Comparison of Feed Forward Neural Network Training Algorithms for Intelligent Modeling of Dielectric Properties of Oil Palm Fruitlets

Ojo O. Adedayo, M.M. Isa, A. Che Soh, Z. Abbas

Abstract– Adequate data of the dielectric properties of oil palm fruitlets and the development of appropriate models are central to the quest of quality sensing and characterization in the oil palm industry. In this study, an Artificial Neural Network (ANN) was designed, optimized and deployed to model the dielectric phenomena of microwave interacting with oil palm fruitlets within the frequency range of 2-4GHz. The ANN training data were obtained from Open-ended Coaxial Probe (OCP) microwave measurements and the quasi-static admittance model, the ANN was trained with four different training algorithms: Levenberg Marquardt (LM) algorithm, Gradient Descent with Momentum (GDM) algorithm, Resilient Backpropagation (RP) algorithm and Gradient Descent with Adaptive learning rate (GDA) algorithm. The performance of the ANNs in comparison with measurement data showed that the dielectric properties of the samples under test were accurately modeled, and the LM and RP ANNs can be employed for rapid and accurate determination of the dielectric properties of the oil palm fruitlets.

Index Terms - Artificial Neural Network, complex permittivity, dielectric properties, training algorithms.

I. INTRODUCTION

The complex permittivity of organic materials, made up of the dielectric constant and the loss factor, is the property that helps in understanding the interaction of the materials with electromagnetic energy [1], [2]. In order to obtain this information, several analytical methods have been established for a wide range of materials using a variety of microwave techniques; these include resonant cavity technique, free-space technique, and the open-ended coaxial probe (OCP) technique. The Open-ended Coaxial Probe (OCP) technique offers the unique advantages of broadband response, non-destructivity, passivity, and ease of set up [3]. Computational intelligence and optimization of processing resources have received a great deal of attention in the last few decades, and Artificial Neural Networks (ANNs) have taken a large share of that. Other recent intelligent techniques that have been applied in solving complex optimization problems include Artificial Fish Swarm Optimization (AFSO) [4] and Adaptive Neuro-Fuzzy Inference System (ANFIS) [5]. ANNs are massive interconnection of information processing structures inspired by the functioning of the brain [6] with their components and operations mimicking the natural human neural intelligence.

In isolation, the computational powers of these neurons are minimal. However, when massively connected they offer great computational power. The parallel distribution of information offers ANNs the ability to model complicated nonlinear processes through repeated adaptation of associated weights.

The above qualities have been explored by researchers in modeling nonlinear systems without prior specification of the mathematical relationships between variables [7] as evident in applications such as: prediction of properties of ceramic materials [8], electrical resistivity [9], and resonant frequency of electrically thin and thick circular microstrip antennas [10].

In recent times, Artificial Neural Networks have witnessed an increasing interest as a fast and adaptable tool for developing accurate models in the design of microwave devices, components and systems. Typical examples are shielded multilayered coplanar waveguides [11], and microstrip antenna design and analysis wherein neural networks have proven to be simpler than and as good as the classical techniques. Power Electronics and Control Engineering disciplines have also witnessed an explosion of interests in applications of Artificial Neural Networks (ANNs). This has been more pronounced in the area of fault localization, fault detection and prediction, rotor resistance, flux, torque and speed estimation, this is as a result of the ability of neural networks to learn patterns and generalize quickly. In addition to their desired quality of quick learning and generalization, the popularity of neural networks has been informed by several other advantages they offer: Ease of use, non-linearity, high performance, few expert knowledge requirement, robustness and flexibility [12].

In Microwave Engineering, one of the more recent applications of Artificial Neural Networks (ANNs) is evident in the development of a software which runs on the platform of artificial neural network for the determination of reflection coefficient with a six-port reflectometer. Also, Artificial Neural Networks (ANNs) were recently used as a tool for the extraction of the dielectric profiles of lossless stratified medium from the knowledge of the complex reflection coefficients [13].

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In all these applications, the accuracies of the solutions are largely dependent on the architecture of the neural network as well as the suitability of the training algorithm used. Training algorithms are computational procedures and functions that are employed in training Artificial Neural Networks for function approximations. These algorithms serve as ANN training tools whose parameters are optimized in order to solve the problem in a particular domain.

