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Automated FSS Design and Optimization with Time Series Forecasting Process through Combined CNN-RNN Model

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***Abstract*—In this work, an automated-oriented methodology in combination with intelligent technique is presented, leading to design and optimize a frequency selective surfaces (FSS) geometry. The FSS configurations include periodic unit cells of which designs iterative cycles of simulations are usually required. For this case, firstly we present a procedure for automatically configure the FSS structure and afterward, a neural network that is the combination of convolutional neural network (CNN) and recurrent neural network (RNN) is employed for its optimization. The proposed methodology leads to automatically configure the FSS structure, and to predict the performances of the generated design in at specific frequencies within the initial frequency band. The modeling process is executed considering the combination of electronic design automation (EDA) tool as CST studio suite, and numerical analyzer as MATLAB. The effectiveness of the proposed method is validated by designing an FSS operating as multi-band device in the 6.2-6.4 GHz, 7.9-8.4 GHz, and 10.7-11.4 GHz frequency bands. Finally, a prediction of the input scatting parameter of the optimized structure obtained through CNN-RNN model is performed.**

***Index Terms*—Automated, Convolutional neural network (CNN), Frequency selective surface (FSS), Forecasting, Modeling, Optimization, Prediction, Recurrent neural network (RNN).**

I. Introduction

IN the last years, wireless communication is growing faster and faster; it requires transferring of expanding amount of data in an improved accurate way [1]. For electromagnetic (EM) shielding, frequently required also for security reasons, performer frequency selective surface (FSS) structures, exhibiting narrow notches, high roll-off, etc., are required. They become critical in the fifth-generation (5G) devices, and the performances have to extend over the associated wide frequency bands [2]. Modeling and development of methods to achieving suitable output performances for such complex designs require significant research effort. One of them paving the way of this development is the utilization of neural networks (NNs) [3]–[7]. Recently various studies are devoted to this concept; some of them are recall below.

In [8], a vector-graph-feature-extraction method along with deep neural network (DNN) is presented for firstly characterizing the EM metasurface and then estimating EM spectrum from exact configuration. In order to fasten the design process of metasurface, a DNN is employed in [9] for extracting an equivalent circuit. A Fourier subspace-based deep learning method is employed in [10] for FSS inverse design that helps in reducing the geometrical dimensions of structure parameters. The presented method is compact and stable enough to assure communications in noisy environment. A broadband FSS structure is designed in [11] through the equivalent circuit model backed DNN considering minimum mean square error as observable of the design. In another study, [12], the physics-informed NN with embedded analytical models is presented which is suitable for various periodic structures and is fast enough for inverse designs. The NN-based approach with an adjoint gradient-based design method is introduced in [13] where the initial unit cell is produced by an inverse network and consequently the computational time is effectively reduced. For the inverse design of the FSS configuration in [14], a data-physics-driven NN is presented. The equivalent circuit model-backed NN approach is presented in [15] for optimizing the FSS structure operating at the desired frequency and exhibiting the required bandwidth.

This current contribution is devoted to present an automated-oriented methodology in which firstly the FSS structure is generated automatically and afterward, the hybrid convolutional neural network (CNN)-recurrent neural network (RNN) is employed (see Fig. 1). As the first phase, the configuration is generated by the combination of CST Microwave Studio (as the electronic design automation -EDA- tool) and MATLAB™ (as the numerical analyzer) in which visual basic (VBA) is considered as the main coding environment. Then, as the second phase, the CNN-RNN network is trained and constructed for optimizing the FSS structure in terms of geometrical parameters and output performances. Alike the benefits of DNNs, this method is efficient enough in

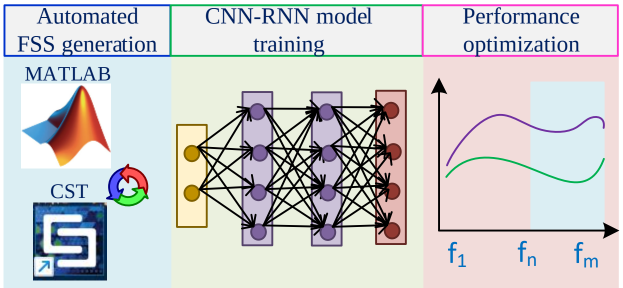

Fig. 1. Proposed automated methodology for designing and optimizing an FSS configuration.

minimizing the computational simulation time. For proving the effectiveness of our proposed automated approach, we design and optimize a FSS operating in various frequency bands, namely 6.2-6.4 GHz, 7.9-8.4 GHz, and 10.7- 11.4 GHz.

