Machine Learning Algorithms for Enhancement of a Dual Square FSS for Sub 6G Applications

Dr. Deepika Lokesh, Narayanaswamy J, Manjunatha M K

Dept. of AIML, C Byregowda Institute of Technology, Kolar
Dept. of AIML, C Byregowda Institute of Technology, Kolar
Dept. of AIML, C Byregowda Institute of Technology, Kolar

---***---

Abstract - Frequency Selective Surfaces (FSS) play a very critical role now-a-days in electromagnetic engineering, which enables precise control of electromagnetic wave propagation for various applications. This conference article explores the integration of Machine Learning (ML) algorithms to optimization of the structure to achieve enhanced performance and efficiency for Sub 6G applications (6 GHz and 2.4 GHz). The Double Square Frequency Selective Surface (DS-FSS) consists of two distinct layers of square shaped periodic patterns. This configuration pro- vides greater flexibility in tailoring the overall frequency response compared to single layer FSS. A comprehensive data set has been prepared by simulating the electromagnetic responses from the Equivalent Circuit Model (ECM) which are fed to the ML algorithm to extract the features and build the regression model and to estimate the optimal parameters. The ML algorithms used are Linear Regression and Random Forest. These are then validated against the electromagnetic simulations using HFSS Software.

Key words: Equivalent Circuit Model (ECM), Double Square Frequency Selective Surface (DS-FSS), Linear Regression, Random Forest.

1.INTRODUCTION

In the evolving world of wireless communication technology, the quest for efficient and reliable transmission has been a concern. The continuous demand for higher data rates, has led to the significant necessity to attend the Electromagnetic Interference (EMI) issues and Compatibility. When unattended, this can lead to increased electromagnetic interference that can disrupt nearby electronic equipment or other wireless devices. Shielding effectively blocks or attenuates these un- wanted electromagnetic signals, reducing the potential for EMI [1]. Shielding can protect against external interference, ensuring that the intended signals arrive at their destination with minimal corruption. This is vital for maintaining signal integrity and achieving reliable wireless communication. As wireless technology continues to evolve, new frequency bands and communication methods are being explored, which in turn increases the potential risks of electromagnetic interference.

Many strategies for improving shielding efficacy have been proposed, however some of them have limitations. FSS provides the best possible way to optimize the structure for improved Shielding Effectiveness (SE) by heuristic approach [2]. Most of the limitations can be overcome by using the FSS to gain the optimal S-paramters (S21 and S11) by adjusting the geometric parameters using ML algorithms [3] [4]. Firstly, the values of physical dimensions are swept from minimum to maximum value. The Equivalent circuit model is drawn and lumped element approach is followed to find the design equations for Inductance and Capacitance [5]. Data sets are prepared from the ECM and are fed to the ML algorithm to get trained. Regression model is built on the basis of the provided data sets. Inverse modelling [8] is done to estimate the optimum values of dimensions based on the provided output specifications such as -50 dB for S21. Now, the Mean Square Error is calculated by comparing the desired and estimated results. Finally, these results are validated against the structures which have been simulated using EM Simulation software.

2.Body Of Paper

i) Proposed cell unit model

The double square cell unit model is shown in Fig. 1 it includes two square conducting strips present on a substrate. The substrate is made up of the dielectric material Rogers 5880 and has a 1.6 mm thickness. In Fig. 1, The periodicity of the cells is denoted by p. (i.e., size of the unit cell including the gap between the two unit cells). The outer side of a square loop is represented by d4. where is the length of the outer square's side, and d2 is the length of the inner square. D1 represents the gap between inner square and outer square and D2 represents the gap between two unit cells. These gaps accounts for the capacitance considered in the lumped element model (ECM) since a dielectric medium forms in between these gaps.

