Forecasting Exports of Tea from India : Application of Arima Model

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Abstract

Exports form an integral part of decision making for a large country like India. Tea is an important beverage which is homogeneously essential in the domestic sector and across the globe, transcending geographical boundaries, social groups and ages. About seventy three percent of the world's tea exports come from four countries, including India. This paper uses time series model namely ARIMA to make short term forecasting of tea exports in India using 79 monthly observations. The battery of diagnostic tests are conducted to examine the efficacy of the model hence built. The model ARIMA (1,1,0) has the lowest AIC and BIC criteria, since it has two parameters following the principle of parsimony ,this model is chosen An eight period ahead export of tea is predicted. The observations indicate a rising trend in exports. The model fitting is compared with SES and HES to show that ARIMA has higher fitting accuracy than exponential smoothing. The implications of the results developed in the paper is useful for considering short term market fluctuations in export of tea in India.

Keywords : *ARIMA model, forecasting, export, tea ,India.*
JEL Classification : *C 53, F 17, F 23.*

1. INTRODUCTION

Time series model for forecasting is of vital significance to several real-world spheres. Numerous research has been pursued in the recent decade in this field. The literature discusses many models, used in time series forecasting, however the accuracy and efficiency of model building may vary. The basic purpose in time series model is to judiciously gather sample observations and study the observations, in order to construct a suitable model that reflects the characteristic structure of the relevant observations. This relevant model may be used to make forecasts by generating future observations of the series. In sum time series model building help us to ascertain the future by studying the past. Time series model building is of immense importance in economics, business and trade. This paper deliberates on the future of India's short term export performance of tea , using monthly time series data from June 2010 to December, 2016, the data sets are obtained from Directorate General of Commercial Intelligence and Statistics. Tea has been accepted is a popular

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beverage across the globe, irrespective of age groups, geographical areas and socio economic status. The world wide exports of tea during 2015 stand at 1805 million kilograms. However the production of tea is concentrated mainly in China, India, Sri Lanka and Kenya. These countries together share about 73 % of world export market in 2015. Table (1) reports the production and export behavior of major tea producing countries of the world. Tea in India is mainly grown in Assam, West Bengal, Tamil Nadu and Kerala. The finest tea are found in Darjeeling, Assam and in the Nilgris. During 2015-2016 India recorded the highest production of tea (1233.14 million kilograms); Tea Board, 2015-2016. Again after a span of long thirty five years in the financial year 2015-2016 India's export of tea reached 232.92 million kilograms. The countries which imported tea from India are Russia, Germany, Iran, Pakistan, Poland, Bangladesh, China, U.K. and the UAE. Against this backdrop it is interesting to study the variation in export of tea and predict the future trend of exports particularly to enable the export councils to develop their proper marketing and evaluation strategy.

Table 1.
Production and Exports of Major Tea Producing Countries of the World, 2015

Countries	Production, Share in Percent	Export, Share in Percent
China	43	18
India	23	13
Kenya	7	25
Sri Lanka	6	17
Others	21	27

Source: Tea Board of India: Annual Report, 2015

Autoregressive Integrated Moving Average (ARIMA) model is applied here to study the forecasting behaviour. ARIMA models are extensively used stochastic time series model ,in various areas of economic forecasting, for example in predicting inflation (Olajide et al, 2012). The acceptance of the ARIMA model is particularly due to its ability to represent varieties of time series, further the well formulated Box-Jenkins methodology has enabled the optimal model developing task. However a shortcoming of building ARIMA model is the behavioural assumption of linearity associated with the observations which may make the model building redundant in many cases. Besides the ARIMA model, this study will compare forecasting results from simple exponential smoothing (SES) and holt two-parameter exponential smoothing (HES) to investigate the effectiveness of the ARIMA model. The paper is designed as follows Section II makes a brief review of the literature on time series forecasting behaviour with ARIMA model in economics . The broad objectives of the study are discussed in Section II.I. The methodology and data sets utilized is explained in Section III. The major results are discussed in Section IV, finally the paper is concluded in Section V.

2. REVIEW OF LITERATURE

The literature on ARIMA model application in forecasting is varied and immense. Verma et al (2016) developed ARIMA model to forecast coriander prices for a mandi in Rajasthan.The paper concludes that such study will enable our farmers to take proper cropping choices.Sankaran, S. (2014) uses seasonal auto regressive integrated moving average model to forecast the daily demand for fresh vegetables in Mumbai (India), wholesale market. The study concludes that the model developed could be used to forecast with a mean absolute percentage error of 14 percent. Paul et al (2013) using SARIMA model forecast monthly export behavior of meat from India. The study demonstrates an increasing behavior in the case of meat exports from India. Upadhyay (2013) uses Box Jenkins methodology to get a best fit ARIMA model to forecast export and import of wood based panel in India using time series data for 1996/97 -2011/2012.The Bayesian criteria and mean absolute percentage error are used to obtain the best fit model. Mehmmood (2012) utilizes ARIMA model to forecast export from Pakistan to the SAARC countries. The study concludes that ARIMA (1,1,4) is the most suitable model to forecast Pakistan's exports. The paper observes that the responsibility lies on the government of the country to boost export potential products. Pattranurakyothin and Kumnungkit (2012) uses the ARIMA model to predict the export behavior of rubber in Thailand. Weerapura and Abeynayake (2012) uses ARIMA model to forecast tea production in Sri Lanka during 2011, the results were compared with Exponential Smoothing techniques. The paper concludes on the need to develop model and update data sets to predict the future of tea industry in Sri Lanka.

