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Power price forecasting using an ARIMA-EGARCH model in texas market

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Abstract
There are several class of models to forecast electricity price and time series is one of the popular class. ERCOT market is different from other markets because it is very volatile market and is the subject of interest by many market participants. This paper attempts to forecast power prices in ERCOT market for short term.

Keywords: Power prices, ARIMA, time series, short term, ERCOT

1. Introduction
In past decade or so, in order to increase efficiency in electrical supply chain - generation, transmission and distribution - and to make the power market competitive, many countries have deregulated their domestic electricity markets. With this deregulation, the market participants trade power & its derivatives like any other commodity or financial asset to meet their physical power obligations and to speculate & make money. The primary players in this market are i) Power Generators ii) Whole Sellers iii) and Retail Distributors. The transmission portion is still regulated in all countries and their role is limited to physical transmission of power at a fixed tariff. On top of this, there is a "System Operator" which is responsible for physical transmission of electricity and to maintain the reliability of transmission grid. For Texas market, the system operator is called as ERCOT (Electricity Reliability Council of Texas). Power Generators represent the supply side, Retail Distributors represent the demand side and the Whole Sellers facilitate the transactions between them. The power price settles only at real time - when the electricity physically flows - and is determined by the system operator by matching demand and supply of power. Although, there are several sub-markets within the power market and even more number of instruments but the most important one is the "Day Ahead Market", which refers to the flow of power for each hour of next day. This is the most important market, because this market determines the physical flow of electricity, is the most active one and all products are derivative of this product only.

In the day-ahead market, generators submit their capacity schedule along with offer price while whole sellers 7 retail distributors submit their demand schedule along with bids by 9:00 am every day for the next operating day. ERCOT matches the supply and demand of the bi-lateral contracts but this doesn`t accounts for all of the electricity needs in "Day Ahead Market". As one comes closer to the operating hour, the participants have an opportunity to revise their supply / demand schedules and prices through something called as "Hour Ahead Market" and "30 Minute Market". But the actually demand is not completely known until the "Real Time" when the electricity actually flows. At the real time, the system operator i.e. ERCOT takes control of all the physical generators and other equipment s in the system, ensures that all contractual and non-contractual demands are met, maintains the system reliability and determines the price. In real time, demand and hence the price can be very different from the one projected even in prior hour; because demand is driven by weather conditions, individual power consumptions and because something of events like congestion, burn up of lines of the physical transmission lines and occasionally hurricanes. This is compounded by the fact that unlike other commodities electricity can`t be stored, the marginal cost of generators is a convex function and it is these factors that make electricity the most volatile commodity in financial market.

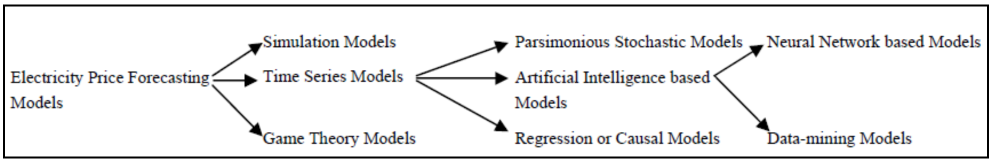
The price discovery mechanism in power market is called as "Locational Marginal Pricing" (LMP); in LMP, the incremental cost of providing next unit of power is the "Settled" price for that particular interval for a particular node, if there is no congestion. If there is congestion, cost to relieve congestion is added to the incremental cost. All market participants who choose to be float with market and are price takers, will settle their transaction at this price.
Because of the physical constraints mentioned above and the unique price discovery mechanism, price electricity prices exhibit high frequency, high volatility, seasonality, time-varying volatility with asymmetries, and even negative prices. The purpose of this paper is to develop a model for forecasting hourly power prices for "Day Ahead Market" for three zones of the Texas market *viz*: North Zone, Houston Zone and South Zone and gauge the performance of the model. The secondary objective of the paper is to verify the presence of time-varying volatility, check whether shocks to volatility is asymmetric and whether an inverse leverage effect is present in Texas market.

2. Literature Review

There is a whole gamut of methodologies that have been applied for forecasting electricity prices. These can be broadly classified into three categories

- **Simulation Models:** These models attempt to mimic the real time situations by estimating all the parameters *viz*. demand, generation, physical flow of electricity, weather conditions and even physical flow of electricity in grids. While this methodology is very detailed, it suffers from two drawbacks, namely the implementation complication of simulation model and high computational cost.
- **Game Theory Model:** These models are more of "Economic" models and these models basically forecast the strategies of market participants and identify optimal solutions.
- **Time series Models:** These models use the past behavior of electricity prices and / or some exogenous variables to forecast future electricity prices. Within this group, there are three categories of models a) Stochastic Models b) Artificial Intelligence Models c) and Regression Methodology. A summary of these methodologies (Girish *et al*. 2013) [3] is present in the Table 1 below.

Table 1: Electricity Price Forecasting Methodology Summary



The major advantages of using traditional statistical models are their simplicity, explicitness of model structures, accuracy of prediction results, and ease of implementation. Different variants of ARIMA models have been used to forecast prices like Autoregressive Integrated Moving Average (ARIMA), and ARMA with exogenous variables (ARMAX) models. Simple ARIMA models are inefficient because they fail to explain the non-linear & asymmetric behaviour and time varying volatility of power prices; In order to correctly model the electricity prices, ARIMA-EGARCH models have been used for forecasting. One such model is by Bowden & Payne named "Short Term forecasting of electricity prices for MISO Hubs: Evidence from ARIMA-EGARCH models". This model has been replicated here in part for the Texas market.

3. Data

In Texas, ERCOT determines prices every 15 minutes at each Hub and this price is called as "Real Time Locational Marginal Price" (RTLMP). Hourly Hub price has been calculated by taking an average of the 15 minutes prices for every hour. Since there are many hubs within a zone, Zonal price has been arrived at by calculating an arithmetic mean of hourly prices of all hubs within that zone. The unit of analysis, for this paper is Zonal Hourly prices calculated by above methodology. The zonal hourly prices represent the price of physical power but it is good for financial instruments as well because all settlements on financial deals are done on hourly RTLMP only. Also, unlike other commodities like Oil & Natural Gas, physical power doesn't enjoy any premium over financial power. Although, RTLMP is available at 15 minute granularity, the hourly granularity was chosen for modelling purposes primarily because of two reasons: i) in the capital market, power is transacted at hourly level or in blocks of hour rather than at 15 minute level ii) Modelling prices at 15 minute level will make it more complicated both in terms of number of observations and in terms of distribution assumptions. The 15 minute interval data for the three zones was downloaded from ERCOT's website. The data has been collected for a period of six months from January 1st 2009 to June 30th 2009 which has yielded 4,344 rows of data. A summary of the statistics is shown in Table 2 below.

Table 2: Summary statistics for North, Houston and South zones prices in \$/Mwh

	North	Houston	South
Min.	-24.5	-24.5	-24.5
1st Qu.	18.2	18.2	18.0
Median	24.0	24.0	23.7
Mean	29.0	32.1	34.2
3rd Qu	31.8	31.9	31.6
Max.	1700.9	1203.3	2115.3

Across the three zones, the power prices vary over a wide range from \$-24.5 to \$2115.3. Across the three zones, median price varies over a narrow range of \$23.7 to \$24.0 while mean prices hovers in range of \$29.0 to \$34.2. Maximum prices can shoot over thousand dollars (in times of congestion) and on windy nights it can fall below zero. Unlike other markets, negative price is possible in power markets. Wind generators have zero marginal cost and are granted free "Emission Certificates" from government for producing clean power which can be traded in market. Hence these wind generators can afford to generate power even when the prices are below zero as long as they make money on the emission certificates.

4. Methodology and Econometric Analysis

To come up a model for forecasting RTLMP, ARIMA-EGARCH model has been developed via Box-Jenkins (Box and Jenkins, 1976) [9] framework: to start with, the price time series was made stationary, the model structure was identified, then parameters were estimated and lastly a series of diagnostic checks were done on residuals. This methodology is along the lines of work done by Nogales *et al*. (2002) [4], Contreras *et al*. (2003) [5], Cuaresma *et al*. (2004) [6], and Conejo *et al*. (2005) [7].

4.1 Stationary Test

Before zonal hourly prices can be fitted to any model, they need to meet the stationary condition. To start with, a time series plot of the zonal hourly prices was plotted as shown in Figure 1 below (North zone). The time series plot doesn't reveal anything outright: the plot seems very volatile; while it is not trending in any direction per se but it gives no clue whether the prices have stochastic drift or a deterministic trend.

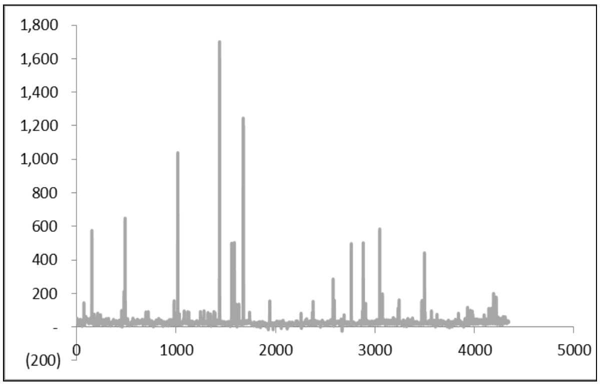


Fig 1: Plot of North Zone Power prices

To detect the stationary in the time series, the formal unit root tests were carried out. The result from Dickey Fuller (DF) and KPSS tests is shown in Table 3 below.

Table 3: Dickey Fuller and KPSS tests on raw data for North, Houston and South zones.

	North	Houston	South
Dickey Fuller	-28.25	-33.98	-29.39
KPSS (p Value)	0.01	0.01	0.01

Result from DF test, follows Tau distribution and upon comparing with critical values, null hypothesis is rejected, which implies that prices are stationary. But the p values from KPSS test is 0.01, which allows us to reject the null (that price is stationary) and hence implies that prices are non-stationary.

