

Forecasting and Planning for Solid Waste Generation in the Kumasi Metropolitan Area of Ghana: An ARIMA Time Series Approach

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Abstract: One major challenge facing the Kumasi Metropolitan Area (KMA) is the inability of city authorities to manage solid waste due to lack of proper planning and the inability of the authorities to forecast and predict the quantity of solid waste that will be generated in the coming years, based on current trends. This research, which is a predictive study, uses the Autoregressive Integrated Moving Average (ARIMA) time series model to explore the dynamics of solid waste generation and also forecast monthly solid waste generation in the KMA. This study used monthly solid waste generation data from 2005 to 2010 that was obtained from the solid waste department of the Kumasi Metropolitan Assembly. The data was analyzed by applying ARIMA time series model. The results showed that in general, the trend of solid waste generation peaked in December 2008. The analysis indicated that ARIMA (1, 1, 1) was the best model for forecasting solid waste generation in the KMA. The forecast revealed that for the next couple of years, the generation of solid waste will continue to increase as a result of the high rate of urbanization in the metropolis. The research is therefore of the view that sustainable solid management programmes should be put in place to rescue the current situation and also plan for the anticipated solid waste predicted by the research.

Keywords: Solid waste, Autoregressive (AR), Moving Average (MA) and ARIMA

1.0 Introduction

Managing Solid waste effectively and efficiently is a continually growing problem at global, regional and local levels and one of the most intractable problems for local authorities in urban centers. With continuous economic development and an increase in living standards, the demand for goods and services is increasing at an unprecedented rate, resulting in a commensurate increase in per capita waste generation (Narayana, 2008). In most developing countries, the problem is compounded by rapid urbanization, the introduction of environmentally unfriendly materials, changing consumer consumption patterns, lack of political commitment, insufficient budgetary allocations and ill motivated (undedicated) workforce. In Ghana, deficiencies in solid waste management (SWM) are most visible in and around urban areas such as Accra, Tema and Kumasi where equally important competing needs and financial constraints have placed an inordinate strain on the ability of the authorities to implement proper SWM

strategies in tandem with the rapid population growth (Oteng-Ababio, 2011). Consequently, most of the urban landscape is characterized by open spaces and roadsides littered with refuse; drainage channels and gutters choked with waste; open reservoirs that appear to be little more than toxic pools of liquid waste; and beaches strewn with plastic solid waste. The insidious social and health impact of this neglect is greatest among the poor, particularly those living in the low-income settlements (UN-Habitat, 2010).

In Ghana the provision of waste management services has always been viewed as the responsibility of the central government. This is because the legal and legislative frameworks guiding the provision of solid waste management services originate from the central government. The Ministry of Local Government, which has a supervisory role over the Metropolitan, Municipal and District Assemblies (MMDAs), provides the general policy framework for waste management. This involves identifying key stakeholders in the sector, defining their roles,



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establishing the modalities for awarding contracts and setting the standards for the organization of waste management. Within the framework provided by the Ministry of Local Government, the MMDAs award contracts for waste collection; determine the levels of service and charges; decide where to provide/who to receive what level of service; acquire equipment; and find land space for waste disposal. However, the costs involved, coupled with the increasing rate of waste generation due to high urban population growth rates, have made it difficult for collection to keep pace with generation, thus posing serious environmental hazards. The uncollected waste clogs drains leading to flooding and impacting negatively on public health. Data from the Ghana Health Service indicate that six (6) out of the top ten (10) diseases in Ghana are related to poor environmental sanitation, with malaria, diarrhea and typhoid fever jointly constituting 70% - 85% of out-patient cases at health facilities (MLGRD, 2010a). malaria remains the number one killer in Ghana, accounting for 17,000 deaths, including 2,000 pregnant women and 15,000 children below the age of five”, a quarter of all child mortality cases and 36% of all hospital admissions over the past 10 years” (Daily Graphic, November 3, 2005: 11). The Ghana Medical Association also stipulates that about five million children die annually from illnesses caused by the environment in which they live (World Bank, 2007). In Kumasi, a GHS (2010) report states that, “out of the cholera cases reported to health facilities, 50% came from Aboabo and its environs (Subin Sub-Metro) where solid waste management is perceived to be the worst”. Poor waste management practice also places a heavy burden on the economy of the country. Rapid urbanization over the past decades has resulted in high population concentration in major Ghanaian cities, including the Kumasi metropolitan area, thereby increasing pressure on urban infrastructure and services. Thus, the demand for environmental services such as water and waste disposal has increased tremendously (Songsore et al., 2005). The lack of waste disposal services has resulted in waste accumulation and unsanitary environmental conditions in many parts of these cities.

The Kumasi Metropolitan Area (KMA) is increasingly experiencing rapid rate of high population growth. It is estimated that over 2,022,919 million people live in the metropolitan area with a growth rate of 5.4 per cent annually (KMA, 2010). Despite numerous benefits of urbanization, the metropolitan area remains largely hostage to poor and dysfunctional infrastructure. One manifestation of the

city’s poor infrastructure is its inability to manage and organize adequate collection and safe disposal of the solid waste within its jurisdiction, generated from the production and consumption activities. As a result, the KMA is saddled with a worsening waste situation which is proving to be intractable and threatening public health and the environment. In 1995, the rate of domestic waste generation in Kumasi was estimated at 600 tons per day (Post, 1999). By 2005, 1,000 tons of solid waste was generated each day in the city; three years later, the KMA was collecting 1,200 tons a day, and a 2010 KMA document shows that 1,500 metric tons of waste is now generated in Kumasi each day (KMA, 2010). The reasons for the KMA’s inability to manage solid waste effectively is largely due to rapid urbanization, poor financing capacity of authorities and lack of safe waste disposal sites which is reflection of the weak planning capacity of the city authorities. The lack of proper planning for waste management services eventually leads to the inability of the authorities to predict and forecast the quantity of waste to be generated. The cyclical mantra of planning is thus invoked: planning to predict or predicting to plan.

The study aims at forecasting the monthly quantity of solid waste to be generated for the next four years based on monthly data for 2005-2010 using Time-Series Approach and makes recommendations for effective management of solid waste in the KMA. The study will also contribute to the menu from which practitioners can identify appropriate, cost effective and sustainable strategies for efficient solid waste collection, handling and disposal systems. Ultimately, the results of the study will be useful not only for future policy formulation and implementation but more importantly, for other cities that are experiencing similar solid waste management problems.

