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Price forecasting of Brinjal: A statistical evaluation

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Abstract
A timely and reliable forecast of prices for different agricultural crops is highly needed and required for now a day. Forecasting of prices for agricultural commodities remains difficult because they are influenced by many factors. The uncertainty of future price, production and consumption level makes agricultural market strategy and investment planning difficult. Perishability, price changes and seasonal nature of vegetables affect a lot to the vegetable prices. In the present study linear, quadratic and exponential trends were used for trend studies and forecasting purpose. Also ARIMA, ARCH/GARCH models and Artificial Neural Network (ANN) were employed for the study. For the studying error behaviour Jarque-Bera test was utilized. Statistical comparisons were made for different models using Root Mean Squared Error (RMSE) and Mean Absolute Per cent Error (MAPE). Jarque-Bera test results showed that none of the model residuals followed normal distribution. In all, the comparison of different models tried in the study to forecast prices for Brinjal the Artificial Neural Network (ANN) model on the basis of RMSE value performed better as compared to all the models studied.

Keywords: Forecasting, ARIMA, ANN, ARCH/GARCH, RMSE etc.

1. Introduction

Because of the high volatility for prices of agricultural commodities over the past decade, the importance of accurate price forecasting for decision makers has become even more acute. The uncertainty of future price, production and consumption levels make agricultural market strategy and investment planning difficult. The ability to predict many types of events seems natural today due to advent of technological breakthrough. There are various forecasting models in use. One of the most important and widely used time series model is the Auto Regressive Integrated Moving Average (ARIMA) model. Recently, Artificial Neural Network (ANN) modeling has attracted much attention as an alternative technique for estimation and forecasting in economics and finance (Zhang *et al.*, 1998) [15].

2. Materials and Methods

The required data for present study were collected from Agriculture Marketing website http://agmarknet.gov.in/ of Ahmedabad market for the duration of 15 years from January 2003 to December 2017. Statistical analysis for price forecasting was done using different statistical softwares R and MS-Excel. The following methods of analysis were utilized for the present study:

2.1 Time Series Analysis

The relationship between time series components is assumed to be additive or multiplicative, but the multiplicative model is most commonly used method in case of price analysis (Kumar, 2010) [6]. The multiplicative model is represented as:

$$Yt = Tt \times Ct \times St \times It$$

Where, t = 0, 1, 2, …, n; Yt = The original observation at the time period 't'; and Tt, St, Ct, It are Trend, seasonal, cyclical and irregular variations for a time period 't'.

2.1.1 Trend analysis

Trend analysis fits a particular type of trend line or curve to a time series data. Trend analysis was carried out by fitting following form of trend curves:

Linear trend : Yt = a + bt
Quadratic trend : Yt = a + bt + ct2
Exponential growth trend : Yt = abt

Where, Yt = price values at time t, a = intercept parameter, b & c = slope parameters and t= time period.
Comparison of these trends was done on the basis of values of R2 and standard error for best forecasting trend.

2.2 Autoregressive Integrated Moving Average (ARIMA) Models
Box and Jenkins (1970) [3] introduced the Autoregressive Integrated Moving Average (ARIMA) models. The main application of this methodology is in the area of short term forecasting and it requires at least 50 data points to carry out an analysis using Univariate Box Jenkins (UBJ) approach. This method is superior to other methods when the data is reasonably for longer period and there is a stable correlation pattern among past observations (Singh, 2012). Some of the basic concepts associated with this methodology are-

2.2.1 Stationarity
Before applying the ARIMA methodology, the time series should be checked for stationarity. A time series is said to be stationary if its properties are unaffected by a change of time origin. A time series must satisfy these stationarity conditions in order to be eligible for the application of this methodology.

