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Price forecasting of groundnut: By an artificial neural network

PM Shivaswamy and KB Murthy

Abstract
The present study analyzes the forecasting of price of groundnut in selected market of Karnataka. The monthly time series data over a period of 20 years from January 2002 to August 2021 were collected from Agricultural Produce Marketing Committees (APMC's) located at Hiriyur. Different neural networks *viz*., NN1, NN2, NN3, NN4 and NN5 were carried out to know the best forecasting model during study the period. The results revealed that the R^2 value to be 0.97, average absolute error to be 100.91, average means square error was 18672.71 and correlation coefficient was 0.99 in NN2 model as shown in Table 1. The results suggested that NN2 model to be best fit for forecasting of price groundnut in Hiriyur market by considered all the parameters.

Keywords: Prices of groundnut and different neural networks

1. Introduction
Agriculture is one of the important activities in both developed and developing countries which provide basic raw materials to human beings and various agro-based industries.

Prices play a vital role in predominantly agriculture like India. It determines not only what shall be produced but also how much to be produced. The price system is a powerful tool to transmit essential economic information and stimulate appropriate decision by producers and consumers. Price is the most important determinant of profit or loss in the farm enterprise. In farm enterprise, time factor is very important, while crops are grown in one period and are harvested in another period. This long gestation period exercise significant influence on price determination. Therefore, the prices prevailing during the marketing period are of great consequence.

In a country which depends mainly on agriculture, it is absolutely necessary to modernize the age-old traditional agriculture. The transformation of agriculture into dynamic business proposition is primarily a techno-economic process, which can be accelerated by providing a suitable environment to the farmers. The upward trends in arrivals are associated with development in technology of production, input supply and infrastructure (Mundinamani *et al*., 1993) [6]. Instability in the farm prices tends to cause inefficient allocation of resources and induce income fluctuations over time and across different categories of farmers. This results in distribution of changes in cropping pattern in the economy. On the contrary, a stable price level would provide incentive to the producers to increase the production of required commodities there by helping to achieve balanced growth of the economy.

Farmers always experience with lower prices for their produce when bumper crop is harvested. They always commit the mistake in disposing off their produce at right time in order to get remunerative prices for their produce. Usually, they sell their produce when there is a glut in the market that is, immediately after the harvest of the crop. For this inappropriate time of sale, one can quote several reasons, but among them the most important is lack of awareness and knowledge about the proper time to sell their produce. This kind of study also helps in formulating appropriate policy measures to contain both over production as well as the forecasting of the remunerative prices for the commodity.

The performance of Artificial Neural Network (ANN) model has been studied by Hebb (1949) [1], Hopfield (1982) [2], Glen Donaldson *et al*. (1996) [4], Peter Zhang *et al*. (2003) [5], Hung *et al*. (2004) [3], Mani *et al*. (2005).

Najafi *et al*. (2007) have studied wholesale prices of selected crops, namely, tomato, onion and potatoes in Fars Province, Iran, were predicted for various time horizons by using common methods of forecasting and artificial neural networks (ANN).

Sreekanth *et al*. (2009) [7] studied the performance of artificial neural network (ANN) model, i.e. standard feed-forward neural network trained with Levenberg–Marquardt algorithm, was examined for forecasting groundwater level at Maheshwaram watershed, Hyderabad, India. The model efficiency and accuracy were measured based on the root mean square error (RMSE). The model provided the best fit and the predicted trend followed the observed data closely. Thus, for precise and accurate groundwater level forecasting, ANN appeared to be a promising tool. The behaviour of market prices has been studied by Ganqiong, L. X. (2011), Li Wang (2013), Meena *et al.* (2014) [8], Ozer *et al.* (2013) [9], Ratna *et al.* (2011) [12], Rani *et al.* (2012) [11], Sahu *et al.* (2013) [13], Wang *et al.* (2013), Vasanth Kumar *et al.* (2015) [14], Vasanth Kumar *et al.* (2016) [15] and Yegnanew, A. S. (2012), Ramachandra *et al*. (2012) [10] have studied an econometric analysis of sunflower arrivals and prices.

