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Time Series Forecasting of Solid Waste Generation in Arusha City - Tanzania

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Abstract

Statistical time series modeling is widely used in prediction and forecasting studies. This study intends to analyze, compare and select the best time series model for forecasting amount of solid waste generation for the next years in Arusha city - Tanzania among ARMA/ARIMA and Exponential Smoothing models. The past data used are monthly amount of solid waste collected by the city authorities from year 2008 to 2013. The result indicated that ARIMA (1, 1, 1) outperformed other potential models in terms of MAPE, MAD and RMSE measures and hence used to forecast the amount of the solid waste generation for the next years.

Keywords: ARIMA models, Exponential Smoothing models, time series, MAPE, MAD, RMSE

1. Introduction

Solid waste are materials of all sorts regarded as useless and are disposed. In urban areas there are disposal points in various locations for people to dispose. In African cities poor management of solid waste is a common phenomenon due to budgetary problems, mismatching plans and inadequate information about the amount of solid waste generated by residents (Simelane and Mohee, 2012). Forecasting of solid waste generation rate is therefore important to city authorities to help them in the policy making and proper planning of operations related to solid waste management. Arusha city in Tanzania is one of the cities facing the problem of inefficient collection and disposal of solid waste. Population is among the major factors contributing to high amount of solid waste generation. Arusha city has a population of about 416,442 with an average annual increase rate of about 2.7% (NBS, 2013). With this population, if no proper measures taken to improve its management relative to the increasing population, consequences are bad. Furthermore, there are no published figures of solid waste generation and their trend in Tanzanian cities. The effect of uncollected solid waste include possible diseases outbreak and also blocks the city drainage systems bringing rise to other problems. This fact motivated this study of forecasting solid waste generation in the next five years so that Arusha city authorities can have useful information about the dynamics of solid waste generation to aid in their planning and operations.

The selection of a technique to forecast a subject depend on many factors – the accuracy desired, the context of forecast, the relevance and availability of statistical data, the time period to be forecast, the cost/benefit of the forecast, easiness of interpretation, guidelines from the literature and implementation (Armstrong, J. S., 2011). In this study, statistical modeling techniques ARIMA and Exponential smoothing are used. Ebenezer et al (2013) analyzed ARIMA models in forecasting Kumasi Metropolitan Area solid waste generation and obtained substantial results which were useful to the KMA authority. In their study, ARIMA (1, 1, 1) was selected as the best model. A study on application and evaluation of forecasting methods for municipal solid waste generation conducted in Kaunas – Lithuania in Eastern Europe exposed difficult in forecasting of municipal solid waste generation due to lack of data and selection of methods for the available data. The study implemented regression analysis for social – economic indicators of solid waste generation and time series analysis. Time series forecasting were found to be most accurate for forecasting short interval variation and results were useful to decision – makers in developing countries (Ingrida, R., et al, 2012).

2 Statistical Model

Time series analysis goes through specified set of procedures and the results at one stage is a decisive factor on what to do in the next stage. This study used a popular Box – Jenkins approach. This approach involves about four stages before real forecasting namely stationarity checking, model identification, parameter estimation and diagnostic checking. The approach use historical data as it input to generate future values. The models' work under assumptions that the data available are mean and variance stationary and the random errors or the difference between observed and forecasted values are uncorrelated. See Box and Jenkins (1976), Brockwell and

Davis (2002), Montgomery, Jennings and Kulahci (2008), Chatfield (2000) for details of these steps.

Most real life time series are stochastic. A stochastic time series is stationary if its statistical properties such as mean and variance do not change over time. Plots of the original data, autocorrelation (ACF) and partial autocorrelation (PACF) are examined for trend, seasonal components, cyclic and outliers. If these patterns are observed they can be removed by differencing the series to obtain stationary residuals (Brockwell & Davis, 2002). An alternative for stationarity checking is the Dickey – Fuller unit root test. This determines if a time series needs differencing or not (Stevenson, 2003).

