Additional Acceleration of Antenna Optimal Characterization with Modeling Support

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Abstract **–** Optimal characterization is assumed to provide the best solution for the designed cost function among the possible solutions within the specified range. These processes can take a long time depending on the applications and computer hardware used. Here, the optimization process is supported by ANN modeling in order to shorten the current optimization processes as much as possible. For this purpose, the selection of design parameters of the bowtie patch antenna (BPA) is presented as a multi-dimensional, multi-objective modeling-supported design optimization problem. The operating frequency of the proposed antenna is 28 GHz, which is the standard for millimeter wave band and 5G technologies. To overcome this challenging design optimization, a new, fast and powerful optimization algorithm was used by modifying the non-dominant sorting genetic algorithm (NSGA)-III, and the optimal characterization of the microwave antenna design was achieved. Although the proposed method gives the same results compared to the existing process, it takes much less time. Therefore, it is possible to shorten the process and reduce costs without the need for extra applications or hardware. As a whole, the proposed design optimization process is an efficient, fast and reliable solution for all design problems.

Index Terms **–** Accelerated optimal characterization, antenna applications, modeling support, non-dominated sorting genetic algorithm, optimization.

I. INTRODUCTION

In recent years, antenna design for 5G systems has become very popular in the communication world and has become one of the most demanded topics. As a result of the developments so far, this technology will be used almost all over the world by the end of 2024 [1] (delay may occur due to pandemic conditions). International Mobile Telecommunications (IMT) and International Telecommunications Association (ITU) boards have stated their requirements for 5G. In addition, in the final statement of the 2019 World radiocommunication conference, the operating frequencies of 5G antennas were reported as 25, 38 or 66 GHz [2]. In another statement, the Federal Communications Board (FCC) specified the operating frequencies of 5G antennas as 28 or 38 GHz, and for open source and unlicensed work, 37 or 64-71 GHz [3, 4]. It has been reported that the channel bandwidth of the system should be a minimum of 1000 MHz for 6 GHz and above and a minimum of 100 MHz for a frequency below 6 GHz [5, 6].

Pareto optimal characterization for microwave elements has been demonstrated in [7]. In a similar study, the optimal characterization of a microwave transistor was addressed as a multi-objective optimization problem [8]. The older version of the algorithm used in the study was non-dominated sorting genetic algorithm (NSGA)-II [9, 10], which is a method used in antenna design optimization problems in the literature [11, 12]. Additionally, the other compared method, a multi-objective evolutionary algorithm based on decomposition (MOEA/D), is used for the pattern synthesis of a Vivaldi linear array [13], for the design of a compact broadband circularly polarized helical antenna [14], for the synthesis of the shaped beam pattern of an antenna array [15] used. NSGA-II and MOEA/D have been used to overcome the problems stated in conventional antenna design [16]. In [17], MOEA/D was proposed for antenna design. In another study, a simple base station antenna using two bow-tie dipoles has been proposed [18], developed for a compact log-periodic dipole array [19], and proposed as an automation design scheme for compact, high-isolation multiplex systems [20]. However, a modeling-assisted optimization problem solving method has not yet been found. Bowtie patch antenna (BPA) different frequencies [21, 22] and different design types pi- and U-shaped [23, 24] are available in the literature.

As an optimization technique, NSGA-III uses the MATLAB 2021a toolbox. The basic framework of the proposed multi-purpose NSGA-III algorithm is similar to that of NSGA-II, although it incorporates significant changes [25]. Keeping variety among population members in NSGA-III, on the other hand, helps by supplying

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and adaptively updating a collection of well-distributed reference points, as detailed in [25, 26]. The ideal characterization of the NSGA-III, a new, quick, and powerful optimization technique, is considered to be obtained in this work to handle the tough optimization problem of the 5G-28 GHz microwave antenna design. Furthermore, the Method of Moments (MoM) was employed to precisely quantify the gain and S_{11} performance measurements of the antenna design when the geometric design parameters changed. The acquired performance measure was then utilized to generate a cost function for use in the design optimization issue. By using the MATLAB 2021a application at 28 GHz, the design problem for 5G antennas in accordance with the 5G criteria mentioned above has been solved.

The remainder of this paper is briefly structured as follows. Section II discusses the antenna design parameters and geometric form. The objective and cost function of the multi-objective optimization problem are discussed in Section III. Section IV discusses the functioning component. Literature comparison and self-criticism are made in Section V. Section VI concludes the paper.

