Predicting Rectangular Patch Microstrip Antenna Dimension Using Machine Learning

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Abstract —When designing a microstrip antenna, the designers determined the desired parameters. However, the simulation software can only give the parameters result based on the given dimension. Therefore, optimization is required to meet the desired parameters. The designers usually do the optimization by the trial-error process. This research conducts machine learning implementation to predict the microstrip antenna dimension. The study focused on rectangular patch microstrip antenna with resonant frequency ranged from 1-8 GHz. The dataset used to make the prediction is obtained from simulation with antenna width ranged from 19-63 mm and length 10-54 mm. There are four algorithms employed: decision tree, random forest, Support Vector Regression (SVR), and Artificial Neural Network (ANN). Among all algorithms, random forest with estimator 15 gives the best result with Mean Square Error (MSE) value is 3.45. From the obtained result, the researchers can estimate the rectangular patch microstrip antenna dimension based on the desired parameters, which can't be done by the antenna simulation software before.

Index Terms—Microstrip, prediction, machine learning

I. Introduction

A microstrip antenna is an antenna fabricated using a copper-etched Printed Circuit Board (PCB) with a spesific patch shape on one side and a ground plane on the other side. This antenna has been used extensively for various applications, such as mobile communication [1], radar [2], military [3], Internet of Things (IoT) [4], and healthcare system [5]. Its compact size, low-cost fabrication, lightweight, and easy integration makes microstrip antenna highly popular. Despite its various advantages, the microstrip antenna also has several disadvantages, such as poor gain, spurious radiation, low efficiency, and narrow bandwidth [6]. Many techniques have been implemented to reduce those drawbacks, such as miniaturization [7], low-loss substrate usage, and patch shape alteration.

There have been tremendous patch antennas explored for years, such as rectangular, circular, equitriangular, and annular-ring [8]. A rectangular patch antenna is considered one of the most commonly used among other patches [9]. It is simple in terms of geometry and analysis. This patch also has a symmetric radiation pattern. Therefore, it is easier for analysis.

When designing an antenna, the designers have already had the desired parameters. For example, the resonant frequency is 2.4 GHz, the return loss must be less than -15 dB on the resonant frequency, the bandwidth is bigger than 100 MHz, or the gain is more than 2 dB. If these parameters aren't achieved, optimization is required.

Traditionally, antenna design steps are started with antenna dimension calculation. This calculation is performed to find the width and length of the antenna patch and transmission line feed. The calculation result is then used as a reference for the antenna dimension in simulation. The simulation is performed by using an electromagnetic wave simulator. There are several softwares available for antenna design and simulation. They are Ansys High-Frequency Structure Simulator (HFSS), ZELAND IE3D, Althair FEKO, Antenna Magus, and CST Microwave Studio. After that, the simulation result parameters are observed. Important parameters are the resonant frequency, return loss, Voltage Standing Wave Ratio (VSWR), gain, and impedance value. Usually, the simulation result doesn't give the desired parameters even though the antenna dimension has the same size as the calculation result. It happened because in the calculation process, the environment of the antenna is considered as a vacuum. While in the simulation process, the condition of the environment can be controlled. In order to meet the desired parameters, the optimization is conducted by either changing the size of the antenna or the substrate. The optimization process is usually done by trial and error method. Since it is based on trial and error, the optimization process can take an unexpectedly long time. Until recently, the simulator can only do the calculation based on the given antenna dimension. No simulator provides a function where the designer can input the desired parameters to find the suitable antenna dimension.

With the fast-growing computational ability, it is possible to make a prediction using Artificial Intelligence (AI). Machine learning, a subset of the AI field, can make a forecast based on the given dataset. There are numerous machine learning algorithms that can be used to make a prediction, such as Support Vector Machine (SVM), decision tree classifier, linear regression, and random forest regression [10].

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In this paper, research on machine learning algorithm implementation to predict a rectangular patch microstrip antenna dimension is conducted. By using machine learning algorithms, it is expected that from antenna parameters, such as resonant frequency, return loss, and bandwidth, the antenna dimension can be predicted. Thus, it can help the antenna designers escape the never-ending loop of the trial and error optimization process. There are four algorithms used in this research: decision tree, random forest regression, Support Vector Regression (SVR), and Artificial Neural Network (ANN). Those algorithms are selected because they can calculate regression for non-linear data, as the dataset used for this research is non-linear.

