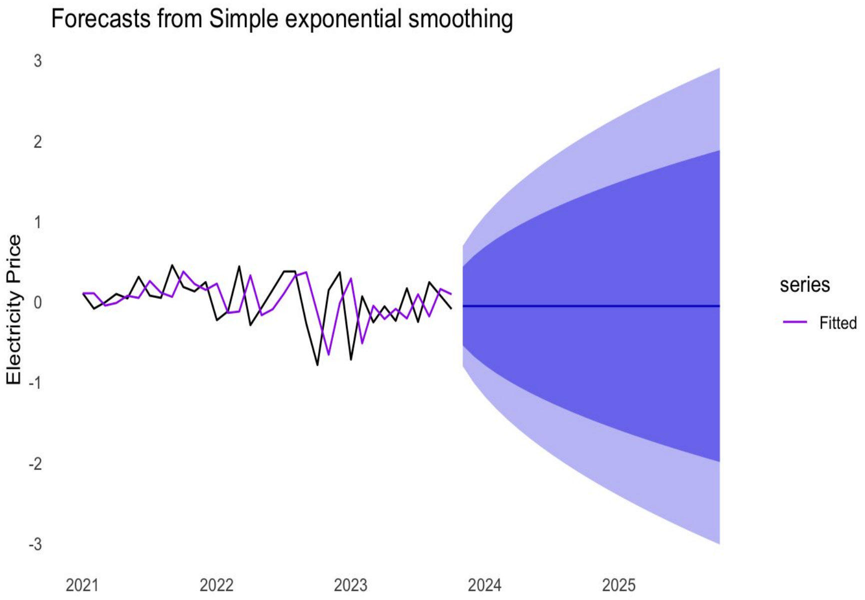

Monthly Electricity prices
400
300
200
100
0
2016
2018
2020
2022
2024
series
Data
Seasonally Adjusted
Trend

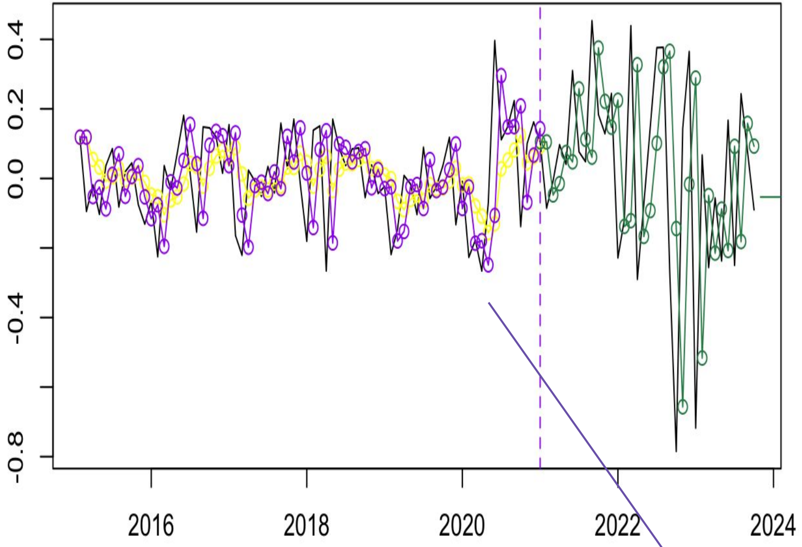

STL Decomposition of Electricity prices
data
trend
seasonal
remainder
2016
2018
2020
2022
2024

Applying logarithmic transformation and log-differencing



Simple Exponential Smoothing (Electricity Price)





