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FuzzyARIMA: A Novel Fuzzy Based Autoregressive Integrated Moving Average Model for Coconut Price Forecasting

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ABSTRACT

The global haul for Coconut and coconut-based products has surged in recent decades, leading to fluctuating Coconut prices that are challenging to predict accurately. Effective price modelling is crucial for achieving reliable forecasts. Numerous studies have explored various models to predict Coconut prices, with the autoregressive integrated moving average (ARIMA) being globally used in time series forecasting. However, an inherent problem of price fluctuations, characterized by uncertain and nonlinear behaviour, makes traditional ARIMA models inadequate. The traditional ARIMA model relies on linearity and is prone to being affected by outliers and noise, reducing its effectiveness with complex or uncertain data. In response, fuzzy logic has emerged as a successful method for handling nonlinear and uncertain data patterns over the past two decades, mainly through the fuzzy-based autoregressive moving average model (FuzzyARIMA), which excels in volatile and uncertain series. The FuzzyARIMA model uses fuzzy logic to address uncertainty and non-linearity, enhancing its performance in such situations. Hence, the proposed FuzzyARIMA is recognized as a versatile approach for Coconut price forecasting. This study aims to embed linear and nonlinear time series models for Coconut price forecasting, exploring a hybrid approach that integrates ARIMA with deep fuzzy logic. The main objective is to assess how this integration improves prediction accuracy, focusing on monthly wholesale prices of Coconut from various markets in Andhra Pradesh (Rajahmundry), Karnataka (Mangalore), and Kerala (Kozhikode) covering the period from January 1, 1995, to December 31, 2022. These three states are major coconut producers in India, and within them, these specific markets hold significant importance for the coconut trade. Therefore, these have been chosen for this study. Experimental results demonstrate that the proposed FuzzyARIMA method achieves over 10 per cent improvement in Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) values compared to the ARIMA model in all three markets: Rajahmundry, Mangalore, and Kozhikode. This suggests that the FuzzyARIMA model significantly outperforms the traditional ARIMA model in forecasting Coconut prices, offering potential benefits for farmers, exporters, and governments in maximizing future profits.

Keywords: ARIMA, fuzzy logic, fuzziness, time-series forecasting, uncertainty

JEL codes: C22, C53, O13, Q11, Q13

I

INTRODUCTION

India is the largest Coconut producer globally, contributing approximately 31.45 per cent of the world's total production in 2021-2022, with an output of 19.247 million nuts. This crop significantly impacts the nation's economy, adding around 307498 million rupees to the gross domestic product (GDP) (Source: India Brand Equity Foundation (IBEF); https://www.ibef.org/exports/coconut-industry-india). The Coconut palm is vital for food security and provides livelihood opportunities to over 12 million people in India. Additionally, it supplies fibre to more than 15,000 coir-based industries, employing nearly 600,000 individuals. Most of India's Coconut production is concentrated in Kerala, Karnataka, Tamil Nadu, and Andhra Pradesh,

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collectively accounting for 89.13 per cent of the Coconut growing area and 90.04 per cent of the total production. India plays a crucial role in the global market for Coconuts and related products. In 2021-2022, India's Coconut exports surpassed 3236.83 crore rupees, a 41 per cent increase from the previous year. This robust export growth is fueling job creation in various Coconut based products such as Coconut chips, oil, milk, sugar, water, honey, and jaggery, which are experiencing high demand internationally (INDIAN TRADE PORTAL; Ministry of Commerce and Industry; GoI. (https://www.indiantradeportal.in//)). Coconuts contribute to No Poverty (SDG 1) and Zero Hunger (SDG 2) by offering livelihoods and ensuring food security for millions. Therefore, the current study aims to forecast Coconut prices, allowing stakeholders to make informed decisions for government policy formulation and farmer planning. This will help stabilize markets and improve production efficiency, as accurate forecasts are essential for effective risk management and optimal resource allocation.

