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Original Article

Comparing the Forecasting Performance of Seasonal Arima and Holt -Winters Methods of Births at a Tertiary Healthcare Facility in Ghana

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ABSTRACT

Introduction: Studies have shown periodic variations in the number of births using different mathematical models. A study conducted at the Korle-Bu teaching hospital obtained Seasonal Autoregressive Integrated Moving Average (SARIMA) model on a monthly number of birth for an 11-year data. However, this study did not compare the obtained model with other forecasting methods to determine the method that will best explain the data. This study sought to compare seasonal SARIMA model with Holt-Winters seasonal forecasting methods for an 11-year time series data on the number of births..

Methods: Data were analysed in R software (version 3.3.3). Holt-Winters and seasonal ARIMA forecasting methods were applied to the birth data. The errors of the out – of-sample forecast of these methods were compared and the one with the least error was considered the best forecasting method.

Results The in-sample forecasting errors showed that SARIMA (2,1,1) x (1,01,) was the best among the other models. The out-of-sample errors also showed that all the SARIMA models had lower errors compared to the Holt-Winters form of additive and multiplicative methods based on the forecasting accuracy indices of the monthly number of births for an 11-year period. It was also found that the months with very high statistically significant number of births over the period was from March to August.

Conclusion: The SARIMA models were superior to the Holt-Winters models. This is essential for optimal forecasting of the number of births for planning and effective delivery of Obstetrics services..

Introduction

Currently, it is becoming increasingly important for forecasts not to be done merely based on intuition and experience but rather on rigorous scientific methods (1) (2). Various forms of forecasting methods including Autoregressive Integrated Moving Average (ARIMA), Moving Average, linear regression, Artificial Neural Networks, Holt-Winters and decomposition models have been applied across disciplines such as business, management, economics, agricultural and healthcare and their importance have been proven in several studies (2-7). A seasonal ARIMA model had also been used in forecasting Tuberculosis incidence in literature (8) (9). Other comparative studies have also been done in assessing the performance between different forecasting methods (1) (10) (11).

Trends and variations in births among women over a period of time have been studied across the world (12) (13) (14). Forecasts of births and birth rates are essential to understanding potential population sizes over a specified period. Studies

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have shown forecasting results of birth using time series models. A study by Onwuka et al.(15) indicated ARIMA (0, 1, 2) as the most adequate model for forecasting monthly normal child-birth delivery using the Box-Jenkins time series. In addition, a study by Essuman et al.(16) using a Box-Jenkins approach yielded a seasonal ARIMA (2,1,1) x (1,0,1)12 of an 11-year univariate time series data from 2004 to 2014. The authors found the forecasted number of births was between 750 and 970 over the period for the year 2015 with the least occurring in January and highest in May respectively.

The ARIMA model has been broadly studied and used in various research for forecasting as a result of their good-looking theoretical attributes and its varied provable supporting shreds of evidence (17). Apart from the multiplicative method of Holt-Winters, ARIMA model also has equivalence with a number of exponential smoothing models (17). Holt-Winters (HW) model has been used in forecasting the number of assisted childbirth in Ghana (18). It is often appropriate to use the HW model when trend and seasonality are observed in the series. The previous study done by Essuman et al.(16) showed trend and seasonality in the birth data over the period but did not compare the obtained SARIMA model with the HW forecasting method. This provoked the question; could the Holt-Winters forecasting model be a better method than the seasonal ARIMA model on the number of births data? Also, it is important to compare the obtained model with other forecasting methods in order to select the optimal forecasting method relating to the birth data; this was lacking in the other studies reviewed(15)(18).

Therefore, the aim of this study was to compare the forecasting performance of seasonal ARIMA and Holt-Winters models of the monthly number of births at the Korle-Bu Teaching Hospital in Ghana. A secondary aim was to determine the month(s) with the significant number of births over the period.

Method

A time series analysis of monthly data consisting of 132 number of births from 2004-2014 at the Department of Obstetrics and Gynaecology, Korle Bu Teaching Hospital (KBTH) was used.

Data was captured in Microsoft Excel 2010 and analysis were done in R statistical software version 3.0.3. Holt winters and seasonal ARIMA forecasting methods were used.

