Modeling and Forecasting Maternal Mortality; an Application of ARIMA Models

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Abstract

This study examines maternal mortality ratios at the Okomfo Anokye Teaching Hospital in Kumasi from the year 2000 to 2010. The study explores the feasibility for application of Box-Jenkins Approach to time series autoregressive integrated moving average (ARIMA) in modeling and forecasting Maternal Mortality ratios (MMR). Analyses were based on data available at the Bio-Statistics Department of the Obstetrics& Gynaecology directorate of the facility. The result shows that the hospitals Maternal Mortality Ratio (MMR) was relatively stable but had a very alarmingaverage quarterlyMMR of 967.7 per 100,000 live births which is about twice the National ratio of 451 per 100,000 live births. With AIC (581.41), we conclude that the ARIMA (1,0,2) model is adequate for forecasting quarterly maternal mortality ratios at the hospital.

Key words: ARIMA Model, Bio-statistics, MMR, Forecasting, Box-Jenkins Approach,Unit Root test, ADF test, AIC, KATH

1.0 Introduction

Maternal mortality is defined as the death of a woman while pregnant or within 42days of termination of pregnancy, irrespective of the duration and site of the pregnancy, from any cause related to or aggravated by the pregnancy or its management (WHO–ICD 10).An estimated 529,000 women die each year worldwide from pregnancy-related complications, of which about 90% occur in developing countries, the worst affected being Africa, including Ghana (UN Millennium Project, 2006).Globally, the lifetime risk for maternal death is 1 in 74 women. In industrialised countries this risk is 1 in 2,800 while the least developed countries face a 1 in 16 chance of dying during childbirthin their lifetime (DFID, 2004)**.** Maternal hemorrhage, obstructed labour, postpartum sepsis, eclampsia, unsafe abortion and anemia are among the leading causes of death among pregnant women in developing countries. Contributory factors include lack of access to good quality maternal and neonatal health services and strong adherence to negative cultural beliefs and practices (AbouZahr&Wardlaw, 2001 and WHO, 2005).These complications of pregnancy contribute significantly to the high levels of maternal and neonatal mortality in Sub-Saharan Africa.

The fifth Millennium Development Goal is to improve maternal health, with a target to reduce thematernal mortality ratio by three quarters, between 1990 and 2015. Yet maternal mortality indeveloping countries has barely decreased over the past decade, and in parts of Africa it hasincreased. Ghana's target was to reduce the 1990 maternal mortality ratio of 740 per 100,000 live births by 3/4 to 185 per 100,000 live births by 2015.In recent years, Ghana's maternal mortality ratio (MMR) declined from 560 deaths out of 100,000 live births in 2005, to 451 deaths in 2007 (WHO, 2005; Ghana DHS, 2007). However, statistics from Kumasi show that maternal deaths then began rising. In 2007, Kumasi's MMR was 359 out of 100,000 live births while in 2008 it was 397 out of 100,000 live births (KMHD, 2009).The majority of maternal deaths in Kumasi (about 93%) occurred at KATH, most likely because this hospital is the referral hospital for complicated medical emergencies.

In this study, our main objective is to model and forecast eight (8) quarterly maternal mortality ratios of the facility outside the sample period. The post-sample forecasting is very important for health related policy makers to foresee ahead of time the possible future requirements to design strategies and effective policies to combat any expected high mortality ratios in the facility and the country of Ghana. Forecasts will also play a crucial role on the anticipated future maternal mortality ratios in our quest to meeting the MDG 5.

We also believed that this research will serve as a literature for other researchers who wish to embark studies on maternal mortality in Ghana.

In order to model the maternal mortality ratios, the study starts by analyzing the general behavior of quarterly maternal mortality ratiosof the KomfoAnokye Teaching Hospital from January, 2000 to December, 2010 for a comprehensive understanding. Following the Box-Jenkins approach, we apply ARIMA models to our time series data in other to model and forecast future quarterly maternal mortality ratios of the Teaching Hospital. When it comes to forecasting, there are extensive number of methods and approaches available and their relative success or failure to outperform each other is in general conditional to the problem at hand. The motive for choosing this type of model is based on the behavior of our time series data. Box and Jenkins (1976) propose an entire family of models, called Autoregressive Integrated Moving Average (ARIMA) models. It seems applicable to a wide variety of situations. They have also developed a practical procedure for choosing an appropriate ARIMA model out of this family of ARIMA models. However, selecting an appropriate ARIMA model may not be easy. Many literatures suggest that building a proper ARIMA model is an art that requires good judgment and a lot of experience.

