DETERMINATION OF REFLECTANCE VALUES OF HYPERICUM'S LEAVES UNDER STRESS CONDITIONS USING ADAPTIVE NETWORK BASED FUZZY INFERENCE SYSTEM

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Abstract: The effects of water stress and salt levels on hypericum's leaves were examined on greenhouse-grown plants of *Hypericum perforatum* L. by spectral reflectance. Salt levels and irrigation levels were applied 0, 1, 2.5 and 4 deci Siemens per meter (dS/m), 80%, 100% and 120% respectively. Adaptive Network based Fuzzy Inference System (ANFIS) was performed to estimate the effects of water stress and salt levels on spectral reflectance. As a result of ANFIS, it was found that there was close relationship between actual and predicted reflectance values in *Hypericum perforatum* L. leaves. Performance of ANFIS was examined under different numbers of epoch and rules. On the other hand, RMSE, correlation and analysis time values were found as outputs. Correlation was 99%. The estimation of optimal ANFIS model was determined in 3*3*3 number of rules with 400 epochs.

Key words: *Reflectance, ANFIS, hypericum, salt, water stress*

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1. Introduction

Saint John's wort (*H. perforatum* L.) has been domesticated and produced in a large scale in field conditions of different production areas of the world. Most of the biological activities of the plants have been reported namely, photodynamic, antiviral, antiretroviral, antibacterial, antipsoriatic, antidepressant and antitumoral, inflammatory and antiangiogenic effects [1]. The bioactive constituents in the plants

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are naphthodianthrones, phloroglucinols, flavonoids, phenylpropanes, essential oils, amino acids, xanthones, tannins, procyanidins, and other water-soluble components [2]. Today, *H. perforatum* is the most popular medicinal plant used in the treatment of mild to moderate depression. As a result, the market for only *H. perforatum* has exceeded $210 million in the U.S.A and $570 million worldwide annually [3].

Salts come with the irrigation water and are accumulated and concentrated in the soil as water evaporates and are taken up by crops. The levels of salinity in the soil must be selected not to harm the crop growth. This is usually done by applying enough water to satisfy crop requirements and leach out salts from the root zone [4]. However, the implementation of this approach is limited by drainage and shallow water table problems, environmental concerns regarding the amount and composition of the drainage effluents, limited quantity and low quality of the water for agriculture as well as economic aspects [5]. Reflectance is a very important parameter and it shows us plant behavior under stress conditions.

Fuzzy inference systems (FISs) can properly describe the complex and non-linear phenomena with the precise rules. The rules are typically in if–then format with different matching degrees for a given operational situation [6]. Intelligent techniques like FIS and Artificial Neural Network have been used to solve the real-world problems in recent years. The combination of those two powerful approaches has resulted in the emergence of Adaptive Neuro-Fuzzy Inference System (ANFIS) [7].

The most significant advantage of using ANFIS is that all its parameters can be trained like a Neural Network within the structure of a Fuzzy Logic system [8].

ANFIS has many applications in many areas, such as function approximation, intelligent control, time series prediction, and agricultural information [9, 10, 11]. In ANFIS, it has generated a large number of rules for the system, but not all the rules are being used. This is one of the advantages of ANFIS where the best rules from the system will be extracted.

2. Material and Methods

2.1 Plant Material

Seeds were obtained from Ondokuz Mayis University, Bafra Vocational School in Turkey. They were germinated under a 16 h light: 8 h dark cycle. Newly emerged seedlings were transferred to pots, 26 cm in diameter, filled out with a peat, pearlite and soil (1+1+1) mixture. They were watered daily until reached maturity. After maturation, the pots were moved to greenhouse conditions.

2.2 Salt stress and water deficiency experiments

City water supply with electrical conductivity (ECi: 0.4 dS/m) was used as irrigation water during experiment. The three different salts NaCl, $CaCl_2$ and $MgCl_2$ at their doses of 0.4 (control, S0), 1 (S1), 2.5 (S2), 4 (S3) and 8 (S4) dS/m were used as salt stress experiments. The doses were selected from the previous publications [12, 13].

