

BIO-INSPIRED PREDICTIVE INSIGHT AND OPTIMIZATION STRATEGY FOR ELECTROMAGNETIC SHIELDING IN HYBRID POLYMER COMPOSITES

Arun Sebastian^{1,2*}, and Asaletha Raghavan¹

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Abstract

The Machine learning-based EMI shielding effect prediction on polymer composite materials is of supreme importance in modern electronic applications as this shielding serves as a robust protective barrier, safeguarding electronic components from electromagnetic interference. But, capturing the multifactorial nature of the composites and handling multi-objective optimization is still difficult to achieve with the existing machine-learning approaches. Hence, this research proposes a novel “Bio-inspired Predictive Insight and Optimization Strategy” for improving the efficacy of prediction and optimization of the EMI shielding effect of polymer composites. Polymer composites have complex structures with multiple components, leading to nonlinear relationships with EMI shielding effectiveness. This results in a high-dimensional search space, making the search for effective solutions computationally demanding and time-consuming. Here, the “Bayesian-Enriched Genetic Programming” approach captures the multiple parameters such as filler loading, matrix type, and processing conditions effectively to reduce this high-dimensional space complexity. The “Multi-objective Dominant Crowding Seagull (MDCS) optimization” model effectively addresses the challenges of traditional optimization algorithms by optimizing multiple conflicting objectives and EMI shielding. The comparison results show that the proposed method outperforms other methods with a higher prediction accuracy of 98.7%, faster training time of 19 seconds and quicker prediction time of 6 seconds.

Keywords: EMI shielding optimization; Genetic algorithm; Multi-objective optimization; Polymer composite; Seagull optimization

¹ Cochin University College of Engineering, Kuttanadu, Kerala, 688504, India. E-mail: arunsebastn@cusat.ac.in; asalethar@cusat.ac.in

² Department of Electrical and Electronics Engineering, Saintgits College of Engineering, Kottukulam Hills, Pathamuttom P.O., Kottayam, Kerala, 686532, India.

* Corresponding author

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Introduction

Because computers and cellphones are used by so many people on a daily basis, electromagnetic (EM) waves have become a part of our lives. Because electromagnetic waves can transfer energy and information swiftly, they are valuable in many fields, including radio communication, electrical and electronic engineering, medicine, and so on. Electromagnetic waves can provide comfort by aiding in communication, microwave heating, medical imaging, remote sensing and the like, but they can also have certain drawbacks like radiation exposure and interference. It can disrupt communication and navigation systems. Electromagnetic interference can cause electronics to operate poorly, malfunction or stop working completely. Electromagnetic interference shielding is a critical consideration in modern electronics, and composite materials have emerged as effective solutions to address this challenge. Composite materials play a crucial role in electromagnetic interference shielding due to their unique combination of diverse properties. These materials are typically composed of two or more constituents with distinct physical or chemical characteristics, such as metal particles embedded in a polymer matrix or carbon fibers dispersed in a resin. (Ayub *et al.*, 2021). For instance, the metallic elements within the composite facilitate the reflection and absorption of electromagnetic waves, while the non-conductive matrix helps to disperse and isolate these waves. This shielding effect is crucial in ensuring the proper functioning of electronic systems by minimizing the risk of signal distortion or degradation (Raagulan *et al.*, 2020; Rong *et al.*, 2023).

The creation of a hybrid polymer composite based on polyetherimide involves a sophisticated fabrication process that leverages the unique properties of various conducting polymers and nanomaterial fillers. Specifically, polyacetylene and multi-walled carbon nanotubes (MWCNT) are dispersed within the polyetherimide matrix, forming a composite material with enhanced electrical conductivity and mechanical strength. The incorporation of polyacetylene, a conductive polymer with π -electron delocalization, facilitates the development of a conductive network within the polymer matrix, allowing for efficient charge transport (Ram *et al.*, 2019). Simultaneously, the addition of MWCNT, with its excellent mechanical properties and high aspect ratio, enhances the composite's structural integrity and electrical conductivity. To further optimize the composite's performance, a graphene substrate is introduced,

providing a stable platform for the dispersion of conducting polymers and nanofillers. The graphene substrate serves as a support matrix and contributes to the overall conductivity of the composite due to its excellent electronic properties (Ayub *et al.*, 2021). The synergy of these components results in a hybrid polymer composite that exhibits superior electrical conductivity, mechanical strength, and thermal stability, making it an attractive candidate for applications in electronic devices, sensors, and other advanced technological systems where EMI shielding and robust material properties are of supreme importance (Guo *et al.*, 2021; Wen *et al.*, 2020).