Accurately predicting events and phenomena is essential for making better decisions under uncertain conditions. Modelling temporal price series helps extract valuable features from the data and allows for future extrapolation based on this information. Various stochastic processes are employed to model and predict specific time series. Since the 1930s, the well-known Autoregressive Integrated Moving Average (ARIMA) model (Box *et al.*, 2007) has been a dominant method in time series analysis. In agricultural and horticultural data, the ARIMA model has been widely applied and well-documented in the literature (Harris *et al.*, 2012; Bhardwaj *et al.*, 2014; Paul, 2015; Jadhav *et al.*, 2017; Noureen *et al.*, 2019; Kumar and Baishya, 2020; Srivastava *et al.*, 2022; Mapuwei *et al.*, 2022; Khan, and Singh, 2022). Rakshit and Paul (2024) described time series forecasting models for agricultural commodity price forecasting. Wani *et al.* (2015) developed market integration models for apple price forecasting in India. Precise forecasting of Coconut prices is crucial for India's trading strategy. It enables farmers, exporters, and the government to plan effectively and maximize future profits. Predicting Coconut prices in time series is particularly challenging due to their volatility. Agriculture price fluctuations affect commodity supply and demand, impacting consumers and farmers significantly. These fluctuations create income uncertainty for farmers, complicating government efforts to implement stable policies. Various methods (Allen, 1994; Abeygunawardana *et al.*,1996; Brintha *et al.*, 2015; Abeysekara and Waidyarathne, 2020; Prasert and Rungreunganun, 2021), including the ARIMA model, have been employed to model and forecast Coconut prices. However, ARIMA models are designed for linear data and may not always be suitable for nonlinear practical problems, especially in horticultural crops where prices are influenced by unpredictable factors such as seasonality and market conditions. The fluctuation of Coconut prices is characterized by uncertain and evolving behaviours over time. Factors contributing to these fluctuations include economic pricing strategies, shifts in market demand for Coconut, and variations in the quality and quantity of Coconut products. Therefore, devising an appropriate methodology to forecast Coconut prices remains a challenge. Nowadays, time series data has been increasingly modelled using deep intuitionistic fuzzy logic. The primary advantage of fuzzy sets and theory lies in their flexible functional form and their capability as universal function approximations. They effectively solve problems involving uncertain, fuzzy, and nonlinear data patterns. Numerous contemporary challenges benefit from these capabilities, such as forecasting stock markets with unpredictable behaviours that evolve. Fuzzy logic has also been applied in various studies to address the pricing of horticultural commodities. Due to the substantial uncertainty and volatility inherent in Coconut commodity price data, there is a heightened need to address the uncertainty or vagueness present in the data, as ARIMA models often fail to capture these characteristics. To tackle these uncertainties and ambiguities, Zadeh (1965) introduced the concept of fuzzy sets (FS) using fuzzy logic and membership functions, which can effectively model uncertainty and ambiguity. Song and Chissom (1993) further advanced this idea by developing the fuzzy time series model and applying it to the enrollment data from the University of Alabama. Atanassov (1986) expanded upon Lotfi Zadeh's fuzzy sets by introducing intuitionistic fuzzy set theory. This theory incorporates additional levels of uncertainty and hesitation, allowing for the representation of membership degrees, non-membership degrees, and a hesitation degree, thus better capturing the uncertainty and indecision commonly encountered in real-world scenarios. This highlights the key differences between fuzzy logic and intuitionistic fuzzy logic, as well as the significant advantages of deep fuzzy logic over Zadeh's basic fuzzy set theory. Leveraging this fuzzy logic, numerous researchers (Ghosh *et al*., 2016; Dwivedi *et al*., 2023) have developed models for effectively predicting future values. Lah *et al*. (2022) introduced a temperature prediction approach that combines ARIMA with fuzzy data preparation techniques during preprocessing. Their methodology employed standard deviation methods to create fuzzy triangles, effectively managing fuzzy data.

This study introduces a hybrid deep fuzzy autoregressive moving average (FuzzyARIMA) model motivated by the complexity of price fluctuations for Coconut price prediction. The primary aim of this article is to evaluate and compare the predictive capabilities of an efficient fuzzy-based ARIMA model for estimating aggregate prices of coconut across various markets in India. The hybrid approach integrates intuitionistic fuzzy logic (IFL) with the ARIMA model to leverage the strengths of both linear and nonlinear modelling techniques. The study explores the effectiveness of this model in forecasting Coconut prices, emphasizing how hybrid models can complement each other in capturing diverse patterns within Coconut price data and enhancing forecasting precision. The proposed FuzzyARIMA model aims to assist farmers, exporters, and government entities in optimising future profitability. To assess the performance of these proposed models, Coconut price data from various markets in India, such as Rajahmundry markets in Andhra Pradesh, Mangalore market in Karnataka, and Kozhikode in Kerala, are used, employing statistical measures such as root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE).

