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Forecasting of Monthly Average Wholesale Prices of Tomato: An Application of Hybrid Time Series Models

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Abstract

The focus of the present study is to give short term forecast of monthly average wholesale prices of tomato using hybrid time series models. For this Hybrid models of the linear seasonal autoregressive moving average (SARIMA) and the nonlinear Artificial Neural Network (ANN) have been considered for estimating and forecasting the monthly average wholesale prices of tomato. The monthly average wholesale prices of tomato from January 2010 to December 2022 have been obtained from different markets of Haryana. The goodness of fit of SARIMA model has been measured using Akaike Information Criteria (AIC), log likelihood (LL), Root Mean Square Error (RMSE) & Mean Absolute Percentage Error (MAPE). The performance of ANN models has been measured using performance measures RMSE & MAPE. The post-sample forecast accuracy has also been measured using MAPE and standard error of prediction (SEP in %). The results of the study showed that the Hybrid (SARIMA+ANN) models have been performed better as compared to SARIMA models for forecasting the monthly average wholesale prices of tomato. The results of this study may be useful for policy makers and various stakeholders in helping them to take appropriate decisions for making arrangements for procurement, distribution, storage, and trading in local and foreign markets, as well as for managing the right inventory in advance.

Keywords: Price Forecasting, MAPE, SARIMA, Hybrid Models and SEP

Introduction

Agricultural price forecasts are intended to be useful for farmers, governments and agribusiness industries. The ability to accurately forecast the agricultural commodities prices is an important concern for both policy maker and business circles. The Autoregressive Integrated Moving Average (ARIMA) model is a popular time series model for predicting the future values based on previous values. The popularity of ARIMA model's stems from its statistical properties as well as the well-known Box-Jenkins methodology [7, 8] used in model construction. However, the ARIMA model is unable to capture the nonlinear behaviour of the series. Therefore, over the last two decades, a number of studies on nonlinearity of time series data has been increasing

rapidly. The SARIMA model is a time series model which is used to deal with the seasonal and linear behaviour of agricultural commodity prices series. Various researchers including [1, 4, 5, 12, 13, 18, 21-26, 29] have been tried to study the seasonality of the time series data. Kumar *et al.* [19] used SARIMA models to forecast the tomato prices for rainy season harvest period. (August to October). Stationarity of time series data is an important part of SARIMA models for model identification and estimation of prices. SARIMA models are not useful when time series exhibit nonlinear dynamic behaviour such as asymmetry, frequency amplitude dependence, and volatility clustering. In general, time series data exhibit both linear and nonlinear behaviour therefore no single model can identify all characteristics of the time series data.

Zhang [30] proposed a Hybrid ARIMA and Neural Network (NN) model for time series forecasting and concluded that the proposed Hybrid methodology took advantage of the unique strengths of ARIMA and ANN models in linear and nonlinear modelling. Kumar *et al.* [15] used discriminant function analysis for pre-harvest forecast of rice yield based on meteorological parameters. Jha and Sinha [17] applied ANN and ARIMA methodology for time series forecasting and found that the proposed feed-forward TDNN can handle the nonlinearity of monthly wholesale price of oilseed in India as compared to linear models. Ayub and Jafri [3] compared the forecasting performance of ARIMA, ANN and Hybrid (ARIMA-ANN) models for Karachi stock prices. Yollanda and Devianto [28] developed a Hybrid SARIMA-ANN model to forecast tourist arrivals at Minangkabau International Airport. Wu *et al.* [27] proposed a novel Hybrid approach SARIMA + LSTM (seasonal autoregressive integrated moving average combined with long short-term memory) to predict daily tourist arrivals to Macau SAR, China. Jerbi and Chaabene [16] used neural networks for European call prices. Therefore, the present study is planned to compare the forecasting performance of the SARIMA and SARIMA-ANN models.

Methodology

Data set

The time series data of monthly average wholesale prices of tomato from January 2010 to December 2022 obtained from the website <https://agmarknet.gov.in> for Panipat and Kurukshetra markets of Haryana have been used in the study. The time series data have been divided into two parts: first for the development of the models and second for post validity checking of the fitted models. The first part considers 144 observations of data from January 2010 to December 2021. These observations were used to develop the forecasting models. In the second part, the values of the forecasting performances measures of the developed models were calculated using 12 observations of data from January 2022 to December 2022.

