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Forecasting of monthly arrivals and price of tender coconut in Maddur market, Karnataka using seasonal time-series models

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Abstract
Karnataka stands third in the production of coconuts after Kerala and Tamil Nadu. In Karnataka, about 14 per cent of the total production of coconut is harvested in the form of tender nuts, which is confined to Mandya, Bengaluru, Mysore and Hassan districts. Maddur APMC market is one of the world's largest tender coconut hubs. Every day, about four million tender coconuts are brought to the APMC market. Marketing of tender coconut plays a significant role in the movement of commodities from the producer to the consumer and stabilizing prices. Thus, in the present study, two univariate time-series models *viz*. Holt-Winters' Exponential Smoothing (H-WES) and seasonal ARIMA models were fitted to monthly arrivals and price data of tender coconuts in Maddur for the period from April 1997 to March 2018. Based on the lowest AIC and BIC, and perusal of ACF and PACF plots, SARIMA (1, 1, 1) $(2, 1, 1)_{12}$ and ARIMA (1, 1, 3) models were respectively selected as the best models for estimating and forecasting arrivals and prices of tender coconut. The results showed that the seasonal ARIMA model better performed than the H-WMES model for forecasting arrivals and prices of tender coconuts. The seasonal ARIMA model could be successfully used for modelling as well as forecasting of monthly price of forecasting arrivals and prices of tender coconuts.

Keywords: Tender coconut, time-series analysis, Holt-Winters exponential smoothing, Seasonal ARIMA, arrivals and prices, Maddur APMC, Karnataka

Introduction

The coconut palm tree (*Cocos nucifera* Linn.) is one of the most natural and valuable gifts to mankind. Considering the versatile nature of the crop and the multifarious uses of its products, the coconut palm is eulogised as Kalpavruksha (the Tree of Heaven). India being the largest coconut producing country in the world occupies 31 per cent of global production. Coconut palm provides food security and livelihood opportunities to more than 12 million people in India. More than 15,000 coir-based industries employ nearly 6 lakh workers of which 80 per cent are women. The crop contributes around Rs. 2,50,000 million to the country's GDP and earns export revenue of around Rs.43,654 million (Anonymous, 2016) [1]. India ranks first in production (21,665 million nuts) and productivity (10,119 nuts/ha.) of coconut and ranks third in the area (2,141 thousand ha.) under coconut. Indonesia stands first in area (3610 thousand ha.) under coconut, ranks second in production (16354 million nuts) and productivity (4530 nuts/ha.) and the Philippines ranks second in the area (3502 thousand ha.) under coconut, ranks third in production (14696 million nuts) and productivity (4196 nuts/ha.). The largest share of coconut production in 2014 was recorded in India (31.02%) followed by Indonesia (23.42%) and Philippines (21.04%) and other countries 24.52 per cent (Anonymous, 2014) [2].

Traditional areas of coconut cultivation in India are the states of Kerala, Karnataka, Tamil Nadu, Andhra Pradesh, Goa, Orissa, West Bengal, Puducherry, Maharashtra and the Island territories of Lakshadweep and Andaman & Nicobar. Karnataka stands third in production of coconuts by producing 5128.84 million nuts, which constitutes 23.13 per cent of India's production after Kerala: 7429.39 million nuts (33.51%) and Tamil Nadu 6171.06 million nuts (27.83%) during the year 2015-16. The four southern states *viz*. Kerala, Tamil Nadu, Karnataka and Andhra Pradesh are the major coconut-producing states in India accounting for more than 90 per cent of area and production (Anonymous, 2016) [1].

Nowadays, tender coconut is becoming more popular as a health and energy drink by replacing artificial soft drinks. Coconut water is highly recommended by fitness and nutrition experts as a rehydrating agent. It has a caloric value of 17.4 per 100 gm. On a percentage basis, coconut water is 94.5 per cent water, the rest would contain: Protein (0.15 to 0.55%), fat (0.10%), ash (0.46%), and carbohydrates (4.40%). Tender coconut water has been given intravenously to cholera epidemic victims in Sri Lanka, Indonesia, Bangladesh and India. Tender coconut water being rich in potassium and other minerals plays a major role in increasing urinary output (Ravi Kumar, 2012) [3].

In Karnataka, about 14 per cent of the total production of coconut is harvested in the form of tender nuts, which is confined to Mandya, Bengaluru, Mysore and Hassan districts. The production of coconut is localised while the consumption is spread throughout the country. Though Kerala tops the list at the national level for coconut production, it is largely used for oil extraction while the fruits from Mandya, Ramanagara and Tumkuru are known for their high-water content.

Maddur APMC market is one of the world's largest tender coconut hubs (Naveena and Arunkumar, 2016) [4]. Every day, about four million tender coconuts are brought to an exclusive market set up by the Agricultural Produce Marketing Committee on the Bengaluru-Mysore highway. The nuts are brought by farmers and harvesters from Maddur, Mandya, Chamarajnagar, Kollegal, Malavalli, Bannur, Nagamangala, Pandavapura, K. R. Pet and Srirangapatna (Ravi Kumar, 2012) [3]. Over 60 per cent of these tender coconuts are loaded onto 300 trucks and sent to New Delhi, Mumbai, Pune, Kolkata, Goa, Hyderabad, Ahmedabad and other places. The rest are sold within Karnataka.

Marketing of tender coconut plays a significant role in the movement of commodities from the producer to the consumer and stabilizing prices. The planned increase in agricultural output must be coordinated with changes in the demand and supply for agricultural commodities and marketing. This can be achieved only when the producer’s share in the consumer’s rupee increases considerably irrespective of the volume of the marketable surplus produced by the farmers. Usually, fluctuation in price occurs due to changes in market conditions created in response to seasonal and annual variations in production (Mohan Kumar *et al.*, 2009) [5]. The seasonal variation in arrivals and prices of tender coconut is more due to supply factors than due to demand factors (Mohan Kumar, *et al*., 2011a [6]. Thus, modelling and forecasting of monthly market arrivals and prices over the years using widely accepted sophisticated statistical tools is of much practical importance (Mohan Kumar, *et al*., 2011b) [7].

