STOCHASTIC CHARACTERISTICS AND MODELING OF RELATIVE HUMIDITY OF OGUN BASIN, NIGERIA

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ABSTRACT

Extreme events of atmospheric phenomena are often non-deterministic in nature, and this has been a major constraint in achieving agricultural sustainability in most developing countries.To facilitate this study, 29 years information of the observed relative humidity of Ogun basin was obtained from the Federal Ministry of Water Resources, Abeokuta, Nigeria. The data collected covers the periods between 1982 and 2009 and were pre-whitened and aggregated into monthly and annual time series. The stationarity of the time series data was achieved through Mann-Kendal non-parametric test and spectral analysis. The Mann-Kendal Z-value obtained is -1.37, which gives no reason to expect the presence of trend in the time series. The spectral density plot showed high variance to lower frequency, and this signifies a positive correlation. No evidence of seasonal effect in the series as clearly depicted by the monthly Periodogram. The autoregressive AR-model, moving average MA-model and autoregressive moving average ARMA-models were fitted for the parameter, with the aid of Akaike Information Criterion (AIC), and error terms of FE, MAE, MSE and MAPE. ARMA model of order (2, 2) was found to be the most parsimonious for predicting relative humidity. Results are highly accurate and promising for all models based on Lewis' criteria. Prediction scheme applied in this research could be considered in situations where database is a problem during model development.

Keywords: ARMA model, Autocorrelation, Forecasting,Prediction andRelative humidity

INTRODUCTION

Atmospheric water vapor is widely recognized to be a key climate variable. It is the dominant greenhouse gas and provides a key feedback for amplifying the sensitivity of the climate to external forcings (Held and Soden, 2000; Soden and Held, 2006). Water vapor is also an important component of the hydrological cycle. Future increases in water vapor in response to a warming climate are fundamentally linked to the expected changes in moisture convergence, precipitation extremes, meridiunal energy transport and an overall weakening of the atmospheric circulation (Held and Soden, 2006).

Relative humidity represents the amount of water vapor which is in the atmosphere. They primarily come from the evaporation of surface water and superficial layers of soil, from plant and animal respiration and from some technological processes. Atmospheric humidity can be expressed in 3 ways: relative, absolute and maximum. The relative humidity is at maximum (100 %) when the air becomes saturated. If the air becomes saturated, condensation of water vapor (present in the air) occur leading to the formation of tiny water droplets. Millions of such water droplets come together to form clouds. So, if the humidity is more (or relative humidity becomes maximum), it leads to the formation of clouds and subsequent precipitation (Tsoho, 2008).Humidity control is important in many engineering applications, such as space air conditioning, storage warehouses, process industries and many others (Rakesh and Arun, 2014).

MATERIALS AND METHOD

The name ‘Ogun basin’ is derived from two major rivers that drains within; Rivers Ogun and Osun, though they have smaller tributaries like; Sasa, Ona, Ibu, Ofiki, Yewa rivers etc. The basin under consideration is located in South Western Nigeria. The entire basin is bounded by Oyo state in the north, Osun and Ondo States in the east and Lagos State in the South.

The Ogun basin covers the whole of Ogun State, located in southern Nigeria, bordered geographically by latitudes 6^0 26^I N and 9^0 10^I N and longitudes 2^0 28^I E and 4^0 8^I E. About 2% of the basin area falls outside Nigeria in the Benin Republic. The land area is about 23,000km^2. The relief is generally low, with the gradient in the North-South direction.

The two major vegetation zones that can be identified the area are the high forest vegetation in the north and central parts, and the swamp/mangrove forests that cover the southern coastal and floodplains, next to the lagoon. It has two distinct seasons throughout the year. The monthly rainfall distribution in the study area shows a distinct dry season extending from November through March and a rainy season divided into two periods: April – July and September – October. The mean annual rainfall data for 30 years showed a variation from about 1,150mm in the northern part to around 2,285mm in the southern extremity. The estimates of total annual potential evapotranspiration have been put between 1600 and 1900mm. (Ewomoje and Ewomooje, 2011).

Data Collection and Pre-whitening

The humidity data used for this study were obtained from the federal ministry of water resources, Abeokuta, Nigeria. The data collected covered a period of twenty nine years (1982-2009). These values were obtained by the use of GPS (global position system) equipment. Data preprocessing is an important task in almost all modeling techniques. The data obtained are the time series types which are collected monthly for a period of 29 years. For the purpose of this study, the mean annual values of the data were first determined before use.