Groundnut (*Arachis hypogaea* L.) is an annual legume primarily grown for high quality edible oil (36 – 54% on dry matter basis) and easily digestible protein (12 – 36%) in its seeds. It is cultivated worldwide in tropical, sub-tropical and warm temperature areas located between 400 N to 400 S. In India, it is spread over an area of 6.7 million ha with production of 7.3 million tones and productivity of 1155 kg/ha with a world production of 35.9 million tonnes at an area of 25.2 million ha.

The crop can be grown successfully in places receiving a minimum rainfall of 500mm and a maximum of 1250 mm. The rainfall required for pre-sowing operations (preparatory cultivation) is 100 mm; for sowing it is 150 mm and for flowering and pod development an evenly distributed rainfall of 400-500 mm is required. The groundnut however, cannot stand frost, long and severe drought or water stagnation.

In spite of such increase in price, interestingly not much effort has been made to analyze the changes scientifically and look for the reason for such variations in price. Hence it was thought that the statistical analysis of price behavior by different forecasting models would provide insight into the reasons for variation. It is hoped that the identification of the best forecasting model would help the consumers as well as suppliers in taking appropriate decisions.

Naturally forecasting is one of the main objectives of time series analyses having the art of saying what will happen in the future rather than why. There are various forecasting models in use now days. Forecaster can choose his own method of forecasting based on his knowledge and available external information. As the process goes on, this procedure can be modified to meet the conditions and to satisfy the current situation. Different forecasting models may be fitted more or less equally well to the data, but they forecasts different future values.

Unfortunately, there will be many occasions when analysts are not going to be certain which forecasting method or model is best one and there will be situations where it will appear that several models could do the job quite successfully. Even if we are certain of how to make a decision, we might work with different parameters and generate several forecasts, which will, again, raise the question of the best forecasts.

2. Material and Methods

Realizing the above mentioned facts, the present study was conducted to forecast the prices of groundnut at Hiriyur market. A time series data on monthly market on prices for the period of 20 years from January 2002 to August 2021 were collected from the Agricultural Produce Marketing Committees (APMC's) located at Hiriyur.

2.1 Agricultural Produce Market Committee (APMC), Hiriyur

Hiriyur is a taluk headquarter in Chitradurga district, here groundnut plays an important role in the agricultural economy of Hiriyur taluk. This is an important trading Centre particularly for groundnut. Hiriyur market was brought under regulation in the year 1948 under the provisions of the Bombay agricultural produce market act 1939. The jurisdiction of the market committee covers the whole of Hriryur taluk. Since its inception, this market is known for trading groundnut and second largest market in Karnataka after Challakere.

2.2 Artificial Neural Network (ANN)

Subject of neural networks has matured to a great extent over the past few years and are successfully applied across wide range of areas as biology, finance, medicine, engineering, geology and physics. It is a fact that these networks are attempt to model the capabilities of human brain. Statistical perspective neural networks are interesting because of their potential use in computation problems.

Artificial neural networks can be defined as information processing tools which mimic or copy the learning methodology of the biological neural networks. It derives its origin from human nervous system, which consists of massively parallel large interconnection of large number of neurons, which activate different perceptual and recognition task in small amount of time.

Structural constituent of human brain are known as neurons and they are interconnected in complex way. Typically human brain has approximately 10 billion neurons and 6 trillion inter connections, with recognising capacity of about 10^{-3} seconds. But in ANN can interconnect or mimic very small part of it in order to do specific task. Signals are passed between neurons over connection links, each connection link associates a weight with the input which multiplies the signal transmitted and each neuron applies an activation function to its net input to determine its net output.

ANNs imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data are imprecise and noisy. Thus they are ideally suited for the modelling of agricultural data which are known to be complex and often non-linear. A very important feature of these networks is their adaptive nature, where "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available.

2.3 Basics of artificial neural networks

The terminology of artificial neural networks has developed from a biological model of the brain. A neural network consists of a set of connected cells: The neurons. The neurons receive impulses from either input cells or other neurons and perform some kind of transformation of the input and transmit the outcome to other neurons or to output cells. The neural networks are built from layers of neurons connected so that one layer receives input from the preceding layer of neurons and passes the output on to the subsequent layer.

