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Comparative Analysis of Hybrid SARIMA-GARCH and Neural Networks for Chilli Price Forecasting

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ABSTRACT

India's global dominance in red chilli production necessitates accurate price forecasting due to its volatile nature. The present study investigated the effectiveness of SARIMA-GARCH and ANN models in forecasting daily modal prices of red chillies in the Khammam market of Telangana. A dataset from January 2007 to December 2023 was employed and it was found that ANN model (2-30-1) outperformed SARIMA (2,1,3) (1,1,1)12 – GARCH (1,1) model in terms of forecast accuracy. These findings can inform farmers' decisions and aid policymakers in mitigating price volatility.

Keywords: Price volatility, price forecasting, SARIMA, GARCH, ANN

JEL codes: C22, C45, C53

I

INTRODUCTION

India is the leading producer of red chillies with 1.98 million metric tons production in the year 2023-24 which accounts for 43 percent of the global output. This surpasses major competitors like China, Thailand, Ethiopia, Bangladesh and Pakistan. Despite having 70 percent of domestic consumption, India is also the top chilli exporter, exporting 28,732 metric tons (INR 6000 crores) (Source: Spices Board, 2024). Nevertheless, chilli cultivation faces formidable challenges, primarily characterized by price volatility. Even in periods of plentiful harvests, the chilli market experiences significant price fluctuations, creating a complex and uncertain environment for farmers, traders, and policymakers (Sai *et al.*, 2022). Considering its global economic importance, precise price forecasting is essential. Numerous studies (Sabu & Kumar, 2020; Muflikh *et al.*, 2021; Xu & Zhang, 2021; Harshith & Kumari, 2024) emphasise that accurate predictions help farmers plan their cultivation and marketing strategies effectively, while policymakers can use this information to support the agricultural sector and mitigate the impact of market volatility.

Historically, SARIMA methodology was widely used due to its simplicity and efficacy in capturing linear trends and seasonality while GARCH methodology was used to capture the underlying volatility (Liu *et al.*, 2024; Zhang & Yan, 2024). However, recent breakthroughs in artificial intelligence and machine learning have paved the way for neural networks to emerge as reliable forecasting tools. Several studies (Anand *et al.*, 2024; Atesongun & Gulsen, 2024; Ramadhan *et al.*, 2024) have

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demonstrated the superior performance of neural networks, particularly in their ability to decipher complex non-linear relationships and process voluminous datasets.

With this background, the study aims to:

1. To develop a hybrid SARIMA-GARCH and ANN models for forecasting chilli prices in Khammam market of Telangana.

2. To assess and contrast the forecasting performance of ANN against SARIMA-GARCH.

II

MATERIALS AND METHODS

The chilli market of Khammam district was purposively selected as it is the leading district in the state in terms of chilli production. Secondary data pertaining to the daily modal prices of Khammam market were collected from the AGMARKNET website (www.agmarknet.gov.in) for the period January 2007 to December 2023. To evaluate the accuracy of the forecasting models, additional data of daily modal prices was also collected for the period January 2024 to March 2024. Two forecasting models namely Seasonal Autoregressive Integrated Moving Average–Generalized Autoregressive Conditional Heteroscedasticity (SARIMA-GARCH) and Artificial Neural Network (ANN) were employed to capture both seasonality and volatility.

Autocorrelation Function (ACF)

It measures the linear relationship between lagged values of a time series and is defined as (Pandey *et al.*, 2019):

$$\rho_k = \frac{Cov\,(y_t, y_{t-k})}{\sigma^2} = \frac{E[(y_t - \mu)(y_{t-k} - \mu)}{\sigma^2} \qquad \ldots\ldots\ (1)$$

Where $\rho_k$the autocorrelation at lag k is, y_t is the time series value at time t while μ and σ^2 is the mean and variance of the series respectively. ACF plot helps in identifying the seasonal and non-seasonal parameters of the SARIMA-GARCH model.

Partial autocorrelation function (PACF)

It quantifies the correlation between y_t and y_{t-k} after removing the effects of intermediate lags. PACF can be represented in the form of a linear regression as below (Pandey *et al.*, 2019):

$$y_t = \phi k_1 y_{t-1} + \phi k_2 y_{t-2} + \ldots + \phi k_k y_{t-k} + \epsilon_t \qquad \ldots\ldots\ (2)$$

Where, ϕk_k is the partial autocorrelation at lag k, ϵ_t is the white noise error term. PACF plot indicates the autoregressive (AR) order in the SARIMA model. A sharp cutoff in PACF after lag p is usually considered to be the AR order.

