Application Of Hybrid Model For Forecasting Prices Of Jasmine Flower In Bangalore, India

Sunil, Satyanarayana, Sachin Acharya, Arun Kumar Jogi

Abstract: The medicinal uses of Jasmine are well documented. It is used to enhance the immunity of the body, treatment of anxiety, stress, and sunstroke. The leaves are used in the treatment of mouth disease, treatment of cuts and wounds. The Jasmine plant is also the source of exotic fragrance. It is an important scent noted in perfumes and has herbal properties and hence today, Jasmine flowers are of much economic importance. Farmer's decision making on production of Jasmine depends on future price to be realised during the period of cultivation. Hence forecasting accuracy plays a vital role in Jasmine production. A hybrid model has been considered an effective way to improve the forecast accuracy. In this paper, hybrid model of SARIMA-ANN is proposed for forecasting the prices of Jasmine flower. We also compared the performance of hybrid model with traditional SARIMA model, ELM, MLP and NNETAR (ANN). The study concluded that the hybrid model of ARIMA-ANN is more appropriate model for forecasting the prices of Jasmine flower. The best model is used to forecast prices for next 12 months.

Keywords: SARIMA, ANN, Extreme Learning Machine, Multi –Layer Perceptron

1. Introduction

The word jasmine has been derived from the Arabic word "Yasmin" which means fragrant flower. Jasmine mostly has star-shaped flowers that are in yellow or white colours. These grow on vines or as shrubbery. Jasmine has their own importance since ancient times and is being used for decoration, worshiping as well as in satisfying the aesthetic feelings. Jasmine is one of the major commercial flower crops of south India. It has spiritual significance and is one of the few flowers that are being sold throughout the year. In Karnataka, jasmine has been cultivated in all most all districts. The most commonly cultivated Jasmine species are Jasminum multiform (kakada) ,asminumsamabac (gundumallige), Jasminum grandiflorum (JajiMallige) and Jasminumauriculatum (Soojimallige).It is mainly used for extraction of scented oil. India exports this oil mainly to England, United States of America, Holland, Sweden, Japan, Norway and European Union. The technique of time series analysis is the most important tool for evaluating the economic performance of any crop in future. Farmer's decision making on production of Jasmine depends on future price to be realised during the period of cultivation. Hence this study have been taken up to forecasting future prices of jasmine which will help the farmers to facilitate informed decisions to choose the profitable crops before sowing the crops.

- *Sunil, Department of Statistics Mangalore University, Mangalagangothri. Email: sunildevadiga073@gmail.com*
- *Satyanarayana, Sachin Acharya, Arun Kumar Jogi, Department of Statistics Mangalore University, Mangalagangothri*

2. Methodology

2.1 Introduction to Time series Analysis:

A Time Series (TS) is a sequence of observation ordered in equally spaced, discrete time intervals.A basic assumption in any time series analysis / modelling that some aspects of past pattern will continue to remain the future. Suitable forecasting time series model can be developed with minimum forecasting error. Atleast 50 observations are necessary for performing TS analysis, as propounded by Box Jenkins who were pioneers in TS modelling. The four main objectives in time series analysis are Description, Explanation, Prediction and Control. Time series analysis start by plotting the data and look for non-stationary components. Then eliminate these components using different methods, in order to have a stationary data. After identifying a suitable probability model for the time series, this model can be used for prediction. The statistical methodology available for analysing time series is referred to as Time Series Analysis.

Analysis of Time Series:

Step1: Time profile

Plot the observed time series X_t versus time point t in a graph. Examine whether data contains trend, seasonality and cyclic variations.

Step2: Making series stationary

Remove the non-stationary components from observed series by estimation techniques or by differencing methods.

Step3: Model building

Build an appropriate time series model for the stationary time series making use of sample autocorrelation and partial autocorrelation function.

Step4: Diagnostic checking

Once we fit the appropriate time series model next, we are going to check whether fitted model is good fit for the series using residual series of fitted time series model. If all autocorrelation of residual series is insignificant then fitted model is good fit for stationary series.

Step5: Forecasting

It is the main objective of time series analysis. It will be achieved by forecasting the stationary series then inverting transformation described in step2 to arrive at forecast of the observed data.

2.1.1 Auto Correlation Function (ACF):

Autocorrelations referred to the observations in a time series are related to each other and is measured by the simple correlation between current observation(X_t) and observations from k periods before the current one(X_{t-k}) i.e. for a given series Xt, autocorrelation at lag k is the correlation between the pair (Xt, Xt_{-k}) by r_k. A consistent estimator of the ACF is the sample autocorrelation function. It is defined as:

$$r_k = \frac{\sum_{t=1}^{n-k}(x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^{n}(x_t - \bar{x})^2}$$

In order to identify the underlying process, it is useful to check whether these coefficients are statistically nonzero or more specifically, to check whether$X_t$is a white noise. Then a usual test of individual significance can be applied, i.e., H_0: p_k =0 against H_1:$p_k \neq 0$ for any k=1, 2….. The null hypothesis H0 would be rejected at the 5% level of significance if $|r_k|>1.96\sqrt{n}$. Usually, the correlogram plots the ACF jointly with these two-standard errors bands around zero, approximated by $\pm 2\sqrt{n}$, that allow us to carry out this significance test by means of an easy graphic method. We are also interested in whether a set of m autocorrelations are jointly zero or not, that is, in testing H_0:p_1=p_2=……..=p_m=0. The most usual test statistic is the Ljung-Box statistic:

$$Q_{LB} = n\,(n+2)\sum_{k=1}^{m}\frac{r_k^2}{n-k}$$

That follows asymptotically a $\chi^2_{(m)}$ distribution under H_0.

