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Forecasting Tea Auction prices in Sri Lanka: Box-Jenkins modeling approach

KEYWORDS Tea auction prices, SARIMA, Forecasting

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ABSTRACT Tea production plays a vital role in economy of Sri Lanka. Sri Lanka is the 3rd largest exporter and 4th largest producer of tea in the world. Therefore, it is useful to study the behavior of tea auction prices and develop a suitable model to forecast tea auction prices precisely. The objective of this study is to use Box-Jenkins modeling approach to forecast the tea auction prices in Sri Lanka. This study used the monthly tea auction prices in Sri Lanka over the period 1996 to 2016. According to AIC, SBC, MSE and R2 the most suitable model to forecast the tea auction prices in Sri Lanka is Seasonal Autoregressive Integrated Moving Average (SARIMA) (1,0,0)(0,1,0)12. Adequacy of the fitted model has been tested using ADF test, LM test, White's General test and Jarque-Bera test criteria. Forecasting performance of the fitted model is measured by using mean absolute percentage error (MAPE) criteria.

INTRODUCTION

Tea production plays a vital role in economy of Sri Lanka, and accounts for 2% of GDP, contributing over US $1.5 billion in 2013 to the economy of Sri Lanka. It employs, directly or indirectly, over 1 million people, (Industry Capability Reprt, Tea Sector, 2014). This has placed Sri Lanka in the positions of 3rd largest exporter, 4th largest producer of tea in the world (Annual Report, 2011). Sri Lanka is renowned for its high quality tea and as the 3rd biggest tea producing country globally, has a production share of 9% in the international sphere, and one of the world's leading exporters with a share of around 23% of the global demand (Industry Capability Reprt, Tea Sector, 2014).

There are several tea auction markets around the world which are primarily located in major cities of tea growing countries. They are, Sri Lanka (Colombo), three auctions in India (Calcutta, Cochin, Guwahati), Indonesia, Kenya and Malawi (Dharmasena & Bessler, 2003). Sri Lankan tea is marketed mainly through the weekly auctions held at the Colombo Tea Auction Center (CTAC) (The Tea Auction, n.d.).

Forecasting tea auction prices is useful for tea planters and people who employ in tea industry as they can have an idea on their future earnings in tea industry. They can allocate resources effectively, reduce transaction costs, improve efficiency of transactions and reduce risk of tea planters. The objective of this research is to develop a model to forecast tea auction prices in Sri Lanka using Box-Jenkins modeling approach.

LITERATURE REVIEW

There are a few research on auction prices of tea. Tea auction prices are naturally noisy and nonstationary in nature (Hettiarachchi & Banneheka, 2012). They forecasted the seasonally adjusted prices of the CTAC using Time series regression with Generalized Least Squares and Artificial Neural Network. Dharmasena & Bessler, 2003 studied international black tea markets and tested the ability of forecasting tea auction prices using Vector Auto-regression models. Hewapathirana & Tilakaratne (2012) explored the temporal behavior of the prices of black tea at the CTAC and assessed the co-integration among the monthly black tea prices at eight international tea auction centers. They used seasonally adjusted data to capture co-integration among the series and forecasted the series using the Vector Error Correction models. Induruwage, Tilakaratne, & Rajapaksha (2015) identified seasonal co-integration relationship in tea auction centers and fit seasonal error correction model. Nyaga and Doppler (2009) used dynamic models to assess impact of changing tea prices on family income of smallholders in Kenya. They used dynamic models for a period of ten years assuming only the current trend for the entire period.

METHODS AND MATERIALS

This study used monthly tea auction prices (Rs/Kg) in Sri Lanka over the period 1996 to 2016. Prices from September 1996 to November 2015 are used to fit models and prices from December 2015 to September 2016 are used to validate the model. EVIEWS version 6 and MINITAB version 14.0 were used to analyze the data set.

Most of the time there is seasonality in monthly data for which high values tend always to occur in some particular months and low values tend always to occur in other particular months. In this case, S = 12 (months per year) is the span of the periodic seasonal behavior. Therefore Seasonal Autoregressive Integrated Moving Average (SARIMA) model is useful in situations when the time series data exhibit seasonality-periodic fluctuations that recur with about the same intensity each year. This characteristic makes the SARIMA model adequate for studies concerning monthly tea auction prices.