When time series has achieved stationarity, model identification is done by examining the ACF and PACF plots. The order are identified by matching the patterns of ACF and PACF plots. When ACF decays quickly then spikes observed in PACF gives the AR order and when PACF decays quickly, ACF's significant lags give the order of MA terms. When both ACF and PACF plots decays mixed model is considered. Parameters of the identified models are estimated by method of maximum likelihood, moments or the method of least square (Brockwell and Davis, 2002).

Diagnostic checking involves checking if the estimated parameters adequately fit the data. Examination of residual autocorrelation is one such method in which the plots of ACF and PACF residuals are checked for white noise properties. If the model sufficiently fit the data, the autocorrelation of the residual should not be significantly different from zero for lags greater than one. Another approach in checking adequacy of the fitted model is by computing Ljung – Box statistic.

When the observed time series are stationary and need no differencing, the ARMA (p, q) is fitted. The general equation of ARMA (p, q) is:

$$\left(1-\phi_1 B - \ldots - \phi_p B^p\right) X_t = (1-\theta_1 B - \ldots - \theta_q B^q) a_t$$

Where p and q are the orders of autoregressive and moving average components respectively, B is the backshift operator, X_t is the quantity predicted at time t, ϕ_p and θ_q are parameters.

When the observed data needs differencing to achieve stationarity, the ARIMA (p, d, q) is fitted. The general equation for ARIMA (p, d, q) is:

$$\left(1-\phi_1 B - \ldots - \phi_p B^p\right)(1-B)^d X_t = (1-\theta_1 B - \ldots - \theta_q B^q) a_t$$

Where d is the order of differencing.

Exponential smoothing models existing in the literature are Simple/single Exponential Smoothing (SES), Double Exponential (Holt) Smoothing (DES)/Linear Exponential Smoothing and Triple Exponential Smoothing (TES). Simple exponential smoothing is for series which are stationary, double exponential smoothing are for series which exhibit trend and triple exponential smoothing is for series with trend and seasonality. The general equations for the three models are shown next (Mentzer, 2005).

Simple Exponential Smoothing (SES) has one smoothing equation with one parameter:

$$F_{t+1} = \alpha X_t + (1-\alpha) F_{t-1}$$

Double exponential smoothing (DES) has two smoothing equations with two parameters:

$$L_t = \alpha X_t + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \gamma (L_t - L_{t-1}) + (1-\gamma) T_{t-1}$$

$$F_{t+p} = L_t + p T_t$$

Triple exponential smoothing has three smoothing equations with three parameters:

$$L_t = \alpha X_t + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \gamma (L_t - L_{t-1}) + (1-\gamma) T_{t-1}$$

$$S_t = \delta (X_t - L_t) + (1-\delta) S_{t-1}$$

$$F_{t+p} = L_t + p T_t + S_{t+p-l}$$

Where $L_t =$ current level, $T_t =$ current trend level $S_t =$ Current seasonality level

$F_{t+p} =$ Forecast after period p, and $\alpha, \gamma, \delta =$ smoothing parameters

Various fit and performance criteria are used to choose the best forecasting model. These performance criteria include Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), Root Mean Squared Error (RMSE), R – square, Akaike Information criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC).

