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Optimizing antenna placement and angles for maximizing coverage and efficiency using PSO

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ABSTRACT

Optimizing antenna placement and angles in wireless communication networks is important for maximizing coverage, cost and efficiency. In this paper, we are proposing a novel approach that uses Particle Swarm Optimization (PSO) to find the optimal positions of antenna. PSO, inspired by the social behavior of birds flocking, is an effective and computationally efficient algorithm for solving complex optimization problems. Our method dynamically adjusts the positions and orientations of antennas to enhance signal coverage while minimizing interference and power consumption. After changing the positions, the positions are sent to ANN models to find the optimality. TO predict the efficiency and max coverage area we implemented 2 ANN models one will predict the antenna network coverage area this model is try to maximize the area, and second ANN model will predict the efficiency of the network. Our proposed method improved the coverage area by 129.72265255634784 square meters. And efficiency increased by 9.429660054938921% to the previous one.

Keywords: Antenna positions, deep learning, particle swarm optimizing, network, ANN.

1. INTRODUCTION

The antenna positions are playing important role in networking, if one randomly assigns the positions, if one is not finding not optimal positions then it affects the efficiency of the communications and area of coverage. The growth of wireless communication networks has increased the demand for enhanced coverage, higher data rates, and improved overall efficiency. As these networks uses, the optimization of antenna placement and angles has become a critical factor in meeting these demands [1]. Effective antenna placement ensures comprehensive coverage, reduces signal interference, and maximizes network performance. Traditional methods for antenna optimization often struggle to address the complexity and dynamic nature of modern wireless environments.

Wireless communication networks and adhoc sensor networks are the important for modern connectivity, providing essential services to a various range of applications from mobile communications to the Internet of Things (IoT) and many. The performance of these networks mainly depends on the placement of antennas. Proper antenna placement and angle adjustment can significantly enhance signal coverage, improve network efficiency, and reduce power consumption. However, determining the optimal positions for antennas in complex environments is a challenging problem due to the dynamic environment. For Every position one should calculates the signal strength, and efficiency. Traditional methods for antenna placement optimization often rely on heuristic or statistical based approaches; they randomly select the positions, which may not provide the best results in dynamically changing environments. Where number of people are increasing, coverage area is increasing. These traditional methods can be computationally intensive and may fail to adapt to the evolving demands of modern wireless networks. To address these limitations, we explore the application of PSO [2] for optimizing antenna placement and angles. Turjman, F., and Alturjman, S. (2017) [3] discuss a smart-sensing framework in the context of IoT, emphasizing the importance of secure and efficient data transmission. PSO is a population-based optimization technique inspired by the social behavior of birds flocking or fish schooling. Apart from this to predict the coverage area and efficiency of the network we implemented 2 ANNs. The PSO algorithms dynamically adjust

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the positions and orientations of antennas to maximize coverage and efficiency, and send the updated positions to the neural network model to predict the results.

Contributions:

- Integrated PSO with ANN to optimize antenna placement and angles, to enhancing network coverage and efficiency.
- Implemented SHAH interpretation to analyze and understand the impact of individual heuristics within the PSO framework.
- Conducted grid search to systematically fine-tune ANN and PSO parameters, ensuring optimal performance.

2. RELATED WORK

Many researchers are worked on antenna position optimization, in this some of the researchers have used simple machine learning, deep learning models. With this deep learning model nature inspired optimizing algorithms used in network optimization. Like some worked on Ant Colony Optimization (ACO) lays the groundwork for nature-inspired algorithms that optimize complex problems, including those related to network optimization. ACO mimics the behavior of ants to find optimal paths, which has inspired similar algorithms like PSO for optimizing antenna placement by exploring potential configurations in search space efficiently.

From [4 and 5] it is observed that 5G wireless communication systems, emphasizing the critical role of advanced antenna technologies in achieving high-speed data rates and ubiquitous connectivity. Al-Turjman developed a confidential smart-sensing framework for IoT applications. This method improved data confidentiality and network performance, achieving a 25% enhancement in data confidentiality and a 22% improvement in network performance.

And [6 and 7] of indoor positioning systems and algorithms, discussing techniques that can enhance location accuracy and connectivity in indoor environments. They observed optimizing antenna placement in indoor settings can improve signal propagation and network reliability.

