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A layer-sensitivity based artificial neural network for characterization of oil palm fruitlets

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ABSTRACT

This paper presents an intelligent means of addressing characterization and grading problems in the oil palm industry for the purpose of quality control. A Layer-Sensitivity Based Artificial Neural Network (LSB_ANN) which updates its layer weights based on sensitivity analysis was designed to predict the oil content and dielectric constant of mature oil palm fruitlets. The LSB_ANN was designed, optimized and trained with 604 data points obtained from laboratory microwave coaxial sensor measurements within 2-4 GHz. The performance evaluation of the model when tested with a separate set of data showed that the properties of the fruitlets were accurately modeled. To further investigate the generalization ability of the trained neural network, three other neural network training algorithms were deployed for the same dataset. A multi-criteria evaluation of the performances of the networks showed that the proposed LSB_ANN outperformed the other three in generalization accuracy, time and computing resources. The LSB_ANN therefore represents a handy tool for rapid and intelligent characterization of oil palm fruitlets for quality control and research purposes.

Keywords: Open-ended coaxial sensor, Sensitivity analysis, Artificial neural network, Training algorithms, Dielectric properties, Oil palm fruitlets.

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1. INTRODUCTION

The oil palm is the world's most common source of edible oil with an annual yield of 4.2 tonnes per hectare and global annual yield of 45 million tonnes (Ong et al., 2011). Apart from direct human consumption, oil palm has also found extensive use in other products including biodiesel, sugar and fibreboards (Ismail et al., 2011). Due to the rising stakes of massive palm oil production and in order to achieve optimum production yield, it is imperative to device a means to accurately and rapidly grade oil palm fruitlets before bunches are selected for major production. The major challenge with this step however is that the fruitlets are non-homogeneous in mesocarp; made up of oil, fibre and water. This heterogeneous nature coupled with the need for nondestructive sensing, suitability for insitu measurement, ease of setup, computing speed and efficiency makes the prospect of softcomputing and microwave sensing an appealing solution.

Artificial Neural Network (ANN) is a connection of processing elements which learns patterns by mimicking the natural human brain in adapting associated layer weights (Rodger, 2014; Erzin et al., 2010). ANN has been widely applied in many fields for pattern matching, modeling and classification over the last few decades just as much as other softcomputing techniques – Adaptive Neurofuzzy Inference System (ANFIS) (Negnevitsky, 2005), Fish Swarm Optimization (FSO), and Genetic Algorithm (Otkovic, 2013). ANN has the advantages of relatively fast convergence, ability to model complex nonlinear systems, and large data space generalization capacity. The two major areas for improvement however are training speed and avoidance of local minima convergence.

Several approaches have been taken to address this; the standard backpropagation algorithm, the linear least square methods and the widely reported second order training algorithms that include the Quasi-Newton (Ghaffari et al., 2006), Conjugate Gradient and Levenberg-Marquardt algorithms (Castillo and Guijarro-berdi, 2006).

In this work, an ANN which updates its layer weights based on analysis of its sensitivity to the inputs is proposed for characterizing oil palm fruitlets. Firstly, the theoretical basis of the analytic method for extracting the oil contents and dielectric properties from measured data is described, then the weight update procedure and structure of the LSB_ANN are elucidated and its performance evaluated.

2. MATERIALS AND METHODS

In this section, we describe the details of the procedure employed in the extraction of the oil contents of the oil palm fruitlets using microwave measuring techniques.

2.1 Data Measurement and Analytic Extraction of Oil Content and Dielectric Properties

Microwave energy within the frequency range of 2-4 GHz was directed onto faintly sliced fleshy mesocarp of clean samples of matured oil palm fruitlets through a carefully calibrated microwave open-ended coaxial sensor. The coaxial sensor was connected to a computer coupled Vector Network Analyzer (VNA). As a result of the impedance mismatch at the interface between the fruitlet and the sensor, a complex reflection coefficient Γ was observed. The observed reflection coefficients were then fitted into the normalized susceptance and conductance equations (Equations 1 and 2) (Blackham and Pollard, 1997; You et al., 2012) and the dielectric mixture model (Abbas et al., 2005) to obtain the actual complex permittivity and the oil content of the fruitlets.

where a and b are the inner and outer radius of the coaxial sensor respectively, J_0 is the Bessel function of order zero and Si is the sine integral. ε is the permittivity, k_0 is the wave number and K is a constant that is a function of the dimensions of the sensor and the dielectric material within the sensor.

