

Trend Analysis Forecast of Malaria Cases in Private Hospitals in Nigeria.

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Abstract

The comparative examination of trend models was investigated in this paper. On malaria cases in private hospitals in Nigeria. Four time series trend models were fitted using monthly data from 2015 to 2021: linear trend model, quadratic trend model, exponential trend model, and s-curve trend model. The s-curve trend model was determined to have the least MAD and matched the data the best. The s-curve trend model was used to produce a six-month projection of malaria cases in Nigerian private hospitals, which revealed that malaria cases in the hospitals would decline during the following six months, from January to June 2022.

Keywords: Trend Analysis, Forecast, Malaria Cases, Private Hospital, Trend Models.

Introduction

As a statistical tool, time series analysis examines previous data and models it to provide forecasts for the future. Past observations of a phenomena must be acquired in order to make any prognosis regarding the future. As a result, a time series may be described as a collection of observations made over a period of time.

Where the values $Y_1, Y_2, \dots, Y_n$ are of variable Y at periods $t_1, t_2, \dots, t_n$, this may be expressed mathematically. There are many types of motions in time series, including secular trend, seasonal variation, cyclical variation, and irregular variation. As a result, time series analysis has shown to be an effective tool for predicting macroeconomic variables. When structural changes are occurring in an economy, econometric models are not better to time series techniques, according to Christ (1951).

Malaria is one of the world's most critical health issues today. The World Health Organization estimates that over 300 million cases of malaria are diagnosed each year, with two to three million people dying as a consequence of the disease. Malaria is the only vector-borne illness on the WHO's Disability Adjusted Life Years (DALYS) List. It is important to consider health issues like as malaria, which have a significant impact on Nigeria's mobility and death rate. Nigeria has a population of approximately 123.9% of the world's population. A considerable portion of the population lives in rural regions, where they lack access to drinkable water and proper health care. Nigeria is also a low-income country that is already burdened by a massive foreign debt. It is at risk of going deeper into debt as it deals with a sick population whose well-being is critical to the country's economic growth. In the past, chloroquine was a frequent malaria therapy.

Malaria is caused by four types of plasmodium protozoa: plasmodium Vivax, which is more common in low-endemic regions, Plasmodium Ovale, and Plasmodium Falciparum, which is the most hazardous of the four. In both the mosquito vector and the human host, the plasmodium Faciparum has a life cycle. The malaria mosquito, Anopheles gambiae, is the vector that transmits the disease. Malaria prevalence is determined by the quantity of

female anopheles species, the mosquito's proclivity to bite, the pace at which it bites, its lifespan, and the rate at which the plasmodium parasite develops within the mosquito. When a female mosquito bites and drinks the blood of a person infected with malaria parasites, she gets infected with the parasites, which she then passes on to the next human victim she bites. Malaria takes eight to 10 days to incubate in a human host. The mosquito and the plasmodium parasite must be able to survive in order for malaria to spread.

Malaria has been one of humanity's biggest burdens, with a fatality rate unrivalled by any other contemporary illness save TB (Sudhakar, & Subramani, 2007). Its position as Africa's greatest cause of mortality among children under the age of five years has not changed (Houeto et al., 2007). Because of its high prevalence rate among the poorest continents and nations, this illness is sometimes referred to as "the poor's sickness" (Worrall et al., 2003). Fever, chills, headache, shaking, and joint problems are some of the symptoms of malaria. According to Nchinda (2005), sub-Saharan Africa was never included in the global malaria eradication campaign since the time corresponded with colonial and early postcolonial periods, and indigenous peoples had little or no ability to launch and continue an eradication programme.

There are many variables that contribute to the disease's return in Nigeria and Africa as a whole. In Africa, poverty adds to the frequency of malaria. Many of the world's poorest people, according to Pattanayak *et al.* (2003), live in malaria-infested regions. Due to financial constraints, many folks do not have access to appropriate health care. In the event of an epidemic, a vulnerable country's economic status plays a role in determining preparedness and control measures (Sudhakar & Subramani, 2007).

