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Artificial Neural Network and its Benefit in Modeling and Efficient Yield Analysis of Antennas

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***Abstract*—This paper presents yield-aware antenna sizing and modelling through artificial neural network (ANN) leading to an accurate and efficient synthesis process. In the proposed methodology, the suitable amount of data is provided and then Quicksort algorithm is employed for categorizing the most/least effectiveness of each parameter. Finally, the ANN is trained and used for optimizing the design parameters leading to find optimal output specifications. The performance is named as yield analysis, and it accelerates in predicting the effects of variations in the antenna's dimension and it leads to find the optimal design parameters in a shortest time without any further simulation effort. The developed process results in accurate yield predictions of antenna dimensions with reduced time. To validate the efficiency of the proposed method, three antennas from the recently published literature are considered, and then our presented method is employed for optimizing them and quantify the computational time in modelling. The simulation results demonstrate that using the proposed method, there is approximately 25% speed-up in modelling, sizing, and optimizing antennas.**

***Index Terms*—Antenna, artificial neural network (ANN), Quicksort algorithm, sizing antenna, variation, yield analysis.**

I. Introduction

Antennas are one of the most important devices in the fifth generation (5G) and sixth generation (6G) technologies that are employed in the communication systems [1]. Suitable bandwidth (BW) with the low-profile geometry are important specifications leading to improved performances in the wireless systems [2], [3]. Microstrip antennas are frequently used for their features to fulfill the above requirements.

For designing high performance microstrip antennas, their geometry and the location of the feeding point(s) must be sized and determined suitably. For this case, strong optimization methods are required [4] to obtain increased performance of antennas. Recently, some optimization as particle swarm optimization [5], ant colony optimization [6], and grey wolf optimizer [7] have been used for designing antennas; however, intelligent algorithms, machine learning, and artificial neural network (ANN) have proved their effectiveness over these optimization methods [8]–[11]. These methods are learning-based methods that model the relationships between input and output data.

Even though, the ANN is intelligent enough in modeling and sizing antennas, however due to the complexity of the antennas, sizing process can go to almost infinite loop hence it can last long time [12]. For this case, effective yield analysis can be done for predicting the variation of the antenna parameters [13] and determining the suitable step-size of changing design parameters.

In comparison with the recently published literature related to yield analysis [14]–[17], and to the best of authors' knowledge, the proposed approach, i.e., yield analysis based on the ANNs is sporadically mentioned in the scientific literature. This paper presents a new method of efficient yield analysis for modeling and sizing antennas. The proposed method is employed using an ANN where the effectiveness of the design parameters is determined by the Quicksort algorithm. In the proposed procedure, firstly suitable amount of dataset is generated and then Quicksort algorithm is employed for sorting and determining the most/least effectiveness of design parameters. This action estimates the suitable step-size of tuning where the ANN is employed for predicting the output performances of determined design parameters by the Quicksort algorithm. For validating the proposed method, three antennas from [18] and [19] are designed and the overall simulation results with the conventional tuning optimization and the proposed method are compared. The obtained practical simulation results show that the proposed method can speed up the overall antenna modeling and sizing up to 25%.

The paper is organized as follows: Section II provides a procedure of developing the yield-aware synthesis. Section III describes the practical implementation of the proposed procedure, and the last section is devoted to conclusions.

II. Proposed Yield Analysis for Antenna Designs Through the ANN

This section is dedicated to describe the proposed method of modeling and sizing antennas based on the yield-aware analysis. This synthesis is executed in three important steps: 1) generating suitable amount of dataset; 2) employing the Quicksort algorithm; and 3) training the ANN for modeling and sizing the antennas. Figure 1 graphically presents the proposed method for sizing antenna with the sufficient yield.