The structure of this paper is as follows: Section 2 outlines the methodologies employed in this study. Section 3 details the outcomes of using the FuzzyARIMA model for predicting Coconut prices. Section 4 summarizes the research and offers conclusions.

II

METHODOLOGY

Auto-Regressive Integrated Moving Average (ARIMA) Model

The ARIMA (p, d, q) model, which is probabilistic, has been utilized in various fields of predictive studies. Initially applied to the time series modelling and forecasting by Box and Jenkins in 1970, the ARIMA model comprises three components: autoregressive (AR) part, integrated (I), and moving average (MA) part. The development of an ARIMA model involves three key steps: Identification of the model, Estimation of Parameter, and Diagnostic Checking. Model identification entails determining the order of the model by utilizing the sample autocorrelation function (SACF) and the sample partial autocorrelation function (SPACF). The SACF measures the correlation between its past and future values. In the ARIMA model, parameter estimation involves calculating the coefficients for the autoregressive and moving average portions. This process generally employs techniques like maximum likelihood estimation or least squares to fit the ARIMA model to the data accurately. The residuals (white noise) of the models are evaluated using the correlogram (plot of SACF and SPACF), Ljung-Box Q tests, and the Durbin-Watson test to ensure the adequacy of the models.

The ARIMA (p,d,q) model can be represented as given equation (1).

$$x_t = a + \pi_1 x_{t-1} + \pi_2 x_{t-2} + \cdots + \pi_p x_{t-p} + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \beta_2 \varepsilon_{t-2} - \cdots - \beta_q \varepsilon_{t-q} \qquad \ldots(1)$$

where, x_t is the *d* times differenced series of given data at time $t(\in N)$; a is constant; $\varepsilon_t$is the residual term with zero mean and constant variance; $\pi_1 x_{t-1} + \pi_2 x_{t-2} + \cdots + \pi_p x_{t-p}$ is the AR part of order p, with $\pi_1, \pi_2, \ldots, \pi_p$ being AR parametres; and $\varepsilon_t - \beta_1 \varepsilon_{t-1} - \beta_2 \varepsilon_{t-2} - \cdots - \beta_q \varepsilon_{t-q}$ is the MA part of order q with $\beta_1, \beta_2, \ldots, \beta_q$ being MA parameters.

Proposed Deep Intuitionistic FuzzyARIMA Model

Unlike fuzzy time series approaches, which rely solely on membership functions, Intuitionistic Fuzzy Logic (IFL) systems incorporate membership and non-membership variables to establish fuzzy relationships. Consequently, IFL systems typically utilize more data than the traditional fuzzy technique. This enhanced data usage in Intuitionistic Fuzzy Time Series (IFTS) modelling improves predictive capabilities for tackling real-world time series problems. If $\mathcal{A}$ is the universal set and $\mathcal{A}_1, \mathcal{A}_2, \ldots, \mathcal{A}_c$ are the intuitionistic fuzzy sets defined on $\mathcal{A}$ and $y_t; (t \in N)$, represents the given time series with membership and non-membership values are

$\mathcal{M}_{\mathcal{A}_1}(t), \mathcal{M}_{\mathcal{A}_2}(t), \dots, \mathcal{M}_{\mathcal{A}_c}(t)$ and $\mathcal{N}_{\mathcal{A}_1(t)}, \mathcal{N}_{\mathcal{A}(t)}, \dots, \mathcal{N}_{\mathcal{A}_c(t)}$ respectively. Then According to (Egrioglu *et al*., 2019), intuitionistic fuzzy sets $(\mathcal{F}_t)$ can be represented as $\mathcal{F}_t = \{y_t, \mathcal{M}_{\mathcal{A}_1}(t), \mathcal{M}_{\mathcal{A}_2}(t), \dots, \mathcal{M}_{\mathcal{A}_c}(t), \mathcal{N}_{\mathcal{A}_1}(t), \mathcal{N}_{\mathcal{A}_2}(t), \dots, \mathcal{N}_{\mathcal{A}_c}(t)\}$ (2)

The following steps are used in the proposed FuzzyARIMA model.

