

A dark blue vertical bar on the left side of the slide, with a blue arrow pointing right from its center.

12/5/2018

# Time series and Forecasting

Case Study

Several thin, curved lines in dark blue and light gray originating from the bottom left corner and extending upwards and to the right.

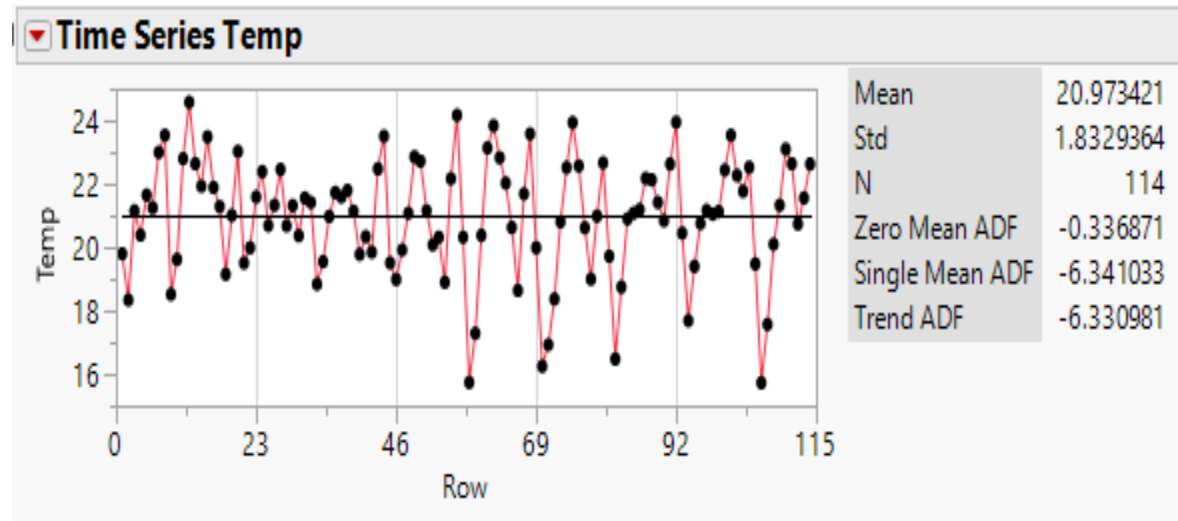
Jay Bhanushali

The software used in this report is JMP

1)

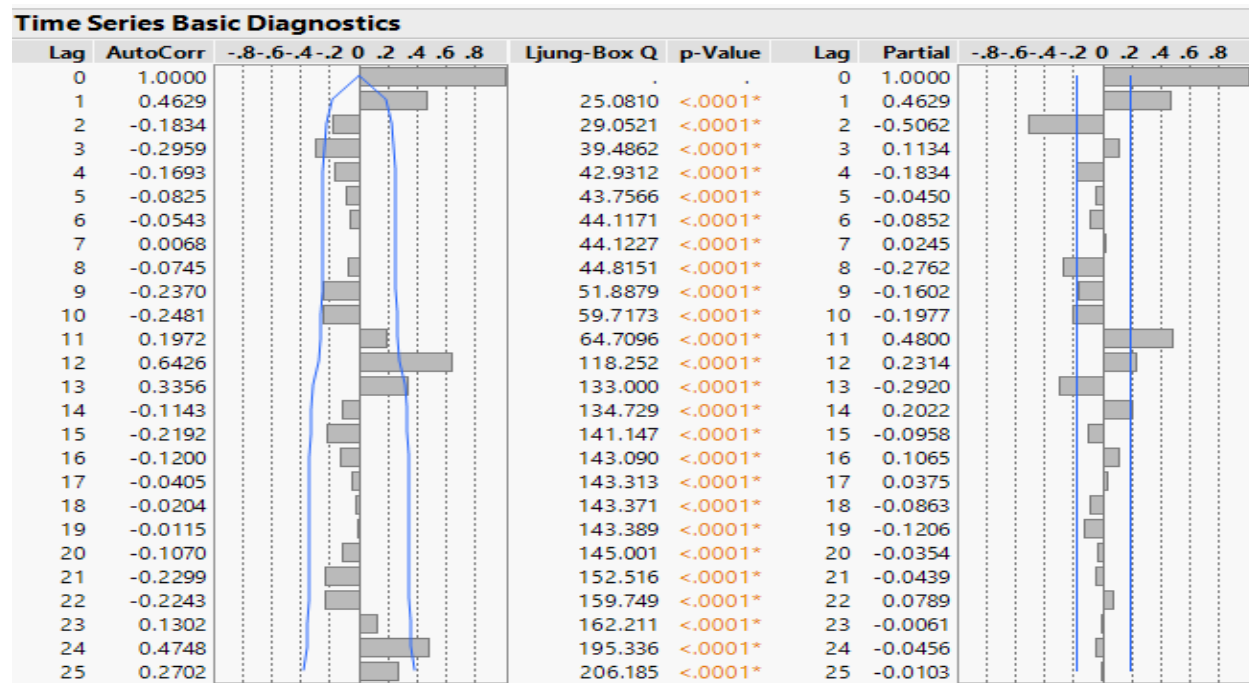
Holt-Winter's Forecasting method:

The Time-series output from JMP is as follows:



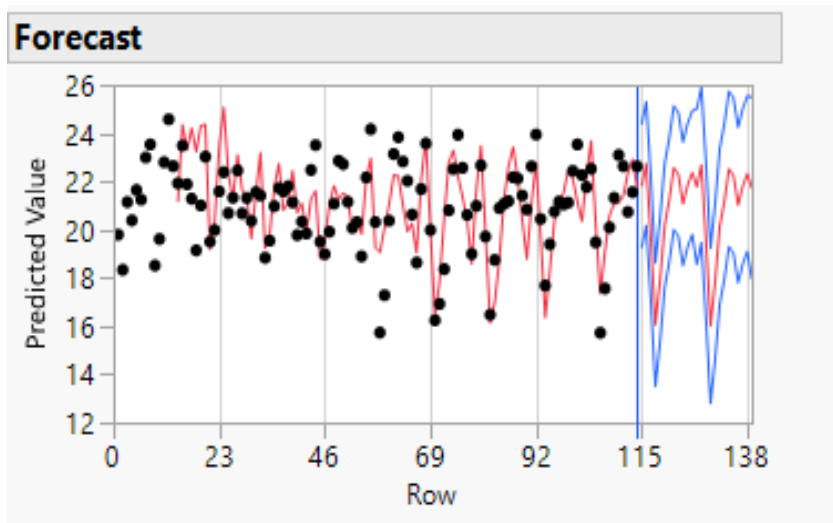
From the Time-series plot, we can see that there is no significant amplitude increase as it is almost constant. Thus, we use the Holt-Winter's additive method for our problem.