For water deficiency experiments, firstly control pots were irrigated with city water supply fully and left to leak. Then the amount of irrigation water not leaked but hold by pots was determined as the required water (W). Thus, a total of 3 water amounts W1, W2 and W3 (80, 100 and 120 % of required water, respectively) were used. The experimental design was a factorial experiment in completely randomized plan with 3 replications. Thus 45 pots were used. The experimental factors were combined as the following and applied in 18 times with 2–3 days intervals.

2.3 Reflectance Measurements

The reflectance measurements between 325 – 1075 nm were made by means of a spectroradiometer (model Field Spec Pro FR, ASD, Boulder, USA). The device was placed at height of 120 cm from soil surface with a tripod. Three spectral measurements were made for each pot.

2.4 Data analyses

All experiments were conducted using completely randomized designs that included ten treatments with three replications. Adaptive Neuro-Fuzzy Infrence System was performed by MATLAB software Matlab ® R2012a (7.14.0.739) 32-bit (win32).

2.5 Anfis

Adaptive Neuro-Fuzzy Infrence System (ANFIS) technique was presented by J. S. Jang [14]. The number of membership functions must be equal to the number of rules. To present the ANFIS architecture, a common rule set with two fuzzy if-then rules based on a first order Sugeno model are considered:

Rule 1: If x is $A1$ and y is $B1$, then $f1 = p1x + q1y + r1$

Rule 2: If x is $A2$ and y is $B2$ then $f2 = p2x + q2y + r2$ where:

x and y are the inputs, Ai and Bi are the fuzzy sets, fi are the outputs within the fuzzy region specified by the fuzzy rule and p_i, q_i, r_i are the design parameters that are determined during the training process. ANFIS architecture is as shown (Fig. 1) [15].

ANFIS has a five-layer architecture as described below [14]:

Layer 1: Every node i in this layer is an adaptive node with a node function.

$O_{1,i} = \mu_{A_i}(x)$, for $i = 1, 2$, or

$O_{1,i} = \mu_{B_{i-2}}(y)$, for $i = 3, 4$,

where x, y is the input to node i and A_i, B_i is a linguistic label (such as "small" or "large") associated with this node. In other words, $O_{1,i}$; is the membership function of A_i, and it specifies the degree to which the given x satisfies the quantifier A_i. For example, if the gaussian membership function is employed $\mu_{A_i}(x)$, given by

$$\mu_{A_i}(x) = \exp\left[-\left(\frac{x - b_i}{a_i}\right)^2\right]$$

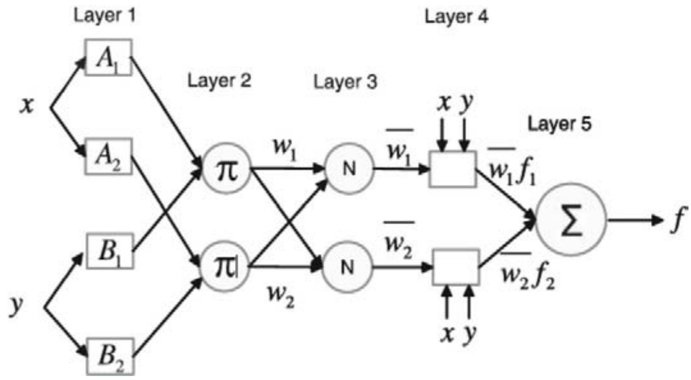

Fig. 1 *ANFIS architecture.*

where $\{a_i, b_i\}$ is the parameter set of the membership function. This parameters are referred to as premise parameters.

Layer 2: Every node in this layer is a fixed node labeled Π. This layer involves fuzzy operators; it uses the AND operator to fuzzify the inputs. The output of this layer can be represented as:

$$O_{2,i} = w_i = \mu_{A_i}(x) * \mu_{B_i}(y), \qquad i = 1, 2$$

Layer 3: Every node in this layer is a fixed node labeled N .The ith node calculates the ratio of the i-th rule's firing strength to the sum of all rule's firing strengths:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i \qquad i = 1, 2$$

where $\bar{w}_i$ is an outputs of this layer which are called normalized firing strengths.

Layer 4: Every node i in this layer is an adaptive node. The output of each node is simply the product of the normalized firing strength and a first order polynomial.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \qquad i = 1, 2$$

where $\{p_i, q_i, r_i\}$ are the consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled $\sum$. This node computes the overall output as the summation of all incoming signals.