Naz (2012) uses ARIMA forecasting methodology to forecast export of dates from Pakistan. Datta&. Mukhopadhyay (2012) uses ARIMA model to forecast export of software services in India, the study has important implications for future of software trade in IndiaBadmus&Ariyo (2011) uses ARIMA model to forecast production of maize in Nigeria. Sankar (2011) using ARIMA methodology to forecast export of fish in Tamil Nadu (India).The study uses the ACF, PACF criteria along with Box-Ljund statistic to choose the appropriate model. Gijo (2011) using Box-Jenkins seasonal auto regressive integrated moving average model forecasted the monthly demand for tea in India. The paper concludes that such study is important in planning production activities more efficiently.

Balogh , Kovacs et al (2009) uses ARIMA on forecasting of international tourists arrival to India for 2007-2010 and also to Thailand . This study has immense association in analysis of the balance of payments of the concerned countries. The paper observes that tourism will be on a growing trend for both the countries. Aidan et al (1998) uses an ARIMA framework to forecast Irish inflation. The paper uses two approaches namely the Box Jenkins method and the objective penalty function methods. The paper categorically gives the steps required to develop an ARIMA time series model. Gupta (1993) using monthly data over the period January, 1979 to July, 1991 developed an ARIMA model to forecast tea production in India. The paper establishes a sound model building exercise.

From the preceding analysis it is amply demonstrated that ARIMA model is a major forecasting tool for linear time series observations.. The current exercise attempts to select the best fit ARIMA model to forecast export of tea in India, the model supremacy is tested with simple exponential smoothing (SES) and holt two-parameter exponential smoothing (HES) . In this exercise selection of the model is based on the principle of parsimony. To determine the forecast accuracy a class of five performance measure is used.

3. OBJECTIVES OF THE STUDY

The Major Objectives of the study is as follows :

i) To find out whether the sample of observations are stationary or not. If the observations are not stationary the observations are to be altered into stationary using appropriate conversion.

ii) To choose the best ARIMA model following the principle of parsimony and selection principles.

iii) Forecasting based on SES and HES methods is compared with the chosen best fit ARIMA model.

iv) Finally , forecasting the export in value of tea for the next eight points (out sample forecast) with efficacy.

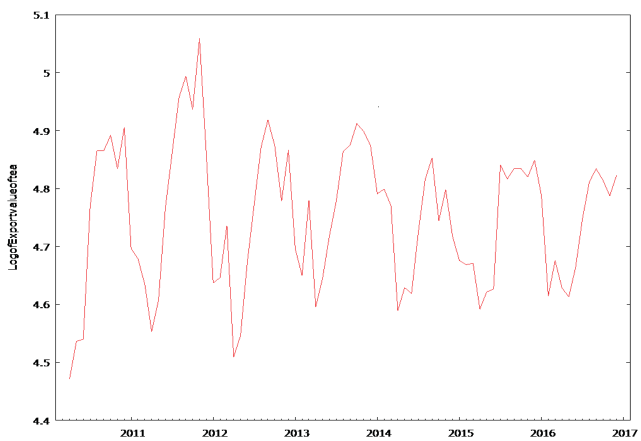
4. ON DATA SETS AND METHODOLOGY APPLIED

Data Sets

The paper has obtained data sets from Directorate General of Commercial Intelligence and Statistics, http://dgciskol.nic.in. The observations are from June, 2010 to December

2016, (seventy nine observations). Figure (1) shows the time series sequence graph of the total observations. The descriptive statistics of the sample data are found in Table (II). From the Figure (1) it is detected that even though some oscillations occur in the series the movement of the series is increasing. The variables are converted into their natural logarithmic forms, (Gujarati, 2003).

Figure 1.
Log of Export Value of Tea in Months, June (2010) to December (2016), India



Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

Table 2.
Descriptive Statistics of Tea Trade in Value (Monthly Observations), India

Measures	Log of Export in Values (tea)
Mean	4.7519
Maximum	5.0590
Minimum	4.4717
Standard Deviation	0.12315
Coefficient of variation	0.025915
Skewness	-0.099039
Kurtosis	-0.63064

Source: Directorate General of Commercial Intelligence and Statistics . Compilation Self

5. ON ARIMA MODEL

Autoregressive Integrated Moving Average (ARIMA) model is popularly used in time series forecasting. The fundamental postulation made to use this model is that the considered time series is linear and keeps to a specific statistical distribution, namely the normal distribution. The Autoregressive (AR), Moving Average (MA) and Autoregressive Moving Average (ARMA) models are subclasses of ARIMA model.

ARIMA (p,d,q) is a linear model originating from the autoregressive model AR (p), the moving average model MA (q) and thus the combination of the two AR (p) and MA (q) is the ARIMA (p,d,q). The model is developed as follows :

$$\left.\begin{array}{l} \Phi\,(B)\,\nabla^{d}\,x_t = \Theta\,(B)\,\varepsilon_t \\ E\,(\varepsilon_t) = 0,\ Var\,(\varepsilon_t) = \sigma_z^2,\ E\,(\varepsilon_t\,\varepsilon_s) = 0,\ s \neq t \\ Ex_s\,\varepsilon_t = 0,\ \forall_z < t \end{array}\right] \quad (1)$$

Where *p, q* are orders of the AR model and MA model respectively, *d* is the number of series difference. Her *p, d, q* are all integers ε_t. indicates the estimated residual at each time period. For optimal conditions the model should be independent and distributed as normal random variables with mean = 0. σ_z^2 is the variance of the residuals.

$$\nabla^{d} = (1 - B^{d})$$

$$\Phi\,(B) = (1 - \phi_t B) - \cdots - \phi_p B^{p}$$

$$\Theta\,(B) = 1 - \theta\_\,(1)\,B - \cdots - \theta\_(q)\,B^{Q}$$

Here Φ (B) and Θ (B) are polynomials in B of degrees *p* and *q*. B is backward shift operator.