In conducting this research, a dataset consists of resonant frequency, return loss, bandwidth, width, and length of a rectangular patch microstrip antenna is obtained from antenna simulation using CST microwave studio. The simulation is conducted by trying various antenna dimensions from 10 to 63 mm with resonant frequency ranged from 1 to 8 GHz. Then, the prediction is made using the algorithms. MSE value for simulated and predicted antenna dimensions is analyzed to measure the prediction performance.

The organization of this paper is as follows. Section one discusses, in brief, the content of the paper. Section two describes the dataset. Section three explains the research method. Section four tells the result. And section five concludes the paper.

II. Dataset

In this research, a rectangular patch microstrip antenna simulation is conducted using an electromagnetic wave simulation software called CST Microwave Studio to obtain a dataset that will be used to make predictions. Three parameters are observed in simulation: resonant frequency, return loss, and bandwidth.

The resonant frequency in the antenna is the frequency where the cancellation of inductance and capacitance value happens, resulting in high power pass. This frequency is indicated by the return loss reaches the lowest value. The return loss is the loss in returned or reflected power caused by the discontinuity or mismatch impedance between the transmission line and the antenna patch. This power is measured by comparing the input power with the reflected power. Return loss is usually calculated in the logarithmic scale with the decibel (dB) unit. The higher the return loss, the more power is reflected. That means the bigger the mismatch value between the transmission line and the antenna patch. Return loss is closely related to bandwidth. Bandwidth is a range of frequencies over which the antenna is allowed to operate. In this paper, the antenna bandwidth is calculated from the frequency range where the return loss value is less than -10 dB.

In this paper, CST Microwave Studio is used as simulation software. An FR-4 substrate with dielectric constant 4.3, thickness 1.6 mm, and copper-plating 0.035 mm is used. Various rectangular patch antenna dimension is simulated with width and length ranging from 10 to 63 mm with resonant frequency ranging from 1 to 8 GHz. The simulation results are collected into one Comma-Separated Value (CSV) file. The dataset consists of 215 records and is divided into five features: the resonant frequency, return loss at the resonant frequency, bandwidth, length, and width of the antenna patch. The first three features are used as independent variables, while the latter two are used as dependent variables. The Table I below shows each variable description.

TABLE I: DATASET FEATURES MEASUREMENT UNIT

Features	Description
Rf	The resonant frequency of antenna, measured in GHz
RL	The return loss value in resonant frequency, measured in dB
BW	The bandwidth of the antenna, measured in MHz
L	Antenna patch length, measured in mm
W	Antenna patch width, measured in mm

III. Rectangular Patch Antenna Simulation

The simulation is conducted using CST Microwave Studio. This software works based on the Finite Integration Technique (FIT) and Transmission Line Matrix (TLM) for time domain-based simulation for high-frequency components [11]. FIT is derived from an integral form of Maxwell equations. It's resulting in matrix equations that can be used to solve numerical simulation in the time domain [12]. In TLM, the simulation is modeled into cells and the electromagnetic field propagates among cells. TLM has a high capability in modeling lossy, dispersive, and nonlinear components [13].

For the simulation, an FR4 substrate is used. The utilization of this substrate is based on the fact that this substrate is widely available on the market. Therefore, when the designed antenna is going to be fabricated, there will be no difficulty. Antennas with various dimensions are simulated for this research to obtain parameter values from different antenna sizes. First, the antenna with the desired shape and dimension is designed in the workspace. Fig. 1 shows the designed antenna.

TABLE II: ANTENNA DIMENSION AND THE VALUE

Parameter	Description	Value
ε_r	Dielectric Constant	4.3
Hs	Substrate Thickness	1.6 mm
Wg	Substrate Width	76 mm
Lg	Substrate Length	58 mm
Ht	Copper-plate Thickness	0.035 mm
gpf	Gap Width	1 mm
Wf	Transmission Line Width	3.137 mm
fi	Transmission Line Length	8.85 mm
W	Patch Antenna Width	19-63 mm
L	Patch Antenna Length	10-54 mm

After the dimension is determined, the antenna is simulated using a time-domain solver. When the simulation is finished, the required parameters are

observed. They are the resonant frequency, return loss, and bandwidth. Then the patch antenna dimension is changed. After that, the simulation is started again. For the patch antenna width, the simulated dimension ranged from 19-63 mm. While for patch antenna length, the dimension ranged from 10-54 mm. Table II shows the value for each dimension of the rectangular patch antenna.