2.2.2 Stationarity Tests
Other than Augmented-Dickey Fuller (ADF) and Phillips-Perron (PP) tests, the most commonly used stationarity test, the KPSS test, is due to Kwiatkowski, Phillips, Schmidt and Shin (1992). They derive their test by starting with the model:

$$y_t = \beta' D_t + \mu_t + u_t$$

$$\mu_t = \mu_{t-1} + \varepsilon_t, \varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$$

Where, Dt contains deterministic components (constant or constant plus time trend), ut is I(0) and may be heteroskedastic. Notice that μt is a pure random walk with innovation variance σ2ε. The null hypothesis that yt is I(0) is formulated as H0: σ2ε = 0, which implies that μt is a constant. Although not directly apparent, this null hypothesis also implies a unit moving average root in the ARMA representation of Δyt. The KPSS test statistic is the Lagrange multiplier (LM) or score statistic for testing σ2ε = 0 against the alternative that σ2ε > 0 and is given by:

$$KPSS = \frac{\left(T^{-2} \sum_{t=1}^{T} \hat{S}_t^2\right)}{\hat{\lambda}^2}$$

Where $\hat{S}_t = \sum_{j=1}^{t} \hat{u}_j$, $\hat{u}_t$ is the residual of yt on Dt and $\hat{\lambda}^2$ is a consistent estimate of the long run variance of ut using $\hat{u}_t$.

2.2.3 Autoregressive models
This simply means that any given value Y(t) can be explained by some function of its previous value, Y(t-1), plus some unexplainable random error, E(t). An AR model with only 1 parameter may be written as:

Y(t) = A(1) * Y(t-1) + E(t)

Where, Y(t) is time series under investigation, A(1) is the autoregressive parameter of order 1, Y(t-1) is the time series lagged 1 period and E(t) is the error term of the model.

2.2.4 Moving average models
Moving average parameters relate what happens in period t only to the random errors that occurred in past time periods, i.e. E(t-1), E(t-2), etc. A moving average model with one MA term may be written as follows:

Y(t) = -B(1) * E(t-1) + E(t)

The term B(1) is called an MA parameter of order 1. The negative sign in front of the parameter is used for convention only and is usually printed out automatically by most computer programs.

2.2.5 Mixed models or ARMA/ARIMA models
ARIMA methodology allows models to incorporate both autoregressive and moving average models together (mixed models). The models developed by this approach are usually called ARMA/ARIMA models. A combination of autoregressive (AR), integration (I) - referring to the reverse process of differencing to produce the forecast, and moving average (MA) operations are used in these models. ARIMA model is usually stated as ARIMA (p, d, q). This represents the order of the autoregressive components (p), the number of differencing operators (d) and the order of the moving average (q).

ARIMA (p,d,q) is expressed in the following form:

Yt = θ0 +Φ1Yt-1+ Φ2 Yt-2 +………..+ Φp Yt-p + et – θ1et-1- θ2et-2 -…….- θ et-q,

Where Yt and et are the actual values and random error at time t, respectively, Φi (i = 1,2,…….,p) and θj (j = 1,2,……,q) are model parameters, p and q are integers. Random errors et are assumed to be i.i.d. with mean zero and the constant variance, σe^2.

2.2.6 Main stages in fitting Box - Jenkins models
Box and Jenkins proposed a practical three-stage procedure for finding a good model.

Stage 1 Identification: At the identification stage two graphical devices, an estimated Autocorrelation *function* (ACF) and an estimated Partial autocorrelation function (PACF) are used to measure the correlation between the observations within a single data series. These functions assist in the decision of AR and MA orders of the model.

Stage 2 Estimation: Generally method of least squares is used to estimate the parameters. The quality of the coefficients is measured by their statistical significance.

Stage 3 Diagnostic checking: At this stage we determine whether the estimated model is statistically sound or not. The basic way of analyzing the goodness of the model is to check the residuals of the fitted model and the tool for analyzing the residuals is the residual ACF. It is assumed that they are independent of each other.

Some of the diagnostic checks are mentioned below:
1) **Over fitting method:** It uses more parameters than necessary. But the main difficulty in the correct

identification is not getting enough clues from the ACF because of inappropriate level of differencing.

