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Adaptive network-based inference system models on multiband patch antenna design

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Abstract: In this study, an adaptive network-based fuzzy inference system (ANFIS) for multiband microstrip patch antenna (MMPA) modeling is proposed. The MMPA includes a single patch with inverted L-shaped stubs on the edges. The antenna production process needs iterative runs of the electromagnetic (EM) simulator, fabricating and testing the simulated antenna to find the optimum geometry. Production processes (design, simulation, fabrication, and testing) and the cost computation time add to the overall manufacturing expenses. A computer-aided modeling approach using the ANFIS is developed and trained with data acquired from the EM simulators, Sonnet Suites and AWR AXIEM, and measurement data. The overall data set includes 7777 input-output pairs, of which 3338 are used for the testing of the ANFIS model. The trained ANFIS model provides accurate and reliable results compared with the EM simulators and measured data.

Key words: Adaptive network-based fuzzy inference system, multiband microstrip patch antennas, EM simulator, modeling

1. Introduction

Microstrip patch antennas (MPAs) have advantageous properties, such as having a low profile, light weight, conformal structure, low design cost, and ease of integration with other microwave circuits and devices [1–4]. Although MPAs have extensive applications in military and commercial fields, the narrow bandwidth of less than 5% compared to the operating frequency is a major problem to be solved. Broadband and multiband MPAs (MMPAs) are proposed to overcome the disadvantage of operating with a narrow bandwidth. MMPAs are realized by placing a half-wavelength shorted stub or quarter-wavelength open-circuit stub on the MPA edges. The stub offers capacitive impedance below the resonance frequency and inductive impedance above the resonance frequency of the MPA and causes a multiresonance response [5–8].

MPAs have a 2-dimensional radiating patch on a thin dielectric substrate and can therefore be categorized as 2-dimensional planar components for analysis purposes. The analysis methods can be grouped into 2 groups. In the first group, the transmission line model (TLM), cavity model (CM), and multiport network model (MNM) are based on the equivalent magnetic current distribution around the patch edges, similar to slot

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antennas. In the second group, the full-wave numerical analysis methods, method of moments, finite-element method (FEM), spectral domain technique, and finite-difference time-domain method are derived from the electric current distribution on the patch conductor and ground plane, similar to dipole antennas [1].

In this study, the modeling of an inverted L-shaped stubbed MMPA using an adaptive network-based fuzzy inference system (ANFIS) model is presented. The ANFIS model is trained with various training algorithms and optimization methods to achieve the highest accuracy. The proposed computer-aided modeling aims to avoid iterative design processes, which increase the computation time and fabrication expenses. For instance, microwave engineers must redesign and simulate the entire structure repeatedly once a tuning process is applied to the device under focus. As the device gets complicated, these production processes (design, simulation, fabrication, and testing) carry intense loads in terms of time, engineering resources, and cost. The proposed ANFIS model avoids repetitive simulations and fabrications once a comprehensive data library that includes simulated and measured data is accomplished. Consequently, the computer-aided design models assist in diminishing the overall production costs.

The proposed model can be used to analyze all types of configurations that cannot be handled by the TLM due to variation of field in the orthogonal direction to the direction of propagation. In the CM and MNM, the arbitrary shapes cannot be accurately analyzed and numerical techniques are applied for complex geometries. However, numerical methods carry a high computation load and time to solve electromagnetic (EM) problems. The proposed model can be applied to complex geometries through an affordable computation time compared with numerical methods.

2. ANFIS applications for MMPAs

An ANFIS was developed by Jang and its structure is the same as that of the fuzzy model, which has a set of fuzzy if-then rules with appropriate membership functions (MFs) to generate the stimulated input-output pairs [9]. The ANFIS can be utilized to model the input and output mapping relation through a learning procedure to determine the optimum parameters of a given fuzzy inference system.

