Forecasting Future Customer Call Volumes: Case Study

Karimi Njeru
Department of Mathematics
Catholic University of Eastern Africa
Nairobi, Kenya.
ritakare@gmail.com

Dr. Karanjah Anthony N.
Department of Mathematics,
School of Science
Maasai Mara University
Narok, Kenya.
karanjah@mmarau.ac.ke;

Dr. J. Ivivi
School of Mathematics
University of Nairobi
Nairobi, Kenya.
ivivi.mwaniki@gmail.com

Abstract— Forecasting future volumes of customer calls in call centers has proved to be a tedious and challenging task. This study, using time series analysis proposes two adequate ARIMA (p, d, q) models that are suitable to forecast two volumes of customer calls, IVR Hits Volumes and Offered Call volumes. 1472 times series data points from date 01/01/2014 to 11/01/2018 were obtained from a call center based in Kenya on the two variables of interest (IVR Hits Volumes and Offered Call volumes).

The appropriate orders of the two models are picked based on the examination of the results of the ACF and PACF plots. The AIC criterion is used to select the best model for the data. The best ARIMA model for log IVR Hits volumes is ARIMA (5, 1, 3) with $MSE = 0.01126$ and the best ARIMA model for log Offered Call Volumes is ARIMA (6, 1, 3) with $MSE = 0.01569$. The two models are recommended to model and forecast the daily arrival volumes of customer call data. The obtained forecast will be used in providing insights for appropriate workforce management.

Keywords- *Call Center, Forecasting, Time series, Workforce Management*

*****

1. Introduction

The Kenyan telecommunication industry is growing at a very high rate. A study conducted by Bratton (2013), indicate that at least 65% of the Kenyan population has access to a phone today. There are three main telecommunication companies in Kenya all with established call centres. Service delivery and customer satisfaction being the key manual guiding the centers, high techniques and process of scheduling are required. In a research conducted by Esmaeili and Horri (2014), they explained that customer satisfaction should be primal for a company to thrive in a stiffly competed market.

All the activities in a call center are guided by the number of calls that are received in different time periods. Successful operation of a call center requires the management to have insights of the future volumes of calls that are to be received in various times periods. However, this has in most occasions proven to be a difficult task. Different operations team have had difficulties on determining which are the best approaches and methods to use to forecast the numbers of future calls that are expected, Ibrahim & L'Ecuyer (2013). The main objective of this study is therefore to propose sufficient ARIMA (p, d, q) models for future call volumes at the call centre used for the case study.

2. The model

2.1 Time Series Methods for Forecasting Volumes of Customer Calls

Barrow (2016), defines a time series as a sequence of observed data points that are measured at equidistant intervals of time. Time series analysis has been applied in various fields, for example, in finance, time series models have been used and applied in predicting the behaviour and prices of certain instruments and commodities in the markets (Chatfield, 2016). In a call center, we may denote the number of calls received in the call as W_t, at a certain time period *t*, the volume of calls in the previous time period are denoted as W_{t-1}. In time series analysis, a model that utilizes only past values of the time series to forecast future values is called an Autoregressive (AR) process. According to Babu and Reddy (2014), the model is mathematically represented as follows;

$$W_t = \emptyset_1 w_{t-1} + \emptyset_2 w_{t-2} \pm \dots + \emptyset_p w_{t-p} + \varepsilon_t \quad (1)$$

Where ε_t is the error term, $\emptyset_1, \emptyset_2 \dots\dots \emptyset_p$ are the parameter weights of the model. They relate series W_t to the lags $W_{t-1}, W_{t-2} \dots W_{t-p}$ and are estimated form the sample data.

A model that uses past random disturbances or noise (also referred to as past shocks) is described as a Moving average process (MA). According to Chatfield (2004), the algebraic representation of MA (q) is given by:

$$W_t = \varepsilon_t + \emptyset_1 \varepsilon_{t-1} + \emptyset_2 \varepsilon_{t-2} \dots + \emptyset_p \varepsilon_{t-p} \quad (2)$$

Where $\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}$ are the error terms (white noise), assumed to follow a normal distribution. $\emptyset_1, \emptyset_{2\dots}$ are the parameter weights of the model. They relate the series W_t to the error terms.