SARIMA Model

SARIMA model is an extension of ARIMA framework by incorporating seasonal autoregressive (AR), seasonal differencing (D) and seasonal moving average (MA) terms (Pandey *et al.,* 2019). The general multiplicative form of the SARIMA model is expressed as (Wang *et al.,* 2005):

$$Y_t = (1\text{-}B^d)\,(1\text{-}B^s)^D\, e_t \qquad \text{……..(3)}$$

Where $(1\text{-}B^d)$ is the differencing of order d, $(1\text{-}B^s)^D$ is the seasonal differencing of order D and e_t is the standard error with zero mean and standard deviation of one. SARIMA model identification was performed using ACF and PACF plots, while parameters were estimated using maximum likelihood estimation.

Testing for ARCH effects

To test the presence of volatility in chilli price time series, two statistical tests namely Ljung-Box Q test and ARCH-LM (Lagrange Multiplier) test were applied.

a. Ljung-Box Q test

LBQ test evaluates whether the residuals from a fitted time series model are independently distributed. When applied to squared residuals, it helps detect autocorrelation in the time series (Ghiyal & Kumar, 2024). The LBQ statistic is calculated as:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k} \qquad \text{…….. (4)}$$

Where, n is the number of observations, $\hat{\rho}_k$ is the autocorrelation of squared residuals at lag k, h is the number of lags tested. If the p-value of the test statistic is less than 0.05, we reject the null hypothesis of no autocorrelation and suggest the presence of volatility clustering.

b. ARCH-LM test

This test involves regressing the squared residuals on their own lags. The representation of this test as given by Yildirim and Bekun (2023) is as follows:

$$\widehat{\epsilon_t^2} = \alpha_0 + \alpha_1\,\widehat{\epsilon_{t-1}^2} + \alpha_2\,\widehat{\epsilon_{t-2}^2} + \ldots + \alpha_q\,\widehat{\epsilon_{t-q}^2} + \mu_t \qquad \text{………(5)}$$

From which the test statistic can be computed as:

$$LM = nR^2 \quad \text{……… (6)}$$

The interpretation of ARCH-LM test is analogous to that of LBQ test wherein the low p-value indicates the presence of ARCH effect in the time series suggesting the volatility.

GARCH model

This model was originally proposed by Engle (1986) as ARCH and later was generalised by Bollerslev (1986) as the GARCH model. It allows for conditional variance to depend on both past squared residuals and past variances. The GARCH(*p*,*q*) model is defined as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \epsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 \quad \text{……….. (7)}$$

Where σ_t^2 is the conditional variance at time t, ϵ_{t-1}^2 is the lagged squared residual while ω, α_i , β_j are non-negative parameters with α_i representing ARCH terms and β_j representing GARCH terms.

SARIMA-GARCH hybrid framework

In the hybrid methodology, the residuals from the SARIMA model were used for modelling the GARCH component (Pandey *et al.*, 2019; Zaim *et al.*, 2023; Ghiyal & Kumar, 2024). This framework enables the SARIMA component to capture the deterministic structure while the GARCH component models the stochastic volatility in the residuals. The SARIMA-GARCH is expressed as follows:

$$Y_t = \text{SARIMA}\,(p, d, q)\,(P, D, Q)_S + \epsilon_t, \quad \epsilon_t \sim N\,(0, \sigma^2_t) \quad \text{……..(8)}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \epsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 \quad \text{…….. (9)}$$

In the present study, the hybrid SARIMA–GARCH model was implemented using the “forecast” and “rugarch” packages in R software version 4.3.2.

Artificial Neural Network (ANN)

ANNs are biologically inspired computational models that can learn complex patterns and make accurate predictions. They consist of interconnected nodes or neurons, organized in layers. Input signals are processed through these layers, with each neuron applying an activation function to determine its output (Anggraeni *et al.,* 2018; Forestal *et al.,* 2021; Harshith& Kumari, *et al.,* 2024). ANNs are categorized into two primary types: Single Layer Perceptrons (SLPs) and Multi-Layer Perceptrons (MLPs).