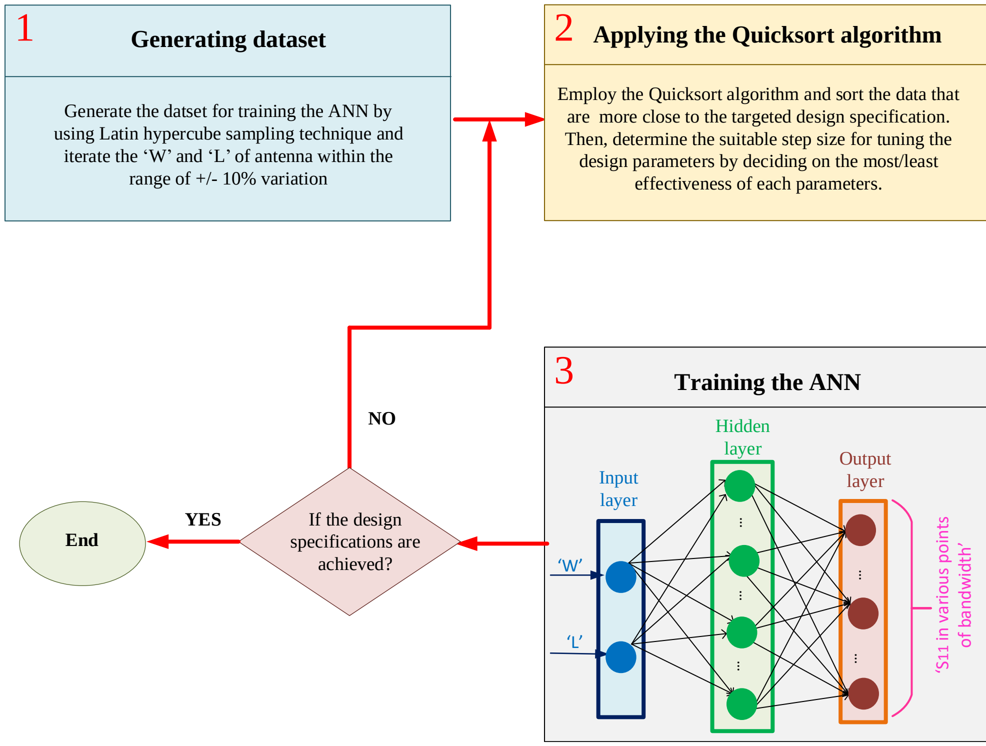

Fig. 1. General perspective of the proposed method for an effective yield analysis in modeling antennas using an ANN.

The detail descriptions of each step leading to providing effective yield analysis in sizing the antennas are as following:

A. Dataset generation (Step-1)

The very initial and important step for constructing the ANN, is generating suitable amount of dataset. For this case, the initial configurations of antennas are designed and then the design parameters including width ('W') and Length ('L') of antennas are iterated using the Latin hypercube sampling technique [20] within the range of $\pm 10\%$ of current points. While these design parameters are iterated, the output specifications S_{11} in various points of the frequency band are extracted. In constructing the ANN, the input layer features can be 'W' and 'L' of antennas and the output feature in the output layer of ANN can be the S_{11} performance in various points of the considered frequency band. These generated large amount of data are namely as training, validation and testing data (X_{Train}, X_{Val}, and X_{Test}), where corresponding desired outputs are (Y_{Train}, Y_{Val}, and Y_{Test}) sets. All the achieved data set is divided into three groups of training, validation, and testing data with the rates of 70%, 15%, 15%, respectively.

B. Quicksort algorithm implementation (Step-2)

The Quicksort algorithm is typically used for partitioning the array of data into the smaller parts [21]. Hence, for our problem it is used for sorting and categorizing the data from most to least effectiveness in terms of targeted output specifications. From the large amount of generated data, this algorithm selects and classifies the set of data that are more closer to the targeted output specifications in terms of S_{11} for our problem. Then, the effectiveness of widths and lengths in approaching to the targeted output can be estimated and the tuning direction (incremental or decremnetal) of design parameters can be decided.

This algorithm can accelerate the overall performance where the suitable step size of tuning with the most/least effectiveness of each design parameters (i.e., 'W' and 'L') are determined. Hereby, in tuning the design parameters the correct direction of tuning, increasing or decreasing the parameters, can be estimated.