The other model in time series that utilizes both past shocks and past values is the Autoregressive-Moving Average (ARMA) process. The ARMA (p, q) is generally denoted as:

$$W_t = \emptyset w_{t-1} + \theta(L)\varepsilon_t \quad (3)$$

ISSN: 2454-4248
12– 16

All these models based on the assumption of stationary, where mean, variance, and the auto covariance do not vary over time. Stationarity of a time series in most occasions is achieved through various statistical transformations. Box and Ljung (2015), explained differencing as one of the most commonly used method of achieving stationarity of a time series. The first order differencing for example can be denoted as$Z_t = W_t - W_{t-1}$. The first order however only eliminates 'drift'. The second difference of the time series eliminates trend. Seasonal differencing may also be necessary to attain a sufficient model to forecast customer call volumes. An ARMA model for a differenced time series is referred to as an ARIMA model.

2.2 The ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) theory is a time series analysis principle used in forecasting future events with reference to time. An ARIMA- Model is applied to a set of data series if the series is weakly stationary. Chatfield, (2016), defined that it is sufficient to use ARIMA (Autoregressive Integrated Moving Average) model if a data series is at least stationary. According to Chatfield (2016), the ARIMA model is given by:

$$W_t = \sum_{i=1}^{p} \alpha_i L^i W_t + \sum_{i=1}^{p} \theta_i L^i W_t \varepsilon_t + \varepsilon_t \qquad (4)$$

Where L is the lag operator in the series

$$L^k \mathbf{W}_t = \mathbf{W}_{t-k} \qquad (5)$$

In the above ARIMA equation, α_i are the coefficients of the ith autoregressive terms in the data series. θ_i are the moving average coefficient of the *i* th term. ε_t are defined as the residuals in the series. The residuals are assumed to be independent and normally distributed random variables with mean zero and variance σ^2.

3. Methodology

3.1 Data Overview

The data accessed from the Call Centre was available in terms of daily totals from 1st January, 2014 to 11th January, 2018. The data obtained from this call center is taken as a classical representation of all call centers in the country and the general telecommunication industry call centers. The data extracted had eight variables, the main variables of interest include;

(i). Dates: described as the specific date on which the data was captured.

(ii). IVR hits: these are the daily number of calls that are received on the Interactive voice system.

(iii). The Offered volumes: these are the number of call that move from the IVR system to the trunk lines awaiting service.

The analysis of daily data, according to Ibrahim and L'Ecuyer (2013), require the data points to be at least 100 in size, in this study 1472 data points are available.

3.2 Box-Jenkins Methodology

The study takes the Box-Jenkins Methodology approach for modelling. This method takes up three iterative steps;

(i). Model identification – it is the first step in the methodology where the model structure of AR, MA, or ARIMA are examined and identified. According to Box and Jenkins (1976), best model can be identified by examining the PACF and ACF through plots.

(ii). Estimation of parameter of the model – in this step, Maximum likelihood estimation or nonlinear least-square estimation techniques are employed to estimate the models coefficients.

(iii). Model diagnostic- this is an important step as it ensure the adequacy of the model. The residual of the model should have mean zero (independently and identically distributed) and the parameters estimates should be statistically significant for the sufficiency of the model. According to Avramidis and L'Ecuyer (2005), misspecification can be identified by cross examination of the following plots: residual means and variance plots over time, ACF and PACF plots, and performing Box – Ljung test.

(iv). Forecasting – The adequate models selected are used to forecast values of the of the arriving customer call volumes for at least 100 days ahead.