Four trend models will be used in this study to assess the movement of malaria epidemics in Nigerian private hospitals. These models include the linear trend model, quadratic trend model, exponential trend model, and S-curve model, with the goal of determining the best model that fits malaria epidemics in private hospitals in Nigeria and, more importantly, making malaria case forecasts in the understudied hospital.

Malaria

Malaria has been studied by many individuals. This chapter is devoted to a review of some malaria-related literature. Plasmodium falciparum, plasmodium vivax, plasmodium ovale, and plasmodium malariae are four species of plasmodium protozoa (single celled parasites) that cause malaria in humans. Plasmodium falciparum is the most common and fatal of these species, accounting for the majority of infections. Several research have been conducted on various areas of the illness, ranging from parasitology to medicine development (chemotherapy) to disease eradication via the use of insecticide-treated nets and insecticides.

The danger of malaria in the Machodinho resettlement region in Brazil's Amazonian rainforest was investigated (Castilla & Sawyer, 1993). Economic status and knowledge of the mosquito's importance and behaviour in transmitting malaria were found to be significant factors in determining prevalence risk, regardless of whether or not preventive measures such as DDT house spraying and cleaning of vector breeding sites are implemented in endemic areas. However, the researchers discovered that having a higher socioeconomic position, as well as having a better understanding of the vector and having dwellings sprayed with DDT, reduced the likelihood of infection. They proposed that a more positive interpretation is that disease prevention programmes should work harder and more intensely on behalf of poorer people, particularly migrants, in order to reduce disease burden. Sharma et al. (2001) investigated socioeconomic factors as well as human behaviour in relation to malaria in a cross-section of India's Sundargarh district. They claimed that

low socioeconomic position and socio-cultural characteristics have a significant impact in the persistence of high malaria transmission levels. Human behaviours such as hamlet location, kind of malaria transmitted, sleeping patterns, outdoor activities after nightfall, lack of information about the illness, and treatment seeking behaviour are all important predictors of malaria transmission, according to the researchers.

Malaria is also a serious issue in Papua New Guinea, where it causes a significant amount of illness and death. This is because, in addition to causing human misery, it also places a significant strain on health-care resources and obstructs economic progress. A malaria vaccine has been proposed as the best, most cost-effective, and safe public health approach for reducing malaria's impact (Reeder, 2001).

Lin et al., (2009) investigated the link between falciparum malaria in endemic provinces and imported malaria in non-endemic provinces of China using time series analysis. The predictor variable was initially fitted using an autoregressive integrated moving average model. According to AIC and goodness-of-fit criteria, the seasonal ARIMA (1, 1, 1) and (0, 1, 1) models for malaria incidence matched the data the best of all the models examined.

Briet et al, (2008) developed a model for predicting malaria in Sri Lanka in the near run. On monthly time series of district malaria cases, exponential moving average models, autoregressive integrated moving average models with seasonal components, and seasonal multiplicative autoregressive integrated moving average (ARIMA) models were compared for their ability to predict the number of malaria cases one to four months ahead. The best model for forecasting and forecasting error differed significantly between districts. For example, in the district of Ampara, the best model for a one-month forecasting horizon was an ARIMA (2, 1, 1) with seasonality through a harmonic with a one-year period and a harmonic with a six-month period. The ARIMA (0, 1, 2) model incorporating seasonality via a first order seasonal autoregressive and a first order seasonal moving average component proved optimal for the district of Ampara over longer forecasting horizons.

Using an ARIMA model, Contreras et al. (2003) created a model for forecasting next-day power prices in mainland Spain and California markets. Their model was able to predict the 24 market clearing prices for the following day. For predicting time series, the ARIMA model is a useful tool.

Guerrero (2003) A good model for anticipating malaria cases has to be created. The sum of the residuals squares divided by the sample size represents the model fitting quality. Its goal is to assess the model's ability to generate sample data (i.e., to determine how similar the modelled and actual series are).

