Received: 6 February 2021 | Revised: 21 April 2021 | Accepted: 30 April 2021

DOI: 10.1049/mia2.12137

IET Microwaves, Antennas & Propagation

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH PAPER

Automated optimization for broadband flat-gain antenna designs with artificial neural network

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Funding information

Istanbul Technical University the Scientific Research Project Unit, Grant/Award Number: Grant No. MGA-2018-41201

Abstract

An automated optimization process for designing and optimising high-performance single microstrip antennas is presented. It consists of the successive use of two optimization methods, bottom-up optimization (BUO) and Bayesian optimization (BO), which are applied sequentially, resulting in electromagnetic (EM)-based artificial neural network modelling. The BUO method is applied for the initial design of the structure of the antennas whereas the BO approach is successively implemented to predict suitable dimensional parameters, leading to broadband, high flat-gain antennas. The optimization process is performed automatically with the combination of an electronic design automation tool and a numerical analyser. The proposed method is easy to use; it allows one to perform the design with little experience, because both structure modelling and sizing are performed automatically. To verify the power of the proposed EM-based method experimentally, two single microstrip antennas have been designed, optimised, fabricated, and measured. The first antenna has flat-gain performance (6.9–7.2 dB) in a frequency band of 8.8–10 GHz. The second has been designed to perform in the 8.7- to 10-GHz band, where it exhibits flat-gain performance with reduced fluctuation in the range of 6.7–7 dB. The experimental results are in good agreement with the numerical data.

1 | INTRODUCTION

The importance of communication systems (CSs) including various types of antennas have noticeable challenges, such as in fifth-generation (5G) and sixth-generation (6G) networks [1–3]. Microstrip patch antennas are the most commonly used class in wireless CSs because of their well-known advantages; they are cost-effective, and they have an easy fabrication process and acceptable bandwidth (BW), and medium gain performance obtained with a low-profile geometry [4]. Because of the growth in population leading to data traffic in CSs, requirements of improved antennas have been sensed to provide suitable BW and almost constant high gain in the considered frequency band(s) [5–7].

The design of antennas by traditional and conventional simulations based on continuous optimizations is problematic from different viewpoints: the complexity of antenna structures is dictated by the experience of the designer, which limits the development of particular structure(s) [6, 8, 9]. To tackle these problems, various optimization methods have been reported: the differential evolution algorithm [9], spider monkey optimization [10], and particle swarm optimization [11]. These methods are useful solutions for designing and optimising antennas; however, they cannot provide a fully automated optimization-oriented process and some manual interruptions are required [12]. Functional surrogate modelling [13, 14], which is the particular case of machine learning [15, 16], has received the attention of designers to model microwave and radio-frequency circuits more accurately in an automatic fashion without depending on the previous familiarity of designers. These techniques can be applied to high-level circuit projects using computer-aided design tools [17]. Among the various functional surrogate modelling techniques, an artificial neural network (ANN) can model input–output