2.0 Methodology

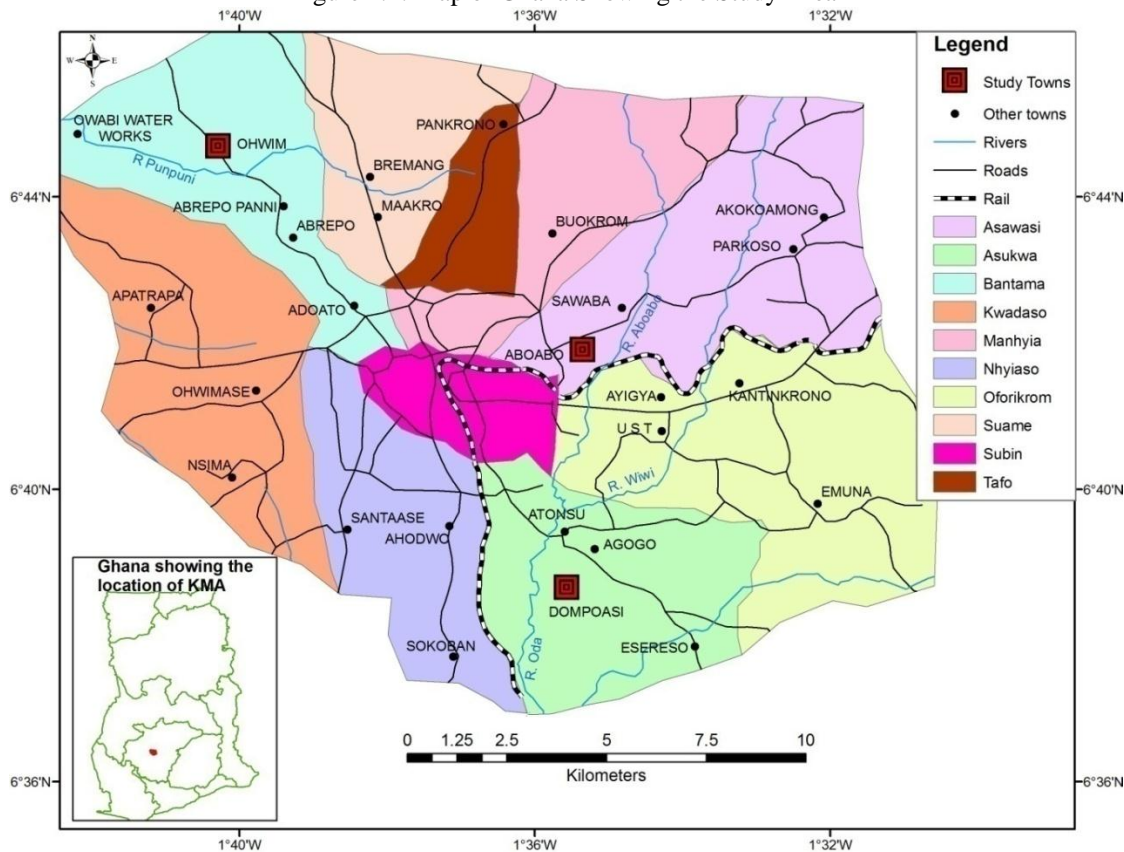
2.1 Study Area

Kumasi is located in the transitional forest zone and is about 270km north of the national capital, Accra. It is between latitude 6.35° – 6.40° and longitude 1.30° – 1.35°, an elevation which ranges between 250 – 300 metres above sea level with an area of about 254 square kilometres. The unique centrality of the city as a traversing point from all parts of the country makes it a special place for many to migrate to. The Metropolis falls within the wet sub-equatorial type. The average minimum temperature is about 21.5°c

and a maximum average temperature of 30.7⁰c. The average humidity is about 84.16 per cent at 0900 GMT and 60 per cent at 1500 GMT. The moderate temperature and humidity and the double maxima rainfall regime (214.3mm in June and 165.2mm in September) have a direct effect on population growth and the environment as it has precipitated the influx of people from every part of the country and beyond its frontiers to the metropolis. This is chiefly because the climatic conditions are not harsh. Kumasi is the second populous metropolitan area in Ghana after the capital, Accra. Over 2,022,919 million people are estimated to live in the Metropolitan area with a

growth rate of 5.4 per cent annually (KMA, 2010). The high population growth has serious consequences on health care delivery if it is not accompanied by improvement and increase in health oriented infrastructure and service provision. Rapid population growth means high rate of waste generation, overcrowding and pressure on existing environmental sanitation infrastructure and sanitation service. When such a high population is anticipated there is the need for planning for new infrastructure and maintenance of existing ones to prevent them from running down as a result of excessive pressure.

Figure 2.1: Map of Ghana Showing the Study Area



2.2 Data collection

The study basically relied on secondary data obtained from the waste management department of KMA. The data obtained was the total annual waste generation from 2005 to 2010. Additionally, an extensive review of the existing literature on solid waste management was carried out. Lastly, we conducted in-depth interviews with officials from the Environmental Protection Agency (EPA), Kumasi Metropolitan Assembly (KMA) private solid waste companies and site managers on their general role in

managing solid waste in the KMA.

2.3 Time Series Model

This study was carried out on the basis of waste generation data from the period 2005 to 2010 collected from primary source. The data was model using Autoregressive Integrated Moving Average (ARIMA) stochastic model popularized by Box-Jenkins (1976). An ARIMA (p, d, q) model is a combination of Autoregressive (AR) which shows

that there is a relationship between present and past values, a random value and a Moving Average (MA) model which shows that the present value has something to do with the past residuals. The ARIMA process can be defined as:

$$\varphi(Q)(\Delta^d y_t - \lambda) = \theta(Q)e_t$$

Where

y_t = solid waste waste in tonnage

λ = Mean of $\Delta^d y_t$

$$\varphi(Q) = 1 - \varphi_1 Q - \dots - \varphi_p Q^p$$

$$\theta(Q) = 1 - \theta_1 Q - \dots - \theta_q Q^q$$

φ_i = The i^{th} autoregressive parameter

θ_i = The i^{th} moving average parameter

p , q and d denote the autoregressive, moving average and differenced order parameter of the process respectively. Δ and B denote the difference and backward shift operators respectively. The estimation of the model consists of three steps, namely: identification, estimation of parameters and diagnostic checking

Identification step:

Identification step involves the use of the techniques to determine the values of p , q and d . The values are determined by using Autocorrelation function (ACF) and Partial Autocorrelation function (PACF). For any ARIMA (p , q , d) process, the theoretical PACF has non-zero partial autocorrelations at lags 1, 2, ..., p and has zero partial autocorrelations at all lags, while the theoretical ACF has non zero autocorrelation at lags 1, 2, ..., q and zero autocorrelations at all lags. The non-zero lags of the sample PACF and ACF are tentatively accepted as the p and q parameters. For a non stationary series the data is differenced to make the series stationary. The number of times the series is differenced determines the order of d .

Estimation of parameters:

The second step is the estimation of the model parameters for the tentative models that have been selected.

Diagnostic checking:

The estimated model must be checked to verify if it adequately represents the series. Diagnostic checks are performed on the residuals to see if they are randomly and normally distributed. Here, the Anderson-Darling test for normality was used. Also, the residual plot versus the fitted values was used to check if the residuals are randomly scattered. An overall check of the model adequacy was made using the Ljung-Box Q statistics. The test statistics is given by:

$$P_n = m(m+2) \sum_{k=1}^m (m-k)^{-1} r_k^2 \approx \chi_{n-r}^2$$

Where

r_k^2 = the residuals autocorrelation at lag k

n = the number of residuals

m = the number of time lags included in the test

When the p -value associated with the Q is large the model is considered adequate, else the whole estimation process has to start again in order to get the most adequate model.