SLPs have only input and output layers, while MLPs include one or more hidden layers for non-linear processing (Basnayake *et al.,* 2022).

For the present study, a multilayer feedforward network architecture with backpropagation was employed using the "neuralnet" package in R. The time series modeling approach adopted is the Neural Network Autoregressive (NNAR) model which combines AR modeling for time series dependence and ANN for capturing non-linear relationships. The optimal number of lags was determined using the Akaike Information Criterion (AIC), resulting in an NNAR (*p*, *k*) model.

Neural Network Autoregressive (NNAR) model

The NNAR model with *p* lags and *k* neurons in the hidden layer is denoted as NNAR (*p, k*). This employs a feedforward network architecture wherein the lagged values act as inputs (Zhang *et al.,* 1998; Maleki *et al.,* 2018). The general structure of NNAR model can be expressed as:

$$\widehat{y_t} = f\ (y_{t-1}, y_{t-2}, \dots, y_{t-p};\ \theta) \qquad \dots\dots\dots (10)$$

Where, $\widehat{y_t}$ is the predicted value at time t, $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ are the lagged inputs, θ is the set of network parameters including weights and biases.

Considering a typical NNAR network with a single hidden layer and logistic activation function, the output function can be represented as (Maleki *et al.*, 2018):

$$\widehat{y_t} = \sum_{j=1}^{k} w_j^{(2)} . \sigma \left(\sum_{i=1}^{p} w_{ji}^{(1)}\ y_{t-i} + b_j^{(1)} \right) + b^{(2)} \qquad \dots\dots\dots (11)$$

After the best-performing ANN model is chosen, the residual analysis is performed to analyse the randomness and normality. Ljung –box test, residual histogram, and Q-Q plot were chosen for this analysis (Adenomon & Emmanuel, 2024).

Forecast accuracy metrices

The following metrices have been used for evaluating the performance of forecasting models as suggested (Maleki *et al.*, 2018; Adenomon & Emmanuel, 2024):

1. *Mean Absolute Error:* It measures the average magnitude of errors in a set of forecasts.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (12)$$

Where n is the number of data points (samples) and ∑ is the Sum over all data points

2. *Root Mean Square Error (RMSE):*

$$\text{RMSE} = = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (13)$$

3. *Mean Absolute Percentage Error (MAPE):*

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| x\ 100 \quad (14)$$

Where $y_i \neq 0$

4. *Forecast Error (%):*

$$\text{Forecast Error (\%)} = \frac{|y_{actual} - y_{predicted}|}{y_{actual}}\ x\ 100 \quad (15)$$

III

RESULTS AND DISCUSSION

The analytical results of the time series data in the present study are divided into four sections namely data preprocessing, exploratory data analysis (EDA), testing stationarity, and model fitting & diagnostics.

3.1 Data preprocessing

Data preprocessing involves initial data cleaning, handling missing values, and normalizing the dataset. Five missing values were identified and filled using the forward fill imputation technique. Further, the data was normalized using the “minimax scaler” package in R.

3.2 Exploratory Data Analysis (EDA)

Descriptive statistics:

The statistical summary of the data is presented in Table 1. The mean modal price over 23 years period was calculated to be Rs. 8003.39 per quintal, with a standard deviation of Rs. 4686.02 per quintal, indicating a considerable variation in prices.

TABLE 1. STATISTCAL SUMMARY OF THE DATA

Particulars	Value (Rs/quintal)
Count	2936.00
Mean	8003.39
Std. Deviation	4686.02
Min	1000.00
25th Percentile	4400.00
50th Percentile (Median)	6500.00
75th Percentile	10200.00
Max	23518.00

As illustrated in Fig. 1, red chilli prices remained relatively stable between Rs. 3,000 and Rs. 7,000 per quintal from 2008 to 2014. A notable upward trend emerged after 2015, with prices climbing to approximately Rs. 12,000 per quintal by 2017. However, 2018 witnessed a sharp decline, with average prices falling to as low as Rs. 2,500 to 3,000 per quintal. This significant drop was largely attributed to subdued domestic and international demand, a decline in global market prices, and inadequate storage infrastructure. From 2019 onwards, prices began a steady recovery, eventually reaching a peak of over Rs. 20,000 per quintal by 2022.