ARIMA models are especially suited for short term forecasting. This is because the model places more emphasis on the recent past rather than distant past. This emphasis on the recent past means that long-term forecasts from ARIMA models are less reliable than short-term forecasts, see Pankratz (1983).Also in the history of maternal mortality forecasting, this model has proved to perform better as compared to other models.The forecasting advantage of ARIMA model compared to other time series models have been investigated by many studies. For example,Elard Koch (2009) on behalf of The Chilean Maternal Mortality Group, Faculty of Medicine, University of Chile, used (ARIMA) models to analyze maternal mortality ratio (MMR) and abortion mortality ratio (AMR) from 1960 to 2007 and found MMR to have decreased from 293.7 to 18.2 per 100,000 live births. The Ethiopian Government through their Ministry of Health (MOH Ethiopia, 2000) analyzed trends and developed a model for prediction of Health and Health related indicators. The determinants of the established trends were identified using ARIMA models in STATA. Among the mortality indicators considered in their study, it was only Maternal Mortality Ratio that showed statistically significant decrement within the study period.

The Journal of China Medical University in March 2011 conducted a study to explore the feasibility for application of time series ARIMA model to predict the maternal mortality ratio (MMR) in china so as to provide the theoretical basis for continuing to reduce the MMR. ARIMA model was established based on the MMR of China from 1991 to 2009. It was found that ARIMA model fitted very well, the residual autocorrelation function graph showed the residuals were white noise sequences, the prediction results showed that maternal mortality ratio in national urban and rural areas would be 30.39 ‰, 24.73 ‰ and 28.80 ‰ in 2010, which showed MMR, would decline and reach a lower level. The researchers concluded that the fitting result in ARIMA model of the incidence of the MMR is satisfactory, the forecasting achieve good effects, which also provides scientific basis for the prevention and control of maternal mortality ratio. In most of those researches, ARIMA model tends to perform better in terms of forecasting compared to other competent time series models.Similarly, this study explores the feasibility for application of time series ARIMAin the modeling and forecastingof Maternal Mortality ratios.

The structure of the remaining paper is as follows: Section 2 describes the materials and Box Jenkins methodology, Section 3 analyzes our maternal mortality ratios data and illustrates how the theoretical methodology can be applied for modeling and forecasting. Section 4 presents the concluding remarks which include findings, comments and recommendations.

2.0 Materials and Methodology

2.1 Data

The data used in this study was a quarterly Maternal Mortality Ratios recorded at the OkomfoAnokye Teaching Hospital (KATH) from January 2000 to December 2010.The data is obtained from the Bio-Statistics Department of the Obstetrics &Gynecology directorate of the Teaching Hospital.

2.2 ARIMA model

The ARIMA model is a combination of two univariate time series model which are Autoregressive (AR) model and Moving Average (MA) model.

These models are to utilize past information of a time series to forecast future values for the series. The ARIMA model is applied in the case where the series is non-stationary and an initial differencing step (corresponding to the "integrated" part of the model) can make ARMA model applicable to a integrated stationary process. The acronym ARIMA stands for "Auto-Regressive Integrated Moving Average." Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. A non-seasonal ARIMA model is classified as an "ARIMA (p, d, q)" model, wherep,d,q are integers greater than or equal to zero withpbeing the number of autoregressive terms, d the number of non-seasonal differences, and qthe number of lagged forecast errors (moving average) in the prediction equation. (seeHurvich and Tsai, 1989; Kirchgässner and Wolters, 2007; Kleiber and Zeileis, 2008; Pankratz, 1983; Pfaff, 2008)

A process, $X_t$is said to be ARIMA (p, d, q) if $\nabla^d X_t = (1 - B)^d X_t$ is ARMA (p, q). In other words the process should be stationary after differencing a non-seasonal process d times.

