Hybrid Evolutionary Computing Assisted Irregular-Shaped Patch Antenna Design for Wide Band Applications

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Abstract *– A novel optimization concept for modeling irregular-shaped patch antenna with high bandwidth and efficient radiation attributes is proposed in this paper, along with the ability to accomplish the design at a reduced computational and cost burden. A revolutionary computing perception is established with Gravitational Search Algorithm (GSA) and Quantum Based Delta Particle Swarm Optimization (QPSO), now known as GSA-QPSO. The suggested model employed the GSA-QPSO algorithm strategically interfaced with a high-frequency structure simulator (HFSS) software through a Microsoft Visual Basic script to enhance irregular-shaped antenna design while maintaining wide bandwidth with suitable radiation efficiency over the target bandwidth region. The optimally designed microstrip patch antenna is fabricated on an FR-4 substrate with a surface area of 30×30×1.6 mm*^{3}*. The evaluated outcome shows 96 % supreme radiation efficacy at 2.4 GHz whereas overall effectiveness is above 84% over the entire frequency range, with a nearly omnidirectional radiation pattern. In terms of impedance bandwidth, the suggested antenna offers 126.6 % over the operational frequency range from 2.34 GHz to 10.44 GHz. Fabrication and measurement results are also used to validate the simulated results. It exhibits the proficiency of the offered antenna design to be used for real-world wideband (WB) communication drives.*

Keywords*: Evolutionary Computing, GSA, QPSO, Microstrip Patch Antenna, Wideband, Radiation Efficiency*

1. INTRODUCTION

The demand for portable wireless communication systems has risen exponentially over the past few years due to high-speed demands across socio-industrial, defense, and scientific applications. Consequently, academia and industry have been encouraged to develop more effective solutions for Quality-of-Service (QoS) and Quality-of-Experience (QoE) purposes. To meet aforesaid demands, wireless antenna and allied technology have a decisive role to enable QoS and/or QoE-centric communication under the different operating conditions. The increased use of WB/UWB technologies in recent years has required antennas to be more efficient and robust to provide communications services within expanded bandwidths. Noticeably, a higher bandwidth doesn't guarantee optimal communication, as an antenna requires robustness towards a wider frequency range, and sufficient radiation even at the reduced design cost and size. This as a result has broadened the horizon for academia-industries to achieve an antenna solution with optimal design, and radiation performance even over the larger bandwidth [1]. Considering available antenna technologies, the microstrip patch antenna (MPA) is perceived as one of the most favorable antennas for wireless transmission. Being cost-efficient, lightweight, and easier to implement MPA is used in major contemporary UWB applications [1-4]. Moreover, the MPAs can be found on both planar as well as non-planar surfaces, making them suitable for the applications serving satellite communication, remote sensing, defense communication, and radio-frequency identification drives [5-8]. Structurally, the aforesaid patches were connected through a specific patch, often called element-step sized. In order to operate it over the target bandwidth, the far-field radiation characteristics are changed by selecting the optimal shape and size value. Undeniably, it expands the horizon for further research. However, in practice, finding an optimal design with different constraints and objectives, such as resonant frequency, BW, miniaturized design, or optimal material is a complex task [2-7]. A design optimization, especially when applied to WB applications, has been recognized to be more complex [7]. This is because inappropriate design parameters and material selection may cause a shift in bandwidth and corresponding resonant frequency that eventual can impact the overall performance of desired communication systems [9]. As above specified fact as motivation, different MPA design approaches have been recommended, which are primarily based on analytical and numerical approaches. These design approaches have their restraints. For example, the analytical approach is easy and suitable for fixed structures of patches. Whereas, numerical approaches are relevant for all shapes of the patch but undergo tedious cycle events. However, both design concepts undergo low controllability over higher operating frequency and BW [10]. Consequently, it limits their application in major at-hand wireless communication purposes. Typically, a patch antenna undergoes such detrimental performance due to random size selection (in the case of smaller size, it forces it to incline towards higher frequency and lower bandwidth) and shift in operating frequency, which is common in contemporary adaptive modulation and multi-rate transmission systems [1] [8-9]. Though, optimal selection of design parameters of MPA such as patch size, substrate thickness, dielectric constant and feeding method, etc., can help achieve to operate over the desired frequency range [10-12]. There have been several investigations conducted with such motives; however, retaining stable and controllable performance with optimal trade-offs between dimension and performance has remained a challenge [9] [13]. During the past few years, artificial neural network (ANN) or data-driven machine learning (ML) based approaches have been proposed to estimate a suitable set of design parameters for MPA design. Some of the key methods such as neuro-computing concepts [14-26] performed design parameter estimation; however, their optimality towards a robust solution remained an unexplored story. This is because most of the existing systems focused on design optimization by learning a set of input patterns, irrespective of the end outcomes and its realistic patterns or performance for WB application. As well, these approaches didn't consider the key limitations of ML methods like local minima and convergence. Though few efforts have been made toward using heuristic-based design parameters estimation; however, the majority of the existing approaches failed in addressing inherent problems such as convergence, inappropriate fitness estimation, and more importantly varying operating condition centric optimization.