2) The residuals of ACF and PACF considered random when all their ACF's are within the limits.
3) Ljung-Box test statistic was used to check whether the auto correlations for these residuals are significantly different from zero. It can be computed as follows (Ljung and Box, 1978):

$$Q= n(n+2)\sum(n-k)-1\ rk^2$$

Where, Q is distributed approximately as a Chi-square statistic with (m-p-q) degree of freedom. Here, n = N – D, D = Differencing, m = Maximum lag considered, N = Total number of observations and rk = ACF for lag k.

4) The minimum Akike Information Coefficient (AIC) criterion is used to determine both the differencing order (d, D) required attaining Stationarity and the appropriate number of AR and MA parameters (Shruthi, 2015), it can be computed as follows:

$$AIC\ (p + q) = N\ \sigma^2 + 2(p + q)$$

Where, σ^2 = Estimated MSE, N = Number of observations (p + q) = Number of parameters to be estimated

These diagnostic checking helps to identify the differences in the model, so that the model could be subjected to modification, if need be.

2.3 The ARCH and GARCH Models

Most of the statistical tools are designed to model the conditional mean of a random variable. The tools described here differ by modeling the conditional variance, or volatility of a variable. The variance of the dependent variable is modeled as a function of past values of the dependent variable and independent or exogenous variables. ARCH models were introduced by Engle (1982) [4] and generalized as GARCH (Generalized ARCH) by Bollerslev (1986) [2].
Let suppose the disturbance term of Yt sequence, et has a conditional variance of σ2t. Then for model GARCH (p, q) (Bera and Higgins, 1993) [1]:

$$\sigma^2_t = \alpha_0 + \alpha_1 e^2_{t-1} + \dots\dots\dots + \alpha_q e^2_{t-q} + \beta_1 \sigma^2_{t-1} + \dots\dots\dots + \beta_p \sigma^2_{t-p}$$

Where the inequality restrictions, $\alpha_0 > 0$, $\alpha_i \geq 0$ for i = 1, …,q and $\beta_i \geq 0$ for i = 1, …,p are imposed to ensure that the conditional variance is strictly positive.

2.4 Artificial Neural Networks (ANNs)

Artificial Neural Network (ANN) is a concept of knowledge engineering from the branch of science of Artificial Intelligence (AI) designed by adopting the human nervous system, where the main processor of the human nervous system is in the brain. The ability of ANN in learning is designed in such a way as the performance of the human brain, in which humans have the ability to process information, remember and perform calculations (Salman *et al.*, 2018) [10]. Some problems that can be solved with ANN are prediction, classification, optimization and pattern recognition (Shitap, 2015) [11]. In the present study for ANN, Neuralnet package in R statistical software was utilized for analysis purpose.

The structure of the neural network consists of three layers *viz.*, input layer, hidden layer and output layer. The basic objective of ANNs is to construct a model for mimicking the intelligence of human brain into machine. Development of ANNs was biologically motivated. Salient features (Kumar, 2010) [6] of ANNs are mentioned below.

- ANNs are data-driven and self-adaptive in nature.
- ANNs are inherently non-linear.
- ANNs are universal functional approximators.

The output of the model is computed using the following mathematical expression:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{0j} + \sum_{j=1}^{q} \beta_{ij} y_{t-i}\ _n\right) + \varepsilon_{t,}\ \forall t$$

Here *yt-i* (*i* = 1,2,..., *p*) are the *p* inputs and yt is the output. The integers *p*, *q* are the number of input and hidden nodes, respectively. α*j* (j = 0,1,2,...,*q*) and βij (*i* = 0,1,2,..., *p*; *j* = 0,1,2,...,*q*) are the connection weights and εt is the random shock. α0 and β0j are the bias terms and g(x) is the nonlinear activation function.