II. ANTENNA ARCHITECTURE

A planar variation of bionic dipole antennas is the bowtie antenna. Bowtie antennas are one of the most commonly used antenna types for communication systems and ground penetrating radar (GPR) applications. Bowtie antennas offer several advantages such as small weight, cheap cost, low profile and symmetrical emission pattern. It also offers ultra-wideband solutions with high bandwidth [21]. There are design possibilities in different shapes and geometries, for example, there are modified examples with U [23] and pi [24] shaped slots. The frequency value can go up to 28 GHz, which is the candidate standard for 5G technologies [22]. The reflection coefficient is defined as the ratio of the amplitude of the reflected signal to the amplitude of the transmitted signal. Determining antenna performance is the most basic parameter. Directivity, another important parameter, is the ratio of the power density in the direction where the antenna radiates maximum radiation to the power density of an isotropic antenna of the same power at the same distance. Directional antennas are antennas that can emit very strong radiation and receive very strong signals when receiving. The gains of such antennas are large wherever they are directed. Where it is not directed, it is very low. Thus, unwanted noise or broadcasts are prevented. The measure of the directivity ability of a lossless antenna is the antenna gain. This value is closely related to the directivity of the antenna. Unlike the directivity of the antenna, which only describes its directivity characteristics, antenna gain also includes the efficiency of its antenna and therefore also represents the actual radiated power. This power is usually less than the power provided by the sender. However, since measuring this power is easier than measuring directivity, antenna gain is more often used as directivity. Assuming that the antenna is a lossless antenna, the directivity can be taken equal to the antenna gain. However, the performance measurements of the design largely depend on the geometric design values. Bowtie antenna design can therefore be considered a multi-purpose, multi-dimensional design optimization issue. A triangular-shaped microstrip bowtie antenna is considered in this study on the application of the NSGA-III algorithm for Pareto optimization of antenna design. Figure 1 and Table 1 show the diagram of the antenna design and its design parameters.

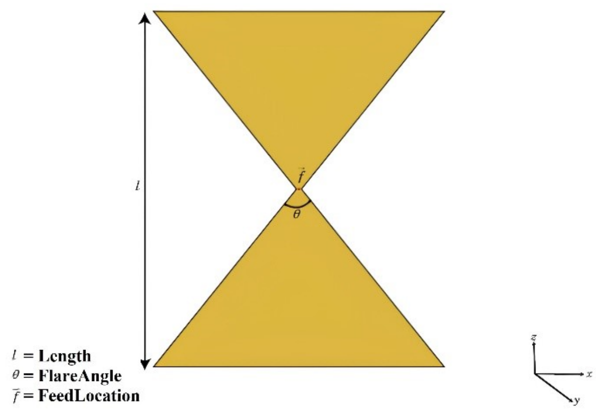

Fig. 1. Bowtie antenna.

Table 1: Antenna design parameters

Parameter	Value	Definition
Length (meters)	0.001-0.04	Planar bowtie length
Flare angle (degrees)	5-90	Planar bowtie flare angle
Conductor	PEC	Type of metal material
Tilt	0	Tilt angle of antenna

The design optimization of bowtie antenna is performed by NSGA-III algorithm using the optimization variables given in Table 1. All these processes were performed by a computer with 8th generation Intel Core i7 CPU, 3.20 GHz processor and 8 GB RAM.

III. MULTI-OBJECTIVE OPTIMIZATION

Evolutional multi-objective optimization methods have proven their age in finding many successful combined and diversified non-dominant solutions in optimization problems with two or more goals since the early 90s. Of course, in problems involving multiple goals and functions, there are usually many optimization problems with three or more input and output values [27, 28]. For this reason, evolutional multi-objective optimization algorithms are expected to research and develop by addressing this problem for the last five years. Many objective issues pose difficulties in an evolutional multi-objective optimization algorithm as with any optimization algorithm. The most significant of them is the presence of a high number of non-dominant solutions in the solution set, which expands the archive solution set. If these non-dominant solutions occupy a large place in the solution set, the algorithm may have great difficulty in dominating a sufficient number of new solutions. This situation significantly slows down the search process of the algorithm [29, 30]. Another challenge is that enacting a large-scale problem can be a challenging task, so evaluating the performance of the algorithm used in later decision-making situations can be misleading and difficult. For this reason, performance evaluation criteria hyper volume measure [31] and other criteria [29, 32] are computationally meaningless or too costly. Using the diversity protection operator crowd-distance [25], clustering [33] operators as a third challenge, the solution can increase the cost in terms of computation.