Step1. Find the optimum number of clusters (m) through the elbow method. Initialize the membership values $(\mathcal{M}_{jt})$ by using equation 3.

$$\mathcal{M}_{jt} = \frac{\mathcal{U}_{jt}}{\sum_{j=1}^{m} \mathcal{U}_{jt}} \tag{3}$$

where, y_{jt} $(t = 1,2, \dots, N)$ is the characteristic value of time series data in j^{th} cluster and $\mathcal{U}_{jt}(j = 1,2, \dots, m; t = 1,2, \dots, N)$ is random variable generated from uniform distribution and N is the total number of observations

Step2. Cluster centres are calculated by equation (4).

$$M_j^* = \frac{\sum_{t=1}^{N} (\mathcal{M}_{jt})^{\alpha} y_{jt}}{\sum_{t=1}^{N} (\mathcal{M}_{jt})^{\alpha}} ; \tag{4}$$

where, α is the index of fuzziness.

Step3. The membership values $(\mathcal{M}_{jt})$ generated from equation (3) are tempered by equation (5) and are saved as $\mathcal{M}_{new}$.

$$\acute{\mathcal{M}}_{jt} = \frac{1}{\sum_{r=1}^{m} \left(\frac{l_{jt}}{l_{rt}}\right)^{2/(\alpha-1)}} \tag{5}$$

where, l_{rt} is computed by

$$l_{rt} = \sqrt{(y_{rt} - M_r^*)^2} . \tag{6}$$

Step4. If $\mathcal{M}_{new} = \mathcal{M}_{old}$, again initialize the membership values and repeat the aforementioned process. If the difference between the new value of $(\mathcal{M}_{new})$ and the old value of $(\mathcal{M}_{old})$ is less than ε, a small positive number then the $\acute{\mathcal{M}}_{jt}$ is taken as modified membership values.

Step5. Using the modified membership values, intuitionistic fuzzy membership values $(\mathcal{M}_{jt}^*)$ are obtained by using equation (7), which are saved into a matrix $\mathcal{M}_{old}$.

$$\mathcal{M}_{jt}^* = \acute{\mathcal{M}}_{jt} + \mathcal{H}_{jt} \tag{7}$$

where, $\mathcal{H}_{jt}$ is the hesitation index calculated as

$$\mathcal{H}_{jt} = 1 - \acute{\mathcal{M}}_{jt} - \left(\left(1 - \acute{\mathcal{M}}_{jt}^{\alpha}\right)\right)^{1/\alpha} . \tag{8}$$

Step6. Non-membership values are computed by equation (9).

$$\mathcal{N}_{jt} = 1 - \mathcal{M}_{jt}^* \tag{9}$$

The hesitation degree represents uncertainty or ambiguity in assigning a data point to a particular cluster. It measures how unclear the clustering process is by showing the extent to which a data point might belong to multiple groups. A higher degree of hesitation for a data point signifies greater uncertainty in its cluster assignment.

Step7. Final intuitionistic fuzzy membership and non-membership values are calculated using modified membership values by equations (7) and (9).
Step8. The initial parameters of the ARIMA model were set based on the patterns identified in the SACF and SPACF.
Step9. Construct the fuzzy-based ARIMA model using the membership and non-membership values as exogenous variables. Given equation (10) represents the FuzzyARIMA model.

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \beta_2 \varepsilon_{t-2} - \cdots - \beta_q \varepsilon_{t-q} + \boldsymbol{\mathcal{M}}\boldsymbol{m} + \boldsymbol{\mathcal{N}}\boldsymbol{n} \quad (10)$$

where, $\boldsymbol{\mathcal{M}}$ and $\boldsymbol{\mathcal{N}}$ are the membership and non-membership vectors, respectively, and $\boldsymbol{m}$ and $\boldsymbol{n}$ are the corresponding coefficient vectors; α's are the AR coefficients with p lags, and β's are the MA coefficients with q lags.