The ARIMA model process is executed in the following steps :

1. Identification of the ARIMA (*p,d,q*) order.
2. Estimation of the coefficients.
3. Fitting test on the estimated residuals and Diagnostic Testing
4. Forecasting the future from given set of data.

a) **Identification of the ARIMA (p,d,q) order :** The first step in building a ARIMA model in equation (1) is to check stationarity of the time series data. If the series does not show stationarity, it has to be made stationary by proper differencing. To check the stationarity, first the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) of the original time series are to be plotted, if the series are not stationary then proper differenced order is required to make the series under consideration stationary. Using Correlogram analysis the p and q of the model is to be fitted , this is based on iterative process and on the Goodness of Fit, the Akaike's and Bayesian Information criteria is used here.For AR(p), the ACF tails off at the order of p but the PACF cutoff, for MA (q) , the ACF cutoff but PACF tails off at the order of q, again for ARMA (p, q) none of the ACF and PACF tail off.

b) **Estimation of the coefficients :** The model expressed in equation (1) has to be been assessed by iterative process till residual sum of squares become least.

c) **Fitting test on the estimated residuals and Diagnostic Testing :** The adequacy of the fitted model can be checked by diagnostic checking. This involves the task of examining the residuals from the fitted model to see whether there is evidence of non-randomness. The correlogram of the residuals is calculated and it can be seen how many coefficients are significantly different from zero. If there are N number of observations 1/√N gives an upper bound for the standard error of the residuals. The values, which fall outside the ±2/√N are significantly different from zero. The test statistic used for checking the randomness of the residuals is Ljung Box Statistic (Ljung and Box, 1978). Ljung Box statistic is expressed as

$$Q = N\,(N + 2)\,\Sigma_{k=1}^{h} \frac{\hat{p}_k^{z}}{N - k} \qquad (2)$$

Where N is the number of observations, $\hat{\sigma}_k$ is the autocorrelation of order lag k and h stands for the number of lags being tested. For H0 : Q ~ χ_h^2. For H_A : Q > $\chi^2_{1-a,h}$ where $\chi^2_{1-a,h}$ stands for the α – *quantile* of the chi-squared distribution with h degrees of freedom. The ACF of the residuals is plotted to check the adequacy of the fitted model.

d) **Forecasting the future from given set of data :** Finally the ARIMA model is used to forecast results, with upper and lower limits .The upper and lower limits provide a confidence interval implying any realization within the interval will be accepted.

Due to the importance of application of time series forecasting models , the accuracy of the model built has to be scrutinized. This is done through application of various forecast performance measure. This study has used the following forecast performance measure to test the accuracy of the model. Before elaborating on the measures the following definitions are important- Let be y_t the actual value, f_z be the forecasted value; then the forecast error can be written as $e_t = y_t - f_z$, the size of the sample is denoted by n. Let $\bar{Y} = \frac{1}{n} = \Sigma_{t=1}^{n} y_t$ be the mean value of the observations and = is accordingly the variance of the set of observations.

Mean Forecast Error (MFE)

This is denoted as MFE $= \frac{1}{n} = \Sigma_{t=1}^{n} e_t$. (3)

It is essentially a measure of average of deviation of forecasted values from the actuals.

Mean Absolute Error(MAE)

This denoted as MAE $= \frac{1}{n} = \Sigma_{t=1}^{n} |e_t|$ (4)

This measures the average absolute deviation of forecasted values from the original series.

Mean Absolute Percentage Error (MAPE)

This is denoted as MAPE $= \frac{1}{n} = \Sigma_{t=1}^{n} \left| \frac{e_t}{y_t} \right|$ x 100. (5)

This denotes the percentage of average absolute error of occurrence.

Mean Percentage Error (MPE)

This is denoted as MPE $= \frac{1}{n} = \Sigma_{t=1}^{n} \left| \frac{e_t}{y_t} \right|$ x 100. (6)

This indicates the percentage of average error of occurrence while the forecasting is made.

Root Mean Squared Error (RMSE)

This is defined as RMSE $= \sqrt{\frac{1}{n} \Sigma_{t=1}^{n} e_t^2}$ (7)

Theil's U-Statistics

This is derived as U $= \frac{\sqrt{\frac{1}{n} \Sigma_{t=1}^{n} e_t^2}}{\sqrt{\frac{1}{n} \Sigma_{t=1}^{n} f_t^2} \sqrt{\frac{1}{n} \Sigma_{t=1}^{n} y_t^2}}$ (8)

This is a normalized measure of total forecast error.

Here $0 \leq U \leq 1$; $U = 0$ indicates perfect fit. However it must be noted that the measure is affected by change of scale and data transformation. For good forecast accuracy *U* statistic should be close to zero.

e) **On Exponential Smoothing :** This paper compares ARIMA results with exponential smoothing method. Exponential smoothing fits the trend of the series. The formulations for simple exponential smoothing (SES) and holt two parameter exponential smoothing (HES) are elaborated in equations (9) and (10) respectively:

SES $\hat{x}_t = ax_t + (1-\alpha)\hat{x}_{t-1}$ (9)

HES $\left.\begin{aligned} \hat{x}_t &= ax_t + (1-\alpha)\hat{x}_{t-1} + r_{t-1} \\ r_t &= g(\hat{x} - \hat{x}_{t-1}) + (1-g)r_{t-1} \end{aligned}\right\}$ (10)

