

PARAMETER OPTIMIZATION IN DESIGN OF A RECTANGULAR MICROSTRIP PATCH ANTENNA USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM TECHNIQUE

K.V. Rop¹ D.B.O. Konditi² H.A. Ouma³ S.M. Musyoki¹

1. Department of Telecommunication and Information Engineering, Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya, vikrop@gmail.com, smusyoki@yahoo.com

2. Faculty of Engineering, Multimedia University, Nairobi, Kenya, onyango_d@yahoo.com

3. Department of Electrical and Information Engineering, University of Nairobi, Nairobi, Kenya, houma@ieee.org

Abstract- Modern wireless systems are placing greater emphasis on antenna designs for future development in communication technology because the antenna is a key element in the overall communication system. A Microstrip Antenna is well suited for wireless communication due to its light weight, low volume and low profile planar configuration which can be easily conformed to the host surface. In this paper, an optimization method based on adaptive neuro-fuzzy inference system (ANFIS) for determining the parameters used in the design of a rectangular microstrip patch antenna is presented. The ANFIS has the advantages of expert knowledge of fuzzy inference system (FIS) and the learning capability of artificial neural network (ANN). By calculating and optimizing the patch dimensions and the feed point of a rectangular microstrip antenna, this paper shows that ANFIS produces good results that are in agreement with Ansoft HFSS 13.0 simulation results.

Keywords: Microstrip Antennas (MSAs), Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy Inference System (FIS), Artificial Neural Networks (ANNs).

I. INTRODUCTION

The sizes and weights of various wireless electronic systems (e.g. mobile handsets) have rapidly reduced due to the development of modern integrated circuit technology. In many wireless communication systems, there is a requirement for low profile antennas. These antennas are less obstructive and in addition, snow, rain, or wind has less effect on their performance [1]. Microstrip patch antennas are an example of low profile antennas. Microstrip antennas (MSAs) antennas are used in for example, high performance aircraft, spacecraft, satellites, and missiles, where size, weight, cost, performance, ease of installation, and aerodynamic profile are constraints. These attractive features have increased MSA popularity and application and stimulated greater research effort to understand and improve their performance. MSAs however have limitations in terms of

bandwidth and efficiency; all imposed by the very presence of the dielectric substrate [2]. Often, MSAs are also referred to as patch antennas because of the radiating elements (patches) photo-etched onto the dielectric substrate. The radiating patch may be square, rectangular, circular, triangular, and any other configuration. In this paper, the rectangular microstrip patch antennas are considered.

In the past, analytical and numerical methods have been used to design microstrip patch antennas. The analytical methods, based on some fundamental simplifying physical assumptions regarding the radiation mechanism of antennas, are the most useful for practical designs as well as for providing a good intuitive explanation of the operation of MSAs. However, these methods are not suitable for many structures, in particular, if the thickness of the substrate is significant. The numerical methods are mathematically complex, and still cannot make a practical antenna design feasible within a reasonable period of time. They also, require strong background knowledge, and have time-consuming numerical calculations which need very expensive software packages [3].

Recently, many papers have reported various improved methods used in designing of microstrip patch antennas including the use of various forms of artificial intelligence [2]. In this paper, a method based on the adaptive neuro-fuzzy inference system (ANFIS) is presented to effectively calculate and optimize the patch dimensions of a coaxial probe fed rectangular microstrip patch antenna. Many papers that have been written on the same field have concentrated on optimizing only one feature (e.g. resonant frequency, patch length/width, or feed points etc.) in the design of MSA. In this paper, a new artificial intelligence based method is presented for calculating and optimizing the three important features in a design of an MSA; the patch length, patch width, and the feed point. The final results are then validated with the simulation results using Ansoft HFSS antenna simulation software.

II. OVERVIEW OF MICROSTRIP PATCH ANTENNAS

In its most basic form, a microstrip patch antenna consists of a radiating patch on one side of a dielectric substrate and a ground plane on the other side as shown in Figure 1. The bottom surface of a thin dielectric substrate is completely covered with metallization that serves as a ground plane [4].