3.0 Results and Discussions

3.1 Trend Monthly Solid wasted data from January to December 2010

Figure 3.1 shows the pattern of monthly solid waste data (in tonnage) obtained from the Kumasi Metropolitan Assembly (KMA, Ghana) between January, 2005 and December, 2010. We observed a rather irregular variation that seems to repeat over months, with maximum peak at 2008 (i.e. December), which recorded 72811.10 tons in solid waste. The minimum solid waste amount in tons was 6461.20, which occurred in September, 2005. Again, the pattern of monthly solid waste data shows a non-stationary trend, with evidence of seasonality being suggested.

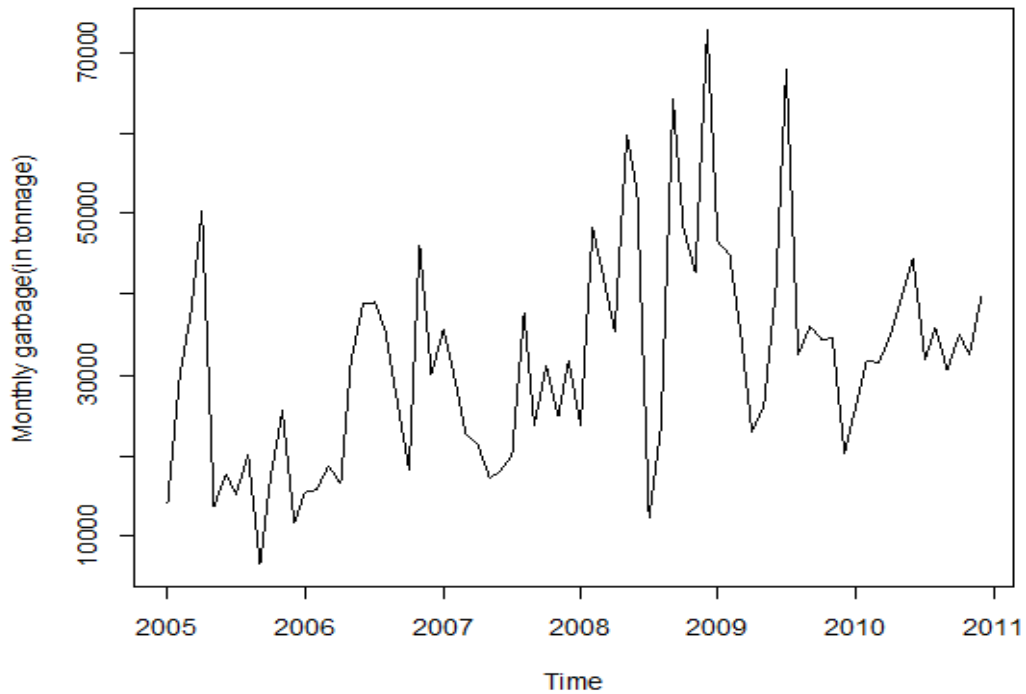


Figure 3.1: Monthly solid waste generation from January to December 2010

Furthermore, the data was then decomposed to make more evident the existence/ non-existence of the various components of the series as shown in figure 3.2.

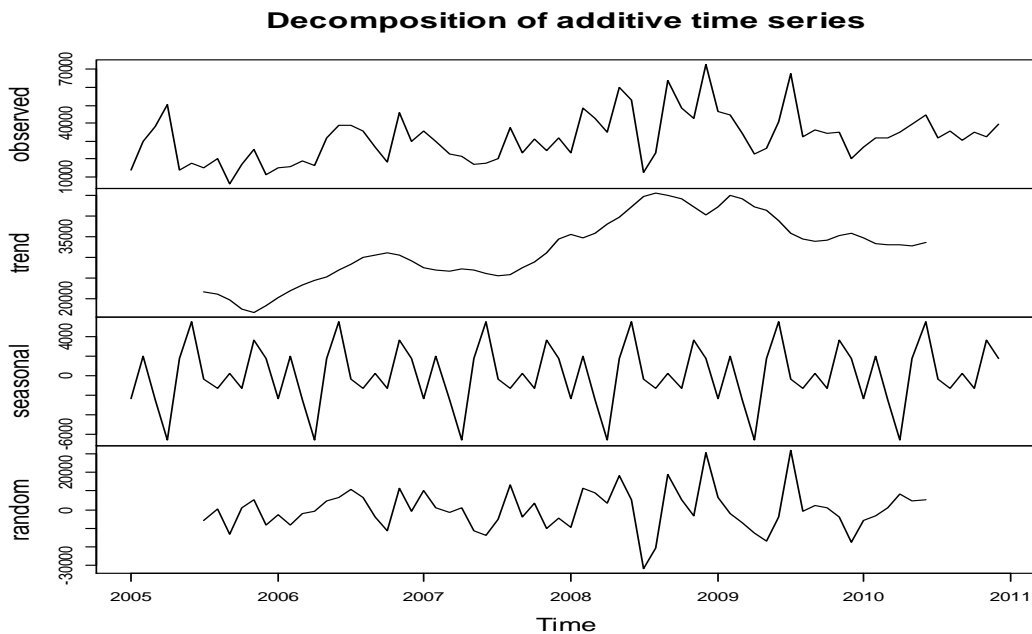


Figure 3.2: Decomposition of the Solid Waste Data series.

After decomposition, it was observed clearly that the data exhibits a non-systematic linear trend but the

existence of seasonality is suggested. This is because the pattern displayed in figure 3.2 could be as a result

of the irregular component in the time series.

3.2 Summary Statistics of Solid Waste Generated in the KMA

This section shows the quantity of solid waste generated by month in the KMA between 2005 and

2010. The minimum of data generated was 6461 tons and this occurred in September, 2006 and the maximum amount of generated is approximately 72,810 tons which also happened in December, 2008, table 3.1.

Table 3.1: Summary Statistics of Solid Waste Generated in the KMA

Minimum	1 st Quartile	Median	Mean	3 rd Quartile	Standard deviation	Maximum
6461	21120	31770	31800	38860	13509.38	72810

On the average, the amount of solid waste generated is somehow closer to the median figure. This may somehow indicate a symmetric behaviour of the solid waste data distribution. We tested for stationarity and clearly from Figure 3.1 and 3.2, it was observed clearly that the solid waste data series is non-stationary. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was therefore, computed to validate this claim. This was based on the values of KPSS Level =

1.0358, Truncation lag parameter = 1 and p-value = 0.01. The conclusion was that at an α (alpha) 5% level of significance, we reject the Null hypothesis that the solid waste data series is trend or level stationary since the p-value (0.01) < 0.05, and hence the series indeed non-stationary.

Our data being non-stationary, we used first order differencing and stationary was attained (Figure 3.3).

