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A study on crop yield prediction and adaptive neuro-fuzzy modeling

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Abstract
Most of greenhouse growers desire a determined amount of yields in order to accurately meet market requirements. The purpose of this paper is to explore the dynamics of neural networks in forecasting crop (tomato) yield using environmental variables; here we aim at giving accurate yield amount. We use the Adaptive Neuro-Fuzzy Inference System (ANFIS).
ANFIS has only one output node, the yield. One of the difficult issues in predicting yield is that remote sensing data do not go long back in time. Therefore any predicting effort is forced to use a very restricted number of past years in order to construct a model to forecast future values.

Keywords: Neural Networks, Adaptive-network-based fuzzy inference system (ANFIS), Crop, yield forecasting

1. Introduction
ANFIS is considered as a class of adaptive networks that perform as a framework for adaptive fuzzy inference [1] systems. Generally, it is a multilayer feed forward adaptive network where each node realizes a particular node function of its corresponding inputs and the nodes in ANFIS include adaptive and fixed ones, and ANFIS is characterized with the parameter set that is the union of the parameter sets associated with all adaptive nodes.
The use of a neuro-fuzzy system for crop yield [7] estimate has some interesting characteristics. All the variables that are input into the system are associated with varying degrees of accuracy. Some ambiguity comes from measurement error and generality. Using fuzzy sets instead of the actual values as inputs, we aim at shifting to the semantics of the data rather than its measure [1].
It is well known that with neuro–fuzzy modeling there is the alternative to use a fuzzy set as the output. In this case, yield would be expressed for example as low, normal of high with each of those three borders corresponding to a fuzzy set. We do not imply however that seeking a crisp (non-fuzzy) value is a more exact approach than seeking a trend expressed in fuzzy sets (low, medium, etc.).
But although the accuracy of prediction is probably the same in both expressions of desired output, people are more used to and feel more confident in looking at number rather than a membership function. ANFIS is a system that accepts numerical inputs and produces a single out value. ANFIS is susceptible to the “curse of dimensionality”.
The training time increases exponentially with respect to the number of fuzzy sets per input variable used. To illustrate this let us consider a system with 8 input variables that are coded into two fuzzy sets (e.g. low, high) and has 256 rules. If we chose now to use three linguistic variables instead of two (say low, medium, high) the number of fuzzy rules becomes 6561. This phenomenon limits in practice the choice of input variables as well as the expression of those variables into meaningful fuzzy sets.
The system is trained by leaving one year out and using all the other data. We then evaluate the deviation of our estimate compared to the yield of the year that is left out. The procedure is applied to all the years and the average forecasting accuracy is given.

1.1 Anfis structure
Adaptive Neuro-Fuzzy Inference System (ANFIS) Fuzzy logic was introduced by [1] to represent and manipulate data and information in which there are various forms of uncertainty. Fuzzy rule-based systems use linguistic variables to reason using a series of logical rules that contain IF-THEN rules which connect antecedent(s) and consequent(s), respectively. An antecedent is a fuzzy clause with certain degree of membership (between 0 and 1).
Fuzzy rules can have multiple antecedents connected with AND or OR operators, where all parts are calculated simultaneously and resolved into a single number. Consequents can also be comprised of multiple parts, which are then aggregated into a single output of a fuzzy set.
Fuzzy inference [8] is a process of mapping from a given input to an output using the fuzzy set methods. The fuzzification component transforms each crisp input variable into a membership grade based on the membership functions defined. The inference engine then conducts the fuzzy reasoning process by applying the appropriate fuzzy operators in order to obtain the fuzzy set to be accumulated in the output variable. The defuzzifier transforms the fuzzy output into a crisp output by applying a specific defuzzification method.
The adaptive neuro-fuzzy inference system (ANFIS) proposed by [4, 3, 13] implements a Sugeno fuzzy inference method. The ANFIS architecture contains a six-layer feed forward neural network. Layer 1 is the input layer that passes external crisp signals to Layer 2, known as the fuzzification layer, to determine the membership grades for each input implemented by the given fuzzy membership function. Standard ANFIS architecture consists of five layers of nodes.
Out of the five layers, the first and the fourth layers consist of adaptive nodes while the second, third and fifth layers consist

of fixed nodes. The adaptive nodes are associated with their respective parameters, get duly updated with each subsequent iteration while the fixed nodes are devoid of any parameters.
ANFIS use a strategy of hybrid training algorithm to tune all parameters. It takes a given input/output data set and constructs a fuzzy inference system whose membership function parameters are tuned, or adjusted, using either a back propagation algorithm in combination with a least squares type of method. There are many parameters one can select to obtain better results in ANFIS.
For the most common case, these parameters are: the number and type of membership function for each input, the training epoch number. The number of input membership functions: two membership functions for each of the seven input variables model. The bell MF was chosen as MFs for this specific ANFIS, the training epoch number 10, the ANFIS network has a total of 128 fuzzy rules and one output.

