

Time series Analysis and Modeling

Energy Demand Forecasting

DATS 6313

Brooklyn Chen

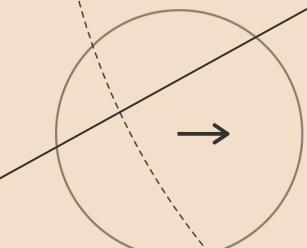


Table of content

	Page
Table of content	xii
Table of figures and tables	xv
Abstract	1
Introduction	2
Description of the dataset	3
Stationary	8
Time series Decomposition	10
Feature Selection	13
Holt–Winters method	14
Base–models	15
Linear Regression	19
ARMA, ARIMA and SARIMA model	21
Levenberg Marquardt algorithm	24
Deep Learning Model	25
Final Model Selection	26
Forecast Function	27
Summary and Conclusion	28

Table of figures and tables

	Page
Table 1 Smart Meter Energy(kW) – Raw Data	4
Table 2 Feature Selection	13
Table 3 ARMA model by Levenberg Marquardt Algorithm	24
Table 4 Final Model selection	26
Figure 1.1 kW versus date	5
Figure 1.2 ACF/PACF of kW	6
Figure 1.3 Correlation Matrix with the Pearson's correlation coefficient	7
Figure 2.1 ACF/PACF of Raw Data	8
Figure 2.2 Rolling Mean and Variance of Raw Data	8
Figure 2.3 ADF and KPSS of Raw Data	8
Figure 2.4 ACF/PACF of First Order Differencing	9
Figure 2.5 Rolling Mean and Variance of First Order Differencing	9
Figure 2.6 ADF and KPSS of First Order Differencing	9
Figure 2.7 1st Oder Differencing of kW	9
Figure 3.1 Cycle–Trend of kW	10
Figure 3.2 STL applied to kW(1)	11
Figure 3.3 STL applied to kW(2)	11
Figure 3.4 Seasonal Adjusted of kW	12

Table of figures and tables

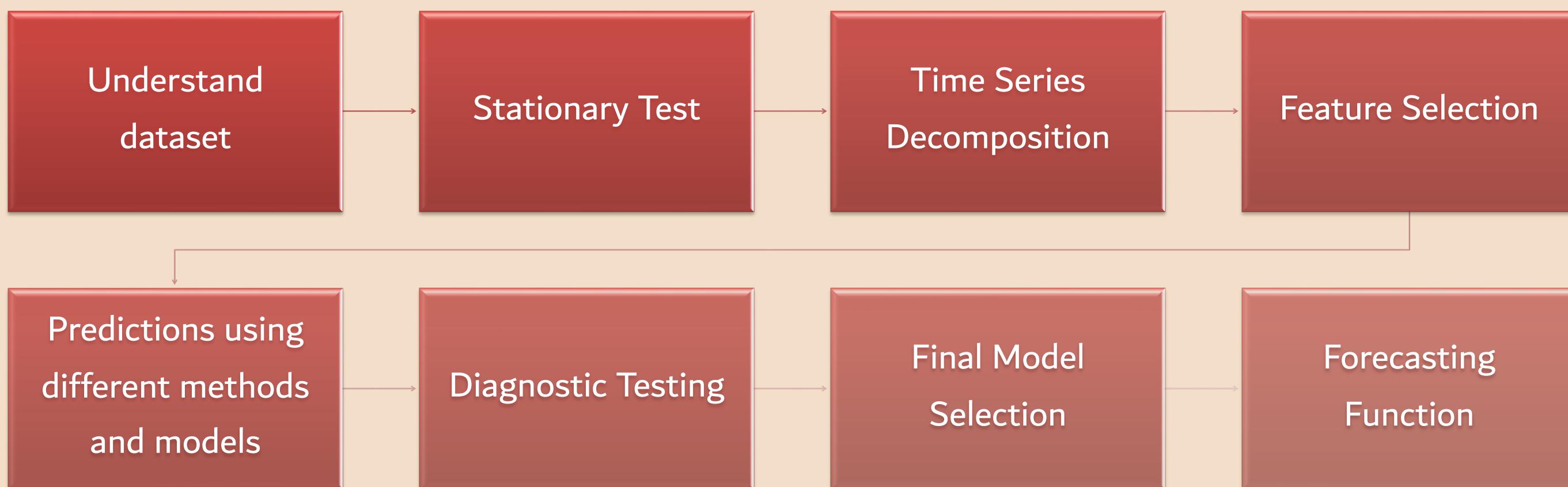
	Page
Figure 4.1 Holt–Winter Method	14
Figure 4.2 Average Forecast Method	15
Figure 4.3 ARIMA(2, 0, 2) Model	15
Figure 4.4 Naïve Forecast Method	16
Figure 4.5 MethodDrift	17
Figure 4.6 SES Method	18
Figure 5.1 OLS Regression Results(1)	19
Figure 5.2 OLS Regression Results(2)	20
Figure 6.1 AIC and BIC of ARIMA Model	21
Figure 6.2 GPAC Table	22
Figure 6.3 ARMA model summary	23
Figure 6.4 ARIMA model summary	23
Figure 6.5 SARIMA model summary	23
Figure 7.1 Multivariate LSTM Model	25

Abstract

In this study, I aimed to forecast kW, a dependent variable, using three electricity-related variables: **KWh, kVARh, and kVAR**. These variables measure energy, power, and reactive power and are commonly used in power system analysis. I used different models to predict **kW**, evaluated their performance, identified the optimal model, and developed the forecasting function for kW.

Introduction

Time series analysis and modeling process



Description of the dataset

The independent variables

- **kWh** (kilowatt-hour) :
used to measure electricity consumption. One kilowatt-hour is equal to the energy consumed by using one kilowatt of power for one hour.
- **kVARh** (kilovolt-ampere reactive hour)
a unit of reactive power of a power system. Reactive power is power generated by capacitors or inductors for regulating voltage and current.
- **kVAR** (kilovolt-ampere reactive)
a unit of reactive power used to measure the reactive power in a power system for maintaining stable voltage and preventing overload in the power system.

The dependent variable

- **kW** (kilowatt)
used to measure the rate at which electricity is used. One kilowatt is equal to a power consumption or production rate of 1000 watts per second.

Description of the dataset

Table 1 Smart Meter Energy(kW) – Raw Data

serial	kWh	kW	kVArh	kVAR	Time_stamp
3098000032	10.854	0	7.814	0.002	2018/3/1 15:30
3098000032	10.75	0	7.813	0	2018/3/1 14:30
3098000032	12.325	0.086	8.302	0.076	2018/3/5 9:00
3098000032	12.372	0.094	8.345	0.086	2018/3/5 9:30
3098000032	12.415	0.086	8.386	0.082	2018/3/5 10:00
...
3098000032	6781.4	0.982	1721.24	0.406	2019/3/31 22:00
3098000032	6781.92	1.04	1721.32	0.46	2019/3/31 22:30
3098000032	6782.52	1.192	1721.39	0.498	2019/3/31 23:00
3098000032	6783.12	0	1721.47	0.436	2019/3/31 23:30
3098000032	6783.84	0	1721.55	0	2019/4/1 0:00

References

Zahid, A. (2020, January 24). *Smart Meter Energy(kW) demand forecasting*. Kaggle. Retrieved May 4, 2023, from <https://www.kaggle.com/datasets/asimzahid/smartergykw-demand-forecasting>

Description of the dataset

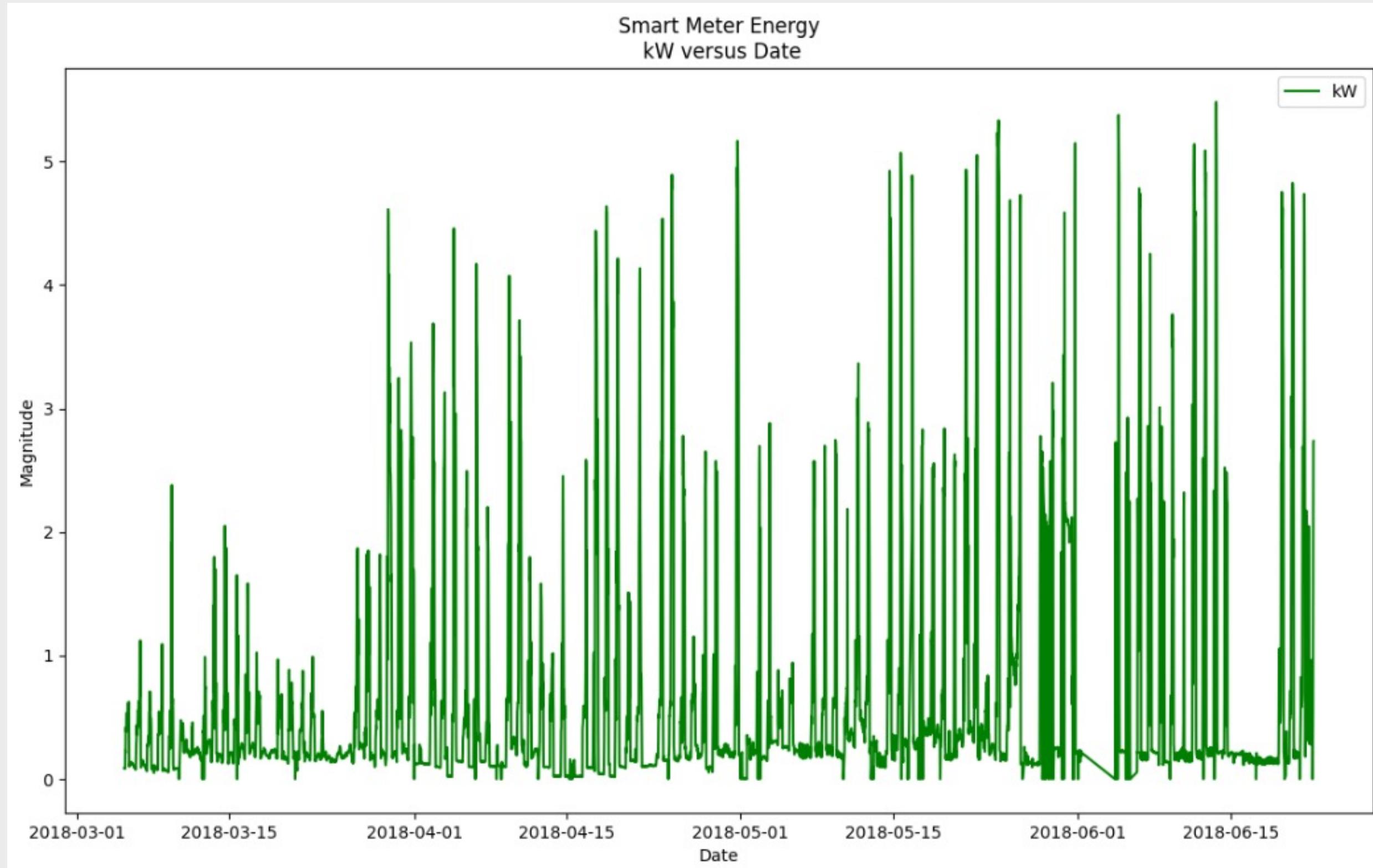


Figure 1.1 kW versus date

No obvious trend or seasonality can be seen in this plot, which needs further analysis.

Description of the dataset

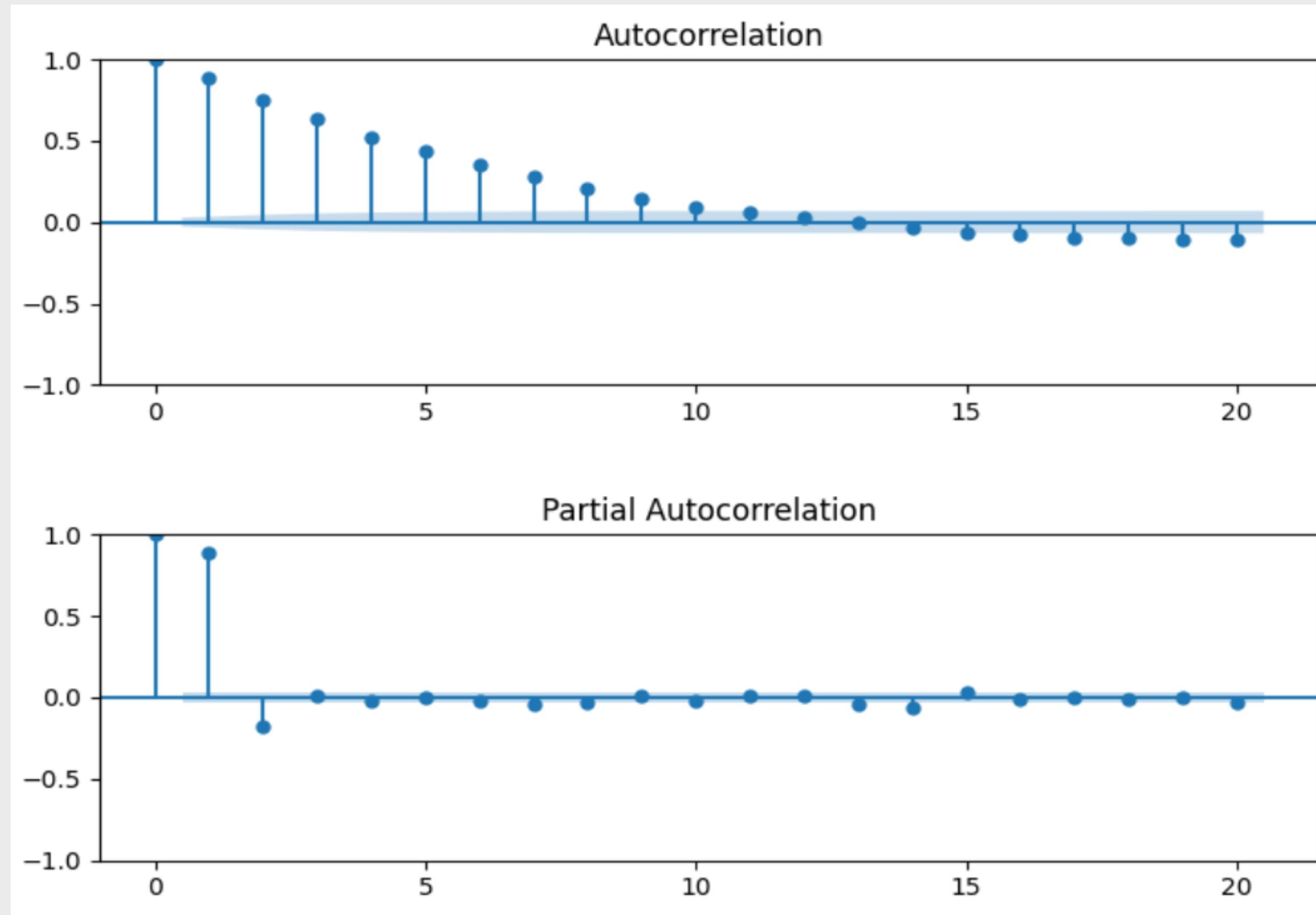


Figure 1.2 ACF/PACF of kW

The graphs suggest that ARMA (1, 0) or ARMA (2, 1) would be appropriate for the time series.