The purpose of this study was to find a suitable statistical model to forecast the monthly arrivals and prices of tender coconut using two time-series models *viz*. Holt-Winters Exponential Smoothing (H-WES) and Seasonal ARIMA models. The forecasting of market arrivals and prices is considered to be important as a guide to the producer to market his produce and to the consumer to purchase his needs at the right time. It also serves as a guide to the government to operate its policy measures (procurement and buffer release) at the appropriate time.

2. Materials and Methods

The data for the study are confined to arrivals and prices of tender coconut into the tender coconut market, Maddur, which is situated on the premises of the Agricultural Produce Market Committee (APMC), Maddur, Mandya district. The secondary data about monthly arrivals (in thousand nuts) and monthly prices (in rupees per thousand nuts) of tender coconuts for the period of April 1997 to March 2018 were collected from APMC, Maddur. Monthly arrivals are the total arrivals in a month and monthly prices are the modal prices in a month.

2.1 Holt-Winters Exponential smoothing

The exponential smoothing (ES) technique is one of the most successful forecasting methods which assigns exponentially decreasing weights as the observations get older. In other words, recent observations are given relatively more weight in forecasting than older observations. The moving average method and exponential smoothing method deal with almost any type of data as long as such data are non-seasonal. When seasonality does exist, however, these methods are not appropriate on their own (Makridakis *et al*. 1998) [8].

Holt’s method was extended by Winter’s to capture seasonality directly. The Holt-Winters’ method is based on three smoothing equations, one for level, one for trend, and one for seasonality. It is similar to Holt’s method, with additional equations to deal with seasonality. Holt-Winters Exponential Smoothing (H-WES) methods are widely used when the data shows trend and seasonality (Makridakis *et al*. 1998) [8]. It has two types of models, one is the Holt-Winters’ additive method (additive trend, additive seasonality) and another Holt-Winters’ multiplicative method (additive trend, multiplicative seasonality). In this study, we make use of the Holt-Winters additive approach, which provides some simple rules based on the variances of differenced time series for choosing an appropriate exponential smoothing method. Holt-Winters additive method of smoothing requires primary estimation of parameters level (α), trend (β) and seasonal (γ) indices and is given as

Level: $L_t = \alpha\,(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1})$
Trend: $b_t = \beta\,(L_t - L_{t-1}) + (1-\beta)b_{t-1}$

Seasonal: $S_t = \gamma\,(Y_t - L_t) + (1-\gamma)S_{t-s}$

Forecast: $F_{t+m} = L_t + mb_t + S_{t-s+m}$

where s is the length of seasonality, L_t represents the level of the series, b_t denotes the linear trend components, S_t is the multiplicative seasonal components, F_{t+m} is the forecast for the m period ahead and a, b and g are level, trend and seasonal smoothing constant or the weights respectively, which are lies between 0 and 1.

2.2 box-Jenkins approach for forecasting

Box-Jenkins procedure is concerned with fitting a mixed Auto-Regressive Integrated Moving Average (ARIMA) model to a given set of data. The main objective in fitting this ARIMA model is to identify the stochastic process of the time series and predict future values accurately. Originally, ARIMA models have been studied extensively by George Box and Gwilym Jenkins and their names have been frequently used synonymously with general ARIMA processes applied to time series analysis, forecasting and control. However, the optimal forecasts of the future value of a time series are determined by the stochastic process for that series. A stochastic process is either stationary or non-stationary. The first thing to note is that most time series are non-stationary and the ARIMA model refers only to stationary (Box *et al*., 2015) [9].

2.2.1 Autoregressive Integrated Moving Average (ARIMA) Model: ARIMA (*p, d, q*)

A generalization of ARMA models which incorporates a wide class of non-stationary stationary time-series is obtained by introducing the differencing into the model. The simplest example of a non-stationary process which reduces to a stationary one after differencing is a random walk. A process $\{y_t\}$ is said to follow an Integrated ARMA model, denoted by

ARIMA (*p, d, q*), if $\nabla^d y_t = (1-B)^d \varepsilon_t$ is ARMA (*p, q*).

The model is written as

$$\varphi(B)(1-B)^d y_t = \theta(B)\varepsilon_t$$

where $\varepsilon_t \sim WN(0, \sigma^2)$,
WN indicating White Noise.
The integration parameter *d* is a nonnegative integer.
When *d* = 0, ARIMA (*p, d, q*) ≡ ARMA (*p, q*).

2.2.2 Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

Sometimes the series exhibit perceptible periodic patterns for instance, the price and arrivals of agricultural commodities usually have a seasonal pattern process in general.
Then ARIMA notation can be extended readily to handle seasonal aspects. In its general form, the Seasonal ARIMA model is characterized by a notation as ARIMA (*p, d, q*) (*P, D, Q*)$_s$ is given by

$$(1-\varphi_p B)(1-\Phi_p B^s)(1-B)(1-B^s)y_t = (1-\theta_q B)(1-\Theta_q B^s)\varepsilon_t$$

Where *B* is the backshift operator (*i.e.* $By_t = y_{t-1}$, $B^2 y_t = y_{t-2}$ and so on), '*s*' the seasonal lag and 'ε_t' and '*t*' a sequence of independent normal error variables with mean 0 and variance σ^2. $\Phi's$ and $\varphi's$ are respectively the seasonal and non-seasonal autoregressive parameters. $\Theta's$ and θ's are respectively seasonal and non-seasonal moving average parameters. The order *p* and *q* are orders of non-seasonal autoregressive and moving average parameters respectively, whereas *P* and *Q* are that of the seasonal autoregression and moving average parameters respectively. Also '*d*' and '*D*' denote non-seasonal and seasonal differences respectively (Box *et al*., 2015) [9].
The main stages in setting up a Box-Jenkins forecasting model are the following:
1. Identification
2. Estimating the parameters
3. Diagnostic checking and
4. Forecasting