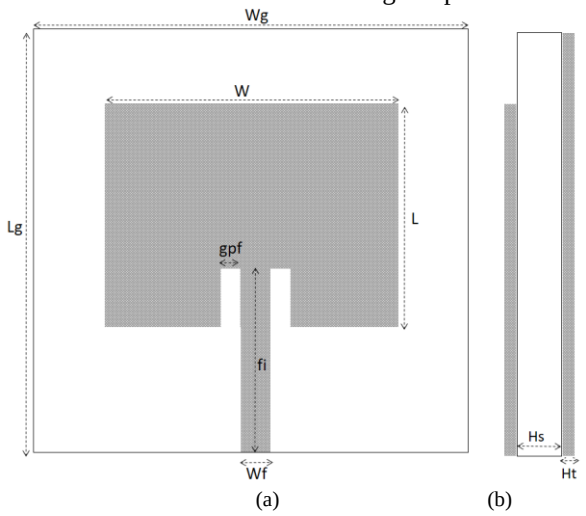

Fig. 1. Antenna dimension for simulation (a) Front View (b) Side View

All simulation parameter results are collected into one CSV file. This file is going to be used as the dataset to make the prediction.

IV. Machine Learning Algorithm Implementation

Four algorithms are used to make the prediction: decision tree, random forest, SVR, and ANN. These algorithms are chosen because they can be used to calculate regression. Since the desired output is in numerical value, regression is the most suitable method to make predictions. These algorithms can also work on non-linear data. The algorithm for prediction is implemented using python3. This programming language is chosen because it is easy to implement and has numerous available libraries supporting data processing, machine learning algorithms, and data visualization.

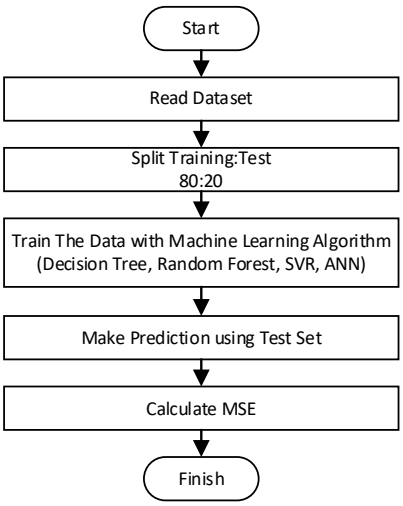

Fig. 2. Machine learning algorithm implementation flowchart

Fig. 2 shows the machine learning algorithm implementation to predict the rectangular patch antenna dimension. First, the dataset is read. Then the dataset is split into an 80% training set and a 20% test set based on the recommendation on [14]. After that, the training set is trained using a machine learning algorithm with different parameters. After training is completed, the next step is to make the prediction using the test set. At last, MSE is calculated between the prediction result and actual data.

A. Decision Tree

A decision tree is a supervised machine learning algorithm. It is a predictive model to calculate the target value using a set of binary rules. This algorithm predicts the target value by learning a simple decision rule started from the root node of the tree, then followed the branch node related to the value and jumped to the next node until the terminal node is reached [15]. To tune the prediction result, the random state variable is used. This variable controls the randomly selected trained features and samples based on the heuristic algorithm [16].

B. Random Forest

The random forest algorithm belongs to a supervised machine learning algorithm family that consists of several decision trees that build up into a forest. In this forest, each tree represents independently sampled random vector values [17]. In the algorithm, the number of trees is represented by the number of estimators. The higher the number of estimators, the more the trees. The more the number of estimators, generally the result will be better. But it also consumes more computational capability that leads to a longer calculation time.

C. Support Vector Regression

SVR is also an algorithm used to calculate regression. The basis of this algorithm is to fit the error within a certain margin. In this research, the Radius Basis Function (RBF) kernel is used. This kernel generates a new feature by calculating the distance between all other points to a specific point. Two parameters are used to tune the prediction result: epsilon and gamma. Epsilon defines the error margin, while gamma defines the influence of the trained data. The lower the epsilon value, the higher the accuracy. The lower the gamma, the more constraint the prediction. This resulted in an inability to capture the data complexity [16].

