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Modelling Wind Speed on Some Meteorological Variables as a Source of Power Generation

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Abstract: ***Wind speed modelling and forecasting is pertinent in order to have a power system that is reliable and secured. The Vector Autoregressive model and the logistic regression model were applied on a 23-year monthly data obtained from the Meteorological Agency FCT Abuja Nigeria. The Vector Autoregressive model shows that none of the meteorological variables namely; Monthly rainfall, Monthly temperature, and Monthly relative humidity, significantly affect Monthly wind speed. It was also found that each of the meteorological variables have varying effects on Wind speed over a future time horizon as depicted by the variable. The Wind speed was also model using the logistic regression where it was found that there is no statistically significant difference between Wind speed and the meteorological variables. To this end, this study posits that wind speed is not significantly being influenced by the meteorological variables. That is to say most of this metrological variable will not be able to generate enough heat in other to influence the wind speed for a sufficient power generation.***

Keywords: Modelling, Vector Auto Regressive model, Logistics Regression Model Wind Speed and Meteorological Variables

1. Introduction

1.1 Background to the Study

With the advent of science and technology, the demand for electrical energy becomes inevitable. Nigeria is a country endowed with abundant energy resources like coal, solar, water (Dam), wind and so on which can be used as a form of electricity generation. Despite the abundance of these energy resources, there is inconsistent supply of electricity, which may be due to underutilization of the potentials.

Wind energy is the fastest growing renewable source of energy. With respect to this, the need for wind speed modelling and forecasting becomes paramount. Energy generation by wind is of great advantage because wind turbines do not produce any form of pollution when sited strategically. Moreover, it blends with the natural landscape. The utilization of wind energy will ensure the growth of socio-economic development and improvement in the quality of life of the citizens. The demand for more sustainable energy sources is on the increase in order to address the growing needs of humans. It is also in line with taking care of the environment and the minimal use of natural resources, which means there is an urgent need for developing renewable energy.

Wind energy is now becoming the current trend in renewable energy as it addresses rising energy demand while being nature friendly at the same time. In the long run, electricity generated from the wind turbines cost less than the conventional power plants since it does not consume fossil fuel. Researches on the potentials of wind energy in some major cities in Nigeria show high wind speed in Lagos, Maiduguri, Enugu, Jos, Kano, Funtua and Sokoto (Idris*et al.*, 2012).

The gathering of wind data is important for the wind farm beginning from its feasibility to its actual operation. Prior to the construction of a wind farm, at least one year of meteorological study is necessary and a detailed verification of the specific on-site wind conditions are necessary. Meteorological values, more specifically wind speed and wind direction are necessary for the calculation of the wind farm's yearly electrical generation profile. The harnessing of Kinetic energy through the wind has been used for centuries, be it in form of powering sail boats, wind mills, or furnaces (Aliyu and Mohammed 2014). But it was not until 1979 that the modern wind power industry began in earnest with the production of wind turbines. The use of wind energy as a form of renewable energy gained momentum in the 80s and 90s and there are now thousands of wind turbines operating all over the world (Minh *et al.*, 2011). The modern and most commonly used wind turbine has a horizontal axis with twoor more aerodynamic blades mounted on the shaft. These blades can travel at over several times the wind speed, generating electricity which is captured by a medium voltage power collection system and fed through the power transmission network (Garba and Al-Amin, 2014).

Wind energy is unarguably the most economic renewable energy apart from hydropower, its usage, versatility and ability to use it as a decentralized energy form make its applications possible in rural areas where it is technically and economically feasible in the country. Winds are caused by the uneven heating of the atmosphere by the sun, irregularities of the earth's surface, and rotation of the earth. Wind flow patterns are modified by the earth's terrain, water bodies and vegetative cover (Reddy *et al.*, 2015). The major challenge of using Wind as a source of energy is that winds are intermitted, and it is not available always when electricity is needed.

Wind speed forecasting is essential for a secured and reliable power system for a particular site. This research forecasts wind speed in Nasarawa state using the Vector Auto Regressive (VAR) model. The explanatory variables used are rainfall, Temperature, and relative humidity, in addition, the wind significance influence were also studied in relation to wind speed using the Logistic Regression model.

1.2 Statement of the Problem

The growing demands of energy supply by mankind has triggered the potentials of using wind energy due to its constant availability and nature-friendly environment. The importance of wind energy cannot be over emphasized. Wind energy can be seen as the energy of the future for Nigerians if properly harnessed and utilized. For example, the 10MW Katsina wind farm project which is owned by the Federal Ministry of Power is a pioneer project in Nigeria aiming to generate 10MW of power via wind turbine with the Federal Government's desire to boost electricity generation and have constant power supply. Wind Speed modelling and forecasting are necessary for a reliable and secure power system. It is therefore of paramount importance to study the impact of meteorological variables on wind speed. Cherisetal (2014) used vector autoregressive model in modelling wind speed in the presence of some meteorological variables which are humidity, temperature, and pressure. The result of this study showed that none of the meteorological variables namely Humidity, Temperature and Pressure significantly affected wind speed over time.

However, the researcher apply the vector autoregressive model, and logistics regression model in studying the wind speed and direction of influence in Nasarawa State with some selected meteorological variables which are rainfall, temperature and relative humidity.

1.3 Aim and Objectives of the Study

To model and forecast wind speed using vector autoregressive model, variance decomposition and logistics regression in the presence of some metrological variables.

1.4 Objectives

1) VAR modeling of wind speed on rain fall, temperature and relative humidity
2) To perform logistics regression modeling of wind speed on rain fall, temperature and relative humidity.

1.5 Significance of the Study

This study will serve as a contribution to existing literatures on modelling of wind speed in the scientific world. In addition, the result of the study will be of paramount importance to the Nasarawa State Government, the Federal Government and also the Nigeria meteorological agency as it creates awareness on the important of wind speed; can also provide valuable information on the expected daily and seasonal load. The model which will be adopted can be used as a tool by the government in making forecasts on wind speed in order to facilitate policy planning.

1.6 Scope of the Study

The data used for this study is a 23 year monthly data from 1998 to 2020 obtained from the Nigeria meteorological Agency.

Techniques for Data Analysis and Model Specification

The techniques used in this research for data analysis is Vector autoregressive model (VAR MODEL).

What is VAR.? It is a simple autoregressive model.

Autoregressive is due to the appearance of the lagged value of the dependent variable in the right-hand side and the term vector is due to the fact that vector of two of more variables is included in the model.

The VAR approach by passed the need for structural modeling by treating every variable as endogenous in the model as a function of the lagged value of all endogenous variable in the system.

VAR is commonly used for forecasting system of inter-related time series and for analysis the dynamic impact of random disturbance on the system of variable.

