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# Enhanced Prediction of Gain and Bandwidth for Metamaterial Antenna Using Machine Learning and Metaheuristic Optimization

## *Metamalzeme Anten için Sezgisel Optimizasyon ve Makine Öğrenmesi Kullanılarak Kazanç ve Bant Genişliğinin Gelişmiş Tahmini*

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## Abstract

The ongoing demand for improved performance in modern communication systems has driven recent developments in electromagnetic component design. Integrating metamaterial unit cell structures into antenna designs can be a solution for improving electromagnetic radiation properties of antennas. Also, in the antenna design process, both the achievement of multiple performances (such as size, gain, bandwidth, and return loss) and time efficiency have become increasingly important, and this is accomplished through advanced techniques like Machine Learning (ML) integrated with optimization algorithms. The purpose of this research is to develop an ML model for estimating the performance of a metamaterial antenna (gain and bandwidth). The Particle Swarm Optimization heuristic algorithm is used to optimize the hyperparameters of the ML models (Random Forest and Support Vector Machine). The ML models were evaluated using a comparison table in terms of $R^2$, MAE, MSE, and RMSE. The PSO-SVM hybrid model showed better predictive performance than PSO-RF, with MSEs of 0.0003 for gain and 0.0020 for bandwidth. The optimized ML models can be used to predict antenna gain and bandwidth more accurately.

**Keywords:** Bandwidth, hyperparameter tuning, machine learning, metamaterial antenna, PSO.

## Öz

Modern haberleşme sistemlerinde sürekli olarak daha iyi performans talebi, elektromanyetik bileşen tasarımında güncel gelişmelere yol açmıştır. Metamalzeme birim hücre yapılarının anten tasarımlarına entegre edilmesi, antenlerin elektromanyetik ışıma özelliklerini iyileştirmek için bir çözüm olabilir. Ayrıca, anten tasarımı sürecinde, hem çoklu performansların (boyut, bant genişliği, kazanç ve geri dönüş kaybı gibi) elde edilmesi hem de zaman verimliliği giderek daha önemli hale gelmiştir ve bu, optimizasyon algoritmaları entegre edilmiş Makine Öğrenimi (ML) gibi gelişmiş teknikler aracılığıyla gerçekleştirilmektedir. Bu çalışma, bir metamalzeme antenin performansını (kazanç ve bant genişliği) tahmin etmek için bir ML modeli geliştirmeyi amaçlamaktadır. ML modellerinin (Rastgele Orman ve Destek Vektör Makinesi) hiperparametrelerini optimize etmek için Parçacık Sürü Optimizasyonu sezgisel algoritması kullanılmıştır. ML modelleri, $R^2$, MAE, MSE ve RMSE açısından bir karşılaştırma tablosu kullanılarak değerlendirilmiştir. PSO-SVM hibrit modeli, PSO-RF ile karşılaştırıldığında daha iyi tahmin performansı (kazanç için MSE = 0.0003, bant genişliği için MSE = 0.0020) göstermiştir. Optimize edilmiş ML modelleri anten kazancını ve bant genişliğini daha doğru bir şekilde tahmin etmek için kullanılabilir.