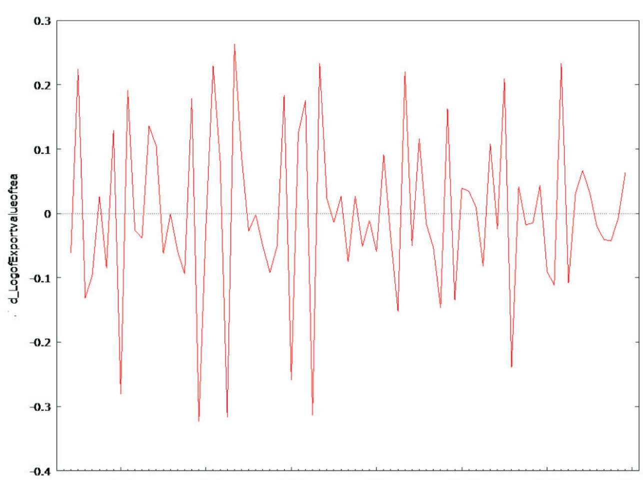
Here α and γ are smoothing coefficients. r_t denotes the variable of the trend series.

6. RESULTS AND DISCUSSION

a) **Model Identification :** ARIMA model is estimated only after converting the series of observations (sample data) considered for forecasting into a stationary series. The stationary series imply the values vary over time only around a constant mean and a constant variance. First we ascertain whether the series of observations of the sample data are stationary or not , observing from Figure (1) it is obvious that the series is non stationary. Non-stationary in mean is corrected through appropriate differencing of the data series under consideration. From Figure (2) it is obvious that the series at first difference is stationary. We confirm the stationarity of the series at first difference by performing unit root test, the Augmented Dickey Fuller Unit Root test is calculated in this exercise. The estimated ADF test results are shown in Table (III), from the observations we conclude that the series under first difference is stationary. So we adopt d = 1 for our ARIMA model (p, d, q).

Figure 2.

Log of Export Value of Tea (At First Difference); in Months, June (2010) to December (2016), India



Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self.

Table 3.
Dickey-Fuller test for unit root

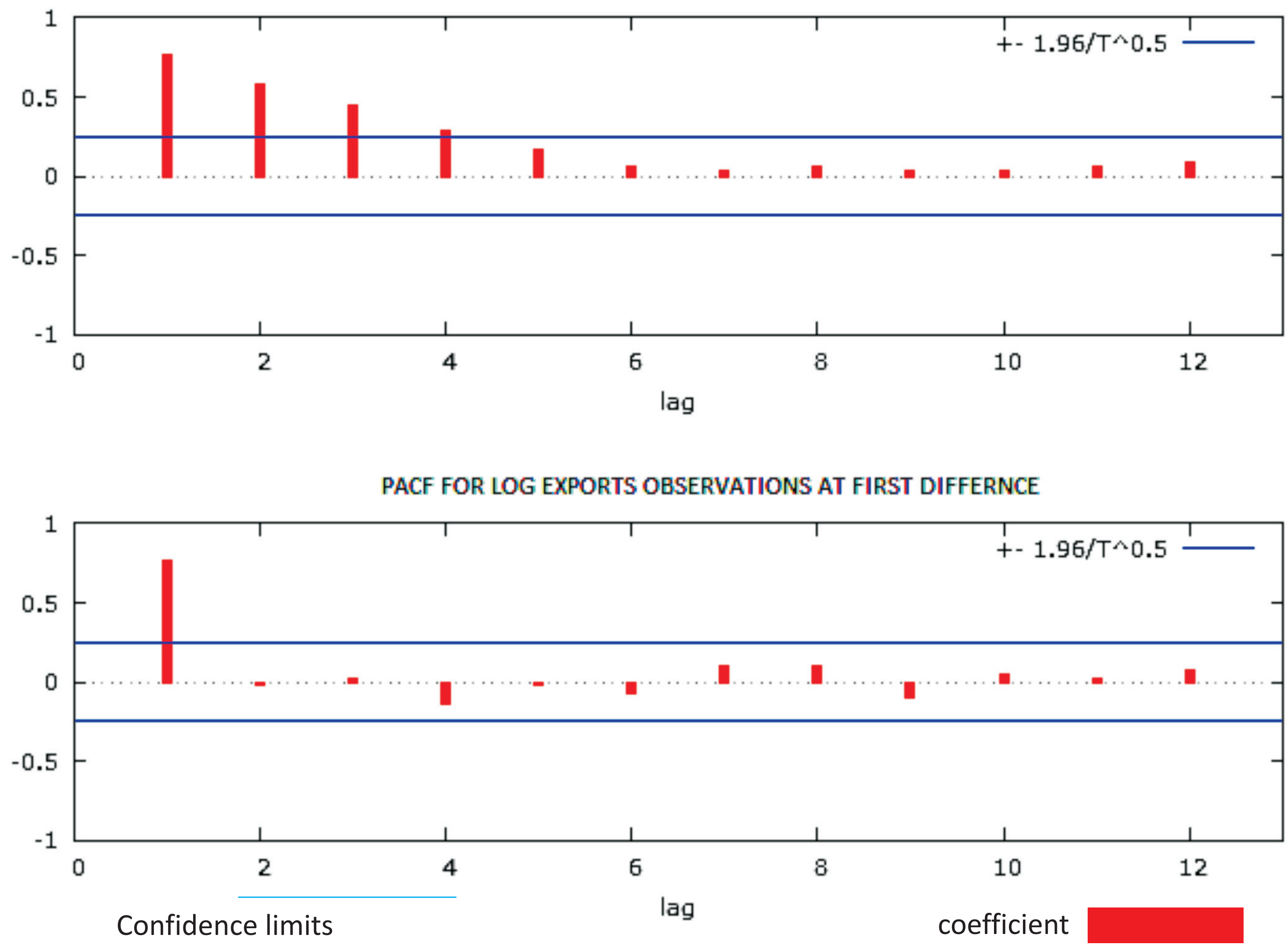
Test Statistic
-8.568*

Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

Notes: *Critical Value at 1 per cent-4.086 Critical Value at 5 per cent-3.471; Critical Value at 10 per cent-3.163. The sample data are at first difference.

