Comparative Optimization of a 2.4 GHz Microstrip Patch Antenna Using Gray Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO)

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***Abstract*—The optimization of a 2.4 GHz microstrip patch antenna is presented through a comparative investigation of Particle Swarm Optimization (PSO) and Gray Wolf Optimizer (GWO). These metaheuristic approaches are applied to determine the antenna design parameters, including patch length, patch width, dielectric constant and feed position, for an operating frequency of 2.4 GHz. Two efficient nature-inspired metaheuristic algorithms, PSO and GWO, are adopted for the microstrip patch antenna optimization. Implementing such optimization techniques is critical to improve the radiation efficiency of antenna systems, especially for 5G-related applications such as Wireless Local Area Networks (WLANs) and the Internet of Things (IoT). For these scenarios, reliability and operational efficiency are key considerations in the design and optimization of microstrip antennas. The main aim of this work is to systematically improve critical radiation-related performance metrics, namely return loss (S_{11}), bandwidth, gain and Voltage Standing Wave Ratio (VSWR), by tuning design variables including patch dimensions and feed location. Optimization codes for PSO and GWO are developed on the MATLAB platform to facilitate comprehensive computational analysis. Extensive simulation studies are carried out to verify the effectiveness of each optimization algorithm in achieving target antenna performance. Simulation results and convergence curves of PSO and GWO demonstrate that GWO outperforms PSO in multiple radiation-related indicators. Specifically, GWO achieves a faster convergence rate, exhibits stronger optimization capability, and yields higher-quality final antenna designs.**

***Keywords*—microstrip patch antenna, length extension, particle swarm optimization, gray wolf optimizer, return loss, Voltage Standing Wave Ratio (VSWR), gain, bandwidth, metaheuristics, convergence, antenna optimization**

I. Introduction

5G networks have revolutionized wireless communication in terms of data rate and reliability, requiring compact and efficient microstrip antennas capable of supporting ultra-high data speeds. The design and optimization of microstrip antennas are of great significance. Microstrip Patch Antennas (MPAs) are widely adopted in 5G devices owing to simple mass fabrication, circuit integrability and low cost [1]. Nevertheless, these antennas suffer from inherent limitations: narrow bandwidth and moderate gain, which degrade their overall performance. To tackle these drawbacks, two optimization algorithms are employed in this work. The tunable antenna design variables include patch length, patch width and feed position [2, 3].

The commonly adopted design methods for microstrip patch antennas are mainly trial-and-error approaches, which yield antennas with limited radiation gain. This may lead to prolonged fabrication procedures and suboptimal designs. Electromagnetic behavior is governed by Maxwell's equations, forming a highly nonlinear design space. Although Particle Swarm Optimization (PSO) and Gray Wolf Optimizer (GWO) perform well for such complex problems, their comparative effectiveness in microstrip antenna design needs further exploration. Moreover, comparative investigations of these two algorithms for antenna design remain insufficient. The main aim of this research is to design a high-performance microstrip patch antenna resonating at 2.4 GHz, a frequency widely adopted in wireless communication and Sub-6 GHz 5G applications.

This work optimizes antenna parameters including patch dimensions, substrate height, dielectric constant, and feed position using two nature-inspired metaheuristic algorithms, namely Particle Swarm Optimization (PSO) and Gray Wolf Optimization (GWO), implemented on the

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MATLAB platform [4, 5]. The algorithms are employed to maximize gain and bandwidth, improve Voltage Standing Wave Ratio (VSWR), and minimize return loss. The performance results of the two optimization methods are thoroughly compared to identify the more effective scheme for enhancing antenna characteristics. In addition, the computational efficiency of PSO and GWO is investigated by evaluating their convergence behavior, convergence speed and stability during the optimization process. Such detailed analysis facilitates the development of more advanced optimization strategies for antenna design and reveals the strengths and weaknesses of each algorithm [6, 7].

