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An Efficient Antenna Parameters Estimation Using Machine Learning Algorithms

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Abstract—A smart antenna synthesis approach is described as automatically choosing the optimum antenna type and providing the best geometric characteristics under the demands of antenna performance. Different antenna performance characteristics are examined, and using decision tree classifier, the optimal antenna is suggested using an intelligent antenna selection model. Finally, the geometric characteristics of the antenna are given before the fuzzy inference system is developed by merging five primary learners to fully exploit the benefits of each type of learner. Rectangular patch antenna, pyramidal horn antenna, and helical antenna are the three types of antennas that are classified by a decision tree classifier, and the optimal antenna size parameters are determined using a fuzzy inference method. The performance of decision tree classifier measured using accuracy and FIS is measured using Mean Square Error (MSE) and MAPE. The system demonstrates excellent capability in parameter prediction with antenna categorization with a MAPE of less than 5.8% and accuracy over 99% achieved in our proposed method. The recommended methodology might be widely applied in actual smart antenna design.

1. INTRODUCTION

Antennas need to be developed with more precision and efficiency because they are crucial to the functionality of consumer devices. Knowledge-based neural network, KNN algorithm, artificial neural network, and Dielectric Resonator Antenna (DRA) are only a few of the Machine Learning (ML) algorithms used in this method for fine-tuning dielectric resonator antennas. ML models can be used to determine reflection coefficients for a given resonator height, resonator radius, resonant frequency, and aperture radius [1, 2]. This research proposes using artificial neural networks for antenna development and optimization in Wireless Body Area Network (WBAN) applications. Antenna design heavily depends on the selected substrate. Choosing the substrate material and other design criteria for an antenna takes time. In order to shorten development time and increase performance, engineers can use artificial neural network (ANN) to determine optimal values for design parameters and substrate materials [3]. Nan et al. suggest a deep learning model that establishes the model's structure for developing ultra-wideband (UWB) antennas. They created Deep Belief Network and Extreme Learning Machine Surrogate Models (DBNELM) model, which has good accuracy, significantly improving antenna design efficiency and the ability to minimize root mean square error values [4]. Gaussian process, least absolute shrinkage and selection operator (LASSO) semi-supervised learning, ANNs techniques [5], single-output Gaussian process regression (SO-GPR), multioutput Gaussian process regression (MO-GPR), regression based learning algorithm is proposed in this research. The suggested approach is utilised to minimize the training and testing error values for rectangular patch antenna [6]. Wu et al. estimated an ML based antenna optimization technique for parameter estimation in efficient way.

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They developed a multi-stage collaborative machine learning model (MSCOML) which can reduce computation time without affecting accuracy.

Three types of antennas namely single band, broad band, and multi-band antennas were considered, and S_{11} and gain are the two parameters used for antenna design. Normalized root mean squared error (NRMSE) values of S_{11} and gain for all three types of antennas were presented. The proposed MSCOML method provides low NRMSE and high accuracy with less computational time [7]. To represent the antenna performance with varied parameters, a novel ANN model is proposed in this study.

The Support Vector Machine (SVM) data classification technique is used to group the geometrical variables into the relevant categories in each branch [8]. A-shaped microstrip patch antennas for ultra-high frequency applications need to have a resonance frequency. Kayabasi developed two distinct ML algorithms, namely Multi-Layer Perceptron (MLP) and KNN algorithm. These models are quicker, simpler to use and give more precise findings for the APAs' resonance frequency than conventional Artificial Neural Network (ANN) based ML algorithms [9]. Abbasi Layeg et al. proposed ANFIS technique for enhancing bandwidth in two equal slots of a microstrip patch antenna [10]. In this study, a particle swarm optimization (PSO) algorithm was used to determine the optimal size of a circular patch antenna for a specified resonance frequency. The objective function of the method is an ANN ensemble model [11]. This study estimates the operating frequency of a microstrip antenna operating in the ultra-high frequency band using Adaptive Neuro-Fuzzy Inference System (ANFIS), SVM classifiers, and fuzzy inference system (FIS) models [12]. In this research, we show that the performance of an ANN ensemble is superior to that of its component ANN model [13]. To better understand the resonance frequencies of dual-band patch antenna, this research suggests a model based on the Gaussian process regression. Even when there are many design variables present, GPR can produce extremely good predicting results with relatively modest training datasets [14]. Particle swarm optimization and neural networks, two machine learning techniques, have been combined to provide a user-friendly tool for designing stacking patch antennas specifically for satellite communication applications throughout the whole X-Ku band [15]. The proposed method involves a multilayer feed forward back propagation ANN with a single hidden layer used to estimate the resonance frequency of a circular microstrip antenna, and other patch antenna parameters may also be predicted using ANN with great accuracy [16]. This paper details the process followed to create and test a Triple Hilbert fractal defected ground structure (HDGS) antenna that operates on two different frequencies. DGS has proved effective in constructing multiband antennas [17]. The Surrogate model assisted differential evolution for antenna synthesis (SADEA) technique for effective antenna synthesis is described in this paper. According to experimental results, SADEA can outperform more well-known methodologies in terms of efficiency by a ratio of three to seven while providing highly optimised design options that are comparable to traditional evolutionary algorithms for antenna synthesis [18]. In this study, a tiny hybrid fractal antenna (GCHFA) with biological uses is developed. The feed placement of the designed antenna has been optimised using the Firefly algorithm [19]. In order to evaluate the effectiveness of pyramidal horn and corrugated horn antennas, this technique proposes wide band methodologies based on the ANFIS. It was found that the results generated by the suggested methods were comparable to those generated by a full-wave solver. It has been discovered that ANFIS algorithms operate more quickly and accurately to forecast horn antenna performance [20]. Shi et al. suggested a reconfigurable reflect array antenna that uses deep learning and Convolutional Neural Network (CNN) to estimate various parameters effectively. They created a CNN model that can speed up computations without sacrificing accuracy. The suggested CNN approach offers great accuracy with minimal computation time [21]. Dual-band operation is necessary for mobile communication. For dual-band frequency operations, normal mode helical antenna is frequently employed. Traditional helical antenna is made by trial and error. The helix's mathematical parameters are adjusted from a standard geometry until the necessary properties are attained. In this paper, Jagadeesh and Kumar present a procedure for fabricating a dual-band helical antenna [22]. A monopole antenna optimization approach for Radio Frequency Identification (RFID) sensor based on Back-Propagation (BP) neural networks was proposed by Wan et al. [23]. They created a machine learning model using BP neural networks that can speed up computations without sacrificing accuracy [23]. Kim et al. suggested a broadband antenna optimization approach based on artificial neural networks (ANNs) for accurate parameter estimation. They created the Hybrid Genetic Algorithm with Particle swarm optimization (HGPSO) model, which can speed up computations without compromising precision. This suggested method predicts the input impedance of broadband antenna using ANN [24]. Fuzzy logic is employed in this work to optimize the various parameters such as S_{11} and Voltage Standing Wave Ratio (VSWR) [25]. According to the detailed literature survey presented above, it is found that many researchers have proposed a machine learning model for antenna type's classification in efficient way with good accuracy results, but very few researchers attempted antenna parameter estimation after antenna classification. Also they compromised with computational time, and the accuracy of parameter estimation can also be further improved. The proposed (DT + FIS) method effectively classifies the three types of antennas namely microstrip antenna, horn antenna, and helical antenna using decision tree classifier as well as predict antenna parameters using fuzzy inference systems. Antenna width & antenna length for microstrip patch antenna, wire diameter & helix diameter for helical antenna, length& width for horn antenna can be predicted by fuzzy inference systems with good accuracy and low computational time.