Let $Y_t = Y_1 + Y_2 + .. Y_n$ be a time series of data. Suppose that et is a white noise with mean zero and constant variance. A SARIMA model with S observations per period, denoted by SARIMA (p,d,q)(P,D,Q)s, is given by

$$(1-B)^d(1-B^s)\phi_p(B)\varphi_P(B^s)Y_t = \theta_q(B)\delta_Q(B^s)e_t$$

Where ,

$$\varphi_P(B^s) = 1 - \varphi_1 B^s - \varphi_2 B^{2s} - \ldots - \varphi_P B^{PS},$$
$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p,$$
$$\delta_Q(B^s) = 1 - \delta_1 B^s - \delta_2 B^{2s} - \ldots - \delta_Q B^{Qs},$$
$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q,$$

B-backward shift operator, φ-coefficient seasonal autoregressive, ϕ - coefficient nonseasonal autoregressive, θ- coefficient nonseasonal moving average, δ- coefficient

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seasonal moving average, P- order seasonal autoregressive, p- order nonseasonal autoregressive, d - order of differencing nonseasonal, D- order of differencing seasonal, s- length of seasonality, q- order nonseasonal moving average, and Q- order seasonal moving average.

Using autocorrelation function (ACF), partial autocorrelation function (PACF) and degree of differencing, appropriate autoregressive (AR) and moving average (MA) terms are determined. Models are selected using AR and MA terms determined. Akaike information criterion (AIC), Schwartz's Bayesian Criterion (SBC), Mean Square Error (MSE) and coefficient of determination (R2) are used as the model selection criteria and select the best model among the selected models. Lower AIC, SBC, MSE values and higher R2 indicate better fit.

Augmented Dickey- Fuller (ADF) test, Lagrange's Multiplier (LM) test, White's General test, Jarque-Bera (J-B) test are used to verify adequacy of the fitted model. ADF test is used to check whether the series has a unit root. LM test is used to test the serial correlation among residuals. White's General test is used in order to check constant variance of residuals. The normality assumption is checked by using Jarque-Bera test, which is a goodness of fit measure of departure from normality, based on the sample kurtosis and skewness. Forecasting performance of the SARIMA model are measured by using mean absolute percentage error (MAPE) criteria.

RESULTS AND DISCUSSION

The graphical representations of the original and average tea prices by months are presented in Figure 1(a) and 1(b) respectively. It is clear that the monthly tea auction prices in Sri Lanka has an increasing trend with some fluctuation over the study period i.e., the variance is unstable which leads the tea price series is not stationary. Furthermore figure 1(b) shows that there are monthly differences (seasonality). Then twelfth difference series is plotted and presented in figure 1(c). It clearly shows that the twelfth differenced tea price series does not have trend nor seasonality which leads the data becomes stationary. ACF and PACF graph for twelfth difference series are presented in figure 1(d) and 1(e) respectively. The ACF shows spikes at lag 1, 2 and not much else until about lag 11. It suggests that AR (1) and AR (2) terms for the differenced series. The PACF also shows spikes at lag 1, 2 and suggests that MA (1) and MA (2) terms for the differenced series. Therefore different models were tried and model selection criteria are presented in table 1. It indicates that AR (1) model has lower AIC, SBC, MSE and higher R2 values. Thus SARIMA (1,0,0)(0,1,0)12 model is selected and checked adequacy of the model. The estimates of the parameters of the fitted model are shown in Table 2.

Table 1: Model selection criteria considering different SARIMA models

Model	R^2	AIC	BIC	MSE
AR(1)	81.98	9.36	9.37	26.04
AR(2)	62.8	10.08	10.10	37.44
MA(1) MA(2)	71.1	9.84	9.87	32.99

Table 2: Parameter Estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.929	0.028	32.987	0.000