The structure of the proposed FuzzyARIMA model is described in Figure 1.

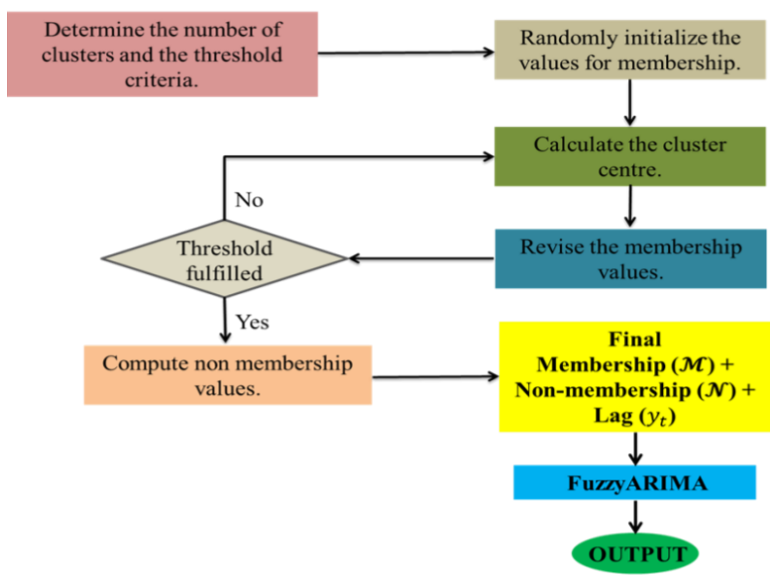


Figure 1. The architecture of FuzzyARIMA model

III

RESULTS AND DISCUSSION

Monthly wholesale prices (in Rs per 000' nuts) of Coconut from different markets in Andhra Pradesh (Rajahmundry), Karnataka (Mangalore), and Kerala (Kozhikode) have been collected from the indiastat portal (www.indiastat.com). The Coconut prices considered for the present study are from January 1995 to December 2022. Table 1 provides summary statistics for the Coconut price data from different markets in India.

TABLE 1. SUMMARY STATISTICS OF THE MONTHLY PRICES OF COCONUT FOR THREE DIFFERENT MARKETS IN INDIA

Descriptive statistics	Rajahmundry	Mangalore	Kozhikode
Mean	6841.941	10213.497	6870.150
Standard Error	218.149	405.547	216.476
Median	4900.000	6200.000	4900.000
Mode	3800.000	20000.000	2900.000
Standard Deviation	3992.786	7422.737	3962.158
Kurtosis	-0.624	-0.457	-0.612
Skewness	0.857	0.949	0.881
Range	14750.000	27600.000	14100.000
Minimum	2000.000	2400.000	2650.000
Maximum	16750.000	30000.000	16750.000
Coefficient of variation (%)	58.357	72.676	57.672

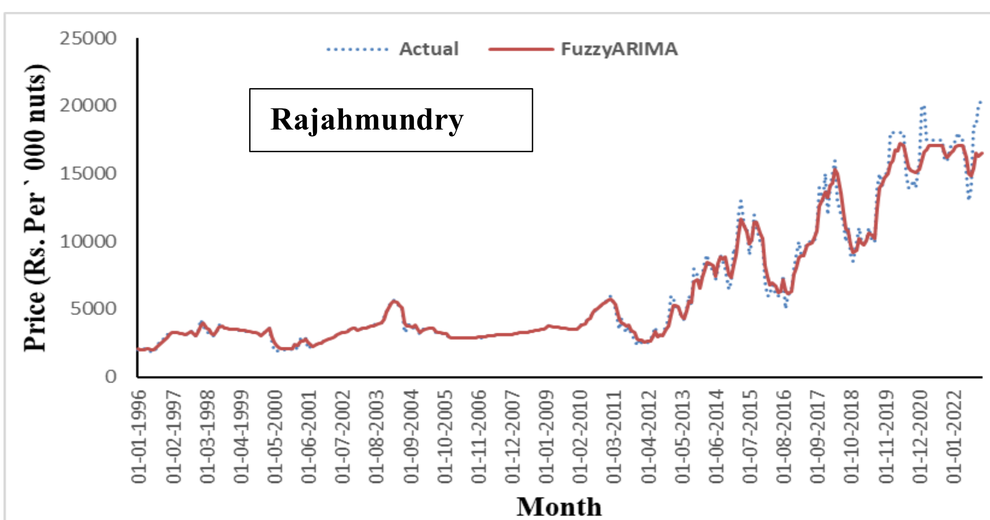
Table 1 shows that the average price is highest in the Mangalore market in Karnataka and lowest in the Rajahmundry market in Andhra Pradesh over the study period. Kurtosis values indicate a platykurtic distribution across all markets. The variability in the price series, as represented by the coefficient of variation (CV), ranges from a minimum of 57.7 per cent in Kozhikode to a maximum of 72.7 per cent in the Mangalore market. For all markets, the high CV values indicate significant price volatility, emphasizing the need for implementing fuzzy logic.