1.7 Model Specification

$LNMWS_t = \alpha_1 + \sum_{s=1}^{k} a_{1i} LNMWS_{t-s} + \sum_{m=1}^{k} b_{1m} LNMRF_{t-m} + \sum_{j=1}^{k} c_{1j} LNMTEMP_{t-j} + \sum_{n=1}^{k} d_{1n}$
$LNMRH_{t-n} + U_1 t$
$LNMRF_t = \alpha_2 + \sum_{s=1}^{k} a_{2i} LNMWS_{t-s} + \sum_{m=1}^{k} b_{2m} LNMRF_{t-m} + \sum_{j=1}^{k} c_{2j} LNMTEMP_{t-j} + \sum_{n=1}^{k} d_{2n}$
$LNMRH_{t-n} + U_2 t$
$LNMTEMP_t = \alpha_3 + \sum_{s=1}^{k} a_{3i} LNMWS_{t-s} + \sum_{m=1}^{k} b_{3m} LNMRF_{t-m} + \sum_{j=1}^{k} c_{3j} LNMTEMP_{t-j} + \sum_{n=1}^{k} d_{3n}$
$LNMRH_{t-n} + U_3 t$
$LNMRH_t = \alpha_4 + \sum_{s=1}^{k} a_{4i} LNMWS_{t-s} + \sum_{m=1}^{k} b_{4m} LNMRF_{t-m} + \sum_{j=1}^{k} c_{4j} LNMTEMP_{t-j} + \sum_{n=1}^{k} d_{4n}$
$LNMRH_{t-n} + U_4 t$

Where
k is the optimal lag
$\alpha$is the Intercept
a_i, b_m, c_j, $d_n$are short run coefficient of the model adjusted
$U_{it}$are the Residuals in the equations.
Which can be also be re-arranged in matrix form as:

$$\begin{bmatrix} WndsP_t \\ RnF_t \\ TmP_t \\ RhM_t \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix}$$
$$+ \begin{bmatrix} a_{11} & b_{11} & c_{11} & d_{11} \\ a_{21} & b_{21} & c_{21} & d_{21} \\ a_{31} & b_{31} & c_{31} & d_{31} \\ a_{41} & b_{41} & c_{41} & d_{11} \end{bmatrix} \begin{bmatrix} \mathrm{WndP}_{t-1} \\ \mathrm{RnF}_{t-1} \\ TmP_{t-1} \\ \mathrm{Rhm}_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{bmatrix}$$

2. Model Selection

Most recent approaches used as criteria for choosing the order of a model without going through hypothesis testing are:

2.1 Final Prediction Error (FPE).

The FPE criterion for pthcrder model is given by pth order model is given by

$$FPE_p = \sigma_p^2\left(1+\frac{P}{N}\right)$$

Where

$\sigma_p^2$is the unbiased estimates of σ^2 after fitting the pth order model. That is. $\hat{\sigma}_p^2 = \frac{RSS_p}{N-p}$

2.2 Akaike Information Criterion (AIC)

Akaike (1973, 1974a) introduced an intonation criterion called AK in the literature. It is defined as $AIC(k) = -2In(Maximum)likelihood) + 2k$

Where

k is the number of parameters in the model. Minimizing Ln(L), AIC reduces to $AIC(k) = nLn\sigma_e^2 + 2k$ where L stands for likelihood function of sample and n is the effective number of observations.

2.3 Bayesian Information Criterion (BIC)

Shibata (1976) showed that the AIC criterion tends to overestimate the order of the autoregression. Akaike (1978, 1979) developed a Bayesian extensilon of the minimum AIC procedure called BIG which is given by

$$BIC(k) = nIn(\hat{\sigma}_e^2) - (n-k)In\left(1-\frac{k}{n}\right) + kIn(n) + kIn\left[\left(\frac{\hat{\sigma}_x^2}{\hat{\sigma}_e^2} - 1\right)/k\right]$$

Where

$\hat{\sigma}_e^2$is the maximum likelihood estimate of σ_e^2

k is the number of parameters and

$\hat{\sigma}_x^2$is the sample variance of the series. Through a simulation study, Akaike (1978) claimed that the BIC is less likely to overestimate the order of the autoregression.

2.4 Schwartz's Bayesian Information Criterion (SBIC)

This criterion is similar to Akaike's BIG. Schwartz (1978) suggeste a Bayesian Criterion of model selection given as $SBIC(k) = nIn\hat{\sigma}_e^2 + kIn(n)$

For all the criteria considered, the optimal model order is determined for which the criterion is minimum.

2.5 Test of Stationarity

There are two (2) basic tests for stationarity in a variable namely: Augmented Dickey Fuller (ADF) and Philiph Perron (PP).

The ADF test: This assumed that the error term μ_t was uncorrelated. Therefore, a test was developed known as (ADF) by adding a lagged value of the dependent variable Δy.

$\Delta Wndsp_t = \alpha_t + \alpha_{2t} + \delta Wndsp_{t-1} + \mu_t$

$\Delta Wndsp_t = \alpha_t + \alpha_{2t} + \delta wndsp_{t-1} + \alpha_i + \Sigma\Delta Wndsp_{t-1} + \epsilon_t$

That is,

$\Delta Wndsp_{t-1} = (Wndsp_{t-1} - Wndsp_{t-2})$

$\Delta Wndsp_{t-2} = (Wndsp_{t-2} - Wndsp_{t-3})$while

The (PP) Test: This assumed that error terms μ_t are independently and identically distributed.

Therefore, ADF adjust the DF test to take care of possible serial correlation in the error terms by adding lagged difference term of the regression while the PP test use non parametric statistical methods to take care of the serial correlation in the error terms without adding lagged difference terms even though the asymptotic distribution of the ADF & PP are using the same test Statistic.

In conclusion: The ADF is recommended for his study.

Estimating of Parameters

The parameters of a vector autoregressive model (VAR) can be estimated using either;

1) Least squares method or
2) Maximum Likelihood equivalent

Least Square Method

Suppose the sample $\{X_t\}_{t=1}^n$ is available such that:

$$X_t = \emptyset_0 + \emptyset_1 X_{t-1} + \cdots \emptyset_p X_{t-p} + a_t$$

Then VAR$_{(p)}$ model can be written as

$$X_t^1 = X_t^1\beta + a_t^1$$

Where $Z_t = (1, X_{t-1}^1, \ldots, X_{t-p}^1)^1\ as\ (kp+1)$ dimensional vectors and

$$\beta^1 = [\emptyset_0, \emptyset_1, \ldots, \emptyset_p]k\ k\ x\ (k_p+1)\ matrix.$$

The Least square estimate of β is

$$\hat{\beta}\left[\sum_{t=p+1}^{p} Z_t\, Z_t^1\right]^{-1} \sum_{t=p+1}^{p} Z_t^p\, Z_t$$

The Least square residual is

$$a_1 = X_t - \sum_{t=1}^{p} \hat{\emptyset}\, X_{t-1}, \quad t = p+1 \ldots, n.$$

And the Least Square estimate is $\sum$ is

$$\sum_{i=1}^{n} = \frac{1}{n-(k-1)p-1}\sum_{t=p+1}^{n} \hat{a}_t\, \hat{a}_t^1$$

For a stationary VAR$_{(p)}$ model with independent error terms a_t, it can be shown that the least square estimate $\hat{\emptyset}$ is consistent.

If $\hat{b} = vec(\beta)$, the $\hat{b}$ is asymptotically normal with mean Vec[β] and covariance matrix

$$Cov(\hat{\beta}) = \sum^{n} \otimes \left(\sum_{t=p+1}^{n} X_t\, Z_t^1\right)^{-1}$$

Where

$\otimes$denotes the kuecker product.