2. SYSTEM DESCRIPTION

The suggested smart antenna synthesis structure is depicted in Fig. 1. The fuzzy inference system model and intelligent classification module are the two parts that make up the overall structure of the smart antenna synthesis system. The appropriate antenna type is selected for the system's first classification step by entering the electromagnetic indicators of the antenna's gain, bandwidth, reflection coefficient, and resonant frequency via a well-trained decision classifier algorithm classification model. The fuzzy inference system model then provides further information about the ideal antenna parameter design. First, the control variate approach is used to examine the effect of the antenna's characteristics on the implementation of the entire system. Since each antenna has a separate set of parameters, simulating different values for each parameter would result in an excessively huge dataset and consume a lot of computing power. As a consequence, the analytical formulae in the published literature are used

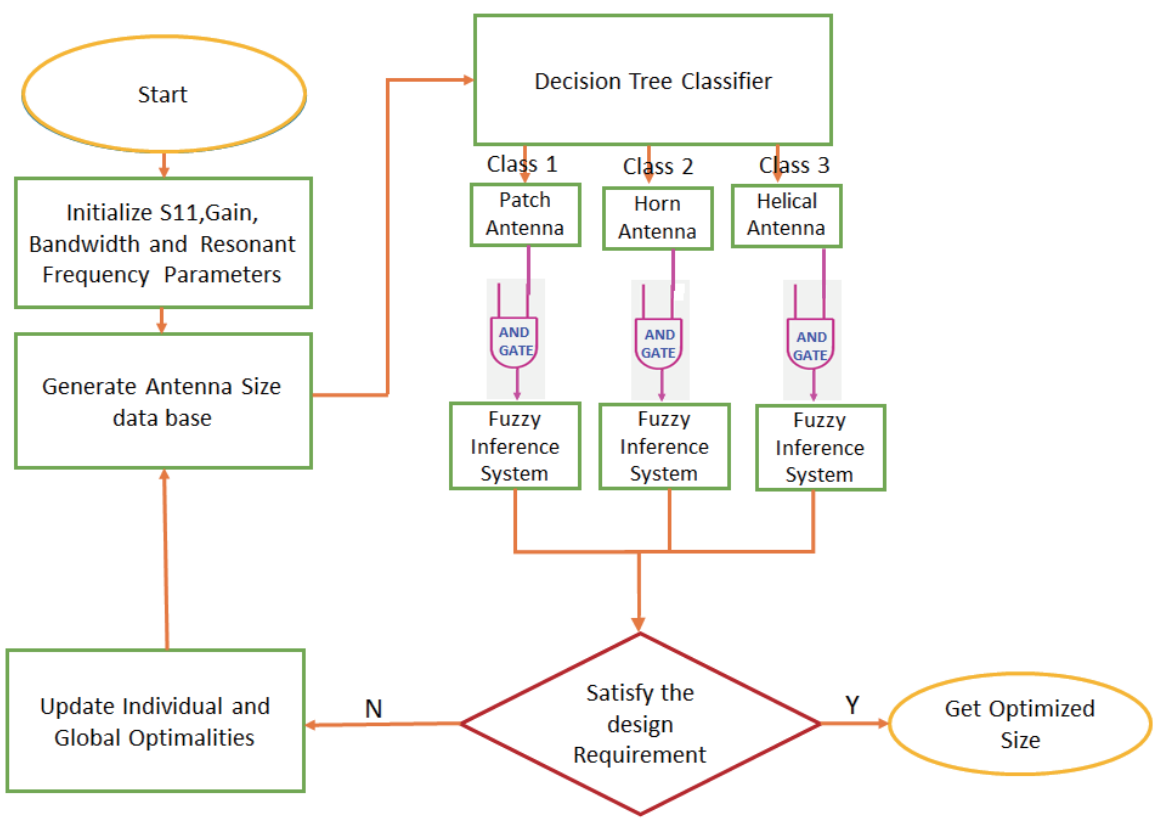


Figure 1. Proposed intelligent antenna synthesis system.