2.1.2 Partial autocorrelation function (PACF):

Partial autocorrelations are used to measure the degrees of association between X_t and X_{t-p} when X effects at other time lags 1, 2, 3,..., p-1 are removed. The auto covariance coefficient $\gamma_k$at lag k measures the covariance between two values X_t and X_{t+k} separated by interval of time. The partial autocorrelation function is estimated by the OLS coefficient from the expression that is known as sample PACF. Under the assumption that X_t~ WN (0,σ 2), the distribution of the sample coefficients in large samples is identical to those of the sample ACF. In consequence, the rule for rejecting the null hypothesis of individual non significance is also applied to the PACF. The bar plot of the sample PACF is called the sample partial correlogram and usually includes the two standard error bands $\pm 2\sqrt{n}$ to assess for individual significance.

2.2 Testing for the presence of seasonality component:

H_0: Time series is free from seasonal variation

v|s

H_1: Time series contains seasonal variation

Test statistic is $\chi_0{}^2 = \frac{12\sum_{j=1}^{D}(M_j - \frac{C(D-1)}{2})^2}{CD(D+1)} \sim \chi^2_{(D-1)}$

D-seasonality periods, C-total number of years, M_j -sum of the ranks for the j^{th} period .If chi-square calculated is more than chi-square table value, we reject H_0 and conclude that there is seasonal variation is there in the data.

2.3 Augmented Dickey Fuller test:

An augmented Dickey-Fuller test tests the null hypothesis that a unit root is present in a time series sample. The alternative hypothesis is stationarity or trend stationarity. It is an augmented version of the Dickey-Fuller test for a larger and more complicated set of time series data. The augmented Dickey-Fuller statistic, used in the test, is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence

H_0:$\gamma = 0$ i.e. unit root is present

v|s

H_1: $\gamma < 0$i.e. no unit root is present.

$$DF_T = \frac{\hat{\gamma}-1}{SE(\hat{\gamma})}$$

2.4Autoregressive Integrated Moving Average (ARIMA) Model:

Let $\{X_t,\ t \in I\}$ denotes a non-stationary time series, non-stationary due to trend component. Let $\{\epsilon_t, t=\pm 1, \pm 2, ...\}$ is a sequence of white noise. Then $\{X_t, t \in I\}$ is said to follow autoregressive integrated moving average process if it is has the representation.

$$\emptyset(B)(1-B)^d X_t = \theta(B)\epsilon_t$$

Where $\emptyset(B)=1-\beta_1 B-\ldots\ldots-\beta_p B^p$

$\theta\ (B)=1-\alpha_1 B-\ldots\ldots-\alpha_q B^q$

$\alpha_1,\alpha_2,\ldots\ldots,\alpha_q$are MA parameters,$\beta_1,\beta_2,\ldots\ldots,\beta_p$ are AR parameters Where d is the difference required to make given time series data to stationary time series. This model is also known as Box-Jenkins model

2.5Seasonal Autoregressive Integrated Moving Average (SARIMA) Model:

2.5.1 Modelling Seasonal Time Series:

Seasonal effect refers to certain influences which appear in data at a particular time of a yearand all repeated annually. Essentially there are two kinds of seasonal effect on time series data namely deterministic and probabilistic. A deterministic seasonal effect is that component which influences a time series either positively or negatively and which appears at a regular interval with some precisely measurable regular pattern. Stochastic seasonal components do not possess any definite pattern and usually influence the time series randomly at a regular interval.

2.5.2 Seasonal Time Series with Deterministic Component:

Time series with deterministic seasonal components can be eliminated simply by differencing the series with appropriate distance.

2.5.3 Stochastic Seasonal Time series:

Time series with seasonal effect do not necessarily recur with exact pattern. They often occur with random intensity, although they reappear at the same time during the year. Such seasonal influences are statistically distributed over time. Such seasonal influence ontime series data is referred to as stochastic seasonal effect. In such case future seasonal effect can be realized from the past observed values. The stochastic seasonal models in general can be expressed by three different classes of models namely MA model, AR model, mixed ARMA model. Consider a time series which contains trend, stochastic seasonality and trend in seasonality then we make use of integrated or multiplicative model written in the form ARIMA(p, d, q)(P,D,Q)$_s$.Where 'p' and 'q' denotes non-seasonal ARMA coefficient, 'd' denotes number of non-seasonal difference. P-Number of multiplicative AR coefficient, Q-Number of multiplicative MA coefficient, D-Number of multiplicative differencing required to remove trend in seasonality, s-Seasonal period or distance. Multiplicative seasonal ARIMA (p, d, q)(P,D, Q)^s has the representation

$$\emptyset(B)\emptyset(L)(1-B)^d(1-L)^D X_t$$

Where $L=B^S$

$$\emptyset(B) = 1-\beta_1 B - \ldots - \beta_p B^p$$
$$\theta(B) = 1-\alpha_1 B - \ldots - \alpha_q B^q$$
$$\emptyset(L) = 1-\emptyset_1(L) - \ldots - \emptyset_p L^P$$
$$\theta(L) = 1-\theta_1(L) - \ldots - \theta_Q L^Q$$

