Surrogate Modeling for Designing and Optimizing MIMO Antennas

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***Abstract*—This papers presents the design and optimization of multiple-input and multiple-output (MIMO) antennas through intelligent methods namely as: surrogate modeling. The optimization process is performed automatically with the combination of Microwave Studio (Dassault Systèmes) and MATLAB numerical analyzer. The proposed optimization method aims to find the optimal solution for the total active reflection coefficient (TARC) specification, S_{11}, and S_{12} by using shallow neural network. This methodology leads to efficiently size the design parameters of MIMO antenna and to optimize S-parameters and TARC specification jointly . To validate the proposed method, an ultra wideband MIMO antenna in the frequency band of 3.1 GHz to 10.6 GHz is designed and optimized.**

***Index Terms*—multiple-input and multiple-output (MIMO), particle swarm optimization (PSO), shallow neural network (SNN), surrogate modeling, sizing, total active reflection coefficient (TARC).**

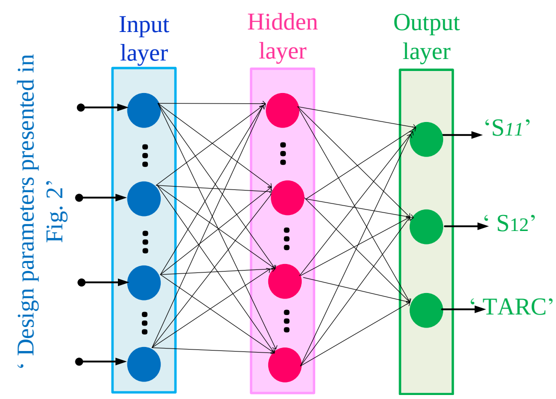

Fig. 1. Proposed SNN for predicting the optimal design parameters.

I. Introduction

For the next generation communication systems include sixth-generation (6G) technology, high performance antennas play important roles [1]. From the various configurations of antennas, multiple-input and multiple-output (MIMO) antennas are recently used in the industrial applications due to the increased capability in transferring high amount of data [2]. Hence, designing and optimizing high performance MIMO antennas in terms of bandwidth, gain, and total active reflection coefficient (TARC) specifications are the targets by the engineers.

Recently, various optimization methods as chicken swarm optimization [3], artificial bee colony algorithm [4], and genetic algorithm [5]–[7] in the domain of antenna designs are presented recently. However when the design parameters are lot, these methods by themselves are not enough in the optimization process and advanced intelligent-based methods are required. Recently, machine learning and artificial neural networks have proved their beneficial aspects in designing and optimizing complex designs [8]–[11].

This paper presents surrogate modeling method to optimize design parameters of the MIMO antenna in an effective way. For this case a shallow neural network (SNN) is employed where in the output layer, the TARC specification with S-parameters are predicted automatically result in optimal design parameters. The proposed method tackles the problem of sizing MIMO antenna and optimizes the antenna based on the MIMO's output specifications. This work is organized as follows: Section II presents the proposed methodology in optimizing MIMO antenna. Section III devotes to provide the related simulation results. Finally, Sec. IV concludes this manuscript.

II. MIMO Antenna Design Methodology

The proposed method in this manuscript is based on optimizing various design parameters of MIMO antenna. For this case the SNN (i.e., a network with one hidden layer) is trained for optimizing the MIMO antenna in terms of TRAC, S_{11}, and S_{12} specifications. The general definition of this specification is as (1) that it depends on S-parameters (i.e., $\mathrm{S}_{11}, \mathrm{S}_{12}, \mathrm{S}_{21}, \mathrm{S}_{22}$).

$$TARC = \sqrt{((\mathrm{S}_{11} + \mathrm{S}_{12})^2 + (\mathrm{S}_{21} + \mathrm{S}_{22})^2)/2} \quad (1)$$

After configuring the MIMO antenna and determining the design parameters, the SNN can be constructed by providing suitable amount of data set. In order to achieve this amount of data, firstly the automated environment between CST and MATLAB must be arranged [2]. Then, the design parameters are iterated randomly with variation boundary of $\pm 10\%$ from the initial points where this performance results in suitable amount of data set. Then the SNN network is trained by using (2) where X_{Train} and Y_{Train} are the input data (i.e.,