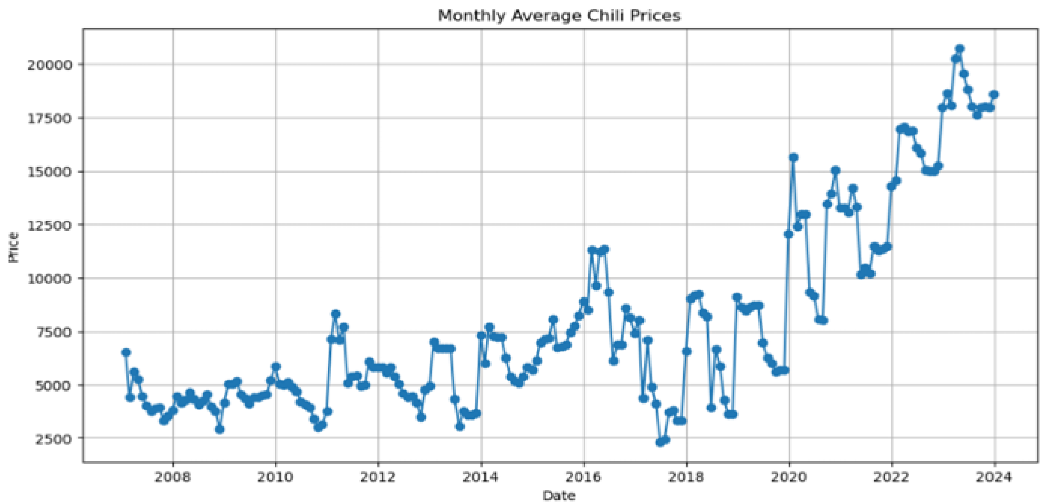


Figure 1. Time Series Graph of Red Chilli Prices

3.3 Time series decomposition

The multiplicative decomposition of the time series is depicted in Fig 2. The first graphical plot depicts the temporal fluctuations. From the second plot, it can be observed that red chilli prices have had an upward trend over the past decade. The third plot depicts the seasonal fluctuations and it is observed to be cyclic, with prices potentially peaking and troughing at regular intervals. The last plot represents the residual component that often captures the random noise or irregular events that affect prices.

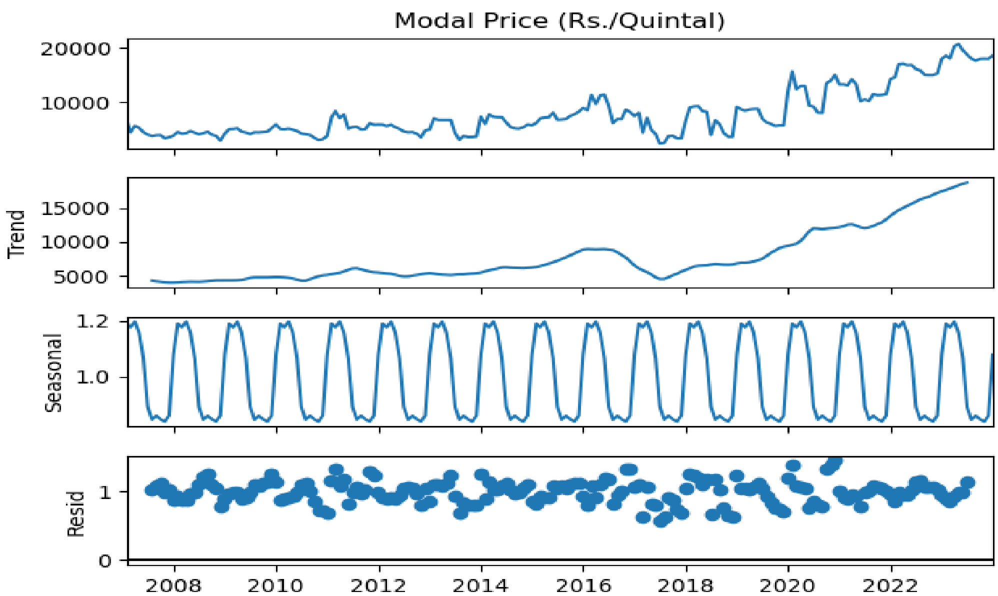


Figure 2. Multiplicative Decomposition of Dataset

3.4 Testing stationarity

Augmented Dickey Fuller (ADF) test has been performed to test the stationarity of the time series and the results are indicated in Table 2. The calculated ADF statistic (1.36) is significantly greater than the critical values (1%, 5%, and 10%), suggesting a unit root. Moreover, the extremely high p-value (close to 1), indicates the data is non-stationary.

