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# Tomato Price Forecasting - A Comparison between ARIMA, GARCH and ANN

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**ABSTRACT**

Price forecasting is an integral part of commodity trading and price analysis. India is the second largest producer of tomato in the world after china with production of 21 million tonnes accounting for 11.02% of world's tomato production. Tomato is the second most important vegetable crop after potato. Vegetables, especially tomatoes, need more accurate price predictions due to its perishable nature and seasonality. In recent years, the prices of tomato have been fluctuating very much. This increases the risk for tomato growers. For this in the present study, ARIMA (3,1,4), GARCH (1,1) and ANN [14–8-1] models are developed for forecasting of tomato price and amongst them ANN [14–8-1] is found to be the best forecasting model and used this for the forecasting of tomato prices for Varanasi, Uttar Pradesh, India.

**Keywords:** Tomato, ARIMA, GARCH, ANN, Price

Tomato (*Solanum lycopersicum* L.) belongs to the family of Solanaceae and is the second most important vegetable crop after potato. It is cultivated for fresh fruit and processed products. India is the second largest producer of tomato in the world after china with production of 21 million tonnes accounting for 11.02% of world's tomato production. Andhra Pradesh is the largest producer of tomato, with a total production of 2.74 million tonnes in the year 2017-18, and shares 13.9% of all India tomato's production (Marti *et al.* 2016). Varanasi is one of the major tomato growing districts of Uttar Pradesh.

Tomato season in India prevails throughout the year. The peak season of tomato in India is mostly at the beginning and at the end of the year. Tomato contains many health-promoting compounds and is easily integrated as a nutritious part of balanced diet (Marti *et al.* 2016). Tomatoes contain higher amounts of oxidants called lycopene, and antioxidant called carotene which can help prevent cancer and given the fruit a distinct red colour. Tomatoes are used in a variety of dishes including salads, ketchup, purees, sauces, and other processed foods.

Vegetables, especially tomatoes, need more accurate price predictions due to its perishable nature

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and seasonality. There were wide fluctuations in prices of tomatoes in different months, prices sometimes increase 10 times compared to prices during the peak harvest period. Price forecasting is an integral part of commodity trading and price analysis. Tomato price forecasting can provide significant and useful information to tomato growers making production and marketing decisions. In order to develop a viable strategy for dealing with volatile farm prices, one must understand how and why agricultural prices change (Norwood, F.B. and Lusk, J.L, 2008). So, there exists a need to forecast the tomato prices in the wholesale market to evaluate the marketing opportunities in time for all the tomato growers. In recent years, the prices of tomato have been fluctuating very much, this increases the risk for tomato growers. This leads to a considerable risk and uncertainty in the process of price modeling and forecasting. Therefore, the importance of accurate price forecasts for tomato growers is even more serious. The main purpose of produce price forecasts is to enable producers to make more informed decisions and manage price risk. Therefore, the study was therefore taken up with following specific objectives: (1) To test and identify appropriate statistical model out of ARIMA (Autoregressive Integrated Moving Average), sGARCH (standard Generalized Autoregressive Conditional Heteroscedasticity) and ANN (Artificial Neural Network) models for forecasting of tomato prices, and (2) To forecast prices of tomato with the help of found to be best time series forecasting model for Varanasi, Uttar Pradesh, India.

Boateng *et al.* (2017) formulated a model for tomato prices and found that predictability of the model increases with seasonal-ARIMA (SARIMA). Kumar and Baishya (2020) studied forecasting of potato prices in India and concluded that ARIMA was suitable in some states whereas SARIMA model gave best results for other states. Kumar *et al.* (2021) worked on the price forecasting of onion for Varanasi market of Uttar Pradesh, India using ARIMA, ARFIMA and ARMA-GARCH models. They found on the basis of MAPE, MSE, RMSE and Theil's U statistics, that ARMA-GARCH model gave better forecast results than others. Yazzi *et al.* (2011) compared the two models of ARIMA and GARCH while attempting to predict the WTI crude oil prices for the period January 2, 1986, to September 30, 2009. The study found GARCH (1, 1) to be better than ARIMA (1,2,1) as it is able to better capture volatility through the non-constant of conditional variance. Bhardwaj *et al.* (2014) while predicting the daily price of gram found that GARCH is a better model than ARIMA for estimating the daily price of Gram. In the present study, ARIMA, GARCH and ANN models are developed and best forecasting model were used for the forecasting of tomato prices in Varanasi, Uttar Pradesh.