Seasonal Autoregressive Moving Average (SARIMA) Model

SARIMA is a commonly used model for linear and seasonal time series data analysis and forecasting. Suppose, a time series has N number of observations denoted by $\{y_t | t = 1, 2, \dots, N\}$ is created by a SARIMA $(p, d, q) \times (P, D, Q)_s$ process [11] by following equations:

$$\phi(B)(1-B)^d \phi(B^s)(1-B^s)^D y_t = c + \theta(B)\Theta(B)\varepsilon_t \quad (1)$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 \dots \dots \phi_p B^p \quad (2)$$

$$\phi(B^s) = 1 - \phi_1 B^s - \phi_2 B^{2s} \dots \dots - \phi_p B^p \quad (3)$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 \dots \dots - \theta_p B^p \quad (4)$$

$$\Theta(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} \dots \dots - \Theta_p B^p \quad (5)$$

$$SARIMA = ARIMA \underbrace{(p, d, q)}_{Non-seasonalpart} \times \underbrace{(P, D, Q)_s}_{Seasonalpart} \quad (6)$$

Where, B is back shift operator, s is number of observations in a year, $\phi(B)$ is the non-seasonal Auto-Regressive operator (AR), $\phi(B)$ is the Seasonal Auto-Regressive (SAR), $\theta(B)$ is the non-seasonal Moving Average (MA), $\Theta(B)$ is of the Seasonal Moving Average (SMA) operator of order p, P, q, Q respectively, d and D is order of non-seasonal and seasonal differencing respectively.

$$\begin{cases} D = 0, & \text{time series has no seasonality effect} \\ D \geq 1, & \text{time series has seasonality effect} \end{cases}$$

and ε_t is considered as residual.

In the SARIMA model building process Identification, parameter estimation, diagnostic checking, and forecasting are all iterative steps. The differencing transformation is required to make the series stationary during the identification step. When the observed time series exhibits trends & seasonal behaviour, the non-seasonal and seasonal differencing are used to remove the trend and seasonality before applying SARIMA model. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to determine the order of the MA, SMA, AR, SAR terms in SARIMA model. The preferred model is then statistically tested to see if it accurately describes the series. Further, when the model is appropriately specified, then the residuals should behave like white noise [19], that is, serially uncorrelated with zero mean and constant variance.

Hybrid (SARIMA-ANN) Model

Hybrid model is a combination of linear and nonlinear models that is typically used to improve

the forecast accuracy. In general, the mathematical form of combining linear and nonlinear models is as follows:

$$y_t = L_t + N_t + \varepsilon_t \quad (7)$$

Where, L_t is a linear component and N_t is a nonlinear component of the model. This Hybrid model is estimated in two steps: first step is to model the linear component to obtain the residual, and then apply a nonlinear model to this residual series to deal with the nonlinear component. In the present study, SARIMA model have been used in the first step to handle the linear component Let e_t (residual) be the nonlinear component obtained from the SARIMA model which is given below:

$$e_t = Y_t - \hat{L}_t \quad (8)$$

Where, $\hat{L}_t$ is the estimated value of Y_t from linear SARIMA model at time t. Then, ANN model have been used for modelling residual series obtained from SARIMA model is as follows:

$$e_t = f(e_{t-1}, e_{t-2} \dots \dots e_{t-p}) + e_t = \hat{e}_t + \varepsilon_t \quad (9)$$

Where, $\hat{N}_t$ is estimated value and ε_t is the residual of non-linear ANN model at period t. Hence, the forecast value of the Hybrid SARIMA-ANN model is as follows:

$$\hat{Y}_t = \hat{L}_t + \hat{e}_t \quad (10)$$

Model Validation/Evaluations

The model is evaluated quantitatively using the Mean Absolute Percentage Error (MAPE), Standard Error of Prediction (SEP in %), Root Mean Square Error (RMSE) and Relative Deviation (RD in %)

$$MAPE = \frac{100}{n} \times \sum_{i=1}^n \left| \frac{O_i - E_i}{O_i} \right| \quad (11)$$

$$SEP = \frac{100}{\bar{y}} RMSE \quad (12)$$

$$\text{Where } RMSE = \left[\frac{1}{n} \sum_{i=1}^n (O_i - E_i)^2 \right]^{\frac{1}{2}} \quad (13)$$

Where, O_i , $\bar{y}$ and E_i are the observed, mean and predicted values of Y and n is the number of observations used in the validation set.

Results and Discussion

SARIMA Model Results

Figure 2, revealed that the trend and seasonality have been observed in prices of selected markets and series became stationary after taking first differencing of de-seasonal time series. De-seasonal time series were obtained by removing the estimated seasonal component from observed price series or seasonal differencing.

