Received Date: 08/01/2020 Acceptance Date: 22/01/2020 Publication Date: 31/01/2020

A COMPARISON OF ARIMA & ANN MODELS FOR PRODUCTION OF WHEAT IN THE STATE OF KARNATAKA

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Abstract: *If the data is linear and non-stationary, the models viz. Auto-Regressive (AR), Moving Average (MA), and Auto-Regressive Moving Average (ARMA) models cannot be used. So, an another important forecasting technique called Auto-Regressive Integrated Moving Average (ARIMA) with (p , d , q) terms can be used. The best feature of Artificial Neural Networks when it is applied to forecasting data is its inherent capability of nonlinear modeling without any presumption about the statistical distribution of the given data. Model selection criteria based on RMSE for ARIMA and Artificial Neural Networks (ANN) are computed and compared. An appropriate model has to be framed effectively for the production wheat data in the state of Karnataka taken during the period from 2001-02 to 2016-17 (16 years).*

Key Words: *Auto-Regressive (AR), Moving Average (MA), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), Neural Networks, Artificial Neural Networks (ANN), Root Mean Square Error (RMSE) and Akaine's Information Criterion (AIC).*

1. INTRODUCTION:

The Most widely used important statistical tools for traditional forecasting techniques for stationary and linear data are Auto-regressive (AR) with p terms, and Moving Average (MA) with q terms They are combined together to form Auto-regressive Moving Average (ARMA) with (p,q) terms in the model, where p is the Auto-regressive terms and q is the Moving Average terms. When the data is non-stationary, we use ARIMA (p,d,q) model which is also known as Box-Jenkin's Methodology, where d is the time lagged differencing. When d= 0, it becomes simply ARMA with p and q terms model.

A Neural Network is a simplified model of the same way that the human brain processes information. It works by stimulating a large number of inter-connected processing units that resembles abstract versions of neurons. The processing units are organized in layers. They are arranged into three parts in a neural network:

a) An input layer with unit(s) representing the input field(s),
b) One or more hidden layers, and
c) An output layer with unit(s) representing the target field(s).

The units are connected with varying connection strengths (or weights). Input data are presented in the first layer and the values are propagated from each neuron to every neuron in the next layer. Eventually, a result shall be delivered from the output layer.

The main contributors in the field of traditional forecasting and neural networks are Yule (1926), Walker (1931), Slutzky (1937), Wold (1938), Box and Jenkins (1976), Young (1982), Arash Bahrammirzaee,(2010), Mehdi Khashei., Mehdi Bijari (2010), Prapanna Mondal, Labani Shit, and Saptarsi Goswami (2014), Kishore Kumar J., T. Gangaram, and A. Mohan Babu (2019)

2. OBJECTIVES:

The important objectives of our current paper are outlined as follows:

- To study the forecasting techniques by applying ARIMA and Neural Networks Models in our methodology.
- To compare the above models by computing the RMSE.
- To study the patterns in the production of Wheat in the state of Karnataka during 16 time periods (i.e., from 2001-02 to 2016-17).
- To forecast the production of Wheat for the next 10 years.
- To compute AIC for ARIMA model.
- To analyze the forecasted results by applying the suitable forecasting.
- To point out the future development in view of Indian agricultural scenario.

3. METHODOLOGY:

a) ARIMA Model : -

INTERNATIONAL JOURNAL FOR INNOVATIVE RESEARCH IN MULTIDISCIPLINARY FIELD ISSN: 2455-0620 Volume - 6, Issue - 1, Jan – 2020
Monthly, Peer-Reviewed, Refereed, Indexed Journal with IC Value: 86.87 Impact Factor: 6.497
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The terms ARIMA (p , d , q) model can be represented as

$$\left[1-\beta(1+\alpha_1)+\alpha_1\beta^2\right]X_s=\lambda_1+e_s-\mu_1 e_{s-1}$$

$$X_s=(1+\alpha_1)X_{s-1}-\alpha_2 X_{s-2}+\lambda_1+e_s-\mu_1 e_{s-1} \quad \ldots.. \quad (1)$$

In this above form, the ARIMA models look like a conventional Regression Equation except that there is more than one error on the right hand side.