**Anahtar Kelimeler:** Bant genişliği, hiperparametre ayarı, makine öğrenmesi, metamalzeme anten, PSO.

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## 1. Introduction

In the last decade, major improvements have been made in the microstructure and electromagnetic components of wireless communication technologies. As communication systems evolve towards higher data rates and more compact devices, the need for antennas that offer improved performance features, such as wider bandwidth, reduced size, and minimal signal loss, has become more important than ever. Different methods were studied to obtain the desired antenna performance. Optimization of some design parameters, such as feed position, substrate thickness, and geometrical dimensions, is part of the microstrip antenna design process. These design parameters are significant for achieving the desired antenna performance, such as improved radiation characteristics, enhanced bandwidth, and optimal gain (Khan et al., 2015; Bereket et al., 2023; Karasu et al., 2025). The integration of metamaterials into antennas is a solution for increasing the antenna gain and bandwidth (Tzouras and Koulouridis 2024). Achieving the desired (optimal) performance in antenna design, accurately determining the design parameters of the antenna, and the associated metamaterial unit cells are important research topics. The investigation of Machine Learning (ML) is ongoing and has been applied extensively in many different fields of data analysis. However, the complexity of antenna design continues to rise daily, which inspires antenna designers to take advantage of ML's strong competencies to develop reliable models that can be used for quick and smart antenna design optimization (Khafaga et al., 2022). Many researchers and professionals have recently studied ML for antenna design parameter optimization. Electromagnetic simulation software is typically used to determine the optimal values of these parameters. Although electromagnetic simulation software is widely used to design antennas for optimal parameter values to obtain the desired performance, it often requires significant computational time. On the other hand, ML-based methods, such as the one introduced in this study, offer a more efficient alternative by enabling fast and accurate antenna estimation (Abdelhamid & Alotaibi 2022).

A holistic approach to optimizing antenna and metamaterial structures both reduces computational time and increases the success of the resulting prototypes in practice. In recent years, various ML and optimization methods such as Particle Swarm Optimization (PSO), Genetic Algorithms, and Artificial Neural Networks have gained significant attention for providing fast and effective solutions (Vaz 2019b; El-Kenawy et al., 2022; Karasu & Ünaldı 2022; Haque et al., 2023; Alphonse et al., 2024; Haque et al., 2024). The two most widely used optimization methods in antenna design applications are PSO (Clerc 2010) and Differential Evolution (DE) (Price et al., 2005). The PSO method, which produces the finest capability of finding a solution without becoming constrained in local minima, is among the best widely used stochastic algorithms (Manohari et al., 2023). Khafaga et al. (2022) introduced an innovative optimization algorithm known as the adaptive dynamic sine cosine fitness grey wolf optimizer algorithm. They used five regression models, including Multi-Layer Perceptron (MLP), Decision Tree (DT), Support Vector Machines (SVM), and Random Forest (RF), for the design parameters of a double T-shape antenna. Wang et al. (2020) discussed how to develop high-performance materials and customized mechanical parts using Artificial Intelligence and ML techniques. Zhang et al. (2020) provided an overview of design and optimization methods based on evolutionary algorithms and ML for the smart manufacturing of photonic devices. In (Abdelhamid & Alotaibi 2022), the authors presented a deep learning network to accurately estimate the bandwidth of a metamaterial antenna and compared it with methods based on SVM, MLP, K-Nearest Neighbors, and ensemble models, which were performed on the dataset (Vaz 2019a). The same dataset was used in this study (Jain et al., 2024). They predicted key antenna parameters such as bandwidth, gain, and S11 by investigating four ML models - RF, Extra Trees, CatBoost, and XGBoost. A model to predict metamaterial antenna performance was proposed by El-Kenawy et al. (2022), which consisted of an RF algorithm, resulting in Root Mean Squared Error (RMSE) of 0.0891 for gain and 0.0102 for bandwidth. RF combined with the Gaussian Process was tested on the same dataset for predicting the results of the bandwidth parameters and |S11| in (Thao et al., 2024). The achieved RMSE and $R^2$ values reached 0.11 and 0.99, respectively.

In this study, the RF and SVM algorithms were used to predict the bandwidth and gain of a metamaterial antenna. PSO was used to determine the optimal values of the SVM and RF hyperparameters by minimizing the Mean Squared Error (MSE) on the training dataset. The model results were compared in terms of $R^2$, Mean Absolute Error (MAE), MSE, and RMSE performance metrics. The predicted results were compared with the simulated results obtained by electromagnetic simulation. The results show that the developed models demonstrate efficient prediction, making them suitable for use in the computational optimization of antenna designs.