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_1}, \qquad i = 1, 2$$

ANFIS is used to hybrid learning algorithm which integrates Gradient Descent and Least Squares Estimation algorithm. The hybrid algorithm is composed of a forward pass and a backward pass. Tab. I shows that two passes in the hybrid learning procedure for ANFIS.

Parameters	Forward Pass	Backward pass
Premise	Fixed	Gradient Descent
Consequent	Least-squares estimator	Fixed

Tab. I *Hybrid learning algorithm for ANFIS.*

3. Result and Discussion

In this study, reflectance was estimated as output parameter using wavelength, salt stress, and water deficiency as input parameters. The best estimation data set was determined by analyzing the statistical parameters for testing and training data set. The data set consist of 9012 samples. Samples of 67% (6000) was used for training and 33% (3012) for testing. Each sample was randomly chosen for training and testing for ANFIS. Randperm function was used by MATLAB.

Training and testing data set randomly chosen have got the same result. Reflectance has got normal distribution and the value changes 0.0-1.0 (training data distribution: 0.4853 ± 0.3055 and test data distribution: 0.4835 ± 0.3060). This result shows us that this network is reliable. The results of these tests indicate that the most important factors to achieve the adequate performance are usually the training data sample and the number of membership functions. The results of the ANFIS models demonstrate that ANFIS can be successfully applied to find reflectance prediction according to the salt, water stress and wavelength. The contribution of this paper is to focus on the detailed reflectance estimation. These results are based on the analysis of a number of inputs; the research confirms that the reflectance estimation is functional. One of the key challenges in reflectance estimation is to find expensive devices and time consuming. In this study, the proposed model is estimated with high accuracy and reliability reflectance.

The data set was divided into two separate parts: the training and the testing. The best-fit ANFIS model setting was selected based on a comparison of RMSE values, correlation and elapsed time for different epoch numbers. This model setting was composed for the number of membership functions assigned to each ANFIS structure. Over fitting, numbers of membership functions, training options (data samples, epoch number, elapsed time) were taken into consideration in relation to ANFIS system training. Features of the computer were Windows Vista™ Business, Intel® Core™ 2 CPU, 2.4 GHz, 2 GB RAM ve Matlab R2012a (7.14.0.739) 32-bit (win32).

The required number of membership functions was determined through trials, and based on RMSE and correlation. It indicated that ANFIS model was very sensitive to number of membership functions. Performace values of ANFIS were evaluated to different number of fuzzy rules for the three input sets (Tab. II). The input paremeters were water amounts (WA), salt (S), weavelength (WL) and output paremater was reflectance for the ANFIS.

RMSE and correlation played important roles in determining ANFIS model which were consisted different number of fuzzy rules. The lowest and the highest RMSE were 0.0209 and 0.0966 for training, 0.0231 and 0.0979 for testing. Correlation was 95% and this value showed that the ANFIS model got high accuracy.

Number of Fuzzy Rules	Number of linear parameters	Number of nonlinear parameters	Epoch	Elapsed Time (sn)	RMSE Train	RMSE Test	Correlation Train	Correlation Test
2*2*2	32	12	100	17	0.0966	0.0979	0.9486	0.9474
			200	32	0.0941	0.0951	0.9514	0.9504
			300	49	0.0549	0.0569	0.9837	0.9825
			400	63	0.0516	0.0536	0.9856	0.9845
			500	79	0.0514	0.0534	0.9857	0.9847
3*3*3	108	18	100	127	0.0876	0.0901	0.9580	0.9557
			200	252	0.0833	0.0858	0.9621	0.9599
			300	373	0.0725	0.0749	0.9714	0.9696
			400	500	0.0257	0.0273	0.9964	0.9960
			500	621	0.0244	0.0260	0.9968	0.9964
4*4*4	256	24	100	672	0.0472	0.0494	0.9880	0.9869
			200	1293	0.0337	0.0359	0.9939	0.9931
			300	2014	0.0259	0.0280	0.9964	0.9958
			400	2591	0.0242	0.0262	0.9969	0.9963
			500	3344	0.0234	0.0254	0.9971	0.9966
5*5*5	500	30	100	3154	0.0432	0.0458	0.9900	0.9887
			200	6365	0.0346	0.0372	0.9936	0.9926
			300	9591	0.0212	0.0234	0.9976	0.9971
			400	12678	0.0209	0.0231	0.9977	0.9971
			500	16047	0.0209	0.0231	0.9977	0.9971

