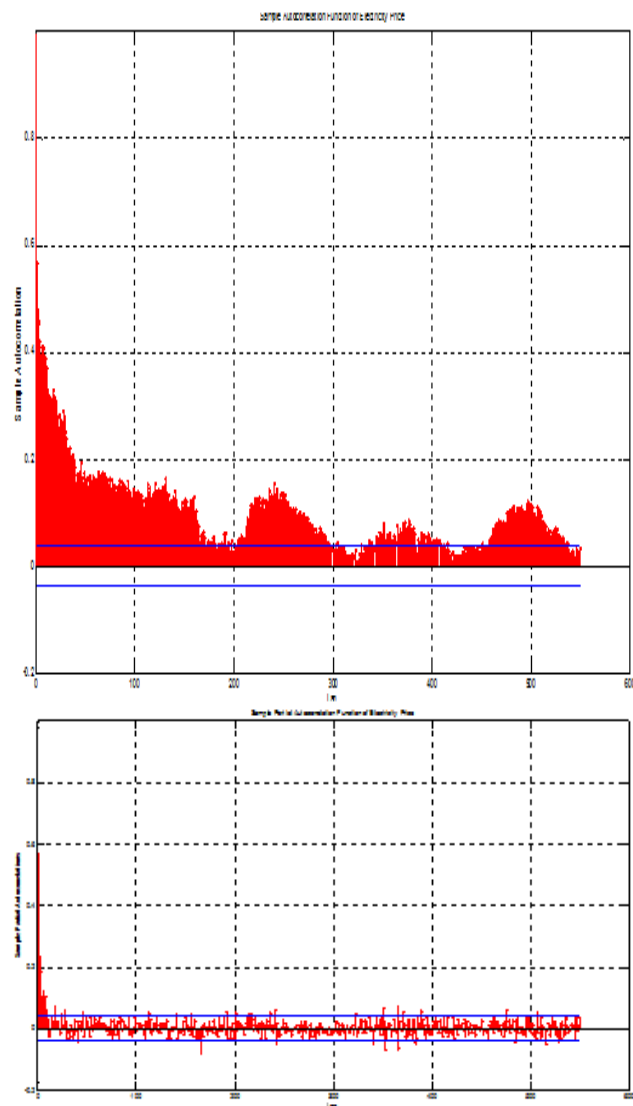






Dickey-Fuller test. From the analysis of stationary of the time series of variables Electricity\_Price, Oil\_Price, Gas\_Price, and TSX\_Index. The plots of these variables show clearly that the variables oil prices, gas prices, and TSX index are non-stationary. To be in a position to use these variables in time series analysis, we considered several transformations to change them to stationary time series. A logarithm transformation of the variables oil price, gas price, and TSX index was conducted to change the time series to stationary. And according to the plot and the Augmented Dicker-Fuller tests, the transformed variables are stationary and ready to be used in the model, from the statistical point of view. Further analysis of this work is focused on the electricity prices. The autocorrelation and the partial autocorrelation analysis of electricity variable are run. Despite the electricity variable being stationary, it exhibiting complicated autocorrelation (ACF) and partial autocorrelation structures (PACF) that consist of seasonal lags