Figure 3, showed ACF and PACF plots of stationary series and the appropriate order of MA (q) and SMA (Q) were expected to be lie between $0 \leq q \leq 2$ and $0 \leq Q \leq 1$. Also, PACF plot of stationary series showed that autocorrelations at lag 2, 12 and 24 are significant hence, an appropriate order of AR (p) and SAR (P) were expected to be lie between $0 \leq p \leq 2$ and $0 \leq P \leq 2$ for Panipat market. Similarly, order of MA (q) & SMA (Q) and order of AR (p) and SAR (P) were expected to be lie between $0 \leq q \leq 2$ & $0 \leq Q \leq 2$ and $0 \leq p \leq 2$ & $0 \leq P \leq 2$ respectively for Kurukshetra market.

Table 1 showed that the models SARIMA (1,1,1) (1,1,1)₁₂ and SARIMA (1,1,1)(1,1,0)₁₂ based on minimum value of AIC (2010.09), LL(-1001.05), RMSE (424.23), MAPE(19.83) and AIC (2009.60), LL (-999.80), RMSE (420.75), MAPE (19.29) for prices of tomato in Panipat and Kurukshetra markets respectively.

In Tables 2, all estimated parameters were found significant at 5% level of significance. Also, the values of estimated parameters were less than one which indicating that the parameters meet the stationary and invertibility conditions. The selected models for prices of tomato in Panipat and Kurukshetra markets are given below:

$$(1 - 0.97B^{12})(1 - 0.71B)(1 - B)(1 - B^{12})y_t = (1 + 0.98B^1)(1 - 0.96B^{12})\varepsilon_t \quad (11)$$

$$\text{and } (1 - 0.51B^{12})(1 - 0.71B^{12})(1 - B)(1 - B^{12})y_t = (1 + 0.95B^2)\varepsilon_t \quad (12)$$

Figures 4 and 5 indicated that there is no autocorrelation in the residual series of prices of tomato in Panipat and Kurukshetra markets. The SARIMA forecast was produced using the forecast R package [14].

Hybrid Model Results

Figure 6, indicated that the residuals obtained from selected models were non-linear. The Brock-Dechert-Scheinkman (BDS) test was also used for checking the nonlinearity of residuals obtained from selected models [2, 9, 10]. Therefore, artificial neural network (ANN) models have been used to model the nonlinear pattern of the residuals. The ANN models with three-layered feed forward neural network that is trained for 10×10^6 epochs with a learning rate of 0.001 and a threshold of 0.01 have been used. The number of nodes in the hidden layer has been

optimized using a trial-and-error method. The hidden layer with different neurons and activation functions was used to find the best fitted model.

Table 3 gave the value of RMSE and MAPE for training and testing dataset. ANN (12-5-1), and (12-7-1) models were selected based on lowest values of RMSE and MAPE for testing set for prices of tomato in Panipat and Kurukshetra markets respectively. In Table 4, the observed and predicted values of best-fit SARIMA and SARIMA-ANN models on prices of tomato were given for both markets. In Table 5, the values of performance measures such as MAPE and SEP for SARIMA and Hybrid (SRIMA-ANN) models have been given for the validation data set with various forecast horizons of prices of tomato.

Conclusion

In this study, the forecasting performance of SARIMA and Hybrid (SARIMA-ANN) models for monthly average wholesale prices of tomato have been compared for selected markets of Haryana. It was found that SARIMA (1,1,1) (1,1,1)₁₂ and SARIMA (1,1,1) (1,1,0)₁₂ models gave the better forecast for 1 and 3 months ahead based on SEP and MAPE values as compared to hybrid models for selected markets. Whereas, the hybrid models SARIMA (1,1,1) (1,1,1)₁₂ + ANN (12-5-1) and SARIMA (1,1,1) (1,1,0)₁₂ + ANN (12-7-1) provided better forecasting accuracy based on lowest values of performance measures like MAPE and SEP for 6, 9, and 12 months ahead forecast. Hence, based on the present study, it is concluded that hybrid time series models gave better short term forecast for forecasting the prices of Tomato. The results of the present study are based on tomato prices of some specific markets so these may be changed due to climatic conditions of other regions.