ANFIS applications in the field of radio frequency (RF) antenna modeling have been widely applied during the last decade. The resonant frequency computation and synthesis of electrically thin and thick microstrip antennas [10,11], input resistance [12], bandwidth, and resonant frequency computation of various microstrip antennas were studied in the literature [13–15].

2.1. Inverted L-shaped stubbed MMPAs

Initially, the single patch dimensions at the center frequency of 5 GHz are determined using well-studied theoretical Eqs. (1) through (6). The width and length of the patch are computed as 790 and 950 mil, respectively, for the Rogers Duroid 5880 substrate (ε_r = 2.2 and h = 31 mil). Next, the inverted L-shape stubs are attached to the edges of the antenna to achieve a multiband response, and the proposed geometry is simulated and tuned using EM simulators, Sonnet Suites, and AWR AXIEM. The identically shaped antennas with various substrates (a range of dielectric constants and thicknesses), physical patch dimensions (a range of widths, lengths, and stub lengths), and stub widths (sw), are simulated. These simulation processes are repeated for a variety of center frequencies ranging from 1 to 15 GHz. Finally, the simulated antennas are fabricated based on the availability of the substrates. The training and testing sets are generated using both the simulated and measurement results. The proposed antenna shape of the MMPA is depicted in Figure 1.

$$W = \frac{c}{2f_r}\left(\frac{\varepsilon_r + 1}{2}\right)^{-1/2}, \tag{1}$$

$$\varepsilon_{eff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left[1 + \frac{12h}{W}\right]^{-1/2}, \tag{2}$$

$$\Delta l = 0.412h\left(\frac{\varepsilon_{eff} + 0.3}{\varepsilon_{eff} - 0.258}\right)\left(\frac{W/h + 0.264}{W/h - 0.8}\right), \tag{3}$$

$$L = \frac{c}{2f_r\sqrt{\varepsilon_{eff}}} - 2\Delta l, \tag{4}$$

$$R_{in} = \frac{45\lambda_o^2}{W^2}, \tag{5}$$

$$Z_{oT} = \sqrt{R_{in} \times 50}. \tag{6}$$

Here, W and L denote the width and length of the rectangular patch, respectively. ε_{eff} is the effective dielectric constant, Δl denotes the uncertainty of the patch length, R_{in} is the input resistance of the patch, and Z_{oT} is the characteristic impedance of the microstrip feed line.

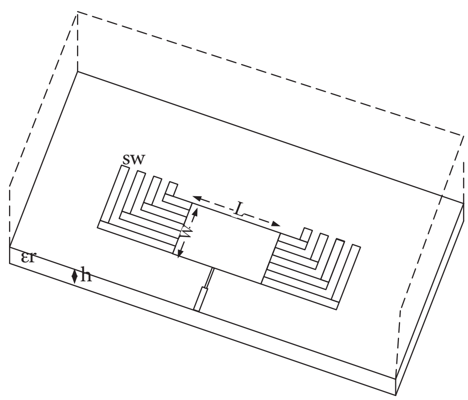

Figure 1. MMPA geometry.

2.2. Simulation process

The designed MPA geometry is simulated using Sonnet v13.56 and AWR v10 AXIEM, which produce EM analysis results utilizing the open-boundary method of moments. The main parameters used for the simulation processes are the dielectric constant and height of the substrate and frequency range of the simulation. The thickness of the air layer over the antenna is selected as at least 10 times greater than the substrate thickness. Since the electrical antenna size varies with the operating frequency, the meshing cell size is selected as small as possible to increase the accuracy and mesh the antenna with more cells.

The microstrip feed line is selected as the feeding method rather than the coaxial probe due to the easiness of fabrication and keeping the total structure as planar as possible [16]. The feeding point is selected at the center of the patch width to achieve symmetry and lessen the analysis time. The feeding line dimensions are computed to match the antenna input impedance to a 50-Ω subminiature version A connector. A quarter-wave microstrip feed line is attached to the feeding line to simply solder the connector. The quarter-wave feed lines are selected to achieve the highest possible gain values at the resonant frequencies. The antenna gain can be adjusted for a fixed resonance frequency as the quarter-wave line alters.