Suppose p is the number of auto-regressive terms, q is the number of Moving Average terms and d is the degree of differencing and the model is represented as ARIMA (p,d,q) models.

Further, derivatives can also be taken into account by considering the Auto-Regressive or Moving Average trends that occur at certain points of time.

Let us have ARIMA model with pth order auto-regressive terms given by

$$Y_s=\alpha_0+\alpha_1 Y_{s-1}+\alpha_2 Y_{s-2}+\ldots+\alpha_p Y_{s-p}+\varepsilon_s \quad \ldots.. \quad (2)$$

The ARIMA model having Moving Average model with q terms is given by $Y_s=\lambda+\varepsilon_s-\theta_1\varepsilon_{s-1}-\theta_2\varepsilon_{s-2}-\ldots-\theta_q\varepsilon_{s-q}$ ….. (3)

ARIMA model having AR with p terms and MA with q terms is given by

$$Y_s=\alpha_0+\alpha_1 Y_{s-1}+\alpha_2 Y_{s-2}+\ldots+\alpha_p Y_{s-p}+\varepsilon_s-\theta_1\varepsilon_{s-1}-\theta_2\varepsilon_{s-2}-\ldots-\theta_q\varepsilon_{s-q} \quad \ldots. \quad (4)$$

Now, ARIMA (0,1,1) model is given by

$$Y_s-Y_{s-1}=\varepsilon_s-\theta_1\varepsilon_{s-1} \quad \ldots.. \quad (5)$$

Now, ARIMA (0,1,1) forecasting model in exponential smoothing is given by

$$\hat{y}_{s+1}=y_s-\theta_1(y_s-\hat{y}_s)=(1-\theta_1)y_1+\theta_1\hat{y}_s \quad \ldots.. \quad (6)$$

b) NEURAL NETWORKS : -

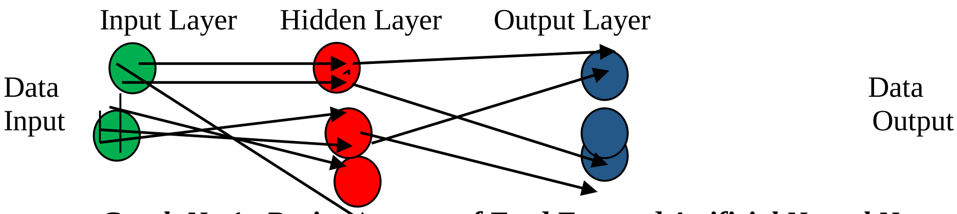
If the time series data is non-stationary, then an effective forecasting techniques are introduced, called Artificial Neural Networks. These techniques are data driven and self adaptive by nature. In the last few decades, lot of research has been carried-out in Artificial Neural Networks.

Neural networks approach has been suggested as an alternative technique to forecasting and gained huge popularity in last few years. The basic objective of neural networks is to construct a model for stimulating the intelligence of human brain into machine. Similar to the work of a human brain, artificial neural networks try to recognize regularities and patterns in the input data, learn from experience and then provide generalized results based on their known previous knowledge.

Artificial Neural Networks: -

More popularly used artificial neural networks in forecasting problems are multi-layer perceptrons, which use a single hidden layer feed forward neural networks. The model is defined by a network of three layers, namely Input layer, hidden layer and output layer, connected by acyclic links.

There may be more than one hidden layer. The nodes in various layers are called processing elements. The three layer feed forward architecture of artificial neural network models can be diagrammatically shown below:



Graph No.1. Basic structure of Feed Forward Artificial Neural Network

The output of the model is calculated using the following expression:

a) $$y_i=\alpha_0+\sum_{j=1}^{q}\alpha_j g\left(\beta_{oj}+\sum_{i=1}^{p}\beta_{ij}y_{i-1}\right)+\in_i,\ \forall i \quad \ldots.. \quad (7)$$