Tab. II *According to different number of rules ans eopch to ANFIS performance.*

According to number of rules and epoch training time, the elapsed time for training increased. The system must be modelled with maximum correlation, minimum training time and minimum RMSE. Increasing the number of membership functions per input does not necessarily increase model performance, but usually leads to model overfitting. The RMSE and correlation values were used to determine the best number of fuzzy rules and epoch number in order to select the best-fit model. The best ANFIS model was chosen according to 3*3*3 number of rules with 400 epoch and correlation 99% (Tab. II).

The network produced by the values of ANFIS were very similar to actual reflectance (Fig. 2).

The ANFIS model with the smallest RMSE after one epoch of training, got a greater potential of achieving a lower RMSE when given more epochs of training. Fig. 3 shows the error curves for 500 epochs of training and testing. The training and testing errors decreased from 100 to 400 epoches after decreasing initially reaches a plateau. We used the test data set RMSE and correlation value as a true measure of the model's performance.

It has been aimed that the correlation should be over 99%, RMSE and calculating duration should be relatively lower. The highest point of the values obtained was at 3*3*3 number of rules and 400 epoch. Normalization was made in itself to compare the performance data accurately. It was formulized as max((Normalize_Correlation-Normalize_RMSE) / Normalize_Elapsedtime). The best model occured when the test error was minimal. RMSE and 400 epoch were the important point of this research. When the epoch number increased, error didn't decrease.

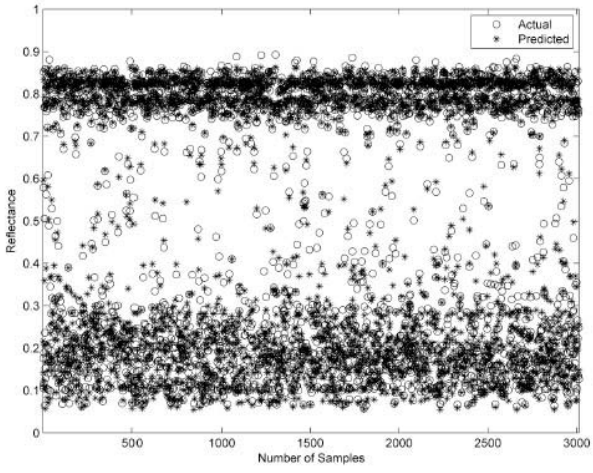

Fig. 2 *Relationship between actual and predicted reflectances (Number of Fuzzy Rules: 3*3*3, Epoch: 400).*

The same result can also be seen in 4*4*4 and 5*5*5 rules (Fig. 3 and Fig. 4). When we compare the actual data to train and test data, the network produced data with high accuracy. Training R^2 was 0.9964 for training and R^2 was 0.9960 for testing (Fig. 5).