The ACF and PACF plots are as follows:





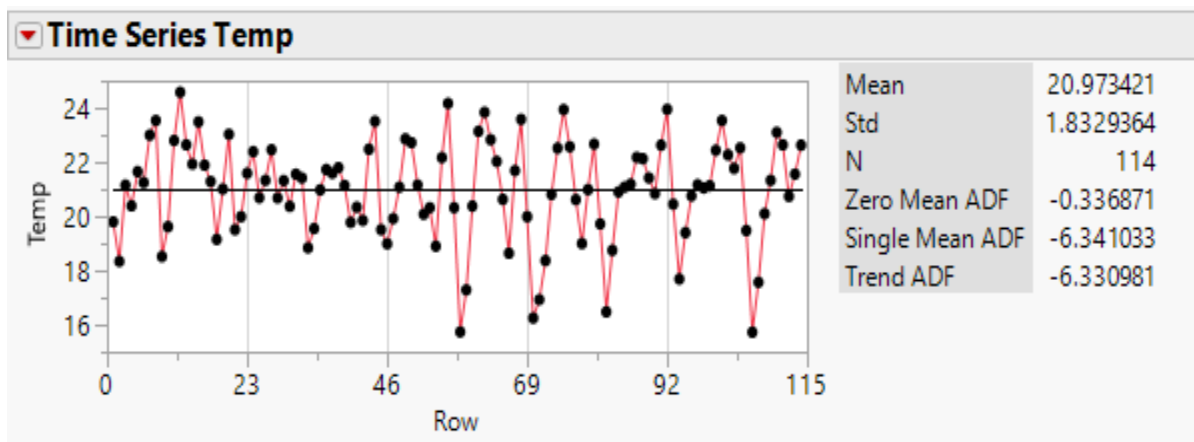
The forecast plot is as follows:



2)

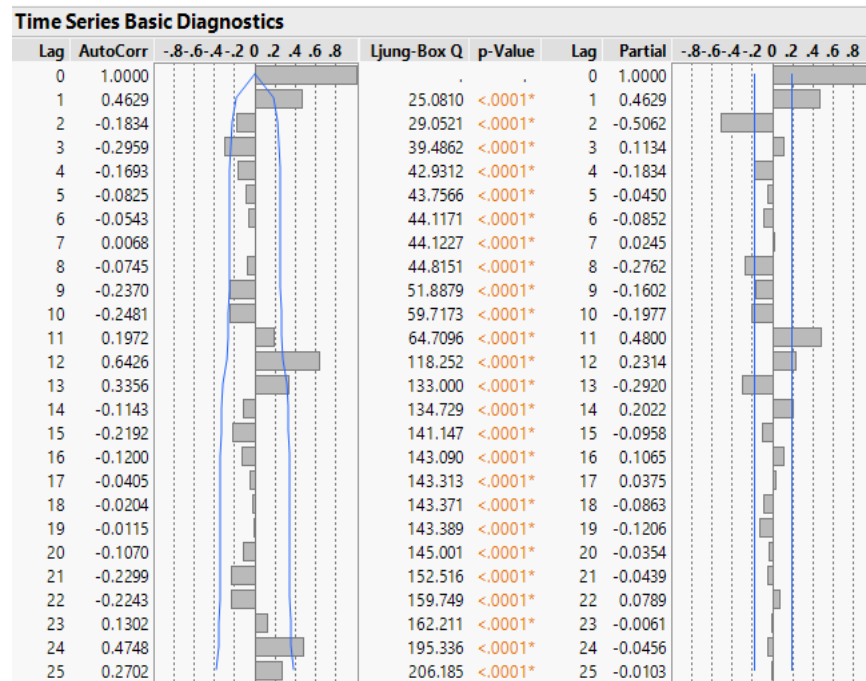
Modeling ARIMA model on the temperature time-series:

The time-series plot is as follows:



As we can see from the time-series plot from above, this is stationary seasonal time-series.

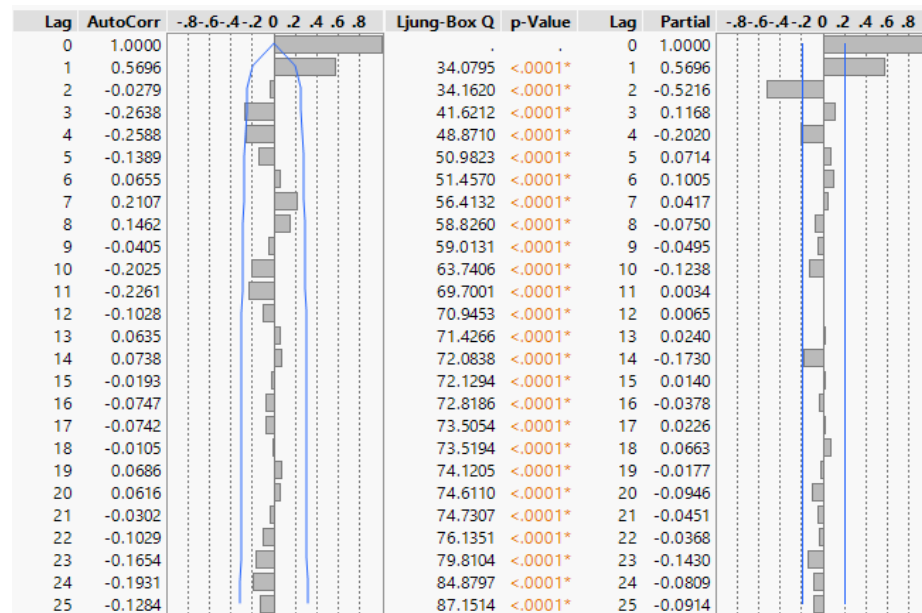
The ACF and PACF plots are as follows:



Both ACF and PACF plots have some season component which are significant in it which has to be modeled out. From the plots above, we can see a cut-off pattern on both ACF and PACF plots, suggesting the best model might be an ARMA model with seasonal component.

Now we apply a seasonal difference of order 1 to see if the seasonal components in ACF and PACF are still significant.

The ACF and PACF plots are given as:



Now we can see that the seasonal components are no more significant. The cut-off pattern can be seen in both the plots, suggesting we should try an ARMA model after the seasonal differencing:

We consider 2 candidate models for comparison:

- 1) ARIMA (2, 0, 1) x (0, 1, 0)<sub>12</sub>
- 2) ARIMA (2, 0, 0) x (0, 1, 0)<sub>12</sub>

### ARIMA (2, 0, 1) x (0, 1, 0)<sub>12</sub>

The model summary and the parameter estimates are given below:

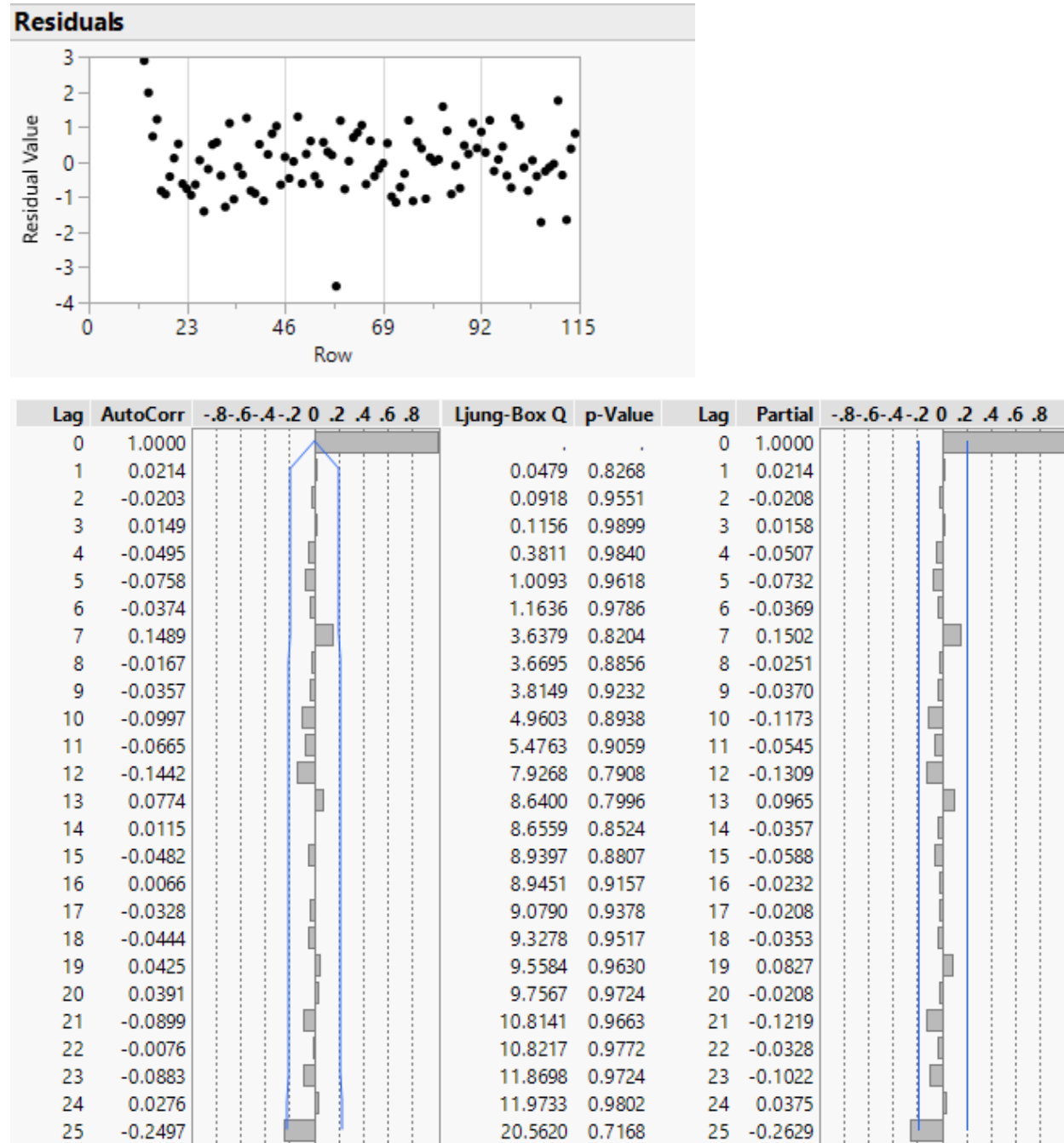
Model: Seasonal ARIMA(2, 0, 1)(0, 1, 0) <sub>12</sub>									
Model Summary									
DF		98	Stable	Yes					
Sum of Squared Errors		77.6823524	Invertible	Yes					
Variance Estimate		0.79267707							
Standard Deviation		0.89032413							
Akaike's 'A' Information Criterion		270.968381							
Schwarz's Bayesian Criterion		281.468272							
RSquare		0.75307253							
RSquare Adj		0.74551353							
MAPE		3.43939289							
MAE		0.70569686							
-2LogLikelihood		262.968381							
Parameter Estimates									
Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob> t	Constant	Mu	
AR1,1	1	1	0.6254392	0.1626991	3.84	0.0002*	Estimate	-0.0451508	
AR1,2	1	2	-0.3947507	0.1380724	-2.86	0.0052*	-0.034735		
MA1,1	1	1	-0.4005426	0.1719332	-2.33	0.0219*			
Intercept	1	0	-0.0451508	0.1554803	-0.29	0.7721			

As we can see, all the parameters are significant except the MA1 component which is not as significant as others, suggesting this model is still considered as valid.

The accuracy measures are given as:

Model	DF	Variance	AIC	SBC	RSquare	MAPE	MAE
Seasonal ARIMA(2, 0, 1)(0, 1, 0) <sub>12</sub>	98	0.7926771	270.96838	281.46827	0.753	3.439393	0.705697

Residual analysis:



We can see from the residuals that the residuals are random and there is no auto-correlation left. Thus, suggesting that this model is indeed valid candidate.

**ARIMA (2, 0, 0) x (0, 1, 0)<sub>12</sub>**

The model summary and the parameter estimates are given below:

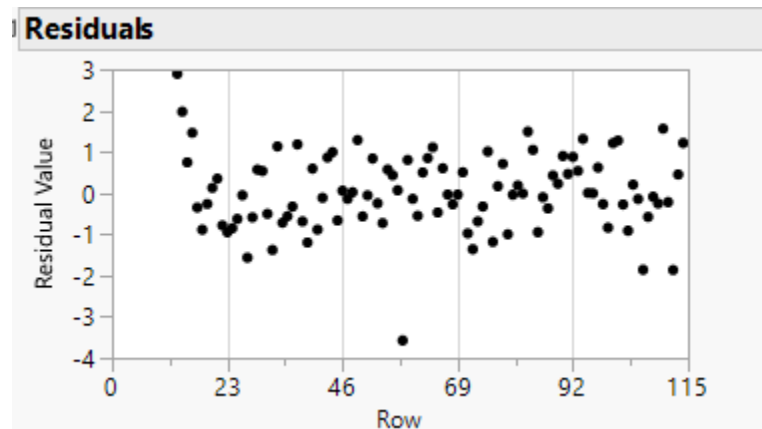
Model: Seasonal ARIMA(2, 0, 0)(0, 1, 0) <sub>12</sub>									
Model Summary									
DF			99	Stable	Yes				
Sum of Squared Errors			80.4430925	Invertible	Yes				
Variance Estimate			0.81255649						
Standard Deviation			0.90141915						
Akaike's 'A' Information Criterion			272.434216						
Schwarz's Bayesian Criterion			280.309135						
RSquare			0.7452899						
RSquare Adj			0.74014424						
MAPE			3.43816534						
MAE			0.70624372						
-2LogLikelihood			266.434216						
Parameter Estimates									
Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob> t	Constant	Mu	
AR1,1	1	1	0.9041737	0.0834660	10.83	<.0001*	Estimate	-0.0516304	
AR1,2	1	2	-0.5696798	0.0869097	-6.55	<.0001*	-0.0343603		
Intercept	1	0	-0.0516304	0.1325805	-0.39	0.6978			

As we can see, all the parameters are significant, suggesting this model is valid.