2.2 The LSB_ANN Framework

For a particular neural network problem domain, the choice of cost function for finding optimal solution in the training algorithm is as important as the choice of the type of the entire training algorithm or neural network architecture. In addition to speed of convergence and minimal usage of processing resources, sensitivity weight update mechanism has been selected in this work to enhance the quantification of the system performance not only with respect to the targets but the input space as well.

Table 1. The boundaries of the input and output parameters of the ANN

	Parameter	Min	Max
Inputs	Frequency (GHz)	2.00	4.00
	Magnitude of Γ	0.54	0.9700
	Phase of Γ	-27	38.5
Outputs	Dielectric constant	8	45
	Oil content	22.5	54.98

The single-hidden-layer model framework (shown in Fig. 1) consists of the input layer, the normalization layer, the LSB_ANN and the output.

$$\frac{G}{Y_0} = K\int_0^{\frac{\pi}{2}} \frac{1}{\sin\theta}\left[J_0\left(k_0\sqrt{\varepsilon}b\sin\theta\right) - J_0\left(k_0\sqrt{\varepsilon}a\sin\theta\right)\right]^2 d\theta \tag{1}$$

and

$$\frac{B}{Y_0} = \frac{K}{\pi}\int_0^{\pi} 2\mathrm{Si}\left(k_0\sqrt{\varepsilon(a^2+b^2-2ab\cos\theta)}\right) - \mathrm{Si}\left(2k_0\sqrt{\varepsilon}a\sin\left(\frac{\theta}{2}\right)\right) - \mathrm{Si}\left(2k_0\sqrt{\varepsilon}b\sin\left(\frac{\theta}{2}\right)\right) d\theta) \tag{2}$$

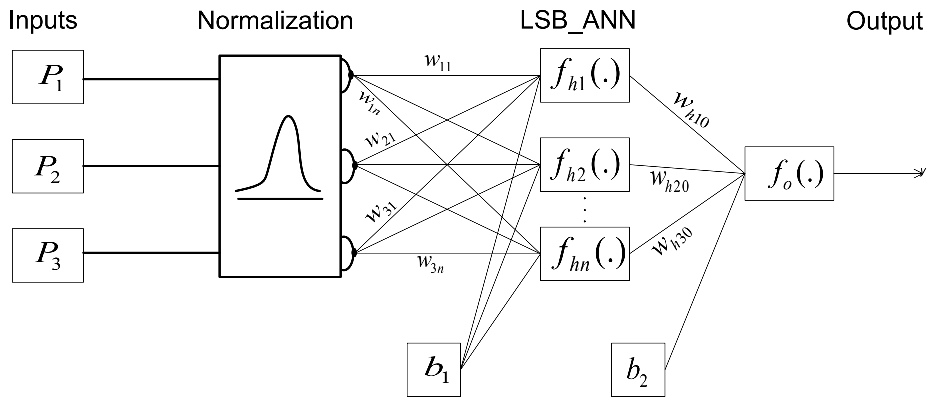

Fig. 1. The model framework of the LSB_ANN

The inputs P_1, P_2, P_3 of the system are the measured angle of the reflection coefficient, the frequency (GHz) and the magnitude of the reflection coefficient, respectively, and the maximum and minimum values of these variables are presented in Table 1. The aim of the network is to compute the oil content and dielectric constant of oil palm fruitlet from the information supplied as its inputs. Harnessing the flexibility offered by MATLAB computing environment, the inputs were normalized and supplied to the network for training, the outputs were evaluated and the error surface was continuously examined to avoid overfitting. The properties of the feedforward neural network are presented in Table 2.

