



## Machine Learning Techniques for the Optimization of Polymer Composites Used in EMI Shielding

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### Abstract

The increasing use of electronic devices has led to the rising challenge of electromagnetic interference (EMI), necessitating efficient shielding materials. However, adding excessive fillers to polymer composites to enhance EMI shielding often results in higher costs, poor dispersion, and mechanical weakness. This research proposes a hybrid polymer composite using a Graphene substrate combined with conductive polymers like polyacetylene and multi-walled carbon nanotubes (MWCNTs), aimed at improving EMI shielding performance while maintaining mechanical integrity. The proposed design and optimization approach are assessed using ANSYS-HFSS software. To further enhance the prediction and optimization of EMI shielding effectiveness, a novel "bio-inspired predictive insight and optimization strategy" is introduced. This strategy employs "Bayesian-enriched genetic programming" to handle the complex, nonlinear relationships in polymer composites, addressing the multi-objective optimization challenges. Additionally, the "multi-objective dominant crowding seagull (MDCS) optimization" model is used to optimize conflicting objectives and EMI shielding simultaneously, demonstrating improved shielding efficiency and superior performance in terms of prediction accuracy (98.7%), faster training time (19 seconds), and quicker prediction time (6 seconds). The results suggest that this combined approach can significantly enhance the mechanical, electrical, and EMI shielding properties of polymer composites, offering a promising solution for modern electronic applications.

### 1. Introduction

Electromagnetic interference (EMI) has emerged as a significant issue due to the swift progress in the electronics sector and telecommunications networks. Conducting polymers present a practical

solution for EMI shielding applications (Ravindren et al., 2019). Various essential types of conducting polymers have been developed through nanoelectronics and nanotechnology (Panda and

Acharya, 2019). Polymer nanocomposites, consisting of polymer matrices and nanoscale reinforcement phases, are frequently utilized in composite materials because of their processing and shaping convenience. Graphene, a two-dimensional material with nanoscale diameter and thickness, is employed to enhance the thermal and electromagnetic interference shielding capabilities of nanocomposites (Ha et al., 2019). It has been applied in radar absorption and EMI shielding for hybrid compounds incorporating Graphene Nano platelets as fillers. Based on extensive literature and documentation, we propose an innovative polymer composite containing Graphene to enhance EMI shielding effectiveness. This work is organized into seven chapters: the first chapter serves as an introduction, the second details the completed work, the third outlines design of polymer composite, fourth chapter presents the results of ANSYS simulation, fifth and sixth chapter explain the machine learning techniques used and seventh chapter explains the result of machine learning techniques. [1-3]

## 2. Advanced Polymer Composite with Graphene Content for EMI Shielding

The electromagnetic interference (EMI) resulting from high-frequency electrical radiation has become a significant threat to information security. To ensure effective shielding, it is essential to maintain high electrical conductivity, which is typically achieved through the use of filler particles. However, the presence of inferior filler particles can lead to severe electrical percolation issues and inadequate device impedance, drastically diminishing the conductivity of the composite. Additionally, an excessive amount of filler can destabilize the shield at elevated temperatures due to poor dispersion within the matrix and limited thermal stability. Consequently, a novel Intercalated Polyacetophenimide matrix can be developed, incorporating multiwalled carbon nanotubes as fillers to enhance the intrinsic conductivity and overall performance of the shield. The composition of Polyacetophenimide will include Polyetherimide, di-butyl sebacate, thiophene, and acetylene polymers. This discussion focuses on the creation of an innovative polymer composite containing Graphene. It elaborates on the selection process for various polymer composites, the mixing of these materials

in different ratios, and the methods for incorporating Graphene and Multi-Walled Carbon Nanotubes as fillers. The Coupled Magnetic Stirrer technique is employed for the amalgamation of different polymers, while the Coupled Nano Stratum technique is utilized for the integration of the Graphene substrate (Guan et al., 2018).