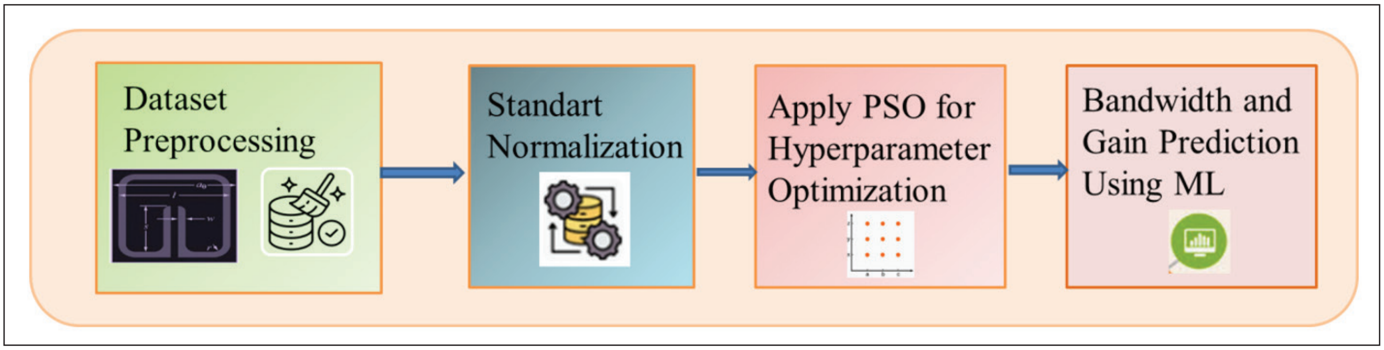


**Figure 1.** Flow chart of gain and bandwidth prediction of a metamaterial antenna.

## 2. Methodology

The dataset used in this study was obtained through electromagnetic simulations of a metamaterial antenna, as described in (Vaz 2019a, Vaz 2019b). The general structure of the presented methodology is illustrated in Figure 1. The process begins with a fundamental preprocessing stage, which includes handling missing values and formatting the data. In the second step, standard normalization was applied to scale the features, ensuring that all input variables contributed equally to the learning process. In the third step, PSO is applied to optimize the hyperparameters of ML models. Subsequently, the dataset was split into training and testing subsets. Finally, the SVM and RF algorithms were employed to predict the gain and bandwidth of the metamaterial antenna and run 10 times. The prediction results were evaluated based on the best and worst run, and the average of 10 runs. Each step of the proposed approach is given in detail in the following subsections.

### 2.1. Dataset

In this research, an open-access data set was used to predict the gain and bandwidth of the metamaterial antenna, which was obtained through Kaggle (Vaz 2019a). It contains 13 features (structural design parameters, gain, VSWR, bandwidth, and S11). It also includes a total of 572 records. The details of the dataset are presented in Table 1. A total of 63 missing values were detected in the bandwidth feature, and these samples were removed from the dataset.

**Table 1.** Summary of the dataset used (Alphonse et al., 2024).

| Feature | Definition | Minimum | Maximum | Standard deviation | Mean |
|---|---|---|---|---|---|
| **Wm** | Width and height of the split ring resonator cell | 2142.90 | 6964.30 | 691.58 | 2244.05 |
| **W0m** | Gap between rings | 162.86 | 651.43 | 184.91 | 400.59 |
| **dm** | Distance between rings | 77.14 | 488.57 | 150.90 | 275.43 |
| **tm** | Width of rings | 214.29 | 696.43 | 69.16 | 224.41 |
| **rows** | Number of split-ring resonator cells in an array | 3 | 7 | 1.44 | 4.10 |
| **Xa** | Distance between antenna patch and array | 0 | 10776 | 3287.86 | 4063.25 |
| **Ya** | Distance between split-ring resonator cells in the array | 2142.9 | 16607 | 5136.19 | 6947.47 |
| **gain** | Antenna gain | -5.65 | 3.24 | 0.68 | 2.68 |
| **VSWR** | Voltage Standing Wave Ratio of the antenna | 1.04 | 8.38 | 1.91 | 2.09 |
| **bandwidth** | Bandwidth of the antenna | 32.76 | 124.74 | 11.55 | 118.04 |
| **s** | Return loss of the antenna | -33.90 | -2.08 | 7.90 | -16.11 |
| **pr** | Power radiated by the antenna | 0.04 | 0.23 | 0.05 | 0.19 |
| **p0** | Power accepted by antenna | 0.19 | 0.50 | 0.09 | 0.46 |