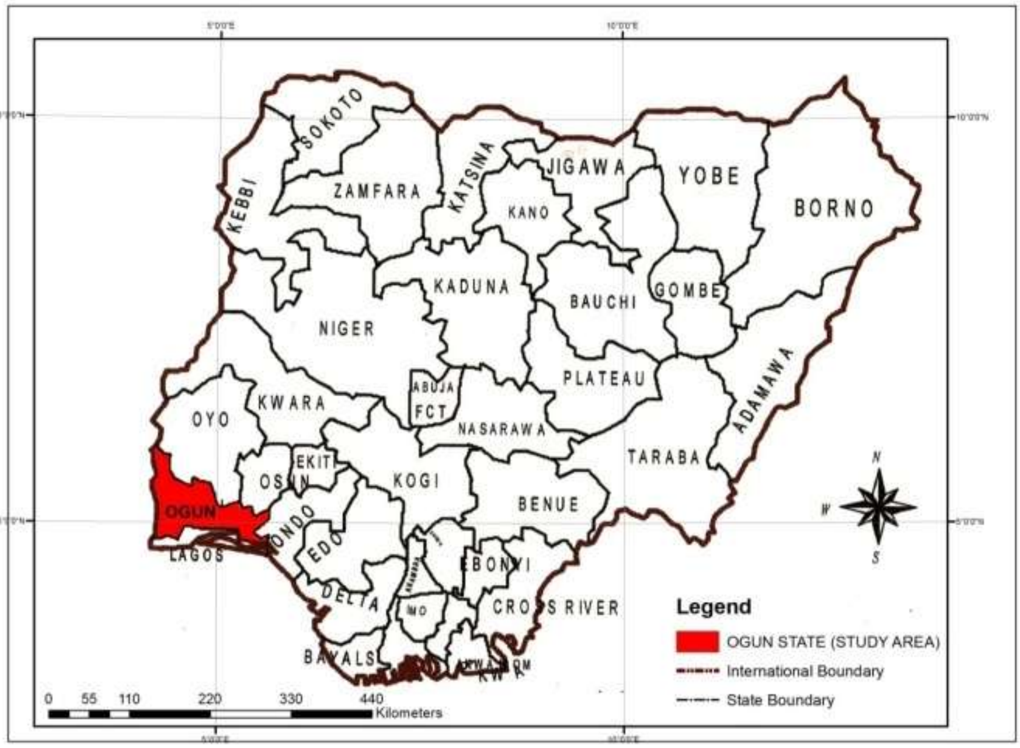

Figure 1: Map of Nigeria showing the study Area.

Test for Trend and Serial Correlation

The Mann-Kendal non-parametric test was considered for trend detection in the annual time series data because of its robustness and unique advantages over other methods. To check for serial correlation, the Durbin-Watson test was considered. The tests were carried out in order to know which modeling techniques will best fit the data to be use.

Time series data are generally represented in the form:

$$T(t) = Tr + P(t) + \varepsilon(t) \qquad 1$$

Where, $T(t) = time\ series, Tr = trend\ component, P(t) = periodic\ component\ and, \varepsilon(t) = stochastic\ component.$

In order to check for the stationarity of the data, the following equations were considered:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(X_j - X_k)$$

Where, X_j and X_k are the annual values in years j and k, j > k, respectively, and

$$sgn(X_j - X_k) = \begin{cases} 1 & if\ \ X_j - X_K \quad > 0 \\ 0 & if\ \ X_j - X_k \quad = 0 \\ -1 & if\ \ X_j - X_k \quad < 0 \end{cases} \qquad 3$$

$$VAR(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p-1)(2t_p+5)\right] \quad 4$$

Where, q is the number of tied groups and t_p is the number of data values in the p^{th}group.The values of S and VAR(S) are used to compute the test statistic Z as follows

$$Z = \begin{cases} (S-1)/Var(S)^{1/2} & S > 0 \\ 0 & S = 0 \\ (S+1)/Var(S)^{1/2} & S < 0 \end{cases} \quad 5$$

Source: Longobardi and Villan (2009)

The Mann-Kendall test was carried out in accordance with the works of Otache, Ahaneku and Mohammed, (2011); Edwin and Otache, (2014) and Chatfield (2004), with the aid of the excel template of ‘MAKESEN’s version 1. Lo’s modified R/S test was also done to ascertain if the trend persisted. To check for serial correlation, the Durbin-Watson test was considered. The tests were carried out in order to make sure the time series data conforms to the basic criteria for stochastic modeling. No trend and cyclic components were observed from the result obtained, therefore, only the stochastic component was considered.