Statements and Declarations

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The time series datasets used during the current study are available in the government repository, <https://agmarknet.gov.in>

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Table 1: SARIMA Model Goodness of Fit Measures

SARIMA	AIC	LL	RMSE	MAPE
		Panipat		
(1,1,1)(1,1,1)₁₂	2010.09	-1001.05	424.23	19.83
(1,1,1)(0,1,1) ₁₂	2189.97	-1089.98	448.99	20.43
(1,1,1)(1,1,1) ₁₂	2011.76	-1005.88	425.38	19.99
(2,1,1)(0,1,1) ₁₂	2229.7	-1109.85	560.47	25.07
(1,1,2)(0,1,1) ₁₂	2190.34	-1089.17	444.31	20.85
(1,1,2)(1,1,1) ₁₂	2245.58	-1119.79	455.05	20.75
		Kurukshetra		
(1,1,1)(1,1,0)₁₂	2009.60	-999.80	420.75	19.29
(1,1,1)(1,1,1) ₁₂	2212.31	-1102.15	526.02	24.33
(1,1,0)(1,1,1) ₁₂	2189.97	-1089.98	448.99	20.43
(1,1,2)(0,1,1) ₁₂	2025.02	-1008.51	436.63	20.03
(1,1,0)(1,1,0) ₁₂	2245.89	-1118.95	599.75	27.53
(1,1,1)(0,1,1) ₁₂	2228.91	-1110.46	560.84	27.37

Table 2: Estimated parameters of selected SARIMA model for training data set

	Estimate	SE	Z value	P- value
Panipat				
AR1	0.71	0.06	10.97	<0.01
MA1	-0.98	0.01	-82.07	<0.01
SAR1	0.97	0.01	56.11	<0.01
SMA1	-0.96	0.09	-9.80	<0.01
Kurukshetra				
AR1	0.71	0.05	11.86	<0.01
MA1	-0.95	0.04	-21.16	<0.01
SAR1	0.51	0.07	7.29	<0.01

Table 3: RMSE and MAPE values for the ANN model for residuals series of SARIMA

Neural Network structure					Training set		Testing set	
Activation function	Input Node	Hidden Node	Rep.	Output Node	RMSE	MAPE	RMSE	MAPE
Panipat								
Logistic	12	5	5	1	78.74	48.41	52.75	29.25
	12	6	3	1	71.41	31.83	46.07	22.24
	12	8	2	1	65.44	30.39	49.12	21.75

Tanh	12	4	1	1	55.99	24.68	36.01	17.06
	12	5	1	1	26.53	21.98	21.29	9.31
	12	7	2	1	58.46	16.31	26.59	16.58
Kurukshetra								
Logistic	12	7	2	1	60.71	53.63	46.61	14.11
	12	9	3	1	47.73	42.23	38.73	9.98
	12	10	2	1	41.74	3.81	24.27	11.27
Tanh	12	4	3	1	40.01	30.22	33.30	8.17
	12	6	1	1	38.15	38.71	31.96	9.65
	12	7	2	1	25.28	9.87	10.11	3.77

Table 4: Observed and predicted values of SARIMA and Hybrid model

Month	Panipat			Kurukshetra		
	Observed	SARIMA	Hybrid	Observed	SARIMA	Hybrid
Jan-22	1361.94	1401.77	1410.41	1643.68	1679.81	1701.81
Feb-22	1192.85	1289.87	1508.19	1200.45	1301.75	1495.59
Mar-22	1279.92	1341.93	1588.81	1435.56	1490.38	1775.70
Apr-22	1279.92	1563.40	1384.39	1422.36	1136.93	1658.60
May-22	2196.63	1578.01	2379.48	1999.94	1329.11	2201.51
Jun-22	2193.63	1608.87	1958.69	1956.29	1356.65	1698.74
Jul-22	1754.04	2174.62	1525.32	1884.11	1591.49	1601.60
Aug-22	1705.2	2159.64	1634.89	1716.72	1461.15	2113.05
Sep-22	2429.03	2014.77	2776.26	2549.59	2107.12	2920.14
Oct-22	2429.03	2006.15	2482.86	2453.35	2226.31	2367.73
Nov-22	1649.86	2104.41	1609.59	1883.07	2559.54	1810.85
Dec-22	1359.22	1821.20	1545.88	1501.92	2050.31	1718.21

Table 5: Predictive accuracy measures of selected best fitted models for prices of tomato

Forecast horizons	Panipat				Kurukshetra			
	SARIMA		Hybrid		SARIMA		Hybrid	
	MAPE	SEP	MAPE	SEP	MAPE	SEP	MAPE	SEP
1 month	2.92	2.29	3.56	2.79	2.20	2.00	3.54	3.22
3 months	5.30	4.05	18.04	14.77	4.82	3.86	17.27	14.53
6 months	15.48	21.29	13.55	12.18	16.45	21.54	15.28	13.75
9 months	17.84	22.52	12.53	13.23	16.28	20.68	16.03	15.93
12 months	19.96	23.36	10.93	11.92	19.02	22.98	13.83	14.34