Considering it as motivation, in this research paper a state-of-art new and robust hybrid evolutionary computing assisted polyline MPA design is proposed to be used for WB applications. This paper contributed a new hybrid evolutionary computing concept by using GSA and QPSO, here onwards called GSA-QPSO for irregular-shaped MPA design optimization. Noticeably, the key intention behind the use of the hybrid heuristic co-evolutionary concept is to improve the accuracy of the radiator design results, while avoiding any possible local minima and convergence issues. The proposed model used the GSA-QPSO algorithm strategically interfaced with HSFF through Microsoft Visual Basic (VB) script to enhance irregular-shaped MPA design while maintaining reflection coefficient (S_{11}) below -10 dB over the target BW region. The proposed model is simulated for the different test cases, which deliver the varying coordinates of the MPA. In terms of the reflection coefficient, three different cases are observed to get the optimum coordinate parameters of the designed MPA. Finally, for case 3, the exhibited MPA provides 126.6 % impedance BW above the frequency scope of 2.34 to 10.44 GHz. The optimum designed model is fabricated on an FR-4 substrate with an area of 30×30×1.6 mm^3.

The remaining sections of this research manuscript are divided as follows. Section II discusses some of the key literature about MPA design optimization, followed by a proposed system in Section III. Section IV presents the implementation while the simulation results and discussion are given in Section V. The overall research conclusion is discussed in Section VI. References used in this manuscript are given at the end of the manuscript.

2. RELATED WORK

This section reviews existing literature along with a discussion of future research challenges. A genetic algorithm (GA) technique is proposed to optimize the geometry of square-shaped MPA for WB and broadband applications [27-28]. Therefore, Silva et al. [29] suggested a circular-ring MSA design optimization by using the self-organizing GA (SOGA) technique with UWB features. The simulated and experimented antenna provides wide bandwidth of more than 9 GHz and 6 GHz. In [30], the authors introduced a multi-adaptive neuro-fuzzy inference system (MANFIS) to predict the bandwidth of the U-shape slot-loaded RMPAs design. They found the PSO-MANFIS model provided more accurate results than the GA-MANFIS model. Conversely, Mir et al. [31] investigated an automated optimization procedure based on Bayesian-optimization (BO) and bottom-up-optimization (BUO) to design the MPA for broadband with high flat-gain features. The initial structure of the MPA is designed by the BUO approach while the BO process is applied to forecast appropriate dimensional parameters. In [32], the curve fitting-based PSO technique is presented to design a "plus" shape slotted MPA for BW improvement with resonant frequency at 2.4 GHz.

Table 1. Comparison of the proposed antenna with some recently reported optimization techniques.

Ref.	Size (mm^2)	Operational frequency (GHz)	Bandwidth (%)	Optimization technique	Applications
23.	33.4×40.6	3.1 to 5.495	55.73	MLPFFBP and RBF	WLAN
24.	15.528×18.40	9.91 to 10.5	5.78	MLPFFBP and RBF	Wideband
27.	38.4×38.4	10.6 to 11.15	5.05	GA	Wideband
28.	30×30	2.3 to 2.6	12.24	GA	Broadband
29.	33×28	3.8 to 9.6	88.23	SOGA	UWB
30.	34.9×31.3	2.0 to 10.75	137.25	MANFIS–PSO	UWB
31.	20×18	8.7 to 10	13.90	BUO and BO-ANN	Broadband
32.	38×47.6	1.795 to 2.95	46.99	PSO	Wi-MAX, WLAN
33.	34×33.35	2.94 to 10.98	115.35	PSO	UWB
36.	24×24.4	3.1 to 10.6	109.48	PSO	UWB
39.	30×30	3.1 to 10.6	109.48	GSA	UWB
Proposed	**30×30**	**2.34 to 10.44**	**126.6**	**GSA-QPSO**	**Bluetooth, WLAN, Wi-Max and UWB**

Therefore, the authors developed an irregular-shape MPA [33] and rectangular MPA [34] for UWB

application where PSO is applied to estimate design parameters under unknown dimensional specifications. Nonetheless, a differentia-evolution (DE) based estimation method is recommended to design a square monopole antenna, but the overall dimensions of the antenna are not justified [35]. However, a miniaturized stepped-triangular MPA design parameter is tuned for WB application with the PSO technique [36]. Thus, various types of printed MPA using PSO [37] and using hybrid GA-PSO [38] can be designed for UWB applications.