2.4.1 Data processing or normalization

Prior to experimenting and testing, preprocessing data needs to be done to scaling (normalizing) the inputs and targets.
The following is the normalization equation.

$$x' = \frac{x - \min value}{\max value - \min value}$$

Where, x is the Actual data, x' the normalized data, min value is the minimum value and max value is the maximum value.

2.4.2 Training and testing

Training set is the data set used to adjust the weights on the neural network. A set of examples used for learning that is to fit the parameters [i.e., weights] of the classifier to tune the parameters [i.e., architecture, not weights] of a classifier. Testing set is the data set used only for testing the final solution in order to confirm the actual predictive power of the network.

2.4.3 Activation functions

Activation function transmits information from the input layer to output layer after the passage of activity - a certain threshold. An activation function is defined by f(s), which is output of neurons (s is the weighted sum of inputs). Various types of activation functions are linear and sigmoid functions (Logistic and Hyperbolic functions).

2.4.4 Learning algorithm

Learning algorithm is a procedure of modifying weights and biases of network *i.e.* method of driving next changes that might be made in ANN, while Training algorithm is a procedure whereby network is actually adjusted to do a particular job.

2.4.5 Cross validation

Cross Validation is a validation technique by dividing data randomly into k section and each part will be done classification process. Cross validation will experiment as much as k. In general, the test k is performed 10 times to estimate the accuracy of estimation (Salman *et al.*, 2018) [10].

2.5 Evaluation of Behaviour of Forecasting Error
After fitting different forecasting models behaviour of normal distribution of errors were tested by using Jarque-Bera test for normality. The test statistic is always nonnegative. If it is far from zero, it signals the data do not have a normal distribution (Jarque and Bera, 1987) [5].

2.6 Evaluation of Forecasting Methods
Evaluation of these forecasting methods was done by standard criterion like Root Mean Square Error (RMSE), Mean Absolute Per cent Error (MAPE) etc. (Kumar, 2010) [6].

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2}$$

Where Ft is the forecasted value for time t, at is the Actual value for time t, n is the total number of forecasts.

3. Results and Discussion
In the present study statistical evaluation of different forecasting models for price forecasting of Brinjal was done. Fifteen year price data for Brinjal crop was collected from the Agriculture Marketing website http://agmarknet.gov.in/ of Ahmedabad market for the duration of 15 years from January 2003 to December 2017.

Table 1: Brinjal price data properties

Min value	Max value	Range	Mean	Median	Standard Deviation
181.25	3730.43	3549.18	826.03	679.99	487.44

3.1 Forecasting by trend analysis
In the present study trend analysis was used to forecast Brinjal prices. Different forms of trends fitted and the best fitted trend has been selected on the basis of minimum value of error measures MSE, RMSE and MAPE values. For prices of Brinjal among different fitted trends exponential trend was performing better although it has a very low value of R-square (36.1%). Best fitted trend (exponential trend) to Brinjal price is expressed as:

Yt = 407.26*1.006t

3.2 Forecasting using arima model
ARIMA Models were fitted based on the ACF and PACF for Brinjal prices. An examination of ACF and PACF values revealed that there is non-stationarity in the data, also KPSS test is used to perform stationarity checks and it was found that the series is stationary after first order differencing. Several models were tried and ARIMA model (1, 1, 3) was found performing better in case of Brinjal prices.

Table 2: Parameter estimates for fitted ARIMA model for Brinjal price

Parameter	Estimate	Standard error	t-value	p-value
MU	5.0444	1.0418	4.8421	< 0.01
AR1,1	0.4289	0.1474	2.9108	0.0041
MA1,1	-1.1007	0.1480	7.4371	<0.01
MA1,2	0.3220	0.1567	2.0549	0.0414
MA1,3	-0.2213	0.0825	2.6818	0.0080

3.2.1 Diagnostic checking for fitting adequate model
For diagnostic checking of models minimum AIC (2647.13) and BIC (2668.32) values were observed and ARIMA model (1, 1, 3) performed better for Brinjal price forecasting. Ljung-Box test statistic (30.44) was used to check autocorrelations among residuals of fitted model and it was observed as non-significant (p-value 0.0630) at five per cent level of significance which indicates that there is no autocorrelation among residuals of the fitted model.

