International Academic Institute for Science and Technology

International Academic Journal of Business Management
Vol. 6, No. 1, 2019, pp. 110-119.

ISSN 2454-2768

International Academic Journal of Business Management

www.iaiest.com

A bottom-up hierarchical forecasting of broadband penetration in India using ARIMA & DES approaches

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Abstract

Broadband connectivity has been linked with economic growth and is accelerating human progress. On a global platform, the penetration of broadband in India is still not convincing. A host of initiatives are aimed at empowering our society digitally, especially the 'Digital India' programme of Government of India. While major research thrust is found in areas of policy and technology issues, broadband usage through handheld devices, and its likes, sparse empirical evidences are found on the future of broadband penetration in Indian context. This study aims to plug the under explored area uniquely by predicting the digital connectivity status in India through broadband medium using bottom-up hierarchical forecasting approach. Here, separate forecasts are made for individual levels of hierarchy, the wireless and the wireline mediums, and aggregation of them done finally to arrive at the total forecast of the higher level. To identify the best fitted model that may be used for prediction, two alternative methods; auto regressive integrated moving average (ARIMA) and double exponential smoothing (DES) techniques have been used and hierarchical forecast made with it till 2020. The error estimates indicate that the ARIMA model fits better than the DES model for both wireless and wireline broadband series. From the study results it may anticipated that wireless medium would drive broadband connectivity in future. Further, by 2020, wireless broadband coverage in India is expected to reach 800Mn which means a penetration of 58%. The hierarchical forecast of total broadband reach is expected to touch 821Mn with 59.4% penetration. Even a conservative estimation of the same is projected at 646Mn i.e. 47% penetration, which is a massive growth from 85.7Mn in 2014.

Keywords: ARIMA, double exponential smoothing, broadband, bottom-up forecasting

DOI: 10.9756/IAJBM/V6I1/1910014
Received:8 February 2019/Accepted:6 May 2019/Published:18 June 2019

1. Introduction

Internet is one of the major innovations in the last century and has brought massive changes in the life and work of people around the world (Devezas, Linstone & Santos, 2005). Broadband is revolutionizing online footprint for businesses, entertainment and public services, with a speed 160 times faster than a dial-up connection (Jayakar & Park, 2013). Only 2,80,000 subscribers in India have access to a high-speed fibre optic connection (Siwach & Kumar, 2015). The average internet speed in India now stands at 4.1 Mbps and the performance is considered to be poor compared to other countries in the Asia Pacific region (ITU, 2015). The government of India, with the vision of 'Digital India' (Prasad, 2018) has allocated 5 billion to build high speed broadband highways connecting all the villages, government departments, universities, R&D institutes, etc. The National Optical Fibre Network (NOFN)project, worth 200 billion and funded by the Universal Service Obligation Fund, aims at providing broadband access to the country's 250,000 villages involving a mammoth task of laying 600,000 km of fibre across the country (BBNL, 2015). Even private sector participation, with Reliance stepping into the broadband sector with the rollout of JioGigaFiber, expects to grab 50 million users (Kudikala, 2018). The competition from private players is expected to increase efficiency and bring down the price of high speed digital services. Broadband penetration, both wired and wireless, is expected to enormously impact technological, economic, social changes and propagate the revolution of social inclusion. The broadband development scenario in Indian context is action packed with a host of initiatives in pipe line. The fact that this area has been under-researched in India, emerged as an area of research interest. With multifold implications of broadband penetration, it becomes imperative to examine its future dynamics.