This work therefore explores these requirements as they apply to modeling the dielectric properties of oil palm fruitlets, considering the Levenberg Marquardt (LM) algorithm, Gradient Descent with Momentum (GDM) algorithm, Resilient Backpropagation (RP) algorithm and Gradient Descent with Adaptive learning rate (GDA) algorithm.

II. BASIC PRINCIPLES

Complex permittivity extraction by open-ended coaxial probe technique derives from the properties of electromagnetic wave propagating in a coaxial waveguide (illustrated by Fig. 1). When microwave of a particular frequency propagates through a coaxial line connected to a Vector Network Analyzer (VNA) and terminated at the other end by a sample under test, reflection occurs at the boundary between the line and the sample as a result of impedance mismatch. This reflection coefficient Γ is obtained from the VNA and then used together with the physical and electrical properties of the sensors or media in obtaining the complex permittivity ε^*. The ideal analysis after the measurement phase would be to directly compute the complex permittivity of a sample for the obtained reflection coefficient. Unfortunately, this step requires a great deal of processing resources as optimization of several nonlinear expressions is involved [14].

Therefore a number of methods have been devised for the extraction of the complex permittivity of materials from the measured reflection coefficient. One of these is the inverse solution obtained from the admittance model [15 - 18], in which the complex permittivity of the material under test is obtained from a system of equations derived from the theoretical properties of electromagnetic waves [19].
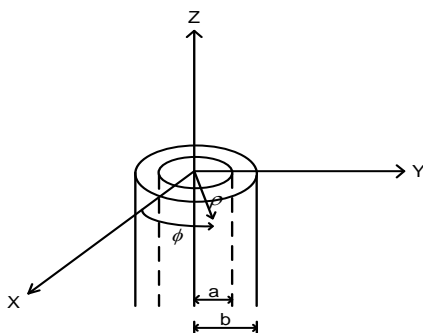

Fig. 1. The annular end of a coaxial probe showing H-field and E-field directions.

The load admittance Y for a sample-terminated coaxial line is given by equation (1).

$$Y = G + jB \qquad (1)$$

G and B are the aperture conductance and susceptance respectively. The aperture conductance is expressed as:

$$G = Y_k \int_0^{\frac{\pi}{2}} \frac{1}{\sin\theta} (F_b - F_a)^2 d\theta. \qquad (2)$$

Where

$$Y_k = \frac{Y_0\sqrt{\varepsilon}}{\ln\left(\frac{b}{a}\right)\sqrt{\varepsilon_c}}, \qquad (3)$$

$$F_b = J_0\left(k_0\sqrt{\varepsilon}b\sin\theta\right), \qquad (4)$$

and

$$F_a = J_0\left(k_0\sqrt{\varepsilon}a\sin\theta\right). \qquad (5)$$

And the aperture susceptance is expressed as:

$$B = \frac{Y_k}{\pi} \int_0^{\pi} (2F_1 - F_2 - F_3)\, d\theta. \qquad (6)$$

Where

$$F_1 = Si\left(k_0\sqrt{\varepsilon(a^2 + b^2 - 2ab\cos\theta)}\right), \qquad (7)$$

$$F_2 = Si\left(2k_0\sqrt{\varepsilon}a\sin\left(\frac{\theta}{2}\right)\right), \qquad (8)$$

$$F_3 = Si\left(2k_0\sqrt{\varepsilon}b\sin\left(\frac{\theta}{2}\right)\right), \qquad (9)$$

The operator Si is the sine integral and J_0 is the Bessel function of order Zero, k_0 is the wave number at the frequency in use, a is the radius of the inner conductor of the coaxial line and b is the radius of the outer conductor. ε_c is the relative permittivity of the dielectric within the transmission line, while ε is the relative permittivity of the sample under test [20]. Expansion of equations (2) and (6) for a b/a ratio of 3.1538 is given by equations (10) and (11).

$$G = Y_k[G_0K^4 - G_1K^6 + G_2K^8 + \cdots] \qquad (10)$$

$$B = Y_k[B_0K + B_1K^3 - B_2K^5 + \cdots] \qquad (11)$$

Where

$$K = k_0\sqrt{\varepsilon}a \qquad (12)$$

where $\varepsilon_c = 2.1$ is the relative permittivity of Teflon within the transmission line, and ε is the complex permittivity of the oil palm fruitlet sample. For this work, the radius of the inner conductor of the coaxial line is *1.3mm* while that of the outer conductor is *4.1mm*.