Here y_{i-1} (i = 1,2,..., p) are the p inputs and y_i is the output. The integers p *and* q are the number of input and hidden nodes respectively. α_j (j= 0,1,2,...,q) and β_{ij} (i= 0,1,2,..., p; j=0,1,2,...,q) are the connection weights and ε_i is the random shock associated in the model, α_0 and β_{0j} are the bias terms. Usually, the logistic sigmoid function:

INTERNATIONAL JOURNAL FOR INNOVATIVE RESEARCH IN MULTIDISCIPLINARY FIELD ISSN: 2455-0620 Volume - 6, Issue - 1, Jan – 2020
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$$g(x) = \frac{1}{1+e^{-x}}$$

is applied as the nonlinear activation function. Other activation functions, such as linear, hyperbolic tangent, Gaussian, etc. can be used.

b) The feed forward artificial neural networks model given by the expression (7). Infact, it performs a non-linear functional mapping from the past observations of the forecasting to the future value, i.e.,

$$y_i = f(y_{i-1}, y_{i-2}, \ldots, y_{i-p,w})$$

Where **w** is a vector of all parameters and *f* is a function determined by the network structure and connection weights.

c) To estimate the connection weights, non-linear least square procedures are used, which are based on the minimization of the error function :

$$F(\psi) = \sum_i e_i^2 = \sum_i (y_i - \tilde{y}_i)^2 \quad \ldots\ldots \quad (8)$$

Here ψ is the space of all connection weights.

d) The optimization techniques used for minimizing the error or residual function (8) are called Learning Rules.

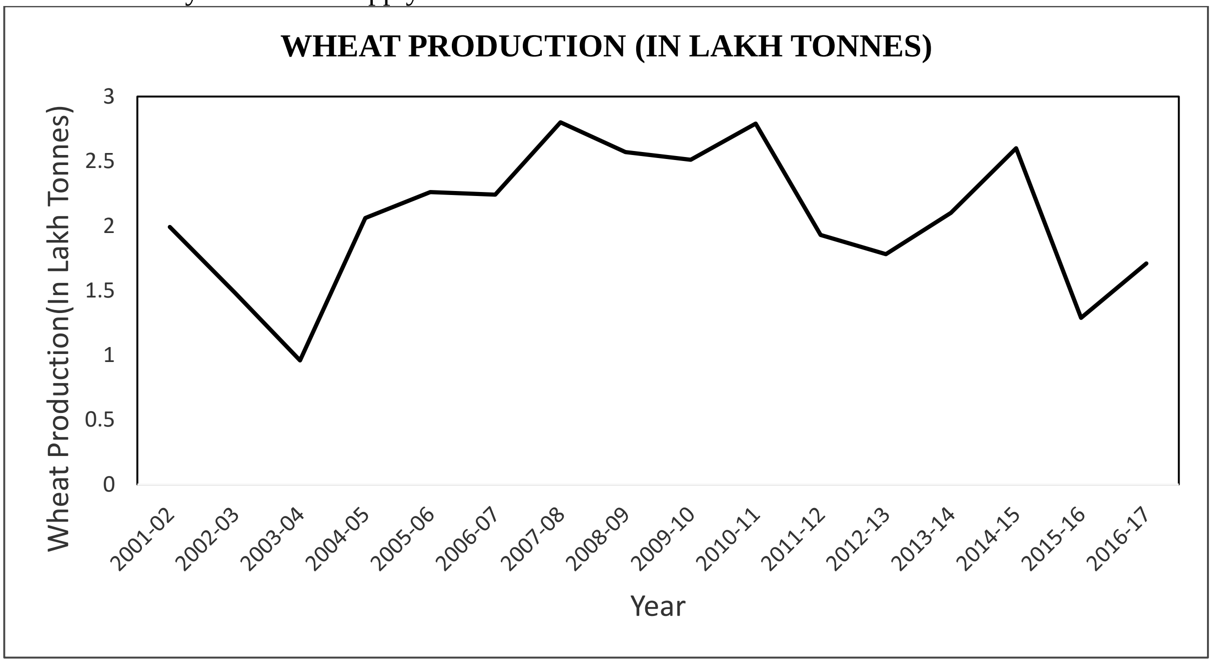
The best known learning rule in literature is the Back propagation or Generalized delta rule .