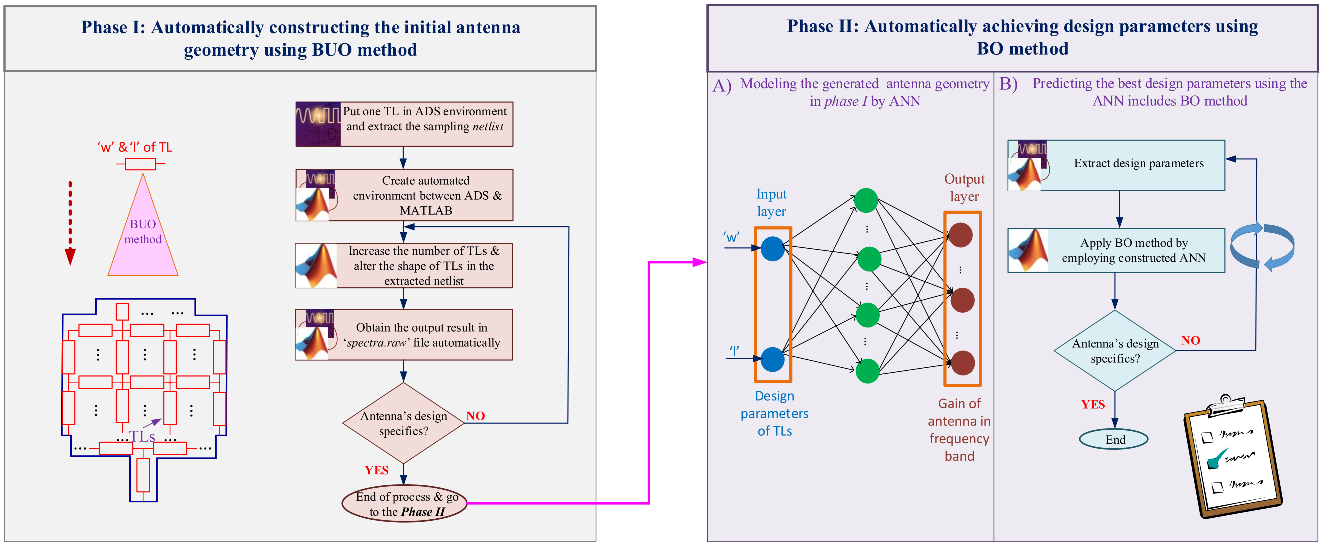

FIGURE 1 Flowchart of proposed optimization method leading to automatically designing wideband flat gain single antennas

relations more effectively and can decrease the possibility of errors during the design [18–20]. In other words, ANN can solve the problem of multiple-objective functional optimization by dealing with a high-dimensional dataset [21–23].

Aiming to improve the impedance BW and gain the performance of single microstrip antennas, electromagnetic (EM)-based bottom-up optimization (BUO) with Bayesian optimization (BO) is sequentially applied automatically to generate an initial geometry of the antenna aiming to obtain suitable design parameters. The proposed optimization method attempts to design and size single antennas with average flat-gain performance in a wider frequency band with respect to the starting configuration. An EM-based BUO method presented in [24] is firstly applied for constructing the initial antenna geometry modelled with transmission lines (TLs). Then, the EM simulation-based BO method is imposed to obtain wide BW and almost flat high-gain single microstrip antennas by predicting the best design parameters. The BO method is based on the Gaussian process (GP) [25] and effectively solves the design problem of high-dimensional structures [26, 27]. To validate the proposed optimization method, two single antennas operating in the 8- to 11-GHz frequency band have been designed, optimised, prototyped and experimentally characterised. The optimization process has been automated with the combination of an electronic design automation tool (ADS) and a numerical analyser (MATLAB). The achieved optimal design parameters result in improved impedance BW and good flat-gain performance.

To the best of the authors' knowledge, an optimization-oriented antenna design is presented for the first time, in which the general configuration with the sizing of single antennas is achieved automatically with no human interruption. In the first phase, the general configuration of the antenna is extracted by employing the BUO method. This algorithm starts modelling the antenna with one TL and then increases the number of TLs and tests and replaces them with various TL-microstrip models to achieve the initial acceptable performance in terms of the S-parameter and gain. Then, in the second phase, by applying the BO method, the optimised sizes of all included TLs are predicted using the constructed ANN. With no dependence on the designer's experience, the single antenna is designed automatically with reduced time expense. To validate the proposed optimization-oriented method, two microstrip antennas are designed, optimised, and fabricated.

This work is organised as follows: Section 2 provides a short summary of the theory of the proposed BO method. Section 3 describes the BO process to improve the impedance BW and gain for designing and optimising general-shape microstrip patch antennas. The simulation and measurement results of two designed and optimised antennas are presented in Section 4. Finally, the last section is devoted to conclusions.

2 | BAYESIAN OPTIMIZATION

A sequential design strategy is presented to approach the best and most suitable project parameters in designing single microstrip antennas of a complex layout. For this purpose, the implemented global optimization that aims improving objective functions in a minimum number of steps is the BO method. The basic criterion of such a method is to use the GP model [25] and then an acquisition function to decide on the number of samples. The acquisition function includes two factors: expected improvement (EI) and the probability of improvement (PI): PI defines the most possible points in the search space where improvement will take place; and EI is known as an efficient global optimization that ensures a balance between local optimization and the global search. By considering sampling points in a k dimensional space, that is, $\underline{x} = [x_1,\ldots,x_k]$, the values of the functions for these points are considered an a prior function $[f(x_1),\ldots,f(x_k)]$. The new/final points are chosen by considering the output responses of input data as $\underset{\sim}{x} = \text{argmax}_{\underset{\sim}{x} \in R^k}[\text{EI}(\underset{\sim}{x}) \cdot \text{PI}(\underset{\sim}{x})]$. If the maximum a posteriori metric is maximised, it corresponds to the most suitable project parameters that have been achieved.