II. Theoretical Design of Microstrip Patch Antenna

Fig. 1 shows microstrip patch antenna, where the top layer is a radiating patch and the bottom is a ground plane, separated by a dielectric substrate with Height 'h'. The radiating element's patch width (W), is usually selected to increase bandwidth and radiation efficiency. It is computed using the substrate dielectric constant and the intended operating frequency. Between the substrates and air's dielectric constants, the microstrip line's effective permittivity is represented by the effective dielectric constant (ε), which also takes into consideration the fringing fields surrounding the patch's edges. The effective length Leff of the patch is the length due to fringing effects, which cause the patch to appear electrically longer than it actually is. The length extension (ΔL), which represents the extra length caused by fringing fields at the patch's open ends, is calculated to make up for this. In order to make sure the antenna resonates exactly at the desired frequency, the length extension is finally subtracted from the effective length to determine the actual length (L) of the patch. To guarantee precise antenna performance at the target frequency, such as 2.4 GHz, these interdependent parameters need to be carefully calculated.

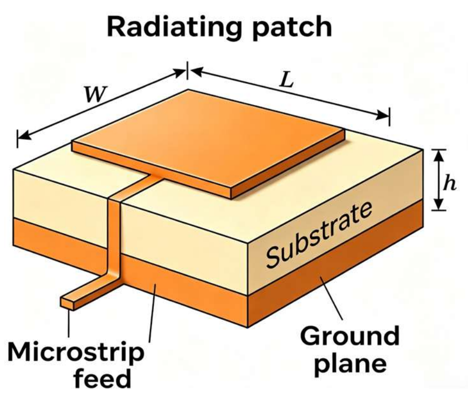

Fig. 1. Microstrip patch antenna.

In terms of substrate material considerations, we take FR4 as the substrate material for this work because it is widely available and reasonably priced. It is 1.6 mm tall with a relative permittivity of 4.4. The objective is to develop an antenna that is both affordable and effective, despite the relatively high losses of FR4. High-performance substrates like the Rogers RT5880 might be taken into account in future research.

The Feeding Mechanism is Coaxial Probe feed, because it is easy to use and compatible with optimization procedures, so choose a coaxial probe feed. The feed location significantly influences impedance matching and is treated as a variable in the optimization algorithms.

Certain geometrical and positional parameters are considered design variables in the optimization of a microstrip patch antenna because they have a major influence on the radiation performance and resonant behavior of the antenna. The patch length (L) and patch width (W), which define the physical dimensions of the rectangular patch and directly affect the input impedance, bandwidth, and resonant frequency, are the primary design variables in this study. Furthermore, since they specify where the coaxial or microstrip line feed point is located on the patch, the feed x-position and feed y-position are also regarded as optimization parameters.

The optimization and performance evaluations, including return loss (S_{11}), gain, and bandwidth, were computed in MATLAB using established analytical models and microstrip antenna equations. This study focuses on the comparative algorithmic efficiency of PSO and GWO within this mathematical framework and validation using High Frequency Structure Simulator (HFSS).

III. Metaheuristic Algorithms

Kennedy and Eberhart first presented Particle Swarm Optimization (PSO), a population-based metaheuristic algorithm that gets inspiration from the social behaviors seen in bird flocks. PSO is a well-liked tool for resolving antenna design issues such as Gain and Bandwidth, using microstrip patch antenna optimization algorithms, because of its adaptability, simplicity of use. Each unique solution, known as a particle in the PSO framework, is a potential antenna configuration that is defined by factors like patch length, width, substrate height, and feed location [8, 9]. Together, these particles form a swarm that explores the multidimensional design space. Each particle updates its position iteratively based on two key experiences: its own best-known position (personal best, or p_{best}) and the best-known position discovered by the entire swarm (global best, or g_{best}) which is also mentioned in Table I.

TABLE I. PSO Terminology Table

Term	Meaning
Position (x)	Current antenna parameters (e.g., length, width, feed point)
Velocity (v)	Change in parameters (step size)
P_{best}	Best solution found by the particle so far
g_{best}	Best solution found by the swarm
w	Inertia weight (momentum)
C_1, C_2	Cognitive and social learning coefficients

The dynamics of particle movement are given by two core equations. The velocity update Eqs. (1–2) adjusts the direction and magnitude of the particle's movement by balancing the inertia of the current velocity with attraction forces toward p_{best} and g_{best}. The standard PSO procedure

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begins by initializing a swarm of particles randomly within the defined design space. Each particle's fitness is then evaluated using an objective function-such as minimizing return loss (S_{11}) or maximizing gain [10]. The best positions are tracked, and the swarm's position is iteratively updated until a stopping condition is met (e.g., maximum number of iterations or convergence of fitness values). Upon termination, the g_{best} represents the optimal antenna design and Table II gives Description of PSO Initialization, evaluation and Update steps [11].