1.2 Research work
The ANFIS has two types of parameters. Firstly, the premise parameters specify the shape of the fuzzy sets. Secondly, the consequent parameters are the polynomial coefficients of the linear equations in the fuzzy rule. In Fig.3, the premise parameters of fuzzy set A1 are a1, b1 and c1 and the consequent parameters of fuzzy rule number 1 are p1, q1 and r1. The patterns (P) of training data are used to determine the parameters by minimizing the square error (E) between ANFIS output (fpA) and training output (fpT).
When the consequent parameters are solved, the premise parameters are fixed. Then, the ANFIS output is only a function of consequent parameters. The problem can be rearranged as follows. Xp is a vector of training inputs in a pattern p. Wipis a weight of rule i when feed an input pattern p.

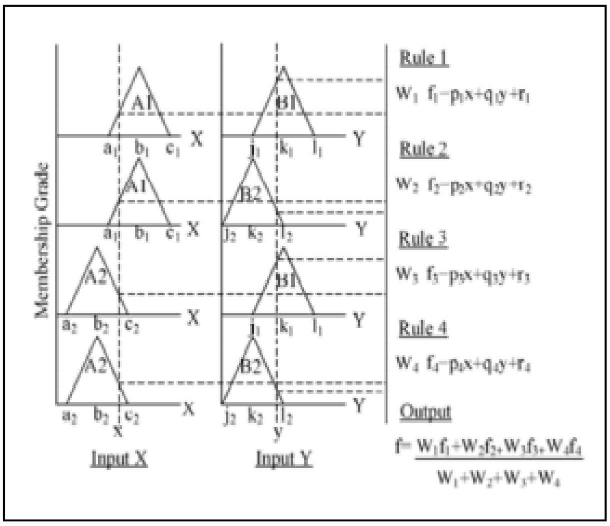


Fig 3: ANFIS algorithm

ANFIS training can use alternative algorithms to reduce the error of the training. A combination of the gradient descent algorithm and a least squares algorithm is used for an effective search for the optimal parameters. The main benefit of such a hybrid approach is that it converges much faster, since it reduces the search space dimensions of the back propagation method used in neural networks [13].

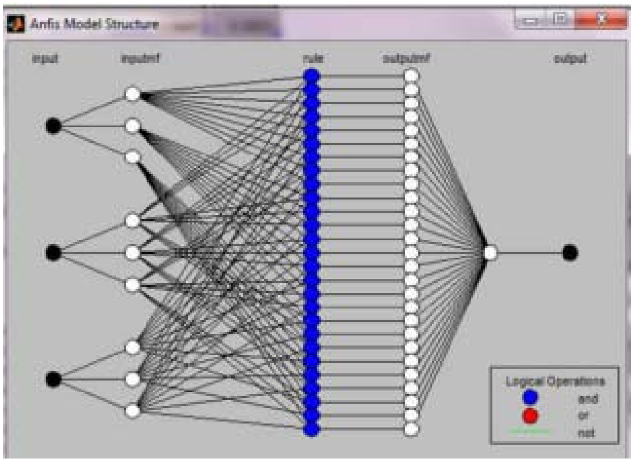


Fig 4: proposed ANFIS structure

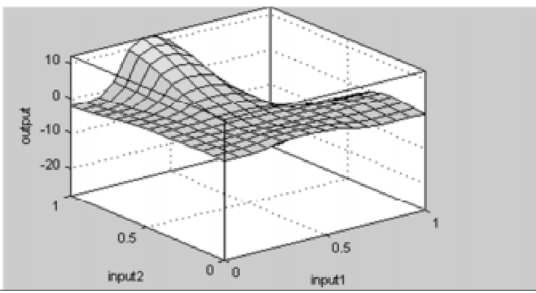
In the medical context, fuzzy approaches have been used in many areas, including in the prediction of patients' survival rate [11], [12] and for relapse probability. ANFIS is very stable. The results remain almost the same in subsequent runs with the same input. On the other hand, we tested standard neural networks that proved to be quiet unstable. We tested a feed-forward multi-layer perceptron trained by the back propagation algorithm.

2. Results
"Actual" row is the actual yield realized at training data, while the other row shows the overall yield estimate. From the result obtained, we can say that the prediction gives a 88% level of accuracy which is considered satisfactory and more stable than other results obtained by MLP which was 82% level of accuracy. The graphs of prediction accuracy are given in Table 1.

Table 1

	ANFIS	ANN (MLP)
Learning epochs	3	1000
Training error (RMSE)	0.093	0.116
Testing error (RMSE)	0.089	0.118

Table 1. Accuracy results comparing with MLP



3. Conclusions
This effort showed that a neuro-fuzzy configuration can be used for tomato yield prediction for the region with acceptable results. In future we intend to make other experiments with the

same basic configuration. We will use different parameters as inputs and second test more different ANFIS configurations.

We believe that parameters such as the number of fuzzy sets, the type of membership functions as well as considering different parameters per input, should receive more experimental effort. Also a possible way is to use a genetic algorithm to select the optimal values.

The calculation of transfer capability by using ANFIS is suitable for the application which rapidly updates the value. Given the representation of fuzzy inference systems, in which knowledge is encoded as a set of explicit linguistic rules that can be easily understood by people without technical expertise, it is hoped that this will allow the incorporation.

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