It is feasible to solve multi-objective optimization issues by using evolutional optimization procedures, which typically involve two or more goals. To address the multi-objective optimization issue in this article, a modified NSGA-III method will be employed.

A. Multi-objective optimization for generic formulation

A minimized multi-objective optimization problem with N goals is defined as follows:

$$\begin{aligned}&\textit{Minimize } \overrightarrow{y} = F\left(\overrightarrow{x}\right) = \left[f_1\overrightarrow{x}, f_2\overrightarrow{x}, \ldots, f_N\overrightarrow{x}\right]^T,\\&\textit{subject to } g_j\left(\overrightarrow{x}\right) \leq 0, \quad j = 1, 2, \ldots, M,\\&\textit{where } \overrightarrow{x} = \left[x_1, x_2, \ldots, x_p\right]^T \, \varepsilon\, \Omega.\end{aligned}$$

The variable $\vec{y}$ is an objective vector, the variable g_j represent restrictions, and the variable $\vec{x}$ is a P-dimensional vector expressing choice variables inside a parameter space Ω. The area filled by objective vectors is referred to as objective space. The relevant space is the subspace of goal vectors meeting the requirements [7, 34, 35].

B. Non-dominated sorting genetic algorithm accelerated by modeling

Since the current optimization processes are undesirably long and hardware upgrades or other tools will increase the cost, optimization is supported by modeling. For this purpose, it was modeled using a multi-layer perceptron (MLP) with reduced data using the Latin hypercube sampling (LHS) method before optimization. There is a similar study in the literature [36]. Then, the modeled parts will be included in the optimization process and a unified structure will be created.

We use a reference point-based multi-objective evolutionary algorithm following the NSGA-II framework. This highlights population members that are not dominant but are close to a set of provided reference points. The NSGA-III used can be applied to multi-objective testing problems containing 2 to 15 targets. mNSGA-III was used in this study by making a series of modifications on the existing NSGA-III. First of all, a cutoff point was added among the results found. For results that fall outside the desired limits, the cost is shown to be high and the algorithm is forced to find the desired results. Subsequently, after calculating the targets, before creating the solution archive, ANN modeling is added and the solution archive is multiplied. By reducing the number of iterations to reach the minimum cost value, less costly results can be obtained in terms of optimization time. In addition, a feasible solution set was created by combining all the results found in each step and the selection process was made from that set. A version of this converted into a mathematical model is shown in Fig. 2. As defined in Fig. 2, the process begins with the definition of algorithm parameters, especially population size, maximum iteration and weight coefficients. Here, the most important innovation, ANN model support, is specified externally. Thus, a decrease of up to 8 times in optimization time was observed. Again, as can be seen in Fig. 2, if the ANN contains a model, this time saving is achieved by skipping the calculation part. All of this results in achieving optimal characterization.

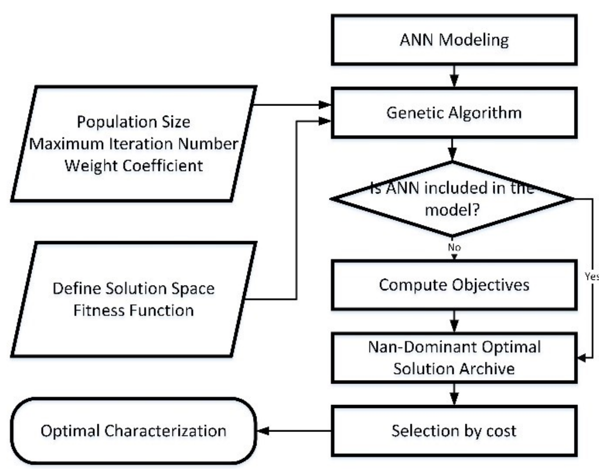

Fig. 2. Flow chart of microwave antenna by modeling accelerated non-dominant sorting genetic algorithm (NSGA)-III optimal solution modification.