This work is organized as follows: Section II is devoted to introducing the methodology that is based on designing the FSS structure automatically along with optimizing the FSS configuration with the CNN-RNN model. The practical implementation of proposed method is verified by the presented simulation results in Sec. III. Finally, Sec. IV concludes this work.

II. Proposed Automated Methodology

The main concept of the proposed method is to automatically configure an FSS structure, and to optimize the performance of the generated design through the presented NN. Figure 1 presents the general flowchart of proposed method in a nutshell, and this section devotes to introduce the detail steps leading to employ the proposed approach.

As the first step, the automated environment between EDA tool (here CST Microwave Studio) and numerical analyzer (here MATLAB™) are created that are combined and matched together [16]. Afterward with the help of visual basic (VBA) environment in CST tool [17] and coding script in MATLAB, the FSS configuration is generated [18]. This step helps in accelerating the design process along with conforming data generation that is required importantly for training any NN.

After generating the initial structure of the unit cell, the FSS is built with, the whole configuration is optimized by the presented structure in Fig. 2. This network [19] is used for sizing the FSS structure leading to optimize the design in terms of S_{11} specification. This hybrid network is employed in this study since the CNN is good-enough for extracting spatial features from the complex geometrical structures and the RNN is effective in predicting the sequential time series performances. Hence the combination of these networks result in improved performance in optimizing and predicting the outcomes over frequency.

III. Simulation Results of Optimized FSS Structure

The automated procedure presented in the previous section is applied for designing and optimizing a FSS structure, and this section devotes to present the related implemented results. For this case, by getting a design idea introduced in [20], we employ a new optimization process which is fully automated and NN-based method is executed. Here, an Intel Core i7-4790 CPU @ 3.60 GHz equipped with 64.0 GB RAM is used as the execution environment.

Figure 3 presents the automatically configured FSS design. The process is started by considering an FR4 substrate with relative permittivity of ε_r=4.1 and a thickness of 0.5 mm. Then the structure starts with a ring/loop shape resonator, and the process consists of adding additional rings/loops around the central one.

After generating the initial structure of the unit cell of the FSS geometry, it is time for obtaining the optimal geometric values. For this case, firstly the training data is produced by iterating the initial design parameters randomly with the range of [$\mp$5%, $\mp$10%, and $\mp$15%] which results in 1200 multi-segment S_{11} specifications. Collecting this kind of data will help in initializing the NN construction presented in Fig. 2 in which the 'rule of thumb' is employed for determining the detailed structure of the CNN-RNN model (i.e., hyperparameters). The whole generated data is divided in to three subsections as training data, validation data, and testing data with the ratio of 70%, 15%, and 15% respectively. The accuracy of the trained network is presented in Fig. 4 that is less than 0.2 value in terms of root mean square error (RMSE) and loss function which show great results over iterations.

The configured design in Fig. 3 is optimized by the CNN-RNN model leading to have geometric values of $W_1 = L_2$=14 mm, L_1=12 mm. The width of each loop is $w_l = 1\pm0.1$ mm, while the air-gaps between them have a width of $w_a = 1\pm0.1$ mm.

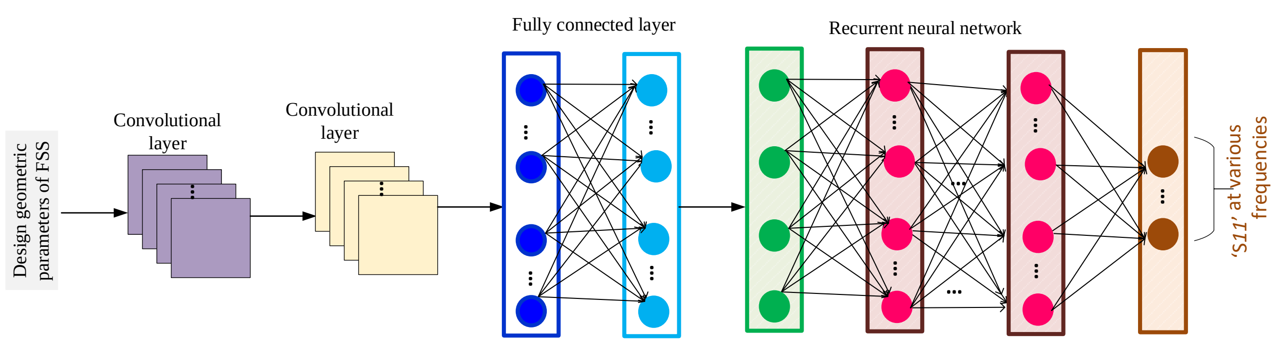

Fig. 2. Combination of CNN and RNN for optimizing the FSS structure.