Description of the dataset

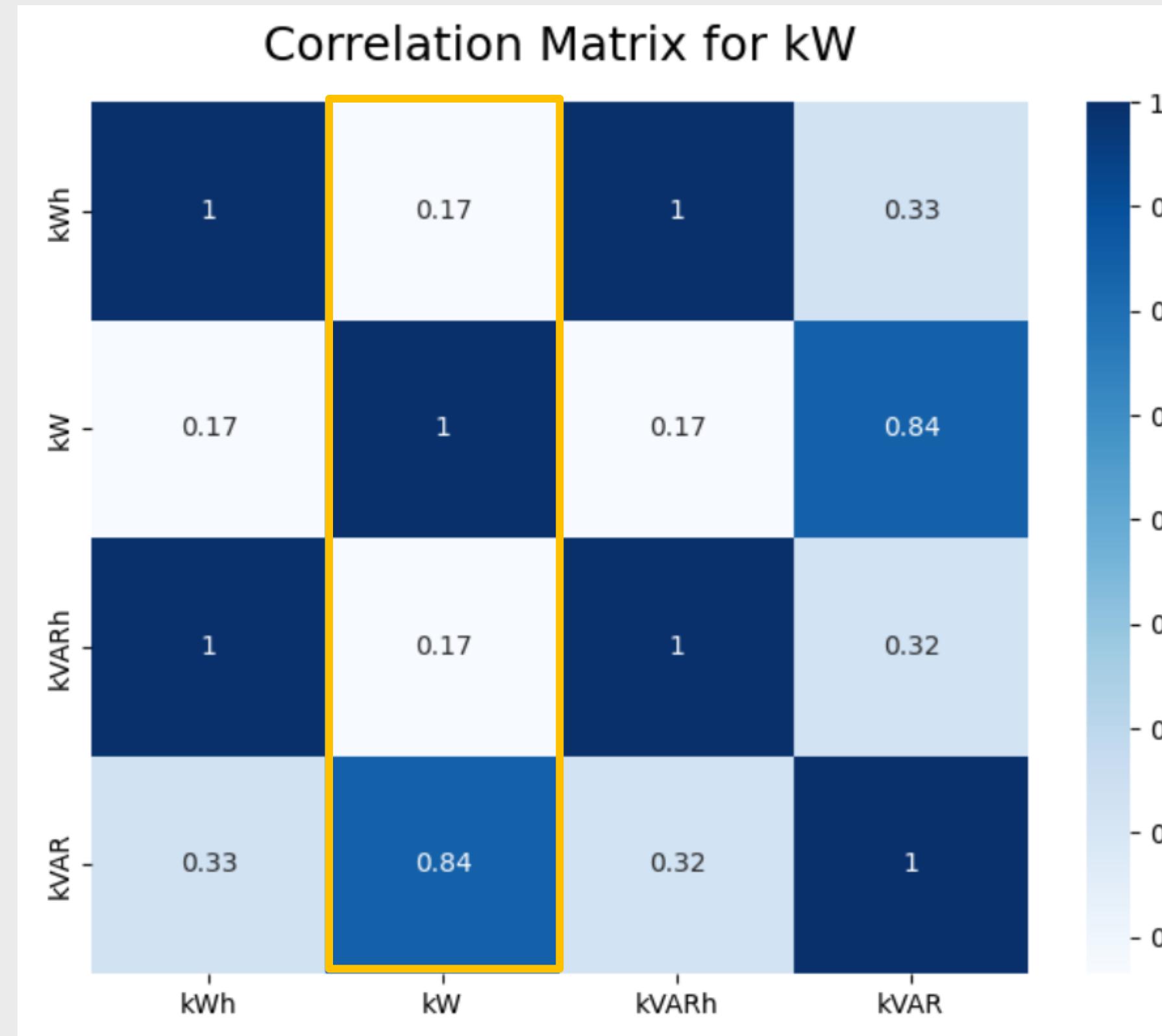


Figure 1.3 Correlation Matrix with the Pearson's correlation coefficient

Stationary raw data

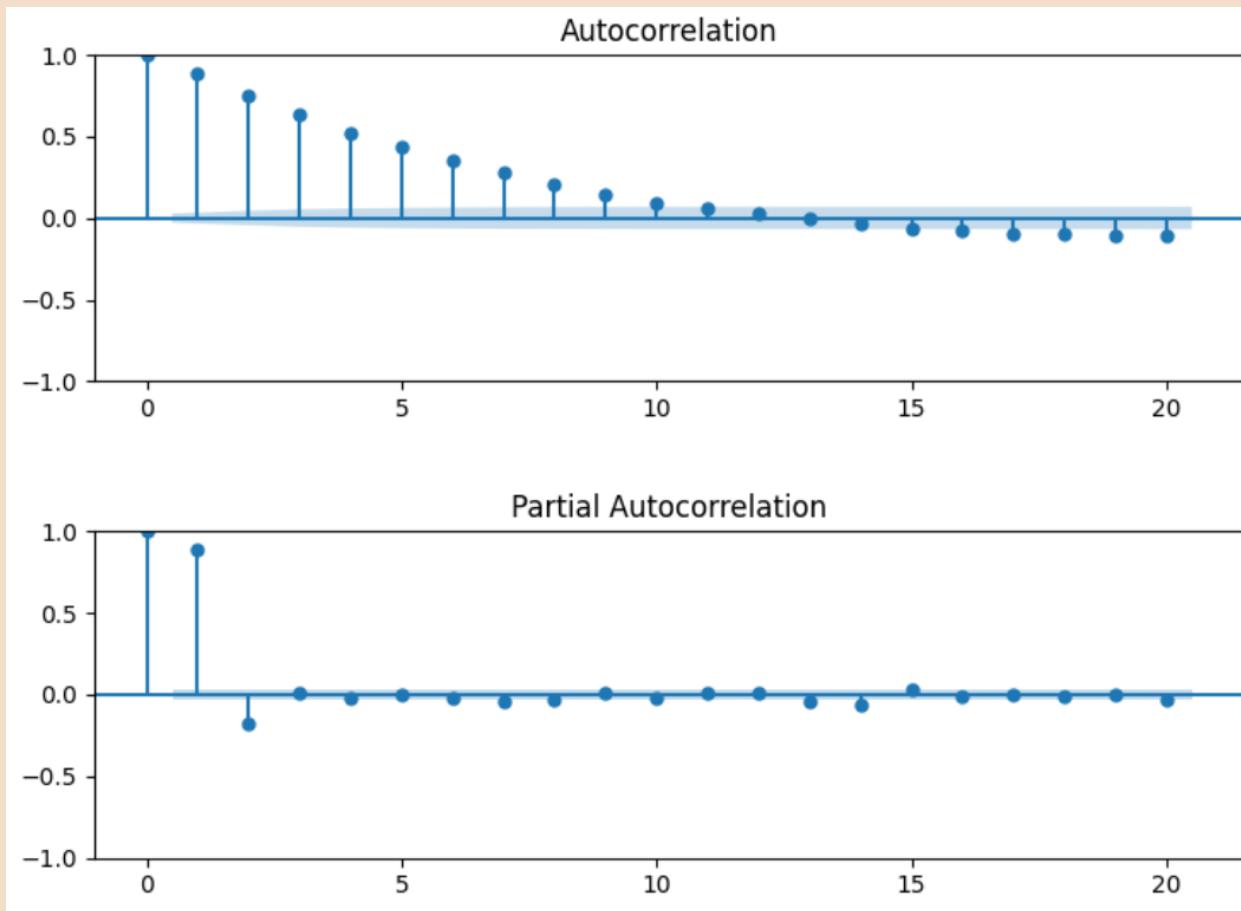


Figure 2.1 ACF/PACF of Raw Data

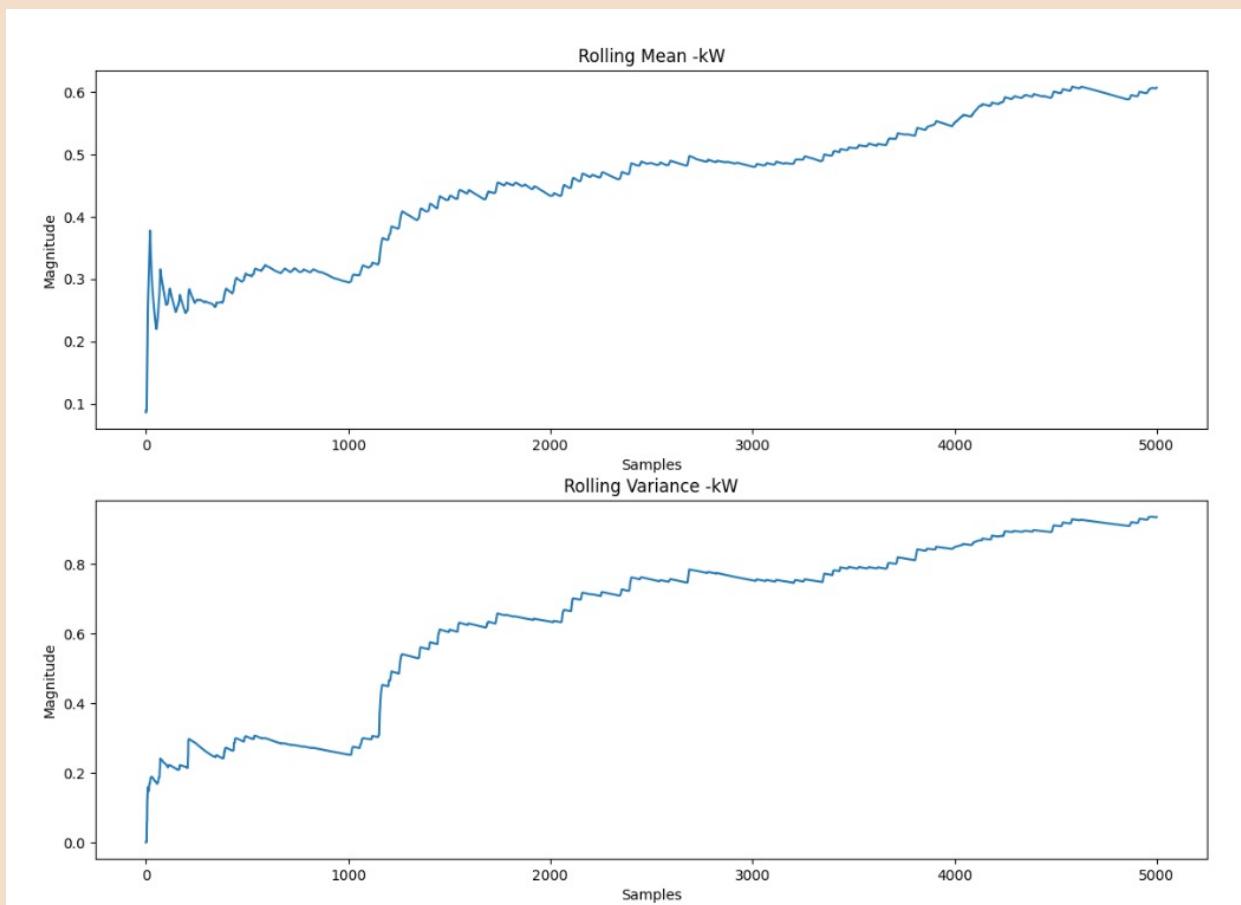
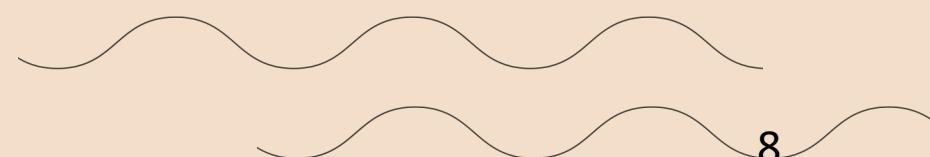


Figure 2.2 Rolling Mean and Variance of Raw Data

```
ADF Statistic: -16.17
p-value: 0.00
Critical Values:
1%: -3.43
5%: -2.86
10%: -2.57
Results of KPSS Test:
Test Statistic      2.108622
p-value            0.010000
Lags Used        37.000000
Critical Value (10%) 0.347000
Critical Value (5%) 0.463000
Critical Value (2.5%) 0.574000
Critical Value (1%) 0.739000
dtype: float64
```