Since DF test, checks only for I (1) stationary condition, the DF test could be flawed especially if the raw price is not integrated of order one. To further analyze whether these time series are stationary, the ACF and PACF plots (correlogram) and the correlation table were generated. As shown in Figure 2 below (North zone), there is a strong correlation in hourly prices especially in the beginning region (in-circled in red) and in the middle region (in-circled in blue). For North zone, ACF correlation at first lag is as high as 0.69 and is significantly high for up to 7th lag; but perhaps the autocorrelations at lags 2 and above are merely due to the propagation of the correlation at first lag. This assumption is confirmed upon analyzing the PACF plot which has a significant positive spike only at lag 1 (all though it has negative spikes at 4th and 5th lag). Similarly, in the middle region, in the vicinity of 19 to 30 lags, both the ACF and PACF plots depicts a region of high correlation, with correlation peaking at 24th lag (ACF: 0.434 and PACF: 0.136). Like above in the middle region too, correlation at 24th lag is propagating to subsequent lags. These plots are very different from those of a stationary process, say for example white noise: the ACF and PACF plot of white noise is randomly centered around mean in both the directions and are not significant. This implies that the North zone prices are not stationary àand differencing is required before proceeding further.

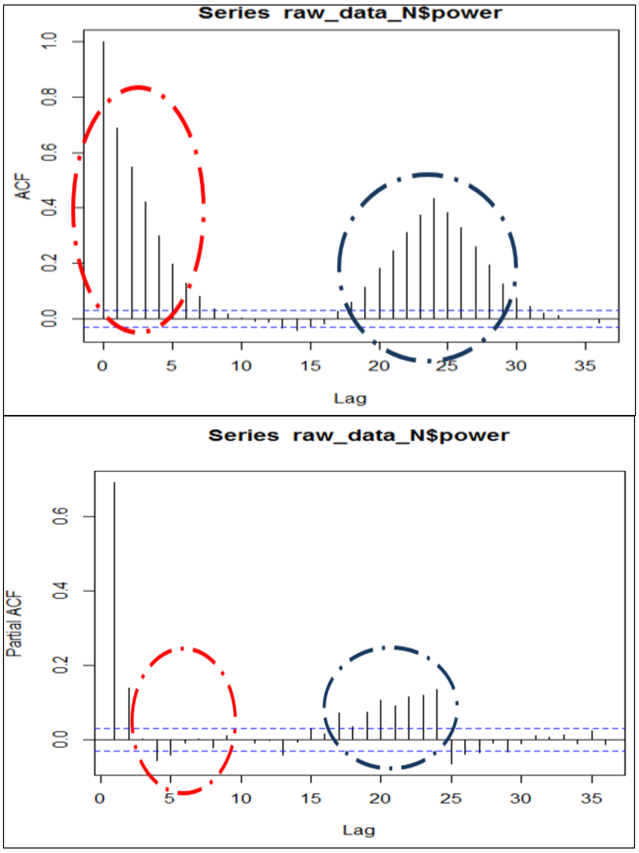


Fig 2: ACF & PACF plots of North Zone Power prices

Intuitively, it makes a lot of sense for the power prices to depict such a correlation. Power prices are function of demand and demand in turn is a function of "Electrical Activity" in the zone. Since the amount of electrical activity don`t change substantially between two successive hours, prices in consecutive hours depict high correlation. Similarly, the amount of "Electrical Activity" in a given hour on two successive days is almost the same, the prices are strongly correlated with prices 24 hours back. For example "Electrical Activity" at say 9:00 am on two consecutive days is almost same and hence a strong correlation in prices.

A similar story holds true for power prices in Houston and South zones. In these zones also, the hourly prices are strongly correlated with prices in previous hour and prices 24 hours back and their ACF and PACF plots looks very similar to that of North zone. Please refer to Appendix A for ACF and PACF plots of all the three zones.

To make the series stationary, non-seasonal first order differencing and seasonal twenty-fourth order differencing is required. After differencing, formal stationary test Augmented Dickey Fuller (ADF) was carried out on the differenced data and it was found to be stationary as shown in the Table 4 below. This modification is consistent with Bowden and Payne, 2008.

Table 4: ADF test on differenced data for North, Houston and South zones.

	North	Houston	South
Augmented Dickey Fuller	-20.72	-20.31	-20.27

For the North zone, the ADF test yielded -20.72, for Houston zone it yielded -20.31 and for South zone, it was -20.27. For all the three zones, the ADF value is beyond the critical values from Tau table and so null hypothesis was rejected. To further ascertain that the series is stationary, the ACF and PACF correlogram and tables for differenced series were generated and it confirmed that the differenced series is stationary. Please refer to Appendix B for ACF & PACF correlogram on differenced data. For ADF test above, number of lags was calculated using a thumb rule suggested by Schwert (1989) and is given by following formula:

$$\text{Lag}_{\text{Maximum}} = \{12 * (N/100)^{0.25}\}$$ where N is the number of observation.

The number of lags was calculated to be 30.

4.2 ARMA Model

Now that the data is stationary, it can be fitted into an ARMA model. To determine the lags for ARMA model, the ACF & PACF plots and correlation table for differenced series was analyzed. The detailed analysis only for north zone has been presented here but a similar analysis was carried out for other zones also.

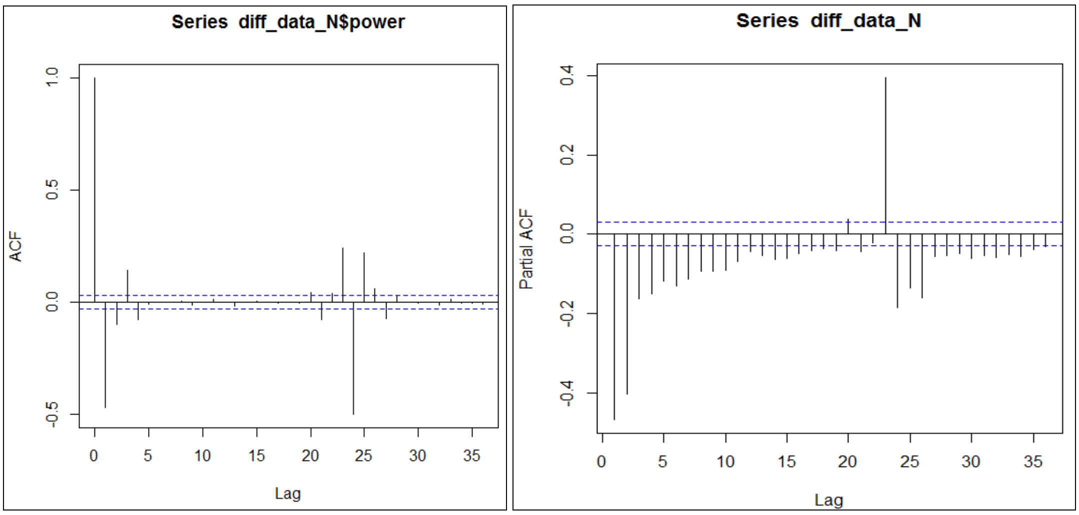


Fig 3: ACF & PACF plots of North Zone differenced prices

Table 5: ACF and PACF correlation table for North Zone differenced prices.

ACF		PACF		ACF		PACF	
Lag	Correlation	Lag	Correlation	Lag	Correlation	Lag	Correlation
1	-0.467	1	-0.467	19	-0.004	19	-0.042
2	-0.097	2	-0.403	20	0.045	20	0.037
3	0.146	3	-0.162	21	-0.078	21	-0.045
4	-0.076	4	-0.150	22	0.039	22	-0.023
5	-0.006	5	-0.118	23	0.245	23	0.394
6	-0.001	6	-0.131	24	-0.497	24	-0.184
7	0.001	7	-0.113	25	0.221	25	-0.137
8	0.006	8	-0.092	26	0.062	26	-0.161
9	-0.013	9	-0.093	27	-0.072	27	-0.057
10	0.002	10	-0.091	28	0.034	28	-0.054
11	0.013	11	-0.069	29	0.003	29	-0.048
12	0.003	12	-0.043	30	-0.001	30	-0.062
13	-0.018	13	-0.054	31	0.002	31	-0.053
14	0	14	-0.064	32	-0.012	32	-0.058
15	0.007	15	-0.061	33	0.012	33	-0.053
16	0.001	16	-0.049	34	-0.003	34	-0.056
17	-0.002	17	-0.042	35	-0.002	35	-0.04
18	0.002	18	-0.038	36	-0.005	36	-0.033

From the correlation graph and table above, one can see i) an MA effect in the region of 1st, 2nd and 4th lag ii) a substantial MA effect in the region of 24th to 27th lag iii) and AR effect in the 23rd and 3rd lag. Given this, many ARMA model with different orders can be potentially fitted. Several models were fitted to the data and the Table 6 below shows a summary statistics for them. As shown in the table, the ARIMA (23,(1,24)) has the least Conditional Sum of Squares (CSS) and AIC values and hence is the best ARMA model for North zone. Q refers to Ljung Box statistics; its value is the same for all the models and hence is not really a deciding factor here.

Houston Zone

For Houston zone, as shown in Figure 4 below, there is i) an MA effect in the region of 1st and 2nd lag ii) a second MA effect in the region of 24th to 26th lag & 29th lag iii) and AR effect at 23rd and 25th lag. Again several models of different orders were fitted and relevant statistics from the same has been summarized in Table 7 below. In this case, ARMA (25,(1,24)) was chosen because it has the least CCS (16,082,400) and AIC (47,804) values.

