International Journal of Applied Mathematical Research, *4 (2) (2015) 393-403*
www.sciencepubco.com/index.php/IJAMR
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doi: 10.14419/ijamr.v4i2.3629
Research Paper

Time series analysis of water consumption in the Hohoe municipality of the Volta region, Ghana

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Abstract

Water is considered as a lifeline of all living things, especially humans; hence its availability is a critical component in the measurement of human wellbeing through the Human Development Index (HDI). Its production and distribution in Ghana, particularly in the Hohoe Municipality of the Volta Region is a challenge. This study seeks to identify the best-fit time series model to the water consumption data in the Hohoe Municipality and to forecast water consumption in the Municipality. This underpins the development of a time-series model for forecasting water consumption levels of the residents, institutions and businesses in the municipality. Several time series models, including AR, MA, ARMA, ARIMA and SARIMA were fitted to the data, and it emerged that the most adequate model for the data was ARIMA (2, 1, and 2). The model was then used to forecast the consumption for the next four years, to advise Ghana Water Company Limited in the municipality to meet the demand of the people.

Keywords: *Human Development; Municipality; ARIMA Model; Forecasting; Consumption.*

1. Introduction

Water is required by all living creatures for survival. It is also required for economic growth and development [3]. According to the UN World Water Development Report (2006), water is an essential life-sustaining element. It pervades our lives and is deeply embedded in our cultural backgrounds." The achievement of the millennium development goals depends largely on improved water supply and sanitation in the developing countries in which Ghana is not an exception. The World Health Organisation [3] recommended that 75 litres of water a day is necessary to protect against household diseases and 50 litres a day necessary for basic family sanitation. The international consumption figures released by the 4th World Water Forum [11] indicate that a person living in an urban area uses an average of 250 litres/day. With these figures in mind, experts need to factor in population increase and forecast for the production and consumption of water in the area.

The Hohoe Municipality is one of the eighteen districts in the Volta Region of Ghana with Hohoe as its capital and administrative centre. According to the Ghana Statistical Service report (2010), it has a population of 262,046 made up of 126,239 and 135,807 males and females respectively. The population size has grown by almost 81% from the year 2000. In terms of water supply in the municipality, the Ghana Water Company Limited and DANIDA have been effective in resolving many problems identified in 1992 were more than 60% of the population lack good drinking water and sanitation facilities. Very old machines, broken-down hand pumps and other equipment have either been replaced or repaired for efficient water production and distribution in the municipality.

Majority of the people of the Municipality (about 65%) are engaged in agricultural production. The technology employed in agricultural production in the municipality is largely the traditional cutlass and hoe. Mechanised farming is very limited and the rate of adoption of other agricultural-related technologies is equally low. Farming is entirely rain-fed as there are no irrigation facilities, and this culminates in low productivity. Access roads to farming centres are also poor thus hampering the marketing of the products. These together with the absence of storage facilities give rise to high post-harvest losses.

2. Related works

Initial works in water demand forecasting have included regression and time series analyses by Jain [5]. Salas [10] formulated a general time series model for water use on any time interval. Their model contains a polynomial trend in mean and standard deviation, a periodic mean and standard deviation, and an autoregressive (AR) short-memory component. The model residuals were fitted by the normal, log-normal, or gamma distributions. They also calculated the cross-correlation and coherence functions between monthly water use and rainfall and between monthly water use and temperature.

Maidment [8] created a time-series model based on precipitation and temperature and included the Box-Jenkins transfer function. A year after, they applied the model to nine cities in three states in USA [9], their models achieved overall correlation of determination (R2) ranging from 61 to 96 percent. Zhou [12] developed a forecasting model for Melbourne, Australia. Using a time-series analysis, they proposed that demand was comprised of base, seasonal, climatic, and persistence components.

Gato [2] used a similar time series model as Zhou [12] but added temperature and precipitation thresholds into their model. Aside from time-series analysis, more complicated algorithms have been used to forecast demand. Lertpalangsunti [7] created a model using the artificial neural network (ANN) and applied the model in an attempt to predict the demand for the city of Regina.

Bougadis [1] compared a time-series approach and ANN in demand prediction for the city of Ottawa. Khan [6] compared the support vector machine with ANN and an autoregressive model to forecast water level for Lake Erie. Hererra [4] compared the results from four methods, including ANN, projection pursuit regression, multivariate adaptive regression splines, and random forests and support vector regression in the forecasting of water demand for a water district servicing approximately 5000 customers in south-eastern Spain.