Figure 2.3 ADF and KPSS of Raw Data

The raw dataset is not stationary



Stationary first order differencing

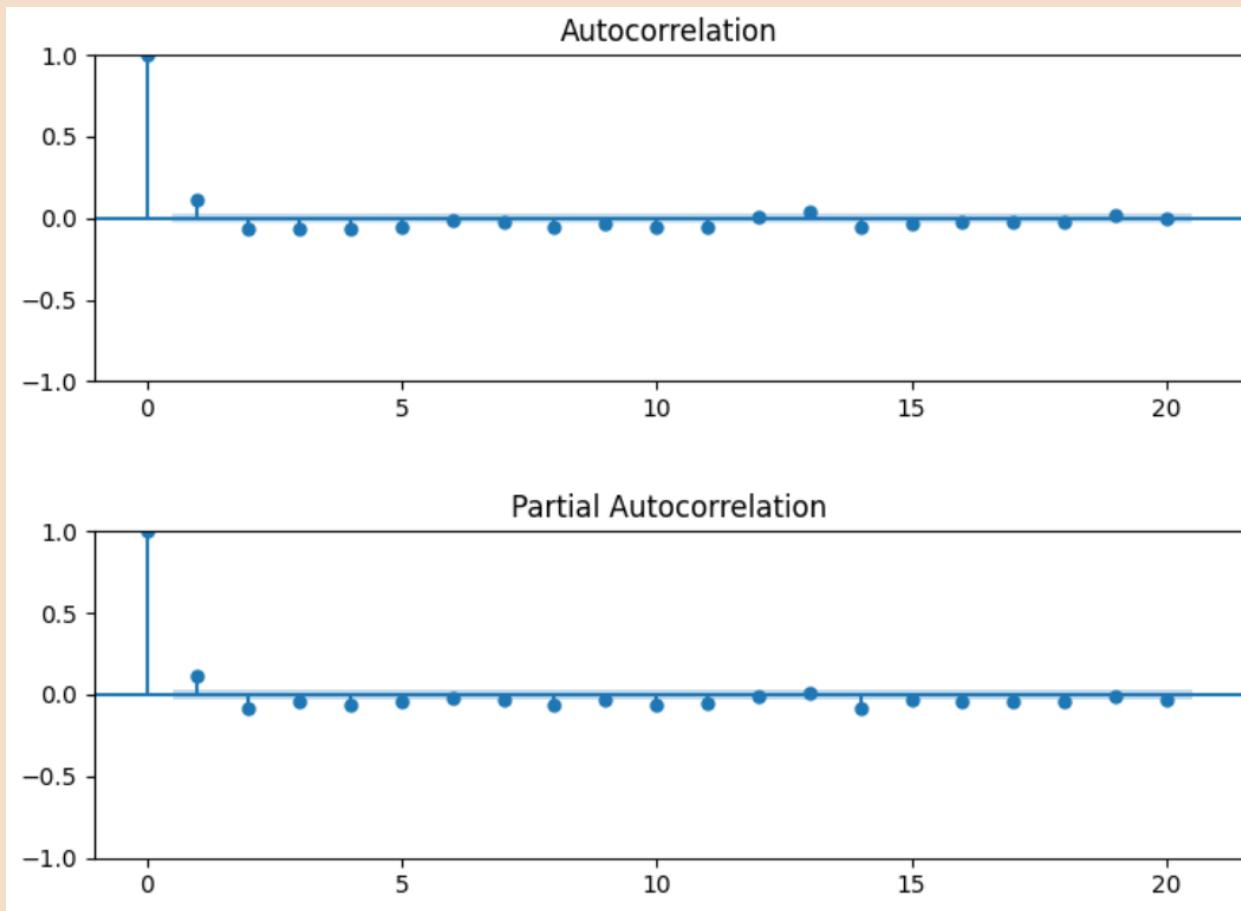


Figure 2.4 ACF/PACF of First Order Differencing

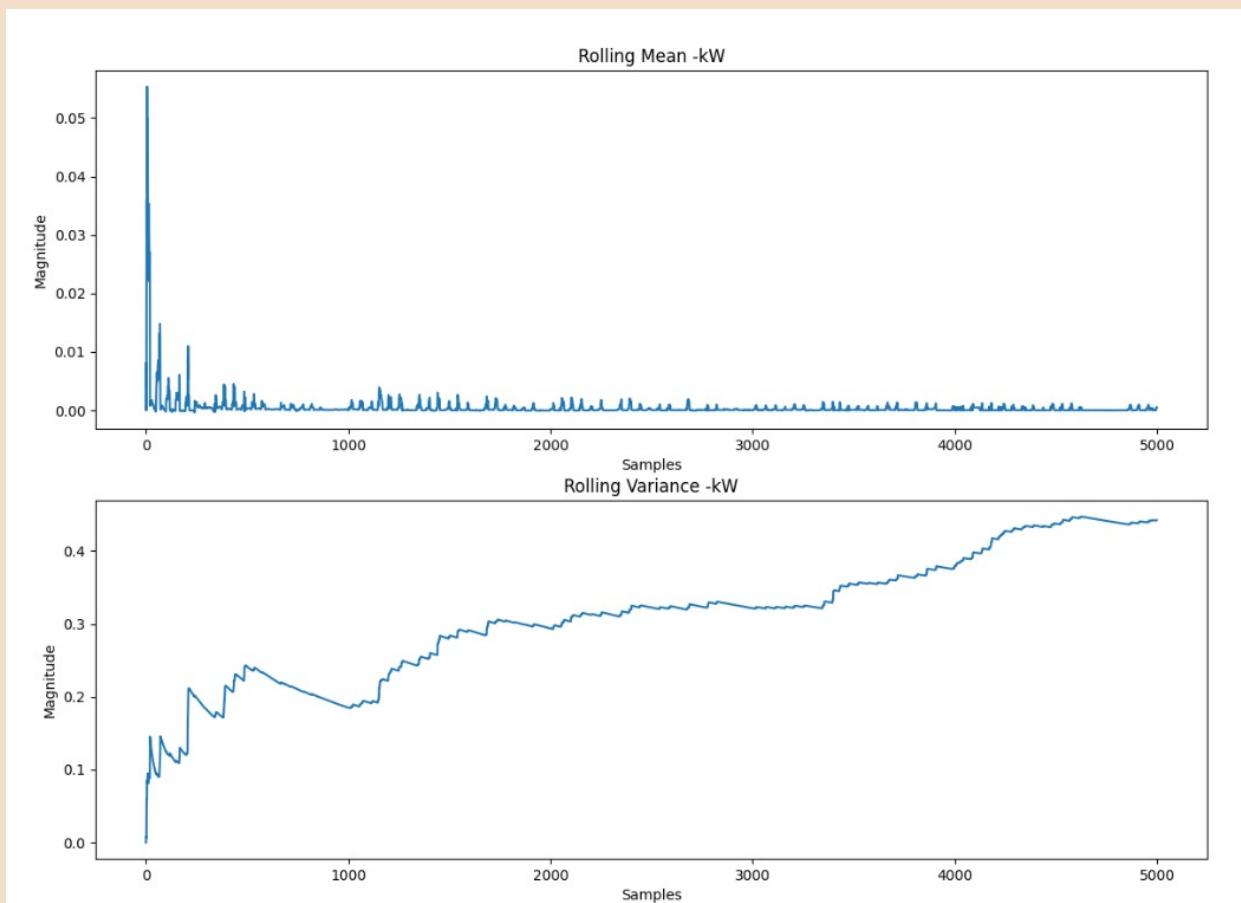


Figure 2.5 Rolling Mean and Variance of First Order Differencing

```
ADF Statistic: -20.60
p-value: 0.00
Critical Values:
1%: -3.43
5%: -2.86
10%: -2.57
Results of KPSS Test:
Test Statistic          0.007547
p-value                 0.100000
Lags Used              35.000000
Critical Value (10%)   0.347000
Critical Value (5%)    0.463000
Critical Value (2.5%)  0.574000
Critical Value (1%)   0.739000
dtype: float64
```

Figure 2.6 ADF and KPSS of First Order Differencing

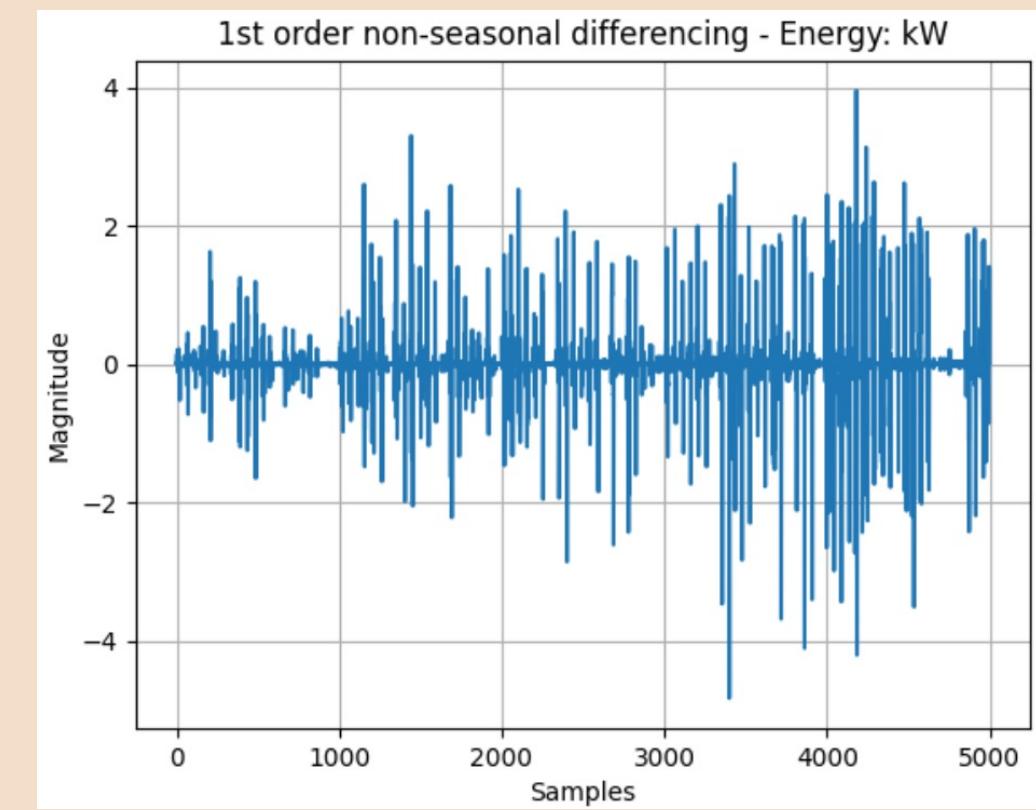
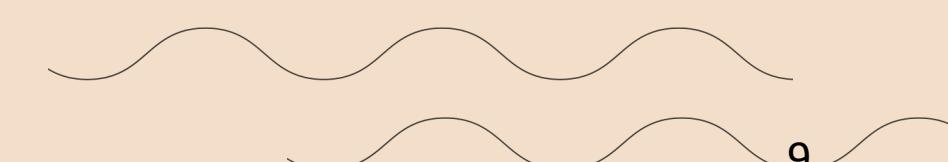


Figure 2.7 1st Oder Differencing of kW

The dataset is stationary after the transformation.



Time series Decomposition

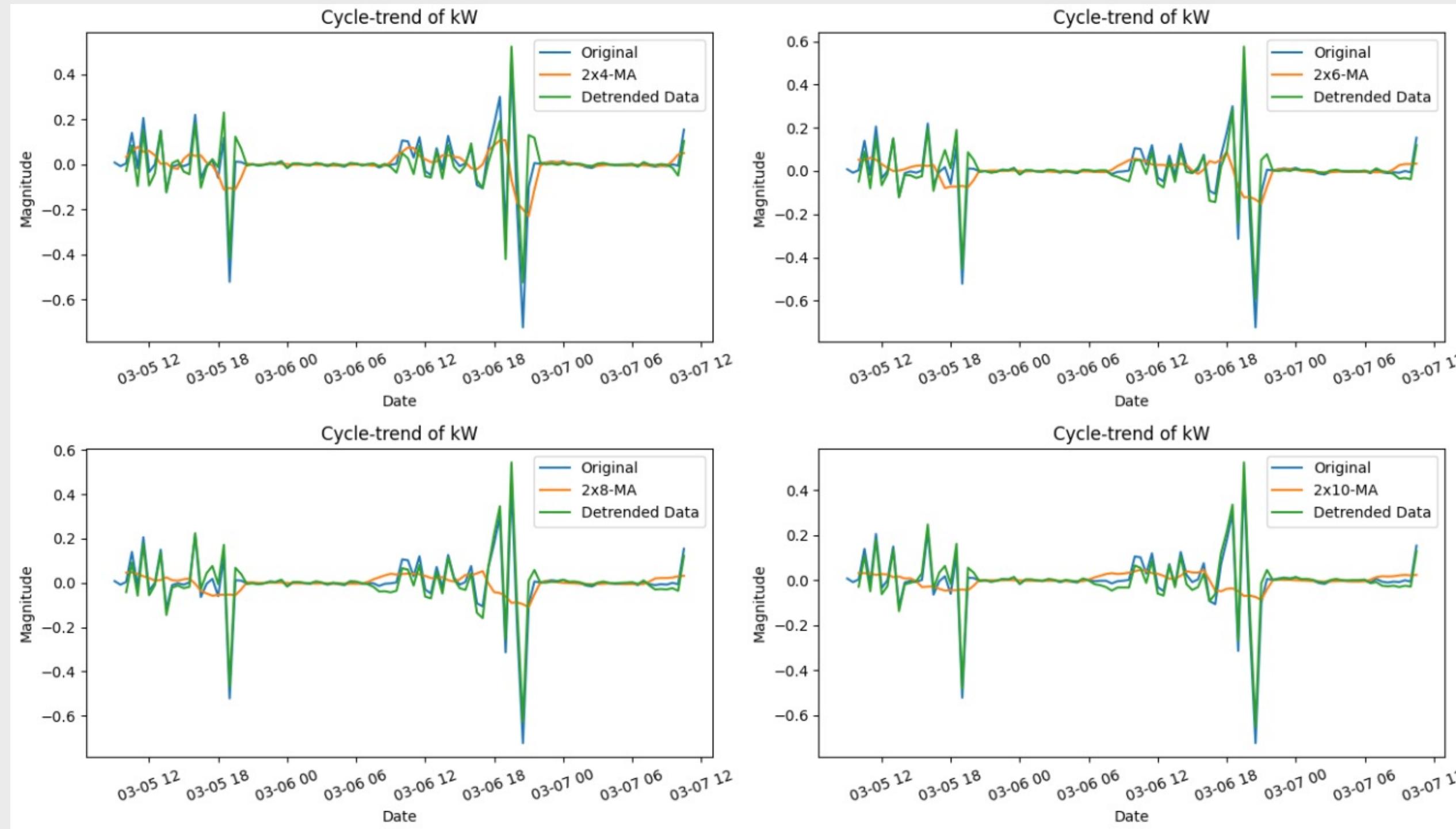


Figure 3.1 Cycle-Trend of kW

There seems no trend-cycle in the data after differencing

Time series Decomposition

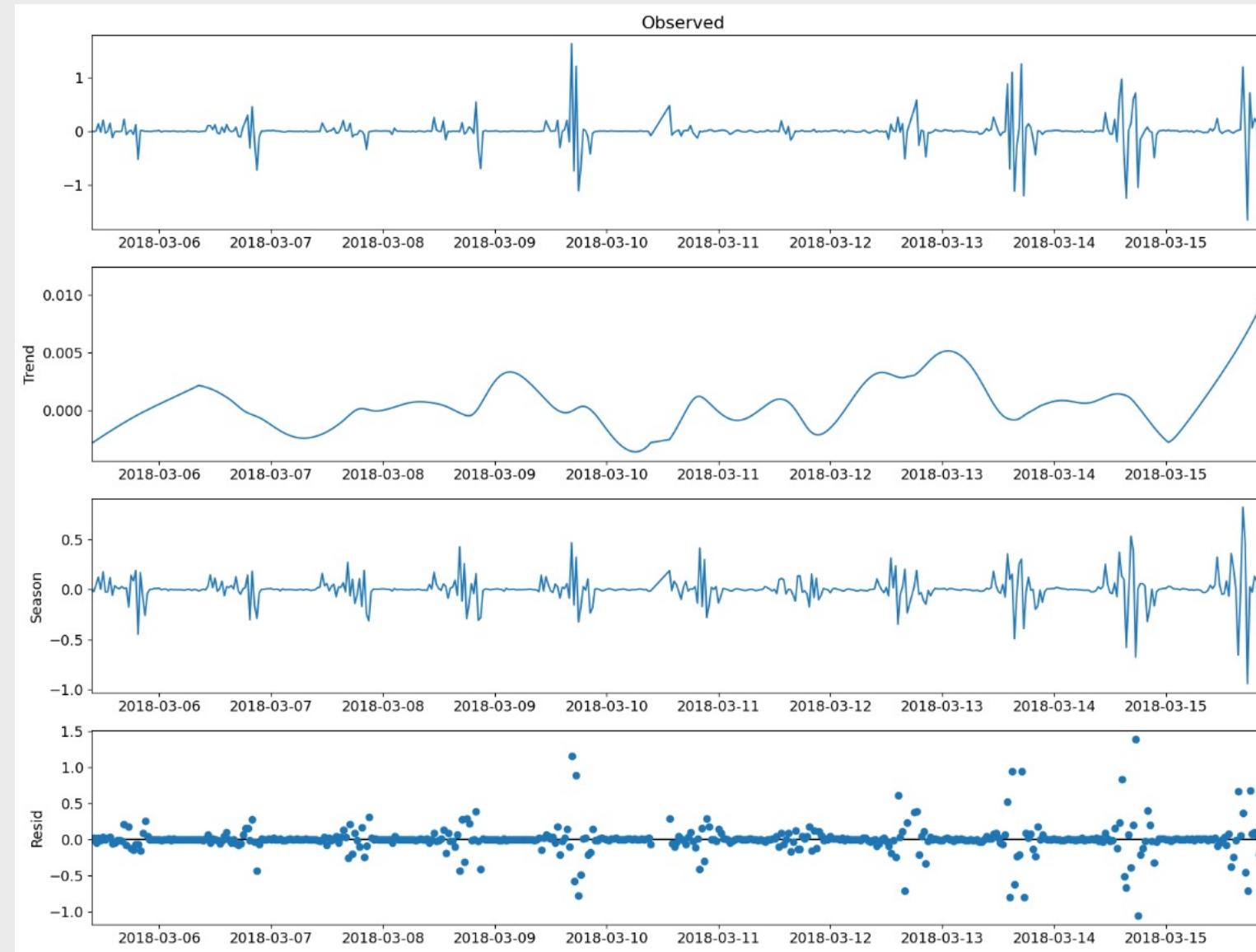


Figure 3.2 STL applied to kW(1)