Identification of models

The foremost step in the process of modelling is to check for the stationarity of the series, as the estimation procedures are available only for stationary series. The structure of autocorrelation and partial correlation coefficient plots may provide clues for the presence of stationary or non-stationary. Another way of checking for stationarity is to fit a first-order autoregressive model for the data and test whether the coefficient 'ϕ_1' is less than one or go for Augmented Dickey-Fuller (ADF) test. If the model is found to be non-stationary, stationary could be achieved mostly by differencing the series.
A good starting point for time series analysis is a graphical plot of the data. It helps to identify the presence of trends. Before estimating the parameter (*p, q*) of the model, the data are first examined to decide about the model which best explains the data. This is done by examining the sample ACF and Partial Auto-Correlation Function (PACF) of differenced series y_t. The sample auto correlations for *k* time lags can be found by:

$$\hat{\rho}_k(y_t) = r_k(y_t) = \frac{C_k(y_t)}{C_0(y_t)};$$

where

$$C_k(y_t) = \frac{1}{n}\sum_{t=1}^{n-k}(y_t - \bar{y}_t)(y_{t+k} - \bar{y}_t);\ k = 1, 2, \dots, n$$

$$k = 1, 2, \dots, n$$

$$t = 1, 2, \dots, n-k$$

$$\bar{y}_t = \frac{1}{n}\sum_{t=1}^{n} y_t$$

n = Length of time period

The next step in the identification process is to find the initial values for the orders of seasonal and non-seasonal parameters, *p, q,* and *P, Q*. They could be obtained by looking for significant autocorrelation and partial autocorrelation coefficients. Say, if second order auto correlation coefficient is significant, then an AR (2) or MA (2) or ARMA model could be tried to start with. Yet another application of the autocorrelation function is to determine whether the data contains a strong seasonal component. This phenomenon is established if the autocorrelation coefficients at lags between *t* and *t*-12 are significant. If not, these, coefficients will not be significantly from zero.
Both ACF and PACF are used as an aid in the identification of appropriate models. There are several ways of determining the order of the type of process, but still, there is no exact procedure for identifying the model.

Estimation of parameters

At the identification stage, one or more models are tentatively chosen that seem to provide statistically adequate representations of the available data. The precise estimates of the parameters of the identified models are obtained by Maximum Likelihood Estimation (MLE). Standard computer packages like SPSS and SAS are available for finding the estimates of relevant parameters using iterative procedures. Or obtain Least Square Estimates of the parameters which are having minimum error sum of squares.

$$S(\varphi, \theta) = \sum_{t=1}^{n} e_t^2(\varphi, \theta)\ ;\ t = 1, 2, 3, \dots, n$$

The MLE method is used in the present analysis for estimating the parameters.

Diagnostic checking of the model

After having estimated the parameters of a tentatively identified ARIMA model, it is necessary to do diagnostic checking to verify that the model is adequate.
Examining ACF and PACF of residuals may show an adequacy or inadequacy of the model. If it shows random residuals, then it indicates that the tentatively identified model was inadequate. When an inadequacy is detected, the checks

should give an indication of how the model need be modified, after which further fitting and checking takes place.

One of the procedures for diagnostic checking mentioned by Box-Jenkins is called over fitting *i.e.* using more parameters than necessary. But the main difficulty in the correct identification is not getting enough clues from the ACF because of inappropriate level of differencing. The residuals of ACF and PACF are considered randomly when all their ACF's were within following the limits:

$$-1.96\sqrt{\frac{1}{n-12}} \leq residuals\ (r_k) \leq 1.96\sqrt{\frac{1}{n-12}}$$

Hence, the randomness of the ACF satisfies the condition of diagnostic checking.

It is also used Ljung and Box 'Q' statistic for whether the auto correlations for those residuals are significantly different from zero. It can be computed as follows.

$$Q = n(n+2)\sum_{k=1}^{h}(n-k)^{-1}\,r_k^2$$

Where

h = Maximum lag considered

n = Number of observations

rk = ACF for lag *k*

m=*p*+ *q*+P+Q = Number of parameters to be estimated.

In addition, Q is distributed approximately as a Chi-square statistic with (*h*-*m*) degree of freedom. If the p-value associated with the Q statistic is small (p-value<0.05 or 0.01), the model is considered inadequate. The analyst should consider a new or modified model and continue the analysis until a satisfactory model has been determined.

The minimum Akaike's Information criterion (AIC) and Schwartz Bayesian Information Criterion (SBIC) is used to determine both the differencing order (*d*, *D*) required for attaining Stationarity and identify the appropriate number of AR and MA parameters. It can be computed as follows.

$$\text{AIC} = -2\ln(L) + 2m$$

$$\text{BIC} = -2\ln(L) + mln(n)$$

where,

σ^2 = Estimated MSE

n = Number of observations

m = *p*+ *q*+P+Q = Number of parameters to be estimated

This diagnostic checking helps us to identify the differences in the model, so that the model could be subjected to modification, if need be.

Forecasting

The principal objective of developing an ARIMA model for a variable is to generate a sample period forecast for the same variable. The ultimate test for any model is whether it can predict future events accurately or not.

The accuracy of forecasts was tested using Root Mean square error (RMSE) and Mean average percentage error (MAPE).