Similar to PSO, authors [39] proposed a GSA function based on the concept of gravitational force and mass interaction. Detailed analysis revealed that GSA can be superior to classical GA, PSO, etc. based approaches. A study conducted by the authors [40], which compared GSA against a PSO-based optimization technique that was designed for the synthesis of ring array MPA (RA-MPA), revealed that GSA is more effective, particularly in terms of fitness values and time. In [41], the authors designed a reconfigurable RA-MPA using GSA, while the same method [42] was applied to estimate the dimensional features of the rectangular MPA. However, it exists a simple antenna design employing an equivalent transmission line model without significant attention to WB application demands and operating environment. The most of above reported literature focused on design optimization of MPA. Therefore, a novel optimization concept based on GSA and QPSO for the modeling of irregular-shaped patch antenna with desired BW is proposed in this paper. Brief comparisons in terms of antenna surface area dimensions, operating frequency band, optimization techniques, and their applications are also reported in Table 1 with some recently stated literature.

3. PROPOSED MODEL AND METHODS

This section primarily discusses the overall proposed system and its implementation.

In sync with the overall research intend, where the key emphasis has been made on designing a state-of-art new heuristic-based irregular-shaped MPA design for WB applications. In this research, we focused on designing an irregular-shaped MPA with multiple cones to reduce design complexity, while retaining wider BW.

Unlike classical heuristics algorithms such as GA, PSO, and even GSA, etc., which are often criticized for their local minima and convergence limitations, in this paper, a new hybrid evolutionary computing concept is proposed by applying QPSO and GSA to perform irregular-shaped antenna design optimization. The proposed GSA-QPSO model with a state of art new weighted Average Personal Best Position (APBP) and Adaptive Local Attractor (ALA) not only intends to alleviate the at-hand convergence and local optima problem but also exploits efficient local search ability (by GSA) to ensure highly accurate and computationally efficient optimization solution. In other words, in the suggested GSA-QPSO model, QPSO (Note: we applied Quantum based Delta PSO model with Levy's flight-based particle positioning concept using Mantegna algorithm) at one hand exploits optimal "social thinking" ability to estimate global (gbest) values, while GSA helps to strengthen its "local search ability". Being a co-evolutionary approach [PSOGSA], the proposed algorithm performs in parallel, where each contributes to estimating the optimal design parameters of the targeted irregular-shaped MPA design with higher bandwidth performance while maintaining lower (-10 dB) S_{11} output. The proposed GSA-QPSO model has been integrated with the finite element method (FEM) using HFSS to obtain optimal design parameters of the irregular radiator for wider BW.

Before discussing the system implementation, a snippet of the proposed GSA-QPSO model is given in the subsequent sections.

3.1. GRAVITATIONAL SEARCH ALGORITHM (GSA)

GSA is a recently evolved heuristic search algorithm that uses the conception of Newton's law of gravity and object motion [43]. Similar to the other models, GSA at first initializes the population where it considers the initial random locus of the N agents. The random N agents are deployed as (1).

$$X_i = \left(x_i^1, \dots, x_i^d, \dots, x_i^D\right) \quad \text{for } i = 1,2, \dots, N \tag{1}$$

Where D signifies the search space's dimension while x_i^d refers to the i[th] agent present in the d[th] dimension. Thus, each participating agent is considered an object and the mass of each participating agent is obtained in the form of the fitness value of the current population. Mathematically, the mass of each participating object or agent is estimated using the fitness value, as defined in (2-3). Where, $q_i(t)$ and $M_i(t)$ state the fitness value and the mass of the i[th] agent, correspondingly. Noticeably, these values are obtained over the at-hand t[th] iteration.

$$q_i(t) = \frac{fit_i(t) - Worst(t)}{best(t) - Worst(t)} \tag{2}$$

$$M_i(t) = \frac{q_i(t)}{\sum_{j=1}^{N} q_j(t)} \tag{3}$$

Considering the minimization issue, the best solution and worst solution are defined as best(t) and worst(t), using (4) and (5), respectively.

$$best(t) = \min_{j \in \{1,\dots,N\}} fit_j(t) \tag{4}$$

$$worst(t) = \max_{j \in \{1,\dots,N\}} fit_j(t) \tag{5}$$

Now, considering Newton's law of gravitation, the cumulative force active on an i[th] agent from another j[th] agent can be estimated using (6). The parameter $R_{i,j}$ signifies the Euclidian distance existing between i[th] and j[th] agents, while ϵ represents a constant value.