2.3. Fabricated inverted L-shaped stubbed MMPA

The simulated antenna is fabricated utilizing an LPFK milling machine and measured with an Agilent E5071C ENA series network analyzer. The antenna is fabricated using Rogers Duroid 5880 substrate with a dielectric constant of 2.2 and height of 31 mil. The 9 resonance frequencies below −10 dB are measured as 1122.5 MHz, 2828.75 MHz, 4858.75 MHz, 5812.5 MHz, 6626.25 MHz, 7265 MHz, 11,097.5 MHz, 12,305 MHz, and 14,142.5 MHz, and the corresponding bandwidths are determined as 5 MHz, 20 MHz, 22 MHz, 70 MHz, 44 MHz, 43.75 MHz, 78.75 MHz, 87.5 MHz, and 96.25 MHz, respectively. Since the antenna substrate is thin, the realized bandwidths are quite narrow in some resonance frequencies. The fabricated antenna of the Rogers Duroid 5880 is shown in Figure 2.

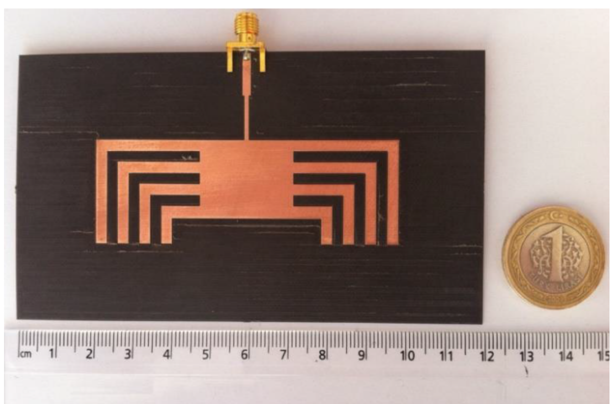

Figure 2. The fabricated MMPA.

2.4. Training process of the ANFIS

In this study, a Sugeno-type fuzzy inference system model is proposed to estimate the MMPA scattering parameters using algorithm parameters with Gaussian-type MFs. An input-output paired set of 4439 is utilized for the training process of the proposed ANFIS architecture and is given in Figure 3, where the square nodes, called adaptive nodes, are adopted to represent the parameter sets in the nodes that are adjustable. The circle nodes, called fixed nodes, are adopted to represent the parameter sets that are fixed in the system [10].

The fuzzy if-then rules based on a first-order Sugeno model with 3 MFs for each input can be stated as:

Rule 1: If (ε_r is MF11) and (fr is MF21) and (swtr is MF31), then B_1 = F1 (ε_r, fr, swtr),

Rule 2: If (ε_r is MF11) and (fr is MF21) and (swtr is MF32), then B_2 = F2 (ε_r, fr, swtr),

...

Rule 27: If (ε_r is MF13) and (fr is MF23) and (swtr is MF33), then B_{27} = F27 (ε_r, fr, swtr),

where ε_r, *fr* and *swtr* are inputs, *MFij* denotes the j*th* MF of the i*th* input, B_k represents the output of the k*th* rule, and *Fk* is the k*th* MF output with k = 1,2,...,27 and i,j = 1,2,3.

Figure 4 illustrates the black-box representation of the proposed ANFIS model with input-output parameters.