In the field of electromagnetic interference shielding, machine learning (ML) methods have emerged as powerful tools for predicting and optimizing the shielding effectiveness of composite materials. Various ML algorithms, including regression models, neural networks, and ensemble methods, have been employed to analyze complex relationships between material properties and EMI shielding performance. (Chang *et al.*, 2021, Chaudhary and Panwar, 2023). These models utilize datasets that encompass a diverse range of composite formulations, incorporating variables such as filler type, concentration, and dispersion characteristics (Kumar *et al.*, 2023; Lee *et al.*, 2020). Furthermore, ML techniques facilitate the optimization of composite materials by predicting the most effective combinations of constituents for achieving desired EMI shielding properties. This process involves iterative learning from data, enabling the algorithm to adapt and refine its predictions over time. The ability of ML models to handle large datasets and complex interactions between various factors makes them valuable tools in the pursuit of designing composite materials with tailored EMI shielding capabilities (Li *et al.*, 2022).

Despite the promising strides made in leveraging machine learning methods for predicting EMI shielding effectiveness and optimizing composite materials, several challenges persist in this field. One significant challenge lies in the complexity and multidimensionality of the data involved. EMI shielding is influenced by a multitude of factors, including the type and concentration of fillers, the dispersion quality, and the composite's overall structure. Capturing these intricate relationships accurately within ML models requires extensive and representative datasets, often challenging to acquire due to the diversity of composite formulations and manufacturing processes (Shu *et al.*, 2019; Sidi Salah *et al.*, 2020).

Additionally, the interpretability of ML models poses a challenge, because the intricate black-box nature of certain algorithms may hinder a clear understanding of the underlying mechanisms governing EMI shielding predictions. Moreover, the dynamic nature of material properties, influenced by environmental conditions and aging effects, adds a layer of complexity that requires continuous model adaptation (Li *et al.*, 2021; Zhao *et al.*, 2023). Because researchers address these challenges, the integration of domain knowledge, improved data collection methods, and the development of more interpretable ML models are essential for overcoming the hurdles and advancing the predictive capabilities of ML in optimizing composite materials for EMI shielding applications (Narayanan *et al.*, 2023; Zhou *et al.*, 2020). The main contribution of this proposed machine learning approach is as follows:

- The composite material selected is the hybrid polymer composite based on polyetherimide which is fabricated by the dispersion of conducting polymers like polyacetylene and MWCNT fillers with a graphene substrate (Sebastian and Raghavan, 2023).
- The non-linear parameter relationship and high-dimensional search space complexity are handled by a novel Bayesian-enriched genetic programming (GP) to help improve the EMI shielding effect optimization.
- The conflicting proportional relationship of each property of material with other properties is captured and handled by a novel multi-objective dominant crowding seagull optimization thereby improving the prediction accuracy.

These factors are considered in this research work to improve the prediction and optimization of the EMI shielding effect of the selected hybrid polymer composite material. The content of the paper is organized as follows: section 2 contains a description of the proposed methodology and its working process, and section 3 contains a discussion of the proposed model evaluation, performance, and comparative analysis. Finally, section 4 concludes the paper.

Bio-inspired Predictive Insight and Optimization for EMI Shielding in Hybrid Polymer Composites

Machine learning based EMI shielding effect prediction and optimization models for polymer composite materials offer a transformative approach to advancing materials engineering. These models

leverage the power of data-driven algorithms to accurately forecast the electromagnetic interference (EMI) shielding effectiveness of composite materials. By integrating relevant features such as filler concentrations, composite thickness, and substrate properties, these models provide insights into the complex interplay of variables influencing EMI shielding. Furthermore, the optimization capabilities of machine learning enable the identification of optimal compositions, facilitating the design of polymer composites with enhanced EMI shielding properties. However, the current machine-learning techniques still struggle to handle multi-objective optimization and capture the multifactorial character of composites. Hence, a bio-inspired predictive insight and optimization strategy has been proposed for improving the prediction and optimization of the EMI shielding effect of the selected polymer composites. In this proposed approach, there are two novel methods used, one is Bayesian-enriched genetic programming and another is multi-objective dominant crowding seagull optimization which will be explained in the upcoming sections.

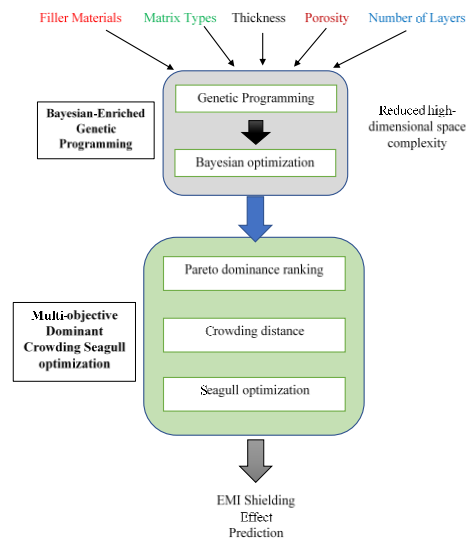


Figure 1. Proposed EMI shielding prediction and optimization approach

Figure 1 shows the overall process of the proposed machine learning based optimization approach for EMI shielding in the selected hybrid polymer composite material. The problem identification and the motivation of this research with novel solutions are explained below.