2.6 Maximum Likelihood Method

The coefficients of the model are the same as those of least square estimate in 11.4.1. However, the estimate of $\sum$ is

$$\sum^{n} = \frac{1}{n-p}\sum_{t=p+1}^{n} \hat{a}_t\, \hat{a}_t^1$$

2.7 Order Determination

There are two basic approaches

1) **Sequential Chi-Square Test**

Let P be a positive integer (max.lag) for k > 0, consider the hypothesis

H_O: $VAR_{(k)}$

H_I: $VAR_{(k-1)}$

To test H_O: $\emptyset_k = 0$

$H_I \emptyset_k \neq 0$ $\quad in\ autoregression$

$$X_t = \emptyset_0 + \emptyset_1 X_{t-1} + \cdots, \emptyset_k X_{t-k} + a_t$$

In multivariate case, we ca use the likelihood ratio (LR) test in multivariate linear regression.

Let $\sum_i^n$ be the ML estimate of $\sum$ ting a $VAR_{(i)}$ model to X_t, then the LR test statistic is

$$M_{(k)} = -\left(n - p - \frac{3}{2} - mk\right) In\left[\frac{|\sum k|}{|\sum k - 1|}\right]$$

Where

$\sum_i^n$ are ML estimate of $\sum$ using $t = p + 1 \ldots, n$ for large n, $M_{(k)}$ is approximately a chi-square distribution with m^2 degree of freedom.

2) **Information Criteria: AIC, IC, etc.**

They are

$$AIC(K) = In\left|\sum_k^n\right| + \frac{2}{n}/m^2$$

$$BIC(k) = In\left|\sum_k^n\right| + \frac{In(n)}{n}/m^2$$

$$HQ(K) = In\left|\sum_k^n\right| + \frac{2In(In(n))}{n}/m^2$$

Where

$\sum_k^n$ is MLE of $\sum$ under normality.

Note that: Asymptotically, AIC overestimate the true order with positive probability whereas BIC and HQ criteria estimate the order consistently.

Model Checking

Use either of the following:

1) Residual Plot or
2) Q_k^m statistic already defined above.

Basic Assumptions and Properties of VAR Processes

Stable VAR (p) Processes

The object of interest in the following is the VAR(p) model (VAR model of order p),

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \mu_{t,}\ t = 0, \pm 1, \pm 2, \ldots, \qquad (2.1.1)$$

Where

$yj\ is\ the\ (y_t, \ldots, yKt)'\ is\ a\ (K\ x\ 1)$ random vector, the A_i are fixed (K x K) coefficient matrices, $v = (v1, \ldots, vk)'$ is a fixed (K x 1) vector of intercept terms allowing for the possibility of a nonzero mean $E(y_t)$. Finally, $\mu_t = (\mu_{1t} \ldots, \mu_{Kt})'$ is a K-dimensional white noise or innovation process, that is, $E(u_t)\, 0, E(\mu_t \mu_t') = \sum \mu\ and\ \sum(\mu_1 \mu_t') = 0\ for\ s \neq t$. The covariance matrix is• assumed to be nonsingular if not otherwise stated.

At this stage, it may be worth thinking a little more about which process is describe by (2.1.1). In order to investigate the implications of the model let us consider the VAR(1) model.

$$y_t = v + A_1 y_{t-1} + \mu_t.. \qquad (2.1.2)$$

If this generation mechanism starts at some time t = 1, say, we get

$$y_1 = v + A_1 y_0 + \mu_1,$$

$$y_2 = v + A_1 y_2 + \mu_2 = v + A_1(v + A_1 y_o + \mu_1) + \mu_2$$

$$= (I_K + A_1)v + A_1^2 y_0 + A_1 \mu_1 + \mu_{2,}$$

$$y_t = (I_K + A_1 + \cdots + A_1^{t-1})v + A_{1y_0}^t + \sum_{i=0}^{t-1} A_{1\mu_{t-1}}^i$$

Hence, the vectors $y1, \ldots, yt$ are uniquely determined by $y0, \mu_1, \ldots, \mu_t$. Also, the joint distribution of $y1, \ldots, yt$ is determined by the joint distribution of $y0, \mu_1 \ldots, \mu_t$

Although we will sometimes assume that a process is started in a specified period, it is often convenient to assume that it has been started in the infinite past. This assumption is in fact made in (2.1.1). What kind of process is consistent with the mechanism (2.1.1) in that case? To investigate this question we consider again the VAR(1) process (2.1.2). From (2.1.3) we have

$$y_t = v + A_1 y_t + \mu_1,$$

$$= \left(I_K + A_1 + \cdots + A_1^j\right)v + A_1^{j+1} y_{t-j-1} + \sum_{i=0}^{t-1} A_{1\mu_{t-1}}^i$$

If all Eigen values of A1 have modulus less than 1, the sequence A, i = 0, 1, … is absolutely summable (see Appendix A, Section A.9.1). Hence, the infinite sum

$$\sum_{i=0}^{\infty} A_{1\mu_{t-1}}^i$$

exists in mean square (Appendix C, Proposition C.9). Moreover

$$= \left(I_K + A_1 + \cdots + A_1^j\right)v \xrightarrow[j \to \infty]{} (I_K - A_1)^{-1} v$$

(Appendix A, Section A.9.1). Furthermore, A_1^{j+1}converges to zero rapidly as $j \to \infty$ and, thus, we ignore the term $A_1^{j+1} y_{t-j-1}$ in the limit. Hence, if aJl eigenvalues of A1 have modulus less than 1, by saying that yj is the VAR(1) process (2.1.2) we mean that yt is the well-defined stochastic process

$$y_t = \mu \sum_{i=0}^{\infty} A_{1\mu_{t-1}}^i, \quad t = 0, \pm 1 \pm 2, \ldots, \qquad 2.1.4$$

Where:

$$\mu = (I_K + A_1)^{-1} v$$

The distributions and join distributions of the y_t's are uniquely determined by the distributions of the μ_t process. From Appendix C3, Proposition C.10, the first and second moments of the yt process are seen to be

$$E(y_t) = \mu \qquad for\ all\ t$$

And

$$\Gamma_y(h) = E(y_t - \mu)(y_{t-h} - \mu)'$$

$$= lim \sum_{i=0}^{n} \sum_{j=0}^{n} A_1^i E\left(\mu_{t-1} \mu_{t-h-j}'\right)(A_1^j)'$$

$$= lim \sum_{i=0}^{n} A_1^{h+1} \Sigma_\mu A_1^{i'} = \sum_{i=0}^{\infty} A_1^{h+i} \Sigma_\mu A_1^{i'}$$

Because $\sum(\mu_1 \mu_t') = 0\ for\ s \neq t$ and $E(\mu_1 \mu_t') = \sum_\mu$ for all t.

