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# A comparison of ARIMA & NNAR models for production of wheat in the state of Andhra Pradesh

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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, 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 Neural Network Autoregressive (NNAR) models are computed. An appropriate model has to be framed effectively for the production of Wheat data in the state of Andhra Pradesh taken during the period from 1982 to 2022 (for 40 years).

**Keywords:** Auto-Regressive (AR), Moving Average (MA), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), Neural Network Autoregressive (NNAR) model, Root Mean Square Error (RMSE) and Akaine's Information Criterion (AIC)

## 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 in these models. 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 forecasting and neural networks are Box and Jenkin's (1976) [3], Mehdi Khashei., Mehdi Bijari (2010) [15], Prapanna Mondal, Labani Shit, and Saptarsi Goswami (2014) [16].

## Objectives

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

1. To study the forecasting techniques by applying ARIMA and Neural Network Autoregressive
2. (NNAR) Models in our methodology.

3. To compare the above models by computing the RMSE.
4. To study the patterns in the production of Wheat data in the state of Andhra Pradesh during 40 (for Forty) time periods (i.e., from 1982 to 2022).
5. To forecast the production of Rice for the next 8 years.
6. To compute AIC for ARIMA model.
7. To analyze the forecasted results by applying the suitable forecasting.
8. To point out the future development in view of Indian agricultural scenario.

**Methodology**

**a) ARIMA Model**

**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 considered by considering the Auto-Regressive or Moving Average trends that occur at certain points of time.

Let us have ARIMA model with $p^{th}$ order auto-regressive terms given by

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

The ARIMA model having Moving Average model with q terms is given by

$$Y_s=\lambda+\varepsilon_s-\theta_1\varepsilon_{s-1}-\theta_2\varepsilon_{s-2}-\ldots-\theta_q\varepsilon_{s-q} \quad \ldots \quad (3)$$

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

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

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 technique 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.

**Neural Network Autoregressive (NNAR) Model**

Simple mathematical models of the brain form the basis of artificial neural networks (ANN), which are used in forecasting. Complex linear and nonlinear relationships between the response and its predictors are possible with their help. Lagged values of the dependent variable y are used as inputs to the feed-forward neural network, which also has a single hidden layer of size nodes. The model is valid for a wide variety of fitted repetition networks, all of which have initial weights chosen at random. When making predictions, these are then averaged. The network is optimized for making predictions in a single step.

**Neural network auto regressive (NNAR) with one hidden layer**

In this research, we focus exclusively on feed-forward networks with a single hidden layer, and we designate the number of lagged inputs and the number of hidden nodes in the network with the notation NNAR (p, kp, k). For instance, a neural network with a hidden layer consisting of five neurons and using the previous nine observations (yt 1, yt 2,..., yt 9) to predict the current output yt yt is called a NNAR (9, 5) model. Without the constraints on the parameters to assure stationary, the NNAR (p, kp, 0) model is similar to the ARIMA (p, 0, kp, 0, 0) model.

Each layer of nodes in a multilayer feed-forward network receives inputs from the layers above it. All of a layer's nodes' outputs become inputs for the following layer. A weighted linear combination of the inputs to each node is used. A nonlinear function is then applied to the result, and the result is then output. For example, the inputs into hidden neuron jj in Fig 1 are merged linearly to provid $z_j=b_j+\sum w_{i,j}x_{i.}$ ……... (7)

In the hidden layer, this is then modified using a non – linear function such as a sigmoid,