A neuron is a real function of the input vector ($y_1,..,y_k$). The output is obtained as $f(x_j) = f(\alpha_j + \sum_{i=1}^{k} w_{ij} y_j)$, where f is a function, typically the sigmoid (logistic or tangent hyperbolic) function. A graphical presentation of neuron is given in figure below. Mathematically a multi-layer perception network is a function consisting of compositions of weighted sums of the functions corresponding to the neurons.

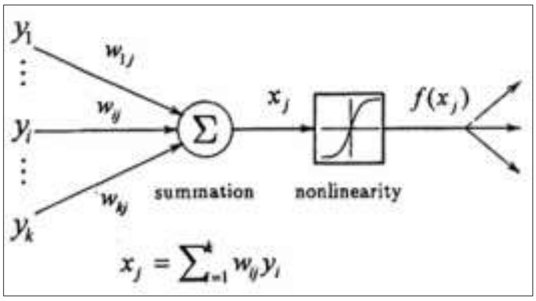

Fig 1: Single neuron

2.3.1 Pattern of Connections between the Neurons

The pattern of connections between the neurons and the propagation of the data is what constitute the topology of the networks. On the basis of pattern of connections, the two main networks are:

2.3.1.1 Feed-Forward Neural Network

Network information flow forward from the input layer to the output layer without any feedback loops. It involves three layers:

- The input layer contains the predictors.
- The hidden layer contains unobservable nodes, or units. The value of each hidden unit is some function of the predictors; the exact form of the function depends in part upon the network type and in part upon user-controllable specifications.
- The output layer contains the responses. Since the history of default is a categorical variable with two categories, it is recoded as two indicator variables. Each output unit is some function of the hidden units. Again, the exact form of the function depends in part on the network type and in part on user-controllable specifications.

2.3.1.2 Single Layer Feed-forward Neural Networks

It is a simple design of neural networks that allow only unidirectional forward connections among nodes. That is why it is called feed-forward neural network or Perceptron.

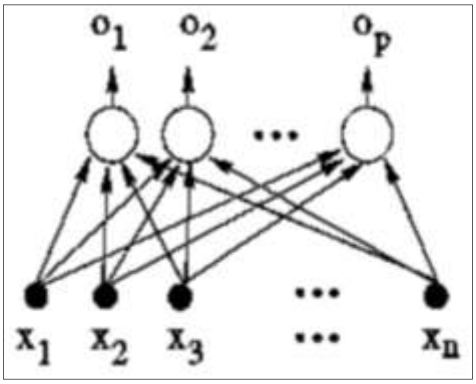

Fig 2: Architectural graph of feed-forward neural network

2.3.1.3 Recurrent Neural Networks (RNN)

On contrary to feed forward neural network where the values move from input to hidden and then hidden to output layers (no values are feedback to earlier layers), this network allows feedback connections also. For instance, hidden unit can connect with itself over a weighted connection, hidden units can be connected to input units, or even connect all units with each other (Fig. 3.4).

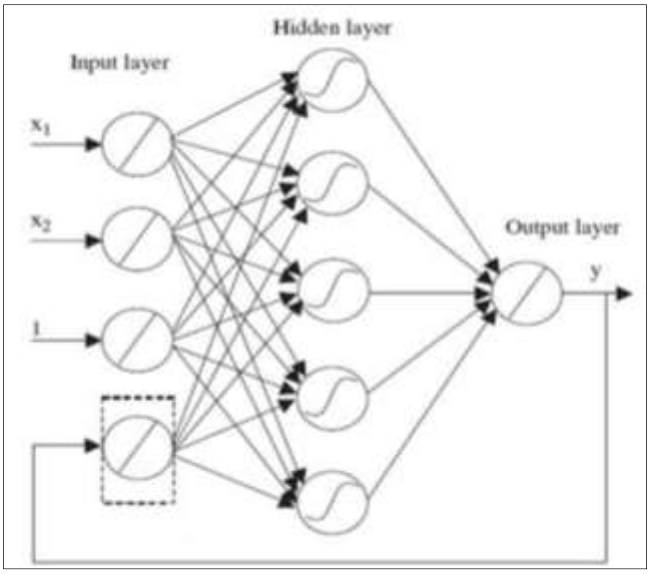

Fig 3: Architectural graph of Recurrent Neural network

2.4 Learning/Training methods

Learning methods in neural networks can be broadly classified into three basic types: supervised, unsupervised and reinforced.

