

PRE HARVEST PRICE FORECASTING OF BENGALGRAM PRICE IN TELANGANA BY USING ARIMA MODEL

R.VIJAYA KUMARI¹, G. RAMAKRISHNA², VENKATESH PANASA³ and A. SREENIVAS⁴

^{1,2,3&4}Agricultural Market Intelligence Centre, College of Agriculture, PJTAU, Rajendranagar, Hyderabad

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ABSTRACT

Accurate pre-harvest price forecasting is essential for enabling farmers to make informed production and marketing decisions and for improving the effectiveness of agricultural market intelligence. The present study aimed to develop an appropriate Autoregressive Integrated Moving Average (ARIMA) model for forecasting Bengalgram prices in Telangana using monthly market price data collected from April 2002 to December 2025. The Box–Jenkins methodology, comprising model identification, parameter estimation, and diagnostic checking, was employed using SAS software. Several ARIMA models were evaluated based on Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), parameter significance, and residual diagnostics. Among the candidate models, **ARIMA (112)** was selected as the best-fit model, exhibiting the lowest AIC (4075.07) and BIC (4087.66) values. The residual diagnostics confirmed that the model residuals were white noise, indicating an adequate model fit. The model forecasted Bengalgram prices in the range of **INR 5,100–5,400 per quintal** during the pre-harvest period. Validation of the forecasts against observed market prices showed a **percent deviation of only “0.96%”,** demonstrating high forecasting accuracy.

Key Words: ARIMA, Bengalgram, Box–Jenkins methodology, Market intelligence, Price forecasting.

Bengalgram (*Cicer arietinum* L.), commonly known as chickpea, is the most extensively cultivated pulse crop in India, accounting for nearly 40 per cent of the country's total pulse production. India is the world's largest producer and consumer of Bengalgram, contributing more than two-thirds of global production. During 2025–26, Bengalgram was cultivated over 96.60 lakh hectares in India, with an estimated production of 125.14 lakh tonnes. Major producing states include Maharashtra, Rajasthan, Madhya Pradesh, Gujarat, Uttar Pradesh, and Andhra Pradesh. In Telangana, Bengalgram is an important pulse crop cultivated predominantly in districts such as Nirmal, Kamareddy, Adilabad, Sangareddy, Nizamabad, and Gadwal. During 2025–26, the crop occupied about 0.76 lakh hectares in the state, with an estimated production of 1.50 lakh tonnes and a productivity of 1,769 kg ha⁻¹.

Despite its economic importance, Bengalgram prices exhibit considerable fluctuations due to variations in production, arrivals, procurement policies, minimum support price (MSP), domestic demand, exports, imports, weather conditions, and market sentiment. Such price volatility creates uncertainty among farmers and other market participants, making it difficult to determine the appropriate time for marketing the produce. Therefore, developing reliable statistical models for

forecasting market prices is essential for strengthening agricultural market intelligence and supporting evidence-based decision-making.

Time-series forecasting models have been widely used in agricultural economics to analyse historical price behaviour and generate short-term forecasts. Among these, the Autoregressive Integrated Moving Average (ARIMA) model developed under the Box–Jenkins methodology has gained wide acceptance because of its ability to capture temporal dependence in historical data and provide accurate forecasts using only past observations. ARIMA models have been successfully applied to forecast agricultural commodity prices, production, and demand in several studies, demonstrating their usefulness for market intelligence and policy planning.

Considering the importance of Bengalgram in Telangana and the need for timely price information, the present study was undertaken to develop an appropriate ARIMA model for forecasting pre-harvest Bengalgram prices using historical monthly market price data. The study aims to identify the best-fitting ARIMA model, generate reliable short-term price forecasts, and evaluate the forecasting performance of the selected model. The findings are expected to support farmers, traders, policymakers, and agricultural extension

agencies by providing scientifically generated price forecasts that facilitate informed marketing decisions and improve the effectiveness of agricultural market intelligence.