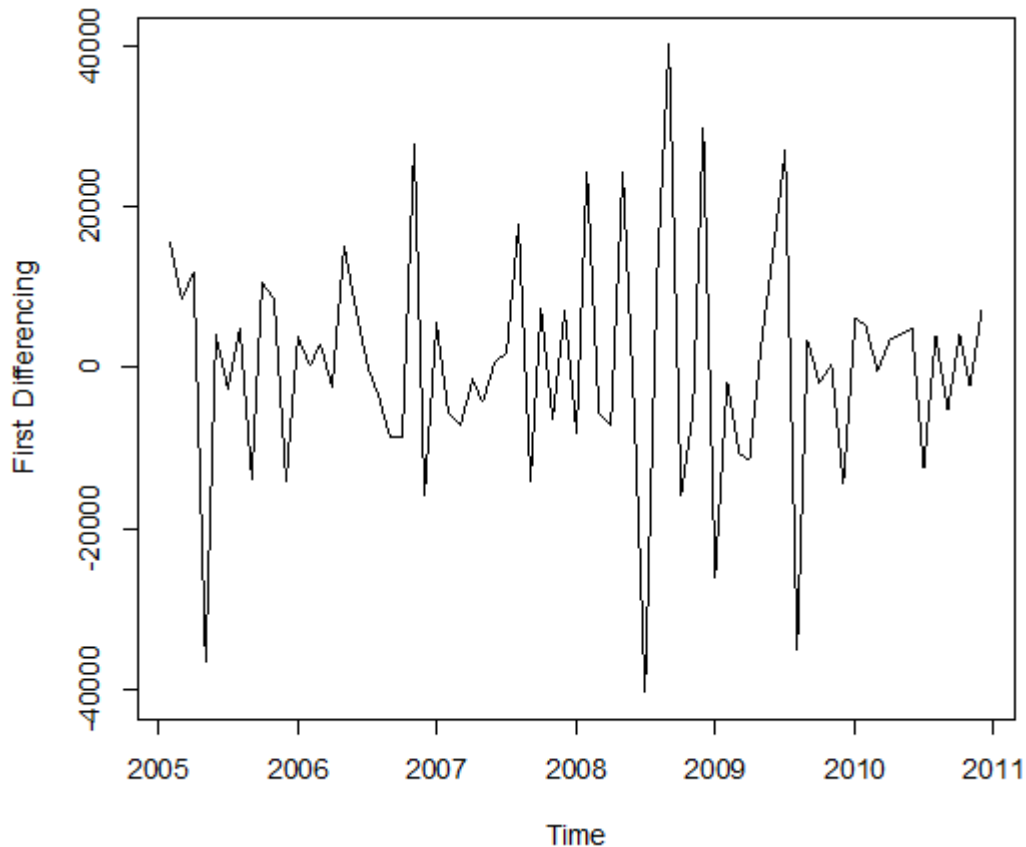


Figure 3.3 First Difference of Solid waste Data

From Figure 3.3, it can be seen that the differenced series looks stationary, as the observations somehow

beat about a constant mean. The validation on stationarity of differenced data was performed using

the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test on the difference data series. an α (alpha) 5% level of significance, we fail to reject the Null hypothesis that the differenced solid waste data series is trend or

level stationary since the p-value (0.1) > 0.05, and hence conclude that the series is indeed trend stationary.

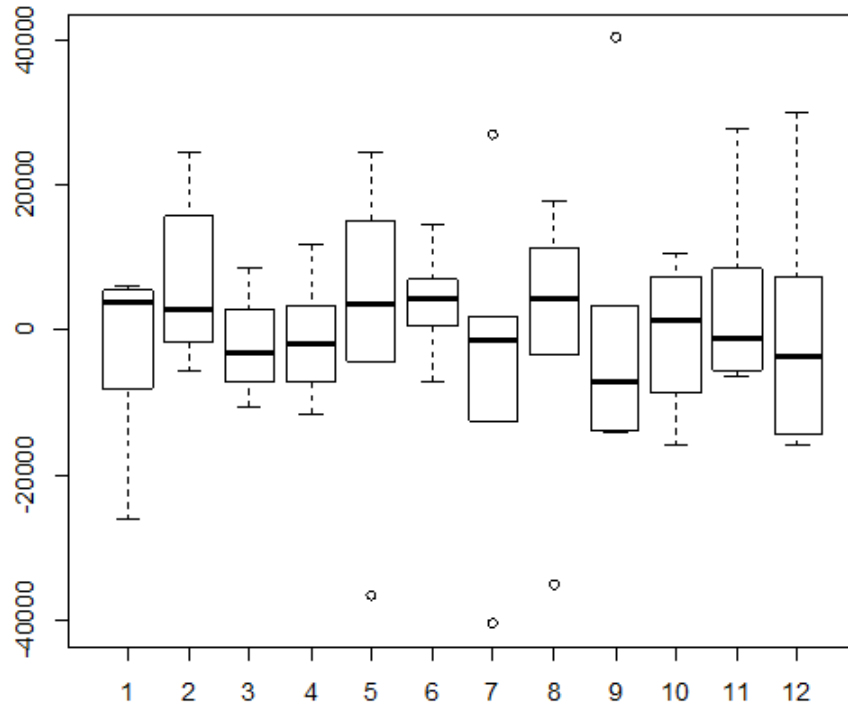


Figure 3.4 Show Boxplot of Difference Data

It can be seen from figure 3.4 that the means for each month were relatively close and showed no obvious pattern of seasonality. Also, since the solid waste data series was only differenced once to attain stationarity, we can therefore conclude that our data is non-seasonal. This is because for non-seasonal data, at most a first order differencing is usually sufficient to attain apparent stationarity. Again, if **3.3 Model Identification**

there was significant seasonality, the autocorrelation plot should have shown significant spikes at lags equal to the period of the series. For example, for monthly data, if there is a seasonality effect, we would expect to see significant peaks at lag 12, 24, 36, and so on (although the intensity may decrease the further out we go).

all lie within the significant bounds, hence showing no significant peaks.

