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Artificial Intelligence Based Deep learning Surrogate Model for Design Optimization of Microstrip Frequency Selective Surface

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***Abstract*— This paper centers on the utilization of Artificial Intelligence (AI) based surrogate-model assisted optimization methods for having high performance microwave circuit elements such as Frequency Selective Surfaces (FSS). The fusion of the Modified-Multi Layer Perceptron (M2LP) and a meta-heuristic optimization algorithm Honey-Bee-Mating Optimization (HBMO) algorithm was pursued to improve the design of the FSS unit. The M2LP surrogate model offers a unique strategy for regression problems which makes it a suitable solution tool for optimization of complex microwave designs such as FSS. The outcomes derived from the optimized FSS design parameters obtained from M2LP-HBMO models are compared with the findings obtained from the 3D EM-simulation model. The purpose of this comparison was to verify that the response of the 3D EM simulation model, matches exactly with the proposed approach. As a result, it was seen that the proposed M2LP surrogate effectively optimizes FSS designs for various applications within the given domain.**

Keywords*— *Data driven, Surrogate model, Frequency selective surface, HBMO, 5G, Optimization.

I. INTRODUCTION

In recent years, Frequency Selective Surfaces (FSS) have become a research topic in more and more areas. FSS are formed by periodically arranging the dielectric layer and the metal surface printed on it. These periodic structures work like resonators and have a resonance frequency. The contact of an electromagnetic wave to the FSS creates a current density on the surface. Therefore, the current distribution on the FSS is affected by the resonance pattern. In this direction, the resonance frequency depends on the geometric structure of the FSS. The resonance pattern of the unit cell has an effect on determining the resonance frequency [1].

Another important parameter that needs to be analyzed in order to get the desired efficiency on FSS is their thickness. According to their structure, FSSs are divided into thick and thin. While the thickness value of the structure applied on the dielectric plate is $t < 0.001\ \lambda_0$ (λ_0 represents the wavelength at the resonance frequency), it is called thin; when $t > \lambda_0$, it is called thick FSS, which is used in designs as a high-pass filter. The most important difference between thick and thin structures is; while thin structures are compact and cost effective; thicker structures are heavier, more difficult to fabricate and more costly [2].

The size of the FSS is a parameter that directly affects the resonance frequency. The dipole with a length that is an exact multiple of half wavelength ($\lambda_0/2$) gives the operating frequency (f_0) of the FSS design. Therefore it exhibits completely reflective (resonant) properties. Likewise, when the semi circumference of the FSS in the circular loop is an exact multiple of $\lambda_0/2$, it exhibits a similar reflection (resonance) behaviour.

Considering the above mentioned parameters, precise calculations are required to obtain the desired resonance response in the microstrip FSS structure. The generally preferred method in FSS design is the use of electromagnetic simulation tools [3]. Despite the advantage of providing high-precision measurements, EM simulations are disadvantageous in solving computationally large and complex problems such as optimization and tolerance analysis. The duration of the EM simulation can take a very long time depending on the granularity of the optimization targets [4].

One of the recommended approaches to reduce this time and obtain more effective results is the Data-driven surrogate model [5-6]. The effective utilization of contemporary AI methodologies and optimization techniques have proven to be efficient approaches in achieving exceptional levels of EM-performances.

In this study, a new approach centered on artificial intelligence to design of FSS is discussed. M2LP is a effective AI regression architecture where traditional artificial neural network architecture is improved by deployment of complex elements of Deep Neural Networks (DNN). The mentioned complex elements can briefly summarized as, modern activation functions ReLU and/or ELU, which can prevent vanishing gradient problems and enhance the convergence-rate of training process. Batch normalization which is a method that is proposed to address the issue of internal covariate shift. It is aimed to bring a different perspective to FSS design with the techniques examined within the scope of this study.

II. FSS AND SURROGATE MODEL

In this section, artificial intelligence algorithms used for regression modeling are introduced. These algorithms used will help in finding the modeling that best optimizes the resonance response of the FSS according to geometric parameters. The best of these algorithms was chosen and modeling was done based on this algorithm.