3. Research methodology

The demand for water can be influenced by certain factors, such as changes in weather conditions, changes in yearly patterns, population change, and industrial and agricultural activities. The research looks at forecasting the demand for water based on population change using time series based on MA, AR, ARMA, and ARIMA models.

3.1. Autocorrelation function (ACF)

Autocorrelation refers to the correlation of a time series with its own past and future values.

Autocorrelation is also called “lagged correlation” or “serial correlation," which refers to the correlation between members of a series of numbers arranged in time.

The first- order autocorrelation coefficient is the simple coefficient of the first N–1 observations, t =1, 2… N-1 X_t : t =2, 3… N. The correlation between X_t and X_{t+1} is given by,

$$r_1 = \frac{\sum_{t=1}^{N-1} (x_t - X_1)(x_{t+1} - X_2)}{\left[\sum_{t=1}^{N-1} (x_t - X_1)^2\right]\left[\sum_{t=1}^{N-1} (x_t - X_1)^2\right]} \quad (3.1)$$

$$r_1 = \frac{\sum_{t=1}^{N-1} (x_t - X)(x_{t+1} - X)}{\sum_{t=1}^{N} (x_t - X)^2} \quad (3.2)$$

Where is the mean of the first N – 1 observations. As the correlation coefficient given above measure correlation between successive observations, it is called the autocorrelation coefficient or serial correlation coefficient. For N reasonably large, the difference between the sub-period means X_1 and X_2 can be ignored and r_1 can be approximated as by Equation (3.2) can be generalised to give the correlation between observations separated by k years:

$$r_k = \frac{\sum_{t=1}^{N=k} (X_t - X)(X_{t+k} - X)}{\sum_{t=1}^{N}(X_t - X)^2} \quad (3.3)$$

3.2. Partial autocorrelated function

Partial autocorrelation function measures the degree of association between Yt and Yt+k when the effect of another time lags on Y are held constant. The Partial Autocorrelation Function PACF denoted by the set of partial autocorrelations at various lags k are defined by (k=1,2, 3…). The set of partial autocorrelations at various lags k are defined by.

$$r_{kk} = \frac{r_k - \sum_{j=1}^{k-1} r_{k-1,j} r_{k-1}}{1 - \sum_{j=1}^{k-1} r_{k-1,j} r_j} \quad (3.4)$$

Where, $r_{k,j} = r_{k-1,j-r_{kk}\ r_{k-1},k-1}$ j =1, 2…k-1

Specifically, partial autocorrelations are useful in identifying the order of an autoregressive Model. The partial autocorrelation of an AR (p) process is zero at lag p+1 and greater.

3.3. Autoregressive (AR) models

An autoregressive model is simply a linear regression of the current value of the series against one or more prior values of the series. The value of p is called the order of the AR model. AR models can be analyzed with one of the various methods, including standard linear least squares techniques. They also have a straightforward interpretation. A common approach for modelling univariate time series is the autoregressive (AR) model:

$$X_t = \mu + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + A_t \quad (3.5)$$

Where Xt is the time series, at is white noise, and with μ denoting the process mean. An autoregressive model of order p, denoted by AR (p) with mean zero is generally given by the equation:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \varepsilon_t \quad (3.6)$$

Or

$$X_t = \phi_1 L_1 + \phi_2 L_2 + \ldots + \phi_p L_p + \varepsilon_t \quad (3.7)$$

When $\phi(L) X_t = \varepsilon_t$

$$\phi(u) = 1 - \phi_1 u^1 - \phi_2 u^2 - \ldots - \phi_p u^p \quad (3.8)$$

Where L, is the lag operator $\phi_1, \phi_2, \ldots, \phi_p$ are constants with $\phi_p \neq 0$ are the autoregressive model parameters and ε_t is the random shock or white noise process, with mean zero and variance σ_ε^2. Replace Xt by Xt - μ. That is

$$X_t - \mu = \phi_1(X_{t-1} + \mu) + \phi_2(X_{t-2} + \mu) + \ldots + \phi_p(X_{t-p} + \mu) + \varepsilon_t \quad (3.9)$$

$$X_t = \alpha + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \varepsilon_t \quad (3.10)$$