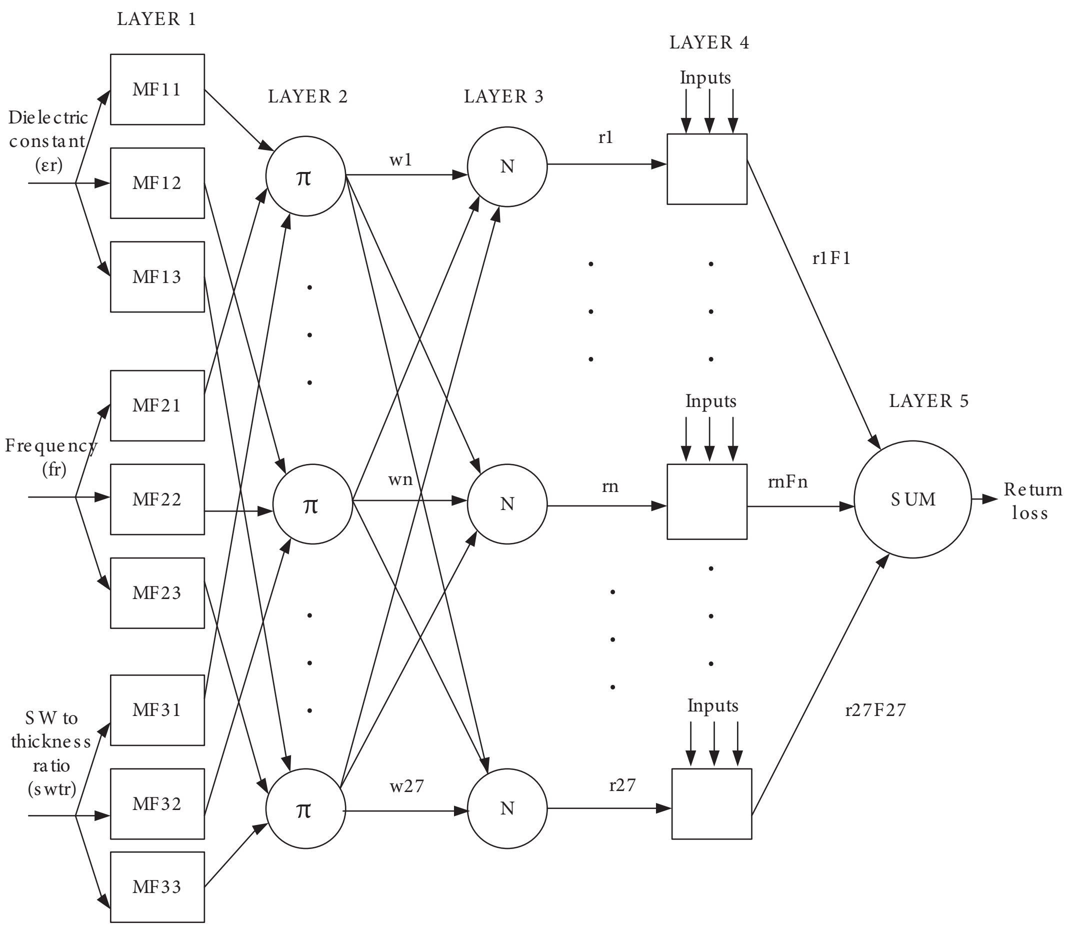

Figure 3. Proposed Sugeno-type ANFIS architecture.

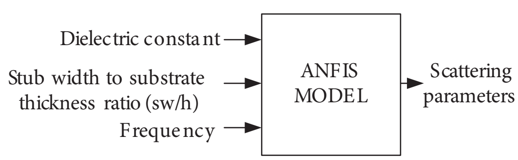

Figure 4. Proposed ANFIS model.

2.5. Test process of ANFIS

The accuracy of the generated ANFIS model depends on the training data set, which must be selected properly to characterize the design range of interest. In this study, the ranges of the data sets are $1.2 < \varepsilon_r < 3.02$ for the substrate dielectric constant, $0.8 < \text{swtr} < 6$ for the stub width to substrate thickness ratio, and $1 < \text{f} < 15$ GHz for the operating frequency. The training and testing data are acquired using both the EM simulators and actual measurements. An input-output paired set of 3338 is utilized for the testing process of the proposed ANFIS models, which are trained with the hybrid learning and backpropagation optimization methods. The Gaussian MFs have 2 parameters, $\{\gamma_i \sigma_i\}$, that change the shapes of the MFs as shown in Eq. (7).