Autoregressive Moving Average (ARMA) Models for Relative Humidity

The Mann-Kendal test result gives an insignificant Z-value of -1.37, and by this, the null hypothesis of no trend in the time series of relative humidity is accepted. The Box Jenkins (2008) methodology was applied in the model identification, parameter estimation and diagnosis test before the prediction. Based on the ACF and PACF of the training data, in conjunction with the serial iteration, an autoregressive, AR – model of order (5), a moving average, MA – model of order (4), and an autoregressive moving average, ARMA – model of order (2, 2) were found suitable for fitting the time series. The results of the serial iteration for all model parameter identification were also confirmed by the performance of the Akaike Information Criterion and Bayessian Information Criterion (AIC/BIC) test as presented in Tables 1, 2 and 3. As shown in the tables, the model parameters occupying rows with least values of AIC/BIC are considered the best for model building. With the aid of MINITAB software version 16.0, the model equations were build and presented in Table 4. The equations were used to generate values for validating the 3 models and presented graphically as shown in Figures 2, 3 and 4. The Lewi’s error scaling system (i.e. considering the MAPE), was used in comparing the accuracy of the models, and all models were found to be accurate (i.e. MAPE values < 10%). Table 5 presents the summary of error determination for the 3 models developed.

Table 1: AR - Model order selection for relative humidity

Model Order (P)	Sum of Sqrs (SS)	AIC/BIC Value	Constant ©	Mean (μ)
1	2501.16	131.259	44.843	77.969
2	2483.84	133.058	48.463	78.014
3	2346.77	133.411	36.728	77.961
4	2342.17	135.355	38.558	77.980
5	**1595.36**	**126.219**	**68.695**	**78.757**

Table 2: MA - Model order selection for relative humidity

Model Order (q)	Sum of Sqrs (SS)	AIC/BIC Value	Constant (c)	Mean (μ)
1	2473.65	130.938	-	78.001
2	2451.95	132.683	-	78.046
3	1942.34	127.926	-	78.081
4	**1641.81**	**125.051**	**-**	**78.162**
5	1703.14	128.115	-	77.755

Table 3: ARMA - Model order selection for relative humidity

S/No.	Model Order (p,q)		Sum Sqrs (SS)	AIC/BICValue	Constant (c)	Mean(μ)
1	1	1	2455.24	230.373	66.201	78.033
2	1	2	2448.26	232.291	35.069	78.012
3	2	1	2522.62	233.159	77.193	78.027
4	**2**	**2**	**2454.58**	**136.71**	**46.726**	**78.069**
4	1	3	1916.03	227.182	15.857	77.542
5	3	1	2345.94	233.052	38.409	77.964
6	2	3	2224.89	233.516	24.986	78.145
7	3	2	1883.31	228.683	61.887	77.875
8	3	3	1933.35	231.443	70.785	78.017
9	1	4	2051.78	231.167	8.589	77.563
10	4	1	2125.42	232.190	56.107	77.773
11	2	4	1690.61	227.552	14.124	79.445
12	4	2	1496.33	224.012	84.376	77.074
13	3	4	1853.25	232.216	11.435	78.130
14	4	3	1487.09	225.832	95.797	77.058
15	4	4	1415.38	226.399	200.55	77.083
16	1	5	1444.03	222.980	31.947	78.243
17	5	1	1571.02	225.425	59.562	79.108
18	2	5	1356.54	223.168	41.395	78.449

Table 4: Best Model Equations obtained for the 3 Models on Relative Humidity

S/No.	Model Type	Model Order	Model Equation
1	AR	5	$y_t = 68.695 + 0.5900y_{t-1} - 0.1615y_{t-2} + 0.1744y_{t-3} + 0.2666y_{t-4} - 0.7418y_{t-5} + \varepsilon_t$
2	MA	4	$y_t = 78.162 - 0.7346\varepsilon_{t-1} - 0.2293\varepsilon_{t-2} - 0.1278\varepsilon_{t-3} - 0.5050\varepsilon_{t-4} + \varepsilon_t$
3	ARMA	2, 2	$y_t = 46.726 + 0.3413y_{t-1} + 0.0602y_{t-2} - 0.1023\varepsilon_{t-1} + 0.1416\varepsilon_{t-2} + \varepsilon_t$