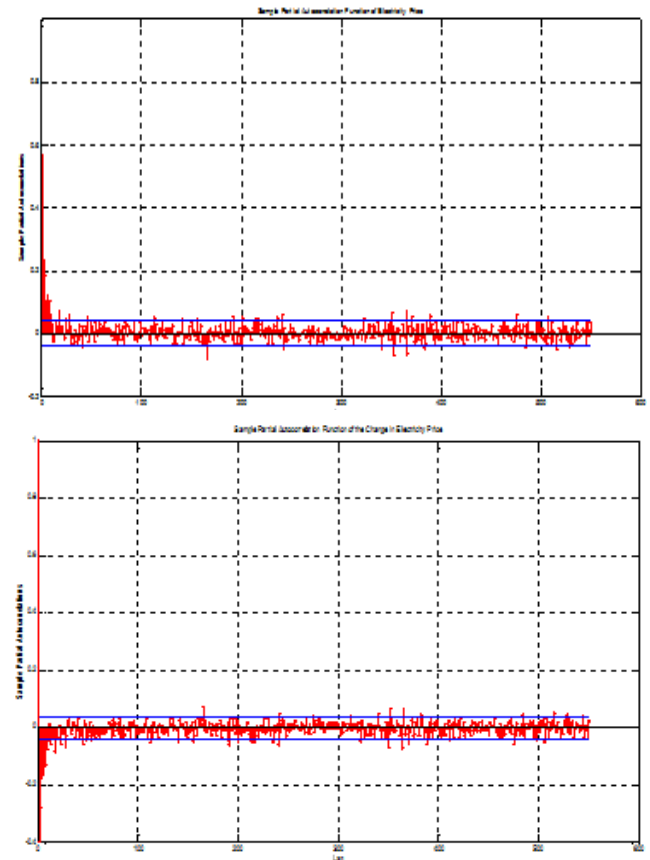
The diagrams below shows the auto correlation functions and partial autocorrelation function of the electricity prices exhibit some seasonal effects.



To remove the seasonal effects we conduct one lag differencing step, which is we subtract the previous day

price with the current day's price. From the differenced electricity prices, we computed the ACF and the PACF. From this differenced electricity price the seasonal effect are very minimal and the plot of the ACF and the PACF clearly shows that.

The plots of the partial autocorrelation function and the autocorrelation function for the differenced electricity prices.



The autocorrelation function and the partial autocorrelation function plot, we see that the electricity prices before differencing were not stationary but after the differencing the changed electricity prices we stationary. Thus we used the differenced electricity prices to for further analysis and determine the best model for analysis.

## 6. Main Results

In this part we investigate different models by estimating them using the method of maximum likelihood. To determine which the best model is we ranked the model on the bases of the Akaike information criterion (AIC) and the Bayesian information Criterion (BIC). In this case the model that had the lowest AIC score was selected to be the best model. Also the model with the lowest BIC score was selected to be the best. Further, on these best model we look at the following properties; relatively low AIC an BIC scores, the residuals are uncorrelated, the models is stationary and leads to stable forecasts and finally the significant of the coefficients at 5% significant level according to the likelihood ratio tests. The model selection for both the electricity prices and the electricity price change was done for different combinations of the R, M, P, Q and

the seasonal lags to determine the model whose coefficients are significant. The following combinations of the R= 2, 3, 4; M=1, 2,3; P=2, 3; Q=1,2 and the seasonal lag from the subsets (11, 21, 84,126, 252). The seasonal lags corresponds to 11 days that is half a month, 21 days 1 month ,84 days 4 months, 126days 6 month and finally 252days corresponds to 1 year. Majority of the model selected failed the Ljung-Box-Pierce Q-test for the departure from the randomness based on the autocorrelation function of the residuals. Some of the model captured the autocorrelation structure and passed the Ljung-Box pierce Q-test, thus led to non-stationary solutions with explosives forecast. When the electricity change is used as the dependent variable in the model and tested on the entire 1152 candidate model. We find that the BIC perform better than the AIC. Thus we use the BIC to select the optimal model. The following results are obtained and used to select the best model.