2.6 Identification:

The foremost step in the process of modelling is to check for the stationarity of the series, as the estimation procedures are available only for stationary series. A cursory look at the graph of the data and structure of autocorrelation and partial autocorrelation coefficients may provide clues for presence of stationarity. The next step in the identification process is to find the initial values for the orders of seasonal and non-seasonal parameters P,Q and p, q. they could be obtained by looking for significant autocorrelation and partial autocorrelation coefficients.

2.7 Accuracy Measures

In forecasting, our objective is to produce and optimum forecast that has no error or as little error as possible, which leads us to the minimum mean square error forecast. This forecast will produce an optimum future value with the minimum error in terms of the mean square error criterion.

2.7.1 RMSE

The Root Mean Square Error (RMSE) (also called the root mean square deviation, RMSD is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. The RMSE of a model prediction with respect to the estimated variable X model is defined as thesquare root of the mean squared error.

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{h}(X_{obs,i}-X_{model,i})^2}{n}}$$

WhereX_{obs} is observed values and X model is modelled values at time/place i.

2.7.2 MAE

The mean absolute error, or MAE, is calculated as the average of the forecast error values, where all of the forecast values are forced to be positive. Forcing values to be positive is called making them absolute

$$\text{MAE}=\frac{\sum_{i=1}^{N}|x_i-\hat{x}_i|}{N}$$

Where:

$\{x_i\}$ is the actual observations time series

$\{\hat{x}_i\}$ is the estimated or forecasted time series

N is the number of non-missing data points

2.7.3 MAPE

The mean absolute percentage error (MAPE), also known as mean absolute percentage deviation (MAPD), is a measure of prediction accuracy of a forecasting method. It usually expresses accuracy as a percentage, and is defined by the formula:

$$M=\frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t-F_t}{A_t}\right|$$

where A_t is the actual value and F_t is the forecast value. The differenceA_t between and F_t is divided by the actual value A_t again. The absolute value inthis calculation is summed for every forecasted point in time and divided by the number of fitted points n. Multiplying by 100 makes it a percentage error.

2.8 Neural Network

A neural network is a biologically inspired nonlinear parallel computing paradigm for information processing and exploratory analysis having a distinct ordering among the sets of neurons arranged as input and output layers with zero or more processing layers that are interconnected by signal channels and fine-tuned by training algorithm. A neural network is a set of connected input/output units in which each connection has a weight associated with it. The weights are adjusted during the learning phase to help the network predict the correct class label of the input tuples. Neural network learning is also referred to as connectionist learning due to the connections between units. Neural networks involve long training times and are therefore more suitable for applications where this is feasible. They require a number of parameters that are typically best determined empirically such as the network topology or "structure." Advantages of neural networks, however, include their high tolerance of noisy data as well as their ability to classify patterns on which they have not been trained. They can be used when you may have little knowledge of the relationships between attributes and classes. They are well suited for continuous-valued inputs and outputs, unlike most decision tree algorithms. They have been successful on a wide array of real-world data, including handwritten character recognition, pathology and laboratory medicine, and training a computer to pronounce English text. Neural network algorithms are inherently parallel; parallelization techniques can be used to speed up the computation process. In addition, several techniques have been recently developed for rule extraction from trained neural networks.

2.8.1 Components of neural network:

1) Network architecture: Learns relationship between inputs and output values.

2) Activation and transfer function: Transform input values using sanative strengths to a neuron.

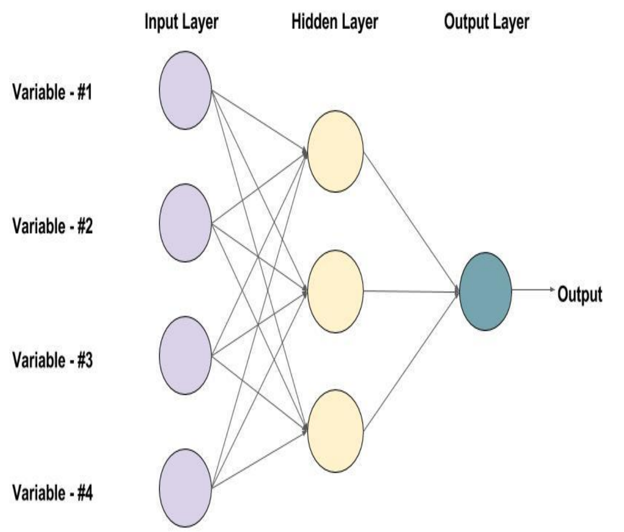
3) Synaptic weights: They are pre specified by user and is obtained from previous runs of the model.

