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Application of Time Series Modelling for Predicting the Export Potential of Indian Leather Footwear

Jagathnath Krishna K.M.*,NithiyananthaVasagam S., Giriyappa, K. and Chandramouli, D.

Economics Research Division, CSIR-Central Leather Research Institute,Adyar, Chennai-600020, India
* E-mail of the corresponding author: jagath.krishna@gmail.com

Abstract

Indian leather industry plays a vital role in contributing towards Indian economy. Also it is the core strength of the Indian footwear industry. According to the Indian leather industry about 37% of the total leather export value is from leather footwear. This shows the importance of studying the trends in leather footwear export, to assist in decision making process. This article proposes a time series model based on monthly export values of leather footwear from India during January, 1999 to March, 2013. In this article based on the information criterion, we identified ARIMA (1, 1, 1) (1, 2, 2) model as a reasonable model to predict the export values of leather footwear from India. This proposed model is used to forecast the export values of leather footwear for the year 2013 – 2014.

Keywords: AIC, BIC, leather footwear export, forecast, SARIMA model, time series

1. Introduction

Indian leather industry plays a vital role in contributing towards Indian economy. Also it is the core strength of the Indian footwear industry. India is the second largest global producer of footwear after China. Many global retail chains seeking quality products at competitive prices are actively sourcing footwear from India. While leather shoes and uppers are produced in medium to large-scale units, the sandals and chapels are produced in the household and cottage sector. The industry is poised for adopting the modern and state-of-the-art technology to suit the challenging international requirements and standards. India produces more of gent's footwear while the world's major production is in ladies footwear. In the case of chapels and sandals, use of non-leather material is prevalent in the domestic market. Leather footwear exported from India are dress shoes, casuals, sport shoes, sandals, boots.

With changing lifestyles and increasing affluence, domestic demand for footwear is projected to grow faster than ever before. The Indian footwear sector has matured from the level of manual footwear manufacturing methods to automated footwear manufacturing systems. Many units are equipped with In-house Design Studios incorporating state-of-the-art CAD systems having 3D Shoe Design packages that are intuitive and easy to use. Many of the footwear industries in India are having excellent facilities for physical and chemical testing. The Indian footwear industry is gaining strengths towards maximizing benefits.

The strength of India in the footwear sector originates from its command on reliable supply of resources in the form of raw hides and skins, quality finished leather, large installed capacities for production of finished leather & footwear, large human capital with expertise and technology base, skilled manpower and relatively low cost labour, proven strength to produce footwear for global brand leaders and acquired technology competence, particularly for mid and high priced footwear segments. India is now a major supplier of leather footwear to world market.

The export value of leather footwear from India during the last financial year (April, 2012 to March 2013) is reported to be about Rs. 91638.2 million, which shows a substantial increase of Rs. 9342.6 million compared to that of previous period. Among the total export revenue from leather and allied products from India, the leather footwear alone constitutes nearly about 37% share annually. But once we look into the monthly export values, one can observe high fluctuations. Hence, the industry is looking forward to know the trends in export as well as its future. The information on export is available to the industry with a lag period of three to six months. Updated information on the current status of the export will give an idea to the industries to plan for the proper investment and to the decision makers to frame appropriate policies.

The literature review reveals that there are a very few articles that deals with modelling and analysis of the export values of different products. There are some studies related to export projections of rubber and marine products (See Venugopal and Prajneshu (1996), Tatiporn and Kanchana (2012)) which make use of statistical modelling techniques for predicting the export trends. This motivated us to look into the export performance of leather footwear through statistical modelling techniques like time series analysis.

The time series modelling finds applications in wide range of areas including economics, finance, medicine, meteorology, etc. (Brockwell and Davis (1996), Box and Jenkins (1970), Shumway and Stoffer (2006)). For the present study, we considered the monthly leather footwear export data from January, 1999 to March, 2012. The footwear export value for one year, April, 2012 to March, 2013 is used for validating the identified model. After validation, the data from January, 1999 to March, 2013 is considered for predicting the export value for the year 2013-2014. The section 2 will deal with the methodology adopted for the study. In section 3, the model identification, estimation and validation of the model along with the forecast is presented. Finally some concluding remarks are given in section 4.