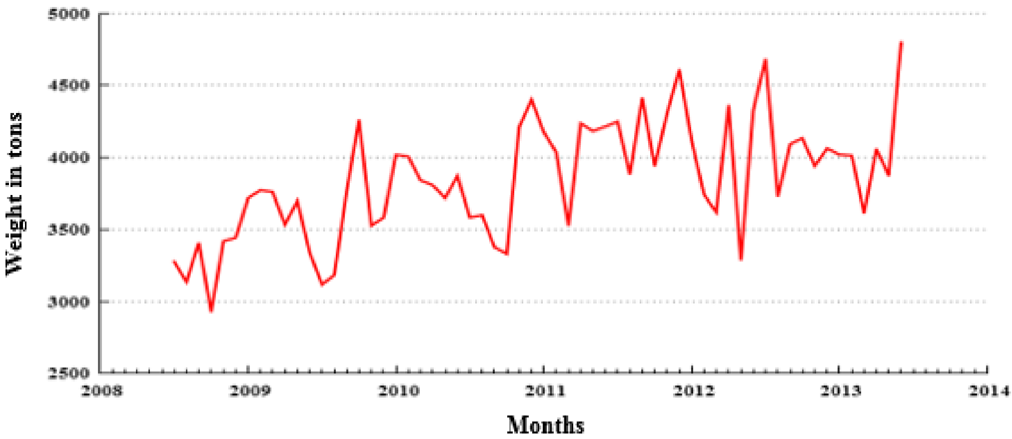
3. Results and discussion

Data used in this study were records of monthly amount of solid waste collected for disposal from Arusha City by health department of the city council from July 2008 to December 2013. A total of 66 observations are available, of which 60 are used for model formulation and 6 hold of for model validation.

3.1 Stationarity test

In stationarity test we examine presence of trend, seasonal, cyclic and other irregular components. If these elements are found, then the series is non-stationary. Visual observation of plot in figure 1 shows an increasing trend with fluctuations across time. The minimum value is 2927 in October 2008, the first quartile is 3572, the median is 3855.5, the third quartile is 4143.5 and the maximum value is 4798 in June 2013

Figure 1. Graph of original series for solid waste generation



These statistics indicate the presence of trend in mean since left hand side of the plot is lower than the right hand side. The fluctuations differences also suggest trend in variance. There are no evidence of seasonal components since no regular peaks and troughs that are observed and it is assumed that the data are non-seasonal. The entire dataset mean and variance are computed and compared with the mean and variance of the split first half and second half of the dataset. The results are shown in table 1 gives strong evidence of presence of trend or seasonality as mean and variance changes across time. Correlograms test for stationarity is also considered.

Table 1. Computed Mean and Variance

	Entire dataset	First half	Second half
Mean	3848.16	3621.87	4074.47
Variance	167768.72	121766.81	113600.53

Observation of the plots of autocorrelation (ACF) and partial autocorrelation (PACF) functions indicates that the autocorrelations do not come to zero for several lags. Lags 1, 2, 3, 7, 10 and 12 of the autocorrelation are significantly different from zero at 0.05 confident interval. This is a sign of non-stationarity.

Figure 2. ACF and PACF of observed series.

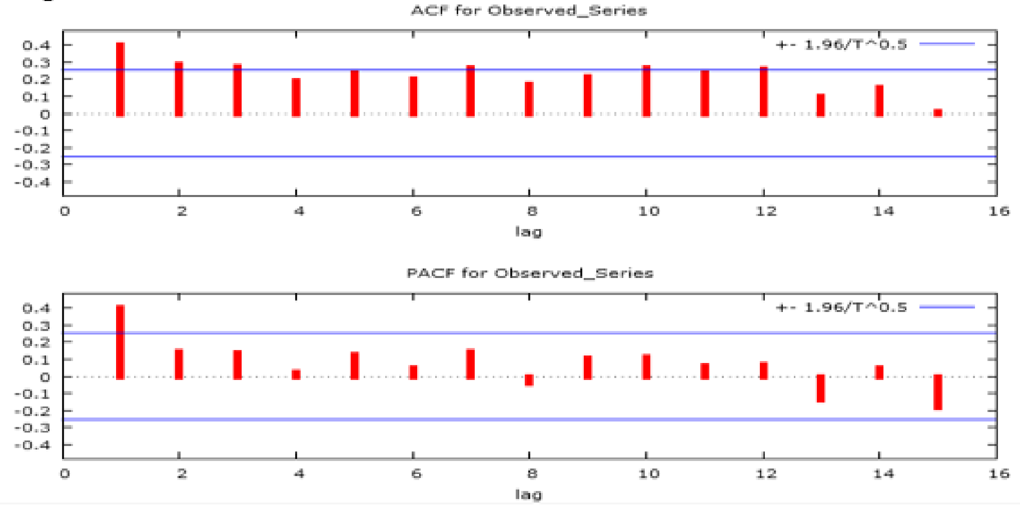
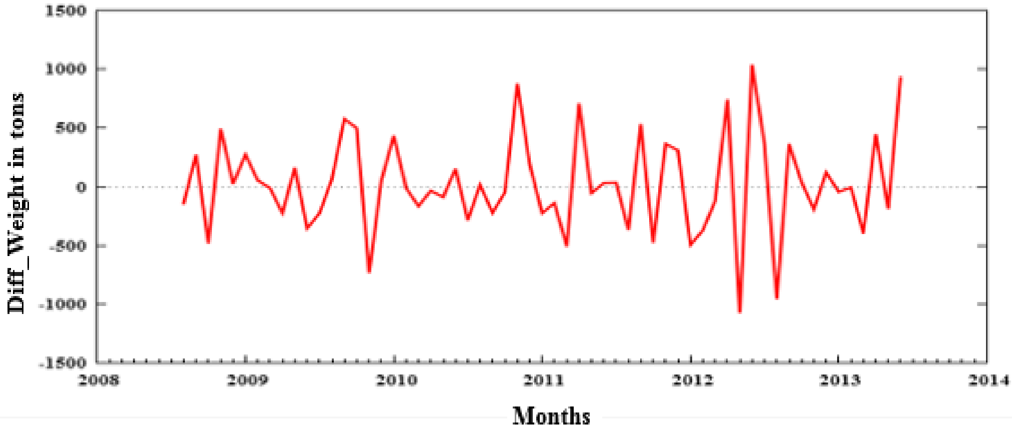