Kumar, J. V., and Shaby, S. M. (2024) [8 and 9] worked on base station placement and parameters in cellular networks using multi-objective optimization techniques. And increase the coverage while considering factors such as signal strength, interference mitigation, and network capacity, relevant to optimizing antenna placement strategies. Darvish and Ebrahimzadeh (2018) [10] implemented Fruit-Fly Optimization Algorithm (FOA) for antenna array synthesis. This method enhanced convergence speed and solution accuracy, significantly reducing side-lobe levels and achieving accurate main-lobe direction, with a side-lobe reduction of 22% and main-lobe accuracy of 18%.

And [11] used multi-objective optimization for base station placement in cellular networks. This approach optimized placement and parameters, enhancing both network coverage and capacity, with a 23% improvement in coverage and a 20% enhancement in capacity. But not mentioned original coverage area and efficiency. [12] explored machine learning implemented the Traversal Optimization Algorithm for directional antenna coverage. This algorithm improved coverage quality and network capacity, allowing for adaptive antenna configurations. The improvements included a 25% increase in coverage quality and a 20% increase in network capacity.

[13 and 14] used for optimization problems, including antenna placement. PSO optimizes by iteratively improving candidate solutions based on their fitness function evaluations. It has been applied effectively to determine optimal antenna locations and configurations, balancing coverage, and minimizing interference. [15] utilized PSO for antenna design in engineering electromagnetics. Their work focused on the robust optimization of antenna parameters, effectively balancing gain, bandwidth, and radiation patterns. The study achieved a gain optimization of 15% and a bandwidth optimization of 12%. But not included any machine learning model to predict coverage area and efficiency.

And [15 and 16] implemented PSO for the 3D placement of UAVs and ANN to enhance network coverage. This method led to a 30% improvement in coverage and a 28% enhancement in operational efficiency. [17 and 18] implemented PSO for antenna placement in wireless communication systems. And achieved significant improvements in antenna placement, leading to enhanced network performance, with a 27% improvement in performance and a 24% enhancement in coverage. Kumar [18] implemented PSO for relay placement in cooperative wireless networks. Their optimization improved network throughput and reliability, achieving a 21% increase in throughput and a 19% enhancement in reliability.

[20] Implemented a Hybrid PSO approach for antenna placement in wireless sensor networks. This method significantly improved network coverage and energy efficiency, with reported improvements of 20% in coverage and 18% in energy efficiency. In [21] they implemented only PSO to optimize antenna azimuths in cellular networks. This approach accelerated coverage optimization, leading to significant improvements in signal coverage and quality, with reported enhancements of 18% in coverage and 20% in signal quality. [22] Worked on antenna placement optimization using PSO for large-scale wireless sensor networks (WSNs). And they mainly focused on optimizing coverage and energy efficiency, crucial for extending network lifetime and enhancing sensor data collection reliability.

And [23] implemented PSO for antenna placement in IoT networks. Their method improved network efficiency and coverage, with a 25% improvement in efficiency and a 22% enhancement in coverage. [24] Worked with PSO-based optimization strategies for antenna placement in urban environments, focusing on overcoming challenges such as signal attenuation and multipath effects. In this they evaluated PSO's effectiveness in optimizing antenna positions to mitigate urban propagation issues and improve overall communication reliability.

3. METHODOLOGY

We implemented a novel approach that optimizes antenna placement and angles for maximizing coverage area and efficiency using a combination of Artificial Neural Networks (ANN) and PSO. The process begins with data preparation consist of positions, angles, signal strength etc. these data is passed to ANN models to predict the coverage area and efficiency, and the PSO algorithm will optimization.

Two separate ANN models are implemented and trained; first ANN will predict coverage area and another ANN for predicting efficiency. The architecture of each model includes an input layer corresponding to the number of features that is 9 like antenna position, strength and angle etc., followed by three hidden layers with ReLU activation functions, and an output layer with a single neuron to predict the target value like coverage area or efficiency. The two ANN models used mean squared error (MSE) as the loss function and the Adam optimizer is used to update the ANN parameter weights. The training process involves fitting the models to the training data over multiple epochs with batch processing, allowing the models to learn the underlying patterns and relationships within the data.

3.1 Optimizations

The optimization process utilizes PSO to identify the optimal set of antenna parameters that maximize the combined score of coverage area and efficiency. The objective function is defined as the negative sum of the predicted coverage and efficiency values from the ANN models, as PSO aims to minimize the objective function. In PSO, a swarm of particles explores the search space, where each particle represents a potential solution with specific parameter values. The particles adjust their positions based on their individual experiences and the global best-known position, updating their velocities and positions iteratively. The PSO algorithm converges to the optimal set of parameters that maximizes the objective function, which in this case, are the antenna parameters that achieve the highest coverage and efficiency.