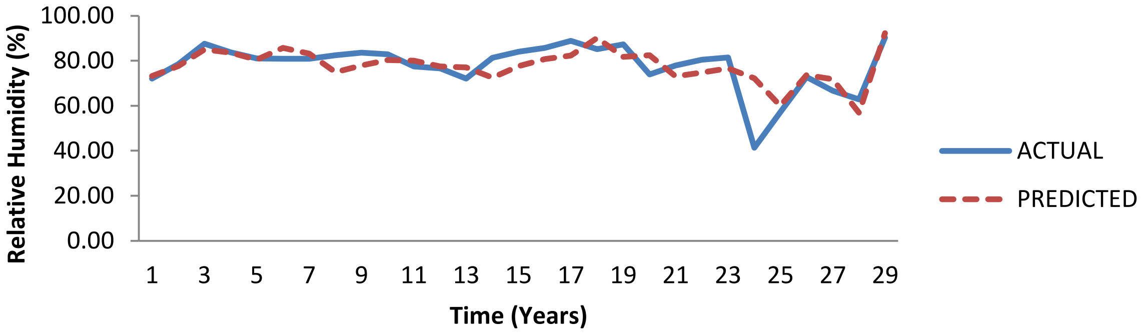

Fig. 2: Relative Humidity Plot for AR (5) Model

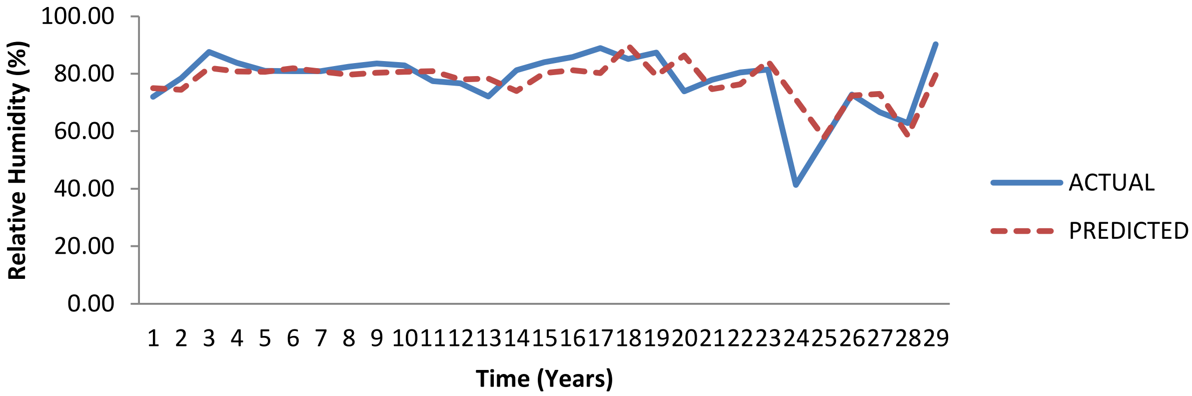

Fig. 3: Relative Humidity Plot for MA (4) Model

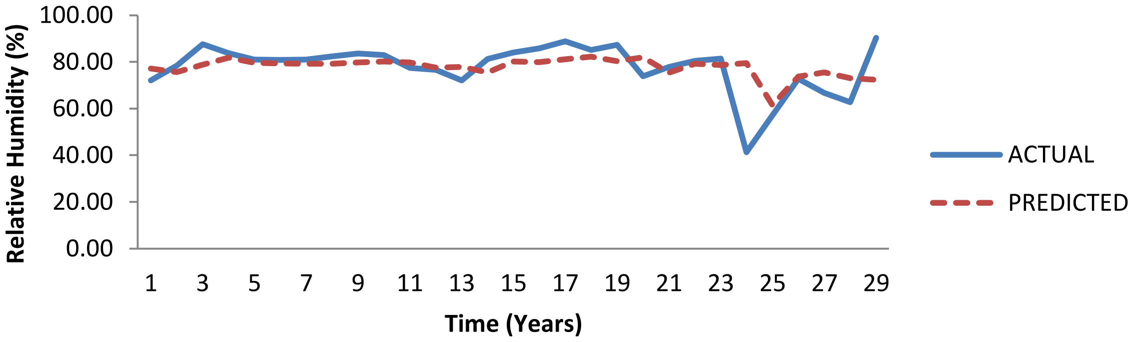

Fig. 4: Relative Humidity Plot for ARMA (2, 2) Model

Table 5: Summery of Error Values for Relative Humidity

Model Type	Model Order	Forecast Error	MSE	RMSE	MAPE (%)
AR	5	2.09	55.01	27.08	7.62
MA	4	4.57	56.61	27.50	7.60
ARMA	2, 2	0.99	84.64	31.64	9.01