Now the task is to find suitable values for p, q in the ARIMA model. The correlogram and the partial correlogram of the stationary series i.e. the first difference order of the sample data is examined . Figure (3) plots the auto correlation function (ACF) and partial autocorrelation function (PACF) respectively of the sample of observations at first difference.

Figure 3.
ACF and PACF of Log Exports of Tea, Observations in first difference
ACF of Exports of Tea, Observations at First Difference



Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

From Figure (3) it is found that the ACF tails off and PACF cutoff at the order of 1. So according to the identification principle explained in Section (III) the model is determined as AR(1). By iterative process various ARIMA models were fitted, the model with minimum normalized BIC values and AIC values are chosen. The model ARIMA(1,1,0) has the lowest AIC and BIC criteria, since it has two parameters following the principle of parsimony ,this model is chosen, Table (IV) reports all the AIC and BIC set of observations for different ARIMA model generated.

Table 4.
ARIMA (p, d, q) with AIC and BIC criteria

ARIMA (p, d, q)	AIC	BIC
ARIMA (1,1,1)	-135.2122	-123.3649
ARIMA (1,1,0)	**-112.5548**	**-105.4465**
ARIMA(0,1,1)	-125.3844	-115.9066

Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

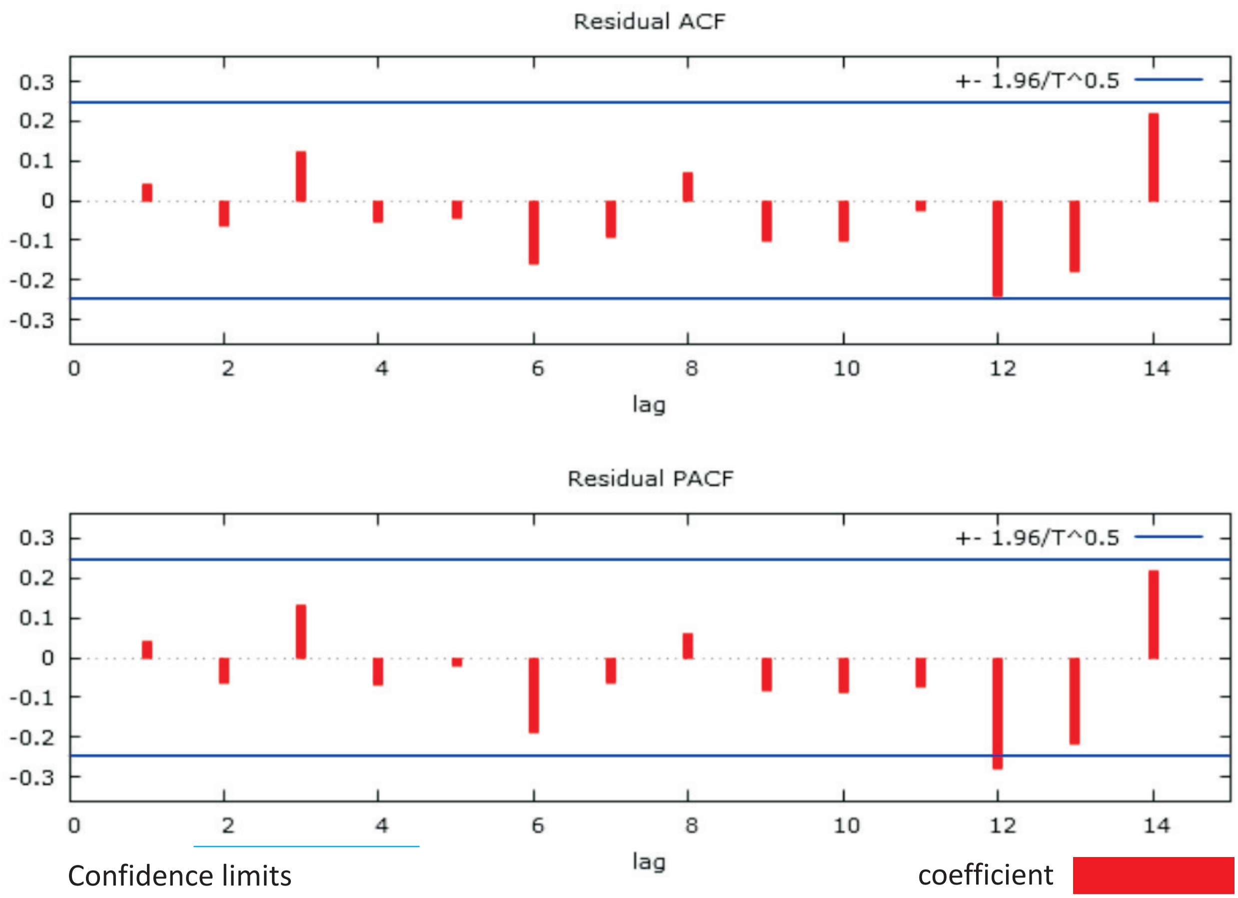
b) **Model estimation :** The ARIMA procedure fits the model with a certain number of coefficients which are significant. The P-value determines the significance level of the coefficients. The test result generate all parameters to be significant.