Polymer composites pose a formidable challenge for accurate modeling of their electromagnetic interference shielding effectiveness due to their intricate and multi-faceted structures.

Characterized by multiple interacting components, such as filler materials, matrix types, thickness, porosity, and the number of layers, these composites exhibit nonlinear relationships among these constituents. The complexity arises from the dynamic interactions and synergies among the various components, creating a highly intricate and non-linear functional space. This complexity further extends to the interdependence of material properties, making the traditional analytical and empirical methods insufficient for capturing the nuanced behavior of these composites. Thus, the resulting high-dimensional search space, representing the myriad possible combinations and configurations of these interacting components, presents a significant computational and modeling challenge. Hence, a novel Bayesian-enriched genetic programming is proposed in which the genetic programming captures the variation in composite material properties such as filler materials, matrix types, thickness, porosity, and the number of layers and Bayesian optimization is utilized to reduce the high-dimensional space complexity by detecting and processing the parameter variations captured in the previous step. Moreover, different material properties often have conflicting relationships. For example, increasing the filler content in a composite might enhance EMI shielding but could negatively impact mechanical strength or thermal conductivity. The existing EMI shielding optimization approaches do not effectively balance these conflicting objectives and are inefficient in navigating these trade-offs to find balanced solutions. Hence, a novel multi-objective dominant crowding seagull optimization is proposed in which the Pareto dominance ranking helps in identifying the proportional relationship among the property variables and preserving non-dominated solutions, forming the Pareto front (set of solutions) which provides better solutions regarding conflictions without compromising performance, and vice versa. The crowding distance encourages finding the spread of solutions in the Pareto front, promoting a diverse set of non-dominated solutions. Finally, the EMI shielding effect is predicted using seagull optimization by capturing the spread of dominant solutions in the previous step. With this MDCS optimization, the proportional relationship among each property of the material is effectively captured and an improved prediction is achieved. The upcoming sections explain the processes involved in this proposed method in detail.

Material Selection and Analysis

In this analysis, a hybrid polymer composite based on polyetherimide with a Graphene substrate is used for EMI shielding effect analysis (Sebastian

and Raghavan, 2023). Polyetherimide, thiophene, and acetylene polymers are combined with di-butyl sebacate through a modified coupled magnetic stirrer technique, ensuring thorough dispersion. Subsequently, a new methodology involving a crosslinked graphene substrate is applied, enhancing the shield's performance in terms of electrical conductivity and thermal stability. This improvement is achieved through the adoption of an innovative coupled nano stratum coating technique, which uniformly coats the graphene substrate using a specifically designed die to achieve the required thickness. This process involves the integration of heating elements, facilitating the formation of a polymer film on the graphene substrate. The properties of this material are used in the proposed machine learning based optimization approach for further analysis of EMI shielding prediction and optimization.

Bayesian-Enriched Genetic Programming

In order to reduce the high-dimensional complexity, the "Bayesian-enriched genetic programming" method is introduced which effectively captures the non-linear functional space among multiple parameters such as filler loading, matrix type, thickness, porosity, and the number of layers in polymer composite materials through an innovative combination of genetic programming and Bayesian principles. In the initialization phase, the genetic programming component represents each polymer composite structure as an evolving tree, encoding the diverse parameters at various nodes and leaves. As the evolutionary process unfolds, genetic operators such as crossover and mutation introduce variability, enabling the algorithm to explore intricate relationships between parameters. The Bayesian-enriched aspect becomes pivotal during fitness evaluation, where Bayesian methods are integrated to update the probability distributions associated with different parameter combinations. This enrichment guides the algorithm's focus towards regions of the parameter space that show promise, dynamically adapting as the optimization progresses. The result is an iterative evolution that involves optimizing the polymer composite structures for EMI shielding as well as providing probabilistic insights into the significance of each parameter, offering a nuanced understanding of the complex interplay among filler loading, matrix type, thickness, porosity, and the number of layers in achieving enhanced EMI shielding effectiveness.

This proposed Bayesian-enriched genetic programming has the following processing steps as mentioned in the flow chart given in Figure 2.

