International Journal of Applied Science and Engineering
2014. 12, 1: 1-8

Multi-Adaptive Neuro-Fuzzy Inference System for Dielectric Properties of Oil Palm Fruitlets

Ojo O. Adedayo[a*], M. M. Isa[a], A. Che Soh[a], and Z. Abbas[b]

[a] *Department of Electrical and Electronic Engineering, Faculty of Engineering, University Putra Malaysia*
[b] *Department of Physics, Faculty of Science, University Putra Malaysia*

Abstract: Accurate dielectric models are required for proper sensing and characterization of materials especially for the purpose of quality control. In this work, a multi-Adaptive Neuro-Fuzzy Inference System (ANFIS) was designed to model the complex permittivity of the mesocarps of oil palm fruitlets within the frequency range of 2-4GHz. The system consists of two ANFIS models with same sets of inputs; one ANFIS model for the dielectric constant and the other for the loss factor. Training data were obtained from laboratory microwave measurements with the aid of Vector Network Analyzer (VNA) and used for the ANFIS model. The evaluation of the performance of the model confirms the suitability of the multi-ANFIS model for rapid and accurate determination of the dielectric properties of the fruitlets.

Keywords: ANFIS; dielectric properties; oil palm fruitlets; sensing.

1. Introduction

The knowledge of the intrinsic electrical properties of materials is very essential for the purpose of electromagnetic sensing and quality control. These properties which give experts insight into the phenomena of electromagnetic interaction with materials being characterized include the complex permittivity, the dielectric constant and the loss factor [1-3]. Over the years, many methods have been employed in order to obtain this information for oil palm for the purpose of characterization and quality grading in the oil palm industry. These methods range from mere physical inspection to weighing, destructive chemical and microwave techniques, and nondestructive microwave techniques [4, 5]. In all these methods, the main area of focus for improvement has been the speed of sensing, instrumentation and computational complexity, nondestructivity, cost, rigor of implementation, and suitability for in-situ measurement. These are the areas in which soft computing have proven to be very helpful.

Soft computing has found extensive applications in solving different problems in the engineering domain within the last few decades owing to their general ability to model complex systems with satisfactory accuracy and speed. Artificial Neural Network (ANN) [6-8], Fuzzy Inference System (FIS) [9-12], swamp computing and Genetic Algorithm (GA) [13-17] are a few intelligent approaches that have enjoyed successful attention and applications in wide areas. In this same category, Adaptive Neuro-Fuzzy Inference System (ANFIS) has come into limelight as an artificial intelligence method but with an advantage of blending the concept of knowledge

* Corresponding author; e-mail: adedayoojoy@gmail.com

Received 8 May 2013
Revised 20 August 2013
Accepted 8 October 2013

based fuzzy programming with data based Artificial Neural Network (ANN) pattern learning techniques [18-22], this makes ANFIS more attractive than any of its constituent soft computing techniques because the rules are listed in more human friendly languages which helps in troubleshooting and design. In the area of dielectric spectroscopy and characterization for example, ANFIS models have been employed successfully for the complex task of determining the dielectric properties of polyesters under numerous conditions, the analysis of the performance of the system showed that this approach is capable of good generalization and attaining an impressive precision level for problems in this domain [23].

In this work, a multi-ANFIS has been employed for characterizing oil palm fruitlets using their dielectric properties obtained from laboratory microwave measurements. The structure of a basic ANFIS is first described, the network framework employed is described next, and the method, results and discussion are also presented.

1.1. Adaptive neuro-fuzzy inference system

Basically, an ANFIS is a trained fuzzy inference system implementing the Sugeno model [23]. It is made up of the membership layer, the fuzzification layer, the normalization layer, the deffuzification layer and the fifth layer, the output layer. In each of these different layers (Figure 1), there are processing elements called nodes and these nodes perform different functions depending on the layers to which they belong.

