Journal of Artificial Intelligence and Data Science (JAIDA)
e-ISSN: 2791-8335
https://dergipark.org.tr/pub/jaida

Vol. 3, No. 1, pp. 22-26, 2023
Research Article
Received: 01/05/2023 Accepted: 03/06/2023

Data Driven Modelling of Microstrip Frequency Selective Surface for X Band Applications

Aysu BELEN

Abstract

Efficient and accurate modelling approaches have become necessary in computational science and engineering due to the rising complexity and high dimensionality of physical and engineered systems. The utilisation of data-driven surrogate modelling has surfaced as a potent methodology to overcome the disparity between computationally expensive simulations and prompt, dependable predictions. The current study offers a thorough examination of data-driven surrogate modelling methods as they pertain to the optimisation and design of microstrip frequency selective surfaces (FSSs) within microwave systems. In this discourse, we delve into the rudiments of surrogate modelling, diverse categories of surrogate models, and their respective merits and demerits in the realm of FSS modelling. The utilisation of widely used Artificial Intelligence algorithms is implemented for the purpose of data-driven surrogate modelling, and their efficacy is evaluated through the Relative Mean Error metric. The research findings indicate that the M2LP surrogate model exhibits optimal performance in the specific scenario under investigation. Furthermore, the Honey Bee Mating Optimisation algorithm is utilised to optimise the design of FSS. The results of our study demonstrate that data-driven surrogate modelling is an efficient and effective method for designing and optimising microstrip frequency selective surfaces (FSSs). Specifically, our approach yielded a gain improvement of nearly 3 dB within the chosen frequency band. The forthcoming research endeavours to investigate the optimisation of more intricate FSS designs for analogous applications that encompass broader operation bands.

Keywords: Antenna; data driven; gain enhancement; optimization; surrogate model.

1. Introduction

In the realm of computational science and engineering, the increasing complexity and high dimensionality of physical and engineered systems have intensified the demand for efficient and accurate modeling approaches. Traditional simulation-based models often require immense computational resources and time, posing significant challenges for time-sensitive decision-making and optimization tasks [1]. To address this issue, data-driven surrogate modeling has emerged as a powerful and versatile methodology that bridges the gap between computationally expensive simulations and rapid, reliable predictions. Surrogate models, also known as metamodels are approximate representations of the underlying systems, providing valuable insights into their behavior while significantly reducing the computational burden. By leveraging data obtained from a limited number of simulations or experiments, these models facilitate the exploration of vast design spaces and enable efficient optimization, uncertainty quantification, and sensitivity analysis. Moreover, they have found widespread applicability in various disciplines, such as fluid dynamics, materials science, structural engineering, and microwave engineering modelling [2].

Frequency Selective Surfaces (FSSs) have emerged as a crucial element in the design and optimization of modern microwave and millimeter-wave systems, driven by the rapidly increasing demand for high-performance communication, sensing, and radar technologies [3]. As periodic structures that selectively transmit, reflect, or absorb electromagnetic waves based on their frequency, FSSs enable the tailoring of electromagnetic responses and offer a versatile means for controlling the interaction between waves and structures. Among the various FSS design approaches, microstrip-based FSSs have garnered significant interest due to their compactness, low profile, ease of fabrication, and integration with planar technologies [4].

While traditional FSS design methodologies have demonstrated considerable success, the growing complexity of microwave systems and the increasing demand for high-performance solutions have spurred the need for more efficient and accurate design approaches. Data-driven surrogate modeling has emerged as a powerful tool for addressing this need, providing a means to rapidly and accurately predict the performance of microstrip FSSs while significantly reducing the computational burden typically associated with full-wave electromagnetic simulations [5]. By leveraging a limited set of simulation or experimental data, surrogate models enable the efficient exploration of vast design spaces, facilitating the optimization of FSS performance and the identification of novel design configurations.