4) Training algorithm: Simulates learning algorithm.

5) Training and testing sets: Builds intelligence to solve practical problems.

2.8.2 Multilayer Perception Method (MLP):

A multilayer feed-forward neural network consists of an input layer, one or more hidden layers, and an output layer. A multilayer feed forward neural network is an interconnections of perceptron's in which data and calculations flow in a single directions, from the input data to the outputs. The number of layers in a neural network is the number of layers of perceptron's. The simplest neural network is one with a single input layer and an output layer of perceptron's. The next most complicated neural network is one with two layers. This extra layer is referred to as a hidden layer. In general, there is no restriction on the number of hidden layers. The back propagation algorithm performs learning on a multilayer feed-forward neural network. It iteratively learns a set of weights for prediction of the class label of tuples. However, increases the number of perceptron's increases the number of weights that must be estimated in the network, which in turn increases the execution time for the network. Instead of increasing the number of perceptron's in the hidden layer to improve accuracy, it is sometimes better to add additional hidden layers, which typically reduce both the total number of network weights and the computational time.

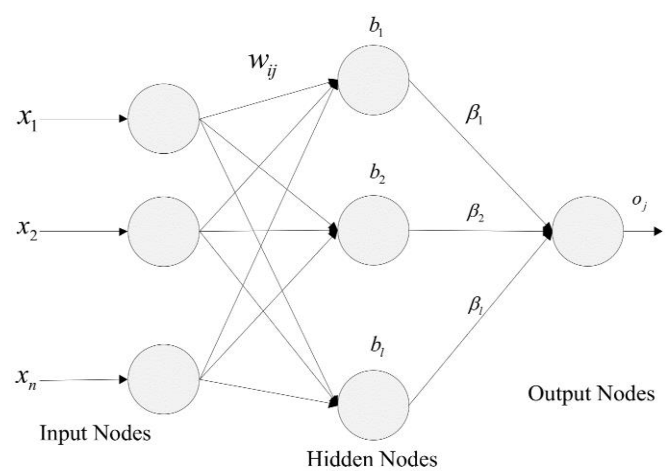


An example of a Feed-forward Neural Network with one hidden layer (with 3 neurons)

Each layer is made up of units. The inputs to the network correspond to the attributes measured for each training tuple. The inputs are fed simultaneously into the units making up the input layer. These inputs pass through the input layer and are then weighted and fed simultaneously to a second layer of "neuron like" units, known as a hidden layer. The outputs of the hidden layer units can be input to another hidden layer, and so on. The number of hidden layers is arbitrary, although in practice, usually only one is used. The weighted outputs of the last hidden layer are input to units making up the output layer, which emits the network's prediction for given tuples. The units in the input layer are called input units. The units in the hidden layers and output layer are sometimes referred to as neuroses, due to their symbolic biological basis, or as output units. It is a feed-forward network since none of the weight's cycles back to an input unit or to a previous layer's output unit. It is fully connected in that each unit provides input to each unit in the next forward layer. Each output unit takes, as input, a weighted sum of the outputs from units in the previous layer. It applies a nonlinear (activation) function to the weighted input. Multilayer feed-forward neural networks are able to model the class prediction as a nonlinear combination of the inputs. From a statistical point of view, they perform nonlinear regression. Multilayer feed-forward networks, given enough hidden units and enough training samples, can closely approximate any function.

2.8.3 Extreme Learning Machine (ELM):

Extreme learning machine are feed-forward neural networks for classification, regression, clustering and prediction, compression and feature learning with a single layer or multiple layers of hidden nodes, where the parameters of hidden nodes need not be tuned. These hidden nodes can be randomly assigned and never updated or can be inherited from their ancestors without being changed. In most cases, the output weights of hidden nodes are usually learned in a single step, which essentially amounts to learning a linear model. In most cases, ELM is used as a single hidden layer feed-forward network. These models are able to produce good generalization performance and learn thousands of times faster than networks trained using back propagation.



2.8.4 Back propagation:

Back propagation is a method used in artificial neural networks to calculate a gradient that is needed in the calculation of the weights to be used in the network.

Back propagation algorithm: Back propagation is a neural network learning algorithm. Back propagation learns by iteratively processing a data set of training tuples, comparing the network's prediction for each tuple with the actual known target value. The target value may be the known class label of the training tuple (for classification problems) or a continuous value (for numeric prediction). For each training tuple, the weights are modified so as to minimize the mean-squared error between the network's prediction and the actual target value. These modifications are made in the "backwards" direction (i.e., from the output layer) through each hidden layer down to the first hidden layer. In general, the weights will eventually converge, and the learning process stops.