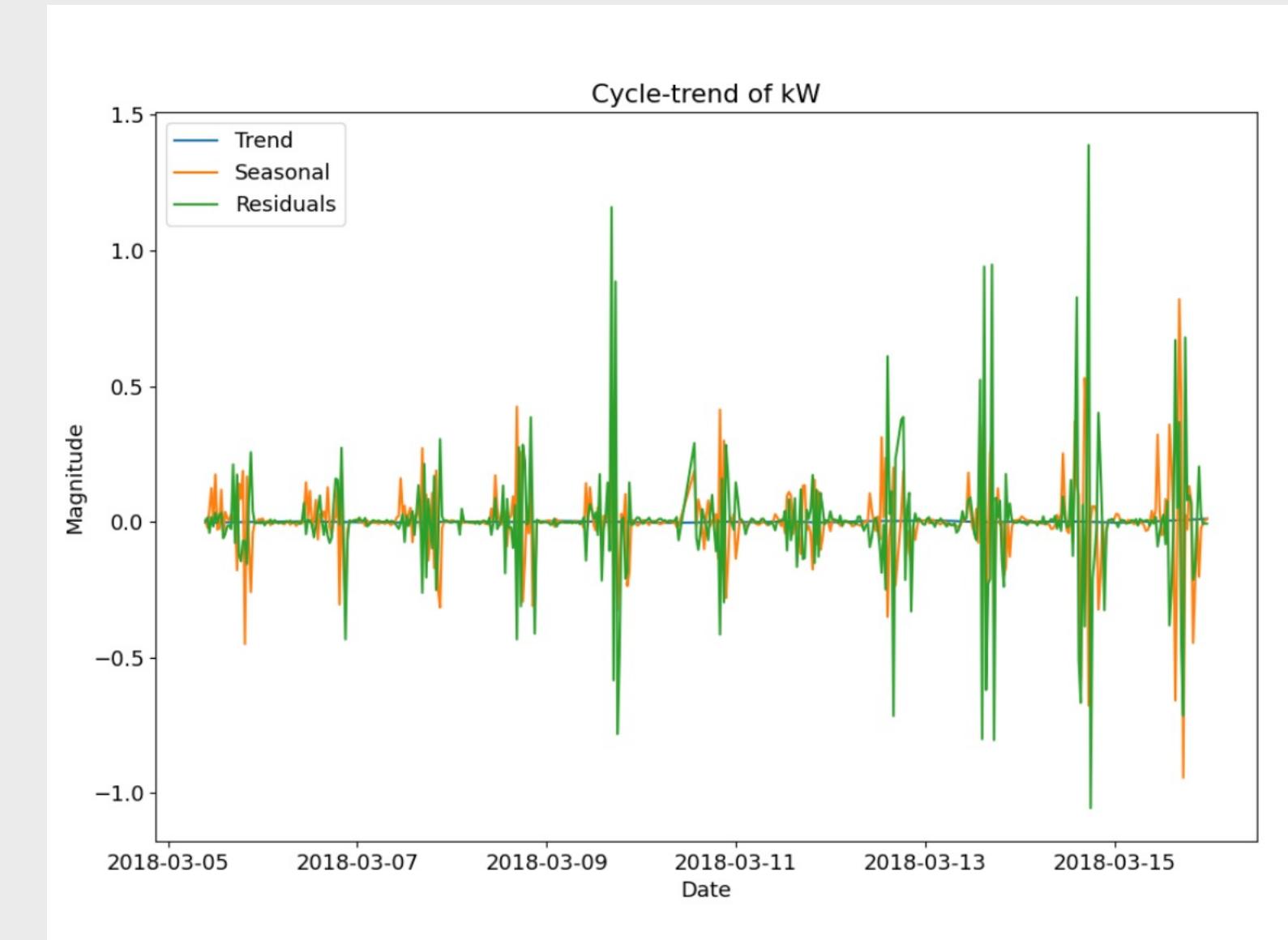
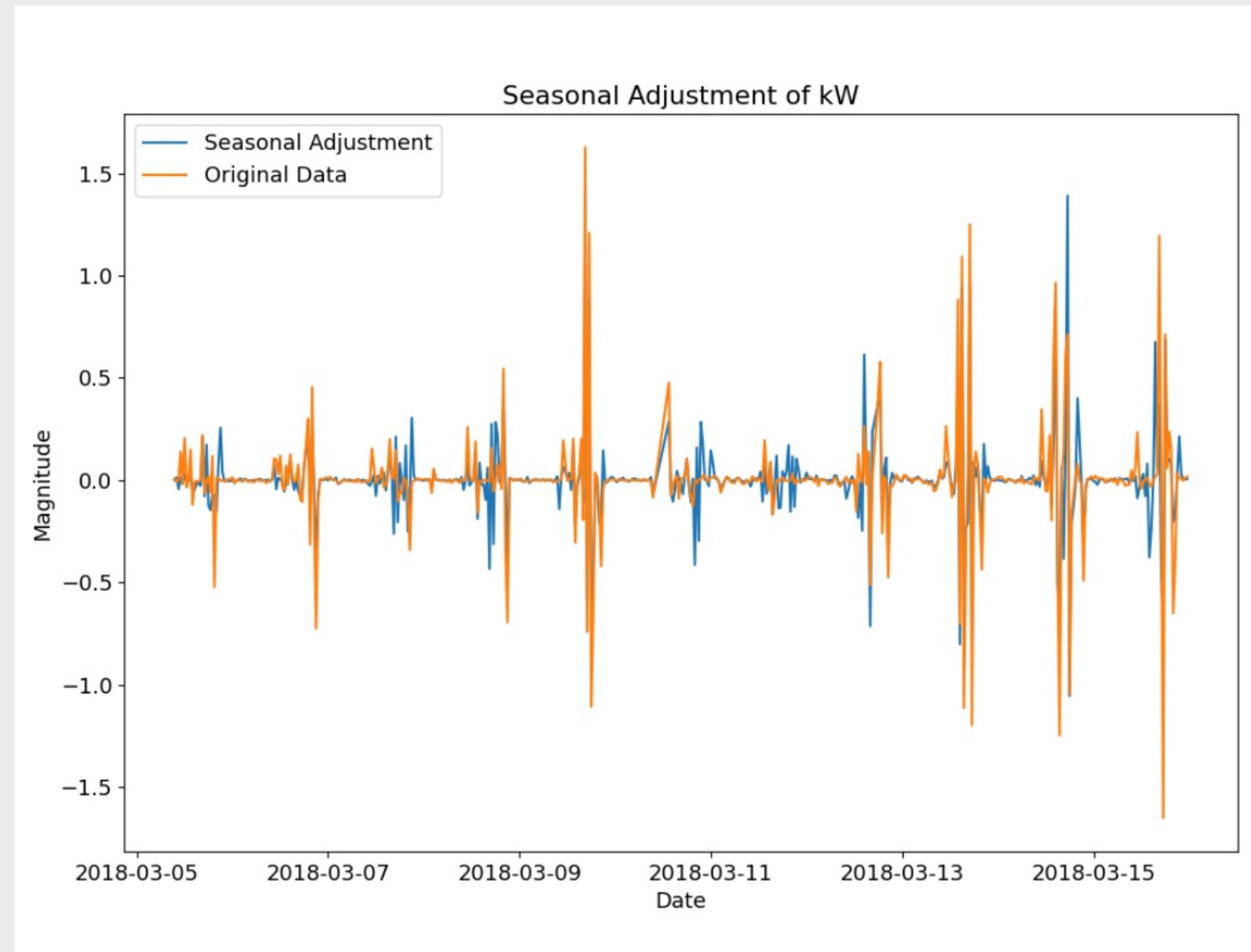


Figure 3.3 STL applied to kW(2)

The plots above show the STL decomposition where the seasonal component repeated patterns in the data that occur at fixed intervals and changed slightly over time. On the other hand, there is little to no trend in the data.

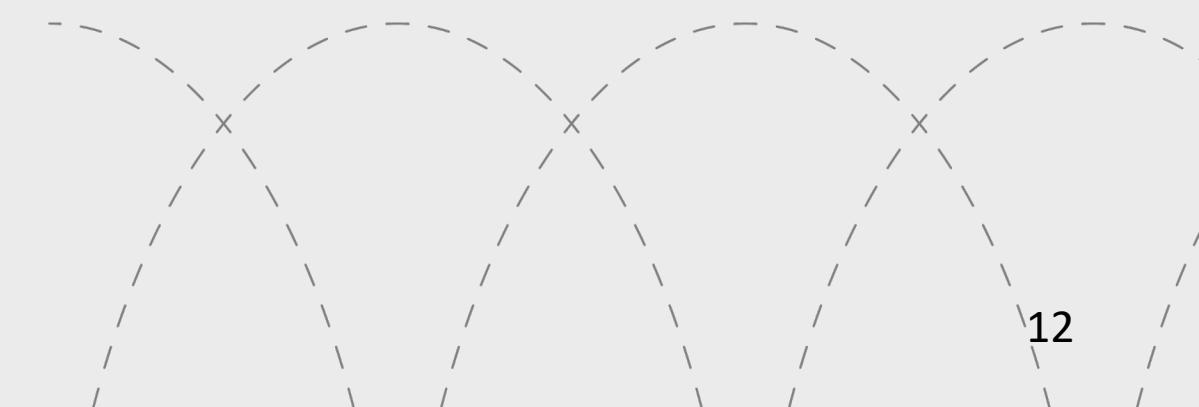
Time series Decomposition



The strength of trend for this data set is 0.0
The strength of seasonality for this data set is 0.349

Figure 3.4 Seasonal Adjusted of kW

After first-order differencing, the strength of its trend and seasonality became weak



Feature Selection

	Backward Stepwise Regression	VIF	PCA	Simple Linear Regression
Selected Features	kVAR, kWh	kVAR, kVARh	kWh, kVAR	kVAR
AIC	3943.71	4055.25	-7105.85	7313.22
BIC	3968.88	4067.83	-7086.30	7326.26
Adjusted R-squared	0.78	0.84	0.72	0.71
SVD Analysis (Singular Values)	[5.73950677e+04 1.51333983e+01]	[2.32236685e+04 1.53012682e+01]	[5.73950677e+04 1.51333983e+01]	NA
Condition Number (k)	3792.6093	1517.761	3792.6093	1
Collinearity	v	v	v	x