## 3. Novel Polymer Composite Design and Preparation Method

Recently, conductive filler materials have been utilized in conjunction with conducting polymer-based electromagnetic interference shields to enhance both the conductivity and thermal resilience of the shielding. In this context, the polymer matrix consists of a combination of polyetherimide and conducting polymers such as acetylene and thiophene, which we propose to name Polyacetophenimide. Polyetherimide is a thermoplastic renowned for its exceptional performance in engineering applications, characterized by high strength and stiffness at elevated temperatures, dimensional stability, long-term heat resistance, and commendable electrical properties. We have opted for a blend of conductive polymers (acetylene and thiophene) that exhibit superior characteristics, as the EMI shielding material must possess conductive capabilities while minimizing the quantity of filler used. The properties of the Polyetherimide polymer (Ahmad et al., 2017) are detailed in Table 1 below. The properties of Multi-Walled Carbon Nanotubes are presented in Table 2, while the properties of Thiophene are outlined in Table 3 (Roncali, 1992). Lastly, the properties of Acetylene (West, 1980) are illustrated in (Table 1)

**Table 1 Properties of Polyetherimide**

<b>Density</b>	1,270 (kg/m <sup>3</sup> )
<b>Melting point</b>	219 (°C)
<b>Thermal conductivity</b>	0.22 (W/mK)
<b>Tensile modulus</b>	3,276 (MPa)
<b>Tensile strength</b>	126 (MPa)
<b>Poisson's ratio</b>	0.36
<b>Coefficient of thermal expansion</b>	5.58×10 <sup>-6</sup> (C <sup>-1</sup> )
<b>Glass transition temperature</b>	227 (°C)
<b>Melt index</b>	0.42 (g/min)
<b>Linear thermal expansion</b>	3.3 (°C)

**Table 2 Properties of MWCNTs**

Purity %	98%
-OH Content	1.76 Wt%
Outer diameter	10-20 nm
Inner diameter	5-10 nm
Length	0.5-2.0 $\mu\text{m}$
Surface area	>200 $\text{m}^2/\text{g}$
Density	0.22 $\text{g}/\text{cm}^3$
Electrical conductivity	>100 $\text{S}/\text{cm}$

**Table 3 Properties of Thiophene**

Molar mass	84.14 $\text{g}/\text{mol}$
Density	1.051 $\text{g}/\text{mL}$
Melting point	-38°C
Boiling point	84°C
Magnetic susceptibility ( $\chi$ )	-57.38 $\cdot 10^{-6} \text{ cm}^3/\text{mol}$
Refractive index ( $n_D$ )	1.5287

**Table 4 Properties of Acetylene**

Molar mass	26.038 $\text{g}\cdot\text{mol}^{-1}$
Density	1.1772 $\text{kg}/\text{m}^3$
Melting point	-80.8°C
Conductivity	4.4 $\times 10^{-5}$ Siemens/cm
Magnetic susceptibility ( $\chi$ )	-12.5 $\times 10^{-6} \text{ cm}^3/\text{mol}$

### 3.1. Rule of Mixtures Formulae

In order to find the permittivity, permeability and density we use rule of mixtures formulae

$$\epsilon = (1 - V_m) \epsilon_m + V_f \epsilon_f \text{ --Equation 1 [4]}$$

Where  $\epsilon$  - permittivity,  $V_m$  - Volume fraction of matrix,  $\epsilon_m$  - permittivity of matrix,  $\epsilon_f$  - permittivity of fiber. The permittivity value and volume fraction of each component is shown in Table 5

**Table 4 Permittivity Value and Volume Fraction of Components**

Material	Volume fraction		Permittivity value
polyetherimide	50 = 0.5	Matrix	2.25
polyacetylene	15=0.15	Matrix	2
mwcnt	5=0.05	Fiber	60
polythiophene	15=0.15	Matrix	6
di butyl sebacate	15=0.15	Matrix	4.5
Graphene 6.9			

$$V_m = (0.5 + 0.15 + 0.15 + 0.15) / 4 = 0.2375$$

$$V_f = 0.05$$

$$\epsilon_m = 60$$

Substituting all values in equation 3 we get permittivity as 5.8

Also permittivity of graphene is 6.9

Therefore, permittivity is  $= (5.8 + 6.9) / 2 = 6.35$

### 3.2. Permeability

$$P = P_m + 2P_m \frac{P_f - P_m}{P_f + P_m - V_f(P_f - P_m)}$$

Where  $P_m$  - permeability of matrix composite,  $P_f$  - permeability of the fiber composite,  $V_f$  - Volume fraction of the fibre. The permeability value and volume fraction of each component is shown in Table 6