C. ANN construction (Step-3)

After generating the dataset and also estimating the effectiveness of included design parameters, it is time to train and construct the ANN. With the achieved dataset in Step-1, the ANN is constructed by defining design parameters, i.e., 'W' and 'L', as the input features and the S_{11} at various points in the whole band. The hidden layer consists of one layer with neurons that are achieved using the 'rule of thumb' [22]. The network can be trained using the 'trainNetwork' in MATLAB (see (1)). Afterwards, some part of output responses are predicted (Pred) with the help of testing data as presented in (2). Since, the accuracy factor of any ANN is significant, it is determined by the difference between the actual testing outputs, i.e., Y_{Test}, and predicted outputs, i.e., Y_{Pred}. In our proposed ANN, the rectified linear unit (ReLU) function is used as the activation function.

$$\mathrm{net} = \mathrm{trainNetwork}(X_{\mathrm{Train}}, Y_{\mathrm{Train}}, \mathrm{layers}, \mathrm{options}) \quad (1)$$

$$Y_{\mathrm{Pred}} = \mathrm{predict}(\mathrm{net}, X_{\mathrm{Test}}) \quad (2)$$

After accurately training the ANN, this model can be used as the representative of real antenna. The ANN provides the output responses to the entered design parameters. By using the Quicksort algorithm in Step-2, the ANN is now intelligent enough for deciding on the step-size of design parameters for tuning. If the targeted output specification is not achieved, the Quicksort algorithm is re-applied and provides the most/least effectiveness of design parameters for deciding on the step-size tuning of parameters where the ANN is estimating the output specification. This loop is continued up to obtaining the desired design goals.

III. Practical Implementation with Simulation Results

For validating the proposed methodology, we employ the approach to the three different antenna designs where the design parameters have been achieved through traditional tuning optimization. The structures in Figg. 2, 3, and 4, named as antenna-1, antenna-2, and antenna-3, are used for comparing the overall simulation time in designing with tuning method and proposed method.

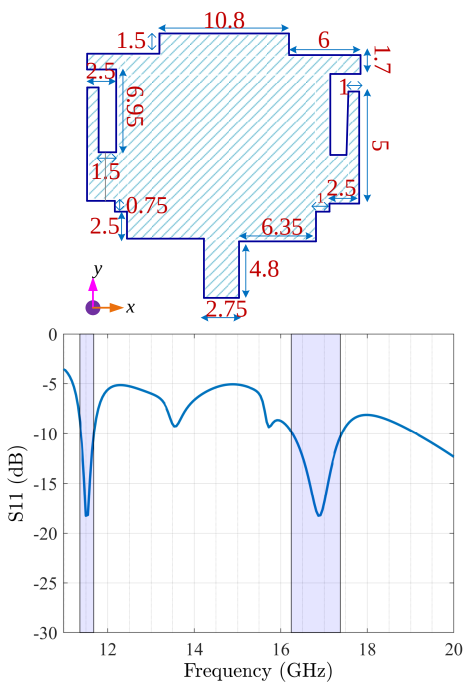

Fig. 2. Microstrip antenna used for Ku-band frequency (antenna-1).

Antenna-1 is designed on the substrate with the relative permittivity (ε_r) of 4.3, loss tangent ($\tan\delta$) of 0.025, and thickness of 1.6 mm [18]. The operating frequency bands of this antenna are between 11.35-11.68 GHz and 16.3-17.43 GHz as shown in Fig. 2.

The second antenna, antenna-2, is designed on the Rogers substrate with ε_r, $\tan\delta$, and thickness of 3, 0.0011, and 1.52 mm, respectively. This antenna works in the frequency bands of 9.13-9.56 GHZ and 10.1-10.9 GHz as Fig. 3 illustrates [18].

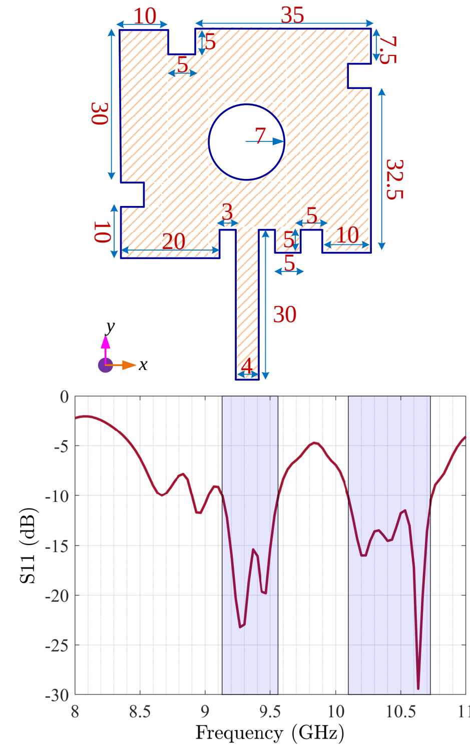

Fig. 3. Microstrip antenna used for X-band frequency (antenna-2).