The final formulation of the model is

$$x_t - 0.003 = 0.4924\, x_{t-1} + \varepsilon_t \qquad (11)$$

c) **Diagnostic Checking :** This step involves checking the residuals of the model to see if they contain systematic pattern, this is examined through the autocorrelations and partial autocorrelations of the residuals at various lag order. Figure (4) shows the ACF and PACF of the residuals. It is evident that the ACF of the residuals are well within the significant bounds. Similarly all the PACF of the residuals are within significant limits. So there is no autocorrelation in the forecast residuals. Thus the ARIMA model fitted is a good fit. The histogram in Figure (5) enable us to infer that the errors are normally distributed. Again the Box Ljung test statistic presented in Table (V) for lag order upto 20 suggest the acceptance of null hypothesis of zero autocorrelation.

Figure 4.
ACF and PACF of Forecast Error (Residuals)



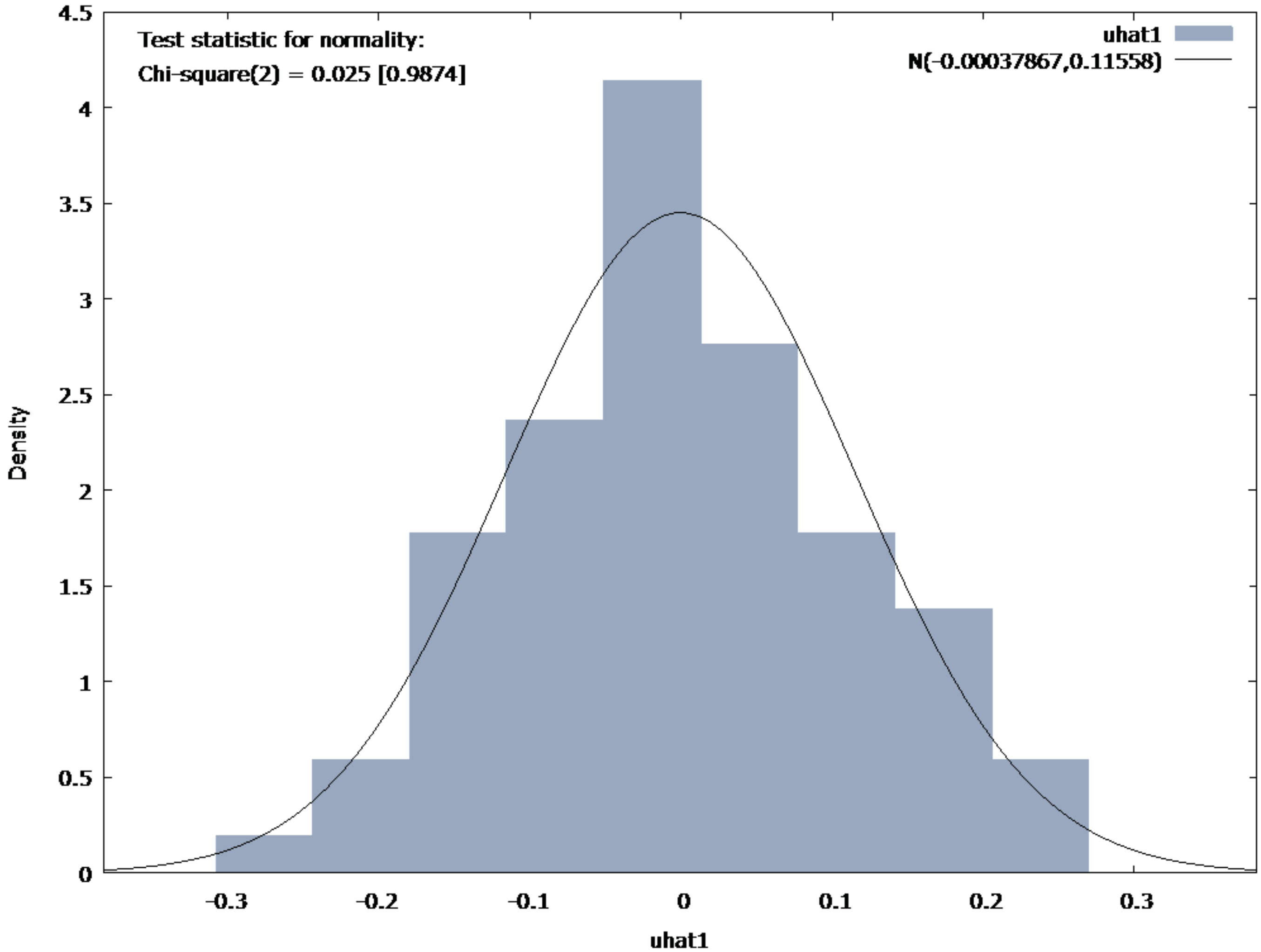
Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

Table 5.
Box Ljung Test Statistics

Test	? [2]	p-value
Box-Ljung	12.894	0.3205

Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

Figure 5.
Histogram of (Residuals)



Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

d) **Forecasting :** After performing the battery of diagnostic checking now the task is to forecast ARIMA (1,1,0) model. Forecasting can imply forecasting sample period forecasts and post sample period forecasts. Sample period forecasting are used to test the model developed and post sample period forecast gives the genuine utility of the model built. Both the two types of forecasts are presented in Table (VIa) and (VIb) respectively. The post sample period forecasting indicate that the exports of tea will be maintaining the trend as evident from monthly obesrvations. Figure (6) gives the graphical representation with confidence interval of exports in India.