C. Objective and cost functions

Among the antenna measurement functions, S_{11} and 90-degree directivity, which are among the most basic parameters determining the performance of the antenna explained in detail in the previous section, were chosen as reference points. Since multi-objective optimization problems try to converge the two selected objective function values to zero at the same time, functions that will keep the directivity parameter high and the S_{11} parameter low are tried to be selected. According to all these, the following objective functions are defined.

Objective functions:

$$OF_1 = \min\{e^{-\frac{directivity}{wc_1}}\}, \quad (1)$$

$$OF_2 = \min\{e^{\frac{S_{11}}{wc_2}}\}. \quad (2)$$

Here, the maximum reference points are given as directivity$\geq$0 and the minimum reference points are given as S_{11} <=0. Thus, the algorithm will try to optimize both performance parameters at the same time according to the importance of the determined weight coefficients (wc_{1-2}). The objective functions used in the optimization of the algorithm are collected to determine the cost function that will be used to demonstrate the success of the results in comparison with each other and are used to create the cost function:

$$cost = OF_1 + OF_2. \quad (3)$$

Objective functions (1-2) to be used in the optimization process have been selected since analysis is required for predefined performance parameters at a frequency of 28 GHz. It was tried to determine the result with the minimum average cost (3) taken over 10 runs with the determined goal functions.

In this optimization process, the decision variables are antenna length (meters) and flare angle (degrees), respectively. Since the importance of the requirements is different, trials have been made for different weight coefficients (wc_1, wc_2).

IV. RESULTS

A. Comparison of ANN aided and unaided NSGA-III and MOEA/D

First, the performance of NSGA-III was compared with a recently proposed MOEA/D procedure. The default parameters of the algorithm used (MOEA/D) are given as crossover percentage (P_c)=0.5, maximum iteration=30, archive=100 and population (N)=100. The default parameters of the proposed algorithm (NSGA-III) are given as percentage of crossover used (P_c)=0.5, mutation (P_m)=0.5, maximum iterations=30 and population (N)=80. Experiments were conducted for four different conditions in total. The results of two different algorithms are presented, with and without modeling support. Figure 3 shows typical cost and function evaluation number (FEN) variations with a repeat of the best performance. It was selected from 10 different studies for MOEA/D and NSGA-III with and without ANN support. As seen in the figure, the proposed algorithm showed more successful results than its rival. With ANN support, the steps to reach the MOEA/D minimum cost were reduced from 26 to 23. Similarly, NSGA-III also decreased from 16 to 13. Thus, the optimum was reached approximately 20% earlier in NSGA-III. In addition, since the ANN modeling part added to the very beginning of the application shown in Fig. 2 and the archive part created with these models skipped the calculation part of the lenses, there was an approximately 8-fold decrease in the total time.

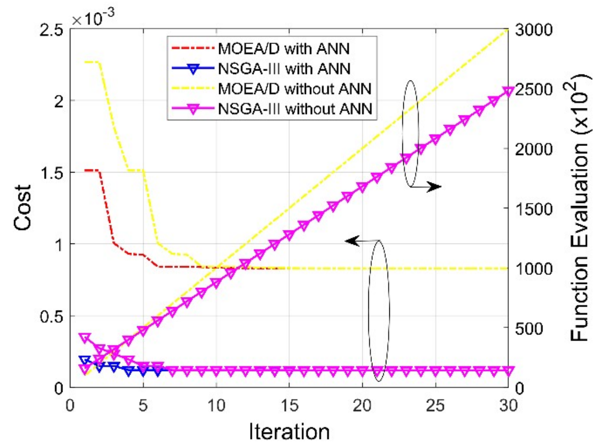

Fig. 3. Typical cost and FEN variations with iteration of the best performance of NSGA-III and MOEA/D algorithms selected from 10 runs for multi-objective optimization.

B. Optimal parameter set selection for optimization

Instead of starting from a single point, genetic algorithms seek from a collection of points. It is vital to select the algorithm settings that are best for this purpose. The algorithm's default settings are supplied as follows: population (N)=80; crossover percentage (P_c)=0.5; mutation (P_m)=0.5; maximum iterations (I)=30. For the 28 GHz algorithm, tests with various population characteristics have been conducted. With a duplicate of the best performance chosen from 10 distinct runs with crossover percentage (P_c)=0.5, mutation (P_m)=0.5 and population (N)=30, 50, 80. Figure 3 displays typical cost and FEN fluctuations. Additionally, a numerical summary of the cost and FEN changes from Fig. 4 is provided in Table 2. The best parameter set was determined to be crossover percentage (P_c)=0.5, mutation (P_m)=0.5, maximum iteration=30 and population (N)=50 based on the graph and table. The chosen optimal parameters will be used to continue the investigation in the next section.