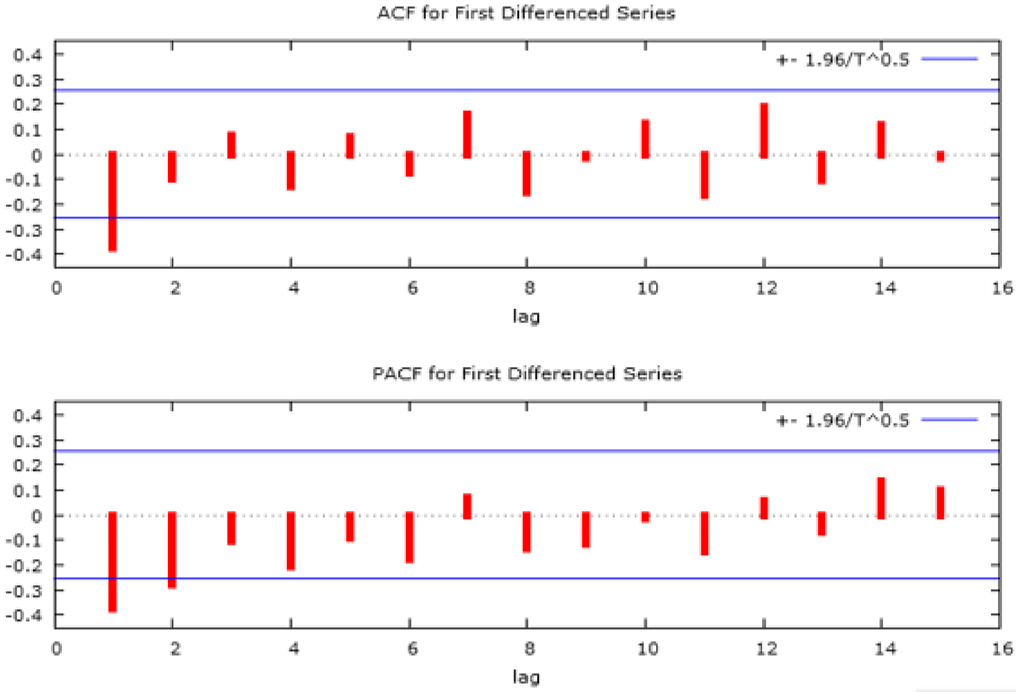
Figure 3. Graph of first differenced series for the solid waste series.



The conclusion is that the series is non-stationary and need to be differenced once to achieve stationarity. Figure 3 is a plot of first differenced series of the original series, the plot show that the first differenced data is more stable about the zero mean.

