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ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR OKRA YIELD PREDICTION

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ABSTRACT

This paper, adaptive neuro-fuzzy inference system for okra yield prediction, describes the use of neuro -fuzzy inference system in the prediction of okra yield using environmental parameters such as minimum temperature, relative humidity, evaporation, sunshine hours, rainfall and maximum temperature as input into the neuro-fuzzy inference system, and yield as output. The agro meteorological data used were obtained from the department of agro meteorological and water management, Federal University of Agriculture, Abeokuta and the yield data were obtained from the Department of Horticulture, Federal University of Agriculture, Abeokuta. MATLAB was used for the analysis of the data. From the results, the maximum predicted yield showed that at minimum temperature of 24.4 °C, relative humidity of 78.3% and evaporation of 5.5mm, the yield predicted is 1.67 tonnes/hectare.

Keywords: Crop yield, Prediction, agro meteorological data, cultivation, harvest.

INTRODUCTION

In Nigeria, it is possible to cultivate diverse crops due to varied climatic conditions. Among these crops, okra (*Abelmoschus esculentus*) is an important vegetable crop which provides food for the nation's fast-increasing population and has export potential for foreign exchange earnings. One of the severe threats to agricultural productivity in Nigeria and Africa at large is climate change (Odjugo, 2010). Crop failure on account of climate changes have a severe repercussion not only on the country's economy but also on the availability of food.

Crop prediction is the art of estimating crop yields and production before the harvest, typically a couple of months in advance (FAO, 2013). The forecasting of crop yield may be done by using three major objective methods: biometrical characteristics, weather variables and agricultural inputs (Agrawal *et al.* 2011). These approaches can be used individually or in combination to give a composite model.

The need for quantitative statistical crop yield forecast outlooks has been felt for quite some time. A beginning towards its realization has been made by undertaking a study of past crop yield in relation to meteorological parameters, principally rainfall and temperature. Several studies have been conducted to forecast crop yield using weather parameters (Pankaj, 2011; Stathakisa *et al., 2006*;). Such forecast studies, based on statistical models need to be reiterative and for different agro-climatic zones, due to visible effects of changing environmental conditions and weather shifts at different locations and areas. There is a need to develop area specific forecasting models based on time series data to help the policy makers for taking effective decisions to counter adverse climatic situations in food production. Nowadays, there are a lot of yield prediction models, which have been generally classified into two groups: statistical models, and crop simulation models (e.g. CERES). Nonetheless, the recent applications of Artificial Intelligence (AI) techniques, such as Artificial Neural Networks (ANNs), Fuzzy Systems and Genetic Algorithm have shown to be more effective in solving these problem. The application of AI-techniques can make models easier and more accurate for complex natural systems with many inputs (Smith *et al., 2009*; Kefaya *et al.,* 2012; Kosko, 1992).

Adaptive Neuro Fuzzy Inference System (ANFIS) which is an integration of neural networks' features and fuzzy logic has the potential to capture the benefits of both fields in a single framework. The ANFIS utilizes linguistic information from the fuzzy logic as well as the learning capabilities of an artificial neural network(Czogala and Leski, 2000; Ehret *et al*., 2011; Snehal and Sandeep, 2014). An ANFIS is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. It is considered generally as a multilayer feed forward adaptive network, where each node performs a particular function with its corresponding input parameter set.

ANFIS ARCHITECTURE

For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs and one output. The rule base contains the fuzzy if-then rules of Takagi and Sugeno's type (Takagi and Sugeno, 1983) as follows:

If x is A and y is B then z is f(x,y)

where A and B are the fuzzy sets in the antecedents and z = f(x, y) is a crisp function in the consequent. Usually f(x, y) is a polynomial for the input variables x and y. But it can also be any other function that can approximately describe the output of the system within the fuzzy region as specified by the antecedent. When f(x,y) is a constant, a zero order Sugeno fuzzy model is formed which may be considered to be a special case of Mamdani fuzzy inference system where each rule consequent is specified by a fuzzy singleton. If f(x,y) is taken to be a first order polynomial a first order Sugeno fuzzy model is formed. For a first order two rule Sugeno fuzzy inference system, the two rules may be stated as:

Rule 1: If x is A1 and y is B1 then $f_1 = p_1x + q_1y + r_1$
Rule 2: If x is A2 and y is B2 then $f_2 = p_2x + q_2y + r_2$

Here type-3 fuzzy inference system proposed by Takagi and Sugeno (1983) is used. In this inference system the output of each rule is a linear combination of the input variables added by a constant term. The final output is the weighted average of each rule's output. The corresponding equivalent ANFIS structure is shown in Fig. 1. The individual layers of this ANFIS structure are described below:

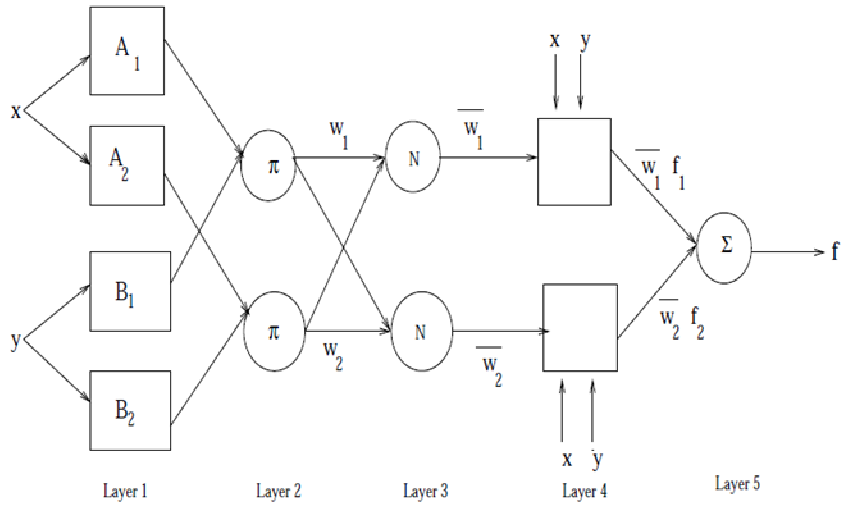

Figure 1: ANFIS Architecture

Layer 1 (**Fuzzification layer**): every node ***I*** in the layer 1 is an adaptive node. The outputs of layer 1 are the fuzzy membership grade of the inputs, which is given by:

$$O_i^1 = \mu_{A_i}(\mathrm{x}) \tag{1}$$

where, x is the input to node i, A_i is the linguistic variable associated with this node function and μA_i is the membership function of A_i. Usually $\mu A_i(x)$ is chosen as

$$\mu_{A_i}(\mathrm{x}) = \frac{1}{1+[\left(\frac{x-c_i}{a_i}\right)^2]^{b_i}} \tag{2}$$

Or

$$\mu_{A_i}(\mathrm{x}) = exp\{-\left(\frac{x-c_i}{a_i}\right)^2\} \tag{3}$$

Layer 2 (Rule layer): Output is the product of all the incoming signals to it and can be represented as,

$$O_i^2 = \omega_i = \mu_{A_i}(\mathrm{x}) \times \mu_{B_i}(\mathrm{x}), \quad i = 1,2 \tag{4}$$

Layer 3 (Normalization layer): Every node in this layer is fixed. Each i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of firing strengths of all the rules. The output from the i^{th} node is the normalized firing strength given by,

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} \quad i = 1,2 \tag{5}$$

Layer 4 (Defuzzification layer): The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial.

$$O_i^4 = \overline{\omega_i} f = \overline{\omega_i}(p_i x + q_i y + r_i), \quad i = 1,2 \tag{6}$$

where w_i is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the consequent parameter set.
Layer 5 (Summation neuron): Summation of all incoming signal is computed, i.e.

$$O_i^4 = overall\ output = \sum_i \overline{\omega_i} f_i = \sum_i \frac{\omega_i f_i}{\omega_i} \tag{7}$$

STUDY AREA

The purpose of this study is to develop forecasting model for predicting the yield of okra at the Federal University of Agriculture, Abeokuta, Ogun State, Nigeria. Yield data of okra for ten years (2004-2014) was collected from the Department of Horticulture, Federal University of Agriculture, Abeokuta. Monthly agro meteorological data of ten years (2004-2014) was also collected from the Department of Agro-Meteorological and Water Management, Federal University of Agriculture, Abeokuta. Six weather parameters considered are; minimum temperature, maximum temperature, relative humidity, rainfall, sunshine hours and evaporation.