AYSU BELEN; İskenderun Technical University, Iskenderun Vocational School of Higher Education, Department of Hybrid and Electric Vehicles Technology, Hatay,Türkiye, e-mail: aysu.belen@iste.edu.tr; 0000-0001-5038-424X

This paper presents a comprehensive investigation of data-driven surrogate modeling techniques applied to the design and optimization of microstrip frequency selective surfaces in microwave systems. We begin by discussing the fundamentals of surrogate modeling, including key concepts such as regression, interpolation, and dimensionality reduction, and their relevance to microstrip FSS design. Subsequently, we delve into various types of surrogate models, such as polynomial regression, Gaussian process models, artificial neural networks, and deep learning-based approaches, highlighting their strengths and limitations in the context of FSS modeling.

2. FSS Design and Its Surrogate Model Representation

The researched unit element for the FFS design is depicted schematically in figure 1. Table 1 contains the design variables for the cell and their respective ranges. Figure 2 shows a parametric analysis of the variables. It should be noticed that every variable has a sizable impact on the element's resonance frequency. The parameters must be simultaneously optimised in a global sense in order to get the best design variables for a given scattering parameter response. However, direct EM-driven is quite costly in terms of computing. Regression models based on artificial intelligence (AI) are used in this work to lower CPU expenses. Both the training and test (holdout) data sets need to be somewhat modest in size in order to retain minimal costs. Here, the model is built using 500 training samples produced via Latin-Hypercube Sampling (LHS) and 100 hold-out samples. Each sample is an evaluation of a scattering parameter vector over the frequency range of 2 to 10 GHz with a 0.1 GHz increment. Some design variables are assumed to be constants or functions of other variables in order to reduce the overall number of design variables/problem dimensions.

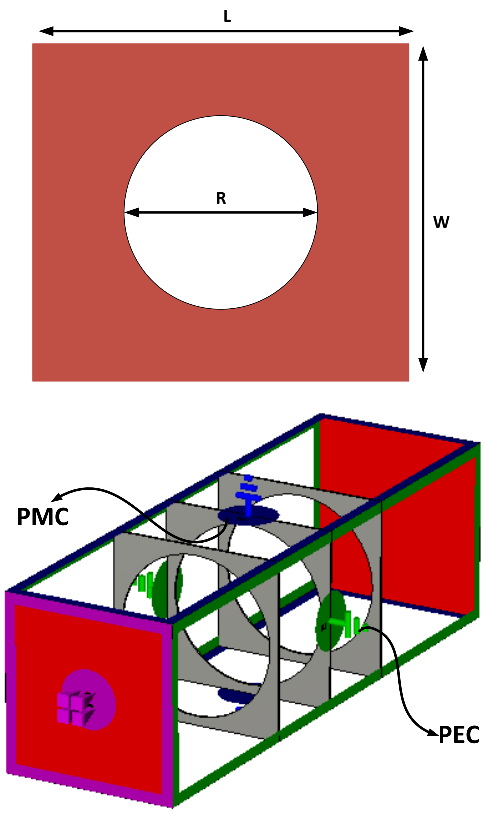


Figure 1. *Schematic of the proposed FSS element.*

TABLE 1. *Design variables and their variation limits*

Parameter	Lower	Upper	Parameter	Lower	Upper
L	10	30	R	5	20
W	10	30	G	5	20

This study employs prevalent Artificial Intelligence algorithms for data-driven surrogate modelling, and their outcomes are exhibited in Table 2. The results presented in this study were derived through a k-fold validation technique with k=5, in conjunction with an extra hold-out dataset comprising of 200 samples. Also Bayesian Optimization algorithm is used for determination of hyper-parameters. The Relative Mean Error (RME) metric (Eq. 1) was utilised to evaluate the performance of the model. The Modified Multi-layer Perceptron (M2LP) is an enhanced version of the traditional multi-layer perceptron (MLP), an artificial neural network model that maps sets of input data onto a set of appropriate outputs. The MLP, while effective, has certain limitations when it comes to computational speed and the ability to handle complex problems. The M2LP aims to overcome these limitations by implementing adjustments in the design of the MLP architecture.M2LP will be employed as the ideal model for this study case, because it has the lowest error value in both the hold-out and k-fold validation data sets.