**Table 6 Permeability Value and Volume Fraction of Components**

Material	Volume fraction		Permeability value
polyetherimide	50 = 0.5	Matrix	0.01
polyacetylene	15=0.15	Matrix	3 $\times 10^{-8}$
mwcnt	5=0.05	Fibre	3
polythiophene	15=0.15	Matrix	0.1
di butyl sebacate	15=0.15	Matrix	5.4
Graphene 82.95			

$$P_m = (0.01 + 3 \times 10^{-8} + 0.1 + 5.4) / 4 = 1.377$$

$$P_f = 3$$

Substituting values of  $P_m$ ,  $P_f$ ,  $V_f$  in equation 2 we get,  $P = 2.41$

Also the Permeability of graphene is 82.95

Therefore overall permeability  $= (2.41 + 82.95) / 2 = 42.68$

### 3.3. Density

$$\rho V = \rho_m V_m + \rho_f V_f \text{ (Equation 3)}$$

Where  $\rho_m$ ,  $\rho_f$  - density of matrix and fibers,  $V_m$ ,  $V_f$  - Volume matrix and fibers.

The density value and volume fraction of each component is shown in Table 7

**Table 6 Density Value and Volume Fraction of Components**

Material	Volume fraction		Density value
polyetherimide	50 = 0.5	Matrix	1.2
polyacetylene	15=0.15	Matrix	0.4
mwcnt	5=0.05	Fiber	0.22
polythiophene	15=0.15	Matrix	1.05
di butyl sebacate	15=0.15	Matrix	0.940
Graphene = 2.65			

$$V_m = (0.5 + 0.15 + 0.15 + 0.15) / 4 = 0.2375$$

$$V_f = 0.05$$

$$\rho_m = (1.2 + 0.4 + 1.05 + 0.940) / 4 = 0.8975$$

$$\rho_f = 0.22$$

Substituting all values in equation 3 we get  $\rho = 0.22$

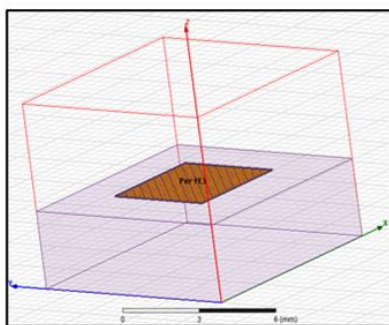
Also the density of graphene is 2.65

Therefore, total density is  $(0.22 + 2.65) / 2 = 1.435$

From this the properties of novel polymer composites are found. The new Polymer composite can be named Polyacetophenemide. As Graphene and MWCNT are added its properties are also considered for calculation. So the calculated values are given in ANSYS HFSS simulation software. [5]

#### 4. Simulation Details and Result

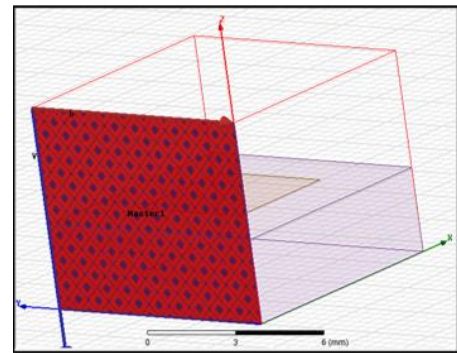
The simulations that were run and the performance analysis of the suggested structure are described in this section. A comparison section is also provided to demonstrate how the suggested shield material has improved. ANSYS HFSS was then used to analyse the EMI shield for the recommended work. The model's inputs are the mass density, permeability, and dielectric permittivity. Using the rule of mixtures formula for the composite shield material, the input values are determined. Equations (1), (2), and (3) are used to determine the dielectric permittivity of the composite (Ávila et al., 2015) and are provided as input. S parameters were used to calculate the shield's distinctive performance values. The parameters S21 and S12 indicate the transmission coefficient, which is ascertained by the S parameter plot, while S11 and S12 represent the reflection coefficient. (Figure 1) [6]