The Holt-Winters method is widely used on time series which exhibit patterns of increasing or decreasing trend with the presence of seasonality. It is useful for forecasting time series in the short, medium, and long-term periods. The technique is different from other forecasting methods in the sense that it does not depend on the fit from any statistical modelling technique. Rather, it uses iterative steps to produce forecast values. The Holt-Winters seasonal method encompasses the forecast equation and three smoothing equations namely: level (ℓ_t), a trend (b_t), and the seasonal component represented by s_t, with smoothing parameters α, β and γ. The Holt-Winters forecasting method is classified according to the behaviour of the seasonal component. These are the additive and multiplicative methods.

The additive method is preferred when the seasonal variations are roughly constant through the series, while the multiplicative method is preferred when the seasonal variations are changing proportionally to the level of the series. Both the additive and multiplicative methods were applied to the data and the best was selected based on their predictive performance.

The Holt-Winters additive method equation is expressed:

Forecast: $\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t-m+h_m^+}$.(1)

Level: $\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ ...(2)

Trend: $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ .. ...(3)

Seasonal: $s_t = \gamma^*(y_t - \ell_t) + (1-\gamma^*)s_{t-m}$ ....(4)

and the Holt-Winter multiplicative method is also expressed as:

Forecast: $\hat{y}_{t+h|t} = (\ell_t + hb_t)s_{t-m+h_m^+}$ (5)

Level: $\ell_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1})$ (6)

Trend: $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$. (7)

Seasonal: $s_t = \gamma \frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1-\gamma)s_{t-m}$ (8)

Where y_t is the observed series, s is the length of the seasonal cycle, ℓ_t gives the level of the series, b_t denotes the trend, and $\hat{y}_{t+h|t}$ is the forecast for m-periods. α, β and γ are the smoothing parameters with a range of probability values; 0≤ α ≤1, 0≤β ≤1, 0≤γ ≤1.

The ARIMA model

is the operator for the MA term and is given as θ (B) = 1 + θ1B + θ2B2+ ... + θqBq .

Where p and q represent the number of lags for the AR and MA terms respectively and d is the order for the integration term.

The seasonal model is denoted as ARIMA (p, d, q) × (P, D, Q)s. Where p, d and q are the order of AR, differencing and MA respectively of non-seasonal component whilst P, D and Q are the order of AR, differencing and MA respectively of the seasonal component and the s is the number

Box-Jenkins forecasting approach put forward as Autoregressive Integrated Moving Average (ARIMA) model was used.

The ARIMA model is expressed as

$$\phi(B)(1-B)^d Y_t = \theta(B)\,\omega_t \quad (9)$$

Where ϕ (B) is the operator for the AR term and is given as :

$\phi(B) = 1 - \phi_1 B - \phi 2\, B^2 - \ldots - \phi P B P$ and θ (B) of periods per season. The general form of the seasonal model is expressed as:

$$(1-\Psi_p B)(1-\Phi_P B^S)(1-B)(1-B^S)y_t = (1+\theta_q B)(1+\Theta_Q B^S)w_t$$

(10)

Where $(1-\Psi_p B)$ and $(1-\Phi_P B^S)$ are the respective non-seasonal and seasonal autoregressive (AR) component of the model. $(1-B)(1-B^S)$ is the difference factor for both non-seasonal and seasonal. $(1+\theta_q B)$ and $(1+\Theta_Q B^S)$ are the moving average (MA) models for non-seasonal and seasonal component respectively with wt as the white noise.

The Box-Jenkins approach involved model identification, parameter estimation, model diagnostics and forecasting. A time series of the data was plotted, but the data was log-transformed and plotted again. Non-stationarity was confirmed using Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test on the transformed data. The transformed data were differenced once to attain stationarity accounting for the order (d) in the model. An autocorrelation function (ACF) was plotted to determine the order (p) of AR and partial autocorrelation function (PACF) to determine the order (q) of MA. The model obtained was assessed for seasonality and compared to other seasonal and non-seasonal models. The model with the smallest Akaike Information Criterion Corrected (AICc) and Bayesian Information Criterion (BIC) was selected as the best model.