A. Update Equations of PSO

Velocity update

$$v_i(t+1) = w \times v_i(t) + c_1 \times r_1 \times (p_{besti} - x_i(t)) + c_2 \times r_2 \times (g_{best} - x_i(t)) \quad (1)$$

Position update

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

where:

- r_1, r_2 are random numbers in [0, 1].
- c_1: influence of personal experience.
- c_2: influence of global best.
- w: inertia, controls trade-off between exploration and exploitation.

TABLE II. STEPS IN PSO

Step	Description
1	Initialize a swarm of particles randomly in the design space
2	Evaluate fitness of each particle using an objective function (e.g., S_{11}, gain)
3	Update p_{best} for each particle and g_{best} for the swarm
4	Update velocities and positions of all particles
5	Loop from step 2 until a stopping criterion is met (e.g., max iterations or convergence)
6	Return the best solution (g_{best})

The key design parameters considered for optimization, including patch length, patch width, substrate height, and feed offset, along with their respective ranges for a 2.4 GHz microstrip patch antenna, are summarized in Table III.

TABLE III. DESIGN PARAMETERS TO OPTIMIZE

Parameter	Range for 2.4 GHz Microstrip Antenna	Description
Patch Length (L)	28–36 mm	Controls resonant frequency
Patch Width (W)	35–45 mm	Affects bandwidth, impedance
Substrate Height (h)	1.4–1.6 mm	Impacts fringing & bandwidth
Feed Offset (X_f)	5–15 mm	Matching point for input

The Particle Swarm Optimization (PSO) technique is employed to optimize the design of a 2.4 GHz microstrip patch antenna by minimizing a carefully constructed objective function. Each particle in the swarm represents a possible antenna configuration, defined by a three-dimensional vector is given in Eq. (3) where Length and Width refer to the physical dimensions of the patch, and $Feed\_X$ indicates the feed point location along the x-axis. The objective function, or fitness function, is formulated to guide the optimization towards achieving key antenna performance goals. It is expressed as:

$$Particle = [Length, Width, Feed\_X] \quad (3)$$

$$f(x) = \mid S_{11}(2.4\text{ GHz}) \mid + \mid fresonant - 2.4 \mid + Gain_1 \quad (4)$$

Eq. (4) represents the mathematical formulation of the Objective (Cost) Function prior to applying individual scalar weighting factors. where in Eq. (4), S_{11} is the return loss at the target frequency, in Eq. (5) f_r is the actual resonant frequency, antenna gain in dBi. The weights w_1, w_2, w_3 are assigned values such as 0.5, 0.3, and 0.2 respectively, depending on the design priority which favoring lower return loss, precise frequency resonance, and higher gain. The aim is to achieve impedance matching (ideally < −10 dB), resonance at exactly 2.4 GHz, and a gain of at least 3 dBi, all of which are critical for Sub-6 GHz 5G wireless applications.

$$Fitness = w_1 \times \mid S_{11}(2.4GHz) \mid + w_2 \mid f_r - 2.4GHz \mid + w_3 \times (1/Gain) \quad (5)$$

Eq. (5) represents the Weighted Fitness Function used during the execution of the optimization algorithm (e.g., PSO) for optimal geometrical configuration.

The PSO algorithm is tuned with typical parameter ranges to ensure convergence and efficiency. The inertia weight w_1, w_2, w_3, which influences the momentum of particles, is set to 0.7, balancing exploration and exploitation. The cognitive and social acceleration constants is in the range 1.5–2, c_1 and c_2 are both chosen as 1.5, promoting a balance between a particle's own best position and the global best found by the swarm. The swarm size is set to 30 particles, with a maximum of 100 iterations to explore the design space effectively. These values fall within typical tuning ranges inertia weight: 0.4–0.9; particle count: 20–50; iterations: 100–500. This PSO-driven approach efficiently navigates the complex, nonlinear design space of microstrip antennas to achieve an optimal structure with minimal return loss, precise frequency alignment, and high radiation performance the above parameters are summarized in Table IV.