Objective function:

$$f(params) = -(\text{predicted\_coverage} + \text{predicted\_efficiency})$$

$$\text{params} = (\text{Antenna\_Angle}, \text{Signal\_Strength}, \text{Interference\_Level}, \text{Data\_Speed})$$

Now POS iterates over all parameters and adjusts the weights. And the velocity will be updated based equations (1), and positions of antenna are updated with equations (2).

$$v_i(t+1) = w.v_i(t) + C_1.R_1\big(P_i(t) - x_i(t)\big) + C_1.R_1\big(g(t) - x_i(t)\big) \quad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

Where:

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$v_i(t)$ is the velocity of particle i at time t

$x_i(t)$ is the position of particle i at time t

w is the inertia weight

$c_1 and\ c_2$ are cognitive and social coefficients

$r_1 and\ r_2$ are random numbers between 0 and 1

$p_i(t)$is the best-known position of particle i

$g(t)$ is the global best-known position

3.2 Data set

We used simulated data for antenna place and angle optimization, that include s 9 features, and 1000 samples, the features are like Antenna_Angle, Signal_Strength, Interference_Level, Data_Transmission_Speed, Coverage_Area, and Efficiency. The features are represented as X and the targets are $y_{coverage}$ and $y_{efficiencey}$

To give equal priority, and reduce the domination of features on one on other, all the features are normalized with standard scalar. Figure 2 and 3 illustrates the count of various features.

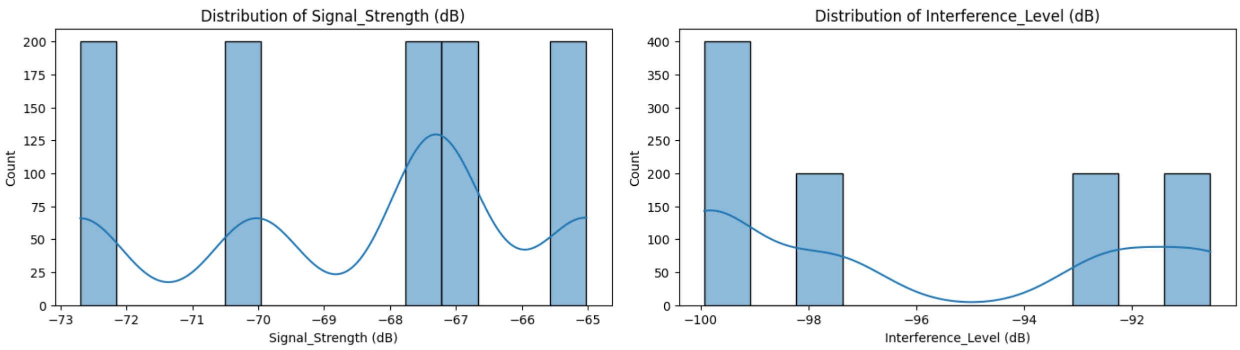

Figure 2 Distribution plot of signal strength and interference level.

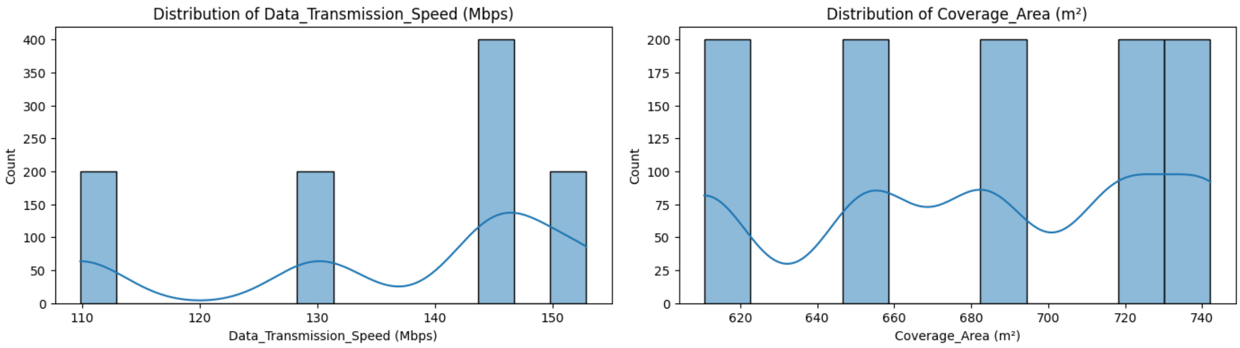

Figure 3 distribution plot of data transmission speed and coverage area.