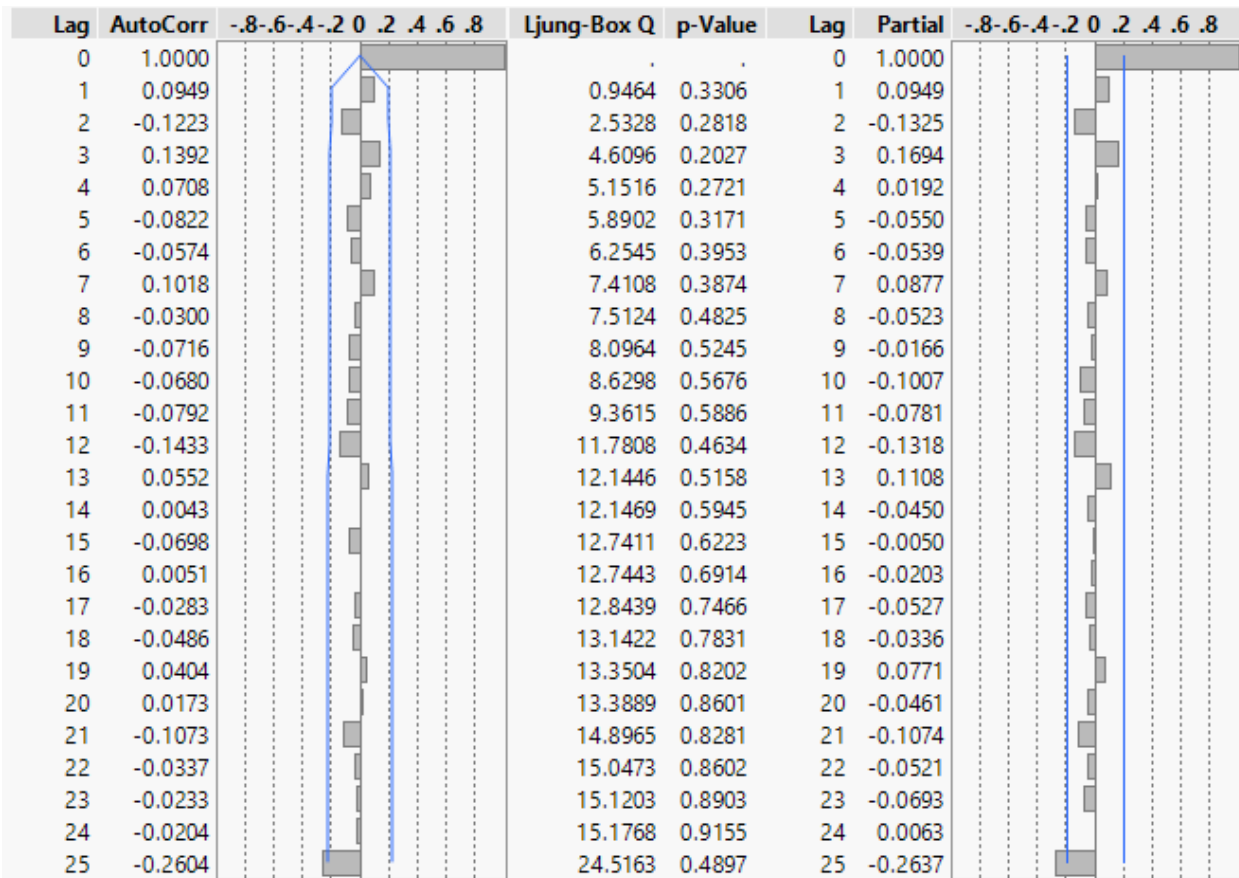
The accuracy measures are given as:

Model	DF	Variance	AIC	SBC	RSquare	MAPE	MAE
Seasonal ARIMA(2, 0, 0)(0, 1, 0) <sub>12</sub>	99	0.8125565	272.43422	280.30913	0.745	3.438165	0.706244

Residual analysis:







We can see from the residuals that the residuals are random and there is no auto-correlation left. Thus, suggesting that this model is indeed valid candidate.

Model selection:

As both the candidate models are valid, we compare the accuracy measures for selecting the best model for Temperature time-series

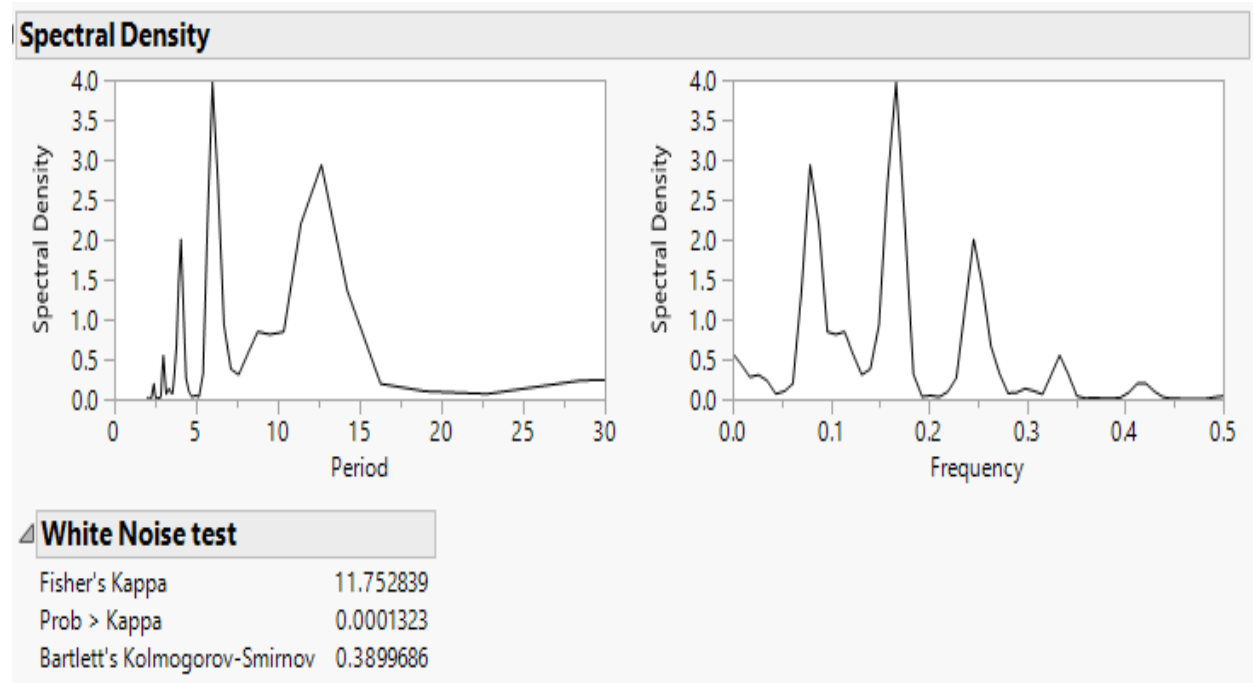
Model	DF	Variance	AIC	SBC	RSquare	MAPE	MAE
Seasonal ARIMA(2, 0, 1)(0, 1, 0) <sub>12</sub>	98	0.7926771	270.96838	281.46827	0.753	3.439393	0.705697
Seasonal ARIMA(2, 0, 0)(0, 1, 0) <sub>12</sub>	99	0.8125565	272.43422	280.30913	0.745	3.438165	0.706244

We select ARIMA (2, 0, 0) x (0, 1, 0)<sub>12</sub> as all the parameters are significant and the accuracy measures are good.

3)

Spectral analysis of Temperature process:

The spectral density of the temperature process is depicted below:



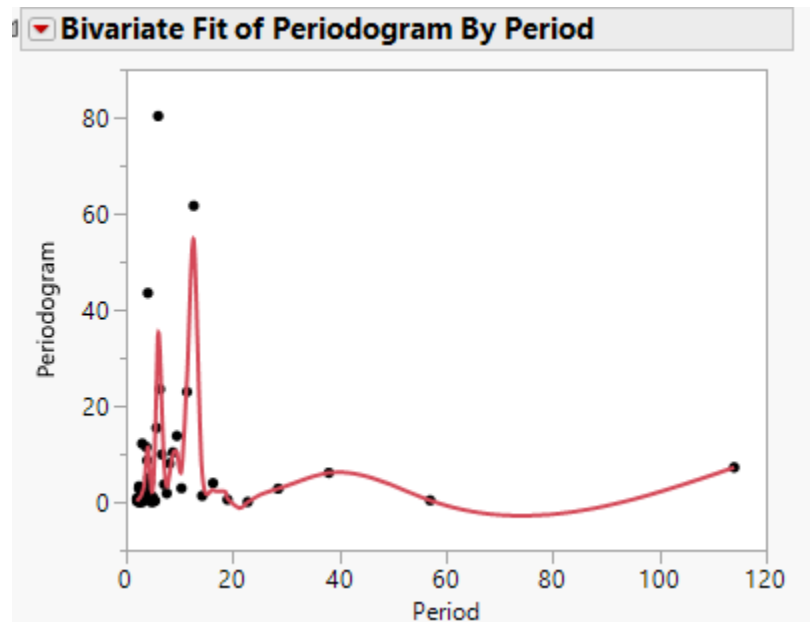
From the above plots, we can see that the Fisher's Kappa statistic is significant as the p-value is below 0.05. Thus, suggesting that there exists one underlying periodic component in it. From the Spectral Density Vs Period plot, we can see that there is a significant and prolonged peak at period 12, which indicates that we have a seasonal period of 12 months.