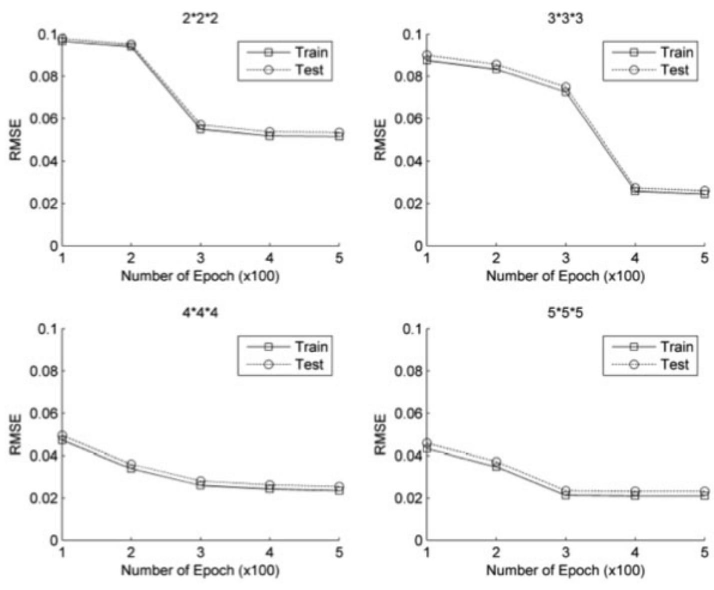

Fig. 3 *RMSE values for the different numbers of fuzzy rules of ANFIS.*

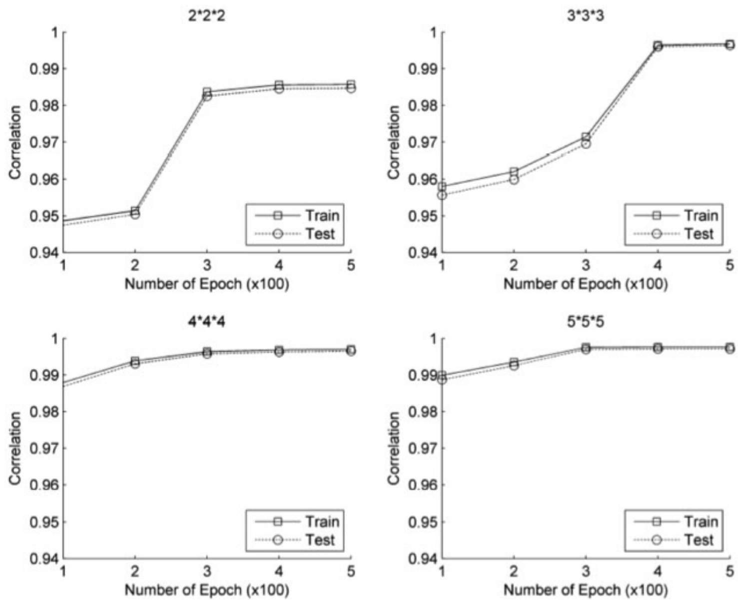

Fig. 4 *Correlation values for the different numbers of fuzzy rules of ANFIS.*

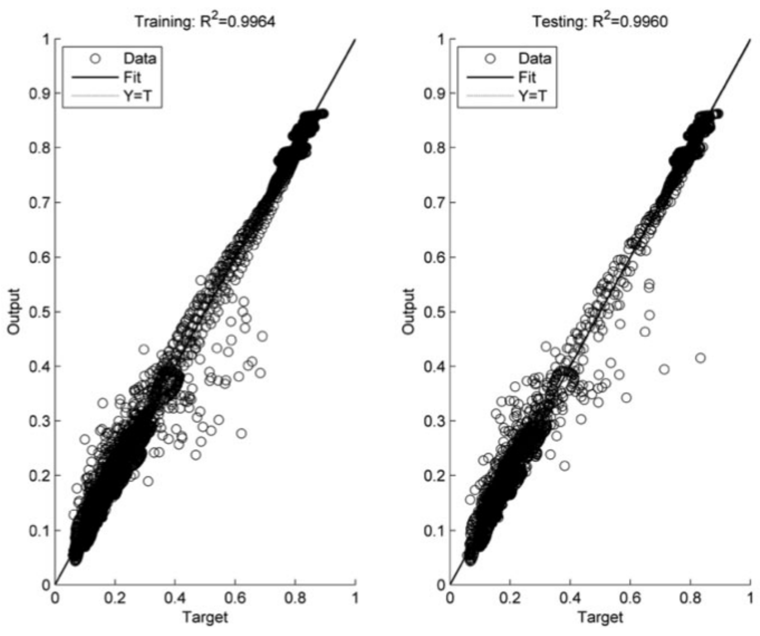

Fig. 5 *The linear regression of targets relative to outputs.*

4. Conclusion

This paper introduced the Adaptive Neuro-Fuzzy Inference System as a reasoning engine to deliver reflectance estimation for precision agriculture applications. The performance of ANFIS was evaluated using standard error measurements which revealed the optimal setting necessary for better predictability and correlations, which showed relationship between actual and predicted reflectances. Future research will revise the rules, inputs, number and type of membership functions, the epoch numbers used, and training sample to further refine the ANFIS model.

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