Where $\alpha = \mu(1 - \phi_1 - \phi_2 - \ldots - \phi_p)$

3.4. Moving average (MA) models

Moving Average (MA) is another common approach for modelling univariate time series. Moving average model of order q is (MA (q)) is given by

$$X_t = \mu + A_t + \theta_1 A_{t-1} + \theta_2 A_{t-2} + ... + \theta_q A_{t-q} \quad (3.11)$$

Where $\theta_1, \theta_2, ... \theta_q$ are constants with $\theta_q \neq 0$ Xt is the time series, μ is the mean of the series, A_{t-i} and are white noise. A moving average model of order q, with mean zero, denoted by MA (q) is generally given.
By:

$$X_t = A_t + \theta_1 A_{t-1} + \theta_2 A_{t-2} + ... + \theta_q A_{t-q} \quad (3.12)$$

where $A_t \sim WN(0, \sigma^2)$

The MA (q) process can also be written in the following equivalent form $X_t = \theta(u) A_t$ where the moving average operator

$$\theta(u) = 1 + \theta_1 u + \theta_2 u^2 + ... + \theta_q u^q \quad (3.13)$$

3.5. Autoregressive moving average (ARMA) models

Autoregressive and Moving Average processes can be combined to obtain a very flexible Class of univariate processes (proposed by Box and Jenkins), known as ARMA processes. The time series Xt is an ARMA (p, q) process, if it is stationary and

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + \varepsilon_t + X_t = A_t + \theta_1 A_{t-1} + \theta_2 A_{t-2} + ... + \theta_q A_{t-q} \quad (3.14)$$

4. Data analysis and results

This section applied the models described in Section 4 to forecast water consumption in Hohoe. A fortnight demand data in (m3) obtained from Ghana Water Company Limited for the years 2009, 2010, 2011 and 2012 were used to forecast for the next four years.

Table 1: Fortnights Consumption of Water in (M3) from Hohoe Municipality

2009		2010		2011		2012	
Fortnights	Data	Fortnights	Data	Fortnights	Data	Fortnights	Data
1	22245	28	25647	55	25721	81	30264
2	23415	29	24040	56	22025	82	29400
3	18319	30	22846	57	24366	83	29443
4	20675	31	23672	58	22419	84	26045
5	23220	32	24257	59	24010	85	24479
6	21514	33	24883	60	24326	86	29499
7	22398	34	22570	61	22700	87	29401
8	21639	35	23668	62	23267	88	28795
9	21852	36	23587	63	24127	89	25445
10	19862	37	23903	64	24480	90	28226
11	22953	38	24212	65	24519	91	27472
12	21338	39	21968	66	22486	92	30105
13	22356	40	17108	67	22368	93	29269
14	22904	41	22043	68	21314	94	30946
15	22161	42	25449	69	24226	95	30434
16	23786	43	22464	70	22994	96	27631
17	22827	44	23261	71	23972	97	29408
18	21072	45	22546	72	22151	98	28826
19	21044	46	21541	73	23032	99	27922
20	23374	47	21414	74	21173	100	26002
21	22245	48	19759	75	22133	101	28573
22	22551	49	19063	76	21766	102	30056
23	24274	50	21036	77	28054	103	31325
24	24086	51	24270	78	29265	104	29275
25	25394	52	24599	79	16325	105	30330
26	23241	53	25358	80	30179	106	30507

4.1. Preliminary analysis

A dimension of the preliminary analysis for examining non-stationarity of the data is by considering the trend analysis plot of 106 fortnight water consumption between 2009 and 2012 as shown in Figure 4.1.