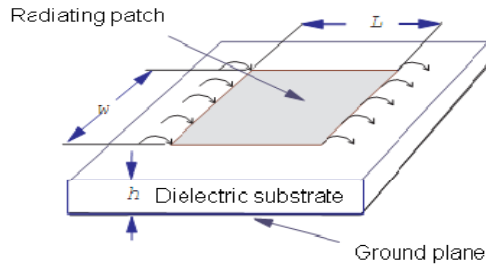


Figure 1. Structure of a rectangular microstrip patch antenna

The essential property for consideration in any antenna design is Directivity, Gain, Bandwidth, and Efficiency. Also, depending upon their geometry, MSAs can produce different polarizations. The common and typical types of polarization include the linear (horizontal or vertical) where the path of the electric field vector is back and forth along a line and circular (right hand or the left hand) polarization where the electric field vector remain constant in length but rotates around in a circular path [5].

MSAs can be fed by a variety of methods which are classified into two categories; contacting and non-contacting. The most popular contacting feed techniques used are the microstrip line fed and coaxial probe fed, while the most popular non-contacting feed techniques are aperture coupling fed and proximity coupling fed [6]. Coaxial probe fed (shown in Figure 2) is the most common feed technique used in the design of microstrip patch antennas due to its low spurious radiation, easy fabrication, and easy input impedance matching, and was thus used in this work.

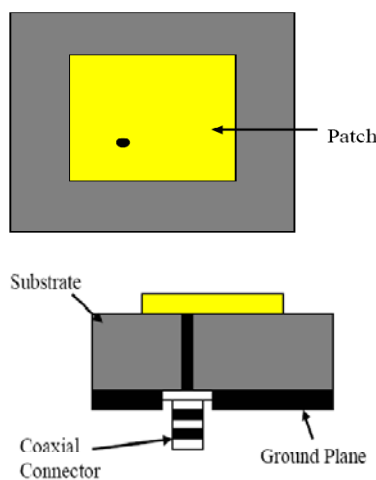


Figure 2. Diagram of a coaxial probe feed technique

III. RECTANGULAR MICROSTRIP PATCH ANTENNA DESIGN METHODOLOGY

A. Design Specifications

The rectangular microstrip antenna is made of a rectangular patch with dimensions width (W) and length (L) over a ground plane with a substrate thickness (h) and dielectric constant (ϵ_r) as shown in Figure 1. There are numerous substrates that can be used for the design of microstrip antennas, and their dielectric constants are usually in the range of $2.2 < \epsilon_r < 12$. The steps followed in the design of rectangular MSAs as discussed in [1] [3] [4, 7, 11] are as follows;

The Patch Width (W) for efficient radiation is given as;

$$W = \frac{v_o}{2f_r} \sqrt{\frac{2}{\epsilon_r + 1}} \quad (1)$$

where, W is the Patch width, v_o is the speed of light, f_r is the resonant frequency, and ϵ_r is the dielectric constant of the substrate

The Effective Dielectric Constant (ϵ_{reff}) - Due to the fringing and the wave propagation in the field line, an effective dielectric constant (ϵ_{reff}) must be obtained from Equation (2).

$$\epsilon_{reff} = \frac{\epsilon_r + 1}{2} + \frac{\epsilon_r - 1}{2} \left[1 + 12 \frac{h}{W} \right]^{-1/2} \quad (2)$$

where, ϵ_{reff} is the effective dielectric constant and h is the height of the dielectric substrate

The Effective Length (L_{eff}) for a given resonance frequency f_r is given as;

$$L_{eff} = \frac{c}{2f_r \sqrt{\epsilon_{reff}}} \quad (3)$$

The Length Extension (ΔL) is given as;

$$\Delta L = 0.412h \frac{(\epsilon_{reff} + 0.3) \left(\frac{W}{h} + 0.264 \right)}{(\epsilon_{reff} - 0.258) \left(\frac{W}{h} + 0.8 \right)} \quad (4)$$

The Patch Length (L)

$$L = L_{eff} - 2\Delta L \quad (5)$$

The Bandwidth (BW)

$$BW\% = 3.77 \left(\frac{\epsilon_r - 1}{\epsilon_r^2} \right) \left(\frac{W}{L} \right) \left(\frac{h}{\lambda_o} \right) * 100\% \quad (6)$$

where, λ_o is the wavelength in free space.