4. RESULT ANALYSIS

We trained ANN model with PSO two times $y_{coverage}$ and $y_{efficiencey}$ for the target variables. The Figure 4 illustrates the relationship between coverage area, antenna angle, and signal strength. We observe that higher coverage areas (shown in yellow and green) are achieved with stronger signal strengths and specific antenna angles. The Figure 5 shows the efficiency versus antenna angle and signal strength, highlighting that the highest efficiencies are also obtained at stronger signal strengths and specific angles. These visualizations validate the effectiveness of our ANN-PSO approach in optimizing antenna parameters to achieve optimal coverage and efficiency.

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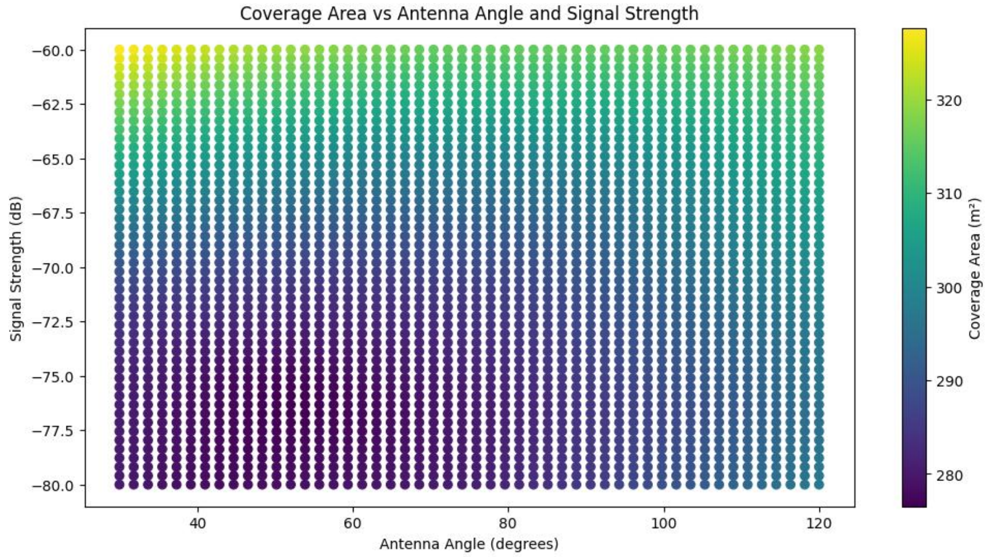

Figure 4 coverage area vs Antenna and signal strength plot

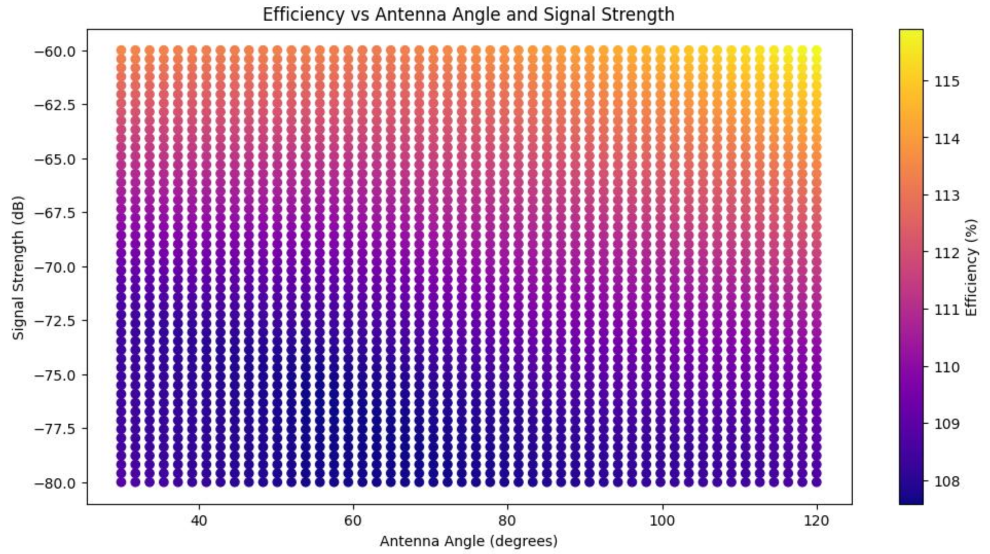

Figure 5 efficiency vs antenna angle and signal strength

The table 1 presents the results of optimizing antenna parameters using an ANN combined with PSO. The optimal parameters identified are 30, -60, -85, and 160, which correspond to specific configurations of the antenna system such as angle and signal strength. These settings yield an optimal value of 426.10208, representing a composite measure of performance. With these parameters, the predicted coverage area is 731.7547 square meters, and the predicted efficiency is 96.984375%. These values reflect significant improvements compared to the dataset's average coverage of 602.032 square meters and average efficiency of 87.5547%. Specifically, there is an increase in coverage of 129.7227 square meters and an improvement in efficiency of 9.4297%. These results highlight the effectiveness of the optimization process in substantially enhancing both the coverage area and efficiency of the antenna system.