3.3 Forecasting using arch/garch model
ARCH/GARCH models are used to analyze volatility of any financial time series data. It shows the dependency of time series data over squared error terms and conditional variance of error terms.

3.3.1 Test for ARCH effects
The Box-Jenkins approach has a basic assumption that the residuals remain constant over time. Thus ARCH Lagrange's Multiplier test was carried out on the square of the residuals obtained after fitting the ARIMA model and it was found that LM test statistic (126.3070) was found asymptotically significant (p-value < 0.01) up to the lag order 4 for the fitted ARIMA model, which indicates strong presence of ARCH effects in the Brinjal price series.

Table 3: Parameter estimates for fitted GARCH model of Brinjal price

Fitted model: ARMA (1, 1) + GARCH (1, 1)			
Parameter estimates			
Parameter	**Estimate**	**Standard error**	**p-value**
Mu	139.9228	50.5094	0.0056
AR1	0.8095	0.0721	< 0.01
MA1	-0.4327	0.1081	< 0.01
Omega	1613.6440	1569.6966	0.3040
Alpha1	0.1405	0.0572	0.0140
Beta1	0.8787	0.0470	< 0.01

3.3.2 Fit statistics of fitted GARCH model for Brinjal price
Minimum AIC (14.5775), BIC (14.6840) values were used as a criterion while deciding better model among different tried models. Ljung-Box test statistics (0.0082) was found non-significant (p- value 0.9279), indicating no presence of autocorrelations among residuals of the fitted model. LM test statistic (0.5842) was found non-significant (p- value 0.4447) indicating no ARCH effect or no presence of heteroscedasticity for squared residuals.

3.4 Forecasting using artificial neural network (ANN)
Different combinations of number of lags for input covariates and number of nodes in hidden layer were tried for fitting neural network to Brinjal price. Here nth lag value is defined

as the n month apart price data. Neural network with four, two and one nodes in input, hidden and output layers respectively was found better performing for Brinjal price forecasting.

Table 4: Neural network information for Brinjal price

Input layer	Covariates	Time.point, lag1, lag2, lag3
	Number of nodes	4
	Rescaling method of covariates	Min max method
Hidden layer	Number of hidden layers	1
	Number of nodes in hidden layer	2
	Activation function	Hyperbolic tangent
Output layer	Dependent variable	Price
	Number of nodes	1
	Rescaling method for scale dependents	Min max method
	Activation function	Linear/identity
	Error function	Sum of squares

3.4.1 Training and testing
Observations from April 2003 to March 2015 were used as training data set and the observations from April 2015 to December 2018 were used as data for testing.

3.4.2 Cross-validation
Five-fold cross validation procedure is also performed for validation check for fitted model and the average RMSE value was found to be 472.71.

3.5 Behaviour of forecast error
Jarque Bera test was performed to check the error behaviour of different fitted models (Raval, 2018). For residuals of different fitted models to forecast Brinjal price JB test statistic value for all the models were found asymptotically significant, indicating that none of the model residuals follow normal distribution.

3.6 Forecast accuracy
For forecast accuracy measure standard measures RMSE and MAPE were utilized (Kumar, 2010) [6]. Lowest RMSE value among fitted models for Brinjal price was found for ANN, followed by ARCH/GARCH model. Whereas, lowest MAPE value among fitted models for Brinjal price was found for ARCH/GARCH model followed by ANN. However, MAPE is a biased measure of forecast accuracy (Tofallis, 2015), so ANN was considered as the best fitted model among fitted models.