This dataset consists of 336 observations, which are partitioned into train and testing sets in an 80:20 ratio. The training set includes the first 268 months of observations used for model construction, while the remaining 68 months' observations are designated for evaluating the accuracy of the proposed models. To compare the models, three error metrics are calculated: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE), as shown in Table 2. The selected evaluation metrics like Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) together provide a comprehensive evaluation of model performance in forecasting coconut price series. These metrics offer insights into the accuracy and precision of the forecasts, addressing different aspects of prediction errors and their variability. By utilizing this range of evaluation tools, the assessment captures multiple facets of model effectiveness, including accuracy, reliability, and robustness, supporting informed decision-making in real-world forecasting scenarios.

TABLE 2. PERFORMANCE COMPARISON OF THE PROPOSED MODELS

Market	Model Accuracy	RMSE	MAPE	MAE
Andhrapradesh (Rajahmundry)	FuzzyARIMA	1677.557	7.10	1233.632
	ARIMA	2197.953	10.70	1655.426
Karnataka(Mangalore)	FuzzyARIMA	4375.941	15.00	3778.749
	ARIMA	5145.308	16.50	4256.174
Kerala(Kozhikode)	FuzzyARIMA	142.524	1.00	111.419
	ARIMA	1582.876	12.20	1291.156

Table 2 indicates that the FuzzyARIMA model outperforms the traditional ARIMA model across all three accuracy measures. In the Rajahmundry market, the proposed FuzzyARIMA model shows a 50 per cent improvement in MAPE values and over 30 per cent improvement in RMSE and MAE values compared to the traditional ARIMA model. Similarly, for the Mangalore market, the improvements are 18 per cent in RMSE, 10 per cent in MAPE, and 13 per cent in MAE values compared to the ARIMA model. A similar trend is observed in the Kozhikode market in Kerala. Thus, the proposed model surpasses the ARIMA model in effectively handling uncertainty and volatility. The actual and predicted plots of the FuzzyARIMA models are shown in the figure below.



