International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161

Available at http://inpressco.com/category/ijcet

Research Article

Performances of Multi-Adaptive NeuroFuzzy Inference System and Artificial Neural Network Models for Dielectric Properties of Oil Palm Fruitlets

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Accepted 20 June 2015, Available online 28 June 2015, **Vol.5, No.3 (June 2015)**

Abstract

Extraction of the dielectric properties of materials through open ended coaxial probe is a widely accepted microwave sensing technique and the prospect of application of soft computing techniques in this area is gaining significant attention. This paper therefore compares the performances of Multi-Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) models for the complex permittivity of oil palm fruitlets which were obtained from laboratory microwave measurements in combination with the rational function model. The Multi-ANFIS consists of two ANFIS models which were designed, optimized and trained for the dielectric constant and the dielectric loss factor of the fruitlets, while the ANN was designed with two outputs to achieve the same aim from the same set of input data. The results show that while both soft computing techniques performed satisfactorily in modeling the dielectric properties of the samples under test, the unique ability of ANFIS to modify its human-friendly rules together with its efficiency even with reduced training data make it a readily preferable choice.

***Keywords**: ANFIS, Artificial Neural Network, dielectric constant, characterization, oil palm fruitlets.*

1. Introduction

Identification and modeling of system parameters from observed data is central to the quest for better understanding and analysis of complex systems (Worden *et al*., 2007). For the purpose of sensing and characterization of materials through the information offered by their complex permittivities, researchers are gradually switching interest from traditional system identification methods which involve the complete *priori* knowledge of the system detailing the explicit mathematical relationships between the input and output variables (Jiang *et al*., 2012) to several modern soft computing techniques (Faridah *et al*., 2011; Hasan & Peterson, 2011). This is due to the increasing concern of speed, noise filtration, throughput time, processing resources, and the growing complexities of modern day processes (Lahmiri, 2011).

Even though these techniques are at most grey models in the sense that the mathematical relationships between variables cannot be explicitly reproduced, they yet remain favorites for modeling complex nonlinear processes. This is mostly due to their ability to learn input-output patterns and map them with great accuracy - typical of Artificial Neural Networks (ANNs), the capability of Fuzzy Systems (ANFIS and Fuzzy logic) to generate rules and parameters using human-friendly linguistic variables and logic which spans over the range of complete inclusion and absolute exclusion, and the possibility of inculcating biological principles of reproduction, mutation and crossover into computing using Genetic Algorithm (GA) (Silva *et al*., 2013).

These techniques have enjoyed a wide range of applications in different Engineering fields over the last decade and in this work, ANFIS and ANN have been applied for modeling the dielectric properties of oil palm fruitlets at 2-4GHz in effort to understand the response of the fruitlets to electromagnetic energy and for sensing and characterization purposes. The theoretical basis for the extraction of the dielectric properties of the samples is first described, the basic structures of ANN and ANFIS are described next, details of the models are presented and their performances evaluated.

2. Theoretical Background

A. Extraction of Dielectric Properties

Accurate data on the dielectric properties of oil palm fruitlets is an essential information in the oil palm

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industry, this is particularly relevant in the aspect of sensing, grading, evaluation and quality control. Microwave techniques have served as a collectively helpful approach in this regard because of their desirable advantage of being useful for nondestructive sensing. To obtain this information, several microwave techniques could be employed including Open-Ended Coaxial Probe (OCP) technique (Blackham & Pollard, 1997; Bobowski, 2012; Castro-Giraldez *et al.,* 2010; Shull, 2001), Free-space techniques (Oral & Ortega, 2006) and Resonant Cavity/Transmission line techniques (Bartley & Begley). For the OCP technique, microwave energy from a Vector Network Analyzer (VNA) is directed onto the samples through open ended coaxial probes terminated by coaxial sensors, the reflection coefficient observed at the sample interface as a result of a mismatch of impedance values at the interface is measured. These values are then fitted into appropriate models to extract the dielectric properties of the samples under test (Bobowski, 2012; Komarov & Wang, 2012).

The permittivity of the samples under test could be extracted from the expression of the normalized aperture admittance Y of a coaxial probe (eq. (1)) (Anderson & Stuchly, 1994).

$$Y = \frac{\sum_{n=1}^{4}\sum_{p=1}^{8}\alpha_{np}(\sqrt{\varepsilon_r})^{p}(sa)^{n}}{1+\sum_{m=1}^{4}\sum_{q=1}^{8}\beta_{mq}(\sqrt{\varepsilon_r})^{q}(sa)^{m}} \tag{1}$$

where α_{np} and β_{mq} are the coefficients of the model at program points np and mq respectively which are obtained by calibrating and measuring with samples of known dielectric properties, a is the inner radius of the coaxial line, ε_r is the permittivity and s is the complex microwave frequency in use. Equation 1 then results in a series of complex equation in ε_r which can be solved to obtain the permittivity of the material under test.

B. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Since the introduction of Fuzzy Logic (Zadeh, 1965), it has served as the foundation upon which several improvements have been made. Adaptive Neuro-Fuzzy Inference System is one of such which combines the learning capacity of feed forward neural networks with fuzzy logic inference system. These properties have made ANFIS attractive to researchers in modeling different problems. Examples of these applications include classification of Electroencephalogram (EEG) signals, modeling of compressive strength of lightweight geopolymers (Nazari & Khalaj, 2012), vehicle queue management (Mucsi *et al.*, 2011) and calculation of tip speed ratio in turbines (Ata & Kocyigit, 2010). Apart from the input layer, the structure of a typical Sugeno-type ANFIS is made up of a number of nodes segmented into five different layers; each node in different layers performs different function (Figure 1).

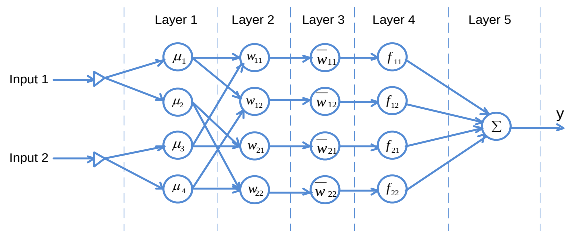


Figure 1: Basic structure of an ANFIS

ANFIS contains a rule base that is populated by a number of IF-THEN rules that describe the system being modeled. For example, for a two-input one-output system with inputs x_1 and x_2 and output y, the system rule could be written as:

Rule 1: $If\ x_1$ is A_1 and x_2 is B_1;
THEN $y_1 = \alpha_1 x_1 + \beta_1 x_2 + c_1$;
Rule 2: $If\ x_1$ is A_2 and x_2 is B_2;
THEN $y_2 = \alpha_2 x_1 + \beta_2 x_2 + c_2$;

where $A_n, B_n, \alpha_n, \beta_n$ and c_n are the coefficients which define the consequent and antecedent parts of the rule.

-Layer 1: Nodes in this layer perform the fuzzification function. This is the layer in which the membership functions μ_n and their associated parameters are represented. These membership function parameters are tuned by the training algorithm to obtain the values which most closely map the input-output pattern of the system.

-Layer 2: This layer estimates the strength of the rule by performing multiplication operation. The nodes in this layer serve as AND operators on the linguistic values of the antecedent portion of the rules.

-Layer 3: Nodes in this layer perform the normalization function where the firing strength of each rule is divided by the sum of the firing strengths of all the rules. This step is essential in order to avoid the possible loss of information from individual rule strengths that are either too low or too high.

-Layer 4: This layer is the adaptive layer whose nodes apply a combination of backpropagation algorithm and least squares method to train the membership function parameters of the Fuzzy Inference System (FIS) to map the given training pattern.

-Layer 5: This layer performs the summation function for all the outputs of layer 4 and serves as the overall output of the system. It computes the sum of the consequent parts of the rules.

Basically, the input patterns are applied at the input of the ANFIS and the system computes the output and errors based on the initial parameters of the membership function. The process is repeated for other input patterns and the parameters of the membership functions are adapted until a combination that satisfactorily models the problem is achieved or the specified maximum number of epochs is attained.

C. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are massive interconnections of layered processing elements called neurons which essentially mimic the biological process of human learning and intelligence (Wu *et al.*, 2013). Over the last few decades, ANNs have enjoyed a wide range of applications across many fields mostly due to their ability to learn and recognize complex patterns. Structurally, most ANNs are made up of three types of layers: the input layer which accepts data for the network, a number of hidden layers which enable the network to map complex nonlinear patterns, and the output layer which represents the output of the entire network (*Neshat et a*l., 2011).

Each neuron in a layer is connected to other neurons in the next layer through associated weights (Figure 2). As the input signals x_n propagate through the network from the input to the output, the values of these weights w_n and bias b_n (if applied) are modified by the training algorithm as they are applied to the activation function f_{hn}. The performance of an ANN is therefore largely dependent on its architecture and the training algorithm employed.

A widely used iterative algorithm which has made huge success for different Engineering applications is the backpropagation algorithm or its variants. This algorithm basically involves the forward propagation of the input signals through the network to the output, the calculation of the errors (the observed difference between the output and the target), the propagation of these errors back through the network, and the eventual modification of the associated weights and biases accordingly.