$$s(z)=\frac{1}{1+e^{-z}} \quad \ldots\ldots\ldots\ldots\ldots \quad (8)$$

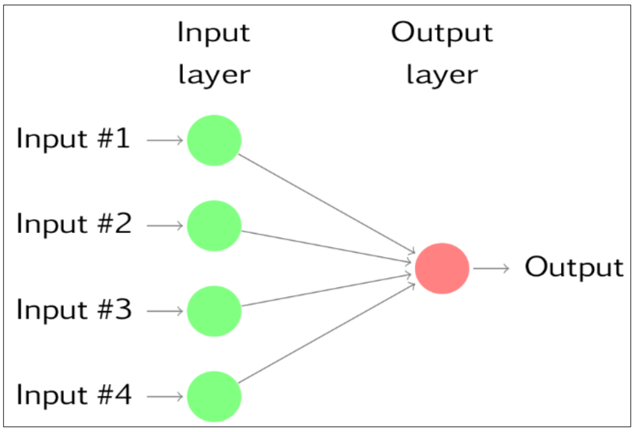


**Fig 1:** Simple neural network with input layer

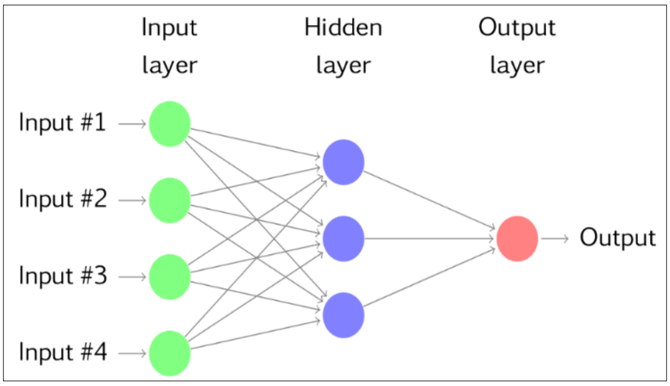


**Fig 2:** Neural network with four inputs and one hidden layer to give the input for the next layer. This tends to reduce the effect of extreme input values, thus making the network somewhat robust to outliers.

The values for b1, b2, b3, and w1, 1..., w4, 3 are "learned" from the data, as are the values for w1, 1..., w4, 3. Weights typically have their values capped so they don't get too large. The "decay parameter," or weight-restricting parameter, is typically equal to 0.1. The initial values for the weights are chosen at random, and they are subsequently modified based on the data that has been collected. As a result, the predictions made by a neural network contain some degree of chance. For this reason, the network is often trained multiple times with varying random seed values. There needs to be an up-front agreement on how many nodes will make up each hidden layer.

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

## Empirical Analysis

### Forecasting for wheat production using Arima

Descriptive statistics for wheat yield are provided in Table No. 4.6, where an average yield of 722.1512 (Kg/Hectare) and a Standard Deviation of 203.5357 can be found. Since no outliers were found in the Sugarcane data set, the result of the Grubb's test is 1.8362. We infer that the Wheat production data is normally distributed since the Jarque-Bera test, employed to examine its normality, yielded a result of 1.8866, which was not statistically significant at the 0.05 level.

**Table 1:** Descriptive Statistics of the yield of Wheat (1982-2022)

| Wheat Production (In Lakhs Tonnes) | |
|---|---|
| Mean | 722.1512 |
| Median | 696.8000 |
| Maximum | 1095.900 |
| Minimum | 374.5000 |
| Std. Dev. | 203.5357 |
| Skewness | 0.184794 |
| Kurtosis | 2.016225 |
| Jarque-Bera test | 1.8866 (0.3893) |
| Grubbs test | 1.8362(1.00) |