TABLE 2. ADF TEST RESULTS OF ORIGINAL DATA

Particular	Value
ADF Statistic	1.36
p-value	0.99
Critical value (1%)	-3.46
Critical value (5%)	-2.88
Critical value (10%)	-2.57

3.5 SARIMA Modeling

As the ADF test indicated the data to be non-stationary, a first-order differencing has been performed. The stationarity of the first differenced data has been confirmed by the ADF test and from the Table 3, it can be observed that the ADF statistic (-9.07) is significantly less than all the critical values (1%, 5%, and 10%), suggesting the absence of a unit root. Additionally, the extremely low p-value (0.00) indicates that the differenced data is stationary.

TABLE 3. ADF TEST RESULTS AFTER FIRST DIFFERENCING

Particular	Value
ADF Statistic	-9.07
p-value	0.00
Critical value (1%)	-3.46
Critical value (5%)	-2.88
Critical value (10%)	-2.57

The seasonal MA (Q) can be estimated from the ACF plot of Figure 3. The plot shows spikes at various lags and dotted blue lines indicate confidence interval. It can be observed from the plot that a significant negative spike is observed at lag 12 indicating the presence of a seasonal moving average component of order one, SMA(1). Hence, a seasonal MA(1) term was considered in model identification. A comparable derivation for determining the order of SMA has also been done by Zaim *et al.* (2023). Similarly, seasonal AR (P) can be estimated from the PACF plot. A clear and statistically significant negative spike is observed at lag 12, which is the first seasonal lag. All subsequent seasonal lags (24, 36, 48) fall within the confidence intervals, indicating a sharp cutoff after the first seasonal lag. Consequently, SAR component of order 1 was considered for model identification.

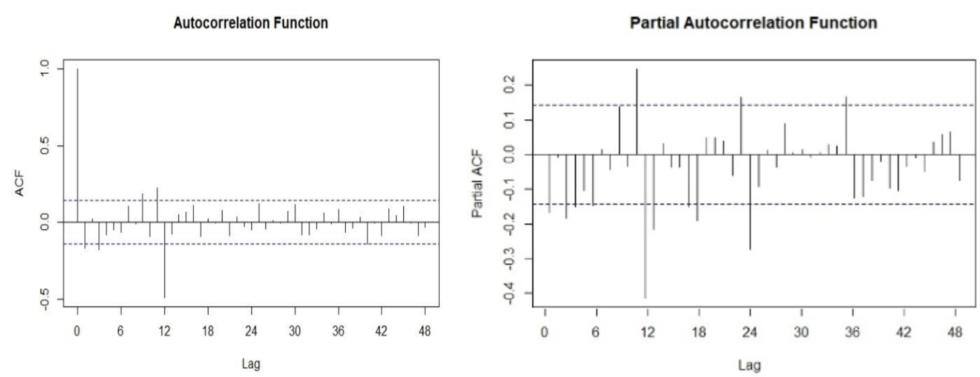


Figure 3. ACF and PACF Plots of Time Series With 48 Lags

Numerous possible combinations of non-seasonal (p, d, q) and seasonal (P,D,Q) parameters were tested to identify the best-fit model for forecasting chilli prices. The selection of the best model was based on two primary criteria namely, minimum Akaike Information Criterion (AIC) and highest Ljung-Box p-value. The values of these criteria for the top ten best-performing models are presented in Table 4. It can be observed from the table that SARIMA (2,1,3)(1,1,1)[12] outperformed all other tested models with the least AIC of 3327.88 and the highest Ljung-box p-Value of 0.07. A similar kind of approach has also been undertaken by Pandey *et al.* (2019) to select the best SARIMA model.

Table 5 presents the diagnostic analysis results of the SARIMA (2,1,3)(1,1,1)[12] model and it can be inferred that the model fits well and also the Ljung-box test (Q = 26.28, df = 17, p = 0.0696) shows that there is no significant autocorrelation.