Table 2 Feature Selection

Holt–Winters method

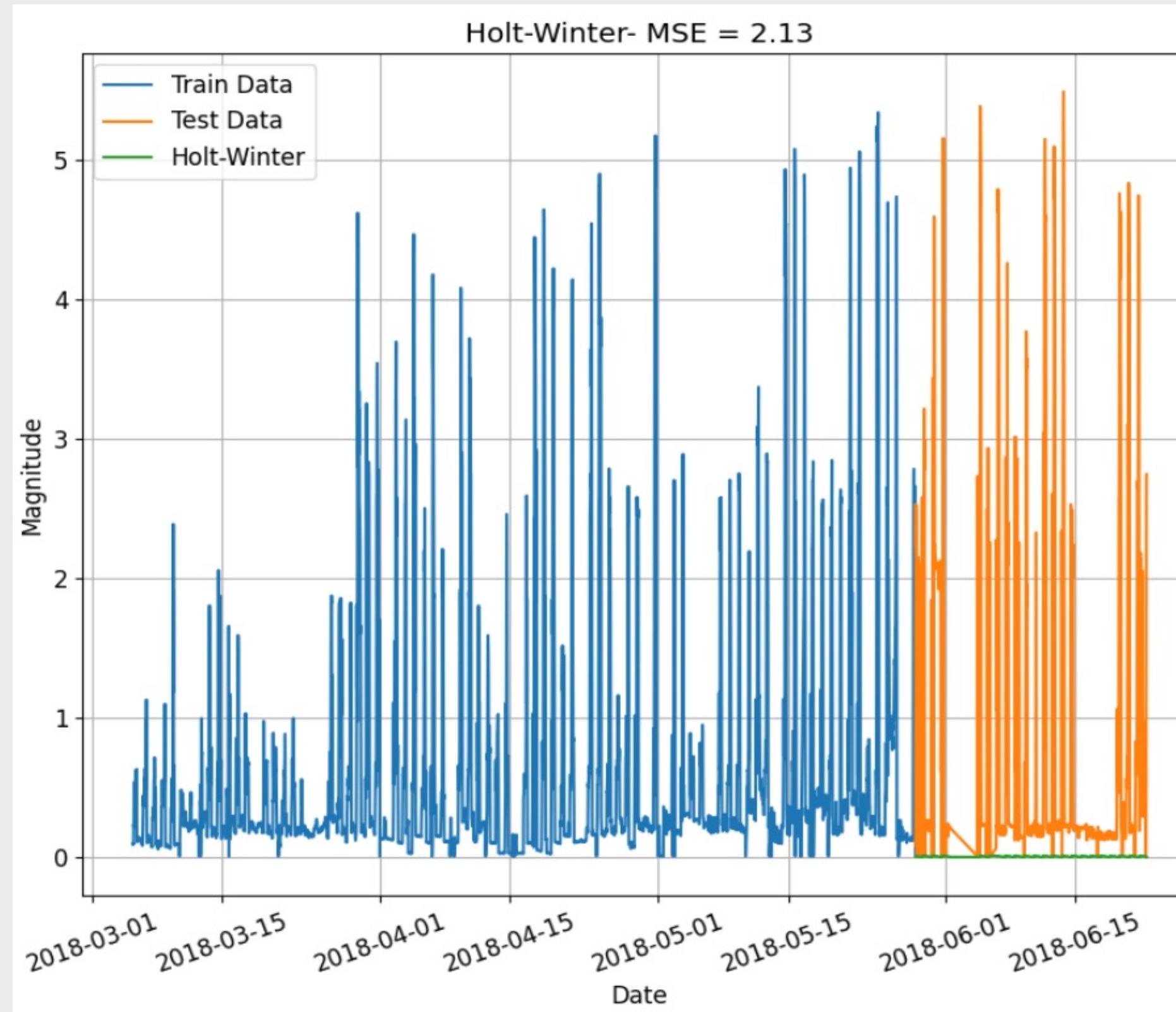


Figure 4.1 Holt–Winter Method

Mean square error for Holt–Winter is 2.13

Residual Mean: 0.8359

Residual Variance: 1.4276

Base–models

Average

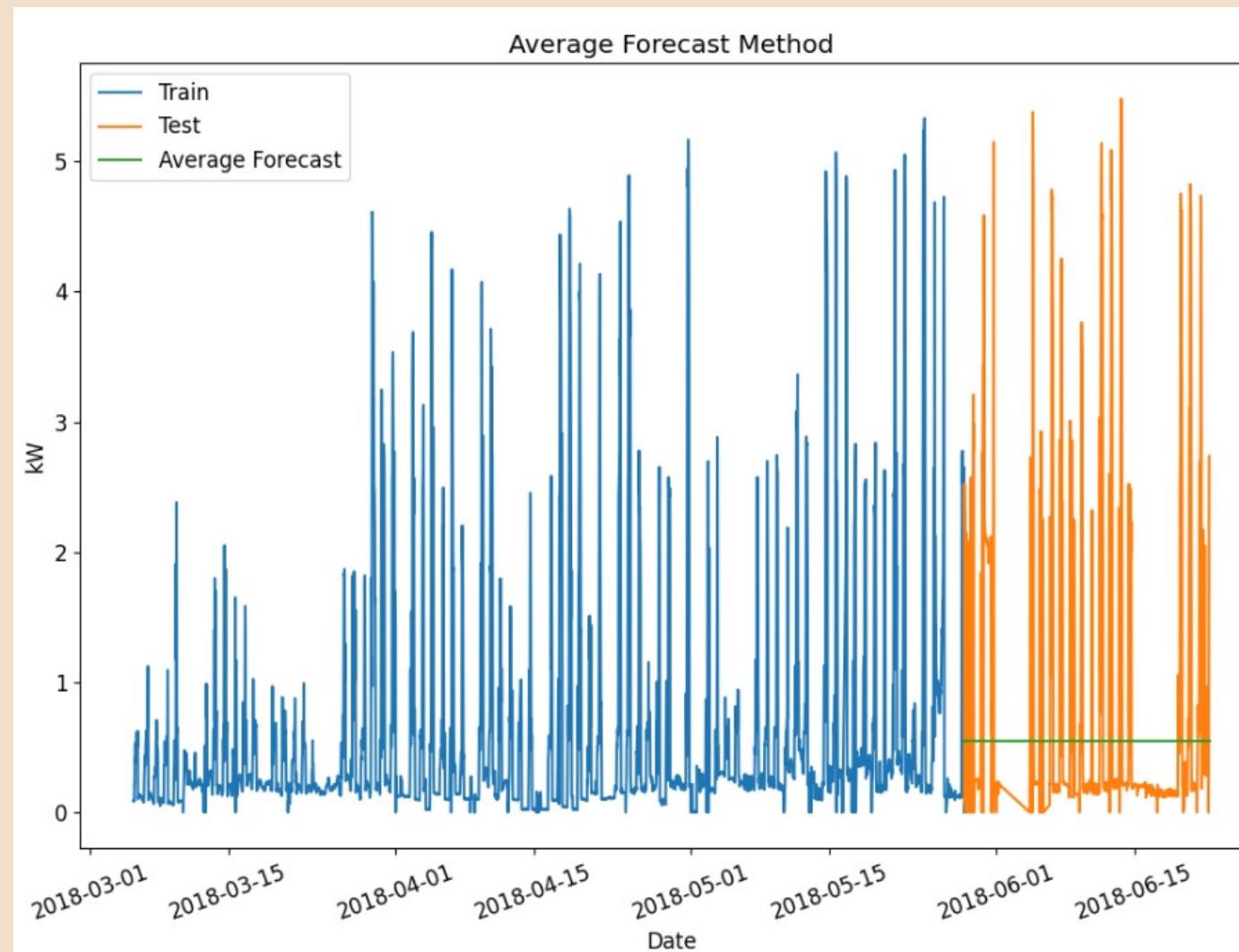


Figure 4.2 Average Forecast Method

RMSE: 1.2284
Residual Mean: 0.2835
Residual Variance: 1.4286

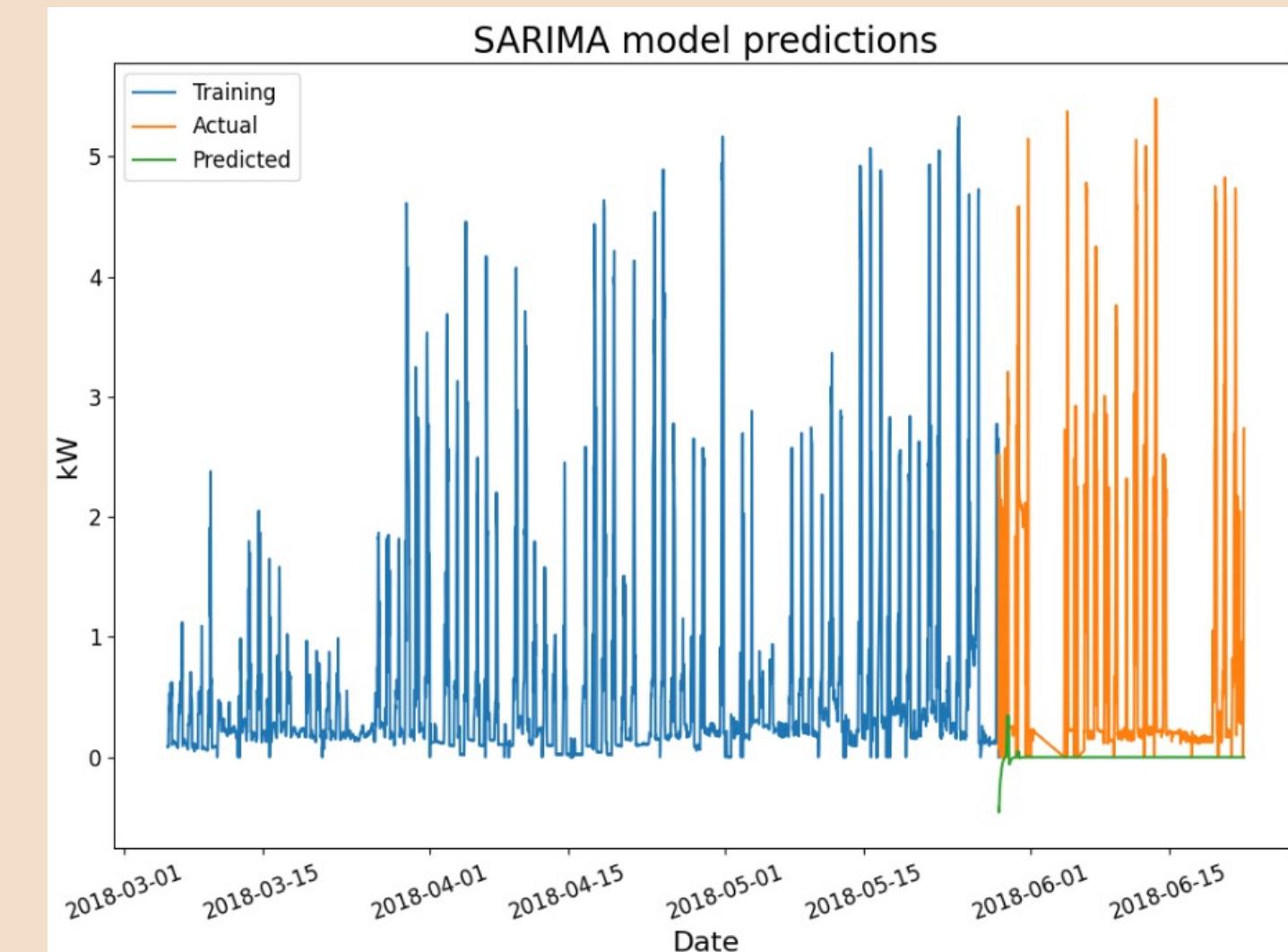


Figure 4.3 ARIMA(2, 0, 2) Model

RMSE: 0.42
Residual Mean: 0.0000
Residual Variance: 0.1785

Base–models

Naïve

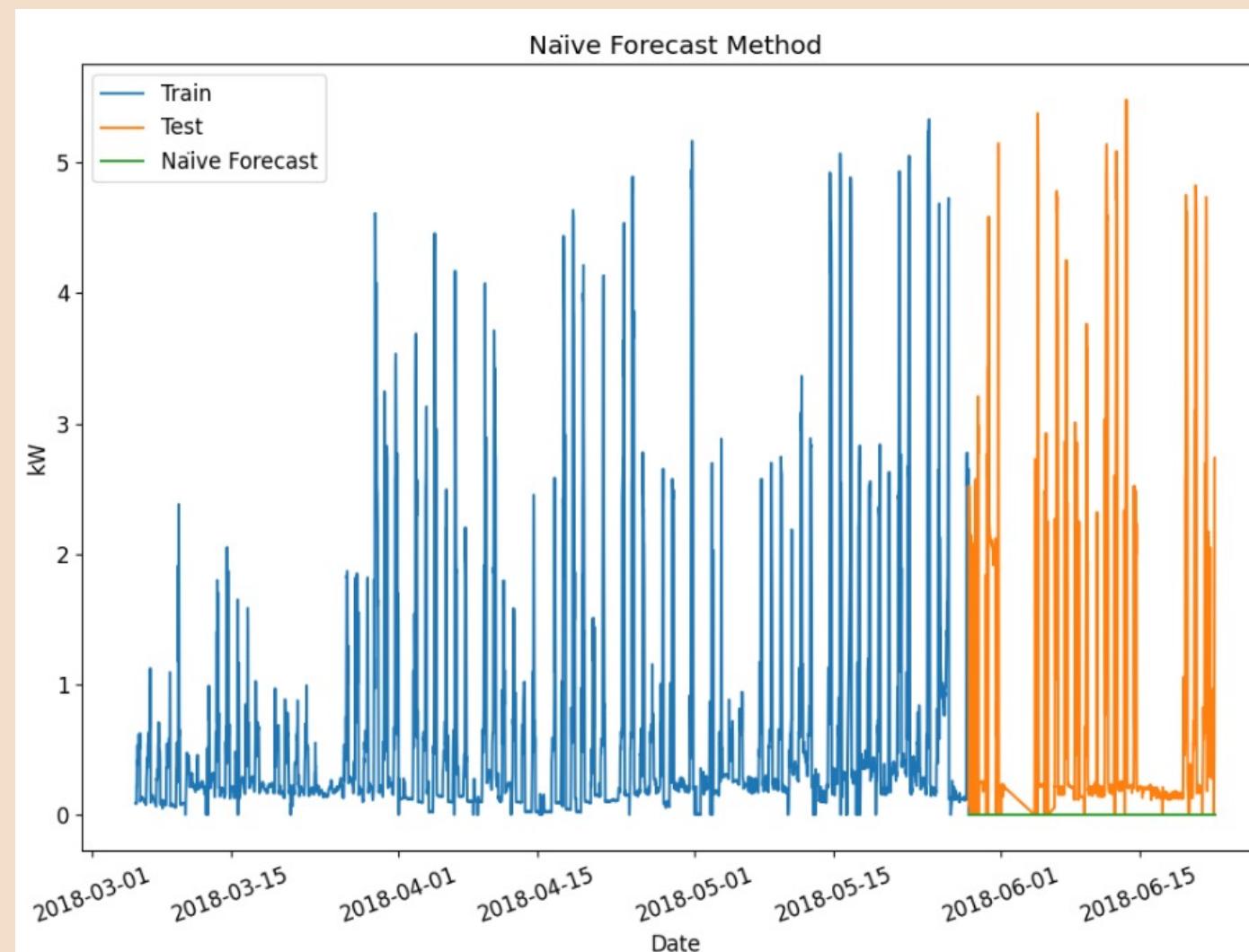


Figure 4.4 Naïve Forecast Method

RMSE: 1.4575
Residual Mean: 0.8342
Residual Variance: 1.4286

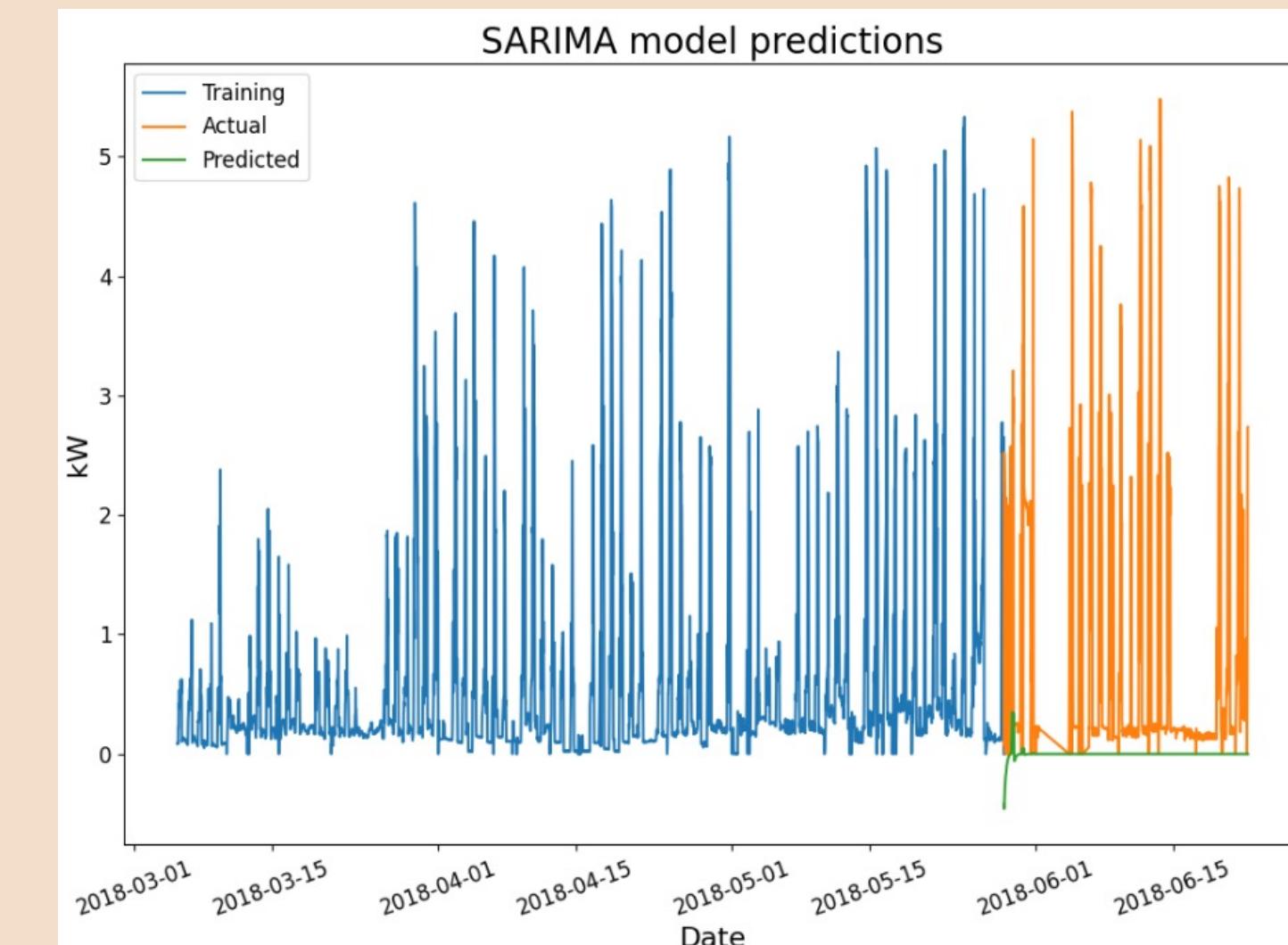


Figure 4.3 ARIMA(2, 0, 2) Model

RMSE: 0.42
Residual Mean: 0.0000
Residual Variance: 0.1785

Base–models

Drift

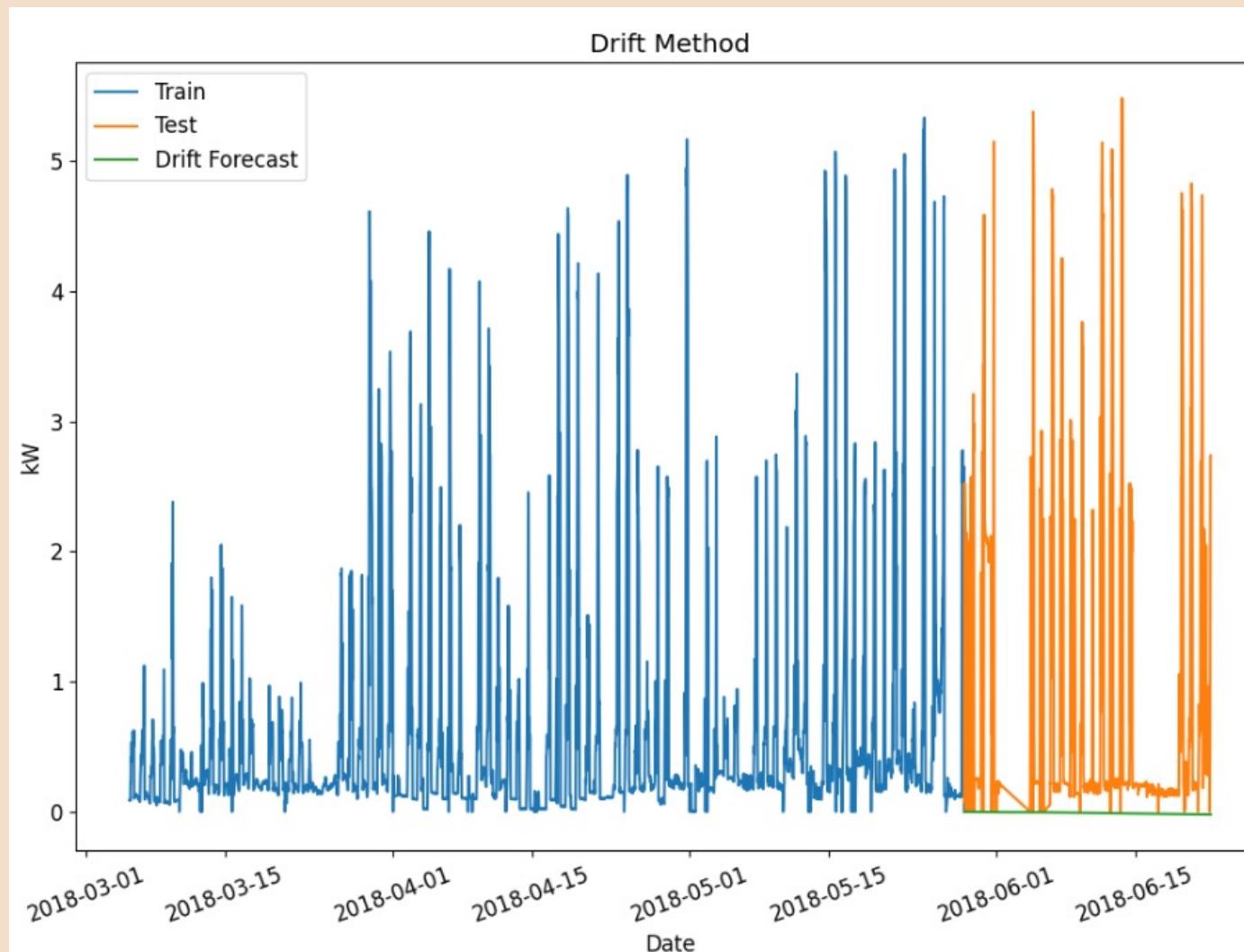


Figure 4.5 Drift Method

RMSE: 1.4631
Residual Mean: 0.8449
Residual Variance: 1.4266

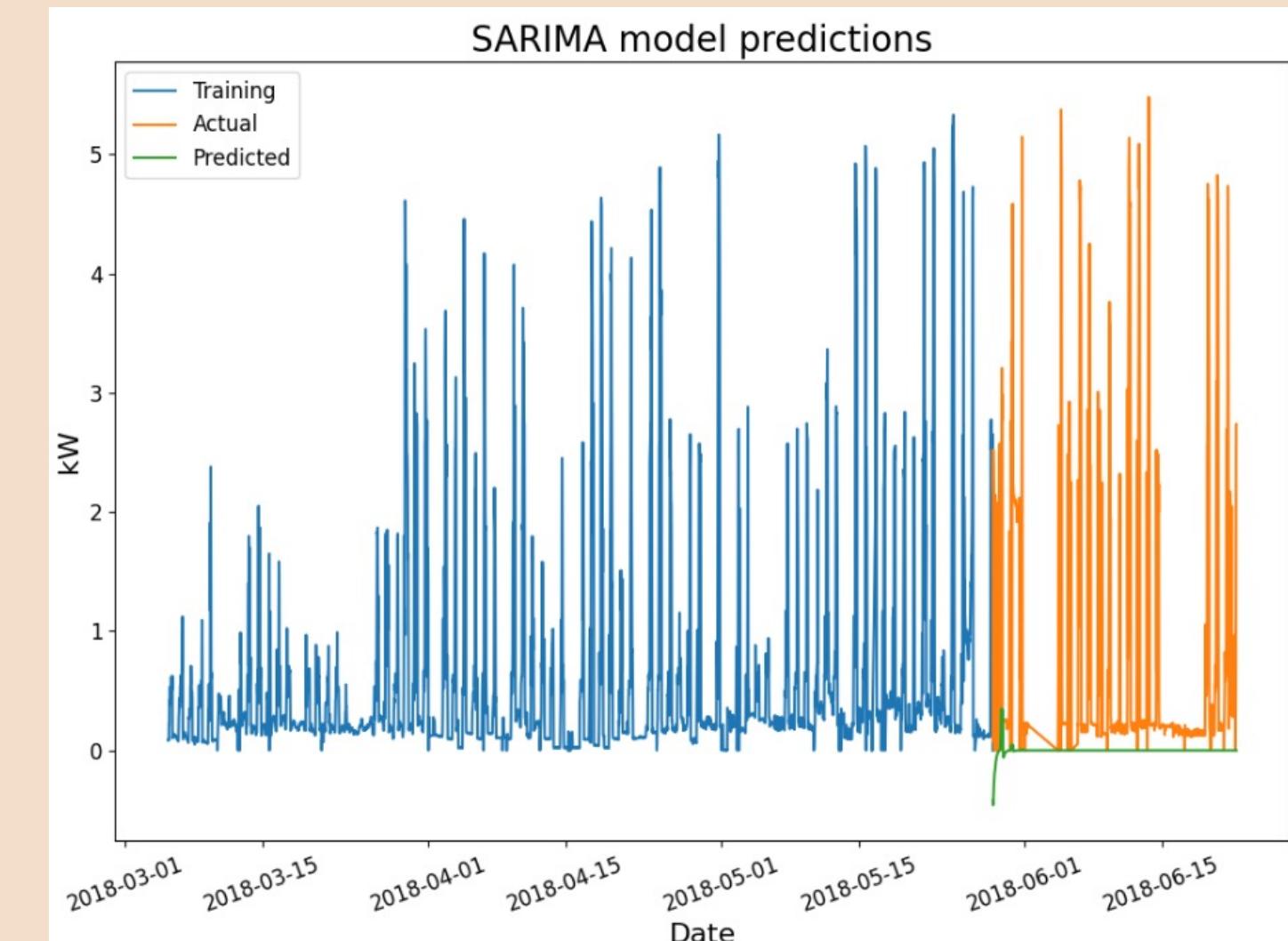


Figure 4.3 ARIMA(2, 0, 2) Model

RMSE: 0.42
Residual Mean: 0.0000
Residual Variance: 0.1785

Base–models

SES

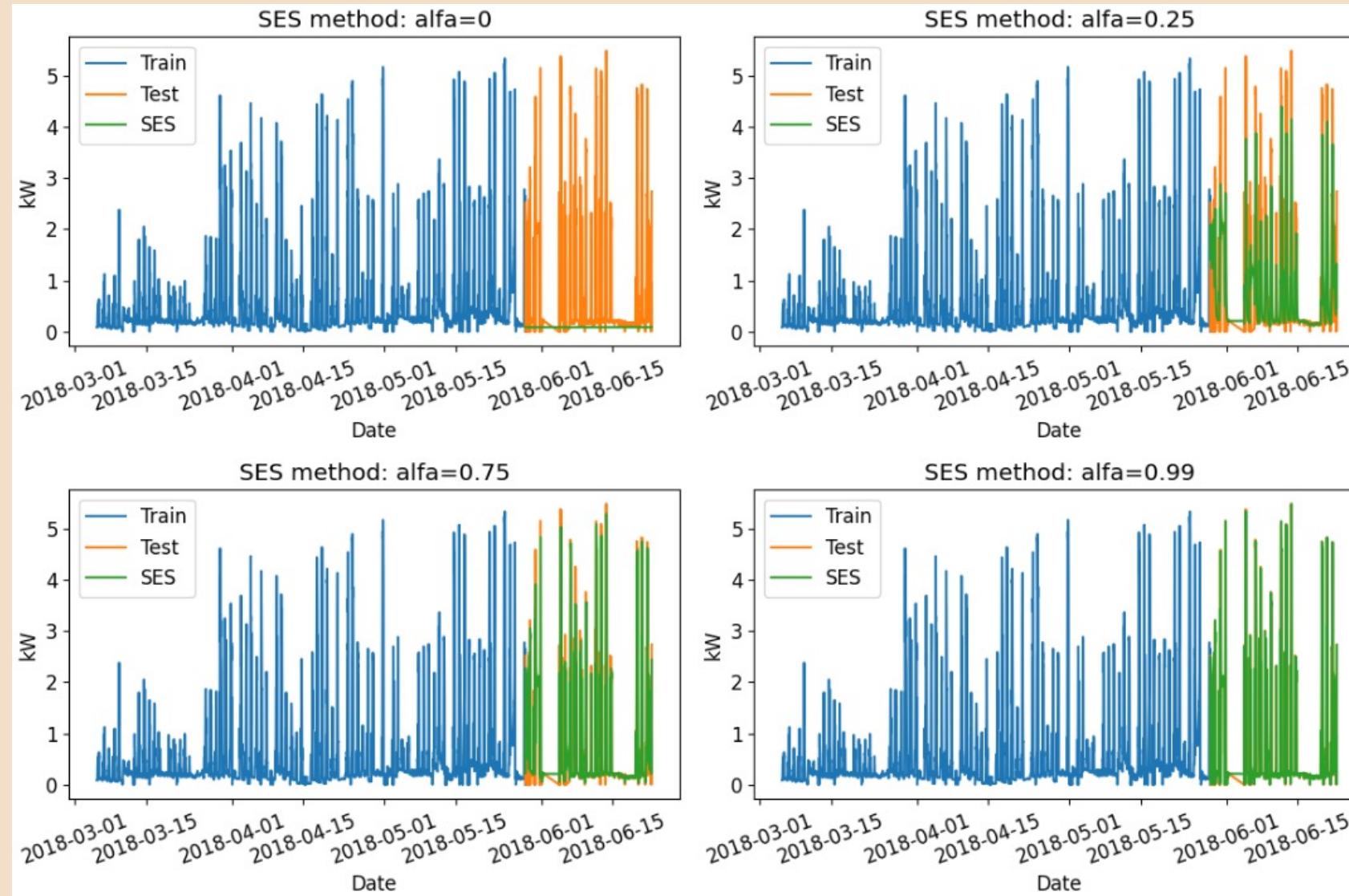


Figure 4.6 SES Method

RMSE: 1.4101
Residual Mean: 0.7482
Residual Variance: 1.4286

RMSE: 1.5157
Residual Mean: -0.0008
Residual Variance: 2.2974

RMSE: 1.6559
Residual Mean: 0.0027