1. A Theoretical basis of research

As per the World Bank report, in the developing countries, a 10% increase in broadband penetration increases the per capita GDP by 1.38% (Siwach & Kumar, 2015). They further opine that with a large number of subscribers, mostly concentrated in urban areas, there is a huge economic opportunity in rural India. One may find several similar observations on the immense power of broadband penetration in the way citizens socialize, work and educate themselves, keep themselves gainfully and healthily engaged (Bojnec & Ferto, 2012; Kolko, 2012; Jayakar & Park, 2013; Jiménez et al., 2014). Upgradation of human capital in knowledge based economy through broadband diffusion is also highlighted (Johnson, Manyika & Yee 2005). Empirical researches further observed that income, educational level, urbanisation, and competition have a positive impact on the diffusion of broadband (Lee & Brown, 2009). According to Ramamurthi (2007), the broadband services can be best provided through wireless technology in rural India. Sparse empirical evidences are available on future of broadband penetration in Indian context, with most studies focusing on the potential of broadband usage through the rapidly penetrating handheld devices, especially the smartphones. Considering the positive outlook of the government and private players on developing broadband infrastructure to build a socially inclusive India, an estimation of penetration of it has remained under explored for both the hierarchical components, wireless and wireline medium. This unexplored domain intrigued the researchers as an area where further meaningful research may be conducted using time series data for individual hierarchies and finally aggregate the forecasts that is not only of academic interest but also of relevance to practitioners in this field. A hierarchical time series is a collection of several time series that are linked together in a hierarchical structure. Following literature, we found three existing approaches to hierarchical time-series forecasting. It usually involve either a top-down method or a bottom-up method or a combination of both and is often referred to as the middle-out approach. The top-down method involves forecasting the aggregated series, then

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disaggregating the forecasts based on the historical or forecast proportions (Gross & Sohl 1990; Athanasopoulos et al., 2009). The bottom-up method involves forecasting each of the disaggregated series at the lowest level of the hierarchy, and then using aggregation, forecasts at higher levels of the hierarchy (Kahn 1998) is found out. The middle-out method starts at an intermediate level of the hierarchy chosen by the user, and then aggregation is used to obtain forecasts at higher levels and disaggregation is used to obtain forecasts at lower levels. In the present study, both wireline broadband and wireless broadband form the lowest level of hierarchy, also called the nodes. They aggregate to total broadband at the highest level of the hierarchy.

The rest of the paper is organized as follows. Section 2 highlights the study objectives. Section 3 provides an overview on the research methodology and also mentions the data source. Section 4 details the analysis and findings while in section 5 conclusion is drawn.

2. Research Objectives

Three inter-related objectives were framed that best serves the scope of the study. The first objective intends to develop the best fitted model for predictive purpose. The second objective is aimed at forecasting broadband subscription using the model developed while the third objective uses the forecast values to predict its penetration in Indian context.

3. Research Methodology

The statistical approaches to time series forecasting appears to find large popularity. Within its domain, the single, double and triple exponential smoothing techniques make up the family of exponential smoothing models and they hold expansive use in forecasting (Bermudez, Segura, & Vercher, 2007). Substantial use of double exponential smoothing (DES) is seen across varied areas of forecasting (T. Booranawong & A. Booranawong, 2017; Karmaker, Halder & Sarker, 2017). The other most accepted and widely used approach include that of Box-Jenkins auto regressive integrated moving average, ARIMA, models (Maria & Eva, 2011). Christodoulos, Michalakelis and Varoutas (2010) describes its versatility as a method that is capable of analysing practically most of the time series data sets. Literature exposes huge applications of ARIMA covering diverse areas ranging from demand estimation of consumer goods (Dhini, Surjandari, Riefqi & Puspasari, 2015) to retail sales forecasting (Ramos, Santos & Rebelo, 2015). Applications are also found in financial sector (Edward & Jyothi, 2016; Alwadi, 2015), in service sector (Farhath et al., 2016) and in health care (Soyiri & Reidpath, 2013; Jing, 2017) among various other applications areas. The next section discusses the theoretical framework of ARIMA and DES.

ARIMA Model: The Box-Jenkins Approach

An ARIMA model is rooted to the parametric time series models, the autoregressive moving average models (ARMA). Hanke and Wichern (2015) expresses the p^{th} order autoregressive process; AR (p) and the q^{th}-order moving average process; MA (q) in equation 1 and 2 respectively.