The mutual reactance between two unit cells are negligible and can be ignored when a single cell analysis is being done. The conducting strip width is denoted as a1 and a2 for

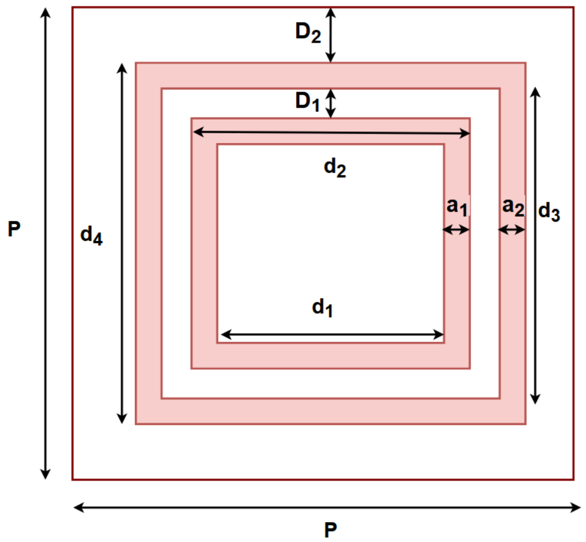

Fig. 1. Proposed Double Square Loop FSS

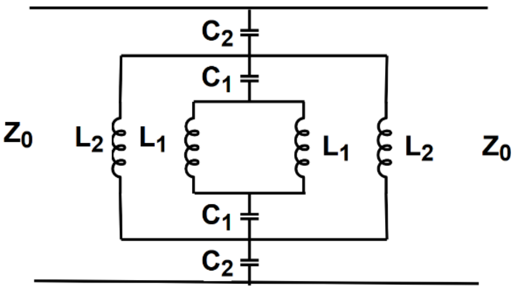

Fig. 2. Equivalent circuit for the proposed design

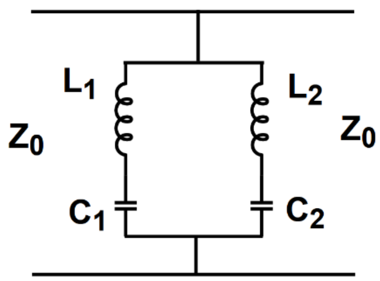

Fig. 3. Equivalent Circuit Model (ECM)

inner square and outer square respectively. The width of these strips accounts for the inductance represented in the equivalent circuit model as the nature of current flow in the conducting strip forms inductance.

Fig. 2 depicts the lumped element model for the proposed structure and Fig. 3 shows the simplified equivalent circuit model of the proposed design. The ECM can be constructed by connecting the lumped elements (L and C) in series. Since, two inductance and capacitance are formed due to inner and outer squares, both are connected in parallel to avoid the violation of Kirchoff's laws. Here, L1 and C1 represents the inductance and capacitance of inner square where as L2 and C2 represents that of the outer square. The equations for the lumped elements are formulated by their reactance for inductive elements and succeptance for capacitive elements. The Inductive reactance are given by,

$$\frac{X_{L_1}}{Z_0} = \frac{d_2}{p} * F(p, 2a_1, \lambda_1, \theta) \quad (1)$$

$$\frac{X_{L_2}}{Z_0} = \frac{d_4}{p} * F(p, 2a_2, \lambda_2, \theta) \quad (2)$$

where, Z0 is the free space impedance given by 120π or 377Ω and function F is defined in [3]. The capacitive succeptances are given by,

$$\frac{B_{C_1}}{Y_0} = \frac{4d_2}{p} * F(p, 2D_1, \lambda_1, \theta) \quad (3)$$

$$\frac{B_{C_2}}{Y_0} = \frac{4d_4}{p} * F(p, 2D_2, \lambda_2, \theta) \quad (4)$$

The S-parameters are calculated from the equivalent circuit model by formulating the ABCD-parameter matrix and then converting it into the S-parameter matrix. The ABCD- parameter matrix for a shunt admittance is given as

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ Y_{eq} & 1 \end{bmatrix} \quad (5)$$

Now, the ABCD parameters are converted into S-parametersusing the formulae,

$$S_{11} = \frac{A + BY_0 - C/Y_0 - D}{A + BY_0 + C/Y_0 + D} \quad (6)$$

$$S_{21} = \frac{2}{A + BY_0 + C/Y_0 + D} \quad (7)$$

Here S21 indicates the transmission co-efficient and S11 indicates the reflectivity. S21 also acts as a measure of shielding effectiveness which is given by the formula,

$$SE(dB) = -10log_{10}\left(\frac{P_t}{P_r}\right) \quad (8)$$

where Pt and Pr are transmitted and reflected power respectively.

ii) Methodology Adopted

The machine learning algorithms adopted to optimize the design are linear regression and random forest which helps to build the regression model and estimate the optimal geometric values.

