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ON TIME SERIES MODELS AND PREDICTION OF DEPOSITS AND LOANS OF RURAL BRANCHES OF COMMERCIAL BANKS IN NIGERIA

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Abstract: This study develops best time series model for the prediction of deposits and loans of rural branches of commercial banks in Nigeria. The time series models proposed for predicting deposits and loans were autoregressive bilinear and autoregressive integrated bilinear models. The parameters of the proposed models were estimated using Newton-Raphson iterative method. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to determine the order of the models. To determine the best model, the residual variance was used. Estimation of parameters witnessed a unique, consistent and convergent estimator and the best derived model was used to predict the future deposits and loans.

Keywords: Deposits, Loans, Parameters, Newton-Raphson.

INTRODUCTION

Building probability model for time series data is an important activity that enables a statistician to understand the underlying random mechanisms generating the series as it provides invaluable assistance in forecasting the future. Linear time series, such as the autoregressive (AR) models, have been widely and successfully used in many fields.

Nevertheless, in some situations linear time series models may be insufficient in explaining the underlying random mechanisms. Thus; a natural alternative that suggests itself is nonlinear models. Undoubtedly, the nonlinear time series models are more complex than linear ones for several reasons. These are difficult parameter estimation of these models; intricate studying of statistical properties of most nonlinear models and sampling distribution of the estimates; and lastly, difficult evaluation of optimal forecasts for several steps in the future from these models. Yet despite these problems it seems reasonable to expect that in many situations nonlinear time series model should work better than a linear time series one.

Special nonlinear models considered by SubbaRao (1981) are known as bilinear (BL) time series models. Thus; many researchers have studied various bilinear models (e.g., Pham and Tran 1981, Gabr and SubbaRao 1981, Rao *et al.,* 1983, Liu 1992, Cathy 1997, Gonclaves *et al.,* 2000, Shangodoyin and Ojo 2003, Wang and Wei 2004, Boonchai and Eivind 2005, Bibi 2006, Doukhan *et al.,* 2006, Drost *et al.,* 2007, Usoro and Omekara 2008, Ojo 2009, Shangodoyin *et al.,* 2010, Ojo 2011). In the light of the above, we shall look at linear and bilinear time series models of deposits and loans of rural branches of commercial banks in Nigeria.

The rural branches of the commercial banks are the branches that are outside the cities and towns; the major activity of the occupants of rural area is farming. The occupants are also involved in small and medium scale enterprise. Rural banks can also be defined as those banks headquartered in rural markets. This study is sought to model and predict deposits and loans in the rural branches of the commercial banks in Nigeria.

METHODOLOGY

Autoregressive Model

Suppose that $\{\in_t\}$ is a purely random process mean zero and variance σ_e^2, then a time series $\{X_t\}$ is said to follow an autoregressive process of order p if it satisfies the difference equation:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + \varepsilon_t \qquad (2.1)$$

Where,

ε_t is a Gaussian process

$\phi_1, \phi_2, ..., \phi_p$ is a finite set of weight parameter

$E\{X_t\} = \mu = 0$

In backward shift operation presentation this model can be written as;

$(1 - \phi_1 \mathrm{B} - \phi_2 \mathrm{B}^2 - .... - \phi_p \mathrm{B}^p) X_t = \varepsilon_t$

i.e. $\Phi(\mathrm{B}) X_t = \varepsilon_t$ where

$$\Phi(\mathrm{B}) = 1 - \phi_1 \mathrm{B} - \phi_2 \mathrm{B}^2 - .... - \phi_p \mathrm{B}^p \qquad (2.2)$$

and the equation $\Phi(\mathrm{B}) = 0$ is called the characteristics equation. To ensure stationary, the roots of the characteristic equation $\Phi(\mathrm{B}) = 0$ must lie outside the unit circle. The estimate of the parameter $\phi_i, i = 1,2,.......,p$ can be obtained by Yule Walker method.