2.9 Neural Network Auto regression model:NNETAR:
A feed-forward neural network is fitted with lagged values of y as inputs and a single hidden layer with size nodes. The inputs are for lags 1 to p, and lags m to MP where m=frequency(y) . If xreg is provided, its columns are also used as inputs. If there are missing values in y or $x_{reg,}$ the corresponding rows (and any others which depend on them as lags) are omitted from the fit. A total of repeats networks is fitted, each with random starting weights. These are then averaged when computing forecasts. The network is trained for one-step forecasting. Multi-step forecasts are computed recursively. For non-seasonal data, the fitted model is denoted as an NNAR (p,k) model, where k is the number of hidden nodes. This is analogous to an AR (p) model but with nonlinear functions. For seasonal data, the fitted model is called an NNAR(p,P,k)[m] model, which is analogous to an ARIMA(p,0,0)(P,0,0)[m] model but with nonlinear functions.

2.9.1ARIMA-ANN Hybrid model:
Hybrid model is a combination between linear and nonlinear models that usually be used for increasing the forecast accuracy. In general, the mathematical form of combination between linear and nonlinear models is as follows: $Y_t = L_t + N_t + e_t$, Where L_t is a linear component and N_t is a nonlinear component of the model. In this paper, NN is used for modelling the nonlinear component. Estimation of this hybrid model is done in two steps. The first is modelling the linear component to get the residual and then applying a nonlinear model to this residual for handling the nonlinear component. In this paper, ARIMA model is used for handling the linear component. Assume at is residual at period t from the first linear model or ARIMA model. i.e. $a_t = Y_t - \widehat{L_t}$ Where $\widehat{L_t}$ is the forecast of linear model at period t. Then, NN is applied for modelling at as follows:

$$a_t = f\,(a_{t-1}, a_{t-2}, \ldots a_{t-p}) + e_t = \widehat{N_t} + e_t$$

Where f(.) is a nonlinear function from the NN model and e_t is the residual of this NN model. Hence, the forecast value of the hybrid ARIMA-ANN model is as follows

$$\widehat{Y_t} = \widehat{L_t} + \widehat{N_t}$$

3. Data Analysis and Results
This data set used in the study is download from the website "National Horticulture Board". The dataset contains monthly price of Jasmine flower over the year 2009-2018. The data from the year 2009-2017 is taken as training data and 2018 year data is taken as testing data. The analysis is carried out using R software.

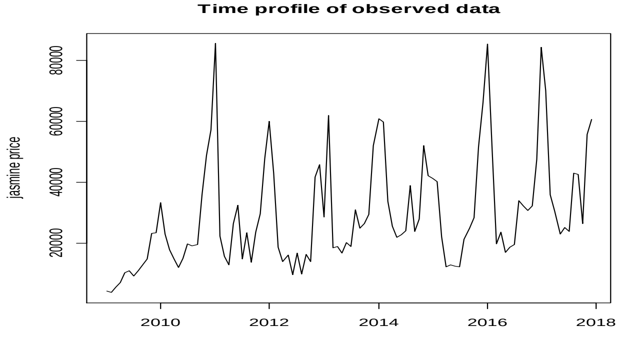


Fig 1: *Time series plot for the Jasmine price of Bangalore*

From above figure we observe that data has both seasonal component and trend component.

Man Kendall test – test for trend

H_0: There is no trend in the series
v|s
H_1: There is a trend in the series.

tau = 0.374, 2-sided p-value = 2.22e-16
Since the computed p-value is less than the significance level alpha=0.05, we reject the null hypothesis and conclude that there is trend in the given data.

Rank-sum test –test for seasonality:
H_0: There is no seasonal variation in the data.
H_1: There is seasonal variation in the data.

Chi-square calculated value is 64.57265 and Chi-square critical value is 19.67514. Since calculated value of chi square is greater than critical value of chi -square we reject H0 and conclude that there is seasonal variation in the data. Then we removed seasonal component from the data

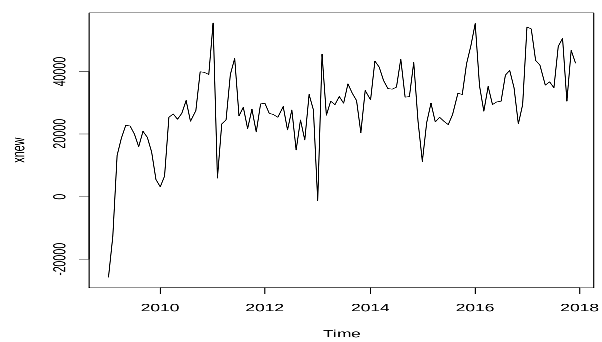


Fig.2: *Plot of de-seasonal series*

Variance difference method: Now data has only trend component. Therefore we carried out variance difference method to make the given series stationary. Variance of given time series is 166473178.Variance of first difference series is 131546350.Variance of second difference series is 354061538.Since variance of second difference series is more than the variance of first difference series, first difference series is stationary.

ARIMA Model
Based on the ACF and PACF plot we fitted the different arima model with different order. We select the best model for which AIC value is minimum and p value maximum.