Nkpordee and Nduka (2018) investigated the use of time series analysis in the forecasting of malaria epidemic outbreaks in Nigeria. The study's secondary data came from the Nigerian National Bureau of Statistics (nbs), Social Statistics. By taking into account the ACF and PACF correlograms, the study effort used Box-Jenkins (1976) approach to create an appropriate mathematical model. The model ARIMA(1,0,1) was used to anticipate monthly reported cases of malaria with a 16-month lead, resulting in a series with a progressive rise and fall. The study also looked at the monthly average of malaria cases recorded. It was suggested that the government assure the availability of treated bed mosquito nets, pesticides, anti-malaria medications, and other items in Nigeria's rural communities.

Eke et al., (2015) conducted a comparison of three time series trend models on Nigeria's gross domestic product. This study used yearly data from 1982 to 2012 to fit three time series trend models on Nigeria's Gross Domestic Product: a linear trend model, a quadratic trend model, and an exponential trend model. It was discovered that the exponential trend model had the lowest MAPE and best suited the data. The exponential trend model was

used to create a five-year projection for Nigeria's Gross Domestic Product, which revealed that the country's Gross Domestic Product would increase during the next five years.

Problem Statement

Malaria poses a significant threat to human development. Underdevelopment is both a cause and a result of it. Malaria is the leading cause of morbidity in Nigeria, accounting for 40 to 60 percent of all outpatient visits. It's also the largest cause of death in children under the age of five, a major source of adult morbidity, and the top cause of missed workdays.

Despite the disease's destructive impacts, Nigerians do not fully comprehend the value of a malaria-free environment in fostering economic growth and poverty reduction. Perhaps the magnitude of malaria's impact has not been quantified in a way that would persuade politicians, policymakers, programme managers, and development partners to devote the necessary attention and resources to combating this dreadful disease. This research aims to fill up the gaps with relevant knowledge.

Purpose of the Study

The study's goal is to look at how to compare the four trend models, including linear, quadratic, exponential, and s-curve and used the best among the four to forecast the trend of malaria cases in Nigeria. The study's specific goals are:

1. To get estimates for the parameters (α_0 , α_1 and α_2) in the relevant models.
2. For each model, we will obtain the (MAPE, MAD, and MSD).
3. For each of the separate models, we determine the trend analysis plot for the malaria cases.
4. Compare the results of the four trend models and choose the one that has the least MAPE, MAD, and MSD as the best model for determining the sort of trend that the malaria cases followed.
5. Forecast the malaria cases in private hospitals in Nigeria for the next 6 months using the best trend model built.

Scope and Limitation of the study

The study focuses on a comparative analysis of trend models, including linear, quadratic, exponential, and s-curve approaches, in order to determine the best model that, when applied to any of the malaria data in this study, will reduce malaria cases in Nigeria, specifically monthly malaria cases in private hospitals in Nigeria, over an 84-month period from January 2015 to December 2021.

However, due to a lack of time, facts, and related literature, the researcher focuses his attention on the monthly cases of malaria epidemic in private hospitals in Nigeria, rather than using secondary records from private hospitals in Nigeria. This research focuses on four different trend models (Linear, Quadratic, Exponential and S-Curve).

METHODS AND MATERIALS

Research Design

This research employed a cross-sectional design and focused on comparing trend models, including linear, quadratic, exponential, and s-curve approaches.

Nature and Source of Study Data

The gathered and utilised data for this research is secondary statistical data collected from survey information on the Nigerian malaria pandemic from the records department of monthly malaria cases at a private hospital in Nigeria, covering the period January 2015 to

December 2021. Data from long-term malaria cases in Nigeria was utilised. The information is available upon request.

Data Analysis Tools

The parameters that make up the models are obtained using the MINITAB (version 20.0) tool. The researcher used this programme to estimate the parameters for Linear, Quadratic, Exponential, and S-curve models to make record assessment easier. The parameters for these models were also obtained using the MINITAB programme (version 20.0).

Model Specification

The linear trend model, quadratic trend model, exponential trend model, and S-curve model will be employed in this research.

The Linear Trend Model

Trend analysis by default uses the linear trend model:

$$Z_t = \alpha_0 + \alpha_1 X_t + \mu_t \quad (1)$$

In this model, α_1 represents the average change from one period to the next.