Because the condition for the eigenvalues of the matrix A1 is of importance, we call a VAR(1) process stable if all eigenvalues of A1 have modulus less than 1. By Rule (7) of Appendix A.6, the condition is equivalent to

$$\det(I_K - A_{1Z}) \neq 0 \quad for /z/ \leq 1.$$

It is perhaps worth pointing out that the process yt for $t = 0, \pm 1, \pm 2, \ldots$ may also be defined if the stability condition (2.1.7) is not satisfied. We will not do so here because we will always assume stability of processes defined for all $t \in Z$.

The previous discussion can be extended easily to VAR(p) processes with p > 1 because any VAR(p) process can be written in VAR(1) form. More precisely, if yt is a VAR(p) as in (2.1.1), a corresponding Kp-dimensiona1 VAR(1)

$$Y_t = v + AY_{t-1} + U_t$$

Can be defined, where

$$Y_t := \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \\ (Kpx1) \end{bmatrix}, v := \begin{bmatrix} v \\ 0 \\ \vdots \\ 0 \\ (Kpx1) \end{bmatrix}$$

$$A := \begin{bmatrix} A_1 & A_2 & \ldots A_{p-1} & A_p \\ & 0 & & 0 \\ I_k & & \cdots \quad 0 & 0 \\ & I_k & & \vdots \\ 0 & & \ddots \quad 0 & \\ \vdots & & \vdots & \\ 0 & 0 & \cdots & 0 \\ & & I_K & \\ & (K_p \text{ x } K_p) & & \end{bmatrix}, U_t := \begin{bmatrix} U_t \\ 0 \\ \vdots \\ 0 \\ (Kpx1) \end{bmatrix}$$

Following the foregoing discussion, Y_t is stable if

$$\det(I_{Kp} - \mathbf{A}z) \neq 0 \quad \text{for } |z| \leq 1. \quad (2.1.9)$$

Its mean vector is

$$\boldsymbol{\mu} := E(Y_t) = (I_{Kp} - \mathbf{A})^{-1}\boldsymbol{\nu}$$

and the autocovariances are

$$\Gamma_Y(h) = \sum_{i=0}^{\infty} \mathbf{A}^{h+i} \Sigma_U (\mathbf{A}^i)', \quad (2.1.10)$$

Where

$\Sigma_U := E(U_t U_t')$. Using the $(K \times Kp)$ matrix

$$J := [I_K : 0 : \cdots : 0], \quad (2.1.11)$$

The process Y_t is obtained as $Y_t = JY_t$, Because Y_t is a well-defined stochastic process, the same is true for Y_t Its mean is $E(y_t) = J\mu$ which is constant for all t and the autocovariances $\Gamma_y(h) = J\Gamma Y(h)J'$ are also time invariant.

It is easy to see that

$$\det(I_{Kp} - \mathbf{A}z) = \det(I_K - A_1 z - \cdots - A_p z^p)$$

(see Problem 2.1). Given the definition of the characteristic polynomial of a matrix, we call this polynomial the reverse characteristic polynomial of the VAR(p) process. Hence, the process (2.1.1) is stable if its reverse characteristic polynomial has no roots in and on the complex unit circle. Formally Y_t is stable if

$$\det(I_K - A_1 z - \cdots - A_p z^p) \neq 0 \quad \text{for } |z| \leq 1. (2.1.12)$$

This condition is called the stability condition.

In summary, we say that y is a stable VAR(p) process if (2.1.12) holds and

$$y_t = JY_t = J\mu + J\sum_{i=0}^{\infty} \mathbf{A}^i U_{t-i}. \quad (2.1.13)$$

Because the $U_t := (U_t', 0, \ldots, 0)'$ involve the white noise process 'uj, the process Yt is seen to be determined by its white noise or innovation process. Often specific assumptions regarding 'U_t are made which determine the process y_t by the foregoing convention. An important example is the assumption that μ_t is Gaussian white noise that is, '$U_t \sim N(0, \Sigma_\mu)$ for all t and μ_t and μ_s are independent for $s \neq t$. In that case, it can be shown that y_t is a Gaussian process, that is, sub-collection $y_t, \ldots, y_{t+h}$ has multivariate normal distributions for all t and h.

The condition (2.1.12) provides an easy tool for checking the stability of a VAR process. Consider, for instance, the three-dimensional VAR(1) process.

The Moving Average Representation of a VAR Process

In the previous subsection we have considered the VAR(1) representation

$$Y_t = \nu + \mathbf{A}Y_{t-1} + U_t$$

of the VAR(p) process (2.1.1). Under the stability assumption, the process has a representation

$$Y_t = \mu + \sum_{i=0}^{\infty} \mathbf{A}^i U_{t-i}. \quad (2.1.16)$$

This form of the process is called the moving average (MA) representation, where Y_t is expressed in terms of past and present error or innovation vectors U and the mean term it. This representation can be used to determine the autocovariances of Y and the mean and autocovariances of y can be obtained as outlined in Section 2.1.1. Moreover, an IVIA representation of y can be found by premultiplying (2.1.16) by the (K x Kp) matrix J := [1K 0 : 0] (defined in (2.1.11)),

$$y_t = JY_t = J\mu + \sum_{i=0}^{\infty} J\mathbf{A}^i J' J U_{t-i}$$

$$= \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i}. \quad (2.1.17)$$

Here $\mu := J\mu$, $\phi_i := JA^iJ'$ and, due to the special structure of the white noise process U_t, we have $U_t = J'JU_t$ and $JU_t = \mu_t$. Because the A^i are absolutely summable, the same is true for the ϕ_i,

Lj_will also consider other MA representation of a stable VAR(p) process. The unique feature of the present representation is that the zero-order coefficient matrix $\phi_0 = I_K$ and the white noise process involved consists of the error terms t of the VAR representation (2.1.1). In Section 2.2.2, the t will be seen to be the errors of optimal forecasts made in period t - 1. Therefore,

Stationary Processes

A stochastic process is stationary if its first and second moments are time invariant, In other words, a stochastic process y is stationary if

$$E(y_t) = \mu \quad \text{for all } t \quad (2.1.26a)$$

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and

$$E[(y_t-\mu)(y_{t-h}-\mu)'] = \Gamma_y(h) = \Gamma_y(-h)' \quad \text{for all } t \text{ and } h = 0,1,2,\ldots. \tag{2.1.26b}$$

Condition (2.1.26a) means that all yt have the same finite mean vector μ and (2.1.26b) requires that the autocovariance of the process do not depend on t but just on the time period h the two vectors y_t and y_{t-h} are apart. Note that, if not otherwise stated, all quantities are assumed to be finite. For instance, μ is a vector of finite mean terms and $\Gamma_y(h)$ is a matrix of finite covariances. Other definitions of stationarity are often used in the literature for example, the joint distribution of n consecutive vectors may be assumed to be time invariant for all n. 'We shall, however, use the foregoing definition in the following. We call a process *strictly stationary* if the joint distributions of n consecutive variables are time invariant and there is a reason to distinguish between our form. By our definition, the white noise process μ_t used in (2.1.1) is an obvious example of a stationary process. Also, from (2.1.18) we know that a stable VAR(p) process is stationary. We state this fact as a proposition.

Proposition 2.1 (Stationarity Condition)
A stable VAR(p) process y, t 0, ±1, +2, . . ., is stationary.