TABLE 4. BEST PERFORMING SARIMA MODELS

Model	AIC	Ljung-Box p-value
SARIMA(2,1,3)(1,1,1)$_{[12]}$	3327.88	0.06956
SARIMA(2,1,3)(2,1,1)$_{[12]}$	3329.83	0.05745
SARIMA(3,1,2)(1,1,1)$_{[12]}$	3328.13	0.05121
SARIMA(2,1,3)(1,1,2)$_{[12]}$	3330.04	0.04542
SARIMA(2,1,3)(2,1,2)$_{[12]}$	3331.80	0.03687
SARIMA(3,1,2)(1,1,2)$_{[12]}$	3330.41	0.03593
SARIMA(3,1,2)(2,1,2)$_{[12]}$	3332.08	0.02627
SARIMA(3,1,1)(1,1,1)$_{[12]}$	3330.35	0.02124
SARIMA(1,1,1)(1,1,1)$_{[12]}$	3330.77	0.01920

TABLE 5. SARIMA MODEL DIAGNOSTIC RESULTS

Model	ME	RMSE	MAE	MPE (%)	MAPE (%)	MASE	ACF1
SARIMA(2,1,3)(1,1,1)$_{[12]}$	118.63	1258.51	796.20	-0.61	11.33	0.391	-0.006

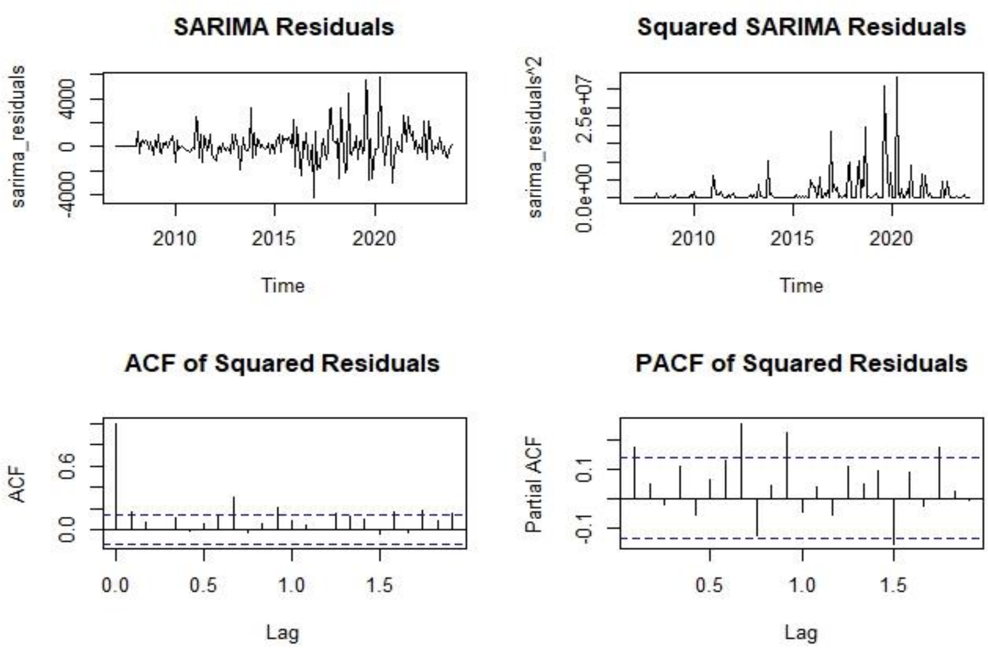
3.6 GARCH modeling on SARIMA residuals

The residuals of the SARIMA model were used to test for the presence of autocorrelation and heteroscedasticity for assessing the suitability of GARCH model. Two tests namely the Ljung-Box test and ARCH-LM test were employed and the results are given in the Table 6 below.

TABLE 6. ARCH EFFECT TEST RESULTS

Test	Chi-squared statistic	p-value
Ljung-Box test	44.81	0.00
ARCH-LM	35.45	0.00

It can be observed that the p-value of both the tests were significantly less than 0.05 and thus we reject the null hypothesis of no ARCH effect. These statistically significant results indicate the presence of autocorrelation and volatility clustering, thus suggesting the suitability for GARCH model (Ghiyal & Kumar, 2024). This is further validated by ACF and PACF of squared residuals presented in figure 4. Figure 4. ACF and PACF of Squared Residuals



Further, the best fit GARCH model was selected based on three criteria namely AIC, BIC, and log-likelihood. Based on these criteria, the GARCH(1,1) model emerged as the best-fit model with an AIC of 16.95, BIC of 17.01 and log-likelihood of –1724.84. The parameters of the estimated SARIMA-GARCH were tabulated in Table 7. Though the intercept term was found to be statistically insignificant, the conditional variance parameters, $\alpha 1$, and $\beta 1$ were highly significant and their sum (0.99) suggests a high degree of volatility persistence.