The Feed Co-ordinates - Using coaxial probe-fed technique, the feed points are calculated as;

$$Y_f = W / 2 \quad (7)$$

$$x_f = \frac{L}{2\sqrt{\epsilon_{reff}}} \quad (8)$$

where, Y_f and X_f are the feed co-ordinates along the patch width and length respectively

The Plane Ground Dimensions - It has been shown that MSAs produces good results if the size of the ground plane is greater than the patch dimensions by approximately six times the substrate thickness all around the periphery [13].

$$L_g = 6h + L \tag{9}$$

$$W_g = 6h + W \tag{10}$$

where, L_g and W_g are the plane ground dimensions along the patch length and width, respectively.

B. Architecture of Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS network is organized into two parts like fuzzy systems. The first part is the antecedent and the second part is the conclusion, and the two are connected together by rules to form a network. The ANFIS architecture consists of five layers namely; fuzzy layer, product layer, normalized layer, de-fuzzy layer, and summation (total output) layer as shown in Figure 3 below. In the figure, a circle indicates a fixed node, whereas a square indicates an adaptive node [3, 8, 9, 14].

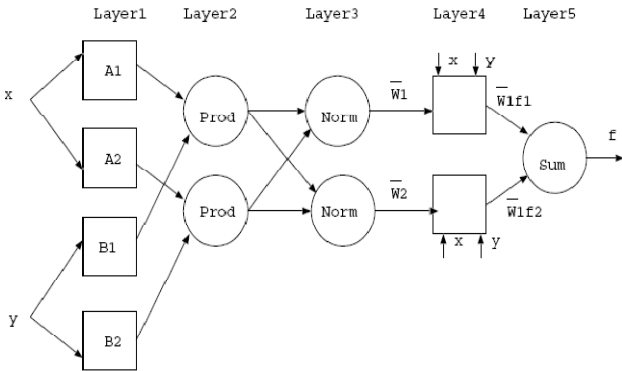


Figure 3. Architecture of an ANFIS

Assume that the fuzzy inference system under consideration has two inputs x and y and one output z . Based on a first-order Sugeno model, a typical rule set with two fuzzy if-then rules can be expressed as;

Rule 1: If x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$ (11)

Rule 2: If x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$ (12)

where, A_1, B_1, A_2 and B_2 are fuzzy sets, p_i, q_i and r_i ($i = 1, 2$) are the coefficients of the first-order polynomial linear functions.

The five layer of Figure 3 are as follows.

Layer 1 is the Fuzzy Layer, in which x and y are the input of nodes A_1, B_1 , and A_2, B_2 , respectively. A_1, B_1, A_2 , and B_2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership relationship between the output and input functions of this layer can be expressed as;

$$O_{1,i} = \mu_{A_i}(x) , i = 1,2 \tag{13}$$

$$O_{1,j} = \mu_{B_j}(y) , j = 1,2 \tag{14}$$

where $O_{1,i}$ and $O_{1,j}$ denote the output functions, whereas μ_{A_i} and μ_{B_j} denote the membership functions, respectively.

Layer 2 is the Product Layer that consists of two nodes labeled Prod. The output w_1 and w_2 are the weight functions of the next layer. The output of this layer ($O_{2,i}$) is the product of the input signal and is defined as;

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_j}(y) , i, j = 1,2 \tag{15}$$

Layer 3 is the Normalized Layer which calculates the ratio of the i th rule's firing strength to the sum of the entire rule's firing strengths. The output is denoted as $O_{3,i}$ and is defined in Equation (16).

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} , i = 1,2 \tag{16}$$

Layer 4 is the De-fuzzy Layer whose nodes are adaptive. p_i, q_i and r_i denote the linear parameters which are also called consequent parameters of the node. The de-fuzzy relationship between the input and output of this layer can be defined as Equation (17), where $O_{4,i}$ denotes the Layer 4 output.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{17}$$

Layer 5 is the Total Output Layer whose single node is labeled as Σ . The output of this layer denoted as $O_{5,i}$ is the total of input signals. The results can be expressed as;

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{18}$$

Substituting Equations (3)-(16) into Equations (3)-(18) yields

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{19}$$

ANFIS uses Sugeno FIS model. The Sugeno fuzzy model provides a systematic approach to the generation of fuzzy rules from a set of input-output data pairs. The ANFIS systems also employs the use of hybrid learning algorithm by combining the least-squares method (LSM) and the back-propagation (BP) algorithm for its learning and training process.