$$Gauss\left(x;\gamma_i,\sigma_i\right) = e^{-\frac{(x-\gamma)^2}{2\sigma^2}} \tag{7}$$

The proposed ANFIS model is trained for 3 to 8 MFs and 1000 epochs. The number of rules is 512 ($8 \times 8 \times 8$) for 8 MFs. The Gaussian MF is specified by 2 parameters; therefore, the ANFIS contains a total of 2096 fitting parameters, where 48 ($8 \times 2 + 8 \times 2 + 8 \times 2$) are the premise nonlinear parameters and 2048 (4×512) are the consequent linear parameters. There are a total of 1078 nodes on the proposed ANFIS model. In Figure 5, the estimated and actual measurements and the simulated return losses are depicted versus the frequency range. The ANFIS models the return loss more accurately than the EM simulator, because the training set is acquired among the measurement data. Since the number of rules and parameters increases as the number of MFs is enhanced, the total ANFIS modeling time and required memory also increase with the accuracy. The modeling accuracy can also be augmented by sampling additional training data around the resonance frequencies. Since the substrate is thin and the MPAs naturally have narrow bandwidths, the sharp discontinuity in the resonance frequencies causes errors in the modeling. This can be handled by taking more samples in these regions as the simulator or measurement device capability allows.

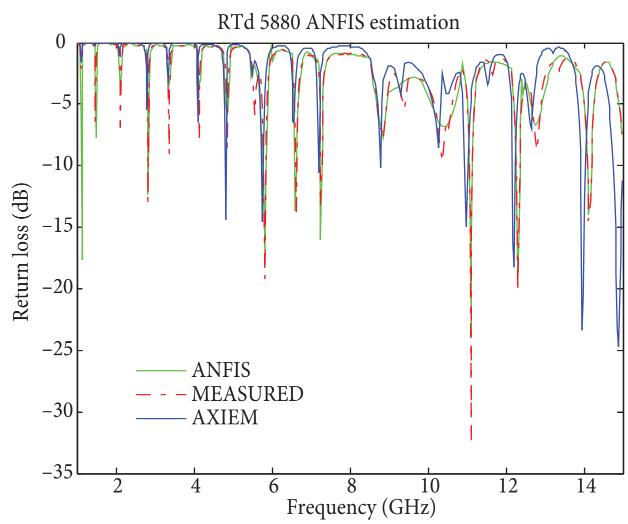

Figure 5. Return loss vs. frequency estimation of the ANFIS model.

The frequency, dielectric constant, and stub width to the substrate height are selected as the input parameters of the proposed model, in which the input-output relation must be clearly defined. As new input parameters are inserted into the model, it becomes complicated and is tougher to train. For instance, if the stub number is taken as a variable parameter and altered, the number of resonances changes. Next, the modeling problem converts to an optimization problem. In this study, a total of 8 inverted L-shaped stubs are attached to the antenna. The proposed ANFIS model can be applied to 2-, 4-, and 6-stubbed antennas under a fixed stub number and physical shape. This study aims to model as diverse as possible antennas with various substrates and antenna dimensions to avoid repetitive production processes.

Figure 6 illustrates the antenna gains for some resonant frequencies. Nine resonance points are determined among the overall frequency ranges, of which 4 provide sufficient gain and cross polarization. This still satisfies the proposed multiband characteristic of the MPA. The cross polarization values are around –40 dB for each frequency. The computed gain values alter between 6.11 dB and 11.44 dB.

The Table presents the ANFIS return loss outputs for some resonant frequencies and the computed error percentage compared with the desired test outputs, which include both the simulation and measurement results. The modeling accuracy can be improved as the number of sampling points around the resonant frequency is boosted. When the ANFIS optimization algorithms are compared, the hybrid learning provides better estimation results than the back propagation method, which introduces 158.8% more error.