A Brief Survey of Literature

Meyler *et al.* (1998) drew a framework for ARIMA time series models for forecasting Irish inflation. Prajneshu and Venugopalan (1998) applied this model as well as other parametric statistical modeling techniques, like polynomial function fitting, and nonlinear mechanistic growth modeling for describing trends in marine fish production data of the country. Husain and Bowman (2004) assessed the performance of three types of commodity price forecast - a) based on judgment, b) relying exclusively on historical price data, and c) incorporating prices implied by commodity futures for close to 15 commodities using spot and future prices. They concluded that spot prices tend to move toward futures prices over the long run, and error-correction models exploiting this feature produce more accurate forecasts. Singh *et al.* (2007) applied statistical models for forecasting rice production in India. Chen *et al.* (2010) predicted agri-commodity prices using asset pricing approach and demonstrated the prevalence of structural breaks, emphasizing the importance of controlling the same. Elangbam Haridev Singh (2013) developed forecasts of international tourism demand for Bhutan by selecting appropriate model both ARIMA as well as exponential smoothing. Paul *et al.* (2014) applied models for livestock and dairy production in India under time series framework. Paul *et al.* (2015) applied the autoregressive fractionally integrated moving-average (ARFIMA), ARFIMA model searches for a non-integer differencing parameter d to difference the data to capture long memory. The model is applied for modelling and forecasting of daily retail price of pigeonpea in Karnal during January, 2011 to July, 2013. Kumari *et al.* (2019) ARIMA approach has been applied for modeling and forecasting of green gram prices in Telangana.

MATERIAL AND METHODS

Data description

The major sources of price data on selected commodities include the official records of Directorate of Economics and Statistics, Government of Telangana, and the official websites of marketing departments of both Andhra Pradesh and Telangana states.

The monthly average price data of selected commodities in selected markets from April 2002 to 2007

December was obtained from Directorate of Economics and Statistics, Government of Telangana. The same data from 2008 January onwards was collected from websites tgmarketing.

Autoregressive Integrated Moving Average (ARIMA) Model

A generalization of ARMA models which incorporates a wide class of non-stationary time-series is obtained by introducing the differencing into the model. ARIMA econometric modeling takes into account historical data and decomposes it into an autoregressive (AR) process where there is a memory of past events and integrated (I) process which accounts for stabilizing or making the data stationary, making it easier to forecast, and a moving average (MA) of forecast errors, such that the longer the historical data, the more accurate forecast will be as it learns from over time. The simplest example of a non-stationary process which reduces to a stationary one after differencing is Random Walk. A process $\{y_t\}$ is said to follow an Integrated ARMA model, denoted by ARIMA (p, d, q).

The ARIMA methodology is carried out in three stages, viz. identification, estimation and diagnostic checking. Parameters of the tentatively selected ARIMA model at the identification stage are estimated at the estimation stage and adequacy of tentatively selected model is tested at the diagnostic checking stage. If the model is found to be inadequate, the three stages are repeated until satisfactory ARIMA model is selected for the time-series under consideration. An excellent discussion of various aspects of this approach is given in Box *et al.* (2007). Most of the standard software packages, like SAS, SPSS and E Views contain programs for fitting of ARIMA models.

Estimation of Parameters

Estimation of parameters for ARIMA model is generally done through Nonlinear least squares method. Fortunately, several software packages are available for fitting of ARIMA models. To this end, in this paper, SAS software package is used. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) values for ARIMA model are computed by:

Akaike's information criterion (AIC):

$$AIC = \log \hat{\sigma}^2 + 2 \frac{p + q}{n}$$

where $\hat{\sigma}^2$ is the estimated variance of e_t

Schwarz's Bayesian Information criterion (SC, BIC, or SBC):

$$BIC = \log \hat{\sigma}^2 + 2 \frac{p + q}{n} \log(n)$$

Usually, the model with the smallest AIC or BIC values are preferred. While the two criteria differ in their trade-off between fit and parsimony, the BIC criterion can be preferred because it has the property that it will almost surely select the true model.

ACF and PACF plots of the residuals

In the model-building process, if an ARIMA (p, d, q) model is chosen (based on the ACFs and PACFs), some checks on the model adequacy are required. A residual analysis is usually based on the fact that the residuals of an adequate model should be approximately white noise. Therefore, checking the significance of the residual autocorrelations and comparing with approximate two standard error bounds, i.e., $\pm 2/\sqrt{n}$ are need.

Data preparation and model selection

The input series for ARIMA needs to be stationary. A stationary series should have a constant mean, variance, and autocorrelation through time. The purpose of identification phase is to determine the differencing required for producing stationary and also the order of non seasonal AR and MA operators for a given series. When the observed time series presents trend, differencing and transformation are often applied to the data to remove the trend and stabilize variance before an ARIMA model can be fitted. The input time series show upward trend with spike see. Fig 2. Then we differentiated onetime non seasonal and one time seasonal, the result being stabilized over mean (see fig 1). This model is then used for prediction purposes. Patterns are more difficult to recognize. When the order of at least one of the two components (AR or MA) is clearly detectable, the other can be identified by attempts in the following step of parameter estimation. Finally, the existence of a seasonal component of length s is underlined by the presence of a periodic pattern of period s in the ACF.

