FORECASTING MEASLES VACCINE REQUIREMENT BY USING TIME SERIES ANALYSIS

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FORECASTING MEASLES VACCINE REQUIREMENT BY USING TIME SERIES ANALYSIS

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ABSTRACT

BACKGROUND
Child Immunisation is an important activity and is carried out at all levels of health care services. At Primary Health Centres and subcentres, vaccine requirement is calculated by fixed formula. It is difficult to estimate vaccine requirement where denominator is not known as in the case of the Government Medical College.

The objective of this study is to forecast Measles vaccine requirement by using time series analysis, at Government Medical College, Latur.

MATERIALS AND METHODS
The present study was record based; undertaken at Government Medical College, Latur. The data regarding Measles vaccine used during the years 2009-10 to 2014-15 was taken from immunisation book. This month wise data was fed in MS-excel and analysed using software SPSS version 21.0. Method used for time series analysis was Expert Modeller for best model fit. Time series analysis and forecasting was done using best-fit model i.e. Simple seasonal model for measles vaccine.

RESULTS
A total of 8015 doses of measles vaccine were given during the years 2009-10 to 2014-15 at Government Medical College, Latur. Ljung-Box Q statistics was not significant. Forecasting for Measles vaccine was done up to 2018-19. The vaccine requirement calculated for August 2018 is 134 with 225 and 42 as upper and lower confidence level. It was 136 for February 2019 with 231 and 40 as upper and lower confidence level respectively.

CONCLUSION
Simple seasonal model of Time series analysis can be used to forecast Measles vaccine requirement at Medical Colleges.

KEYWORDS
Measles Vaccine Estimation, Time Series Analysis, Simple Seasonal Model.

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BACKGROUND
Immunisation is one of the most cost effective public health interventions and was first introduced in India in 1978.[1] This important activity is carried out through Primary Health Centres, Subcentres, Rural Hospitals, Tertiary Care Hospitals, etc. The live attenuated vaccines are derived from disease-causing viruses or bacteria that have been weakened under laboratory conditions. They replicate in a vaccinated individual, but because they are weak, they cause either no disease or only a mild form of the disease. Examples are BCG, Measles and the Oral Polio Vaccine. The MoHFW, Govt. of India launched Mission Indradhanush in December 2014 as a special drive to vaccinate all unvaccinated and partially vaccinated children under UIP.[2]

Traditionally vaccine requirement is estimated with the following steps especially, where head count is known or can be done i.e. denominator. The head count can be conducted through the

Community Needs Assessment Approach or the biannual/annual survey method. For infants, the headcount would provide a point estimate for the year. From that, monthly estimate is calculated. A wastage rate of 25% or a wastage multiplication factor (WMF) of 1.33 is allowed for all vaccines. So, the wastage multiplication factor for Measles vaccine, is also 1.33.[2]

Time series analysis is a specialised area of statistics to which many marketing researchers have had limited exposure, despite it having many important applications in Marketing research. Two popular univariate time series methods are exponential smoothing (e.g., Holt-Winters) and ARIMA (autoregressive integrated moving average).[3] Forecasting techniques are important tools in operational management for creating realistic expectations.[4]

So this study was conducted to estimate vaccine requirement where head count cannot be done; for ex. Medical colleges, where people come from various districts and their number is not fixed i.e. denominator is not known.

Objective
To forecast Measles vaccine requirement by using time series analysis, at Government Medical College, Latur.

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MATERIALS AND METHODS

Study Design

The present study was cross sectional; record based study.

Study Setting

Government Medical College, Latur; A Tertiary Care Hospital attached to Government Medical College.

Data Collection

The data regarding Measles vaccine used during previous six years i.e. from 2009-10 to 2014-15 was collected from Immunisation Report Book maintained at Immunisation Clinic of Government Medical College .

The month wise data of above six years was fed in MS-excel. This pre-processed data was then imported in Statistical Package for Social Sciences (SPSS) version 21.0 and statistical analysis was done.

Then, following steps were followed: analyse- for casting-create models. Method used was Expert Modeler. While there was another method called ARIMA, we used Expert Modeler for best model fit. In statistics, we display fit of measures Ljung-Box statistics and number of outliers by given model.