III. MATERIALS AND METHODS

The ANN training data used for this work was obtained from laboratory microwave measurements. Firstly, one end of a coaxial cable was connected to a computer-coupled VNA and the other end connected to a coaxial sensor and the entire setup was calibrated for one-port measurement. The sensor end of the cable was impressed against the fruitlets and the reflection coefficients at the probe-fruitlet interface were obtained within the frequency range of 2-4GHz. The dielectric constant, normalized susceptance, normalized conductance, and the values of their respective expansion constants G_0, G_1, G_2… and B_0, B_1, B_2… were obtained using equations (1) - (9). These resulted in sets of complex equations in ε^* which was solved to obtain the global value of the complex permittivity for each program point.

At a percentage mesocarp fiber content of 16%, the moisture contents of the oil palm fruitlets for the dielectric constants obtained were obtained from oil palm moisture content calibration curve [21], and the corresponding oil contents of the fruitlets were obtained from equation (6), where Oc is the percentage oil content and Mc is the percentage moisture content relative to the mesocarp of the fruitlet.

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$$Oc = 87.38 - 1.08Mc \qquad (13)$$

Then 201 sets of results were obtained and used in training an ANN with three input neurons, one hidden layer of eight neurons and three output neurons, transig transfer function was applied for the hidden layer while the output neurons used the linear transfer function. This configuration yielded a matrix of 24 input weights (iw_{11}, iw_{12}, iw_{13}, ... iw_{38}) and another of 24 layer weights (lw_{11}, lw_{12}, lw_{13}, ...,lw_{38}). The three inputs of the ANN are: frequency f (GHz), the magnitude of the reflection coefficient $|\Gamma|$ and the phase of the reflection coefficient, while the moisture content, the oil content and the dielectric constant were the training targets. The ANN model framework is shown in Fig. 2.
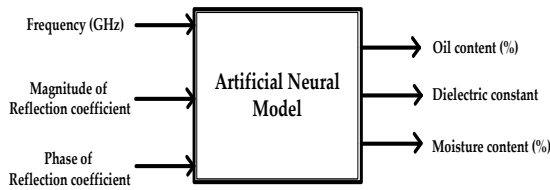

Fig. 2. The ANN model framework

The Feed-Forward Back-propagation ANN was then trained in turn with four different algorithms: the Levenberg-Marquardt (LM) algorithm, the Gradient Descent with Momentum (GDM) algorithm, Resilient Backpropagation (RP) algorithm and the Gradient Descent with Adaptive learning rate (GDA) algorithm, and terminated after the stop criteria for optimum results were reached. The details of the network weight update mechanism for each of the four algorithms are presented in table 1.

Algorithm	Adaptation	Description
Gradient Descent with Adaptive Learning Rate (GDA)	$\Delta_{w_k} = \alpha \dfrac{\Delta E_k}{\Delta w_k}$	The initial network output and error are calculated. Using the current learning rate, new weights and biases are calculated at each epoch.
Resilient Back propagation (BP) Algorithm	$\Delta_{w_k} = -sign\left(\dfrac{\Delta E_k}{\Delta w_k}\right)\Delta_k$	Only the sign of the partial derivative is considered in determining the direction of the weight update [22].
Levenberg-Marquardt (LM) Algorithm	$\Delta w = (J^T J + \mu I)^{-1} J^T e$	The weight update involves the computation of the Jacobian matrix J and the network error vector e.
Gradient Descent with Momentum Algorithm (GDM)	$\Delta_{w_k} = -\alpha_k . g_k + p\Delta_{w_{k-1}}$	Momentum is added by a fraction change of the new weight.