4. Results

The objective of workforce management in a call center is to ensure maximum transition of calls from waiting lines to answered calls. Therefore, in this analysis, we investigate models that can adequately forecast the daily incoming number of customer calls on the IVR switch (IVR hits volumes), and the incoming number of calls on the waiting lines (Offered volumes).

The analysis of the 1472 data points was done using applications of various statistical analysis techniques with the aid of 'R' (build 3.4.3) statistical software and time series packages; 'tseries', 'forecast', 'TTR', 'Zoo' and 'Xts'. The results are discussed using plots as follows.

4.1 Time series plots for the variables under investigation

The daily IVR hits and Offered call volumes between 01/01/2014 and 11/01/2018 are plotted each against time.

 ISSN: 2454-4248
12– 16

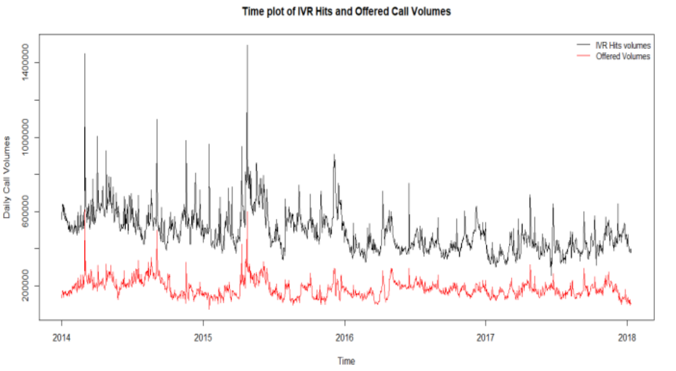

Figure 1: Time plot for Daily IVR Hits, and Offered Calls volumes

From the above time plots, it is clear that the series from the two variables are non-stationary. We decompose the time series data to investigate the existence of trend, seasonal, and random components.

4.2 Stationarity analysis using the ACF, PACF, KPSS and Dickey-Fuller

Autocorrelation function and Partial Autocorrelation function plot are established to further investigate if the two time series under investigation are stationary. Figure 2 and Figure 3 below are the ACF and PACF plots of the two variables.

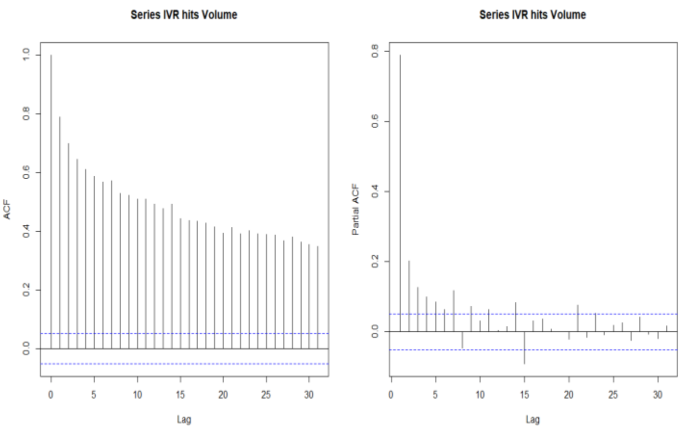

Figure 2: ACF and PACF plots of IVR hits volumes

Figure 3: ACF and PACF plots of IVR offered call volumes

The ACF and the PACF plots of the two series clearly depicts the series are non – stationary. From the plot we can see evidence of seasonal wave pattern that decrease moderately with increase in lag. The seasonal patterns decay constantly with time. From the plots, the two series, IVR Hits daily volumes and daily offered call volumes are non-stationary and therefore, require differencing to attain stationarity.

Further tests of stationarity are carried out to confirm the conclusions obtained from visual analysis of seasonal stationarity.

4.3 The Unit Root Test

We test the hypothesis below using the Augmented Dickey Fuller Test:

Augmented Dickey Fuller Test			
	Dickey Fuller	**Lag Order**	**p-value**
IVR Hits	-6.0588	11	0.0187
Offered	-5.8284	11	0.0123

Table 1: The results on the Augmented Dickey Fuller Test

H_0: The customer calls series has a unit root (i.e. there is seasonality)

H_1: The series is stationary

In this test we reject the null hypothesis if the Dickey fuller is more negative than the tabular value and the $p-value \leq 0.01$.