to identify the factors that have a substantial impact on each antenna type's outcomes, and the HFSS toolbox is then used to produce the electromagnetic simulation results that correspond to those variables. By continually training DC Algorithm (DCA) with cross-validation and integrating existing datasets with different antenna types, a reliable classification model is produced. Decision Tree (DT) classifiers are effectively applied in a wide range of fields. Their capacity to extract descriptive decision-making information from the given data is their most significant quality. From training sets, decision trees may be produced for different antenna sets. Information is learned by the DT in the form of a tree, which can also be expressed as a number of specified rules. The DT classifier's key strength is in its flexibility in making use of multiple feature subsets and decision rules at various points throughout the classification process. It is possible to forecast the appearance of pyramidal and conical corrugated horn antennas by utilising a model created with an FIS. Many models built on the FIS have been produced. For any given set of design parameters, these models may be utilised to precisely forecast the polarization and cross-polarization radiation patterns as well as the horn return-loss characteristics.

The output of the specific class becomes one, and the output of the other classes becomes zero when the Decision Tree Classifier (DTC) correctly predicts the antenna. DTC output is supplied into an AND gate, which only enables the FIS when the two inputs are the same. The specifics of the optimum antenna size parameters for the associated input design parameters, such as S_{11}, resonant frequency, bandwidth, and gain, are recorded as datasets in FISs. The values for the optimum antenna size parameters are then provided once the fuzzy inference system has been tested with a certain design parameter and compared with stored datasets.

3. METHODS DESCRIPTION

3.1. Microstrip Antenna

Figure 2(a) illustrates the rectangular patch antenna with a generalized overview and numerous geometric parameters, such as the patch width (w) and length (l). The structure of a microstrip antenna consists of ground plane with a dielectric substrate and radiating patch. Any shape is possible for the metal patch on the front surface, but it is often rectangular, as seen in Fig. 2(a). The antenna can be excited in a variety of ways. One such approach entails attaching the microstrip antenna at one of its edges after feeding it from a microstrip line.

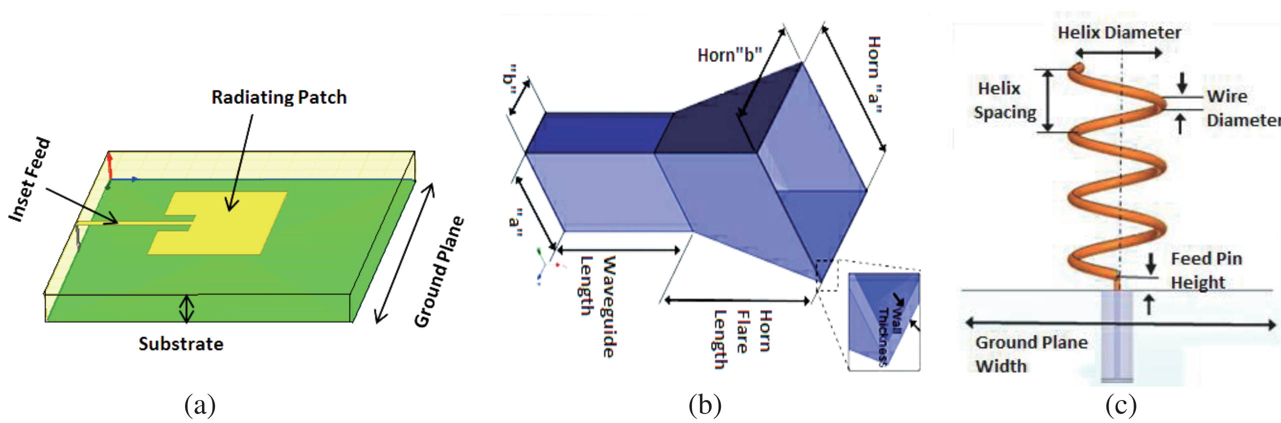


Figure 2. (a) Microstrip antenna. (b) Pyramidal horn antenna. (c) Helical antennas.

Figure 2(b) depicts the pyramidal horn antenna's structural layout. The wall thickness, waveguide length, horn flare length, horn diameter (h_d), and horn length (h_l) are some of the geometric parameters of this pyramidal horn antenna. An E plane horn and an H plane horn are the two sectoral horns that made up of pyramidal horn, which has a rectangular or square aperture. The radiation patterns of the two sectoral horns are multiplied to create the pyramidal horn's radiation pattern. Due to its wide pattern in the narrow plane, sectoral horns are rarely employed as radiators on their own. Fig. 2(c) depicts the helical antenna's structure. The ground plane width, feed pen height, helix diameter (h_d), wire diameter (w_d), and other geometrical features are all present in this antenna. This antenna operates in both the Very High Frequency (VHF) and Ultra High Frequency (UHF) bands because helical antennas are the most fundamental antennas that are frequently used in ultra-high frequencies. These antennas are formed of conducting wire that has a helix shape. This antenna stands out for a number of reasons, including its broad bandwidth, strong gain, and circular polarization. An antenna with a feeder line connecting the ground plate to a conducting wire twisted into a helical shape is referred to as a helical antenna, sometimes known as a helix antenna [26].

4. RESULT AND DISCUSSION

4.1. Dataset

The antenna patch that is rectangular and compact, the helical antenna with wide bandwidth, and the pyramidal horn antenna with high gain are selected as the leading candidates based on the antennas' general characteristics. Table 1 displays the estimated ranges for the antenna performance metrics.

Table 1. Estimated antenna performance parameters.