We shall apply the different forecasting methods are Auto Regressive Integrated Moving Average (ARIMA) and Neural Networks Models to forecast the production of Wheat in the State of Karnataka.

4. EMPIRICAL ANALYSIS:

4. 1 FORECASTING WHEAT PRODUCTION USING ARIMA:

If we observe the Wheat production time series graph in the graph no. 2, the mean value of the first three periods is 1.47, the mean value of the next three periods is 2.18, the mean value of the next three periods is 2.64 and the mean value for the next 3 periods is 2.03. All the four mean values are significantly different which is showing that the time series is a non-stationary. We need to apply difference on this data to transform the data into time series.



Graph No. 2. Time Series Graph for Wheat Production data.

To identify the correct periods for the Auto Regressive (p), moving average (q) and difference (d), we can use the Akaike information criterion (AIC). We built several models with different AR, MA and difference periods and calculate AIC for the model, Now, we can select the model with the lowest AIC value as best model and the AR, MA and difference periods as the best periods. In the graph no. 3, we can see the comparison between different models and their AIC values. If we observe the graph, we can see for the AR period 2 and MA period 1 and difference period 1 the AIC value is very less. So, we can select the Auto Regressive period as 2 and Moving Average period as 1 and transform the Wheat Production data by taking difference period as 1.

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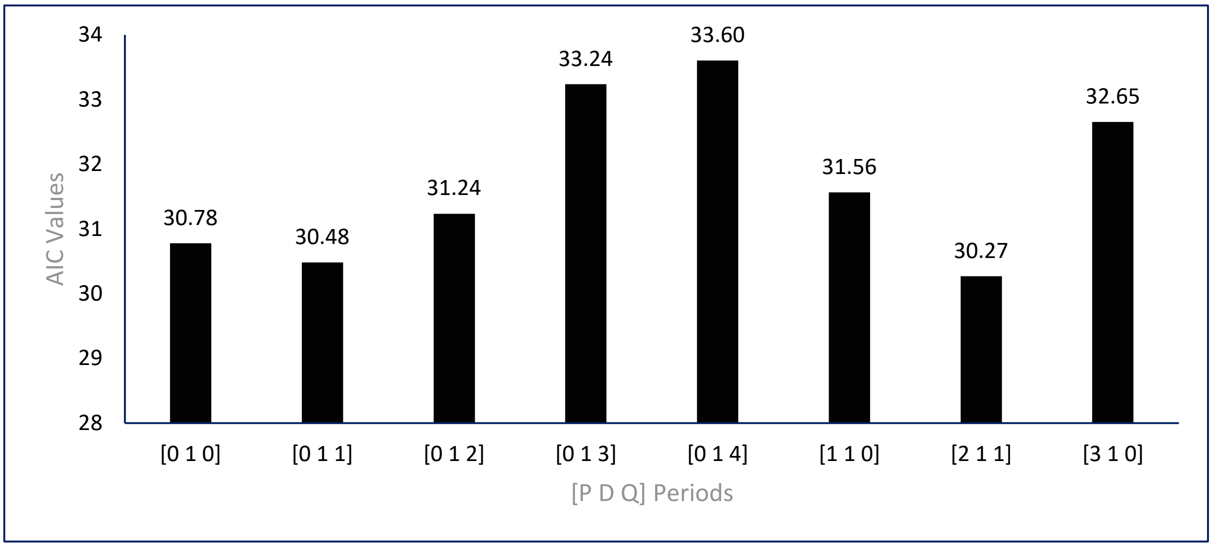
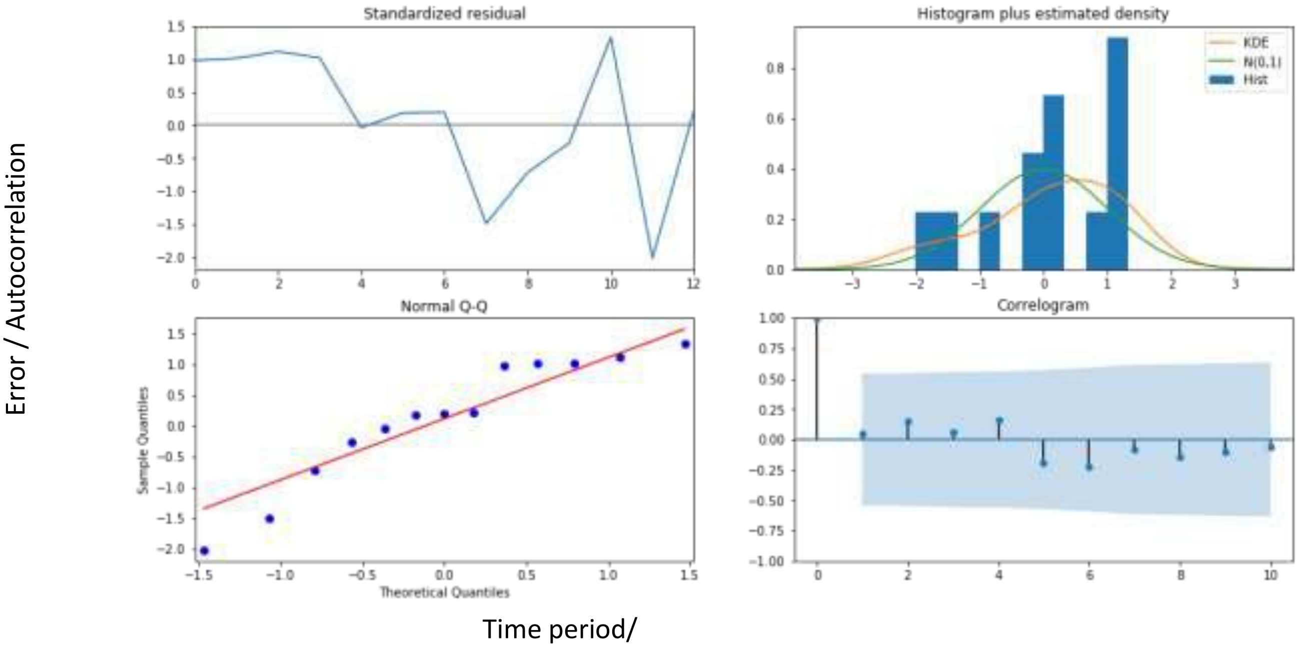