Table 2. Properties and parameters of the LSB_ANN

ANN Parameters	Description/ Value
Type of transfer function (hidden layer)	Sigmoid
Type of transfer function (output layer)	Linear
Weight update mechanism	Sensitivity/SSE
Total number of neurons	24
Total number of weight elements	164
Maximum epochs	700

Firstly, the LSB_ANN was initialized with random weights *w* with corresponding initial errors *e* and the MSE (Mean Squared Error) and SSE (sum of squared error) were evaluated. If for subsequent iterations, the magnitude of the difference between the network sensitivities of the current and previous iteration is less than the allowed value, or the MSE check for the current iteration is less than that of the previous, the network is considered to approach convergence.

The network output is:

$$y_{ij} = f_i\left(\sum_{n=0}^{N} w_{in}p_{nj}\right), i = 1,2,\dots,I; \quad j = 1,2,\dots,J \quad (3)$$

Where *f* is the layer transfer function operator. *N*, *J* and *I* are the number of inputs, number of training data points and the number of outputs respectively.

Because the transfer function is fully invertible, the desired network weight learning was achieved by evaluating and minimizing the difference between the network output and the target using the SSE.

$$E = \sum_{j=1}^{J}\sum_{i=0}^{I}\left(\sum_{n=0}^{N} w_{in}p_{nj} - f_i^{-1}(y_{ij})\right)^2 \quad (4)$$

Therefore we can find

$$\frac{\partial E}{\partial w_{ij}} = 2p_{kj}\sum_{j=1}^{J}\left(\sum_{n=0}^{N} w_{in}p_{nj} - f_i^{-1}(y_{ij})\right); \quad (5)$$

$k = 0, 1, \dots, N;$ For each and all outputs

As a result, the sensitivity of the network with respect to each input is expressed as:

$$\frac{\partial E}{\partial y_{ks}} = -\frac{2}{f_i'(y_{ks})}\left(\sum_{n=0}^{N} w_{kn}p_{ns} - f_k^{-1}(y_{ks})\right) \quad (6)$$

And for the output;

$$\frac{\partial E}{\partial P_{ks}} = 2\sum_{i=1}^{I}\left(\sum_{n=0}^{N} w_{in}p_{ns} - f_i^{-1}(y_{is})\right)w_{ik} \quad (7)$$

The weight update was finally achieved by the Taylor series estimation of the sensitivity of the cost function *E*.

$$y = y - \tau\frac{E(y)}{\|\nabla E\|^2}\nabla E \quad (8)$$

The training process was stopped whenever the validation error began to increase beyond the training error or the maximum epoch of 700 was reached. The training data consists of 604 data points and the testing data consists of 75 data points. After the training phase, the network was deployed and simulated with a new set of data and the performance was evaluated using the VAF, RMSE and R indices.

2.3 Input Data Normalization

The input data normalization operation was carried out in order to eliminate the chance of input weight bias. This enables the network to assign equal importance to several values of input regardless of their magnitude. Moreover, input normalization enhances training speed and computation because it bandlimits the inputs to a boundary of 0 and 1, which drastically reduces the searching space to a unitary hypercube (Sheela and Deepa, 2013). This makes weight decay and Bayesian estimation significantly easier. For each network input P_i, the corresponding normalized value $\overline{P_i}$ is obtained as:

$$\overline{P_i} = P^t{}_{min} + \left(\frac{P_i - P_{min}}{P_{max} - P_{min}}\right)(P^t{}_{max} - P^t{}_{min}) \quad (9)$$

Where P_i, P_{max}, and P_{min} is the actual input data, the maximum input value and the minimum input values respectively, while $P^t{}_{max}$, and $P^t{}_{min}$ are the maximum and minimum values of the target respectively.

