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Forecasting of enrolment of national health insurance in Dodoma region of Tanzania using autoregressive integrated moving average model

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Abstract
The National Health Insurance Fund (NHIF) was set up in Tanzania in 2001 as a mandatory scheme, offering comprehensive benefit package for its citizen. NHIF membership enrolment forecasting is very essential in managing and providing good and quality health services to the citizens. Majority of decision makings like introduction of new health programs and infrastructure improvements are easily made with the aid of NHIF membership forecasts. In this paper, the data of NHIF membership enrolment of Dodoma region from 2002 to 2016 have been modeled by using Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) technique to ascertain the growth in the membership of NHIF. The NHIF membership has been further forecasted to the financial year 2016/2017 to 2017/2018 (twenty four months) using seasonal ARIMA (1,2,0) (0,0,1) [12] for male, seasonal ARIMA (0,2,0) (1,0,0) [12] for female and seasonal ARIMA (0,2,1) (0,0,1) [12] for total combined population. The models have been validated using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Ljung-Box statistic values, graphical techniques like time series plots, Q-Q plots and histograms and p-values. The study also explores briefly the recourses required to support current and forecasted NHIF members.

Keywords: Auto-regressive Integrated Moving Average (ARIMA), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Ljung-Box statistic, Q-Q plot.

1. Introduction
There are four main health insurance schemes in Tanzania described as National Health Insurance Fund (NHIF), which is mandatory for public servants and voluntary for informal sectors, Community Health Fund (CHF/TIKA), which is community based voluntary pre-payment scheme established with the objective of enabling communities to access affordable health services, Social Health Insurance Benefits scheme (SHIBS), which is a mandatory for the private formal sector who contribute to the National Security Fund (NSSF) and Private health Insurance (PHI) which is the scheme mostly covers the private formal sectors and is voluntary scheme. The main objective for the establishment of the National Health Insurance fund was to administer the scheme and to formulate and promulgate policies for sound administration of the scheme. Later the membership base was extended to cover all public servants in 2002. The National Health Insurance scheme is a social policy that caters for the most vulnerable in society through the principle equity, solidarity, risk sharing, cross subsidization, re-insurance, subscriber/community ownership and value for money, good governance and transparence in health care delivery.

The National Health Insurance Fund of Tanzania has attractive packages that are offered to its beneficiaries through credited heath facilities. The NHIF benefits consist of eleven services, which include- Registration and consultation, Medicine and medical supplies, Investigations, Surgical services, Inpatient care services including Intensive Care Unit (ICU) and High Dependency Unit (HDU), Physiotherapy and rehabilitation services, Eye and optical services, Spectacles, Dental and oral health services, Retiree health benefits and Medical/orthopedic appliances.

Upon admission in hospital, a National Health Insurance Fund member is accorded services and the hospital make a claim to the fund for reimbursement (NHIF, 2013). The Tanzanian Health Sector Strategic Plan III indicates a commitment to the expansion of pre-payment schemes as a means of generating complementary financing for health service provision and, ultimately, achieving universal coverage, with 30% coverage targeted by 2015 (United Republic of Tanzania, 2008). Insurance for Africans is still a long way off for the majority because they are still struggling to meet their food and day to day needs. The factors which led to the low insurance penetration in Africa are as follows; lack of human capital and expertise, poor legal and judicial systems, people do not trust the financial services provider, lack of reliable information and communities often make use of informal forms of insurance rather than using the services of formal insurance (Lodney Lester, 2011) [9].

Health insurance market is small by regional and global standards in Tanzania; however, it is growing rapidly. The figures released by the Ministry of Health and Social Welfare (MOHSW) during its 2011 Technical Review Meeting suggest that around 17.1% of the national population are insured by the NHIF/CHF/TIKA(7.3% by the NHIF, 9.8% by the CHF/TIKA) (Ally, 2011) [3-2]. A further estimated 1% is insured through the remaining schemes (SHIELD data), resulting in an estimated 18.1% total national coverage.

There is wide variation in health insurance coverage by socioeconomic status. Unsurprisingly, health insurance cover is higher among the rich. Tanzania DHS (2010) [13]. indicate that 15% of the richest groups were insured compared to 2% of the poorest groups. Richer groups were covered by a wide range of health insurance schemes, whereas poorer groups were only covered by the CHF/TIKA.

The intention of National Health Insurance Fund is to provide health services to its members during the need of treatment or body checking. The fund is dedicated to provide support to its beneficiaries to access health services, which need to know the number of membership enrollment and plan for the future.

With this background, it has been planned in this paper to study the trend of membership registration and to select the best models for forecasting membership registration for the next twenty four months because it is important for policy makers to plan and provide the best services according to the time and needs of the customers.

This study examines the potential to predict future NHIF membership registration based upon the historical record of members for male, female and total population using Box-Jenkins technique. The study findings will help the National Health Insurance Fund management as well as the policy makers in the government for motivating and improving the membership drive further more so that not only rich citizen but also poor citizen be benefitted by the NHIF program for the better future of the country.

2.0 Review of Literature

2.1 Theoretical literature review

The NHIF coverage in Tanzania is still low as compared to other East African countries such as Rwanda 91%, and Kenya 21% (NHIF, 2010). The adult population has health insurances amounting to nearly 1.2 million individuals in Tanzania by 2011.

The determination of whether the health care services exist by health financing system (Carrin & Chris 2005) [4], pointed that the World Health Organization (WHO) committed to develop their health financing systems so that all people have access to services in order to avoid to suffer financial hardship in need of getting services, aimed reaching a universal health coverage (WHO, 2010).

Acharya *et al.* (2012) [1]. found that there is no evidence to support widespread scaling up of social health insurance schemes as means of increasing financial protection from health shocks or of improving access to health care. The study also found that the health insurance schemes must be designed to be more comprehensive in order to insure that the beneficiaries attain desirable levels of health care utilization and have higher financial protection.

Addae-Korankye (2013) [2]. study used survey design involving both quantitative and qualitative methods. The study revealed that NHIS is very potential mechanism in removing the financial barrier to get equitable access to health services for all citizens. The government and national health insurance authority (NHIA) required enforcing the application of the income classification category with the accompanying appropriate premium in order to meet the condition of risk pooling and social solidarity.

The study entitled Assessment of Innovative Strategies on Service Delivery at the National Hospital Insurance Fund by Nyaberi and Kwasira (2015) [17]. used multiple regression analysis to fit the data of NHIF. The organization objectives archived through the Iris and Fingerprint techniques. Reduction of financial losses to the organization and promote the efficiency of delivery through biometric techniques.

The study by Sunday *et al.* (2015) [19] used descriptive qualitative study utilizing an evaluation study design approach. Since many people cannot manage cost of health services indicates that health care is still a very big global problem. Majority of household still use the out-of-pocket payment for health care. This problem is particularly severe in developing countries in which many people live in poverty.

National health insurance for South Africa December 2015 version 40 also found that by 2030 South Africa should have made significant efforts in moving towards universal health coverage and this will be critical to realizing the vision of long and healthy life for South Africans. The NHI requires the establishment of strong governance mechanism and improves accountability for the use of allocated funds (RSA, 2015).

The study carried out by Kumburu (2015) [7] entitled National Health Insurance Fund in Tanzania as a Tool for Improving Universal Coverage and Accessing to Health Care Services. The study applied a multiple case cross-sectional design where by purposively and snowball techniques used. He found that reimbursement of NHIF bills to health care providers takes long time contrary to NHIF reimbursement policy (within 60 working days) with the limitation that some of the NHIF benefits and packages services, which are supposed to be provided to NHIF members, are not provided. He gave a recommendation that there is a need for reviewing benefits and packages services and mechanism of reimbursement of NHIF bills and NHIF and health facilities providers must ensure that there is equal treatment between NHIF members and those who pay by cash.