A. Support Vector Regression Machine

SVM has been used successfully in classification and regression problems in recent years. SVM is a fast learning machine based on solid mathematical foundations that connect generalization and optimization theories. In general, they are machines that have the potential to perform regression with highly non-linear functions, because these non-linear functions are created in a suitable feature space and treated as a linear function. SVM is gaining growing interest in theoretical and engineering applications with its many attractive features. It is used in subjects such as pattern recognition, voice recognition, function estimation and optimal control. The primary application of SVM areas are engineering and economics, and it is also used as a solution method to classification, regression and prediction problems. SVM learning theory is based on the principle of a small number of samples instead of an infinite number of samples, and therefore the computational cost is quite low. Universal minimum is guaranteed due to the use of convex objective function in the optimization process. Moreover, in the SVM optimization process, the coefficients of the approximation function (structural risk) are minimized, not the empirical risk like ANN. This creates complete risk minimization for a learning machine. With all these main working principles, SVM brings definite advantages over other methods [7-8]. Choosing the right kernel is the trickiest part of SVM problems. Some of the most used kernel functions are p ranked kernel, p-order polynomial kernel, and Sigmoid kernel. They are given in the Eq. (1), Eq. (2) and Eq. (3) respectively.

$$K(u,v) = (<u,v>)^p \tag{1}$$

$$K(u,v) = (<u,v> +1)^p \tag{2}$$

$$K(u,v) = \tanh (a <u,v> -\gamma) \tag{3}$$

B. Gaussian Process Regression

GPR models are generally applied when there is a case of non-linear regression and classification. Since the estimates are probabilistic, empirical confidence intervals can be calculated and based on these it can be decided whether the estimate needs to be readjusted in a region of interest. It is versatile as different Kernel functions can be used for the decision function [9-10]. The Gaussian process f(x) is parameterized with m(x) evaluated at points x and x′. The function can be defined as:

$$m(x) = E\,(f(x)) \tag{4}$$

$$Cov(f(x)),f(x')) = k(x, x';\theta) = E((f(x)-m(x))f(x')-m(x'))) \tag{5}$$

Here, "θ" denotes the set of hyperparameters.

The mean function is generally considered zero because it expresses the central tendency of the function [11]. The covariance function contains information about the shape and structure of the function to be created [12]. The connection between input and output parameters is stated as follows:

$$y = f(x) + \varepsilon \tag{6}$$

Here, the value of ε is assumed to be independent and a Gaussian distribution with zero mean and variance of σ_n^2 is distributed over it.

C. Ensemble Learning

Ensemble learning (EN) method is a machine learning technique that combines several underlying models to produce a single optimal predictive model. In problems with complex decision boundaries, using a single classifier may not be sufficient. Therefore, using ensemble learning can be fruitful [13].

D. Multi-Layer Perceptron

Multilayer perceptrons are used when the relationships between the input and output of the artificial neural network are nonlinear. Multilayer perceptrons (MLP) work especially effectively in classification and generalization situations. Intermediate layers process the information from the input layer and transmit it to the next layer. There may be more than one intermediate layer in this layer. Thus, it will be effective in solving complex problems [14].

E. Modified Multi-Layer Perceptron

In the Multi-Layer Perceptron (MLP) model, the aim is to minimize the error, that is, the difference between the output produced by the network and the real output. This is achieved by propagating the error throughout the network. For this reason, the MLP model is also called the Backpropagation model or Error Propagation model. MLP model consists of three layers: input layer, hidden layer (intermediate layer) and output layer. The number of hidden layers can be more than one. The input layer does not have the task of processing information, but is responsible for ensuring that the input or inputs coming from the outside world are transmitted to the hidden layer. Hidden layers process information from the input layer or the information from the previous intermediate layer. The output layer produces the output of the network by processing the information coming from the intermediate layer.