2.4.1 Supervised learning

In this, every input pattern that is used to train the network is associated with an output pattern, which is the target or the desired pattern. A teacher is assumed to be present during the learning process, when a comparison is made between the network's computed output and the correct expected output, to determine the error. The error can then be used to change network parameters, which result in an improvement in performance.

2.4.2 Unsupervised learning

In this learning method, the target output is not presented to the network. It is as if there is no teacher to present the desired patterns and hence, the system learns on its own by discovering and adapting to structural features in the input patterns.

2.4.3 Reinforced learning

In this method, a teacher though available, does not present the expected answer but only indicates if the computed output is correct or incorrect. The information provided helps the network in its learning process. A reward is given for a correct answer computed and a penalty for a wrong answer. But, reinforced learning is not one of the popular forms of learning.

2.5 Development of an ANN model

In this study all the neural networks have been built by SPSS 16.0 software. The various steps in developing a neural network model are (Jha, GK 2009):

2.5.1 Variable selection

The input variables important for modelling variable(s) under study are selected by suitable variable selection procedures.

2.5.2 Formation of training, testing and validation sets

For models development, data set is divided into three distinct sets called training, testing and validation (hold out) sets. The training set is the largest set and is used by neural network to learn patterns present in the data. In a training of the network, through different learning algorithm *viz*. Back propagation, Levenberg - Marquardt and Conjugate gradient descent were used for the detecting the pattern in the data and the testing set is used to evaluate the generalization ability of a supposedly trained network means used to track errors during training in order to prevent overtraining. The holdout sample is another independent set of data records used to assess the final neural network; the error for the holdout sample gives an "honest" estimate of the predictive ability of the model because the holdout cases were not used to build the model.

The ANN structure for a particular problem in time series prediction includes determination of number of layers and total number of nodes in each layer. It is usually determined through experimentation as there is no theoretical basis for determining these parameters. It has been proved that neural networks with one hidden layer can approximate any non-linear function given a sufficient number of nodes at the hidden layer and adequate data points for training. In this study, we have used neural network with one hidden layer. In time series analysis, the determination of number of input nodes which are lagged observations of the same variable plays a crucial role as it helps in modelling the autocorrelation structure of the data. The determination of number of output nodes is relatively easy. In this study, one output node has been used. It is always better to select the model with a smaller number of nodes in the hidden layer as it improves the out of the sample forecasting performance and also avoids the problem of over-fitting.

2.5.3 Activation Functions

Activation functions are mathematical formulae that determine the output of a processing node. Each unit takes its net input and applies an activation function to it. Nonlinear functions have been used as activation functions such as logistic, tan(h) etc. The purpose of the transfer function is to prevent output from reaching very large value which can 'paralyze' neural networks and thereby inhibit training. Transfer functions such as sigmoid are commonly used because they are nonlinear and continuously differentiable which are desirable for network learning.

2.5.3.1 Sigmoid function

The commonly used activation function is sigmoid function. The reason behind this is because of its easy differentiable property function. This one commonly used because they are nonlinear and continuously differentiable which are desirable for network learning.

It includes following functions:

Logistic function: Domain of this function is [0, 1].

$$f(s) = \frac{1}{1+\exp(as)} \qquad \dots (1)$$

Where 'a' is a slope parameter. This activation functions range from 0 to 1, (Fig. 3.5).