### 2.2. SVM and RF

SVM is a widely used ML algorithm for estimation problems. It creates separable classes based on kernel functions by transforming the original input space into a higher-dimensional space using the maximum margin (Guhathakurata et al., 2021; Yalçın & Ünaldı 2022). C, gamma, and epsilon SVM hyperparameters are used to optimize by PSO. C is a penalty parameter that helps provide a balance between having a wide margin and achieving low training error. Epsilon is a tolerance margin that allows small prediction errors to be simply ignored. Gamma is the kernel coefficient for the radial basis function and denotes the influence of individual training samples on the decision boundary.

RF is a popular ensemble learning algorithm based on DT. It builds a number of decision trees and combines their outputs to improve prediction accuracy and prevent overfitting. The max_depth and n_estimators parameters are selected to tune and optimize. max_depth is the maximum depth of each tree, and n_estimators is the number of trees. Shallow trees can better generalize to new and unseen samples, and increasing the number of trees often improves the predictive performance. Deeper trees can capture complex patterns in greater detail by focusing more on the training data, but this leads to the model overfitting. Using a larger number of trees generally yields more accurate and reliable predictions, but may require more computational cost and processing time.

As mentioned, the choice of hyperparameters significantly impacts the performance of ML methods. Hyperparameter tuning is essential to ensure an optimal balance between model complexity, accuracy, and generalization capability.

### 2.3. Hyperparameter Tuning and PSO

ML models can be quite sensitive to how their hyperparameters are set, and tuning hyperparameters can substantially enhance the model's performance. In this study, hyperparameter tuning for SVM and RF methods was performed with the PSO algorithm.

PSO is a metaphor-based metaheuristic optimization algorithm. It was developed by Kennedy & Eberhart (1995) and was discovered through a simulation of the social behavior of bird flocking or fish schooling (Gad 2022, Vanneschi & Silva 2023). PSO helps to search the parameter space and minimize/maximize the fitness/objective function. Due to its ease of implementation, flexibility, versatility, and the small number of hyperparameters, it has been successfully applied to solve diverse optimization problems over many areas (Yalçın 2012, Abualigah 2025). The basic steps of the PSO algorithm are shown in Figure 2.

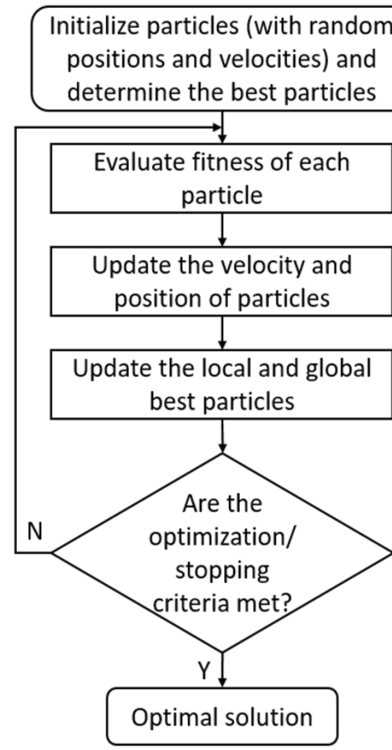


**Figure 2.** Flowchart of the PSO algorithm.

## 3. Experimental Study and Results

The Google Colab platform and Python programming language were used to build the models. Scikit-Learn, Pandas, NumPy, Pyswarm, and Matplotlib Python libraries were utilized to develop ML models. The dataset was divided into two subsets: 80%:20% training and test datasets. There are 407 samples in the training dataset and 102 samples in the test dataset. The data were then normalized using Standard Scaler (mean = 0 and standard deviation = 1 of each feature). MSE was used as the optimization objective for PSO. The swarm size is 10, and the number of iterations is 20. The models were trained on the training data using given SVM hyperparameters (C, epsilon, and gamma) and RF hyperparameters (n_estimators and max_depth). The bounds of the hyperparameters used for optimization are given in Table 2.