A. Linear Regression (LR)

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 06 | June - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

In machine learning, one of the most used regression techniques is linear regression. It is a linear approach to model the relationship between a dependent variable (technically called the target variable) With one or more factors that are independent (technically called the features). If there is just one independent variable in the model, it may be shown as

$$y = mx + b \tag{9}$$

where m is the slope of the line, which represents the influence of x on y, b is the y-intercept, y is the dependent variable (the goal that we are attempting to forecast), and x is the independent variable (the feature utilized for the prediction). Finding the most significant linear fit that minimizes the discrepancy between estimated and actual values is the primary objective of this approach. Linear regression makes some assumptions about the data such as independence of errors, constant variance and normality of residuals. The evaluation metric used are Mean Square Error (MSE), Absolute Error (MAE), and R-squared (co-efficient of determination). This algorithm is widely used because of its simplicity and its fast training (computationally efficient).

Algorithm 1 Linear Regression Algorithm

Training data D, Testing data T, Number of epochs E, learning rate γ, Weights, $W_0, W_1, ..., W_k$
Initialize weights with small value
for epoch = 1 to E **do**
  for each $(x_1, x_2, ..., x_n$ and $y_1, y_2, ...y_n) \in$ D in random order **do**
    $\hat{y_n} \leftarrow W_0 + \sum_{n=1}^{k} W_n x_n$
    if $(\hat{y_n} > 0.5 \& y = 1) or (\hat{y_n} < 0.5 \& y = -1)$ **then**
      continue
      $W_0 \leftarrow W_0 + \gamma * 2 * (\hat{y_n} - y_n)$
    end if
    for i = 1 to k **do**
      $W_n \leftarrow W_n + \gamma * 2 * (\hat{y_n} - y_n) x_i$
    end for
  end for
end for

B. Random Forest (RF)

For both classification and regression applications, Random Forest is a potent ensemble machine learning approach. This algorithm aims to reduce the variance of a base model (usually decision trees) by aggregating predictions from multiple mod- els. In the case of regression, To build a reliable regression model, Random Forest builds an ensemble of decision trees and aggregates their predictions. It's better than a single decision tree, which may easily over fit the training data. The "random" in Random Forest comes from two sources of randomness: Bootstrapping (sampling with replacement) from the training data and random feature selection. These strategies ensure every tree in a forest gets training on a little different collection of data and employs a slightly distinct subset of features, therefore increasing variety and decreasing overfitting. Random Forest uses decision trees as base models. A subset of the characteristics and data are used to individually train each decision. These trees are usually deep and can capture complex relationships in the data. For regression tasks, the predictions from individual trees are aggregated to make the final prediction. Typically, the mean (average) of the tree predictions is used as the final output.

Algorithm 2 Train and Predict RF Regression Model

function TRAIN_RF_REGRESSION($x_1, x_2, ..., x_n, y_1, y_2, ...y_n$, N_ESTIMATOR, MAX_FEATURES)
  forest = empty
  for i = 1 to n_estimators **do**
    bs_x_n,bs_y_n = create bootstrapsample(x_n, y_n)
    Selected_features = Randomly(X_n, max_features)
    tree = BuildDecisionTree(bs_x_n, bs_y_n,Selected_features)
    forest.append(tree)
  end for
  return forest
end function
function PREDICT_RF_REGRESSION(FOREST,NEW_DATA)
  predictions = empty list
  for tree in forest **do**
    prediction = prediction_decision_tree(tree,new_data)
    predictions.append(prediction)
  end for
  final_prediction = mean(predictions)
  final_prediction
end function

iii) Results and Validation

There are two stop bands in the response of the designed FSS: one from 2 GHz to 2.9 GHz (BW 900 MHz) with respect to -10 dB and another stop frequency band from 5.2 GHz to 7.4 GHz (BW 2.2 GHz) and pass band from 3.6 GHz to 4.1 GHz (BW 500 MHz). The optimal dimensions are predicted using ML algorithms and the random forest algorithm gives the best results. To ensure good shielding efficacy, these anticipated dimensions are verified using EM modeling software. The optimized geometric dimensions are p = 20 mm, d4 = 19.3 mm, d3 = 18.65 mm, d2 = 15 mm, d1= 13.2 mm, a1 = 1.8 mm, a2 = 0.65 mm, D1 = 1.5 mm, D2= 0.35 mm. The S-parameters have been plotted for different incident angles from 0◦ to 80◦ with a stable bandwidth which is shown in Fig. 4. In Fig. 5, shielding effectiveness has been plotted against frequency for different incident angles.