Autoregressive Integrated Model (ARI)

The Autoregressive Integrated Process is represented using the model

$\psi(B) X_t = \phi(B) \nabla^d X_t + e_t$ where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 .... - \phi_p B^p$

(1) $\phi(B)$ will be called the autoregressive operator; it is assumed to be stationary, that is the roots of $\phi(B) = 0$ lie outside the unit circle

(2) $\psi(B) = \nabla^d \phi(B)$ will be called the generalized autoregressive operator; it is a non stationary operator with d of the roots of $\psi(B) = 0$ equal to unity.
If $\psi(B) = \nabla^d \phi(B)$ and $\psi(B) = \phi(B)(1 - B)^d = 1 - \psi_1 B - \psi_2 B^2 .... - \psi_{p+d} B^{p+d}$ then the general model $\psi(B) X_t = \phi(B) \nabla^d X_t + e_t$ may be written as

$$X_t = \psi_1 X_{t-1} + ... + \psi_{p+d} X_{t-p-d} + e_t \qquad (2.3)$$

Autoregressive Bilinear Models

A time series X_t is an autoregressive bilinear process of order (p, 0, r, 1) if it satisfies the model

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \left(\sum_{i=1}^{r} \beta_{i1} x_{t-i} \right) e_{t-1} + e_t \qquad (2.4)$$

Where; p is the order of the autoregressive component and r,1 is the order of the nonlinear component. $\phi_1, \phi_2, ..., \phi_p$ are the parameters of the autoregressive component and $b_{11}, ..., b_{r1}$ are the parameters of the nonlinear component; {e_t} is a sequence of independent, identically distributed random variables with mean zero and variance σ^2.

The Vector Form of Autoregressive Bilinear Models BL (p, 0, r, 1).

It is convenient to study the properties of a process when the model is in the state space form because of the Markovian nature of the model Akaike (1974).

Let

$$\underset{p\times p}{\Phi} = \begin{pmatrix} -\Phi_1 & -\Phi_2 & -\Phi_3 & ..... & -\Phi_{p-1} & -\Phi_p \\ 1 & 0 & 0 & ..... & 0 & 0 \\ 0 & 1 & 0 & .... & 0 & 0 \\ 0 & 0 & 0 & ..... & 1 & 0 \end{pmatrix}$$

$$\underset{r\times r}{B_j} = \begin{pmatrix} b_{11} & b_{21} & b_{31} & .... & b_{r1} \\ 0 & 0 & 0 & .... & 0 \\ 0 & 0 & 0 & .... & 0 \end{pmatrix} \quad j=1$$

and vectors $\underset{1\times p}{C^T} = (1,0,0,.....,0)$, $H' =$ (1, 0, ..., 0) and let $\underset{1\times p}{X^T} = (X_t, X_{t-1}, ..., X_{t-p+1})$, (Here T stands for the transpose of a matrix) t = ...-1, 0, 1,..... With this notation, we can write the model (2.4) in the vector form as:

$$\mathbf{X}_t = \Phi \mathbf{X}_{t-1} + \mathbf{B}\mathbf{X}_{t-1} e_{t-1} + \mathbf{C} e_t \qquad (2.5)$$

Autoregressive Integrated Bilinear Models

We define autoregressive integrated bilinear models as follows:

$$\psi(B) X_t = \phi(B) \nabla^d X_t + \left(\sum_{k=1}^{r} b_{k1} X_{t-k} \right) e_{t-1} + e_t, \qquad (2.6)$$

Denoted as BL (p, d, 0, r, 1),

Where; $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 .... - \phi_p B^p$ and

$$X_t = \psi_1 X_{t-1} + ... + \psi_{p+d} X_{t-p-d} + \left(\sum_{k=1}^{r} b_{k1} X_{t-k} \right) e_{t-1} + e_t . \qquad (2.7)$$

$\phi_1, ..., \phi_p$ are the parameters of the autoregressive component; $b_{11}, ..., b_{r1}$ are the parameters of the nonlinear component and $\phi(B)$ is the autoregressive operator. *P* is the order of the autoregressive component; *r, 1* is the order of the nonlinear component and

$\psi(B)=\nabla^d\phi(B)$ is the generalized autoregressive operator. ∇^d is the differencing operator and *d* is the degree of consecutive differencing required to achieve stationary.