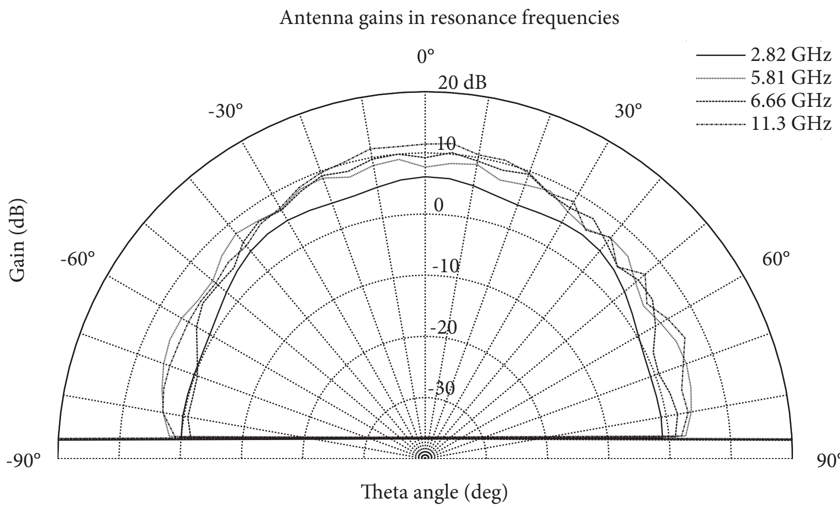

Figure 6. Antenna gains in the resonance frequencies.

Table. Comparison of ANFIS modeling outputs vs. the desired test values (* indicates the measured results).

Antenna parameters (mil)					Resonant frequency (GHz)	Return loss (dB)		Error percentage (%)
L	W	sw	h	ε_r	f_r	Desired	ANFIS	ANFIS
950	790	115	31	2.2	2.8288	–12.923*	–12.3076	4.76
950	790	115	31	2.2	5.8213	–19.183*	–16.9678	11.55
950	790	115	31	2.2	6.6	–13.944*	–13.6498	2.10
950	790	115	31	2.2	11.2988	–14.815*	–16.3448	10.32
700	570	120	20	3.02	3.9575	–18.0083	–17.1126	4.97
700	570	115	20	3.02	8.3063	–17.1766	–17.9980	4.78
700	570	110	20	3.02	11.5088	–17.2607	–17.6923	2.50
700	570	105	20	3.02	13.1888	–12.5002	–11.5628	7.49
1070	850	120	60	2.94	4.5175	–15.8367	–13.8534	12.52
1070	850	120	60	2.94	7.8950	–26.4594	–24.0645	9.05
1070	850	115	60	2.94	11.7188	–13.7821	–13.6765	0.76
1070	850	110	60	2.94	14.7375	–21.2971	–20.9589	1.58
570	470	65	70	1.2	8.2538	–17.3120	–16.2210	6.30
570	470	65	70	1.2	9.89	–31.6930	–29.2283	7.77
570	470	70	70	1.2	12.3660	–11.6310	–11.9101	2.39
570	470	75	70	1.2	13.5630	–17.5630	–18.3192	4.30
950	730	100	125	2.2	4.3775	–11.0520	–11.0353	0.15
950	730	105	125	2.2	4.9988	–22.1160	–22.5825	2.10
950	730	110	125	2.2	6.7925	–12.6390	–12.7177	0.62
950	730	115	125	2.2	8.8575	–23.1890	–24.0371	3.65
Average percentage error								4.98

3. Conclusions

An ANFIS-based modeling technique was proposed to estimate the scattering parameters of MMPAs with various substrates and dimensions. The ANFIS results were compared with the desired test outputs containing the EM simulator and measurement results. The suggested method provides faster, lower-cost, highly accurate, and reliable results, which proves that the complex nonlinear relations between the input and output parameters in the field of antenna computer-aided design can be handled using ANFIS models. As the training data sets get larger and statistically have enhanced sampling on the intended parameter ranges, the ANFIS modeling capacity increases. ANFIS models can be easily adapted to various RF microwave modeling problems to shorten the overall production processes.

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