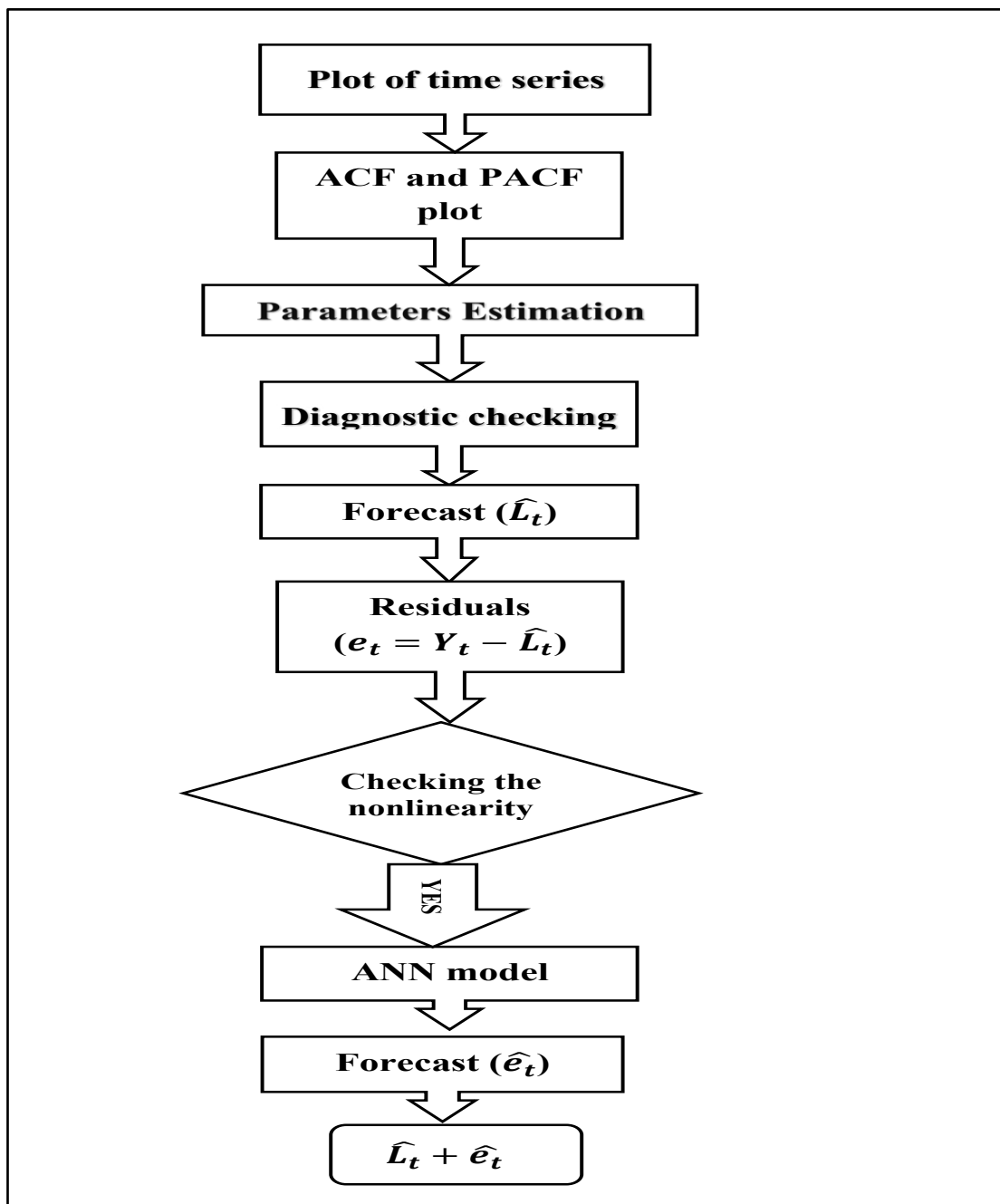


Figure1: Systematic diagram of SARIMA+ANN models