Table 5: Forecasting of Brinjal price

Month and year	Actual value (₹/q)	Forecast (₹/q) with different models			
		TREND	ARIMA	ARCH /GARCH	ANN
Jan-18	889.42	1202.55	880.29	830.55	978.64
Feb-18	726.09	1209.77	977.06	812.26	966.89
Mar-18	733.70	1217.03	1085.18	797.45	969.15
Apr-18	548.91	1224.33	1136.94	785.46	914.17
May-18	651.85	1231.68	1161.71	775.76	904.23
Jun-18	1002.00	1239.07	1173.57	767.90	981.71
Jul-18	913.00	1246.50	1179.25	761.54	1043.23
Aug-18	1645.83	1253.98	1181.97	756.39	1235.81
Sep-18	1300.00	1261.50	1183.27	752.23	1295.10
Oct-18	863.04	1269.07	1183.89	748.85	1208.05
Nov-18	622.50	1276.69	1184.19	746.12	1029.06
Dec-18	1108.33	1284.35	1184.33	743.91	978.64
	t-test	3.692 (p = 0.04)	2.374 (p = 0.037)	1.529 (p = 0.154)	1.385 (p = 0.194)

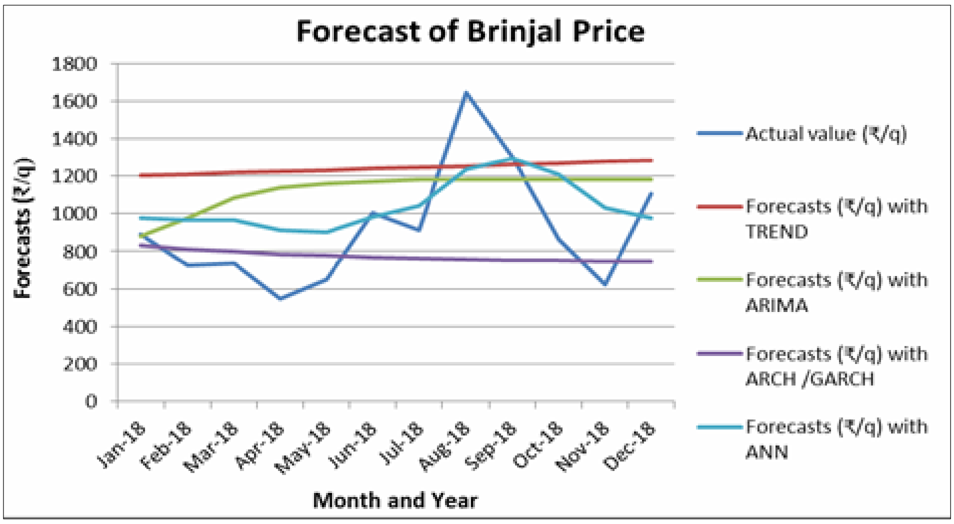

Fig 1: Forecasts of Brinjal price

4. Conclusion
Forecasting of prices for agricultural commodities is always and will remain difficult because such data are greatly influenced by economical, international trade, political and even natural shocks. Perishability and seasonal nature of vegetables affect a lot to the vegetable prices. Forecasting acts as an early warning signal and helps the policy makers to get insights of future prices and to manage the resources needed.

Exponential trend performed better for Brinjal price, although it was having very low R- squared values (0.361) indicating poor fitting. ARIMA model (1, 1, 3) performed better for Brinjal price. For ARCH/GARCH models ARMA (1, 1) + GARCH (1, 1) fitted well to Brinjal prices. For neural networks in case of Brinjal prices a single hidden layer neural network with two neurons in hidden layer was found fitting well, here three lag values and time point was used as input. Jarque-Bera test was utilized for the forecast error behaviour and significant values of test statistic were found in all the fitted models indicating none of model residuals follow normal distribution. For evaluating the forecast accuracy of different models RMSE and MAPE values were utilized.

The comparison of all the methods for price forecasting of Brinjal, ANN models were found superior among models studied.

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