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \dots\dots\dots\dots + \emptyset_p Y_{t-p} + \varepsilon_t \quad \text{..... (1)}$$

$$Y_t = \mu + \varepsilon_t - w_1 \varepsilon_{t-1} - w_2 \varepsilon_{t-2} - \dots\dots\dots - w_q \varepsilon_{t-q} \quad \text{..... (2)}$$

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Here Y_t : response variable at time 't'; $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$: response variable at time lags (t-1), (t-2), …, (t-p) respectively, $\emptyset_0, \emptyset_1, \dots, \emptyset_p$: coefficients to be estimated, μ represents the constant mean of the process, ε_t: error at time 't' which actually represents the effect of variables not explained by the model and $\varepsilon_{t-1}, \dots, \varepsilon_{t-q}$: error at time lags (t-1), …, (t-q).

The AR models are appropriate for stationary time series and equation (3) represents the general form of an ARMA (p,q) model. Models for non-stationary series, called the autoregressive integrated moving average models is denoted by ARIMA (p,d,q) which gives highly acceptable results for short to medium term forecasting, where d: order of differencing. For a stationary time series (d = 0) ARIMA model reduce to the ARMA model.

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t - w_1 \varepsilon_{t-1} - w_2 \varepsilon_{t-2} - \cdots - w_q \varepsilon_{t-q} \quad \text{..... (3)}$$

ARIMA model building is done in stages. The three main stages include model identification, estimation followed by final selection of the model. The details under each of these steps are:

Model Identification – After checking stationarity in data set (Dickey & Fuller, 1979), sample auto correlation function (ACF) and partial autocorrelations (PACF) are compared with the theoretical ARMA models summarized in Table 1. Finally the best model is identified based on AIC (Akike, 1974) or BIC (Schwarz, 1978) values and principle of parsimony.

	Autocorrelations	Partial Autocorrelations
MA (q)	Cut off after order q of the process	Die out
AR (p)	Die out	Cut off after the order p of the process
ARMA (p,q)	Die out	Die out

Source: Hanke, J.E. and Wichern, D. (2015). Business Forecasting

Model Estimation –Assessment of error and t-values of coefficients is a requisite (Cooper & Hedges, 1994; Adhikari, 2013). Mean absolute error (MAE) and mean absolute percentage error (MAPE) have been considered in the study.

Model Checking – The residuals of the best fitted or selected model is tested. The tests include Ljung-Box test (Ljung & Box, 1978), auto regressive conditional heteroscedasticity (ARCH) test (Engle, 1982) and normality assumption using Jarque-Bera test (Jarque & Bera, 1980). The residuals must be free from serial correlation, however, it is useful but not mandatory for the residuals to also meet normality and ARCH assumptions (Hyndman, 2014).

Double Exponential Smoothing (DES)

This method of Holt (2004) adjusts for the trend in the time series data and is represented by three equations.

i. Exponentially smoothed series, $L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$

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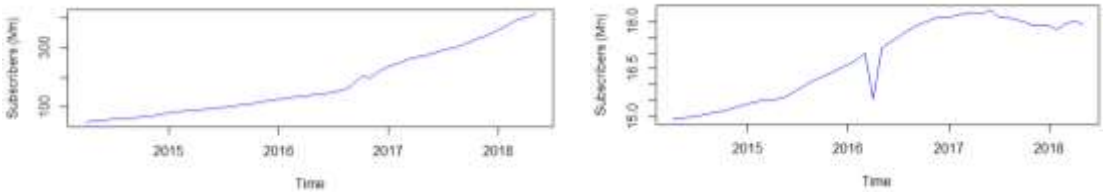
ii. The trend estimate, $T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$

iii. The forecast for *p*-periods into the future, $\hat{Y}_{t+p} = L_t + pT_t$

where L_t is estimate of the current level; α is smoothing constant $(0 < \alpha < 1)$; Y_t represents new observation in period *t*; β is the smoothing constant for the trend estimate $(0 < \beta < 1)$; T_t is the trend estimate and is the future forecast periods; $\hat{Y}_{t+p}$: forecast for *p*-periods into the future.