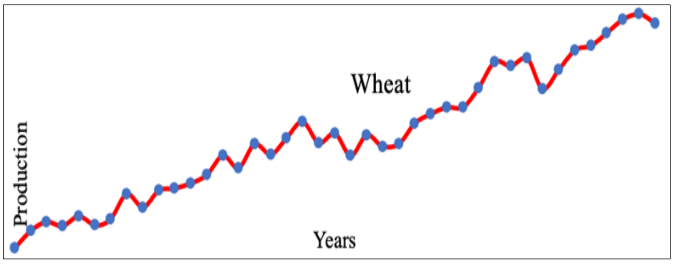


**Fig 3:** Time series graph for wheat production data

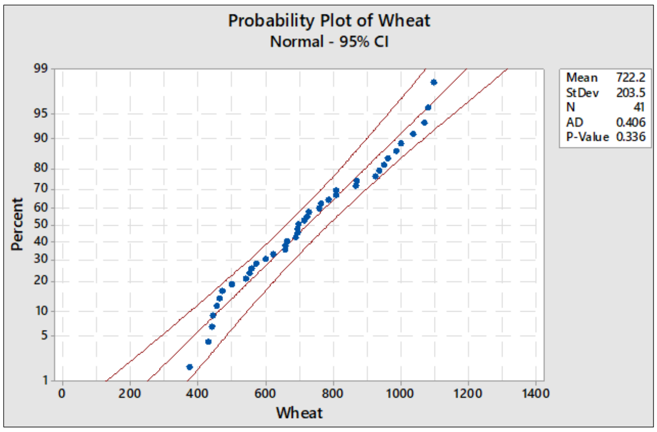


**Fig 4:** Probability plot of Wheat production

The probability plot can be used to check if a data set has a particular distribution, such as the normal distribution. All of the data points should lie inside the 95% confidence interval when plotted against a theoretical distribution, and the line connecting the points should be almost straight. The data on Wheat production matches forecasts.

### Model selection for analysis of errors

The following are the best forecasting models for different ARIMA (p, d, q) and NNAR (p, q) models as given below:

**Table 2:** Best forecasted models of ARIMA (p, d, q) and NNAR (p, q) models

| Model | ARIMA (p, d, q) | RMSE | MAPE | MSE | AIC |
|---|---|---|---|---|---|
| 1 | ARIMA (0, 1, 1) | 38.572 | 4.365 | 0.752 | 412.95 |
| 2 | ARIMA (1, 1, 0) | 44.776 | 5.359 | 0.935 | 422.68 |
| 3 | ARIMA (0, 1, 2) | 43.639 | 5.051 | 0.877 | 422.71 |
| 4 | ARIMA (2, 1, 0) | 43.868 | 5.100 | 0.883 | 423.12 |
| 5 | ARIMA (0, 1, 0) | 43.779 | 5.672 | 0.975 | 422.41 |
| 6 | NNAR (1, 1) | 42.464 | 4.924 | 0.850 | 438.55 |

The ARIMA (0, 1, 1) model is the best-fitting one for Wheat output. Parameter estimation taking into account ideas from, Box-Jenkin's (1976) [3]. Different series were employed to make the series stationary for both area and production. In this case study, both Wheat cultivation and output were found to be stationary in their respective first difference series. Table 4.9 displays the results of evaluating several possible ARIMA models and accepting the one with the lowest Akaike's Information Criterion (AIC), the lowest Mean Absolute Percentage Error (MAPE), and the highest $R^2$ value.

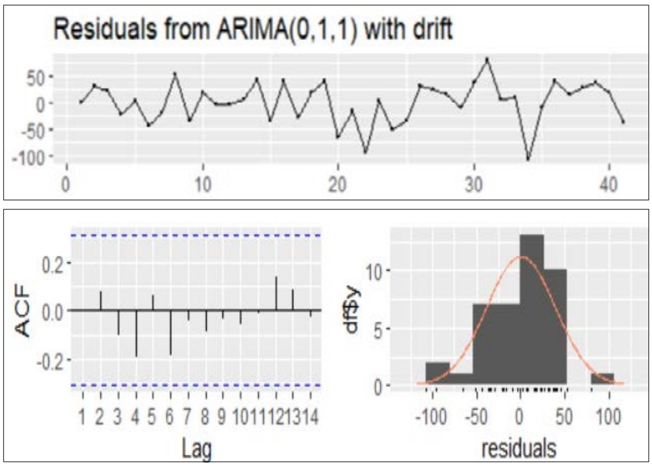


**Fig 5:** Residuals analysis for wheat Production ARIMA (0, 1, 1) model

**Forecasting for wheat production using ARIMA and NNAR models**

The following are forecasted values of the next eight years of Wheat production for Auto-regressive Integrated Moving Averages ARIMA (0, 1, 1) model and Neural Networks Auto-regressive NNAR (1, 1) model as shown in the table No 3.