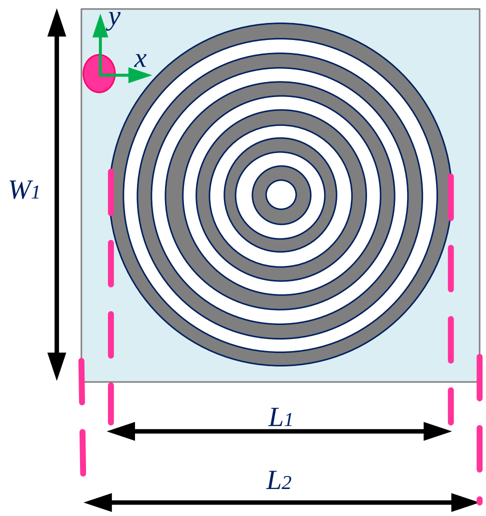

Fig. 3. Generated automated FSS structure with the optimized values.

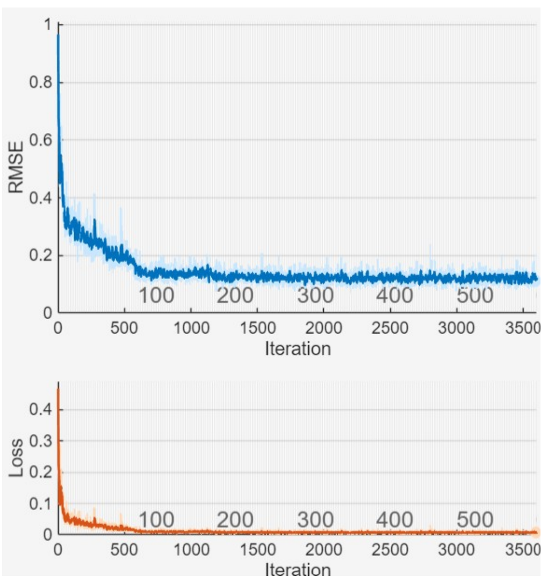

Fig. 4. Accuracy representation of trained NN; RMSE value (top), and loss function (bottom) over iteration.

The S_{11} performance over frequency for the optimized FSS structure is presented in Fig. 5; matching notches from 6.2-6.4 GHz, 7.9-8.4 GHz, and 10.7-11.4 GHz can be identified. Additionally, Fig. 6 presents the S_{11} results of various number of loops. The analysis starts with the most inner loop, going up to a total of 6 loops. For each configuration the targeted outcomes are determined and the optimization process is stopped automatically.

For demonstrating the accuracy of the trained NN, from 10.3 GHz up to 14 GHz the S_{11} performance is also predicted by the constructed CNN-RNN model which shows a good agreement with the simulated outcomes as depicted in Fig. 7. Moreover, the excitation power performance of the optimized FSS structure is shown in Fig. 8.

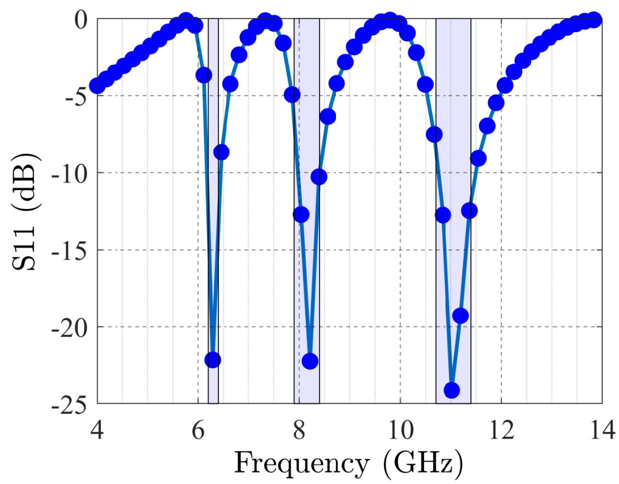

Fig. 5. S_{11} performance of the optimized FSS.