$$f_{ij}^d(t) = G(t) \frac{M_i(t) \times M_j(t)}{R_{i,j+\epsilon}} \left(x_j^d(t) - x_i^d(t)\right) \tag{6}$$

As defined in (7), G(t) describes a function for an iteration time t, that drops exponentially over the period. G0 is the inception value, while the reduction factor and total amount of iterations are denoted by α and T, respectively.

$$G(t) = G_0 e^{-\alpha \frac{t}{T}} \tag{7}$$

So, the overall force acting on an agent i owing to the overall current population is estimated as per (8).

$$f_i^d(t) = \sum_{j \in Kbest, j \neq i} rand_j F_{ij}^d(t) \tag{8}$$

In (8), K_{best} presents the set of the initial K agents possessing the highest mass value, which decreases linearly over time-period t, and thus executing over iterations in result a single agent in K_{best} with the highest fitness value. The component $rand_j$ refers to a linearly deployed arbitrary number placed at the interval of [0, 1]. Noticeably, it is employed to assure the stochastic nature of the detection mechanism. Now, employing the perception of Newton's second rule of motion, the acceleration of the i[th] agent can be attained by (9). Where $F_i^d(t)$ is the entire force acting on ith agent and $M_i(t)$ denotes the mass component of the agent i at time t.

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{9}$$

Now, the agent's velocity is updated by applying equations (10-11).

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{10}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{11}$$

Thus, employing the above-derived equations, the acceleration can be estimated using (12).

$$a_i^d(t) = \sum_{j \in Kbest, j \neq i} \frac{rand_j}{\times M_j(t)} \frac{G(t)}{R_{ij}(t)+\epsilon} \left(x_j^d(t) - x_i^d(t)\right) \tag{12}$$

Accordingly, the positions of masses are estimated as per (11), and once reaching the maximum number of iterations, the anticipated model stops, and the optimal solution is considered the best sub-solution to the at-hand problem.

3.2. QUANTUM-BASED DELTA PSO

Similar to the other heuristic model, PSO is also a kind of stochastic population-based approach, motivated by the cumulative behavior of bird flocks. In this process, each participating particle is considered as a solution, which possesses distinct fitness values and velocities. These possible solutions or candidates (say, particles) can fly across the multidimensional search space by learning from the previous traces or historical information. Noticeably, the key historical information encompasses the memories of the participating particles towards their individual best positions and the global best position in the groups over the search period. Unlike GA systems, PSO is easier to implement due to lower tuning parameters and allied adjustment [44-45]. Despite its superiority, it often undergoes adverse performance such as the local optima, and premature convergence [46]. Numerous efforts have been made to enhance PSO; however, a recent innovation in the form of quantum mechanics and trajectory analysis enabled it to perform more superior [47]. Unlike classical PSO algorithm, QPSO avoids any additional need for a velocity estimator and distinct velocity vector for particles. Moreover, it requires fewer parameters to tune which makes it computationally more efficient. Considering such robustness, in this paper, the hybrid search concept is applied by using the GA-QPSO model to achieve an appropriate convergence rate and global optima. However, achieving it using classical QPSO is highly complex and hence requires enhancing global search capacity and optimal acceleration rate, simultaneously. In the native QPSO model [47], both the average personal best position and local attractor have a decisive impact on overall performance. Noticeably, the average best position signifies the average of the personal best positions of the participating particles and hence doesn't considers the difference of the impact of the different particles possessing different fitness values to search for the optimum solution. It marks questions on the generalization of the classical QPSO model. Though, to achieve better performance authors have made efforts like Gaussian distributed local attractor point-based QPSO (GAQPSO) algorithm [48]. In the GAQPSO model, the local attractor was subjected to the Gaussian distribution whose average value was the original local attractor, as defined in classical QPSO. Unlike [48], Jia et al. [49] developed a weighted sum of particle personal and global best positions as the local attractor to improve the performance. However, it was unable to monitor the population diversity over the computation period and hence is limited to at hand antenna design optimization problem. Additionally, these approaches require ensuring a diversity of solutions (being population-based stochastic optimization problems) [50]. In this reference, nursing the diversity of QPSO to obtain local attractors towards particle optimization can improve the overall performance. Therefore, to balance the local as well as global search ability, in this research paper we applied a set of weighted coefficients which could differentiate the fitness of particles to estimate the "average personal best position" (APBP) even at reduced computational overhead. Here, we applied the GSA algorithm to estimate the set of weighted coefficients which were later used to update the APBP to further improve adaptive local attractor (ALA) for better (design) optimization.