3. Results and Discussions

The graph of the arrivals and prices of tender coconut in the Maddur market is plotted. A perusal of the plot indicated that arrivals show huge fluctuations from minimum arrivals of 10, 51, 350 to 2, 42, 39, 150 thousand nuts and minimum prices of 2, 500 to 11, 000 rupees per thousand nuts. The huge fluctuation of the data set indicated arrivals and price series were non-stationary and revealed strong seasonality. The ability to forecast was tested using Holt-Winters and seasonal ARIMA models for the monthly arrivals and prices of tender coconuts for the period of April 1997 to March 2018.

3.1 Holt-Winters Exponential Smoothing Model for Estimating Arrivals and Prices: Time-series plots of monthly arrivals and price data of tender coconut in the Maddur market during the period from April 1997 to March 2018 have shown the positive linear trend factor and seasonality exist in the time series data. When the time series has a linear trend and seasonality along with constant variability in arrivals and prices, the additive approach is more suitable. Therefore, in this study, we have employed the Holt-Winters Additive Exponential Smoothing method to forecast, which provides some simple rules based on the variances of differenced time series for choosing an appropriate exponential smoothing method. The model consists of three parameters, which are symbolized as α for mean and *β* for trend and γ for seasonality. The best model of the Holt-Winters Exponential Smoothing has been selected based on the lowest value of MSE, RMSE, MAE and MAPE from the combination of α, β and γ which satisfies the condition 0 < α, β and γ <1. Estimates of the Holt-Winters Exponential Smoothing Model Parameter along with its standard error are tabulated in Table 1 and Table 2 respectively for arrivals and prices of tender coconut. The result showed that, the parameters combination of {α=0.6, β=0.000016, γ=0.0000063} and {α = 0.71, β = 0.0000004, γ=0.0000001} are found to be best suitable for arrivals and prices respectively.

Table 1: Estimates of Holt-Winters Exponential smoothing model parameters for forecasting arrivals of tender coconut in the Maddur market.

Model Parameters	Estimate	S.E.	t-statistic
α (Level)	0.6	0.59	10.14**
β(Trend)	0.000016	0.028	0.001^{NS}
γ (Seasonal)	0.0000063	0.046	0.00001^{NS}

** Significant at 1% level of significance NS: Not Significant

Table 2: Estimates of Holt-Winters Exponential smoothing model parameters for forecasting prices of tender coconut in Maddur market.

Model Parameters	Estimate	S.E.	t-statistic
α (Level)	0.71	0.61	11.74**
β(Trend)	0.0000004	0.06	0.00008^{NS}
γ (Seasonal)	0.0000001	0.78	0.01^{NS}

** Significant at 1% level of significance NS: Not Significant

3.2 Box-Jenkins Approach for Forecasting Arrivals and Prices: The forecasting through the Box-Jenkins model is carried out in four stages, *viz*., identification of tentative models based on examination of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). Then, the parameters of the identified models are estimated by the Maximum likelihood estimation method and then the residuals of each of the fitted models are obtained. By examining ACF and PACF plots of residuals may show an adequacy or inadequacy of the model. If it shows random residuals, then it indicates that the tentatively identified model was inadequate. The adequacy of the model is also judged based on the values of the Ljung-Box "Q" statistic. The model has the lowest value of the Akaike Information Coefficient (AIC) and the Bayesian Information Criteria (BIC) statistic is selected as the best model among tentatively identified models for forecasting the future. Both Ex-ante and Ex-post forecasts are done and it was compared with actual values of observation. The results of the forecast and the accuracy of the forecast are tested using test statistics like RMSE, and MAPE. Monthly arrivals and price data of tender coconut in the Maddur market during the period from April 1997 to March 2018 are used to build the forecasting model.

3.2.1 Arrivals of tender coconuts

An upward trend was observed in the arrivals of tender coconuts. AFC and PACF of arrivals are presented in Fig.1; perusal of these plots indicates the existence of non-stationarity and seasonality in the arrival's series. The non-stationary series can be converted into stationary by differencing the original series using a difference technique. It can also be visualized from the plot of ACF and PACF of the series. The decay rate for the ACF of the series is very low. But after differencing of the original series, the decay rate becomes high and the arrival series becomes stationary.

To this end, Augmented Dickey-Fuller (ADF) was used for the test of stationarity, it was found to be a non-stationary series. An examination of the ACF and PACF revealed seasonality at the 12^{th} lag. Each coefficient of ACF and PACF is tested for their significance using a t-test. Further, the presence of a peak at the 12^{th} lag clearly indicates the suitability of the choice of seasonal difference D =1, to accomplish stationary series. The plots of ACF and PACF of differenced (d=D=1) series shown in Fig. 2 up to 25 lags. By examining the ACF and PACF plots of the differenced arrivals series at lag d=D=1, the tentative models were first identified which are presented in Table 3. Based on minimum AIC and BIC values SARIMA (1, 1, 1) $(2, 1, 1)_{12}$ model is selected as the best model among tentative models. An estimate of parameters of selected SARIMA (1, 1, 1) $(2, 1, 1)_{12}$ models are estimated using Maximum Likelihood estimation and then residuals for the best model are obtained by back forecasting. However, the parameter constant mean was found not significant and thus dropped from the model. The estimate of the parameters with corresponding standard error for SARIMA (1, 1, 1) $(2, 1, 1)_{12}$ model are given in Table 4.

Residual analysis was carried out to check the adequacy of the model. The plots of ACF and PACF of residual series are shown in Fig. 3 up to 25 lags. The adequacy of the model is judged based on the values of Ljung and Box "Q" statistic. The Q-statistics value 19.25 was found to be non-significant (p=0.115) indicating white noise of the series and none of the autocorrelation and partial autocorrelation coefficients has fallen outside the limits indicated white noise of the series. Thus, these tests suggest model SARIMA (1, 1, 1) $(2, 1, 1)_{12}$ is adequate.