MATERIALS AND METHOD

The total data is divided into two, namely: training and checking data with the weather parameters serving as the inputs and the yield as the output.

A test to determine the optimal weather parameter combination that influences high yield was carried out using the function 'exhsrch' in MATLAB and the single parameter that has the most influence on the yield is 'relative humidity'. The two input combination that is most influential on the yield are relative humidity and evaporation; and the three input combination that influences the yield most are minimum temperature, relative humidity and evaporation.

Combinations of minimum temperature and relative humidity were considered as the inputs to the model, and yield of the current year was considered as the output. Input space partitioning for model structure identification was done by grid partition. Hybrid learning algorithm was used to train the models for runoff prediction. The proposed ANFIS architecture is shown in Figure 2.

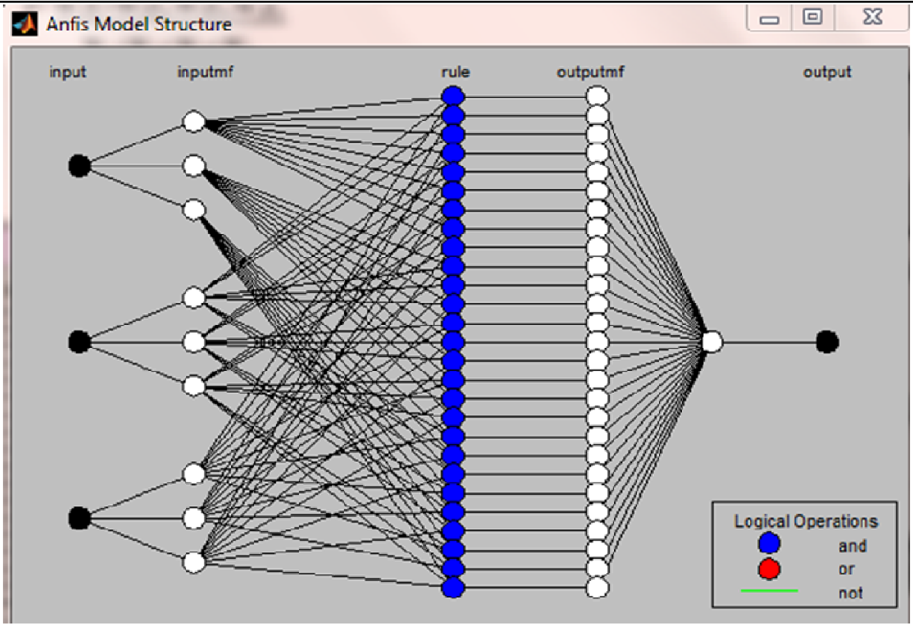

Figure 2: Proposed ANFIS Structure

RESULTS AND DISCUSSION

The training and checking data were now limited to have three inputs: minimum temperature, relative humidity and evaporation, and one output, yield. Both data were loaded into the ANFIS system and appears on the GUI plot as shown in figure 3. The training data appears as circles superimposed with the checking data, appearing as pluses.