3.2.1. Particle Swarm Optimization (PSO)

In PSO, the movement of the participating particles is directed by their corresponding best-known position (pbest) and the best-known position of the entire particles (gbest). In this manner, the location and velocity of the i^{th} participating particle can be estimated as per (13) and (14), respectively.

$$V_i^{t+1} = wV_i^t + c_1r_1(\mathrm{pbest}_i - X_i^t) + c_2r_2(\mathrm{gbest} - X_i^t) \quad (13)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (14)$$

Where, $X_i^t=(x^t_{i1},\ldots,x^t_d,\ldots,x^t_{iD})$ represent the position vector, while $V_i^t=(v^t_{i1},\ldots,v^t_d,\ldots,v^t_{iD})$ corresponds to the velocity vector for i^{th} particle at t^{th} iteration. c_1 and c_2 represent the positive constants controlling the impact of pbesti and gbest on the search process. The other parameters, r_1 and r_2 represent the arbitrary values existing from 0 to 1. In (13), w presents the inertia weight that helps in balancing the algorithm's global and local search ability. Here, the fitness value of each particle's position is estimated as per a certain fitness function. Thus, PSO is executed iteratively to estimate the values of (13) and (14), till it reaches the stopping criteria or the predefined number of iterations. Noticeably, reaching the stopping criteria, the velocity update turns out to be near zero.

3.2.2. Quantum-based PSO (QPSO)

Recalling the suggestions in [44-50], which stated that the convergence of PSO can be accomplished only when the particle converges to its local attractor (for $1 \le d \le D$), $LA^t_i=(la^t_{i1},\ldots, la^t_{id},\ldots, la^t_{iD})$. It can be denoted mathematically in the equations (15-16).

$$\mathrm{la}^t_{id} = \frac{c_1r_1\mathrm{pbest}^t_{id}+c_2r_2\mathrm{pbest}^t_{id}}{c_1r_1+c_2r_2} \quad (15)$$

$$\mathrm{la}^t_{id} = \varphi\mathrm{pbest}^t_{id} + (1-\varphi)\mathrm{gbest}^t_d,\ \varphi\sim \mathbb{U}(0,1) \quad (16)$$

Where the parameter t signifies the number of iterations, while j presents the arbitrary number distributed uniformly over (0, 1), that is $\varphi\sim U(0,1)$. Here, pbest_i presents the best earlier position observed by the i^{th} paticle, while the current global solution i.e. global best position is indicated by gbest. Being motivated by the quantum mechanism and trajectory assessment methods of PSO, the authors [47-48] proposed two models named QPSO and delta potential well model (QDPSO). In QDPSO, the location of the participating particle i, over t^{th} iteration is obtained as per (17), by using Levy's flight method.

$$x^{t+1}_{id} = \begin{cases} \mathrm{la}^t_{id} + \alpha|\mathrm{la}^t_{id} - x^t_{id}|\ln\left(\frac{1}{u}\right), & \text{if rand } \ge 0.5 \\ \mathrm{la}^t_{id} - \alpha|\mathrm{la}^t_{id} - x^t_{id}|\ln\left(\frac{1}{u}\right), & \text{Otherwise} \end{cases} \quad (17)$$

In (17), the parameters u and rand indicate random numbers distributed arbitrarily over (0, 1), while a indicates the positive real number, here we call the contraction-expansion coefficient (CEC), which is defined as a=0.5+0.5 (T-t)/T to balance local as well as global search capability of QDPSO. Where, t and T are iterations and the maximum number of iterations, correspondingly.

$$\mathrm{mbest}^t = \frac{1}{s}\left(\sum_{i=1}^S \mathrm{pbest}^t_{i1}, \ldots, \sum_{i=1}^S \mathrm{pbest}^t_{id}, \ldots, \sum_{i=1}^S \mathrm{pbest}^t_{iD}\right) \quad (18)$$
$$d = 1,2,\ldots D$$

In this method, a global point indicating $\mathrm{mbest}=(\mathrm{mbest}_1,\ldots,\mathrm{mbest}_d,\ldots,\mathrm{mbest}_D)$ and stated as the APBP, which is applied to improve the global search skill. The global point of the t^{th} iteration is obtained using (18). In (18), S presents the number of particles. Therefore, the position of the i^{th} particle in t^{th} iteration is updated as per (19). In this case, mbesttd presents the APBP of the swarm for the d^{th} dimension at the t^{th} iteration.