## MATERIALS AND METHODS

The present study was carried out using daily data of tomato prices for Varanasi market, Uttar Pradesh, India. The daily time series data on tomato prices were taken from website agmarknet.gov.in for the period from 1st January 2017 to 31st December 2021 to forecast the tomato price for further year August 2022 to December 2022. In this daily time series data of tomato price of past five years, there was prices data of some days are missing. To deal with this missing values we applied imputation method in R programming software using "*imputeTS*" package. In the present analysis, the original price data is sub-divided in 80:20 ratio and the data from 1st January 2017 to 30th December 2020 are used for model building as training data and from 31st December 2020 to 31st December 2021 are used for analyze the forecasting performance of the model or for model validation as testing data. The statistical software R v.3.6.2 is used for modeling and forecasting tomato prices in Varanasi. In R v.3.6.2 software, packages "*tseries*", "*Forecast*", "*FinTS*" and "*Fgarch*" were used for modeling and forecasting using ARIMA and ARCH-GARCH and packages "*TSANN*" and "*neuralnet*" were used for modeling and forecasting using Artificial Neural Network (ANN).

### Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA model is among one of the most popular and widely used statistical method for time series forecasting. ARIMA model allows to explain by its past, or lagged values and stochastic error terms. ARIMA model is the combination of three terms, namely AR (Autoregressive) term, I (Integration) and MA (Moving Average). An ARIMA model is represented as ARIMA (p,d,q), where p stands for lag order of Autoregressive term, d stands for differencing and q stands for lag order of Moving Average. ARIMA model is also known as Box-Jenkins models and it is expressed as follow:

$$Y_t = \mu + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_i$$

Where, $Y_t$ is price, μ is the mean of series, $\varphi_1 \ldots\ldots \varphi_p$ are the parameters of AR model, $\theta_1, \ldots\ldots\ldots\ldots \theta_q$ are the parameters of the MA model, $\varepsilon_t$, $\varepsilon_{(t-1)}, \ldots\ldots\ldots \varepsilon_{(t-q)}$ are the noise error term (Box and Jenkins 1970, Brockwell and Davis 1996).

The ARIMA model is developed in four essential steps which are model identification, parameter estimation, diagnostic checking, and model utilization where the forecasting process takes place. Parameters of this model (*p*,*d*,*q*) are experimentally selected at the identification stage. Identification of *d* is necessary to make a non-stationary time series to stationary. A statistical test can by employed to check the existence of stationarity, known as the KPSS test (Kwiatkowski–Phillips–Schmidt–Shin), test of the unit-root hypothesis. At the estimation stage, the parameters are estimated with the help of ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function). Autocorrelation and Partial Autocorrelation Functions is the core of ARIMA model. Order *p* is the lag value after which PACF plot crosses the upper confidence interval for the first time. These *p* lags will act as our features while forecasting the AR time series. Order *q* of the MA process is obtained from the ACF plot, this is the lag after which ACF crosses the upper confidence interval for the first time. The strength of the selected model is then tested by diagnostic checking stage by employing Ljung-Box test. Ljung-Box is a test of autocorrelation in which it verifies whether the autocorrelations of a time series are different from 0. In other words, if the result rejects the hypothesis, this means the data is independent and uncorrelated; otherwise, there still remains serial correlation in the series and the model needs modification. The non significance of the test shows that the chosen model is a good model. To test the suitability of model fit, the Ljung Box test for standardised residuals and standardized squared residuals were performed. If the model is found to be insufficient, the three stages are repeated until satisfactory ARIMA model is selected for the time series under consideration. After getting satisfactory ARIMA model, is used for forecasting the price data of tomato for Varanasi.