Table 6: Comparison of CSS, AIC and Q stat for different models for North Zone

	CSS	AIC	Q10	Q20	Q30
ARMA (23, (1, 24))	17,731,415	48,222	268	271	1,083
ARMA (23, (1, 2, 24))	4,768,501,775	70,881	268	271	1,083
ARMA (23(, 1, 4, 24))	3.3 E+44	418,699	268	271	1,083
ARMA (0, (1, 24))	3.3 E+44	418,699	268	271	1,083

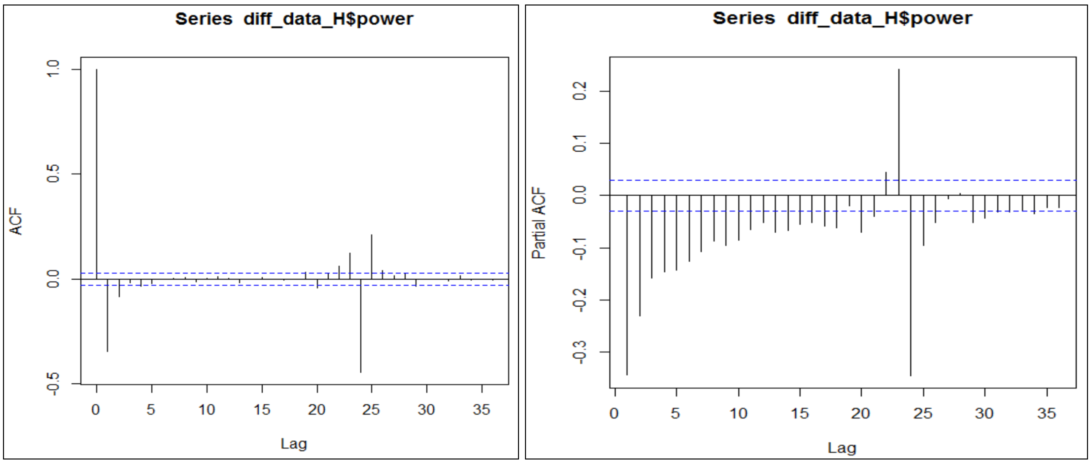


Fig 4: ACF & PACF plots of Houston zone differenced prices

Table 7: Comparison of CSS, AIC and Q stat for different models for Houston Zone

	CSS	AIC	Q10	Q20	Q30
ARMA (25,(1,24))	16,082,400	47,804	201	247	852
ARMA (25,(1,2,24))	19,601,324	48,660	201	247	852
ARMA (23,(1,24))	16,365,847	47,878	201	247	852
ARMA (23(,1,2,24))	20,067,665	48,761	201	247	852

South Zone

Similarly for South zone, as shown in Figure 5 below, there is i) an MA effect in the region of 1st and 2nd lag ii) second MA effect in the region of 24th lag iii) and AR effect in the 22nd and 25th lag. The Table 8 below summarizes the relevant statistics and in this case the ARMA (25,(1,2,24)) model was chosen. The selection criteria remains the same i.e. least CSS and AIC and again Q statistics has no role to play here.

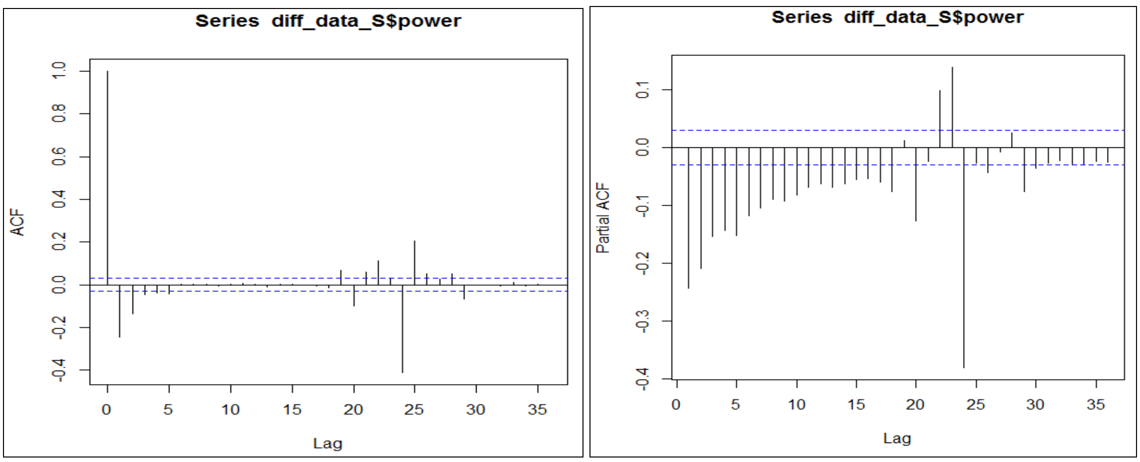


Fig 5: ACF & PACF plots of South zone differenced prices

Table 8: Comparison of CSS, AIC and Q stat for different models for South Zone

	CSS	AIC	Q10	Q20	Q30
ARMA (25,(1,24))	31,290,117	50,678	221	310	601
ARMA (22,(1,24))	32,441,421	50,833	221	310	601
ARMA (25,(1,2,24))	31,102,173	50,654	221	310	601
ARMA (22, (,1,2,24))	32,355,047	50,824	221	310	601

The fitted ARMA models for Texas market are different one from MISO market because of the very nature of the power markets. Texas market is very different from MISO market on all fronts: the type and number of generation units are different, demand characteristics are different because they have different weather patterns, demography and population density. Last but not the least, even the network of the physical power lines is different in these two markets. Even within the Texas market, there are differences in order of ARMA model for the three zones, because there are significant differences in generation capacity, consumption patterns and physical power lines distribution between the three zones. So for the three regions, the ARIMA model is as follows:

$$(1 - B_1)(1-B_{24})\, P_t = \alpha + \beta P_{t-i} + \theta_{t-j}\, \varepsilon_{t-j} + \theta_{t-k}\, \varepsilon_{t-k} + \varepsilon$$

Where

P_t is the hourly power price;
ε is moving average;
α is intercept;
B is the backshift operator;
β is the autoregressive co-efficient;
θ are the moving average coefficients;
i, j, k are the time lags and are different for the three zones.

4.3 ARMA Residuals Analysis

After fitting ARMA model to differenced series, residuals of the ARMA model needs to be analyzed. A detailed analysis for North zone is presented here but a similar analysis was done for all zones.

For Normality check, a histogram of the residuals of the ARMA (23,(1,24)) model was drawn. As shown in Figure 6 below, the curve is sharply peaked at mean and has very thin tails, suggesting that residuals mayn’t be normal. Also, upon drawing the Normal Q-Q plot of the residuals, the resultant graph doesn’t lie on a 45 degree line and it again suggests that the residuals are not normal. Upon doing a formal test, Jarque-Bera (JB) yielded a value of 8323160 which has a Chi-Square distribution with two degrees of freedom and is beyond the critical values. The null hypothesis is rejected and it confirms that residuals are not normal.

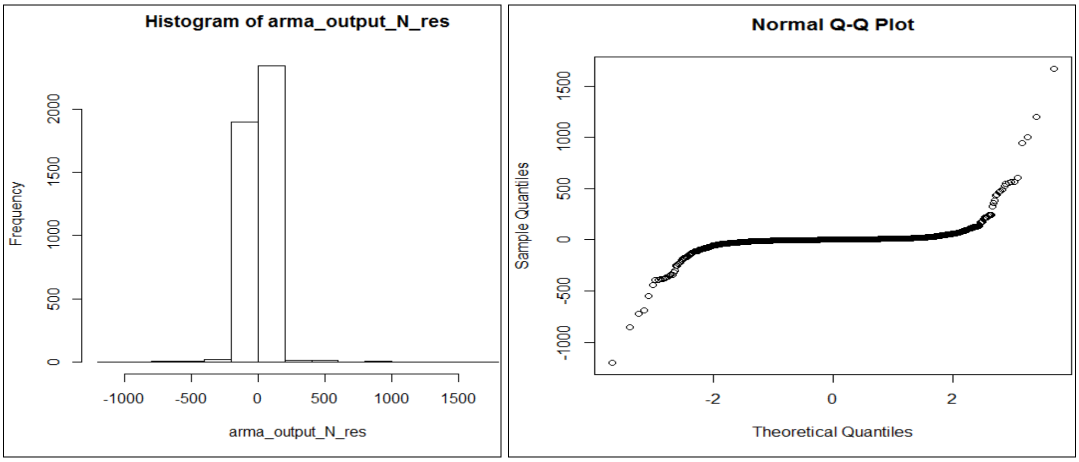


Fig 6: Histogram and Q-Q plot of ARMA (23,(1,24)) residuals for North zone

To do the autocorrelation test, ACF and PACF correlogram was generated using ARMA (23,(1,24)) residuals, and as shown in Figure 7 below, there are significant lags in the region of 1st to 5th lag and 21st and 26th lag. Upon doing a formal Box-Ljung (BJ) test with 30 lags, it yielded a value of 1082.7; this has a Chi-Square distribution with 30 degrees of freedom and falls outside the critical values, implying that there is autocorrelation in residuals.

