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POD DAMAGE MODELING AND FORECASTING IN EARLY MATURING PIGEONPEA (*Cajanus cajan*) FOR CENTRAL ZONE (CZ) OF INDIA

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ABSTRACT

The present investigation was aimed to compare the ability of Autoregressive Integrated Moving Average (ARIMA), Exponential smoothing and Neural network (NN) model for forecasting percent pod damage by pod borer in early maturing pigeonpea yield grown in central zone of India. Based on studies, neural network was found to be more suitable for predicting pigeonpea yield as compared to two other models.

INTRODUCTION

Pigeonpea is a second most important legume crop after Chickpea (Rathod *et al.*, 2016) and is a good source of protein, and other nutrients such as fiber, ash, fat, magnesium, manganese and Vitamins as well (Vinutha and Patil, 2016). Although India is top most producer of pigeonpea but demand is much higher than the production. It is therefore required to minimize the gap between two. One of the major constraints for this gap is considerable damage in pods due to attack of major insect pests directly affecting the loss of yield. Pod borer (*Helicoverpa armigera*) is a key pest inflicting 80 to 90 per cent of loss (Kumari *et al.,* 2017). Hence timely forecast of damage helps policy-maker in deciding the operational strategies for the same. The present investigation therefore provides reliable forecast for percent pod damage by pod borer in early maturing pigeonpea grown in central zone of India, with the help of different statistical forecasting models.

Many researcher have done forecasting for damage by insect pests by linear and non-linear models in which most widely used models were Autoregressive Integrated Moving Average (ARIMA) and Exponential smoothing and Artificial Neural Network (ANN) Model (Zhang *et al.,* 1998; Mastny, 2001; Khashei *et al.,* 2009; Adebiyi *et. al.* 2014; Rathod *et al.,* 2016 and Kumari *et al.,* 2013, 2014a, 2014b and 2017).

ARIMA which is also known as Box-Jenkins model, is suitable to model non-stationary time series data(Box and Jenkins, 1970). It is based on its own past observations of time series as well as previous error terms. This is the most efficient univariate model for short term forecasting having linear relationship among each other and used in various field.

Exponential Smoothing models is another widely used univariate time series model, where recent data are given relatively more weight than the older data. Exponential smoothing method is classified according to the type of trend and seasonality presented in the time series data. It has been successfully applied in many time series forecasting (Kumari, *et al.*,2014b).

Another important model is Artificial Neural Network (ANN) which can approximate linear and non-linear relationship and so also known as universal approximator. Therefore, ANNs provide better results in field of agriculture which is highly unpredictable as compared to ARIMA and exponential smoothing model (Kumari, *et al.*, 2016 & 2017).

This investigation presented a comparison between Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing model and Artificial Neural Network (ANN) technique used for predicting percent pod damage by pod borer in early maturing pigeonpea for central zone of India.

MATERIALS AND METHODS

In the present study, time series secondary data on percent pod damage by pod borer in early maturing pigeonpea were collected for the period 1985-86 to 2011-12 from All India Coordinated Research Project on Pigeonpea (Indian Council of Agricultural Research), from different centers, *viz.*, Khargone, Sehore, Badanpur, S.K. Nagar, Junagarh and Akola of Central Zone (CZ) of India.

Model Development

Autoregressive Integrated Moving Average (ARIMA) model

ARIMA (Box and Jenkins, 1970) aims to describe the autocorrelations in the data. Unlike regression models, the this time series model is function of its own past values and stochastic error terms (white noise). ARIMA model is usually stated as ARIMA (p, d, q) and is expressed in the form:

$$Y_t = \theta_0 + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots\ldots\ldots + \Phi_p Y_{t-p} + e_t - \Phi_1 e_{t-1} - \Phi_2 e_{t-2} - \ldots\ldots - \theta e_{t-q},$$

Where Y_t and e_t are the actual values and random error at time t, respectively, Φ_i (i = 1,2,.......,p) and θ_j (j = 1,2,......,q) are model parameters, p and q are referred to as orders of autoregressive and moving average polynomials respectively. Random errors e_t are assumed to be independently and identically distributed with mean zero and the constant variance σ_e^2. This model set up follows four steps that are model identification, estimation of parameters, diagnostic check and forecasting.

Exponential smoothing (ES) model

Another most successful univariate time series forecasting technique is the exponential smoothing (ES) which is used to produce a smoothed time series. In this technique, forecasts are weighted averages of past observations, with the weights decaying exponentially as the observations get older (Brown, 1963). Exponential smoothing method is classified according to the type of component (trend and seasonality) presented in the time series data. Based on time series data, only two exponential smoothing methods are used *i.e.* simple exponential and double exponential smoothing technique in this investigation.