According to the ADF test results for the series under analysis displayed in Table 1 above, we fail to reject the null hypothesis that the two customer care call series are non-stationary and conclude they are not stationary. The conclusion is made since the more negative the Dickey –Fuller is, the stronger the rejection of the null hypothesis which is not the case here in the results.

An analysis is further done to investigate trend stationarity of the series. The Kwiatkowski–Phillips Schmidt Shin test (KPSS) is used in this analysis. The hypothesis for this test is given by:

H_0:The call center data under investigation is trend stationary

H_1: The series is not stationary

In KPSS, We reject the null hypotheses if the *p*-value ≤ 0.05.

KPSS Test			
	KPSS level	**Lag Parameter**	**P Value**
IVR Hits	7.0582	8	0.01
Offered	1.828	8	0.01

Table 2: KPSS test results

From the KPSS analysis, we reject the null hypothesis that the time series data under investigation is trend stationary and conclude that the two series are not stationary. The *p*-value (0.01) for the two variables is less than 0.05.

The above analysis confirms that the two series under investigation are not stationary. Therefore differencing is require to achieve the required stationary series.

4.4 Seasonal differencing

The Series, IVR hits volume, Offered volumes, are then transformed by obtaining their natural logarithm, and then taking the first difference to attain stationarity. Figure 4 below is a plot of the two series after differencing.

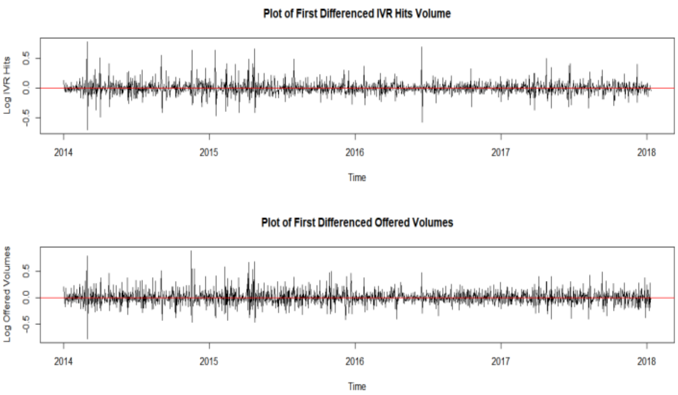

Figure 4: Plots of the seasonally differenced ($d = 1$) call center data

The pattern formed in the two plots indicate that there exist no systemic seasonality, trend, or periodic cycles. Therefore there exist some evidence that data on the two variables is stationary.

4.5 Model building for daily customer call centre data

According to Wooff and Stirling (2015), the process of model building is done in a procedural manner. The processes involved in model fitting include data plotting, data transformation where necessary, identification of order dependence, parameter estimation, running diagnostics, and selection of appropriate model. In this section two univariate ARIMA models are used to model the two volumes of customers call data at the Jambo contact center.

4.6 Model identification

An ARIMA model of order p, d, q, is used to model the two times series data under investigation. The ACF and PACF plots are used in the identification of the values of p and q in each of the model developed. The value of d is the number of differenced done for the series to be stationary. The value of p is identified by observing the spikes of the ACF at the lower lags. The value of q is identified by observing the nature of the spikes in both the ACF and PACF as the lags increases. Looking at the ACF and PACF of the two time series on the customer care data, the following ARIMA models are proposed for, IVR Hits volumes, Offered call volumes, Answered call volumes, and Average Handling time per call.

4.7 Proposed Models for the two variables on call center data

The AIC and the Log likelihood values for each model are computed. The AIC statistic is used to select the best fit for the all the variables under investigation. The best fit to be selected in the model with the lowest AIC value.