**GARCH model:** GARCH models provide a way of modeling conditional volatility. I.e. They are useful in situations where the volatility of a time series is a function of previous levels of volatility also known as volatility clustering. A GARCH model is typically of the following form:

$$\sigma_t^2 = w + \sum_{i=1}^{p} \alpha_i \in_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2$$

which means that the variance ($\sigma_t^2$) of the time series today is equal to a constant (*w*), plus some amount (α) of the previous residual ($\mathcal{E}_{t-1}$), plus some amount (β) of the previous variance ($\sigma_{t-i}^2$). ARCH and GARCH are two most popular and widely used non-linear, time varying volatility models. ARCH stands for Autoregressive Conditional Heteroscedastic and GARCH stands for Generalized Autoregressive Conditional Heteroscedatic models. This models are used when the given time series data have non-constant variance. GARCH is the generalization of ARCH volatility model. The ARCH model has a weakness that is there might be a need of large value of *q*, hence large number of parameters to be estimated. This may lead to difficulties in estimate parameters. After four years an extension from ARCH model was developed namely GARCH in 1986 by Bollerslev. GARCH model is used fewer parameters compares to ARCH model. ARCH/GARCH is necessary to model the volatility of the series. As indicated by its name, this method concerns with the conditional variance of the series.

## Artificial neural network (ANN)

Artificial Neural Networks (ANNs) are nonlinear model that are able to capture various nonlinear structures present in the data set. ANN can estimate any non-linear continuous function up to any desired degree of accuracy. ANN model specification does not require prior assumption of the data generating process, instead it is largely dependent on characteristics of the data. The Artificial Neural Network (ANN) is a data driven, self adaptive, nonlinear and nonparametric statistical method. ANN functions similar to the human brains. They are the powerful tool for modeling, especially when the underlying data relationship is not known.

Fundamental processing element of ANNs is a neuron. At the hidden layers, each neuron computes a weighted sum of its p input signals, for $i = 0,1,2,3....,n$ and then applies a nonlinear activation function to produce an output signal, $Xi$. The model of a neuron is shown in Fig. 1. A neuron $j$ is described mathematically by the following pair of equation:

$$X_i = \Sigma y_i W_{ij}$$

Where $y_i$ the activity is level of the $j^{th}$ unit in the previous layer and $w_{ij}$ is the weight of the connection between the $i^{th}$ and the $j^{th}$ unit. Next, the unit calculates the activity using some function of the total weighted input. Generally, we use the logistic sigmoid function (Bilgili *et al.* 2007) and expressed as:

$$y_i = \left[1 + e^{-x_j}\right]^{-1}$$

The type of ANN used in this study is a Feed-forward neural networks with a single hidden layer and lagged inputs for forecasting univariate time series. A feed-forward neural network is one of ANN where connections between the units do not form a directed cycle. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. It consists of three layers: an input layer, a hidden layer and an output layer. A set of neurons or nodes are arranged in each layer. The number of neurons in the input and output layers is defined depending on the number of input and output variables of the system under investigation, respectively. However, the number of neurons in the hidden layer(s) is usually determined via a trial-and-error procedure. As seen from the Fig. 1, the neurons of each layer are connected to the neurons of the next layer by weights. Fig. 1 represents the structure of Feed Forward Artificial Neural Network with single hidden layer. Now feed-forward neural network is the most popular and most widely used model in many practical applications. In this study, feed-forward neural network is used as the forecasting network.

**Model selection:** When comparing among different specification of ARIMA, GARCH and ANN models, then we select an appropriate model based on Akaike Information Criteria (AIC), and Bayesian Information Criteria (BIC). The accuracy of the forecasted model is assessed with use of lowest value of ME (Mean Error), RMSE (Root Mean Square Error), MAE(mean Absolute Error), MAPE (Mean Absolute Percentage Error), and highest value of R-squared.