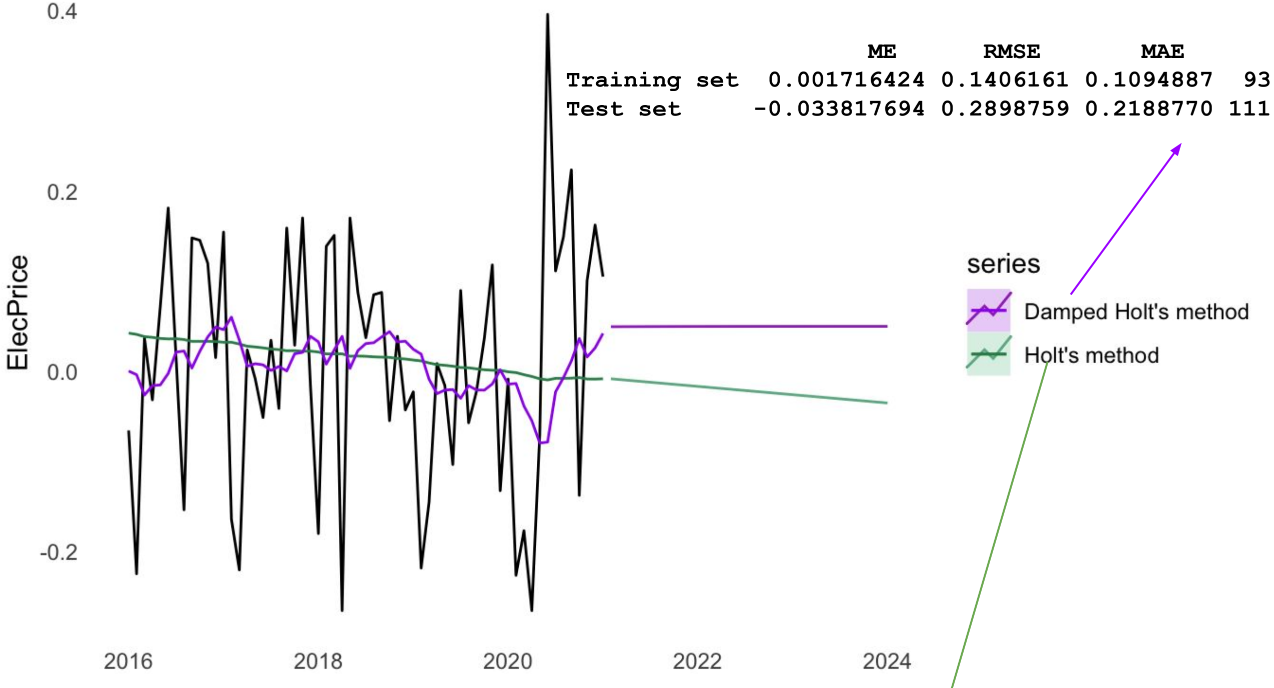
Fitted models with different alpha values

```
ses(y = train_diff, h = 24, initial = "simple", alpha = 0.8)
```

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.003657042	0.1654738	0.1270570	87.81783	213.3918	0.8539169	-0.32375029
Test set	-0.076918349	0.3267021	0.2378115	136.06758	167.0644	1.5982694	-0.02775586

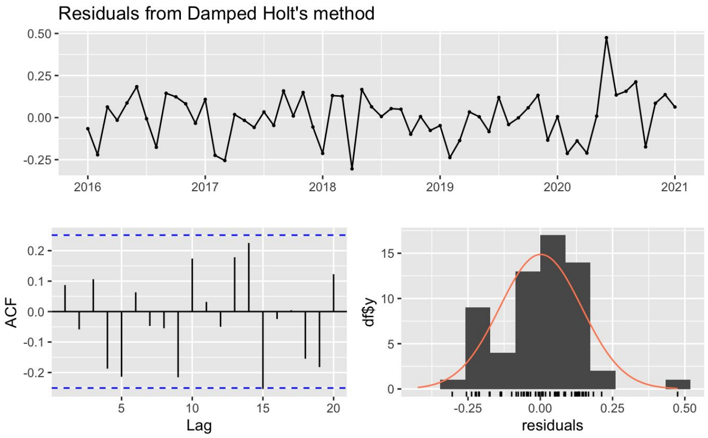
Holt-Winters' linear trend method(extended simple exponential smoothing)