The ex-ante forecast was done using SARIMA (1,1,1) $(2,1,1)_{12}$ and Holt-Winter's Exponential smoothing model and it was compared with actual values of observation. The accuracy of forecasting models are tested using RMSE and MAPE, which are presented in Table 5. Based on the lowest RMSE and MAPE values SARIMA (1, 1, 1) $(2, 1, 1)_{12}$ better performed than Holt-Winter's Exponential smoothing model. The charts of Ex-ante forecast of arrivals by both the models are shown in Fig 4. A perusal of Fig 4 indicates that seasonal ARIMA model has nicely captured the variation of monthly arrivals of tender coconut into the Maddur market.

Both fitted models were be used for forecasting (Ex-post) the arrivals for next 12 months i.e. from April 2018 to March 2019, Ex-post forecasting value along with actual arrivals are tabulated in Table 8.

Table 3: Tentatively identified SARIMA models for Arrivals of tender coconut

Tentative models	AIC	BIC
(0 1 0) (0 1 1)	7704.79	7708.27
(0 1 1) (0 1 1)	7700.92	7707.87
(1 1 1) (0 1 1)	7687.12	7697.55
(1 1 0) (0 1 1)	7685.13	7692.09
(1 1 1) (1 1 0)	7722.35	7732.50
(1 1 1) (1 1 1)	7666.62	7680.52
(1 1 1) (2 1 1)	7661.56	7678.95
(2 1 0) (2 1 0)	7682.09	7695.99
(2 1 1) (2 1 1)	7662.79	7683.65

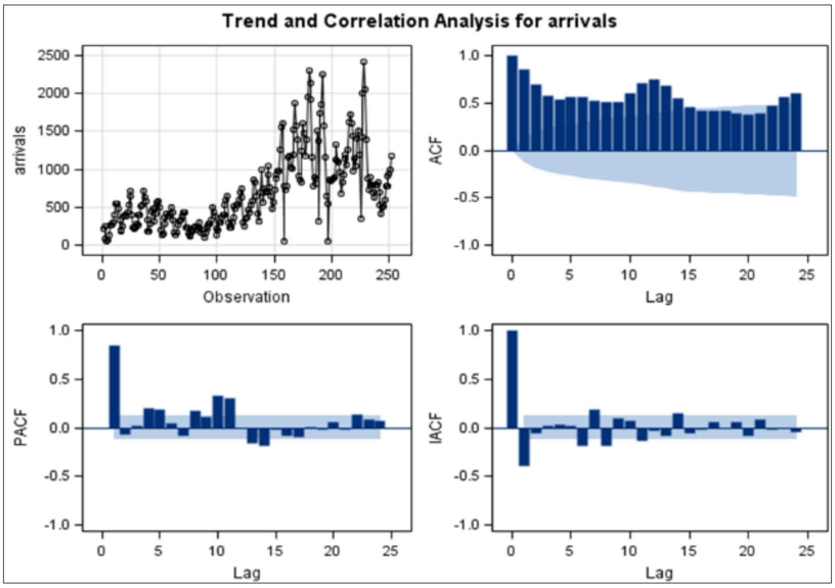

Fig 1: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for arrivals of tender coconuts in Maddur market

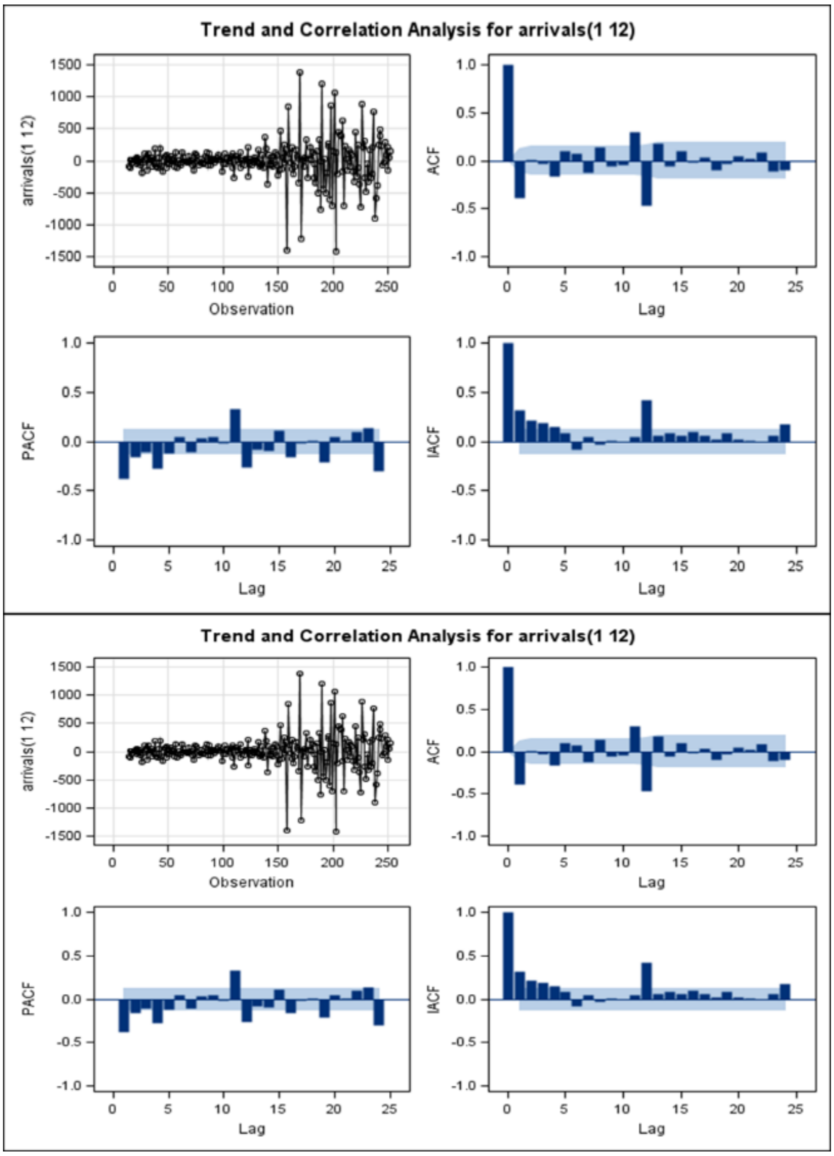

Fig 2: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for arrivals of tender coconuts after differencing series by d=D=1