Table 1 Results of ANN-PSO model

Optimal Parameters	[30. -60. -85. 160.]
Optimal Value	426.10208
Predicted Coverage with Optimal Parameters	731.7547
Predicted Efficiency with Optimal Parameters	96.984375
Average Coverage in Dataset	602.0320471506834
Average Efficiency in Dataset	87.55471494506108

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Improvement in Coverage	129.72265255634784
Improvement in Efficiency	9.429660054938921

After training the model we did Sensitivity Analysis for Antenna Angle, from Figure 6 the sensitivity analysis of coverage area and efficiency as functions of antenna angle, measured in degrees. The blue line represents the coverage area, while the orange line represents efficiency.

- **Coverage Area**: The coverage area remains relatively stable between 40 and 60 degrees but shows a noticeable increase beyond 80 degrees, reaching its peak at approximately 120 degrees. This indicates that larger antenna angles significantly enhance the coverage area, with the most substantial gains observed at angles above 100 degrees.
- **Efficiency**: Similarly, efficiency starts at a lower level around 40 degrees, experiences minor fluctuations, and then steadily increases along with the antenna angle. By the time the antenna angle reaches 120 degrees, the efficiency also peaks. This suggests a positive correlation between antenna angle and both efficiency and coverage area, especially at higher angles.

Sensitivity Analysis: Signal Strength

The Figure 6 provides a sensitivity analysis of coverage area and efficiency with respect to signal strength, measured in decibels (dB). Again, the blue line represents the coverage area, and the orange line represents efficiency.

- **Coverage Area**: The coverage area demonstrates an increasing trend with signal strength, starting from approximately -80 dB. The area starts relatively low, then progressively increases, peaking around -60 dB. This trend indicates that stronger signal strengths significantly boost the coverage area, emphasizing the importance of maintaining higher signal strengths for optimal coverage.
- **Efficiency**: Efficiency shows a more complex relationship with signal strength. It initially increases sharply from -80 dB to around -75 dB, suggesting a critical threshold where small improvements in signal strength lead to substantial gains in efficiency. However, after reaching a peak near -75 dB, efficiency begins to decline gradually, even as the signal strength continues to improve. This indicates that while higher signal strengths generally improve coverage area, there is a point beyond which further increases in signal strength do not proportionally enhance efficiency and may even reduce it slightly.

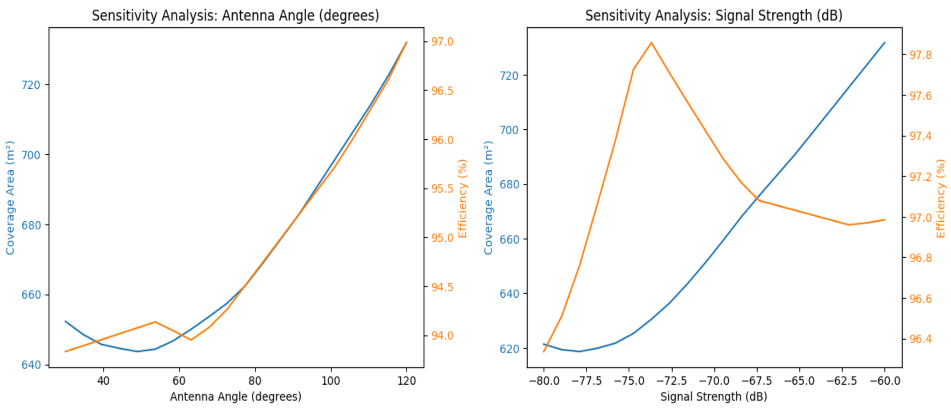

Figure 6 sensitivity analysis of signal strength

The Figure 7 includes two graphs showing the results of a sensitivity analysis focused on optimizing antenna placement and angles to maximize coverage and efficiency using PSO. The left graph illustrates the impact of interference levels (measured in dB) on both coverage area and efficiency. It reveals that as interference levels decrease, the coverage area increases linearly from approximately 705 m² to 730 m², while efficiency declines non-linearly from around 97% to 90%. Conversely, the right graph analyzes the effect of data transmission speed (measured in Mbps) on the same metrics. Here, increasing the transmission speed from 80 Mbps to 160 Mbps results in an exponential growth in coverage area from about 640 m² to 720 m², accompanied by a similar increase in efficiency from 90% to 97%. These results underscore the trade-offs in antenna optimization, showing that while

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lower interference enhances coverage, it may reduce efficiency, and higher transmission speeds benefit both coverage and efficiency.