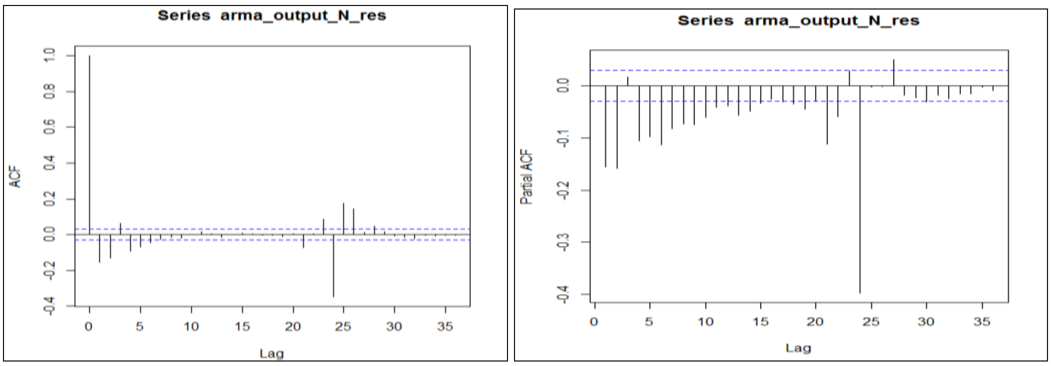


Fig 7: ACF and PACF plot of ARMA (23,(1,24)) residuals for North zone

To test for heteroscedasticity, a plot of residuals was drawn and as shown in Figure 8 below, residuals are not distributed uniformly (in-circled in red) like in case of homoscedasticity. This kind of plot suggests that there could be heteroscedasticity. To confirm this, a formal test for ARCH effect was done with 30 lags; ArchTest yielded a value of 875.6 which has a Chi-Square distribution with 30 degree of freedom and it falls outside the critical values. Based upon this, null hypothesis that "there is no ARCH effect" is rejected.

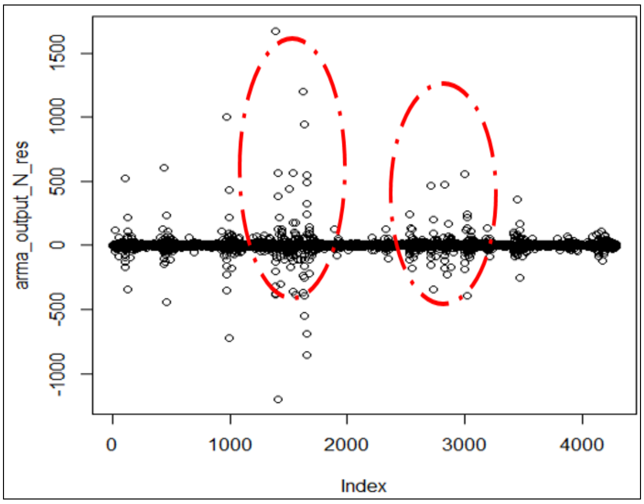


Fig 8: Plot of ARMA (23,(1,24)) residuals for North zone

To further ascertain the presence of heteroscedasticity, a plot of the differenced series was drawn and as is evident from Figure 9 below, the differenced series depicts ample sign of volatility clustering. Given this we need a more sophisticated model to model it properly.

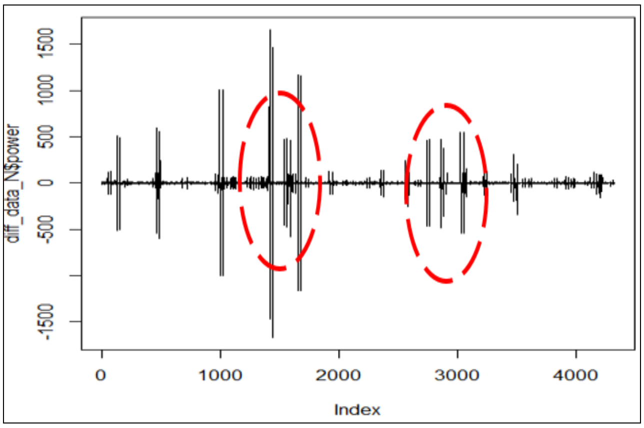


Fig 9: Plot of differenced data for North zone

Similarly, for Houston and South zones, the residuals were found to be non-normal and fail the formal Jarque-Bera test. The ACF and PACF plots of residuals demonstrate significant correlation with distant residuals, fail the formal Ljung Box test and confirm presence of autocorrelation. Like in north zone, the residual for these zones also, are not distributed uniformly, fail the ARCH test which confirms that they have heteroscedasticity. Please refer to Appendix C for Houston and South zone details.

4.4 GARCH Modelling

Since the differenced series above, exhibits conditional heteroscedasticity and raises the possibility of inverse leverage effect, it needs to be model by (G)ARCH, because these models can handle the serial correlation in volatilities very well (Duffie *et al.*, 1998; Escribano *et al.*, 2002; Hadsell *et al.*, 2004; Longstaff and Wang, 2004) [11, 12, 13, 14]. Although there are many variants of GARCH available, Exponential GARCH (EGARCH) is best suited for the job; EGARCH has a non-linear form and can accommodate the asymmetric time varying volatility and inverse leverage effect exhibited by power prices.

Different orders of EGARCH models were fitted but the one with order (1,1) has the maximum MLE and minimum AIC as shown in Table 9 below; also this version makes the model simpler for interpretation and hence was selected for modeling. Besides, there are very minor differences in MLE and AIC values for different models across all the three zones.

Table 9: Comparison of MLE & AIC values for different orders of EGARCH model

		North	Houston	South
EGARCH(1,1)	MLE	-15046.2	-14607.1	-14396.1
	AIC	7.9	7.7	7.6
EGARCH(1,2)	MLE	-15075.6	-14631.7	-14395.5
	AIC	7.9	7.7	7.6
EGARCH(2,1)	MLE	-15052.2	-58514.6	-14391.6
	AIC	7.9	30.9	7.6
EGARCH(2,2)	MLE	-15049.8	-14609.6	-14396.1
	AIC	7.9	7.7	7.6

The specification of an EGARCH (1,1) model is as follows:

$$\text{Log}\ (h_t^2) = \omega + \lambda\ |\varepsilon_{t-1}/\ (h_{t-1})^{0.5}\ | + \gamma\ \{\varepsilon_{t-1}/\ (h_{t-1})^{0.5}\} + \phi\ \log h_{t-1}^2$$

where

h_t^2 is the volatility of the ARMA residuals. Gamma (γ) captures the leverage effect (Bunn & Karakatsani, 2003; Knittel and Roberts, 2005) and is representative of asymmetric effects in response to shocks. If γ is greater than zero, it indicates presence of an inverse leverage effect, when it is less than zero it indicates the leverage effect and when it is zero, the impact on volatility is same for both negative and positive shocks. Omega (ω) is the mean of the volatility equation; Lamda (λ) represents the size effect which indicates how much volatility increases irrespective of the direction of the shock. The last term ϕ indicates the degree of volatility persistence.

Ideally, the ARMA and EGARCH fitting should have been fitted in one step only but because of limitations of R, it couldn't be done in one step. For purposes for this paper, this was carried out in two steps. In first step, only the ARMA model was fitted (step 4.2) and in second step, the residuals of the ARMA model were fitted into EGARCH (1,1) model.

4.5 GARCH Model Residual analysis

A subsequent analysis of the residuals was undertaken to ensure that they are indeed white noise. When a formal ARCH test was done on the residuals to detect heteroscedasticity, it yielded a value of 1.5 (North zone) which is within the critical limits and confirmed that there is no ARCH effect in the residuals. The Q statistics from Ljung Box test yielded a value of 35.98 (North zone) and is again within the Chi Square critical limits; the null hypothesis couldn`t be rejected implying there is no autocorrelation in the residuals. Additionally, the ACF & PACF correlogram of the residuals is similar to that of white noise and suggest that residuals are not correlated shown in Figure 10 below (North zone). Please refer to Appendix D for details of these tests.

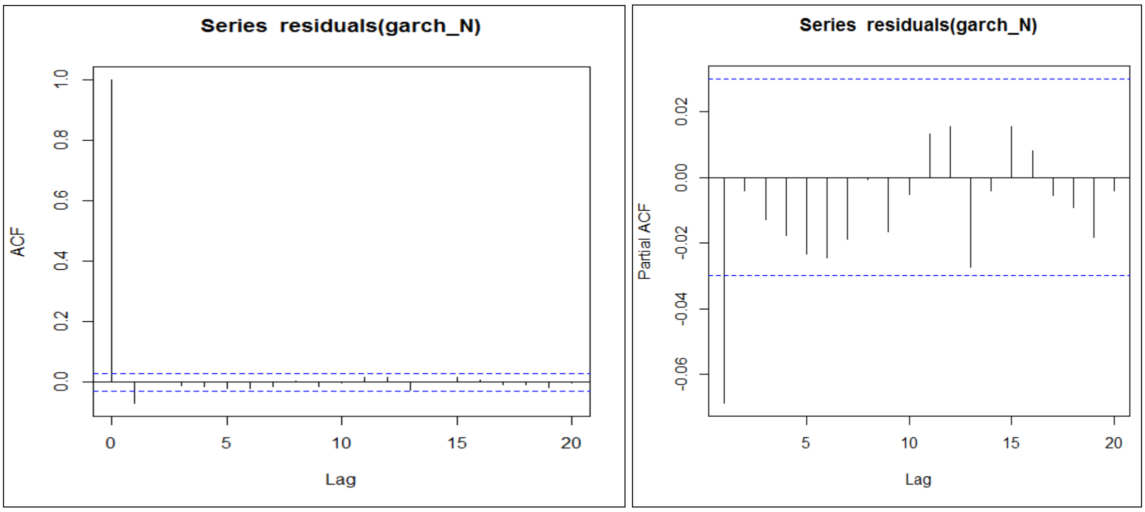


Fig 10: ACF and PACF correlogram of GARCH (1,1) residuals for North zone

4.6 Analysis of Coefficients:

The Table 10 below, consolidates the ARMA coefficients for the three zones. The first row shows the estimated value and the second shows standard error.

All the ARMA co-efficients (excluding the intercepts) have high t statistics; the null hypothesis that they are zero is rejected implying that these coefficients are statistically significant at 0.1% level. Although, the intercept is not significant, but even then it has been included because the CSS and AIC values for models with constant is smaller than for those without constant. For North zone, MA1 term has the highest value (-0.653), implying that prices in prior hour has the highest periodicity. While for the Houston and South zones, the MA24 term has the highest value (-0.929 for Houston and -0.946 for South Zone), implying that in these zones, periodicity with prices 24 hours back is the highest. This makes sense intuitively also: North zone has almost 70% of generation units for whole of Texas, so in this zone "Supply" plays the pivotal role in price determination. Since most of these plants are baseline units - which generate a constant amount of power 24X7- the supply is almost the same between two successive hours and hence prices are high correlated with prior hour prices. While South and Houston zones are more of "Load Zones" with far fewer generation capacities. These areas are also densely populated, have higher demand for power and hence demand plays a pivotal role in price determination. Since the hourly demand / load is almost the same 24 hours apart, prices in these zones are strongly correlated with prices 24 hours back. Invertibility conditions are satisfied for Houston and South zones but not for the North zone.