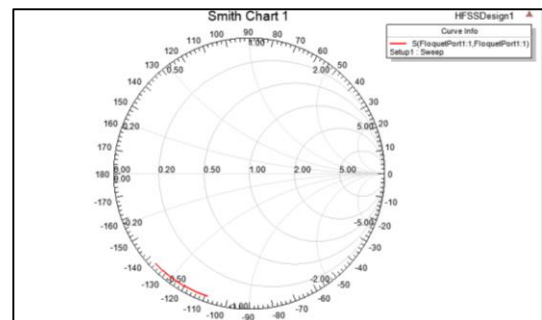
**Figure 1 Model of Strip Material**

The following is a description of the software analysis's findings. A boundary box encloses the model of the strip material in HFSS that is displayed. The shield model was created using a 4x4 cm patch with a 2 mm thickness and a 9x9x3 cm boundary box. Figures 1 and 2 depict it.

The characteristic performance values are given as input. (Figure 2,3)

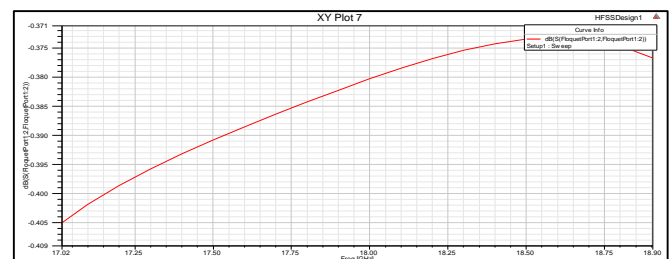


**Figure 2 Model with Boundary Box**



**Figure 3 Smith Chart**

A Smith chart is used to show the system's impedance as a function of frequency. Figure 4.3 depicts it. According to the chart, the source impedance is located on 0.8 circles, while the shield resistance is located on 0.075 circles. As a result, the resistance and impedance are, respectively, 7.5 and 0.8 ohm. Fillers and graphene substrate together hence offer good conductivity and lower resistance values. Because of this, the innovative methods mentioned above enhance the shielding's performance by lowering the amount of filler used, preserving appropriate filler dispersion, enhancing electrical conductivity, raising thermal stability, and improving connectivity. (Figure 4) [7-8]

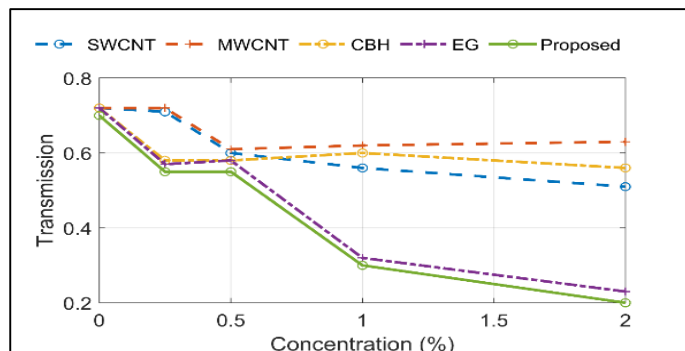


**Figure 4 Transmission Coefficient Curve**

The relationship between the transmitted wave's



amplitude and the incident wave's amplitude is shown by the transmission coefficient curve (Figure 4.4). It measures the net transmitted power, which is represented by the transmission coefficient and was found to be 0.373 at 18.6 GHz, since S12, for which the input and output ports are different. Equation (4) is used to calculate the value of absorption, which is found to be 0.254 based on the values of reflectivity and transmission (Geetha et al., 2009).  $S_A + S_R + S_T = 1$ —Equation(4) [9] where  $S_R$  stands for shield reflection,  $S_A$  for shield absorption, and  $S_T$  for shield transmission. (Figure 5)