**Table 3:** The forecasted value of wheat production using ARIMA and NNAR models

| Year | Wheat production (In lakhs Tonnes) | |
|---|---|---|
| | Forecasted ARIMA (0, 1, 1) | Forecasted NNAR (1, 1) |
| 2023 | 1102.853 | 1070.160 |
| 2024 | 1120.242 | 1071.630 |
| 2025 | 1137.631 | 1072.854 |
| 2026 | 1155.020 | 1073.873 |
| 2027 | 1172.409 | 1074.720 |
| 2028 | 1189.798 | 1075.423 |
| 2029 | 1207.188 | 1076.007 |
| 2030 | 1224.577 | 1076.491 |

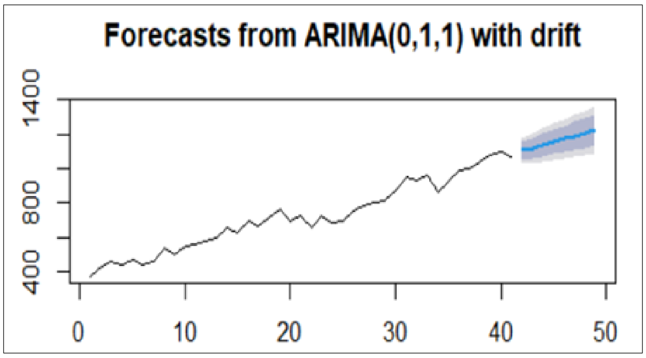


**Fig 6:** Forecasts values of wheat production with ARIMA (0, 1, 1) model

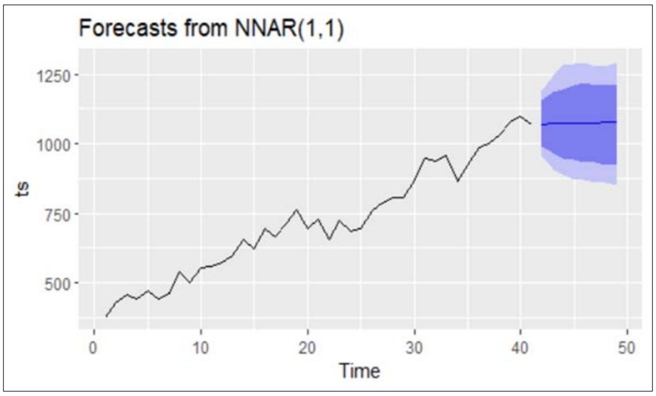


**Fig 7:** Forecasts values of wheat production with NNAR (1, 1) model

Using their own model selection criteria, we compared the ARIMA and NNAR models. In this work, we apply the ARIMA and NNAR models we created to the problem of predicting India's wheat harvest. Forecasts can be divided into two categories: Those based on the ARIMA Model (With periods of zero, one, and two) and those based on the NNAR Model (With periods of zero and two). For the next eight years, from 2023 to 2030, genuine projections are generated for use in planning and other contexts. Table 4.10 displays the resulting predicting values. ARIMA performed better than NNAR in terms of both predictive capacity and forecasting capacities, as demonstrated by this study. We find that the ARIMA (0, 1, 1) model is superior to the NNAR model when making predictions into the future. When compared to the NNAR (1, 1) model, the RMSE for this model was 38.572, the MAPE was 4.365, and the AIC was 412.95.

## Conclusions

In this paper, we have studied the forecasted and future forecasted values of Wheat Production in the State of Andhra Pradesh using ARIMA model and Neural Network Autoregressive (NNAR) Models. These models are studied and applied. In our study,

We can observe that the forecasted values of Wheat Production from 2023 to 2030 for both models in the State of Andhra Pradesh (Graph No. 6 & 7) shows higher production values in ARIMA (0, 1, 1) Model while it shows lesser production in NNAR (1,1) Model.

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