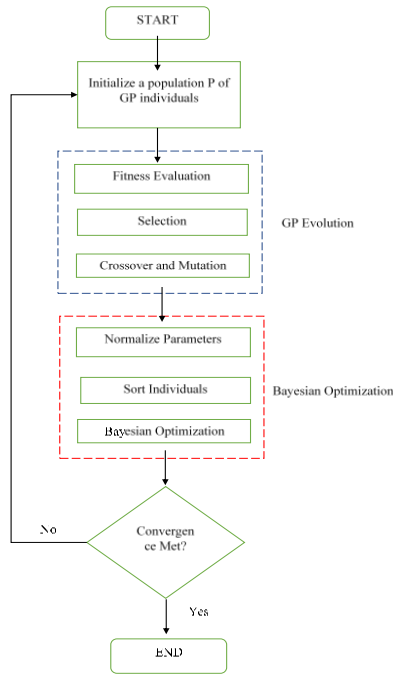


Figure 2. Flow chart of Bayesian-Enriched Genetic Programming

Bayesian-Enriched Genetic Programming

Step 1. Initialization:

Initialize a population P of GP individuals (trees) representing potential solutions. Each individual in the population encodes a unique combination of composite material parameters, including filler loading (FL), matrix type (MT), thickness (TH), porosity (PO), and the number of layers (NL).

Step 2. Genetic Programming (GP) Evolution:

- **Fitness Evaluation:** Evaluate the fitness of each GP individual in the population based on its predictive capability for EMI shielding effectiveness. This is typically done by comparing the predicted shielding effectiveness with actual experimental or simulated data.

Let F_i represent the fitness of individual i . The fitness is typically calculated by a performance metric, such as Mean Squared Error (MSE):

$$F_i = \frac{1}{n} \sum_{j=1}^n (y_{ij} - \hat{y}_{ij})^2$$

where y_{ij} is the actual EMI shielding effectiveness for the j -th data point associated with individual $\hat{y}_{ij}$ is the predicted value for the same data point, and n is the total number of data points.

- **Selection:** Select individuals for reproduction based on their fitness scores. The selection process employs strategies like tournament selection or roulette wheel selection to favor individuals with higher fitness, promoting the propagation of promising solutions.

- **Crossover and Mutation:** Apply genetic operators, namely crossover and mutation, to create new individuals for the next generation. Crossover involves recombining genetic material from two parent individuals, while mutation introduces random changes. These operators introduce diversity in the population and facilitate the exploration of the solution space.

Step 3. Bayesian Optimization (BO):

- **Normalize Parameters:** Normalize the composite material parameters of each individual x_i to a common range, typically $[0, 1]$.

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

This normalization ensures fair comparisons and helps in managing the scale differences among parameters.

- **Sort Individuals:** Sort the individuals based on their predicted EMI shielding effectiveness. This step organizes the population in order of performance, aiding subsequent steps in the algorithm.

- **Bayesian Optimization:** Utilize Bayesian optimization to guide the search. Bayesian optimization considers the individuals' normalized parameter values and total crowding distances as acquisition criteria. The acquisition function, such as Expected Improvement (EI) is used as follows:

$$EI(x) = E[\max(0, f(x_{best}) - f(x))]$$

It updates the probabilistic model of the objective function to intelligently explore the parameter space while exploiting the information gained from previous evaluations.

Step 4. Termination Criteria:

Repeat the GP evolution and Bayesian optimization steps for a predefined number of generations or until convergence criteria are met. Convergence criteria may include reaching a specified number of generations, stable fitness improvement, or other measures indicative of algorithm convergence.

This detailed algorithm integrates the evolutionary capabilities of Genetic Programming with the probabilistic exploration of Bayesian optimization, providing a robust framework for optimizing complex composite material configurations. The interplay between these components facilitates the discovery of optimal solutions in the intricate, high-dimensional parameter space, thereby enhancing the efficiency and effectiveness of the optimization process. Once the non-linear multi factorial characteristics of the material properties have been captured by this proposed approach, the high dimensional complexity is mitigated and the next step is to predict and optimize the EMI shielding effect of the material using MDCS optimization algorithm which is explained in the following section.

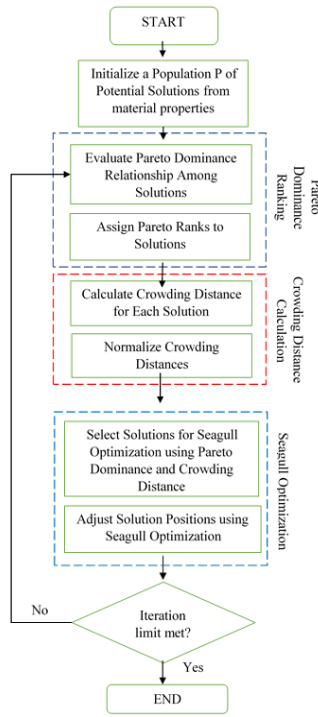


Figure 3. Flow chart of MDCS optimization

Multi-objective Dominant Crowding Seagull (MDCS) optimization algorithm

To improve the EMI shielding prediction accuracy, the MDCS optimization approach is introduced which integrates Pareto dominance ranking and crowding distance as mechanisms for identifying and preserving non-dominated solutions, forming what is known as the Pareto front. The Pareto front represents a set of solutions that provide a superior trade-off among conflicting objectives without sacrificing overall performance. The crowding distance component encourages the algorithm to find a diverse spread of solutions along