Residual Variance: 2.7421

RMSE: 1.6882
Residual Mean: 0.0027
Residual Variance: 2.8500

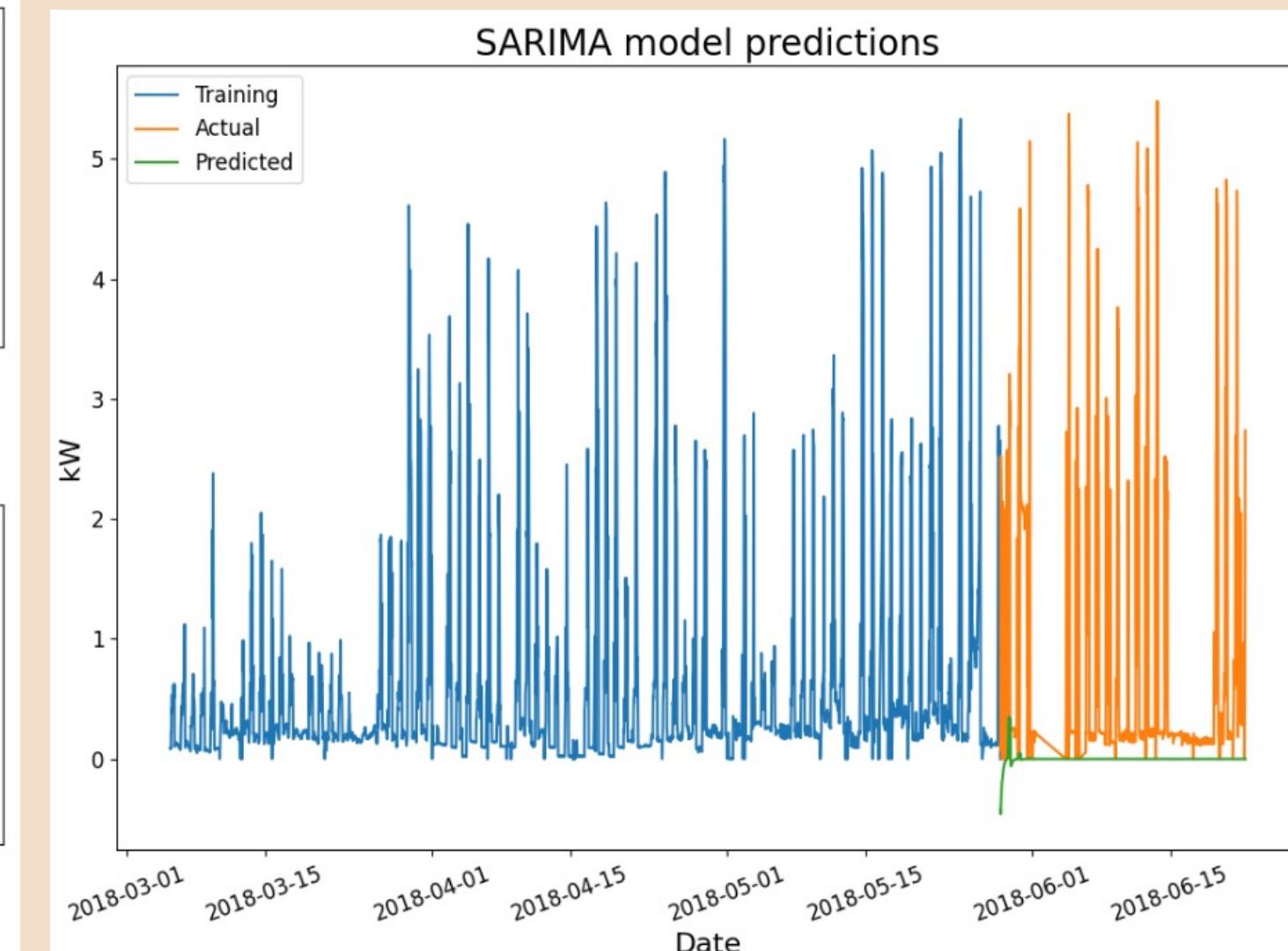


Figure 4.3 ARIMA(2, 0, 2) Model

RMSE: 0.42
Residual Mean: 0.0000
Residual Variance: 0.1785

Linear Regression

OLS Regression Results											
Dep. Variable:	kW	R-squared:	0.780								
Model:	OLS	Adj. R-squared:	0.780								
Method:	Least Squares	F-statistic:	7104.								
Date:	Tue, 09 May 2023	Prob (F-statistic):	0.00								
Time:	00:33:24	Log-Likelihood:	-1985.1								
No. Observations:	4000	AIC:	3976.								
Df Residuals:	3997	BIC:	3995.								
Df Model:	2										
Covariance Type:	nonrobust										
	coef	std err	t	P> t	[0.025	0.975]					
const	-0.1046	0.012	-9.042	0.000	-0.127	-0.082					
kVAR	3.9198	0.033	117.245	0.000	3.854	3.985					
kVARh	-0.0012	5.05e-05	-24.434	0.000	-0.001	-0.001					
Omnibus:	1596.327	Durbin-Watson:		0.319							
Prob(Omnibus):	0.000	Jarque-Bera (JB):		13804.747							
Skew:	1.667	Prob(JB):		0.00							
Kurtosis:	11.469	Cond. No.		1.25e+03							
Test for Constraints											
	coef	std err	t	P> t	[0.025	0.975]					
c0	-0.1046	0.012	-9.042	0.000	-0.127	-0.082					
c1	3.9198	0.033	117.245	0.000	3.854	3.985					
c2	-0.0012	5.05e-05	-24.434	0.000	-0.001	-0.001					
<F test: F=7104.386860063783, p=0.0, df_denom=4e+03, df_num=2>											

