Original Research Article

Estimation of vaccine requirement by using time series analysis

Kendre V V[1*], Mumbare S S[2], Dixit J V[3], Wadagale A V[4]

[1]Associate Professor, Department of Community Medicine, BJGMC, Pune, Maharashtra, INDIA.
[2]Professor and Head, Department of Community Medicine, Ashwini Rural Medical College, Hospital& research center, Kumbhari, Solapur, Maharashtra, INDIA.
[3]Professor and Head, [2]Statistician cum Lecturer, Department of Community Medicine, Government Medical College, Latur, Maharashtra.
Email: mundevarsharani@yahoo.com

Abstract

Background: Routine Immunization is one of the most cost effective public health interventions. This important activity is carried out at all levels of health care services. At PHCs 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. **Objective:** To estimate vaccine requirement using time series analysis, at Government Medical College, Latur. **Material and methods:** The present study was record based; undertaken at Government Medical College, Latur. The data regarding BCG and OPV vaccines used during 2009-10 to 2014-15 was taken from immunization book. This month wise data was fed in MS-excel and analyzed using software SPSS version 21.0. Method used for time series analysis was Expert Modeler for best model fit. Time series analysis and forecasting was done using best-fit models viz. – Winter's additive for BCG and simple seasonal model for OPV. **Results:** A total of 38361 doses of BCG vaccine and 67348 doses of OPV vaccine were given during the years 2009-10 to 2014-15 at Government Medical College, Latur. Ljung-Box Q statistics was significant for BCG and was not significant for OPV. Forecasting was done for BCG and OPV up to 2018-19. The vaccine requirement calculated for August 2018 and February 2019 for BCG and OPV are 681 and 950 respectively. **Conclusion:** Time series analysis can be used to estimate vaccine requirement at Medical Colleges.

Key Word: Vaccine estimation, time series analysis, exponential smoothing

***Address for Correspondence:**
Dr. Varsharani V.Kendre, Associate Professor, Dept. of Community Medicine, BJGMC, Pune, Maharashtra, INDIA.
Email: mundevarsharani@yahoo.com

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INTRODUCTION

Routine Immunization 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 Centers, Subcenters, Rural Hospitals, and Tertiary Care Hospitals etc. Traditionally vaccine requirement is estimated with the following steps especially, where denominator is known. Conduct the head count through the Community Needs Assessment Approach or the biannual/annual survey method. For pregnant women, the headcount would provide a point estimate for only 6 months (as pregnancies in the first trimester may be undetected). Hence, multiply the headcount by 2 to arrive at an estimate for 12 months. 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[2] is allowed for all vaccines. The wastage multiplication factor for OPV is 1.18 and for BCG, it is 2.0[3]. However this method cannot be used in situation where denominator is not known. Time series analysis is a specialized area of statistics to which many marketing researchers have had limited exposure, despite it having many important applications in marketing research (MR). Two popular univariate time series methods are exponential smoothing (e.g.- Holt-Winters) and ARIMA (autoregressive integrated moving average)[4]. Forecasting techniques are important tools in operational management for creating realistic expectations[5]. 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 fix i.e. denominator is not known.

OBJECTIVE

To estimate vaccine requirement using time series analysis, at Government Medical College, Latur

MATERIAL AND METHODS

Study Design: The present study is cross sectional; record based study.

Study Setting: Government Medical College, Latur. A Tertiary Care Hospital is attached to Government Medical College.

