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Time Series Analysis on Admission Rates of Dengue In Medical College Hospital

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ABSTRACT

To develop a prediction model for dengue fever/dengue haemorrhagic (DF/DHF) using time series data over the past one year and to forecast monthly DF/ DHF incidence for the year 2018. Autoregressive integrated moving average (ARIMA) model was used for statistical modelling along with SPSS software. The data has been collected from January 2017 to December 2017 from a tertiary care hospital, mandya District, the reported DF cases showed a seasonal patterns. ARIMA (2, 0, 0) model has been found to be suitable model with least Normalized Bayesian Information Criteria (BIC) of 8.493 and Mean Absolute Percent Error (MAPE) of 125.935. The model explained 60.8% of the variance of the series (stationary R-squared). The forecasted value for the year 2018 showed a seasonal peak in the month of July with an estimated case. Application of ARIMA model may be useful for forecast of cases and impending outbreaks of DF/ DHF and other infectious diseases, which exhibit seasonal pattern.

KEY WORDS: Dengue, Time-Series Analysis, ARIMA Model

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INTRODUCTION

Dengue is a mosquito-borne viral infection. The infection causes flu-like illness, and occasionally develops into a potentially lethal complication called severe dengue. The global incidence of dengue has grown dramatically in recent decades. About half of the world's population is now at risk[1,2]. Dengue, the most frequent arthropod-borne viral disease. Dengue is transmitted between human hosts by several species of day-feeding mosquitoes, such as the Aedes aegypti. Infection can be asymptomatic or it can manifest as undifferentiated febrile illness, known as dengue fever, characterised algae and retro-orbital pain. Some infections result in dengue haemorrhagic fever (DHF), a syndrome that, in its most severe form, can be life-threatening [2].

Cases of DF have been increasing in numbers over the past few years. More alarmingly, the rate of increase has also been showing an upward trend. 50 million cases of DF are estimated to have occurred yearly worldwide, putting a population of 1.8 billion people at risk to DF.

The outbreaks of DF/DHF can be predicted by epidemiological modelling thus enabling the health systems to be in readiness to manage outbreaks. Over the last two decades statistical methods have been developed that could help with such problems. Time series analysis techniques have been increasingly used in the field of epidemiology research on infectious diseases. Thus time series analysis techniques are statistical methods that may offer a potential for statistically analyzing physiologic measurements in the individual patient [4,5,6].

OBJECTIVES

To estimate seasonal variation & fit an ARIMA model for the exciting Dengue Cases**.**

MATERIALS AND METHODS

Reported monthly DF/DHF cases from a tertiary care hospital in Mandya district were collected. It is a retrospective study. The data were collected for a period of 12 months, Starting from January 2017 to December 2017**.**

Inclusion criteria:

Patients with NS1, IgM, IgG (positive cases) were included.

Exclusion criteria:

Patients diagnosed other fevers

Data Description

The data on 1572 patients were collected and the individuals who have symptoms of dengue were examined. . Out of the 1572 patients, 257 cases were positive dengue cases. Each patient have individual I.P Number (In patient number), age is considered to be a discrete variable, ranging from

1 day baby to 87 Years. Most of the patients in the study are from the age group 31 to 40 Years. As per the age is considered, more number are affected in the age group 21 to 30. Most of the patients in the data are male. Some tests such as NS1, IgG, IgM were conducted for dengue positive.

RESULTS

Table 1 shows the Month wise details of Dengue fever Cases

Month	Total No. Of suspected Dengue cases	Positive cases
January	55	3
February	43	0
March	51	0
April	38	0
May	96	8
June	302	39
July	389	114
August	208	63
September	173	32
October	98	12
November	63	2
December	36	1
Total	**1572**	**274**