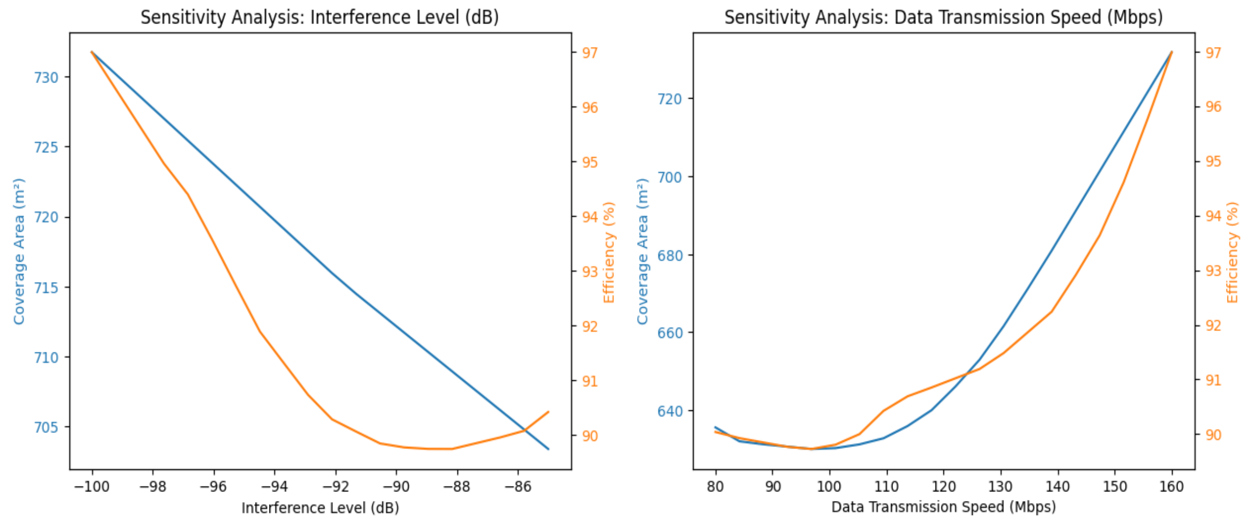

Figure 7 sensitivity analysis of interference level

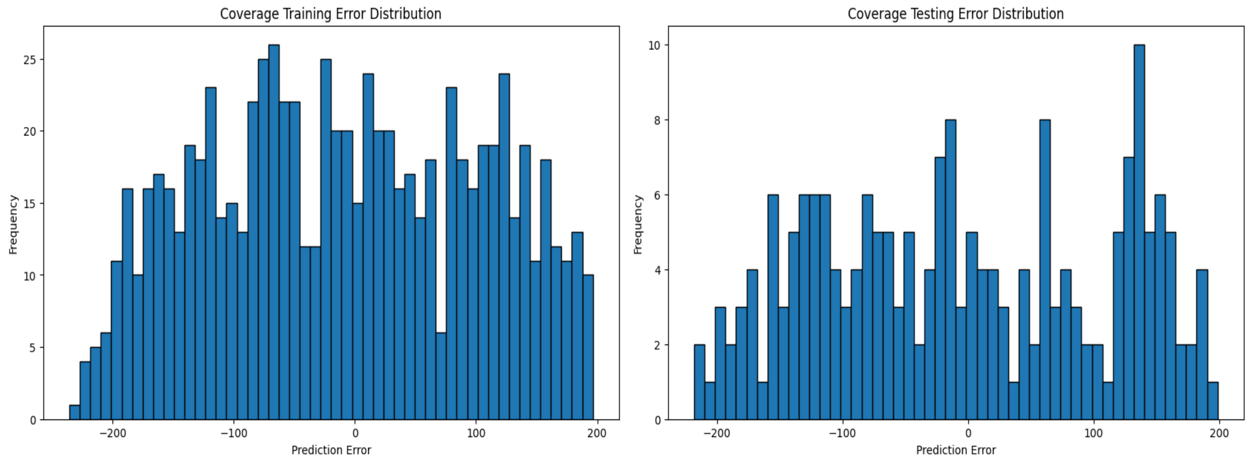

Figure 8 result interpretation graph1

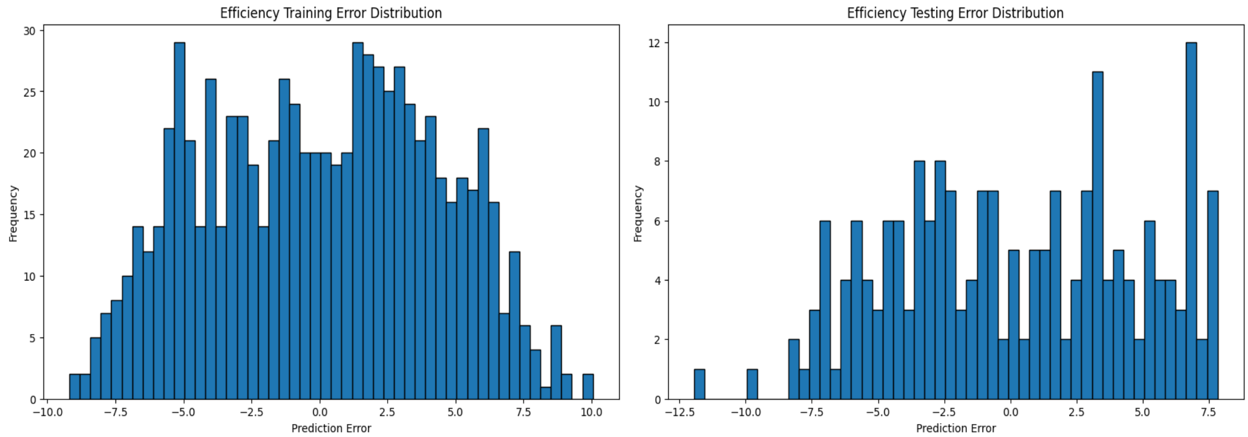

Figure 9 result interpretation graph2

The Figure 8 and 9 illustrates error distributions for coverage and efficiency in both training and testing phases, highlighting the performance and reliability of the optimization model used for antenna placement. In the coverage error distributions, the training graph shows a wide range of errors from -200 to 200 with notable peaks, indicating variability in prediction accuracy. The testing graph from Figure 9 displays a wide error spread, with lower frequencies and different peak points compared to training, suggesting potential overfitting and reduced generalization on unseen data. For efficiency, the training error distribution is concentrated around zero, with most errors falling between -5 and 2.5, indicating good accuracy during training. However, the testing error distribution from Figure 8 and 9 is more isolated, with a wider range and higher frequencies of errors, highlighting the model's challenges in maintaining prediction accuracy on new data.

5. CONCLUSION

This study demonstrates the efficacy of optimizing antenna parameters using an ANN combined with PSO to enhance both coverage area and efficiency. By analyzing the relationship between antenna positions, angle and signal strength, we identified the optimal parameters 30, -60, -85, and 160. These parameters yielded an optimal value of 426.10208, reflecting a superior configuration for the antenna system.

