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A COMPARATIVE STUDY OF TIME SERIES MODELS AND ARTIFICIAL NEURAL NETWORKS - FORECASTING RICE PRODUCTION

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Abstract: The accurate estimation of rice production is very essential to make better planning and decision making for any Government. In this paper, we forecast rice production by using time series model like Auto Regressive Integrated Moving Average (ARIMA). Also, we forecast rice production by using Artificial Neural Networks (ANN) multilayer perceptron model. Further, we find mean absolute error (MAE) and Root Mean Squared Error (RMSE) of the time series model and ANN model. To study the models, we used time series record of rice production in India from 1960 to 2018. Results show that ANN model appears to perform better than conventional time series models in forecasting.

Key words: ARIMA, Artificial Neural Networks, MAE and RMSE, Forecasting.

Introduction: Rice is life for thousands of people. In Asia alone, more than 2,000 million people consume rice as one of the important food grain. Recognising the importance of this crop, the United Nations General Assembly declared 2004 as the International Year of Rice. The theme of International Year of Rice is "Rice is Life" and is a primary food source and is an essential food security, poverty alleviation and improved livelihood. Rice production in India is an important part of the national economy. Rice is the most important crop in India covering one-fourth of the total cropped area and providing to about half of the total population. The people of eastern and southern parts of the country crops paddy and India is one of the world's largest producers of rice.

Raising self sufficiency of national rice has become a strategic issue in the agricultural filed. The ability to forecast the future demand, the farm cultivators to take most appropriate decision. The accuracy of time series forecasting is fundamental to many economical decisions taken by Government in India.

One of most popular and commonly used method for forecasting is auto regressive integrated moving average (ARIMA) model. In the ARIMA model, the desired forecasting is generally expressed as a linear combination. But real world time series are often non-linearity and irregularity. Consequently, the forecasting results obtained by ARIMA model are not so accurate.

In recent years, artificial neural networks (ANN) has been rapidly used in the analysis and time series forecasting because of its excellent and powerful learning capability of non-linear model. The ANN's are very supple computing networks for modelling a broad range of non-linear problems. The advantage of ANN over other non-liner methods is that ANN's are widespread which can fairly accurate a large class of functions with a high degree of accuracy. The ARIMA models and ANN are compared with mixed conclusions in terms of superiority in forecasting.

The main objective of this study is to forecast the rice production using ARIMA, ANN and also to compare the efficiency of methods using their RMSE and MAE.

Materials and Methods

The autoregressive integrated moving average model (ARIMA)

In the year 1970, Box and Jenkins developed ARIMA model. This model is a class of linear model that were planned for linear time series. ARIMA models contains both seasonal and non-seasonal parts and are represented by the following way:

$$\phi_p(B)\Phi_p(B^s)\nabla^d\nabla_s^D z_t = \theta_q(B)\Theta_Q(B^s)a_t$$

Where ϕ_i (i=1,2,.....p), θ_j (j=1,2,.....q), Φ_l (l=1,2,...P) and Θ_k (k=1,2,.....Q) are model parameters, p order of non seasonal auto regression; d number of differencing; q order of nonseasonal moving average; P order of seasonal auto regression; D number of seasonal differencing; Q order of seasonal moving average and s length of season. The general representation of non-seasonal model is known as ARIMA (p,d,q) and can be expressed as the linear expression

$$y_t^{BJ} = \sum_{i=1}^{p}\phi_i y_{t-1} + \sum_{j=1}^{q}\theta_j a_{t-j} + \varepsilon_j = \frac{1}{2}\sum_k (t_{kj} - o_{kj})^2 \qquad (1)$$

The artificial neural network forecasting model: An Artificial Neural Network (ANN) simulates the learning process of human brain. The important advantage of a neural network is its capability to model a complex nonlinear in the data series. The architecture of neural networks consists of three types of neuron layers: input, hidden and output layers. Especially, the ANN model performs a non linear functional mapping from the input observations (y_{t-1}, y_{t-2},........y_{t-p}) to the output value (y_t) i.e.,

$$y_t = a_0 + \sum_{j=1}^{q} a_j f(w_{0j} + \sum_{i=1}^{p} w_{ij} y_{t-i}) + \varepsilon_i \qquad (2)$$

Where, a_j (j=0,1,2,....q) is a bias on the jth unit and w_{ij} (i=0,1,2,.....p; j=0,1,2,.....q) is the connection weights known as synaptic weights between layers of the model, f(.) is the transfer function or activation function of the hidden layer, p is the number of input neurons and q is the number of hidden neurons. The activation function utilized in the study for the neurons of the hidden layer was the logistic sigmoid function that is described by:

$$f(x) = \frac{1}{1 + e^{-x}}$$

This activation function belongs to the class of sigmoid functions and has an advantage characteristics such as being continuous, differentiable at all points and monotonically increasing.