D. Artificial Neural Network (ANN)

ANN is an algorithm that works by mimicking how the nervous system works. In ANN, the number of hidden layers affects the depth of the network. The more the hidden layer, the deeper the network, and the more the network's complexity. The optimizer is an important part of ANN because it determines the loss reduction of the trained data by adjusting the weights and learning rates. Several optimizers in ANN are Stochastic Gradient Descent (SGD), Adaptive Learning Rate Method (Adadelta), Adaptive Moment Estimation (Adam), and Adaptive Gradient Algorithm (AdaGrad) [18].

SGD optimizer updates each training data once at a time. Adadelta is the variation of SGD optimizer that dynamically updates the parameter over time with first-order information only. While SGD updates the trained data in a single time, the Adam optimizer keeps each parameter weight and updates the learning rate separately. AdaGrad optimizer is the extension of Adam that retains each parameter learning rate.

E. Loss Function

In regression calculation, the loss function represents the error of the prediction. The lower the loss function value, the closer the prediction to the real value. There are several loss functions to calculate the error, such as Sum of Errors (SE), Sum of Absolute Error (SAE), Sum of Squared Error (SSE), Mean Square Error (MSE), etc [19]. The advantage of MSE compared to other loss functions is the more the data, the less the aggregate error. MSE averages the error into a single value which beneficial to making it easy to deduce whether the result obtained is good or not. The equation below shows the formula to calculate MSE.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y - y_i)^2 \tag{1}$$

V. Result

In this section, the MSE result for each algorithm is presented. The MSE is calculated by comparing the predicted result with actual data obtained from the simulation.

A. Decision Tree MSE Result

In the decision tree algorithm, the random state is used to tune the prediction. Fig. 3 shows MSE value for the different random states. The MSE is decreased when the random state is increased from 0 to 10, with values ranged from 8.333 to 5.677. Unfortunately, the MSE is increased until it reaches the maximum value of 9.5 when the random state is increased until 20. Then it fluctuates until the random state is 50. The MSE shows the lowest value when the random state is 50. The fluctuating result happens because of the nature of the random state that randomly selects the data.

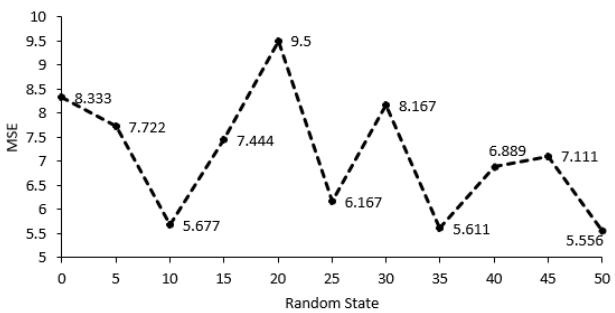

Fig. 3. Decision tree MSE

B. Random Forest MSE Result

Fig. 4 shows the MSE result from simulation and prediction results. As can be seen, the MSE value decreases from 3.95 until it reaches the lowest value at 3.45 when the number of estimators is 15. Unfortunately, the MSE drastically increases until it reaches the highest value of 4.23 when the number of the estimator is increased from 20 to 50. Different MSE result for the different number of the estimator is caused by the nature of random forest regression algorithm itself. Each estimator acts as an independent sampler for the dataset. Therefore, the result has various values.

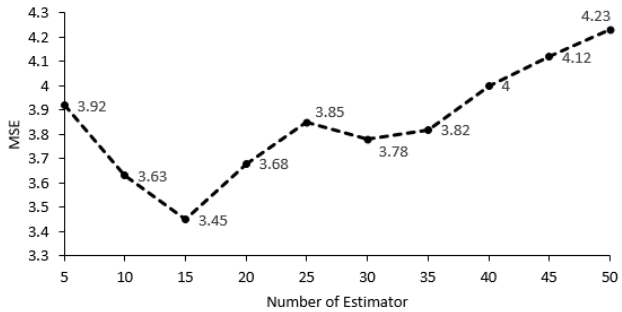

Fig 4. Random forest MSE

C. SVR MSE Result

Fig. 5 shows MSE for different values of epsilon and gamma. When gamma is 0.1, the MSE value is around 64. When gamma is 0.01, the MSE value is around 16. When gamma is 0.001, the MSE value is around 9. And the last when gamma is 0.0001, the MSE value is around 5. Therefore, it can be inferred that gamma plays an essential part in the prediction result. As the gamma parameter decreases, the MSE value also decreases.