We save the columns of spectral density and we see the spectral density value of the first spike. We check the corresponding period value and its frequency. That is the period value and the corresponding frequency.

	Period	Frequency	Angular Frequency	Sine	Cosine	Periodogram	Spectral Density
1	•	0	0	0	0	0	0.5737972359
2	114	0.0087719298	0.0551156606	0.2188367252	0.2803771433	7.2105487237	0.4373570825
3	57	0.0175438596	0.1102313212	0.078059956	-0.009363287	0.3523185888	0.2785298681
4	38	0.0263157895	0.1653469818	0.2483136201	-0.212365624	6.0852522984	0.3045790204
5	28.5	0.0350877193	0.2204626424	0.1961964191	-0.101987721	2.786988219	0.2326655386
6	22.8	0.0438596491	0.2755783029	0.0069810432	-0.02407551	0.0358168136	0.0668293335
7	19	0.0526315789	0.3306939635	0.0633784185	-0.069031887	0.5005868422	0.0992107037
8	16.285714286	0.0614035088	0.3858096241	-0.263241661	0.0001666467	3.9498833861	0.1929483797
9	14.25	0.0701754386	0.4409252847	0.1341592044	0.0691254044	1.2982897787	1.3562978157
10	12.666666667	0.0789473684	0.4960409453	-0.542292501	0.887198184	61.628501121	2.9340192783
11	11.4	0.0877192982	0.5511566059	-0.436164199	-0.460376803	22.924602541	2.195479505
12	10.363636364	0.0964912281	0.6062722665	0.0518625048	-0.218680907	2.8791303427	0.8444174746
13	9.5	0.1052631579	0.6613879271	-0.243077651	-0.427030631	13.762188529	0.8108218014
14	8.7692307692	0.1140350877	0.7165035877	0.0787843266	-0.418833894	10.352841634	0.845734289
15	8.1428571429	0.1228070175	0.7716192483	0.1176913761	-0.356735896	8.0433702724	0.5621635682
16	7.6	0.1315789474	0.8267349088	-0.111016228	-0.139883312	1.8178407954	0.3056650636
17	7.125	0.1403508772	0.8818505694	-0.132743616	-0.216874148	3.6853500285	0.3798604821
18	6.7058823529	0.149122807	0.93696623	0.2725763568	0.3154042503	9.9053295474	0.9345758597
19	6.3333333333	0.1578947368	0.9920818906	-0.445200689	-0.462322305	23.480897359	2.7288681354
20	6	0.1666666667	1.0471975512	0.6619776639	0.9851754386	80.300749123	3.9692652824
21	5.7	0.1754385965	1.1023132118	-0.515439835	0.0714486774	15.434638819	2.2173526924
22	5.4285714286	0.1842105263	1.1574288724	-0.044776085	0.0549316844	0.2862761005	0.3207072068
23	5.1818181818	0.1929824561	1.212544533	0.0090737952	0.0436530241	0.1133114558	0.0323067384
24	4.9565217391	0.201754386	1.2676601936	-0.015540589	0.1387442882	1.1110147826	0.0465374383
25	4.75	0.2105263158	1.3227758541	-0.00694362	-0.004467383	0.0038857678	0.028894376
26	4.56	0.2192982456	1.3778915147	0.0719892479	0.0258889933	0.3336034319	0.0942306982
27	4.3846153846	0.2280701754	1.4330071753	-0.180522048	-0.196813694	4.0654588753	0.2689781015
28	4.2222222222	0.2368421053	1.4881228359	-0.116481712	-0.274098762	5.0557928577	1.147169481

The highlighted are the value of a period which suggests 1 period consists of approximately 12 months, and its corresponding frequency = 0.0789 Hz and the first spike spectral density is spectral density = 2.934

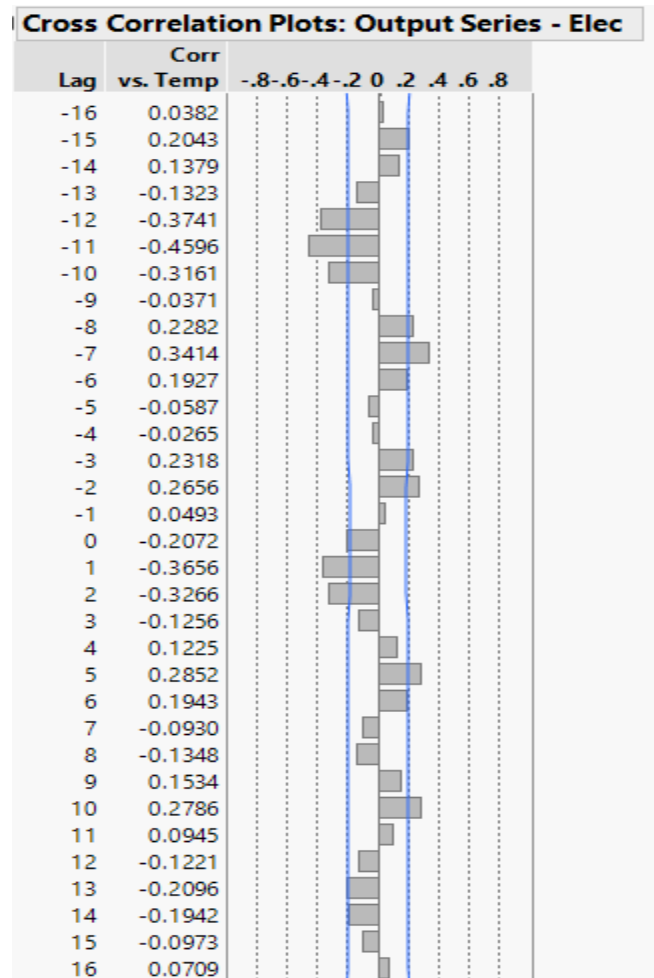
This can be confirmed by the plot below as the highest spike is for approximately 12.



4)

Now we take Temperature as an input and electricity as an output as a cause and effect series. We first see the cross-correlation of the output series to check if pre-whitening is needed.

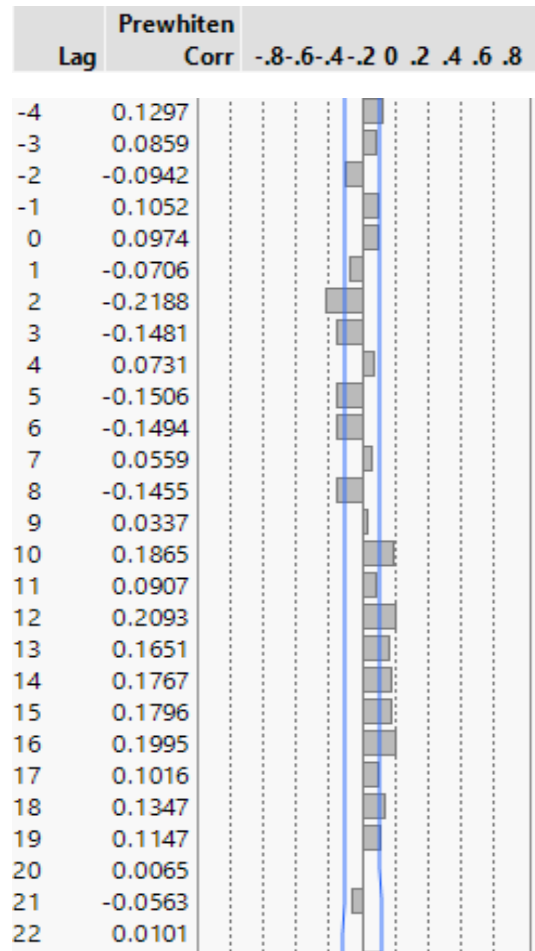
The cross-correlation plot is as follows:



As we can see the seasonal components which are significant, and the correlations are significant for negative lags as well, which is unreasonable. Thus, pre-whitening is needed.