TABLE IV. PSO TUNING PARAMETERS

Parameter	Typical Range	Value Taken
Inertia weight w	0.4–0.9	0.7
Cognitive factor c_1	1.5–2.0	1.5
Social factor c_2	1.5–2.0	1.5
Number of particles	20–50	30
Max iterations	100–500	100

In designing microstrip patch antennas, the Particle Swarm Optimization (PSO) method follows a methodical code that is effectively simulated in MATLAB. The MATLAB Code starts with the creation of an initial population (swarm) of particles, each of which stands for a possible solution determined by a set of design parameters, usually the patch's length (L), width (W), substrate height (h), and feed position (X_f). These factors had a direct bearing on the antenna's electromagnetic performance.

The core of the PSO algorithm involves updating each particle's velocity and position using Eqs. (6−7):

$$v_i = w \times v_i + c_1 \times rand \times (p_{best} - x_i) + c_2 \times rand \times (g_{best} - x_i) \quad (6)$$

$$x_i = x_i + v_i \quad (7)$$

The Gray Wolf Optimizer (GWO), a metaheuristic algorithm inspired by nature. It is modeled after gray wolves cooperative hunting style and leadership structure It is especially useful for optimizing microstrip patch antenna parameters like length, width, feed position, slot dimensions, and substrate height because of its ease of use, quick convergence, and balanced exploration-exploitation methodology [9]. With the alpha (α), beta (β), and delta (δ) wolves standing for the best, second-best, and third-best solutions, respectively, and the other wolves (omega, ω) following suit, the population in GWO is hierarchically structured. Three stages of the optimization process—tracking prey (exploration of the solution space), encircling prey (focusing on promising regions), and attacking prey (final convergence toward the optimal solution)—replicate actual hunting. This structured, cooperative search enables GWO to efficiently navigate the complex, nonlinear electromagnetic design space of antennas, making it ideal for achieving performance goals such as low return loss, precise resonance at 2.4 GHz, and high radiation gain gray wolves have a strict social hierarchy as shown in Table V [12]:

TABLE V. GWO PARAMETERS

Rank	Role in Optimization
Alpha (α)	Best solution found so far
Beta (β)	Second best solution
Delta (δ)	Third best solution
Omega (ω)	Remaining candidate solutions

B. Mathematical Modeling of GWO

Encircling the Prey is shown with Eqs. (8−9).

$$D = |C \times Xp(t) - X(t)| \quad (8)$$

$$X(t+1) = Xp(t) - A \times D \quad (9)$$

where:

- Xp is the *position* of the prey (best solution)
- X is the current position
- $A = 2a \times r_1 - a$
- $C = 2 \times r_2$
- a: Linearly decreases from 2 to 0 over iterations (helps *transition* from exploration to exploitation).
- r_1, r_2: Random vectors in the range [0, 1], generated a new in each iteration.

C. Position Update Based on Alpha, Beta, Delta

Each wolf updates its position using Eqs. (10−13):