2.2 Empirical literature reviews

Empirical literature reviews are knowledge derived from investigation, observation experimentation, or experience. The study analysis by Kuwomu *et al.* (2011) applied the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) regression model to forecast foodstuff prices in Ghana. Using Box-Jenkins Modeling Techniques to Forecast Future Disease Burden and

Identify Disease Aberrations in Public Health Surveillance Report (Garret, 2012) [6] used the data from 2002 to 2008 to make a projection the future disease burden using Box-Jenkins procedures. The accuracy of forecast is determined by conducting 48 forecast trials. The study demonstrates that it is possible to predict future disease burden using Box-Jenkins forecast techniques.

The study carried out by Fusein (2012) [5] entitled Time Series Analysis on Membership Enrolment of National Health Insurance Scheme. He used ARIMA (0, 1, 1) for the month wise data from 2005 to 2010 to forecast the enrolment for the period 2011 and 2012. The study found that the predicted values recorded decreasing from month to month.

The study entitled Forecasting Utilization by Subscribers of the National Health Insurance Scheme by Mohammed (2013) [12] fitted a Seasonal Autoregressive Integrated Moving Average (SARIMA) for data of Nadowli District Mutual Health Insurance Scheme for the period March 2006 to June 2012. The best model identified was ARIMA (0, 1, 0) (1, 0, 0) [12] which used to forecast six months ahead. Validity of the model was tested using standard statistical techniques. The study indicates an increase utilization pattern in the short to medium term due to growing awareness, and he suggested that health care providers in the district should ensure that adequate medical supplies are available.

There were not much studies available on the modelling of national health insurance data as it is clear from the above review. These studies have been carried out on the National Health Insurance Scheme discussing about National Health Insurance Fund at different areas, scope and the methods carried out on those studies as explained clearly above, but those studies did not show the trend analysis of membership enrolment of national health insurance scheme by using ARIMA model as grouped into male, female and total wise.

3. Research Methodology

In this section, we present the methodology used to estimate the trends and selecting the best ARIMA model for forecasting the NHIF membership in Dodoma region, which has been purposely selected to collect data of NHIF membership enrolment. This Region lies inland very close to the center of Tanzania Mainland. Its location attracts the Tanzania Government to establish its Capital in Dodoma Municipality.

3.1 Box Jenkins Methodology

In time series analysis, the Box-Jenkins method, named after the statisticians George Box and Gwilym Jenkins, applies autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA) models to find the best fit of a time series model to past values of a time series. The following are steps for Box-Jenkins methodology:

- Plot the series and identify the trend (is the series trending in the mean/Variance?)
- Test for stationarity (Augmented Dickey Fuller Test, KPSS Test, and PP-Test)
- Transform the series into a stationary series (power transformation /seasonal differencing/ first differencing etc)
- Plot the Autocorrelations and Partial Autocorrelation functions (Identify possible models)
- Estimate the possible models (check for coefficient significance and white noise residuals)
- Select the best models based on the information criteria (the model with lowest AIC and BIC)

3.2 Autoregressive integrated moving average (ARIMA)

A model with only autoregressive terms is referred to as an $AR(p)$ model and one with only moving average terms is referred to as $MA(q)$ model. However, some models contain both terms and these models are termed $ARMA(p, q)$ models, for autoregressive moving average model. This is the case when there is no differencing. When differencing is performed the mixed model is referred to as an autoregressive integrated moving average (ARIMA) model and denoted as $ARIMA(p, d, q)$, where p is the order of auto regression, d is the level of differencing and q is the order of the moving average. The model may be a mixture of these processes and of higher orders and can be presented as under.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \theta_1 W_{t-1} + \theta_2 W_{t-2} + \cdots + \theta_q W_{t-q} + \varepsilon_t \ldots\ldots\ldots (3.1)$$

Where ε_t's are independently and normally distributed with zero mean and constant variance σ^2 for $t = 1,2,3, \ldots n$. In practice, the values of p and q lie between 0 and 3.

3.3 Non seasonal ARIMA models

ARIMA models are models that possibly may include autoregressive (AR) terms, moving average (MA) terms and differencing (integration) operations. When differencing is required in the model it is specified as ARIMA (p, d, q), where the 'd' refers to the order of differencing, "p" is the order of autoregressive and "q" is the order of moving average. A first difference might be used to account for a linear trend in a data set as expressed in equation 3.2.

$$Z_t = X_t - X_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2).$$

If the order of differencing is 2 ($d = 2$), it implies the analyzed variable is given as equation 3.3.

$$Z_t = (X_t - X_{t-1}) - (X_{t-1} - X_{t-2}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3.3)$$

That is a first difference of first differences. To identify a possible model, a time series plot of the observed data series, the autocorrelation function (ACF) and partial autocorrelation function (PACF) are examined to guess the orders of the various terms in an ARIMA. The things to look out for are possible trend, seasonality, outliers, constant variance and non- constant variance.

The autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) all together gives an overall nature of the model. This requires a lot of experience and experimentation (guesses) but the following general guidelines can be applied in identifying the various terms in an ARIMA model.

- If a series has positive autocorrelations out to a high number of lags, then it may need a higher order of differencing.
- If the lag 1 autocorrelation is zero or negative, the series does not need a higher level of differencing. The same is the case if the autocorrelations are all small and with no pattern.
- A stationary series requires no differencing and a model with no order of differencing often include a constant term which represents the mean of the series.

- If a first difference of the series yields only non-significant autocorrelations then the series is called a random walk model as expressed in equation 3.4.
- $X_t = \delta + X_{t-1} + w_t$ … … … … … … … … … … … … … (3.4) .
- (The data are dependent and are not identically distributed; increasing mean and variance through time)
- If the PACF of the differenced series displays a sharp cutoff and or the lag 1 autocorrelation is positive, then consider adding one or more AR terms. The lag beyond which the PACF cuts off is indicative of the number of AR terms.
- If the ACF of the differenced series displays a sharp cutoff and or the lag 1 autocorrelation is negative, then the addition of an MA term should be considered. The lag beyond which the ACF cuts off is the indicated number of MA terms.
- It is possible for an AR term and an MA term to cancel each other's effect and as such if a mixed model, ARMA, seem to fit the data, try a model with one fewer AR term and one fewer MA term and a combination of such manipulations.

3.4 Seasonal ARIMA models (SARIMA)

In a time series, seasonality is a regular pattern of changes that repeats over specific time periods. If s defines the number of time periods until the pattern repeats again, 's' can be define as $s = 12$ (months per year) or $s = 4$ (quarters per year). It may also be days of the week, weeks of the month and so on. In a seasonal ARIMA model, seasonal AR (P) and MA (Q) terms predict X_t using data values and errors at times with lags that are multiples of s (length of season). For example with monthly data ($s = 12$), a seasonal first order AR(1) would use X_{t-12} to predict X_t, and a second order seasonal AR(2) model would use X_{t-12}, and X_{t-24} to predict X_t. Similar a first order seasonal MA (1) model would use the error w_{t-12} as a predictor just as a seasonal MA (2) would use w_{t-12} and w_{t-24} for prediction. Seasonality usually causes the series to be non-stationary because of the seasonal changes in mean. This makes differencing necessary for seasonal data to achieve stationary. Seasonal differencing is defined as a difference between a value and a value with lag that is a multiple of the seasonal period "s". For instance, monthly data ($s = 12$) will have a seasonal difference as indicated in equation 3.5.

$(1 - B^{12})X_t = X_t - X_{t-12}$ … … … … … … … … … … … … … … … … …. (3.5)

The differences from the previous year may be about the same for each month of the year to yield a stationary series. Seasonal differencing removes seasonal trend and can also get rid of seasonal random walk type of non-stationary. It must also be noted that when the data series has trend, non-seasonal differencing may be applied to "detrend" the data. For this purpose, usually a first non-seasonal difference is enough to attain stationarity as shown in equation 3.6.

$(1 - B)X_t = X_t - X_{t-1}$ … … … … … … … … … … … … … … (3.6)

When both seasonality and trend are present it may be necessary to apply both a first order non-seasonal and a seasonal difference. In which case the ACF and PACF of the equation 3.7 needs to be examined.