2.3 The Box and Jenkins (1976) Methodology

Box and Jenkins (1976) proposes a four-step iterative approach to modeling as follows; Model identification, Model parameter estimation, Model checking (goodness of fit) and the forecasting. The four iterative steps are not straight forward but are embodied in a continuous path depending on the set of data under study.

2.3.1 Model identification

In the identification stage of model building, we determine the possible models based on the data pattern. But before we can begin to search for the best model for the data, the first condition is to check whether the series is stationary or not. The ARIMA model is appropriate for stationary time series data (i.e. the mean, variance, and autocorrelation are constant through time). If a time series is stationary then the mean of any major subset of the series does not differ significantly from the mean of any other major subset of the series. Also if a data series is stationary then the variance of any major subset of the series will differ from the variance of any other major subset only by chance (see Pankratz, 1983).

The stationarity condition ensures that the autoregressive parameters in the estimated model are stable within a certain range as well as the moving average parameters in the model are invertible. If this condition is assured then, the estimated model can be forecasted (see Hamilton, 1994). To check for stationarity, we usually test for the existence or nonexistence of what we called unit root. Unit root test is performed to determine whether a stochastic or a deterministic trend is present in the series. If the roots of the characteristic equation (such as equation 2) lie outside the unit circle, then the series is considered stationary. This is equivalent to say that the coefficients of the estimated model are in absolute value is less than 1 (i.e.). There are several statistical tests in testing for presence of unit root in a series. For series with seasonal and non-seasonal behaviour, the test must be conducted under the seasonal part as well as the non-seasonal part. Some example of the unit root test for the non-seasonal time series are the Dickey-Fuller and the Augmented Dickey- Fuller (DF, ADF) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and Zivot-Andrews (ZA) test (see Dickey & Fuller, 1979; Kwiatkowski et al, 1992; Zivot& Andrews, 1992). Also some examples of the unit root test for seasonal time series are Hylleberg-Engle-Granger-Yoo (HEGY) test, Canova-Hansen (CH) test etc (see Canova & Hansen, 1995; Hylleberg et al, 1990; Beaulieu &Miron, 1993).

The ACF and PACF give more information about the behaviour of the time series. The ACF gives information about the internal correlation between observations in a time series at different distances apart, usually expressed as a function of the time lag between observations. These two plots suggest the model we should build. Checking the ACF and PACF plots, we should both look at the seasonal and non-seasonal lags. Usually the ACF and the PACF has spikes at lag k and cuts off after lag k at the non-seasonal level. Also the ACF and the PACF has spikes at lag ks and cuts off after lag ks at the seasonal level. The number of significant spikes suggests the order of the model. Though the ACF and PACF assist in determine the order of the model but this is just a suggestion on where the model can be build from. It becomes necessary to build the model around the suggested order. In this case several models with different order can be considered. The final model can be selected using a penalty function statistics such as **A**kaike**I**nformation **C**riterion (AIC or AICc) or **B**ayesian **I**nformation **C**riterion (BIC). See Sakamoto et. al.(1986); Akaike (1974) and Schwarz (1978).

The AIC, AICc and BIC are a measure of the goodness of fit of an estimated statistical model. Given a data set, several competing models may be ranked according to their AIC, AICc or BIC with the one having the lowest information criterion value being the best. These information criterion judges a model by how close its fitted values tend to be to the true values, in terms of a certain expected value. The criterion value assigned to a model is only meant to *rank* competing models1 and tell you which the best among the given alternatives is. The criterion attempts to find the model that best explains the data with a minimum of free parameters but also includes a penalty that is an increasing function of the number of estimated parameters. This penalty discourages over fitting. In the general case, the AIC, AICc and BIC is calculated as;

$$AIC = 2k - 2\log(L) \quad OR \quad 2k + nlog(\frac{RSS}{n}) \tag{2.0}$$

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \tag{2.1}$$

$$BIC = -2Log(L) + klog(n) \quad OR \ \log(\sigma_e^2) + \frac{k}{n}\log(n) \tag{2.2}$$

Where
k: is the number of parameters in the statistical model
L: is the maximized value of the likelihood function for the estimated model.
RSS: is the residual sum of squares of the estimated model.
n: is the number of observation, or equivalently, the sample size
σ_e^2: is the error variance
The AICc is a modification of the AIC by Hurvich and Tsai (1989) and it is AIC with a second order correction for small sample sizes. Burnham & Anderson (1998) insist that since AICc converges to AIC as *n* gets large, AICc should be employed regardless of the sample size.