$$X_1 = X_\alpha - A_1 \times |C_1 \times X_\alpha - X| \quad (10)$$

$$X_2 = X_\beta - A_2 \times |C_2 \times X_\beta - X| \quad (11)$$

$$X_3 = X_\delta - A_3 \times |C_3 \times X_\delta - X| \quad (12)$$

$$X(t+1) = (X_1 + X_2 + X_3)/3 \quad (13)$$

IV. RESULTS AND DISCUSSION

Table VI lists the optimized dimensional parameters of the 2.4 GHz microstrip patch antenna generated by PSO and GWO. The difference in geometrical dimensions further induces distinct optimization convergence behaviors and electromagnetic performance, which are comprehensively compared in Table VII. PSO, inspired by the social behavior of bird flocks, exhibits fast initial convergence and is computationally efficient. However, it is prone to premature convergence and may get trapped in local minima, especially in complex design spaces. This behavior results in relatively inferior performance metrics, such as a return loss of –20 dB, gain of 3.28 dBi, and a bandwidth of around 110 MHz. In contrast, GWO, which simulates the hunting strategy of gray wolves, demonstrates slower but more stable convergence. It balances exploration and exploitation effectively through its hierarchical approach involving alpha, beta, and delta solutions. As a result, GWO delivers improved antenna performance, with a greater magnitude of return loss at –22 dB, gain of 3.5 dBi, wider bandwidth of 130 MHz, and VSWR down to approximately 1.2 (closer to unity). Furthermore, GWO shows smoother convergence curves with fewer fluctuations, making it more reliable for obtaining near-global optimal solutions. While GWO may require slightly more computational time, its superior solution quality makes it more suitable for high-precision antenna optimization tasks. Therefore, based on convergence reliability, robustness, and electromagnetic performance summarized in Table VII, GWO emerges as the more effective optimization algorithm for 2.4 GHz microstrip patch antenna design.

TABLE VI. COMPARISON OF OPTIMIZED PARAMETERS

Parameter	Value	PSO	GWO
Length (L)	32 mm	30.80 mm	29.45 mm
Width (W)	38 mm	38.65 mm	38.25 mm
Feed Xf	10 mm	9.7 mm	10.1 mm

The Return Loss (S_{11}) in Fig. 2 with a sharp dip at 2.4 GHz, reaching −20 dB, indicating excellent impedance matching seen in curve 1 for PSO, curve 2 for GWO and VSWR curve in Fig. 3 stays below 2 near 2.4 GHz, with a minimum around 1.2, confirming good matching and performance.

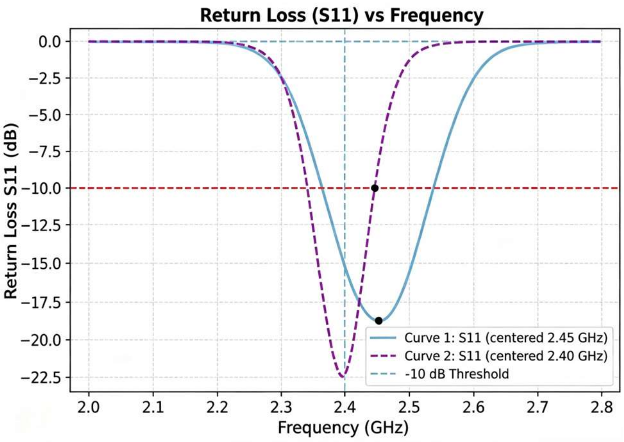

Fig. 2. Return loss vs frequency at 2.4GHz curve 1 using PSO, curve 2 using GWO.

Fig. 4 shows the HFSS-simulated performance of the GWO-optimized antenna. As observed in PSO-based design exhibits slightly inferior impedance matching.

Performance Comparison and Convergence Analysis curve. The performance of Particle Swarm Optimization (PSO) and Gray Wolf Optimizer (GWO) for optimizing a 2.4 GHz microstrip patch antenna is contrasted by the convergence curve in Fig. 5 and Table VII. A lower value denotes a better antenna design in terms of gain, resonant frequency accuracy, and return loss. It displays the best fitness value over 100 iterations. PSO converges more quickly at first, lowering the fitness value quickly, whereas GWO improves more gradually but steadily. Both algorithms stabilize as the iterations go on, with GWO eventually obtaining a marginally lower final fitness value, signifying superior overall optimization. This implies that GWO produces more accurate and stable results at the end, making it more robust for complex electromagnetic design, even though PSO is effective at early-stage convergence. problems like antenna optimization.