Modified Multi-Layer Perceptron (M2LP) is an equivalent convolutional neural network model of the standard multilayer perceptron (MLP). Instead of the traditional training parameters of MLP, more advanced training parameters such as rectified linear unit (ReLU) and Adam training algorithm have been used [15]. A modified multilayer regression (M2LP) perceptron was used to estimate the scattering parameters of the nonuniform microstrip transmission line [16-17].

F. Proposed FSS Design

The proposed FSS design is represented in Figures 1-2. Design variables and their variation limits of the proposed FSS design are given in Table 1. In scientific and technical research, parametric analyses are essential, especially when developing and optimizing complex systems and materials. In the study of frequency selective surfaces (FSSs), the impact of changing particular design parameters, like the "Gap" on scattering parameters is closely examined Figure 3. This thorough analysis is not only a matter of academic integrity which also accomplishes two important goals of (I) it produces a crucial idea on the dataset that will be used in Machine Learning (ML) algorithms later on, and (II) it clarifies the precise influence of individual parameters on the performance characteristics of the FSS. The justification for concentrating on the parametric analysis of a single parameter in spite of the presence of several significant variables is the need to expedite the investigation and improve the lucidity of the results. Through the process of isolating the effect of the "Gap" parameter, researchers are able to offer a precise, comprehensive, and quantitative explanation of how this particular design feature affects the behaviour of the FSS. This focused approach makes it easier to convey the data in a clear and intelligible manner, which is especially helpful for academic papers where length and reader comprehension are important factors. In this work the model is built using 500 training samples generated via Latin-Hypercube Sampling (LHS), alongside 100 hold-out samples. Each sample represents an evaluation of the scattering parameter vector within the frequency range of 2 to 10 GHz, with a 0.1 GHz increment. The results of the mentioned algorithms and their corresponding parameters are given in Table 2.

Hyperparameter optimization represents a critical facet in the development and fine-tuning of Artificial Intelligence (AI) algorithms, especially within the realm of regression analyses that are pivotal for modeling and predicting the behaviour of microwave components. The performance of these AI models is heavily contingent upon the selection of appropriate hyperparameters, which, unlike model parameters learned during training, must be set prior to the training process. These hyperparameters can include learning rates, regularization coefficients, or the architecture specifics of neural networks, among others. Their optimal configuration is paramount to achieving high accuracy, generalizability, and efficiency in predictive models.