Similar to mean equation, all the co-efficients of variance equation - as shown in Table 11 below - also have high t statistics and so the null hypothesis that they are zero is rejected. The sign of gamma term is positive and is statistically significant at 0.1% level and so it confirms the presence of inverse leverage effect in all the three zones.

Table 10: Consolidated ARMA coefficients for North, Houston and south zones

		North	Houston	South
AR23	Coefficient	-0.078		
	Std Error	0.015		
MA1	Coefficient	-0.653	-0.064	-0.027
	Std Error	0.032	0.013	0.006
MA24	Coefficient	-0.301	-0.929	-0.946
	Std Error	0.036	0.010	0.007
AR25	Coefficient		0.169	0.216
	Std Error		0.019	0.016
MA2	Coefficient			-0.030
	Std Error			0.006
Intercept	Coefficient	-0.067	-0.000	-0.001
	Std Error	0.057	0.013	0.009

So, given a positive shock to volatility, the prices will increase more, than in case of negative shock to volatility. Intuitively, when there is an increase in demand, generators with higher marginal costs are required to turn on their power plants, these plants set the LMP and hence market witnesses higher volatility. Also, this effect is highest in case of South zone (1.90), followed by Houston zone (1.89) and then by North Zone (0.995). Again, intuitively it makes sense: the physical power lines between North to South zone and North to Houston zone, have relatively lower capacity and these lines get congested during peak hours. Hence any positive shock - increase in demand in south or Houston zone - will shoot up the price in these zones and hence a significant impact on volatility. The size effect is negative and is also statistically significant at 0.1% level. The impact of shock is highest in Houston (-1.05) and South (-1.00) zones and relatively lower in North zone (-0.27) for the reasons mentioned above. The degree of volatility persistence (Chi) is positive, varies from 0.472 for South zone to 0.736 for North zone and is statistically significant at 0.1% level. Since all the coefficients are highly significant, it implies that volatility is time varying. These statistics combined together very elegantly explain the various characteristics of volatility exhibited by power prices and confirm that volatility is time varying, non-linear, asymmetric and that it exhibits an inverse leverage effect even in Texas market. These results are consistent with those of Bowden & Payne, 2008;

Table 11: Consolidated EGARCH coefficients for North, Houston and South zones

		North	Houston	South
Omega	Coefficient	1.828	3.413	3.471
	Std Error	0.194	0.192	0.215
Lamda	Coefficient	-0.269	-1.050	-1.001
	Std Error	0.055	0.067	0.069
Gamma	Coefficient	0.955	1.894	1.904
	Std Error	0.157	0.085	0.091
Shi	Coefficient	0.736	0.486	0.472
	Std Error	0.030	0.028	0.032

5. Forecasting and Model Evaluation

After the model has been developed, it was used to forecast the prices for first week of July i.e. from 1st July 2009 to 7th July 2009. Four forecast evaluation statistics were used to measure the prediction accuracy: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error(RMSE), and Theil Enequality Coefficient (TEC). Since RMSE and the MAE statistics depend on the scale of the variable, it is best suited when comparing the forecast of same variables across different models, nevertheless they have been used here. But MAPE and the TIC are insensitive to the scale of the variable and hence are better to evaluate the performance of this model. For all these statistics, smaller the value, the better the prediction is from the model.

Mean Absolute Error (MAE): $\sum_{t=T+1}^{T+h} \left| \frac{p1-p2}{h} \right|$

Mean Absolute percentage error (MAPE):

$$[\sum_{t=T+1}^{T+h} \left| \frac{p1-p2}{p2} \right| / \, h \,] \times 100$$

Root Mean Squared error (RMSE):

$$\sqrt{\sum_{t=T+1}^{T+h} \frac{(p1-p2)^\wedge 2}{h}}$$

Theil Inequality Coefficient (TIC):

$$\frac{\sqrt{\sum_{t=T+1}^{T+h} (p1-p2)^\wedge 2/h}}{\sqrt{\sum_{t=T+1}^{T+h} p1^\wedge 2/h + \sum_{t=T+1}^{T+h} p2^\wedge 2/h}}$$

Where
p1 = $\acute{p}_t^j$ forecasted price in period t, at h horizon & p2 = p_t^j actual price in t period at h horizon.

Table 12 below summarizes the forecast evaluation statistics for the models for the three zones. While the TIC varies within a narrow range of 0.17 to 0.26, MAPE has a range of 19.6 to 20.8 These statistics indicate that the model works best for North zone; the ones for Houston and South zones are almost the same.

Table 12: Out of sample model forecasting performance for North, Houston and South zones

	North	Houston	South
MAE	11.8	13.6	12.1
MAPE	19.6	21.6	20.8
RMSE	20.9	23.4	24.7
TIC	0.17	0.24	0.26

6. Conclusion

In light of the above analysis, it can be concluded that the ARIMA-EGARCH model developed for Texas market is a robust one and can be used to forecasting short term prices. These forecasted prices in turn can be used to place bids in the hourly day-ahead market or take speculative positions. The above analysis also confirms that power prices in Texas market exhibits time-varying volatility because of non-storability of power and convex marginal cost. Not only is this volatility time varying but it is also asymmetric to shocks, meaning the positive and negative shocks will have different impact on volatility. Because of the positive sign of gamma in variance equation, the impact of positive shock is greater than the negative ones and confirms the presence of inverse leverage effect.

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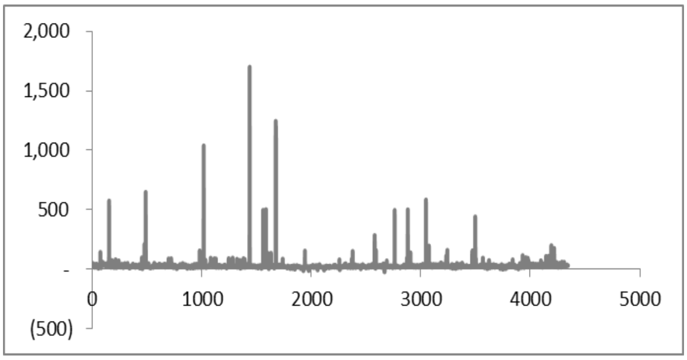
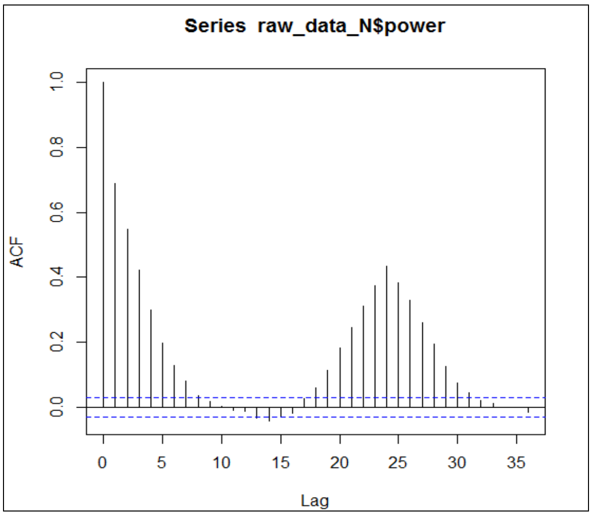
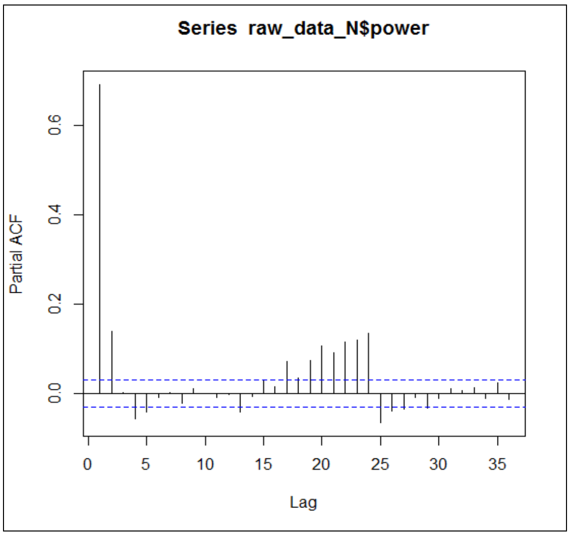
Appendix A: Results for preliminary analysis of raw power prices