Out-of-sample forecast measures of accuracy were determined for both forecasting approaches. The data (2004-2014) was used for modelling and forecasting and the predictability of the model done by comparing the forecast values with the actual data. Then 2012 data was used as the test set for the out of sample forecast measures of accuracy and compared between the two methods. Forecasting accuracies between the competing methods based on errors such as Mean Absolute Error (MAE), Root Mean Square (RMSE), Mean Absolute and Percentage Error (MAPE) were determined. The mathematical expressions for the errors are:

RMSE : $\sqrt{\frac{1}{n}\sum_{t=1}^{n}(e_t)^2}$ …………………. (11)

MAPE: $\frac{1}{n}\sum_{t=1}^{n}|P_t|$ ………………...…….. (12)

where Pt = 100et/yt…………………….…..(13)

MAE: $\frac{1}{n}\sum_{t=1}^{n}|e_t|$ ……………………...….. (14)

Where et is the forecast error for a given period t, yt is the actual value and yt−1 is the actual value from the prior period to the forecast. The forecast method among other competing errors with the minimum error was judged as the best method for the data.

A Poisson regression model was used to determine the months with the significant number of births over the period. The dependent variable was the number of births whilst the independent variables were the months with assigned dummy values {1, 0}.

The Poisson regression is expressed as:

$$f(k,\lambda)=\frac{\lambda^k e^{-\lambda}}{k!}$$ ……………………..….. (15)

Where e is the base of the natural logarithm (e = 2.71828...), k is the number of occurrences of an event, λ is a positive real number, equal to the expected number of occurrences that occur during the given interval. The log-transformed model is log ($u_i = x_i\ \beta$).

Results

The monthly number of births data studied consisted of 132 data time points with 119, 261 as the total number of births over the period (2004-2014). The monthly average number of births for the period studied was 903.5 and One-way Analysis of variance showed that there was a highly statistically significant difference between the monthly number of births for the period studied (F-test= 6.35; p <0.001)

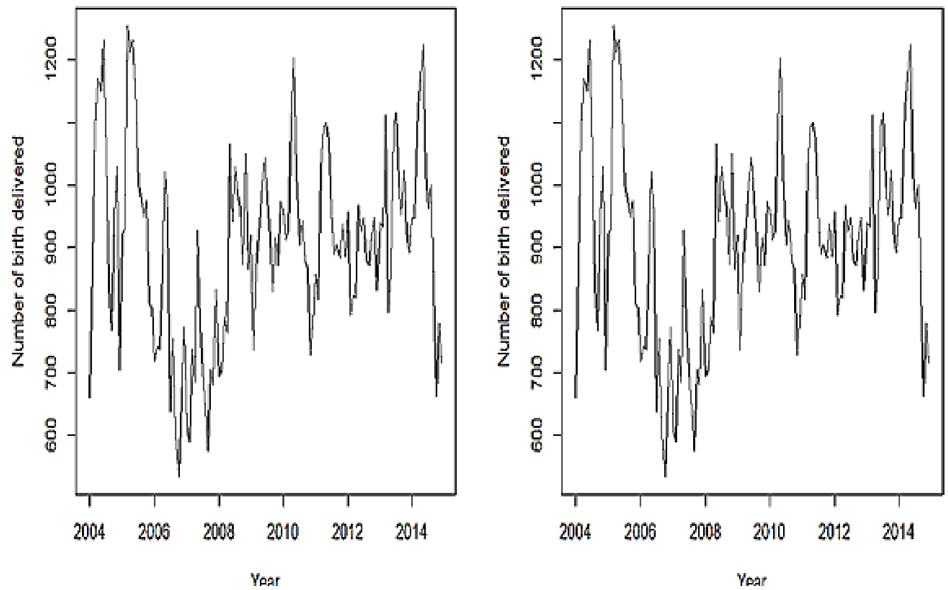

Figure 1.Time Serries Graph of NuBirmber of Birth(Left) and log-transformed of Number of Birth

It was found that the log-transformed of the data at the right of the graph showed regular variations with trend compared to the original data plotted at the left side of the graph in figure 1.