Mean: ARMAX(2,2,5); GARCH(2,1)

Conditional Probability Distribution: T

Number of Model Parameters Estimated: 15

Parameter	Standard Value	T Error	Statistic
C	-0.045742	0.02283	-2.0036
AR(1)	0.35182	0.21111	1.6665
AR(2)	0.038965	0.062431	0.6241
MA(1)	-0.91925	0.21109	-4.3547
MA(2)	0.064845	0.17363	0.3735
Oil_Log_Return	-6.4532	3.224	-2.0016
Gas_Log_Return	7.4388	2.1922	3.3933
TSX_Index_Log_Return	-15.696	7.1896	-2.1831
K	8.7649	1.4208	6.1689
GARCH(1)	0.37406	0.10994	3.4024
GARCH(2)	0.22036	0.082401	2.6743
ARCH(1)	0.40558	0.056897	7.1283
DoF	3.294	0.16791	19.6178

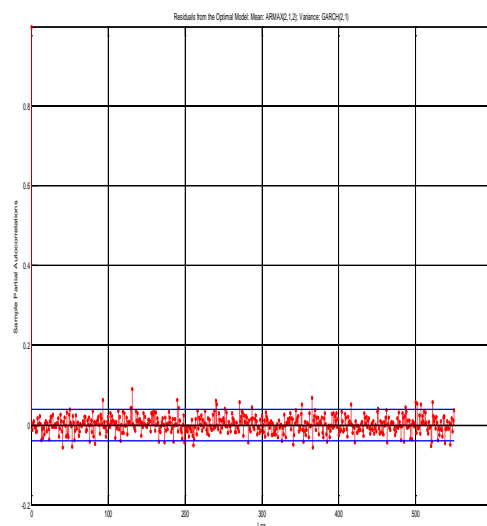
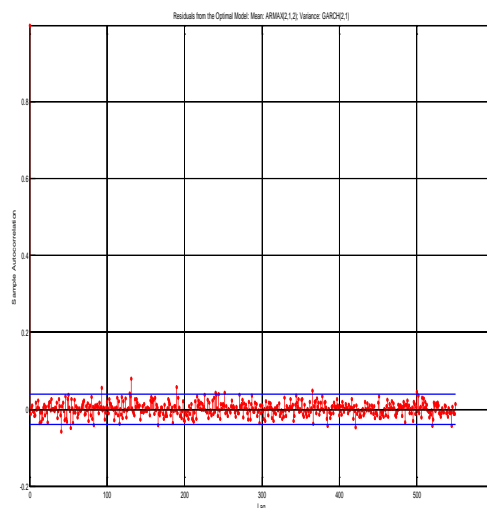
From the above analysis the seasonal lags analysis was statistically insignificant. The residuals also exhibited no autocorrelation, according to the plot of the autocorrelation function and the partial autocorrelation functions as show in the diagrams below.

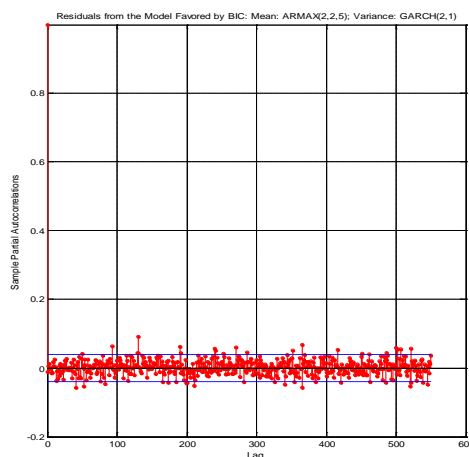
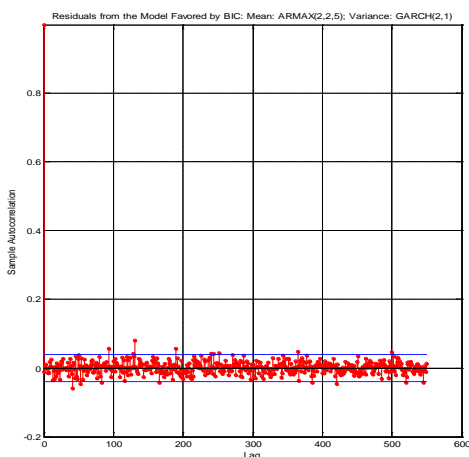
For the refinement of the optimal model, the predictor variables that are highly insignificant are dropped. In the predictor variable TSX-index log return and the second moving average term are still insignificant. We obtain further analysis by dropping either of the two components and the analysis still shows that the model parameters of the predictor variables are insignificant. From this analysis we conclude that both the TSX index log return and the second moving average must be dropped. On dropping the TSX index log return and the second order moving average terms, all the remaining terms in the model are statistically significant at 5% level of significant. Further dropping of the remaining terms lead to contradiction of the likelihood ratio tests and an increase in the value of the AIC and the BIC