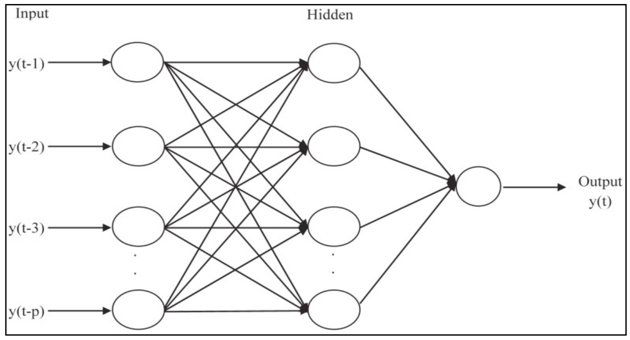


**Fig. 1:** Structure of Feed Forward Artificial Neural Network with single hidden layer

## RESULTS AND DISCUSSION

As discussed earlier, the data set from 1st January 2017 to 30th December 2020 are used for model building as training data and from 31st December 2020 to 31st December 2021 were used for model validation as testing data for modeling and forecasting of all models ARIMA, ARCH-GARCH and ANN.

### Fitting of ARIMA model for forecasting of tomato prices

The ARIMA model is developed in four essential steps. The 1st step is identification in which the time series plot of tomato price of Varanasi is presented in Fig. 2. In this plot the time series data have a random walk pattern and vary randomly with no global trend or seasonality pattern was observed. Here it was observed that the original pattern of the time series data is non stationary. In the case of non-stationary time series, the ACF dies out gradually over time. The correlogram or ACF plot of the time series data of tomato price (Fig. 3) was observed to be non-stationary as the ACF plot dies down extremely slowly. To verify this, the KPSS test for stationarity was performed. In this test the obtained p value is 0.01 therefore we reject the null hypothesis which is the given data is stationary and we were conclude that the given time series data is non-stationary. Differencing is used to make this non-stationary time series become stationary. The value of differencing ($d$) is determined by the function 'ndiffs' in R