Following the GARCH model fitting, the standardized residuals were subjected to a Ljung-Box test to detect any remaining significant autocorrelation. The test yielded a Chi-square statistic of 12.11 with a p-value of 0.44, confirming the absence of significant autocorrelation in the standardized residuals. This indicates that the SARIMA–GARCH hybrid model is appropriately specified and adequately captured both the mean and volatility.

TABLE 7. PARAMETERS OF SARIMA-GARCH MODEL

Parameter	Estimate	Standard Error	t-Value	p-Value
μ	191.17	64.16	2.97	0.00
ω	1582.80	6219.88	0.25	0.80
α_1	0.09	0.02	4.44	0.00
β_1	0.90	0.02	42.07	0.00

3.7 Fitting ANN model

Various network architectures were trained by varying the number of hidden nodes between 4 and 36. It can be observed from Table 8 that the network structure NNAR (2-30-1)$_{[12]}$ incorporating 2 input lags, 30 neurons in a single hidden layer, and 1 output neuron capturing monthly seasonality was found to be superior with a lower MAPE (9.45), RMSE (1003.71), MAE (634.51) and MASE (0.31) values. The description of this best-fit ANN model is depicted in Table 9.

TABLE 8. PERFORMANCE OF FEW NETWORK ARCHITECTURES

Network Structure (1)	MAPE (2)	RMSE (3)	MAE (4)	MASE (5)
2-26-1	9.60	1015.86	646.71	0.36
2-27-1	9.59	1013.85	646.28	0.35
2-28-1	9.57	1013.56	644.03	0.34
2-29-1	9.55	1013.32	643.13	0.32
2-30-1	**9.45**	**1003.71**	**634.51**	**0.31**
2-31-1	9.60	1012.08	644.83	0.32
2-32-1	9.51	1008.14	639.13	0.31
2-33-1	9.55	1008.72	642.33	0.32
2-34-1	9.52	1009.64	639.24	0.31
2-35-1	9.47	1005.84	635.80	0.31

TABLE 9. DESCRIPTION OF 2-30-1 MODEL

Model (1)	Weights (2)	Details (3)
NNAR(2-30-1)$_{[12]}$	151	An average of 100 networks, each of which is a 2-30-1 network with 151 weight options were - linear output units

It can be observed from the table that 100 neural networks, each initialized with distinct random weights were independently trained and their individual forecasts were subsequently averaged to generate the final prediction. Each network architecture consisted of 151 adjustable parameters. Linear activation functions were utilized in the output layer to facilitate accurate modelling of continuous variables.

3.8 ANN residual analysis

The p-value of the Ljung-box test for chilli prices was 0.257 (>0.05), indicating the independence of residuals. This was also confirmed by the visual residual plot displayed in Figure 4. The bell-shaped curve of the residual plot indicates the normality of residuals.