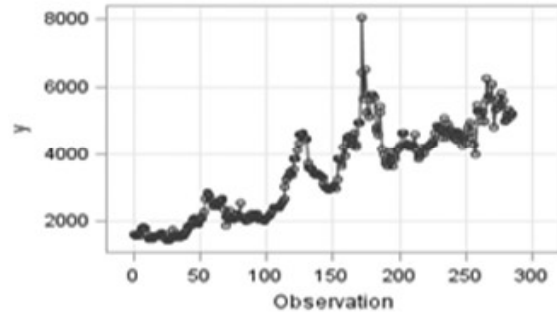


Fig 1: line plot of the original series of bengalgram price

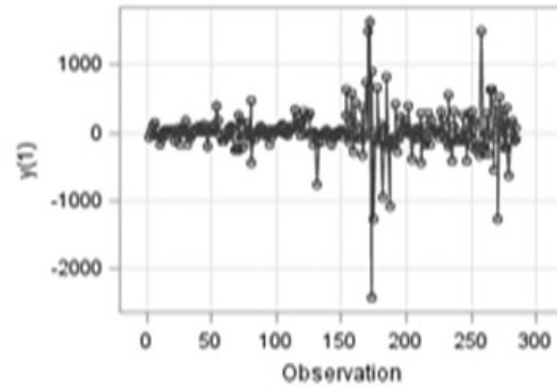


Fig 2: line plot of the first order differenced series of bengalgram price

Estimation and Testing

After identifying the suitable ARIMA (p, d, q) structure, subsequent steps of parameter estimation and testing are performed. Estimation stage consists of using the data to estimate and make inferences about parameters of tentatively identified model. The parameters are estimated such that an overall measure of residuals is minimized. The last stage of model building is the testing or diagnostic checking of model adequacy. This stage determines whether residuals are independent, homoscedastic and normally distributed. Several diagnostic statistics and plots of the residuals are used to examine the goodness of fit. After identifying tentative model, the process is again followed by the stage of parameter estimation and model verification. Diagnostic information may help to suggest alternative model(s). Now, the series is stationary and several models were selected base on their ability of reliability predication. On examining its

autocorrelation functions (ACF) and partial autocorrelation functions (PACF) and on the basis of minimum AIC and BIC values and significance of AR and MA parameters, the ARIMA(112) model is selected. Parameter estimates along with corresponding standard errors of fitted ARIMA(112) model are reported in Table 2.

Table 1. AIC and BIC values for different ARIMA models

Model	AIC	BIC
ARIMA(011)	4081.27	4088.57
ARIMA(110)	4083.18	4090.48
ARIMA(111)	4081.89	4092.84
ARIMA(210)	4083.77	4094.71
ARIMA(012)	4082.64	4093.59
ARIMA(211)	4083.20	4097.80
ARIMA(112)	4075.07	4087.66
ARIMA(212)	4076.37	4094.62

Forecasting

From the above models we further streamline the model by looking at the residual, in order to know that the model has white noise. If the model has white noise then we can use it for forecasting. The residual of ARIMA (112) has white noise (see fig 3). Now, we turn to the application (i.e., forecasting). Our objective is to predict the 3 future values of time series. Table 3 shows monthly forecasted results with confidence limits for time series. Which was INR 5100-5400 per quintal at the time of harvesting.

The forecasts were disseminated to farmers through regional newspapers, website, information bulletins, personal meetings and interactions, social media and other relevant means. Finally percent deviations were calculated by comparing forecasted price to actual price which was present in commodity markets. The actual price range was 5000-5400 Rs/ quintal and percent deviation of actual price from forecast price is -0.96 percent

Table 2. Parameter estimates along with corresponding standard errors.