3 | AUTOMATED ANTENNA DESIGN WITH BOTTOM-UP OPTIMIZATION AND BAYESIAN OPTIMIZATION METHODS SEQUENTIALLY

The process of optimization strategy is done automatically by cooperation between ADS and MATLAB [28]. ADS has a twofold responsibility: (1) to generate simulation results for the considered geometry at the given stage of the optimization, and (2) to prepare all outcomes in an output file. The role of MATLAB is to collect suitable data including training ($_t$), validation ($_v$), and testing ($_T$) data based on splitting in the rates of $\alpha_t = 70\%$, $\alpha_v = 15\%$ and $\alpha_T = 15\%$, respectively. The considered cost function CF is reported in Equation (1):

$$\text{CF} = \overline{S}_{11} - |\Delta G| - |\text{BW} - \text{BW}_{ref}| \qquad [\text{dB}] \tag{1}$$

where $\overline{S}_{11}$ denotes the average value of the input scattering parameter S_{11}, ΔG indicates the ripple of the gain (with respect to the average value) and the factor in the last bracket corresponds to the difference in the BW between the actual value and the reference one (defined with respect to -10 dB). The optimization corresponds to find min CF.

From this point forward, *data* refers to all simulation performances that present the determined split rates to model the antennas geometry accurately. Figure 1 presents the employed two optimization methods for designing and optimising the single antennas. Algorithm 1 summarises the implemented steps for automatically designing and optimising single microstrip antennas using the BUO and BO methods sequentially.

Algorithm 1 Sequentially automated optimization process for designing single microstrip antennas based on BUO and BO methods

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Phase I
1: Apply the EM-based BUO method to define the
initial antenna geometry and configuration
Phase II
2: Extract the related netlist of the
constructed antenna
3: Prepare the dataset for start modelling
the antenna using the EM-based BO method
4: Apply BO method for predicting suitable
design parameters including W and L of all
included TLs
5: If the desired design goals are not
achieved, go to Step 3 and increase the
number of data for reimplementing the BO
method
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Generally, the starting geometry for any low-profile antenna design is a probe-fed microstrip patch antenna loaded with different techniques: (1) modifying the basic shape by cuts at the corner(s), and (2) loading it by reactive loads, which can be TLs of different lengths, shapes and distances from the edges. Optimization of such complex structures described by a large number of parameters requires a multidimensional optimization process. Hence, the proposed optimization method starts by applying the presented BUO method in Mir et al. [24] for automatically constructing the initial shape of the microstrip single antenna (Step 1). The BUO method is an optimization approach that is divided into subsections; it results in more complex designs and circuits. The role of the BUO method is to design the initial antenna model by providing an automatic environment with the combination of MATLAB and ADS software tools. In our problem, we start designing an antenna with one TL. Then we increase the number of TLs and test or replace them with various TL microstrip models to obtain suitable output performance. The function of the algorithm is to increase the number of TLs sequentially to improve S_{11} parameters and gain the performance of the structure. In this step (i.e., Step 1), the initial design structure is achieved. To pass the EM simulation in the ADS and generate the layout, design rules for each TL are implemented in the optimization method [29].

Then, in the ADS platform, the netlist.log of the created initial antenna design in Step 1 is extracted (Step 2). In the extracted netlist file, design parameters such as width (W) and length (L) exist that are altered in a MATLAB platform-developed script. It is working in the background, transparent for the user, and generates the corresponding output file (i.e., *spectra.raw*) that includes the gain performance of the single antenna in the determined BW (Step 3). Step 3 prepares the suitable data (i.e., sampling points). The sampling points include training, validation and testing data (X_{Train}, X_{Val}, and X_{Test}) and corresponding desired outputs (Y_{Train}, Y_{Val}, and Y_{Test}) sets. These data are generated using the Latin hypercube sampling technique [30] within the ±10 and ±15 range of current points achieved from the optimised antenna shape in Step 1. The design parameters are altered in this range to achieve a suitable amount of dataset. The variation boundary can be more or less than ±10 and ±15. The target of this variation is to achieve a suitable amount of dataset. The total achieved dataset is split into three groups of training, validation, and testing data with the rates of 70%, 15%, 15%, respectively (as mentioned earlier). After constructing the ANN with the achieved neuron numbers using the rule of thumb [31], the network is constructed using trainNetwork in MATLAB, as presented in Equation (2) Then, some output responses are predicted (Pred) using testing data, as shown in Equation (3) Finally, accuracy is measured by considering the difference between the actual testing outputs, Y_{Test}, and predicted outputs, Y_{Pred}:

$$\text{net} = \text{trainNetwork}(X_{\text{Train}}, Y_{Train}, \text{layers}, \text{options}) \tag{2}$$

$$Y_{Pred} = \text{predict}(\text{net}, X_{Test}) \tag{3}$$

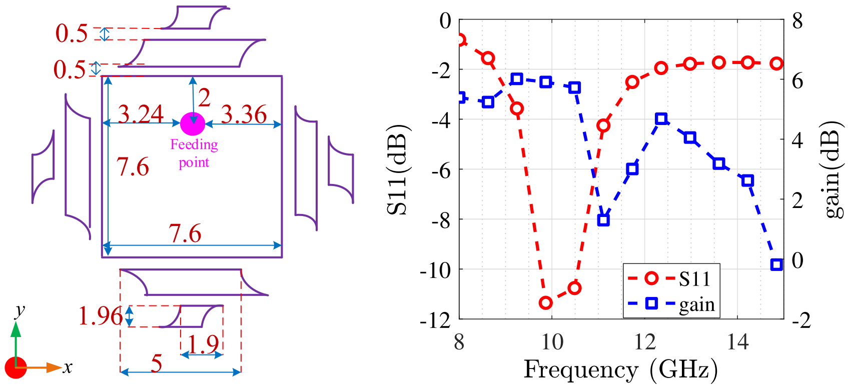

FIGURE 2 Optimised antenna 1 with bottom-up optimization method (left); unit of lines is millimetres; Gain and S_{11} performance of optimised antenna 1 (right)

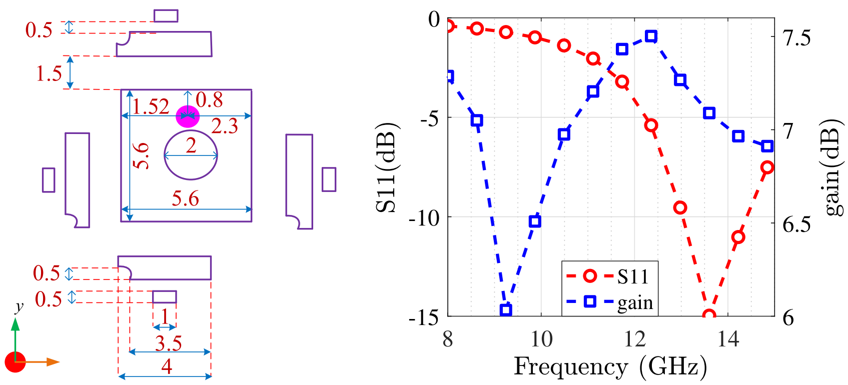

FIGURE 3 Optimised antenna 2 with bottom-up optimization method (left); unit of lines is millimetres; Gain and S_{11} performance of optimised antenna 2 (right)

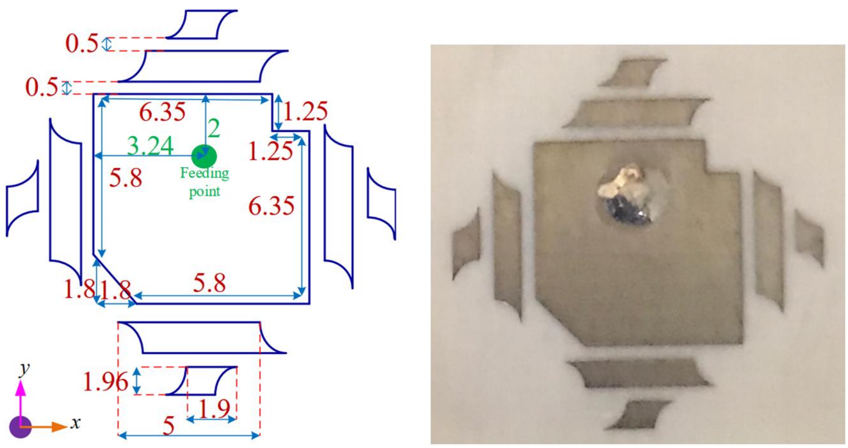

FIGURE 4 Electromagnetic-based optimised antenna 1 with Bayesian optimization method for 300 data points: computer-aided design model used for simulations (left); unit of lines is millimetres; photograph of fabricated prototype (right)