North Zone: Power prices plot

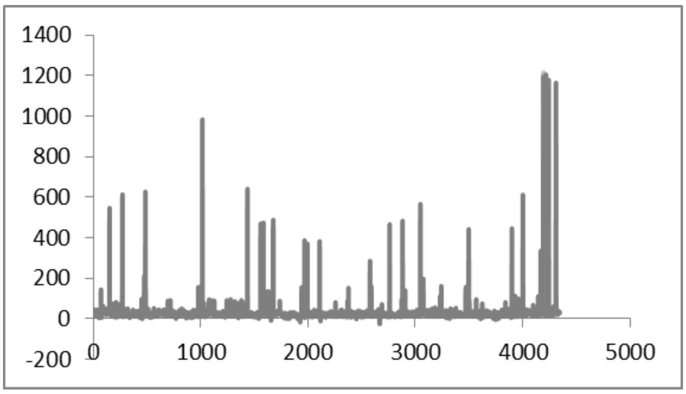


ACF and PACF plots

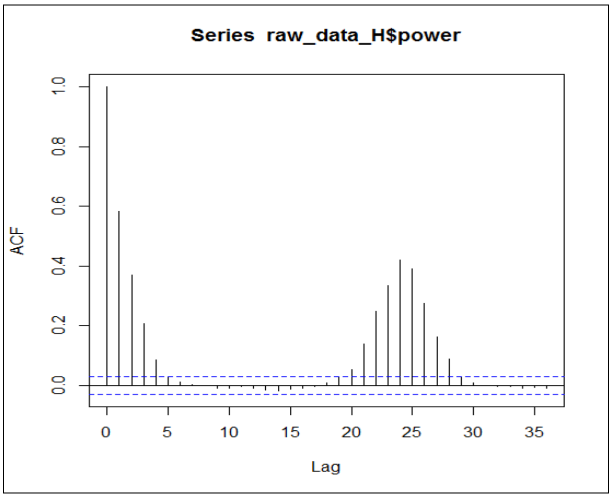


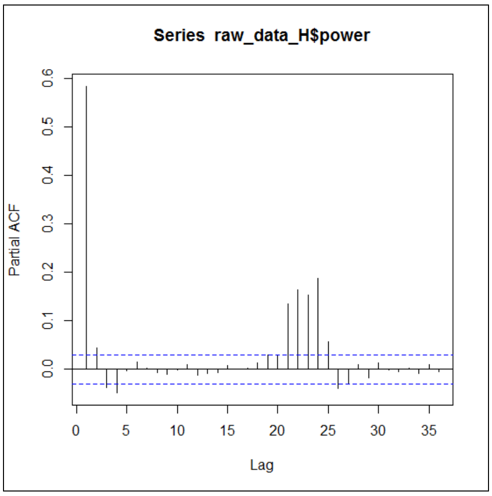


Houston Zone: Power prices plot

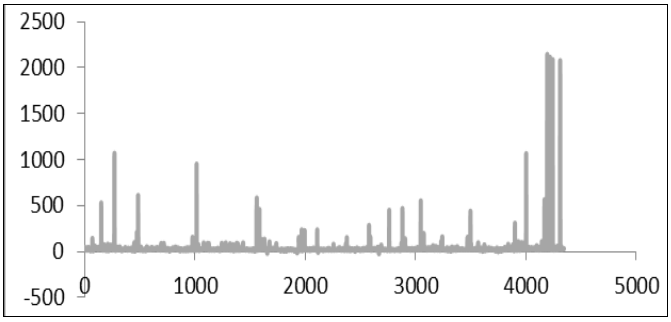


ACF and PACF plots





South Zone: Power prices plot



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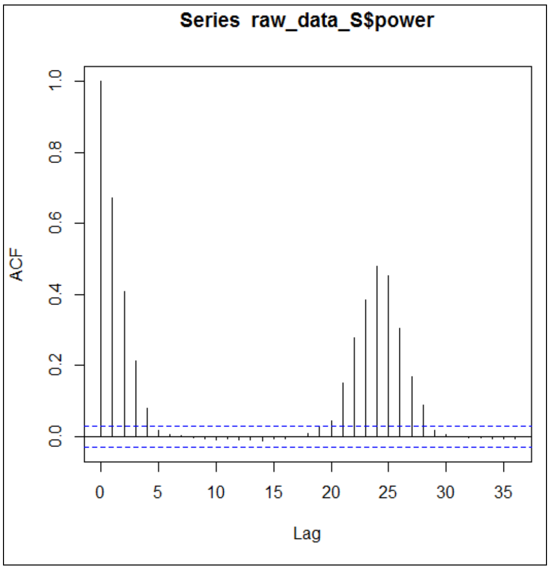
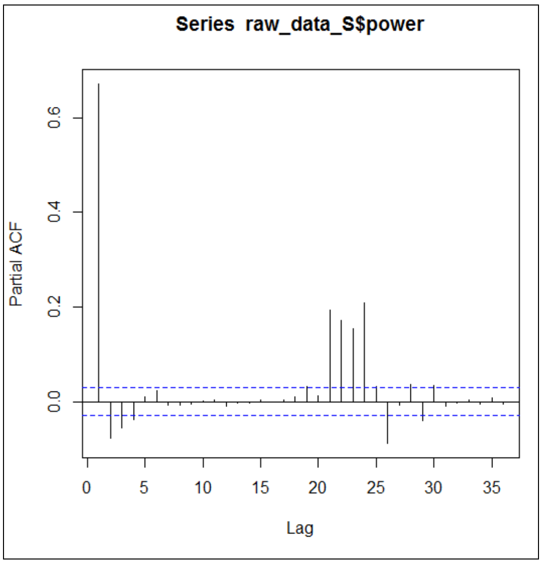
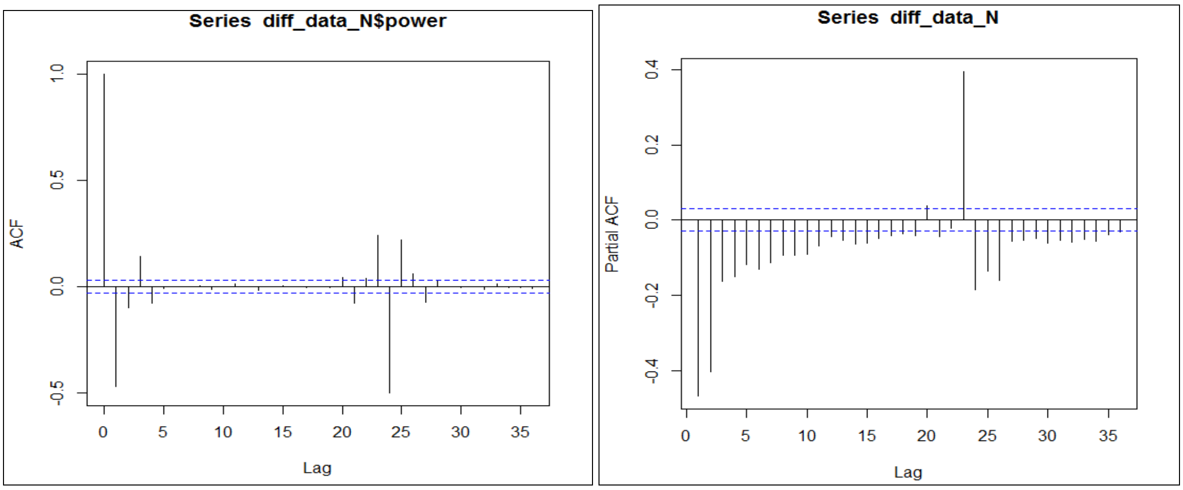
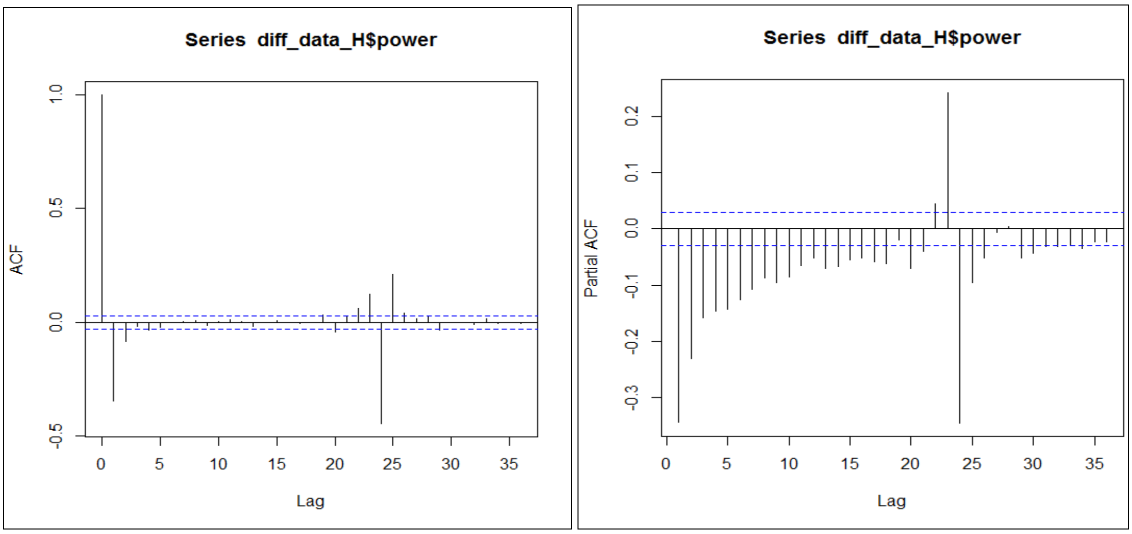




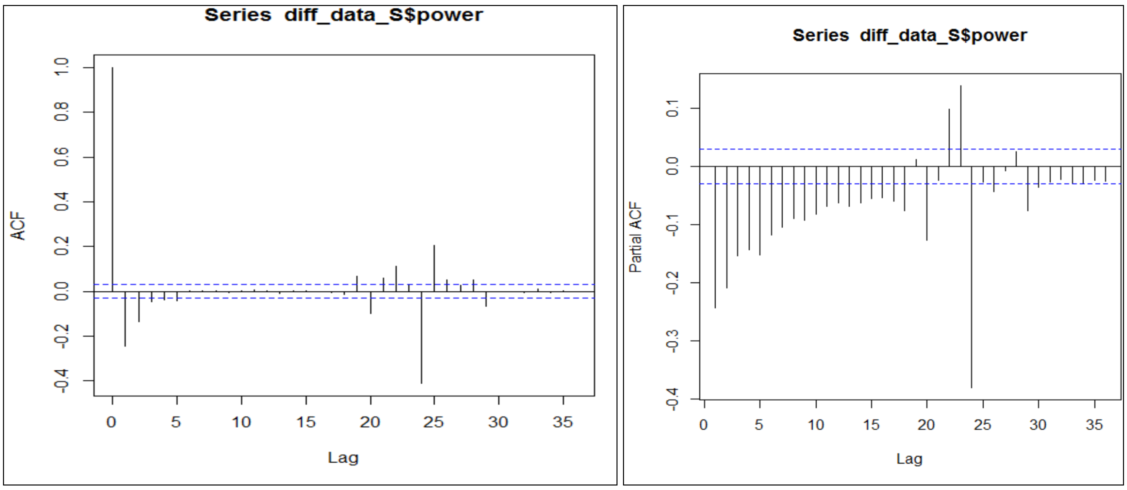
Appendix B: Results for analysis of differenced (stationary) data
North Zone: ACF and PACF plots