Graph no. 3. AIC Values for different (p,d,q) periods for Wheat Production.

Now, we built ARIMA (2,1,1) model for the Wheat production data and in the Table no. 3, we can see the parameter estimates for the model.

To identify the accuracy of the fitted model, we can check the error term. The distribution of the error term is most important in checking the accuracy of the model. In the graph no. 4, we can see how the errors distributed for the actual Wheat production and forecasted Wheat production. If we observe the below graph, the Standardized residual are far away from zero for most of the time periods. In the histogram plot and Normal Q-Q plot, we can observe that the error term is normally distributed and in the Correlogram plot, we can observe that there is no auto-correlation between the error terms. So, as the error terms follow normal distribution and there is no auto-correlation between the error terms. We can say that the fitted model is reliable, but we may need some more data to apply ARIMA forecasting method. We can use this model to forecast the future time period Wheat production values.



Graph no. 4 Diagnostic Measures for errors of ARIMA (2 , 1, 1) Wheat Production Forecasts.

4.2 FORECASTING WHEAT PRODUCTION USING NEURAL NETWORKS : -

In order to construct Neural Network, we need to provide input lag periods and the number of hidden layer, we want in the model. Here for the Wheat production, we used four as the lag periods. With lag period 4 the total data will convert into the following array shape. As we have 16 time periods and we selected 4 as the inputs, from time period 1 to time period 4 will become input for the fifth time period and from time period 2 to time period sixth will become inputs for forecasting the time period sixth etc.,

Shape of train arrays: (12, 4) (12,)

Shape of Test arrays: (12, 4) (12,)

With four lag periods and 8 hidden layers, we constructed the Neural Network models to forecast the Wheat production. If we observe the table no. 4.76, we have input layer with four inputs (four lag time periods) and 8 hidden layers.