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

TABLE 2. *Performance results of algorithms.*

Model	Hyper-Parameters	K-fold/Holdout
SVRM [6]	hyperpar.epsilon=0.2, hyperpar.kernelfunction= Radial basis	9.3% / 10.1 %
Gradient Boosted Tree [7]	hyperpar.learningrate=0.035 hyperpar.Numestimators=4700 hyperpar.depth=4	8.6% / 9.2%
M2LP [8]	hyperpar.depth=3 hyperpar.Numneuron= 64	4.6% % 5.5 %

3. Study Case

The present section employs the M2LP surrogate model to perform design optimisation of the FSS. The Honey Bee Mating Optimisation (HBMO) is a meta-heuristic algorithm that draws inspiration from the mating strategy of Honey Bees, and serves as the search engine. This algorithm has been documented in literature [9]. The HBMO technique is a method that utilises the principles of evolutionary algorithms and is based on population dynamics. In this specific procedure, the most physically capable person (potential solution) is designated as the dominant individual, or Queen Bee. The fertility rate of Queen Bees or queen candidates is determined by the quality of design that corresponds to a specific individual, represented by a parameter vector. In each successive generation, the calibre of the newly generated individuals is evaluated in relation to that of the Queen. The individual possessing superior traits assumes the role of the queen, thereby influencing the production of new individuals in the succeeding generation. This outline pertains to the overarching aspect of the optimisation procedure. The literature contains information regarding the operational intricacies of the algorithm [10]. One of the parameters that has a significant impact on the fitness of the Queen Bee is the consumption of royal jelly. The provision of certain nutrients has been shown to increase the lifespan of a typical bee from a mere thirty days to up to two years. This phenomenon is crucial in the development of a bee into a Queen. This phenomenon is also utilised in the HBMO protocol to facilitate local optimisation.

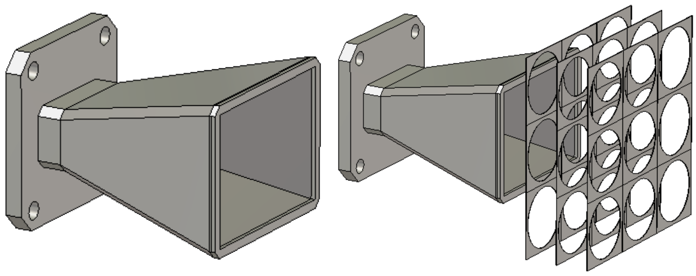
$$\text{Cost} = \sum_{f_{\min_1}}^{f_{\max_1}} \frac{C_1}{\left|S_{11_i}(f)\right|} \tag{2}$$

Here, weighing coefficients C_1= is taken equal to unity. The utilized cost in Eq. (2) is aim to maximize the magnitude of S_{11} values in the given frequency ranges of 10.4 and 10.6 GHz. 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.

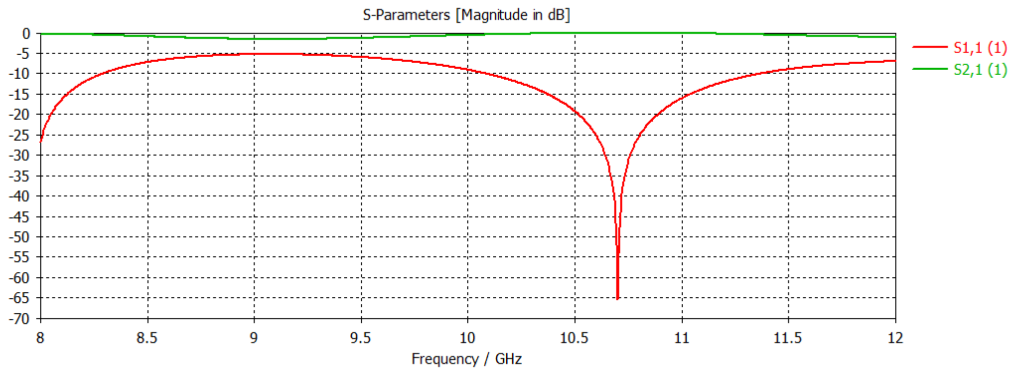
TABLE 3. *Optimal design parameters of FSS design [mm]*