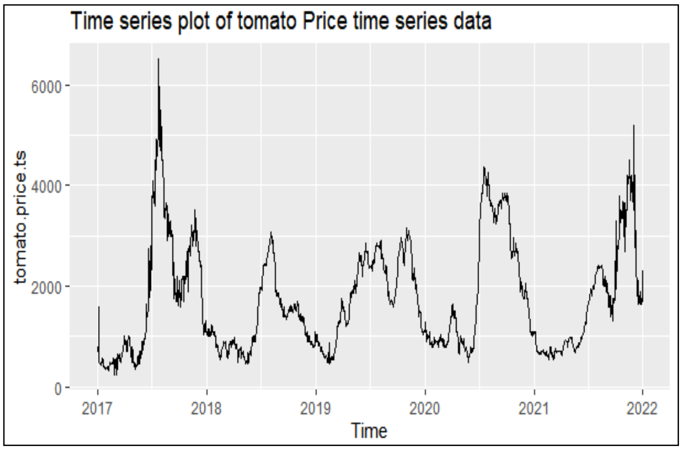


**Fig. 2:** Time series plot of tomato price time series data

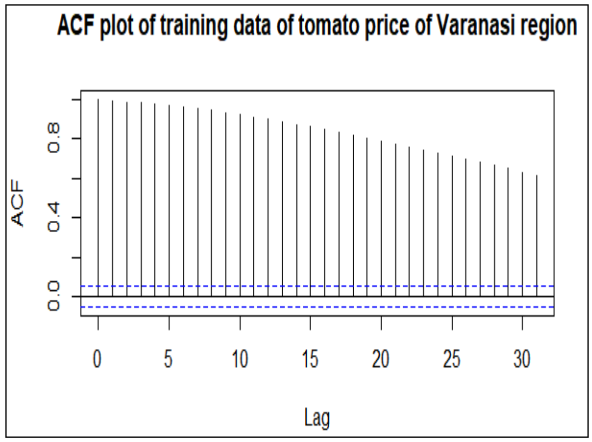


**Fig. 3:** ACF plot of training data of tomato price time series data of Varanasi

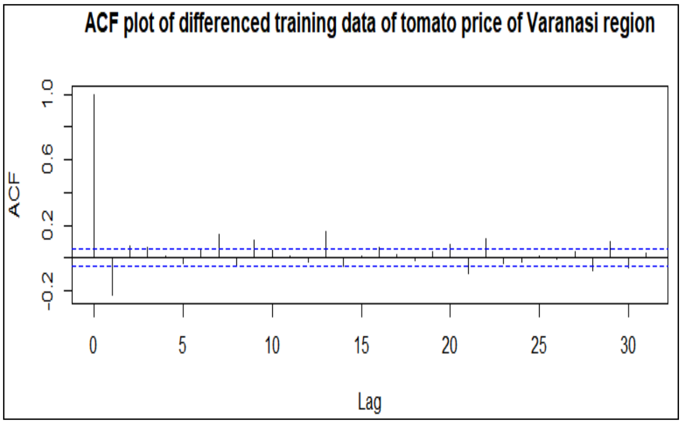


**Fig. 4:** ACF plot of differenced training data of tomato price of Varanasi

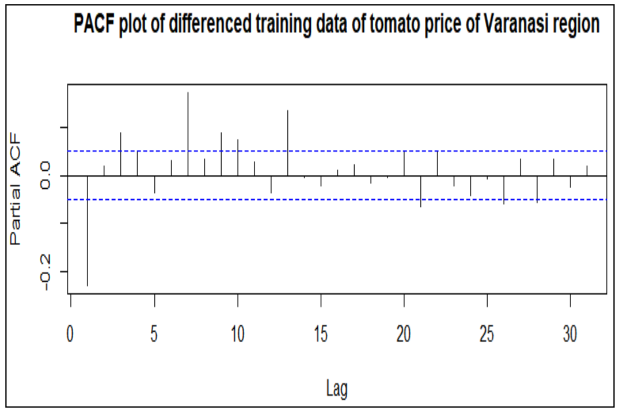


**Fig. 5:** PACF plot of differenced training data of tomato price of Varanasi

**Table 1:** Results of different selection criteria, obtained from different ARIMA models

| Selection criteria / ARIMA Models | AIC | BIC | ME | RMSE | MAE | MAPE% | R Squared |
|---|---|---|---|---|---|---|---|
| ARIMA(1,1,3) | 18418.16 | 18445.04 | 0.2410 | 132.68 | 77.07 | 5.46 | 0.9877 |
| ARIMA(1,1,4) | 18419.8 | 18451.51 | 0.2441 | 132.82 | 77.22 | 5.47 | 0.98775 |
| ARIMA(2,1,2) | 18411.75 | 18438.18 | 0.2471 | 132.51 | 77.41 | 5.49 | 0.98780 |
| ARIMA(2,1,3) | 18414.16 | 18445.87 | 0.2513 | 132.56 | 77.64 | 5.55 | 0.98779 |
| **ARIMA(3,1,4)** | **18382.8** | **18425.09** | **0.0678** | **130.95** | **76.43** | **5.45** | **0.98809** |
| ARIMA(4,1,4) | 18387.61 | 18435.18 | 0.2387 | 131.08 | 77.41 | 5.52 | 0.98806 |

software which we obtained is 1. After differencing the ACF and PACF plots of Differenced training data is presented in Fig. 4 and 5 respectively.

For the determination of best ARIMA model, we experimented with different values of the order of auto-regressive, differencing and moving average terms (p,d,q), as indicated in the table 1. The ARIMA (3,1,4) model is found to best amongst experimented ARIMA model as shown in the table 1 on the basis of lowest value of AIC, BIC, ME, RMSE, MAE, and MAPE and the highest value of R-sqaured. The estimates obtained from the arima model (3,1,4) is presented in the table 2.