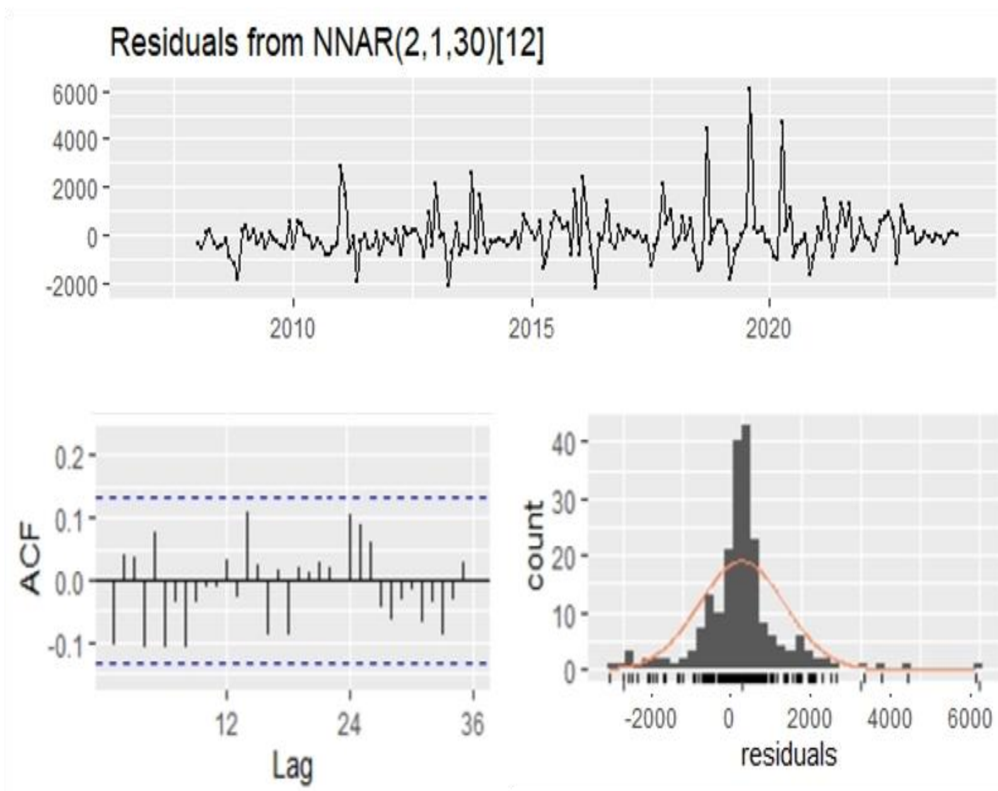


Figure 5. Residual Plot of ANN 2-30-1 Model

3.9 SARIMA-GARCH and ANN forecast results

The forecast results for 2024 and 2025 were generated employing the best-fit models and indicated in Table 10 below.

TABLE 10. FORECAST RESULTS OF SARIMA-GARCH AND ANN

S.No. (1)	Month (2)	SARIMA-GARCH forecast (Rs./Quintal) (3)	ANN forecast (Rs./Quintal) (4)
		2024	
1	January	19002.34	18734.88
2	February	18701.50	19059.09
3	March	19498.02	19364.15
4	April	18227.27	19424.39
5	May	17889.43	19483.39
6	June	18014.62	19520.37
7	July	18199.55	19313.96
8	August	18697.90	19247.95
9	September	19289.49	19169.10
10	October	19594.04	19123.68
11	November	19706.83	19087.26
12	December	19494.49	19062.85
		2025	
1	January	19882.64	18997.42
2	February	19563.61	18866.43
3	March	19524.48	18770.81
4	April	19068.25	18724.80
5	May	18717.23	18696.92
6	June	18808.14	18681.65
7	July	18999.55	18687.13
8	August	19471.88	18692.24
9	September	20045.59	18702.86
10	October	20354.85	18712.20
11	November	20483.88	18721.52
12	December	20299.96	18729.29

3.10 SARIMA-GARCH vs ANN

The actual modal prices were compared with the forecasted prices in the case of both ANN and SARIMA-GARCH of January, February, and March months of the year 2024. It can be observed from Table 11 that ANN outperformed SARIMA-GARCH as indicated by a relatively lower forecast error (%). These results also align with those reported by Sahiner *et al.*, (2023); Wang *et al.*, (2021); Bozkurt *et al.*, (2017).

TABLE 11. COMPARATIVE PERFORMANCE OF ANN AND SARIMA-GARCH

Months (2024) (1)	Actual modal price (2)	Forecasted Prices ANN (3)	Forecasted Prices SARIMA-GARCH (4)	Forecast Error (%) ANN (5)	Forecast Error (%) SARIMA-GARCH (6)
January	18667	18734.88	19002.34	0.36	1.80
February	19577	19059.09	18701.50	2.65	4.47
March	18500	19364.15	19498.02	4.67	5.39

IV
CONCLUSION

The present study developed a best-fit SARIMA-GARCH model SARIMA(2,1,3)(1,1,1)$_{[12]}$ based on its lower AIC value and the best fit ANN model NNAR (2-30-1)$_{[12]}$ based on MAPE (9.45%), RMSE (1003.71%), MAE (634.51%) and MASE (0.31%). A slight advantage in forecast error for ANN was observed over SARIMA-GARCH, indicating its better predictive accuracy. The findings of this study can help farmers make informed decisions and aid policymakers in mitigating price volatility.

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