Figure 5.1 OLS Regression Results(1)

■ Independent Variables: kVAR, kVARh

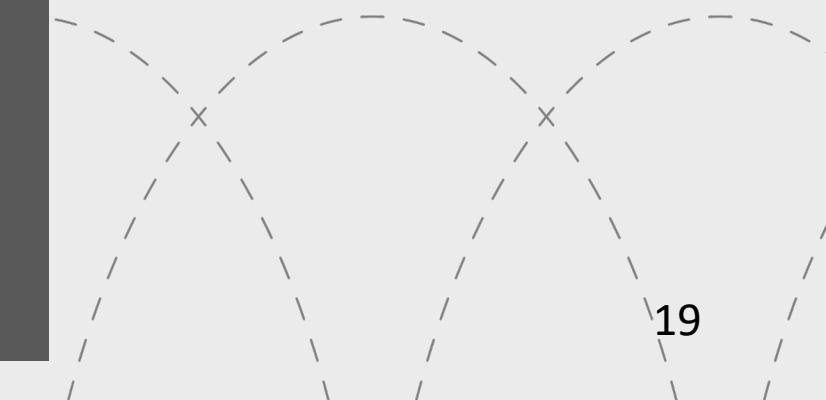
■ RMSE: 0.8312

■ The residual is NOT white

■ lb_stat lb_pvalue
2609.156268 0.0

■ Residuals variance: 0.5331

■ Residuals mean: 0.3973

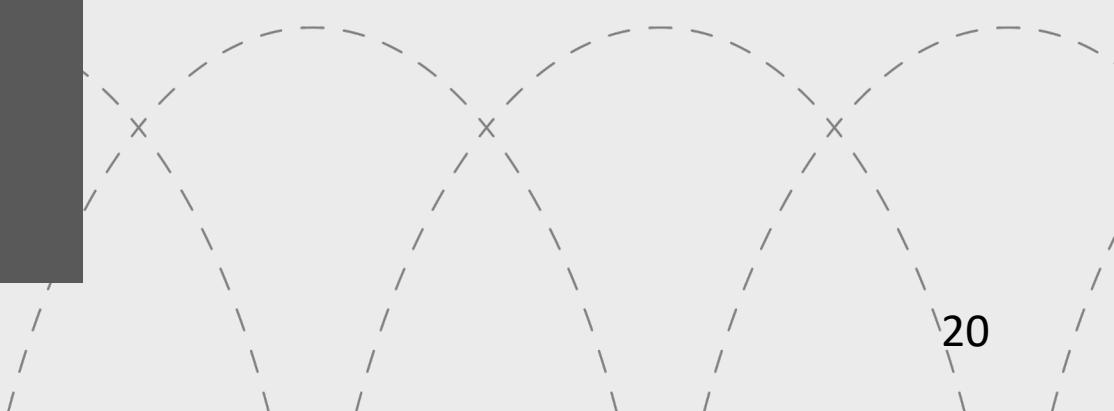


Linear Regression

OLS Regression Results						
Dep. Variable:	kW	R-squared:	0.748			
Model:	OLS	Adj. R-squared:	0.748			
Method:	Least Squares	F-statistic:	1.185e+04			
Date:	Tue, 09 May 2023	Prob (F-statistic):	0.00			
Time:	00:36:25	Log-Likelihood:	-2263.5			
No. Observations:	4000	AIC:	4531.			
Df Residuals:	3998	BIC:	4544.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-0.2687	0.010	-26.589	0.000	-0.288	-0.249
kVAR	3.6109	0.033	108.838	0.000	3.546	3.676
Omnibus:	1249.495	Durbin-Watson:			0.256	
Prob(Omnibus):	0.000	Jarque-Bera (JB):			8080.724	
Skew:	1.329	Prob(JB):			0.00	
Kurtosis:	9.436	Cond. No.			5.19	
Test for Constraints						
	coef	std err	t	P> t	[0.025	0.975]
c0	-0.2687	0.010	-26.589	0.000	-0.288	-0.249
c1	3.6109	0.033	108.838	0.000	3.546	3.676
<F test: F=11845.80580827514, p=0.0, df_denom=4e+03, df_num=1>						

Figure 5.2 OLS Regression Results(2)

- Independent Variables: kVAR
- RMSE: 0.7376
- The residual is NOT white
- lb_stat lb_pvalue
2417.416218 0.0
- Residuals variance: 0.5425
- Residuals mean: -0.0393