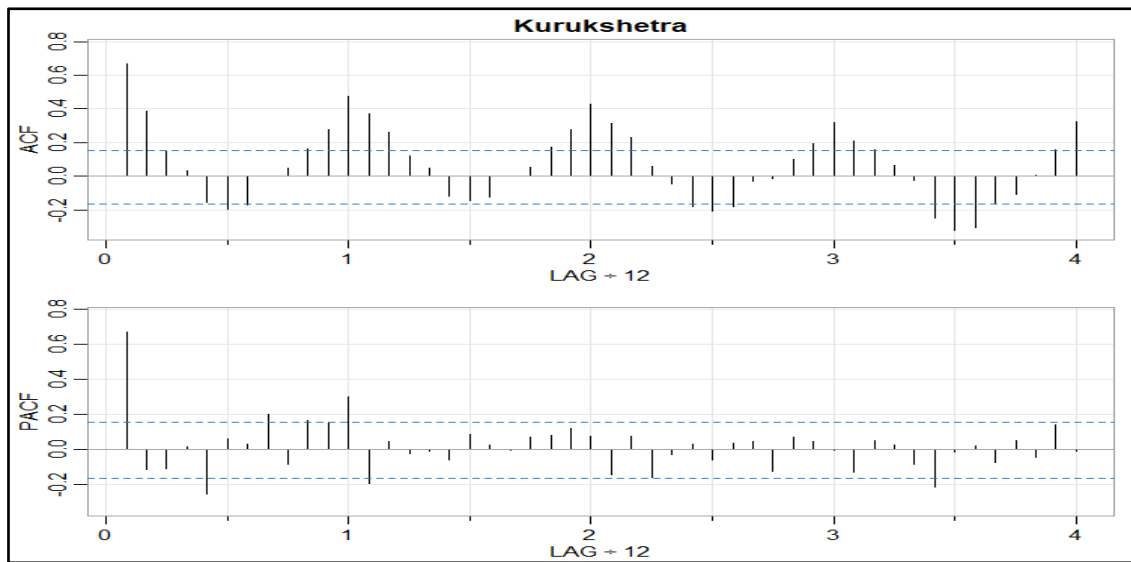
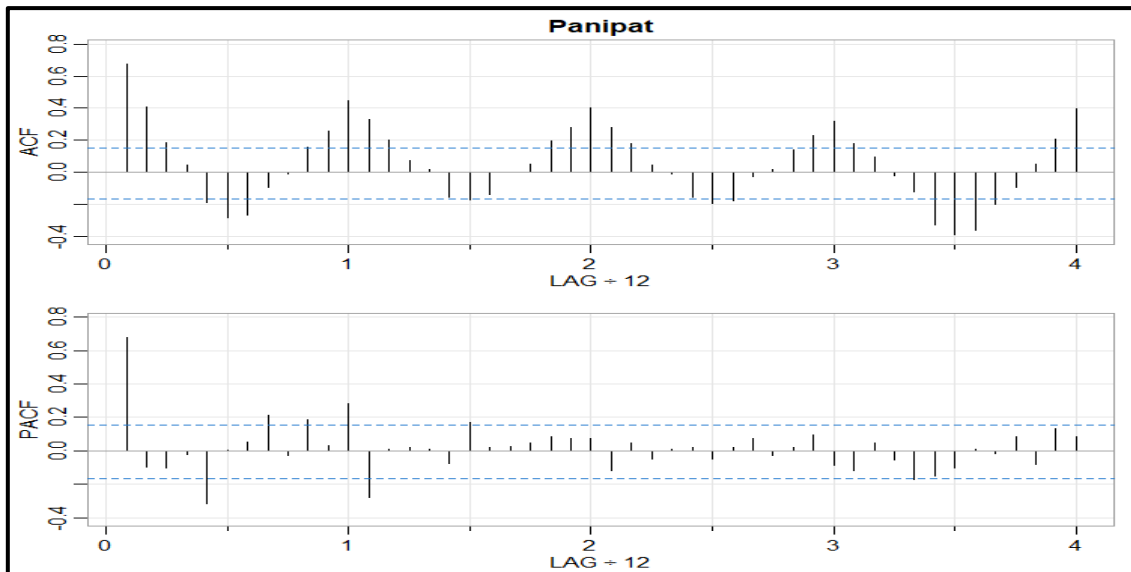
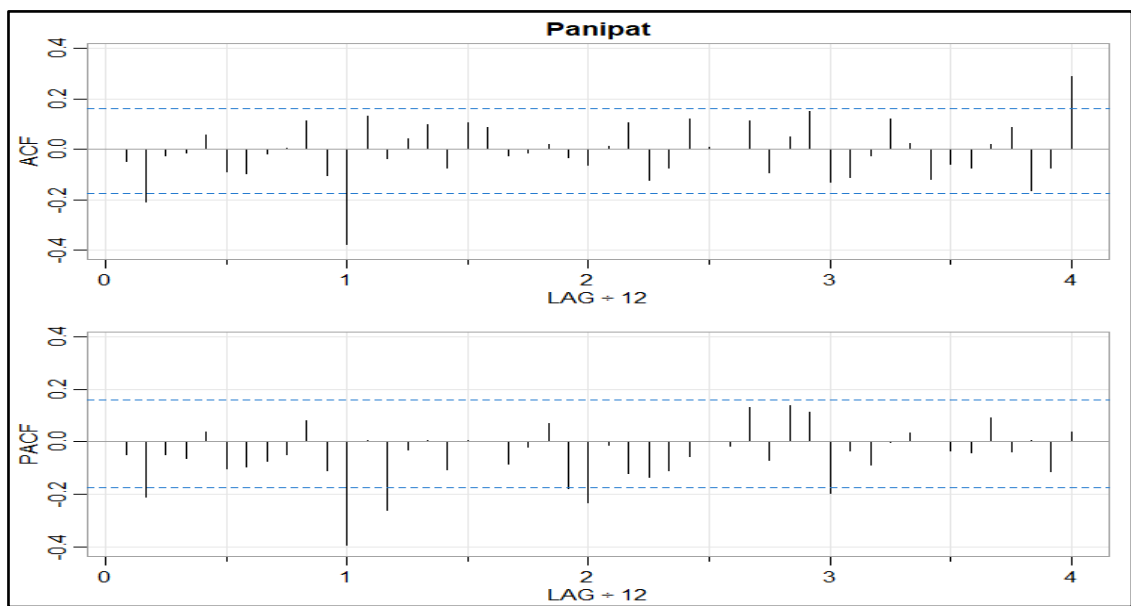