For comparing models, we used stationary R^2, normalised BIC, as model fit statistics and for individual models, we used ACF and PACF plot. In autocorrelation and partial correlations we used natural log transform with difference of 1. The lags used for study were 24. Time series analysis and forecasting was done using best-fit models i.e. Simple seasonal model using SPSS version 21.0.

RESULTS

A total of 8015 doses of Measles vaccine were given during the years 2009-10 to 2014-15 at Government Medical College, Latur. Maximum number of doses were given during the year 2014 and minimum number of doses were given during 2009. Average number of doses and standard deviation is shown in Table 1.

The autocorrelation function (ACF) and partial autocorrelation functions (PACF) were not significant at any lag for the series of Measles vaccine indicating stationarity of the series which is shown in Fig. 1 and Fig. 2. Expert Modeler of SPSS ver. 21 suggested simple seasonal model as the best fit statistical model for Measles vaccine time series data.

Table 2 Shows model statistics. R squared value for Measles model was 0.758. Here, stationary R-squared value was used for comparing models since it provides an estimate of the proportion of the total variation in the series that is explained by the model. This table also shows the Ljung-Box Q statistics and its P-value. It was not significant for Measles model (p= 0.707). The model detected no outlier in the data.

Table 3 shows exponential smoothing model parameters. It shows values of alpha (level) and delta (season) for BCG model. Here, alpha value is indicating prominence of level component in the model with very less seasonal component.

Table 4 shows the Year-wise forecasts for Measles vaccine provided by Simple seasonal model with their upper and lower confidence level. Forecasting was done using the best model selected i.e. simple seasonal model till 2018-19 for Measles vaccine. From this table, we can see that the vaccine requirement for August 2018 is 134 with 225 and 42 as upper and lower confidence level. It was 136 for February 2019 with 231 and 40 as upper and lower confidence level respectively.

Fig. 3 shows the Measles vaccine forecast. It shows wide confidence interval over time.

Month/Year	2009	2010	2011	2012	2013	2014
April	92	66	110	64	112	170
May	119	81	0	107	136	140
June	99	82	161	74	100	130
July	106	64	113	126	164	134
August	63	59	96	106	134	154
September	90	82	74	118	149	133
October	106	88	44	114	168	140
November	91	81	82	90	135	220
December	106	141	77	150	174	130
January	130	105	72	108	165	160
February	82	109	85	130	118	100
March	61	137	116	99	133	160
Total	1145	1095	1030	1286	1688	1771
Mean	95.41667	91.25	85.83333	107.1667	140.6667	147.5833
S.D.	20.39812	26.77219	39.91772	23.74422	23.76144	29.37364

Table 1. Year-wise and Month-wise Measles Doses Used

Model	No. of Predictors	Model Fit Statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-Squared	Normalised BIC	Statistics	DF	Sig.	
Measles-Model_1	0	.758	6.817	12.527	16	.707	0

Table 2. Model Statistics

Model			Estimate	SE	T	Sig.
Measles-model_1	No Transformation	Alpha (Level)	.200	.072	2.774	.007
		Delta (Season)	2.792E-005	.127	.000	1.000