Conditional Least Squares Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr> t	Lag
MU	13.83023	14.02447	0.99	0.3249	0
MA1,1	-0.73911	0.16935	-4.36	<.0001	1
MA1,2	0.26037	0.08483	3.07	0.0024	2
AR1,1	-1.00000	0.16555	-6.04	<.0001	1

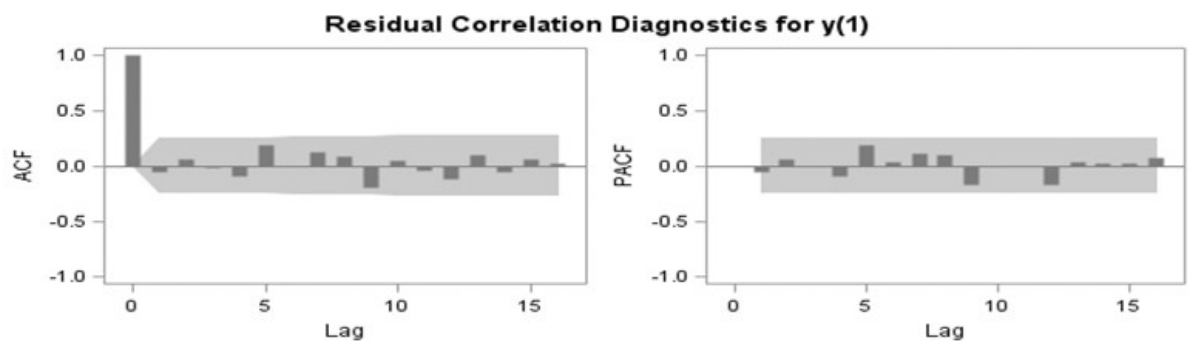
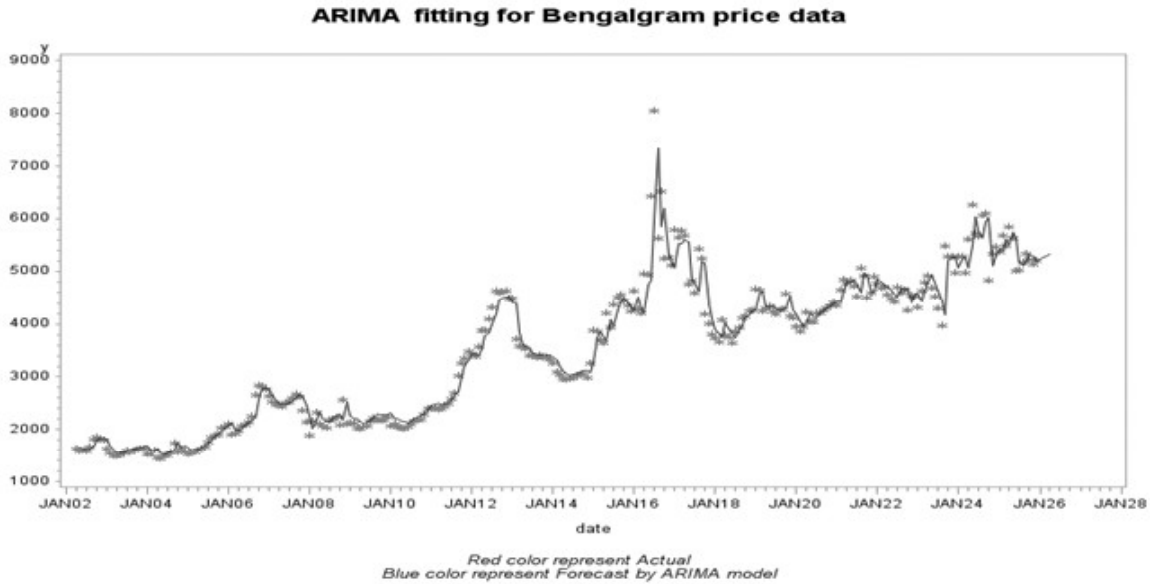


Fig 3. ACF and PACF of the residuals of fitted ARIMA model

Table 3. Forecasts of bengalgram prices in Telangana up to March 2026.

Months	Forecast	Std Error	95% Confidence Limits	
Jan	5225.8517	319.2894	4600.0559	5851.6475
Feb	5235.0771	397.0349	4456.9030	6013.2511
Mar	5253.5122	461.9589	4348.0893	6158.9351

**Fig 4. Bengalgram prices in Telangana actual and forecasted data from the month and year April 2002 to March 2026.**

CONCLUSION

The present study demonstrated the applicability of the Autoregressive Integrated Moving Average (ARIMA) model for forecasting pre-harvest prices of Bengalgram in Telangana using monthly price data. Among the alternative models evaluated, the ARIMA (112) model was identified as the most suitable based on the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, along with satisfactory diagnostic tests indicating white-noise residuals. The model generated reliable forecasts for the pre-harvest period, with forecasted prices ranging from INR 5,100 to 5,400 per quintal. The comparison between forecasted and observed market prices showed a percent deviation of only "0.96%, indicating a high level of forecasting accuracy.

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