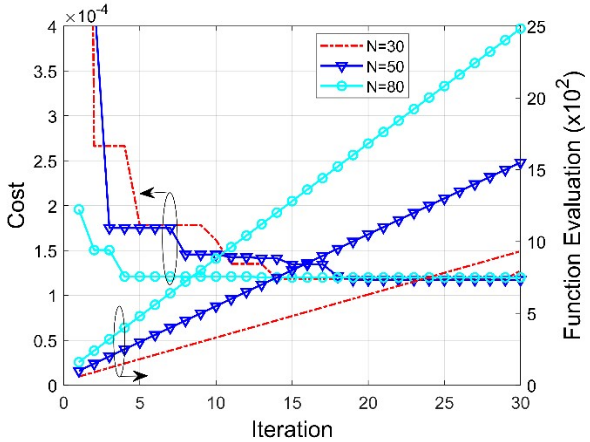

Fig. 4. Typical cost and FEN variations with iteration of the best performance of the algorithm selected out of 10 runs for optimization by population: crossover percentage (P_c)=0.5, mutation (P_m)=0.5 and maximum iteration=30.

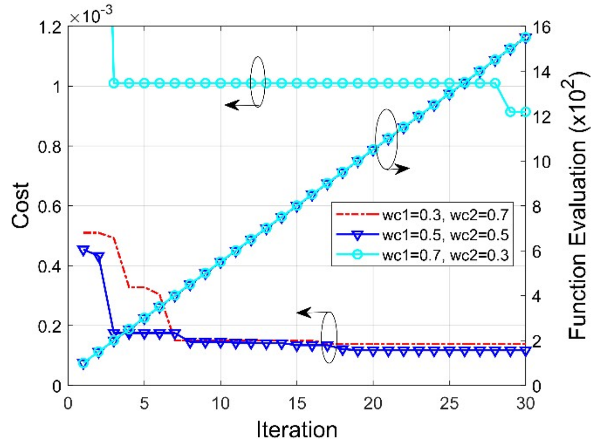

Fig. 5. Typical cost and FEN variations with iteration of the best performance of the selected algorithm over 10 runs for optimization by weight coefficients: crossover percentage (P_c)=0.5, mutation (P_m)=0.5, maximum iteration=30 and population (N)=50.

Table 2: Performance evaluations of the algorithm by population for optimization: crossover percentage (P_c) = 0.5, mutation (P_m) = 0.5 and maximum iteration = 30

Population (N)		**Minimum**	**Maximum**	**Mean**
30	Cost	0.119×10^{-3}	2.307×10^{-3}	0.220×10^{-3}
	FEN	450	60	930
50	Cost	0.117×10^{-3}	0.454×10^{-3}	0.157×10^{-3}
	FEN	1000	100	1550
80	Cost	0.119×10^{-3}	0.196×10^{-3}	0.125×10^{-3}
	FEN	2480	160	2480

Table 3: Performance evaluations of the algorithm according to the weight coefficients for optimization: crossover percentage (P_c)=0.5, mutation (P_m)=0.5, maximum iteration=30 and population (N)=50

wc $_1$	**wc** $_2$		**Minimum**	**Maximum**	**Mean**
0.3	0.7	Cost	0.138×10^{-3}	0.509×10^{-3}	0.197×10^{-3}
		FEN	900	100	1550
0.5	0.5	Cost	0.117×10^{-3}	0.454×10^{-3}	0.157×10^{-3}
		FEN	1000	100	1550
0.7	0.3	Cost	0.914×10^{-3}	4.79×10^{-3}	1.20×10^{-3}
		FEN	1500	100	1550

C. Weight coefficient selection for cost

Determining the weight coefficients inside the cost (3) function is crucial since the working concept of the algorithm aims to obtain the solution with the lowest cost. Weight coefficient-1 (wc_1) represents the directivity parameter in the cost function, while weight coefficient-2 (wc_2) represents the parameter S_{11}. The best performance, chosen from 10 distinct runs, is shown in Fig. 4 along with its repeating typical cost and FEN variations for wc_{1-2}=0.3, 0.5 and 0.7, respectively. Additionally, a numerical summary of the cost and FEN changes from Fig. 5 is provided in Table 3.