$(1 - B^{12})(1 - B)X_t = (X_t - X_{t-2}) - (X_{t-12} - X_{t-13})$ … … … … … … … … … (3.7)

Removal of trend does not imply removal of dependency; the mean part, μ_t, which may include a periodic component, may have been removed. What is actually done is breaking the dependency down to recent things that have happened and long-range things that have happened. Short run non-seasonal behavior may still matter in seasonal data and contribute to a seasonal model. The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. The model is written in the following notation: $ARIMA(p, d, q) * (P, D, Q)S$.

Where

- p : non-seasonal AR orders, d: non-seasonal differencing, q: non-seasonal MA orders, P: seasonal AR orders, D: seasonal differencing, Q : seasonal MA orders, s : seasonal period or $s = time\ span$ of repeating seasonal pattern.

The non-seasonal AR and MA terms are written as given in equation 3.8 and 3.9.

Non-seasonal AR: $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ … … … … … … .. (3.8)

Non-seasonal MA: $\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$ … … … … … … … (3.9)

The seasonal AR and MA terms are written as in equation 3.10 and 3.11.

Seasonal AR: $\Phi_P(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} \ldots - \Phi_P B^{PS}$ … … … … … … … …. (3.10)

Seasonal MA: $\Theta_Q(B^S) = 1 + \Theta_1 B^S + \Theta_2 B^{2S} \ldots + \Theta_Q B^{QS}$ … … … … … … … … (3.11)

3.5 Building ARIMA Models

There are a few basic steps to fitting ARIMA models to time series data. A three-step iterative procedure was used to analysis of historical data. Second, the unknown parameters of the model were estimated by maximum likelihood method. Third, through residual analysis, diagnostic checks were performed to determine the adequacy of the model, or to indicate potential improvements.

3.6 Stationarity checking and Model Identification

The monthly time series data available in NHIF office in Dodoma regarding the enrolment of NHIF members from February 2002 to June 2016 were collected and transformed to stabilize the variance. The natural logarithm and second order ($d = 2$) differencing were done in order to attain stationarity of the data. Stationarity condition was achieved when the series becomes constant in its mean and variance. After suitably transforming the data, the next step was to identify preliminary values of the autoregressive order "p", the order of differencing "d" and the moving average order "q" for model identification. A time series plot of the data suggested that the second differencing was needed. Since differencing was called for, then difference the data, $d = 2$, and inspect the time plot of ∇X_t. Careful examination was done to avoid over differencing because this may introduce dependence where none exists. In addition to time plots, the sample ACF helped in indicating whether differencing was needed. Recall that the ACF of an ARMA model should decay exponentially fast to zero. Slow decay in the sample ACF was an indication that differencing was much needed.

The order selection of the model is very important when we use ARIMA process because the higher order in the model may result in smaller estimated errors. The Akaike Information Criterion (AIC) is a measure of the relative quality of statistical model for a given set of data, which has been used for ARIMA model selection and identification. It was used to determine if a particular model with specified parameters is a good statistical fit and the model with the lowest AIC value should be chosen. The AIC provide a researcher with an estimate of the information that would be lost if a particular model were to be used to display the process that produced the data. The Akaike showed that this criterion selects the model that minimizes:

$AIC = -2(\text{maximized log likelihood} - \text{number of parameters in the model})$.

$AIC = -2\log(L) + 2(p+q+k+1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.12)$.

For more simplified form the Akaike's Information Criterion (AIC) is expressed in equation 3.13.

$AIC = log\sigma^2{}_k + \frac{n+2k}{n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.13)$.

Where $\sigma^2{}_k = \frac{SSE(k)}{n}$, k is the number of parameters in the model. The value of k yielding the minimum AIC specifies the best model.

Correlated Akaike's Information Criterion (AICC) is given in equation 3.14.

$AICc = log\sigma^2{}_k + \frac{n+k}{n-k-2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.14)$.

Where $\sigma^2{}_k = \frac{SSE(k)}{n}$, k is the number of parameter in the model and n is the sample size.

In computing this, if a model has relatively little bias, describing reality well, it tends to provide more accurate estimates of the quantities of interest. The smaller AIC is better the model to be used.

Bayesian Information Criterion (BIC) is expressed in equation 3.15.

$BIC = log\sigma^2{}_k + \frac{klogn}{n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.15)$.

Where $\sigma^2{}_k = \frac{SSE(k)}{n}$, k is the number of parameter in the model and n is the sample size.

BIC is also called the Schwarz Information Criterion (SIC); various simulation studies have tended to verify that BIC does well at getting the correct order in large samples, where as AICC tends to be superior in smaller samples where the relative number of parameters is large.

Autocorrelation functions (ACF) and partial autocorrelation functions (PACF) plots of stationary series was examined to identify the orders of the autoregressive and moving average parameters of the ARIMA model to be formulated. The order of autoregressive part was given by the lag at which PACF cuts off to zero and the order of the moving average was given by the lag at which ACF cuts off to zero.

3.7 Parameter estimation, diagnostic checking, and Forecasting

Maximum likelihood method of estimation has been used to estimate the parameters in the tentatively identified model. As per the objectives of this research work, the parameters such as BIC, MSE, RMSE, MAD MAPE and Ljung-Box statistics were estimated using IBM SPSS statistics 20.

After a tentative model has been fit to the data, its adequacy was examined and for potential improvements residual analysis was also done. Once the specified model is found adequate and hence the appropriate orders p and q are identified, the observations were transformed to a white noise process. The ACF of the residuals for a good model showed that all autocorrelations for the residuals series were non-significant. If this was not the case, the chosen model should be revised. Box-Pierce (Ljung) test was applied to the residuals from the model fit to determine whether residuals are random. Randomness of residuals indicates that the model provides an adequate fit to the data series. A standardized residuals plot mostly indicates that there is no trend in the residuals, no outliers and in general no changing variance across time.

As the last diagnostic check, residual plots like Normal Probability Plot, Residuals versus Fitted Value, Histogram of the Residuals, and Time Series Plot of the Residuals were constructed. They indicate that the fit is indeed acceptable.

In forecasting, the goal is to predict future values of a time series, $\mathrm{X}_{\mathrm{n+m}}, m = 1,2,3, \ldots$ based on the data collected to the present. The researcher considered that the series X_t is stationary and the model parameters are known. Once an appropriate time series model has been fit, it may be used to generate forecasts of future observations. The standard criterion to use in obtaining the best forecast is the mean squared error for which the expected value of the squared forecast errors is minimized as expressed in equation 3.16.

$E[(y_{t+\tau} - \hat{y}_{T+\tau}(T))^2] = E[e_T(\tau)^2] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.16)$.

It can be shown that the best forecast in the mean square sense is the conditional expectation of $y_{T+\tau}$ given current and previous observations, that is, $y_T, y_{T-1}, \ldots$ as illustrated by equation 3.17.

$\hat{y}_{T+\tau}(T) = E[y_{T+\tau} I y_T, y_{T-1}, \ldots] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.17)$

The precision in forecasting was tested using MAPE, RMSE and MAD as explained in equations 3.18, 3.19 and 3.20.

Mean Absolute Percentage Error (MAPE) is the average absolute percentage change between the smoothed and the true values.

$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_t - f_t}{X_t}\right| * 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.18)$.

Express accuracy as a percentage of the error, it is easier to understand than other statistics. Also it allows us to compare forecast of different series in different scales.

Mean Absolute Deviation (MAD) is the average absolute difference between the smoothened and the true value.

$MAD = \frac{1}{n}\sum_{t=1}^{n}|X_t - f_t| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.19)$.

It expresses accuracy in the same units as the data, which helps conceptualize the amount of error.

Root Mean Squared Error (RMSE) is the square root of the average squared difference between the smoothened and the true value.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(X_t - f_t)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (3.20).$$

It is used as a standard statistical metric to measure model performance in different field of studies.

4.0 Data analysis and results

The time series data (February 2002 to June 2016) were used to study the trend pattern of membership registration of National Health Insurance Fund (NHIF) of the Dodoma region, to select the best ARIMA model by using various model criterion methods and to forecast future trend of membership registration for the next twenty four months.