$$x^{t+1}_{id} = \begin{cases} \mathrm{la}^t_{id} + \alpha|\mathrm{mbest}^t_d - x^t_{id}|\ln\left(\frac{1}{u}\right), & \text{if rand} \ge 0.5 \\ \mathrm{la}^t_{id} - \alpha|\mathrm{mbest}^t_d - x^t_{id}|\ln\left(\frac{1}{u}\right), & \text{Otherwise} \end{cases} \quad (19)$$

3.2.3. Population Diversity

Typically, the swarm's participating candidates or the population diversity is vital towards estimating and tuning its optimal path estimation. Population diversity can be estimated as per (20).

$$\sigma^2(t) = \sum_{i=1}^{S}\left(\frac{f_i^{(t)} - f_{avg}^{(t)}}{F}\right), f_{avg}^{(t)} = \frac{1}{S}\sum_{i=1}^{S} f_i^{(t)} \quad (20)$$

Where $\sigma^2(t)$ represents the sum of squared deviations of the particles' fitness values, S stands for the swarm size, $f_i^{(t)}$ is the fitness of the i^{th} particle at the t^{th} iteration, $f_{avg}^{(t)}$ is the average fitness of the swarm at the t^{th} iteration and F is the normalized calibration factor to confine $\sigma^2(t)$. Mathematically, it is denoted as (21).

$$F = \begin{cases} \max\left|f_i^{(t)} - f_{avg}^{(t)}\right|, & \text{if } \max\left|f_i^{(t)} - f_{avg}^{(t)}\right| > 1 \\ 1 & \text{otherwise} \end{cases} \quad (21)$$

3.2.3.1. Weighted APBP and ALA-based QPSO

In QPSO, mbest of the population is tracked by i^{th} particle during the search process. It applies coefficients of the similar weights to form the linear combination of each particle's best position and is unable to differentiate the variance in the impact of the particles possessing different fitness values on guiding particles i to identify the global solution. Classical PSO models often undergo loss of the significant information hidden inside the particles' personal best positions (information). Being a minimization problem, the elite particle would have the minimum objective function value. In other words, the smaller objective function value of a particle would signify a corresponding better fitness value. In this approach, the elite would enable a better solution and therefore it is applied towards APBP estimation by assigning higher weights to the particles possessing better fitness while assigning smaller weights to those with relatively lower fitness values. In the offered model, the weighted APBP values are estimated as per (22) and (23). Consequently, based on the feedback of the fitness values of the particles can be estimated for guiding particles i to attain the global optima solution.

$$r_i(t) = \begin{cases} \frac{1}{S-1}\left(1 - \frac{f_{Obj}^{i}(t)}{\sum_{k=1}^{S} f_{Obj}^{i}(t)}\right), & \text{if } \sum_{k=1}^{S} f_{Obj}^{k}(t) \neq 0 \\ \frac{1}{S} & \text{Otherwise} \end{cases} \quad (22)$$

$$\begin{aligned} mpbest^t &= \sum_{i}^{S} r_1(t) pbest_i^t \\ &= \left(\sum_{i=1}^{S} r_1(t) pbest_{i1}^t, \ldots, \sum_{i=1}^{S} r_i(t) pbest_{iD}^t\right) \end{aligned} \quad (23)$$

In (22-23), t presents the at-hand iteration number, while the objective function value is defined as $f_{Obj}^{i}(t)$. The number of particles in the considered swarm population or particles is S, while $r_i(t)$ refers to the coefficient of the best position which is employed to construct the weighted APBP. Observing (22), one can find that the sum of $r_i(t)$ is 1, where $r_i(t)$ exists between 0 and 1 over the iteration t. If the sum of the objective function values of the all-participating agents will be 0, then coefficient $r_i(t)$ would be 1/S. Otherwise, the smaller $f_{Obj}^{i}(t)$ value leads to a larger $r_i(t)$ value. Summarily, when estimating a weighted APBP to guide the particles in a swarm over a trajectory to get the optimal solution, the larger fitness value of a particle would yield a more significant and near-optimal best position. In this manner, the proposed QPSO model is capable to distinguish the impact of the particles even with the varied fitness values.