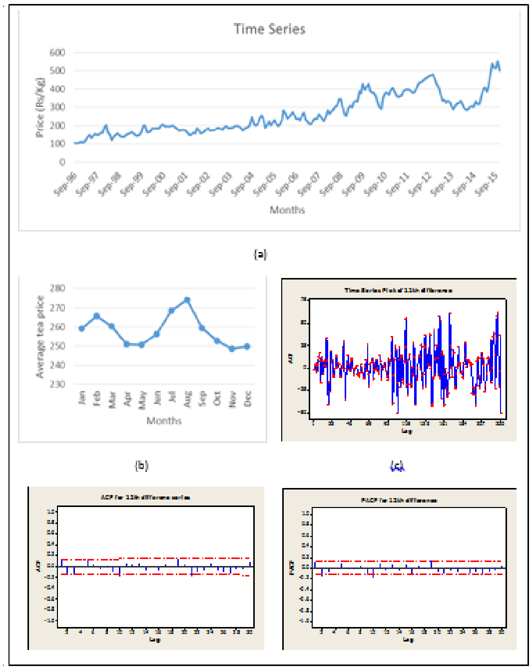

Figure 1: (a) Time series plot for tea auction prices, (b) Plot of average tea price Vs. months, (c) ACF plot for 12th difference series (d) PACF plot for 12th difference series

Graphical representations of residuals are presented in figure 2(a) and 2(b) respectively. Figure 2(a) suggests that there is no significant pattern and hence it can be said that residuals are random. Histogram of residuals (figure 2(b)) illustrates that residuals are followed normal distribution.

P values of ADF test, LM test and White's test are presented in table 3. P value of ADF test indicates that residual series is stationary (p<0.05). According to the p value of LM, it can be confirmed that there is no serial correlation in residuals since the p value is greater than 0.05. P value of White's test confirms that there is no heteroscedasticity in residuals since the p value (p=0.24) is greater than 0.05. Jarque-Bera statistic (5.82) is less than 205.0,2Cand it moderately suggests to accept the normality assumption that is the residuals of the fitted model are normally distributed.

Table 3: Model diagnostic for SARIMA (1,0,0)(0,1,0)12 model

Tests for residuals	Probability
ADF test statistic	0.0000
LM test	0.20
White's General test	0.24

Then fitted SARIMA model is used to forecast tea prices and compared it with observed values. The forecasted values are relatively close to the observed values and MAPE value presented in table 4 is less than 15%. These results indicate that the model provides an acceptable fit to forecast the tea auction prices. Thus, considering all the results it is clear that the fitted SARIMA (1,0,0)(0,1,0)12 model is the best fitted model and adequately used to forecast the tea auction prices in Sri lanka.

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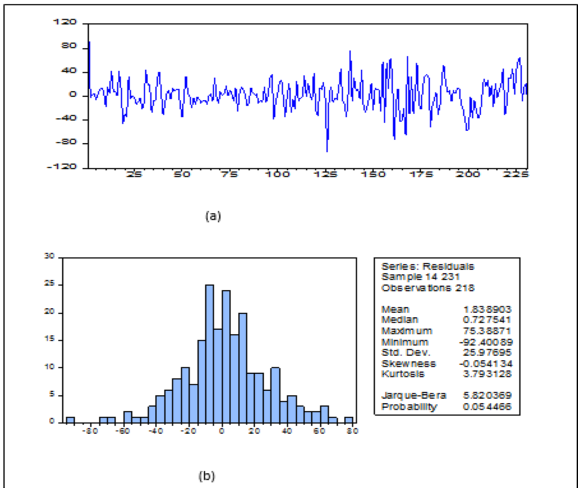

Figure 2: Graphical diagnostics for assessing the SARIMA (1,0,0)(0,1,0)12 model fit: (a) residuals, (b) histogram of residuals

Table 4: Observed tea price and forecasted values obtained from the SARIMA (1,0,0)(0,1,0)12 model

Month	Dec /15	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	MAPE
Observed	492.71	460.36	413.45	379.64	342.47	360.12	390.69	407.34	401.74	434.44	13.35 %
Forecasted	319.45	347.58	379.26	384.56	363.12	386.27	430.97	480.69	466.44	463.23	

CONCLUSIONS

In this study, it is found that the SARIMA (1,0,0)(0,1,0)12 model is well reflected the trend in the tea auction prices in Sri Lanka. The comparison between the original series and forecasted series shows the same manner indicating the fitted model behaved statistically well and suitable to forecast the tea auction prices in Sri Lanka i.e., the models forecast well during and beyond the estimation period. Thus, this model can be used for tea planters, policy makers to make appropriate decisions for tea industry.

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