2.4 Performance Criteria

The essence of performance evaluation of a softcomputing network is to measure the degree of closeness of the network's output to the actual values as obtained from the physical phenomenon. In this work, the coefficient of multiple determination (CMD), the Variance Account For (VAF) and the Root Mean Square Error (RMSE) defined by Equations (10), (11) and (12) respectively, were used to determine the degree of correlation between the target of the softcomputing models and their eventual outputs.

$$CMD = \sqrt{1 - \frac{\sum_{i=1}^{N}(y - \hat{y})^2}{\sum_{i=1}^{N}(y)^2}} \quad (10)$$

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$$VAF = \left[1 - \frac{var(y - \hat{y})}{var(y)}\right] \times 100 \qquad (11)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y - \hat{y})^2} \qquad (12)$$

Where y is the target value, $\hat{y}$ is the output of the network and *var* denotes the statistical variance of its associated operand. A network is regarded as perfect if its VAF is 100% and its CMD is unity (Erzin et al., 2010). However, it is impossible to obtain those values exactly because of uncertainties in design and computation, a network with VAF, CMD and RMSE with a very high degree of closeness to the perfect values are generally regarded as acceptable.

3. RESULTS AND DISCUSSION

In this section, we present the performances of the considered algorithms and the proposed LSB_ANN as well as the convergence curve for the network under different conditions.

3.1 LSB_ANN Network Performance

To validate the performance of the LSB_ANN, three other feedforward neural network training algorithms were deployed in training the same network with same datasets; Gradient Descent with Momentum (GDM) algorithm, Resilient Backpropagation (RP) algorithm and Gradient Descent with Adaptive learning rate (GDA) algorithm. The training performance evaluation of the four algorithms shows that they all converged within the training epochs (Fig. 2). While all four ANN algorithms performed satisfactorily in intelligently characterizing the samples under test, the unique ability of the LSB_ANN to update its network weights in relatively simple procedure and computation speed (Table 3) makes it a ready choice.

Table 3. Comparison of CPU time to best convergence of the algorithms

Network type	CPU time (s)
RP_ANN	1.353
GDA_ANN	2.066
GDM_ANN	1.854
LSB_ANN	1.339

Additionally, the LSB_ANN network algorithm does not involve the storage of large Jacobian matrix data like most second order algorithms do **(**Wilamowski and Yu, 2010**).** This is of particular advantage when modeling problems of very large data. During the training phase, the MSE curve