Data Collection: The data regarding vaccines used viz.BCG and OPV during previous six years i.e. from 2009-10 to 2014-15 was collected from Immunization Report Book maintained at Immunization 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 as analyze-forecasting- create models. Method used was Expert Modeler. While there was another method called ARIMA. But 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 as model fit statistics and for individual models, we used autocorrelation function (ACF) and partial autocorrelation functions (PACF) plot. In autocorrelation and partial autocorrelations we used natural log transform with difference of 1. The lags used for study were 16. Time series analysis and forecasting was done using best-fit models

RESULTS

A total of 38361 doses of BCG 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. For OPV vaccine, total 67348 doses 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 2010.Average number of doses and standard deviation is shown in Table 2. For BCG vaccine, the autocorrelation function (ACF) and partial autocorrelation functions (PACF) were significant for first lag 1 and PACF decays exponentially indicating moving averages(MA) model(fig.1 and 2). The ACF and PACF were not significant at any lag for the series of OPV vaccine (fig.3 and 4) indicating stationarity of the series. Expert modeler of SPSS ver. 21 suggested simple seasonal model as the best fit statistical model for OPV and winter's additive model for BCG time series data. Table 3 shows model statistics. R squared value for BCG model was 0.655 and it was 0.780 for polio model. Here stationary *R*-squared value was used since it provides an estimate of the proportion of the total variation in the series that is explained by the model. Larger values of stationary *R*-squared (up to a maximum value of 1) indicate better fit. A value of 0.78 meant that the model could explain 78% of the observed variation in the series. This table also shows the Ljung-Box Q statistics and its *P*-value. It was not significant for polio model (p= 0.337) and it was significant for BCG model (p= 0.031). Both models detected no outlier in the data. Table 4 shows exponential smoothing model parameters. It shows values of alpha (level), gamma (trend) and delta (season) for BCG model. Here gamma value is more indicating prominence of trend component in the model. In case of polio model values of alpha (level) and delta (season) are shown. Alpha value is more in OPV model indicating prominent level component. Forecasting was done using the best model i.e. simple seasonal model for OPV and winter's additive model for BCG till 2018-19. It is shown in table 5 and table 6 also shown by figures 5 and 6. The vaccine requirement calculated for August 2018 for BCG was 681 with 867 and 496 as upper and lower confidence intervals. For OPV vaccine, for February 2019, it was 950 with 1378 and 522 as upper and lower confidence intervals.

Table 1: Yearwise and month wise BCG doses used

Month/Year	2009	2010	2011	2012	2013	2014
April	460	507	437	458	640	570
May	474	527	456	542	560	536
June	498	530	559	570	570	530
July	340	450	475	528	196	720
August	274	485	534	593	317	678
September	128	490	659	633	560	670
October	640	596	567	594	560	660
November	600	501	493	616	620	720
December	429	544	527	456	618	680
January	509	447	473	496	470	700
February	387	382	472	580	510	652
March	506	511	621	870	580	620
Total	5245	5970	6273	6936	6201	7736
Mean	437.08	497.5	522.75	578	516.75	644.66
S.D.	140.57	54.30	68.53	108.74	132.65	66.63

Table 2: Yearwise and month wise OPV doses used

Month/Year	2009	2010	2011	2012	2013	2014
April	1124	911	804	745	1060	1020
May	1169	846	848	1009	1056	960
June	1137	974	947	955	986	920
July	899	844	817	870	543	1196
August	803	813	908	998	852	1440
September	818	772	933	1440	1074	1060
October	1107	872	824	121	1040	420
November	1179	834	1150	1080	1040	1160
December	802	1026	893	960	990	1300
January	845	785	777	920	820	1132
February	730	717	854	960	894	1000
March	706	870	979	1050	940	1020
Total	11319	10264	10734	11108	11295	12628
Mean	943.25	855.3333	894.5	925.6667	941.25	1052.333
S.D.	183.9586	85.43507	101.6317	301.8836	151.441	248.8107

Table 3: Model Statistics

Model	No. of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
BCG-Model_2	0	.655	26.789	15	.031	0
Polio-Model_1	0	.780	17.787	16	.337	0

Table 4: Exponential Smoothing Model Parameters

Model			Estimate	SE	t	Sig.
BCG-model_2	No Transformation	Alpha (Level)	.001	.024	.042	.967
		Gamma (Trend)	.500	13.342	.037	.970
		Delta (Season)	.001	.123	.005	.996
Polio-Model_1	No Transformation	Alpha (Level)	.100	.059	1.700	.094
		Delta (Season)	9.573E-006	.109	8.822E-005	1.000