Because stability implies stationarity, the stability condition (2.1.12) is often referred to as stationarity condition in the time series literature. The converse of proposition 2.1 is not true. In other words, an unstable process is not necessarily nonstationarity. Because unstable stationary processes are not of interest in the following, we will not discuss this possibility here.

At this stage, it may be worth thinking about the generality of the VAR(p) processes considered in this and many other chapters. In this context, an important result due to Wold (1938) is of interest. He has shown that every stationary process can be written as the sum of two uncorrelated processes z_t and y_t

$$x_t = z_t + y_t,$$

Where
z_t is a deterministic process that can be forecast perfectly from its own past and yt is a process with MA representation

$$y_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i}, \tag{2.1.27}$$

Where
ϕ_0 *is the* I_K, the μ_t constitute a white noise process and the infinite sum is defined as a limit in mean square although the ϕ_i are not necessarily absolutely summable (Hannan (1970, Chapter III)). The term deterministic will be explained more formally in Section 2.2. This result is often called Wold's Decomposition Theorem. If we assume that in the system of interest the only deterministic component is the mean term, then theorem state that the system has an MA representation. Suppose the ϕ_i are absolutely summable and there exists an operator A(L) with absolutely summable coefficient matrices satisfying A(L)ϕP(L) = I_K.Then, ϕ(L) is invertible A(L) = $\phi(L)^{-1}$) and yt has a VAR representation of possibly infinite order,

$$y_t = \sum_{i=1}^{\infty} A_i y_{t-i} + u_t,$$

Where

$$A(z) := I_K - \sum_{i=1}^{\infty} A_i z^i = \left(\sum_{i=0}^{\infty} \Phi_i z^i\right)^{-1} \quad \text{for } |z| \le 1$$

The A can be obtained from the by recursions similar to (2.1.22).

The absolute summability of the A_i implies that the VAR coefficient matrices converge to zero rapidly. In other words, under quite general conditions, every stationary, purely nondeterministic process (a process without a deterministic component) can be approximated well by a finite order VAR process.

This is a very powerful result which demonstrates the generality of the processes under study. Note that economic vriab1es can rarely be predicted without error. Thus, the assumption of having a nondeterministic system except perhaps for a mean term is not a very restrictive one. The crucial and restrictive condition is the stationarity of the system however. We will consider nonstationary processes later. For that discussion it is useful to understand the stationary case first.

An important implication of Wold's Decomposition Theorem is worth noting at this point. The theorem implies that any sub-process of a purely nondeterministic, stationary process yt consisting of any subset of the components of yt also has an MA representation. Suppose, for instance that interest centers on the first M components of the K-dimensional process yt, that is, we are interested in x_t = Fμ and Fyt, where, where F = [I_M : 0] is an (M x K) matrix. Then E(x_t) = FE(yt) Fμ and Γ_x(h) F Γ_x(h)F' and, thus, x_t is stationary. Application of Wold's theorem then implies that x_t has an MA representation.

Computation of Autocovariances and Autocorrelations of Stable VAR Processes
Although the autocovariances of a stationary, stable VAR(p) process can be given in terms of its MA coefficient matrices as iii (2.1.18), that formula is unattractive in practice, because it involves an infinite sum. For practical purposes it is easier to compute the autocoyariances directly from the VAR coefficient matrices. In this section, we will develop the relevant formulas.

Autocovariances of a VAR(1) Process
In order to illustrate the computation of the autocovariances when the process coefficients are given, suppose that Pt is a stationary, stable VAR(1) process

$$y_t = \nu + A_1 y_{t-1} + u_t$$

with white noise covariance matrix $E(\mu_t u_t') = \sum_\mu$ .. Alternatively, the process may be written in mean-adjusted form as

$$y_t - \mu = A_1(y_{t-1} - \mu) + u_t, \quad (2.1.29)$$

Where

$\mu = E(y_t)$, as before. Post multiplying by $(y_{t-h} - \mu)'$ and taking expectations gives

$$E[(y_t - \mu)(y_{t-h} - \mu)'] = A_1 E[(y_{t-1} - \mu)(y_{t-h}$$

Thus, for h = 0,

$$\Gamma_y(0) = A_1\Gamma_y(-1) + \Sigma_u = A_1\Gamma_y(1)' + \Sigma_u$$

and for $h > 0$,

And so on. Some more innovation responses re depicted in Figure 2.9. Although they are similar to those given in Figure 2.5, there is an obvious difference in the response of consumption to an income innovation. While consumption responds with a time lag of one period in Figure 2.5, there is an instantaneous effect in Figure 2.9.

Logistic Regression

This regression is widely used in medical fields because of the nature of outcome variable that is always found in the field. The common type of outcome variable in medical research is the binary response variable. That is the dependent variable has only two possible outcome likes "Yes or No", "Success or Failure", "Normal or Abnormal", "Sick or Health" and so on. Logistic regression analysis is a popular used analysis that is alike to linear regression analysis except that the outcome is dichotomous. The epidemiology module on Regression Analysis provides a brief explanation of the rationale for logistic regression and how it is an extension of multiple linear regression. In essence, we examine the odds of an outcome occurring or not, and by using the natural log of the odds of the outcome as the dependent variable the relationships can be linearized and treated much like multiple linear regression.

Simple logistic regression analysis refers to the regression application with one dichotomous outcome and one independent variable; multiple logistic regression analysis applies when there is a single dichotomous outcome and more than one independent variable.

The outcome in logistic regression analysis is often coded as 0 or 1, where 1 indicates that the outcome of interest is present, and 0 indicates that the outcome of interest is absent. If we define p as the probability that the outcome is 1, the multiple logistic regression model can be written as follows:

$$\hat{p} = \frac{e^{\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki}}}{1 + e^{\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki}}}$$

$\hat{p}$is the expected probability that the outcome is present, X_1 through X_{kt} are distinct independent variables; and b_0 through b_p are the regression coefficients. The multiple logistic regression model is sometimes written differently. In the following form, the outcome is the expected log of the odds that the outcome is present,

$$In\left(\frac{\hat{p}}{1-\hat{p}}\right)$$

$$In\left(\frac{\hat{p}}{1-\hat{p}}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki}$$

Response function in logistic regression

Consider the simple linear regression model:

$$Y_i = a + \beta X_i + \varepsilon_i \qquad \epsilon\{0,1\}$$

As defined earlier, the response (outcome) Y_t is binary taking the values of either 0 or 1. The expected response E(Y_i) has a special meaning in this case. Since E(ϵ_i) = 0, we have:

E(Y_i) = $a + \beta X_i$

Consider Y_i to be a Bernoulli random variable for which we can state the probability distribution as follows:

Table 15.1: Standard coding of Binary logistics

Y_i	Probability
1	$P(Y_i = 1) = P_i$
0	$P(Y_i = 0) = 1 - P_i$

Thus, P is the probability that $Y_i = 1$ and $1 - P_i$ is the probability that $Y_i = 0$. By definition of expected value of a random variable we obtain:

E(Y_i) = $a + \beta X_i = 1 \times \beta X_i = 1 \times P_i + 0 \times (1 - P_i) = P_i$

The mean response:

E(Y_i) = $a + \beta X_i$

$Y_i = 1 \text{for} P_i \geq T_i$

$Y_i = 0 \text{for} P_i < T_i$

Let $Y_i = 1$, if an individual is hypertensive and P_i be the probability that the individual hypertensive, $Y_i = 0$, if an individual is normal.