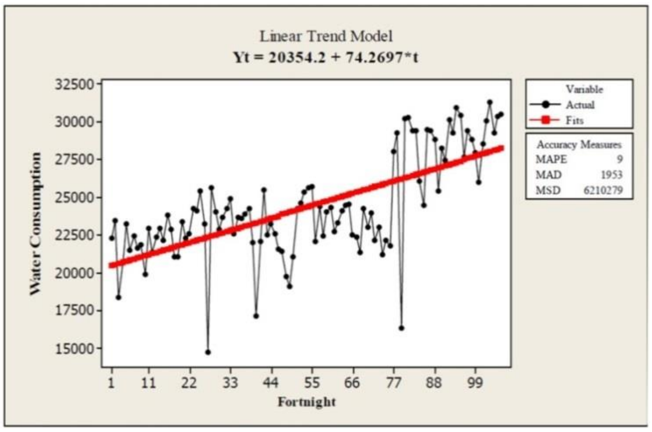

Fig. 4.1: Trend in Fortnight Water Consumption between 2009 and 2012

It is revealed from Figure 4.1 that water consumption in the Hohoe Municipality between2009 and 2012 have been largely non-stationary. The mean is not constant throughout the series as it assumes a fairly stable mean till 26th fortnight. The 27th, 40th and 79th fortnights recorded significantly low water consumption, perhaps due to the insufficient water provision in the municipality. Furthermore, Moving Average (MA) analyses for lags 2, 4 and 8 are in Figures 4.2, 4.3, and 4.4. A comparison of their respective accuracy measures indicates that MA (8) better fits the data.

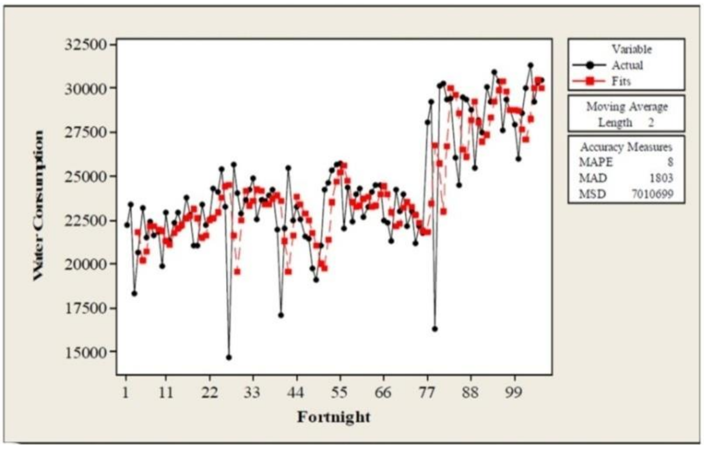

Fig. 4.2: Moving Average (MA) with 2 Averages.

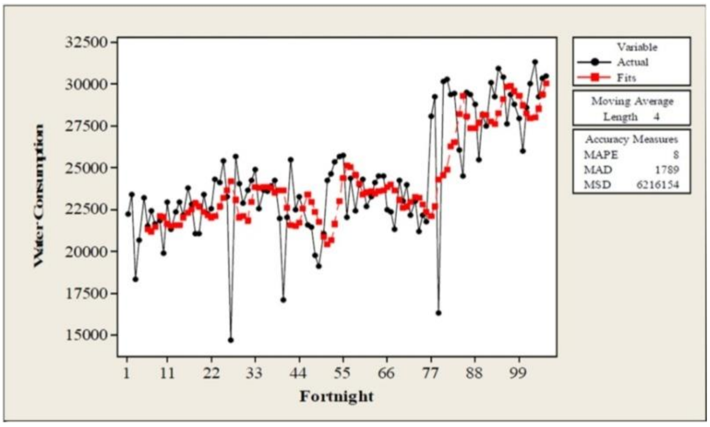

Fig. 4.3: Moving Average (MA) with 4 Averages

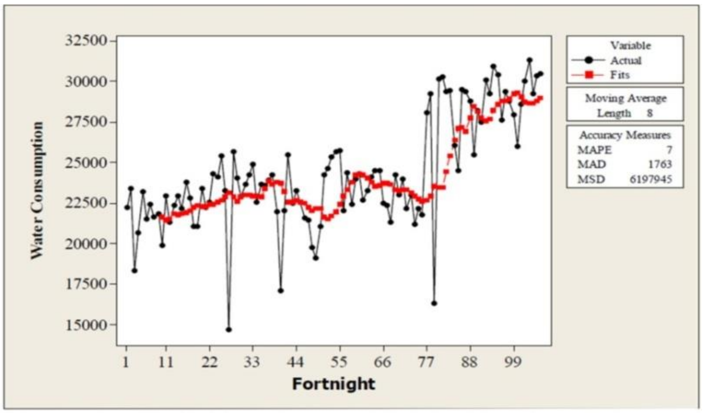

Fig. 4.4: Moving Average (Ma) with 8 Averages

The next step in the model-building procedure is to determine the order of the AR and MA for both seasonal and non-seasonal components. This was suggested by the sample ACF and PACF plots based on the Box-Jenkins approach. From Figure 4.2, the correlations are significant for a large number of lags but perhaps the autocorrelations at lags 2 or and above are merely due to the propagation of the autocorrelation at lag 1. This is confirmed by the PACF plot.
The ACF and PACF plots in Figures 4.5 and 4.6 respectively suggest that q = 2 or 3, and
p = 2 would be needed to describe this data set as coming from a non-seasonal moving average and autoregressive process respectively.