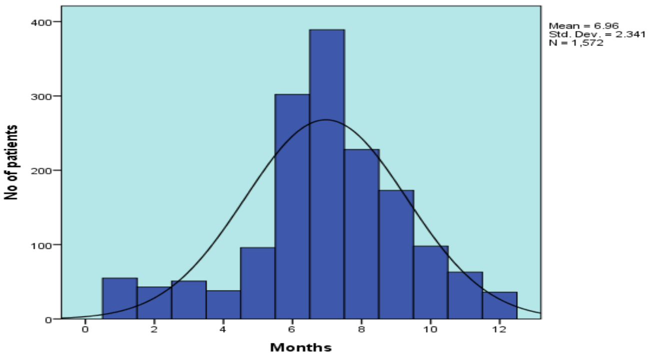


Figure 1

Fig1. Number of recorded Month wise dengue cases as shown in Histogram vs. number of patients. In this diagram there are 1,572 patients among which, most of the patients have entered in the July month, satisfying the normality condition with the mean of 6.96 and Standard deviation of 2.341.

The above data is represented by Pie Diagram according to places from where the patients have entered into the study.

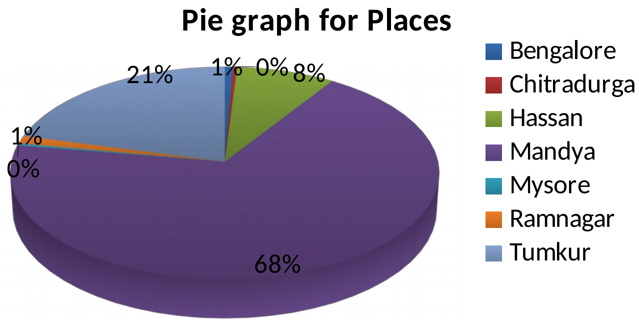
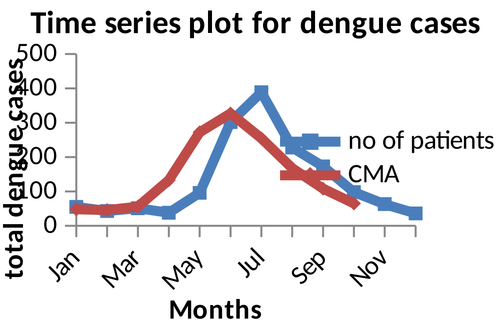


Figure 2: number of recorded dengue cases as per district wise. Here most of the patients have come from Mandya.

Central Moving Averages are calculated for the DF accumulated cases, this data were transformed into a time-series data using SPSS and a plot of the time-series is shown in Fig.3 and Fig 4



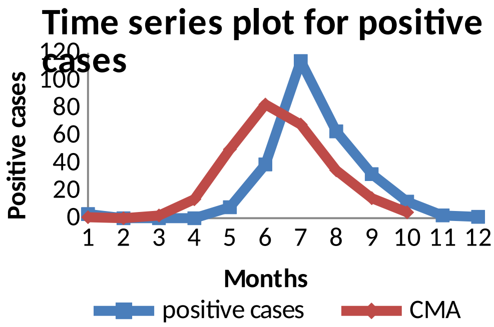


Figure 3: Accumulated Dengue Total Cases in 2017. **Figure 4: Accumulated Dengue positive Cases in 2017.**

fig 3 and fig 4 Shows the plot of accumulated dengue fever cases. The red trend-line shows the Centred moving Averages and blue trend line showing that the number of dengue cases (over-all and Positive cases). There is a gradual increase in the month of June, July and August Compared with other months and there is high peak in the month July.

Trends were calculated by using Method of moving averages and straight line equations.

