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Data Driven Surrogate Modelling of Microstrip Frequency Selective Surface for 5.8GHz WLAN Application

Aysu Belen*

Hybrid and Electric Vehicle Technology, Iskenderun Vocational School of Higher Education, Iskenderun Technical University, Hatay, Turkey

*aysu.belen@iste.edu.tr

Abstract – This study offers a thorough examination of data-driven surrogate modeling approaches used in the development of microstrip frequency selective surfaces in microwave systems. The research centers on the application of surrogate models to improve the effectiveness and productivity of FSS systems. The M2LP model, which is an enhanced version of the Multi-layer Perceptron neural network architecture, exhibited enhanced performance by addressing the constraints associated with the conventional MLP. The system integrated sophisticated activation functions, such as rectified linear units (ReLU) or exponential linear units (ELU), in order to enhance the smooth transmission of gradients and expedite the process of convergence during training. The M2LP methodology presents a succinct yet efficient strategy, rendering it particularly well-suited for the optimization of FSS design. In order to enhance the design of the FSS unit, the integration of the M2LP surrogate model with the Honey Bee Mating Optimization (HBMO) algorithm was undertaken, drawing inspiration from the mating strategy employed by honey bees. The successful implementation of modern artificial intelligence approaches and optimization algorithms has demonstrated significant efficacy in attaining superior levels of performance and efficiency. The validation of the outcomes obtained from the selection of optimal parameters using the M2LP model was conducted by comparing them with the results obtained from the full-wave simulation model. This comparison aimed to ensure that there was a precise agreement between the response of the electromagnetic solver and the proposed data-driven surrogate. The research findings indicate that the surrogate model developed in this study demonstrates effective optimization of FSS designs across a range of applications within the specified domain. In general, this study makes a significant contribution to the development of design methodologies for Frequency Selective Surfaces (FSS) and provides vital insights for future research in the domain of microwave antennas and circuits. Specifically, it focuses on the application of data-driven surrogate modeling and optimization algorithms.

Keywords – Data Driven, Surrogate Model, Antenna, Gain Enhancement, Optimization.

I. Introduction

Frequency Selective Surfaces (FSSs) have become a significant area of interest in the realm of Radio Frequency (RF) applications, owing to their ability to selectively filter electromagnetic waves based on frequency [1-2]. Particularly, microstrip FSSs, which employ conductive patches patterned on a dielectric substrate, offer considerable versatility and ease of fabrication, making them highly suitable for a plethora of applications, including radomes, antenna radars, and absorbers, among others [3-6].

Designing microstrip FSSs entails the precise manipulation of numerous parameters to achieve the desired frequency response [7]. An integral part of this design process involves the use of electromagnetic simulation tools, such as CST Microwave Studio or ANSYS HFSS [8]. These EM-forward models enable the comprehensive simulation of the FSSs' electromagnetic behavior, incorporating critical parameters like geometric dimensions, substrate properties, and incident wave characteristics. The duration required for optimizing an FSS design using EM-forward models can vary widely, depending on the complexity of the design and the granularity of the optimization goals. This process may take several hours to even days, given the potentially vast design space and the computational intensity of the EM simulations [9].

Data-Driven Surrogate Modelling (DDSM) has emerged as a promising approach to circumvent the resource-intensive nature of these optimization procedures [10-11]. DDSM involves creating a simplified model, or surrogate, that approximates the behavior of the complex system based on the data obtained from a set of initial high-fidelity simulations [12]. Once trained, these surrogate models can predict system performance with substantially reduced computational demand, thereby significantly accelerating the design and optimization process [13-15].

The present study offers a thorough examination of data-driven surrogate modelling methodologies employed in the development and enhancement of microstrip frequency selective surfaces for microwave systems. The initial focus of our discussion pertains to the fundamental aspects of surrogate modelling. This includes an examination of key concepts such as regression, interpolation, and computational time reduction, and their applicability to the design of microstrip FSS. The following discourse delves into diverse categories of surrogate models, including Gaussian process models, artificial neural networks, and deep learning-based approaches. The discussion emphasises the respective advantages and drawbacks of these models in the context of FSS modelling for WLAN applications.