Linear forecasting model:

$$Z_t = \alpha_0 + \alpha_1 X_t \quad (2)$$

The Quadratic Trend Model:

$$Z_t = \alpha_0 + \alpha_1 X_t + \alpha_2 X_t^2 + \mu_t \quad (3)$$

Quadratic forecasting model:

$$Z_t = \alpha_0 + \alpha_1 X_t + \alpha_2 X_t^2 \quad (4)$$

The Exponential Trend Model:

$$Z_t = \alpha_0 \alpha_1^x \mu_t \quad (5)$$

Exponential forecasting model:

$$Z_t = \alpha_0 \alpha_1^x \quad (6)$$

The S-curve Trend Model:

The *S-curve model* fits the Pearl-Reed logistic trend model. This accounts for the case where the series follows an S-shaped curve. The model is:

$$Z_t = \frac{10^a}{(\alpha_0 + \alpha_1 \alpha_2^x)} \quad (7)$$

Where

α_0 = Estimated Z intercept

α_1 = Estimated linear effect on Z

α_2 = Estimated quadratic effect on Z

Models Accuracy Measures

To find the best fit model, we will use the one with the minimum accuracy measures (MAPE, MAD and MSD). The model that minimizes the criterion is the fine model. In recent times, several criteria for choosing some of the models have proposed this whole

version which takes the form of Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Mean Squared Deviation (MSD). Some of those standards are discussed below:

Mean Absolute Percentage Error (MAPE): This expresses accuracy as a percentage of the error, because this number is a percentage, and it measures the accuracy of fitted time series values.

$$MAPE = \frac{\sum |(Z_t - \hat{Z}_t) / Z_t|}{n} \times 100 \quad (Z_t \neq 0)$$

(8)

Where Z_t equals the actual value at time t , $\hat{Z}_t$ equals the fitted value, and n equals the number of observations.

Mean Absolute Deviation (MAD): This measures the accuracy of fitted time series values. It expresses accuracy in the same as the data. This helps to theorize the error also.

$$MAD = \frac{\sum_{t=1}^n |(Z_t - \hat{Z}_t)|}{n}$$

(9)

Where Z_t equals the actual value at time t , $\hat{Z}_t$ equals the fitted value, and n equals the number of observations.

Mean Squared Deviation (MSD): This is calculated using the same denominator, n , regardless of the model. This is to enable comparison of MSD values across models. This makes MSD a more sensitive of a usually largest forecast error than MAD.

$$MSD = \frac{\sum_{t=1}^n |(Z_t - \hat{Z}_t)|^2}{n}$$

(10)

Where Z_t equals the actual value at time t , $\hat{Z}_t$ equals the fitted value, and n equals the number of observations.

RESULTS

The Time Series Plot of the Actual Data (Malaria Cases in Private Hospital in Nigeria)

The time series plot of the data in fig. 1 below, displayed the malaria cases in private hospital in Nigeria (2015 – 2021). The plot shows trend movement with seasonal variation. This means we shall model the data by fitting a general time series trend model to the time series data in order to know the model that fits best and make forecasts.

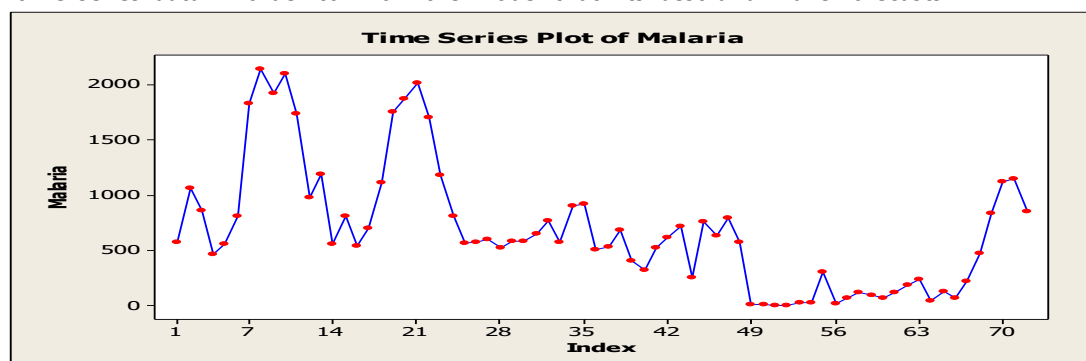


Fig.1 Time series plot of the actual data (Malaria Cases in Private Hospital in Nigeria)

The Linear Trend Model:

The estimated linear trend model of equation (2) is given as $Z_t = 1271 - 15.7900 * X_t$.
The plot of the linear trend model in fig.2 shows that it does not fit the data.