2. Methodology

The method applied for analysing the 13 years of leather footwear export data is discussed in this section. According to Schumway and Stoffer (2006), time series is the characteristics of data that seemingly fluctuate in a random fashion over time. Usually the time series data are assumed to be stationary. If the series is stationary, the modelling of data can be done using auto regressive moving average (ARMA) process. The autoregressive models are formed based on the idea that the current value of the series x_t, can be explained as a function of *m* past values $x_{t-1}, \ldots, x_{t-m}$, where *m* determines the number of steps into the past needed to forecast the current value. The extent to which it is capable of forecasting a data series from its own past values can be assessed by looking into the autocorrelation function. Whereas, a moving-average model is conceptually a linear regression of the current value of the series against current and previous (unobserved) white noise error terms or random shocks. The combination of AR and MA model known as ARMA model is defined as follows.

Definition 2.1: A time series $\{x_t; t = 0, \pm 1, \ldots\}$ is *ARMA (p, q)* if it is stationary and

$$x_t = \phi_1 x_{t-1} + \ldots + \phi_p x_{t-p} + w_t + \theta_1 w_{t-1} + \ldots + \theta_q w_{t-q}$$

Where w_t is the Gaussian white noise processes with $\phi_p \neq 0, \theta_q \neq 0$ and $\sigma_w{}^2 > 0$. The parameters *p* and *q* are called the orders of autoregressive and the moving average respectively.

If the data is non-stationary, either transformation technique or differencing is applied at appropriate lag to achieve stationarity. In many situations, especially in economics and finance, the data are not stationary in general. So a refined model that could accommodate the differencing between the lag becomes important. Box and Jenkins (1970) has developed autoregressive integrated moving average (ARIMA) model that could accommodate the non-stationarity for modelling and prediction. The integrated ARMA or ARIMA model is a broadening of the class of ARMA models to incorporate differencing.

Definition 2.2: A process, $\{x_t\}$ is said to be *ARIMA (p, d, q)* if

$$\nabla^d x_t = (1-B)^d x_t$$

is*ARMA(p, q)*. In general, we will write the model as $\phi(B)(1-B)^d x_t = \theta(B) w_t$.

If $E\left[\nabla^d x_t\right] = \mu$, we write the model as

$$\phi(B)(1-B)^d x_t = \alpha + \theta(B) w_t,$$

where $\alpha = \mu\left(1 - \phi_1 - \ldots - \phi_p\right)$.

For modelling and analysis using ARIMA model, a few steps are involved. First plot a time series graph and search for some trends or outliers. If the variability increases over time, the variance in the data has to be stabilized using transformation. The second step is to identify the values for autoregressive order p, order of differencing d and moving average order q. After fixing the value of d, by looking into the sample auto correlation function (ACF) and partial autocorrelation function (PACF) of the corresponding differenced data, the values for p and q can be identified. After identifying the models, the parameter involved in the model has to be estimated.

The monthly leather footwear export data for a period of 13 years considered for the present study. The autocorrelation plot shows regular fluctuations indicating the presence of seasonal variation. Hence seasonal ARIMA model, a modified ARIMA model to account seasonal and non-stationary behaviour is considered for our study. The seasonal ARIMA or SARIMA model is defined as follows.

Definition 2.3: The seasonal autoregressive integrated moving average model or SARIMA of Box and Jenkins (1970) is given by

$$\Phi_P\left(B^s\right)\phi(B)\nabla_s^D\nabla^d x_t = \alpha + \Theta_Q\left(B^s\right)\theta(B)w_t,$$

where w_t is the usual Gaussian white noise processes. The general model is denoted as *ARIMA (p, d, q) (P, D, Q)$_s$*. The ordinary autoregressive and moving average components are represented by polynomials $\phi(B)$ and $\theta(B)$ of orders p and q respectively and the components $\Phi_P\left(B^s\right)$ and $\Theta_Q\left(B^s\right)$ of orders P and Q, and ordinary and seasonal differencing component by $\nabla^d = (1-B)^d$ & $\nabla^D = \left(1-B^s\right)^D$.

In the final step, among the class of identified models, one model has to be considered which satisfies all the statistical criteria for forecasting. This model should have minimum Akaikie information criteria (Akaike 1969, 1973, 1974) and Bayesian information criteria (Schewarz, 1978).

Definition 2.4: Akaikie's information criteria (AIC) is defined by

$AIC = \ln L + 2k$, where L is the Gaussian likelihood function and k is the number of free parameters.