The performance of the training algorithms were evaluated using Mean Square Error (MSE) and Variance Account For (VAF) defined by equations (14) and (15) respectively.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y - \hat{y})^2 \qquad (14)$$

$$VAF = \left[1 - \frac{var(y - \hat{y})}{var(y)}\right] \times 100 \qquad (15)$$

Where y is the target, $\hat{y}$ is the output of the ANN and *var* denotes the statistical variance of its associated operand. A network is regarded as perfect if its VAF is 100% and its MSE is zero. However, it is impossible to obtain those values exactly because of uncertainties in design and computation, an ANN with VAF and MSE with a very high degree of closeness to the perfect values are generally regarded as acceptable.

IV. RESULTS AND DISCUSSION

The method used in this work is an efficient means of sensing the quality of oil palm fruitlet samples. As shown in Table 2, the dielectric constant of the oil palm fruitlet samples increased with the amount of moisture content. Also, the loss factor decreased with frequency and increased after a minimum (Fig. 4). These relationships can be explained from the dielectric properties of water. Water has a relative permittivity as high as 80 at room temperature, thus 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 1 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 and in substances with high water content.

Table 2: The range of the values of dielectric constant obtained with the sensor for the oil palm fruitlets at 2- 4GHz.

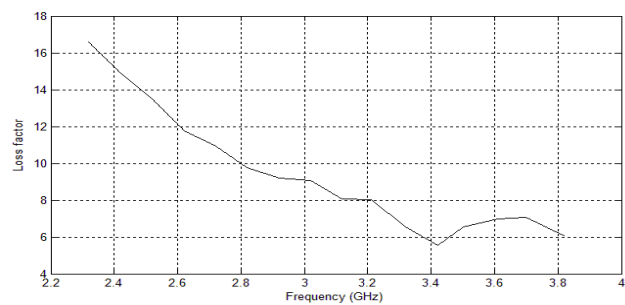| Moisture content (%)	Dielectric constant
30 – 40	6 - 15
40 – 50	15 - 21
50 – 60	21 - 30
60 - 70	30 - 36

Fig. 3. Variation in the loss factor of oil palm fruitlets with frequency at 60% moisture content

The essence of the process of artificial learning is to adapt the network parameters (weights and biases) in order to minimize a total error function E. However, the solution could be either close to the minima or even further away, the algorithms therefore seek to find a global solution by iteratively finding the values of network weights that will reduce E. This solution is essentially of the direction that is opposes the network error gradient $\frac{\partial E}{\partial w_{ij}}$.
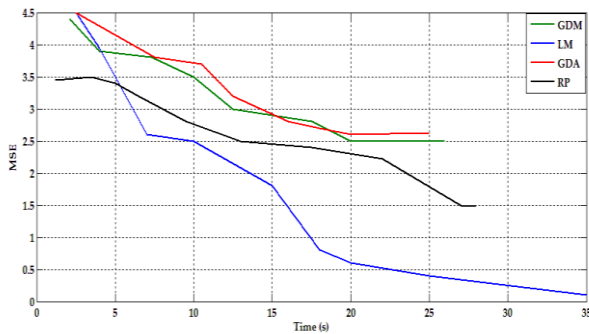
Fig. 4. A plot of the ranges of MSE values obtained for the four algorithms and their durations for 1000 epochs.

In order to obtain this solution, the training algorithm for the network was carefully selected putting the peculiarities and parameters of each algorithm into due consideration. The performances of the four algorithms in predicting the moisture content and the oil content of oil palm fruitlet mesocarp is illustrated in Fig. 5.

The VAF values of the performances of the four algorithms compared with the expected values from the admittance model are presented in table 3. It can be observed that the RP ANN modeled the dielectric phenomena satisfactorily but the best average performance for all four outputs was observed with the LM-trained ANN as the VAF values are closer to 100% in many cases in comparison with the results obtained from the coaxial cable measurements. This clearly indicates that some algorithms are more suited to certain problems and architectures than others.

The average convergence time of each of the four algorithms was evaluated over 1000 epochs, and their corresponding MSE values were obtained. The result showed that, overall, the Levenberg Marquardt algorithm achieved a lower mean square error than the other algorithms (Fig. 4).

Table 3:Performances of the four algorithms for each of the ANN outputs.