The Vector Form of Autoregressive Integrated Bilinear Models BL (p, d, 0, r, 1)

It is convenient to study the properties of a process when the model is in the state space form because of the Markovian nature of the model, Akaike (1974).

Let

$$\underset{p\times p}{\Psi}=\begin{pmatrix}-\psi_1 & -\psi_2 & -\psi_3 & ..... & -\psi_{p+d-1} & -\psi_{p+d}\\ 1 & 0 & 0 & ..... & 0 & 0\\ 0 & 1 & 0 & .... & 0 & 0\\ 0 & 0 & 0 & ..... & 1 & 0\end{pmatrix}$$

$$\underset{r\times r}{B_j}=\begin{pmatrix}b_{11} & b_{21} & b_{31} & .... & b_{r1}\\ 0 & 0 & 0 & .... & 0\\ 0 & 0 & 0 & .... & 0\end{pmatrix}\quad \text{j=1}$$

and vectors $\underset{1\times p}{C^T}=(1,0,0,.....,0)$ and let $\underset{1\times p}{X^T}=(X_t,X_{t-1},........,X_{t-p+d})$, (Here T stands for the transpose of a matrix) t = ...-1, 0, 1,..... With this notation, we can write the model (2.7) in the vector form as:

$$\mathbf{X}_t=\Psi\mathbf{X}_{t-1}+\mathbf{B}\mathbf{X}_{t-1}e_{t-1}+\mathbf{C}e_t \tag{2.8}$$

Estimation of Parameters of BL (p, d,0, r, 1)

The joint density function of $(e_m,e_{m+1},....,e_n)$, where *m* = max(*r*, 1), is given by

$$\frac{1}{(2\pi\sigma_e^2)^{(n-m+1)/2}}\exp\left(\frac{1}{-2\sigma_e^2}\sum_m^n e_t^2\right) \tag{2.9}$$

Since the Jacobian of the transformation from $(e_m,e_{m+1},....,e_n)$ to $(X_m,X_{m+1},....,X_n)$ is unity, the likelihood function of $(X_m,X_{m+1},....,X_n)$ is the same as the joint density function of $(e_m,e_{m+1},....,e_n)$. Thus maximizing the likelihood function is equivalent to minimizing the function $Q(\mathbf{G})$, which is as follows:

$$Q(\mathbf{G})=\sum_{i=m}^{n}e_t^2\ , \tag{2.10}$$

With respect to the parameter $\mathbf{G}=(\psi_1,....,\psi_{p+d};B_{11},....,B_{r1})$. For convenience, we shall write $G_1=\psi_1,G_2=\psi_2,.......,G_R=B_{r1}$, where *R* = *p* +d+$r_1$. Then the partial derivatives of *Q*(**G**) are given by

$$\frac{dQ(\mathbf{G})}{dG_i}=2\sum_{t=m}^{n}e_t\frac{de_t}{dG_i}\qquad (i=1,2,.....,R) \tag{2.11}$$

$$\frac{d^2Q(\mathbf{G})}{dG_i dG_j} = 2\left(\sum_{t=m}^{n} e_t \frac{de_t}{dG_i}\frac{de_t}{dG_j} + \sum_{t=m}^{n} e_t \frac{d^2 e_t}{dG_i dG_j}\right)$$