Definition 2.5: Bayesian information criteria (BIC) is given by

$$BIC = -2\log L + k\log n.$$

Apparently, the difference between the AIC and BIC is the penalty term, instead of $2k$, it is $k*\log n$. However, BIC gives an asymptotically consistent estimate of the order of the true model. After identifying the model, the model parameters are estimated by least square method, where the method can be used for forecasting future values.

3. Results and Discussions

3.1 Modelling and Analysis of Leather Footwear Export Values:

The data used for the present study consists of 159 observations on monthly export values of leather footwear from January, 1999 to March, 2012. The analysis is carried out using R software. The time series plot for the data is given in Figure 1.

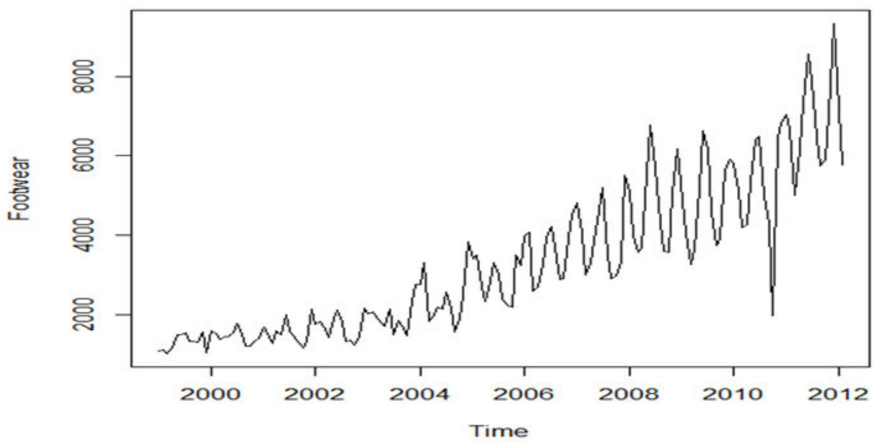

Figure 1: Time series plot for leather footwear export

It can be observed from the Figure 1, that the time series is not stationary and has seasonal variation. Therefore we differenced the original data once at lag 1 and also taken the seasonal difference once and the plot is given in Figure 2.

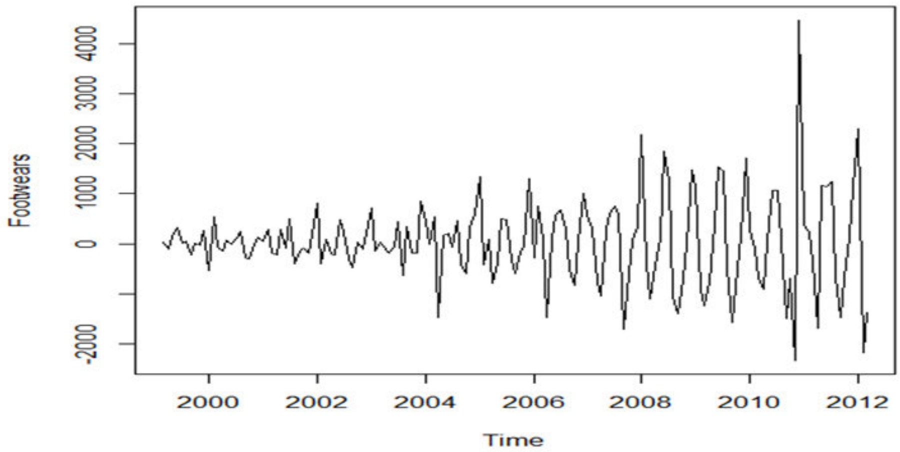

Figure 2: Time series plot with first order ordinary difference and seasonal difference

The differenced series is appeared to be stationary and we confirmed the stationarity by conducting the unit root test, Augmented Dickey Fuller (1979) test. As the p-value for the test is less than 0.05, we reject the unit root null hypothesis at 5% level of significance, which shows the data are stationary. Even though now our data is stationary, to search for possible models for forecasting, we tried with one more seasonal differencing and conducted the unit root test, which also showed significance and is given in Figure 3.