3. Results and Discussion

3.1 Introduction

In this study, Wind speed was modelled in the presence of some selected meteorological variables which are rainfall, temperature and relative humidity. Before we went into the actual modelling, some preliminary works were carried out. The Augmented Dickey Fuller (ADF) test shows that all the variables are stationary, which prompted us to use the Vector Autoregressive model. The AIC was used to select a lag order of 2 for the Vector Autoregressive model. The variables were also tested for autocorrelation of its residuals. There exist no heteroscedasticity from the test result but there exist no autocorrelation at the first two lags. The Vector Autoregressive model was fitted and it was found that there is a linear dependence between Wind speed and temperature in the presence of other meteorological variables. The result of Autoregressive model shows that none of the meteorological variables namely; Monthly rainfall, Monthly temperature, and Monthly relative humidity, significantly affect Monthly wind speed. It was also found that each of the meteorological variables have varying effects on Wind speed over a future time horizon as depicted by the variable. The Wind speed was also model using the logistic regression where it was found that there is no statistically significant difference between Wind speed and the meteorological variables. To this end, this study posits that wind speed is not significantly being influenced by the meteorological variables. That is to say most of this metrological variables will not be able to generate enough heat in other to influence the wind speed for a sufficient power generation.

Time series plot

The first stage in the analysis of any time series data is to plot the data. This gives the time series plot. This plot enables us to visually see the nature of the data and its behavior over time.

From the plots fiqure 1 to 4,given below, consisting of wind speed, rainfall,Temperature,and relative humidity,it can be seen that each of these meteorological variables appear to be stationary over time. A stationarity test was further conducted to certify this claim.

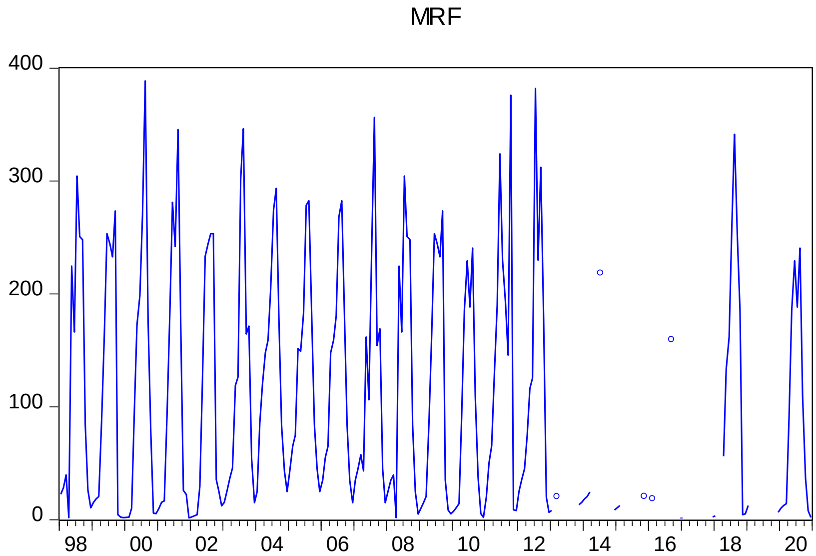

Figure 1: Time Plot of Monthly Rainfall (MRF)

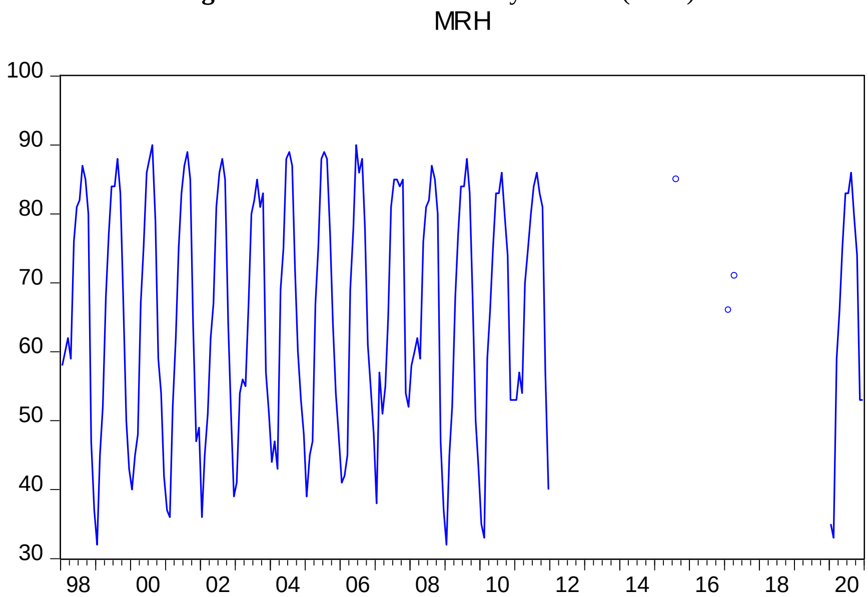

Figure 2: Time Plot of Monthly Relative Humidity (MRH)

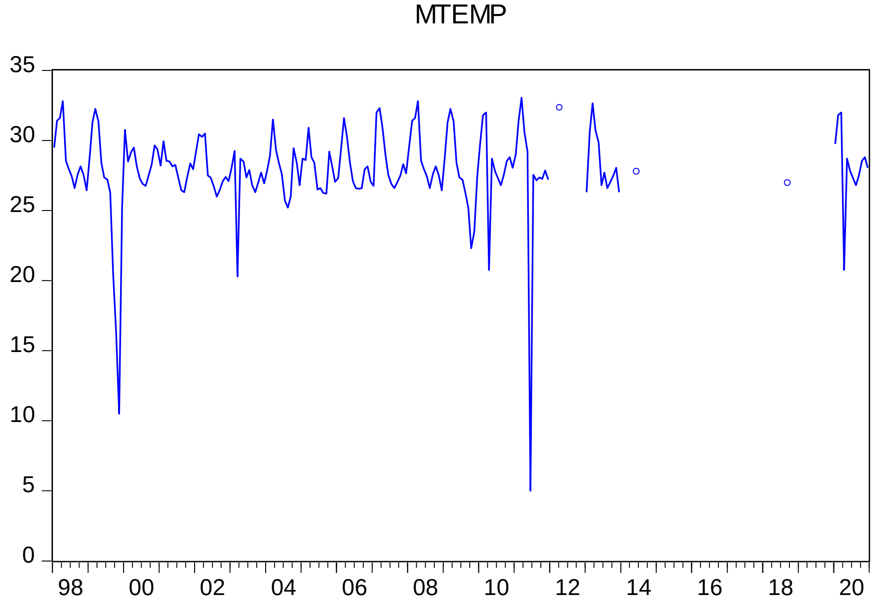

Figure 3: Time Plot of Monthly Temperature (MTEMP)