Table 3. Exponential Smoothing Model Parameters

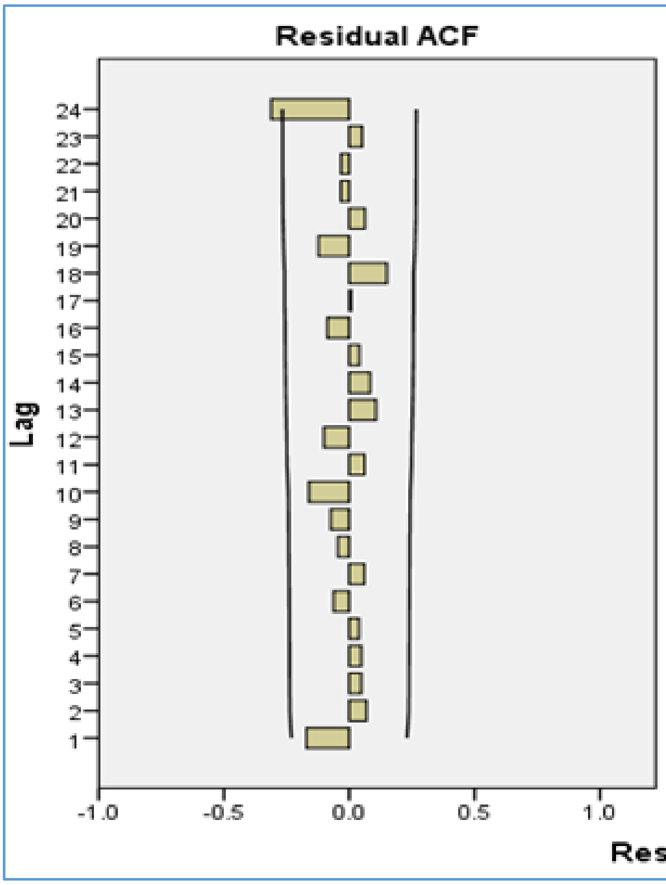

Figure 1

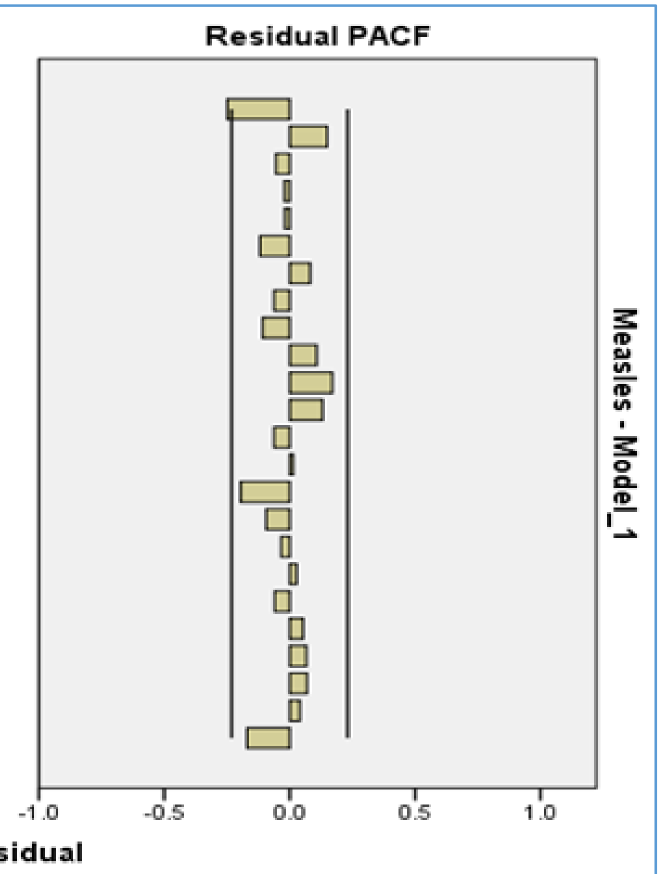

Figure 2

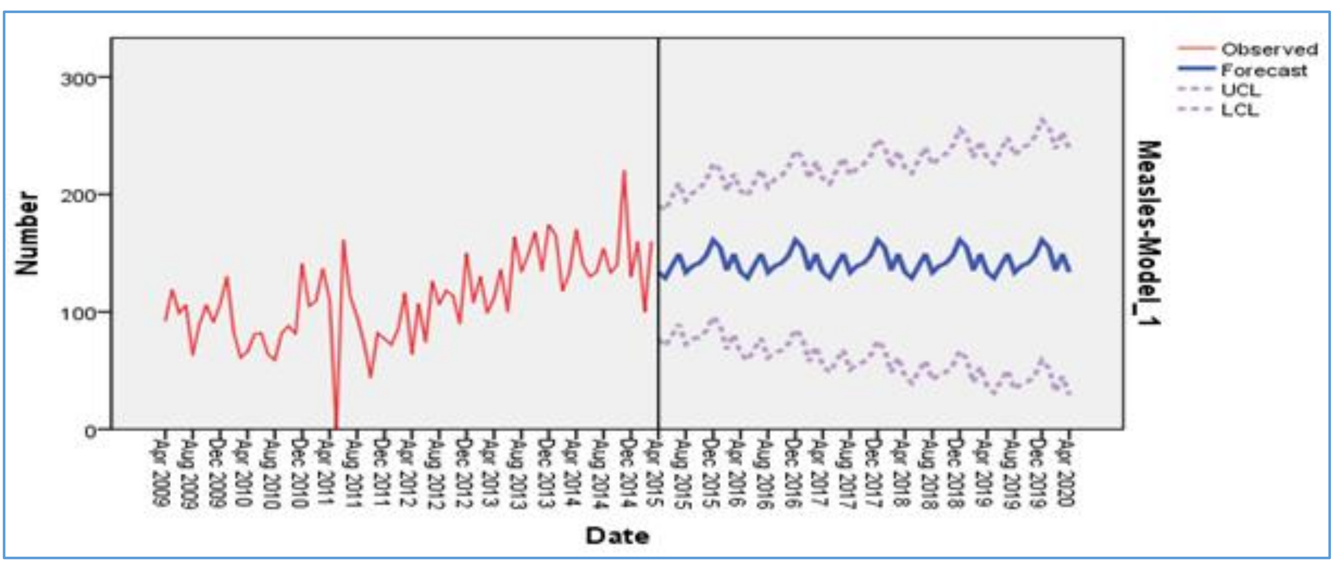

Figure 3. Measles Forecast

Model	Measles -Model_1		
	Forecast	UCL	LCL
Apr. 2015	134	191	77
May. 2015	129	187	71
Jun. 2015	139	198	80
Jul. 2015	149	209	89
Aug. 2015	134	195	72
Sep. 2015	139	201	77
Oct. 2015	142	205	78
Nov. 2015	148	212	84
Dec. 2015	161	226	96
Jan. 2016	155	221	89
Feb. 2016	136	203	68
Mar. 2016	149	217	81
Apr. 2016	134	203	65
May. 2016	129	199	59
Jun. 2016	139	210	68
Jul. 2016	149	221	78
Aug. 2016	134	206	61
Sep. 2016	139	213	66
Oct. 2016	142	216	67
Nov. 2016	148	223	73
Dec. 2016	161	237	85
Jan. 2017	155	232	78
Feb. 2017	136	213	58
Mar. 2017	149	228	71
Apr. 2017	134	213	54
May. 2017	129	209	48
Jun. 2017	139	220	58
Jul. 2017	149	231	67
Aug. 2017	134	216	51
Sep. 2017	139	220	58
Oct. 2017	142	226	57
Nov. 2017	148	233	63
Dec. 2017	161	247	75
Jan. 2018	155	241	68
Feb. 2018	136	223	48
Mar. 2018	149	237	61
Apr. 2018	134	223	45
May. 2018	129	218	39
Jun. 2018	139	229	49
Jul. 2018	149	240	59
Aug. 2018	134	225	42
Sep. 2018	139	231	47
Oct. 2018	142	234	49
Nov. 2018	148	242	54
Dec. 2018	161	256	67
Jan. 2019	155	250	60
Feb. 2019	136	231	40
Mar. 2019	149	246	53

Table 4. Year-wise Forecasts for Measles Vaccine Provided by Simple Seasonal Model

DISCUSSION