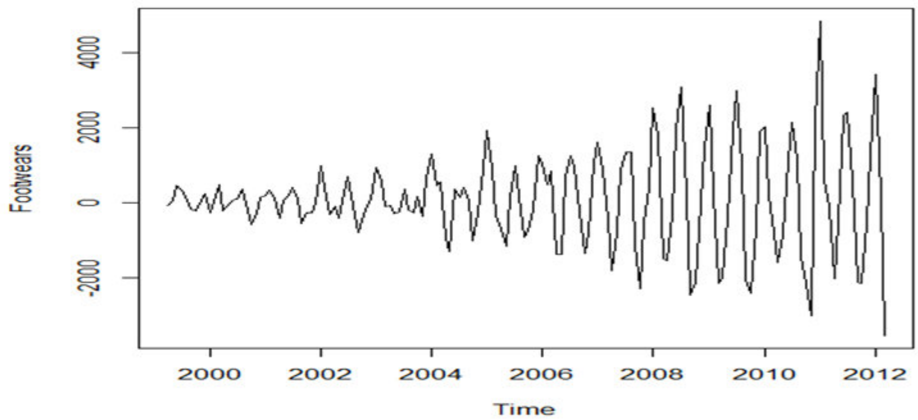

Figure 3: Time series plot with first order ordinary difference and second order seasonal difference

From Figure 2 and 3, it is observed that the series is stationary with few outliers. The ACF and PACF plots of ordinary differencing at lag 1 and seasonal differencing at lag 2 are shown in Figure 4.

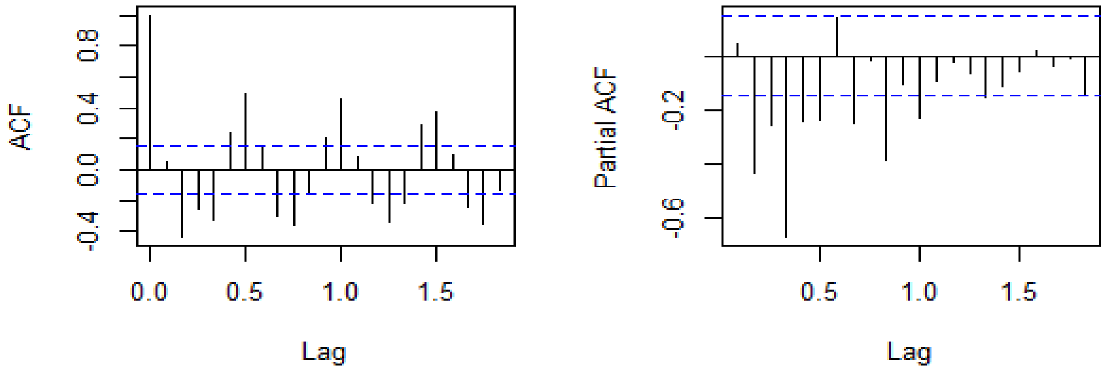

Figure 4: ACF and PACF plot for first order ordinary difference and second order seasonal difference

Based on the ACF and PACF models have been identified. Model selection was made using AIC and BIC, which are a goodness of fit for particular model by balancing the errors of the fit against the number of parameters in the model. For each of the identified model, AIC and BIC values are estimated and are given in Table 1.

Table 1: Comparison of Time Series Models

Model	AIC	BIC
ARIMA(1,1,1)(0,1,1)	2252.68	2264.59
ARIMA(1,1,1)(0,2,1)	2140.24	2151.81
ARIMA(0,1,1)(1,2,1)	2122.9	2134.46
ARIMA(0,1,1)(1,2,2)	**2116.06**	**2130.52**
ARIMA(1,1,1)(1,2,1)	2124.68	2139.34
ARIMA(1,1,1)(1,2,2)	2116.22	2133.56

From Table 1, the model, ARIMA (0,1,1) (1,2,2) which has the least information criteria (AIC, BIC) is considered as the best fit and the corresponding model is specified by

$$\left(1-\Phi_1 B^{12}\right)\nabla_{12}^{2}\nabla x_t = \left(1+\Theta_1 B^{12}+\Theta_2 B^{24}\right)\left(1+\theta B\right)w_t \tag{1}$$