We apply pre-whitening using the model  $ARIMA(2, 0, 0) \times (0, 1, 0)_{12}$  to the input temperature series and obtain the transfer function parameters from the cross-correlation of input series after pre-whitening.

Cross-correlation plot of input series after pre-whitening:



From the plot above, we can take  $b = 2$  as the lag starts from lag 2 and  $r = 0$  as there is no exponential decaying pattern and  $s = 0$  as there is  $w_0$  which is of order 0. i.e. ARMAX (2, 0, 0)

Now we put ARMAX (2, 0, 0) and check its residuals to obtain which ARIMA model is adequate for output electricity model.

The parameter estimates and model summary for ARMAX (2, 0, 0) are:

#### ▼ Transfer Function Model (1)

### Model Summary

DF	110
Sum of Squared Errors	5384.91081
Variance Estimate	48.9537335
Standard Deviation	6.99669447
Akaike's 'A' Information Criterion	755.60223
Schwarz's Bayesian Criterion	761.039228
RSquare	0.13774369
RSquare Adj	0.13004498
MAPE	4.44594337
MAE	5.20236269
-2LogLikelihood	751.602233

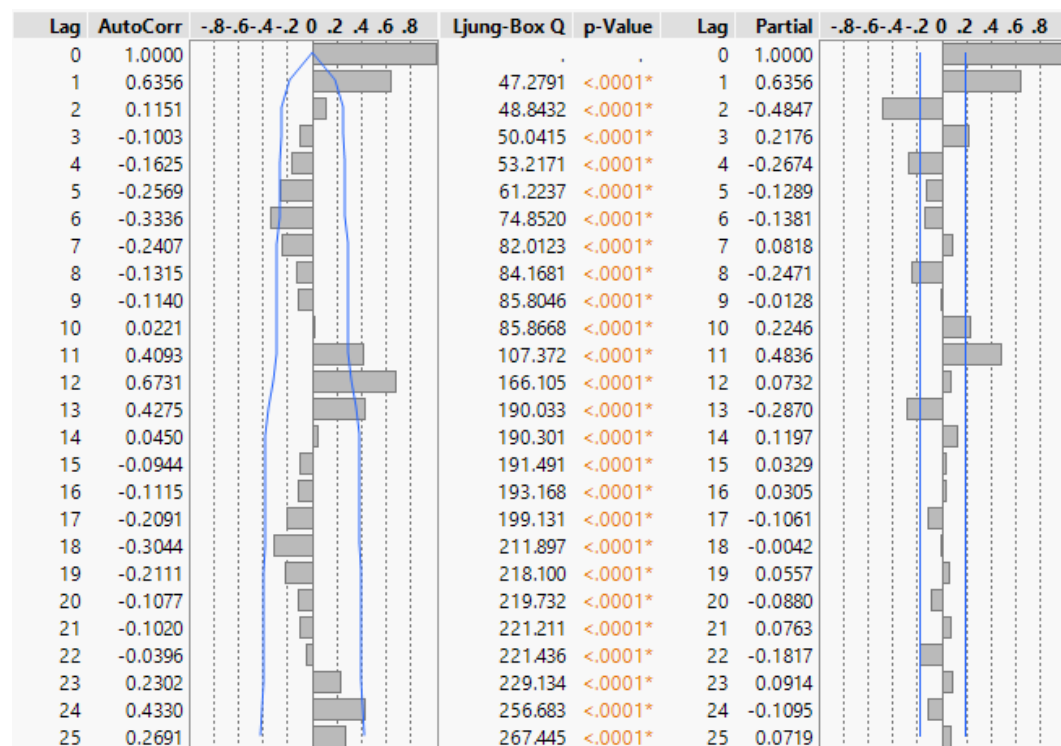
### Parameter Estimates

Variable	Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob> t
Temp	Num0,0	0	0	-1.3289	0.355760	-3.74	0.0003*
	Intercept	0	0	148.2911	7.483111	19.82	<.0001*

$$\text{Elec}_t = \left( 148.2911 - 1.3289 \cdot \text{Temp}_{t-2} \right) + e_t$$

We can clearly see that the ARMAX (2, 0, 0) model is valid as all the parameters are significant.

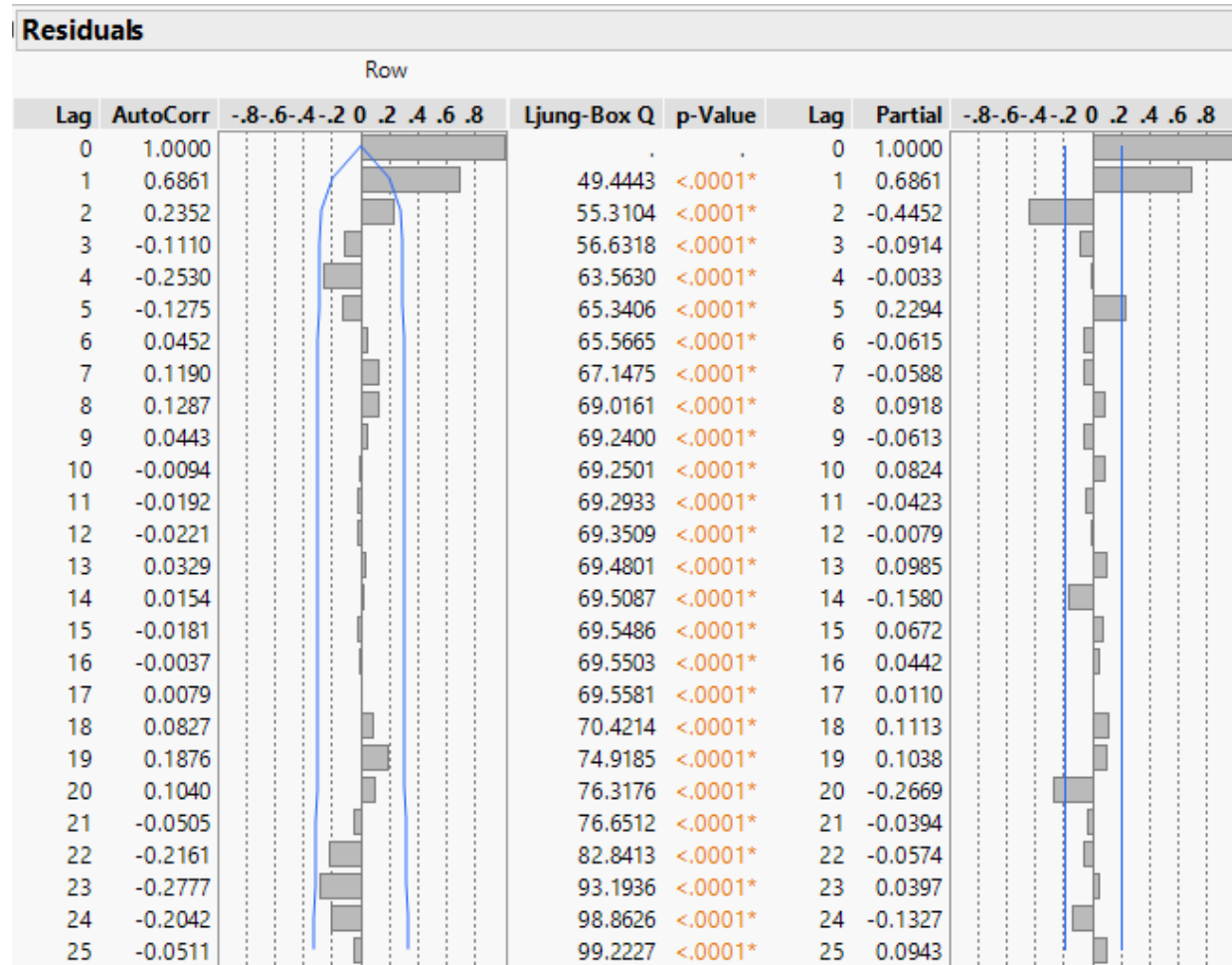
Residual analysis:



From the residuals we can see that there are significant auto-correlations left which should be modeled by an ARIMA model and the seasonal component should be modeled out by a seasonal ARIMA model.

We take seasonal differencing of order 1 and check the residuals ACF and PACF to see which ARIMA model to model the noise for output series

Residual ACF and PACF after seasonal differencing:



From plots above, we can see that there is a cut-off pattern in PACF of order 2 and an exponential decay type pattern in ACF thus we can choose 2 candidate models to model this

- 1) ARMAX (2, 0, 0) + ARIMA (2, 0, 0) x (0, 1, 0)<sub>12</sub>
- 2) ARMAX (2, 0, 0) + ARIMA (2, 0, 1) x (0, 1, 0)<sub>12</sub>

**ARMAX (2, 0, 0) + ARIMA (2, 0, 0) x (0, 1, 0)<sub>12</sub>**

The model summary and the parameter estimates are given below:

Transfer Function Model (3)							
Model Summary							
DF				96			
Sum of Squared Errors				824.33375			
Variance Estimate				8.58681013			
Standard Deviation				2.93032594			
Akaike's 'A' Information Criterion				503.804355			
Schwarz's Bayesian Criterion				514.225036			
RSquare				0.62642001			
RSquare Adj				0.61498389			
MAPE				2.01328613			
MAE				2.39681488			
-2LogLikelihood				495.804355			
Parameter Estimates							
Variable	Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob> t
Temp	Num0,0	0	0	-0.8356678	0.3164668	-2.64	0.0097*
Elec	AR1,1	1	1	0.9906212	0.0888796	11.15	<.0001*
Elec	AR1,2	1	2	-0.4449190	0.0885521	-5.02	<.0001*
	Intercept	0	0	0.6018609	0.6303323	0.95	0.3421

$$\left(1 - B^{12}\right) \cdot \text{Elec}_t = \left(0.6019 - 0.8357 \cdot \left(1 - B^{12}\right) \cdot \text{Temp}_{t-2}\right) + \left(\frac{1}{\left(\left(1 - 0.9906 \cdot B\right) + 0.4449 \cdot B^2\right)}\right) \cdot e_t$$

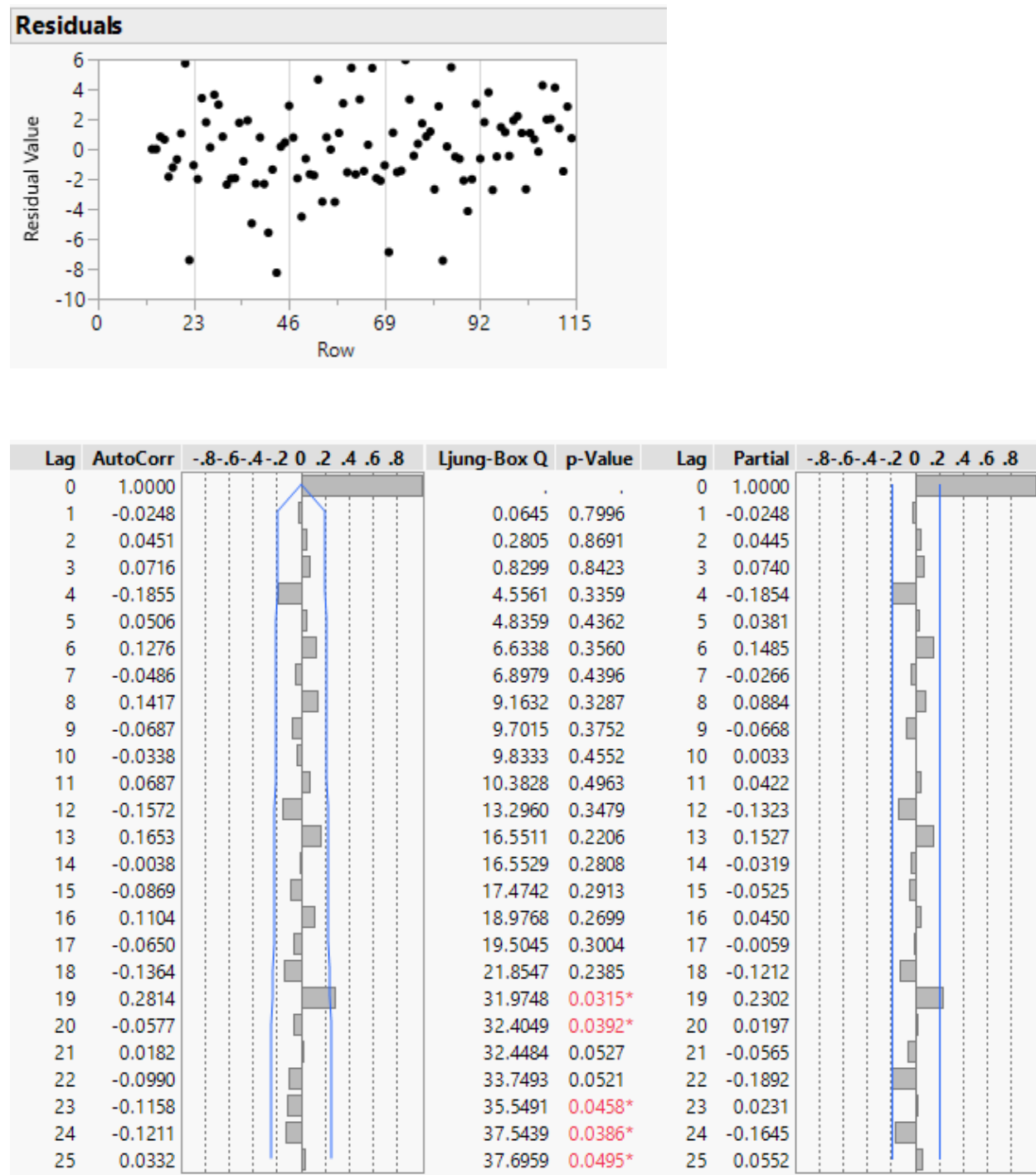
As we can see, all the parameters are significant, suggesting this model is valid.

The accuracy measures are given as:

Model	DF	Variance	AIC	SBC	RSquare	MAPE	MAE
Transfer Function Model (3)	96	8.5868101	503.80436	514.22504	0.626	2.013286	2.396815



Residual analysis:



There is no significant auto-correlation left and the residual plot is random, thus, suggesting this model is valid.