Training Algorithms	VAF Moisture content (%)	VAF Oil content (%)	VAF Dielectric constant (%)
LM	99.51	99.51	98.79
GDA	93.26	94.11	92.64
GDM	89.21	87.16	81.07
RP	98.64	98.81	97.59

A comparison of the expected values as obtained from the coaxial sensor measurement against the eventual outputs of the ANN showed that all four algorithms successfully trained the network, albeit over different training time and accuracies.
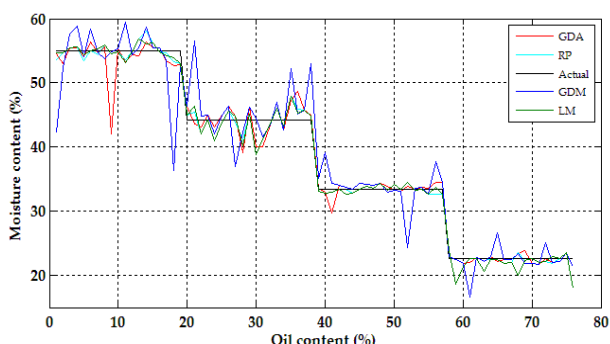

Fig. 5. The oil and moisture content outputs of the ANN for the four algorithms compared with the actual values.

This finding is in agreement with those of [23, 24] in establishing the capabilities of LM algorithm in training Artificial Neural Networks for nonlinear Engineering problems. This result therefore represents a non-destructive and computationally intelligent way of sensing the dielectric properties of oil palm fruitlets from open ended coaxial probe microwave technique. It should be noted that this method can be adapted for other similar materials with proper sensor and computational modifications.

V. CONCLUSION

In this study, a rapid and intelligent method was devised for the measurement of the dielectric properties of oil palm fruitlets from coaxial sensors using Artificial Neural Network. The dielectric constants, moisture content and oil contents of the fruitlets were first extracted from laboratory measurements. Then four training algorithms: Levenberg Marquardt (LM) algorithm, Gradient Descent algorithm (GDA), Resilient Backpropagation (RP) algorithm and Gradient Descent with Adaptive learning rate (GDA) algorithm, were adopted in training a three-input three-output multilayered ANN. In comparison with the results obtained from microwave coaxial sensor measurements and the admittance model, the generalization accuracies of the training algorithms for the three mesocarp properties considered were found to be of the order LM>RP>GDA>GDM.

Finally, the findings of this study reiterate the importance of the selection of proper network architecture, training algorithms and algorithm parameters in Artificial Neural Network modeling. The results also show that Artificial Neural Network algorithms, particularly the Levenberg Marquardt (LM) and the Resilient Backpropagation (RP) algorithm, can be deployed for rapid and consistent determination of the qualities of oil palm fruitlet mesocarps.

REFERENCES

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

[2] Gao M., Tang J., Johnson J. A., & Wang S. Dielectric properties of ground almond shells in the development of radio frequency and microwave pasteurization. Journal of Food Engineering, 112(4), pp. 282–287, 2012.

[3] Gershon D. L., Calame J. P., Carmel Y., Antonsen T. M. & Hutcheon R. M.Open-Ended Coaxial Probe for High-Temperature and Broad-Band Dielectric Measurements, 47(9), pp. 1640–1648, 1999.

[4] Neshat M., Adeli A., Sepidnam G., Sargolzaei M., & Toosi A. N. A Review of Artificial Fish Swarm Optimization Methods and Applications. International Journal on Smart Sensing and Intelligent Systems, 5(1), 107–148, 2012.

[5] Rahmat M., Ling T., Husain A., & Jusoff K. Accuracy Comparison of Arx And ANFIS Model of an Electro-Hydraulic Actuator System. International Journal on Smart Sensing and Intelligent Systems, 4(3), 440–453, 2011.

[6] Wu, Hongbing, Lou Peihuang & Tang Dunbing. Adaptive Dynamic Clone Selection Neural Network Algorithm for Motor Fault Diagnosis. International Journal on Smart Sensing and Intelligent Systems. 6 (2), pp. 482-504, 2013.

[7] May R., Dandy G., & Maier H. Review of Input Variable Selection Methods for Artificial Neural Networks. Artificial Neural Networks - Methodological Advances and Biomedical Applications, pp. 19–42, 2011.