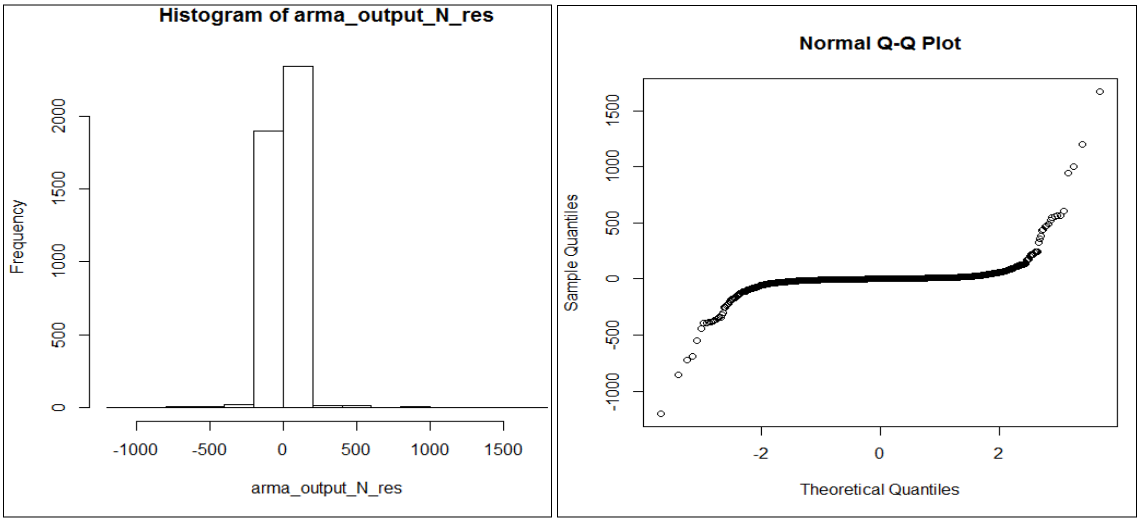
Houston Zone: ACF and PACF plots



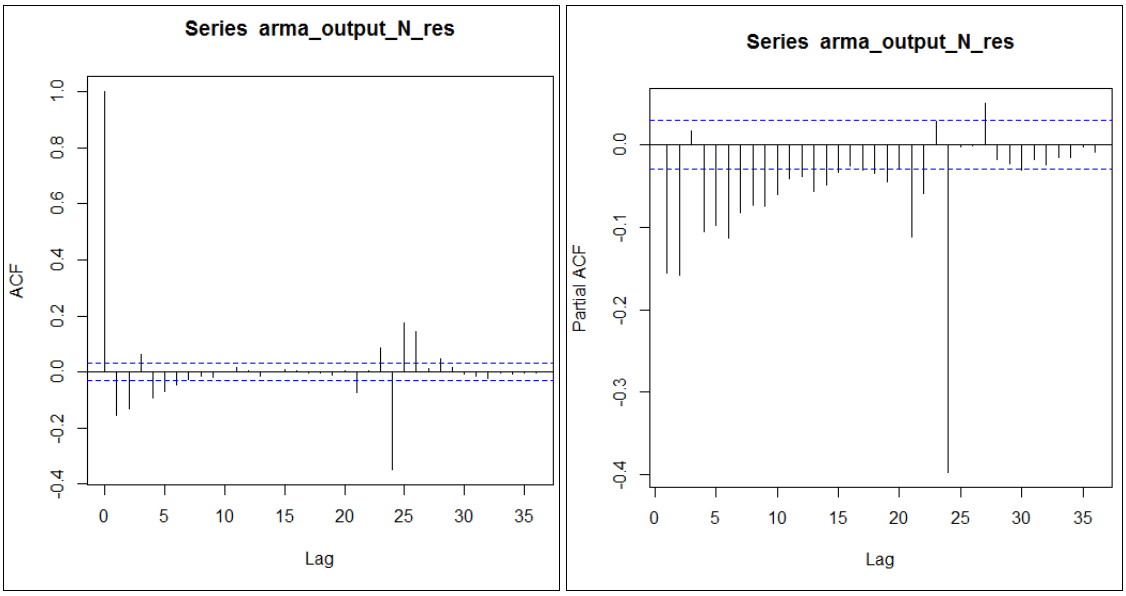
South Zone: ACF and PACF plots



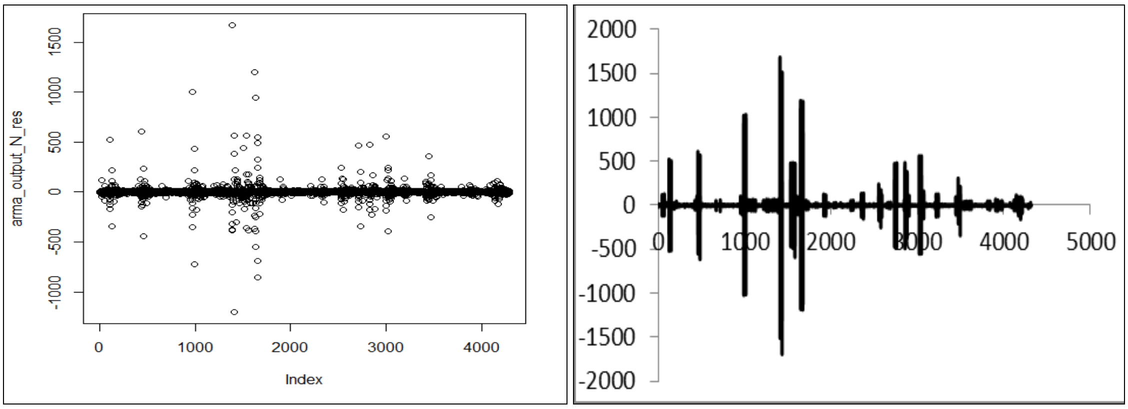
Appendix C: Results from analysis of ARIMA residuals
North Zone: Histogram and Q-Q Plot



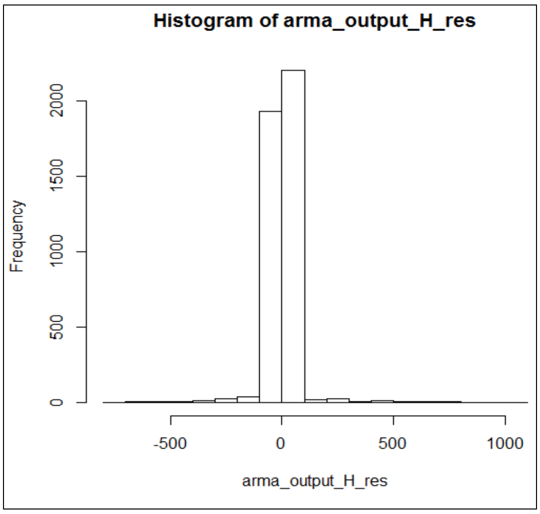
ACF and PACF plots

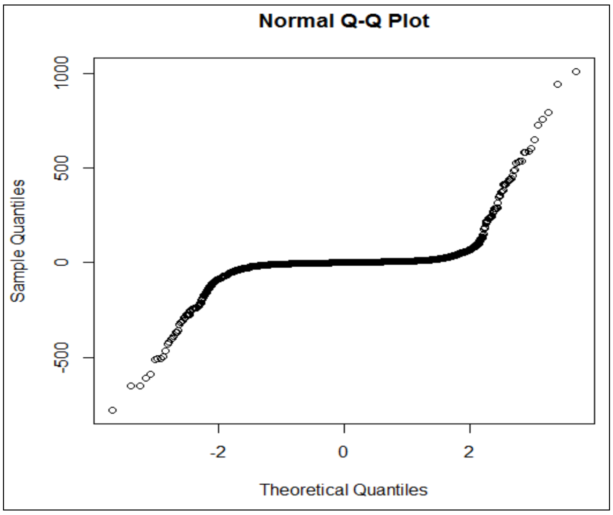


Residual plot for Heteroscedasticity and differenced data plot for volatility tests