Based on the design dimensions, the equivalent circuit is developed, from that inductance and capacitance are calculated. S-parameters have been found out by using L and C by formulating the ABCD parameters. Huge amount of data sets (approx. 5000) were generated by varying the geometry of the design. By varying the dimension d2, from 13 mm to 19 mm, the variation of capacitance C1 is from 0.24

pF to 1.6 pF and the variation of inductance L1 is from 17 nH to 1.65 nH.

Table – 1: Predicted Geometry of Double Square Loop Structure (All in mm).

ML	d_1	d_2	d_3	d_4	a_1	a_2	Time(sec)
LR	13.201	15.01	18.652	19.321	1.8021	0.651	60
RF	12.82	14.982	17.285	19.612	1.7802	0.524	88

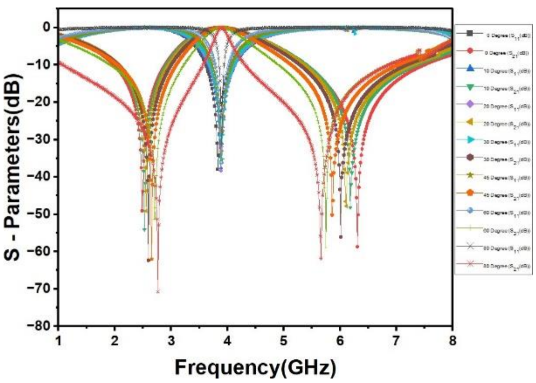

Fig. 4. S - Parameter for different incident angle

Also, by varying the dimension d4, from 18.6 mm to 20 mm, the variation of capacitance C2 is from 0.56 pF to 1.21 pF and the variation of inductance L2 is from 2 nH to 0.65 nH. Table II provides the comparison of trial-and-error method (TE) with ML algorithms like linear regression and random forest. The time taken for the desired results using trial and error method takes 8 hours approx. while the ML algorithms predict it within 60 seconds with 500 epochs.

3.CONCLUSION

In this study, by employing the machine learning algorithms we have optimized the double square loop frequency selective surface. The shielding effectiveness has improved to a significant amount i.e., 57 dB at the resonant frequency 6.3 GHz and 49 dB at 2.4 GHz. This shows that these optimized FSS structures can play a critical role in mitigating interference and improving signal quality within the Sub 6G spectrum. This has significant implications for the seamless operation of Sub 6G communications and the efficient utilization of this frequency band.

Table – 2: Comparison with the existing work

Reference	Freq(GHz)	unit size (mm)	Dielectric Constant	Angular Stability
[3]	6 and 10	18 × 18	2.2	70⁰
[14]	6.29 and 8.35	8.0 × 8.0	4.4	60⁰
[15]	2.45 and 5.34	30 × 30	4.7	30⁰
[16]	2.45 and 5.5	20 × 20	6.55	45⁰
[17]	0.9 and 1.79	24 × 24	2.2	60⁰
[18]	0.93 and 1.72	46 × 46	3.4	60⁰
proposed work	2.4 and 6.3	20 × 20	2.2	80⁰