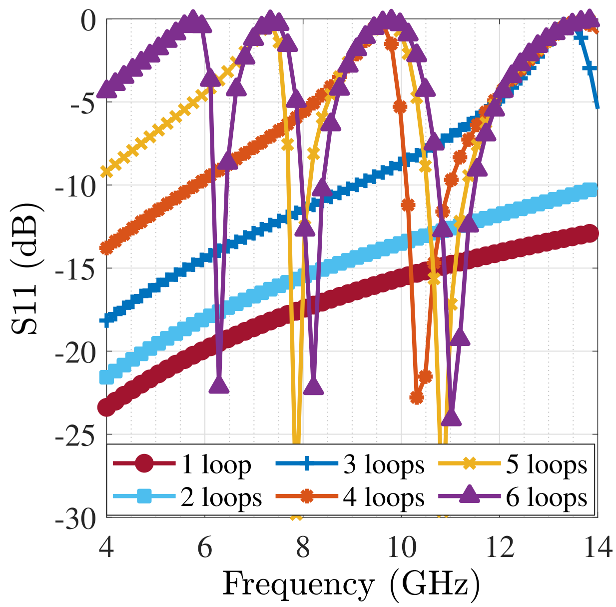

Fig. 6. S_{11} performances of FSS with various number of loops.

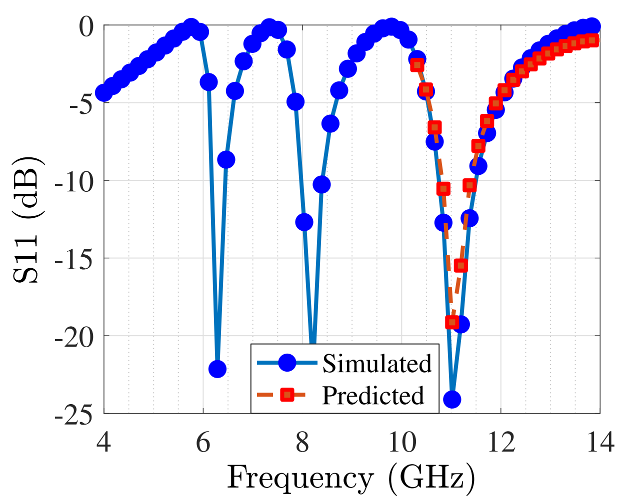

Fig. 7. S_{11} performance comparison between the simulated and predicted outcomes.

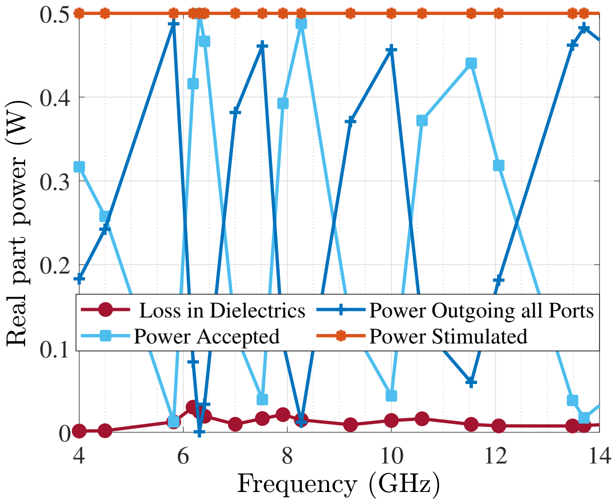

Fig. 8. Excitation power of optimized FSS in (W).

IV. Conclusion

Fully automated optimization process for designing an FSS structure is presented in this work. The methodology includes two phases: in the first step, the general topology of the geometry is determined based on the results obtained from the combination of CST and MATLAB results, in which VBA environment is the main core of the process. Then as the second step, the hybrid CNN-RNN network is executed for optimizing the constructed FSS design along with predicting the outcomes in the determined frequencies. The proposed methodology is validated by designing and optimizing a FSS configuration operating at multi-band frequencies as 6.2-6.4 GHz, 7.9-8.4 GHz, and 10.7- 11.4 GHz. Additionally, the accuracy of the trained NN is verified by predicting specific outcomes over frequencies by making comparison with the simulated ones. This method is flexible enough to be employed for various electromagnetic designs leads to configure and size the determined circuits in an automated way.

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