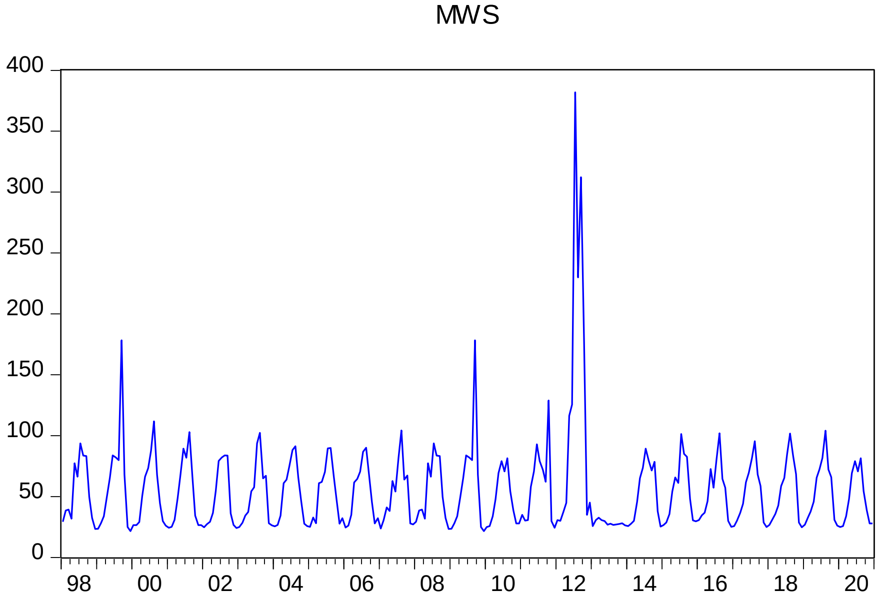

Figure 4: Time Plot of Monthly Wind Speed (MWS)

Table 1: ADF Unit Root Test for stationarity at level

Variables	t-Statistic	Prob. Val.
LNMRH	-3.499083	0.0191
LNMRF	-3.295332	0.0328
LNMTEMP	4.556240	0.0000
LNMWS	-3.435128	0.0233

Source: Author Review Eview 10

Table 1 above shows that at level LNMRH, LNMRF, LNMTEMP, and LNMWS are stationary at level.

Table 2: ADF Unit Root Test for stationarity at first difference

Variables	t-Statistic	Prob. Val.
LNMRH	-4.455040	0.0025
LNMRF	-4.462273	0.0025
LNMTEMP	-8.720498	0.0000
LNMWS	-4.505728	0.0023

Source: Author Review Eview 10

The table 2 above shows that at first difference all the variables are stationary.

Hence we summarize the unit root test in the table below

Table 3: Summary of the Unit Root test of the variables

VARIABLES	Staionarity
LNMRH	I(0)
LNMRF	I(0)
LNMTEMP	I(0)
LNMWS	I(0)

Source: Author Review Eview 10

Table 4: Obtaining optima lag

Variables	Akaike information criterion (AIC)	Schwarz information criterion (SC)
LNMRH	-4.240278	-4.140800
LNMRF	-1.325057	-1.275317
LNMTEMP	-4.964696	-4.914957
LNMWS	-2.367977	-2.318238

Source: Author Review Eview 10

Using the Schwarz information criteria, from the table four above all the variables are having lag structure at one

Estimation of unrestricted VAR model

Table 5: The model estimation of the Vector autoregression estimate

Vector Autoregression Estimates
Date: 04/03/21 Time: 13:29
Sample (adjusted): 2000 – 2020
Included observations: 21 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	INMRF	INMRH	INMTEMP	INMWS
INMRF(-1)	0.089644	-0.086343	0.063138	-0.071033
	(0.45920)	(0.04173)	(0.02284)	(0.12285)
	[0.19522]	[-2.06922]	[2.76393]	[-0.57820]
INMRH(-1)	-0.897560	-0.053397	-0.450392	0.119470
	(6.15298)	(0.55912)	(0.30609)	(1.64615)
	[-0.14587]	[-0.09550]	[-1.47145]	[0.07258]
INMTEMP(-1)	10.98025	2.326880	1.788826	1.668318
	(9.18724)	(0.83484)	(0.45703)	(2.45792)
	[1.19516]	[2.78723]	[3.91403]	[0.67875]
INMWS(-1)	1.725376	0.891617	0.009417	1.027368
	(3.13557)	(0.28493)	(0.15598)	(0.83888)
	[0.55026]	[3.12928]	[0.06037]	[1.22469]
C	-46.46214	-5.829809	-1.324016	-10.94107
	(34.7602)	(3.15864)	(1.72918)	(9.29963)
	[-1.33665]	[-1.84567]	[-0.76569]	[-1.17651]
R-squared	0.527387	0.879313	0.950925	0.689503
Adj. R-squared	0.212312	0.798855	0.918209	0.482505
Sum sq. resids	26.78396	0.221161	0.066281	1.917082
S.E. equation	1.493987	0.135757	0.074320	0.399696
F-statistic	1.673844	10.92883	29.06569	3.330965
Log likelihood	-32.35216	18.01286	30.66515	-4.663671
Akaike AIC	3.938301	-0.858367	-2.063348	1.301302
Schwarz SC	4.385953	-0.410715	-1.615695	1.748954
Mean dependent	4.014211	4.179263	3.265678	3.978076
S.D. dependent	1.683331	0.302697	0.259868	0.555619

Determinant resid covariance (dof adj.)	5.00E-06
Determinant resid covariance	5.33E-07
Log likelihood	32.47362
Akaike information criterion	0.335846
Schwarz criterion	2.126456
Number of coefficients	36

Source: Author Review Eview 10

Table five above, shows the output of the vector autoregression (VAR) model estimation at lag one as seen in the table. Furthermore, The LNMRF shows a significant influence on itself with the past realization of LNMRF associated with 9% increase on LNMRF, subsequently LNTEMP,LNMWS also have a strong significant influence on LNMRF, But LNMRH do not have any significant influence on LNMRF. The LNMRH did not show any significant influence on itself. Subsequently LNMTEMP and LNMWS also have a strong significant influence on LNMRH. The LNMTEMP shows a significant influence on itself, with the past realization of LNMTEMP associated with 179% increase on LNMTEMP, subsequently LNMWS and LNMRF also have a strong significant influence on LNMTEMP, But LNMRH do not have any significant influence on LNMTEMP. The LNMWS shows a significant influence on itself with the past realization of LNMWS associated with 103% increase on LNMWS, subsequently LNTEMP and LNRH also have a strong significant influence on LNMWS, But LNMRF do not have any significant influence on LNMWS.

Table 6: The model estimation of the Vector autoregression estimates

VAR Residual Serial Correlation LM Tests						
Date: 02/20/21 Time: 02:15						
Sample: 1998 2020						
Included observations: 22						
Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	Df	Prob.
1	21.12682	16	0.1737	1.440230	(16, 31.2)	0.1865
Null hypothesis: No serial correlation at lags 1 to h						
Lag	LRE* stat	Df	Prob.	Rao F-stat	df	Prob.
1	21.12682	16	0.1737	1.440230	(16, 31.2)	0.1865
*Edgeworth expansion corrected likelihood ratio statistic.						