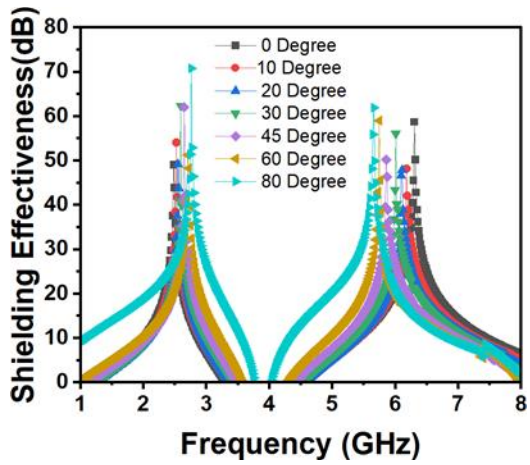

Fig. 5. Shielding Effectiveness for different incident angle

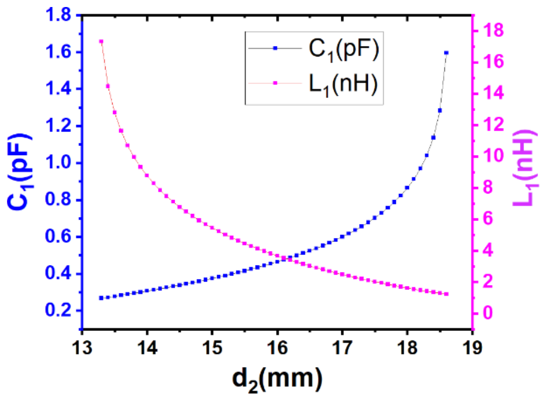

Fig. 6. d2 varying with respect to C1 and L1

But we also have to recognize that the performance of FSS designs may vary depending on specific deployment scenarios, and further research is needed to validate their effectiveness in practical applications. Moreover, the rapid evolution of Sub 6G technology requires ongoing exploration of innovative design techniques and optimization algorithms. In conclusion, our research represents a significant leap in Sub 6G technology in which ML algorithms have been integrated to improve the overall efficiency of FSS operating in Sub 6G band and it is imperative that research continues and provide significant results which contributes for emerging wireless communication systems.

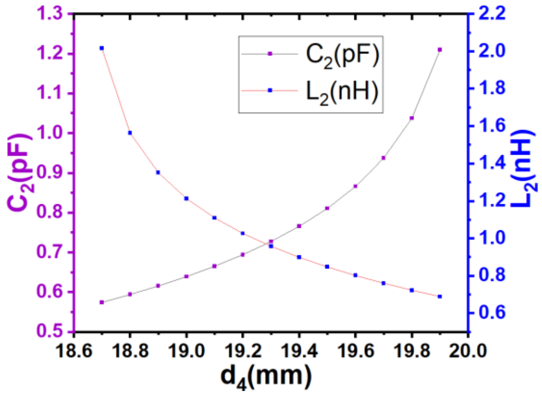

Fig. 7. d4 varying with respect to C2 and L2

ACKNOWLEDGEMENT

We are grateful to our Institution and Management, **C. BYREGOWDA INSTITUTE OF TECHNOLOGY** with its ideals and inspirations for having provided us with the facilities, which has made this research a success.

We would like to thank our beloved Principal **Dr. S N CHANDRASHEKARA, CBIT** for his kind disposition for completing this undertaking successfully.

We express our heart full gratitude to **Dr. DEEPIKA LOKESH,** Professor and HOD, Department of Artificial Intelligence and Machine Learning, CBIT, for giving us guidance, valuable advice and support.

We also thank to all our professors and the entire department of Artificial Intelligence and Machine Learning, for their co-operation and suggestions.

REFERENCES

[1] E. Unal, A. Gokcen and Y. Kutlu, "Effective electromagnetic shielding,"in IEEE Microwave Magazine, vol. 7, no. 4, pp. 48-54, Aug. 2006.

[2] R. Sivasamy, B. Moorthy, M. Kanagasabai, V. R. Samsingh , M. G. N. Alsath, "A Wideband Frequency Tunable FSS for Electromagnetic Shielding Applications," in IEEE Transactions on Electromagnetic Com-patibility, vol. 60, no. 1, pp. 280-283, Feb. 2018.

[3] S. Sairam, D. S. Kumar, S. Sabapathi and S. Angali, "Optimizationof Double Ring Frequency Selective Surface for Sub 5G/X-Band Communications Using Supervised ML and DL Algorithms," in IEEE Transactions on Electromagnetic Compatibility, vol. 65, no. 4, pp. 1057-1062, Aug. 2023.

[4] L. C. M. M. Fontoura, H. W. De Castro Lins, A. S. Bertuleza, A. G. D'assunção and A. G. Neto, "Synthesis of Multiband Frequency Selective Surfaces Using Machine Learning With the Decision Tree Algorithm," in IEEE Access, vol. 9, pp. 85785-85794, 2021.