**Figure 5 Transmission vs Concentration**

Plotting the transmission value vs filler concentration (Banerjee et al., 2020) is shown in Figure 4.5. The suggested material is compared to different filler concentrations of carbon black (CBH), exfoliated graphite (EG), single-walled carbon nanotubes (SWCNT), and multiwalled carbon nanotubes (MWCNT) at concentrations ranging from 0.5 to 2%. Plot demonstrates that the suggested material, with 2% filler addition concentration, has the lowest transmission characteristics capability of 0.2. [10]

### 5. Machine Learning Techniques

Machine learning (ML) techniques have emerged as powerful tools in the field of electromagnetic interference (EMI) shielding, offering advanced capabilities for predicting and optimizing the shielding effectiveness of composite materials. A variety of ML algorithms—such as regression models, neural networks, and ensemble methods—have been employed to decipher the complex relationships between material properties and EMI shielding performance (Chang H et al., 2021; Chaudhary V et al., 2023). These approaches utilize comprehensive datasets that include a wide range of composite formulations, factoring in variables like filler type, concentration, and dispersion characteristics (Kumar R et al., 2023; Lee et al.,

2020). Moreover, ML enables the optimization of material compositions by identifying the most effective combinations of components to achieve desired EMI shielding properties. Through iterative data-driven learning, these models continuously improve their predictive accuracy. Their capacity to manage large datasets and uncover intricate interdependencies makes ML an invaluable asset in developing composite materials with customized EMI shielding capabilities (Li X et al., 2022). This suggested machine learning method's primary contribution is as follows:

- To enhance the optimisation of the EMI shielding effect, a unique Bayesian-enriched genetic programming (GP) handles the non-linear parameter relationship and high-dimensional search space complexity.
- A unique multi-objective dominant crowding seagull optimisation improves prediction accuracy by capturing and managing the conflicting proportional relationship between each material property and other properties.

### 6. Bio-Inspired Predictive Insight and Optimization for EMI Shielding in Hybrid Polymer Composites

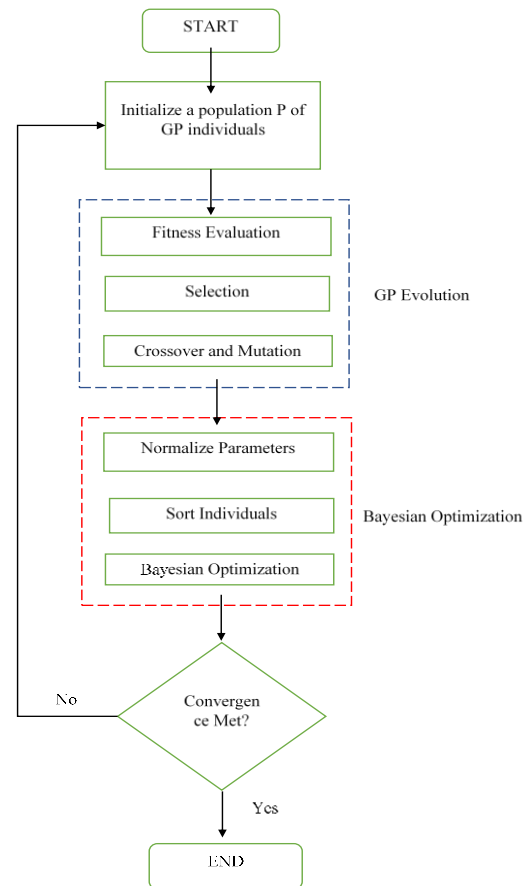
The prediction and optimization models for the EMI shielding effect of polymer composite materials, based on machine learning, represent a groundbreaking advancement in materials engineering. These models utilize data-driven algorithms to accurately predict the effectiveness of electromagnetic interference (EMI) shielding in composite materials. By incorporating key features such as filler concentrations, composite thickness, and substrate characteristics, these models elucidate the intricate relationships among the variables that affect EMI shielding. Additionally, the optimization capabilities inherent in machine learning allow for the determination of optimal material compositions, thereby aiding in the development of polymer composites with superior EMI shielding properties. Nevertheless, existing machine learning methodologies face challenges in addressing multi-objective optimization and in capturing the complex nature of composites. Consequently, a bio-inspired strategy for predictive insight and optimization has been proposed to enhance the prediction and optimization of the EMI shielding effect in selected polymer composites. This approach introduces two innovative methods: Bayesian-enriched genetic

programming and multi-objective dominant crowding seagull optimization, which will be detailed in the following sections. [11-14]