2.3.2 Parameter estimation

The next step in ARIMA model building after the Identification of the model is to estimate the parameters of the chosen model. The method of maximum likelihood estimation (MLE) and other methods can be used in this section. At this stage we get precise estimates of the coefficients of the model chosen at the identification stage. That is we fit the chosen model to our time series data to get estimates of the coefficients. This stage provides some warning signals about the adequacy of our model. In particular, if the estimated coefficients do not satisfy certain mathematical inequality conditions, that model is rejected. Example it is believed that for a chosen model to satisfy ARIMA conditions, the absolute value of the estimated parameters must be always less than unity.

2.3.3 Model diagnostics (goodness of fit)

After estimating the parameters of ARIMA model, the next step in the Box-Jenkinsapproach is to check the adequacy of that model which is usually called model diagnostics.Ideally, a model should extract all systematic information from the data. The part of the dataunexplained by the model (i.e., the residuals) should be small. The diagnostic check is used todetermine the adequacy of the chosen model. These checks are usually based on the residuals ofthe model. One assumption of the ARIMA model is that, the residuals of the model should bewhite noise. A series $\{\mathcal{E}_t\}$ is said to be white noise if $\{\mathcal{E}_t\}$ is a sequence of independent andidentically distributed random variable with finite mean and variance. In addition if $\{\mathcal{E}_t\}$ isnormally distributed with mean zero and variance σ^2 then the series is called Gaussian WhiteNoise. For a white noise series, all the ACF are zero. In practice if the residuals of the modelis white noise, then the ACF of the residuals are approximately zero. If the assumption of are notfulfilled then different model for theseries must be search for. A statistical tool such as Ljung-Box Q statistic can be used to determine whether the series is independent or not.

2.3.4 Forecasting

The last step in Box-Jenkins model building approach is Forecasting. After a model haspassed the entire diagnostic test, it becomes adequate for forecasting. ARIMA models as described by several researchers have provedto perform well in terms of forecasting as compare to other complex models.

To choose a final model for forecasting the accuracy of the model must be higher than that of all the competing models. The accuracy for each model can be checked to determine how the model performed in terms of in-sample forecast. Usually in time series forecasting, some of the observations are left out during model building in other to access models in terms of out of sample forecasting also.

3.0 Results/Modelling

Firstly, the raw quarterly data are plotted and the patterns of MMR for the facility over the period under study are observed. The hospital recorded an appreciably high MMR of about 1152.9 per 100,000 live births in the first quarter of year 2000 but ended that year with mortality ratio of about 858.2 per 100,000 live births. The first three quarters of the following year also recorded high MMR figures of 1017.4, 1002.0 and 1203.0 per 100,000 live births respectively till the last quarter when it dropped sharply to 770.4 per 100,000 live births. Generally, all other years with the exception of 2000, 2001, 2002 and 2005 recorded relatively low MMRs in their first quarters ranging from 923.2 in 2006 to 724.0 in 2010. Maternal mortality ratios declined steadily from the third quarter of 2005 and increased marginally at the last quarter of 2006. The most significant decrease was recorded in 2007 and 2008. Unfortunately, in 2009 instead of continuous decline, the MMR was on the rise. However, it appears to decline after 2010. The highest MMR recorded by the hospital was 1373 per 100,000 live births and this was recorded in third quarter of 2008 while the lowest MMR was 574.5 per 100,000 live births, recorded in last quarter of 2007. The average quarterly MMR recorded within the period was 967.7 per 100,000 live births which ishigher than result from the Ghana Maternal Mortality Survey of 2008. The survey showed a slow decline of maternal deaths from 503 per 100,000 live births in 2005 to 451 per 100,000 live births in 2008, which is an average estimate for the seven-year period preceding the 2008 survey.