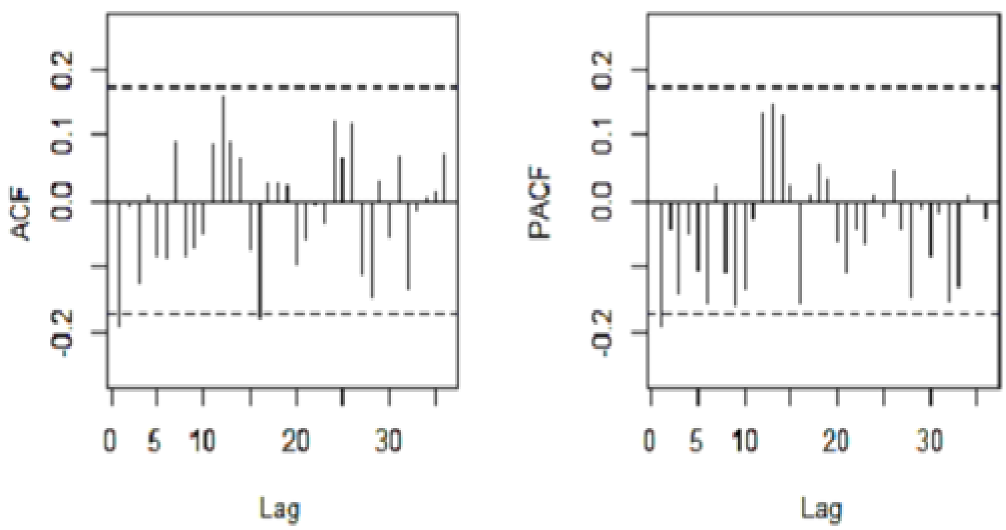

Figure 2. Sample ACF and PACF Graph of the first Difference of the Series

A correlogram plot of the ACF and PACF yielded significant spikes on lag1 exceeding the significance bounds on the respective graphs (Figure 2). There was also an almost significant spike at lag 12 on both plots.

***Table 1**: Comparison of Seasonal Models using AIC 's and BIC's*

Model	AIC	AICc	BIC
SARIMA (3,1,1)(1,1,1)12	-130.00	-129.76	-111.3
SARIMA (3,1,1)(1,0,1)12	-162.71	-161.80	-142.59
SARIMA (3,1,1)(0,0,1)12	-157.71	-156.49	-139.91
SARIMA (3,1,1)(1,0,0)12	-158.43	-157.75	-141.18
SARIMA (3,0,1)(0,1,0)12	-103.09	-102.56	-89.15
SARIMA (3,0,1)(0,1,1)12	-140.15	-139.41	-123.42
SARIMA (3,0,2)(1,1,0)12	-118.39	-117.39	-98.88
SARIMA (1,1,1)(1,0,0)12	-160.57	-160.25	-149.07
SARIMA (1,1,1)(1,0,1)12	-163.98	-163.50	-149.60
SARIMA (1,1,1)(0,0,1)12	-159.55	-159.2	-148.05
SARIMA (1,1,2)(1,0,0)12	-160.26	-159.73	-144.42
SARIMA (2,1,1)(1,0,1)12	-164.21	-163.53	-146.96
SARIMA (2,1,1)(1,0,0)12	-160.38	-159.90	-146.00
SARIMA (2,1,1)(0,0,1)12	-158.95	-158.47	-144.58

Different SARIMA models were formulated and compared to the ARIMA (1,1,1) using their AICc's and BIC's (Table 1). The model with the least AICc and BIC was SARIMA (2,1,1)(1,0,1)12

***Table 2**: Poisson Regression coefficients of monthly number of births*

Variables	Estimate of Coefficients	p-value
Constant	6.726778	2e-16
February	-0.021918	0.1398
March	0.132646	2e-16
April	0.145067	2e-16
May	0.246765	2e-16
June	0.201671	2e-16
July	0.113671	2.45e-15
August	0.068215	2.61e-06
September	-0.004586	0.7563
October	0.013849	0.3465
November	0.025598	0.0809
December	-0.013160	0.3742

A Poisson regression model was fit to the data to determine the month (s) with the significant number of births. It was found that March, April, May, June, July and August were the months with an extremely high significant number of births whilst the rest of the months were not (Table 2).