From Figure 3.5 (A & B), it can be seen from the sample ACF that lag 12 and the other lags following

Figure 3.5 (A) Sampled ACF for Differenced Solid Waste Data

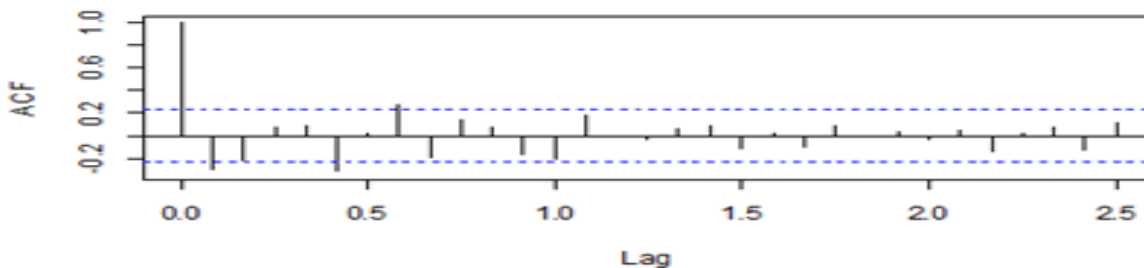
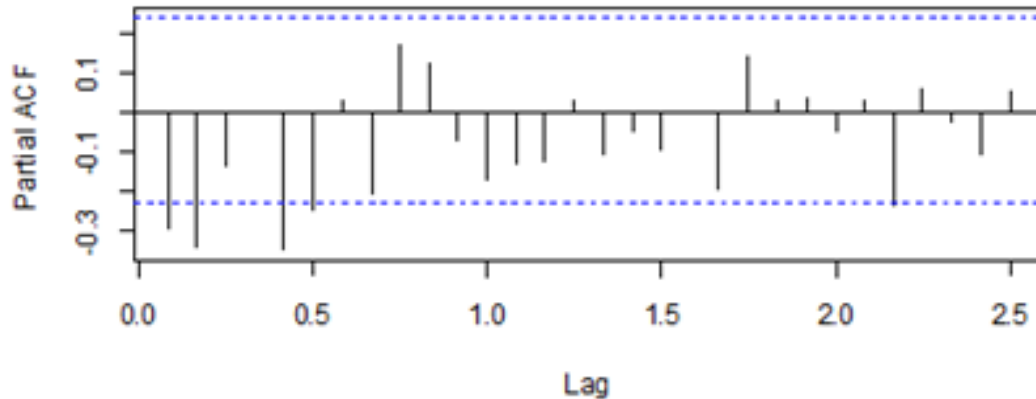


Figure 3.5 (B) Sampled PACF for Differenced Solid Waste data



In order to select the appropriate model and also make more accurate forecasts, we fitted several feasible ARIMA models to the observed data by making reference to the Sample ACF and Sample PACF (in Figure 3.5 above) of the difference data. Since the data was differenced, the fitted ARIMA models would be of order $(p, d=1, q)$.

From the correlogram in figure 3.5, the sample ACF dies down for three (3) successive lags after the first significant lag i.e. lag 1, and there after cuts inconsistently at lag 5 and lag 7. Lags 5 and 7 are however considered not significant, because those may be caused by the irregular component of the series.

Also the partial correlogram revealed that the partial autocorrelations at lags 1, 2, 5 and 6 exceed the significance bounds, and are negative as well. The partial autocorrelations die down after lag 6. Lag 26 is however, considered not significant since this may be due to chance, considering the fact that lag 25, which comes right before it is significantly not far from zero.

From the foregoing analysis, the following ARIMA (Autoregressive integrated moving average) models are therefore possible for the data series:

- ARIMA(2,1,1)
- ARIMA(1,1,2)
- ARIMA(1,1,1)

3.4 Estimation of Parameters and Diagnostic Checking

At this point we proceeded to estimate the parameters and investigate whether the residuals of the selected ARIMA models were normally distributed with mean zero and constant variance, and also whether there were no correlations between successive residuals (i.e. randomness of residuals).

In order to check for correlations between successive residuals, we made use of a correlogram and also the Ljung-Box test to further ascertain the adequacy (randomness) of the model's residual.

Again, in order to check whether the residuals were normally distributed with mean zero and constant variance, we made use of a normality quantile-quantile plot (q-q plot) and a histogram.

If the residuals were normally distributed, the points on the normal quantile-quantile plot should have been approximately linear, with residual mean as the intercept and residual standard deviation as the slope whilst the shape of the histogram shows "a bell-like" shape.

- **ARIMA(2,1,1)**

Coefficients:

ar1	ar2	ma1	drift
0.3566	-0.0364	-1.0000	266.0114
s.e.	0.1192	0.1190	0.0555
		95.5602	

sigma² estimated as 135737828: log likelihood=-767.35

AIC=1544.7 AICc=1545.62 BIC=1556.01

ME	RMSE	MAE	MPE	MAPE	MASE
314.7433	11569.4677	8457.8404	-13.8718	32.4601	0.81252

ACF of ARIMA(2,1,1) Residuals

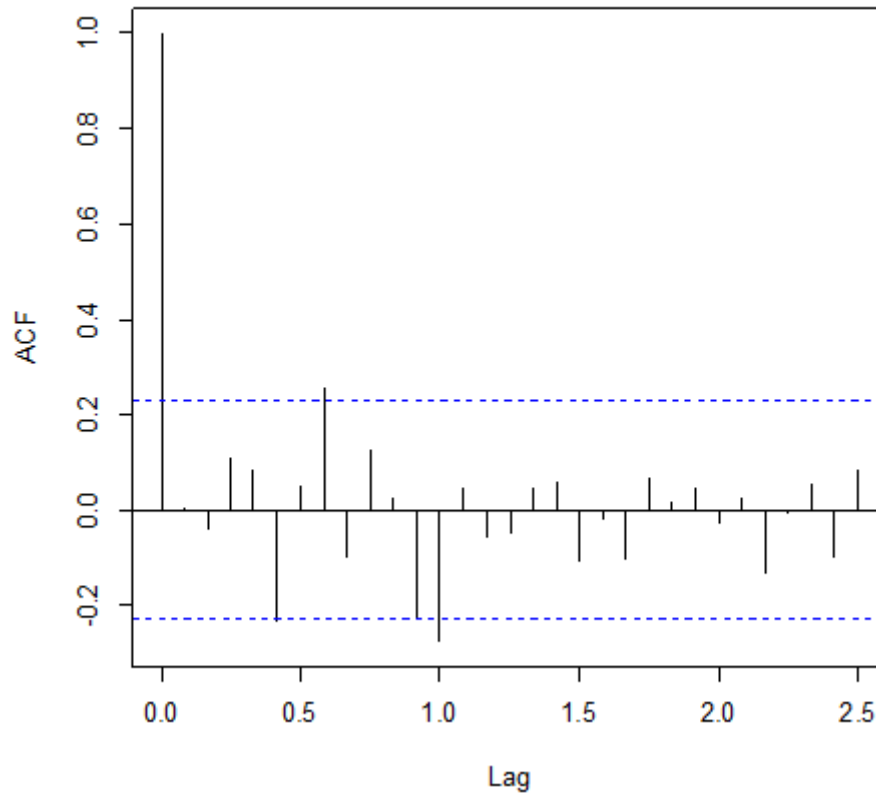


Figure 3.6 ACF of ARIMA (2,1,1) Residuals

Box-Ljung test:

data: model1\$residuals

X-squared = 34.7176, df = 30, p-value = 0.2531

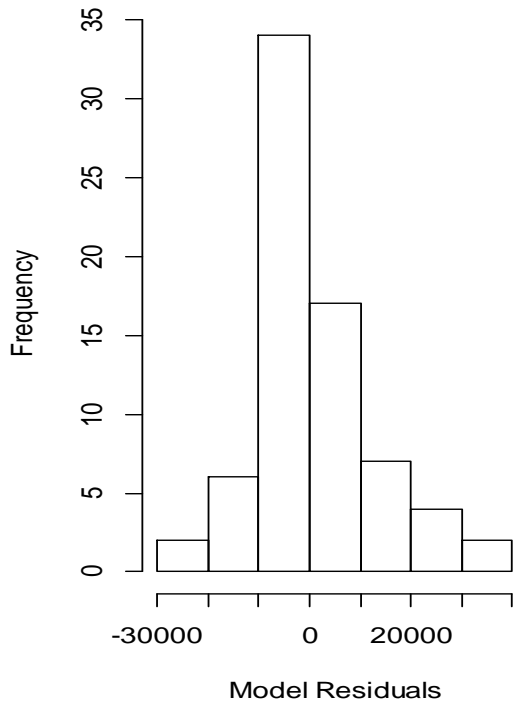
From figure 3.6 above, the ACF of residuals shows that only two (2) out of the 30 lags of the sample autocorrelations exceed the significant bounds, with two other lags just touching the bounds. We can ignore these lags, since the probability of a spike being significant by chance is about one in thirty. The ACF dies down after lag 12 with most lags getting close enough to zero.

This simply gives an indication of non-significant autocorrelation, since we would expect at most two (2) out of 30 sample autocorrelations to exceed the 95% significance bounds.

Also, from the Ljung-box test above, the computed p-value (i.e. 0.2531) is also greater than α (alpha) 5% level of significance.

Hence from these deductions, we failed to reject the null hypothesis that the series of residuals exhibits no autocorrelation and concluded that there is very little evidence for non-zero autocorrelations in the residuals at all lags (i.e. the residuals are independently distributed).

Histogram of ARIMA(2,1,1) residua



Normal Q-Q Plot

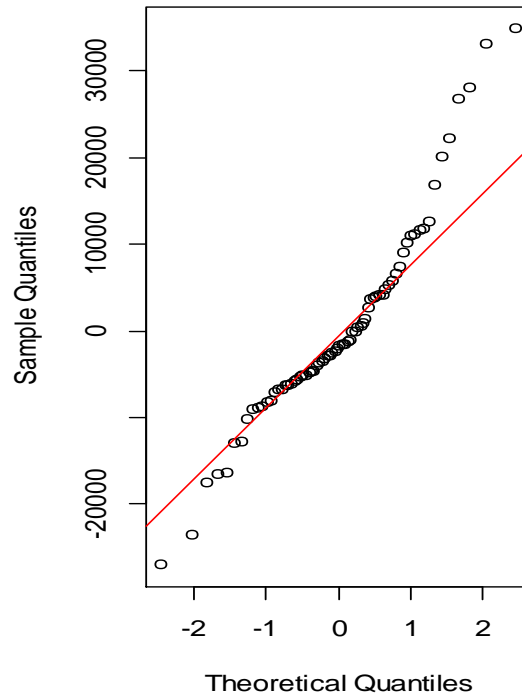


Figure 3.7: Shows the Histogram (left) and Normality plot (right) for the residuals of ARIMA (2,1,1).

From the plot in figure 3.7, the histogram of the residuals displayed provides an indication of a plausible symmetric distribution, thus its shape looks “bell-like” and certainly better for the fitted model. The QQ-normal plot for the residuals also threw more light on this since most of its residuals do not deviate that much from the line of best fit and its distribution looked approximately linear.

- **ARIMA(1,1,2)**

Coefficients:

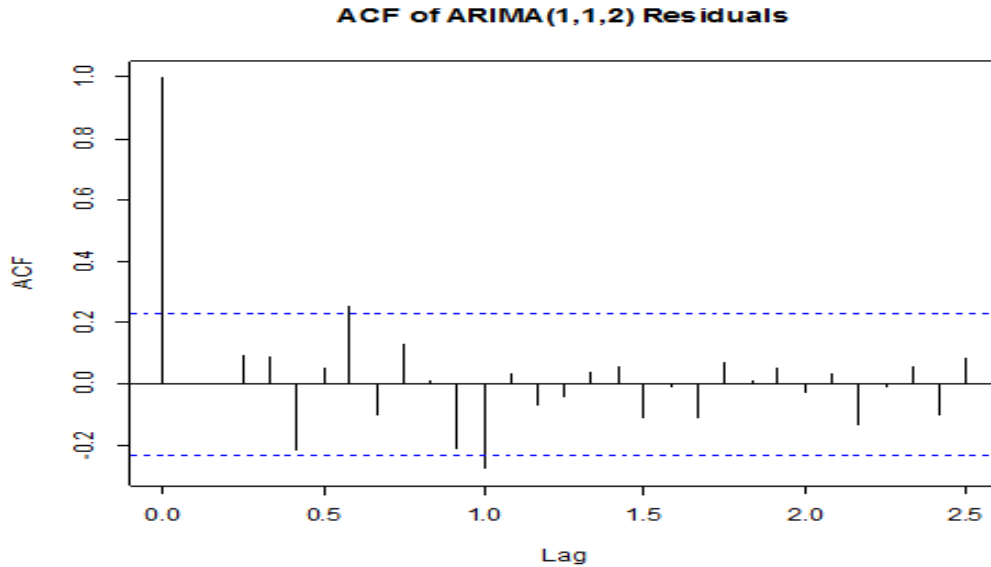
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ar1  ma1  ma2  drift
0.1402 -0.7726 -0.2273 265.9897
s.e. 0.3712 0.3731 0.3687 92.8428