3.1 Model Identification

The model development process was begun by studying the original plot, ACF, PACF and objective test of the raw data to be sure that it is stationary. There are two relevant features from Fig. 3.1. First is that the mean appears to be stationary over the time period. Secondly, with the exception of the extreme case at the fourth quarter of 2008, the rise and fall of the dispersion over the time period is quite stable. If the mean was changing, the trend is removed by differencing once or twice and if the variability was changing, the process may be made stationary by logarithmic transformation. However, as it stands now the data is said to be stationary in mean and in variance. Also, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Augmented Dickey- Fuller (ADF) test were performed. KPSS test is used for verifying whether or not the series is stationary, while Augmented Dickey-Fuller test is used for verifying whether or not there is unit root. From table 3.1, the p value of the KPSS test is greater than printed p-value (0.01), so it accepts the null hypothesis that data is level or trend stationary. This indicates that we may regard the time series to be stationary. While the p value of ADF test is smaller than printed p-value, so it rejects the null hypothesis that data has a unit root. From above results, we find the series to be stationary and there is no unit root. We also plot the graphs for sample autocorrelations function and sample partial autocorrelations function.

Figure 3.2, consists of plots of the ACF and the PACF for the quarterly Maternal Mortality Ratio from 2000 to 2010. 95% confidence brands are plotted in colour blue on the both panels. These two plots are useful in determining the p autoregressive terms and the q lagged error terms. Looking at the sample ACF and PACF plot of the series in Figure 3.2, we apply the Box-Jenkins approach to choose the value p and q by ACF and PACF plot. Generally, we build an AR (p) and compare the AIC, AICc and BIC of all the possible models and find out a model to fit the data better than others, which is the one has the lowest AIC, AICc and BIC values.

3.2 Model Estimation and Evaluation

The procedure for choosing these models relies on choosing the model with the minimum AIC, AICc and BIC. The models are presented in Table 3.2 with their corresponding values of AIC, AICc and BIC. Among those possible models, comparing their AIC, AICc and BIC as shown in Table 3.2, ARIMA (1, 0, 2)and was the appropriate model that fit the data well.

Using the method of maximum likelihood the estimated parameters of the model with their corresponding standard error is shown in Table3.3.Therefore at 95% confidence level, we conclude that all the coefficients of the ARIMA (1, 0, 2) model are significantly different from zero and the estimated values satisfy the stability condition.

3.3 Goodness of fit

In time series modelling, the selection of a best model fit to the data is directly related to whether residual analysis is performed well. One of the assumptions of ARIMA model is that, for a good model, the residuals must follow a white noise process. That is, the residuals have zero mean, constant variance and also are uncorrelated.

From Figure 3.2, the standardized residual reveals that the residuals of the model have zero mean and constant variance. Also the ACF of the residuals depicts that the autocorrelation of the residuals are all zero, that is to say they are uncorrelated. Finally, the p-values for the Ljung-Box statistic in the third panel all clearly exceed 5% for all lag orders, indicating that there is no significant departure from white noise for the residuals. Thus, the selected model satisfies all the model assumptions. Since our model ARIMA (1, 0, 2)satisfies all the necessary assumptions, we can say that the model provide an adequate representation of the data. We therefore write our ARIMA (1, 0, 2) as:

$$X_t = 969.22 - 0.308X_{t-1} + 0.4525\omega_{t-1} + 0.3931\omega_{t-2} + \omega_t \quad (3.1)$$

3.4 Forecasting

Using the model obtained above, we forecast 2011 to 2015 MMR's and compare to the observed values for 2011 from the hospital, with the statistical software R. Comparing the predicted MMR for first quarter 2011 with the observed ratios, we can see that the predicted value (959.0) is close to the true value (996.7)recorded and published by the hospital. Also, this observed values fall inside the confidence interval. Hence, we can say that, ARIMA (1, 0, 2) model is adequate to be used to forecast quarterly Maternal Mortality ratios at the Okomfo Anokye Teaching Hospital Kumasi. The Table 3.5summarizes the forecasting results of the MMR's over the period 2011 to 2015 with 95% confidence interval.