***Table 3**: Parameters and Coefficient of Holt-Winters' additive and multiplicative methods*

		Holt-Winters Method	
		Additive	**Multiplicative**
Smoothing parameters	Alpha(α)	0.3378	0.3346
	Beta (β)	0.0013	0.0020
	Gamma(γ)	0.5766	0.5517
Coefficients	level	6.7397	6.7407
	trend	0.0035	0.0031
	S_1	-0.0574	0.9911
	S_2	-0.1089	0.9833
	S_3	0.0168	1.0014
	S_4	-0.0488	0.9923
	S_5	0.0304	1.0044
	S_6	0.0145	1.0026
	S_7	0.0062	1.0010
	S_8	-0.0129	0.9979
	S_9	-0.1112	0.9838
	S_{10}	-0.1639	0.9761
	S_{11}	-0.0905	0.9864
	S_{12}	-0.1499	0.9780

The smoothing parameters of the Holt-winters ranged between 0 and 1. High values give more weight to recent data whilst lower values give less weight to recent data.

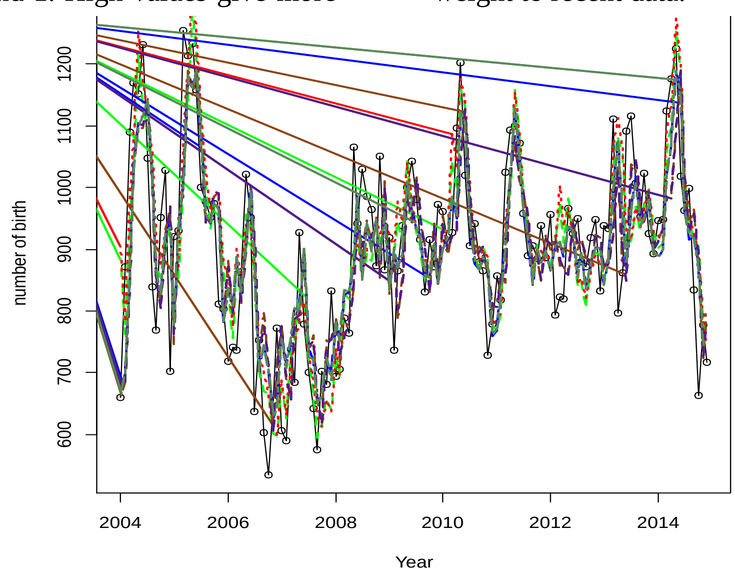

Figure 3: Plot of the in-sample forecast among the forecasting methods. The black colour represents the original data; Green colour is the Holt-Winters (HW) additive method; Red colour HW multiplicative method. Blue SARIMA (2, 1,1)(1,0,1);Pale green SARIMA (3,1,1)(1,0,); Brown SARIMA (1,1,1)(1,0,0) and purple SARIMA(3,`1,1)(1,00)

The in-sample forecasting of the various forecasting methods showed that almost all the methods or models used were closed to the original data set. But SARIMA (2,1,1) x (1,0,1) was closest to the original data compared to the other methods.

Table 4*: Errors for out-of-sample forecast for SARIMA and Holt- Winters*

Models	RMSE	MAE	MAPE
SARIMA(2,1,1) x(1,0,1)12	166.34	147.06	14.95
SARIMA(3,1,1)x(1,0,1)12	171.82	152.46	15.45
SARIMA (1,1,1) x (1,0,0)12	166.42	141.97	14.37
SARIMA(3,1,1) x (1,0,1)12	171.82	152.47	10.20
SARIMA (3, 1,1) x (1,0,0)12	169.90	145.71	14.69
Holt-Winters Additive method	194.81	168.06	16.65
Holt-Winters Multiplicative method	195.70	169.47	16.78

The accuracy of the models was based on the errors indicated in Table 4. The lower the errors of the methods used the better the predictive accuracy or performance of the model. It was found that the the errors in the SARIMA models were generally lower than the Holt-Winters methods.

Discussion

In this research, the Autoregressive Integrated Moving Average (ARIMA) and the Holt-Winters (HW) forecasting models were used on a monthly number of births over an 11-year period from 2004 – 2014 to determine the optimal forecasting method. These forecasting methods have the flexibility to deal with the linearity in problem-solving (17).