Training a network is an important factor for the success of the neural networks. Among the several learning algorithms available, back-propogation is the most popular and most widely used learning algorithm for all neural network problems. The procedure of the Back Propogations is repeated by adjusting the synaptic weights of the connection in the network so as to minimize the error. The gradient descent method is utilized to calculate the weight of the network and adjust the weight of interconnection to minimize the sum-squared error (SSE) of the network which is given by:

$$SSE = \frac{1}{2}\sum_K (Y_K - \widehat{Y_K})^2 \qquad (3)$$

Where, y_k and $\hat{Y}_k$ are the true and predicted output vector of the kth output node.

Actually, the ANN model described in Equation 2 performs a nonlinear functional mapping from the past observation ($y_{t-1}, y_{t-2}, \ldots\ldots y_{t-p}$) to the future value ($y_t$) i.e.,

$$Y_t = f(y_{t-1}, y_{t-2}, \ldots\ldots y_{t-p}, w) + \varepsilon \qquad (4)$$

Where, w is a weight vector for all parameters and f is a function determined by the network structure and connection weights.

Thus, in some senses, the ANN model is very similar to a nonlinear autoregressive model. A major advantage of neural networks is their ability to provide flexible nonlinear mapping between input and output neurons. The ANN can capture the nonlinear characteristics of time series well.

Results and Discussion

In order to validate the forecasting methods for rice yields modelling, the data were collected from Area and Production Statistics, Ministry of Agriculture and Farmers Welfare, India. The rice yields data contains the production of rice from 1960 to 2018 and the time series plot is given in Fig.1.

Fig. 1: Rice Production from 1960-2018

To consider the forecasting performance of different models, each data set is divided into two samples. The first data set is used for training the network i.e., modelling the time series and the remaining were used for testing the performance of the trained network i.e., for forecasting. The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to measure the efficiency of each model for both the training and forecasting data. The MAE and RMSE are defined as:

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t-\widehat{y_t}}{y_t}\right|$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t-\widehat{y_t})^2}$$

Where, y_t and $\hat{Y}_t$ are the observed and the forecasted rice production at the time t, N is the number of observations. The small value of MAE and RMSE in the modelling results the best model.

Fitting ARIMA model to the data: The plots in Fig. 2 shows the plots of the rice production time series indicate that the time series are non-stationary in mean and variance. The first difference (1) was applied in order to remove the trend. The sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) for the first difference series are plotted in Fig. 2. The plot shows that there is seasonality in the series. We find the first difference series becomes stationary.

Fig. 2: ACF and PACF for different series of natural logarithms

Several time series models were identified and the statistical results during training are compared in the Table 1.

Table 1: Comparison of ARIMA models statistical results

ARIMA model	Training	
	RMSE	MAE
(1,1,0)x(1,0,0)	257.231	0.0764
(1,1,0)x(1,0,1)	242.841	0.0724
(1,1,1)x(1,0,0)	257.012	0.0763
(1,1,1)x(1,0,1)	242.755	0.0724

The criterions to judge for the best model based on MAE and MSE show that the ARIMA (1,1,1)x(1,0,1) is a relatively best model.

Fitting neural network models to the data:

One of the key aspect in time series forecasting is the selection of the input variables and the number of neurons in the hidden layer. For the ANN models, there is no systematic approach which can be followed. The universal approximation theorem shows that a neural network with a single hidden layer with a sufficiently large number of neurons can in principle relate any given set of inputs to a set of outputs to an arbitrary degree of accuracy. As a result, the ANN designed in this study are equipped with one single hidden layer.

The number of neurons in the networks has an important consequences for its performance. Too small number of neurons in the network may not give the desired accuracy and too many neurons also may result in an inability for the network to generalize.

Table 2: Comparing forecasting performance

Model	Training		Forecasting	
	RMSE	MAE	RMSE	MAE
ARIMA	242.755	0.0724	516.634	0.1521
ANN	225.895	0.0658	487.281	0.1427

The network was trained using the back-propogation algorithm with a learning rate of 0.001 and a momentum coefficient of 0.9. The networks that yielded the best results for the forecasting set were selected as the best ANN for the corresponding series. The experiment is repeated 10 times and afterwards the average RMSE and MAE are computed. The table 2 shows overall summary statistics for each ANN model in training model selection results for the rice production.

Conclusions

This study examines forecasting performance of artificial neural network (ANN) model compared with ARIMA model in forecasting the rice production. Based on the MAE and RMSE, it is clear that the ANN is more accurate than ARIMA model. The results suggests that the ANN method can be used as alternative to conventional linear combing methods to achieve greater forecasting accuracy.

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