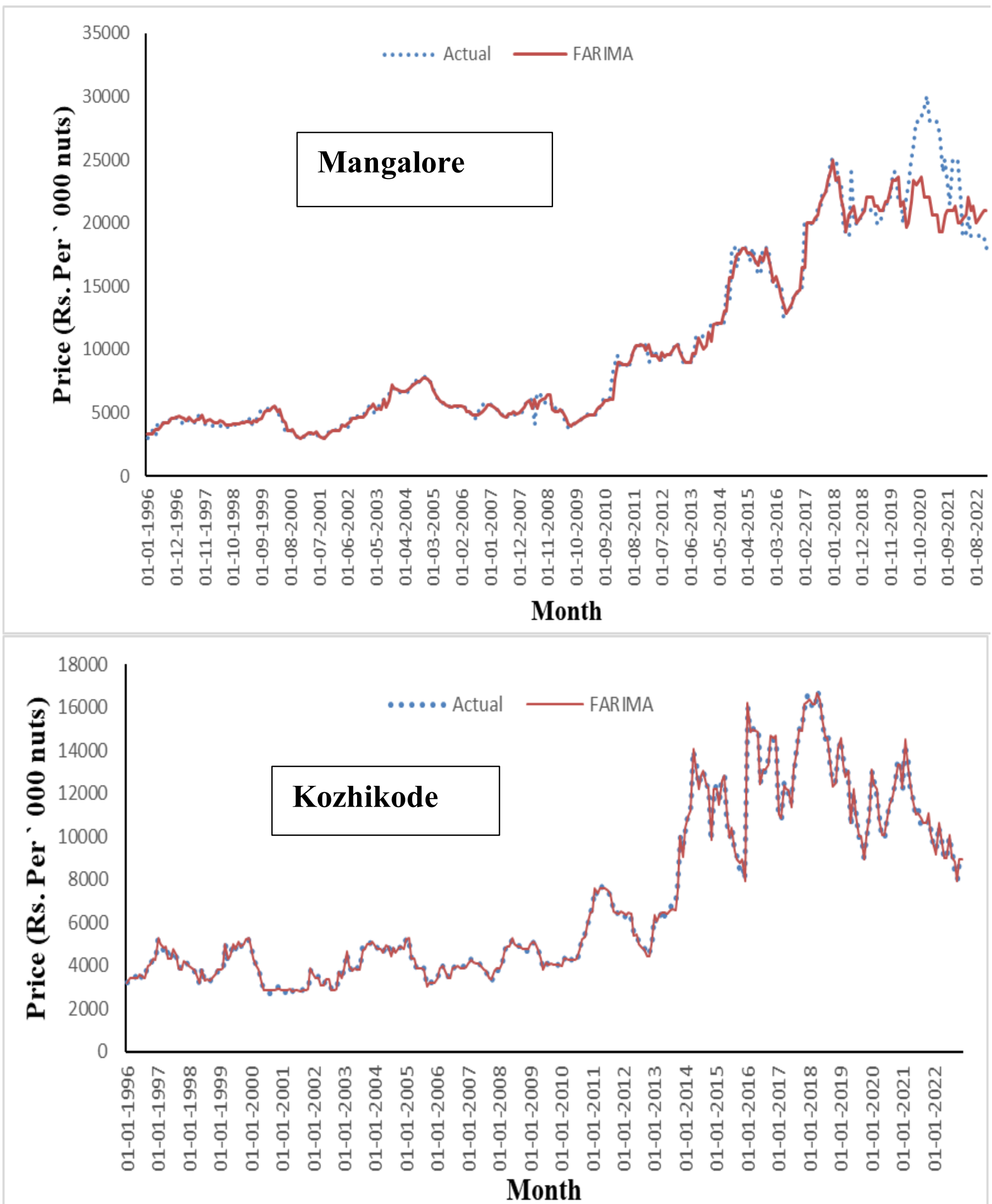


Figure 2. Actual and predicted (FuzzyARIMA) plots of Coconut prices from three different markets in India

IV

CONCLUSIONS

Coconuts are economically significant, providing livelihoods for millions of farmers and contributing notably to GDP, particularly in countries like India. They are crucial for food security due to their diverse nutritional products. The Coconut industry also drives industrial and export growth, with increasing global demand for various Coconut-based products. Moreover, sustainable Coconut farming practices support biodiversity and efficient resource use. Accurate forecasting of Coconut prices is vital for helping stakeholders make informed decisions, manage risks, and optimize resource allocation, thus stabilizing markets and enhancing production efficiency. Given the inherent uncertainty and unpredictability in price data, traditional ARIMA models often fail to deliver satisfactory results. To address these challenges, this study introduces a fuzzy-based ARIMA model, termed FuzzyARIMA, designed to manage the complexities of high uncertainty and volatility. Future research on fuzzy-based models for forecasting could focus on several areas for enhancement. Adding more variables like economic indicators or weather patterns could improve the model's accuracy. Hybrid approaches that combine fuzzy systems with machine learning methods, like neural networks, may offer superior performance. Optimizing fuzzy rules using techniques like genetic algorithms could further refine predictive accuracy. Applying the model to different commodities or regions would help evaluate its broader applicability. Moreover, developing dynamic fuzzy systems that respond to market changes in real-time, improving uncertainty handling, and comparing fuzzy-based models with other advanced forecasting techniques could increase their robustness and effectiveness. The FuzzyARIMA model could be applied to other horticultural crops for price forecasting by effectively integrating fuzzy logic with stochastic processes.

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