The differenced series ACF and PACF plots are indicated in figure 4. The ACF plot shows that autocorrelations are not significantly different from zero except a spike at lag 1. The PACF plot also shows that the partial autocorrelations are not significantly different from zero except spikes that are observed at lag 1 and lag 2. Both

Figure 4. ACF and PACF of differenced series



ACF and PACF seems to decay in somehow sine-cosine fashion. The plots also confirm that the observed series is not seasonal as no patterns of seasonality can be seen.

3.2 Model Identification

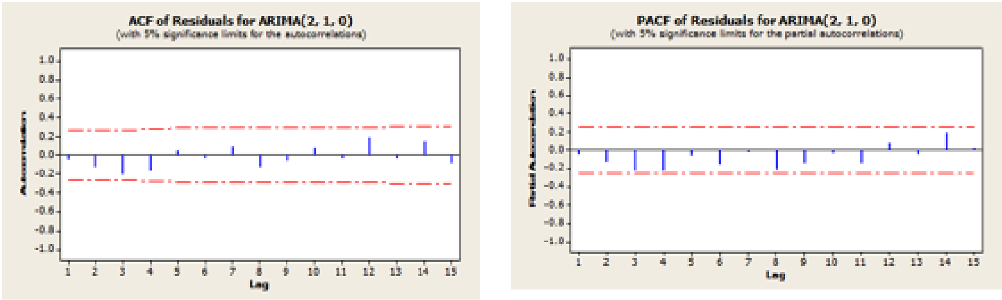
For the first differenced series, ARIMA (p, 1, q) are considered where *d=1* is the order of differencing. The ACF plot of differenced series cuts of at lag 1, assuming that PACF is decaying, ARIMA (0, 1, 1) is proposed. The PACF plot cuts of at lag 2 and assuming that the ACF decays, ARIMA (2, 1, 0) is proposed. In time series modeling it is usual to consider a broad class of potential models by examining correlogram of the raw data and differenced data (Chatfield, 2000). Based on this fact, mixed ARIMA (1, 1, 1) and ARIMA (2, 1, 1) are also included as potential fit the data. Exponential smoothing model fitted is double exponential smoothing (DES). This model is identified because the observed series has trend component only and no seasonality. Double exponential smoothing is usually fit on data with trend.

3.3 Diagnostic checking

Parameters of the potential models were computed with assistance of Minitab software. In each case the residual are examined to ensure that they meet the model assumptions that the residuals are white noise or independently and identically distributed.

ARIMA (2, 1, 0): The ACF and PACF residuals of fitted ARIMA (2, 1, 0) are displayed in figure 5. Clearly they are white noise at 5% significance limit. The computed Ljung-Box statistics has p-values 0.284, 0.404, 0.675 and 0.861 at lag 12, 24, 36 and 48 respectively that are greater than the value of significant level of 5%. The conclusion is that ARIMA (2, 1, 0) has residuals that are independent and identically distributed and hence it is an adequate model for the observed data.

Figure 5. ACF and PACF of the residuals of ARIMA (2, 1, 0)

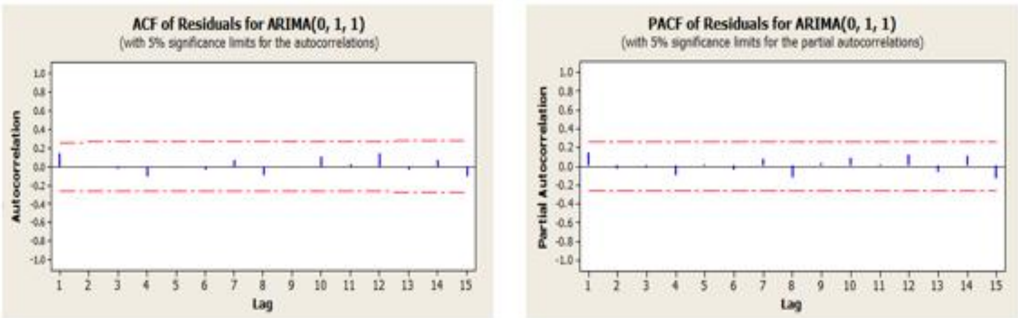


Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24	36	48
Chi-Square	10.9	21.9	28.8	34.9
DF	9	21	33	45
P-Value	0.284	0.404	0.675	0.861