**Table 2:** Parameter Estimates of ARIMA(3,1,4) model for tomato price forecasting in Varanasi

| Sl. No. | Coefficients | Estimates | Standard Error (s.e.) |
|---|---|---|---|
| 1 | ar1 | -0.9454 | 0.0310 |
| 2 | ar2 | 0.8283 | 0.0339 |
| 3 | ar3 | 0.9041 | 0.0262 |
| 4 | ma1 | 0.7080 | 0.0411 |
| 5 | ma2 | -0.9963 | 0.0456 |
| 6 | ma3 | -0.6109 | 0.0363 |
| 7 | ma4 | 0.2385 | 0.0296 |
| 8 | sigma$^2$ | 17245 | |
| 9 | log likelihood | -9183.4 | |

## Fitting of ARCH-GARCH model for forecasting of tomato prices

GARCH models provide a way of modeling conditional volatility. Therefore first we have to test the presence of volatility of residuals or ARCH effect. To perform ARCH-LM test, *"ArchTest"* function was used to determine the presence of ARCH effect in the residuals of ARIMA (3,1,4) model in R software. This test shows that the ARCH effect or the conditional volatility of residuals is present in the time series model. With GARCH (1, 1) model the volatility clustering was detected and it is developed for modeling and forecasting of tomato prices. The parameter estimates of standard GARCH (1,1) ($_s$GARCH) model was presented in the table 3.

**Table 3:** Parameter Estimates of $_s$GARCH model for tomato price forecasting

| Model: ARCH(3,4) - sGARCH (1,1) | | | | |
|---|---|---|---|---|
| **Coefficients** | **Estimates** | **Std. Error** | **t value** | **Pr(>\|t\|)** |
| mu | 3.126625 | 1.129468 | 2.768 | 0.00564** |
| ar1 | 1.00000 | 0.022868 | 43.730 | <2e-16*** |
| ar2 | 0.876449 | 0.021671 | 30.221 | <2e-16*** |
| ar3 | -0.876449 | 0.021671 | -40.444 | <2e-16*** |
| ma1 | -0.041083 | 0.035969 | -1.142 | 0.25338 |
| ma2 | -0.753333 | 0.035561 | -21.184 | <2e-16*** |
| ma3 | 0.130023 | 0.029723 | 4.375 | 1.22e-05*** |
| ma4 | -0.075668 | 0.030901 | -2.449 | 0.01434* |
| omega | 194.497801 | NA | NA | NA |
| alpha1 | 0.079671 | 0.009296 | 8.571 | <2e-16*** |
| beta1 | 0.903864 | 0.007101 | 127.294 | <2e-16*** |

| Information Criterion Statistics: | | Selection criteria | |
|---|---|---|---|
| AIC | 12.00060 | MSE | 1344384 |
| BIC | 12.01871 | RMSE | 1159.476 |
| SIC | 12.00058 | MAPE% | 5.4166 |
| HQIC | 12.00736 | MAE | 837.11 |

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' 1'

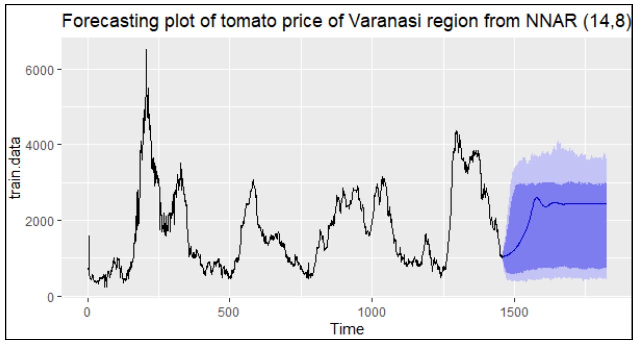


**Fig. 6:** Forecasting plot of tomato price of Varanasi from NNAR (14,8)

## Fitting of Artificial Neural Network (ANN) model

In the present study a multi-layer Feed-Forward Artificial Neural Network including input layer, hidden layer and output layer was used for forecasting univariate time series data of tomato prices. The model of multi-Layer Feed Forward Artificial Neural Network was developed using "forecast" and "neuralnet" package in R software. The number of neurons in input, output and hidden layer depends on practical application. In our study, the number of neuron in input layer, output layer and hidden layer should be set as "nnetar" function in R. In this analysis the fitted model is denoted as an NNAR (p,k) model, where k is the number of hidden nodes and p is the number of input nodes with Sigmoidal and linear activation functions were used as in hidden and output layers respectively. After analysis we obtained NNAR(14,8) ANN model in which the number of neurons in input layers is 14 and the number of neuron in hidden layer is 8 with 1 output layer. Here we observed that 14-8-1 [14 input neurons, 8 hidden neurons, and 1 output neurons] ANN model with total 129 weights. The parameter estimated of ANN model were given in the table 4.