The third antenna, antenna-3, is an implanted antenna that is designed for biomedical applications as Fig. 4 shows [19]. This antenna is embedded in biological tissues, hence its analysis is more demanding in terms of computational effort (time and memory) with respect to amicrostrip antenna in free space. As Fig. 4 shows, the antenna is working in the various frequency bands of 2.40-2.58 GHz, 2.8-3.0 GHz, 3.4-3.6 GHz, 4.2-4.4 GHz, and 5.8-5.94 GHz. The microstrip antenna is supported by a titanium dioxide ($\mathrm{TiO_2}$) substrate with ε_r of 95.

For each of these antennas, the ANN is trained with the accuracy of 75% where the number of neurons is 300 that is obtained by the 'rule of thumb' method. In total for each of the designed antenna, 500 data are generated that is splitted in to training, validation, and testing data. Conventionally, the tuning optimization is used for sizing these three antennas. Fig. 5 (blue bars) shows the total consumed time for designing and sizing these antennas. The red bars also show the consumed time while applying our proposed method. As it can be observed from Fig. 5, the proposed approach leads to reducing the simulation time and considered antennas can be designed and optimized with more than 25% time savings.

IV. Conclusion

In this work, a new effective approach for accelerating the antenna sizing is presented. The proposed method is based on the Quicksort algorithm which determines the most/least effectiveness of design parameters in terms of width and length. The ANN is employed for modeling the antennas and it predicts the output responses of antenna with respect to the selected

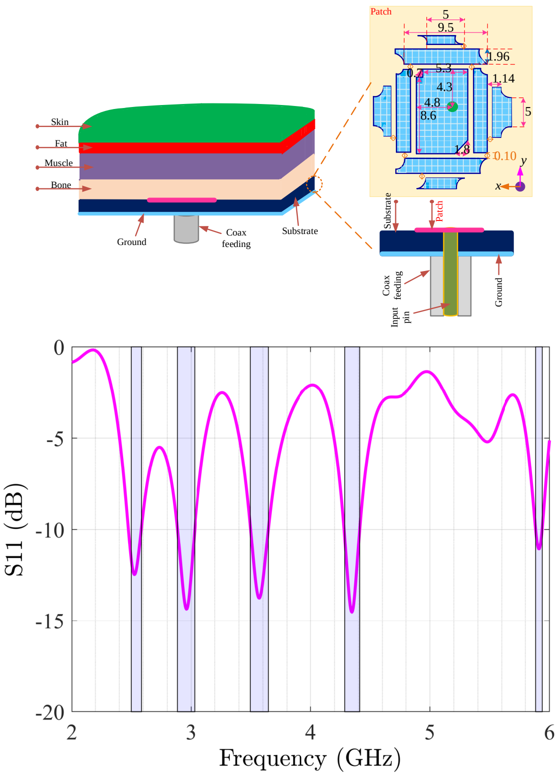

Fig. 4. Implanted antenna for biomedical applications (antenna-3).

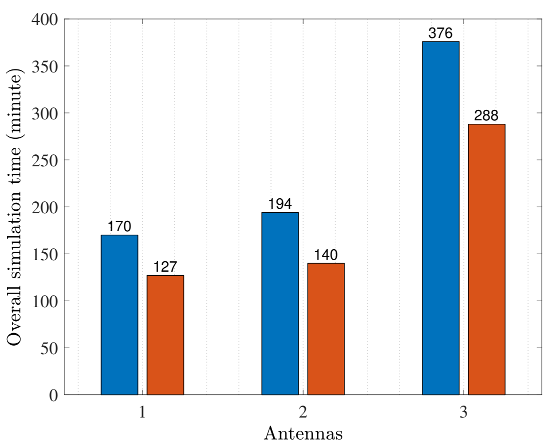

Fig. 5. A bar comparison for the total simulation time in designing reported antennas with the tuning optimization (blue) and proposed method (red).

antenna parameters from the Quicksort algorithm. In this case, the effective and accurate step-sizes for tuning the parameters are determined leading to finding the size of antenna in speedy way. Three antennas from the literature are selected and the proposed method is employed and demonstrates that the yield-aware analysis is working effectively and it speeds up the overall antenna designs in comparison with the traditional tuning optimization.

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