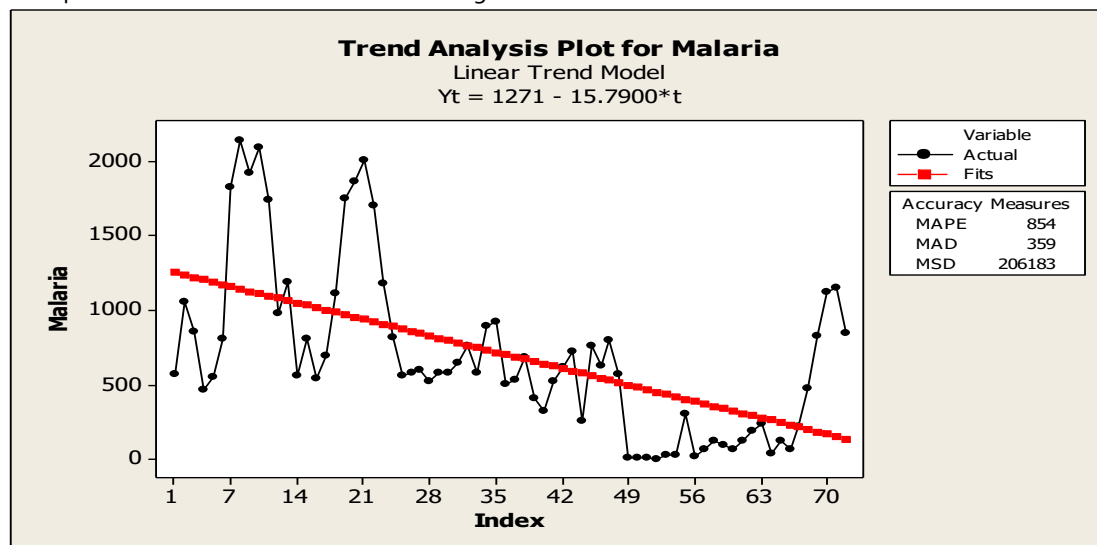


Fig.2 Time series plot of the linear trend model of Reported Cases

Table 1: Accuracy Measures for Linear Trend Model for Malaria Cases in Private Hospital in Nigeria

Accuracy Measures	
MAPE	854
MAD	359
MSD	206183

The accuracy measures of the linear trend model in table 1 show that MAD has a value of 359 while other measures are quite large.

The Quadratic Trend Model:

The estimated quadratic trend model of equation (4) is given as $Z_t = 1466 - 31.6X_t + 0.217X_t^2$. The plot of the quadratic trend model in fig.3 shows that it does not fit the data.