The figures below indicate a time series plot of the monthly membership registration of National Health Insurance Fund (NHIF) of the Dodoma region for the period from February 2002 to June 2016. The membership registration data were classified into male, female and total where by their sequence charts are shown in figures 4.1, 4.2 and 4.3.

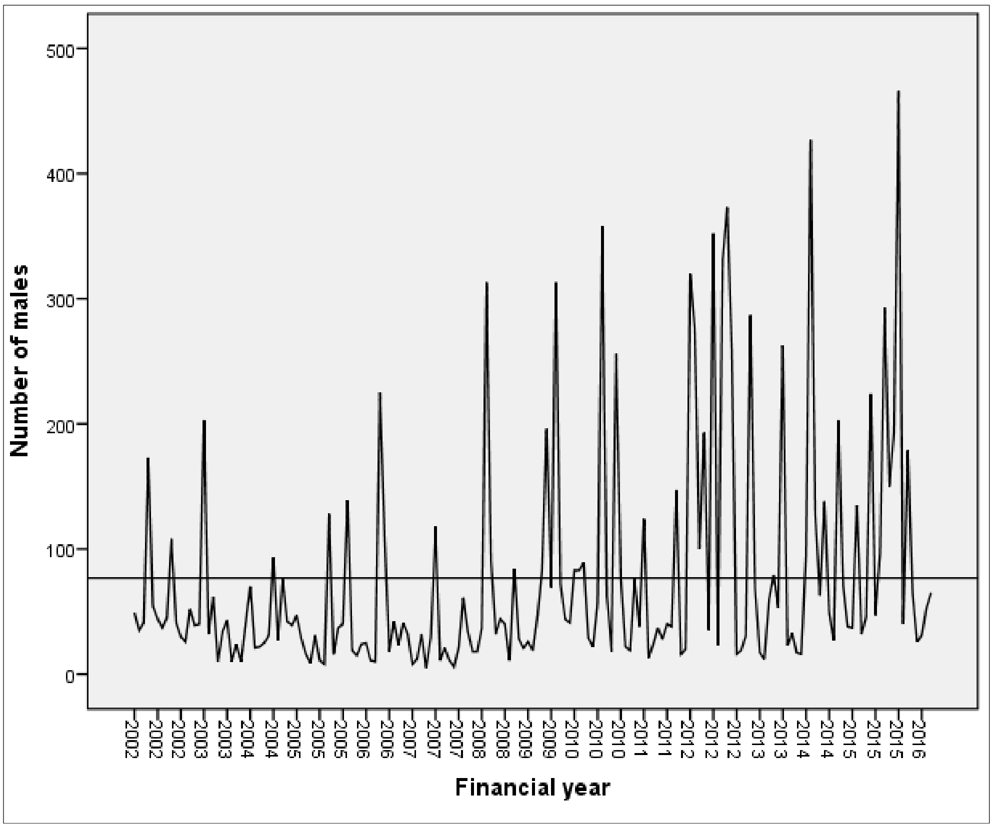

Fig 4. 1: A time series plot of monthly NHIF male data in Dodoma region

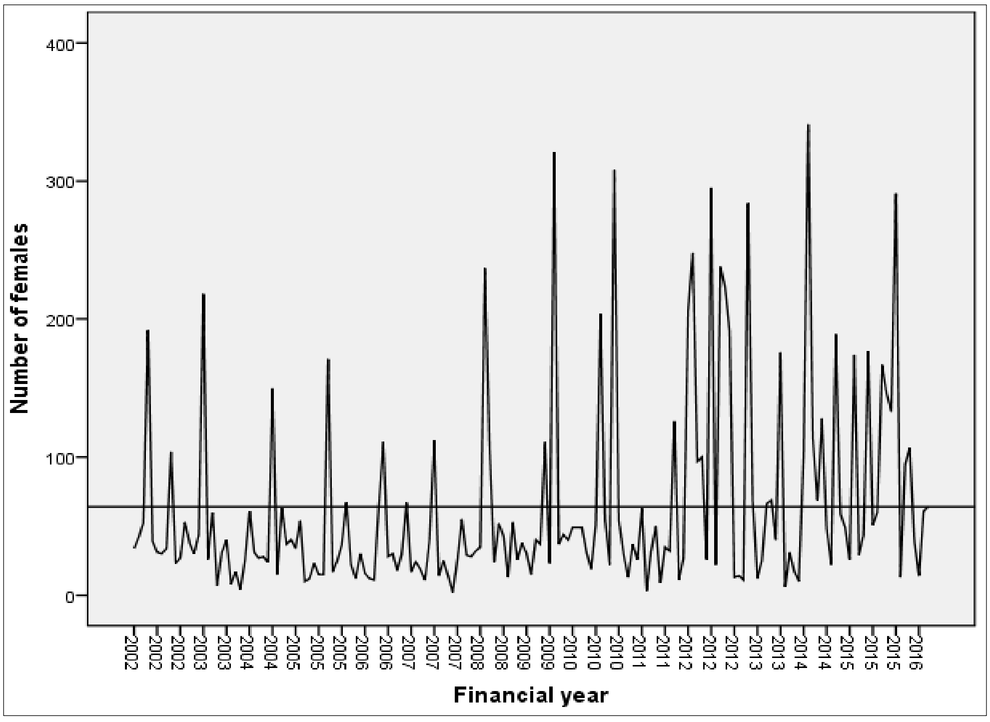

Fig 4. 2: A time series plot of monthly NHIF female data in Dodoma region

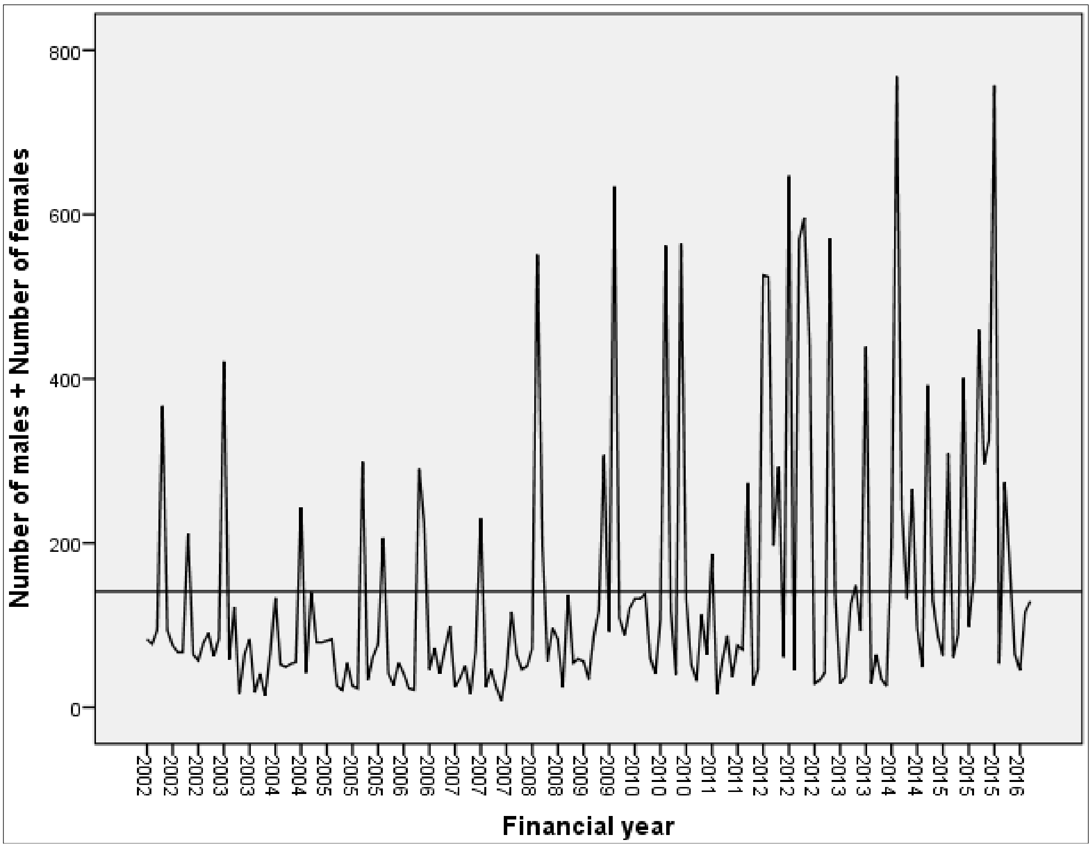

Fig 4. 3: A time series plot of monthly NHIF total data in Dodoma region

It was observed that there was an increasing upward trend but the peaks were not repeated with the same interval of time and not repeated with the same intensity, peaks increasing with increasing time. This shows that the series were not stationary and hence the transformation was taken by natural logarithm and second differencing (d = 2) in order to achieve stationarity of data.

The sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of log transformed and second differenced time series have been obtained and presented in figures 4.4 to 4.9. ACF refers to the way the observation in a time series are related to each other. PACF are used to measure the degree of association between current observation (Y_t) and the observation p periods from the current one (Y_{t-p}).

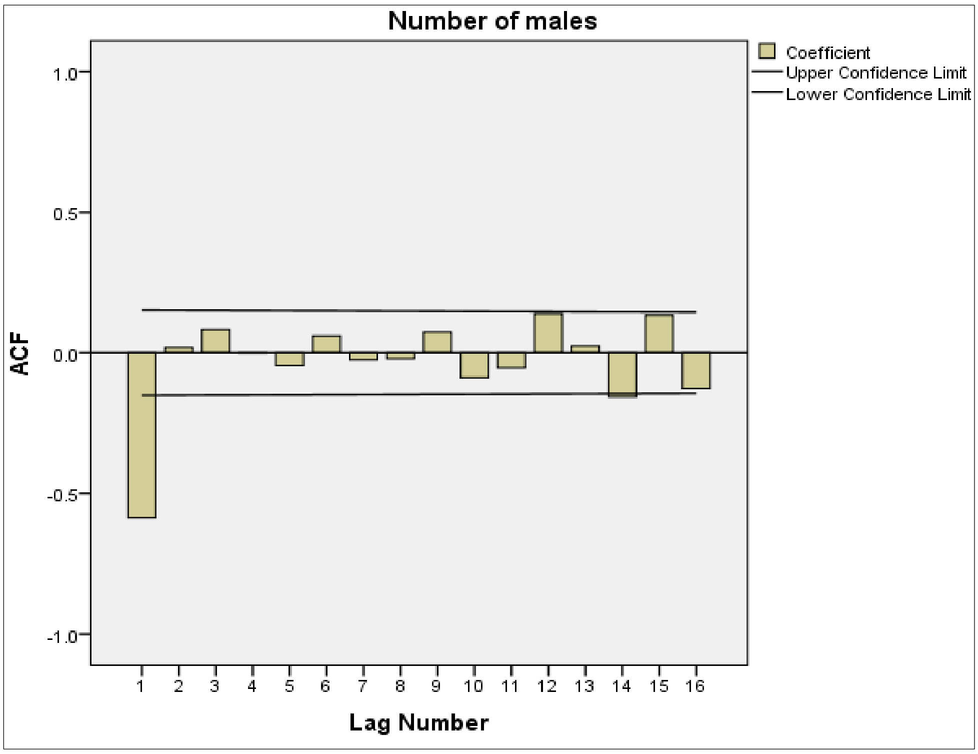

Fig 4.4: ACF of stationary series of male data

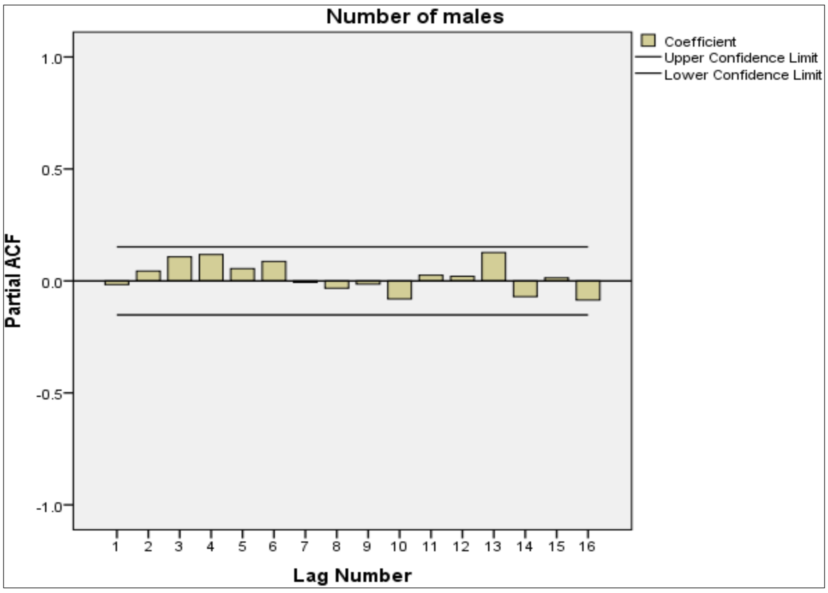

Fig 4.5: PACF of stationary series of male data

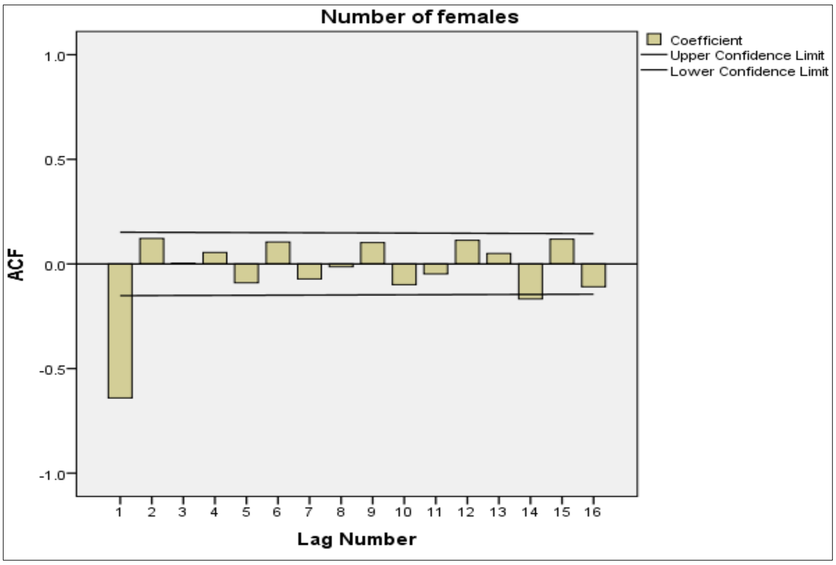

Fig 4.6: ACF of stationary series of female data

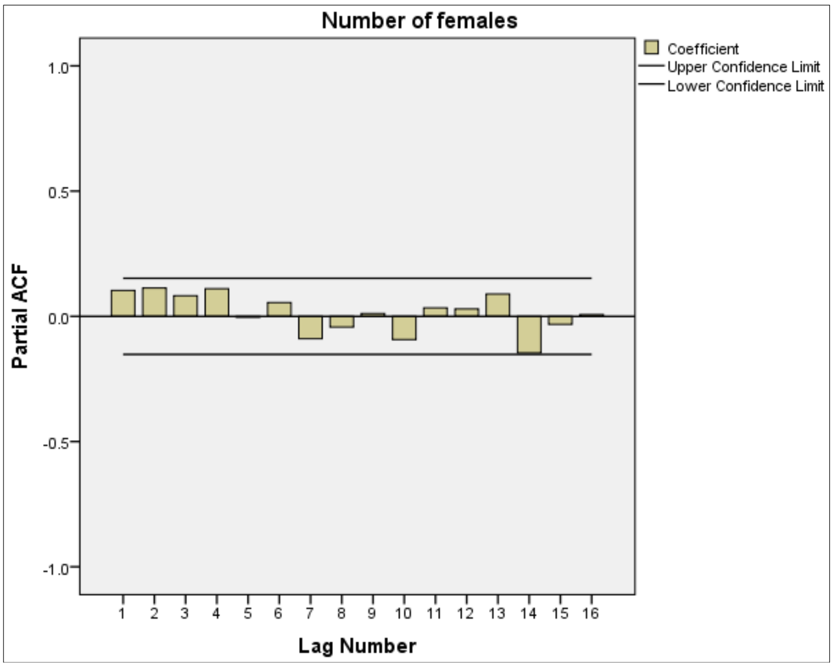

Fig 4.7: PACF of stationary series of female data

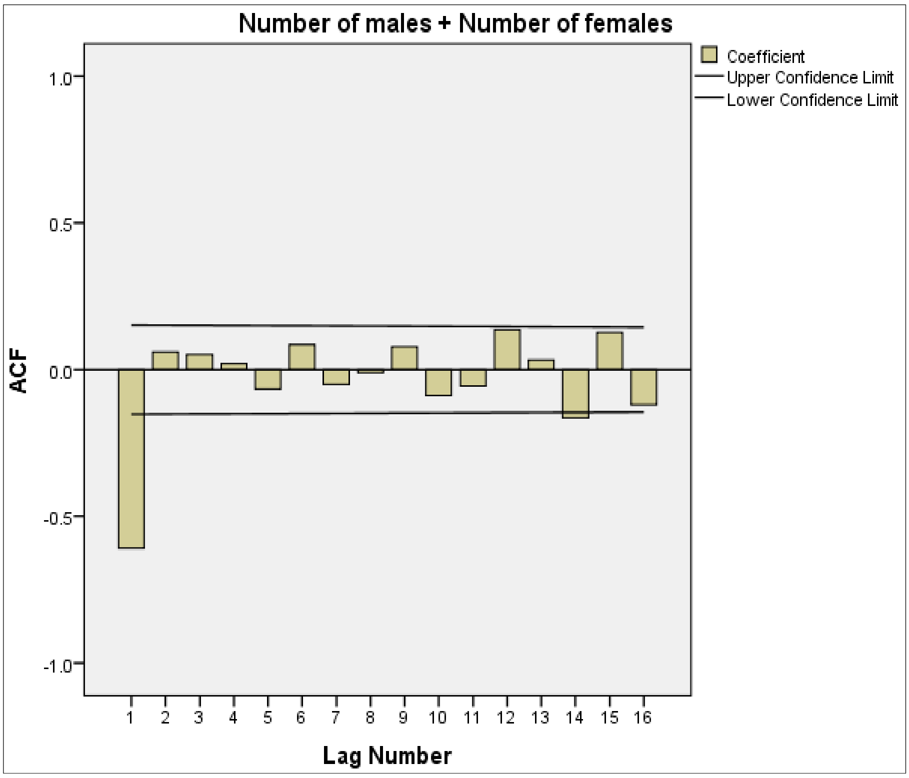

Fig 4.8: ACF of stationary series of total data

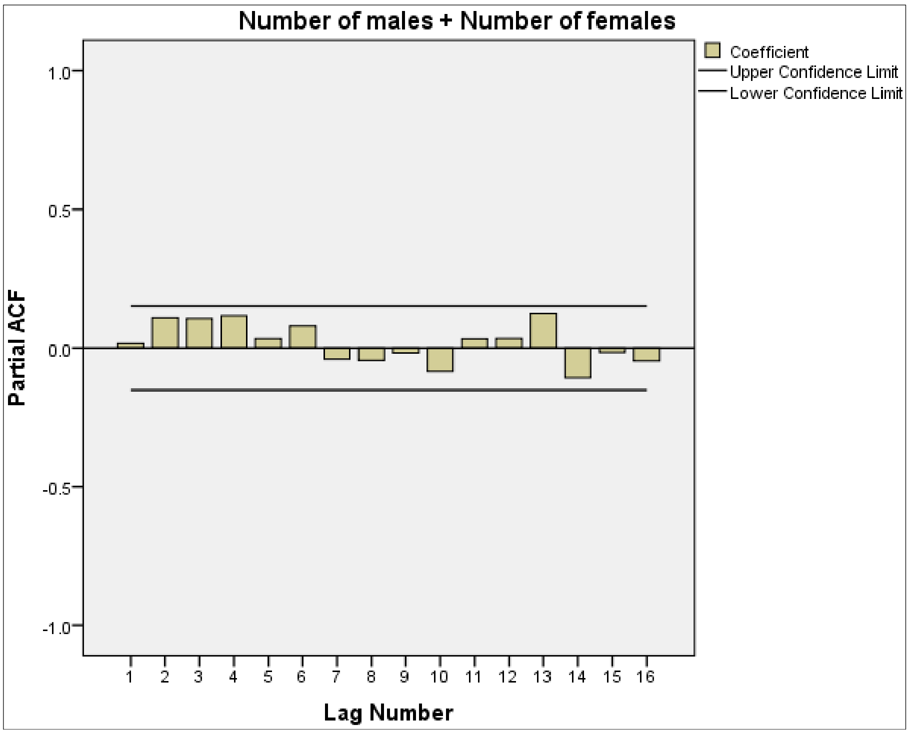

Fig 4.9: PACF of stationary series of total data

The log transformation and second differencing helps to obtain a stationary series as shown in PACF plots that all the lags are within the limits. ACF for both male, female and total of the log transformation and second differenced series show positive autocorrelation at lag-1. The diagrams suggest that there were at least autoregressive term AR (1) for male data, MA (1) term for female data, AR (1) term and moving average term MA (1) for total data with seasonality behavior. The lags of PACF for both male female and total are within the limits, which show that the data now are stationary after taking natural logarithm and second differencing.

The models were identified and selected by taking several combinations of orders of non-seasonal AR term and MA term (p, d, q) and seasonal AR and MA term (P, D, Q). After finding the values of AIC and BIC, from different combination as described in table 4.1, seasonal ARIMA (1, 2, 0)(0, 0, 1)^{12}, seasonal ARIMA(0, 2, 0)(1, 0, 0)^{12} and seasonal ARIMA (0, 2, 1)(0, 0, 1)^{12} has been identified and selected for male, female and total respectively.