[5] V. Krushna Kanth and S. Raghavan, "Equivalent Circuit Analysis of Complementary FSS for Selective EM Shielding," 2018 15th Inter- national Conference on ElectroMagnetic Interference Compatibility (INCEMIC), Bengaluru, India, 2018.

[6] Y. Ma, W. Wang, J. Dong and J. Mo, "Dual-Reject Band FSS Design Using Equivalent Circuit Model," 2021 International Applied Compu- tational Electromagnetics Society (ACES-China) Symposium, Chengdu,China, 2021.

[7] W. Wu, J. Ji, X. Ji and Q. Chang, "A Dual-Layer Ultra-WidebandFrequency Selective Surface for Electromagnetic Field Shielding," 2023International Applied Computational Electromagnetics Society Sympo- sium (ACES-China), Hangzhou, China, 2023.

[8] M. Sedaghat, R. Trinchero, Z. H. Firouzeh and F. G. Canavero, "Com- pressed Machine Learning-Based Inverse Model for Design Optimiza- tion of Microwave Components," in IEEE Transactions on Microwave Theory and Techniques, vol. 70, no. 7, pp. 3415-3427, July 2022.

[9] M. F. Ahmad Fauzi, R. Nordin, N. F. Abdullah and H. A. H. Alobaidy, "Mobile Network Coverage Prediction Based on Supervised Machine Learning Algorithms," in IEEE Access, vol. 10, pp. 55782-55793, 2022.

[10] G. M. Perihanoğlu and H. Karaman, "Geographic Information Systems (GIS) and Random Forests Regression-Based Approach for Path Loss Prediction in the Campus Environment," 2023 31st Signal Processing and Communications Applications Conference (SIU), Istanbul, Turkiye,2023.

[11] V. Chaudhary and R. Panwar, "FSS Derived Using a New Equivalent Circuit Model Backed Deep Neural Network," in IEEE Antennas and Wireless Propagation Letters, vol. 20, no. 10, pp. 1963-1967, Oct. 2021.

[12] M. Nauman, R. Saleem, A. K. Rashid and M. F. Shafique, "A Minia- turized Flexible Frequency Selective Surface for X-Band Applications," in IEEE Transactions on Electromagnetic Compatibility, vol. 58, no. 2, pp. 419-428, April 2016.

[13] I. S. Syed, Y. Ranga, L. Matekovits, K. P. Esselle and S. Hay, "A Single- Layer Frequency-Selective Surface for Ultrawideband Electromagnetic Shielding," in IEEE Transactions on Electromagnetic Compatibility, vol.56, no. 6, pp. 1404-1411, Dec. 2014.

[14] Y. Li, P. Ren, Z. Xiang, B. Xu and R. Chen, "Design of Dual-Stopband FSS With Tightly Spaced Frequency Response Characteristics," in IEEE Microwave and Wireless Components Letters, vol. 32, no. 8, pp. 1011- 1014, Aug. 2022.

[15] Fulya Bagci, Cenk Mulazimoglu, Sultan Can, Emrullah Karakaya, Asim Egemen Yilmaz, Baris Akaoglu, A glass based dual band frequency selective surface for protecting systems against WLAN signals, AEU, Volume 82, 2017, Pages 426-434, ISSN 1434-8411.

[16] U. Farooq, M. F. Shafique and M. J. Mughal, "Polarization Insensitive Dual Band Frequency Selective Surface for RF Shielding Through Glass Windows," in IEEE Transactions on Electromagnetic Compatibility, vol.62, no. 1, pp. 93-100, Feb. 2020.

[17] W. Yin, H. Zhang, T. Zhong and X. Min, "A Novel Compact Dual-Band Frequency Selective Surface for GSM Shielding by Utilizing a 2.5-Dimensional Structure," in IEEE Transactions on Electromagnetic Compatibility, vol. 60, no. 6, pp. 2057-2060, Dec. 2018.

[18] R. Sivasamy, L. Murugasamy, M. Kanagasabai, E. F. Sundarsingh and M. Gulam Nabi Alsath, "A Low-Profile Paper Substrate-Based Dual- Band FSS for GSM Shielding," in IEEE Transactions on Electromag- netic Compatibility, vol. 58, no. 2, pp. 611-614, April 2016.