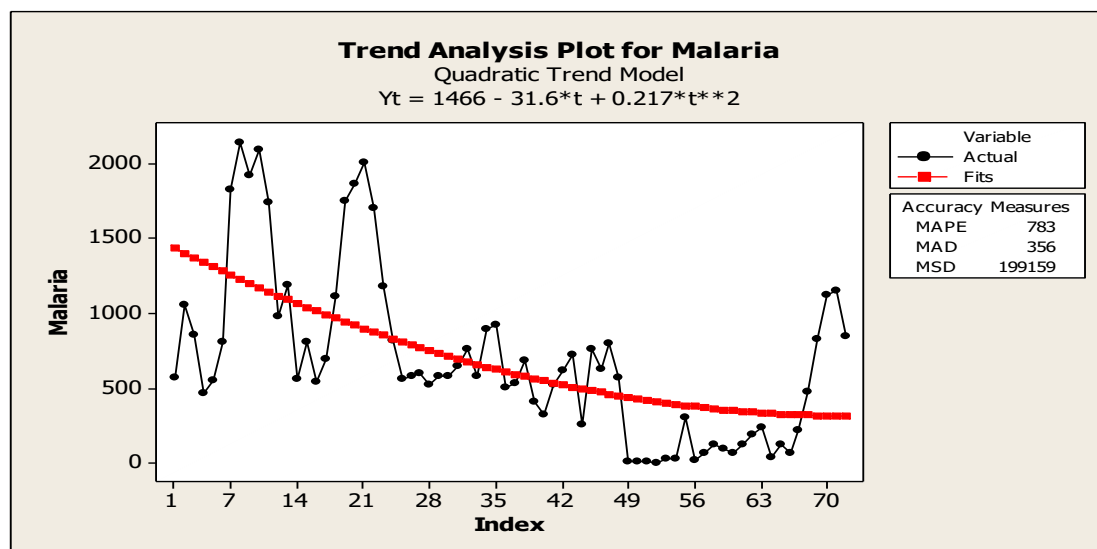


Fig.3 Time series plot of the quadratic trend model of Reported Cases

Table 2: Accuracy Measures for Quadratic Trend Model of Malaria Cases in Private Hospital in Nigeria

Accuracy Measures	
MAPE	783
MAD	356
MSD	199159

The accuracy measures of the quadratic trend model in table 2 show that MAD has a value of 356 while other measures are quite large.

The Exponential Trend Model:

The estimated exponential trend model of equation (6) is given as

$$Z_t = 1555.02 * (0.96172)^x$$

The plot of the exponential trend model in fig. 4 shows that it does not fits the data.

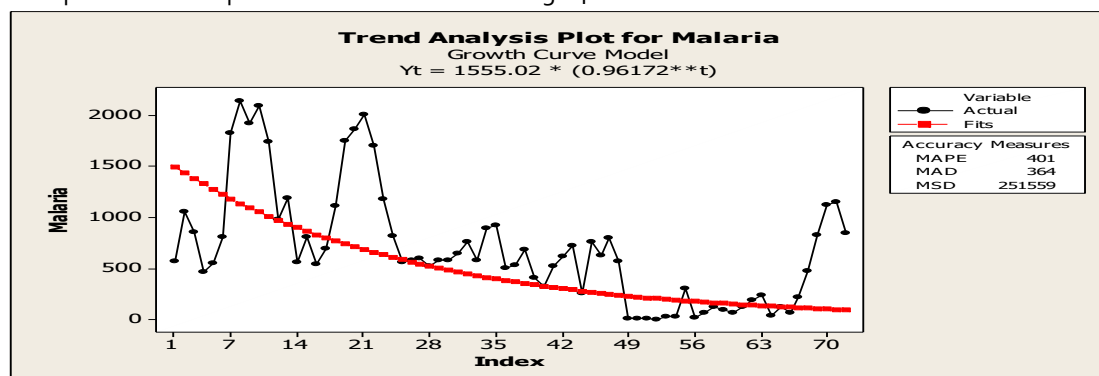


Fig.4 Time series plot of the exponential trend model of Reported Cases

Table 3: Accuracy Measures for Exponential Trend Model of Malaria Cases in Private Hospital in Nigeria

Accuracy Measures	
MAPE	401
MAD	364
MSD	251559

The accuracy measures of the exponential trend model in table 3 show that MAD has a value of 364 while other measures are quite large.

The S-curve Trend Model:

The estimated s-curve trend model of equation (7) is given as

$$Z_t = \frac{10^4}{(10.2971 + 0.00550 * (1.19661)^x)}$$

The plot of the s-curve trend model in fig. 5 shows that it fits the data with minor deviation.