During the learning process, the premise parameters in the Layer 1 and the consequent parameters in the Layer 4 are tuned until the desired response of the FIS is achieved [7]. The hybrid learning algorithm is a two-step process. First, while holding the premise parameters fixed, the functional signals are propagated forward to Layer 4, where the consequent parameters are identified by the LSM. Then, the consequent parameters are held fixed while the error signals, the derivative of the error measure with respect to each node output, are propagated from the output end to the input end, and the premise parameters are updated by the standard BP algorithm. This process is repeated until the results are deemed satisfactory or once it reaches a specified epoch number [10].

The training data presented to ANFIS for training (estimating) membership function parameters should be fully representative of the features of the data that the trained FIS is intended to model. To ensure that the data sets are representative, the testing data sets are also included in the system.

C. Application of ANFIS in the Design of a Rectangular Microstrip Patch Antenna

As discussed above, ANFIS uses a set of data for training of its network. There are two types of data generators (measurements and simulations) for antenna applications. The selection of a data generator depends on the application and the availability of the data generator. In this paper, the ANFIS model shown in Figure 3 with the inputs substrate height (h), resonant frequency (f_r), and dielectric constant (ϵ_r) and the outputs patch width (W_t), patch length (L_t), and the feed point along the width and length (Y_f, X_f) respectively, illustrates how parameters used in the design of rectangular microstrip patch antenna are optimized.

The ANFIS can simulate and analyze the mapping relation between the input and output data through a learning algorithm so as to optimize the parameters used in design of microstrip antennas. The training and test data sets used in this work have been obtained from both simulations and previous experimental works which are documented in various refereed journals.

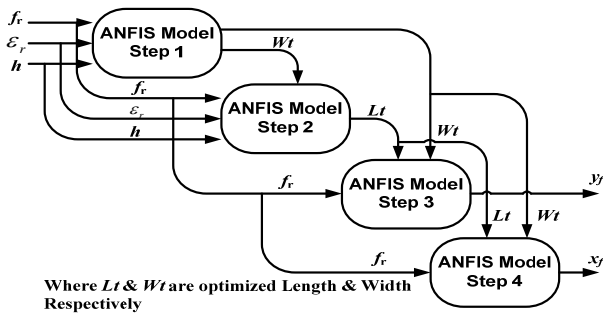


Figure 4. ANFIS Model for Design of Rectangular MSA

As illustrated in Figure 4, the ANFIS model contains four stages. In the first stage, resonant frequency, dielectric constant, and substrate height are used in

optimizing the patch width (W) of the antenna. 90 and 18 data sets were used for training and testing respectively.

The membership functions (MFs) for the input variables f_r , ϵ_r , and h , are 4, 3, and 3 respectively. The number of rules is then 36 ($4 \times 3 \times 3$) and the number of epochs is specified as 700. In the second stage, the antenna patch length (L) is optimized. The three input variables used in first stage are maintained with the addition of the optimized patch width (W_t) as an input variable, therefore, variables f_r , ϵ_r , h , and W_t were used as inputs with L as the output variable to be optimized. 90 training data sets and 16 testing data sets were used in this stage. The MFs for the input variables f_r , ϵ_r , h , and W_t are 4, 2, 2, and 4 respectively thus, the number of rules is 64 ($4 \times 2 \times 2 \times 4$) with the number of iterations specified as 700. The third stage in the ANFIS model is used for optimizing the feed point (Y_f) along the patch width. In this stage, the number of epochs is specified as 600 with 90 testing data sets and 15 testing data sets used. The variables f_r , W_t , and L_t are used as inputs with the MFs as 3, 4, and 4 respectively. This gives the number of rules as 48 ($3 \times 4 \times 4$). Finally, the input variables f_r , W_t , and L_t are used in optimizing the feed point X_f along the path length of the antenna. With 90 testing data sets and 15 testing data used, the number of iterations was specified as 600. The input variables f_r , W_t , and L_t were each allocate the MFs values as 3, 4, and 4 respectively, making the number of rules as 48 ($3 \times 4 \times 4$). The input output relationships are illustrated in Figures 5 and 6.