ARIMA (0, 1, 1): The ACF and PACF residuals of fitted ARIMA (0, 1, 1) are displayed in figure 6. Clearly they are white noise at 5% significance limit. The computed Ljung-Box statistics has p-values 0.874, 0.889, 0.919 and 0.930 at lag 12, 24, 36 and 48 respectively that are greater than the value of significant level of 5%. The conclusion is that ARIMA (0, 1, 1) has residuals that are independent and identically distributed and hence it is an adequate model for the observed data.

Figure 6. ACF and PACF of the residuals for ARIMA (0, 1, 1)

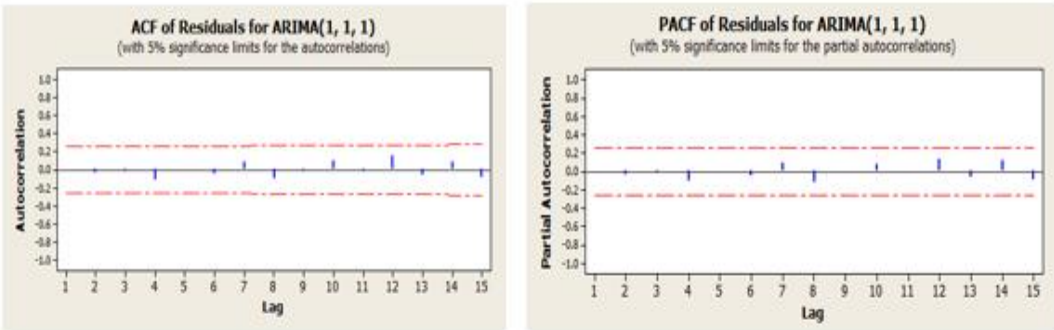


Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24	36	48
Chi-Square	5.2	14.3	23.2	32.7
DF	10	22	34	46
P-Value	0.874	0.889	0.919	0.930

ARIMA (1, 1, 1): The ACF and PACF residuals of fitted ARIMA (1, 1, 1) are displayed in figure 7. Clearly they are white noise at 5% significance limit. The computed Ljung-Box statistics has p-values 0.846, 0.911, 0.957 and 0.980 at lag 12, 24, 36 and 48 respectively that are greater than the value of significant level of 5%. The conclusion is that ARIMA (1, 1, 1) has residuals that are independent and identically distributed and hence it is an adequate model for the observed data.

Figure 7 – ACF and PACF of residuals for ARIMA (1, 1, 1)

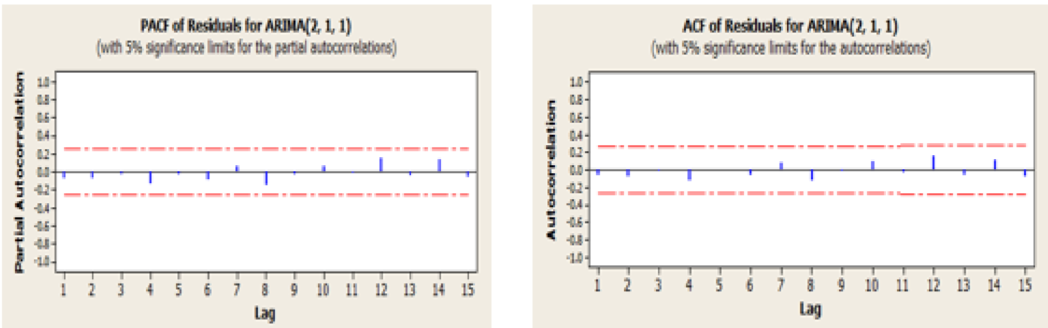


Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24	36	48
Chi-Square	4.9	12.9	20.5	27.7
DF	9	21	33	45
P-Value	0.846	0.911	0.957	0.980

ARIMA (2, 1, 1): The ACF and PACF residuals of fitted ARIMA (2, 1, 1) are displayed in figure 8. Clearly they are white noise at 5% significance limit. The computed Ljung-Box statistics has p-values 0.846, 0.911, 0.957 and 0.980 at lag 12, 24, 36 and 48 respectively that are greater than the value of significant level of 5%. The conclusion is that ARIMA (1, 1, 1) has residuals that are independent and identically distributed and hence it is an adequate model for the observed data.