Figure 2: ACF and PACF plots of actual series



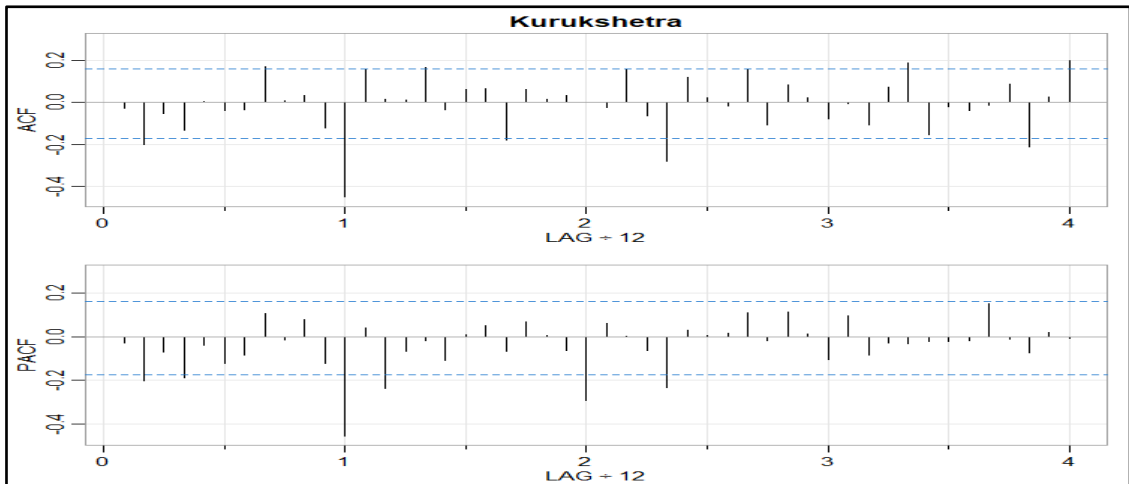


Figure 3: ACF and PACF plots of stationary series

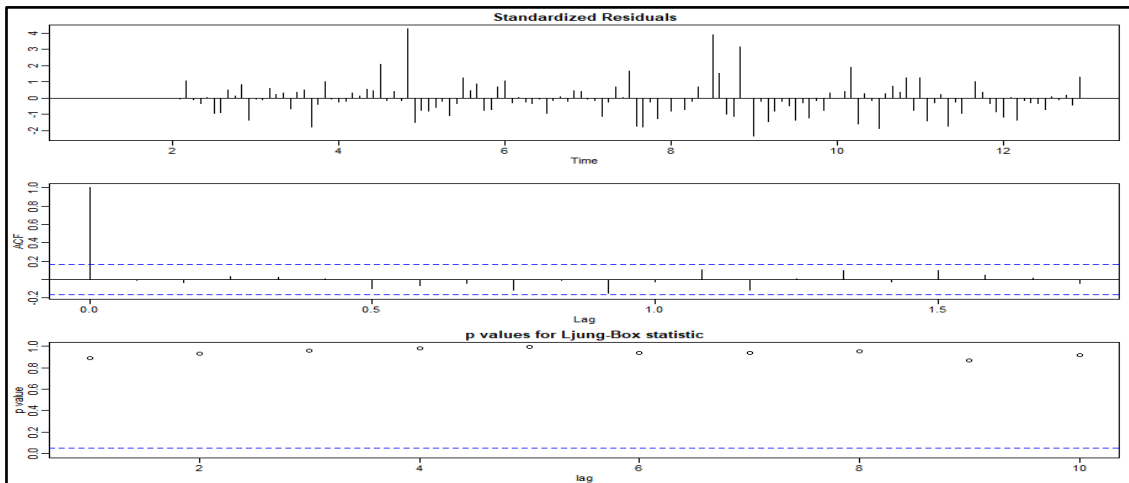


Figure 4: Plot of Residuals from SARIMA $(1,1,1)(1,1,1)_{12}$ model for prices of tomato in Panipat Market