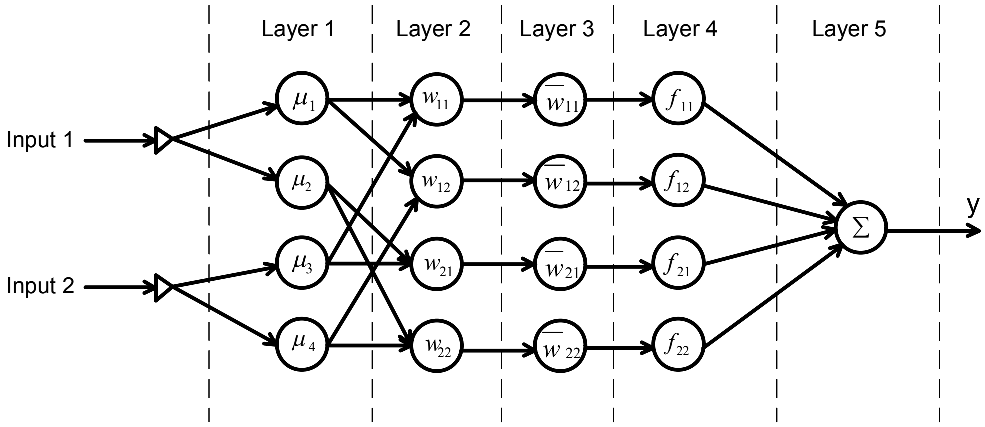

Figure 1. The basic structure of an ANFIS

An ANFIS could be trained to accurately map a certain input matrix into the target output pattern; this is the quality that has particularly found application in this work. In the membership layer, the membership scales of the system inputs are generated depending on the membership function stipulated. These membership functions have certain parameters which define their shape and these parameters are adapted during training to obtain the optimal values of parameters that most closely model the problem domain [21]. The fuzzification layer then determines the strengths of the rules (if … then rules) from their products.

$$\overline{w}_{ij} f_i(x_i) = \overline{w}_{ij}\left[\alpha_{j0} + \sum_{k=1}^{n} \alpha_{jk} x_{ik}\right] \tag{1}$$

$$g(s, x_i) = \sum_{j=1}^{r}\left[w_{ij} f_j(x_i)\right] \tag{2}$$

At the normalization layer, the strength of each rule is normalized with (divided by) the summation of all the individual rule strengths. 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. The output of the node at the defuzzification layer is obtained by combining the normalized strengths of each rule (equation 1), where $\overline{w}_{ij}$ is the normalized form of the strength $\overline{w}_{ij}$ of rule ij, x_i is the input i and α_{jk} is the *k*-th coefficient of the polynomial of the *j*-th rule. Finally, the total network output $g(s, x_i)$ is obtained as the sum of the outputs of the individual nodes from the defuzzification layer (equation 2).

2. Materials and methods

The training data for the dielectric constant ε' and loss factor ε'' used for the adaptive inference system was obtained from laboratory microwave measurements. Connected at one end to a microwave sensor, and the other end to a Vector Network Analyzer (VNA), a coaxial line delivers microwave to oil palm fruitlets within the frequency of 2-4GHz causing reflection at the fruitlet-sensor interface and the reflection coefficients Γ were recorded.

The complex permittivities of the fruitlets were extracted from the measured reflection coefficients by optimization of the equations obtained from equations 3 and 4 using MATLAB.

$$Y_L = j\frac{2\omega\varepsilon^*}{\left[ln(\frac{b}{a})\right]^2}\left[I_1 - \frac{k^2 I_3}{2}\right] \tag{3}$$

Where Y_L is the load admittance, ω is the angular frequency, ε^* is the complex permittivity of the sample, *a* and *b* are the radius of the inner and outer conductors of the coaxial line respectively, *k* is the wave number at the operating frequency, I_1 and I_3 are constants specific to the dimensions of the coaxial line in use and $\widetilde{Y}_L$ is the normalized load admittance for a 50Ω system.