Table 6 (a).
Sample Period Forecast of Log of Export Value of Tea, India

Months	Sample Observations	Forecasted Observation	Residuals
June, 2010	4.76837	4.57218	0.196194
July, 2010	4.86503	4.86318	0.00185083
August, 2010	4.86538	4.95798	-0.0926082
September, 2010	4.89208	4.98603	-0.0939436
October, 2010	4.83422	4.93857	-0.104352
November, 2010	4.90581	4.82247	0.0833415
December, 2010	4.69678	4.92025	-0.223462
January, 2011	4.67884	4.62786	0.0509772
February, 2011	4.63506	4.64245	-0.0073926
March, 2011	4.55305	4.52764	0.0254004
April, 2011	4.60710	4.50655	0.100556
May, 2011	4.76576	4.58005	0.185709
June, 2011	4.86187	4.79258	0.0692865
July, 2011	4.95722	4.95607	0.00115342
August, 2011	4.99385	5.07722	-0.0833734
September, 2011	4.93679	5.06984	-0.133059
October, 2011	5.05900	4.96771	0.0912914
November, 2011	4.85745	5.09304	-0.235591
December, 2011	4.63719	4.80537	-0.168183
January, 2012	4.64634	4.56308	0.0832521
February, 2012	4.73599	4.50101	0.234981
March, 2012	4.50958	4.67171	-0.162132
April, 2012	4.54656	4.46846	0.0780974
May, 2012	4.67361	4.52936	0.144255
June, 2012	4.77350	4.62587	0.147630
July, 2012	4.87130	4.85282	0.0184808
August, 2012	4.91862	4.97991	-0.0612940
September, 2012	4.87398	5.00010	-0.126126
October, 2012	4.77828	4.91267	-0.134391
November, 2012	4.86623	4.75464	0.111585
December, 2012	4.69576	4.84517	-0.149411
January, 2013	4.64993	4.62728	0.0226508
February, 2013	4.77973	4.62283	0.156901
March, 2013	4.59595	4.73283	-0.136883
April, 2013	4.64558	4.55604	0.0895401
May, 2013	4.71877	4.66094	0.0578233
June, 2013	4.77806	4.67615	0.101909
July, 2013	4.86386	4.83525	0.0286112

September, 2013	4.91216	4.92461	-0.0124472
October, 2013	4.89865	4.96031	-0.0616595
November, 2013	4.87456	4.90765	-0.0330896
December, 2013	4.87456	4.90765	-0.0330896
January, 2014	4.79128	4.87723	-0.0859472
February, 2014	4.79927	4.75180	0.0474718
March, 2014	4.77026	4.76620	0.00406610
April, 2014	4.58937	4.72706	-0.137688
May, 2014	4.62904	4.52806	0.100983
June, 2014	4.61877	4.57597	0.0427966
July, 2014	4.72498	4.54941	0.175572
August, 2014	4.81548	4.76865	0.0468249
September, 2014	4.85302	4.86639	-0.0133626
October, 2014	4.74429	4.93214	-0.187859
November, 2014	4.79839	4.75787	0.0405142
December, 2014	4.71736	4.79775	-0.0803854
January, 2015	4.67580	4.66085	0.0149458
February, 2015	4.66867	4.66105	0.00761725
March, 2015	4.67115	4.61903	0.0521213
April, 2015	4.59211	4.65058	-0.0584675
May, 2015	4.62174	4.56405	0.0576913
June, 2015	4.62672	4.60746	0.0192583
July, 2015	4.84108	4.60161	0.239466
August, 2015	4.81675	4.91743	-0.100683
September, 2015	4.83462	4.86989	-0.0352633
October, 2015	4.83462	4.92060	-0.0859743
November, 2015	4.82020	4.82753	-0.0073289
December, 2015	4.84892	4.82133	0.0275883
January, 2016	4.78764	4.85153	-0.0638952
February, 2016	4.61472	4.76927	-0.154551
March, 2016	4.67561	4.55537	0.120242
April, 2016	4.62874	4.61772	0.0110174
May, 2016	4.61318	4.55765	0.0555251
June, 2016	4.66428	4.61871	0.0455644
July, 2016	4.74766	4.65375	0.0939076
August, 2016	4.81129	4.77870	0.0325875
September, 2016	4.83424	4.87327	-0.0390364
October, 2016	4.81469	4.89187	-0.0771854
November, 2016	4.78741	4.83982	-0.0524126
December, 2016	4.82358	4.78128	0.0422951