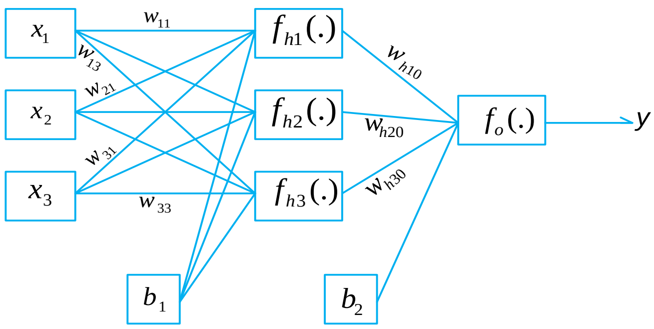


Figure 2: Structure of the ANN

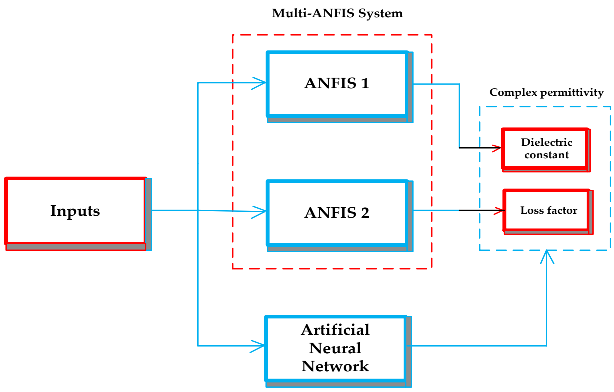


Figure 3: The framework for the Multi-ANFIS and ANN systems

Table 1 Details of each of the ANFIS component of the multi-ANFIS model

ANFIS Parameters	Description/ Value
Type of membership function	Gaussian membership function
Type of training algorithm	Backpropagation optimization
Minimum error tolerance	1×10^{-4}
Maximum epochs	1000
Number of input membership functions	9
Number of output membership functions	27
Number of rules	27
Number of membership function per input	3

Table 2 Details of the ANN model

ANN Parameters	Description/ Value
Type of transfer function (hidden layer)	Sigmoid
Type of transfer function (output layer)	Linear
Training algorithm	Levenberg Marquardt algorithm
Total number of neurons	24
Total number of weight elements	164
Maximum epochs	1000

Table 3 Neural Configurations and their corresponding performances for the ANN

Neural configurations			Regression values R			Performance Evaluation	
Input Layer	Hidden Layer	Output Layer	Training	Validation	Test	VAF (%)	MSE
3	20	2	0.9996	0.9995	0.9606	99.51	0.1257
3	12	2	0.9958	0.9877	0.9862	90.04	1.1371
3	4	2	0.9301	0.9116	0.8994	83.85	1.3211

3. Method

The data of dielectric properties of the oil palm fruitlets used in training the ANFIS and ANN was obtained from the laboratory permittivity measurements on clean oil palm fruitlets using the open-ended coaxial probe nondestructive microwave technique within the frequency range of 2-4GHz using eq. (1). This equation resulted into a complex set of equations in ε_r which was solved using complex root finding technique to obtain the permittivity of the oil palm fruitlets.

The ANFIS model used is a Multiple Input Single Output (MISO) system; this means that there could only be one output produced from a combination of all the inputs. Therefore, a multi-ANFIS structure was designed which consists of two ANFIS; one for the dielectric constant and the other for the loss factor as shown in Figure 3.

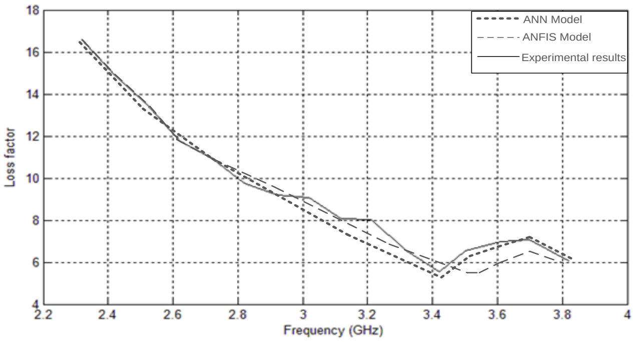
The three inputs of the system are the frequency (GHz), the angle of the reflection coefficient and the magnitude of the reflection coefficient, while the outputs are the dielectric constant and the loss factor. Different ANFIS and ANN architectures and training algorithms were optimized for the best set of configuration and parameters for adequately modeling the dielectric phenomenon. The parameters of the ANFIS are listed in table 1 while those of the ANN are listed in table 2.