4.0 Conclusion

The quarterly maternal mortality ratios recorded from 2000 to 2010 shows no trend in particular, and hence MMR's was relatively stable over the period. The highest MMR recorded by the hospital was 1373 per 100,000 live births and this was recorded in third quarter of 2008 while the lowest MMR was 574.5 per 100,000 live births, recorded in last quarter of 2007. The average quarterly MMR recorded within the period was 967.7 per 100,000 live births which are far higher than result from the Ghana Maternal Mortality Survey of 2008. The survey showed a slow decline of maternal deaths from 503 per 100,000 live births in 2005 to 451 per 100,000 live births in 2008, which is an average estimate for the seven-year period preceding the 2008 survey.

ARIMA (1, 0, 2) model was selected as the appropriate model for predicting future Maternal mortality ratios for the hospital. The model satisfied all conditions of a good ARIMA model and was used to predict MMRs for the next 20 quarters. Comparing the predicted MMR for first quarter 2011 with the observed ratios, we can see that the predicted value (959.0) is close to the true value (996.7) recorded and published by the hospital. Also, this observed values fell within the confidence interval. Hence, we could say that, ARIMA (1, 0, 2) model is adequate to be used to forecast quarterly Maternal Mortality ratios at the Okomfo Anokye Teaching Hospital Kumasi.

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Tables and Figures

Table 3.1: Objective test (unit root test) for drift and trend stationarity of quarterly MMR's

CONSTANT			**CONSTANT + TREND**	
TEST TYPE	Test statistic	Critical value	Test statistics	Critical value
ADF	-3.1419	-2.93	-3.3335	-3.5
KPSS	0.2503	0.463	0.0827	0.146

Table 3.2: AIC, AICc and BIC for the Suggested ARIMA Models

MODEL	**AIC**	**AICc**	**BIC**
ARIMA (1,0,0)	582.64	583.24	588.0
ARIMA (0,0,1)	582.84	583.44	588.19
ARIMA (1,0,1)	584.12	585.14	591.25
ARIMA (1,0,2)	**581.41**	**582.99**	**590.34**
ARIMA (2,0,2)	583.35	585.62	594.05

Table 3.3: Estimate of Parameters for ARIMA (1, 0, 2)

Variable	Estimate	Standard Error
AR(1)	**-0.308**	**0.356**
MA(1)	**0.4525**	**0.3246**
MA(2)	**0.3931**	**0.1452**
	σ^2 = 25369	

Table 3.4: ARIMA (1,0,2) Forecasting Results for Quarterly Maternal Mortality Ratios

YEAR	**QUARTER**	**predicted MMR (per 100,000 live births)**	**Actual MMR (per 100,000 live births)**	**lower limit**	**upper limit**
	1	**959.0**	996.7	**647**	**1271**
	2	**969.6**		**654**	**1285**
	3	**969.1**		**635**	**1303**
2011	4	**969.3**		**634**	**1305**
	1	**969.2**		**634**	**1305**
	2	**969.2**		**634**	**1305**
	3	**969.2**		**634**	**1305**
2012	4	**969.2**		**634**	**1305**