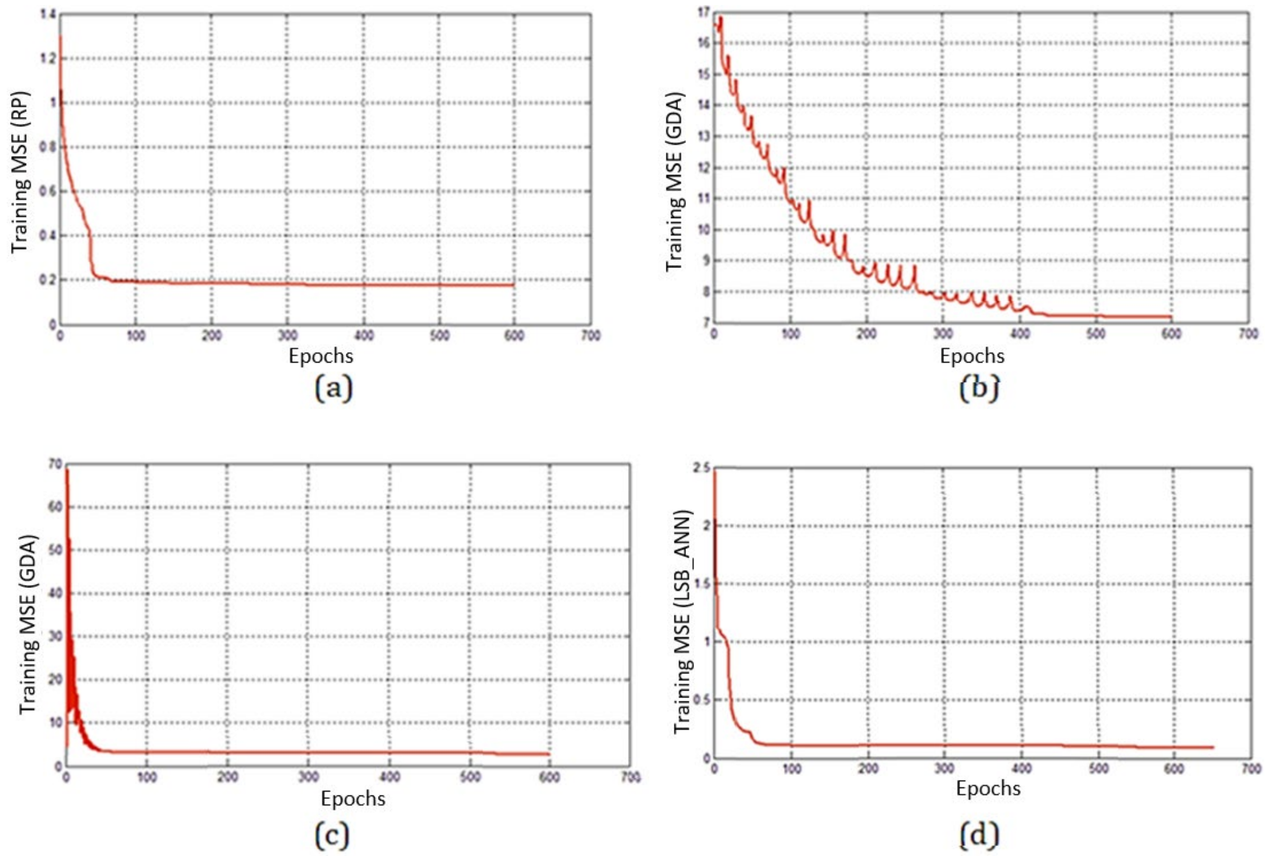

Fig. 2. Plots showing the convergence curves of the four algorithms for training the ANN for the dielectric constant (a) RP (b) GDA (c) GDM (d) LSB_ANN

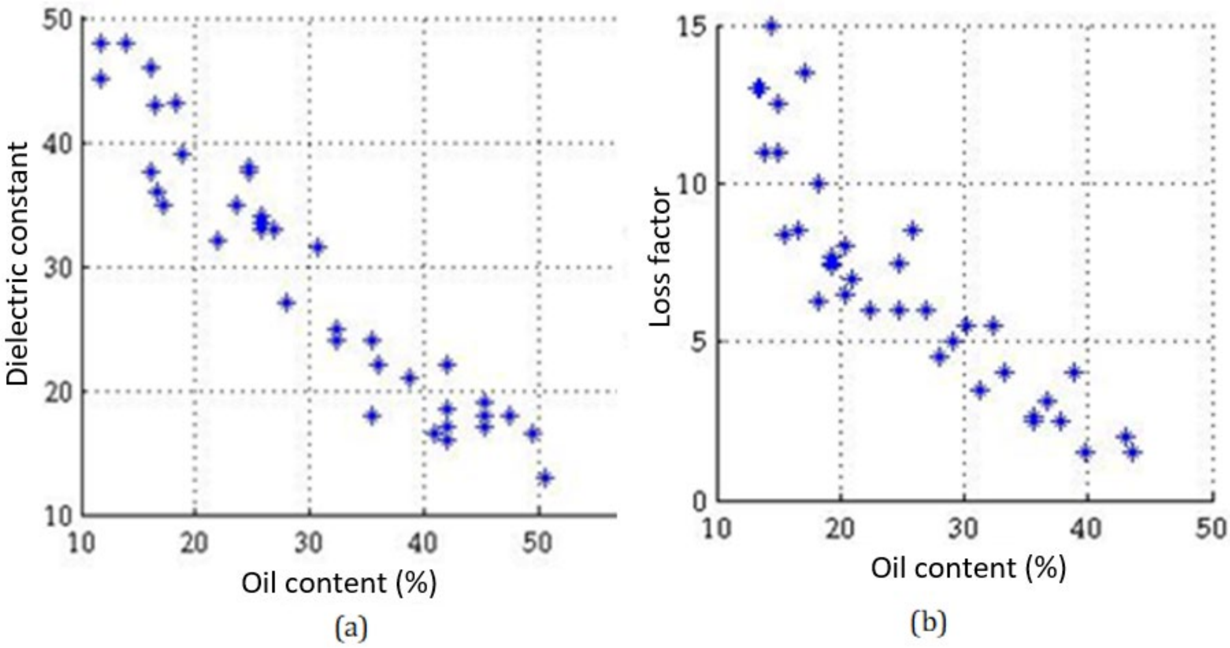

Fig. 3. Different values of measured oil contents at (a) different values of dielectric constants (b) different values of loss factor