Data Collection

Monthly time series data of wireless and wireline broadband (BB) subscribers for the period Apr 2014 – May 2018was collected from the official website of Telecom Regulatory Authority of India (TRAI), a secondary source that is open to all. We had 50 observations for both the data sets which meets the minimum requirement for fairly accurate forecasting using ARIMA (Tseng, 2001). Outlier detection test shows no anomalies in the data set. Figure 1(a) Wireless BB Subscribers in India: 2014-18. Figure 1(b) Wireline BB Subscribers in India: 2014-18.



Source of Figures 1(a) & 1(b): Author's Computation based on secondary data

4. Analysis and Findings

The original time series of both wireless and wireline BB subscription were tested to detect trend, seasonality and stationarity. The test outputs are presented in Table 3. The wireless BB data series was differenced till order 2 while wireline BB data series differenced till order 1 to achieve stationarity. The analysis suggests presence of trend without seasonality in both the data sets.

Table 3. Trend, Seasonality & Stationarity Tests for data series

Type of Test	Name of Test	Output	Remarks
Wireless BB data series			
Trend Analysis (Units Series)	Mann-Kendall test	*p* -value = 2.2e-16	Trend present
Seasonality Analysis (Units Series)	ETS	ETS (M,A,N)	Seasonality absent
Stationarity Test (Units Series)	ADF test	*p* -value = 0.98	Non-Stationary data
Stationarity Test (differenced series; d=1)	ADF test	*p* -value = 0.06	Non-Stationary data
Stationarity Test (differenced series; d=2)	ADF test	*p* -value = 0.01	Stationary data
Wireline BB data series			
Trend Analysis (Units Series)	Mann-Kendall test	*p* -value = 4.2e-15	Trend present
Seasonality Analysis (Units Series)	ETS	ETS (M,A,N)	Seasonality absent
Stationarity Test (Units Series)	ADF test	*p* -value = 0.45	Non-Stationary data
Stationarity Test (differenced series; d=1)	ADF test	*p* -value = 0.01	Stationary data

Source: Author's Computation based on secondary data

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Wireless BB series - Initial examination of PACF (Figure 2(b).) suggests assumption of p as 1 or 2. Option p = 0 needs testing. From ACF (Figure 2(a).) the values of q appear to be 1 and 3 but it remains indecisive. Thus, all possible combinations of p & q had to be tested. At first six different model combinations were compared on the basis of AIC to identify the best one (Table 4) and the estimation of model parameters done separately (Table 5). AIC values suggest ARIMA(0,2,1) to be the best model. Parameter estimation results show ARIMA(0,2,1) with very low MAPE, MAE and highly significant co-efficients with t-statistic > 2, thus satisfying all model estimation tests. Finally, residual diagnostic tests indicate that the selected model do not have any serial correlation, satisfies ARCH conditions but fails normality conditions, though this is not a mandatory criteria to be satisfied as shown in Table 6. The best fit ARIMA(0,2,1) was then compared with the DES model that generated alpha=0.5254, MAE=3.29 and MAPE=1.99. Thus, ARIMA(0,2,1) is chosen as the best fit model for forecasting till Dec-2020 (Figure 4(a) and Table 7).