Table 4.1: Model statistics for tentative ARIMA models

Model	Male		Female		Total	
	AIC	BIC	AIC	BIC	AIC	BIC
ARIMA(0,2,0)(1,0,0)^{12}	604.294	-.063	314.231	-.062	651.690	-.078
ARIMA(0,2,1)(0,0,1)^{12}	529.986	-.049	337.996	-.056	712.438	-.106
ARIMA(2,2,1)(2,0,1)^{12}	593.243	-058	354.761	-.037	642.781	-.093
ARIMA(1,2,0)(0,0,1)^{12}	522.892	-.071	412.076	-.042	624.970	-.101
ARIMA(2,2,0)(1,0,2)^{12}	611.223	-.052	329.805	-.061	705.129	-.087
ARIMA(1,2,1)(0,0,0)^{12}	540.239	-.024	407.321	-.035	634.342	-.105
ARIMA(0,2,1)(0,0,1)^{12}	539.132	-.070	397.326	-.059	621.987	-.120
ARIMA(1,2,2)(1,0,0)^{12}	527.902	-.069	401.238	-.060	645.395	-.098
ARIMA(2,2,2)(1,0,1)^{12}	543.754	-.037	348.961	-.047	637.219	-.116

The software IBM SPSS Statistics 20 (The expert modeler), automatically confirms the best-fitting model for each dependent series. Through expert modeler, the model variables have been transformed where appropriate, using differencing and/or a square root or natural log transformation. The suggested model obtained by IBM SPSS Statistics 20 have been presented in the table 4.2

Table 4.2: The description of the best ARIMA models

Model Description			Model Type
Model ID	Male	Model_1	ARIMA (1,2,0) (0,0,1) [12]
	Female	Model_2	ARIMA (0,2,0) (1,0,0) [12]
	Total	Model_3	ARIMA (0,2,1) (0,0,1) [12]

The models selected for the male, female and total were due to the fact that the following conditions have been satisfied for the model identification and selection: Ljung-Box statistics of the models have p-values greater than α-value (0.05), they have minimum Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) values with degree of freedom as indicated in the table 4.3 for each model.