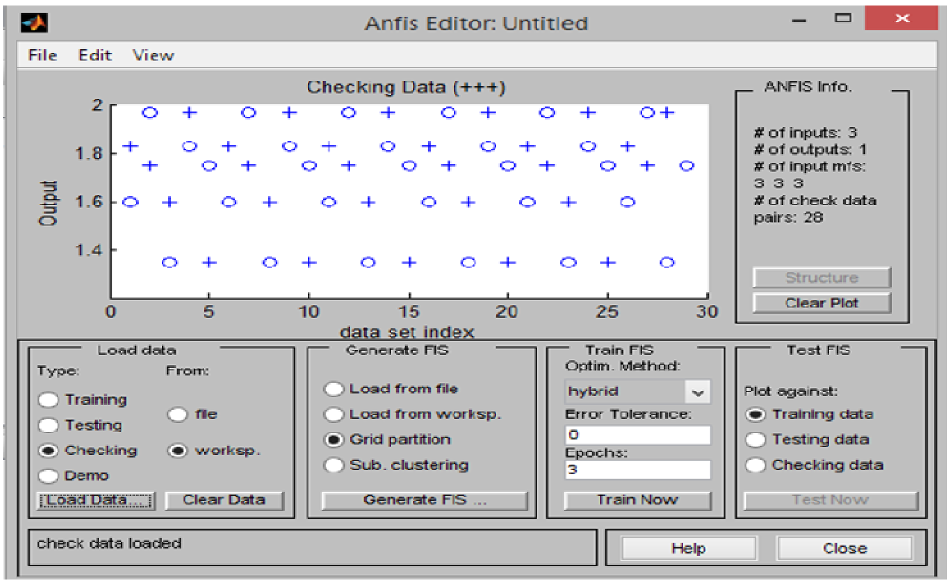

Figure 3: GUI plot showing training data as circles and checking data as pluses

Only three input variables were successively used for the prediction as the ANFIS toolbox automatically generates the rules after running the m file. The fuzzy inference system is generated automatically. Among triangular, bell shaped, trapezoidal and gaussian membership function, the generalized bell membership function was found most suitable for this study (Figure 4).

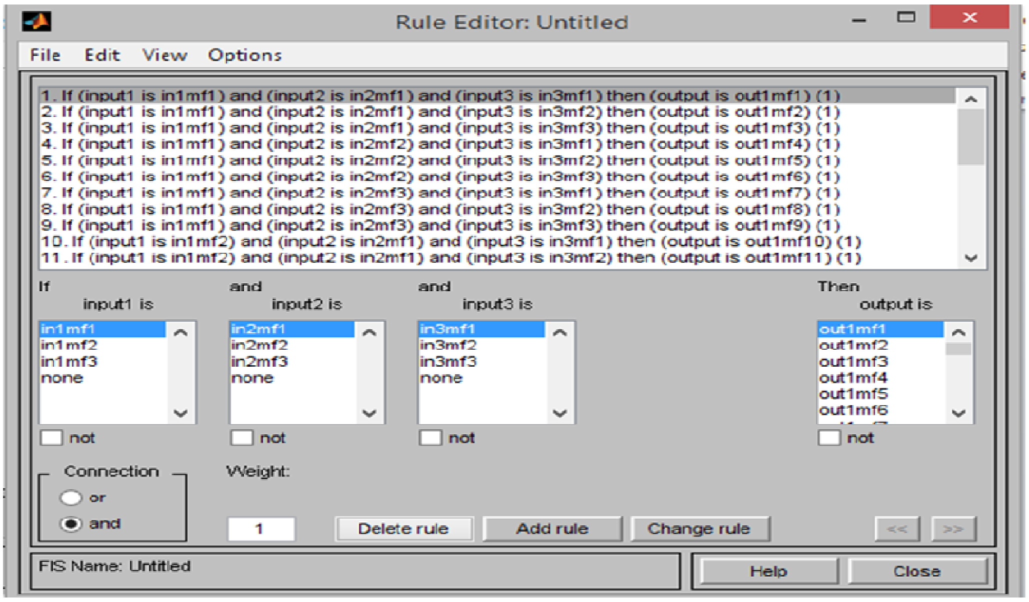

Figure 4: Snapshot of ANFIS editor showing rules

A total of 27 rules were generated in the anfisedit guide. The rules are the guidelines of the prediction format used by the editor. Input 1 is the first input variable which is minimum temperature, input 2 is the second input variable which is relative humidity while input 3 is the third input variable which is evaporation, as shown in Figure 5.