D. S_{11} for bowtie antenna

Figure 6 shows the typical magnitude and frequency variations at 25-32 GHz for S_{11} of three antennas with the best performance for percent transition (P_c)=0.5, mutation (P_m)=0.5, and population (N)=30, 50 and 80. Additionally, the variations in magnitude and frequency

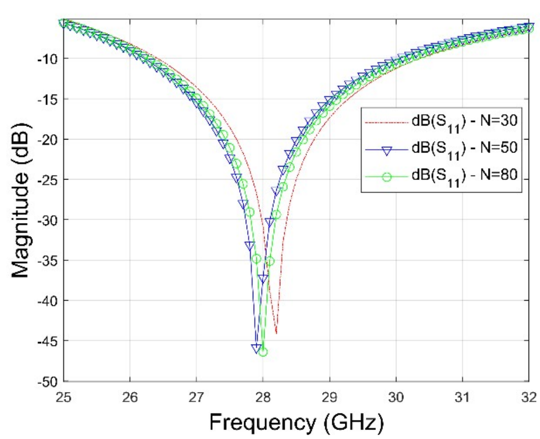

Fig. 6. S_{11} of antenna for the best performance selected among different population values: P_c=0.5, P_m=0.5 and maximum iteration=30.

in Fig. 6 are given in Table 4 as a numerical table. As a result, the increase in the population value gives more result value and increases the cost of optimization. Figure 7 shows the three best performances for population (N)=50, wc_1=0.3, 0.5 and 0.7, and wc_2=0.3, 0.5 and 0.7, in addition to the parameters used in Fig. 6. The S_{11} of the antenna shows typical angle and frequency variations between 25 and 32 GHz. Additionally, the variations of angle and frequency in Fig. 7 are given in Table 5 as a numerical table. It is seen that increasing the weight coefficient of S_{11} is reflected in the results. According to the results in Figs. 6 and 7, it can be said that the bandwidth of the antennas is 26-30 GHz. In addition, using the population (N)=80, wc_1=0.5 and wc_2=0.5 parameters given in Fig. 6, the best result is -47.96 dB S_{11}. Directivity for the result is shown in Fig. 8, and the most successful design parameters were obtained using the 3D EM simulation tool CST Microwave studio. In Fig. 9, the variation of S_{11} is given as typical amplitude-frequency.

Table 4: Numerical form of frequency and S_{11} values in Fig. 6

Population (N)	Frequency (GHz)	S_{11} (dB)
30	28.1	−43.41
50	27.9	−47.27
80	28	−47.96

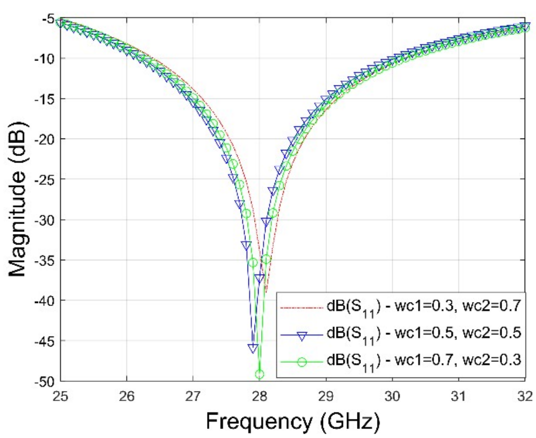

Fig. 7. S_{11} of antenna for the best performance selected among different weight coefficients values: P_c=0.5, P_m=0.5, N=50 and maximum iteration=30.