With the prepared dataset, the BO method is applied to model the antenna and predict the suitable W and L of all included TLs leading to the desired BW and expected gain performance (Step 4). If the determined design goals are not achieved, the number of data are increased and the BO method is reapplied (Step 5). The number of data are increased because accurate modelling highly depends on the number of sampling points; hence, as the amount of dataset is increased, the accuracy of modelling is also increased [32]. Data generation is automatically stopped when the testing accuracy becomes higher than 90%, because this amount of accuracy demonstrates successful modelling of the design [25]. In the proposed optimization process, the objective function is based on the antenna's gain performance in the considered frequency range.

4 | PRACTICAL SINGLE ANTENNA OPTIMIZATION

This section explains the implementation of two optimization methods (i.e., BUO and BO) to designing and optimising single antennas automatically. First, the initial configurations of two antennas with achieved output results using the BUO method are described. Then, the outcomes of two single antennas optimised using the BO method are explained briefly.

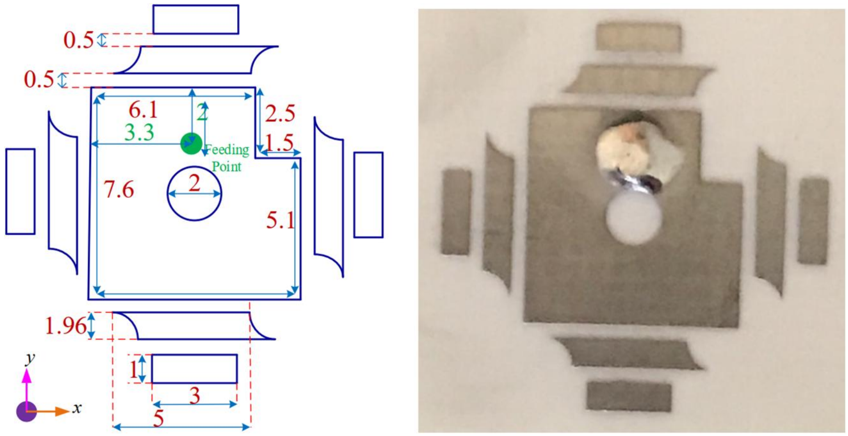

FIGURE 5 Electromagnetic-based optimised antenna 2 with Bayesian optimization method for 300 data points: simulated (left); unit of lines is millimetres; photograph of fabricated prototype (right)

After satisfied output performance is obtained for the determined BW, the optimised antennas are fabricated and measured.

4.1 | Employment of bottom-up optimization method for constructing initial antenna configuration

The initial antenna structures based on the BUO method are presented in this section. We attempted to design single antennas in the X-band (8–12.5 GHz) for application in satellite communication applications [33]. The BUO method generates the initial configuration of the single antennas in terms of band frequency and/or gain performance. In the optimization process, it is constrained to have a suitable flat gain performance in the limited X-band frequency.

Figure 2 represents the first antenna design with the related simulation results in ADS. This antenna (i.e., antenna 1) covers a 9.8- to 10.4-GHz frequency range (700 MHz of −10 dB BW); the gain performance of the structure in that frequency band does not have acceptable behaviour and it has a sharp decrease.

As mentioned, TLs located near the main radiator act as parasitic elements; they are not directly fed (such as directors and reflector(s) in the case of a Yagi-Uda antenna) and are also introduced for tuning. Their presence influences antenna performance in different ways: first it increases the geometrical area and in turn the effective area of the antenna, guaranteeing a higher gain. Second, it introduces additional resonances that will make the overall structure of wideband. The location, dimension and shape of these parasitic elements are all additional degrees of freedom that can be considered during optimization, allowing the required antenna performance to be obtained.

Hence, additional optimization is required to provide high flat-gain performance. Moreover, another single antenna is optimised to prove the reliability of our proposed method. Figure 3 presents the second optimised antenna, labelled antenna 2, with the output results. The working frequency of this antenna is 13.4–14.1 GHz, which is suitable for the K_u band.

Therefore, antenna 1 has a gain problem and antenna 2 has a frequency band problem. Hence, additional optimization based on the BO method is needed to improve S_{11} with gain performance. The final optimised antennas using BO method are expressed next.