values. By analysis the stability of the coefficient estimates of the optimal model by estimating it on different historical sub-intervals, the coefficients estimates do not have much variations. Thus, we accept that the optimal model is attained. The following is the optimal model. From the results of the Ljung-Box pierce Q-test was used to show the residuals exhibit no autocorrelation as follows.

Maximum Lag	Result	P-value	Statistic	Critical Value
10	No autocorrelation	0.9779	3.1397	18.3070
30	No autocorrelation	0.8711	21.5150	43.7730
50	No autocorrelation	0.3786	52.4661	67.5048
100	No autocorrelation	0.4871	99.7893	124.3421

A plot of the autocorrelation function and the partial autocorrelation function that shows no correlation coefficient are shown below. From the above analysis, the p-values are greater than the significant level of 0.05, thus we fail to reject the hypothesis that the data fit the model and conclude that the models significantly fit the data and there is no autocorrelation





From the above plot there are about 5% of the point are outside the bands, which implies that the hypothesis that the autocorrelation and the partial autocorrelation of the residuals are zero is justified.

### 6.1 Forecast

Forecast of the electricity prices using ARMAX and GARCH models.

Sl. No.	Average month observation(2014)	Observed electricity prices	Forecast of electricity price	
			ARMAX(2,1,2)	GARCH(2,1) model
1	January	13.61	10.6812	10.82
2	February	13.29	10.4116	11.35
3	March	18.09	10.1488	11.66
4	April	17.77	9.8926	12.77
5	May	14.90	9.6429	13.66
6	June	14.83	9.3995	14.14
MAPE			0.186256	0.338854
RMSE			3.649345	4.4568461

From above table, the ARMAX (2,1,2) had the lowest root mean square error and the mean absolute percentage error that GARCH (2, 1) model. This indicates that the ARMAX is a better model in forecasting the electricity prices than the GARCH model when there exist exogenous variables.

### 7. Discussion and Conclusion

From the above analysis of the electricity price change, the most optimal model is the ARMAX (2,1,2); GARCH(2,1). Further analysis indicate that the sum of the coefficients on the lagged squared error and the lagged conditional variance was high and close to unity for GARCH(2,1) and ARMAX(2, 1, 2) model. This indicates a high degree of persistence in conditional volatility at Saudi Arabia electricity prices. Thus, the best optimal model for the electricity price change was identified as the GARCH(2, 1), while ARMAX(2, 1, 2) was the best model to predict the electricity prices using the oil log return and the gas log return as the only predictors.

### References

- [1] Nogales, Francisco Javier, et al. "Forecasting next-day electricity prices by time series models." Power Systems, IEEE Transactions on 17.2 (2002): 342-348.
- [2] Birge, John R., and Francois Louveaux. Introduction to stochastic programming. Springer Verlag, 1997.
- [3] Conejo, Antonio J., Miguel Carrión, and Juan M. Morales. Decision making under uncertainty in electricity markets. Vol. 153. Springer, 2010.
- [4] F. J. Nogales, J. Contreras, A. J. Conejo, and R. Espinola, "Forecasting next-day electricity prices by Time Series Model," IEEE Trans. On Power Syst., vol. 17, no. 2, pp. 342-348, Aug. 2002
- [5] Shumway, Robert H., and David S. Stoffer. Time series analysis and its applications. Springer Science+ Business Media, 2010.