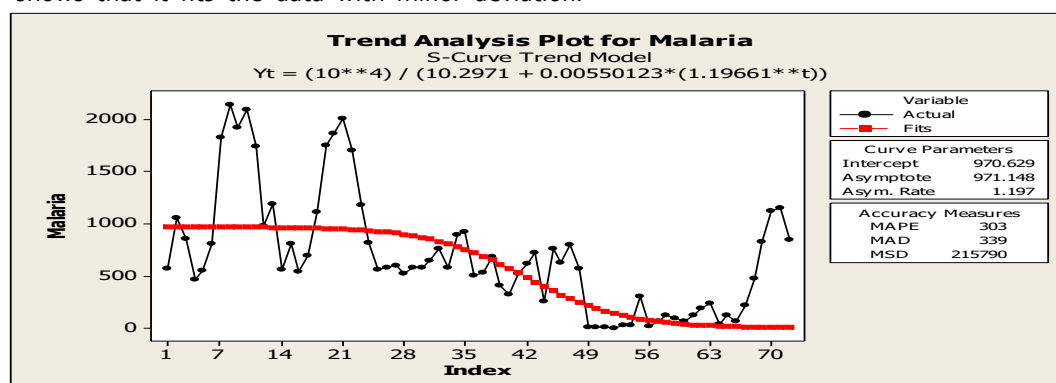


Fig.5 Time series plot of the s-curve trend model of Reported Cases

Table 4: Accuracy Measures of S-curve Trend Model of Malaria Cases in Private Hospital in Nigeria

Accuracy Measures	
MAPE	303
MAD	339
MSD	215790

The accuracy measures of the S-curve trend model in table 4 show that MAPE has a value of 303 while other measures are quite large.

Comparing the Accuracy Measures:

Table 5: Comparative Accuracy Measures of Malaria Cases in Private Hospital in Nigeria

Model	MAPE	MAD	MSD
Linear	854	359	206183
Quadratic	783	356	199159
Exponential	401	364	251559
S-curve	303	339	215790

When comparing the accuracy measurements of these four models in table 5, the MAPE and MSD for all of them are relatively substantial. However, when compared to other models using MAD, which is a more effective measure of the four accuracy measures, the s-curve model has the smallest MAD measure of 339, indicating that malaria cases in private hospitals in Nigeria do not follow a linear trend model; rather, they follow an s-curve trend model. The s-curve trend model will be used to calculate a six-month projection of malaria cases.

Six Months Forecast of the Malaria Cases in Private Hospital in Nigeria

The s-curve trend model prediction of malaria cases in private hospitals in Nigeria suggests that the number of malaria cases in the hospitals would decline, as shown in table 6 below.

Period	Jan. 2022	Feb. 2022	Mar. 2022	April 2022	May 2022	June 2022
Forecast	3.69222	3.08749	2.58154	2.15832	1.80435	1.50834

Discussion of Finding

Four time series models were evaluated in this research to examine the growth behaviour of malaria cases in a private Nigerian hospital. The four models encompassing Linear, Quadratic, Exponential, and S-curve were not all supposed to be able to reflect the long term trend of malaria cases in private hospitals in Nigeria after comparing and analysing the model accuracy metrics of MAPE, MAD, and MSD values of each model. The S-curve trend model, on the other hand, was in the best agreement with real long-term malaria cases in private hospitals in Nigeria, as measured by MAPE, MAD, and MSD values. The real malaria cases were discovered using an s-curve trend model based on the MAD value. The results of this study contradict those of Eke et al., (2015), who found that the exponential trend model had the lowest MAPE and best fit the malaria data.

Conclusion

The best fit model for the data was the s-curve trend model, with the least MAD value, according to the fitting of relevant trend models to malaria cases in private hospitals in Nigeria (2015-2021). The best fit was the s-curve trend model, which was used to anticipate the trajectory of the malaria pandemic in private hospitals in Nigeria. It was

clearly shown that the number of malaria cases in the hospital would decrease during the following six months, from January to June 2022.

Recommendation

Based on the result of this study, the researchers made the following recommendations:

1. The best trend model for forecasting malaria cases in private hospitals in Nigeria was determined as the s-curve trend model.
2. Government intervention programmes, policies, and strategies aimed at socioeconomic and environmental factors that affect health (particularly malaria) should be implemented nationwide.
3. Actual malaria cases were identified using an s-curve trend model, which was determined using the MAD value's model accuracy measure.

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