3.2.3.2. Adaptive Local Attractor (ALA)

Considering an existing study [47-48] [51], where authors found that each participating agent or the particle in PSO intends to converge towards its local attractor (LA). Observing (15) or (16), the LA function amalgamates pbesti and gbest. And therefore, it becomes pertinent to estimate an optimal way to amalgamate the relevant information embedded in the above-stated two best-known positions. Being a population-based stochastic prediction and optimization method; it is expected to encourage the initial population to wander across the search space without converging around local optimal. During the later phase, it becomes necessary to improve convergence towards the global optimum, to realize the best solution. As a result, population diversity is significant in population-based optimization problems, as it impacts their performance. Although high-diversity results in better solution retrieval, particularly in the initial iterations, in the later phase, it is important to utilize a small area of the search space to retain computationally efficient solutions without premature convergence or time exhaustion. Similarly, the experience of each particle has a larger impact on particles after updating their position at the beginning of the next iteration. In contrast, other particles' experience has a higher impact on particles when updating their subsequent position at the later stage of iterations. Observing (20), one can find that $\sigma^2(t)$ exists between 0 and S. In case all particles are found at the same position, $\sigma^2(t)$ turns out to be zero, signifying the strongest (swarm) aggregation degree. On the contrary, $\sigma^2(t)$ changes to be S when all absolute discrepancies between the current fitness values of whole particles and their average fitness values are equal to one. In this manner, the sum of squared deviations of the particles' fitness values illustrates a reducing pattern with the increase in the number of generations. In this reference, a new approach is formulated to estimate the LA using (24). The prime motive of this approach was to improve the global search within a short span or the early part of the optimization to alleviate the problem of convergence and to accomplish the global optima at the end. In this manner, the place of the particle or the agent i over the iteration t is updated as per (25).

$$Al_{id}^t = \varphi \frac{\sigma^2(t)}{S} pbest_{id}^t + (1-\varphi)\left(1 - \frac{\sigma^2(t)}{S}\right) gbest_d^t \quad (24)$$

$$x_{id}^{t+1} = \begin{cases} Al_{id}^t + \alpha\left|mpbest_d^t - x_{id}^t\right| \ln\left(\frac{1}{u}\right), & \text{if rand } \geq 0.5 \\ Al_{id}^t - \alpha\left|mpbest_d^t - x_{id}^t\right| \ln\left(\frac{1}{u}\right), & \text{otherwise} \end{cases} \quad (25)$$

When implementing the proposed QPSO model with weighted APBP and ALA, the position of the particle i can be determined as per (25). Where, $\sigma^2(t)$ refers to the sum of squared deviations of the participating particle's fitness values at t^{th} iteration, over S swarm size, and j is a random number distributed uniformly in the range of (0, 1). In equation (25), the parameter a and u possesses the similar significance as shown in (17), while $mpbest^t_d$ refers to the weighted APBP for the d^{th} dimension at the t^{th} iteration. The ALA is given as Al^t_{id} for i^{th} particle over dth dimension at t^{th} iteration. Thus, the proposed weighted APBP and ALA have been implemented using (24), which estimates the optimal set of parameters for non-linear radiator design.

The overall anticipated model employs the subsequent approach to achieve design parameter optimization.

- Step-1: Initialize population with swarm size S and Max_Iteration count T.
- Step-2: Deploy particles or agents across the swarm with arbitrary position vectors.
- Step-3: Estimate pbest for every agent and gbest for the complete population or swarm.
- Step-4: Estimate population diversity (J) using (20).
- Step-5: Update weighted APBP mpbest as per (23).
- Step-6: Update ALA for each agent using (24).
- Step-7: Update the position of each agent as per (25).
- Step-8: If stopping criteria are not met, go to step 3.

Recalling the fact that being a low-level co-evolutionary concept, both GSA and QPSO algorithms are applied in parallel to estimate the most optimal design parameters for an irregular polyline antenna design with higher BW performance, with minimal S_{11} outputs. A snippet of the integration of the GSA and QPSO model to yield the above-stated result is given as follows:

In order to amalgamate both GSA and QPSO models, the subsequent approach has been applied.

$$V_i(t+1) = w \times V_i(t) + c'_1 \times \mathrm{rand} \times ac_i(t) + c'_2 \times \mathrm{rand} \times \left(\mathrm{mgbest} - x^t_{id}(t)\right) \quad (26)$$

The parameter $V_i(t)$ presents the velocity of the i^{th} agent at t^{th} iteration, while c'_j refers to the weighting factor, and w is a reduction function. Here, rand represents a random number existing from 0 to 1, while $ac_i(t)$ presents the acceleration of the i^{th} agent over t^{th} iteration. The best solution realized so far is given by gbest. Using the GSA-QPSO model, the place of the participating particles is updated iteratively over each iteration using the following equation (27).

$$x^{t+1}_{id}(t+1) = x^t_{id}(t) + V_i(t+1) \quad (27)$$

Functionally, in the GSA-QPSO model, initially, all participating particles or the agents are arbitrarily initialized, where each solution is considered as a candidate solution. Once initializing the model, the proposed model estimates gravitational force, gravitational constant, and consequent forces amongst particles. Subsequently, it estimates the acceleration of the particles, followed by pbest update and acceleration estimation. By doing so, the results show the most optimal velocity and position of the particles, indicating the optimal solution. The details of the hybridization concept can be found in [51].