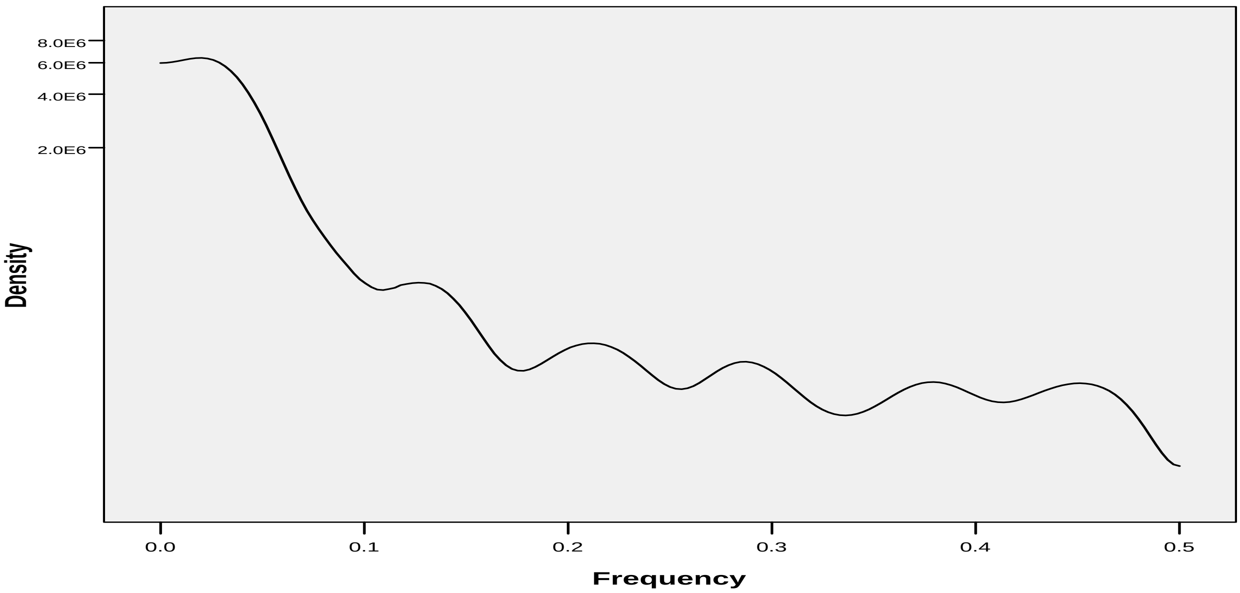

Fig. 5: Spectral Density Plot for Monthly Relative Humidity

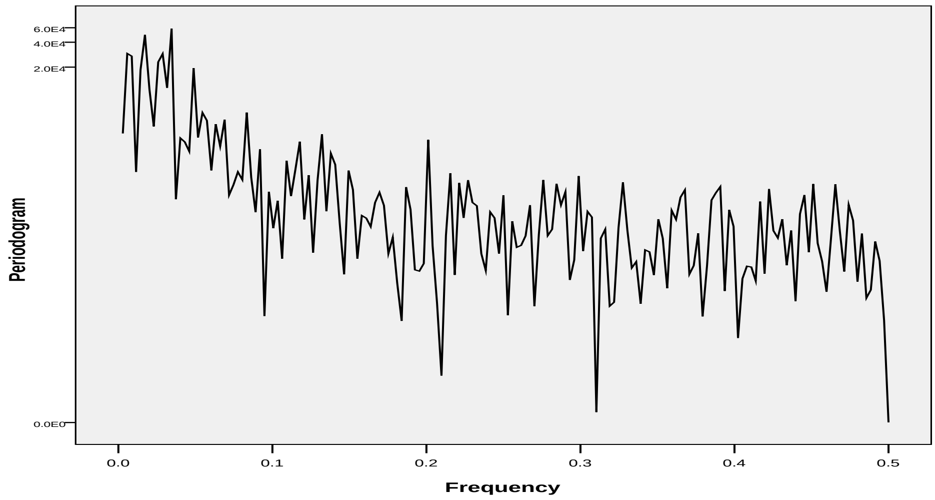

Fig. 6: Periodogram for Monthly Relative Humidity by Frequency

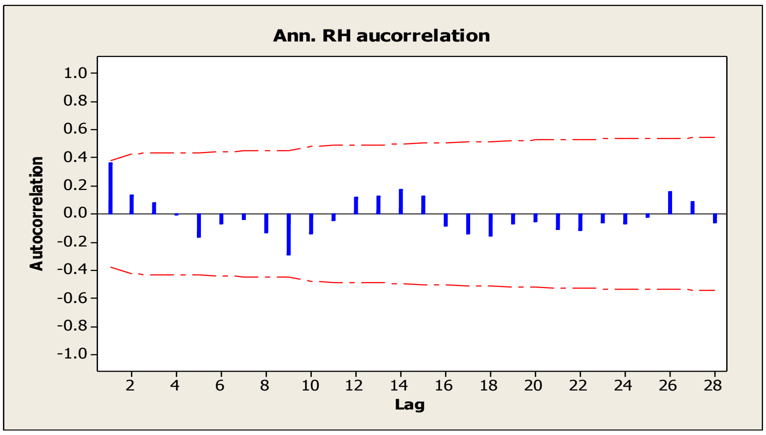

Fig. 7: Autocorrelation Plot for Relative Humidity

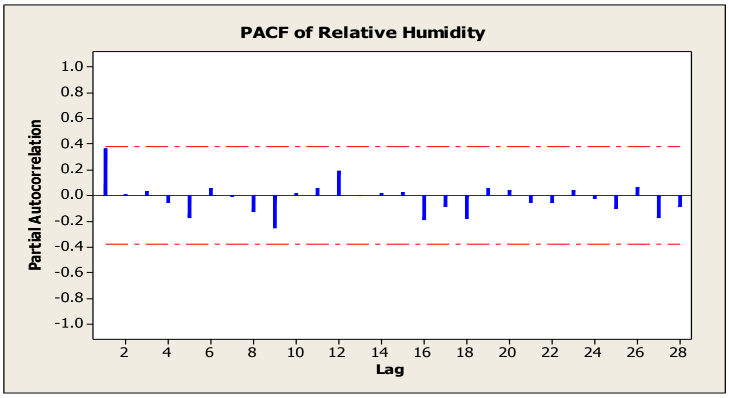

Fig. 8: Partial Autocorrelation Plot for Relative Humidity

CONCLUSIONS

The accessibility torecords of hydrological processes in which relative humidity is one of the major determining factors is imperative for proper guide and timely preparation against extreme events. Several methods have been used to predict hydrological behaviors, but have shown some weaknesses due to thefact that most hydro-meteorological parameters are non-deterministic. The results obtained in this study have been able to demonstrate the robustness of the autoregressive moving average method in the prediction of relative humidity of the study area. No trend was detected in the annual time series of the parameter based on the Mann-Kendal test, though, the linear trend line as obtained by the Sen's slope indicated that there is gradual shift in the relative humidity in a negative pattern. However, it is important that the government and relevant stakeholders are aware of the changes in the trend in order to make proper arrangement in case of extreme events.

The autoregressive AR-model, moving average MA-model and autoregressive moving average ARMA-models were fitted for the parameters considered, with the aid of Akaike Information Criterion (AIC), and error terms of FE, MAE, MSE and MAPE. The parsimonious model was observed to be ARMA (2, 2) based on the least value of AIC. ACF and PACF made the model identification and order selection easier and perfect for effective prediction. The overall results were promising and the prediction scheme applied in this research could be considered in situations where database is a problem during model development. Based on the findings of this study, it is recommended that another modeling method be used using the same data and results obtained be compared to see which of them gives better outcome.

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