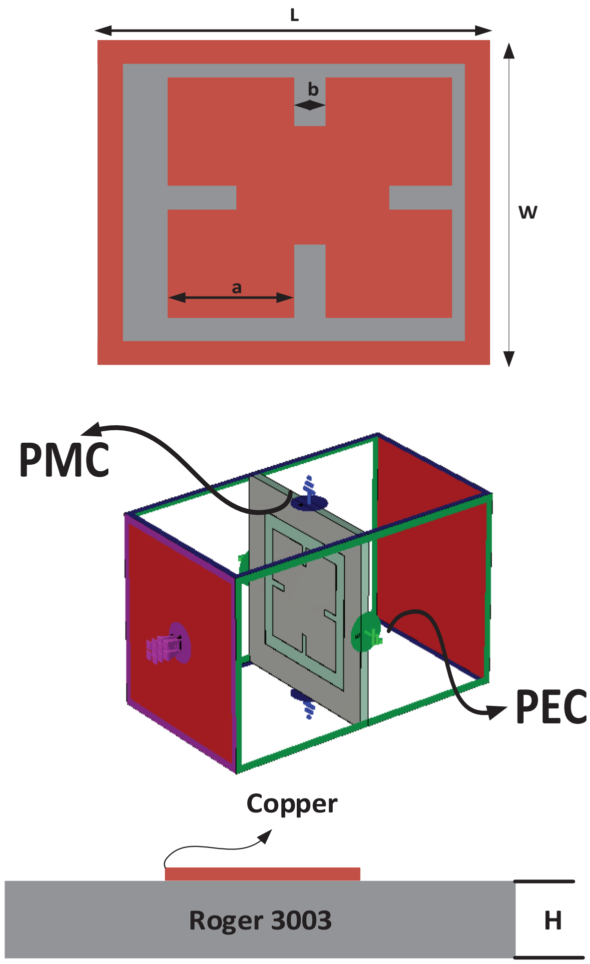

Fig. 1. Schematic of the proposed FSS structure

TABLE I. DESIGN VARIABLES AND THEIR VARIATION LIMITS

Parameter	Lower	Upper
L	10	30
W	10	30
a	5	20
b	5	20

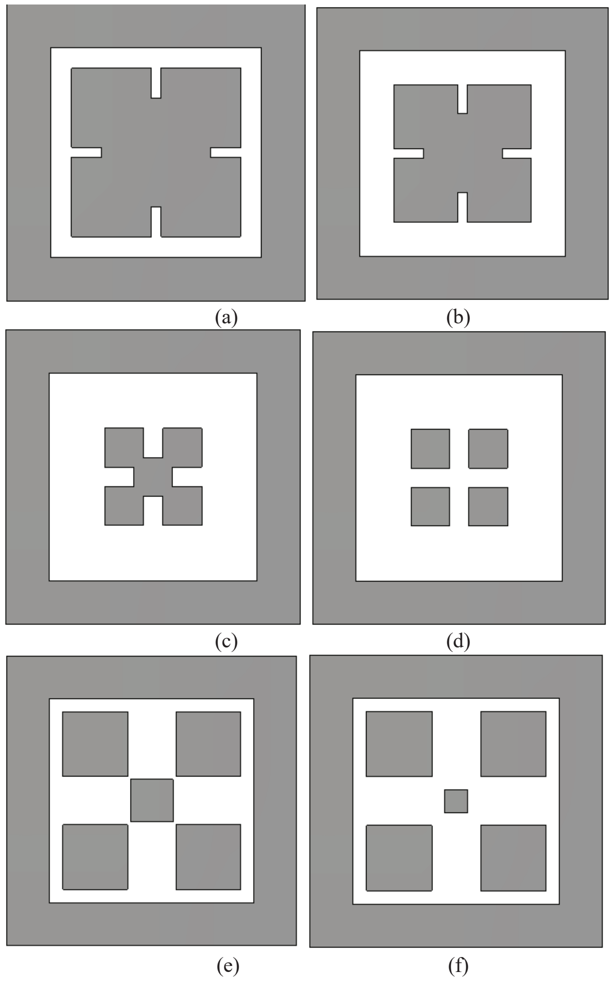

Fig. 2. Geometrical variation of unit cell element for different design parameter combinations.

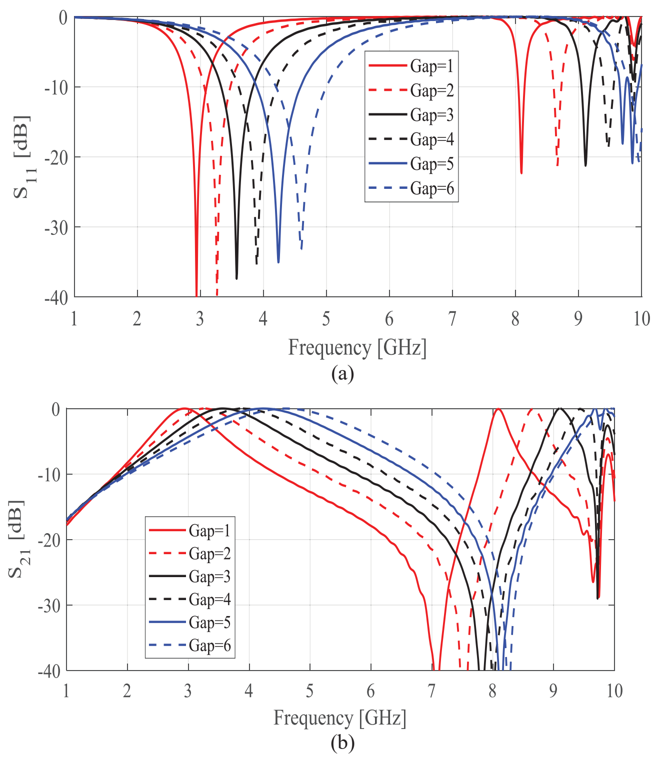

Fig. 3. Scattering parameter (a) S_{11} (b) S_{21}, responses of the unit cell for variation of parameter "Gap" over the operation band.