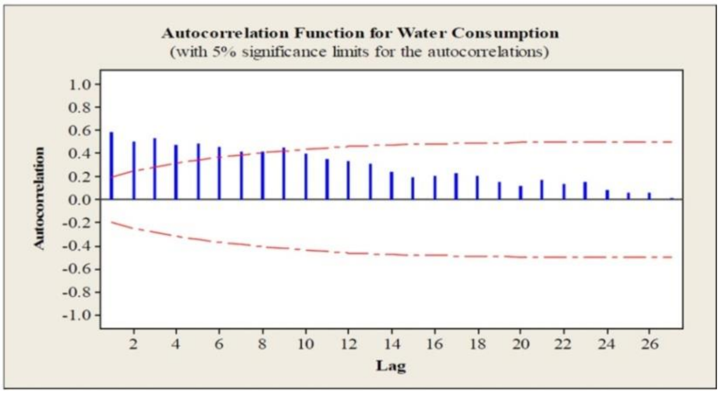

Fig. 4.5: ACF for First Order Differencing.

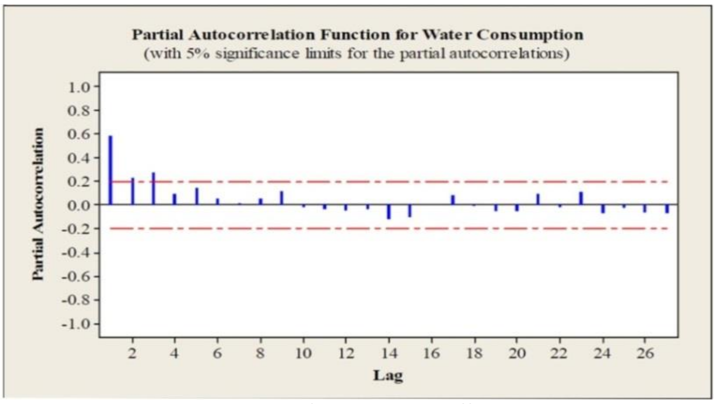

Fig. 4.6: PACF for First Order Differencing

4.2. Seasonal ARIMA model estimations

At this stage, it is important also to consider the seasonality of the data by adopting the seasonal ARIMA models. Looking at the seasonal lags, both ACF and PACF spike at seasonal lag 27 (because there are 27 fortnights in a year) and drop to zero for other seasonal lags suggesting that Q = 1 or 2 and P = 0 or 1 with d = 1 would be needed to describe these data as coming from a seasonal moving average and autoregressive process. Therefore, 15 proposed SARIMA models are presented in Table 4.12 with their corresponding p-values, Chi-square values and degree of freedom.

Table 4.2: Suggested Sarima Models

Model	p-value	Chi-Square	Df
ARIMA (0, 1, 1) (1, 0, 1)27	0.557	7.8	9
ARIMA (1, 1, 1) (0, 1, 1)27	0.798	3.8	7
ARIMA (1, 1, 3) (1, 0, 1)27	0.793	2.4	5
ARIMA (1, 1, 3) (1, 0, 1)27	0.699	2.2	4
ARIMA (1 1, 3) (0, 1, 0)27	0.427	6.0	6
ARIMA (2, 1, 2) (0, 1, 0)27	0.859	3.3	7
ARIMA (2, 1, 1) (1, 1, 1)27	0.534	5.1	6
ARIMA (2, 1, 2) (1, 0, 1)27	0.774	2.5	5
ARIMA (2, 1, 2) (0, 0, 1)27	0.846	2.7	6
ARIMA (2, 1, 3) (1, 0, 1)27	0.699	2.2	4
ARIMA (2, 1, 2) (1, 0, 0)27	0.915	2.0	6
ARIMA (4, 1, 3) (0, 0, 1)27	0.614	1.8	3
ARIMA (3, 1, 1) (1, 1, 1)27	0.011	15.0	5
ARIMA (2, 2, 3) (0, 0, 1)27	0.186	7.5	5
ARIMA (2, 2, 2) (1, 0, 1)27	0.006	16.2	5

A critical comparison of the models based on their respective p-values and Chi-Square values shows, that seasonal ARIMA (2, 1, 2)(1, 0, 0)27 is the appropriate model that best fitted the fortnight water consumption data in the Hohoe Municipality in the Volta Region of Ghana.