**Table 2.** Hyperparameter tuning.

| Method | Parameter | Search Space |
|---|---|---|
| **SVM** | C<br>Gamma<br>Epsilon | 0.1 – 100<br>0.0001 – 1<br>0.001 – 1 |
| **RF** | n_estimators<br>max_depth | 10 – 200<br>2 – 30 |

All models were run separately 10 times. The trained models were tested with the testing subset. Best, worst, and mean $R^2$, MSE, RMSE, and MAE performance metrics were calculated for gain and bandwidth. The performance results obtained for the test dataset and best parameters for SVM and RF are presented in Table 3 and Table 4, respectively.

Our findings show that the proposed model using SVM results in an MSE of 0.0003 for gain and an MSE of 0.0020 for bandwidth (best run); RF results in an MSE of 0.0092 for gain and MSE of 0.0120 for bandwidth (best run). In terms of all metrics, the PSO-SVM hybrid model showed better prediction performance compared to PSO-RF. These results indicate that the dataset is suitable for the proposed PSO-SWM hybrid model and hyperparameter optimization helps improve the model performance.

The obtained results, when compared with similar studies in the literature, reveal that the performance of the proposed model is consistent with the existing studies. In the study (Thao et al., 2024), a model using both RF and Gaussian Process methods resulted in RMSE = 0.11 and $R^2$ = 0.99 for bandwidth and |S11| estimations, respectively. Compared to these values, the low RMSE values obtained with the PSO-SVM model (0.0174 for gain and 0.0451 for bandwidth) indicate that the model provides higher accuracy predictions. SVM's sensitivity to nonlinear relationships, in particular, may have better modeled the complex parameter relationships in metamaterial antenna performance.

The optimized ensemble model proposed by El-Kenawy et al. (2022) used the RF algorithm and achieved RMSE = 0.0891 for gain and RMSE = 0.0102 for bandwidth. Considering the PSO-RF results (gain, RMSE = 0.0961; bandwidth, RMSE = 0.1097), a similar error was obtained in gain estimation, while the error in the bandwidth estimation

**Table 3.** The results for the gain performance metric.

| Method | Best Parameters | Metric | Best | Mean | Worst |
|---|---|---|---|---|---|
| **SVM** | C: 99.86<br>Gamma: 0.0052<br>Epsilon: 0.0015 | $R^2$ | 0.9969 | 0.9952 | 0.9881 |
| | | MSE | 0.0003 | 0.0005 | 0.0011 |
| | | RMSE | 0.0174 | 0.0210 | 0.0339 |
| | | MAE | 0.0054 | 0.0075 | 0.0192 |
| **RF** | n_estimators: 12<br>max_depth: 28 | $R^2$ | 0.9045 | 0.8879 | 0.8756 |
| | | MSE | 0.0092 | 0.0108 | 0.0120 |
| | | RMSE | 0.0961 | 0.1040 | 0.1097 |
| | | MAE | 0.9045 | 0.0.300 | 0.0319 |

**Table 4.** The results for the bandwidth performance metric.

| Method | Best Parameters | Metric | Best | Mean | Worst |
|---|---|---|---|---|---|
| **SVM** | C: 99.987<br>Gamma: 0.0508<br>Epsilon: 0.0239 | $R^2$ | 0.9983 | 0.9891 | 0.9453 |
| | | MSE | 0.0020 | 0.0132 | 0.0661 |
| | | RMSE | 0.0451 | 0.0933 | 0.2571 |
| | | MAE | 0.0305 | 0.0607 | 0.9453 |
| **RF** | n_estimators: 19<br>max_depth: 11 | $R^2$ | 0.9900 | 0.9793 | 0.9770 |
| | | MSE | 0.0120 | 0.0250 | 0.0.279 |
| | | RMSE | 0.1097 | 0.1572 | 0.1669 |
| | | MAE | 0.0287 | 0.0390 | 0.0486 |

was found to be slightly higher compared to the study of (El-Kenawy et al., 2022). This difference may be due to differences in the hyperparameter space specified in the model (e.g., number of trees, maximum depth, sampling rate, etc.) or the distribution of the data subset used. Re-tuning these hyperparameters (e.g., n_estimators, max_depth, min_samples_split, and max_features) through a systematic optimization process can reduce the error, especially in bandwidth estimation of the PSO-RF model.