IV. RESULTS AND DISCUSSIONS

By using ANFIS implemented in MATLAB® platform, training and testing of data sets was carried out. Also using Ansoft HFSS software, simulation was carried out to generate the values of various rectangular MSA parameters namely patch width, patch length, and feed points. Finally ANFIS optimized data were validated with the Ansoft HFSS simulated data and the results tabulated and plotted.

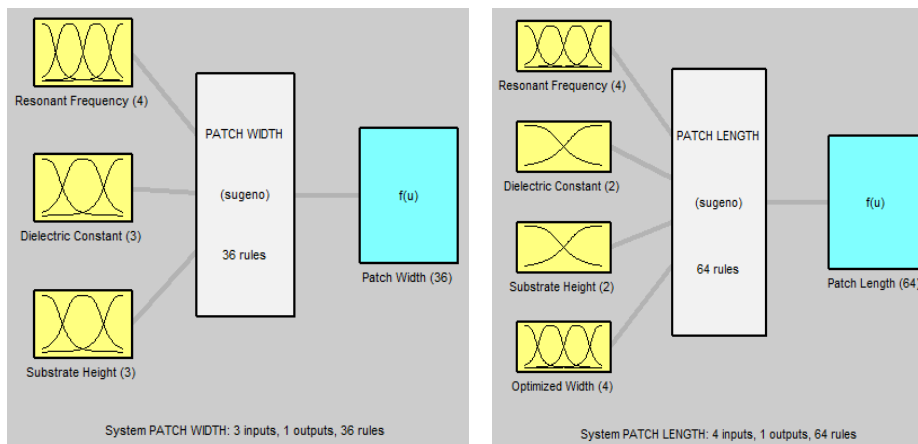


Figure 5. Input output relationship for 1st (patch width) and 2nd (patch length) ANFIS model, respectively

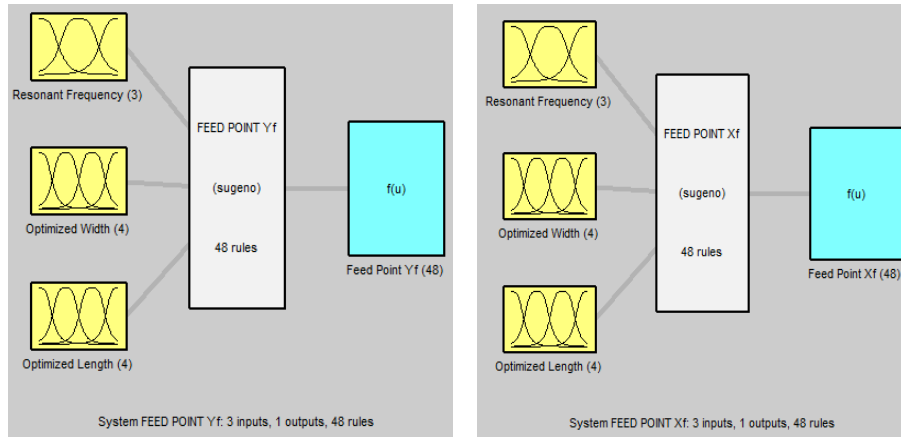


Figure 6. Input output relationship for 3rd (feed point Y_f) and 4th (feed point X_f) ANFIS model, respectively

Table 1. A representative of input variables, ANFIS output, and HFSS simulated data