Parameters	**Helical Antenna**	**Microstrip Patch Antenna**	**Pyramidal Horn Antenna**
S_{11} (dB)	$-13 \sim -17$	$-15 \sim -39.5$	$-17 \sim -27$
Resonant Frequency (GHz)	$1 \sim 6$	$2.4 \sim 5$	$3 \sim 27$
Bandwidth (GHz)	$0.5 \sim 2$	$0.055 \sim 0.104$	$0.25 \sim 0.348$
Gain (dB)	$11 \sim 14$	$5 \sim 7$	$1 \sim 28$

4.2. Decision Tree Classifier

One of the most often used methods for modelling classifiers is the use of decision trees. A DT is a tree structured categorization model that may effectively be inferred from data and is simple to understand, especially for non-expert users. One of the first and most well-known methods for developing discriminatory models was the induction of decision trees, which was independently developed in the statistical and machine learning areas [27].

The confusion matrix for the suggested classification scheme is depicted in Fig. 3(a). The overall number of every column in the confusion matrix indicates the number of predictions for each class, and each column represents the predicted data for that class. The diagonal grid has all the numbers filled in clearly, indicating that all the antennas have their correct stated performances.

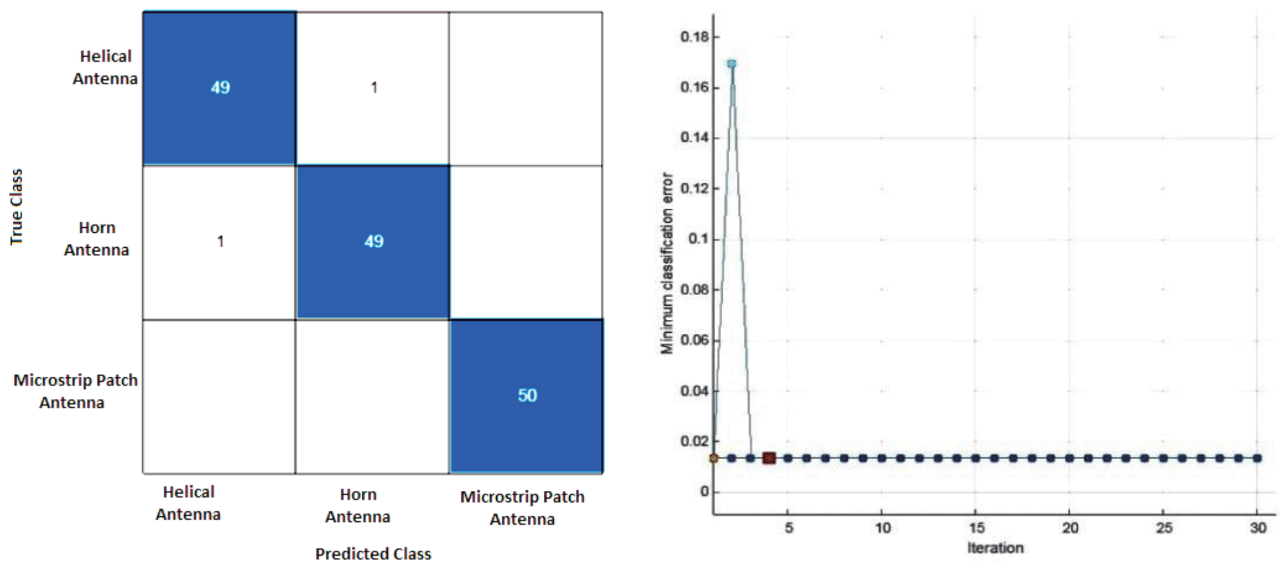
The classification of the error plot is shown in Fig. 3(b). If the actual value and anticipated value are the same, the error is 0. Errors are defined as differences between expected and actual values. The error is positive when the actual value exceeds the expected value. The error becomes negative when the actual value is less than the desired value, and classification error is given in Equation (1).

$$E = A - B \tag{1}$$

where E — error value, A — actual value, B — predicted value.

The workflow for the decision tree algorithm is shown in Fig. 4. When a machine learning model is made, the most important thing to do is choose the best method for the dataset and task.

There is an illustration of the whole dataset, which is then split into two or more sets with the same characteristics. To determine the most important attribute in the dataset, use Attribute Selection Measure. With this measurement, it is easy to pick the best property for each node in the tree. Two of the most common Active Shape Model (ASM) methods are the Gini Index and the Information Gain. After a dataset has been divided into segments depending on a feature, the assessment of changes in entropy is known as information gain. The node or feature with the supreme information gain is split



(a) (b)

Figure 3. (a) Confusion matrix of the classification model. (b) Classification error plot.

first in a DT algorithm, whose constant goal is to increase the value of information gain. It can be determined using Equation (2) and Equation (3).

$$E\left(s\right) = \sum_{i=1}^{c} -p_i \log p_i \tag{2}$$

$$E(s) = -P(a)\log_2 P(a) - P(b)\log 2P(b) \tag{3}$$

Equation (3) gives the expression for entropy, where $p(a)$ stands for yes probability, $p(b)$ for no probability, and s for the total number of samples. It is best to build subsets of the s that contain potential values for the best characteristics. Make the decision tree node with the best attribute distribution. Create new decision trees iteratively using the dataset's created subsets.

Figure 5(a) displays a Receiver Operating Characteristic (ROC) curve plot. Any classifier's performance is indicated by the receiver operating curve. When the ROC curve gets close to one, classification is doing better than expected. The experimental result shows that the AUC of helical and horn antennas is 0.985, which is almost equal to one, and the microstrip patch antenna has an Area Under the Curve (AUC) of one, respectively.

Figure 5(b) displays the plot of the antenna dataset in parallel coordinates. This graph shows how input parameters like S_{11}, resonant frequency, bandwidth, gain, and the standard deviation for each category interact with one another.