Depending on the best run, the predicted results (for PSO-SVM and PSO-RF) and simulated values for both bandwidth and gain are illustrated comparatively in Figures 3 and 4, respectively. As can be seen from the figures, a good agreement is achieved between the simulated and predicted results in terms of both gain and bandwidth. These two hybrid models can accurately predict the antenna bandwidth and gain.

## 4. Conclusion

The performance of the proposed models reveals that they provide high performance in accurately predicting the gain and bandwidth of the metamaterial antenna. These models can be used to accelerate the design process and improve antenna performance. By optimizing the design parameters of antennas and metamaterial unit cells, they offer an alternative for antenna design with high accuracy in complex design spaces. The predicted results are compared with the simulated results, which were obtained by an electromagnetic simulation tool. PSO-SVM with $R^2$ values of 0.9969 (gain) and 0.9983 (bandwidth) outperforms PSO-RF. Results show that the presented method provides a computationally efficient design optimization process for the design of antennas. Different metaheuristic optimization algorithms can be investigated and compared with PSO to

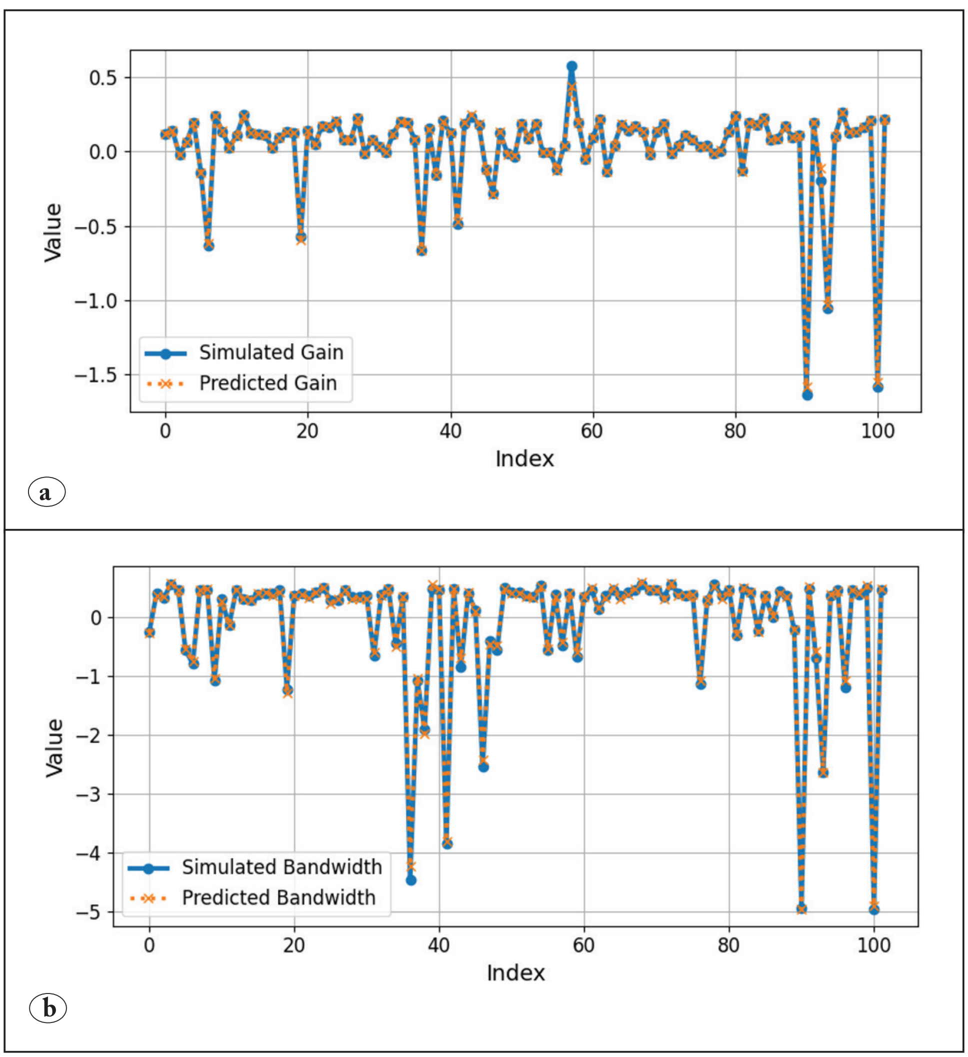


**Figure 3.** PSO-SVM model, (a) gain, and (b) bandwidth predictions.

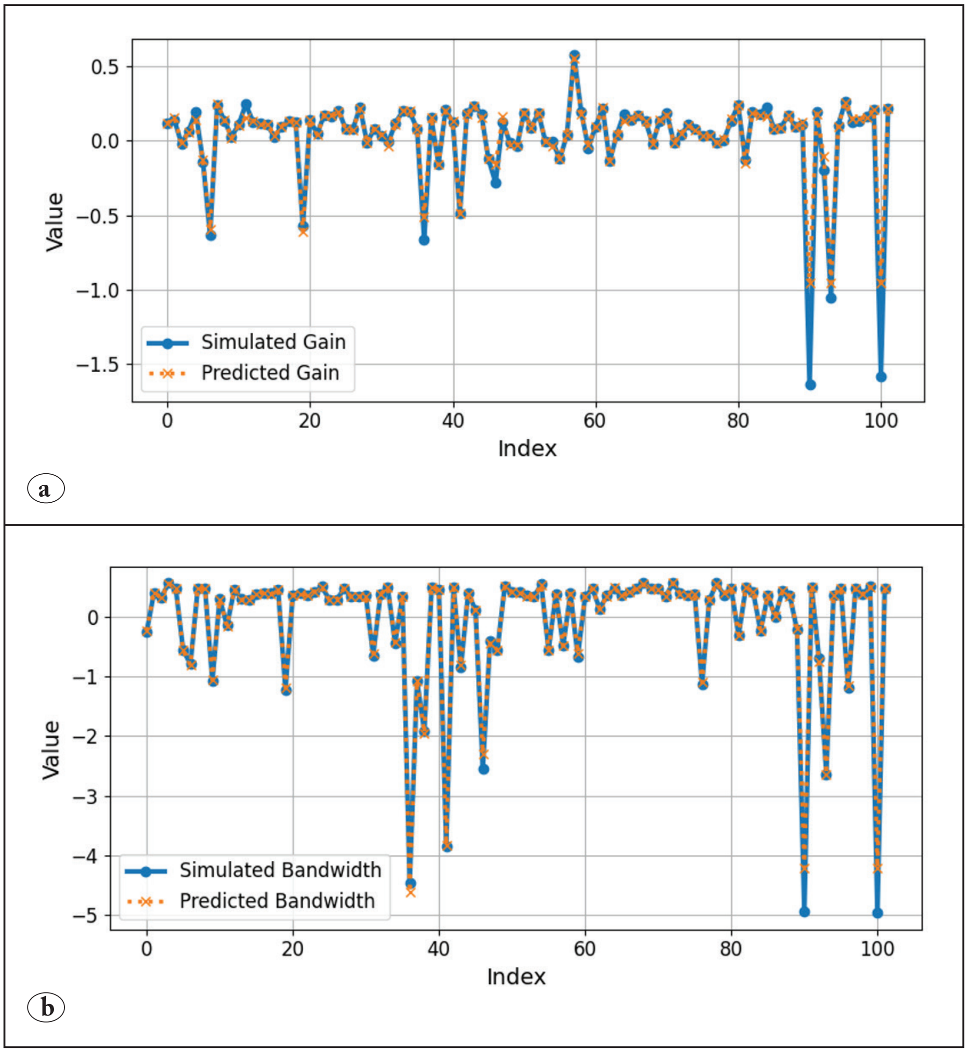


**Figure 4.** PSO-RF model, (a) gain, and (b) bandwidth predictions.

enhance optimization performance in future work. Furthermore, the model's generalization capability can be improved by utilizing comprehensive datasets obtained from different metamaterial antenna structures.

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