sigma^2 estimated as 135322947:  log
likelihood=-767.27

AIC=1544.54  AICc=1545.47  BIC=1555.86
    
```

ME	RMSE	MAE	MPE	MAPE	MASE
313.9182	11551.7732	8545.4932	-13.9012	32.7510	0.82094



3.8 ACF OF ARIMA (1,1,2) Residuals

Box-Ljung test:

data: model2\$residuals

X-squared = 33.8909, df = 30, p-value = 0.2852

From figure 3.8 above, the ACF of residuals shows that only two (2) out of the 30 lags of the sample autocorrelations exceed the significant bounds, with other lags tailing off. This simply gave an indication of insignificant autocorrelation, since we would

expect at most two (2) out of 30 sample autocorrelations to exceed the 95% significance bounds. Also, from the Ljung-box test above, the computed p-value (i.e. 0.2852) is less than α (alpha) 5% level of significance. Hence from these deductions, we fail to reject the null hypothesis that the series of residuals exhibits no autocorrelation and conclude that there is little evidence for non-zero autocorrelations in the residuals at all lags (i.e. the residuals are independently distributed).

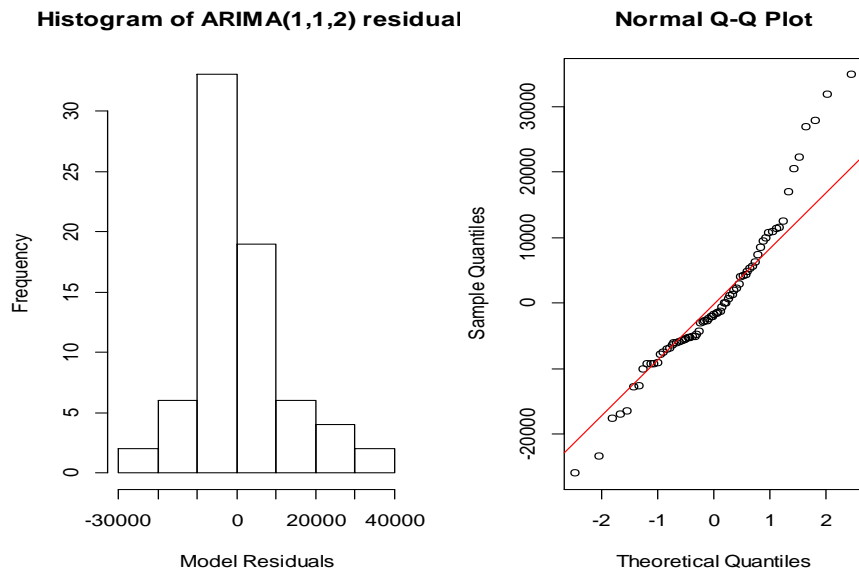


Figure 3.9: Shows the Histogram (left) and Normality plot (right) for the residuals of ARIMA (1, 1, 2).

From the plot in figure 3.9, the histogram of the residuals displayed gives an indication of a plausible symmetric distribution, thus its shape looks “bell-like” and certainly better for the fitted model. The QQ-normal plot for the residuals also threw more light on this since most of its residuals do not deviate that much from the line of best fit and its distribution looks approximately linear.

- **ARIMA(1,1,1)**
Coefficients:

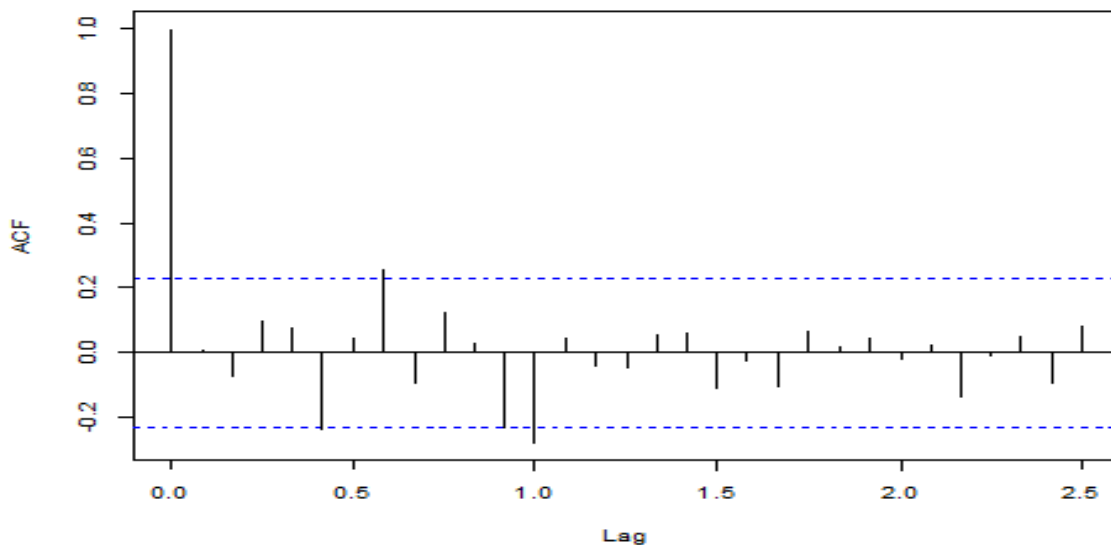
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ar1    ma1    drift
0.3449 -1.0000 265.5104
s.e. 0.1130 0.0526 98.8141
sigma^2 estimated as 136055977:  log
likelihood=-767.4
AIC=1542.79  AICc=1543.4  BIC=1551.84

```

ME	RMSE	MAE	MPE	MAPE	MASE
314.78423	11583.0183	8439.5034	-13.8549	32.3879	0.8108

ACF of ARIMA(1,1,1) Residuals



3.10 ACF of ARIMA (1,1,1) Residuals

Box-Ljung test:

data: model3\$residuals

X-squared = 35.3853, df = 30, p-value = 0.2289

From figure 3.10, the ACF of residuals shows that three (3) out of the 30 lags exceed the significant bounds. The ACF tails off after lag 12, with majority of the lags getting close enough to zero. However, Lag 11 just touches the bounds and we can ignore it,

since the probability of a spike being significant by chance is about one in thirty. This simply gives an indication of insignificant autocorrelation, since we would expect at most three (3) out of 30 sample autocorrelations to exceed the 95% significance bounds.

Furthermore, the computed p-value for the Ljung-Box test computed above is 0.2289, indicating that there is little evidence for non-zero autocorrelations in the residuals for all lags 1-30.

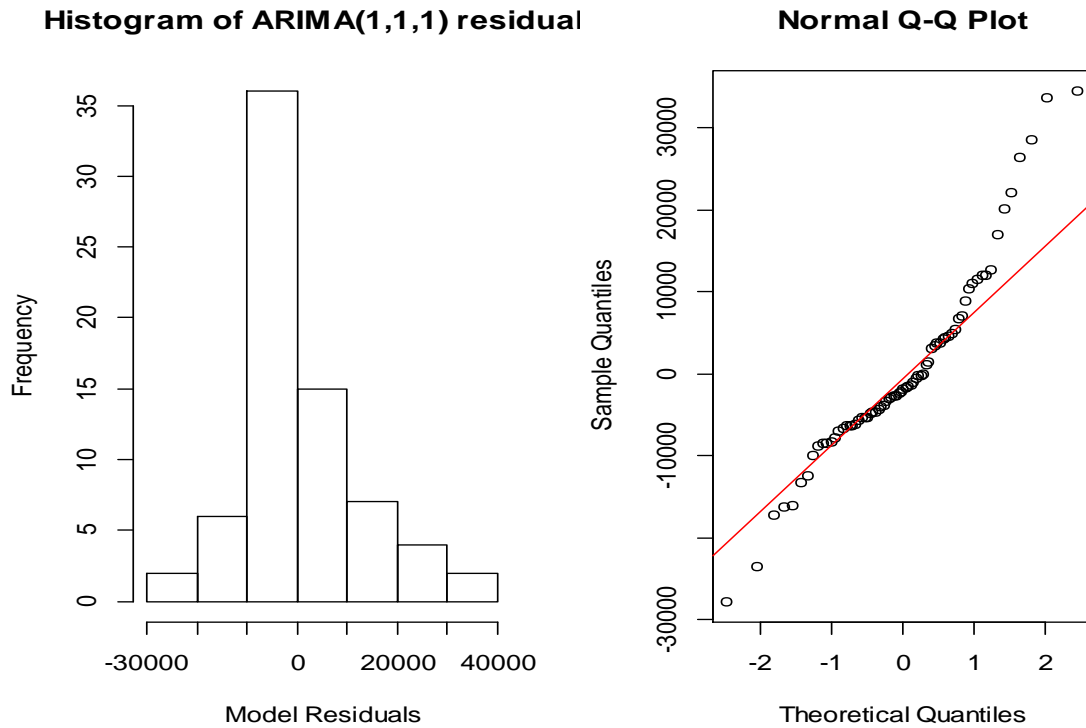


Figure 3.11: Shows the Histogram (left) and Normality plot (right) for the residuals of ARIMA (1, 1, 1).