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[8] Scott D. J., Coveney P. V., Kilner J. A., Rossiny J. C. H., & Alford N. Prediction of the functional properties of ceramic materials from composition using artificial neural networks. Journal of the European Ceramic Society, 27(16), pp. 4425–4435, 2007.

[9] Erzin Y., Rao B. H., Patel, A, Gumaste S. D., & Singh D. N. Artificial neural network models for predicting electrical resistivity of soils from their thermal resistivity. International Journal of Thermal Sciences, 49(1), pp. 118–130, 2010.

[10] Yildiz C., Gultekin S., Guney K., & Sagiroglu S. Neural Models for the Resonant Frequency of Electrically Thin and Thick Circular Microstrip Antennas and the Characteristic Parameters of Asymmetric Coplanar Waveguides Backed with a Conductor. International Journal of Electronics and Communications, 56(6), pp. 396–406, 2002.

[11] Yildiz C. & Türkmen M. A CAD Approach Based on Artificial Neural Networks for Shielded Multilayered Coplanar Waveguides. AEU - International Journal of Electronics and Communications, 58(4), 284–292, 2004.

[12] Karanayil B. & Rahman M. F. Artificial Neural Network Applications in Power Electronics and Electrical Drives. Power Electronics Handbook: Devices, Circuits, and Applications, Elsevier Inc, 3rd Edition, pp. 1139–1154, 2001.

[13] Hasan A., & Peterson A. F. Measurement of Complex Permittivity using Artificial Neural Networks. IEEE Antennas and Propagation Magazine, 53(1), pp. 200–203, 2011.

[14] Gorriti, A. G., & Slob, E. C. Comparison of the different reconstruction techniques of permittivity from S-parameters. IEEE Transactions on Geoscience and Remote Sensing, 43(9), 2051–2057, 2005.

[15] Anderson J. M., Sibbald C. L., & Stuchly S. S. Dielectric Measurements Using a Rational Function Model. IEEE Transaction on Microwave Theory and Techniques, 42(2), pp. 199–201, 1994.

[16] Bobowski J.S. & Johson T. Permittivity measurements of biological samples by an open-ended coaxial line. Progress In Electromagnetic Research, 40, pp. 159–183, February 2012.

[17] You K. Y., Salleh J., Abd Malek M. F., Abbas Z., Ee Meng C. & Kim Yee L. Modeling of Coaxial Slot Waveguides Using Analytical and Numerical Approaches: Revisited. International Journal of Antennas and Propagation, pp. 1–12, 2012.

[18] Komarov V. & Wang J. T. Permittivity and measurement, Encyclopedia of RF and Microwave Engineering, Washington State University, pp. 1–20, 2012.

[19] Blackham D. V, & Pollard R. D. An Improved Technique for Perimittivity Measurements Using a Coaxial Probe. IEEE Transaction on Instrumentation and Measurement, 46(5), pp. 1093–1099, 1997.

[20] Devendra Mistra, Mohinder Chabbra, Benjamin R. Epstein, Mark Mitrotznik. Noninvasive Electrical Characterization of Materials at Microwave Frequencies Using an Open-Ended Coaxial Line : Test of an Improved Calibration Technique. IEEE Transactions on Microwave and Techniques, 38(1), pp. 8–14, 1990.

[21] You, K. Y. Development of a new technique for measurement of dielectric properties of oil palm fruits. Universiti Putra Malaysia, 2003.

[22] Riedmiller, M., & Braun, H. A direct adaptive method for faster backpropagation learning: the RPROP algorithm. IEEE International Conference on Neural Networks, pp. 586–591, 1993.

[23] Kişi, Ö., & Uncuoğlu, E. Comparison of three back-propagation training algorithms for two case studies, 12, 434–442. 2005.

[24] Rus, G., & Gallego, R. (2002). Optimization algorithms for identification inverse problems with the boundary element method. Engineering Analysis with Boundary Elements, 26, 315–327. 2002.

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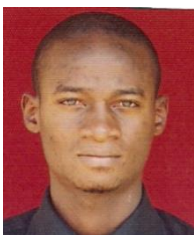
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