Where the partial derivatives of e_t satisfy the recursive equations

$$\frac{de_t}{d\psi_i} + \sum_{j=1}^{s} W_t(t)\frac{de_{t-j}}{d\psi_i} = \begin{cases} 1, \text{ if } i = 0 \\ X_{t-i}, \text{ if } i = 1, 2, \ldots, p \end{cases} \qquad (2.12)$$

$$\frac{de_t}{dB_{k1}} + \sum_{j=1}^{s} W_j(t)\frac{de_{t-j}}{dB_{k1}} = -X_{t-k}e_{t-m} \ (k=1,2,\ldots,r\ ;\ m_i=1) \qquad (2.13)$$

$$\frac{d^2 e_t}{d\psi_i d\psi_i'} + \sum_{j=1}^{s} W_j(t)\frac{d^2 e_{t-j}}{d\psi_i d\psi_i'} = 0 \ (i, i' = 1, 2, \ldots, p) \qquad (2.14)$$

$$\frac{d^2 e_t}{d\psi_i dB_{k1}} + \sum_{j=1}^{s} W_j(t)\frac{d^2 e_{t-j}}{dB_{k1} d\phi_i} + X_{t-k}\frac{d^2 e_{t-mi}}{d\psi_i} = 0$$

$(i=1,2,\ldots,p\ ;\ k_i=1,2,\ldots,r;\ m_i=1)$ (2.15)

$$\frac{d^2 e_t}{d\psi_i d\theta_i} + \sum_{j=1}^{s} W_j(t)\frac{d^2 e_{t-j}}{d\psi_i d\theta_i} = 0 \qquad (2.16)$$

$$\frac{d^2 e_t}{dB_{k1} dB_{k1}'} + \sum_{j=1}^{s} W_j(t)\frac{d^2 e_{t-j}}{dB_{k1} dB_{k1}'} + X_{t-k}'\frac{d^2 e_{t-mi}}{dB_{k1}} = -X_{t-k}\frac{de_{t-m}}{dB_{k1}'}$$

$(k,\ k' = 1,2,\ldots,r\ ;\ m_i m_i' = 1)$ (2.17)

$$W_j(t) = \sum_{j=1}^{s} B_{ij} X_{t-j}$$

We assume that $e_t = 0$ ($t = 1, 2, \ldots, m-1$) and

$$\frac{de_t}{dG_i} = 0, \frac{d^2 e_t}{dG_i dG_j} = 0, \quad (i, j = 1, 2, \ldots, R;\ t = 1, 2, \ldots, m-1)$$

From these assumptions and this equality:

$\frac{de_t}{dB_{k1}} + \sum_{j=1}^{s} W_j(t)\frac{de_{t-j}}{dB_{k1}} = -X_{t-k}e_{t-m}$ ($k=1,2,\ldots,r$; $m_i=1$),it follows that the second order derivatives with respect to ψ_i ($i = 1, 2, \ldots, p$) is zero. For a given set of values $\{\psi_i\}$and $\{B_{i1}\}$ one can evaluate the first and second order derivatives using the recursive equations (2.12), (2.13) and (2.17). Let $V(\mathbf{G}) = \frac{dQ(\mathbf{G})}{dG_1}, \frac{dQ(\mathbf{G})}{dG_2}, \ldots\ldots, \frac{dQ(\mathbf{G})}{dG_R}$

and let $\mathbf{H}(\mathbf{G}) = [d^2 Q(\mathbf{G}) / dG_i dG_j]$ be a matrix of second partial derivatives. Expanding $V(\mathbf{G})$, near $\mathbf{G} = \hat{\mathbf{G}}$ in a Taylor series, we obtain $[\hat{G}]_{\hat{\mathbf{G}}=\mathbf{G}} = 0 = \mathbf{V}(\mathbf{G}) + \mathbf{H}(\mathbf{G})(\hat{\mathbf{G}} - \mathbf{G})$

Rewriting this equation, we have $\hat{\mathbf{G}} - \mathbf{G} = -\mathbf{H}^{-1}(\mathbf{G})V(\mathbf{G})$, thereby obtaining an iterative equation given by $\mathbf{G}^{(k+1)} = \mathbf{G}^{(k)} - \mathbf{H}^{-1}(\mathbf{G}^{(k)})V(\mathbf{G}^{(k)})$, where $\mathbf{G}^{(k)}$ is the set of estimates obtained at the k^{th} stage of iteration. The estimates obtained by the above iterative equations usually converge. For starting the iteration, we need to have good sets of initial values of the parameters. This can be obtained as follows:

Suppose we wish to fit bilinear model BL(p, d, 0, r, 1). We choose the coefficients of the autoregressive integrated models (ARI) part of this model. These coefficients are used as the initial values for starting the iteration of the Newton-Raphson iterative equation.