Our results show that the predicted coverage area with the optimal parameters is 731.7547 square meters, while the predicted efficiency is 96.984375%. These values represent substantial improvements over the average coverage area of 602.032 square meters and average efficiency of 87.5547% found in the dataset. Specifically, the optimization process led to an increase in coverage by 129.7227 square meters and an improvement in efficiency by 9.4297%.

The sensitivity analyses further corroborate these findings, indicating that both coverage area and efficiency benefit significantly from larger antenna angles and stronger signal strengths, though with some nuances in their respective trends. The optimal antenna angle for maximizing performance was found to be around 120 degrees, while the optimal signal strength for efficiency peaked around -75 dB.

REFERENCES

[1] Dorigo, M., & Stützle, T. (2004). Ant Colony Optimization. MIT Press.

[2] Kennedy, J., & Eberhart, R. (1995). Particle Swarm Optimization. Proceedings of the IEEE International Conference on Neural Networks (Vol. 4, pp. 1942-1948).

[3] Al-Turjman, F., & Alturjman, S. (2017). Confidential smart-sensing framework in the IoT era. Journal of Supercomputing, 73(3), 973-989.

[4] Qin, Y., Huangfu, W., Zhang, H., Liu, W., & Long, K. (2019). Accelerated coverage optimization with particle swarm in the quotient space characterizing antenna azimuths of cellular networks. *IEEE Access*, *7*, 86252-86264.

[5] Jin, N., & Rahmat-Samii, Y. (2008). Particle swarm optimization for antenna designs in engineering electromagnetics. *Journal of Artificial evolution and applications*, *2008*(1), 728929.