Table 5: Numerical form of frequency and S_{11} values in Fig. 7

wc_1-wc_2	Frequency (GHz)	S_{11} (dB)
0.3-0.7	28.1	−36.86
0.5-0.5	27.9	−47.27
0.7-0.3	28	−48.96

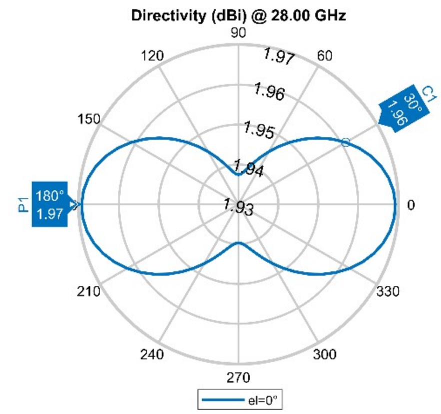

Fig. 8. Directivity of antenna for the best performance selected: P_c=0.5, P_m=0.5, N=80 and maximum iteration=30.

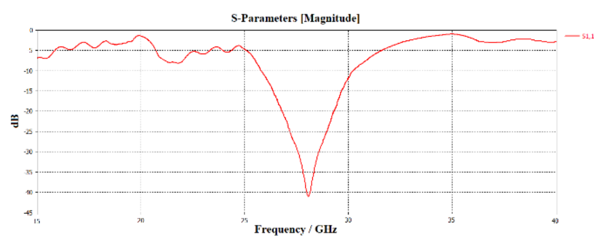

Fig. 9. S_{11} of the antenna from the results using CST (Substrate to RT/Duroid 5880).

V. DISCUSSION

In a similar study, it was stated that the proposed antenna had good performances operating at 28 GHz, with a S_{11} of -30 dB, VSWR below 2, good directivity and the radiation pattern of the proposed antenna providing a good match on the required frequency [22]. In our study, a S_{11} of -49 dB was obtained at 28 GHz. It is stated in detail in Table 6. In another study, two multi-objective optimization meta-heuristic strategies combined with the carrier model NSGA-II and MOEA/D are used to overcome the problems noted in conventional antenna design [16]. A total of 4 hours of process was reduced to 55 minutes with improvement. Thus, the process was made 4.4 times faster. In our study, it was seen that the time was made 8 times faster in total. It is stated in detail in Table 7. When compared with both similar studies, the success of the proposed method was once again confirmed.

At the very beginning of the study, modeling support was not added because the optimization processes for the

Table 6: Comparison of S_{11} values

	Frequency (GHz)	S_{11} (dB)
Current Study	28	−48.96
[22]	28	−30

Table 7: Comparison of optimization time

	Previous Working Time	Subsequent Working Time
Current Study	8X	1 X
[16]	8X	1.4 X

relevant model did not take very long. In similar studies or different models, it was observed that the optimization processes took undesirably long and this situation made optimization inextricable, and the flow of the study evolved in this direction. Architecturally, a longer lasting model could have been chosen. However, this would only prolong the processes and would not have any impact on the confirmation of the success of the application.

In future studies, the processes can be further accelerated by changing the network used in modeling support. Additionally, the suggested method can be tried on models that take more time, such as filter optimization.

VI. CONCLUSION

In the literature, the definition of optimal characterization is defined as the process of finding the optimal solution possible within the range specified by the user. This process may take an undesirably long time due to both the complexity of the problem and hardware inadequacies.

In this study, it has been shown that the current optimal characterization process can be reduced up to 8 times with only ANN support, without requiring any additional hardware or tools. Thus, this and similar optimization processes can be solved much more economically without any additional cost. The proposed ANN modeling addition is only a software add-on and does not require any additional budget. In the application part, compact microstrip single-band antenna designs that can operate in millimeter wave communication are formulated as a multi-objective optimization problem supported by ANN modeling, and are expressed in terms of dominant solutions and variation relations according to the geometric design parameters of the antennas. NSGA-III algorithm has been successfully applied to obtain optimum design values for desired cost functions using MOM technique. The fact that the originally designed system was supported by modeling caused the current optimization process to reach optimum by an additional 20% earlier. In addition to all these, the results in the study were compared with the MOEA/D, a recently proposed EMO algorithm, to compare the superiority of the problem and it was found to be more successful. When compared with similar studies in the literature, more effective results were obtained. As can be seen from the simulation results, the proposed NSGA-III-based design optimization method is an impact algorithm for generating optimal solutions of a microwave antenna in terms of geometric design parameters and performance criteria. In terms of verifying the results with a different program, the most successful design parameter was obtained using the 3D EM simulation tool CST Microwave studio.

In summary, the proposed modeling support can be successfully applied to any optimization algorithm processes and thus significant savings can be achieved in all other optimization processes.

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