In the input layer, there is no parameter to estimate as this is a input layer and for the first hidden layer, the model should estimate 160 parameters and for the second hidden layer, the model has to estimate 528 parameters and for the third, fourth, fifth, sixth, seventh and eighth hidden layers, the model has to estimate 272 parameters for each hidden layers and eight layer, the model has to estimate 17 parameters and the output layer will give one forecast as the output. Overall, the model consider previous 5 time periods as input and in all the hidden layers. It will estimate 2,337 parameters and give one forecast for the sixth time period. After estimating the parameters, the Neural Network model will test them on the Test array for checking the accuracy of the model.

Layer (type)	Shape	Parameters
input_1 (Input Layer)	4	0
.dense_1 (Dense)	32	160
dense_2 (Dense)	16	528
dense_3 (Dense)	16	272
dense_4 (Dense)	16	272
dense_5 (Dense)	16	272
dense_6 (Dense)	16	272
dense_7 (Dense)	16	272
dense_8 (Dense)	16	272
dropout_17 (Dropout)	16	0
dense_129 (Dense)	1	17
Total parameters: 2,337		

Table no. 1. Neural Network Parameters for Wheat Production Forecasts.

In the table no. 2, we can see the RMSE value of 0.2438 for the Wheat Production forecasts, forecasted using Neural Network is better than the RMSE value of 0.3536 using ARIMA (2, 1, 1).

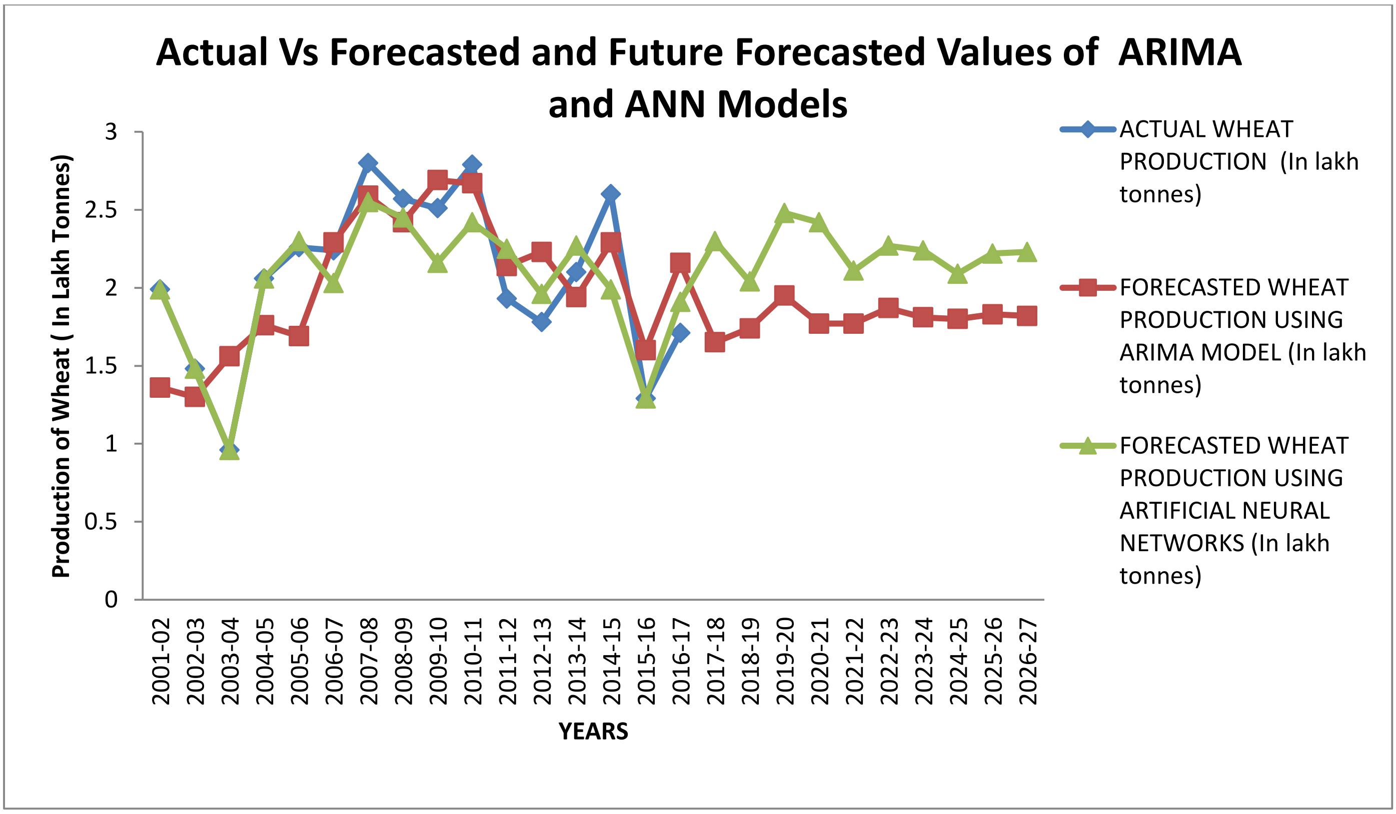
Method	**RMSE**
ARIMA (2, 1, 1)	0.3536
Neural Network	0.2438

