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Neural Network-based Approach to Design FSS Configuration Applicable for Tunable Structures

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Abstract—Frequency selective surfaces (FSSs) have selective transmission/reflection properties and usually consist of an arrangement of periodic unit cells. The design of these complex structures to meet specific properties is time-consuming and usually relies on iterative cycles of simulations. To tackle this demanding process, a machine learning technique with the implementation of a neural network (NN) has proved its effectiveness for designing such structures in recent years. In this work we first design an FSS structure with a new configuration for biasing the lumped elements that are used in tunable structures, and afterwards we use the NN method for predicting the optimal design parameters employed in the constructed FSS shape. This study is conducted by applying the active devices in the FSS structure with cut-slots. The effectiveness of the proposed methodology is verified by employing the trained NN for the constructed structure operating from 2 GHz to 14 GHz.

Index Terms—Biasing network, frequency selective surface (FSS), neural network (NN).

I. INTRODUCTION

Frequency selective surface (FSS) structures are widely used in numerous applications such as reducing radar cross-section, minimizing coupling among antennas, and creating high impedance surfaces [1]. The main design requirements of FSS structures include the incidence angle of the incoming wave and the bandwidth [2]. In the case of conventional FSS structures, due to the dependence on the incidence angle and frequency, there is the critical issue of having reflection and transmission characteristics that meet objectives, which has made designers come up with new techniques [3].

The solution methods include multiplexing of frequencies, harmonic generation, and applying lumped elements. Using lumped elements such as PIN diodes or varactors is one of the most useful ways to achieve reconfigurability, allowing for a tuning of the resonance frequency. To overcome the design difficulties a generative machine learning (ML) method was employed for optimizing metasurface structures, facilitating the scatterer shapes and dimensions [4]. Also, The Bayesian optimization was used in [5] for tuning the internal parameter of an FSS structure.

The main purpose of this work is to introduce a new configuration that uses an indirect biasing by the means of

a control network (CN) method. After constructing the FSS design, the NN-based method is used, leading to a fast design of the optimal design parameters.

This work is organized as follows: Section II presents the proposed method in a nutshell and Sec. III introduces the simulation results achieved with the proposed methodology. Finally, Sec. IV concludes this work.

II. PROPOSED METHODOLOGY IN A NUTSHELL

The NN-based method becomes important since it is facilitating the design process of high-dimensional structures. After generating the initial structure of the FSS, the optimal design parameters can be predicated through the trained NN. This section presents the steps for constructing the NN.

As the first step, the targeted FSS structure must be generated in the 3D EM analysis software and afterwards the design parameters (here the width (W) and length (L) of the configuration as shown in Fig. 1) must be iterated randomly for achieving a suitable amount of data. This amount of data from any numerical analyzer is used for training the NN, in which the input layer presents the design parameters and the output layer is devoted to predicting the TE (transverse electric) and TM (transverse magnetic) reflection and transmission properties for the designed structure.

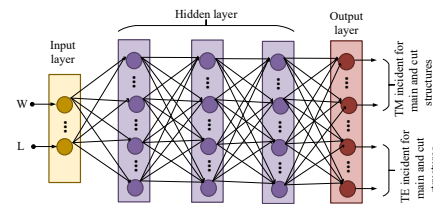


Fig. 1. Proposed NN for achieving optimal design parameters.

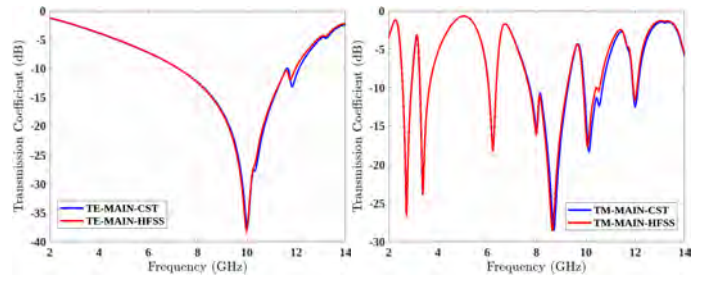
III. SIMULATION RESULTS

The structure in Fig. 2 is built on an FR-4 substrate layer with $\epsilon_r = 4.3$, a loss tangent of 0.025, and a thickness of 1.58 mm and a substrate dimension of 18×18 mm. To introduce

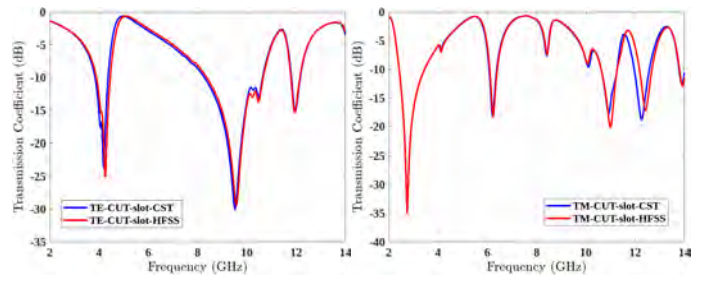
Figure 1 consists of two parts. Part (a) is a top view of the antenna structure, showing a central rectangular patch with a grid of smaller rectangles. Dimensions are indicated: 9mm for the total width, 3.5mm for the left side, and 6.5mm for the right side. Part (b) is an equivalent circuit diagram. It shows a series combination of a capacitor C_1 , a switch S , and a resistor R_1 . The switch S is controlled by a voltage V_{ctrl} . The circuit is shown in two states: OFF-state (switch open) and ON-state (switch closed).

Two states of PIN diodes shown in Fig. 3 (right): ON which the diode is modeled a series resistor-inductor (RL) circuit and OFF, which is modeled as a parallel resistor-capacitor (RC) circuit in series with an inductor, with specific nominal element values provided as follows: $L = 30$ pH, $C = 28$ fF $R_{\text{on}} = 7.8$ k Ω $R_{\text{off}} = 30$ k Ω .

Fig. 5 (left) presents cut-structure in TE mode where the first notch is at 4.2 GHz (-23.78 dB) with a stopband from 3.85 to 4.38 GHz. Additionally, a 2.37 GHz wider stopband occurs from 8.29 to 10.65 GHz, with a notch exhibiting -30.024 dB of attenuation at 9.54 GHz. TM incidence case shown in Fig. 5



(right) has the first frequency stopband between 2.42 to 3.46 GHz (-34.76 dB at 2.75 GHz), and then a second -10 dB stopband occurs from 10.63 to 11.297 GHz with a -17.851 dB frequency notch at 10.945 GHz.



IV. CONCLUSION

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