TABLE 1 Accuracy modelling of antennas depending on number of data

Antenna 1		Antenna 2	
Number of data	Testing accuracy (%)	Number of data	Testing accuracy (%)
50	48.1	50	44.8
100	53.1	100	51.2
150	65.4	150	64.7
200	74.8	200	71.4
250	85.5	250	82.4
300	96.8	300	94.2

4.2 | Fabrication and measurement

This section deals with the optimised design of two microstrip patch antennas, shown in Figures 4 and 5. These antennas have been fabricated on a 20 × 18-mm Rogers (RO4003C) substrate with $\tan\alpha = 0.0027$, $\varepsilon_r = 3.55$ and a thickness of 1.52 mm. Owing to the availability of this substrate in our laboratory, we prefer this substrate. These parameters were obtained from the datasheet from the manufacturer. After the substrate is selected, optimization is employed; the parameters of the substrate are not optimised because they are constant.

As stated in Section 3, the initial design structures are created using the EM-based BUO method. Concerning the first antenna design, a larger impedance BW and acceptable gain are achieved by erasing a triangle at the down left and square on the top right of antenna 1 (Figure 4).

After successfully achieving the initial design requirements with the BUO method, a second design is performed with a change in the shape of the optimised antenna 1. In the second antenna (i.e., antenna 2), shown in Figure 5, a circle with a radius of 1 mm and a rectangular at the top right of the structure were further erased aiming to improve both the S_{11} parameter and gain performance. The arc-circles of the cuts in the TLs located around the main patch are equal to the width of the lines: 1.96 mm. After achieving the initial design shapes with initial design parameters, the suitable and best design parameters, including the W and L of antennas with TLs, are predicted automatically using the EM-based BO method. Comparing Figures 3 and 5, the dimensions of the parasitic elements have changed from 0.5 × 1 to 1 × 3 (mm^2).

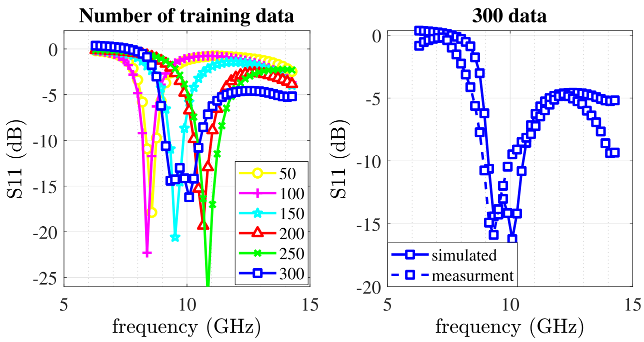

FIGURE 6 S_{11} parameter of antenna 1: simulation results for different numbers of dataset (left); Comparison between best performance (300 data) and measurement (right)

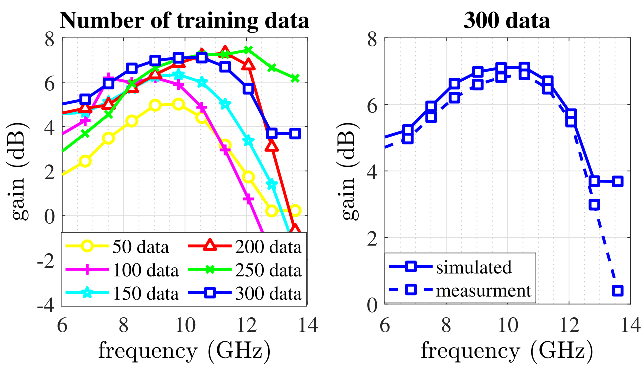

FIGURE 7 Gain of antenna 1. Simulation results for different numbers of dataset (left); Comparison between best performance (300 data) and measurement (right)

After applying the BUO method and extracting the initial structure of antennas, the sampling points are generated, as explained in the previous section. Modelling of the antennas starts with a dataset including 50 data. The number data increases until the antennas are modelled accurately and the desired design goals are achieved. Table 1 shows the accuracy modelling of antennas as a percentage with various data dimensions and illustrates that in the case of 300 data, acceptable modelling accuracy (>90%) is achieved; hence the optimization process is automatically stopped. Determining modelling accuracy with testing data is more important in the BO method; hence, the accuracy that represents the correctly predicted data points out of testing data has been calculated (Table 1). The proposed optimization process was implemented on a PC equipped with an Intel Core i7-8550U CPU at 1.80 GHz with 8.00 GB RAM. For each dataset, the structure of ANN is built using one hidden layer and determined the number of neurons with the rule of thumb. The time cost to generate each group of 50 data is around 15 min. Hence, a total of 300 data are generated in around 1 h 30 min. The final ANNs for both antennas consist of one hidden layer with 200 neurons, resulting in more than 90% testing accuracy when the total generated data are 300, as shown in Table 1.