The FIS of helical antenna using Mamdani Controller is shown in Fig. 6. The input to the FIS is S_{11}, resonant frequency, bandwidth, and gain. Two output parameters are helix diameter and wire diameter.

Figure 7 represents membership function of resonant frequency. Resonant frequency is between 1 and 6 GHz for helical antenna. The membership function of bandwidth is shown in Fig. 8. The value of bandwidth lies between 0.5 and 2 GHz for helical antenna.

The membership function of helix diameter is shown in Fig. 9. The value of helix diameter lies between 1.59 cm and 9.541 cm for helical antenna. The proposed model for helical antenna performance is evaluated in ruler view of tested sample as shown in Fig. 10. For the resonant frequency of 4.2 GHz, gain of 12.48 GHz, bandwidth of 1.7 GHz, and S_{11} of -15.58 dB, the actual geometric parameters are helix diameter 2.272 cm, wire diameter of 0.403 cm, but the proposed model predicts the results as the helix diameter of 2.97 cm and wire diameter of 0.495 cm. In the same way, the parameters of microstrip patch antenna and horn antenna are tested.

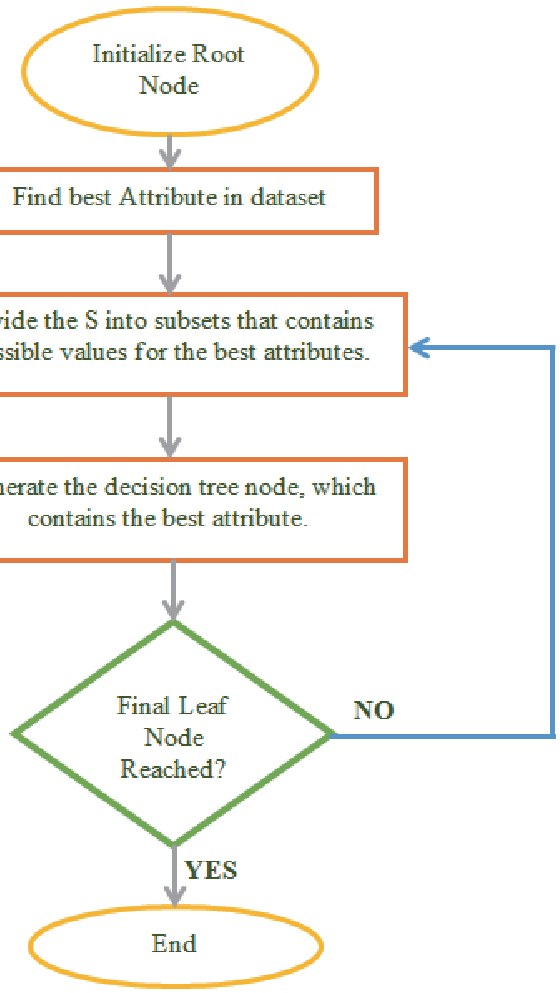
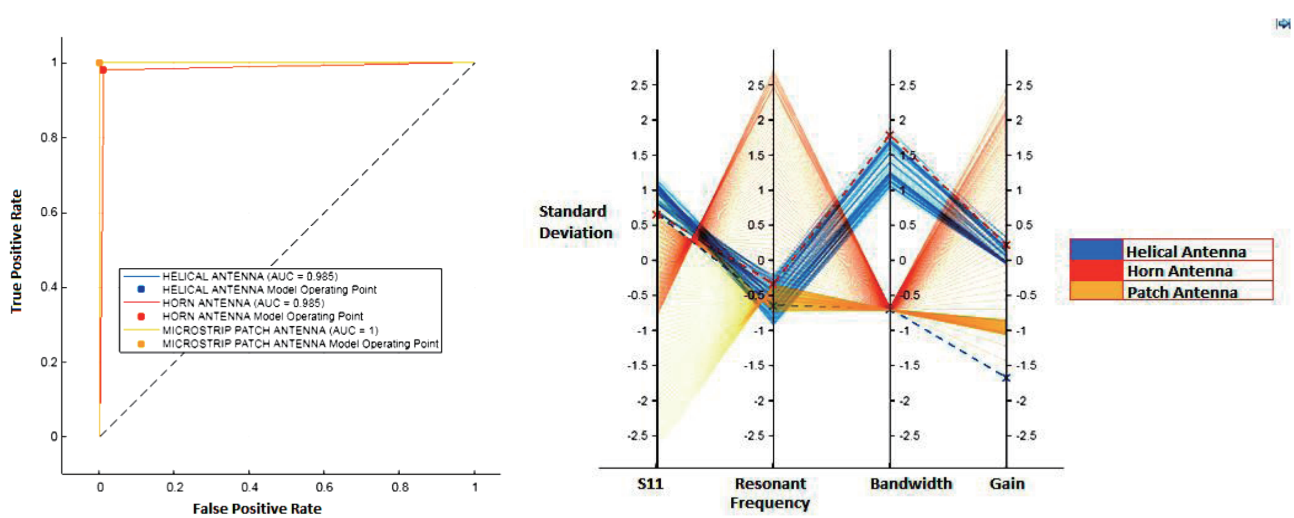


Figure 4. Flow chart for decision tree classifier.



(a) (b)

Figure 5. (a) ROC curve plot. (b) Parallel coordinates plot.