Figure 3.1 plot of MMR patterns from 2000 to 2010

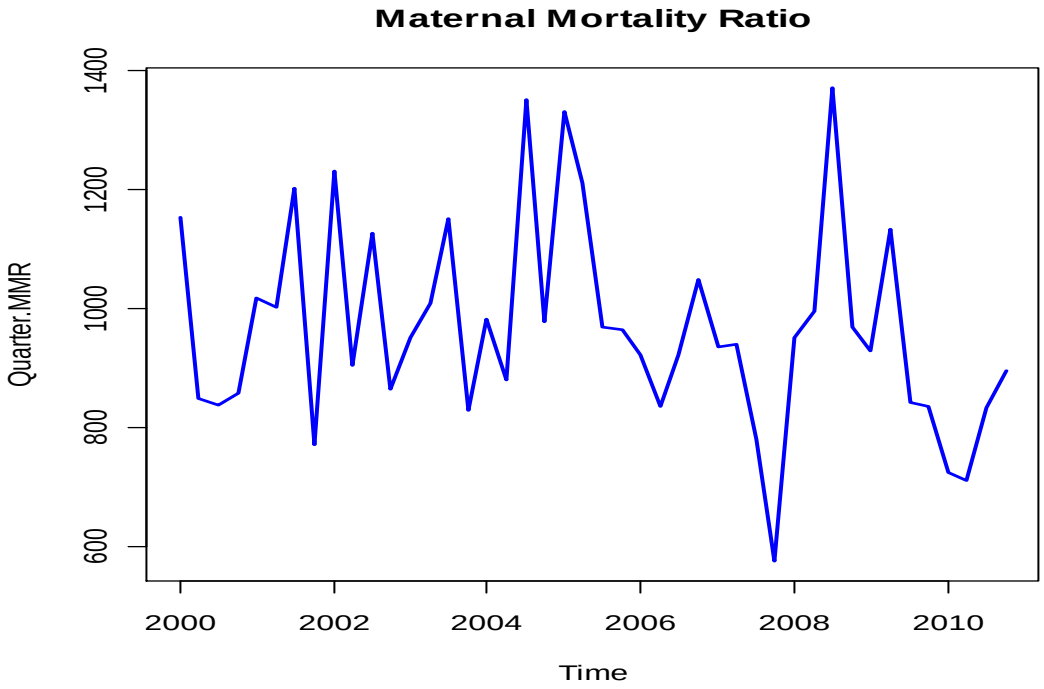

Fig. 3.2 ACF and PACF of quarterly MMRs from 2000 to 2010

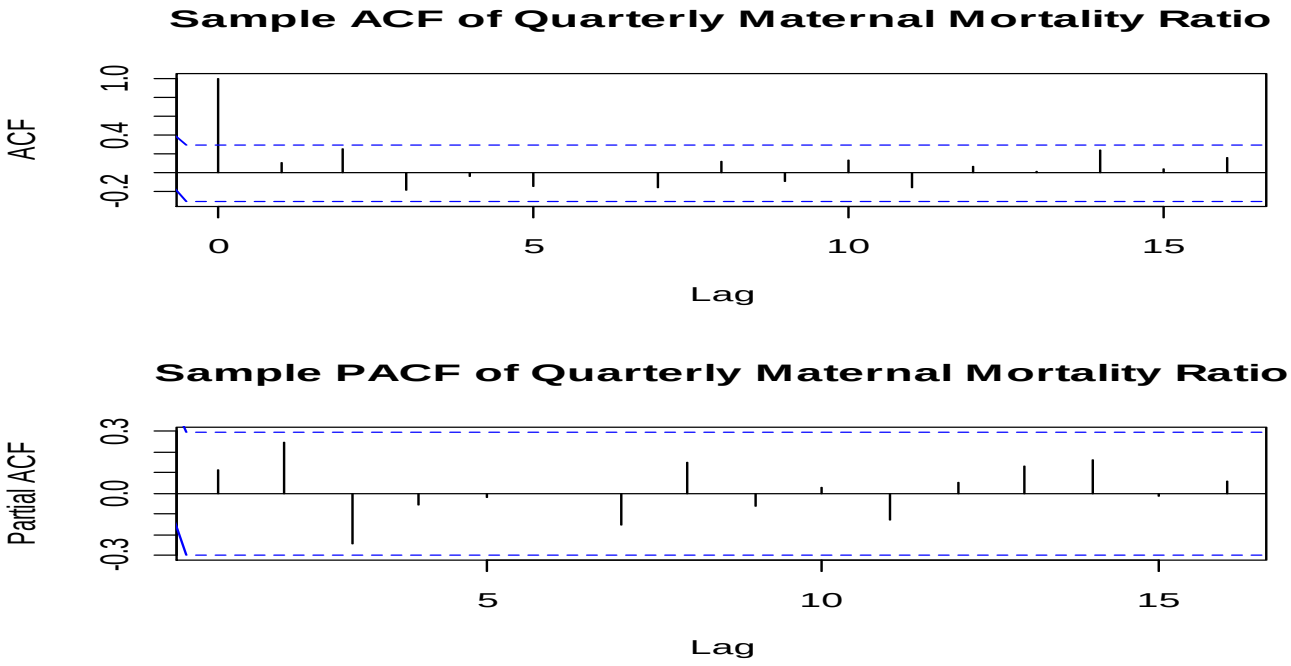