### 6.1. Bayesian-Enriched Genetic Programming

To mitigate the challenges posed by high-dimensional complexity, the method known as 'Bayesian-enriched genetic programming' is proposed. This approach adeptly captures the non-linear functional relationships among various parameters, including filler loading, matrix type, thickness, porosity, and the number of layers in polymer composite materials, through a novel integration of genetic programming and Bayesian principles. During the initialization phase, the genetic programming element represents each polymer composite structure as a dynamic tree, encoding the various parameters at different nodes and leaves. As the evolutionary process progresses, genetic operators such as crossover and mutation introduce variability, allowing the algorithm to investigate complex interrelations among parameters. The Bayesian-enriched component plays a crucial role during the fitness evaluation phase, where Bayesian techniques are employed to update the probability distributions linked to different parameter combinations. This enhancement directs the algorithm's attention towards promising areas of the parameter space, adapting dynamically as optimization advances. The outcome is a continuous evolution that optimizes polymer composite structures for EMI shielding while also providing probabilistic insights into the importance of each parameter, thereby offering a detailed understanding of the intricate interactions among filler loading, matrix type, thickness, porosity, and the number of layers in achieving improved EMI shielding effectiveness. This comprehensive algorithm combines the evolutionary strengths of genetic programming with the probabilistic search methods of Bayesian optimization, creating a strong framework for optimizing complex configurations of composite materials. The interaction between these elements aids in identifying optimal solutions within the intricate, high-dimensional parameter space, thus improving the efficiency and effectiveness of the optimization process. After this proposed method captures the nonlinear multifactorial characteristics of the material properties, it alleviates the high-dimensional complexity, leading to the subsequent

step of predicting and optimizing the EMI shielding effect of the material through the MDCS optimization algorithm, which will be detailed in the following Section. (Figure 6)



**Figure 6 Flow Chart of Bayesian-Enriched Genetic Programming**

This MDCS optimization algorithm incorporates Pareto dominance ranking, crowding distance assessment, and a novel seagull optimization phase to effectively manage the trade-offs and conflicting relationships between various material properties. The seagull optimization process improves the exploration and refinement of solutions, striving for a well-distributed and diverse set along the Pareto front. [15-18]

### 6.2. Result and Discussion

This section outlines the outcomes derived from the proposed machine learning model. The results indicate that the proposed model surpasses others regarding prediction accuracy and dimensional complexity. Additionally, the effectiveness of the suggested method in forecasting EMI shielding is further demonstrated through a comparison with other currently utilized machine learning models.

6.3. System Requirements

OS : Windows 10 Pro  
Processor : Intel(R) Core(TM) i3-4130  
CPU  
RAM : 8GB  
Tool : PYTHON