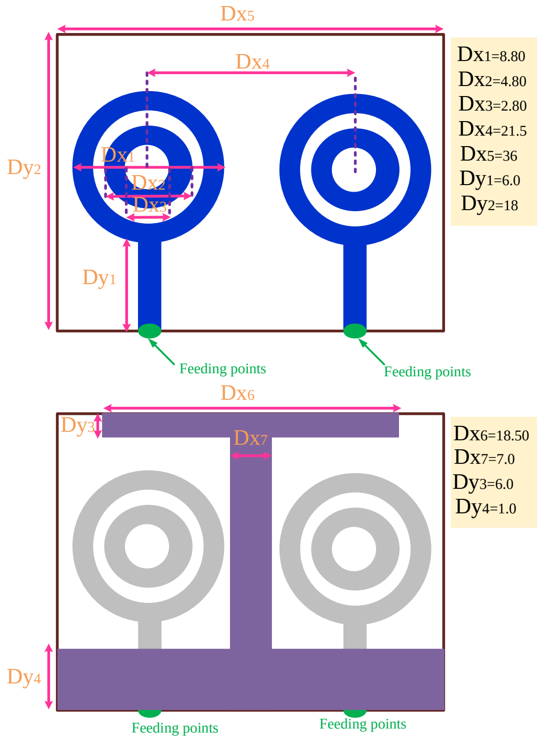

Fig. 2. Proposed MIMO antenna with design parameters targeted to optimize (top), ground plane of antenna (bottom); scale is in mm.

design parameters) and output data (i.e., TARC values, and S-parameters), respectively. Figure 1 presents the proposed neural network that is constructed for predicting the optimal design parameters based-on S-parameters and TARC specifications.

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

III. Simulation Results

This section devotes to firstly introduce the designed and optimized MIMO antenna and afterwards the output specifications of optimized antenna are described. Figure 2 presents the designed MIMO antenna that includes the optimized design parameters with the ground plane. The antenna is designed on FR-4 with relative permittivity ε_r=4.3 and of height of 1.60 mm where the dimension is 56 $\times$18mm^2. Figure 3 presents the three specifications of optimized MIMO (S_{11}, S_{12}, and TARC results) in the ultra-wideband of 3.1 GHz to 10.6 GHz.

IV. Conclusion

This paper presents the intelligent based optimization method for designing and optimizing MIMO antenna leads to have high performance antenna. The configuration of MIMO antenna is complex and determining optimal design parameters is not straightforward. To tackle this drawback, surrogate modeling based on constructing a neutral network is employed in this paper and S-parameters with TARC specifications are optimized automatically, leads to achieve optimal design

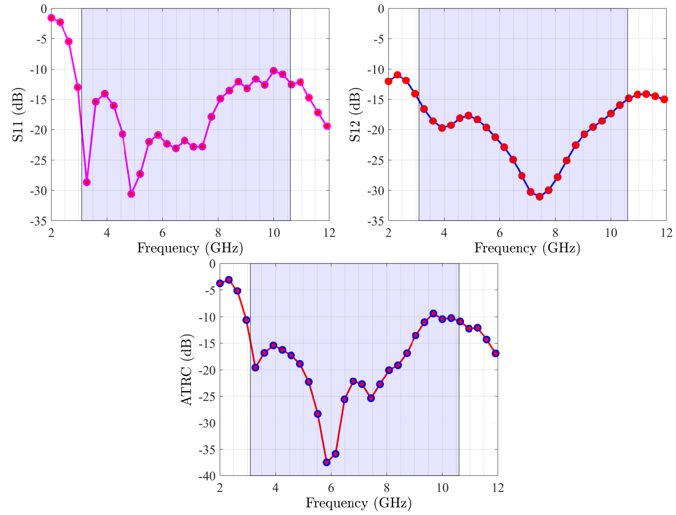

Fig. 3. S_{11}, S_{12}, and TARC specifications of optimized MIMO antenna.

parameters. All the optimization methodology is performed automatically with the combination of Microwave CST and MATLAB. To verify the proposed method, an ultra-wideband MIMO antenna is designed and optimized.

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