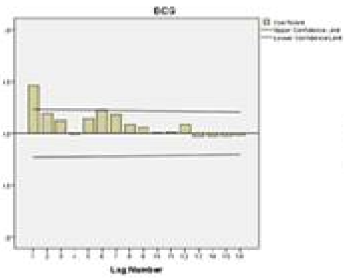

Figure 1

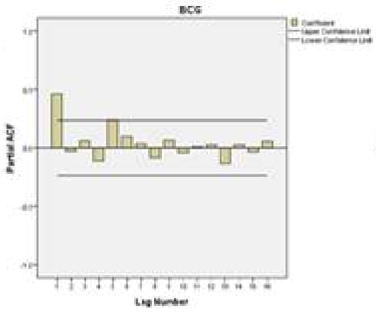

Figure 2

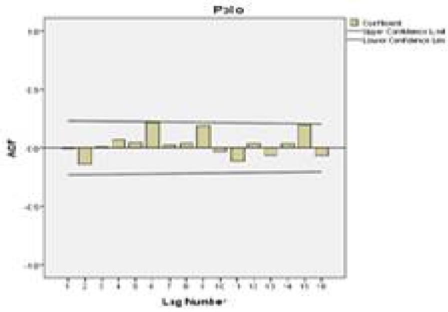

Figure 3

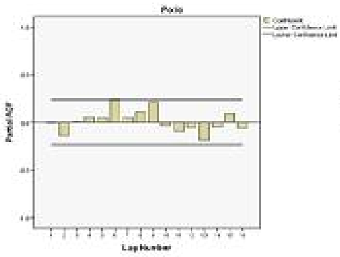

Figure 4

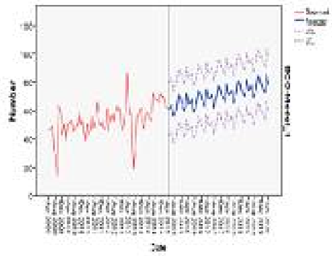

Figure 5

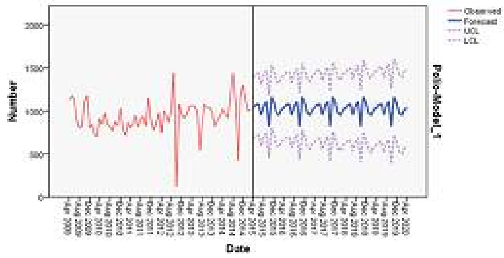

Figure 6

Table 5: Yearwise forecasts for BCG vaccine requirement provided by Winter's additive model

Model	BCG-Model_1		
	Forecast	UCL	LCL
Apr 2015	615	800	430
May 2015	619	804	434
Jun 2015	646	831	461
Jul 2015	555	740	370
Aug 2015	583	768	398
Sep 2015	626	811	441
Oct 2015	706	891	521
Nov 2015	695	880	510
Dec 2015	645	830	460
Jan 2016	619	804	434
Feb 2016	600	785	415
Mar 2016	721	906	536
Apr 2016	648	833	463
May 2016	652	837	467
Jun 2016	679	864	494
Jul 2016	587	772	402
Aug 2016	616	801	431
Sep 2016	659	844	474
Oct 2016	739	924	553
Nov 2016	727	913	542
Dec 2016	678	863	493
Jan 2017	652	837	466
Feb 2017	633	818	448
Mar 2017	754	939	569
Apr 2017	681	866	495
May 2017	684	870	499
Jun 2017	711	897	526
Jul 2017	620	805	435
Aug 2017	649	834	463
Sep 2017	692	877	507