In the present study of time series analysis, Expert Modeler of SPSS version 21 showed Simple seasonal model for OPV which are the types of exponential smoothing. The name "exponential smoothing" is attributed to the use of the exponential window function during convolution.[5] For a given age (i.e. amount of lag), the simple exponential smoothing (SES) forecast is somewhat superior to the simple moving average (SMA) forecast because it places relatively more weight on the most recent observation i.e.it is slightly more "responsive" to changes occurring in the recent past.[6] Whereas it showed ARIMA model in studies conducted by Varun Kumar,[6,7] Sachin S Mumbare.[8] Emrah Onder[4] used exponential smoothing model in his study.

Sachin S Mumbare[8] in his study used Box-Jenkins ARIMA (p,d,q); autoregressive integrated moving averages; non-seasonal models for the analysis and forecasting the average number of children at the time of terminal contraception in each group, till 2020.

He found the time series to be non-stationary, as interpreted by augmented Dickey-Fuller test, so the series was analysed with $d \geq 1$. He compared results of the different models using fit measures like R-square, stationary R-square, mean absolute percentage error, maximum absolute percentage error, and normalised Bayesian Information Criteria. Using these parameters, he identified best-fit model for each group. Also, confirmed the best-fit model using Expert Modeler in SPSS and tested adequacy of the best-fit model by examining autocorrelation function of the residuals. Ljung-Box test statistics was used for the same, similar to the present study. The model was ignored, if the Ljung-Box Q statistics gave significant P-value.