For ARIMA (0,1,1)(1,2,2) model, the estimated parameter values are $\theta = -0.6904, \Theta_1 = -1.4963, \Theta_2 = 0.5316$ and $\Phi = -0.0691$, with standard errors 0.0988, 0.2435, 0.1760 and 0.1981 respectively. Hence the model (1) can be rewritten as

$$\left(1+0.0691*B^{12}\right)\nabla_{12}^{2}\nabla x_t = \left(1-1.4963*B^{12}+0.5316*B^{24}\right)\left(1-0.6904B\right)w_t \tag{2}$$

Where $\{x_t\}$ the original is time series on export of leather footwear and $\{w_t\}$ is the corresponding white noise. The normality test on residuals was performed to test the goodness of fit of the model. The null hypothesis for the test is that the residuals are white noise in nature. The fitted autocorrelation function (ACF) for the residuals shows the residues are following normal distribution. Since the Ljung–Box randomness test fail to reject the null hypothesis (p-value = 0.089 > 0.05) and the Figure 5 gives a clear indication that the residuals are asymptotically normally distributed. Hence our model, *ARIMA (0,1,1)(1,2,2)* is appropriate for prediction.

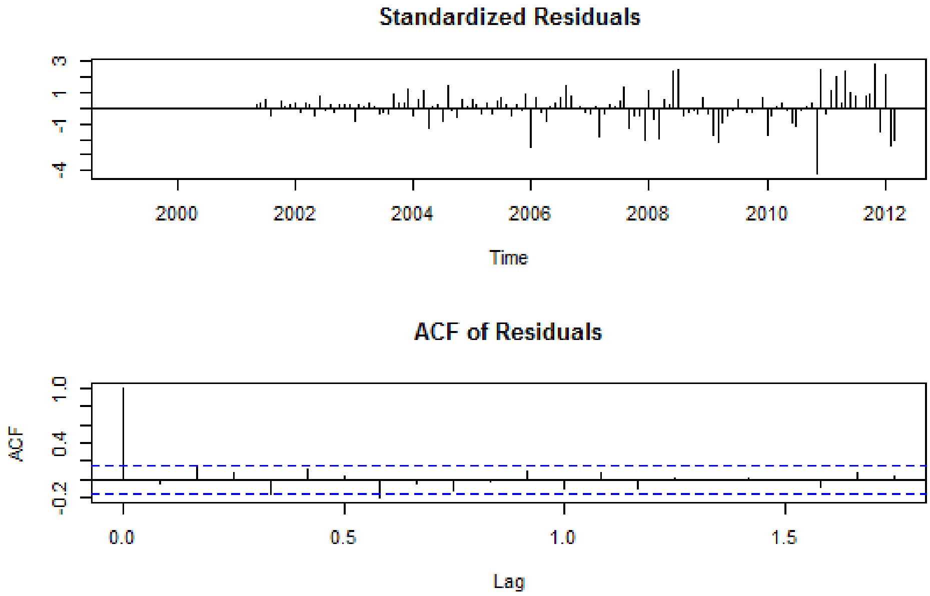

Figure 5: Plots for Residues

3.2 Validation of the Model ARIMA (0,1,1)(1,2,2)

To validate our results, we considered the leather footwear export values for the year April, 2012 to March, 2013 and compared the values with that of the forecast obtained from the identified model ARIMA (0,1,1)(1,2,2). The validations based on the actual values are provided in Table 2.

Table 2: Validation of the Forecast of Leather Footwear Export for the Year 2012-2013 Based on ARIMA (0,1,1)(1,2,2) Model

Forecast of leather footwear export for the year 2012-2013			
Period	**Forecasted value**	**Actual Value**	**% variation**
Apr-12	5468.83	5144.24	6.31
May-12	6127.62	6852.16	-10.57
Jun-12	7573.09	8823.59	-14.17
Jul-12	8998.99	9278.29	-3.01
Aug-12	8541.66	7894.85	8.19
Sep-12	6787.13	6254.33	8.52
Oct-12	5935.47	5418.9	9.53
Nov-12	5246.83	5960.52	-11.97
Dec-12	7848.59	7457.63	5.24
Jan-13	9400.53	8383.82	12.13
Feb-13	8269.73	8002.67	3.34
Mar-13	7153.71	7824.20	-8.57
Total	**87352.18**	**87295.2**	**0.07**

From Table 2, the percentage variation is more for the month of June, 2013 (-14.17%) and the least for July, 2012 (-3.01%). While looking into the one year export value, i.e., the total export value of leather footwear, the overall percentage variation is about 0.07% which is an acceptable amount of error. Keeping this in view, we had carried out further analysis based on the 14 year data starting from January, 1999 till March 2013. By re-doing all the procedures for identification of model, estimation of parameters and validation, we obtained the models given in Table 3.