(Fig. 2d) reveals that the LSB_ANN achieved the lowest training error within the number of training epochs. It was however observed that, even though the GDA, GDM and RP algorithms performed well during the training phase with VAF of 96.33, 97.51 and 98.64 respectively (see Table 4), their generalization capacity fell slightly short of that of the LSB_ANN for the testing data in which the LSB_ANN had a better VAF index.

Therefore, with respect to post-training accuracy over a wider range of inputs, the LSB_ANN outperformed the remaining three algorithms with testing VAF of 97.81 (a property that makes it the best choice for the characterization of the oil palm fruitlets in this work). It therefore boils down to the conclusion that the performance of different type of softcomputing models is application-dependent, a very crucial factor for this difference is the uniqueness of the statistical distribution and range of the input of the application, the network architecture, the number of parameters, as well as the choice of the training algorithm.

The excellent pattern matching and generalization properties of the ANNs give them the ability to accurately model the dielectric response of oil palm fruitlets to electromagnetic energy. The LSB_ANN considered both magnitude and phase of the reflection coefficient thereby elimination the need for expending much processing resources on input selection optimization.

The measured oil content of the fruitlets at different values of dielectric constant and loss factor are shown in Figs 3(a) and 3(b), respectively. Basically, the mesocarp of oil palm fruitlets is made up of three constituents; fiber, water and oil. The fiber is relatively constant once maturity is reached; the oil content of the fruitlets is therefore mainly dependent on the moisture content which is a function of the dielectric constant.

It was observed that the dielectric constant of the oil palm fruit samples increased with the amount of moisture content and decreased with increasing oil content as seen from Fig. 3(a) and 3(b). Similar relationship was observed by (Trabelsi and Nelson, 2006) when the percentage moisture content was used to predict the bulk density of shelled peanuts. This basis for this behaviour can be obtained from the dielectric properties of water. Water has a relative permittivity as high as 80 at room temperature (Rhodes, 2013), therefore the presence of water in samples/materials has a significant effect on the response of such materials to electromagnetic (EM) energy due to high attenuation of the electric component of the EM waves. Even though the relative permeability of water is unity and therefore has insignificant effect on the magnetic component of the electromagnetic waves, the necessary energy cycling between the electric and magnetic component still makes attenuation of EM waves high in water (Castro-Giráldez et al., 2010). This property accounts for varying values of the complex permittivity of the oil palm fruitlets at different moisture/oil contents.

Also, graphical representation of the relationship between the phase, frequency and the magnitude of the reflection coefficient is shown in Fig. 4 (a) and Fig.4 (b). Table 5 shows the outlook of the outputs as predicted by the networks.

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Table 4. Performance indices of the algorithms for the training, validation and testing data

Network	Training		Performance evaluation		
	Training VAF	Validation VAF	CMD	VAF	RMSE
RP_ANN	98.64	97.77	0.9841	96.26	0.9606
GDA_ANN	96.33	96.24	0.9666	94.09	0.9824
GDM_ANN	97.51	96.08	0.9874	93.57	0.9961
LSB_ANN	97.82	97.65	0.9877	97.81	0.9737