II. FSS AND SURROGATE MODEL REPRESENTATION

This scientific study focuses on the design optimization of Frequency Selective Surface (FSS) unit elements. The paper provides a schematic representation of the studied FSS design in Figure 1, along with the corresponding design variables and their respective ranges as detailed in Table 1. In order to achieve the best design variables for a specific scattering parameter response, a global optimization approach that simultaneously optimizes multiple parameters is necessary. However, the direct employment of electromagnetic (EM)-driven optimization can be computationally expensive. To address this challenge, the study employs regression models based on artificial intelligence (AI) techniques, which significantly reduce CPU expenses. To ensure minimal computational costs, both the training and test (holdout) data sets are reasonably sized. Specifically, 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. Furthermore, to streamline the design optimization process, certain design variables are assumed to be constants or functions of other variables, effectively reducing the overall number of design variables and problem dimensions.

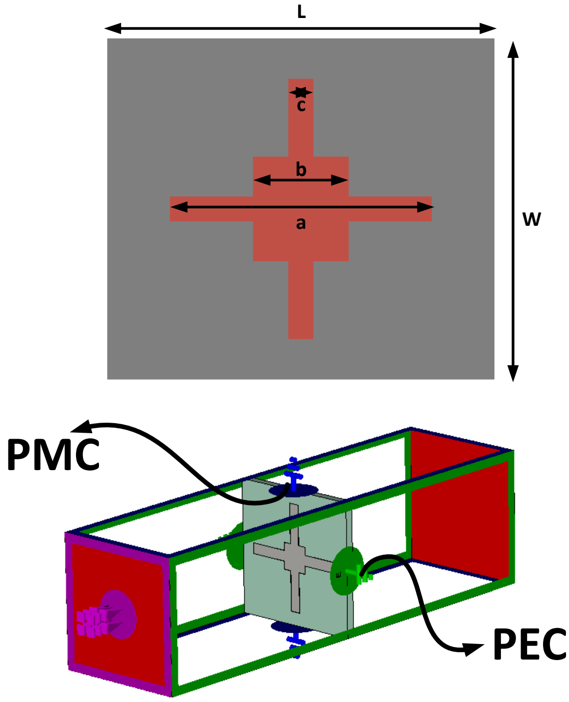

Fig 1. Schematic of the proposed FSS element.

TABLE 1. Design variables and their variation limits in [mm]

Parameter	Lower	Upper	Parameter	Lower	Upper
a	0.5	25	c	0.5	25
b	0.5	25	W=L	10	30

This study employs established Artificial Intelligence algorithms to develop data-driven surrogate models, and their corresponding findings are displayed in Table 2. Series of radiation and state of the art methods are employed for creating the surrogate models such as Support Vector Regression Machine (SVRM) Ensemble Learning (EL), Gaussian Process Regression GPR and Modified Multi-layer Perceptron (M2LP) [16]. M2LP is an advanced variant of the traditional Multi-layer Perceptron (MLP) neural network architecture. It represents an innovative approach that incorporates modifications to enhance the performance and versatility of the standard MLP. M2LP combines the principles of MLP with additional adaptations, providing distinct advantages in various applications. M2LP overcomes the limitations of traditional MLP by incorporating advanced activation functions, such as rectified linear units (ReLU) or exponential linear units (ELU). These functions facilitate efficient gradient propagation, alleviate the vanishing gradient problem, and accelerate the convergence rate during training. In contrast to deep learning architectures, such as deep neural networks or convolutional neural networks, M2LP offers a more concise yet effective approach. While deep learning architectures often require substantial computational resources and large amounts of labeled data, M2LP leverages the benefits of deep networks while maintaining a more manageable and efficient model.

The obtained results were obtained utilizing a k-fold validation technique with k=5, accompanied by an additional hold-out dataset comprising 200 samples. To evaluate the model's performance, the Relative Mean Error (RME) metric (Eq. 1) was employed. In this study, M2LP is deemed the most suitable model for the given case, as it demonstrates the lowest error value across both the hold-out and k-fold validation datasets.

$$RME = \frac{1}{N}\sum_{i=1}^{N}\frac{|Target_i - Predicted_i|}{|Target_i|} \tag{1}$$

TABLE 2. RME values of surrogate models.