Artificial Neural Network (ANN):

Artificial neural network (ANN) is simulation of biological neural network (Haykin, 2001). Structure of ANN consists of three layers (input, hidden and output) of processing units (also termed neurons/ nodes). There are two main steps which is considered during development of ANN architecture *i.e.*, *topology* and *learning* the network. The topology consists of (I) number of layers and number of neurons in each layer (II) activation function for each neuron, (III) whether feedback or feed-forward, and (IV) the connectivity pattern between the layers and the neurons. The learning phase is weight as well as threshold values adjustments. This tasks is completed in three steps i) Training: to decide parameters ii) Validation: to avoid over-fitting and iii)Testing: to test Model ability by their MSE value. In this case, Neural Network architectures were developed by using Levenberg Marquardt (LM) Algorithm as a training algorithm of weight matrix.

RESULTS AND DISCUSSION

ARIMA model construction

In case of fitting ARIMA model for forecasting percent pod damage by pod borer on pigeonpea, out of various ARIMA models with different values of p, d and q, the performance of ARIMA(0,1,0) was found to be the best. The results are shown in the tables 1 and 2.

Table 1 showed that the only value which was found to be statistically significant in this model is constant term with an estimate of 1.250 and a standard error of 0.580. The values of

Table1: ARIMA model parameters

Model	Parameter	Estimate	**SE**	**T**	**Sig.**
Borer-Model_1 Difference 1	Constant	1.250	.580	2.155	.041

Table 2: ARIMA Model fit statistics

Model	R-squared	RMSE	MAPE	MAE	Normalized BIC
borer-Model_1	.831	2.957	8.945	2.279	2.294

Table 3: ANN Model Parameters

Weights	H_1	H_2	Biases	Values
I_1	WI_1H_1 = 0.759	WI_1H_2 = -1.740	BH_1	-1.295
I_2	WI_2H_1 = -0.714	WI_2H_2 = -0.423	BH_2	-0.107
O	WOH_1 = -0.758	WOH_2 = -0.755	B_O	-0.595

Table 4: Performance of ANN, ARIMA and ES model

Results	Model Accuracy and forecasted value	ANN	ARIMA	ES
% Pod damge by pod borer	Forecast	45.23(44.00)	45.25	NS
	RMSE	2.02	2.96	
	MSE	4.09	8.74	
	R square	0.94	0.83	