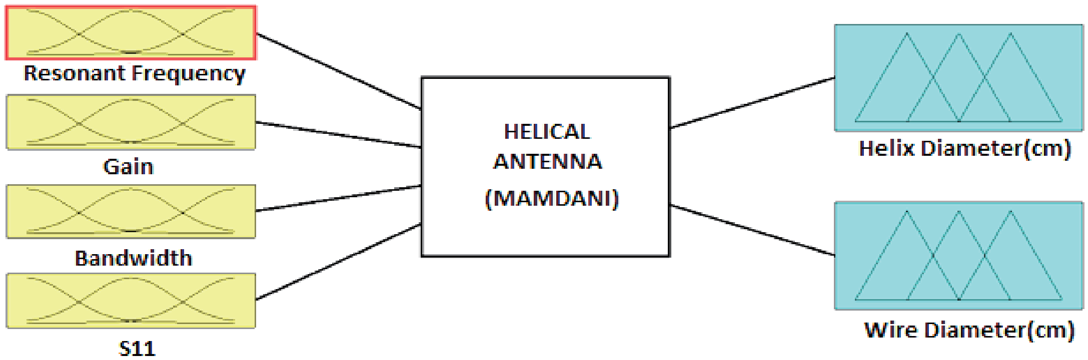


Figure 6. FIS System using mamdani controller.

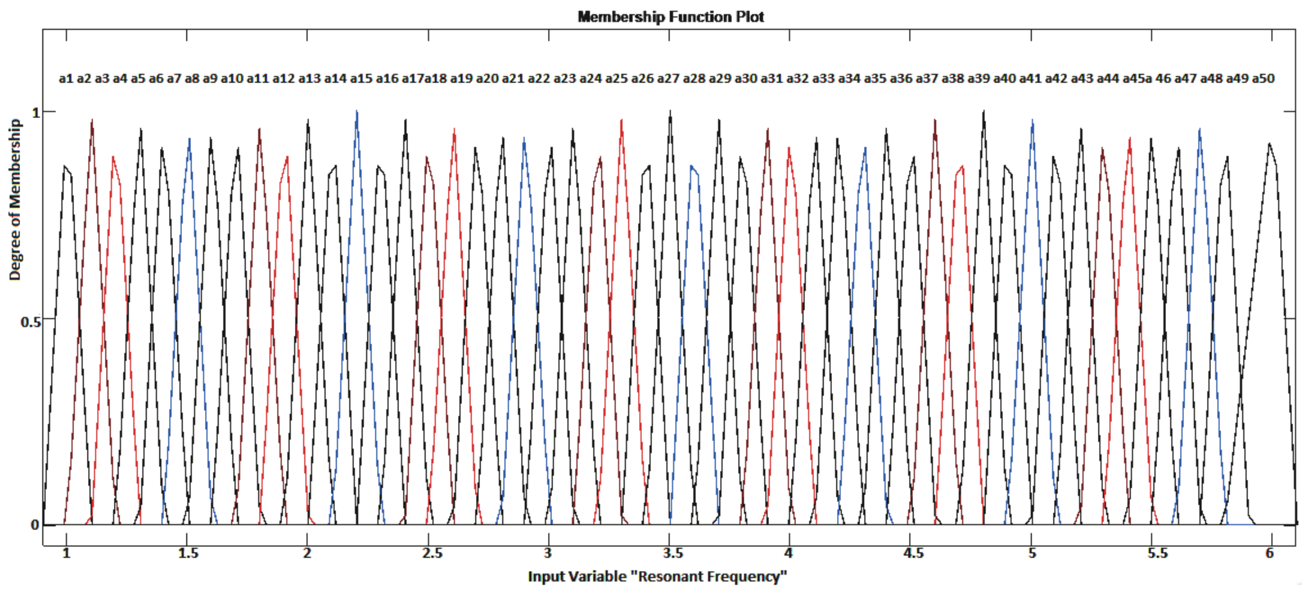


Figure 7. Membership function of resonant frequency.

The performance of tested model is measured using root mean square error (RMSE) and mean absolute percentage error (MAPE) [28] which are mathematically given in Equations (4) and (5).

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{A_i - B_i}{B_i}\right| \tag{4}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(A_i - B_i)^2 \tag{5}$$

where A_i represents the actual calculated value, and B_i represents the predicted value from proposed model. The performance measures such as MAPE and RMSE for microstrip patch antenna, helical antenna, and horn antenna are calculated using Equations (4) and (5). The results are tabulated in Table 2. From Table 2 it is observed that MAPE of microstrip patch antenna is 0.12%; helical antenna is 3.28%; and horn antenna is 5.76% which are very low that indicates a better prediction of the proposed model.

The actual and predicted values of helical antenna helix diameter and wire diameter using fuzzy