$$\widetilde{Y}_L = (\frac{1-\Gamma}{1+\Gamma}) \tag{4}$$

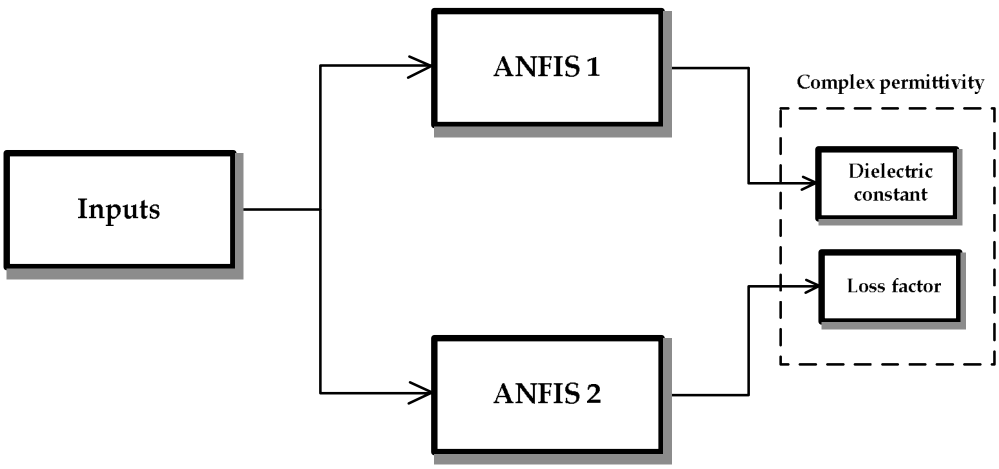

Figure 2. The model framework of the multi-ANFIS system

Two different ANFIS were designed and connected to represent the multi-ANFIS system as shown in Figure 2. The two ANFIS share the same set of training input data but different targets. ANFIS 1 has the dielectric constants of the oil palm fruitlets as targets while the loss factor was the target of ANFIS 2. The system was trained using the backpropagation optimization algorithm which trained the parameters of the membership functions to closely model the complex permittivity data, and the error surface was continuously examined to avoid overfitting. The training process was stopped whenever the minimum error tolerance of 1×10^{-4} or the maximum epoch of 1000 is reached.

The model structure consists of the frequency, the magnitude of the reflection coefficient and the angle of the reflection coefficient as the inputs, each input has three Gaussian membership functions whose shapes are defined by equation 5, where σ and *c* are the optimized membership function parameters.

$$f(x;\sigma,c)=e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{5}$$

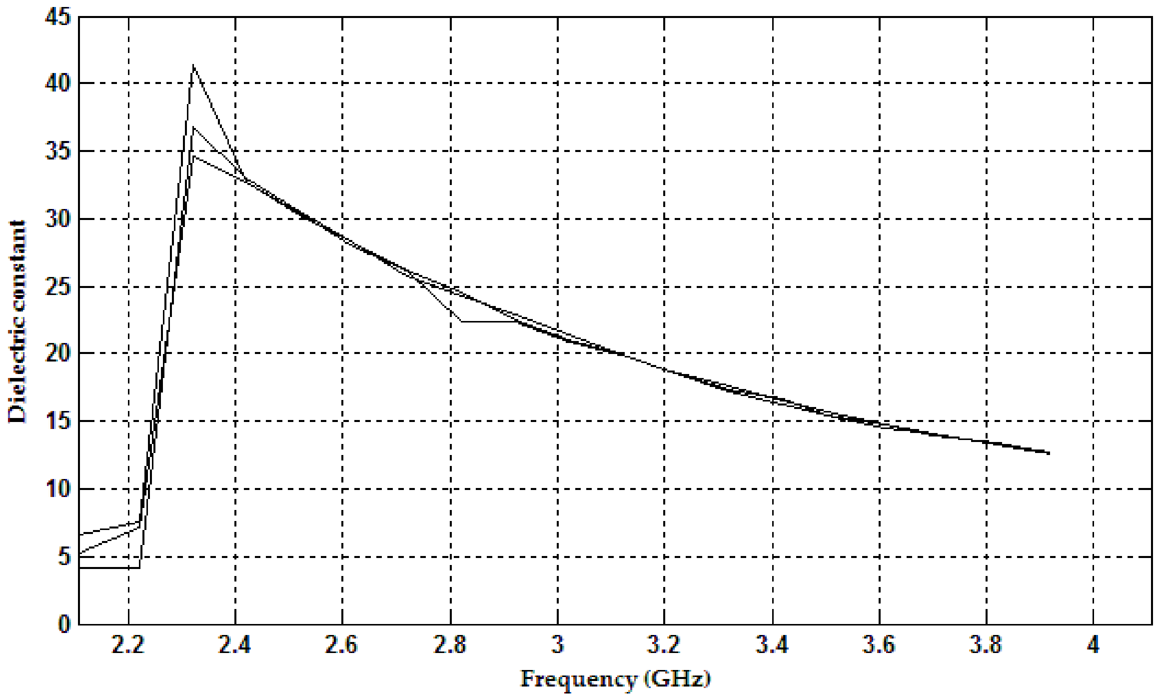

Figure 3. The experimental dielectric profile of the samples

As shown in Figure 4, there are 27 rules in the rule layer of ANFIS 1 and ANFIS 2, a representative of the rules is presented below:

If (magnitude is low) and (frequency is low) and (angle is negative) then (output is outmf1).
If (magnitude is low) and (frequency is high) and (angle is around_zero) then (output is outmf8).
If (magnitude is low) and (frequency is average) and (angle is positive) then (output is outmf6).
If (magnitude is high) and (frequency is high) and (angle is negative) then (output is outmf16).

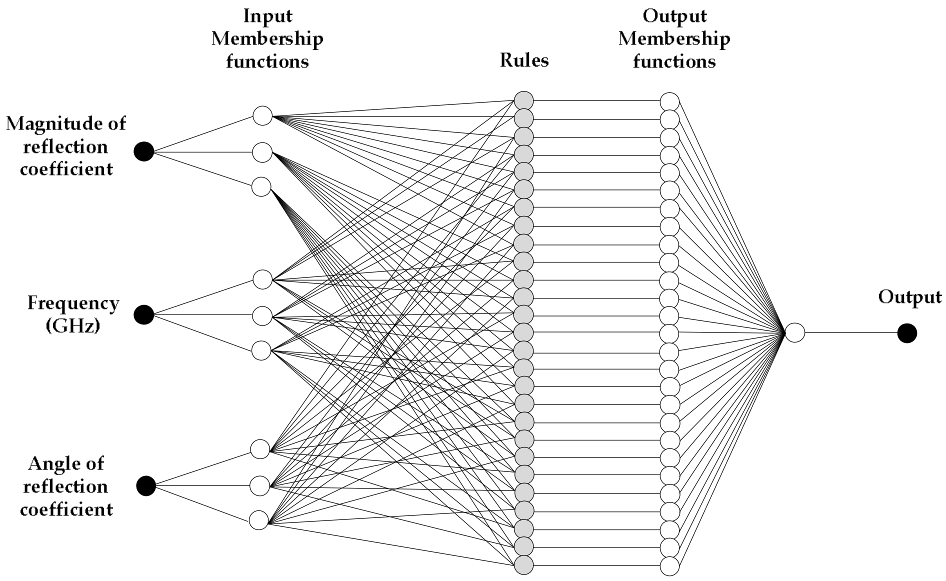

Figure 4. The model structure of each of the two ANFIS in the multi-ANFIS system

3. Results and discussion

Optimization of the Gaussian membership function parameters were achieved by repeated training of the two ANFIS models over 1000 epochs with the backpropagation algorithm. The plot of the actual values of the dielectric constants over three repetitions is presented in Figure 3. The graph shows that dielectric constants of the oil palm fruitlets peaked within the frequency range of 2.3-2.5GHz, even though it is a well established fact that the complex permittivity is a function of the frequency, this pattern may not be unconnected with the sensitivity of the coaxial sensor with respect to the reflection coefficients over that particular frequency range. This trend was also exhibited by ANFIS 1, which further elucidates the fact that an ANFIS model is only as good as the experimental results used in training it.