Varun Kumar [6] in his study on forecasting Malaria Cases Using Climatic Factors in Delhi checked stationarity of the data by autocorrelation function (ACF) and partial autocorrelation function (PACF) which showed a significant peak at a lag of 12 which confirmed the presence of seasonal component in the time series data. These findings were different from the present study where ACF and PACF do not showed significant peak at lag 12. Ljung-Box (modified Box-Pierce) test was used in his study to determine if the model was correctly specified, similar to the study[8] and present study. He used ARIMA (0,1,1) (0,1,0) as suggested by Expert Modeler of SPSS ver. 21 as the best fit statistical model for the same.

In the present study, Stationary R-squared value was used as model statistics as it is preferable to ordinary R-squared when there is a trend or seasonal pattern. Larger values of stationary R-squared (up to a maximum value of 1) indicate better fit.[6]

Varun Kumar[7] in his study on Seasonality of Tuberculosis in Delhi used ARIMA model for seasonality which showed both declining trend and periodic seasonal fluctuations. Seasonal variation was more in his study as compared to the present study.

Win Wah[9] used the seasonal autoregressive moving average (SARIMA), ARIMA models with periodic components, to predict the temporal trends of the more volatile monthly TB risk among residents and non-residents in Singapore and detect seasonality. The model with the lowest value of the AIC (Akaike's Information Criterion) was selected to analyse yearly TB cases.

Using a time series analysis, an exponential model was fitted to the annual incidence rates of suicide (by any method) between 1995 and 2009. Model adequacy was tested using the mean absolute percentage error (MAPE), a measure of how much a dependent series varies from its model-predicted level. Larger values of stationary R-squared (Up to a maximum value of 1) indicate better fit. A value of 0.758 meant that the model could explain 75% of the observed variation in the series. A seasonal pattern exists when a series is influenced by seasonal factor (e.g.-the quarter of the year, the month, or day of week). Seasonality is always fixed and of known period.[10]

Exponential smoothing models are classified as either seasonal or non-seasonal. Simple seasonal model is appropriate for series with no trend and seasonal effect that is constant over time. Its only relevant parameter is smoothing.[11]

CONCLUSION

Expert Modeler was used in this study of time series analysis, it showed simple seasonal model as best fit model which is the type of exponential smoothing. It can be used to forecast vaccine requirement in case of Measles vaccine; as Ljung Box Q statistics was not significant.

Time series analysis and forecasting is an objective method for calculating vaccine requirement as it gives the values with upper and lower confidence interval. It assures optimum supply of vaccine. So it can be used in Medical colleges.

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REFERENCES

[1] Immunization handbook for medical officers: Department of Health and Family Welfare, Ministry of Health and Family Welfare, Government of India, 2008.

[2] Guidelines for Reporting & Management of Adverse Events Following:
Immunization: India, New Delhi, Government of India, 2005. http://www.whoindia.org/LinkFiles/Routine_Immunization_AEFIguidelines_for_reporting.pdf.

[3] Kelvin G. Time series analysis-what it is and what it does. Available from: http://www.quirks.com/articles/time-series.

[4] Emrah Ö, Ali H. Combining time series analysis and multi criteria decision making techniques for forecasting financial performance of banks in Turkey. Int J of Latest Trends in Fin & Eco Sc 2013;3(3):530-55.

[5] Duke. Moving average and exponential smoothing models 2016. Available from: http://people.duke.edu>rnau.

[6] Varun K, Abha M, Sanjeet P, et al. Forecasting malaria cases using climatic factors in Delhi, India: a time series analysis. Malaria Research and Treatment 2014;Article ID 482851:1-6.

[7] Varun K, Abhay S, Mrinmoy A, et al. Seasonality of tuberculosis in Delhi, India: a time series analysis. Tuberc Res Treat 2014;Article ID 514093:1-5.

[8] Sachin SM, Shriram G, Balaji A, et al. Trends in average living children at the time of terminal contraception: a time series analysis over 27 years using ARIMA (p, d, q) nonseasonal model. Indian J Community Med 2014;39(4):223-8.

[9] Hyndman RJ. Cyclic and seasonal time series Hyndsight 2011. Available from: http://robjhyndman.com> hindsight> cyclists.

[10] Win W, Sourav D, Arul E, et al. Time series analysis of demographic and temporal trends of tuberculosis in Singapore. BMC Public Health 2014;14:1121.

[11] Time series exponential smoothing criteria-IBM, 2016. Available from:
http://www.ibm.com>knowledgecenter.