Remarks
Considering the autoregressive integrated bilinear model, when d = 0 the model results to autoregressive bilinear model.

RESULTS

The quarterly data used was extracted from the Statistical Bulletin of Central Bank of Nigeria (CBN) which was collected from the Central Bank of Nigeria (CBN) Dugbe, Ibadan. The study covers a range of fifteen years from 1994 to 2008.

Fitted Models

Autoregressive (AR) Model for Rural Deposits

$$X_t = 0.6987X_{t-1} + e_t$$

Autoregressive Bilinear (ARBL) Model for Rural Deposits

$$X_t = 0.6987X_{t-1} - 5.71E-06X_{t-1}e_{t-1} + e_t$$

Autoregressive Integrated (ARI) Model for Rural Deposits

$$X_t = -0.708510X_{t-1} + e_t$$

Autoregressive Integrated Bilinear (ARIBL) Model for Rural Deposits

$$X_t = -0.708510X_{t-1} - 2.42E-07X_{t-1}e_{t-1} + e_t$$

Autoregressive (AR) Model for Rural Loans

$$X_t = 1.0407X_{t-1} + e_t$$

Autoregressive Bilinear (ARBL) Model for Rural Loans

$$X_t = 1.0407X_{t-1} - 4.75E-06X_{t-1}e_{t-1} + e_t$$

Autoregressive Integrated (ARI) Model for Rural Loans

$$X_t = -0.4062X_{t-1} + e_t$$

Autoregressive Integrated Bilinear (ARIBL) Model for Rural Loans

$$X_t = -0.4062X_{t-1} + 3.02E-05X_{t-1}e_{t-1} + e_t$$

The derived statistics from the above fitted models are given in table1, table 2, table 3 and table 4 below.

Table 1: Derived Statistics from AR and ARBL Models for Rural Deposits

	Autoregressive Model	Autoregressive Bilinear Model
Residual Variance	$(10041.5)^2$	$(9280.4)^2$
R-Squared	0.30	0.4
AIC	21.33	21.22
BIC	21.37	21.26

Table 2: Derived Statistics from ARI and ARIBL Models for Rural Deposits

	Autoregressive Integrated Model	Autoregressive Integrated Bilinear Model
Residual Variance	$(9949.06)^2$	$(9779.4)^2$
R-Squared	0.21	0.21
AIC	21.28	21.24
BIC	21.31	21.28

Table 3: Derived Statistics from AR and ARBL Models for Rural Loans

	Autoregressive Model	Autoregressive Bilinear Model
Residual Variance	$(4922.1)^2$	$(4844.6)^2$
R-Squared	0.794	0.797
AIC	19.87	19.84
BIC	19.90	19.87

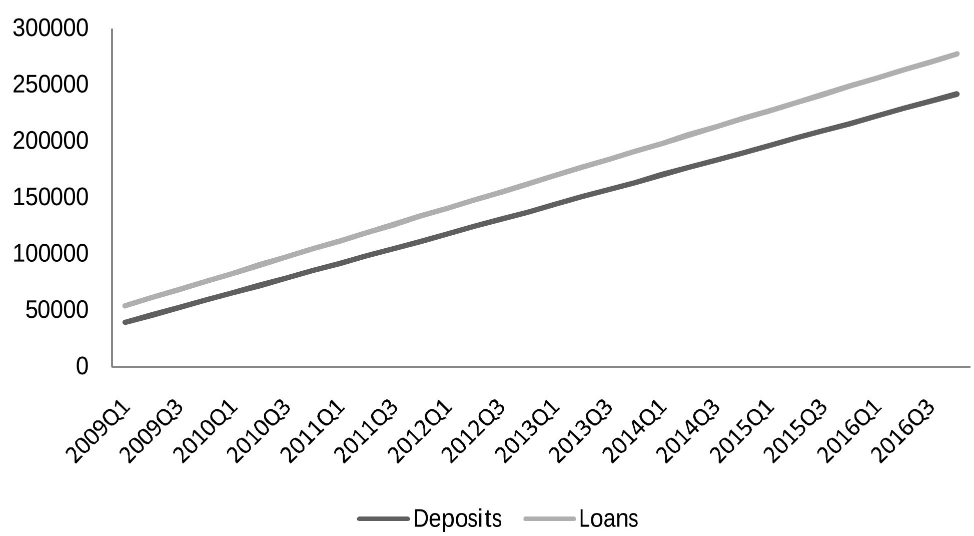
Table 4: Derived Statistics from ARI and ARIBL Models for Rural Loans