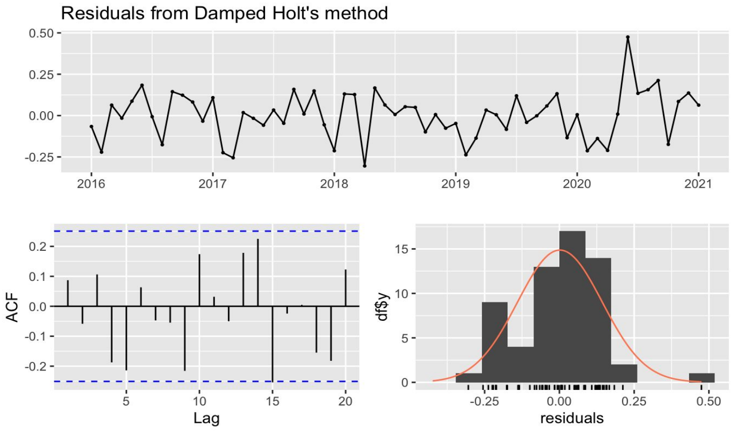
	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.001716424	0.1406161	0.1094887	93.60651	106.0244	0.735845	0.08703607
Test set	-0.033817694	0.2898759	0.2188770	111.90804	113.3208	1.471015	-0.06786891

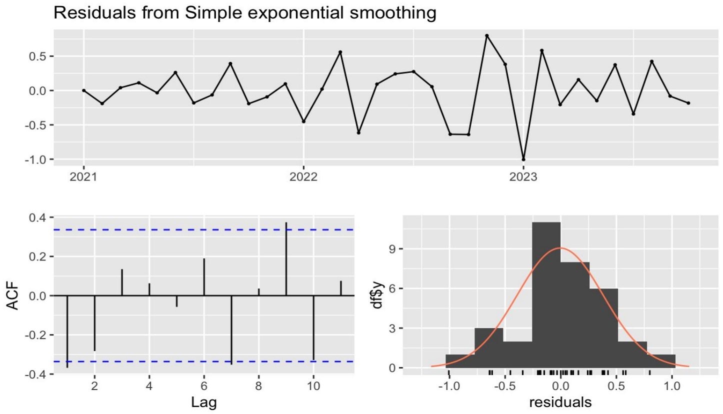


	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-0.007560172	0.1382822	0.1100265	95.62989	105.1843	0.7394596	0.14402242
Test set	0.036583499	0.2886418	0.2276904	98.25271	100.3426	1.5302481	-0.07975078