When the epsilon value is changed, it doesn't give a significant difference as gamma. So, it can be concluded that the epsilon parameter fine-tunes the prediction result. The lowest MSE is reached when gamma is 0.0001 and epsilon is 1.

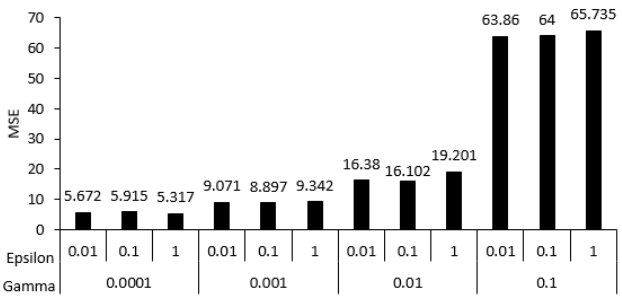

Fig 5. SVR MSE

D. ANN MSE Result

Fig. 6 shows the MSE value of the ANN algorithm with four different optimizers implemented in a five different layers network. Among the four optimizers, SGD gives the worst MSE result with a value of around 173 in all layers. Adam optimizer gives a slightly better

result than SGD, with the highest MSE value of 90.511 at the network with two hidden layers and the lowest MSE value of 49.898 when the network has three hidden layers. Adagrad optimizer displays the highest MSE result of 99.92 when employed in the network with two hidden layers and the lowest MSE value of 39.944 is found at the network with four hidden layers. The best result is demonstrated by the Adadelta optimizer with the highest MSE value of 8.095 with four hidden layers and the lowest MSE value is 4.39 with two hidden layers.

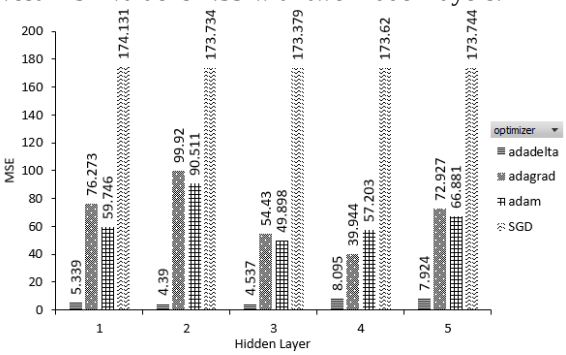

Fig. 6. ANN MSE

E. Prediction Result Comparison

Table III shows the best prediction result from four algorithms with their parameters.

TABLE III. PREDICTION RESULT COMPARISON

Algorithm	Parameter	MSE
Decision Tree	Random State 50	5.556
Random Forest	Number of Estimator 15	3.45
SVR	Gamma 0.0001, Epsilon 1,	5.317
ANN	Hidden Layer 2, Optimizer Adadelta	4.39

As shown by Table III, the decision tree algorithm reaches the lowest MSE of 5.556 when the random state is 50, while the random forest reaches 3.45 when the number of the estimator is 15. For the SVR algorithm, the MSE value of 5.317 is reached when gamma is 0.0001 and epsilon is 1. And the last ANN reaches the lowest MSE of 4.39 when optimizer Adadelta is employed and the network has two hidden layers. Among all algorithms, the random forest algorithm demonstrates the best performance in predicting the rectangular patch antenna dimension.

VI. CONCLUSION

In this paper, a research to predict microstrip dimension using machine learning algorithms is conducted. There are four algorithms used to make the prediction: decision tree, random forest, SVR, and ANN. Based on the comparison result among other algorithms, random forest with the number of estimators 15 gives the best result with MSE 3.45. Therefore, it can be concluded that it is possible for researchers to estimate the rectangular patch microstrip antenna dimension based on the desired parameters, which can't be done by the antenna simulation software before.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Nazmia Kurniawati wrote the machine learning simulation program, analyzed the data, and wrote the paper. Arif Fahmi conducted the antenna simulation and provided the dataset. Syah Alam verified the data and checked the paper. All authors had approved the final version.

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