Table 5. Comparison of selected samples of predicted and measured oil content

Network inputs			Measured oil content (%)	Network outputs for oil content			
P_1 (GHz)	P_2	P_3 (^{0})		RP_ANN (%)	GDA_ANN (%)	GDM_ANN (%)	LSB_ANN (%)
2.10	0.970	11.50	54.98	55.13	50.68	51.31	54.51
2.22	0.980	14.00	54.98	55.12	52.99	52.87	54.67
2.32	0.950	16.50	54.98	56.26	52.60	52.45	54.80
2.42	0.945	18.00	54.98	55.71	53.10	52.86	54.79
2.10	0.949	7.50	44.18	45.50	44.76	44.93	46.72
2.22	0.949	8.50	44.18	43.40	46.97	44.72	42.22
2.32	0.920	10.00	44.18	42.37	45.01	42.26	40.55
2.42	0.913	12.50	44.18	43.78	47.70	43.93	44.45
2.10	0.894	-3.00	33.38	34.67	33.11	35.38	33.23
2.22	0.888	-1.50	33.38	33.04	33.93	35.80	32.16
2.32	0.870	0.00	33.38	33.52	34.19	36.18	31.87
2.42	0.861	2.00	33.38	33.46	35.48	36.06	33.34
2.10	0.788	-27.00	22.58	23.41	23.90	26.07	22.58
2.22	0.733	-27.50	22.58	24.91	23.43	24.13	22.58
2.32	0.744	-26.00	22.58	22.96	23.56	23.81	22.58
2.42	0.735	-25.00	22.58	23.06	23.50	23.42	22.58

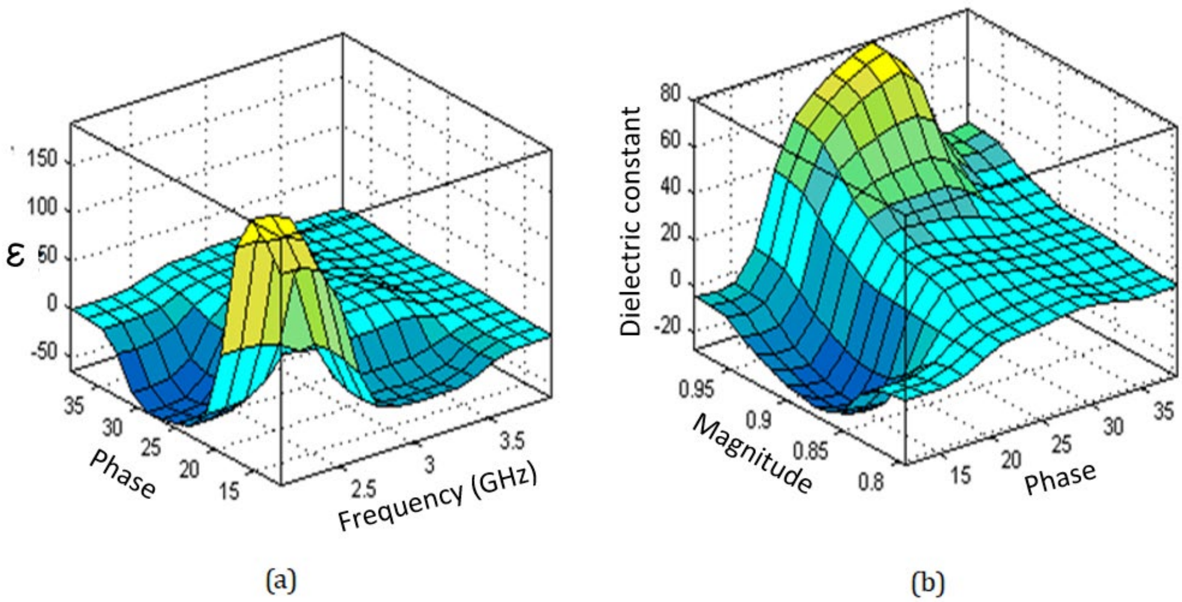

Fig. 4. The input-output surface for (a) the phase and frequency inputs (b) magnitude and phase inputs

4. CONCLUSION

A technique for quickly grading oil palm fruitlets using a combination of microwave measurements and softcomputing techniques was presented in this paper. The findings of this work show that conventional dielectric sensing methods are not suited for accurate oil palm characterization due to its heterogeneous nature, and that updating layer weights using sensitivity analysis improves neural network learning speed significantly. Also, it was shown that the need for the use of computationally intensive admittance equation methods can be avoided by implementing a well-trained layer sensitivity based neural network. This represents a ready tool for accurately characterizing oil palm fruitlets for research purposes as well as *insitu* measurements using information obtained from the dielectric properties and oil content, offering a means of accurately and rapidly extracting the dielectric properties and percentage oil content of oil palm fruitlet mesocarp for any ratio of coaxial cable sensor conductors. This approach eliminates the repeated use of laborious dry oven method for the extraction of moisture and oil content information.