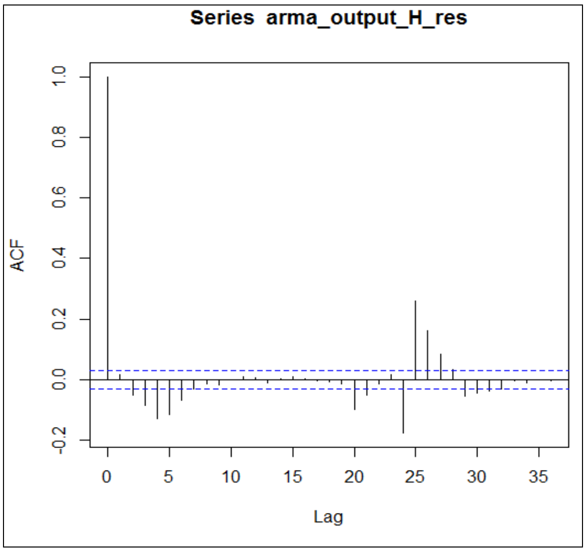


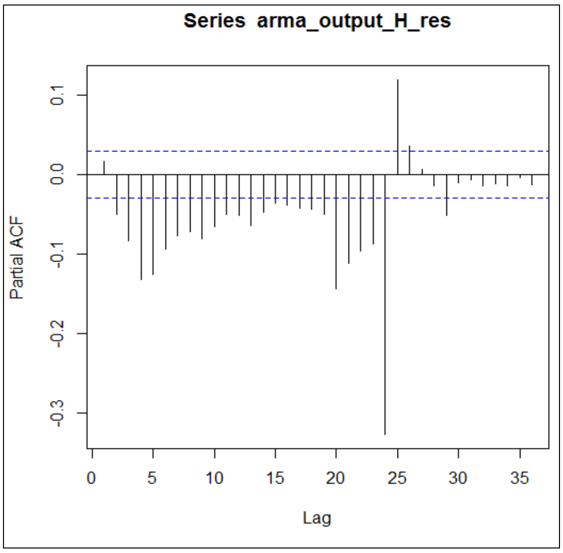
Houston Zone: Histogram and Q-Q plot



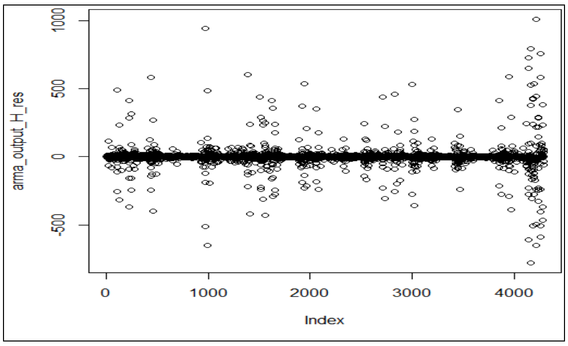


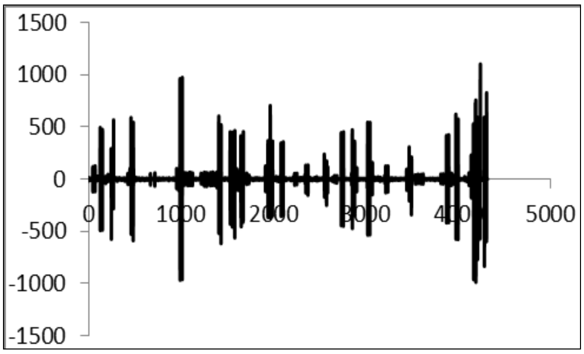
ACF and PACF plots



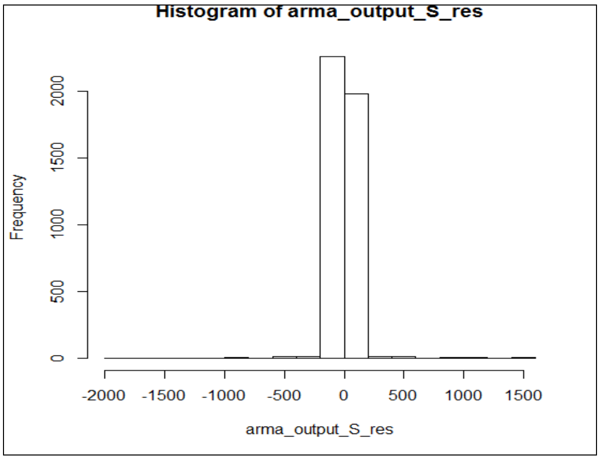


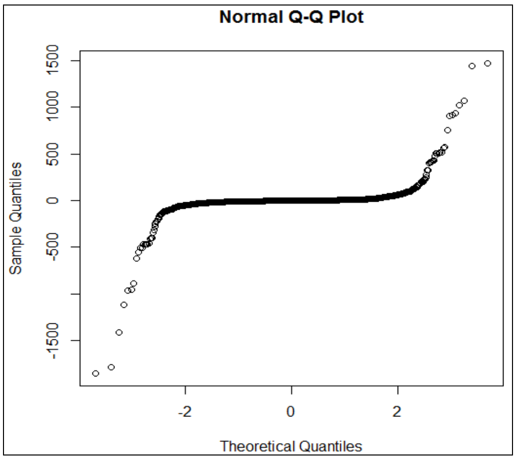
Residual plot for Heteroscedasticity and differenced data plot for volatility tests



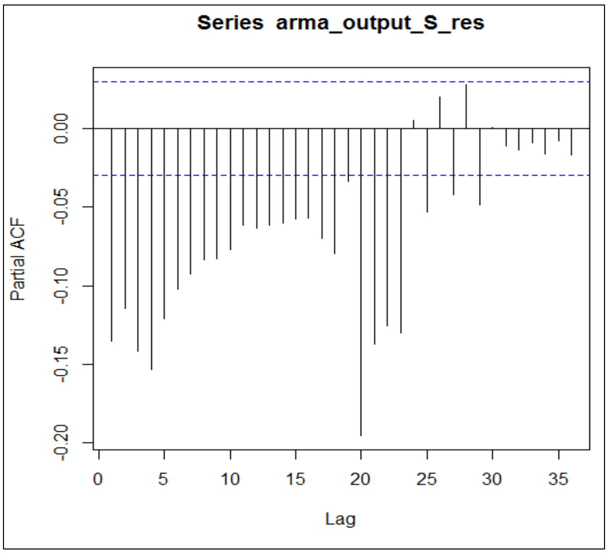


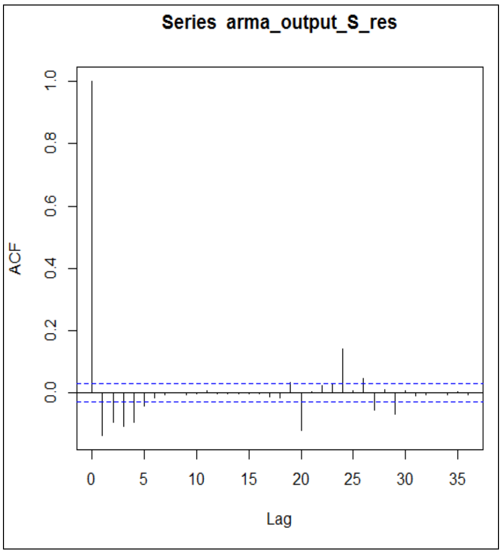
South Zone: Histogram and Q-Q plot

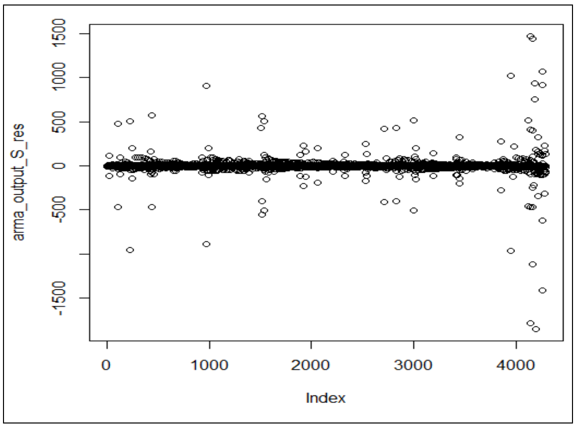


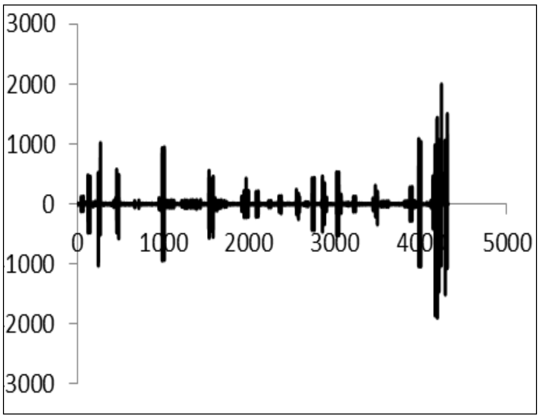


ACF and PACF plots







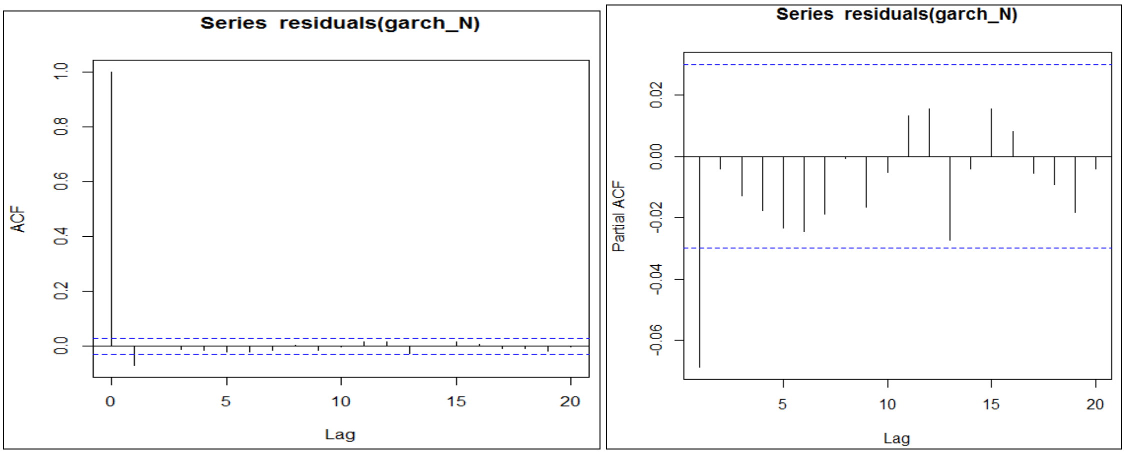


Residual plot for Heteroscedasticity and differenced data plot for volatility tests

Summary of Normality, Autocorrelation and ARCH test

	North	Houston	South
Jarque–Bera	8323160	699465	7033280
Ljung - Box (30 lags)	1082.7	852.3	418.6
ARCH (30 lags)	875.6	1110.3	680.8

Appendix D: Results from analysis of GARCH residuals
North Zone: ACF and PACF plots



Houston Zone: ACF and PACF plots