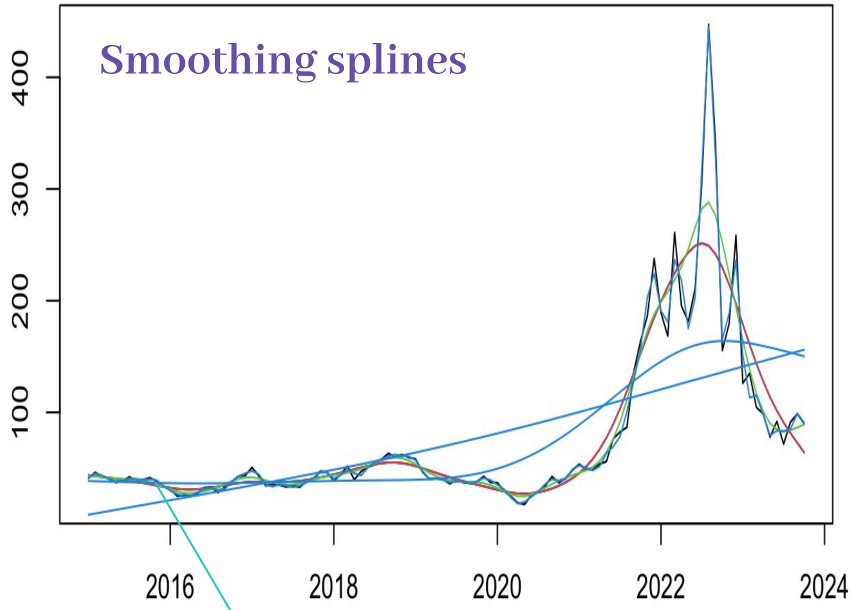
Residuals Holt and Exp Models

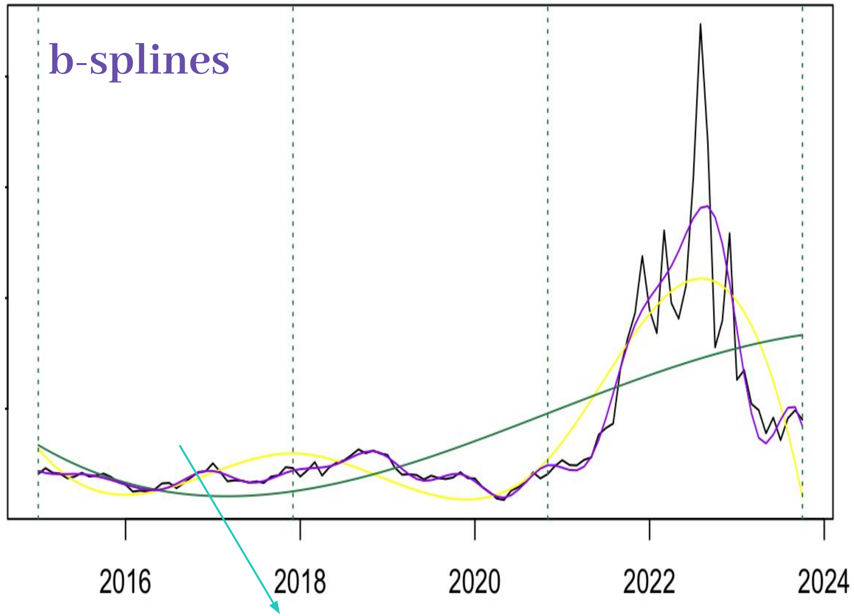






Regression splines Models(Electricity Price)