Model	Hyper-Parameters	K-fold/Holdout
Support Vector Regression Machine	Kernel-function: pol., Type: Epsilon, Epsilon: 0.28.	8.1% / 9.3 %
Ensemble Learning	hyperpar.learningrate=0.035 hyperpar.Numestimators=3200	8.5% / 9.9%
Gaussian Process Regression	Kernel-function: matern5/2; Prediction-method: Block-coordinate-descent; block-size: 1200	6.7% / 7.7%
Modified Multi-Layer Perceptron	hyperpar.depth=4 hyperpar.initial_num_neuron=128	4.2% % 5.1 %

III. STUDY CASE

The current section employs the M2LP surrogate model for the design optimization of the Frequency Selective Surface (FSS). To serve as the search engine for the optimization process, the Honey Bee Mating Optimization (HBMO) algorithm is utilized. Inspired by the mating strategy of Honey Bees, HBMO is a meta-heuristic algorithm that has been extensively documented in the literature [17-18]. Based on population dynamics, HBMO adopts principles from evolutionary algorithms. In this particular procedure, the dominant individual, referred to as the Queen Bee, is the most physically capable person or potential solution. The fertility rate of Queen Bees or queen candidates is determined by the quality of their corresponding design, represented by a parameter vector. With each successive generation, the newly generated individuals' caliber is evaluated in comparison to that of the Queen. The individual exhibiting superior traits assumes the role of the queen, influencing the production of new individuals in the subsequent generation. This outline provides a high-level overview of the optimization procedure, while the literature contains more detailed information on the algorithm's operational intricacies [17]. The fitness of the Queen Bee is significantly influenced by the consumption of royal jelly, a parameter that plays a crucial role in the optimization process. The provision of specific nutrients has been demonstrated to extend the lifespan of a typical bee from a mere thirty days to up to two years. This phenomenon is pivotal in the development of a bee into a Queen and is also employed in the HBMO protocol to facilitate local optimization.

$$Cost(\boldsymbol{x}) = \max\left\{ f \in [f_{c1}, f_{c2}] : |S_{11}(\boldsymbol{x}, f)| \right\} \tag{2}$$

The utilized cost in Eq. (2) is aim to maximize the magnitude of S_{11} values in the given frequency ranges of user, which for this study is taken as 5.6-6 GHz for WLAN applications. The values shown in Table III were derived by the HBMO method employing the cost function in Eq. 2 and the M2LP surrogate model as an ideal model for the chosen operation band.

TABLE 3. Optimal design parameters of FSS design obtained by data driven surrogate model [mm]

a	20	**c**	2
b	5	**W**	25

In order to validate the outcomes achieved from the selection of optimal parameters using the Modified Multi-layer Perceptron (M2LP), a comprehensive full-wave simulation model is constructed in the CST environment (Figure 2). The results demonstrate a highly accurate agreement between the response of EM solver and the proposed data driven surrogate. Thus the proposed surrogate can be efficiently used for optimization of FSS designs for different application within the range of defined domain.

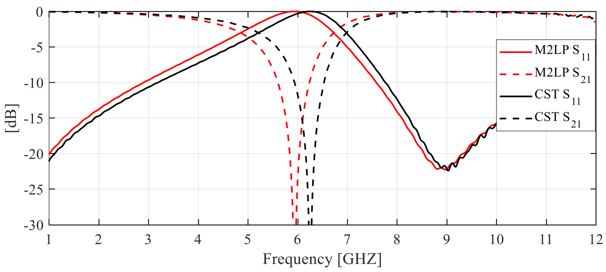

Fig 2. Scattering parameter response of optimally designed FSS

IV. CONCLUSION

This study presented a comprehensive investigation of data-driven surrogate modeling methodologies for the design optimization of microstrip frequency selective surfaces (FSSs) in microwave systems. The utilization of surrogate models, such as Support Vector Regression Machine (SVRM), Ensemble Learning (EL), Gaussian Process Regression (GPR), and Modified Multi-layer Perceptron (M2LP), was explored, and their respective outcomes were reported in Table 2. The M2LP model, an advanced variant of the Multi-layer Perceptron (MLP) neural network architecture, proved to be a superior choice due to its modifications and enhanced performance. By incorporating advanced activation functions like rectified linear units (ReLU) or exponential linear units (ELU), M2LP overcame limitations associated with the standard MLP. It demonstrated efficient gradient propagation, mitigated the vanishing gradient problem, and accelerated the convergence rate during training. In comparison to deep learning architectures, M2LP offered a more concise and manageable yet effective approach, making it highly suitable for the design optimization of FSSs. To optimize the design of FSS units, the M2LP surrogate model was integrated with the Honey Bee Mating Optimization (HBMO) algorithm, which is inspired by the mating strategy of honey bees. The result of optimal FSS design is presented in Fig. 2. In conclusion, this study successfully applied data-driven surrogate modeling methodologies, particularly M2LP, for the design optimization of microstrip FSSs. The integration of advanced artificial intelligence techniques and optimization algorithms proved to be highly effective in achieving superior performance and efficiency. The findings contribute to the advancement of FSS design techniques and offer valuable insights for future research in the field of microwave antennas and circuits.

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