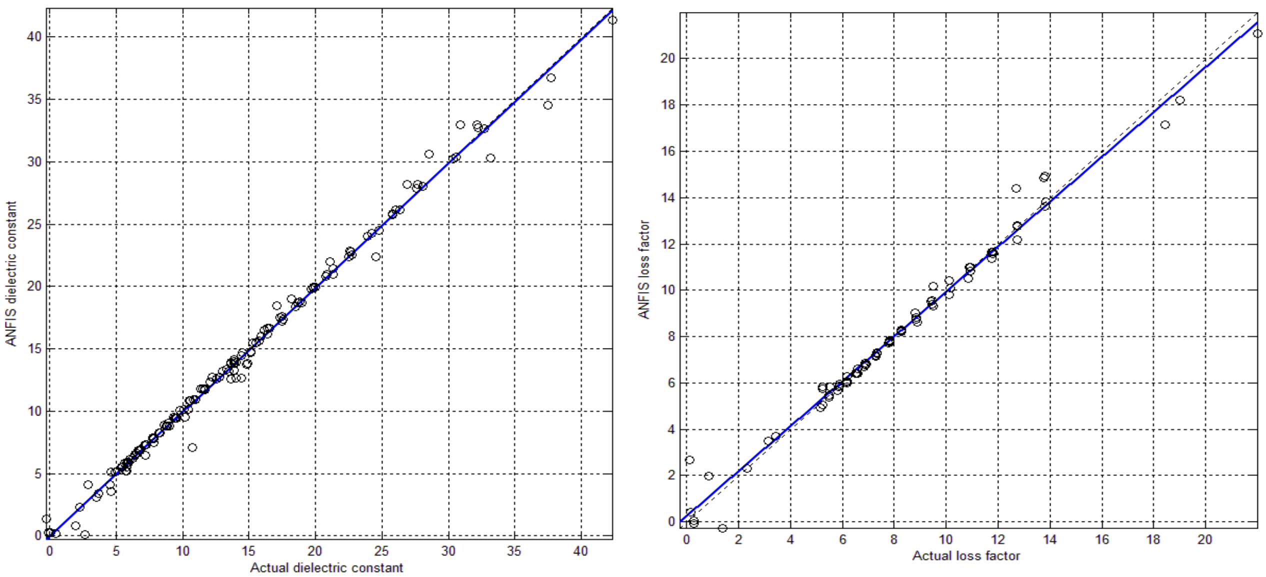

Figure 5. The outputs of both ANFIS compared with the actual loss factor and dielectric constants

Variance Account For (VAF) and Regression plots are the two performance indices employed for evaluating the model performance for this study. These are indices which show the degree of closeness of the outputs of the model to the target values. VAF can range between 0 and 100%, and R values can vary within 0 and 1, with the upper boundaries of both indices being the best performance indicators.

In comparison with the experimental values obtained for the complex permittivities of the fruitlets, the ANFIS 1 VAF values of 99.51% and 97.57% for the training and test dielectric constant outputs respectively and ANFIS 2 VAF values of 98.64% and 94.26% for the training and test loss factor respectively indicate that the system closely represents the dielectric constants and loss factors of the oil palm fruitlets over the frequency range considered. This claim is further highlighted by Figure 5 wherein the performance of the multi-ANFIS system is evaluated against the actual experimental values. The resulting values of the regression coefficients are presented in Table 1.

Table 1. VAFs and R-values for ANFIS 1 and ANFIS 2 for testing and training data

ANFIS Models	VAF values for training data (%)	R-values for training data	VAF values for testing data (%)	R-values for testing data
ANFIS 1	99.51	0.9961	97.57	0.9838
ANFIS 2	98.64	0.9606	94.26	0.9412

It should be noted that a crucial criteria necessary for the successful implementation of this multi-ANFIS system for oil palm characterization is the selection and tuning of the membership function, as well as the accuracy of the microwave complex permittivity extraction model. Generally, for an open-ended coaxial cable microwave technique, the load admittance model described in this work is sufficient.

4. Conclusions

The ability of ANFIS to produce accurate results for a significant range and combinations of input parameters was demonstrated in this work. The results of this work therefore show that the multi-ANFIS system closely models the complex permittivity of the oil palm fruitlets over the frequency range of 2-4GHz, and that this represents a fast, easy and accurate method of characterizing the fruitlets for research and industrial purposes.

References

[1] Trabelsi, S. and Nelson, S. O. 2006. Nondestructive sensing of bulk density and moisture content in shelled peanuts from microwave permittivity measurements. *Food Control*, 17(4): 304-311.

[2] Sosa-Morales, M. E., Valerio-Junco, L., López-Malo, A., and García, H. S. 2010. Dielectric properties of foods: reported data in the 21st century and their potential applications. *LWT-Food Science and Technology*, 43(8): 1169-1179.

[3] Bohleber, P., Wagner, N., and Eisen, O. 2012. Permittivity of ice at radio frequencies: part I. coaxial transmission line cell. *Cold Regions Science and Technology*, 82: 56-67.

[4] Van der Vossen, H. A. M. 1974. Towards more efficient selection for oil yield in the oil palm. *Centre for Agricultural Publishing and Documentation*, 57-58.