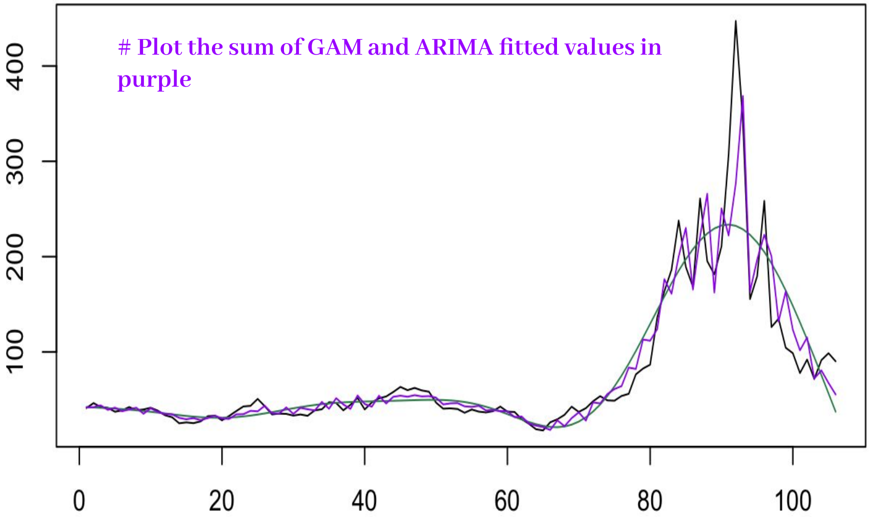
Models with different lambda values

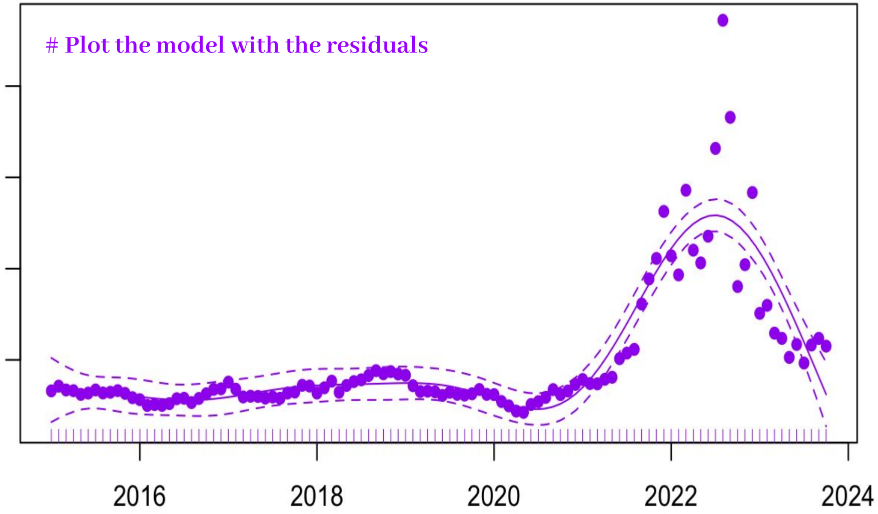
Models with different number of knots

```
s5 <- smooth.spline(time(ts_data),ts_data, lambda=0.00000001)
MSE on test set: 46.00845
RMSE on test set: 6.782953
MAE on test set: 3.830683
```

```
m<-lm(ts_data~bs(time(ts_data),df=20,degree=3))
MSE on test set: 671.9034
RMSE on test set: 25.9211
MAE on test set: 11.07592
```

Generalized Additive Model (Electricity Price)





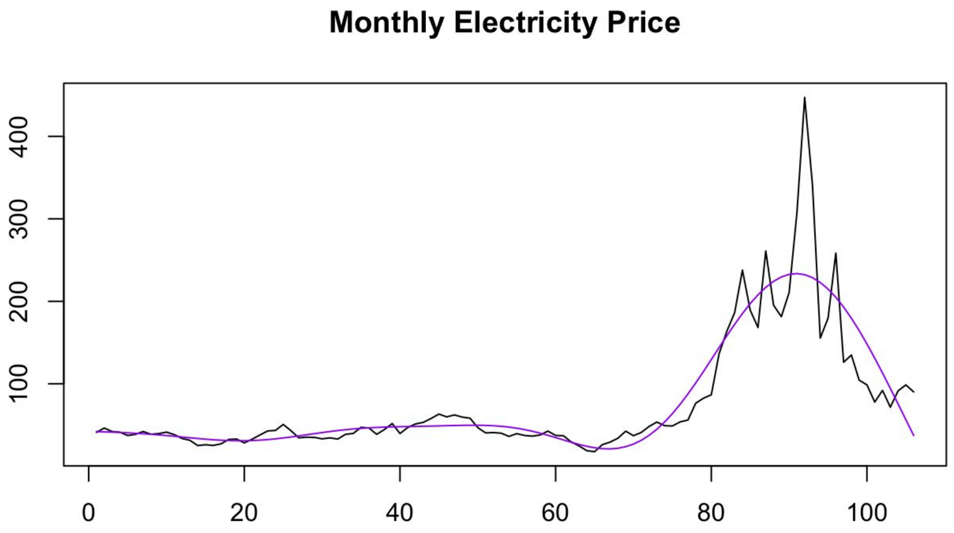

```
# Fit a GAM model
gam_model <- gam(Value ~ s(Date), data = df)

# Extract residuals from the GAM model
gam_residuals <- residuals(gam_model)

# Fit an ARIMA model to the residuals
aarima_model <- auto.arima(gam_residuals)

# Combine fitted values from ARIMA and GAM
fitted_values <- fitted(gam_model) + fitted(aarima_model)
```

```
Mean Squared Error (MSE): 1067.255
Root Mean Squared Error (RMSE): 32.66886
Mean Absolute Error (MAE): 12.84421
Mean Absolute Percentage Error (MAPE): 14.28793 %
R-sq.(adj) =  0.786   Deviance explained = 80.3%
```

Gradient Boosting Machine Model (Electricity Price)

```
Mean Squared Error (MSE): 1326.448
Root Mean Squared Error (RMSE): 36.42044
Mean Absolute Error (MAE): 17.51471
Mean Absolute Percentage Error (MAPE):
19.94091 %
```

	var	rel.inf
	<chr>	<dbl>
Date	Date	86.70051
Demand	Demand	13.29949




```
gbm_model <- gbm(Value ~ Date+Demand, data = df, distribution = "gaussian", n.trees =
1000, interaction.depth = 3,shrinkage=0.01)
```

THANK YOU