Oct 2017	771	957	586
Nov 2017	760	945	575
Dec 2017	711	896	525
Jan 2018	684	870	499
Feb 2018	666	851	480
Mar 2018	786	972	601
Apr 2018	713	899	528
May 2018	717	903	532
Jun 2018	744	930	559
Jul 2018	653	838	467
Aug 2018	681	867	496
Sep 2018	725	910	539
Oct 2018	804	990	618
Nov 2018	793	979	607
Dec 2018	744	929	558
Jan 2019	717	903	531
Feb 2019	698	884	512
Mar 2019	819	1005	633

Table 6: Yearwise forecasts for OPV vaccine requirement provided by simple seasonal model

Model	Polio-Model_2		
	Forecast	UCL	LCL
Apr 2015	1035	1390	681
May 2015	1072	1429	716
Jun 2015	1078	1436	720
Jul 2015	953	1312	593
Aug 2015	1060	1422	699
Sep 2015	1107	1470	744
Oct 2015	822	1187	457
Nov 2015	1165	1532	798
Dec 2015	1086	1455	718
Jan 2016	971	1341	601
Feb 2016	950	1322	579
Mar 2016	1019	1392	645
Apr 2016	1035	1410	660
May 2016	1072	1449	696
Jun 2016	1078	1456	699
Jul 2016	953	1333	572
Aug 2016	1060	1442	678
Sep 2016	1107	1491	724
Oct 2016	822	1207	437
Nov 2016	1165	1552	778
Dec 2016	1086	1475	698
Jan 2017	971	1361	581
Feb 2017	950	1342	559
Mar 2017	1019	1412	626
Apr 2017	1035	1430	640
May 2017	1072	1469	676
Jun 2017	1078	1475	680
Jul 2017	953	1352	553
Aug 2017	1060	1461	659
Sep 2017	1107	1510	705
Oct 2017	822	1226	418
Nov 2017	1165	1571	759
Dec 2017	1086	1493	679
Jan 2018	971	1380	562

Feb 2018	950	1361	540
Mar 2018	1019	1430	607
Apr 2018	1035	1448	622
May 2018	1072	1487	658
Jun 2018	1078	1494	661
Jul 2018	953	1370	535
Aug 2018	1060	1479	641
Sep 2018	1107	1528	686
Oct 2018	822	1244	399
Nov 2018	1165	1589	741
Dec 2018	1086	1512	661
Jan 2019	971	1398	544
Feb 2019	950	1378	522
Mar 2019	1019	1448	589

DISCUSSION

In the present study of time series analysis, expert modeler of SPSS version 21 showed Winter's additive model for BCG and 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. 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[7-8], Sachin S Mumbare[9]. Emrah Onder[5] used exponential smoothing model in his study. Sachin S Mumbare[9] in his study used Box-Jenkins ARIMA (p, d, q); autoregressive integrated moving averages; nonseasonal models for the analysis and forecast the average number of children at the time of terminal contraception in each group, till 2020. He found the time series to be nonstationary, as interpreted by augmented Dickey-Fuller test, so the series was analyzed 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 normalized 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 [7] 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[9] 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[7]. Varun Kumar[8] in his study on Seasonality of Tuberculosis in Delhi used ARIMA model for seasonality which showed both declining trend and periodic seasonal fluctuations. In this study the expert modeler of SPSS ver. 21 suggested Winter's multiplicative model as the best fitted mathematical model. A value of stationary *R*- squared value of 0.698 meant that the model could explain 69.8% of the observed variation in the series. This value is more than that of stationarity R squared of BCG model and less than that of polio model in the present study; indicating better fit of polio model. 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]. Win wah [11] 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 analyze 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[12].

CONCLUSIONS

Expert Modeler was used in this study of time series analysis, it showed simple seasonal model as best fit model in case of OPV. It can be used to estimate vaccine requirement of OPV, as Ljung Box Q statistics is not significant. Expert modeler showed Winter's additive model for BCG, which can be used for estimating BCG vaccine requirement with caution as the Ljung Box Q statistics is significant. Time series analysis and forecasting is 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 at Medical colleges.

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