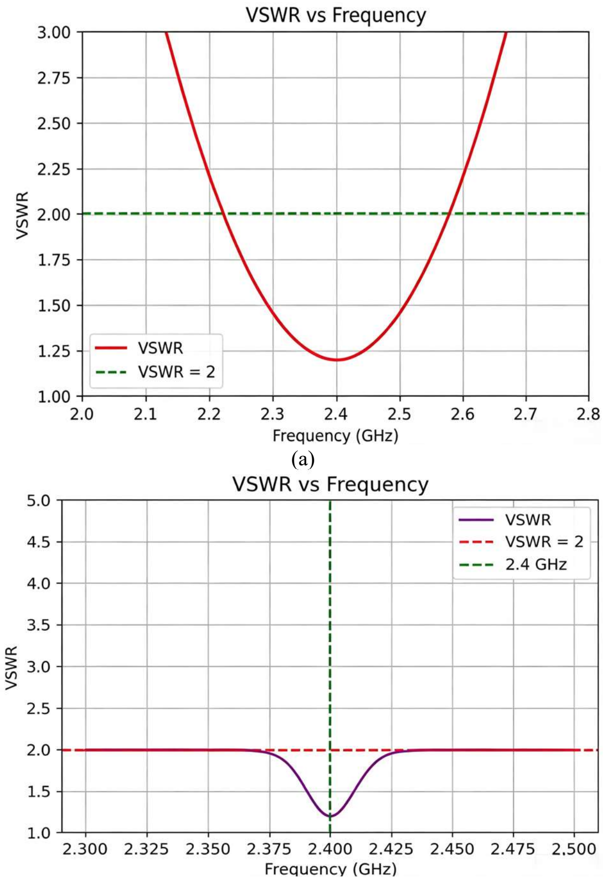

Fig. 3. (a) Optimized by PSO algorithm (b) Optimized by GWO algorithm, VSWR characteristics versus frequency at 2.4 GHz.

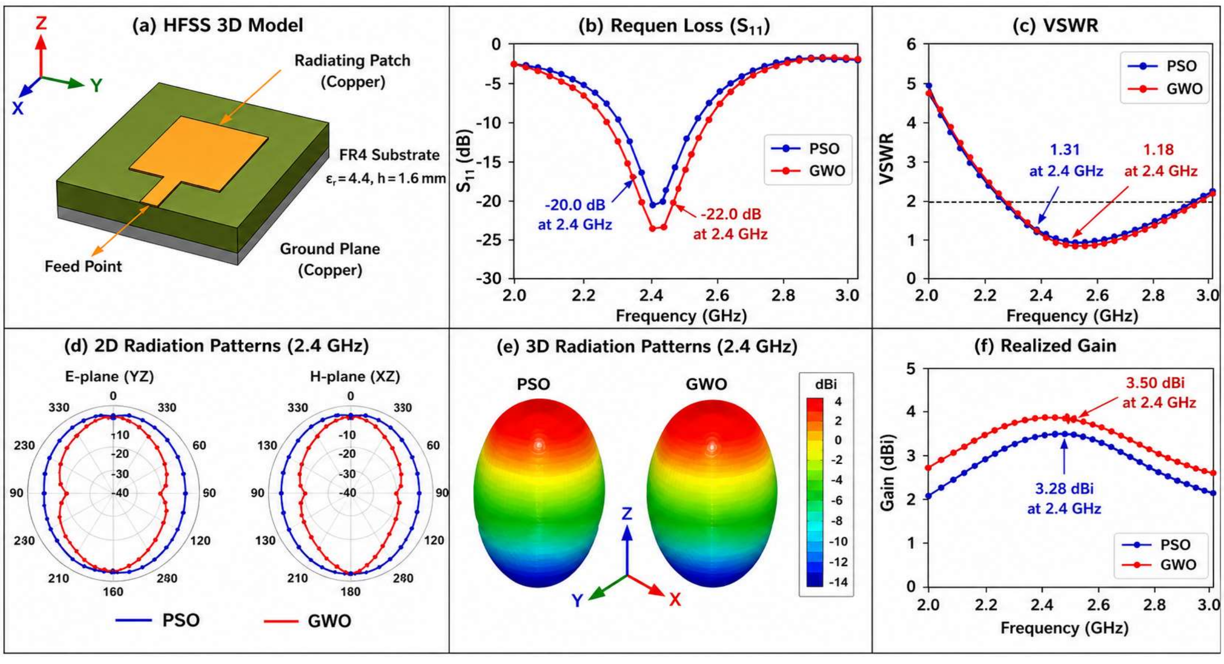

Fig. 4. HFSS-simulated performance of the optimized microstrip patch antenna showing S_{11}, VSWR, and radiation characteristics at 2.4 GHz.