It was found that the two graphs in figure 1 appeared relatively similar except that the variations in the right plot occurred quite regular compared to the left plot; thus the log-transformed birth data was used throughout the analysis in this study. It was observed that between 2007 and 2014, the log-transformed plot showed fairly increasing series implying the existence of a trend in the dataset.

The Augmented Dickey Fuller (ADF) test established that the series was non-stationary (ADF= -3.38, p-value = 0.061). A complementary analysis using Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test also confirmed non-stationarity of the series (KPSS trend = 0.22: p-value = 0.01) indicating there is a trend in the series. However, a test on the first unit root difference of the data showed the series was stationary as confirmed by the ADF test (ADF = 5, p-value = 0.01) and KPSS test (KPSS trend = 0.052; p-value = 0.100).

A correlogram plot of the ACF and PACF produced significant spikes on lag1 beyond the significance bounds on the seperate graphs (Figure 2). Thus the ARIMA (1,1,1) model was formulated.

However, in Figure 2 the authors found that there was an almost significant spike at lag 12 on both plots characterizing a seasonal behaviour of the series.

Therefore, the authors formulated different seasonal models and compared to the empirical ARIMA (1,1,1) model so as to determine the best model for the data. Among the SARIMA models formulated, SARIMA (2,1,1) x (1,0,1)12 was selected since it achieved the least AICc and BIC according to the rule of parsimony(Table 1).

It was found from the poisson regression done that the month of March through to August were recorded the very high significant number of births in the Korle-Bu Teaching Hospital(Table 2).

In Table 3, when the Holt-Winters method was applied to the data, it was found that in both the Holt-Winters additive and multiplicative models, beta had 0.0013 and 0.0031 respectively which are close to zero indicating that the estimate of the slope (bt) of the trend is not updated over the series, and instead is set equal to its initial value. An alpha value of the additive was 0.3378 whilst the multiplicative method was 0.3346 which were relatively low, indicating that the estimate of the level at the current time point is dependent on recent observation and some observations in the more distant past. Therefore, it could be deduced here that as the level changes fairly over the series, the slope of the trend remains approximately the same. However, Gamma was 0.5766 and 0.5517 respectively for both additive and multiplicative methods. These values are strongly indicating that the estimate of the seasonal component at the current time point is just based on upon very recent observations.

Upon observation of the graph in figure 3, SARIMA (2,1,1) x (1,0,1) was closest to the original data compared to the other methods. This means that the residuals of the model SARIMA (2,1,1) x (1,0,1) were much well-behaved compared to the other models .

Regarding the Holt-Winters exponential procedures employed, the authors found that the additive method was superior to the multiplicative method since its accuracy measures RMSE (194.81), MAE (168.06), MAPE (16.65) were minimal compared to the multiplicative method. This was evident in the time plot of the series since it was found that as the level of the series increases, the seasonal variations were roughly the same (Figure 1). Also, the coefficients of the seasonal components of the additive method were approximately the same compared to the multiplicative method as shown in Table 3. All the seasonal models had better predictive errors than the Holt-Winters methods. Among the SARIMA models, SARIMA(2,1,1) x(1,0,1)12 had the least RMSE (166.34) whilst SARIMA (1,1,1) x (1,0,0)12 had the least MAE(141.97) and least MAPE (10.20) produced by SARIMA(3,1,1) x (1,0,1)12. Each predictive error measured tend to vary among the different SARIMA models.

Although SARIMA (2,1,1) x (1,0,1) was noted as the best model based on the AICc and BIC, the best model does not necessarily produce the best forecasting errors.

Conclusion

The results of the comparative analysis between the two forecasting methods; seasonal ARIMA models and Holt-Winters method on the monthly number of birth for an 11-year data have proven that all the seasonal ARIMA models had a better forecasting performance than the Holt-Winters' methods in this study. Thus, SARIMA models were an optimal forecast method for the number of births compared to the Holt-Winters' method in this study. This is essential for optimal forecasting of number of births for planning and effective delivery of Obstetric services

Conflict of interests

The authors declare that they have no competing interest and the finding of the study have not been published in any Journal.

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