IVR Hits Volume Models		Offered Volumes Models	
Model	**AIC**	**Model**	**AIC**
ARIMA(2,1,1)	-2349.91	ARIMA (4,1,3)	-1824.97
ARIMA(4,1,3)	-2360.20	ARIMA (5,1,3)	-1905.69
ARIMA(5,1,2)	-2351.36	ARIMA (6,1,3)	-1910.60
ARIMA(5,1,3)	-2403.75	ARIMA (7,1,5)	-1909.16

Table 3: Statistics for the tentative IVR and Offered call volumes ARIMA models

Table 3 above presents the statistics for the various models that were investigated. The best models for AVR Hits volume and Offered call Volumes are ARIMA (5, 1, 3), ARIMA (6, 1, 3) respectively.

4.8 Parameter Estimation

The models obtained for each of the call volume series are summarized to obtain the parameter estimate as well as present the models that were obtained for each of the variables.

4.81 IVR Hits volumes

The model ARIMA (5, 1, 3) fitted on the daily IVR Hits volumes series is given by:

$$\widehat{W}_t = -1.0706W_{t-1} + 0.2676W_{t-2} + 0.7740W_{t-3} + 0.1923W_{t-4} + 0.1213W_{t-5} + 0.7546\varepsilon_{t-1} + 0.7776\varepsilon_{t-2} - 0.9227\varepsilon_{t-3} \quad (6)$$

The parameters $-1.0706, 0.2676, 0.7740, 0.1923,$ and 0.1213 are the autoregressive parameter weights at lag one up to lag five respectively with reference to $\widehat{W}_t$. The parameters $0.7540, -0.7776,$ and -0.9227 are the moving average parameter weights at lag one up to lag three respectively. The negative parameters have a negative effect on the series $\widehat{W}_t$ while the positive parameters have a positive effect on the series.

4.82 Offered call volumes

The model ARIMA (6, 1, 3) fitted on the daily offered call volumes series is given by:

$$\widehat{W}_t = -1.0555W_{t-1} + 0.3008W_{t-2} + 0.8024W_{t-3} + 0.2614W_{t-4} + 0.2315W_{t-5} + 0.0540W_{t-6} + 0.7505\varepsilon_{t-1} - 0.8022\varepsilon_{t-2} - 0.9355\varepsilon_{t-3} \quad (7)$$

The parameters $-1.0555, 0.3008, 0.8024, 0.2614, 0.2315$ and $0.\,0.0540$ are the autoregressive parameter weights at lag one up to lag six respectively with reference to $\widehat{W}_t$. The parameters $0.7505, -0.8022,$ and -0.9355 are the moving

ISSN: 2454-4248
12– 16

average parameter weights at lag one up to lag three respectively. The negative parameters have a negative effect on the series $\widehat{W}_t$ while the positive parameters have a positive effect on the series.

4.9 Model Validation

To check the adequacy of the models selected, the residuals of the fitted models were obtained. QQ plots of the residuals were visualized to investigate if they originate from a normal distribution. The Figure 5 below shows the Q-Q plots for the two models.

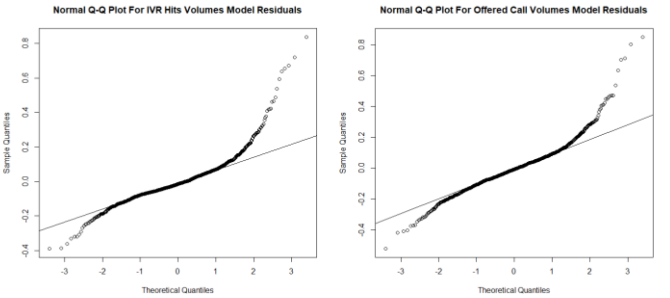

Figure 5: Normal Q-Q plots for the residuals of two selected models.

The residuals of the two models selected, ARIMA (5, 1, 3) and ARIMA (6, 1, 3), appear to approximately follow a normal distribution. Therefore the two are adequate in modelling the two call center volumes series, IVR Hits and Offered call volumes respectively since t.