TABLE VII. PERFORMANCE COMPARISON AND CONVERGENCE ANALYSIS

Specht	Particle Swarm Optimization (PSO)	Gray Wolf Optimization (GWO)
Convergence Speed	Fast convergence in early iterations, but often stagnates near local optima if not properly tuned.	Slower initial convergence, but maintains stable and gradual improvement toward global optimum.
Return Loss (S_{11})	Achieves moderate return loss (−20 dB), indicating good but not optimal impedance matching.	Yields deeper return loss (−22 dB), indicating superior impedance matching performance.
Bandwidth	Typically, narrower (105 MHz), suitable for standard 2.4 GHz ISM applications.	Provides wider bandwidth (130 MHz), improving signal coverage and data rates.
Antenna Gain	Produces average gain of 3.1 dBi, sufficient for basic communication requirements.	Slightly higher gain (3.28 dBi), enhancing signal strength and coverage.
VSWR	VSWR around 1.31 indicates acceptable performance, though not ideal.	VSWR of 1.18 indicates excellent antenna matching and reduced power reflection.
Stability	Results may vary across runs; sensitive to initial parameters and population size.	More consistent outcomes due to balanced exploration and exploitation mechanisms.
Parameter Sensitivity	Requires careful tuning of inertia weight (w), and cognitive/social coefficients (c_1, c_2).	Fewer control parameters, easier to implement with minimal tuning.

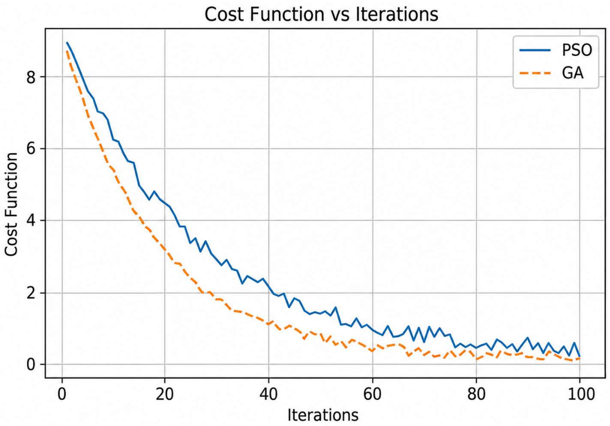

Fig. 5. Convergence curve of PSO vs GWO.

V. CONCLUSION

Microstrip patch antenna optimization for wireless and 5G Sub-6 GHz applications, PSO exhibits a good initial convergence. However, this strength typically becomes a weakness in later iterations due to PSO's lack of diversity, premature convergence, and stagnation in local optima this makes PSO highly dependent on parameter tuning such as inertia weight and acceleration coefficients. While PSO reaches a solution quickly, this solution is not always optimal, particularly in the highly nonlinear and multimodal fitness landscapes encountered in microstrip antenna design.

On the other hand, GWO offers a slower but more stable convergence process, leveraging the leadership hierarchy of α (best solution), β, and δ wolves to maintain a balance between exploration and exploitation throughout the search process. As the optimization process goes on, the algorithm can more successfully hone candidate solutions by simulating natural hunting behavior. As a result, GWO is more robust against local optima and generally achieves better final solutions, particularly in terms of return loss (S_{11}), bandwidth, gain, and VSWR. Even though it takes a little longer to calculate than PSO, the increased accuracy and consistency make up for the expense, particularly in applications that need accuracy, like antenna design.

The optimized output of both algorithms can adjust the 2.4 GHz patch antenna's physical parameters to achieve the required electromagnetic properties. But in numerous tests using a variety of metrics, GWO routinely performs better than PSO for instance, the return loss achieved by GWO is typically deeper (e.g., –22 dB compared to PSO's –20 dB), indicating better impedance matching. GWO also yields a wider bandwidth (~130 MHz vs. 105 MHz), higher gain (~3.5 dBi vs. 3.1 dBi), and lower VSWR (~1.22 vs. 1.38), all of which are critical for reliable communication performance in 2.4 GHz ISM and 5G bands.