Table 1: *Model fitting*

(p,d,q)	Aic	Box Ljung p-value
(0,1,1)	2287.811	0.5448586
(1,1,0)	2294.468	0.653948
(1,1,1)	**2285.472**	**0.8445041**

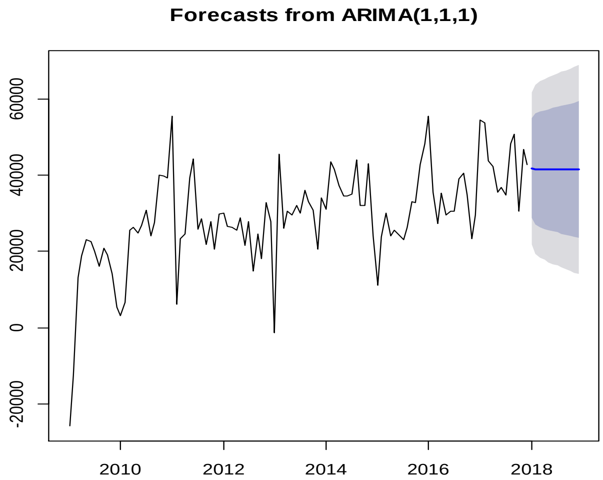


Fig.3: *Forecast from ARIMA (1,1,1) model*

Table 2: *Seasonal auto regressive integration moving average (SARIMA) model:*

(p,d,q)(P,D,Q)	AIC	Box-pierce p value	Ljung -Box pvalue
0,0,1,0,1,1	2095.610	0.5855233	0.3980204
0,0,1,1,1,0	2103.357	0.2462157	0.1176114
0,0,1,1,1,1	2097.105	0.4518975	0.2736137
0,0,2,0,1,1	2092.085	0.9250322	0.8470169
0,0,2,1,1,0	2100.196	0.784991	0.6318981
0,0,2,1,1,1	2093.549	0.8447917	0.7219904
1,0,0,0,1,1	2088.166	0.8637885	0.7652495
1,0,0,1,1,0	2097.915	0.6689054	0.4935107
1,0,0,1,1,1	2089.296	0.7729055	0.6411153
1,0,1,0,1,1	2086.496	0.7640134	0.6475471
1,0,1,1,1,0	2096.971	0.8205095	0.6970694
1,0,1,1,1,1	2087.955	0.7154461	0.5895103
1,0,2,0,1,1	**2086.067**	**0.8258471**	**0.7045662**
1,0,2,1,1,0	2098.524	0.7760122	0.6352056
1,0,2,1,1,1	2087.177	0.77806	0.6404271

From the Table 2, the AIC value for model SARIMA (1,0,2) (0,1,1) is minimum and it has highest p-value . Thus SARIMA (1,0,2) (0,1,1) is the best fitted model.

Plot of actual and forecasted values is given below:

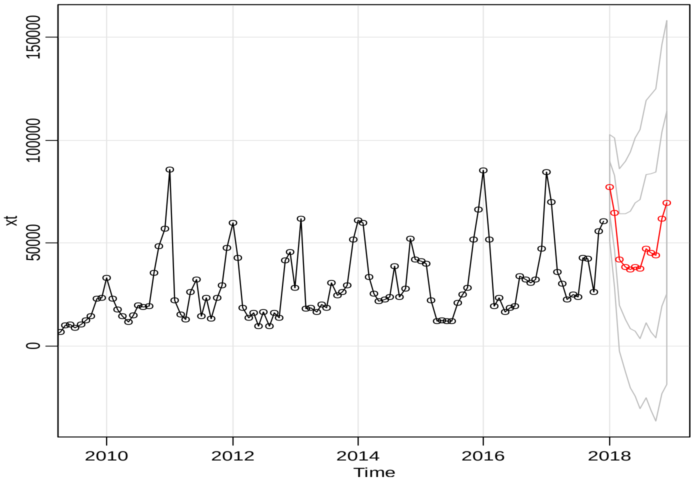


Fig.4: *Forecast from SARIMA (1, 0, 2) (0, 1, 1) model*

Forecasting from neural network:

MLP:

MLP fit with 5 hidden nodes and 20 repetitions. Deterministic seasonal dummies included. Forecast combined using the median operator.

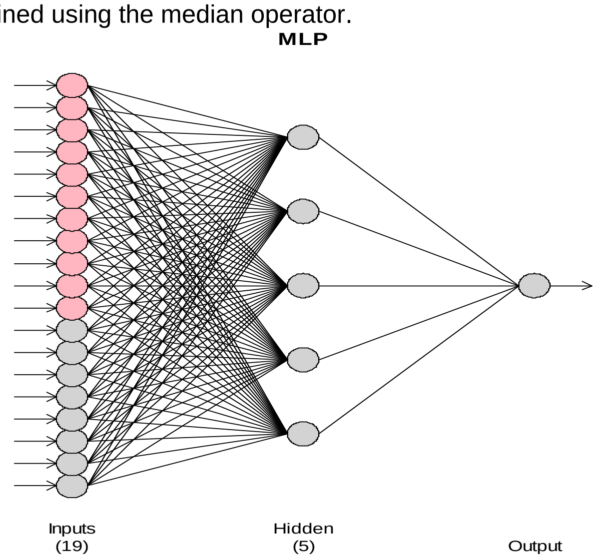


Fig.5: *MLP network*

Plot of forecast from neural network:

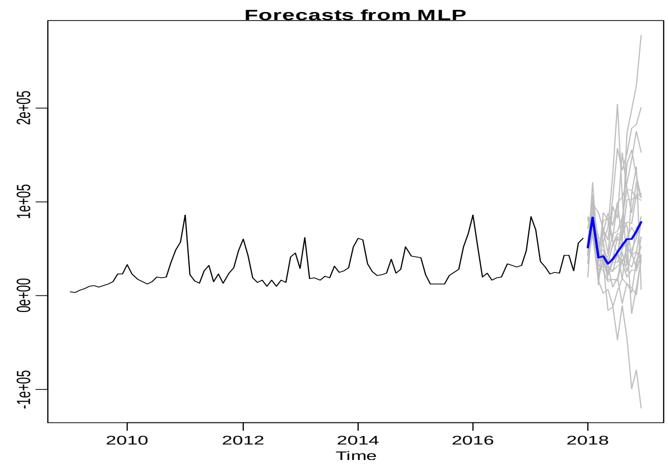


Fig.6: *Forecast from neural network.*

ELM:

ELM fit with 93 hidden nodes and 20 repetitions. Deterministic seasonal dummies included. Forecast combined using the median operator. Output weight estimation using: lasso.

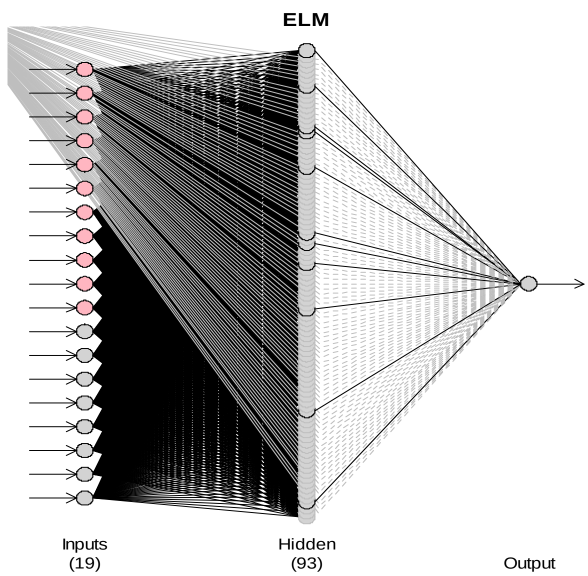


Fig.7: *ELM network*

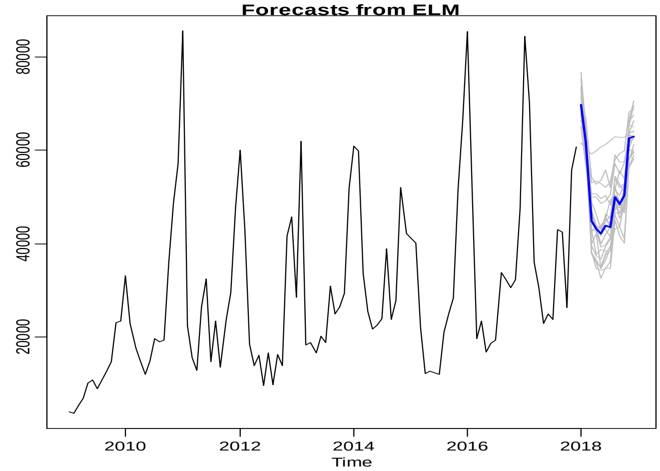


Fig.8: *Forecast from Elm network*

NNETAR:

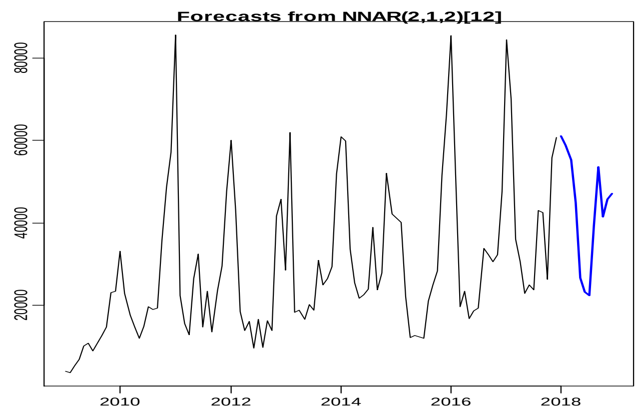


Fig.9: *Forecast from NNETAR network*

ARIMA-ANN hybrid model:

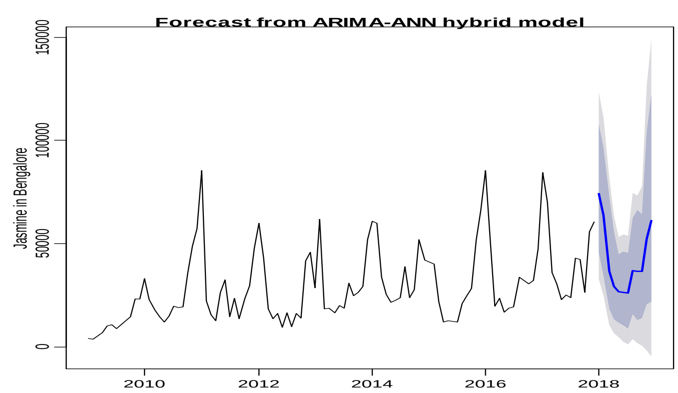


Fig.10: *Forecast from ARIMA-ANN hybrid model*

Table 3: *Accuracy measure for the models ARIMA(1,1,1), SARIMA (1,0,2) (0,1,1), neural network and hybrid model:*