the Pareto front, ensuring a comprehensive exploration of the trade-off space. Finally, the EMI shielding effect is predicted using seagull optimization, leveraging the spread of dominant solutions identified in the earlier steps. Seagull optimization, a metaheuristic algorithm, likely aims to capitalize on the insights gained from the Pareto front and crowding distance metrics to further refine and optimize the EMI shielding performance. The detailed steps in this proposed MDCS method are depicted below in Figure 3.

Multi-objective Dominant Crowding Seagull (MDCS) optimization

Step 1. Initialization:

- Initialize a population P of potential solutions, each representing a combination of material properties. The solution vector is denoted as

$$X_i = [x_{i1}, x_{i2}, \dots, x_{ik}]$$

where k is the number of material properties.

Step 2. Pareto Dominance Ranking:

- Evaluate the Pareto dominance relationship among solutions in the population.
- For each solution X_i , determines its dominance status by comparing it to other solutions. A solution X_i dominates X_j if it is not worse than X_j in all objectives and strictly better in at least one objective.
- Assign Pareto ranks to solutions based on their dominance relationships. The lower the rank, the better the solution.

Step 3. Crowding Distance Calculation:

- For each solution X_i , calculate the crowding distance (D_i) based on the spread of solutions in the objective space. For a maximization problem, crowding distance is calculated as the sum of normalized differences in the objective values of adjacent solutions:

$$D_i = \sum_{m=1}^k \frac{f_m(X_{i+1}) - f_m(X_{i-1})}{f_m^{max} - f_m^{min}}$$

- Normalize the crowding distances to fall within the range $[0, 1]$. This step helps balance the importance of crowding distance against the scale of the objectives.

Step 4. Selection for Seagull Optimization:

- Combine the Pareto dominance ranking and crowding distance information to select solutions for the Seagull Optimization phase.

- Form a subset S of solutions that are not only Pareto dominant but also have higher crowding distances. This selection strategy ensures that diverse and non-dominated solutions are chosen for further refinement.

Step 5. Seagull Optimization:

- Seagull Optimization mimics the flocking behavior of seagulls to update the positions of solutions in the selected subset S .
- Each solution X_i adjusts its position based on its current position, the average position of its neighbors, and a random exploration term:

$$X_i^{new} = X_i + \alpha.Cohesion + \beta.Exploration$$

where α and β control the influence of cohesion and exploration, respectively.

- The Cohesion term attracts the solution towards the average position of its neighbors, promoting convergence.
- The Exploration term introduces a random component, enhancing exploration and preventing premature convergence.
- Repeat the Seagull Optimization process for a specified number of iterations or until convergence.

Step 6. Termination Criteria:

- Repeat steps 2-5 for a predefined number of iterations or until convergence criteria are met. Convergence criteria may include stability in the Pareto front, diversity of solutions, or other measures indicative of algorithm convergence.

This MDCS optimization algorithm integrates Pareto dominance ranking, crowding distance calculation, and the innovative Seagull Optimization phase to effectively address the trade-offs and conflicting relationships among different material properties. The Seagull Optimization process enhances the exploration and refinement of solutions, aiming for a well-distributed and diverse set along the Pareto front.

Overall, the “Bayesian-enriched genetic programming” method is a combination of the evolutionary power of genetic programming with Bayesian principles to navigate the complex, nonlinear functional space of polymer composite materials. This approach initializes a population of evolving trees, encoding various parameters. Through genetic operators and Bayesian-guided fitness evaluation, the algorithm dynamically adapts, iteratively evolving polymer composite structures for enhanced EMI shielding. The Bayesian enrichment provides probabilistic insights into parameter significance, offering a

nuanced understanding of their interplay. Then the “multi-objective dominant crowding seagull” optimization algorithm integrates Pareto dominance ranking, crowding distance, and seagull optimization. This method effectively balances conflicting material properties by preserving non-dominated solutions on the Pareto front and leveraging seagull optimization for EMI shielding refinement. These innovative approaches collectively enhance the optimization of polymer composites, providing a nuanced understanding of their trade-offs and facilitating the discovery of optimal solutions. The next section discusses the results obtained by the performance of the proposed machine learning based EMI shielding prediction and optimization method.