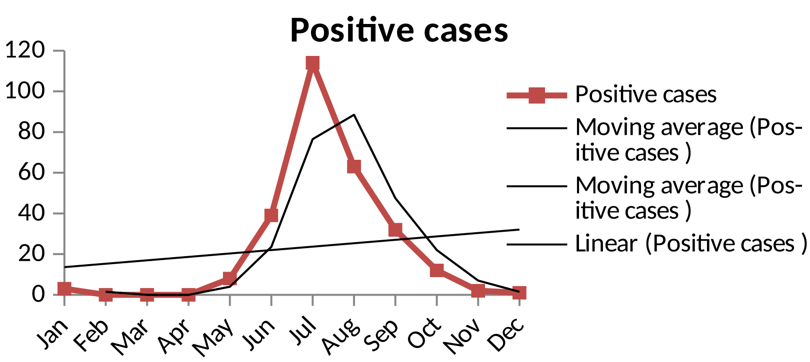


Figure 5

Figure 5 shows the straight line trend using least square method for dengue Positive Cases.Figures shows the month wise trends DF over the past one year and for 2018. The cases showed a similar seasonality, with a peak in the month of July similar to previous year with an estimated cases.

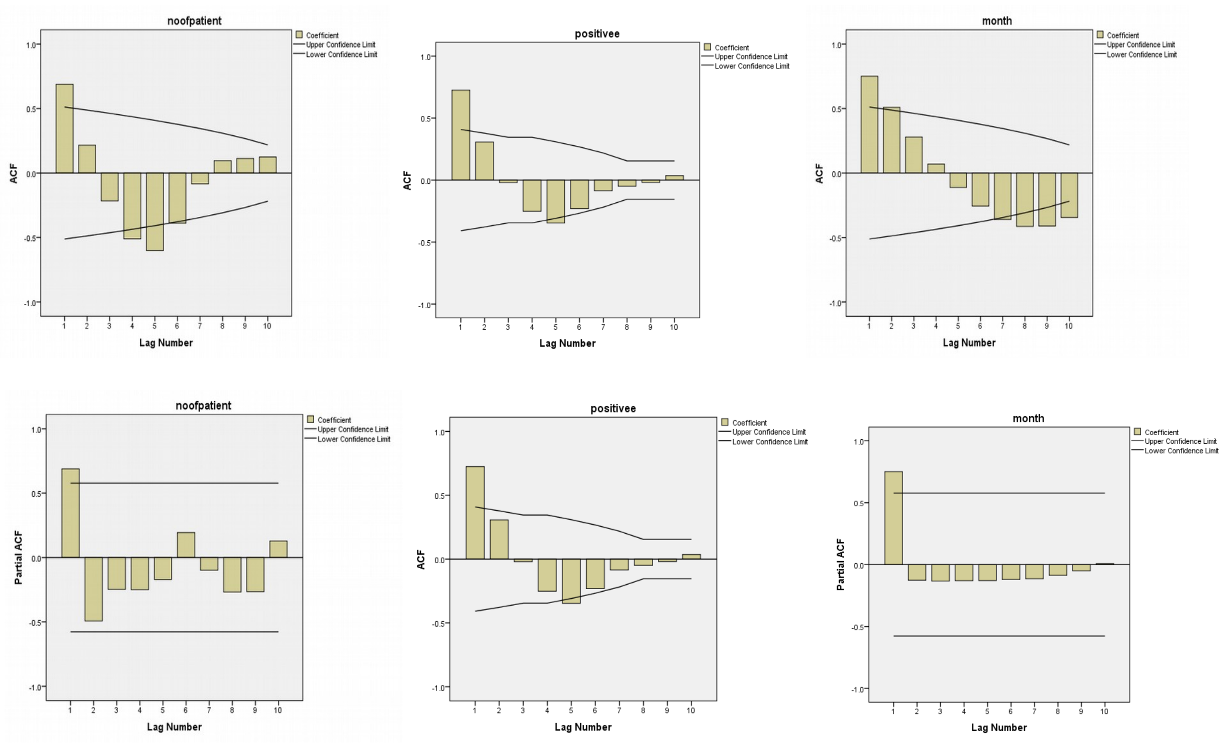
Stationary forecasting methods are based on the assumption that the time series can be rendered approximately stationary. A stationary time series is one whose statistical properties such as mean and variance are constant over time [8,9,10,11]. Seasonality usually causes the series to be nonstationary because the average values at some particular times within the seasonal span may be different than the average values at other times [3].