## Evaluation of Forecasting performance of model

**Table 4:** Forecasting performance of ANN [14 - 8 -1] model

| Model | ME | RMSE | MAE | MPE | MAPE % | MASE |
|---|---|---|---|---|---|---|
| **ANN [14-8-1]** | -0.08508496 | 89.61331 | 59.88943 | -0.6084488 | 4.602708 | 0.8000685 |

## under consideration

The forecasting performance of the models under consideration namely ARIMA (3,1,4), GARCH (1,1) and ANN (14 -8-1) were analysed on the basis of model selection criteria such as lowest value of ME, MAE, RMSE, and MAPE and the highest value of R-squared.

**Table 5:** Forecasting performance of model under consideration

| Models | ARIMA (3,1,4) | sGARCH(1,1) | ANN [14-8-1] |
|---|---|---|---|
| **MAE** | 76.43 | 837.11 | **59.8894** |
| **RMSE** | 132.51 | 1159.476 | **89.6133** |
| **MAPE%** | 5.45 | 5.41 | **4.60** |

From the table 5 were observed that the ANN (14-8-1) model has the lowest value of model validation criteria MAE, RMSE, MAPE. The table 5 were shown the comparative performance of the all three models under consideration. So as a result ANN (14-8-1) model were used for the forecasting of tomato price of Varanasi, Uttar Pradesh.

**Table 6:** Forecasting performance of ANN model for tomato prices time series data set of Varanasi

| Week | Actual prices in ₹/ Quintal of year 2021 | Forecasted Prices in ₹/Quintal of year 2022 |
|---|---|---|
| August | | |
| 1st | 2377 | 2432 |
| 2nd | 2300 | 2441 |
| 3rd | 2076 | 2449 |
| 4th | 1969 | 2450 |
| September | | |
| 1st | 1807 | 2445 |
| 2nd | 1556 | 2441 |
| 3rd | 1604 | 2439 |
| 4th | 1884 | 2448 |
| October | | |
| 1st | 2641 | 2441 |
| 2nd | 3096 | 2442 |
| 3rd | 3365 | 2444 |
| 4th | 3504 | 2444 |
| November | | |
| 1st | 3237 | 2443 |
| 2nd | 3889 | 2445 |
| 3rd | 4121 | 2448 |
| 4th | 4014 | 2442 |
| December | | |
| 1st | 3986 | 2445 |
| 2nd | 2782 | 2442 |
| 3rd | 1884 | 2441 |
| 4th | 1726 | 2446 |

From the table 6, it is clearly show that the ANN model is outperformed in comparison with ARIMA and GARCH. The table of forecasting of tomato prices in Varanasi from ANN[14,8] model for the period of August 2022 to December 2022 is presented in table 6. Forecasting plot of tomato price data from Varanasi from NNAR[14,8] is presented in the figure 6 in which dark blue and light blue sheds are shown the 80% and 95% confidence interval respectively and the blue line shows the forecasted price of tomato for the year 2022.

## CONCLUSION

This research is developed ARIMA, GARCH and ANN model for tomato price forecasting in order to improve the readily available forecasting models with a comparative analysis between ARIMA, GARCH and ANN models for the forecasting of tomato prices in Varanasi, Uttar Pradesh. Referring to the analyzed results, it is proven that the ANN as a forecasting model is a better technique in forecasting obtain a higher accuracy compared to ARIMA and GARCH as the forecasting model by yielding the lowest value of RMSE, MAE, and MAPE. The accuracy results from ANN model are 59.88, 89.61, and 4.60 for MAE, RMSE, and MAPE respectively which pointed out a good accuracy as the values are lower than of the ARIMA and GARCH model.

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