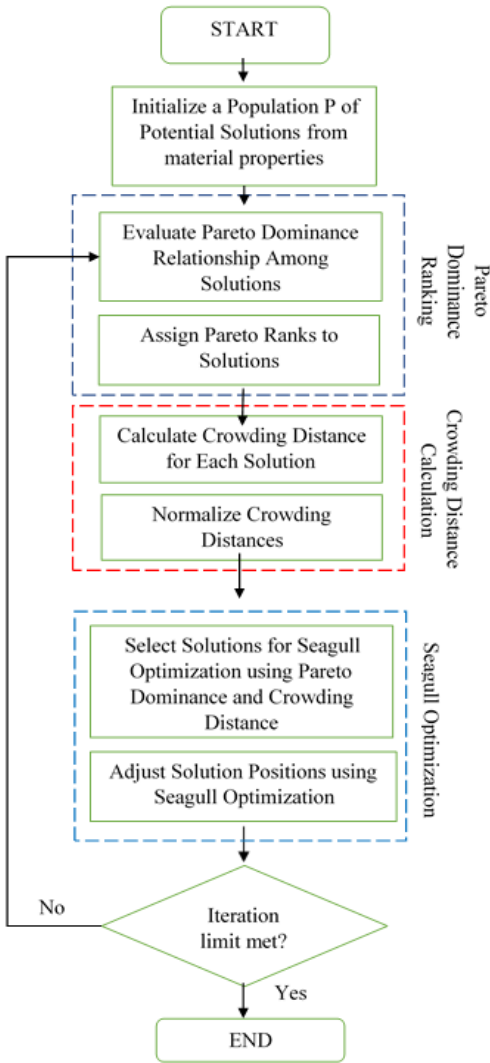


Figure 7 Optimization process flowchart

6.4. Performance Analysis of the Proposed Model

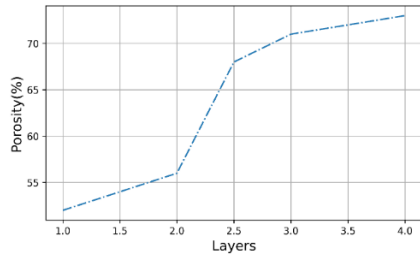


Figure 8 Variation of Porosity with Number of Layers and Thickness

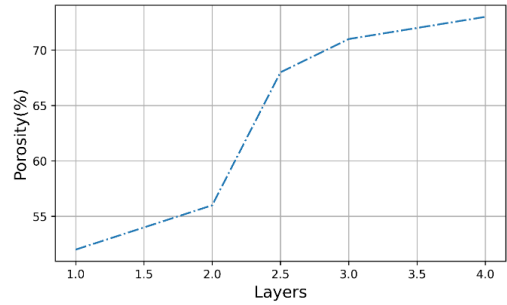


Figure 9 Variation of Porosity with Number of Layers and Thickness

Figure 9 illustrates the percentage change in porosity in relation to the increase in the number of layers and thickness. As shown in Figure 7.1a, an increase in the number of layers correlates with a rise in porosity percentage, reaching approximately 73% at four layers. Furthermore, Figure 7.2b indicates that porosity percentage also rises with layer thickness, achieving around 62% at a thickness of 5cm. The suggested Bayesian-enhanced genetic programming effectively captures these variations and optimizes these values to mitigate high dimensional complexities. (Figure 10)

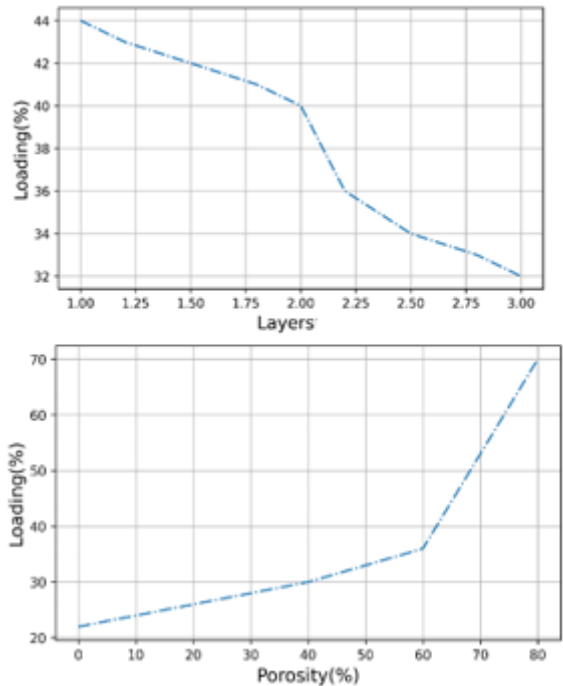


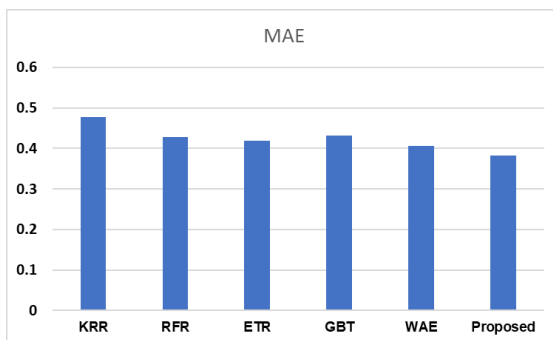
Figure 10 Variation of Loading With Layers and Porosity