In the study, the time series plot of the reported DF/DHF cases displayed seasonal fluctuations and therefore deemed no stationary. SPSS was used to determine the best fitting model. The stationary of the series was made by means of seasonal and nonseasonal differencing. The order of autoregression(AR) and moving average (MA) were identified using autocorrelation(ACF) and partial autocorrelation function (PACF) of the differenced series [3,6,7].

Large autocorrelations were recorded for lags 1, 2 with values 0.25, and 0.27 respectively. The sharp decrease in autocorrelation values after lag 1 indicated no evidence of long-term trend; consequently, there was no need to include a first-lag difference term in the ARIMA model structure (d=0). In Contrast, large auto correlation values were registered at annual lags (and its multiplies), which indicated the need to include 12-month difference term in the models (S=12, D=1). The ACF and PACF plots of the differenced series provided further support for this conclusion. Therefore, a ARIMA (p, 0, q) was selected as the basic structure of the candidate model [11,12,13,14].

Several models were constructed and among several models, the most suitable was selected based on three measures, namely, normalized Bayesian information criteria (BIC), mean absolute percentage error (MAPE), and stationary R squared. Whereas, lower values of BIC and MAPE were preferred, a higher value of stationary squared suggests a greater proportion of variance of the dependent variable explained by the given model [3]. Among the statistical models, ARIMA (2, 0, 0) was selected as the best model, with the lowest normalized BIC of 8.493 and MAPE 125.935 [Table 2]. The model explained 60.8% of the variance of the series (stationary R-squared). The model parameters were significant (p-value <0.001) with MA in the model, seasonal lag 1 of Beta for total patients= 1.080 seasonal lag 1 of Beta for positive cases= 1.204 (SE=0.149). The model was also checked for adequacy through examining the ACF and PACF of the residuals.

1(a) 1(b) 1(c)



2(a) 2(b) 2(c)

Figure **6**. Autocorrelation function (ACF) and Partial autocorrelation function (PACF) of data. 1(a) shows ACF for dengue total cases; 1(b) shows ACF for positive cases; 1(c) shows ACF for month-wise; 2(a) shows PACF for dengue total cases; 2(b) shows PACF for positive cases; 2(c) shows PACF for month-wise.

Table 2. Normalized Bayesian information criteria (BIC), mean absolute

Models	MAPE	Normalized BIC	Stationary R-squared
ARIMA (1, 0, 0)	176.476	8.605	0.413
ARIMA (2, 0, 0)	125.935	8.493	0.608
ARIMA (0, 0, 1)	216.019	8.573	0.424
ARIMA (1, 0, 1)	170.767	8.752	0.500
ARIMA (1, 1, 0)	114.686	8.996	0.189
ARIMA (0, 1, 1)	124.715	8.867	0.226
ARIMA (1, 1, 1)	129.971	9.175	0.273
ARIMA (1, 1, 3)	182.751	10.048	0.154
ARIMA (2, 1, 3)	161.354	10.398	0.287

Percentage error (MAPE) and stationary R-squared values of ARIMA models.

Time Series Modeler

Model Description			Model Type
Model ID	Positive	Model_1	ARIMA(2,0,0)
	No of patient	Model_2	ARIMA(2,0,0)

CONCLUSION:

In this paper, the time-series modelling of accumulated Dengue Cases as reported by the tertiary care hospital. Our analysis of the data has shown that the accumulated DF cases which exhibits a trend and seasonal patterns, among all candidate models, ARIMA(2,0,0) was the most suitable predictive model in our study, which showed the highest variance of the series 60.8% (stationary R-squared) and the lowest normalized BIC of 8.493 and MAPE 125.935 [Table 2]. ARIMA models are useful in modelling the temporal dependence structure of a time series as they explicitly assume temporal dependences between observations. Particularly for seasonal diseases, ARIMA models have been shows to be adequate tools for use in epidemiological surveillance. Our study provides an example of applying a ARIMA model to forecast incidence of DF.

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