Fig. 3.3 plot of model residuals for quarterly MMRs from 2000 to 2010

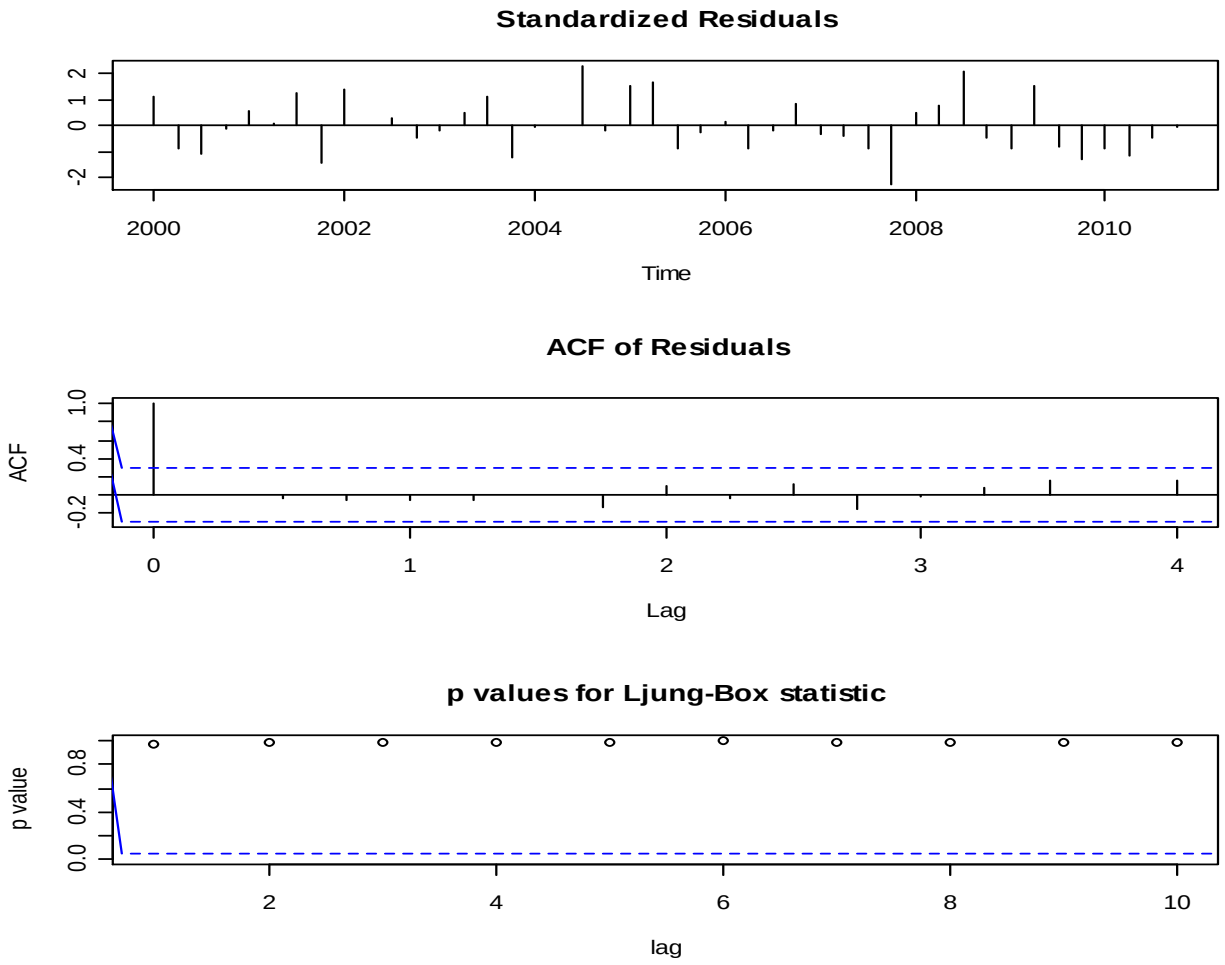

Fig. 3.4 plot of MMR patterns (blue) and fitted values (green) for 2000 to 2010