Figure 10 illustrates the percentage variation in loading relative to the number of layers and porosity. As depicted in Figure 7.2a, there is an inverse relationship between the number of layers and the

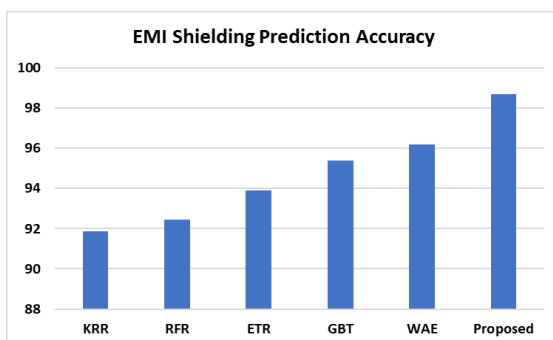
loading percentage, with a calculated loading percentage of 32% for three layers. Conversely, Figure 7.2b indicates a direct relationship between porosity and loading percentage, revealing a loading percentage of 70% at 80% porosity. The proposed MDCS optimization model effectively identifies these proportional variations among the composite material's properties, facilitating improved prediction and optimization. [19]

### 6.5. Performance Comparison of the Proposed Model with Existing Models

This section presents a comparison of the performance of the proposed machine learning-based EMI shielding optimization strategy against other existing models, with the results detailed below. The proposed model is evaluated alongside several established machine learning techniques, including KRR, RFR, ETR, GBT, and WAE (Shi M, et al., 2022). (Figure 11,12) [20-22]



**Figure 11 Comparison of MAE**



**Figure 12 Comparison of Prediction Accuracy**

Figure 12 depicts a comparison of MAE (Mean Absolute Error) of the proposed model with that of the existing methods. This shows that the proposed method achieves lower MAE with the multi-objective dominant crowding seagull optimization when compared to other methods. Figure 7.4 shows a comparison of prediction accuracy of proposed model with different ML methods. Proposed model's accuracy is much better compared to other

models. [23]

### Conclusion

The EMI shield material in this work was developed using polymer matrix materials. The material was subsequently analysed and its various properties were identified using ANSYS-HFSS software. To improve the performance of the EMI shield, Graphene and conductive polymers were added to the selected materials. This was then simulated using HFSS software. Plots and charts produced by the analysis were used to determine the S-parameter characteristics for absorption, reflection, and transmission. Thus, it can be said that at a high frequency of 20 Hz, the shield material has good SE<sub>T</sub> values of 0.373 dB. Lastly, a comparison of the suggested model with varying filler content and material reinforcement revealed a 30.75% increase in absorption. This research presents a promising and comprehensive approach to address the challenges in predicting and optimizing EMI shielding in the selected hybrid polymer composite. The "Bayesian-enriched genetic programming" method integrates genetic programming with Bayesian principles to navigate the high-dimensional and nonlinear parameter space of polymer composites. Then, the "multi-objective dominant crowding seagull optimization" approach integrates Pareto dominance ranking, crowding distance calculation, and seagull optimization and effectively balances conflicting material properties by preserving non-dominated solutions on the Pareto front, encouraging a diverse spread of solutions, and leveraging seagull optimization for further refinement of EMI shielding performance. With an outstanding prediction accuracy of 98.7%, the model surpasses the prevailing models such as KRR, ETR, RFR, GBT, and WAE. Additionally, it demonstrates faster training and prediction times of 19 seconds and 6 seconds, respectively than other existing methods. [24-25]

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