Input Variables			ANFIS Output				Ansoft HFSS			
f_r (MHz)	E_r	h (mm)	W (mm)	L (mm)	Y_f (mm)	X_f (mm)	W (mm)	L (mm)	Y_f (mm)	X_f (mm)
1400	2.2	1.57	84.73	71.52	42.35	24.439	84.7	71.57	0	13.92
2000	2.2	1.57	59.48	49.82	29.65	17.089	59.29	49.82	0	9.69
2500	2.2	1.57	47.24	39.69	23.72	13.666	47.43	39.67	0	7.72
4000	2.2	1.57	29.64	24.43	14.82	8.4848	29.65	24.42	0	4.75
1400	4.3	1.6	65.88	51.41	32.91	12.693	65.82	51.41	0	8.68
2000	4.3	1.6	46.16	35.85	23.04	8.9195	46.07	36.85	0	6.05
7000	4.3	1.6	13.33	9.694	6.584	2.5612	13.16	9.7	0	1.64
1400	10	2.2	45.7	33.67	22.84	11.835	45.69	33.67	0	4.66
3500	10	2.2	18.43	12.98	9.139	4.9159	18.27	12.98	0	1.8
5500	10	2.2	11.7	7.876	5.82	3.1007	11.63	7.88	0	1.09
4000	11.9	1.5	14.76	10.55	7.398	1.8327	14.77	10.55	0	1.4
5500	11.9	1.5	10.81	7.502	5.365	1.0868	10.74	7.5	0	1
6000	11.9	1.5	9.861	6.816	4.934	1.1927	9.84	6.82	0	0.9
8000	11.9	1.5	7.391	4.931	3.699	0.8966	7.38	4.93	0	0.65
1400	9.8	1.5	46.14	34.16	23.06	5.6851	46.11	34.16	0	4.76
3500	9.8	1.5	18.6	13.41	9.231	2.3951	18.44	13.41	0	1.87
6500	9.8	1.5	9.801	6.92	4.948	1.1496	9.93	6.92	0	0.96
7000	9.8	1.5	9.34	6.369	4.66	1.4067	9.22	6.37	0	0.89
1500	5.6	1.56	54.98	42.08	27.52	9.1517	55.05	42.08	0	6.69
2000	5.6	1.56	41.44	31.46	20.64	6.9065	41.29	31.46	0	5
6000	5.6	1.56	13.79	10.05	6.887	2.2909	13.76	10.05	0	1.6
7500	5.6	1.56	10.94	7.876	5.498	1.7482	11.01	7.88	0	1.25

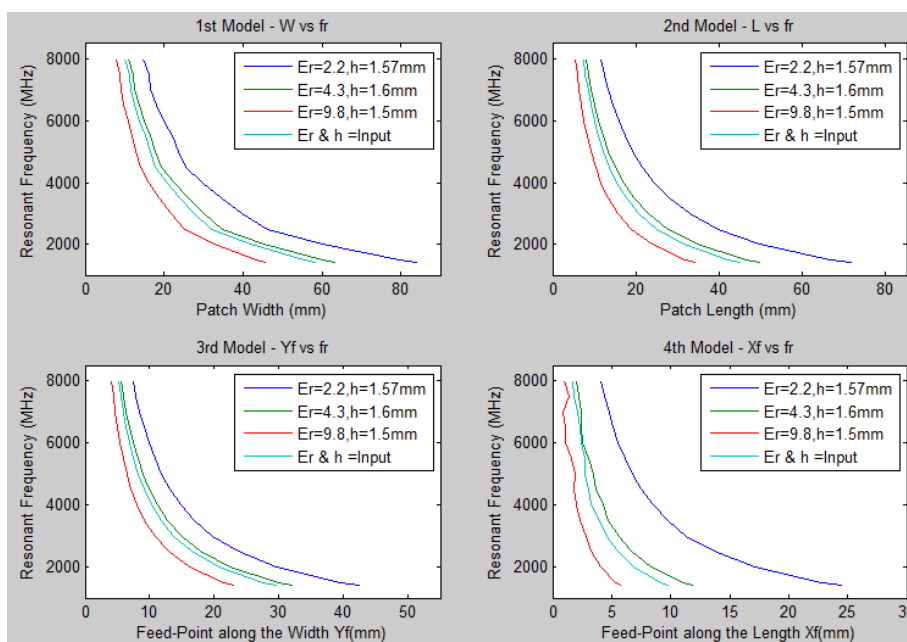


Figure 7. ANFIS output values for rectangular MSA with various dielectric constants and substrate heights

Table 1 shows a representative of the data sets obtained by using both ANFIS (MATLAB) and Ansoft HFSS software. The Ansoft simulated results therefore validates that ANFIS calculates and optimizes the parameters used in building a rectangular MSA effectively.