This would, however, be compared with the non-seasonal ARIMA model for final selection of the most adequate and parsimonious model.

4.3. Model evaluation and selection

From the aforementioned, we have identified two good models, namely, a non-seasonal and seasonal ARIMA model as shown in Tables 4.13 and 4.14 respectively for comparison and selection. We used the conditional-sum-of-squares to find starting values of parameters, then do the Maximum Likelihood Estimate (MLE) for the proposed models. The procedure for choosing these models relied on choosing the model with the maximum p-values for the Ljung-Box statistic (more than 5% as a rule of thumb) and minimum Chi-square values.

Comparing the non-seasonal ARIMA and the seasonal ARIMA models, it can be concluded that the non-seasonal model of (2, 1, 2) is somewhat adequate than the seasonal ARIMA model of (2, 1, 2) (1, 0, 0)27. Hence, ARIMA (2, 1, 2) is the best model and plausible time series model for the fortnight water consumption because of its high p and least Chi-Square values of 0.955 and 2.0 respectively.

Table 4.3: ARIMA (2, 1, 2)

Type	Coefficient	SE	t	p
Constant	126.59	56.37	2.25	0.027
AR 1	-0.4754	0.5375	-0.88	0.379
AR 2	-0.0800	0.1508	-0.53	0.597
MA 1	0.2946	0.5340	0.55	0.582
MA 2	0.4659	0.4789	0.97	0.333

$\chi 2 = 2.1$; $p = 0.955$; $df = 7$

Table 4.4: Estimates of Parameters for SARIMA (2, 1, 2) (1, 0, 0) 27

Variable	Coefficients	SE	t	p
Constant	122.55	60.72	2.02	0.046
AR 1	-0.5697	0.4053	-1.41	0.163
AR 2	-0.1006	0.1410	-0.71	0.477
SAR 27	0.1811	0.1199	1.51	0.134
MA 1	0.2128	0.3988	0.53	0.595
MA 2	0.5279	0.3600	1.47	0.146

$p = 0.735$, $\chi 2= 4.4$, $df = 6$

4.4. Diagnostic analysis

The diagnostic analyses using the ACF of residuals, PACF residuals, and the normal probability plot of the residuals as shown in Figures 4.7, 4.8, 4.9 and 4.10 reveal that the residuals of the model have zero mean and constant variance. The ACF of the residuals depicts that the autocorrelation of the residuals are all zero, that is to say, they are uncorrelated.

Hence, it can be concluded that there is a constant variance among residuals of the selected model, and the true mean of the residuals is approximately equal to zero. Thus, the selected model satisfies all the model assumptions. Since the ARIMA (2, 1, 2) satisfies all the necessary assumptions, it can be inferred that the model provides an adequate representation of the data. Hence, the predictive model would be formulated from the parameter estimates in Table 4.13.

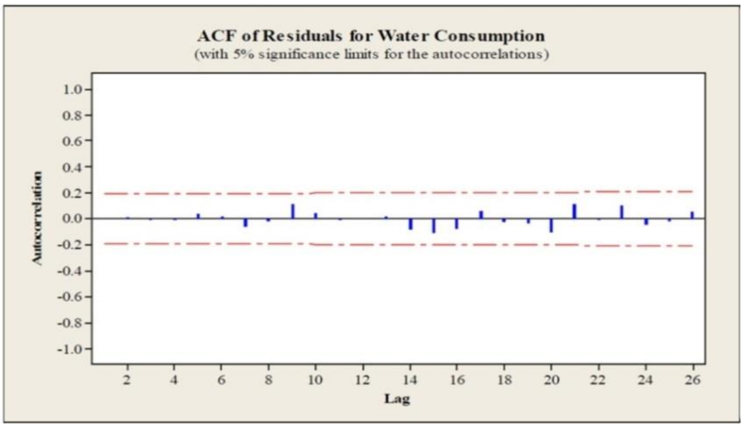

Fig. 4.7: ACF Diagnostic Plot of the Residuals for ARIMA (2, 1, 2) Model.