**ARMAX (2, 0, 0) + ARIMA (2, 0, 1) x (0, 1, 0)<sub>12</sub>**

The model summary and the parameter estimates are given below:

Transfer Function Model (4)							
Model Summary							
DF				95			
Sum of Squared Errors				917.908321			
Variance Estimate				9.66225135			
Standard Deviation				3.10841621			
Akaike's 'A' Information Criterion				518.78811			
Schwarz's Bayesian Criterion				531.813961			
RSquare				0.58401042			
RSquare Adj				0.56685621			
MAPE				2.12175896			
MAE				2.52189329			
-2LogLikelihood				508.78811			
Parameter Estimates							
Variable	Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob> t
Temp	Num0,0	0	0	-0.9472779	0.3112810	-3.04	0.0030*
Elec	AR1,1	1	1	-0.1341455	0.0871759	-1.54	0.1272
Elec	AR1,2	1	2	0.5023514	0.0869433	5.78	<.0001*
Elec	MA1,1	1	1	-0.9999859	0.0316606	-31.58	<.0001*
	Intercept	0	0	0.6494985	0.9424396	0.69	0.4924

$$\left(1 - B^{12}\right) \cdot \text{Elec}_t = \left(0.6495 - 0.9473 \cdot \left(1 - B^{12}\right) \cdot \text{Temp}_{t-2}\right) + \left(\frac{(1+B)}{\left(\left(1 + 0.1341 \cdot B\right) - 0.5024 \cdot B^2\right)}\right) \cdot e_t$$

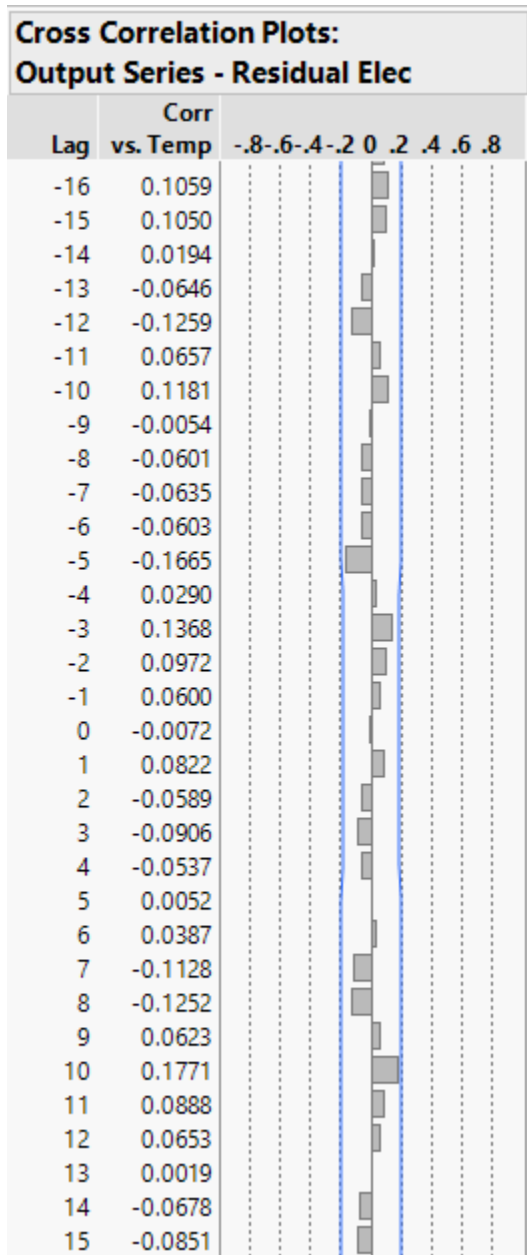
As we can see from the table above, all parameters are not significant for this model.

Thus, we can select ARIMA (2, 0, 0) x (0, 1, 0) to model noise model.

The final model for transfer function is ARMAX (2, 0, 0) + ARIMA (2, 0, 0) x (0, 1, 0)<sub>12</sub>

**To check Independence between the output residual and the input series:**

We now take Temperature as input series and Electricity residuals as an output and compute the cross-correlation:



From the plot we can see that the cross-correlation is only white noise. Thus, the input series and the residual of the output series are independent.

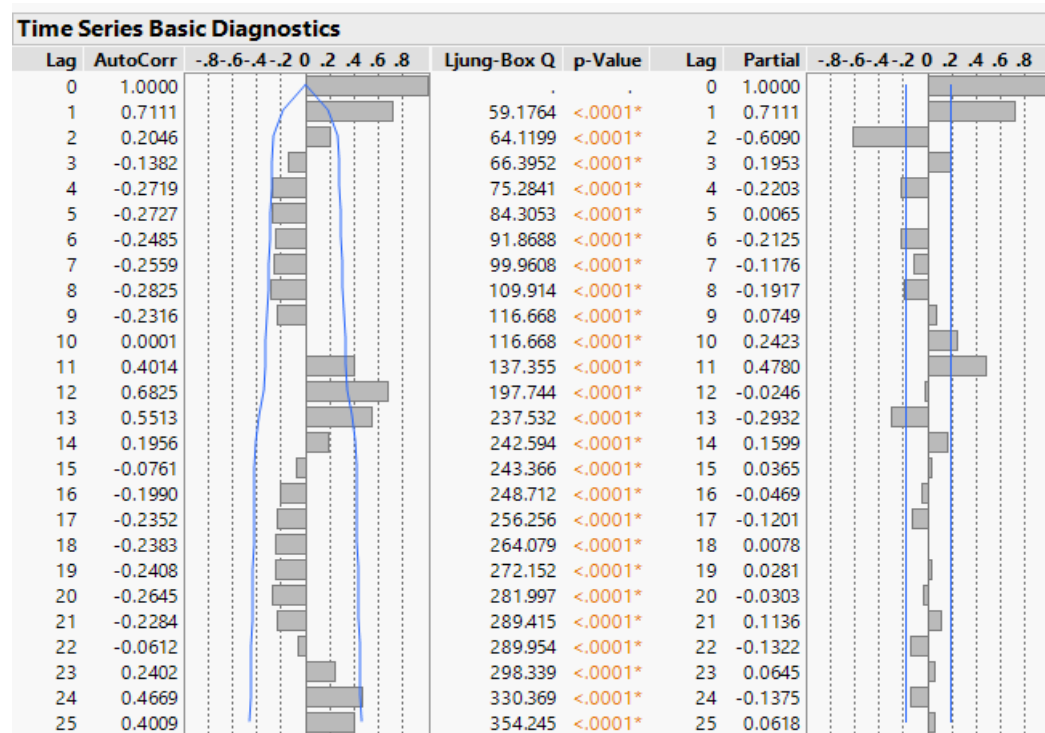
5)

For the forecast process, we fit optimal seasonal ARIMA models separately to both temperature and electricity.

We already have Optimal ARIMA for the Temperature series.

Electricity:

ACF and PACF of electricity time-series are:



As we can see there is some significant seasonal component and AR 2 cut-off pattern. Thus, we will put ARIMA (2, 0, 0) x (0, 1, 0) which is significant by analysis, thus validating our model. We now forecast temperature and electricity separately with their respective ARIMA model.

Forecast for next 6 months

Month	Predicted Temperature	Predicted Electricity
7	23.18910819	121.4144055
8	23.57367519	121.1429699
9	19.58086603	121.9514398
10	15.19227942	127.523679
11	16.99198557	129.3577309
12	19.84934281	129.996468