Figure 8. CF and PACF of the residuals for ARIMA (2, 1, 1)



Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24	36	48
Chi-Square	6.4	14.2	21.4	28.0
DF	8	20	32	44
P-Value	0.602	0.818	0.924	0.971

Double Exponential Smoothing (DES): The double exponential smoothing weights were specified by taking the initial observation as the initial level and zero as initial trend and parameters that minimizes mean squared error (MSE) were computed. The parameters computed are $\alpha = 0.1,\ \ \gamma = 0.02$ correct to significant figure and the initial level and trend are respectively $L_0 = 3278\ and\ T_0 = 0$

3.4 Model Selection

The ARIMA models were compared by means of how best they fit the data. Akaike Information Criterion (AIC), Schwarz Bayesian Criterion of each ARIMA model is computed using gretl software and displayed in table 2.

Table 2. The AIC and BIC for the ARIMA Models

	AIC	BIC
ARIMA (2, 1, 0)	873.92	882.23
ARIMA (0, 1, 1)	862.10	868.34
ARIMA (1, 1, 1)	862.23	870.54
ARIMA (2, 1, 1)	864.22	874.61

Based on results of AIC and BIC, ARIMA (0, 1, 1) and ARIMA (1, 1, 1) have smallest AIC, both are selected because AIC and BIC gives the best fit model but not necessarily the best performing model. These models are compared with double exponential smoothing in terms of its performance in forecasting.

The main objective of this study is to identify the best model that can be used to forecast solid waste generation in Arusha City. The competing models, ARIMA (0, 1, 1), ARIMA (1, 1, 1) and Double Exponential Smoothing (DES) are compared by performance measures; Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Root Mean Squared Error (RMSE). I look at performance during the estimation period and performance in validation period using the hold on data values. The formula used for each of the measures are shown below

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_t - F_t}{X_t}\right| \times 100 \qquad RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(X_t - F_t)^2} \qquad MAD = \sum_{t=1}^{n}\frac{(X_t - F_t)}{n}$$

Table 3. MAD, MAPE and RMSE for Competing Models in Estimation Period

	ARIMA (0 ,1, 1)	ARIMA (1, 1, 1)	DES
MAPE	7.5	7.33	7.42
MAD	286.81	281.13	285.14
RMSE	339.59	334.18	348.60

The results shown in table 3 are performance of the models during the estimation period in which the forecast points are compared with the observed points used for model formulation. The results shown in table 4 are forecast values produced by the models in six months from July 2013 to December 2013 and they are compared with the observed values.

Table 4. Observed and Forecasted Values

Observed	ARIMA (0 ,1, 1)	ARIMA (1, 1, 1)	DES
4523	4227.45	4376.78	4226.12
4358	4241.35	4311.26	4239.43
3970	4255.14	4310.79	4252.74
4039	4269.15	4322.22	4266.05
4014	4283.05	4335.83	4279/36
4420	4296.94	4349.83	4292.67

Table four shows the observed values and the forecasted values using the three potential models. Forecasting performance is computed for each case. The computed MAD, MAPE and RMSE from table 4 are indicated in table 5 below.

Table 5. MAD, MAPE and RMSE in Validation Period

	ARIMA (0 ,1, 1)	ARIMA (1, 1, 1)	DES
MAPE	5.26	4.92	5.25
MAD	219.93	201.50	219.65
RMSE	231.93	233.96	231.05

ARIMA (1, 1, 1) has performed well during estimation as well as during validation period therefore it is chosen to forecast the solid waste. Since the series has been differenced and has a non-zero average trend, a constant term is included in the equation. The equation of the chosen model has the form:

$$(1-\phi_1 B)(1-B)^d X_t = (1-\theta_1 B)a_t + c$$

Where the first difference d =1; X_t is estimated weight at time t, a_t is the white noise, B is the backshift operator and c is a model constant.