Result and Discussion

This section presents the results obtained from the suggested machine-learning model. According to the findings, the suggested model outperforms the others in terms of prediction accuracy and dimensional complexity. The performance of the proposed method in predicting EMI shielding is further illustrated by comparing it with other machine learning models that are currently in use.

System Requirements

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

Performance analysis of the proposed model

This section provides the analysis based on the parameters such as porosity, thickness and number of layers, and loading percentage. Partial dependance plots have also been discussed in this section.

Figure 4 depicts the percentage variation of porosity regarding the addition of the number of layers and the increment in thickness. From Figure 4(a), it can be seen that when the number of layers is increased, the percentage of porosity also increases and it reaches about 73% when the number of layers is four. Also, from Figure 4(b), it is obvious that the percentage of porosity increases with the thickness of the layer and it reaches about 62%, when the thickness is 5cm. The proposed Bayesian-enriched genetic programming captures these variations and these values are optimized to reduce the high dimensional complexities.

Figure 5 represents the percentage variation of the loading with respect to the number of layers and the porosity. From Figure 5(a), it is clear that the

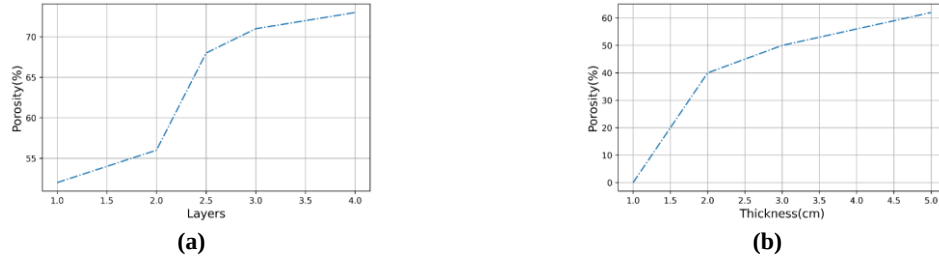


Figure 4. Variation of porosity with the number of layers and thickness

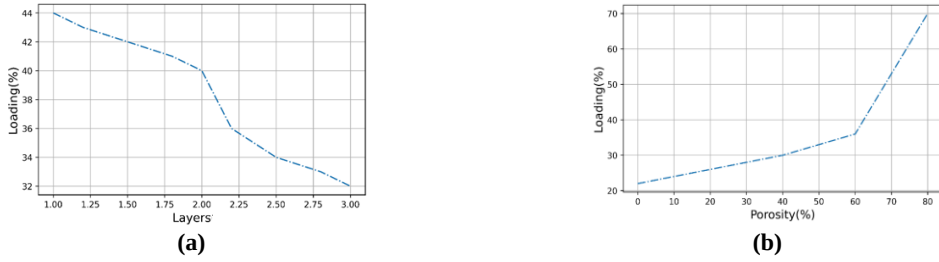


Figure 5. Variation of loading with layers and porosity

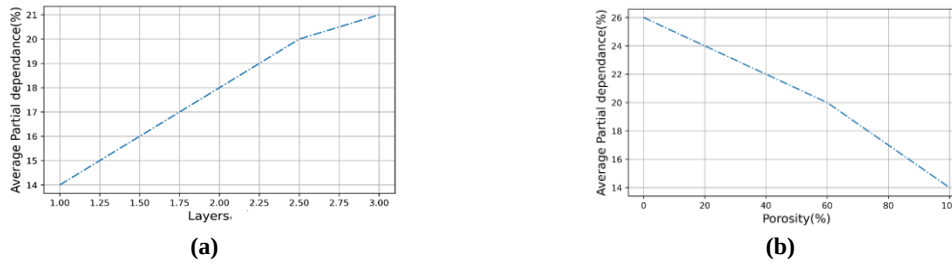


Figure 6. Average partial dependence for number of layers and porosity

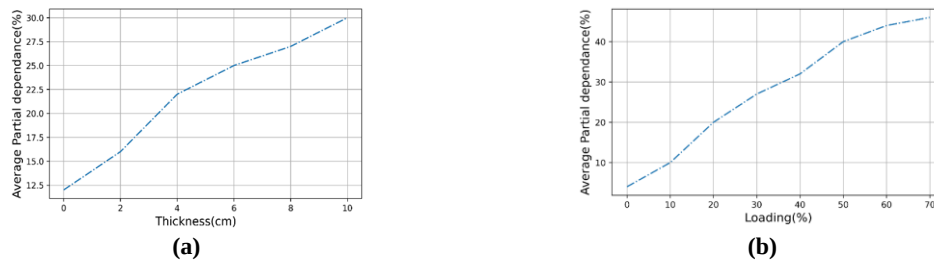


Figure 7. Average partial dependence for layer thickness and loading

number of layers is in inversely proportional to the loading percentage and for three number of layers, the loading percentage was calculated to be 32%. Figure 5(b) shows the direct proportional relationship between the porosity and loading percentage, and the loading percentage was found to be 70% when the porosity was 80%. The suggested MDCS optimization model identifies these proportional variations among the various properties of the composite material to aid in better prediction and optimization.