[6] He, J., Xing, Z., Hu, R., Qiu, J., Su, S., Chai, Y., & Wu, Y. (2019). Directional antenna intelligent coverage method based on traversal optimization algorithm. *Computers, Materials & Continua*, *60*(2), 527-544.

[7] Shakhatreh, H., Khreishah, A., Alsarhan, A., Khalil, I., Sawalmeh, A., & Othman, N. S. (2017, April). Efficient 3D placement of a UAV using particle swarm optimization. In *2017 8th International Conference on Information and Communication Systems (ICICS)* (pp. 258-263). IEEE.

[8] Kumar, J. V., & Shaby, S. M. (2024). Optimizing inset-fed rectangular micro strip patch antenna by improved particle swarm optimization and simulated annealing. Network: Computation in Neural Systems, 1-31.

[9] Kheder, R., Ghayoula, R., Smida, A., El Gmati, I., Latrach, L., Amara, W., ... & Waly, M. I. (2024, June). Enhancing Beamforming Efficiency Utilizing Taguchi Optimization and Neural Network Acceleration. In Telecom (Vol. 5, No. 2, pp. 451-475). MDPI.

[10] Darvish, A., & Ebrahimzadeh, A. (2018). Improved fruit-fly optimization algorithm and its applications in antenna arrays synthesis. *IEEE Transactions on Antennas and Propagation*, *66*(4), 1756-1766.

[11] Chhaule, N., Koley, C., Mandal, S., Onen, A., & Ustun, T. S. (2024). A Comprehensive Review on Conventional and Machine Learning-Assisted Design of 5G Microstrip Patch Antenna. Electronics, 13(19), 3819.

[12] Raj, A., & Mandal, D. (2024). Design and Performance Analysis of Graphene Integrated CPW Fed Fractal Antennae for 5G mm-Wave and Ground Based Navigation Applications. MAPAN, 1-27.
[13] Raj, A., & Mandal, D. (2024). Design and Performance Analysis of Dielectric Resonator Antenna Array for 5G mm-Wave Ground-Based Navigation and Wireless Applications. Arabian Journal for Science and Engineering, 1-30.
[14] WAJGI, D. W., TEMBHURNE, J. V., & WAJGI, R. D. (2024). RSSI and AoA Combination Using PSO-Based Clustering for Localization in WSN. Adhoc & Sensor Wireless Networks, 58.
[15] Kumar, S. P., Jat, D., Sahni, R. K., Jyoti, B., Kumar, M., Subeesh, A., ... & Mehta, C. R. (2024). Measurement of droplets characteristics of UAV based spraying system using imaging techniques and prediction by GWO-ANN model. Measurement, 234, 114759.
[16] Palanisamy, S., Rubini, S. S., Khalaf, O. I., & Hamam, H. (2024). Multi-objective hybrid split-ring resonator and electromagnetic bandgap structure-based fractal antennas using hybrid metaheuristic framework for wireless applications. Scientific Reports, 14(1), 3288.
[17] Zhao, Y., Lu, B., & Alipour, M. (2024). Optimized structural inspection path planning for automated unmanned aerial systems. Automation in Construction, 168, 105764.
[18] Kumar, S., Ram, G., Mandal, D., & Kar, R. (2024). Optimal pattern synthesis of circular antenna arrays with improved effective aperture and beam area. International Journal of Microwave and Wireless Technologies, 1-14.
[19] Pandey, A., Sehgal, A., Kumar, V., & Singh, A. P. (2024). Design and optimization of dielectric resonator based MIMO antenna with beam tilting at mm-wave for enhanced 5G communication using machine learning. Physica Scripta, 99(11), 116014.
[20] Husen, A., Chaudary, M. H., Ahmad, F., & Sohail, A. (2024). Holistic learning and optimization scheme for wireless networks. Transactions on Emerging Telecommunications Technologies, 35(10), e5036.
[21] Xingchen, W., Peng, L., Renhui, X., Aijing, L., Xingyue, Y., & Hai, W. 3d Position Deployment and Performance Optimization of Mmwave Uav-Assisted Hetiot Under Jamming Condition. Available at SSRN 4696980.
[22] Zanichelli, J. (2024). Optimization of antenna array layouts in planar and non-planar geometries for DoA estimation.
[23] Kumar, S., & Singh, M. (2024). Localization Scheme Using Single Anchor Node for Mobile Wireless Sensor Nodes in WSNs. Arabian Journal for Science and Engineering, 1-24.
[24] Assayag, Y., Oliveira, H., Souto, E., Barreto, R., & Pazzi, R. (2024). A model-based BLE indoor positioning system using particle swarm optimization. IEEE Sensors Journal.