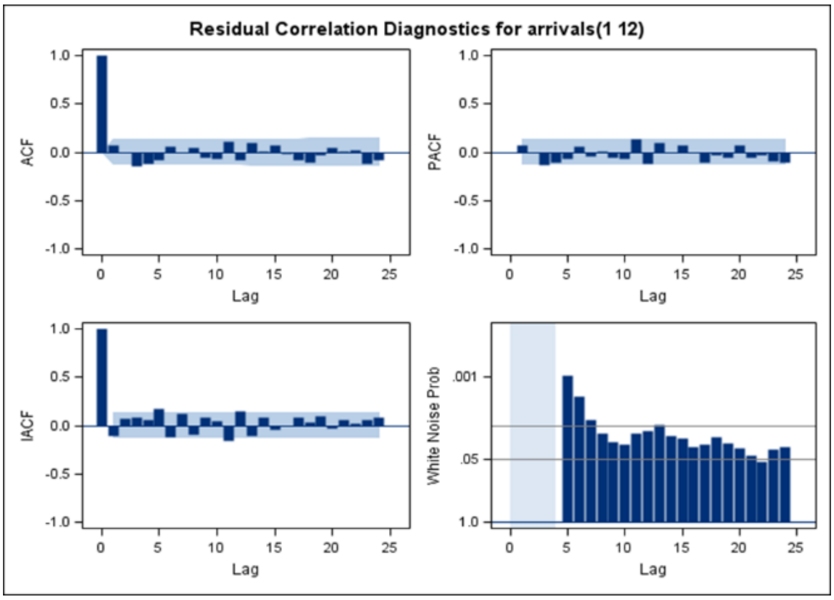

Fig 3: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for residuals SARIMA (1, 1, 1) (2, 1, 1)$_{12}$ model for Arrivals.

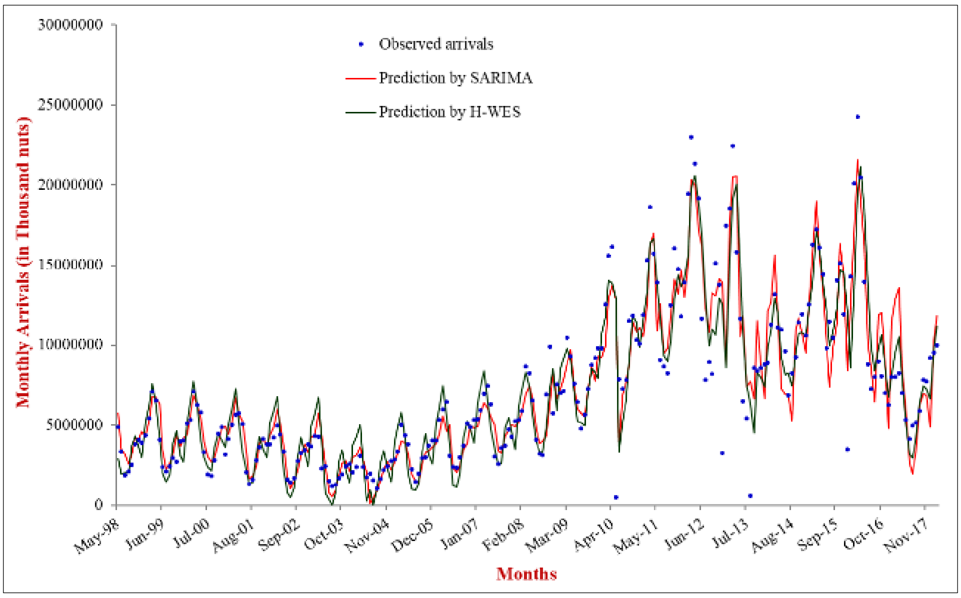

Fig 4: Ex-ante forecast of Arrivals of tender cocoanut in Maddur market

Table 4: Estimates of SARIMA (1, 1, 1) (2, 1, 1)12 model for Arrivals of tender coconut

Parameter	Estimate	Standard Error	t-Value	Approx Pr > |t|
AR (1)	0.33555	0.09889	3.39**	0.0007
MA (1)	0.79047	0.06476	12.21**	<.0001
SAR (1)	-0.31720	0.11709	-2.71**	0.0067
SAR (2)	-0.33100	0.09213	-3.59**	0.0003
SMA (1)	0.45134	0.11779	3.83**	0.0001

** Indicates significant at 1% level of significance

Table 5: Model forecast accuracy criteria

Accuracy criteria	Arrivals Predicted by		Price Predicted by	
	SARIMA	H-WES	SARIMA	H-WES
RMSE	2119526.78	2147802.60	374.39	376.56
MAPE (%)	36.01	39.28	3.67	4.28

3.2.2 Prices of tender coconuts

An upward trend was observed in the prices of tender coconuts. AFC and PACF of prices are presented in Fig.5; perusal of these plots indicates the existence of non-stationarity in the price series. The non-stationary series can be converted into stationary by differencing the original series using a difference technique. It can also be visualized from the plot of ACF and PACF of the series. The decay rate for the ACF of the series is very low. But after differencing of the original series, the decay rate becomes high and the prices series become stationary. To this end, Augmented Dickey-Fuller (ADF) was used for the test of stationarity, it was found to be a non-stationary series. An examination of the ACF and PACF plots at the 12th lag revealed no seasonality in the prices. Each coefficient of ACF and PACF is tested for their significance using a t-test. The plots of ACF and PACF of differenced (d=1) series shown in Fig. 6 up to 25 lags. After examining the ACF and PACF plots of the differenced prices series at lag d=1, tentative models were first identified which are presented in Table 6. On the basis of minimum AIC and BIC values, the ARIMA (1, 1, 3) model is selected as the best model among tentative models. An estimate of parameters of the selected ARIMA (1, 1, 3) model is estimated using Maximum Likelihood estimation and then residuals for the best model are obtained by back forecasting.