L	20	**R**	18
W	20	**G**	11

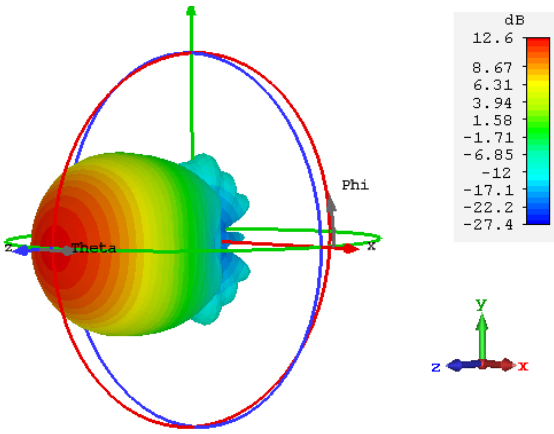
To validate the results obtained from the optimally selected parameter using M2LP, a full-wave simulation model of proposed FSS loaded antenna is modelled in CST environment (Fig. 2). The performance of the optimally designs FSS loaded horn antenna and the antenna without FSS structures are compared and as a results the overall performance of the antenna is clearly seen that being enhanced for the aimed operation band.



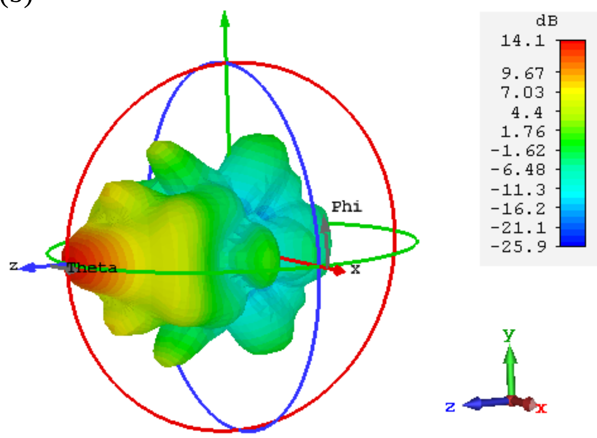
(a)



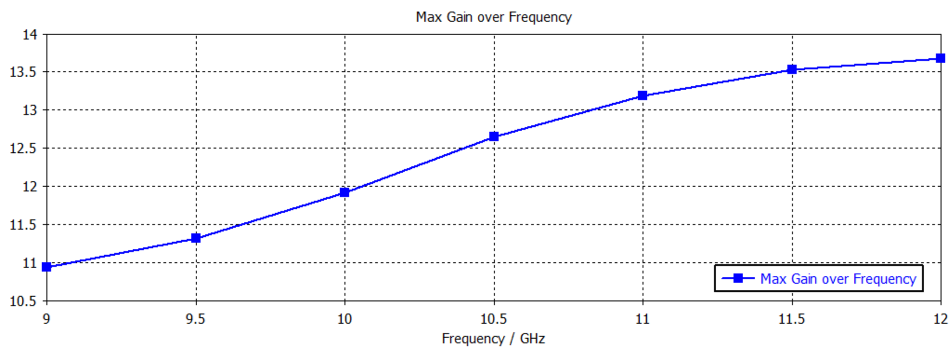
(b)