REFERENCES

Abbas, Z., Shaari, A.H., Khalid, K., Hassan, J., Saion, E. 2005. Complex permittivity and moisture measurements of oil palm fruits using an open-ended coaxial sensor. IEEE Sens. J., 5, 1281–1287.

Blackham, D.V., Pollard, R.D. 1997. An improved technique for perimittivity measurements using a coaxial probe. IEEE Trans. Instrum. Meas., 46, 1093–1099.

Castillo, E., Guijarro-berdi, B. 2006. A very fast learning method for neural networks based on sensitivity analysis. J. Mach. Learn. Res., 7, 1159–1182.

Castro-Giráldez, M., Fito, P.J., Chenoll, C., Fito, P. 2010. Development of a dielectric spectroscopy technique for the determination of apple (Granny Smith) maturity. Innov. Food Sci. Emerg. Technol., 11, 749–754.

Erzin, Y., Rao, B.H., Patel, A., Gumaste, S.D., Singh, D.N. 2010. Artificial neural network models for predicting electrical resistivity of soils from their thermal resistivity Int. J. Therm. Sci., 49, 118–130.

Erzin, Y., Rao, B.H., Singh, D.N. 2008. Artificial neural network models for predicting soil thermal resistivity. Int. J. Therm. Sci., 47, 1347–1358.

Ghaffari, A., Abdollahi, H., Khoshayand, M.R., Bozchalooi, I.S., Dadgar, A., Rafiee-Tehrani, M. 2006. Performance comparison of neural network training algorithms in modeling of bimodal drug delivery. Int. J. Pharm., 327, 126–38.

Ismail, F.S., Khalid, N.E.A., Bakar, N.A., Mamat, R. 2011. Optimizing oil palm fiberboard properties using neural network. Conf. Data Min. Optim., 28–29.

Negnevitsky, M. 2005. Artificial intelligence: A guide to intelligent systems, second edi. Pearson Education Limited.

Ong, H.C., Mahlia, T.M.I., Masjuki, H.H., Norhasyima, R.S. 2011. Comparison of palm oil, Jatropha curcas and Calophyllum inophyllum for biodiesel: A review, Renew. Sustain. Energy Rev., 15, 3501–3515.

Otkovic, I.I. 2013. Calibration of microsimulation traffic model using neural network approach. Expert Systems with Applications, 40, 5965–5974.

Rhodes, M. 2013. Underwater electromagnetic propagation: Re-evaluating wireless capabilities. http://www.hydro-international.com.

Rodger, J.A. 2014. A fuzzy nearest neighbor neural network statistical model for predicting demand for natural gas and energy cost savings in public buildings. Expert Systems with Applications. 41, 1813–1829.

Sheela, K.G., Deepa, S.N. 2013. Neurocomputing neural network based hybrid computing model for wind speed prediction. Neurocomputing, 122, 425–429.

Trabelsi, S., Nelson, S.O. 2006. Nondestructive sensing of bulk density and moisture content in shelled peanuts from microwave permittivity measurements. Food Control, 17, 304–311.

Wilamowski, B.M., Yu, H. 2010. Improved computation for Levenberg-Marquardt training. IEEE Trans. neural networks, 21, 930–7.

You, K.Y., Salleh, J., Abd Malek, M.F., Abbas, Z., Ee Meng, C., Yee, L.K. 2012. Modeling of coaxial slot waveguides using analytical and numerical approaches: Revisited. Int. J. Antennas Propag. 2012, 1–12.