However, the parameter constant mean was found not significant and thus dropped from the model. The estimates of the parameters with corresponding standard error for the ARIMA (1, 1, 3) model are given in Table 7.

Residual analysis was carried out to check the adequacy of the model. The plots of ACF and PACF of residual series are shown in Fig. 7 up to 25 lags. The adequacy of the model is judged based on the values of Ljung and Box "Q" statistics over different lags and outliers. The Q-statistics value 15.95 was found to be non-significant (p=0.317) indicating white noise of the series and none of the autocorrelation and partial autocorrelation coefficients have fallen outside the limits indicated white noise of the series. Thus, these tests suggest model ARIMA (1, 1, 3) is adequate.

The ex-ante forecast was done using ARIMA (1, 1, 3) and Holt-Winter's Exponential smoothing model and it was compared with actual values of observation. The accuracy of the forecast tested using RMSE and MAPE is presented in Table 5. Based on the RMSE and MAPE values ARIMA (1, 1, 3) better performed than Holt-Winter's Exponential smoothing model. The chart of the Ex-ante forecast of prices by both models is shown in Fig 8. A perusal of Fig. 8 indicates that seasonal ARIMA model has nicely captured the variation of monthly price of tender coconut into the Maddur market.

Both fitted models were used for forecasting (Ex-post) the arrivals for the next 12 months i.e. from April 2018 to March 2019, the Ex-post forecasting value along with actual arrivals are tabulated in Table 8.

Table 6: Tentatively identified models for Prices of tender coconut

Tentative models	AIC	BIC
(0 1 1) (0 0 1)	3704.64	3711.69
(0 1 1) (0 0 0)	3702.80	3706.30
(1 1 0) (0 0 1)	3707.35	3717.91
(1 1 1) (0 0 1)	3705.68	3719.78
(0 1 2) (0 0 0)	3704.03	3714.60
(1 1 3) (0 0 0)	3692.85	3703.43
(1 1 1) (0 0 0)	3705.43	3716.01
(0 1 2) (0 0 0)	3700.97	3715.34

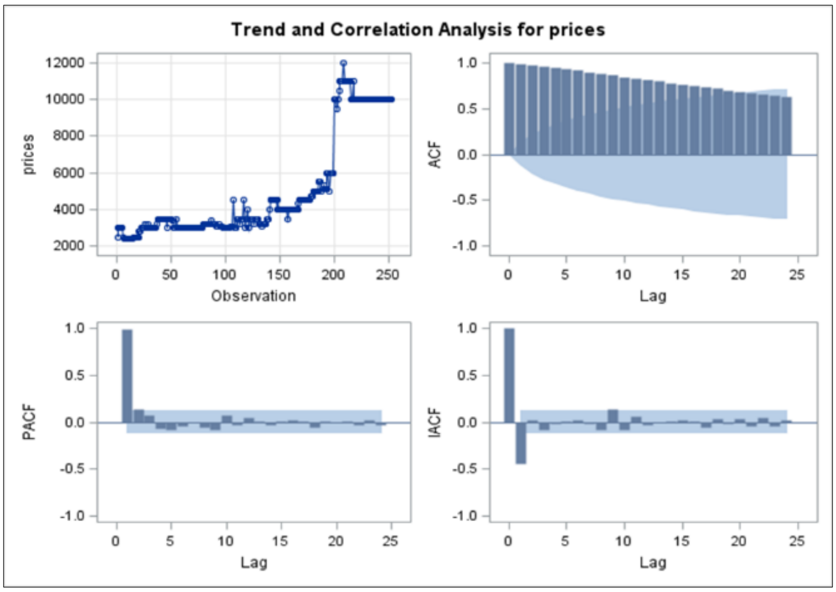

Fig 5: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for prices of tender coconuts in Maddur market

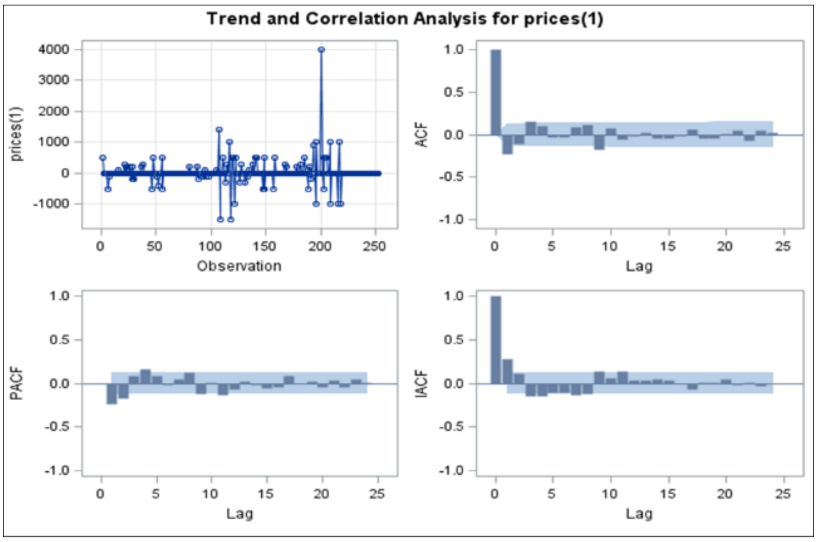

Fig 6: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for prices of tender coconuts after differencing series by d= 1