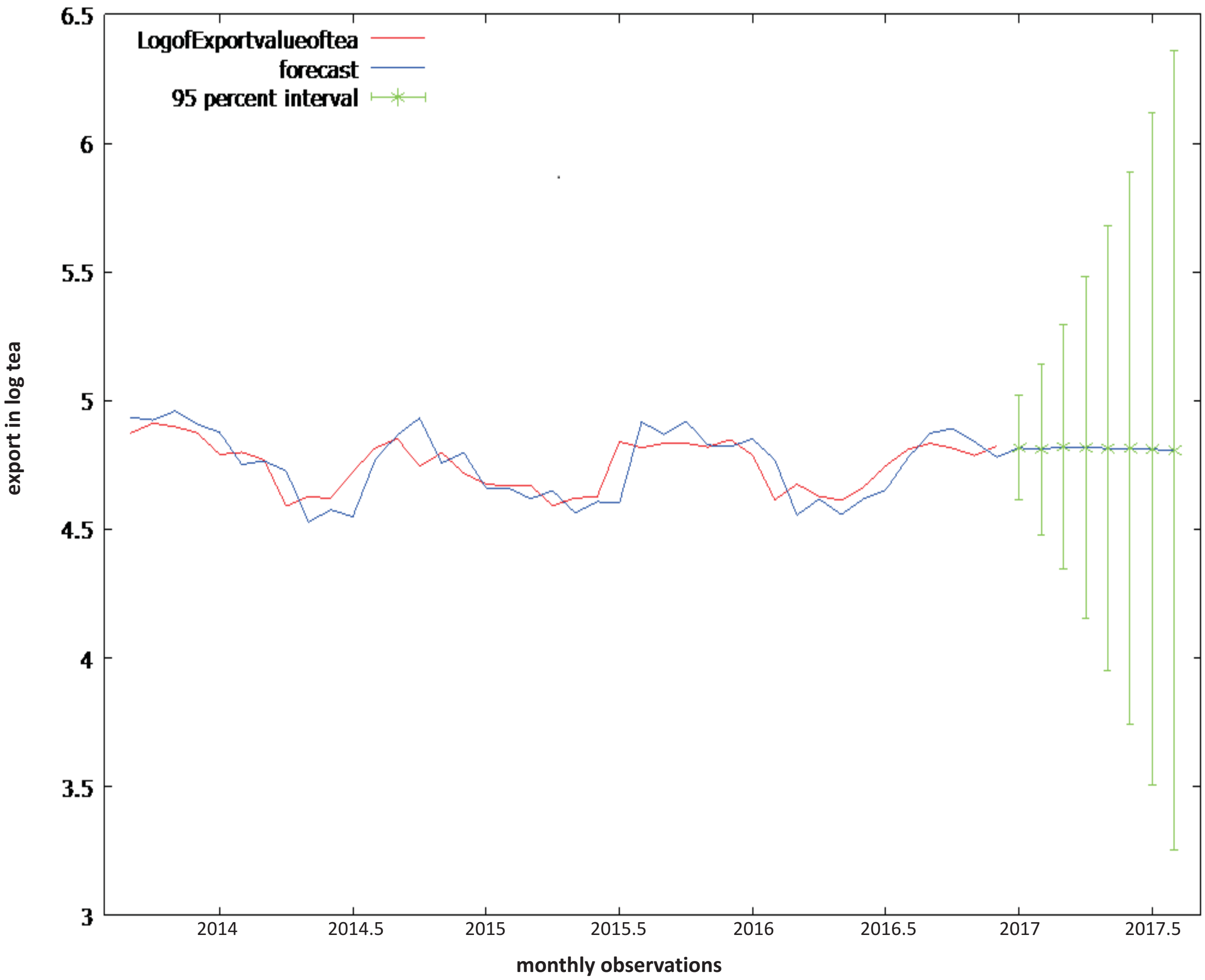
Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

Table 6 (b).
Post Sample Period Forecast of Log of Export Value of Tea, India

Months	Forecasted Observation	Standard Error	95% Confidence Interval
January, 2017	4.81666	0.103589	(4.61363, 5.01969)
February, 2017	4.81140	0.170000	(4.47821, 5.14460)
March, 2017	4.82098	0.242808	(4.34508, 5.29687)
April, 2017	4.81752	0.339290	(4.15252, 5.48251)
May, 2017	4.81500	0.439925	(3.95276, 5.67724)
June, 2017	4.81528	0.548146	(3.74094, 5.88963)
July, 2017	4.81123	0.666874	(3.50419, 6.11828)
August, 2017	4.80707	0.791813	(3.25514, 6.35899)

Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

Figure 6
Forecast Versus Actual



Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

While evaluating the forecast perfomance measure it is found that the mean forecast error is close to zero , again the value of mean absolute error is small. The mean percentage error is also small thereby suggesting good forecast evaluation . The Theil's U is 0.304 suggesting good forecast accuracy. (Table VII)

Table 7.
Forecast Performance Measure (ARIMA model)

Performance Measure	Statistics
Mean Forecast Error	0.000499
Mean Absolute Error	0.084552
Mean Percentage Error	0.012251
Mean Absolute Percentage Error	0.7805
Theil's U	0.304

Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

Next, the results of ARIMA (1,1,0) model forecasting is compared with SES and HES forecasting along with RMSE of the models. The smaller RMSE depict the goodness of the fit of the model.The fitting result shows that the ARIMA is the best forecasting model,Table (VII) .

Table 8.
RMSE and forecasting result of ARIMA, SES and HES

Model	RMSE	Forecasting Observation	Actual Sample observation
ARIMA	0.104	4.8862	4.8713 (July,2012)
SES	0.179	4.7731	
HES	0.198	4.7739	

Source: Directorate General of Commercial Intelligence and Statistics. Compilation Self

7. CONCLUSION

An ARIMA model offers a good technique for forecasting the magnitude of any time dependent variable. The fundamental motive of the study was to choose a model for forecasting export of tea in India. The principle of parsimony was used to fit the relevant model. ARIMA approach takes into consideration the postulate that past values of the series plus previous error terms encompass all the information required for the purposes of forecasting. The foremost benefit of ARIMA forecasting is that it needs observations on the time series only. Again, ARIMA is helpful if forecasting is done on a large set of time series. However ARIMA approaches for forecasting time series are not always convincing . Unlike other economic models they do not assume prior knowledge of any underlying structural associations. So policy simulations cannot be made with ARIMA method of forecasting.

Nevertheless, ARIMA models have been established to be robust particularly for creating short-run forecasts. So the task undertaken in this paper with ARIMA technique provides a formative standard for forecasting the export of tea. It is also evaluated with other forecasting technique to establish its superiority in its own right. The study proposes the ARIMA (1,1,0) as the best model for making forecasting for a period of eight months. It has statistically tested and validated the forecast errors. Thus the predictive power of the model is well derived. This paper is suitable for making the correct choice in business organisations of Indian tea markets.

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