The error difference between the ANFIS and Ansoft HFSS results for the patch width (average of 0.032808) and patch length (Average of 0.90608) is minimal showing how effective ANFIS can be in producing accurate results. However, the error difference with the feed points was significantly large. From the literature, there are no exact formulas for calculating the feed point, and therefore trial and error method is usually used in locating the point with proper impedance matching [11] [12]. This might have therefore caused a bigger error margin for the feed point location.

Figure 7 plots various optimized parameter in relation to the resonant frequency. Various substrate materials with various dielectric constants and height were used in the training and the outputs show that the higher the frequency (with other factors held constant) the smaller the antenna size. With the emphasis on FR4 substrate material with a dielectric constant of 4.3 and substrate

height of 1.6mm at 2GHz, validation was carried out by using Ansoft.

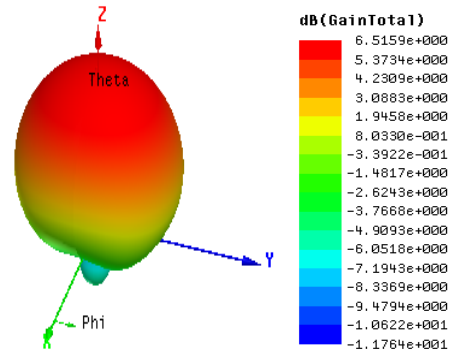


Figure 8. 3D gain diagram

Figures 8 and 10 show the gain of the designed antenna and the input impedance respectively as generated by Ansoft HFSS. The highest gain point is in the z-direction. Figure 9 shows that the return loss is lowest at about 1.95GHz with a bandwidth of about 25MHz.

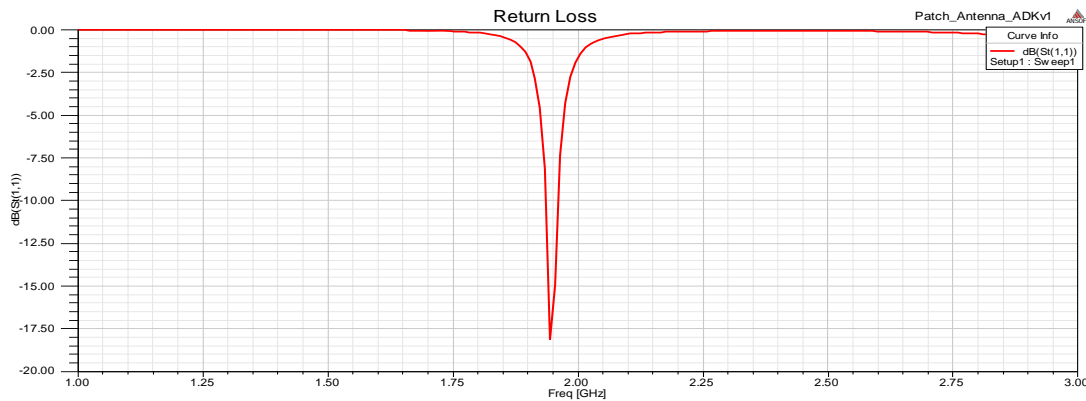


Figure 9. Return loss diagram

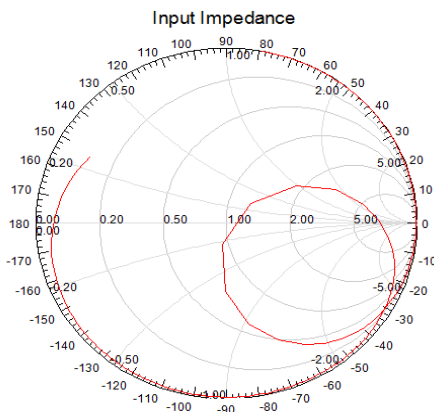


Figure 10. Diagram showing the input impedance

V. CONCLUSIONS

The representative optimized parameters computed by using ANFIS presented in this paper for rectangular microstrip patch antenna are listed in Table 1 including the simulated data form Ansoft HFSS. From the results, it

is clear that ANFIS produces good results in comparison with HFSS software. It can be clearly seen from Table 1 that most results are in good agreement. The agreement shown in these results supports the validity of the ANFIS model proposed in this paper.