Source: Author Review Eview 10

The table 6 above that there is no serial correlation at probability value of 0.1865 which quite okay for the work.

Table 7: Normality test

VAR Residual Normality Tests				
Orthogonalization: Cholesky (Lutkepohl)				
Null Hypothesis: Residuals are multivariate normal				
Date: 02/20/21 Time: 02:20				
Sample: 1998 2020				
Included observations: 22				
Component	Skewness	Chi-sq	df	Prob.*
1	-0.214421	0.168580	1	0.6814
2	-1.386507	7.048804	1	0.0079
3	-0.469118	0.806928	1	0.3690
4	-0.145911	0.078063	1	0.7799
Joint		8.102376	4	0.0879

Source: Author Review Eview 10

From the table seven above the residual of LNMRH, LNMTEMP, LNMWS are normally distributed, while that of the LNMRF cannot be account for, but however the joint normality test for the whole variable show that the residual are normally distributed at lag one.

Table 8: Heteroskedasticity test

VAR Residual Heteroskedasticity Tests (Levels and Squares)		
Date: 02/20/21 Time: 02:32		
Sample: 1998 2020		
Included observations: 22		
Joint test:		
Chi-sq	Df	Prob.
92.23422	80	0.1650
Source: Author Review Eview 10		

The table above shows that there is no heteroscedasticity in the variables

Logistics Regression Analysis
#R-Result [Output]
Call:
glm(formula = WS ~ AvRF + AvTemp + AvRH, family = poisson(link = "log"),
data = data1)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.123068	-0.039543	0.008172	0.035151	0.092225

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for poisson family taken to be 1)

Null deviance: 23.758290 on 22 degrees of freedom
Residual deviance: 0.062191 on 19 degrees of freedom
AIC: 174.09
Number of Fisher Scoring iterations: 3

Table 8: Logistics regression output

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	4.4837791	0.7807688	5.743 ***	9.31e-09
AvRF	0.0047521	0.0011791	4.030 ***	5.57e-05
AvTemp	0.0005196	0.0319560	0.016	0.987
AvRH	0.0045010	0.0079829	0.564	0.573

Source: Author Review Statistical R package

The output begins with echoing the function call. The information on deviance residuals is displayed next. Deviance residuals are approximately normally distributed if the model is specified correctly. In our case, it shows a little bit of positive skeweness since median is not quite zero.

The generalized linear Poisson regression with 'loglink' coefficients for each of the variables along with the standard errors, z-scores, p-values and 95% confidence intervals for the coefficients. The coefficient for AvRF is approximately 0.0048. This means that the expected log count for a -unit increase in AvRF is 0.0048, this signifies rain fall has potential effect on the wind speed. The indicator variable AvTemp compares between AvRH, the expected log count for AvTemp increases by about 0.0005 which is nearly zero. It is therefore not statistically significant in the model as reported by P-value > 0.05. The indicator variable AvRH is as well not statistically significant based on the P-value > 0.05.

Since, the residual difference is small enough, the goodness of fit test will not be significant, indicating that the model fits the data. We conclude that the model fits reasonably well

4. Summary of Findings

In this study, Wind speed was modelled in the presence of some selected meteorological variables which are rainfall, temperature and relative humidity. Before we went into the actual modelling, some preliminary works were carried out. The Augmented Dickey Fuller (ADF) test shows that all the variables are stationary, which prompted us to use the Vector Autoregressive model. The AIC was used to select a lag order of 2 for the Vector Autoregressive model. The variables were also tested for autocorrelation of its residuals. There exist no heteroscedasticity from the test result but there exist no autocorrelation at the first two lags. The Vector Autoregressive model was fitted and it was found that there is a linear dependence between Wind speed and temperature in the presence of other meteorological variables. Though the result of this model shows that each of these variables have no significant influence on Wind speed. The Jarque-Berra test was also used to check the normality of the fitted model, which shows it is normally distributed.considering the fact that the sample size is reasonably large (276>30). The logistic regression model was also applied in modelling Wind speed and wind influence on meteorological variables.

5. Conclusion

This research work modelled wind speed with some selected meteorological variables (Rainfall, temperature,and relative humidity. The result of the stationarity test shows that all the meteorological variables are stationary. Using the Vector Autoregressive model of order 2, it was discovered that there exists a linear dependence between wind speed and temperature in the presence of other meteorological variables. But noneof these variables significantly affect wind speed, though there exist some degree of relationship among them. A five years forecast was also generated using variance decomposition model and the Vector Autoregressive model shows that,The LNMRF shows a significant influence on itself with the past realization of LNMRF associated with 9% increase on LNMRF, subsequentlyLNTEMP, LNMWS also have a strong significant influence on LNMRF, But LNMRH do not have any significant influence on LNMRF. The LNMRH did not show any significant influence on itself. Subsequently LNMTEMP and LNMWS also have a strong significant influence on LNMRH. The LNMTEMP shows a significant influence on itself, with the past realization of LNMTEMP associated with 179% increase on LNMTEMP, subsequently LNMWS and LNMRF also have a strong significant influence on LNMTEMP, But LNMRH do not have any significant influence on LNMTEMP. The LNMWS shows a significant influence on itself with the past realization of LNMWS associated with 103% increase on LNMWS, subsequently LNTEMP and LNRH also have a strong significant influence on LNMWS, But LNMRF do not have any significant influence on LNMWSeve after simulating wind speed the result exhibit pattern.

The forecast error variance in LNMRF is explained by the variable itself, while other variables are strongly exogenous, showing weak forecast influence on LNMRF, meanwhile on the long run, the forecast influence of the LNMRF on itself continues to increase. The forecast error variance in LNMRH is explained by the variable itself, while other variables are strongly exogenous, showing weak forecast influence on LNMRH, meanwhile on the long run, the forecast influence of the LNMRH on itself continues to increase. The forecast error variance in LNMTEMP is explained by the variable itself, while other variables are strongly exogenous, showing weak forecast influence on LNMTEMP, meanwhile on the long run, the forecast influence of the LNMTEMP on itself continues to increase. The forecast error variance in LNMWS is explained by the variable itself, while other variables are strongly exogenous, showing weak forecast influence on LNMWS, meanwhile on the long run, the forecast influence of the LNMWS on itself continues to increase. The generalized linear Poisson regression with 'loglink' coefficients for each of the variables along with the standard errors, z-scores, p-values and 95% confidence intervals for the coefficients. The coefficient for AvRF is approximately 0.0048. This means that the expected log count for a -unit increase in AvRF is 0.0048, **this signifies rain fall has potential effect on the wind spead.** The indicator variable AvTemp compares between AvRH, the expected log count for AvTemp increases by about 0.0005 which is nearly zero. It is therefore **not statistically significant in the model** as reported by P-value > 0.05. The indicator variable AvRH is as well not statistically significant based on the P-value > 0.05.Since, the residual difference is small enough, the goodness of fit test will not be significant, indicating that the model fits the data. We conclude that the model fits reasonably well

That is to say most of this metrological variable will not be able to generate enough heat in other to influence the wind speed for a sufficient power supply.

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