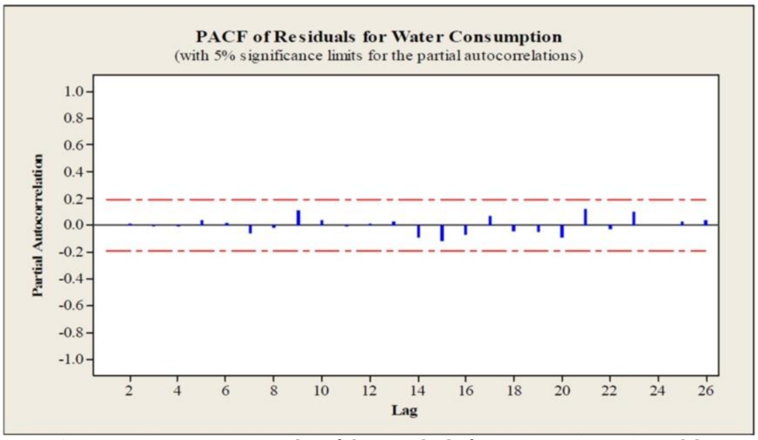

Fig. 4.8: PACF Diagnostic Plot of the Residuals for ARIMA (2, 1, 2) Model.

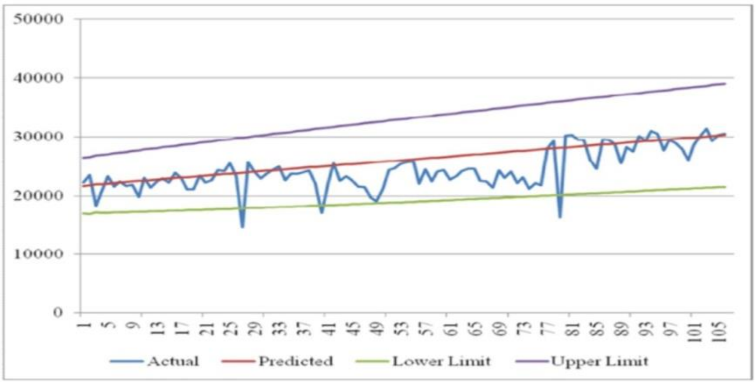

Fig. 4.9: Actual and Predicted Water Consumption Using ARIMA (2, 1, 2)

5. Discussions (forecasting)

Table 4.15 summarises the forecasted values of water consumption in the Municipality over the period of January 2013 to December 2016 fortnightly with 95% confidence level using the ARIMA (2, 1, 2) model, which has a higher p-value of 0.955 (thus, greater than alpha value of 0.05) indicating that it is the best model according to Modified Box-Pierce (Ljung-Box) Chi-Square statistic.