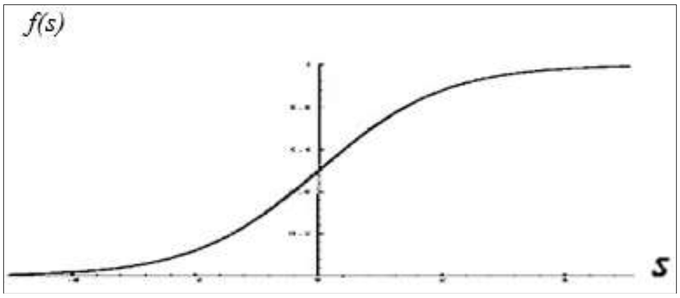

Fig 4: Logistic function

Hyperbolic Tangent function: Domain of this function is [-1, 1].

$$f(s) = \frac{\sinh(s)}{\cosh(s)} = \frac{e^{s}-e^{-s}}{e^{s}+e^{-s}} \qquad \dots (2)$$

This activation function has the advantage of having the output interval, [-1, 1]. Thus it can be used in Artificial Neural Networks that need to approximate functions which can take on negative values (Fig 3.6).

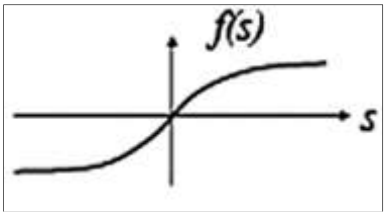

Fig 5: Hyperbolic tangent functions

2.5.3.2 Neural network training

The important aspect of artificial neural Network is its learning and training algorithm which is a procedure for updating and determining weights of the connections. 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.

In the present study method used to estimate the synaptic weights are,

- **Gradient descent:** This method must be used with online or mini-batch training; it can also be used with batch training.
- **Scaled conjugate gradient:** The assumptions that justify the use of conjugate gradient methods apply only to batch training types, so this method is not available for online or mini-batch training.

2.5.3.2.1 Conjugate Gradient Descent algorithm

Numerical optimization theory such as Conjugate Gradient offers a rich and robust set of techniques, which can be applied to train neural networks. These techniques not only focus on the local gradient of the error function, but also make use of its second derivative. The first derivative measures the slope of the error surface at a point, while the second measures the curvature of the error surface at the same point. This information is very important for determining the optimal update direction. As these methods make use of the second derivatives of the function to be optimized, they are typically referred to as second-order methods which also reduce the training time for feed forward neural networks

(Barnard, 1992 and Johansson *et al*., 1992). Hence, the Conjugate Gradient learning algorithm is another alternative procedure to overcome these problems faced by back-propagation (BP) training and Levenberg Marquardt algorithm.

Let J(w) be the objective function to be minimized as the mean squared error

$$J(w) = \frac{1}{N}\sum_n E_n \qquad \dots (3)$$

Where N is the number of patterns in the training set corresponding to the trajectory from time t_0 to t_1, E_n is the output error for the n^{th} pattern and w is the weight vector. E_n is defined as

$$E_n = \frac{1}{2}\sum_2 (d_{kn} - o_{kn}(w))^2 \qquad \dots (4)$$

Where, o_{kn} and d_{kn} are the actual and desired output of the k^{th} output unit in response to the n^{th} input pattern respectively. Thus the objective function becomes

$$J(w) = \frac{1}{2N}\sum_n \sum_k (d_{kn} - o_{kn}(w))^2 \qquad \dots (5)$$

A single evaluation of above equation requires the entire training set to be presented to the network, the errors to be calculated for each pattern, and the results to be summed and averaged. When the number of weights and training patterns increases the cost of computing J (w) also increases. For computation of the gradient of the objective function, J(w), differentiate the above equation with respect to w, yielding

$$g(w) = \frac{1}{N}\sum_n \nabla E_n(w) \qquad \dots (6)$$

Since the Conjugate Gradient algorithm requires both error function and gradient to be evaluated, the calculations should be performed together to maximize efficiency. Johansson *et al*. (1992) proposed the use of Conjugate Gradient method to train neural networks which was utilised in this study.

3. Results and Discussion

The proposed ANN model was applied to forecast the prices of groundnut for selected market. Different number of neural networks has been tried for different data set and the best performing five networks from each data set was selected based on Minimum average absolute error and higher R^2 (Table 1) and used for further analysis. For groundnut price forecasting, 155 data points are considered as training set and 31 data points are considered as testing set.