Table no. 2. RMSE values for Wheat production for ARIMA and Artificial Neural Network. In the table no. 3 and graph no. 4, we can see all the Actual, Forecasted and future forecasted values for the Wheat production using ARIMA(2,1,1) Model and Artificial Neural Networks. If we observe the graph, we can see that the data suggest that the wheat production in the state of Karnataka may remain constant in the next ten years as oppose to the ARIMA forecasts while Artificial Neural Networks forecasts better output in the next ten years.

YEAR	**ACTUAL WHEAT PRODUCTION (In lakh tonnes)**	**FORECASTED WHEAT PRODUCTION USING ARIMA MODEL (In lakh tonnes)**	**FORECASTED WHEAT PRODUCTION USING ARTIFICIAL NEURAL NETWORKS (In lakh tonnes)**
2001-02	1.99	1.36	1.99
2002-03	1.48	1.30	1.48
2003-04	0.96	1.56	0.96
2004-05	2.06	1.76	2.06
2005-06	2.26	1.69	2.30
2006-07	2.24	2.29	2.03
2007-08	2.8	2.59	2.55
2008-09	2.57	2.42	2.45
2009-10	2.51	2.69	2.16
2010-11	2.79	2.67	2.42
2011-12	1.93	2.14	2.25

2012-13	1.78	2.23	1.96
2013-14	2.1	1.94	2.27
2014-15	2.6	2.29	1.99
2015-16	1.289	1.60	1.29
2016-17	1.71	2.16	1.91
2017-18		1.65	2.30
2018-19		1.74	2.04
2019-20		1.95	2.48
2020-21		1.77	2.42
2021-22		1.77	2.11
2022-23		1.87	2.27
2023-24		1.81	2.24
2024-25		1.80	2.09
2025-26		1.83	2.22
2026-27		1.82	2.23

Table no. 3 Actual and Forecasted and future forecasted Wheat Production using ARIMA and Artificial Neural Network Model.



Graph no. 5. Actual and Forecasted and future forecasted Wheat Production using ARIMA and Artificial Neural Network Model.

5. CONCLUSIONS:

In this paper, we have studied the forecasted and future forecasted values of Wheat Production in the State of Karnataka using ARIMA model and Artificial Neural Network Models. These models are studied and applied. In our study,

i) We compare the forecasted and future forecasted values of Wheat Production in the State of Karnataka (Graph No. 5) shows higher production values in ANN while it shows lesser production in ARIMA models.
ii) The RMSE values in ANN is 0.2438 and in ARIMA(2,1,1), it is 0.3536

Hence, it is concluded that Artificial Neural Networks modeling is better than ARIMA modeling.

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