Figure 6 shows how the partial dependence changes with respect to the number of layers and the percentage of porosity. This partial dependence variation is handled by the Bayesian-Enriched

Genetic Programming which captures the multifactorial variations in material properties to improve the optimization. From Figure 6(a), it is seen that the average partial dependence becomes 21% when there are 3 number of layers and it increases with the layers. From 6(b), it is understood that the average partial dependence reduces when the percentage porosity increases, and it is found to be about 22% when the porosity is 40%.

Figure 7 shows how the partial dependence changes concerning the layer thickness and loading percentage. From Figure 7(a), it is perceived that the average partial dependence becomes 22.5% when the layer thickness is 4 cm and it increases with the thickness of the layers. From Figure 7(b), it is

observed that the average partial dependence increases when the percentage loading increases and it is about 40% when the loading is 50%. The average values of partial dependence variations were effectively optimized through Bayesian-enriched genetic programming and aided in the prediction process.

Figure 8 shows how the EMI changes with respect to the layers and thickness. Figure 8(a) shows that as the layers is increased, the samples' EMI completely rises. However, the EMI slows down when the layers is increased by roughly 11. From that we can infer that number of layers should be more than 11. Figure 8(b) demonstrates that the samples' EMI increases as thickness increases, but when the thickness increases by around 5 cm, the EMI decreases. That suggests that the thickness should ideally be greater than 5 cm. The Bayesian-enriched genetic programming method has successfully optimized the average values of partial dependence fluctuations, which helps with subsequent prediction processes.

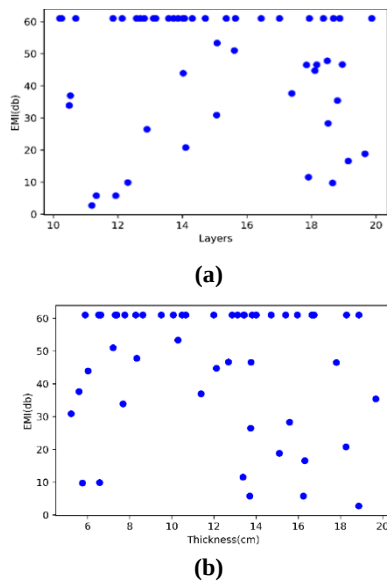


Figure 8. EMI for layers and thickness

Figure 9 illustrates how the EMI varies in relation to porosity and loading. From Figure 9(a), similar results are shown by the loading scatter plot, which shows that when the loading approaches 12%, the rising tendency slows down. From Figure 9(b) it shows a fairly rising trend as porosity increases, with the exception of 15% porosity. The Multi-Objective Dominant Crowding Seagull (MDCS) optimization method has successfully optimized multiple conflicting objectives and EMI shielding to represent the set of trade-off solutions.

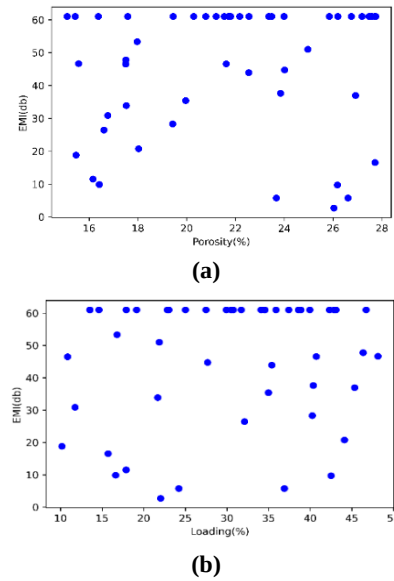


Figure 9. a. EMI for porosity (%) and b. EMI for loading (%)

Performance comparison of proposed model with other existing models

In this section, the performance of the proposed machine learning based EMI shielding optimization strategy is compared with other already available models and better results are listed below. Some existing machine learning methods (Shi *et al.*, 2022) such as KRR, RFR, ETR, GBT and WAE are compared with the proposed model.

Figure 10 depicts the 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. The KRR has the highest MAE of 0.4781 and the WAE has a MSE value of 0.4064, but the proposed method has only 0.3824 MAE value which is lower compared to other methods.