	Autoregressive Integrated Model	Autoregressive Integrated Bilinear Model
Residual Variance	$(4451.4)^2$	$(3843.8)^2$
R-Squared	0.14	0.4
AIC	19.72	19.38
BIC	19.75	19.41

Table 5: Forecast in Million Naira Using Best Bilinear Model of Rural Deposits and Loans

Time	Deposits	Loans	Time	Deposits	Loans
2009Q1	39841.91	54221.00	2013Q1	144125.1	169564.0
2009Q2	46359.61	61429.94	2013Q2	150642.8	176772.9
2009Q3	52877.31	68638.88	2013Q3	157160.5	183981.9
2009Q4	59395.01	75847.81	2013Q4	163678.2	191190.8
2010Q1	65912.71	83056.75	2014Q1	170195.9	198399.8
2010Q2	72430.41	90265.69	2014Q2	176713.6	205608.7
2010Q3	78948.12	97474.63	2014Q3	183231.3	212817.6
2010Q4	85465.82	104683.6	2014Q4	189749.0	220026.6
2011Q1	91983.52	111892.5	2015Q1	196266.7	227235.5
2011Q2	98501.22	119101.4	2015Q2	202784.4	234444.4
2011Q3	105018.9	126310.4	2015Q3	209302.1	241653.4
2011Q4	111536.6	133519.3	2015Q4	215819.8	248862.3
2012Q1	118054.3	140728.3	2016Q1	222337.5	256071.3
2012Q2	124572.0	147937.2	2016Q2	228855.2	263280.2
2012Q3	131089.7	155146.1	2016Q3	235372.9	270489.1
2012Q4	137607.4	162355.1	2016Q4	241890.7	277698.1

Figure 1: Prediction Using Bestbilinear Model (2009-2016) of Rural Deposits and Loans



DISCUSSION

Table 1 gives the summary of statistics of autoregressive and autoregressive bilinear models for rural deposits. It was glaring that autoregressive bilinear model performed better than autoregressive model as indicated by the small residual variance and the values of AIC and BIC. The best prediction equation for rural deposits is $\hat{X}_t = 0.6987X_{t-1} - 5.76E - 06X_{t-1}e_{t-1}$. Table 2 gives the summary of statistics of autoregressive integrated and autoregressive integrated bilinear models for deposits when stationary condition is satisfied.

Also, it was glaring that autoregressive integrated bilinear model performed better than autoregressive integrated model as indicated by the small residual variance and the values of AIC and BIC. The best prediction equation for rural deposits is $\hat{X}_t = -0.708510X_{t-1} - 2.42E - 07X_{t-1}e_{t-1}$. Table 3 gives the summary of statistics of autoregressive and autoregressive bilinear models for rural loans. It was glaring that autoregressive bilinear model performed better than autoregressive model as indicated by the small residual variance and the values of AIC and BIC. The best prediction equation for rural loans is $\hat{X}_t = 1.0407X_{t-1} - 4.75E - 06X_{t-1}e_{t-1}$. Table 4 gives the summary of statistics of autoregressive integrated and autoregressive integrated bilinear models for rural loans when stationary condition is satisfied. Also, it was glaring that autoregressive integrated bilinear model performed better than autoregressive integrated model as indicated by the small residual variance and the values of AIC and BIC. The best prediction equation for rural loans is $\hat{X}_t = -0.4062X_{t-1} + 3.02E - 05X_{t-1}e_{t-1}$.