[5] You, K. Y., Abbas, Z., and Khalid, K. 2010. Application of microwave moisture sensor for determination of oil palm fruit ripeness. *Measurement Science Review*, 10(1): 7-14.
[6] Terzic, E., Nagarajah, R., and Alamgir, M. 2011. A neural network approach to fluid quantity measurement in dynamic environments. *Mechatronics*, 21(1): 145-155.
[7] Erzin, Y., Rao, B. H., Patel, A., Gumaste, S. D., and Singh, D. N. 2010. Artificial neural network models for predicting electrical resistivity of soils from their thermal resistivity. *International Journal of Thermal Sciences*, 49(1): 118-130.
[8] Neshat, N., Mahlooji, H., and Kazemi, A. 2011. An enhanced neural network model for predictive control of granule quality characteristics. *Scientia Iranica*, 18(3): 722-730.
[9] Brás, S., Gouveia, S., Ribeiro, L., Ferreira, D. A., Antunes, L. and Nunes, C. S. 2013. Research in veterinary science fuzzy logic model to describe anesthetic effect and muscular influence on EEG cerebral state index. *Research in Veterinary Science*, 94: 735-742.
[10] Franco-Lara, E. and Weuster-Botz, D. 2007. Application of fuzzy-logic models for metabolic control analysis. *Journal of Theoretical Biology*, 245(3): 391-9.
[11] Hashmi, K., Graham, I., Mills, B., and Hashmi, M. S. 2003. Adjustment approach for fuzzy logic model based selection of non-overlapping machining data in the turning operation. *Journal of Materials Processing Technology*, 142(1): 152-162.
[12] Krajnc, D., Mele, M., and Glavič, P. 2007. Fuzzy logic model for the performance benchmarking of sugar plants by considering best available techniques. *Resources, Conservation and Recycling*, 52(2): 314-330.
[13] Silva, R. P. M., Delbem, A. C. B., and Coury, D. V. 2013. Genetic algorithms applied to phasor estimation and frequency tracking in PMU development. *International Journal of Electrical Power & Energy Systems*, 44: 921-929.
[14] Daneshfar, F. and Bevrani, H. 2012. Multiobjective design of load frequency control using genetic algorithms. *International Journal of Electrical Power & Energy Systems*, 42: 257-263.
[15] Mitra, A., Kundu, D., and Agrawal, G. 2006. Frequency estimation of undamped exponential signals using genetic algorithms. *Computational Statistics & Data Analysis*, 51(3): 1965-1985.
[16] Xu, X. and Wang, S. 2007. Optimal simplified thermal models of building envelope based on frequency domain regression using genetic algorithm. *Energy and Buildings*, 39(5): 525-536.
[17] Vakil-Baghmisheh, M. T., Peimani, M., Sadeghi, M. H., and Ettefagh, M. M. 2008. Crack detection in beam-like structures using genetic algorithms. *Applied Soft Computing*, 8(2): 1150-1160.
[18] Naderloo, L., Alimardani, R., Omid, M., Sarmadian, F., Javadikia, P., Torabi, M. Y., and Alimardani, F. 2012. Application of ANFIS to predict crop yield based on different energy inputs. *Measurement*, 45(6): 1406-1413.
[19] Nazari, A. and Khalaj, G. 2012. "*Prediction Compressive Strength of Lightweight Geopolymers by ANFIS".* Ceramics International.
[20] Jiang, H. M., Kwong, C. K., Ip, W. H., and Wong, T. C. 2012. Modeling customer satisfaction for new product development using a PSO-based ANFIS approach. *Applied Soft Computing*, 12(2): 726-734.
[21] İnal, M. 2008. Determination of dielectric properties of insulator materials by means of ANFIS: a comparative study. *Journal of Materials Processing Technology*, 195(1-3): 34-43.
[22] Daldaban, F., Ustkoyuncu, N., and Guney, K. 2006. Phase inductance estimation for switched reluctance motor using adaptive neuro-fuzzy inference system. *Energy Conversion*

and Management, 47(5): 485-493.
[23] İnal, M. 2008. Determination of dielectric properties of insulator materials by means of ANFIS: a comparative study. *Journal of Materials Processing Technology*, 195(1-3): 34-43.