By applying forecaster XL option in Excel package. The best validated ANN model for groundnut price was NN2 in Hiriyur market as shown in Table 1. The results of Ex-ante and Ex-post forecast are presented in Table 2 by best forecasting model among different networks.

Table 1: Different Neural networks for groundnut price at Hiriyur market

	Groundnut					
		NN1	**NN2**	**NN3**	**NN4**	**NN5**
Hiriyur	Average AE	123.48	100.91	106.15	101.22	108.88
	Average MSE	30821.60	18672.71	20294.47	21054.26	30060.54
	R^2	0.96	0.97	0.96	0.96	0.96
	Correlation	0.98	0.99**	0.98	0.98	0.98

Table 2: Forecasting of groundnut price at Hiriyur market by ANN Model

Month	Actual Price	Forecast	Month	Actual Price	Forecast	Month	Actual Price	Forecast
Jan-02	1396	-	Jun-05	1598	1637.39	Nov-08	1989	2212.16
Feb-02	1432	-	Jul-05	1689	1598.01	Dec-08	2070	2452.35
Mar-02	1237	-	Aug-05	1795	1740.57	Jan-09	2176	2086.37
Apr-02	1389	-	Sep-05	1876	1876.91	Feb-09	2061	2175.07
May-02	1490	-	Oct-05	1867	1757.62	Mar-09	2202	2177.79
Jun-02	1378	-	Nov-05	1972	1892.11	Apr-09	2210	2192.57
Jul-02	1521	1371.12	Dec-05	1486	1559.20	May-09	2235	2158.07
Aug-02	1456	1470.54	Jan-06	1635	1576.86	Jun-09	2274	2247.81
Sep-02	1299	1445.28	Feb-06	1598	1594.64	Jul-09	2208	2172.20
Oct-02	1318	1310.84	Mar-06	1642	1680.83	Aug-09	2146	2121.45
Nov-02	1262	1364.78	Apr-06	1894	1803.68	Sep-09	2052	2099.22
Dec-02	1464	1347.08	May-06	1768	1729.03	Oct-09	2160	2117.34
Jan-03	1576	1496.54	Jun-06	1945	1783.90	Nov-09	2614	2170.53
Feb-03	1408	1520.46	Jul-06	1820	1972.37	Dec-09	2373	2830.48
Mar-03	1641	1435.66	Aug-06	1597	1801.52	Jan-10	2298	2367.44
Apr-03	1599	1529.62	Sep-06	1689	1587.21	Feb-10	2377	2203.72
May-03	1573	1550.45	Oct-06	1798	1754.76	Mar-10	2343	2351.80
Jun-03	1490	1575.65	Nov-06	1870	1889.91	Apr-10	2378	2355.51
Jul-03	1574	1502.55	Dec-06	1796	1769.84	May-10	1890	2174.70
Aug-03	1412	1582.88	Jan-07	1993	1763.46	Jun-10	2740	2676.03
Sep-03	1485	1470.55	Feb-07	1860	1686.46	Jul-10	2793	2780.39
Oct-03	1567	1503.89	Mar-07	2014	1898.29	Aug-10	2590	2523.75
Nov-03	1681	1629.16	Apr-07	2120	1792.13	Sep-10	2840	2856.65
Dec-03	1780	1653.65	May-07	1967	2071.89	Oct-10	2836	2912.63
Jan-04	1526	1726.89	Jun-07	2301	2236.91	Nov-10	2639	2952.34
Feb-04	1469	1535.43	Jul-07	2393	2346.71	Dec-10	2661	2596.04
Mar-04	1525	1455.82	Aug-07	2092	2110.47	Jan-11	2520	2608.82
Apr-04	1638	1615.29	Sep-07	1820	1981.39	Feb-11	2650	2662.10