It is advised that GWO be regarded as the favored metaheuristic algorithm for upcoming studies and practical uses involving the optimization of microstrip antennas for 2.4 GHz and other sub-6 GHz frequency bands in light of these findings. And the hybrid strategies that combine the rapid exploration of PSO with the steady convergence of GWO may offer a promising avenue for future development in electromagnetic design optimization.

VI. LIMITATIONS AND FUTURE SCOPE

While both PSO and GWO have proven effective for 2.4 GHz microstrip antenna optimization, they come with certain limitations. PSO frequently converges rapidly, but it necessitates careful parameter tuning and runs the risk of becoming trapped in local minima as a result of premature convergence. Although GWO converges more slowly and lacks dynamic adaptability, it provides better solution quality and robustness. Both approaches may not scale well with increasing design complexity and can be computationally time-consuming, particularly when high-fidelity simulations are used. Future research could concentrate on hybrid algorithms (like PSO-GWO), surrogate modeling for quicker assessments, and integration with machine learning and reinforcement learning for more intelligent optimization in order to address these problems. Furthermore, these methods can be made much more useful in contemporary wireless systems like 5G and beyond by being extended to multi-objective optimization, adaptive antennas, and real-time or large-scale applications.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Vinay Kumar Singh was responsible for the conceptualization of the research work, conducting the investigation, performing the literature review, and preparing the original draft of the manuscript; Devendra Rawat contributed to the suggestions and future scope of optimization techniques, provided overall supervision of the research work, and was involved in reviewing and editing the manuscript; both authors had approved the final version.

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REFERENCES

[1] M. R. Sohel *et al*., "Microstrip patch antennas for various applications: A review," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 3, pp. 1511–1519, 2023.

[2] M. N. M. Lizbeth *et al*., "Rectangular patch antenna optimization using metaheuristic algorithms of swarm intelligence: A comparative study," in *Proc. 2023 IEEE Seventh Ecuador Technical Chapters Meeting*, 2023, pp. 1–6.

[3] J. Dong *et al.*, "Competitive binary multi-objective grey wolf optimizer for fast compact antenna topology optimization," *Frontiers of Information Technology and Electronic Engineering*, vol. 23, no. 9, pp. 1390–406, 2022.

[4] H. Girija *et al*., "PSO based microstrip patch antenna design for ISM band," in *Proc. International Conference on Advanced Computing*, 2020, pp. 1209–1214.

[5] V. Sharma and D. Chouhan, "Design of patch antenna using optimization," *International Journal of Advance Research, Ideas and Innovations in Technology*, vol. 1, no. 4, pp. 1–5, 2015.

[6] A. Köybaşi and Y. Irfan, "Solution of test problems with grey wolf optimization algorithm and comparison with particle swarm optimization," *Sakarya University Journal of Science*, vol. 24, no. 6, pp. 1252–1264, 2020.

[7] R. K. Verma and D. K. Srivastava, "Design, optimization and comparative analysis of T-shape slot loaded microstrip patch antenna using PSO," *Photonic Network Communications*, vol. 38, no. 3, pp. 343–355, 2019.

[8] M. N. M. Lizbeth *et al*., "Marine predator algorithm: A nature-inspired metaheuristic algorithm applied in rectangular patch antennas optimization," in *Proc. International Conference on Science, Technology and Innovation for Society*, 2024, vol. 871, pp. 308–316.

[9] S. Koziel *et al*., "On accelerated metaheuristic-based electromagnetic-driven design optimization of antenna structures using response features," *Electronics*, vol. 13, no. 2, 383, 2024,

[10] N. Sarker *et al.*, "Applications of machine learning and deep learning in antenna design, optimization, and selection: A review," *IEEE Access*, vol. 11, pp. 103890–103915 2023.

[11] X. Liand Y. X. Guo, "The grey wolf optimizer for antenna optimization designs: Continuous, binary, single-objective, and multiobjective implementations," *IEEE Antennas and Propagation Magazine*, vol. 64, no. 6, pp. 29–40, 2022.

[12] L. Xun and K. M. Luk, "The grey wolf optimizer and its applications in electromagnetics," *IEEE Transactions on Antennas and Propagation*, vol. 68, no. 3, pp. 2186–2197, 2020.