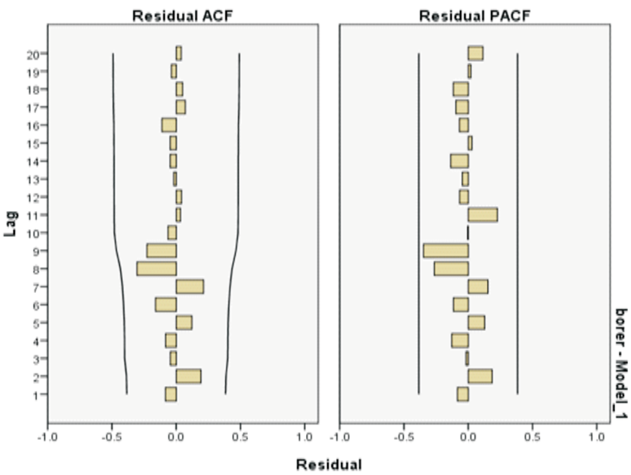

Figure 1: Residual Autocorrelation Check

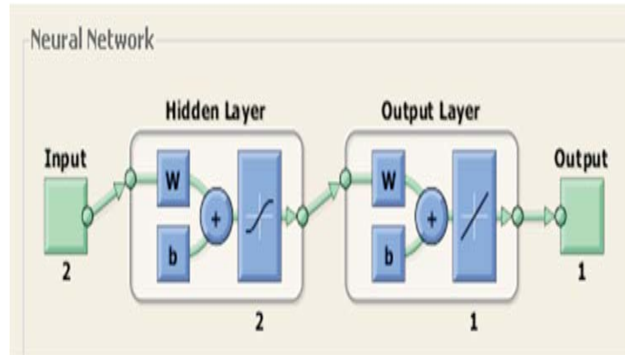

Figure 2: Two-layer feed-forward network

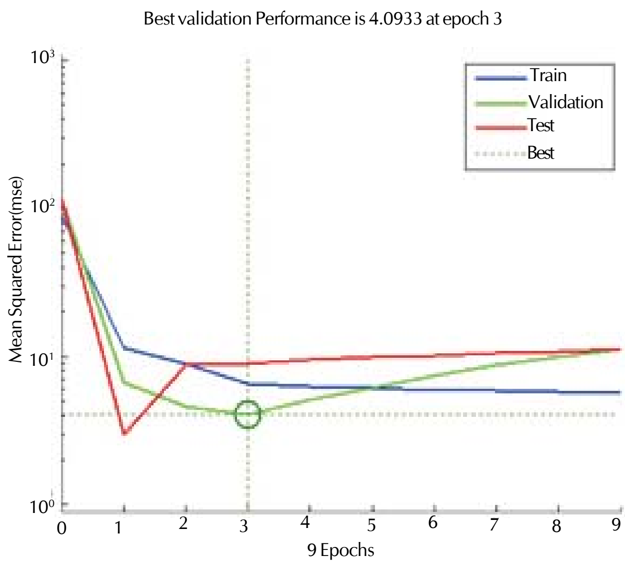

Figure 3: Performance of Levenberg-Marquardt Backpropagation (LM) Algorithm

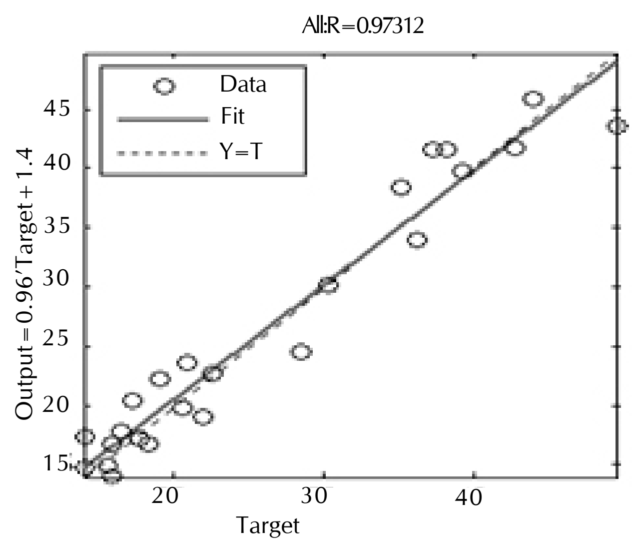

Figure 4: Regression Analysis Plot-LM Backpropagation Algorithm

the fit statistics namely R^2, RMSE (MSE), MAPE, MAE and BIC were found as 0.831, 2.957 (8.74), 8.945, 2.279 and 2.294 respectively at the model fitting phase (Table 2).

Further, residuals of the model were examined by testing the significance of the residual autocorrelation coefficients (Fig. 1). The autocorrelation coefficients were found to be non significant at the Diagnostic Checking Stage showing satisfactory fitting of this model.

The forecasted value of pod damage by pod borer for early maturing variety of pigeonpea during the year 2012-13 was obtained as 45.25% by the ARIMA(0,1,0) model in the Central Zone of India.

Exponential smoothing model construction

In the present study, attempts were made to forecast the percent pod damage by pod borer on pigeonpea with the help of exponential smoothing models. Since, in ES model family, none of the model was found to be significant, hence ES model was not considered appropriate for predicting the data under study.

Artificial neural network model construction

Neural Network architecture was developed with the help of MATLAB Neural Network Toolbox 2010. The network used was a two-layer feed-forward network as given in Fig. 2.

Various ANN architectures were developed with their different parametric values and best to be chosen by their relatively small Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), relatively high R and 5ØEÜ^2 value.

Out of various architecture of Neural Network, the best architecture was chosen having following topology: a) two-layer feed-forward network (one Input and one Hidden Layer) b) Input layer having two lag value of time series values as inputs c) Hidden layer having two node with sigmoid activation function and d) Output layer having one node with Linear activation function.

Therefore, four weights for input to hidden neurons and two weights for hidden to output neurons and three bias values were chosen. Random Data Division Process divides the data set into 70:15:15 for training, validation and testing. Let the two input lag value in input layer were denoted by notation I_i (i=1,2), two hidden node of hidden layer were denoted as H_j

(j = 1,2) and output node is denoted as O then the weights among input and hidden neurons are denoted by WI_1H_1, WI_2H_1, WI_1H_2, WI_2H_2 and among hidden and output neurons WOH_1, WOH_2. Similarly, bias values of three nodes (two hidden nodes and one output node) were denoted as BH_1, BH_2 and B_O. The performance of the proposed network when trained with Levenberg-Marquardt back propagation algorithm was accessed by their Mean Squared Error (MSE) value along with multiple correlation coefficient (R) between observed and predicted outputs. Here parameters of ANN model *i.e.* weights among different nodes and biases value of each node were mentioned in the Tables 3.

From Fig. 3, it was observed that the best validation performance MSE = 4.09 at epoch 3 was obtained. The Regression analysis plot shown in Fig. 4, displayed a linear regression between network outputs and the corresponding targets with the R value as 0.97 (R^2 = 0.94) showing the fit was good for all data sets. The forecasted value of pod damage by pod borer for early maturing variety of pigeonpea during the year 2012-13 was obtained as 45.23% by the ANN model in the Central Zone of India, with Mean Squared Error, Root Mean Squared Error, R and 5ØEÜ^2 4.09, 2.02, 0.97 and 0.94 respectively.

Comparison of ANN, ARIMA and ES

Table 4 reflects that the forecasted value of percent pod damage by pod borer was best explained by ANN model during 2012-13 for early maturing varieties in Central Zone (CZ) with having relatively small value of Root Mean Squared Error (RMSE) 2.02

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