To further prove the validity of the proposed ANFIS model, the practical implementation of the modeled antenna is to be carried out. A lot of research in this field has been with the use of artificial intelligent techniques in calculating the design parameters of various patch antennas. However, not much of this has been directed to optimizing the feed point. The error margin with the feed point is a subject of further research aiming to reduce the same. It also needs to be emphasized that better results may be obtained from the ANFIS either by choosing different training and test data sets from the ones used in this paper or by supplying more input data set values for training. This work therefore shows that ANFIS being fast and accurate can be used to effectively design MSAs and other related work.

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BIOGRAPHIES



K. Victor Rop received his B.S.T. in Electronics Engineering from University of Eastern Africa, Baraton in 2008. He is currently pursuing the M.Sc. degree in Telecommunication Engineering at Jomo Kenyatta University of Agriculture and Technology (JKUAT). He has

worked in various capacities in telecommunication industry and he currently works as an Electrical Engineer/Consultant. His research interests are in the area of artificial intelligence, smart antennas, and audio Visual and video conferencing technologies. He is a member of KSEEE (Kenya).



Dominic B.O. Konditi was born on July 22, 1950 in Kochia, Homa-Bay County, Kenya. He received his M.Eng. degree in Electrical Engineering from Tottori University, Japan in 1991 and Ph.D. degree in Electronics and Computer Engineering from Indian Institute of

Technology (IIT), Roorkee, in 2000. He is currently a Professor and the Director of Center for Sustainability and Development Studies, Multimedia University of Kenya (MMU). He is the former Chair of Kenya Society of Electrical & Electronic Engineers (KSEEE) and the founder Dean of Faculty of Engineering, MMU. He has authored several papers in refereed journals and conference proceedings. In 2003, he received the best paper award in New Delhi, India, for his paper published in the Institution of Electronics & Telecommunications Engineers (IETE) journal. He has been a reviewer of Radio Science Geophysical Society Journal (Washington DC, USA), The New Measurements and Instrumentation Journal (USA), WSEAS journals and conference proceedings (Athens, Greece), ENMA conference proceedings (Bilbao, Spain), SAIEEE Africa Research Journal (South Africa), and JAGST journal (Nairobi, Kenya). He has been cited in Marquis WHO'S WHO in Science and Engineering and Cambridge Bibliographic Society, England. His research interests are in computational electromagnetics, numerical techniques for waveguides, conducting screens and micro-strip lines and apertures as pertains to EMC/EMI and biomedical engineering. He is a member of IEEE (USA), WSEAS (Greece) and KSEEE (Kenya), and Associate Member of IEK (Kenya).



Heywood Absaloms Ouma was born on January 23, 1965. He received his B.Sc. degree (Hons) in Electrical Engineering from University of Nairobi, Kenya, in 1988, M.Eng. in Telecommunication Engineering from the University of Technology, Sydney (UTS),

Australia, in 1993, and Ph.D. in Engineering from the Kanagawa Institute of Technology (KAIT), Kanagawa, Japan in 1998. He is currently a Senior Lecturer and the Chair of Department of Electrical and Information Engineering at the University of Nairobi, Kenya. He has published several papers in refereed journals and conference proceedings. His research interests include genetic algorithm applications in image processing, real-time image processing and biometric image processing. He is a member of the Institute of Electrical and Electronic Engineers (IEEE), and IEEE Computer Society.



Stephen M. Musyoki graduated the D.Eng. degree in Electronics from Tohoku University, Japan in 1991. He is currently a Senior Lecturer and the Chair of Department of Telecommunication and Information Engineering at Jomo Kenyatta University of Science and

Technology (JKUAT), Kenya. He has worked for Japan Atomic Research Institute (JAERI) as a Research Fellow, NEC Corporation (Japan) as a Development Engineer, and Sangikyo Corporation (Japan) as a Senior Engineer. He has published several papers in refereed journals and conference proceedings.