TABLE II. RME VALUES OF SURROGATE MODELS

Model	Hyper-Parameters	K-fold/Holdout
Support Vector Machine	Kernel-function: Gaussian,Epsilon: 0.42	9.2% / 10.4 %
Ensemble Learning	hyperpar.learningrate=0.035 hyperpar.Numestimators=3200	7.9% / 9.1%
Gaussian Process Regression	Kernel-function:ardmatern 3/2; Prediction-method: Block-coordinate-descent;block-size:500	5.1% / 6.8%
Modified Multi-Layer Perceptron	Hyperpar.depth=3 Hyperpar.initial_num_neuron=64	4.1% /4.9 %

III. RESULTS AND DISCUSSION

According to the findings from Table 2, the M2LP algorithm was preferred for FSS design. Among various optimization techniques Honey Bee Mating Optimization (HBMO) algorithm is choosed to serve as the search engine for the optimization process. This algorithm is inspired by the mating behaviour of honey bees and involves a complex process of selection, mating, and mutation to find optimal solutions. In the realm of FSS design, HBMO can be ingeniously applied to determine the optimal set of design variables that contribute to the desired performance [18]. A comparison study was carried out in the EM simulation program to verify the proposed M2LP model. S_{11} and S_{21} results are given in Figure 4 and Figure 5, respectively. According to the results, it is seen that the proposed method is consistent, the difference in the response are in regions where the scattering parameters are lower than -10 dB, which this error is in same magnitude with the models test error (Table 2).

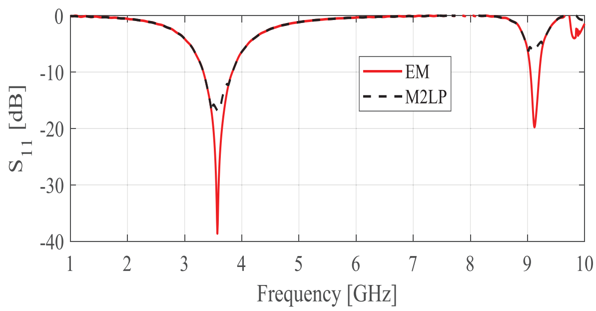

Fig. 4. The S_{11} results of the proposed FSS structure

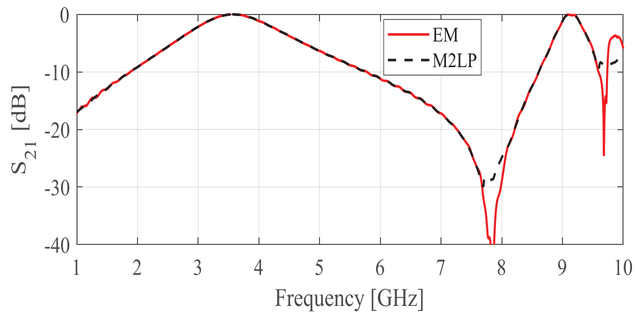

Fig. 5. The S_{21} results of the proposed FSS structure

IV. CONCLUSION

In this study, an artificial intelligence-based perspective has been introduced towards the design optimization of FSS structures, which is a popular topic of recent times. In this context, the performance of various artificial intelligence algorithms was examined. It was concluded that the most suitable algorithm in terms of improved performance and problem solving ability was the M2LP model. M2LP overcame the limitations associated with standard MLP by incorporating advanced activation functions such as rectified linear units (ReLU) or exponential linear units (ELU). It demonstrated efficient gradient propagation, mitigated the vanishing gradient problem, and accelerated the convergence rate during training. The HBMO algorithm was used in the optimization of the proposed FSS. This study showed that advanced artificial intelligence techniques can be used as an alternative to EM software to examine complex structures such as FSS for high frequency applications and achieve superior performance.

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