May-04	1762	1750.79	Oct-07	2108	2149.61	Mar-11	2615	2461.93
Jun-04	1690	1648.49	Nov-07	1970	2150.26	Apr-11	2805	2366.08
Jul-04	1521	1635.08	Dec-07	2013	2056.76	May-11	3124	3101.18
Aug-04	1657	1503.40	Jan-08	2210	2270.08	Jun-11	3079	3256.53
Sep-04	1770	1635.46	Feb-08	2138	2175.57	Jul-11	3550	3380.09
Oct-04	1876	1878.31	Mar-08	2351	2129.04	Aug-11	3125	3143.49
Nov-04	1534	1774.63	Apr-08	2112	2465.57	Sep-11	2500	2479.58
Dec-04	1678	1529.15	May-08	2215	2059.02	Oct-11	3194	3141.17
Jan-05	1760	1669.66	Jun-08	2316	2068.36	Nov-11	3305	3279.57
Feb-05	1775	1824.98	Jul-08	2357	2265.54	Dec-11	3000	3032.37
Mar-05	1798	1694.69	Aug-08	2344	2396.19	Jan-12	3318	3443.31
Apr-05	1850	1792.49	Sep-08	2221	2355.60	Feb-12	2295	2490.03
May-05	1643	1819.37	Oct-08	2251	2132.41	Mar-12	3879	3909.63

Month	Actual Price	Forecast	Month	Actual Price	Forecast	Month	Actual Price	Forecast
Apr-12	3735	3748.90	Sep-15	4548	4413.40	Feb-19	5026	5221.03
May-12	3806	3220.37	Oct-15	4310	4428.59	Mar-19	4318	4348.63
Jun-12	3802	3774.85	Nov-15	4271	4047.84	Apr-19	4786	4799.90
Jul-12	3750	3658.93	Dec-15	3870	3487.65	May-19	4339	3753.37
Aug-12	4385	4203.81	Jan-16	4211	4300.63	Jun-19	3900	3872.85
Sep-12	4359	4295.07	Feb-16	3960	3845.93	Jul-19	4308	4216.93
Oct-12	4330	4275.41	Mar-16	4180	4204.21	Aug-19	5500	5318.81
Nov-12	4494	4415.49	Apr-16	4320	4337.43	Sep-19	6120	6056.07
Dec-12	4353	4137.20	May-16	4456	4532.93	Oct-19	5740	5685.41
Jan-13	3744	4088.35	Jun-16	5292	5318.19	Nov-19	4130	4051.49
Feb-13	3970	4181.65	Jul-16	4340	4375.80	Dec-19	4115	3899.20
Mar-13	3895	3706.10	Aug-16	4000	4024.55	Jan-20	4766	5110.35
Apr-13	3837	3755.72	Sep-16	4445	4397.78	Feb-20	4908	5119.65
May-13	3575	3465.03	Oct-16	4400	4442.66	Mar-20	5653	5464.10
Jun-13	3514	3296.41	Nov-16	4256	4699.47	Apr-20	5245	5163.72
Jul-13	3054	3312.40	Dec-16	4280	4737.48	May-20	5130	5020.03
Aug-13	3532	3631.21	Jan-17	4320	4389.44	Jun-20	4900	4682.41
Sep-13	3119	3124.01	Feb-17	4416	4242.72	Jul-20	4430	4688.40
Oct-13	3076	3087.90	Mar-17	4395	4403.80	Aug-20	4040	4139.21
Nov-13	3357	3253.80	Apr-17	4500	4477.51	Sep-20	4050	4055.01
Dec-13	3011	2851.22	May-17	4060	4344.70	Oct-20	4289	4300.90
Jan-14	3020	3172.45	Jun-17	4100	4036.03	Nov-20	4560	4456.80
Feb-14	2934	2968.43	Jul-17	3510	3497.39	Dec-20	4680	4520.22
Mar-14	3138	3061.01	Aug-17	3640	3573.75	Jan-21	4795	4947.45
Apr-14	2506	2489.93	Sep-17	3670	3686.65	Feb-21	4910	4944.43
May-14	3275	3366.51	Oct-17	3720	3796.63	Mar-21	5150	5073.01
Jun-14	3192	2585.11	Nov-17	3796	4109.34	Apr-21	5070	5053.93
Jul-14	3005	2984.66	Dec-17	3415	3350.04	May-21	4670	4761.51
Aug-14	3899	3748.49	Jan-18	3670	3758.82	Jun-21	4831	4224.11
Sep-14	3640	3479.36	Feb-18	3450	3462.10	Jul-21	4399	4378.66
Oct-14	3504	3535.30	Mar-18	3366	3212.93	Aug-21	4711	4560.49
Nov-14	3489	3607.09	Apr-18	3108	2669.08	Sep-21	-	4630.36
Dec-14	3408	3537.70	May-18	3315	3292.18	Oct-21	-	5222.30
Jan-15	3356	3560.52	Jun-18	3006	3183.53	Nov-21	-	5148.09
Feb-15	3398	3112.11	Jul-18	4250	4080.09	Dec-21	-	5591.70
Mar-15	3402	3405.03	Aug-18	3809	3827.49	Jan-22	-	5354.52
Apr-15	4315	4073.86	Sep-18	4070	4049.58	Feb-22	-	4784.11
May-15	4346	4234.44	Oct-18	4410	4357.17			
Jun-15	4716	4963.64	Nov-18	3856	3830.57			
Jul-15	4669	4760.46	Dec-18	3484	3516.37			
Aug-15	4582	4529.81	Jan-19	4188	4313.31			