ARMA, ARIMA and SARIMA model

ARMA model order determination

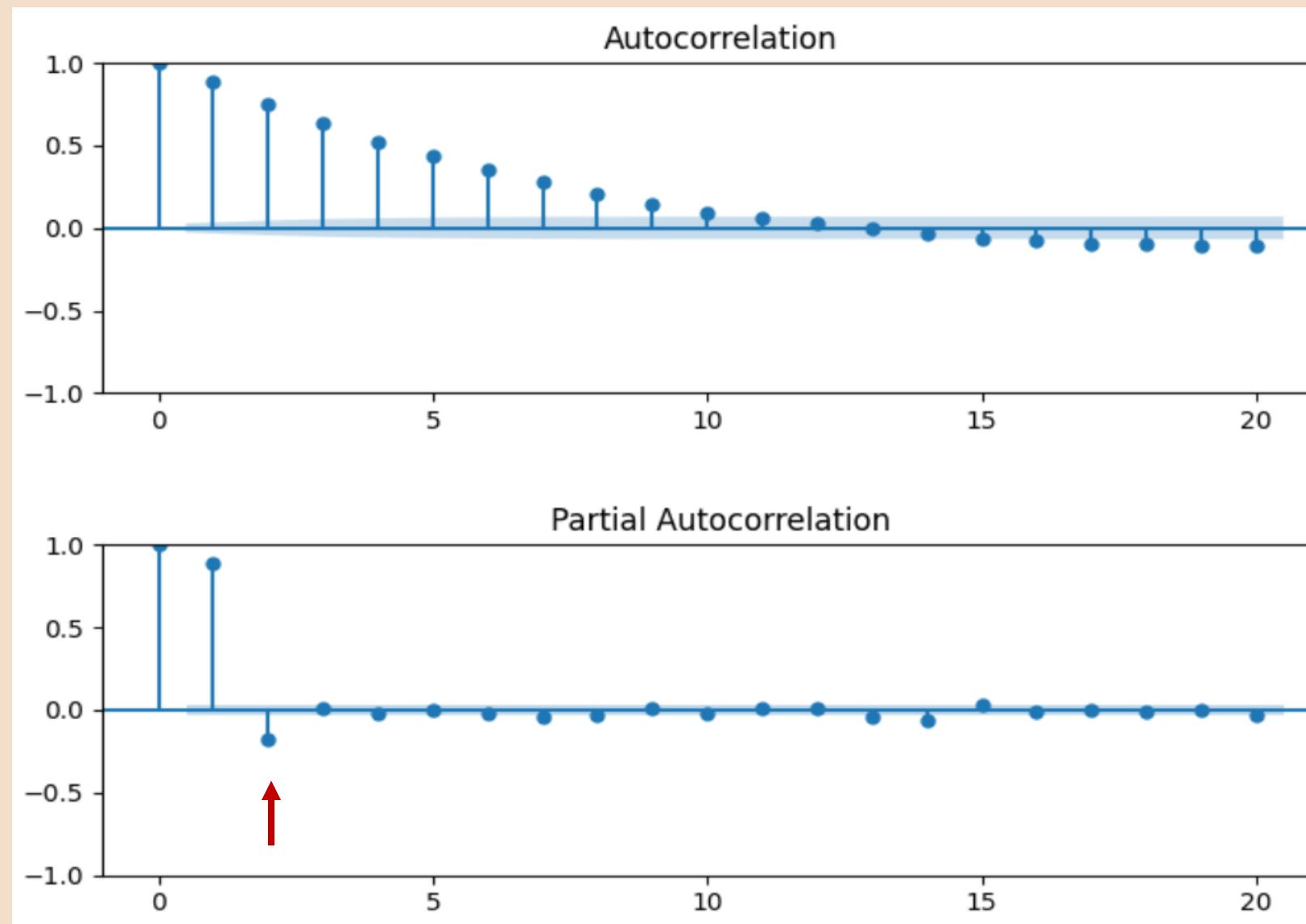


Figure 1.2 ACF/PACF of kW

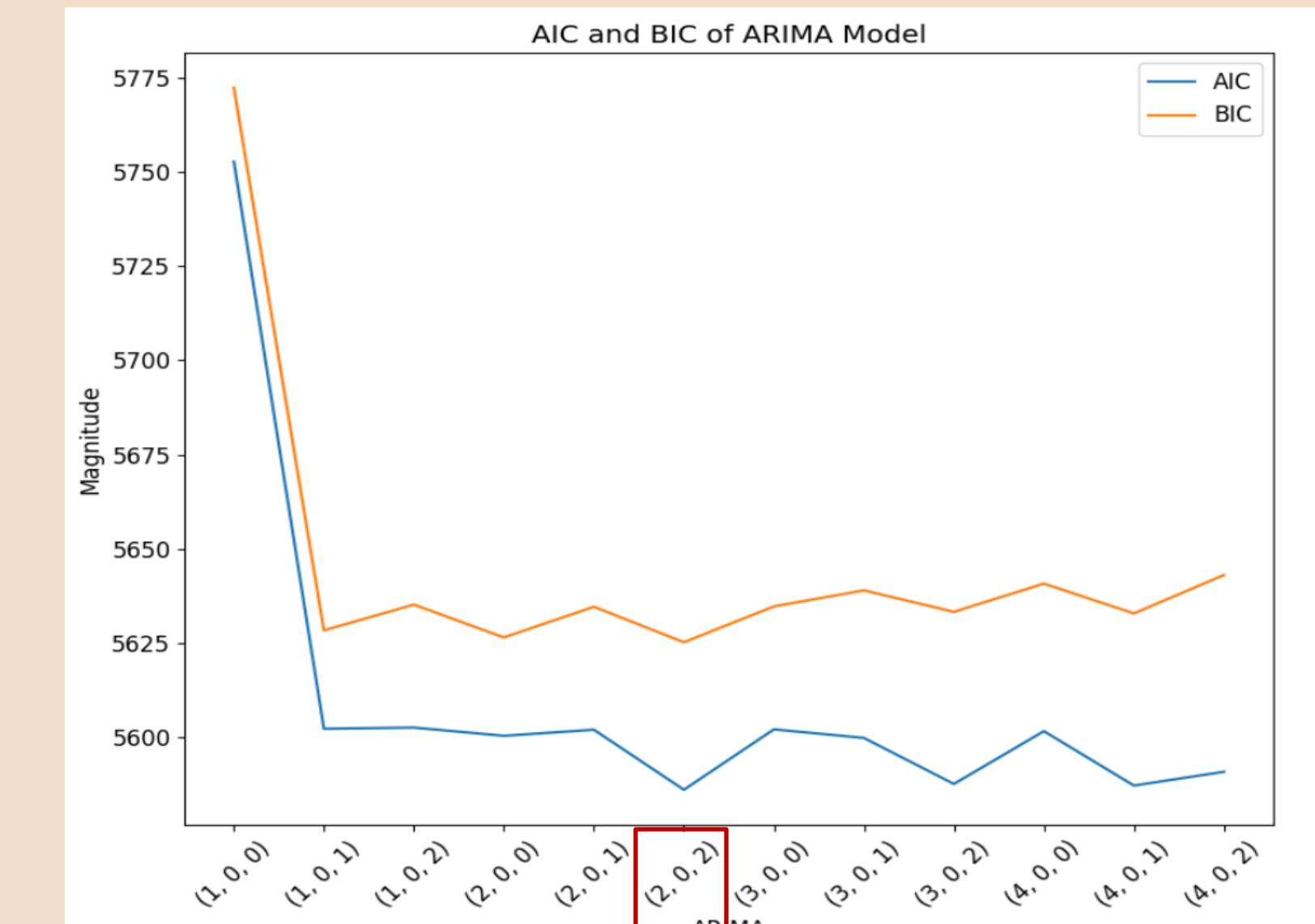


Figure 6.1 AIC and BIC of ARIMA Model

ARMA, ARIMA and SARIMA model

ARMA model order determination

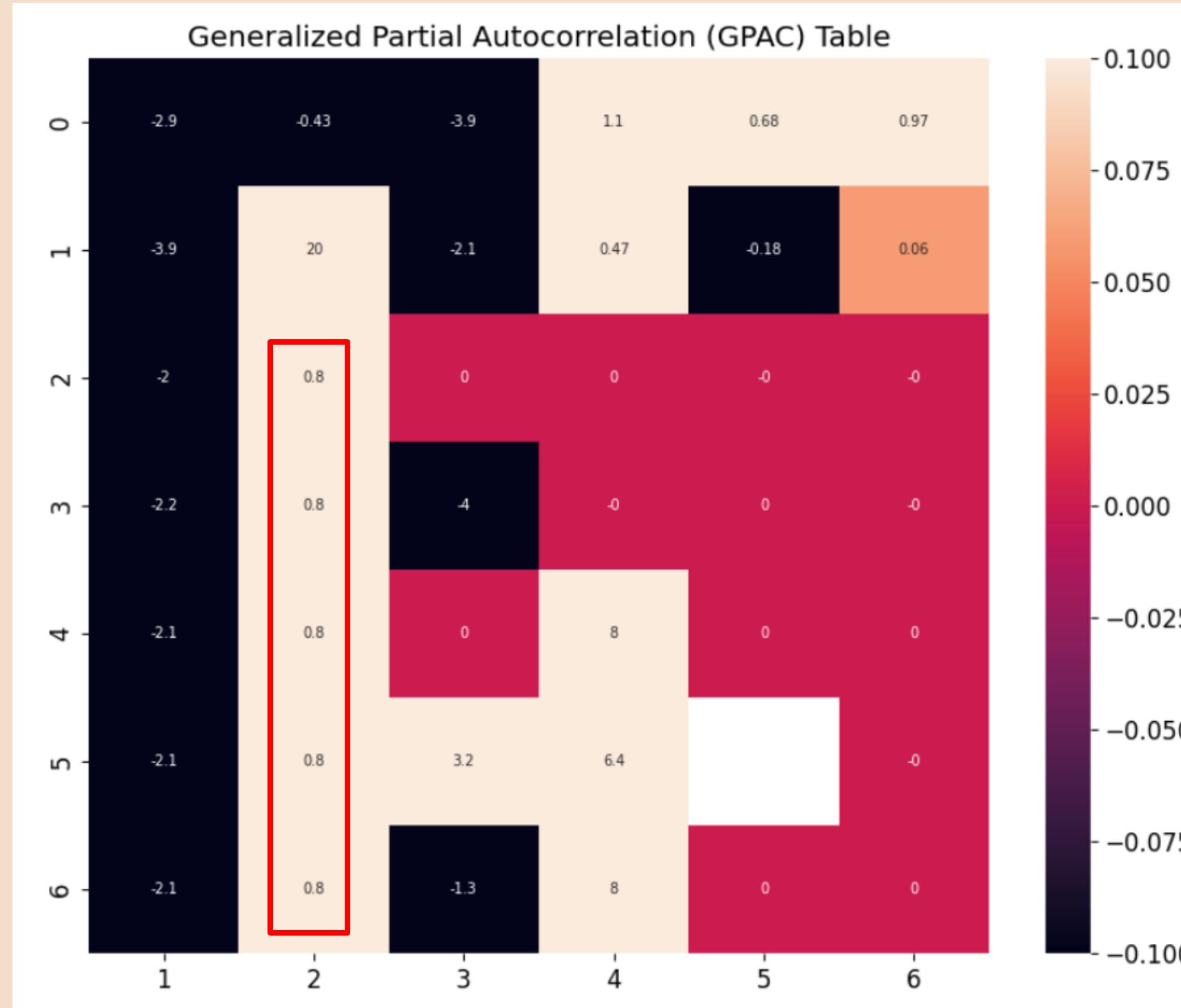


Figure 6.2 GPAC Table

Third, by GPAC table, we can estimate the ARMA order

ARMA, ARIMA and SARIMA model

ARMA model summary

Figure 6.3 ARMA model summary

SARIMAX Results						
Dep. Variable:	kW	No. Observations:	5000			
Model:	ARIMA(2, 0, 2)	Log Likelihood	-2787.078			
Date:	Tue, 09 May 2023	AIC	5586.156			
Time:	03:17:25	BIC	5625.260			
Sample:	0	HQIC	5599.861			
	- 5000					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
const	0.6087	0.064	9.577	0.000	0.484	0.733
ar.L1	1.7778	0.039	45.997	0.000	1.702	1.854
ar.L2	-0.7970	0.032	-24.645	0.000	-0.860	-0.734
ma.L1	-0.7352	0.039	-18.673	0.000	-0.812	-0.658
ma.L2	-0.1495	0.012	-12.562	0.000	-0.173	-0.126
sigma2	0.1785	0.001	124.765	0.000	0.176	0.181
Ljung-Box (L1) (Q):	0.01	Jarque-Bera (JB):	95221.64			
Prob(Q):	0.94	Prob(JB):	0.00			
Heteroskedasticity (H):	4.60	Skew:	0.56			
Prob(H) (two-sided):	0.00	Kurtosis:	24.35			

ARMA(2,2)

AIC: 5586

BIC: 5625

RMSE: 0.42

Residual Mean: 0.0000

Residual Variance: 0.1785

Figure 6.4 ARIMA model summary

SARIMAX Results						
Dep. Variable:	kW	No. Observations:	5000			
Model:	ARIMA(2, 1, 2)	Log Likelihood	-2794.049			
Date:	Tue, 09 May 2023	AIC	5598.097			
Time:	03:18:29	BIC	5630.682			
Sample:	0	HQIC	5609.518			
	- 5000					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
const	1.0011	0.045	22.284	0.000	0.913	1.089
ar.L1	-0.1409	0.040	-3.549	0.000	-0.219	-0.063
ar.L2	-0.9573	0.044	-21.782	0.000	-1.043	-0.871
ma.L1	-0.0411	0.044	-0.935	0.350	-0.127	0.045
ma.L2	0.1789	0.001	150.598	0.000	0.177	0.181
Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	94831.67			
Prob(Q):	0.97	Prob(JB):	0.00			
Heteroskedasticity (H):	4.66	Skew:	0.47			
Prob(H) (two-sided):	0.00	Kurtosis:	24.32			

ARIMA(2,0,2)

AIC: 5598

BIC: 5631

RMSE: 0.42

Residual Mean: 0.0088

Residual Variance: 0.1789

Figure 6.5 SARIMA model summary

SARIMAX Results						
Dep. Variable:	kW	No. Observations:	5000			
Model:	SARIMAX(2, 0, 2)x(1, 0, [], 48)	Log Likelihood	-2819.123			
Date:	Tue, 09 May 2023	AIC	5650.247			
Time:	03:19:03	BIC	5689.350			
Sample:	0	HQIC	5663.952			
	- 5000					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.3727	0.503	0.741	0.459	-0.613	1.358
ar.L2	0.4538	0.444	1.023	0.306	-0.416	1.323
ma.L1	0.6762	0.504	1.342	0.180	-0.311	1.664
ma.L2	0.0730	0.088	0.833	0.405	-0.099	0.245
ar.S.L48	0.1241	0.008	15.725	0.000	0.109	0.140
sigma2	0.1807	0.001	159.442	0.000	0.179	0.183
Ljung-Box (L1) (Q):	1.34	Jarque-Bera (JB):	98867.05			
Prob(Q):	0.25	Prob(JB):	0.00			
Heteroskedasticity (H):	4.63	Skew:	0.22			
Prob(H) (two-sided):	0.00	Kurtosis:	24.78			

SARIMA(2,0,2) D = 48

AIC: 5650

BIC: 5689

RMSE: 0.43

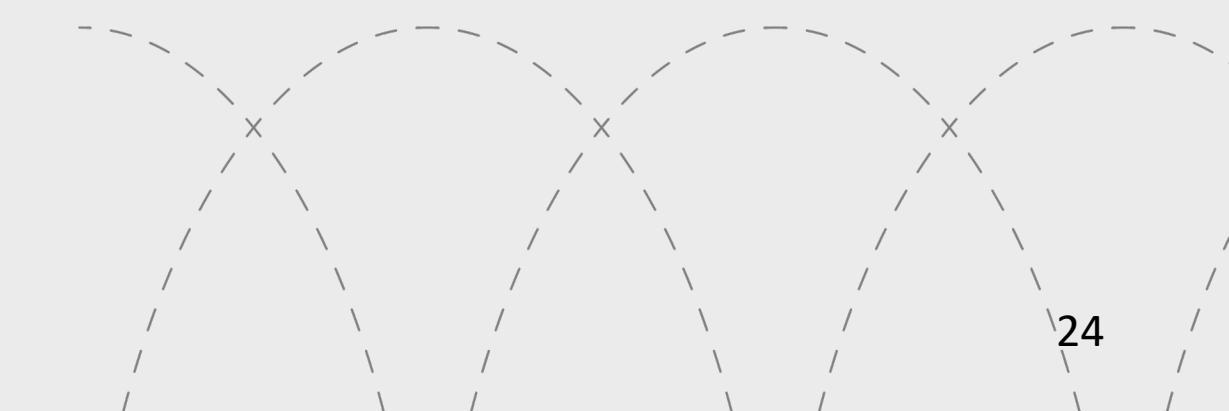
Residual Mean: 0.0533

Residual Variance: 0.1779

Levenberg Marquardt algorithm

	Parameter Estimates	Standard Deviation	Confidence Interval 0	Confidence Interval 1
const	0.609	0.064	0.484	0.733
ar.L1	1.778	0.039	1.702	1.854
ar.L2	-0.797	0.032	-0.860	-0.734
ma.L1	-0.735	0.039	-0.812	-0.658
ma.L2	-0.149	0.012	-0.173	-0.126
sigma2	0.178	0.001	0.176	0.181

Table 3 ARMA model by Levenberg Marquardt Algorithm



Deep Learning Model

Multivariate LSTM Model

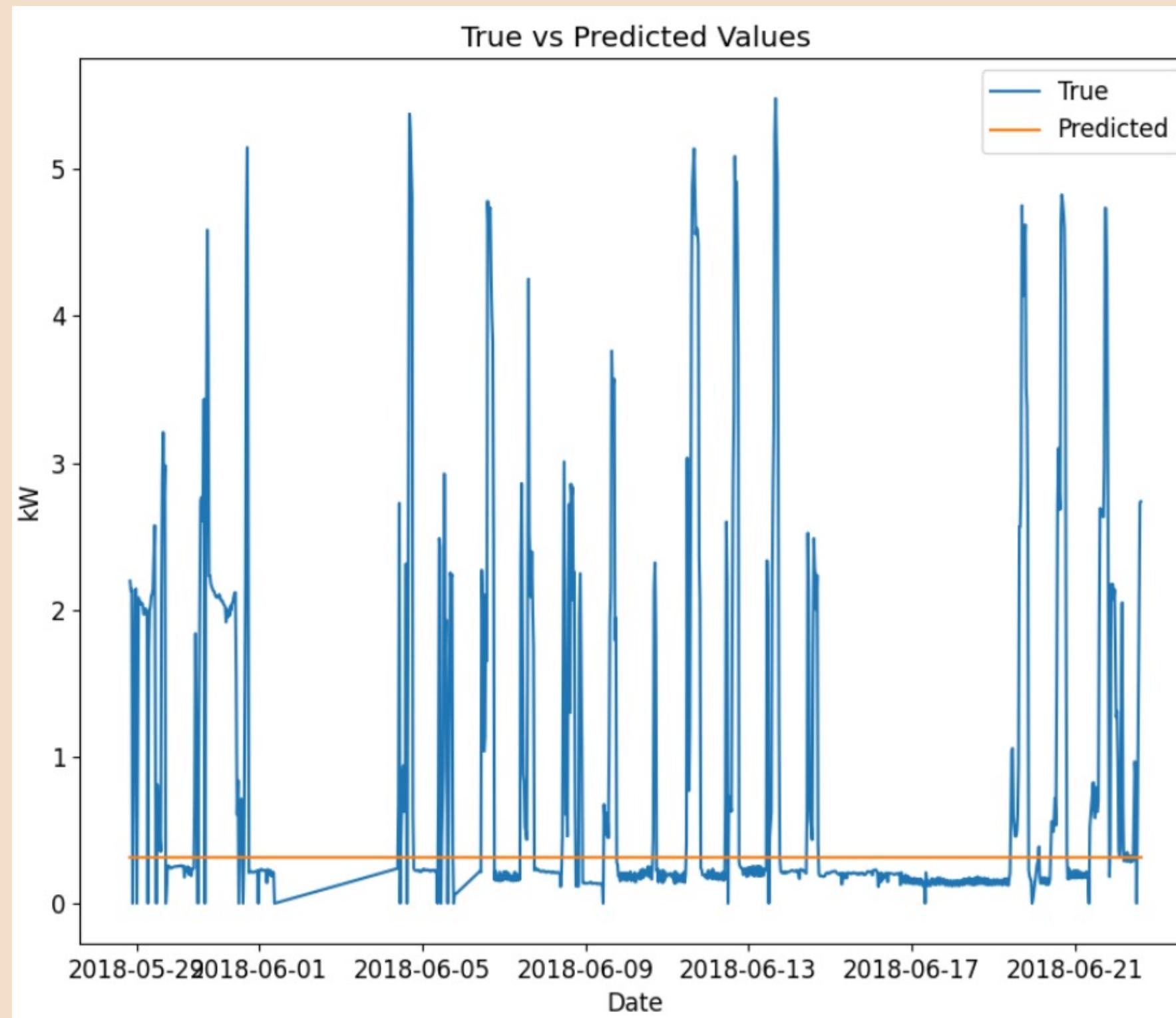


Figure 7.1 Multivariate LSTM Model

Test RMSE: 1.3098
Residual Mean: 0.5382
Residual Variance: 1.4260

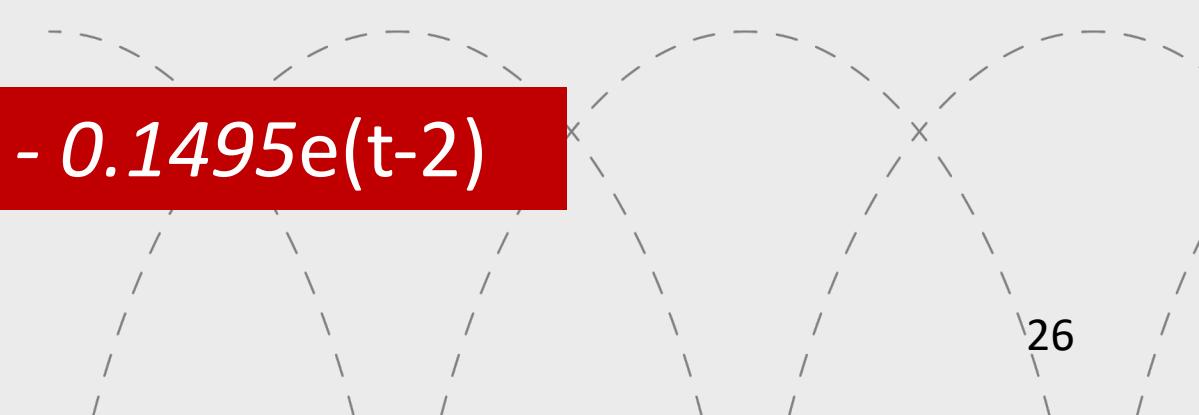
Final Model selection

	Holt-Winters method	Average	naïve	drift	SES	ARIMA (2, 0, 2)	ARIMA (2, 1, 2)	SARIMA (2, 0, 2)48	LSTM
RMSE	2.13	1.2284	1.4575	1.4631	1.4101	0.42	0.42	0.43	1.299
Residual Mean	0.8359	0.2835	0.8342	0.8449	0.7482	0	0.0088	0.0533	0.5382
Residual Variance	1.4276	1.4286	1.4286	1.4266	1.4286	0.1785	0.1789	0.1779	1.4260

Table 4 Final Model Selection

Forecast Function

$$\text{ARIMA}(2,0,2): \hat{Y}(t) = 0.6087 + 1.7778y(t-1) - 0.7970y(t-2) - 0.7352e(t-1) - 0.1495e(t-2)$$



Summary

1. ARMA(2, 2) model fits the best in this dataset
2. The performances of base-model are similar
3. Too few independent variables can affect the analysis
4. Collinearity can significantly impact model performance

Thank You

DATS 6313 Brooklyn Chen