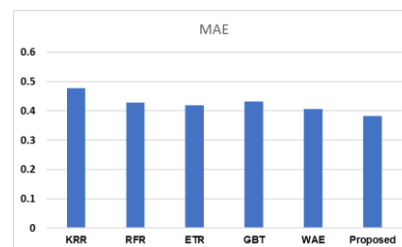


Figure 10. Comparison of MAE

Figure 11 is a comparison of the RSME of the proposed method with other existing methods and it shows that the KRR model has higher RSME of 0.9318 while GBT and WAE had RSMEs of 0.6786

and 0.6865 respectively. The proposed model has a lower RSME value of 0.6209 when compared to other methods taken for comparison. This lower RSME is achieved by the proposed multi-objective dominant crowding seagull optimization model.

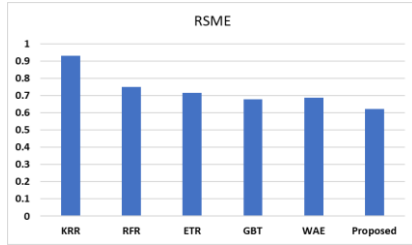


Figure 11. Comparison of RSME

Figure 12 compares the EMI shielding prediction accuracy of the proposed method with the existing models and the results show that the proposed Multi-objective Dominant Crowding Seagull optimization helps achieving a higher accuracy compared to other methods. The RFR has an accuracy value of 92.45% and ETR has 93.9%, but the proposed model achieves a higher accuracy of 98.7% compared to other methods and outperforms them.

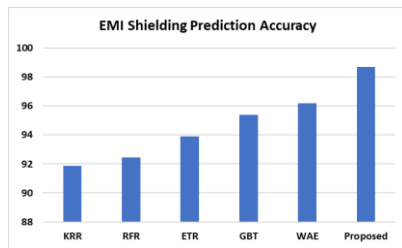


Figure 12. Comparison of prediction accuracy



Figure 13. Comparison of training time

Figure 13 shows the comparison results of the training time of various existing techniques and the proposed approach. The proposed approach gets trained faster than other methods which is demonstrated by its lower training time of 19 seconds. However, the other methods such as KRR, ETR, and WAE have higher training time of 82 sec, 57 sec, and 28 sec respectively. The Bayesian-enriched genetic programming in the proposed

approach reduces high-dimensional space complexity, leading to faster training.

Figure 14 shows the comparison results of the prediction time of different existing techniques and the proposed approach. It is clear that the proposed approach predicts the EMI shielding effect faster compared to other methods which is shown by a lower prediction time of 6 seconds only, but the other methods such as RFR, GBT and WAE have higher prediction time of 39, 20, and 11seconds respectively. This low prediction time is achieved by the proposed Bayesian-enriched genetic programming which effectively handles the multifactorial nature of the composites thereby reducing the complexity and the prediction time.

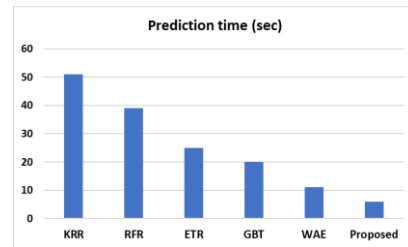


Figure 14. Comparison of prediction time

Overall, the proposed machine learning model for EMI shielding optimization, outperforms existing models such as KRR, RFR, ETR, GBT, and WAE across critical metrics. The model achieves significantly lower Mean Absolute Error (MAE) and Root Mean Square Error (RSME), indicating superior accuracy in predicting EMI shielding effectiveness. Moreover, the proposed approach attains a remarkable prediction accuracy of 98.7%, surpassing other methods, and demonstrates faster training and prediction times (19 seconds and 6 seconds, respectively) compared to counterparts like KRR, ETR, RFR, GBT, and WAE. Finally, the results highlight the efficacy of the proposed approach in achieving superior accuracy and efficiency in EMI shielding optimization.

Conclusion and future scope of work

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. The algorithm initializes a population of evolving trees, representing composite structures. Through

genetic operators and Bayesian-guided fitness evaluation, the algorithm iteratively refines the polymer composite structures for enhanced EMI shielding, providing probabilistic insights into the significance of each parameter. 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. The proposed methodology offers innovative solutions to navigate the complex parameter space, handle conflicting relationships, and optimize the trade-offs among different material properties. The effectiveness of these approaches contributes significantly to the advancement of materials engineering for EMI shielding applications.

This optimization technique may be utilised in the future to investigate the properties of polymer composites that are employed in different contexts. Different combinations of polymer composites are used in acoustic insulation because of their lightweight nature and flexibility. The sound-absorbing capabilities of polymer composites can be improved by adding embedding fillers or porous features. Polymer composites with appropriate filler combinations can be used in thermal management instead of Copper and Aluminium. A crucial way to enhance the thermal conductivity of a polymer involves the incorporation of high thermal conductive fillers within the host matrix. The bio-inspired optimization strategy discussed in this paper can be applied in the preparation of polymer composites loaded with fillers for thermal management and acoustic insulation applications.

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