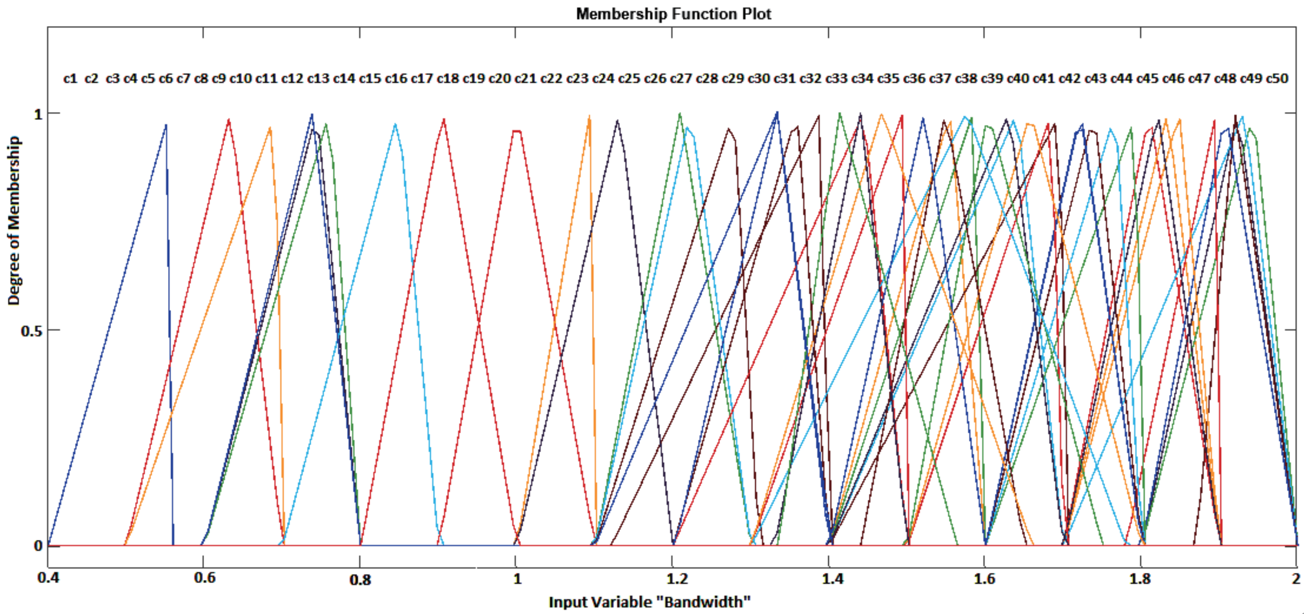


Figure 8. Membership function of bandwidth.

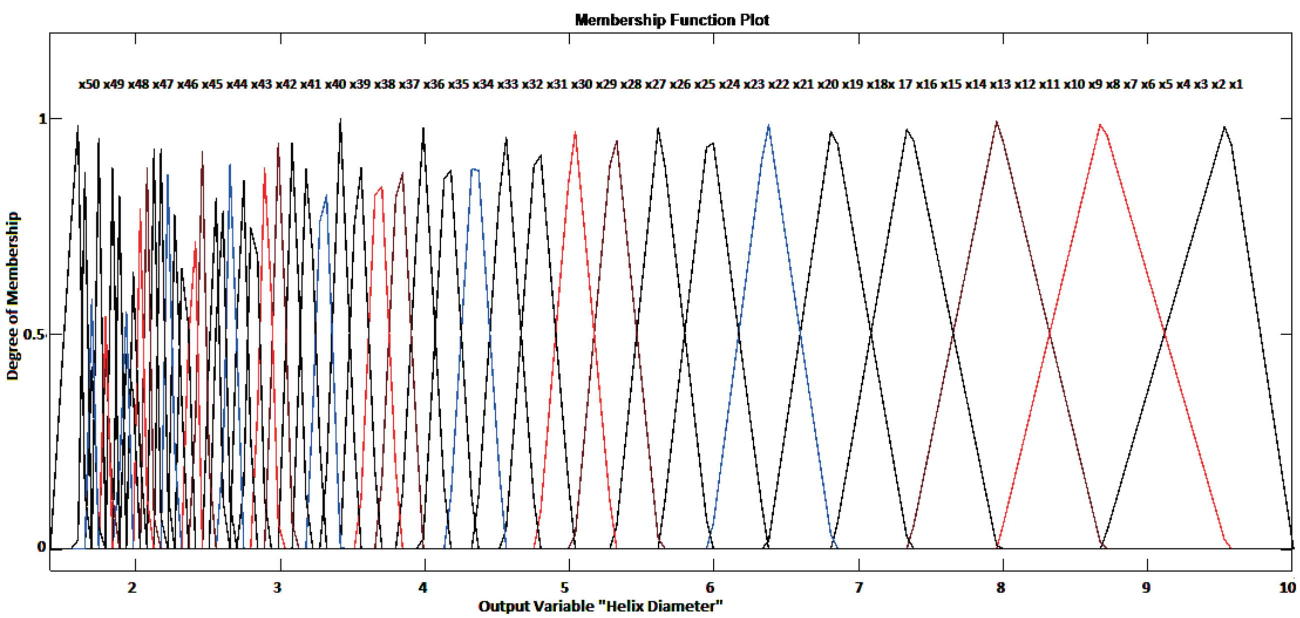


Figure 9. Membership function of helix diameter.

inference system are shown in Fig. 11(a) and Fig. 11(b), respectively. The deviations in the predicted values of antenna helix diameter have been given as error $\in$ which ranges between -4.263 cm and 3.501 cm, with a mean of -0.95106 cm and median -1.0905 cm. The deviations in the predicted values of antenna wire diameter have been given as error $\in$ which ranges between -0.655 cm and 0.652 cm, mean of -0.14322 cm, and median -0.1635 cm. In the same way, the actual and predicted values of microstrip patch antenna and horn antenna are measured.