Expanding the equation gives

$$(1-\boldsymbol{B}-\phi_1 B+\phi_1 B^2)X_t = (1-\theta_1 B)a_t + c$$

$$(X_t-\boldsymbol{B}X_t-\phi_1 BX_t+\phi_1 B^2X_t) = a_t-\theta_1 Ba_t + c$$

$$X_t - X_{t-1}-\phi_1 X_{t-1}+\phi_1 X_{t-2} = a_t-\theta_1 a_{t-1}+c$$

$$X_t = X_{t-1}+\phi_1 X_{t-1}-\phi_1 X_{t-2}+a_t-\theta_1 a_{t-1}+c$$

Parameters have been computed by the method of exact maximum likelihood (ML) using GRETL software and they are $\phi_1 = 0.1829$, $\theta_1 = -1.0000$, $c = 14.0912$

Substituting the parameters in the equation yields

$$X_t = X_{t-1}+0.1829X_{t-1}-0.1829X_{t-2}+a_t+a_{t-1}+14.0912$$

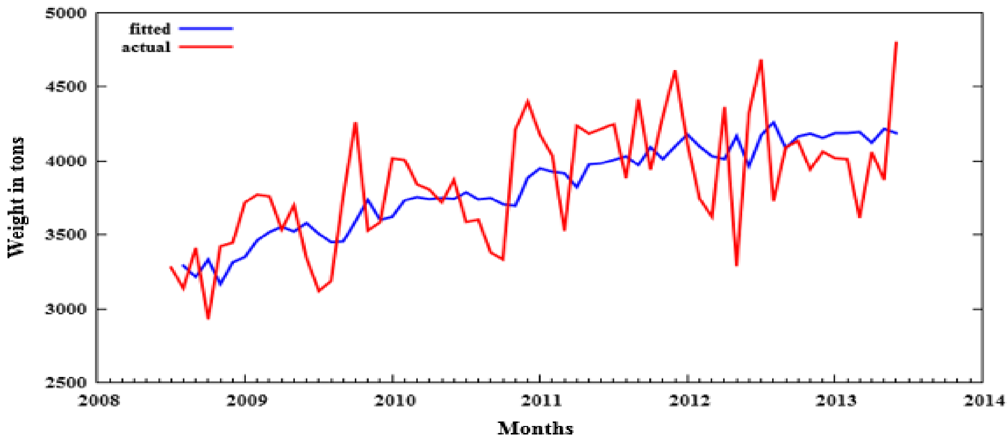
$$X_t = X_{t-1}+0.1829X_{t-1}-0.1829X_{t-2}+a_t+a_{t-1}+14.0912$$

Hence the model formulated is:

$$X_t = 14.0912+1.1829X_{t-1}-0.1829X_{t-2}+a_t+a_{t-1}$$

The plot below represent the actual series and the fitted ARIMA (1, 1, 1).

Figure 9. Plot of actual and fitted ARIMA (1, 1, 1)



4. Summary and Conclusion

This study analyzed, compared and selected the best time series model for forecasting amount of solid waste generated in Arusha city among ARIMA and Exponential Smoothing models. The past data used are monthly amount of solid waste collected by the city authorities from year 2008 to 2013. The data from July 2008 to June 2013 were used to formulate the model and remaining data up to December 2013 were used to validate the selected potential models. The result indicated that ARIMA (1, 1, 1) outperformed other potential models in terms of MAPE, MAD and RMSE measures and hence used to forecast the amount of the solid waste generation for the next years. The forecasted values indicate that by 2018, the monthly generation according to the model will reach 5100 tons with a 95% confidence interval lying between 4440 – 5750 tons. The model is validated and is adequate for forecasting solid waste generation and hence results can be used by city authorities to update their planning of management.

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