Table 4.3: Model fit statistics

Model	Model Fit statistics					Ljung-Box Q (18)		
	Stationary R-squared	R-squared	RMSE	MAPE	Normalized BIC	Statistics	DF	Sig.
Male	.132	.132	.923	20.293	-.071	14.245	18	.580
Female	.060	.060	.941	23.887	-.062	20.887	18	.231
Total	.105	.105	.901	16.407	-.120	18.079	18	.319

Therefore, the models identified and selected were as follows

- The model identified and selected for male was seasonal ARIMA(1,2,0) (0,0,1)^{12}: This include the autoregressive term of order one AR(1), second difference $(d = 2)$ and seasonal moving average term of order one MA(1).
- The model identified and selected for female was seasonal ARIMA(0,2,0) (1,0,0)^{12}: This include the second difference $(d = 2)$ and seasonal autoregressive term of order one AR(1).
- The model identified and selected for total was seasonal ARIMA(0,2,1) (0,0,1)^{12}: This is the combination of second difference $(d = 2)$ with moving average term of order one MA (1) and seasonal moving average term of order one MA (1).

4.1 Parameters estimation

The model parameters have been estimated using IBM SPSS Statistics 20. It is evident from table 4.3 above, that Ljung-Box statistics of 14.245 for male, 20.887 for female and 18.079 for total has p value of 0.580 for male, 0.231 for female and 0.319 for total respectively which are greater than the α-value (0.05). So it is concluded that the models are valid models. The table 4.4 presents the estimates of the parameters for the model, male model consist of AR (p) and seasonal MA (Q) term, female model consists of seasonal AR (P) term and total model consists of MA (q) and seasonal MA (Q) term both at lag 1. Since p-values are less than α-value (0.05) which proves that the parameter estimates fits well the models.

Table 4.4: The ARIMA model parameters estimates

Model description			Estimate	SE	T	Sig.
Male	**Constant**		**3.842**	**.114**	**33.697**	**.000**
	AR	Lag 1	.233	.075	3.123	.002
	MA, Seasonal	Lag 1	-.267	.077	-3.454	.001
Female	Constant		3.702	.093	39.914	.000
	AR, Seasonal	Lag 1	.245	.077	3.162	.002
Total	Constant		4.488	.099	45.381	.000
	MA	Lag 1	-.160	.076	-2.119	.036
	MA, Seasonal	Lag 1	-.264	.077	-3.417	.001

4.2 Model for male membership

The male model is seasonal ARIMA (1, 2, 0)(0, 0, 1)^{12}, which can be written in terms of model parameters as the non-seasonal and seasonal AR and MA terms as in equation 4.1, 4.2, 4.3 and 4.4.

Non-seasonal AR: $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ ... ... (4.1)

Non-seasonal MA: $\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$ ... ... (4.2)

Seasonal AR: $\Phi_P(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} \ldots - \Phi_P B^{PS}$ ... ... (4.3)

Seasonal MA: $\Theta_Q(B^S) = 1 + \Theta_1 B^S + \Theta_2 B^{2S} \ldots + \Theta_Q B^{QS}$ ... ... (4.4)

Then solving, we get

$\Phi_P(B^S)\phi(B)\nabla^D{}_S\nabla^d X_t = \delta + \Theta_Q(B^S)\theta(B)w_t$ ... ... (4.5)

Where $\nabla^d = (1-B)^d$ and $\nabla^D{}_S = (1-B^S)^D$

$(1-\phi_1 B)(1-2B+B^2)X_t = \delta + (1+\Theta_1 B^S)w_t$

$(1-2B+B^2-\phi_1 B+2\phi_1 B^2-\phi_1 B^3)X_t = \delta + w_t + \Theta_1 B^{12} w_t$

$X_t - (2+\phi_1)X_{t-1} + (1+2\phi_1)X_{t-2} - \phi_1 X_{t-3} = \delta + \Theta_1 W_{t-12} + w_t$

$X_t = \delta + (2+\phi_1)X_{t-1} - (1+2\phi_1)X_{t-2} + \phi_1 X_{t-3} + \Theta_1 W_{t-12} + w_t$

$$X_t = 3.842 + 2.233X_{t-1} - 1.466X_{t-2} + 0.233X_{t-3} - 0.267W_{t-12} + w_t \ldots\ldots\ldots (4.6)$$

Where;

S: is the seasonal period= 12

ϕ: is the parameter estimate (Autoregressive estimate) = 0.233

Θ: is the parameter estimate (Seasonal moving average estimate) = -0.267

X_t: is the study variable (Male variable)

B: is the back shift operator such as $By_t = y_{t-1}$, $B^{12}y_t = y_{t-12}$

δ: is a constant number = 3.842

w_t: is a white noise

Therefore the seasonal ARIMA(1,2,0)(0,0,1)^{12} model can mathematically be written as :

$X_t = 3.842 + 2.233X_{t-1} - 1.466X_{t-2} + 0.233X_{t-3} - 0.267W_{t-12} + w_t$

The model has AR term at lag 1, 2 and 3, and seasonal MA term at lag 12.

4.3 Model for female membership

The female model is seasonal ARIMA (0, 2, 0)(1, 0,0)^{12} which can be written in terms of model parameters as the non-seasonal and seasonal AR and MA terms as in equation 4.7, 4.8, 4.9 and 4.10.

Non-seasonal AR: $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ ... ... (4.7)

Non-seasonal MA: $\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$ ... ... (4.8)

Seasonal AR: $\Phi_P(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} \ldots - \Phi_P B^{PS}$ ... ... (4.9)

Seasonal MA: $\Theta_Q(B^S) = 1 + \Theta_1 B^S + \Theta_2 B^{2S} \ldots + \Theta_Q B^{QS}$ ... ... (4.10)

Then by solving

$\Phi_P(B^S)\phi(B)\nabla^D{}_S\nabla^d X_t = \delta + \Theta_Q(B^S)\theta(B)w_t$ ... ... (4.11)

Where $\nabla^d = (1-B)^d$ and $\nabla^D{}_S = (1-B^S)^D$

$(1-\Phi_1 B^S)(1-B)^2 X_t = \delta$

$(1-\Phi_1 B^S)(1-2B+B^2)X_t = \delta$

$(1-2B+B^2-\Phi_1 B^{12}+2\Phi_1 B^{13}-\Phi_1 B^{14})X_t = \delta$

$X_t - 2X_{t-1} + X_{t-2} - \Phi_1(X_{t-12} + 2X_{t-13} - X_{t-14}) = \delta$

$X_t = \delta + 2X_{t-1} - X_{t-2} + \Phi_1(X_{t-12} - 2X_{t-13} + X_{t-14})$

$X_t = 3.702 + 2X_{t-1} - X_{t-2} + 0.245(X_{t-12} - 2X_{t-13} + X_{t-14})$ ... ... (4.12)

Where;

S: is the seasonal period= 12

Φ: is the parameter estimate (Seasonal Autoregressive estimate) = 0.245

X_t: is the study variable (Female variable)

B: is the back shift operator such as $By_t = y_{t-1}$, $B^{12}y_t = y_{t-12}$

δ: is a constant number = 3.702

Therefore the seasonal ARIMA(0,2,0)(1,0,0)^{12} is mathematically written as follows:

$X_t = 3.702 + 2X_{t-1} - X_{t-2} + 0.245(X_{t-12} - 2X_{t-13} + X_{t-14})$

The model has AR term at lag 1, 2, 12, 13 and 14.

4.4 Model for total membership

The total model is seasonal ARIMA (0, 2, 1)(0, 0, 1)^{12} which can be written in terms of model parameters as the non-seasonal and seasonal AR and MA terms as in equation 4.13, 4.14, 4.15 and 4.16.