4. Results and Discussion

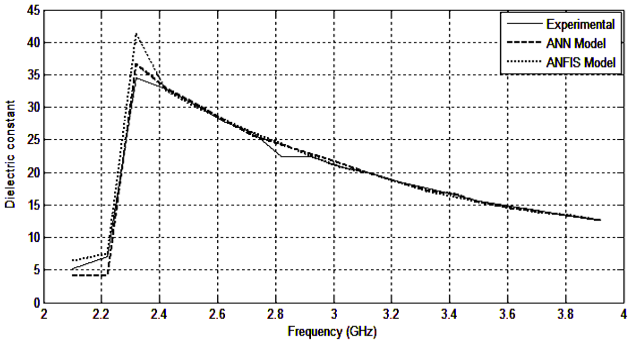
The dielectric constant and loss factor outputs of the multi-ANFIS system and ANN were compared with the measurement results from the open ended coaxial probe microwave sensor, and the performances are presented in Figure 4 (a) and (b). The results show that the outputs from both soft-computing models are quite in agreement with those from laboratory measurements. This consistency substantiates the suitability of the multi-ANFIS and the ANN models for measuring the dielectric properties of oil palm fruitlets within the frequency range of 2-4GHz. For the ANN in this work, table 3 shows the different regression coefficient *R* and Variance-Account-For (VAF) for some of the different neural configurations considered. The results of the optimization show that the 3-20-2 configuration yielded the best performance with a VAF value of 99.51.

However, comparison between the performances of the ANN and the multi-ANFIS shows that even though their performances were similar within the frequency range of 2.3GHz-2.85GHz, the multi-ANFIS performed slightly better than the ANN model within 2.90GHz - 3.45GHz. This behaviour is not unexpected since both techniques are based on the principle of neuro-adaptation wherein the connection weights are modified through repeated training in order to obtain the network configuration that most closely solves the problem at hand.

The development of the Artificial Neural Network and the multi-Adaptive Neurofuzzy Inference systems enables researchers, quality control personnel as well as policy making individuals to make informed decisions with respect to the quality of oil palm fruitlets. This becomes of particular importance when the expected production volume is in order of tonnes as the stakes are high; this necessitates critical fruitlet examination, characterization and accurate determination of oil contents of selected fruitlet samples.



(a)



(b)

Figure 4: The dielectric profile as modeled by the multi-ANFIS and ANN for (a) dielectric constant (b) loss factor

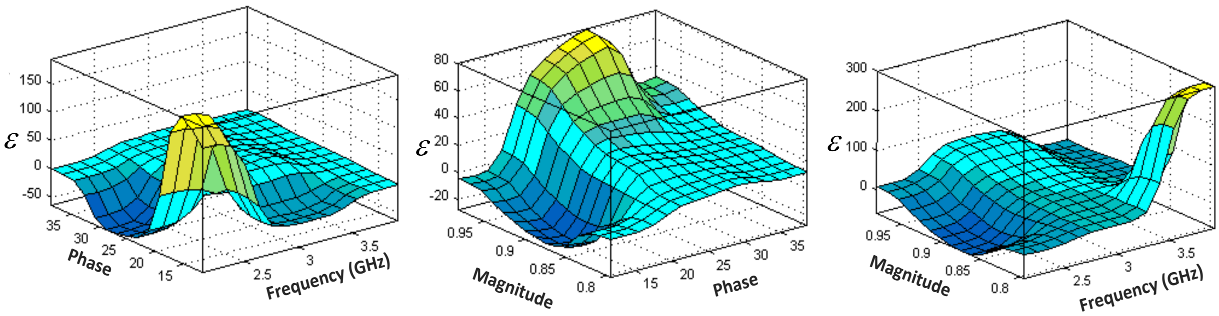


Figure 5: The response surface of the multi-ANFIS model

The dielectric constant response of the multi-ANFIS over the entire range of magnitude and phase of the reflection coefficient within 2-4GHz is illustrated in Figure 5. This shows the range of the output of the system when the rules are modified over the entire range of inputs. As seen in Figure 4, a comparison of the output of the network with the experimental data shows that the dielectric profile of the oil palm fruitlets was accurately modeled.

Conclusion

In this study, dielectric data obtained from laboratory microwave measurement was used in developing an ANN and a multi-ANFIS system suitable for rapid characterization of oil palm fruitlets. The results of the performance analysis show that both systems modeled the dielectric profile effectively. However, the multi-ANFIS performed slightly better than the ANN especially at higher frequencies. This work is a therefore further evidence of the capability of parallel computing techniques in adequately and intelligently sensing and grading organic substances provided the network architectures and parameters are carefully chosen. The quality the prediction of the ANN and ANFIS models are also directly linked to the accuracy of the training data set.

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