Table 3: Comparison of SARIMA Models

Model	AIC	BIC
ARIMA(1,1,1)(0,1,1)	2440.89	2453.12
ARIMA(1,1,1)(0,2,1)	2337.96	2349.87
ARIMA(0,1,1)(1,2,1)	2319.14	2331.05
ARIMA(0,1,1)(1,2,2)	2310.14	2325.04
ARIMA(1,1,1)(1,2,1)	2317.92	2332.8
ARIMA(1,1,1)(1,2,2)	**2306.93**	**2324.79**

From Table 3, it can be observe that the model ARIMA (1,1,1)(1,2,2) is having the least information (AIC, BIC) criteria. Usually in time series modelling, when one incorporates additional information or data, there is a chance for getting a better model with least AIC or BIC than the original. Similarly, we got a revised model while incorporating additional one year data. ARIMA (1,1,1)(1,2,2) model is comparable with that of the model specified in (1), as the difference in the information measure is comparatively marginal. Even though we will use the model ARIMA (1,1,1)(1,2,2) for forecasting next one year data. The model is specified in (3) as follows;

$$\left(1-\Phi_1 B^{12}\right)\left(1-\phi B\right)\nabla_{12}^2\nabla x_t=\left(1+\Theta_1 B^{12}+\Theta_2 B^{24}\right)\left(1+\theta B\right)w_t \tag{3}$$

The parameter estimates for the model is obtained as
$\theta=-0.946, \Theta_1=-1.656, \Theta_2=0.690, \phi=0.302$ and $\Phi=0.033$, with standard errors 0.0797, 0.2407, 0.1885, 0.1071 and 0.1616 respectively. So the model (3) can be rewritten as,

$$\left(1-0.033\times B^{12}\right)\left(1-0.302\times B\right)\nabla_{12}^2\nabla x_t=\left(1-1.656\times B^{12}+0.690\times B^{24}\right)\left(1-0.946\times B\right)w_t$$

Hence the forecast for the year April, 2013 to March, 2014 can be made based on the identified model, *ARIMA (1,1,1)(1,2,2)* and the forecast with its confidence limits is given in Table 4.

Table 4: Forecast of Leather Footwear Export During the Year 2013-2014 Based on ARIMA (1,1,1)(1,2,2) Model

Forecast	Export value in million Rs.	95% Confidence Interval	
		Lower Limit	Upper Limit
Apr-13	6248.34	518.63	7312.26
May-13	7229.05	6098.56	8359.54
Jun-13	9001.28	7857.31	10145.27
Jul-13	10130.55	8981.2	11279.89
Aug-13	9270.02	8117.08	10422.95
Sep-13	7405.37	6249.32	8561.42
Oct-13	6474.47	5315.44	7633.52
Nov-13	6314.63	5152.60	7476.66
Dec-13	8595.31	7430.16	9760.46
Jan-14	10008.33	8839.76	11176.90
Feb-14	9159.61	7988.72	10330.49
Mar-14	8310.92	7137.18	9484.66

This forecast is useful for the industry and policy makers to framing appropriate strategies and policy decisions.

4. Conclusion

The forecasting of time series data is complicated, which requires a good understanding of the data and experience. In this article we identified the SARIMA model, *ARIMA (0,1,1)(1,2,2)* as a reasonable model for forecasting the export value of leather footwear which consists of nearly 37% of the leather export value from India. Validation for this model is made comparison with actual export values for the predicted year. Later by incorporating one more year data and proceeded in the same manner, identified *ARIMA (1,1,1,)(1,2,2)* model based on the information criteria like AIC and BIC. *ARIMA (0,1,1)(1,2,2)* can also be used for forecasting after incorporating the additional one year data, as the BIC value for this model is having only marginal difference of 0.25 compare to that of *ARIMA (1,1,1)(1,2,2)* model. Also statistical test for goodness of fit and Ljung-Box test for independence and unit root test for stationarity is also carried out for confirming the significance of the model. As *ARIMA(1,1,1)(1,2,2)* model satisfies all the criteria, this model is made use for predicting the leather footwear export value for the period 2013-2014.

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