Figure 2(a). ACF of Wireless BB Series (d=2)

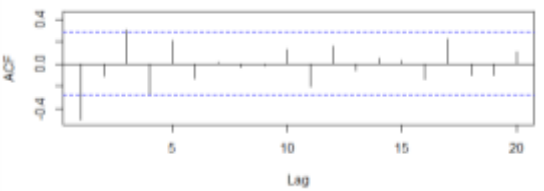
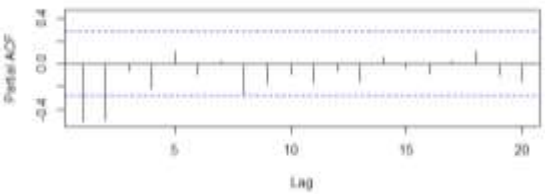


Figure 2(b). PACF of Wireless BB Series (d=2)



Source of Figures 2(a) & 2(b): Author's Computation based on secondary data

Wireline BB series – Preliminary examination PACF (Figure 3(b).) suggests assumption of p as 1 or 0. ACF (Figure 3(a).) clearly suggests values of q to be 1. Three possible combinations of p & q are tested. To start with, the AIC of three different models are compared to identify the best one. Table 4 captures the AIC of wireline broadband series and Table 5 shows the parameter estimates, calculated separately. AIC values suggest ARIMA(0,1,1) with drift to be the best model. Parameter estimates reveal this model to have very low MAPE, MAE and significant co-efficients with t-statistic > 2. Thus, the model qualifies all estimation tests. Residual diagnostic tests suggest ARIMA(0,1,1) with drift do not have any serial correlation, satisfies ARCH test but do not show normal distribution of residuals, as shown in Table 6. Now, the DES model is compared with the best fit ARIMA(0,1,1) with drift. The DES model yields alpha=0.1819, MAE=0.18 and MAPE=1.08. Thus, ARIMA(0,1,1) with drift, having lower error estimates, is better compared to the DES model and forecast made with it till Dec-2020. The graphical plot of wireline broadband subscription forecast which actually represents the wireline broadband penetration forecast is shown in Figure 4(b) while Table 7 shows point forecast values as well as forecast at 80 and 95% level.

Figure 3(a). ACF of Wireline BB Series (d=1)

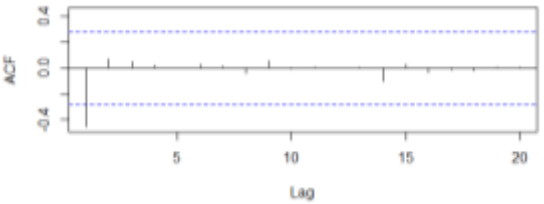
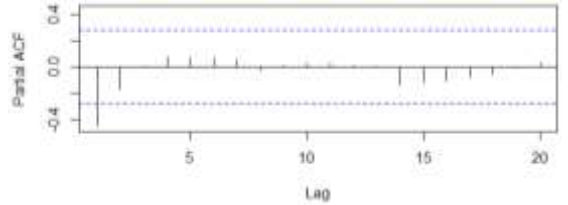


Figure 3(b). PACF of Wireline BB Series (d=1)



Source of Figures 3(a) & 3(b): Author's Computation based on secondary data

DOI: 10.9756/IAJBM/V6I1/1910014
Received:8 February 2019/Accepted:6 May 2019/Published:18 June 2019

Table 4. AIC of ARIMA comparative models

ARIMA Models for Wireless BB	AIC	ARIMA Models for Wireline BB	AIC
ARIMA(0,2,1)	297.6	ARIMA(1,1,1)	28.2
ARIMA(1,2,1)	299.3	ARIMA(0,1,1)	27.4
ARIMA(2,2,1)	299.0	ARIMA(0,1,1) with drift	23.7
ARIMA(0,2,3)	301.1		
ARIMA(1,2,3)	298.9		
ARIMA(2,2,3)	298.2		

Source: Author's Computation based on secondary data

Table 5. Parameter estimation of best ARIMA models

Data Series	ARIMA Models	Co-efficients			T-statistic	Significance	MAE	MAPE
Wireless BB	ARIMA(0,2,1)	ma1	Est.	-0.7779	8.49	Y	3.13	1.79
			s.e.	0.0916				
Wireline BB	ARIMA(0,1,1) with drift	ma1	Est.	-0.4444	7.03	Y	0.15	0.93
			s.e.	0.0632				
		drift	Est.	0.1069	4.59	Y		
			s.e.	0.0233				