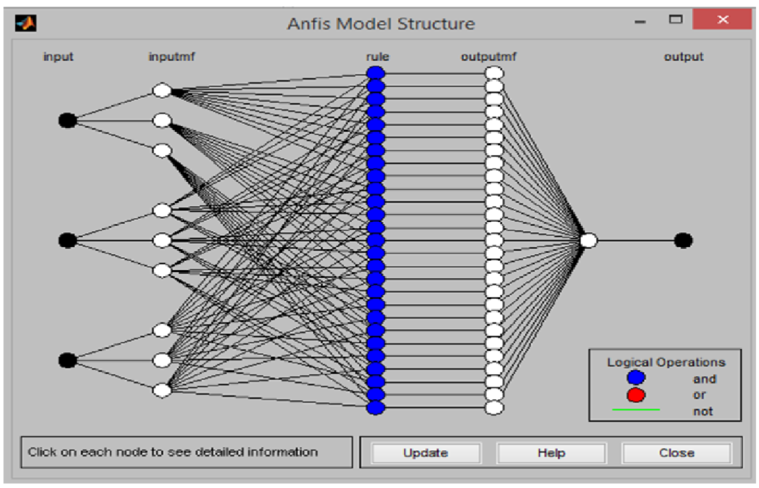

Figure 5: ANFIS Model Structure showing the relationship between each node

Three (3) bells and constant membership functions were used for 50 epochs. The system was trained using the hybrid parameter optimization method and was tested against the trained fuzzy inference system. The output of the trained Fuzzy Inference System (FIS) against the checking data is shown in figure 6.

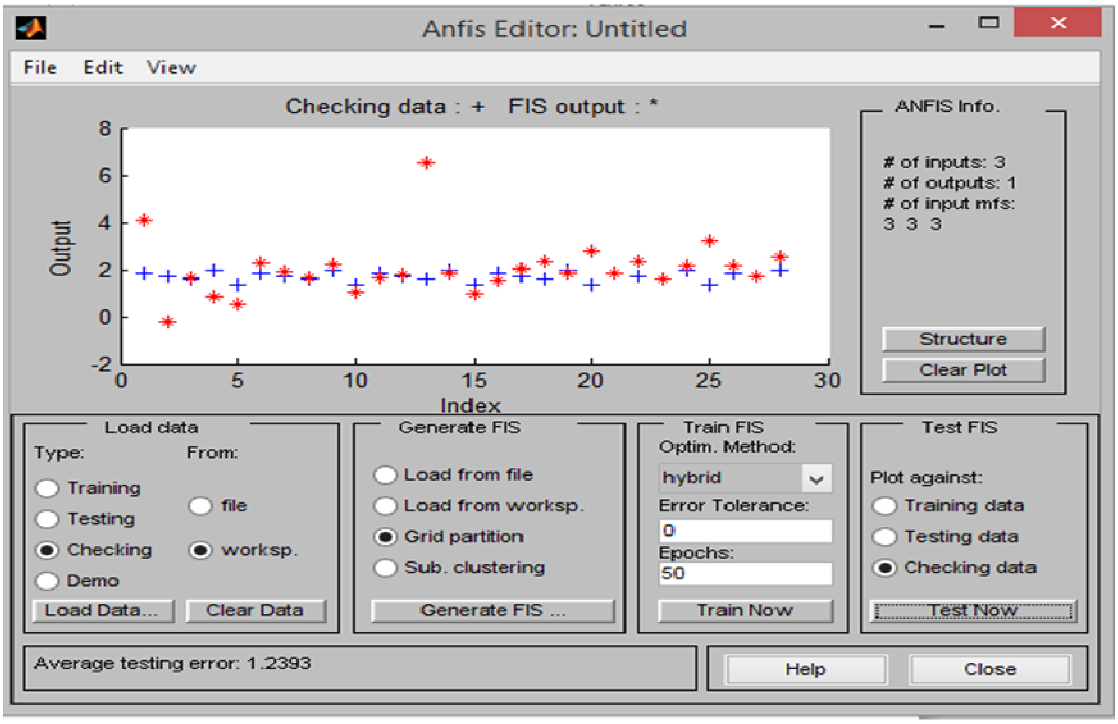

Figure 6: GUI plot of FIS against checking data

As shown in figure 6, the checking data (+) represents the actual yield while the fuzzy inference system output (*) is interpreted as the predicted yield. It can be deduced from the checking data and in figure 6 that at minimum temperature of 24.4^{o}C, relative humidity of 78.3% and evaporation of 5.5mm, the predicted yield was equal to actual yield.

The combination of the input variables that influence the prediction model was also derived. From the results, the input variables that influenced the yield of okra the most are: minimum temperature, relative humidity and evaporation which were the variables used in training the ANFIS. Hence, ANFIS is an efficient model for the prediction of okra yield.

CONCLUSION

The paper explored the dynamics of Adaptive Neuro-Fuzzy Inference System in providing the most likely, precise, traceable and independent prediction of yearly okra yield using some environmental variables.

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