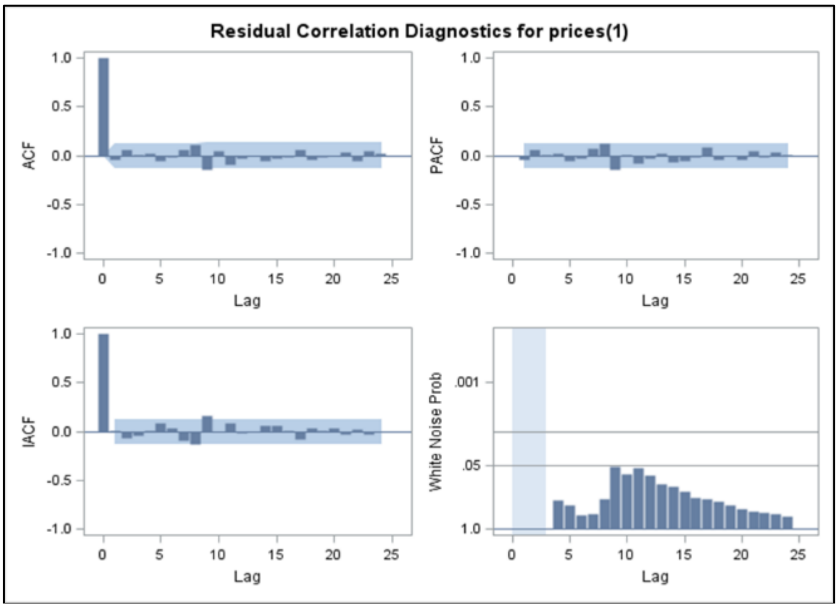

Fig 7: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for residuals from ARIMA (1, 1, 3) model for prices.

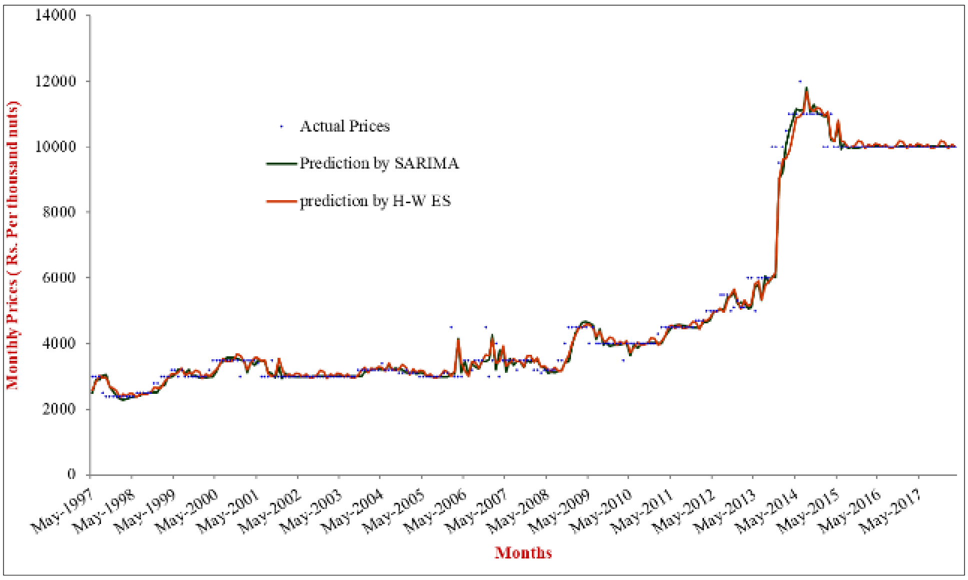

Fig 9: Ex-ante forecast of prices of tender cocoanut in Maddur market

Table 7: Estimates of ARIMA (1, 1, 3) model for Prices of tender coconut

Parameter	Estimate	Standard Error	t-Value	Approx Pr > |t|
AR (1)	0.52944	0.15265	3.47**	0.0005
MA (1)	0.78685	0.12862	6.12**	<.0001
MA (3)	-0.25445	0.04885	-5.21**	<.0001

** Indicates significant at 1% level of significance

Table 8: Ex-post forecasting of arrivals and prices for the next 12 months i.e. from April 2018 to March 2019

Months-Years	Forecasted Arrivals		Forecasted prices	
	SARIMA	H-WES	ARIMA	H-WES
Apr-18	10236792	10868795	10000	10092
May-18	8253974	8586521	10000	10140
Jun-18	4940118	6473790	10000	10097
Jul-18	4936298	5679878	10000	10183
Aug-18	4582946	5743378	10000	10130
Sep-18	7040555	7397131	10000	10111
Oct-18	8456795	8722498	10000	10145
Nov-18	7172366	8339063	10000	10316
Dec-18	3686980	7421043	10000	10411
Jan-19	8797463	9066897	10000	10316
Feb-19	12033738	10622221	10000	10402
Mar-19	14529325	12483851	10000	10387

4. Conclusions

In the present study, two univariate time-series models *viz.* Holt-Winters' Exponential Smoothing and seasonal ARIMA models were fitted to monthly arrivals and prices data of tender coconut in Maddur market which is world largest market for tender coconuts, during the period from April 1997 to March 2018. The results showed that ARIMA model better performed than H-WMES model for forecasting of arrivals and prices of tender coconuts. Seasonal ARIMA model could be successfully used for modelling as well as forecasting of monthly price of forecasting arrivals and prices of tender coconuts. The model demonstrated a good performance in terms of explained variability predicting power. Forecasting the future arrivals and prices of tender coconut will help the farmer to know the demand and price which in turn helps them for planning the harvest tender coconuts and to get good price. Forecasting will also helps Govt, traders, dealers to perform better strategic planning and also to help them in maximizing revenue and minimizing the cost of price.

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