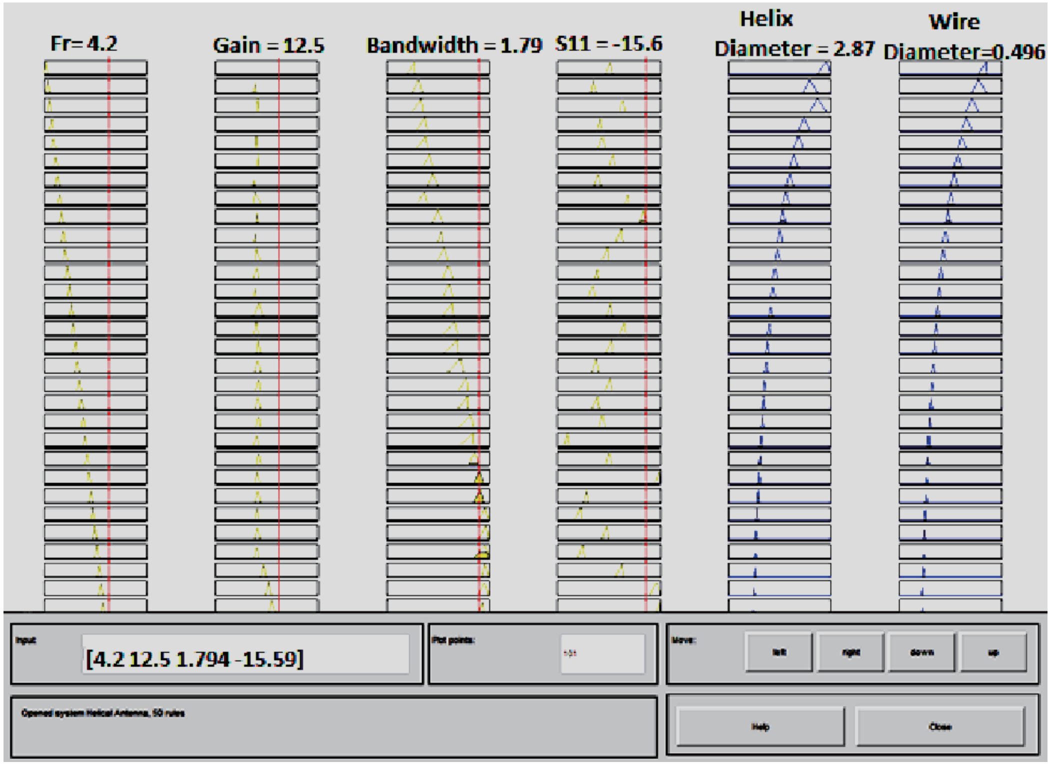
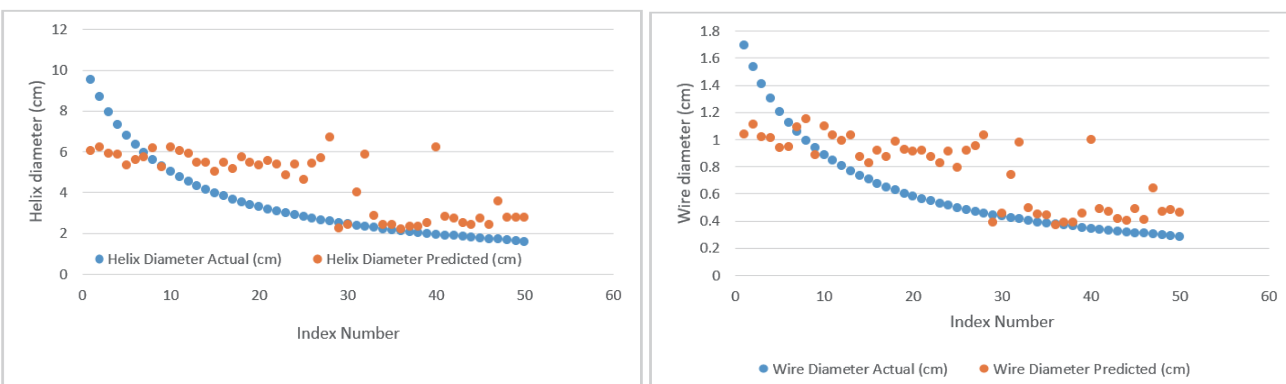


Figure 10. Ruler view of tested sample.



(a) (b)

Figure 11. (a) Comparison between predicted and actual value of helical antenna helix diameter. (b) Comparison between predicted and actual value of helical antenna wire diameter.

4.3. Discussion of Fuzzy Inference System

To compare with other learners, the fuzzy inference system's five primary learners are examined separately. Table 3 compares the fuzzy inference system and the single learner system. As previously noted, all of the MAPE numbers in Table 3 are the output findings that have been averaged. Table 3 shows that FIS learning outperforms other single learners in that it circumvents the single model's tendency to settle into local optimality. The fuzzy inference system paradigm is therefore appropriate for the system's smart antenna synthesis component.

Table 2. Result analysis of fuzzy inference system.

	Microstrip Patch Antenna		Helical Antenna		Horn Antenna	
	Length	Width	Helix Diameter	Wire Diameter	Horn Diameter	Horn Length
MAPE	0.13%	0.11%	3.348%	3.212%	4.51%	7.01%
RMSE	4.03	4.01	17.771	2.886	3.662	3.757
MAPE (average)	0.12%		3.28%		5.76%	

Table 3. Comparison of single learner with DT plus FIS method.

Algorithms	MAPE of Microstrip Patch Antenna	MAPE of Horn Antenna	MAPE of Helical Antenna	Time Complexity (Training Time)	Time Complexity (Testing Time)
CNN	10.596%	14.564%	11.547%	0.998 sec	0.754 sec
SVM	3.557%	6.798%	8.964%	0.562 sec	0.448 sec
K-Nearest Neighbour	5.49%	5.928%	9.64%	0.771 sec	0.562 sec
Gradient Boosting	1.487%	7.208%	7.968%	0.995 sec	0.723 sec
Naive Bayes	1.78%	6.287%	4.798%	0.730 sec	0.568 sec
Proposed Method (DT + FIS)	0.12%	5.76%	3.28%	0.541 sec	0.325 sec

5. CONCLUSION

An intelligent machine learning based antenna classification and geometric parameters prediction model has been developed in this work. Antenna classification model using FIS has been proposed. Antenna classification model using DT classifier provides the accuracy of 99%, and geometric parameter estimation model using FIS provides MAPE of less than 5.8%. The training time and testing time of proposed method are 0.541 sec and 0.325 sec, respectively, which is faster than existing methods. This proposed (DT + FIS) model can be suggested for real time implementation for accurate antenna classification and geometric parameters prediction. In future, antenna classification can be performed using different machine learning algorithm, and geometrical parameters can be predicted using ANFIS.

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