Source: Author's Computation based on secondary data

Table 6. Residual diagnostic test of ARIMA models

Data Series	Model	Box-Ljung Test	ARCH-LM Test	Jarque-Bera Test
Wireless BB series	ARIMA(0,2,1)	*p* -value = 0.5372	*p* -value = 0.0537	*p* -value = 1.01e-07
Wireline BB series	ARIMA(0,1,1) with drift	*p* -value = 0.5574	*p* -value = 0.9054	*p* -value = 2.20e-16

Source: Author's Computation based on secondary data

Figure 4(a). Forecast for Wireless BB

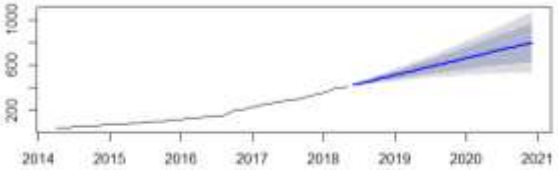
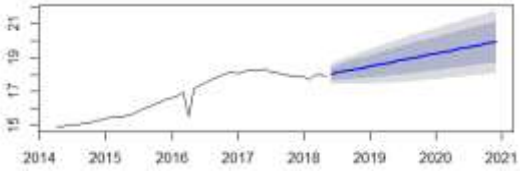


Figure 4(b). Forecast for Wireline BB



Source: Author's Computation based on secondary data

Table 7. Forecast of Wireless Broadband Subscription (in Mn) till 2020.

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Wireless BB					
Dec-2018	501.5	471.6	531.3	455.8	547.1
Dec-2019	651.3	559.0	743.6	510.2	792.5
Dec-2020	801.2	627.6	974.8	535.7	1066.7
Wireline BB					
Dec-2018	18.4	17.8	19.1	17.5	19.4
Dec-2019	19.2	18.2	20.2	17.7	20.7
Dec-2020	19.9	18.7	21.2	18.1	21.8

Source: Author's Computation based on secondary data

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The point forecast values indicate wireless and wireline broadband penetration to touch 801Mn and 20Mn respectively by 2020 which are precisely the forecasts for individual hierarchies. This means 801Mn of the projected 1383Mn Indian population (Census of India) i.e. 58% would have access to wireless broadband internet services. A conservative estimation at 80% confidence level shows 646.3Mn Indian population to have wireless broadband internet services with 47% penetration level. The aggregation of wireless and wireline broadband penetration yields what is known as bottom-up hierarchical forecast for broadband penetration. It is estimated at 821Mn (59.4%) while a conservative estimation shows total broadband penetration to be 646Mn (47%) assuming no duplication among wireless and wireline broadband users.

5. Conclusion

The bottom-up hierarchical predictive analysis on broadband penetration provides gainful insights with the study results highlighting wireline broadband to remain as the more preferred medium of internet connectivity to the wireline medium. The combined broadband penetration is expected to cover 821Mn i.e. nearly 60% of Indian population by 2020. Even a conservative estimation for the same period predicts 47% broadband penetration which is a massive growth from 85.7Mn in 2014 when its penetration was at meagre 7%. Such a sea change is expected to improve the national output, consolidate India's position in the global broadband map, and make social inclusion a near reality. Since the present study is based on statistical methods, future study on the same topic may consider neural network, a machine learning approach, as one of the forecasting tools and comparison drawn with the statistical approaches. Further, the study did not take into consideration the correlations between different hierarchies along different time periods of the data series. Modifications to the existing bottom-up approach may be contemplated.

Acknowledgements

The authors express their gratitude to Mr. Deepak Singh for his support in data collection and its treatment.

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