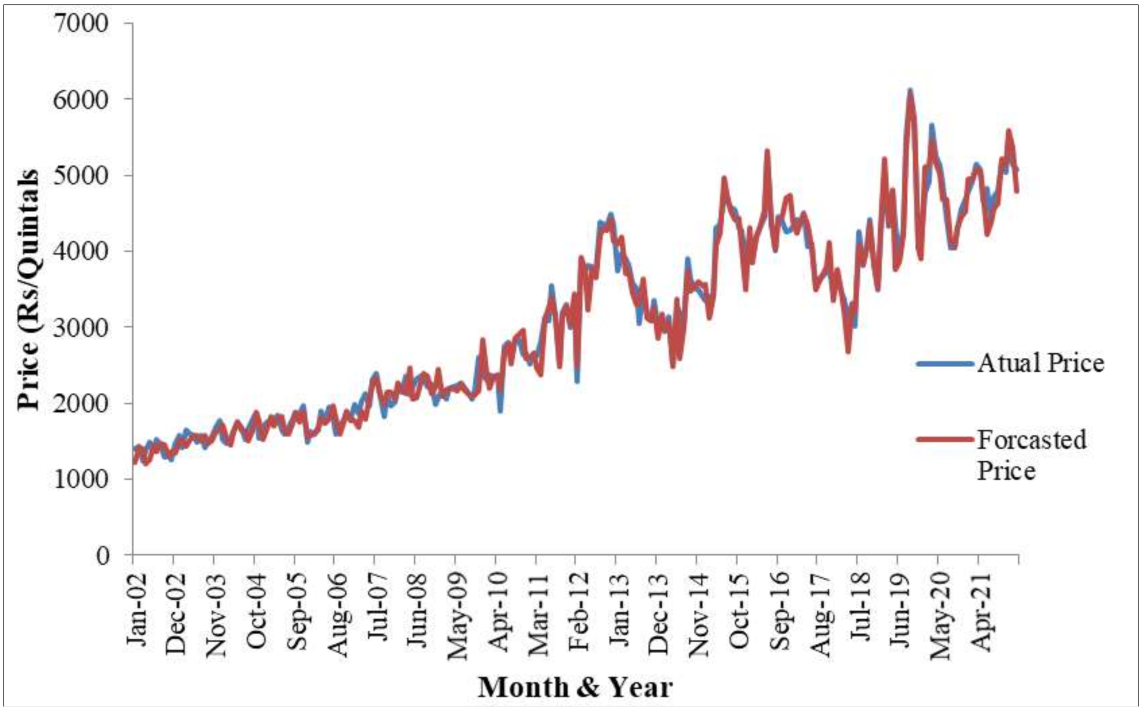

Fig 6: Groundnut price forecasting by ANN method of Hiriyur market

4. Conclusion

This study has demonstrated that the Artificial Neural Network (NN2) to be best among all different methods of forecasting of price of groundnut at Hiriyur market.

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