From the plot in figure 3.11, the histogram of the residuals displayed gives an indication of a plausible symmetric distribution, thus its shape looks “bell-like” and certainly better for the fitted model. The QQ-normal plot for the residuals also throws more light on this since most of its residuals do not deviate that much from the line of best fit and its distribution looks approximately linear.

3.5 Model Selection

In order to select the most appropriate model for our data, we compared all competing models and select

the one with the minimum AIC (Akaike Information Criterion value), Schwartz Bayesian Information Criterion (BIC) and Residual Variance. Other statistical tests like Root Mean Squared Error (RMSE), Mean Abs. Percent Error (MAPE), Bias Proportion or Mean Forecast Error (MFE) and Mean Absolute Scaled Error are also used in testing the forecast accuracy of the fitted models. The best model will be the one that achieves a compromise between the various information criterion values.

Table 3.2: Akaike Information Criterion for the possible Models

Model	Akaike Information Criterion (AIC)	Residual Variance	BIC	MASE
ARIMA(2,1,1)	1544.7	135,737,828	1556.01	0.8125169
ARIMA(1,1,2)	1544.54	135,322,947	1555.86	0.8209374
ARIMA(1,1,1)	1542.79	136,055,977	1551.84	0.8108

From table 3.2, it is clear that ARIMA (1, 1, 1) model is the best model for forecasting since its values are better than that of the other competing models, hence we fail to reject it over the other models. Therefore, the chosen model for the solid waste data series is of the form;

$$Y_t - Y_{t-1} = \alpha_1 (Y_{t-1} - Y_{t-2}) - \theta_1 e_{t-1} + \mu + e_t$$

$$Y_t - Y_{t-1} = 0.3449 (Y_{t-1} - Y_{t-2}) + e_{t-1} + 265.5104 + e_t$$

OR

$$Y_t = (1 + \alpha_1)Y_{t-1} - \alpha_1 Y_{t-2} - \theta_1 e_{t-1} + \mu + e_t$$

$$Y_t = 1.3449Y_{t-1} - 0.3449 Y_{t-2} + e_{t-1} + 265.5104 + e_t$$

This indicates that the fitted model is a linear combination of a previous solid waste value, previous forecast error and a constant.

3.6 Forecasting

We also make forecast using the most adequate fitted model for the next three years. Below is the graph of the forecasts.

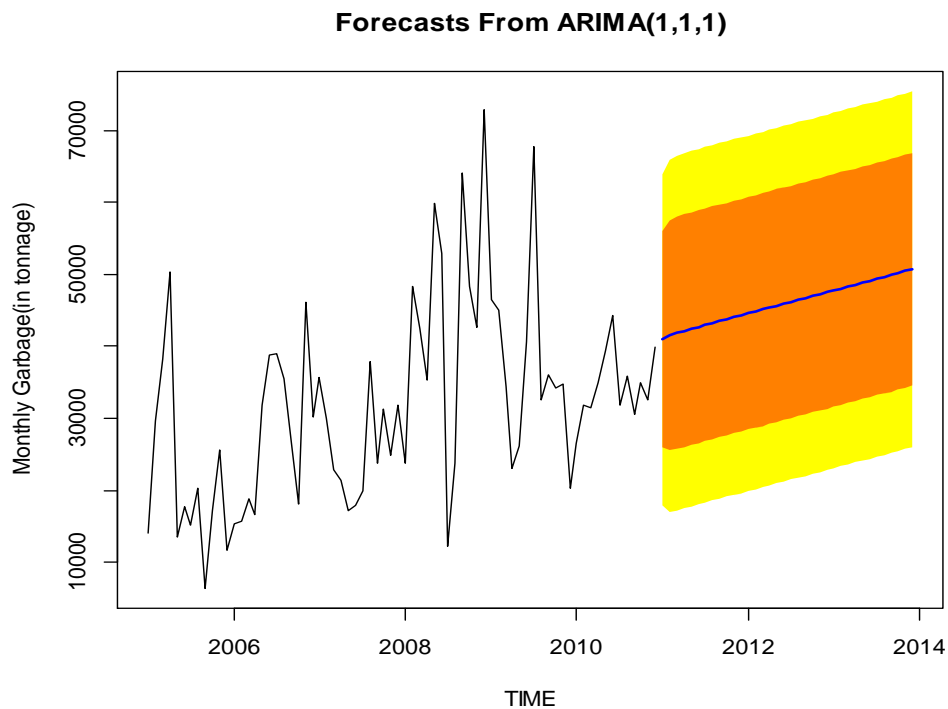


Figure 4.12: The forecasted solid waste values (in tonnage) are shown by the blue line, whilst the orange and yellow shaded areas show 80% and 95% prediction intervals respectively.

The forecasted values and standard errors are given in table 4.3.

Table 4.3: Forecasted Solid waste Values Using ARIMA (1, 1, 1)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
2011	40957.87	41525.34	41895.00	42196.42	42474.32	42744.10	43011.09	43277.11
2012	44604.93	44870.44	45135.95	45401.46	45666.97	45932.48	46197.99	46463.50
2013	47791.05	48056.56	48322.07	48587.58	48853.09	49118.60	49384.12	49649.63

	Sep	Oct	Nov	Dec
2011	43542.79	43808.36	44073.90	44339.41
2012	46729.01	46994.52	47260.03	47525.54
2013	49915.14	50180.65	50446.16	50711.67

Conclusions

The study has demonstrated how ARIMA time series model can be used to predict and forecast the monthly quantity of solid waste that will be generated in the KMA till the end of the year 2013. The research has shown that generally, the poor state of waste management is clearly due lack of forecast data for planning, rapid urbanization, poor financing capacity of local authorities, low technical capacity and management of solid waste and weak enforcement of environmental regulations. The challenge therefore is to develop and promote sustainable solid waste management systems that could anticipate and take into account the quantity of solid waste that could be generated in the foreseeable future. This is what the ARIMA method employed in this research sought to achieve. The paper recommends that since solid waste generation is a function of population growth, waste minimization strategies which may include re-use and recycling should focus the attention of policy makers. Finally, for the KMA to overcome the challenge of managing solid waste there should be proper planning for waste disposal in the city. The sub metros should be empowered to generate enough resource to collect and manage the solid waste in the city so that the health and wealth on citizenry can be enhanced, after all health is wealth.

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