Table 4.5: Forecasted Fortnight Water Consumption for the Next 4 Years

			95% CI	
Year	Fortnight	Forecast	Lower Limit	Upper Limit
2013	1st	29809.6	25129.4	34489.7
2013	2nd	29995.4	25193.0	34797.7
2013	3rd	30089.4	25281.3	34897.5
2013	4th	30156.4	25260.5	35052.4
2013	5th	30243.6	25303.0	35184.3
2013	6th	30323.4	25328.8	35318.0
2013	7th	30405.1	25358.8	35451.3
2013	8th	30486.5	25389.1	35583.8
2013	9th	30567.8	25419.7	35716.0
2013	10th	30649.2	25450.9	35847.5
2013	11th	30730.6	25482.5	35978.7
2013	12th	30812.0	25514.6	36109.3
2013	13th	30893.4	25547.2	36239.5
2013	14th	30974.7	25580.2	36369.3
2013	15th	31056.1	25613.7	36498.6
2013	16th	31137.5	25647.5	36627.5
2013	17th	31218.9	25681.8	36756.0
2013	18th	31300.3	25716.5	36884.1
2013	19th	31381.7	25751.5	37011.8
2013	20th	31463.0	25787.0	37139.1
2013	21st	31544.4	25822.8	37266.1
2013	22nd	31625.8	25858.9	37392.7
2013	23rd	31707.2	25895.4	37518.9
2013	24th	31788.6	25932.3	37644.9
2013	25th	31870.0	25969.5	37770.4
2013	26th	31951.3	26007.0	37895.7
2013	27th	32032.7	26044.8	38020.6
2014	1st	32114.1	26083.0	38145.2
2014	2nd	32195.5	26121.5	38269.5
2014	3rd	32276.9	26160.2	38393.5
2014	4th	32358.3	26199.3	38517.2
2014	5th	32439.6	26238.6	38640.6
2014	6th	32521.0	26278.3	38763.8
2014	7th	32602.4	26318.2	38886.6
2014	8th	32683.8	26358.4	39009.2
2014	9th	32765.2	26398.8	39131.5
2014	10th	32846.5	26439.5	39253.6
2014	11th	32927.9	26480.5	39375.4
2014	12th	33009.3	26521.7	39496.9
2014	13th	33090.7	26563.2	39618.2
2014	14th	33172.1	26604.9	39739.3
2014	15th	33253.5	26646.8	39860.1
2014	16th	33334.8	26689.0	39980.7
2014	17th	33416.2	26731.4	40101.0
2014	18th	33497.6	26774.1	40221.2
2014	19th	33579.0	26816.9	40341.1
2014	20th	33660.4	26860.0	40460.7
2014	21st	33741.8	26903.3	40580.2
2014	22nd	33823.1	26946.8	40699.5
2014	23rd	33904.5	26990.5	40818.5
2014	24th	33985.9	27034.4	40937.4
2014	25th	34067.3	27078.5	41056.0
2014	26th	34148.7	27122.8	41174.5
2014	27th	34230.1	27167.3	41292.8
2015	1st	34311.4	27212.0	41410.8
2015	2nd	34392.8	27256.9	41528.7

2015	3rd	34474.2	27302.0	41646.4
2015	4th	34555.6	27347.3	41763.9
2015	5th	34637.0	27392.7	41881.2
2015	6th	34718.3	27438.3	41998.4
2015	7th	34799.7	27484.1	42115.4
2015	8th	34881.1	27530.1	42232.2
2015	9th	34962.5	27576.2	42348.8
2015	10th	35043.9	27622.5	42465.3
2015	11th	35125.3	27669.0	42581.6
2015	12th	35206.6	27715.6	42697.7
2015	13th	35288.0	27762.4	42813.7
2015	14th	35369.4	27809.3	42929.5
2015	15th	35450.8	27856.4	43045.2
2015	16th	35532.2	27903.7	43160.7
2015	17th	35613.6	27951.1	43276.0
2015	18th	35694.9	27998.6	43391.3
2015	19th	35776.3	28046.3	43506.3
2015	20th	35857.7	28094.2	43621.2
2015	21st	35939.1	28142.2	43736.0
2015	22nd	36020.5	28190.3	43850.6
2015	23rd	36101.9	28238.6	43965.1
2015	24th	36183.2	28287.0	44079.5
2015	25th	36264.6	28335.6	44193.7
2015	26th	36346.0	28384.3	44307.8
2015	27th	36427.4	28433.1	44421.7
2016	1st	36508.8	28482.0	44535.5
2016	2nd	36590.1	28531.1	44649.2
2016	3rd	36671.5	28580.3	44762.7
2016	4th	36752.9	28629.7	44876.2
2016	5th	36834.3	28679.1	44989.5
2016	6th	36915.7	28728.7	45102.6
2016	7th	36997.1	28778.4	45215.7
2016	8th	37078.4	28828.3	45328.6
2016	9th	37159.8	28878.2	45441.4
2016	10th	37241.2	28928.3	45554.1
2016	11th	37322.6	28978.5	45666.7
2016	12th	37404.0	29028.8	45779.1
2016	13th	37485.4	29079.2	45891.5
2016	14th	37566.7	29129.8	46003.7
2016	15th	37648.1	29180.4	46115.8
2016	16th	37729.5	29231.2	46227.8
2016	17th	37810.9	29282.1	46339.7
2016	18th	37892.3	29333.0	46451.5
2016	19th	37973.7	29384.1	46563.2
2016	20th	38055.0	29435.3	46674.8
2016	21st	38136.4	29486.6	46786.2
2016	22nd	38217.8	29538.0	46897.6
2016	23rd	38299.2	29589.5	47008.8
2016	24th	38380.6	29641.1	47120.0
2016	25th	38462.0	29692.9	47231.0
2016	26th	38543.3	29744.7	47342.0
2016	27th	38624.7	29796.6	47452.9

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