From these tables, autoregressive bilinear model emerged as the best for deposits while autoregressive integrated bilinear emerged as the best for loans. Table 5 shows the forecast for rural deposits and loans for the period 2009 to 2016 using the best bilinear model. From figure 1, it was noticed that the amount of loan exceeds that of deposits and this calls for a caution that the banks should strike a balance in deposits and money given out as loans because if this is neglected, it could lead to financial embarrassment when customers who deposited could not withdraw because a larger percentage of commercial bank fund has been used as loans..

REFERENCES

Akaike, H. (1974).“Markovian Representation of Stochastic Processes and Its Application to the Analysis of Autoregressive Moving Average Processes.” Ann. Inst. Stat. Math.26, 363-383.

Bibi A. (2006). “Evolutionary Transfer Functions of Bilinear Process with Time Varying Coefficients”. Computer and Mathematics with Applications 3(4), 331-338.

Boonchai B.K. and Eivind S. (2005). “Multivariate Bilinear Time Series: A Stochastic Alternative in Population Dynamics”. Geophysical Research Abstracts, Volume 7, 02219 @Europeans Geosciences Union 2005.

Cathy, W. S. (1997).“Detection of Additive Outliers in Bilinear Time Series”. Computational Statistics and Data Analysis 24, 283-294.

Doukhan, P., Latour, A., and Oraichi, D., (2006). “A Simple Integer – Valued Bilinear Time Series Model”. Adv. Appl. Prob. 38: 559-578.

Drost F.C., van den Akker R., Werker, B.J.M. (2007). "Note on Integer – Valued Bilinear Time Series Models". Econometrics and Finance Group Center, ISSN 0924-7815, Tilburg University, The Netherlands.

Gabr, M. M. and SubbaRao, T. (1981)."The Estimation and Prediction of Subset Bilinear Time Series Models with Application." *Journal of Time Series Analysis* 2(3), 89-100.

Gonclaves, E., Jacob P. and Mendes-Lopes N. (2000)."A Decision Procedure for Bilinear Time Series Based on the Asymptotic Separation." Statistics, 333-348.

Liu, J. (1992). "On Stationarity and Asymptotic Inference of Bilinear Time Series Models". Statistical Sinica 2(2), 479-494.

Ojo J. F. (2009). "The Estimation and Prediction of Autoregressive Moving Average Bilinear Time Series Models with Applications" *Global Journal of Mathematics and Statistics.* Vol. 1 No 2, 111-117.

Ojo, J.F (2011). Generalized and Subset Integrated Autoregressive Bilinear Time series Models with Applications. *American Journal of Scientific and Industrial Research.* 2(3): 401-408.

Pham, T.D. and Tran, L.T. (1981)."On the First Order Bilinear Time Series Model".*Jour. Appli. Prob.* 18, 617-627.

Rao, M.B., T.S. Rao and Walker, A. M. (1983). "On the Existence of some Bilinear Time Series Models" .*Journal of Time Series Analysis* 4(2), 60-76.

Shangodoyin, D.K. and Ojo, J.F (2003). "On the Performance of Bilinear Time Series Autoregressive Moving Average Models." *Journal of Nigerian Statistical Association* 16, 1-12.

Shangodoyin D.K., Ojo, J.F and Marcin K. (2010). "Subsetting and Identification of Optimal Models in One-Dimensional Bilinear Time Series Modelling." *International Journal of Management Sciences and Engineering Management.* 5(4) 252-260

SubbaRao, T. (1981)."On theory of Bilinear time Series Models" .Jour. R. Sta. Soc. B. 43, 244-255.

Usoro, A.E. and Omekara C.O. (2008). "Lower Diagonal Bilinear Moving Average Vector Models." Advances in Applied Mathematical Analysis 3(1), 49-54.

Wang H.B. and Wei B.C. (2004) Separable Lower Triangular Bilinear Model. *J. Appl. Probab.* 41(1), 221-235

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