To design antenna 1, the EM-based BO method was used to analyse the created first attempt antenna geometry with the BUO method for six different groups of data. Figure 6 shows the return loss (S_{11}) of the first antenna for various dataset dimensions, such as 50, 100, 150, 200, 250, and 300 data. As shown in Figure 6, for 300 data, the best simulation result covers the frequency range of 8.8–10 GHz; that is, 1.2 GHz of −10 dB BW (13.2%) is achieved. The gain performance of this antenna for various data is also depicted in Figure 7, in which for the frequency band and 300 data points, the gain is almost flat, exhibiting a small variation in the interval of 6.9–7.2 dB. By achieving acceptable simulation results for antenna 1, this antenna was fabricated (with the determined design parameters in the 300 dataset group) and measured. Figures 6 and 7 show

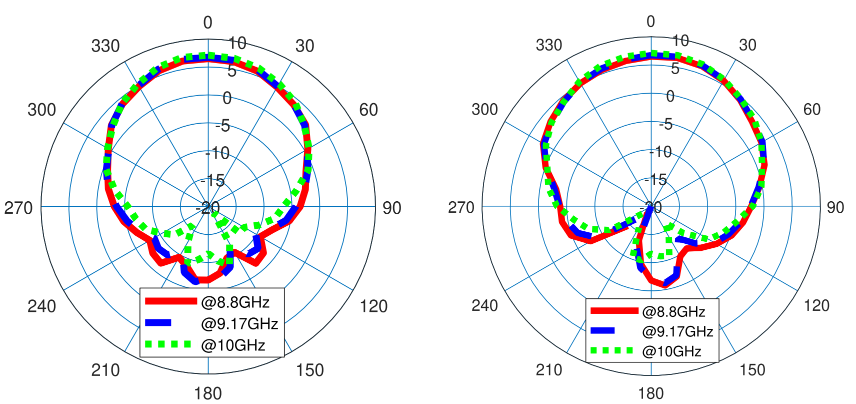

FIGURE 8 Measured radiation pattern of fabricated antenna 1 at f_1 = 8.8 GHz (red), f_2 = 9.17 GHz (blue), and f_3 = 10 GHz (green); ϕ = 0 (left); ϕ = 90° (right)

that the measurement results are in good agreement with the simulations. Measured radiation patterns at 8.8, 9.17, and 10 GHz are reported in Figure 8.

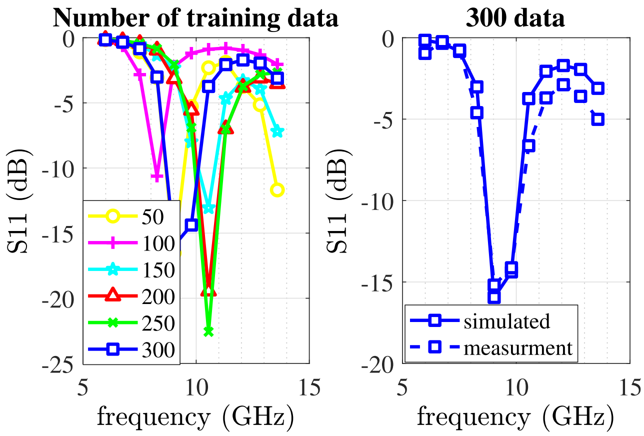

FIGURE 9 S_{11} parameter of antenna 2: simulation results for different numbers of dataset (left); Comparison of best performance (300 data) and measurement (right)

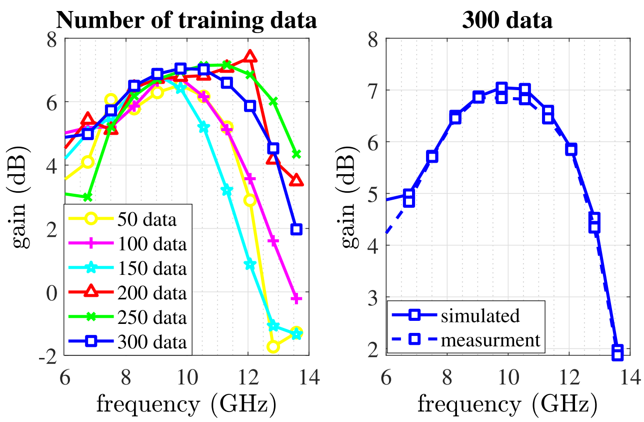

FIGURE 10 Gain of antenna 2: Simulation results for different numbers of dataset (left); Comparison of best performance (300 data) and measurement (right)