Models	**RMSE**	**MAE**	**MAPE**
ARIMA(1,1,1)	25966.39	22649.67	62.92
SARIMA(1,0,2)(0,1,1)	10217.13	6663.61	13.20
MLP	14669.86	13114.94	44.165
ELM	9890.81	7380.57	27.623
NNETAR(ANN)	9912.15	7295.54	27.263
HYBRID(ARIMA-ANN)	**9035.26**	**5526.33**	**8.927**

From the above table we observe that accuracy measures RMSE,MAE and MAPE are low for ARIMA-ANN hybrid model.Therefore ARIMA-ANN hybrid model is the best model for forecasting the prices of jasmine.Then we forecast the Jasmine prices for year 2019 based on hybrid model.The forecasted graph is given below:

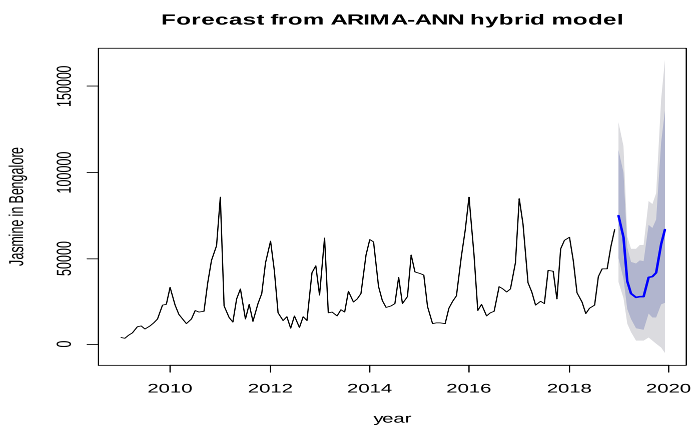


Fig.11: *Future Forecast from ARIMA-ANN hybrid model*

4. Conclusion

In the recent year's fluctuation in flower prices increased significantly with a lot of uncertainty in profitability of growing flowers. Under this scenario, forecasting future prices will help the farmers to facilitate informed decisions to choose the profitable crops before sowing the crops. This paper presents six different models namely ARIMA, SARIMA, ELM, MLP, NNETAR (ANN) and ARIMA-NNETAR. We compared the forecasting accuracy of different models based on MAPE, MAE and RMSE. Based on table 3, the forecasts produced by ARIMA - ANN are better since the RMSE, MAE, MAPE are lower than he forecasts produced by other models. It can be concluded that in case of prices of jasmine in Bangalore, hybrid model improves the forecasting accuracy and can be used as the best model for predicting future prices. The validity of the forecasted value for the year 2018 is checked with the available data. Finally, we forecasted the price of jasmine using the best model for the year 2019.

References

[1]. Brockwell P.J and Davis R.S(2002): Introduction to Time Series and Forecasting, 2nd Ed., Springer.

[2]. Chatfield.C(1980):'An Introduction to the Analysis of Time Series', 2nd Ed., Chapman and hall, Londen.

[3]. Deelip kumar shetty ,Sumithra and Ismail B (2018): Hybrid SARIMA-GARCH model for forecasting Indian Gold price ,Research Review International Journal of Multidisciplinary,Volume-03 ,Issue-08

[4]. Kendall M.G. and Ord J.K. (1990): Time Series, 3rd Ed, Edward Amold.

[5]. Jiawei Han, Micheline Kamber(2002): Data MiningConcepts and Techniques, Morgan Kaufman Publishers, U.S.A.

[6]. Simon Haykin (2012): Neuarl Networks and Learning Machines, 3rd edition, PHI Learning Private Limited, New Delhi

[7]. Box GEP and Jenkins G.M(1976): Time Series Analysis: Forecasting and Control, Holden-day, San Franscisco.

[8]. Darekar A.S, Pokharkar V.G. and Yadav D.B (2016): Onion Price Forecasting In Yeola Market of Western Maharashtra Using ARIMA Technique, International Journal of Advanced Biological Research, 6(04): 551-552.

[9]. Jalika V.N. and Patil B.L(2015): Onion price forecasting in Hubli market of Northern Karnataka using ARIMA technique, Karnataka ,Journal Agricultural Science , 28(2): 228-231.

[10]. Pravin A, Singh D.R and Sivaramane N (2005) : An Application of Box-Jenkins Approach for Forecasting Copra Wholesale Price Series, Indian Society of Agricultural Statistics, 59: 32-47.

[11]. Satyanarayana ,Swathi and Ismail B : Statistical Analysis of Food Grain Prices in Karnataka, Research Review International Journal of Multidisciplinary, Volume-03 Issue-08