4.10 Forecasting

The objective of this investigation was to develop adequate models to forecast various call customer call volumes aspects that enable the workforce management team to plan and make decision that ensure maximum productivity of the call center. Accuracy statistics for the models selected were obtained. The statistics obtained include MSE, RMSE, MAE, and MAPE.

The MSE of the two models 0.01126232 for ARIMA (5, 1, 3) and 0.01569027 for ARIMA (6, 1, 3) are approximately close to zero. Therefore, from the above realization, we conclude that the two models are adequate and accurate to estimate the characteristics of call center volumes.

The Models selected were used to forecast 100 days ahead on all the two customer calls variables. 80% and 95% confidence intervals were obtained for the forecasted values. Plots of the forecasted series were then obtained as shown in Figures 6 below. A sample of 30 forecasted values is also obtained.

IVR Hits and offered call volumes Forecast

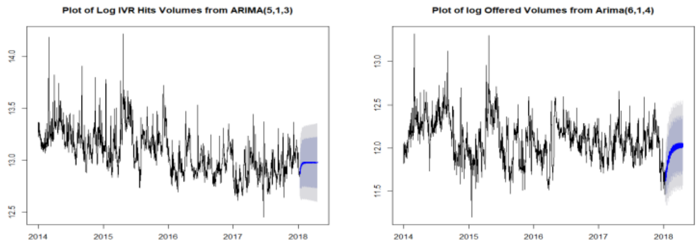

Figure 6: Plot of the IVR Hits Forecasted Values Offered Forecasted Values.

The Figures 8 presents a graphical representation of the a hundred day forecast on IVR Hits and offered call volumes respectively. The deep blue line presents the actual forecast, the lighter blue area following the blue line is the 95% confidence interval of the forecast, and the finale area lightly shaded presents the 80% confidence interval of the forecast.

5. Conclusion

Analysis on the two customers call series, IVR Hits and Offered Volumes yielded results that the ARIMA model is the sufficient time series method for forecasting. The ARIMA (5, 1, 3) and ARIMA (6, 1, 3) are the sufficient models selected to model and forecast IVR Hits and Offered call Volumes. The ARIMA (5, 1, 3) and ARIMA (6, 1, 4) have $MSE = 0.01126232$ and $MSE = 0.01569027$ respectively. The two models obtained can be used to forecast the future customer call volumes. This information about future volumes of calls arriving at the call center will enable the management to adequately plan for demand expected. The forecasted values will see the management ensure the rate of call abandonment is reduced will ensuring that cost of running the center is checked.

6. References

[1] Avramidis, A. N., & L'Ecuyer, P. (2005). Modelling and simulation of call centres. In M. E. Kuhl, N. M. Steiger, F. B. Armstrong, & J. A. Joines (Eds.), Proceedings of the 2005 winter simulation conference (pp. 144–152). IEEE Press

[2] Babu, C. N., & Reddy, B. E. (2014). A moving-average filter based hybrid ARIMA–ANN model for forecasting time series data. *Applied Soft Computing*, *23*, 27-38

[3] Barrow, D. K. (2016). Forecasting intraday call arrivals using the seasonal moving average method. *Journal of Business Research*, *69*(12), 6088-6096

[4] Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.

[5] Bratton, M. (2013). Briefing: Citizens and cell phones in Africa. *African Affairs*, *112*(447), 304-319.

[6] Chatfield, C. (2016). *The analysis of time series: an introduction*. CRC press.

[7] Esmaeili, A., & Horri, M. (2014). Efficiency evaluation of customer satisfaction index in e-banking using the fuzzy data envelopment analysis. *Management Science Letters*, *4*(1), 71-86.

[8] Ibrahim, R., & L'Ecuyer, P. (2013). Forecasting call centre arrivals: Fixed effects, mixed-effects, and bivariate models. Manufacturing & Services Operations Management, 15(1), 72–85