After the first antenna was optimised, one circular slot was made in the centre with a radius of 1 mm and the BO method was used to predict new design parameters. Figure 5 shows the second EM-based optimised antenna with the leading dimensions of the geometry of antenna 2. Figure 9 shows the performance of S_{11} in the operation frequency band of 8.7–10 GHz for various datasets from 50 to 300. When the data size achieves 300, the desired BW is achieved; hence, the optimization process is stopped. The flat-gain performance of the simulated and measured second optimised antenna is 6.7–7 dB. Measured data show a perfect match with the simulated ones, as reported in Figure 9 for the impedance BW and in Figure 10 for the gain. For the second design, the maximum return loss for simulation is −21.3 dB, which occurs at 9.6 GHz, and for measurement, the minimum S_{11} is −20.4 dB at 9.4 GHz.

The measured radiation pattern for the second antenna is shown in Figure 11 at the same frequencies as in Figure 8. Using ANN, this work provides a fully automated environment for optimising multiple-objective antenna designs by first modelling antennas and then sizing the design parameters. The main contribution of this work is that it provides a completely computerised background in which modelling and sizing are performed with decreased human interruption. What previous reported studies lacked [9–11], is a fully automated and holistic environment for optimising antennas without depending on the experience of a designer, as happened here.

5 | CONCLUSION

This study presents an automated optimization strategy by implementing an EM-based BUO method to construct the initial antenna structures; in a second step, it applies an EM-based BO method to size the antennas using an ANN. Accurate modelling of microwave designs is a challenging task that needs a significant computational effort. To reduce this effort, the sequential use of two optimization methods is proposed to shape the geometry of the antennas and then effectively size the design parameters of the antennas. As output, ready-to-fabricate antenna geometries (i.e., layout) are generated automatically without human interruption. All processes

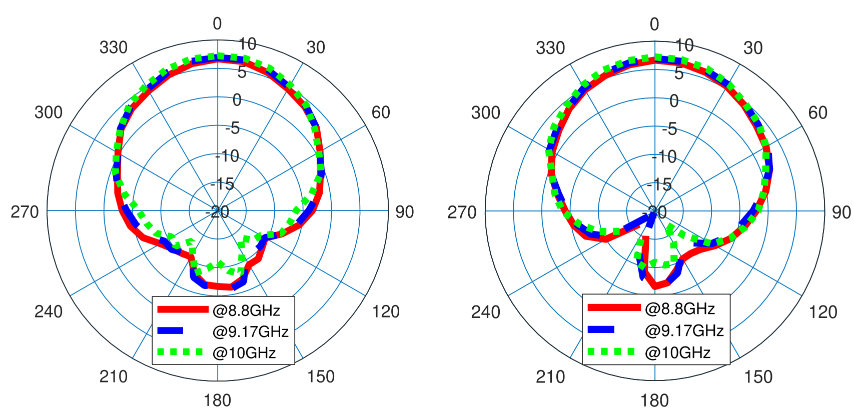

FIGURE 11 Measured radiation pattern of fabricated antenna 2 at f_1 = 8.8 GHz (red), f_2 = 9.17 GHz (blue), and f_3 = 10 GHz (green); ϕ = 0 (left); ϕ = 90° (right)

are performed automatically with a combination of ADS and MATLAB. Verification of the efficiency of the proposed automated optimization process consists of the design of two broadband microstrip patch antennas in the X-band frequency. Experimental results in terms of input scattering parameters and gain are in good agreement with the simulated data.

Our proposed optimization method is flexible and can be improved by considering various substrates, using additional feeding points (to generate circular polarisation, etc.), and employing various types of TLs.

ACKNOWLEDGEMENTS

This work was partially benefited from Istanbul Technical University the Scientific Research Project Unit, under Grant No. MGA-2018-41201.

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How to cite this article: Mir, F., et al.: Automated optimization for broadband flat-gain antenna designs with artificial neural network. IET Microw. Antennas Propag. 15(12), 1537–1544 (2021). https://doi.org/10.1049/mia2.12137