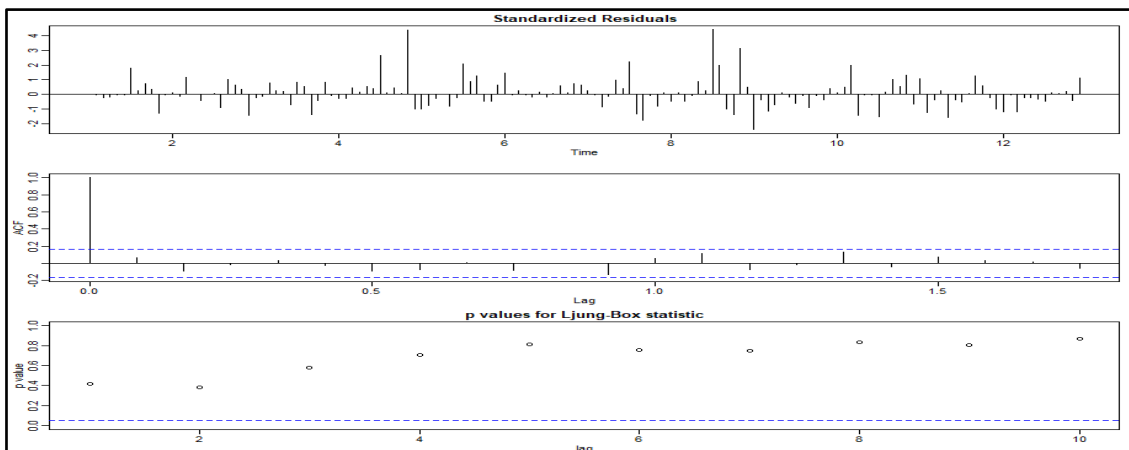


Figure 5: Plot of Residuals from SARIMA $(1,1,1)(1,1,0)_{12}$ model for prices of tomato in Kurukshetra market

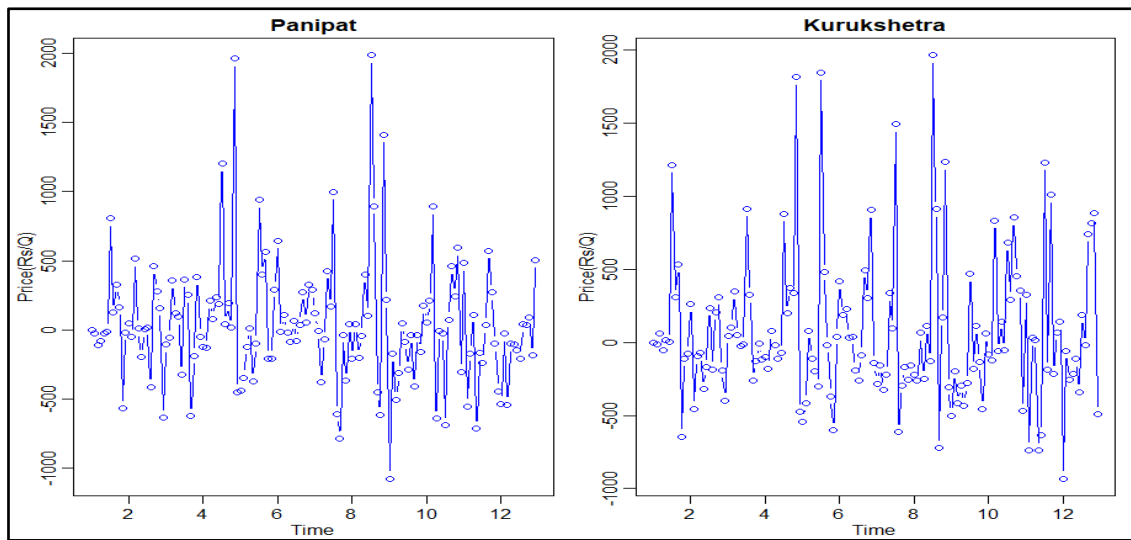


Figure 6: Residual plots of fitted SARIMA models