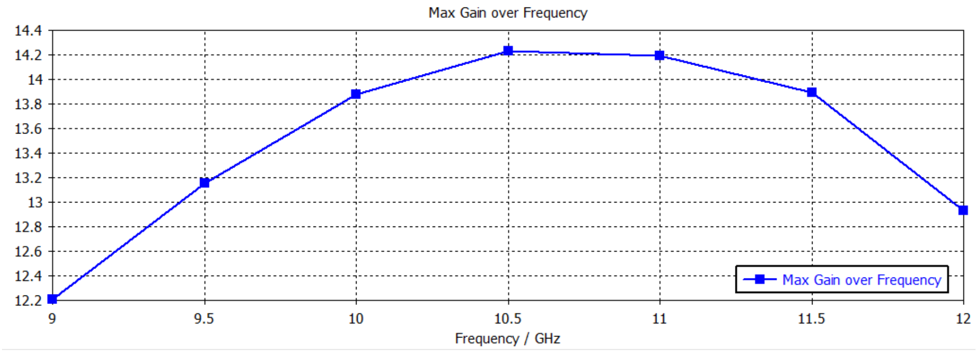
(c)



(d)



(e)



(f)

Figure 2. *3D view of horn and FSS loaded horn antennas, (b) simulated S_{11} of optimal FSS array, simulated gain of (c) Horn antenna, (d) FSS loaded antenna, @ 10.5 GHZ, simulated maximum gain characteristic of (e) Horn antenna, (f) FSS loaded antenna.*

4. Conclusion

Here as it can be observed form the obtained results, by using data driven surrogate modelling design and optimization of a frequency selective surfaces array for performance enhancement of a horn antenna can be achieved in a computational efficient manner. Here gain improvement of almost 3 dB is achieved at the selected frequency band (10.5 GHz) which can be furthered increased with increased number of array element and layer sizes. In future works it is aimed to use more complex frequency selective surfaces designs optimization for similar application with wider range of operation band.

Declaration of Interest

The authors declare that there is no conflict of interest.

References

[1] Cui, C., Hu, M., Weir, J. D., & Wu, T. (2016). A recommendation system for meta-modeling: A meta-learning based approach. Expert Systems with Applications, 46, 33-44.

[2] Mittra, R., Chan, C. H., & Cwik, T. (1988). Techniques for analyzing frequency selective surfaces-a review. Proceedings of the IEEE, 76(12), 1593-1615.

[3] Mahouti, P., Belen, A., Tari, O., Belen, M. A., Karahan, S., & Koziel, S. (2023). Data-Driven Surrogate-Assisted Optimization of Metamaterial-Based Filtenna Using Deep Learning. Electronics, 12(7), 1584.

[4] Koziel, S., Belen, M. A., Çalişkan, A., & Mahouti, P. (2023). Rapid Design of 3D Reflectarray Antennas by Inverse Surrogate Modeling and Regularization. IEEE Access, 11, 24175-24184.

[5] Mahouti, P. (2019). Design optimization of a pattern reconfigurable microstrip antenna using differential evolution and 3D EM simulation-based neural network model. International Journal of RF and Microwave Computer-Aided Engineering, 29(8), e21796.

[6] Smola, A. J., & Schölkopf, B. (2004). A tutorial on support vector regression. Statistics and computing, 14, 199-222.

[7] Persson, C., Bacher, P., Shiga, T., & Madsen, H. (2017). Multi-site solar power forecasting using gradient boosted regression trees. Solar Energy, 150, 423-436.

[8] Calik, N., Belen, M. A., & Mahouti, P. (2020). Deep learning base modified MLP model for precise scattering parameter prediction of capacitive feed antenna. International journal of numerical modelling: electronic networks, devices and fields, 33(2), e2682.

[9] Güneş, F., Demirel, S., & Mahouti, P. (2014). Design of a front–end amplifier for the maximum power delivery and required noise by HBMO with support vector microstrip model. Radioengineering, 23(1), 134-143.

[10] Haddad, O. B., Afshar, A., & Mariño, M. A. (2006). Honey-bees mating optimization (HBMO) algorithm: a new heuristic approach for water resources optimization. water resources management, 20, 661-680.