Non-seasonal AR: $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ ... ... (4.13)

Non-seasonal MA: $\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$ ... ... (4.14)

Seasonal AR: $\Phi_P(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} \ldots - \Phi_P B^{PS}$ ... ... (4.15)

Seasonal MA: $\Theta_Q(B^S) = 1 + \Theta_1 B^S + \Theta_2 B^{2S} \ldots + \Theta_Q B^{QS}$ ... ... (4.16)

Then by solving

$\Phi_P(B^S)\phi(B)\nabla^D{}_S\nabla^d X_t = \delta + \Theta_Q(B^S)\theta(B)w_t$ ... ... (4.17)

Where $\nabla^d = (1-B)^d$ and $\nabla^D{}_S = (1-B^S)^D$

$(1-B)^2 X_t = \delta + (1+\Theta_1 B^S)(1+\theta_1 B)w_t$

$(1-2B+B^2)X_t = \delta + (1+\theta_1 B + \Theta_1 B^S + \Theta_1\theta_1 B^{13})w_t$

$X_t - 2X_{t-1} + X_{t-2} = \delta + \theta_1 w_{t-1} + \Theta_1 w_{t-12} + \Theta_1\theta_1 w_{t-13} + w_t$

$X_t = \delta + 2X_{t-1} - X_{t-2} + \theta_1 w_{t-1} + \Theta_1 w_{t-12} + \Theta_1\theta_1 w_{t-13} + w_t$

$X_t = 4.488 + 2X_{t-1} - X_{t-2} - 0.160w_{t-1} - 0.264w_{t-12} + 0.042w_{t-13} + w_t \ldots\ldots (4.18)$

Where;

S: is the seasonal period= 12

θ: is the parameter estimate (Moving average estimate) = -0.160

Θ: is the parameter estimate (Seasonal moving average estimate) = -0.264

X_t: is the study variable (Total variable)

B: is the back shift operator such as $By_t = y_{t-1}$, $B^{12}y_t = y_{t-12}$

δ: is a constant number = 4.488

w_t: is a white noise

Therefore the seasonal ARIMA(0,2,1)(0,0,1)^{12} is formally can be written as follows:

$X_t = 4.488 + 2X_{t-1} - X_{t-2} - 0.160w_{t-1} - 0.264w_{t-12} + 0.042w_{t-13} + w_t$

The model has MA term at lag 1, and 2, and seasonal MA term at lag 1, 12 and 13.

4.5 Diagnostic checking

The diagnostic checking is concerned with residuals of the models. Correlograms of the residuals of the constructed models have been analyzed for significance. If they are not significantly different from zero, it implies that the models adequately fit the data. The residual plots of ACF and PACF were obtained and the Ljung-Box test showed that the first 24 lag autocorrelations and partial autocorrelations of the residuals are not significantly different from zero, indicating that the residuals are random and that the models provides an adequate fit to the data as shown in table 4.5.

Table 4.5: Autocorrelations and partial autocorrelations of residuals

	Male				Female				Total			
Lag	**ACF**	**SE**	**PACF**	**SE**	**ACF**	**SE**	**PACF**	**SE**	**ACF**	**SE**	**PACF**	**SE**
1	-.017	.076	-.017	.076	.104	.076	.104	.076	.016	.076	.016	.076
2	.044	.076	.044	.076	.123	.077	.113	.076	.109	.076	.109	.076
3	.106	.076	.107	.076	.103	.078	.082	.076	.108	.077	.106	.076
4	.114	.077	.118	.076	.137	.079	.110	.076	.128	.078	.117	.076
5	.057	.078	.055	.076	.036	.080	-.004	.076	.054	.079	.033	.076
6	.101	.078	.087	.076	.089	.080	.055	.076	.112	.079	.080	.076
7	.015	.079	-.007	.076	-.051	.081	-.090	.076	-.007	.080	-.040	.076
8	-.001	.079	-.033	.076	-.021	.081	-.043	.076	-.001	.080	-.044	.076
9	.020	.079	-.014	.076	.007	.081	.011	.076	.010	.080	-.017	.076
10	-.052	.079	-.080	.076	-.087	.081	-.093	.076	-.064	.080	-.085	.076
11	.039	.079	.026	.076	-.001	.082	.034	.076	.031	.080	.032	.076
12	.019	.079	.020	.076	.010	.082	.029	.076	.019	.081	.034	.076
13	.108	.079	.127	.076	.065	.082	.089	.076	.099	.081	.124	.076
14	-.087	.080	-.070	.076	-.141	.082	-.146	.076	-.117	.081	-.108	.076
15	.029	.081	.014	.076	-.029	.083	-.032	.076	.011	.082	-.016	.076
16	-.065	.081	-.085	.076	-.021	.083	.007	.076	-.044	.082	-.047	.076
17	.083	.081	.062	.076	.114	.083	.121	.076	.107	.082	.099	.076
18	.027	.082	.031	.076	-.018	.084	-.006	.076	.002	.083	.023	.076
19	.174	.082	.188	.076	.150	.084	.151	.076	.176	.083	.176	.076
20	.033	.084	.060	.076	-.021	.086	-.039	.076	.006	.085	.021	.076
21	.007	.084	-.004	.076	.045	.086	-.012	.076	.038	.085	-.008	.076
22	-.022	.084	-.081	.076	-.051	.086	-.103	.076	-.039	.085	-.101	.076
23	.095	.084	.037	.076	.072	.086	.055	.076	.098	.085	.044	.076
24	.031	.085	-.027	.076	.000	.086	-.013	.076	.030	.086	-.010	.076

The computed Ljung-Box statistics has p-values 0.713, 0.285 and 0.450 for male, female and total respectively, those are greater than the value of level of significant of 5% as shown in table 4.6.

Table 4.6: Statistics for forecasted errors

Model	Ljung-Box Q(18)		
	Statistics	**DF**	**Sig.**
Noise residual from Male	14.245	18	.713
Noise residual from Female	20.887	18	.285
Noise residual from Total	18.079	18	.450

Parameters of the male, female and total models were computed with assistance of IBM SPSS Statistics 20 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. The ACF and PACF residuals of fitted models they are white noise at 5% level of significance. The seasonal ARIMA(1,2,0) (0,0,1) [12] for male, ARIMA (0,2,0) (1,0,0) [12] for female and ARIMA (0,2,1) (0,0,1) [12] for total male and female have residuals that are independent and identically distributed and hence they are adequate models for the observed data. The residual ACF and PACF show that none of these correlations is significantly different from zero at any reasonable level. Therefore these models are statistically significant and adequate for forecasting purposes.

4.6 Forecasting

In forecasting, the goal is to predict future values of a time series, based on the data collected to the present. Future forecasting for National Health Insurance Fund (NHIF) members in Dodoma region are of particular target of this research work. Seasonal ARIMA (1,2,0) (0,0,1) [12], Seasonal ARIMA (0,2,0) (1,0,0) [12] and Seasonal ARIMA (0,2,1) (0,0,1) [12] are the final forms of the best fit ARIMA models for the time series used to forecast future membership enrollment of Dodoma region for the next twenty four months. The observed and forecasted values were tested and it was found that there is no significant difference in them at 5% level of significance. The forecast inaccuracy is very small with a Mean absolute percentage error (MAPE) of 7.75 for male, 8.8 for female and 6.53 for total with 92.25%, 91.2%, and 93.47% accuracy respectively.

Table 4.7: Forecasted values of male, female and total

Month	Male	Female	Total
Jul-16	98	82	159
Aug-16	73	69	137
Sep-16	82	66	131
Oct-16	75	78	147
Nov-16	112	99	173
Dec-16	80	94	124
Jan-17	64	70	108
Feb-17	75	63	126
Mar-17	107	94	209
Apr-17	78	74	147
May-17	99	69	152
Jun-17	97	85	207
Jul-17	112	99	215
Aug-17	94	74	137
Sep-17	104	80	170
Oct-17	98	73	147
Nov-17	115	98	234
Dec-17	98	82	198
Jan-18	102	80	217
Feb-18	123	63	170
Mar-18	97	109	251
Apr-18	107	69	147
May-18	85	83	152
Jun-18	146	115	267

The forecasted values of NHIF from July 2016 to June 2018 show that there will be an increase of membership registration for both male female and total. The increase of membership registration for these twenty four months is evidently shown in table 4.7 above.

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