4. SYSTEM IMPLEMENTATION

A snippet of the targeted irregular-shaped patch antenna is given in Fig. 1. Fig. 1 presents the initial radiator shape, which is supposed to be processed for optimization to yield an optimal design with expected performance (higher bandwidth and frequency operation while maintaining a lower reflection coefficient (S_{11}). The initial parameters of MPA are established based on the stated concept and calculation [5-7], [37-38]. The suggested MPA model encompasses an irregular-shaped radiator fed by a 50 Ω microstrip line with a predefined length (L_f) and width (W_f). Here, the measurement of L_f is considered as 12.5 mm, while W_f is fixed at 3 mm. As the base material for fabrication, FR-4 substrate is considered with a surface area of 30×30 mm^2 and 1.6 mm thickness. The considered material possessed a relative permittivity of 4.4, while the loss tangent is considered as 0.02.

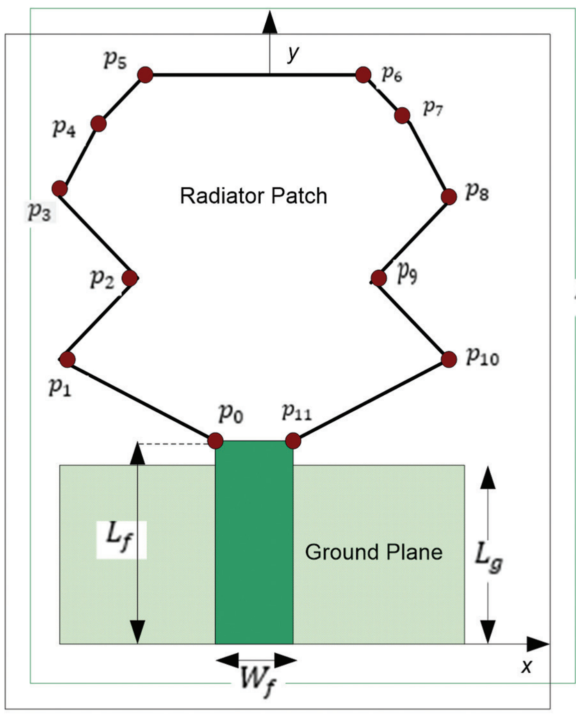


Fig. 1. Initial target irregular-shaped MPA design.

Unlike classical patch antenna designs, ground metallization under the radiator has been avoided to enable proper functionality; however, it required a partial ground length (L_g) of 11.5 mm. The proposed patch antenna design encompassed an irregular-radiator shape that changes shapes with non-linear steps in both x as well as y directions. In the x-direction, there are non-linear steps between x_1 and x_5, with a lower limit of 0.01 mm and an upper limit of 14.5 mm. Δy_1 to Δy_5 represent the varying steps in the y-direction with the lower limit of 0.01 mm and the higher limit of 5 mm. In this model, the left half of the radiator shape is considered as a set of polylines, while another half (i.e., the right half) represents the mirror image. Where maintained the initial coordinate point (p_0) as the output value of $x_0=W_f/2$, along with $y_0=L_f$ (Eq. (28)). Now, the other coordinates of the antenna radiators (i.e., p_1, p_2, p_3, p_4, and p_5) are obtained as per equations (28-39), which are found using the GSA-QPSO algorithm.

$$p_0 = (x_0, y_0,) \tag{28}$$

$$p_1 = (x_1, y_0 + \Delta y_1) \tag{29}$$

$$p_2 = (x_2, y_0 + \Delta y_1 + \Delta y_2) \tag{30}$$

$$p_3 = (x_3, y_0 + \Delta y_1 + \Delta y_2 + \Delta y_3) \tag{31}$$

$$p_4 = (x_4, y_0 + \Delta y_1 + \Delta y_2 + \Delta y_3 + \Delta y_4) \tag{32}$$

$$p_5 = (x_5, y_0 + \Delta y_1 + \Delta y_2 + \Delta y_3 + \Delta y_4 + \Delta y_5) \tag{33}$$

$$p_6 = \left(-x_5, y_0 + \Delta y_1 + \Delta y_2 + \Delta y_3 + \Delta y_{4+\Delta y_5}\right) \tag{34}$$

$$p_7 = (-x_4, y_0 + \Delta y_1 + \Delta y_2 + \Delta y_3 + \Delta y_4) \tag{35}$$

$$p_8 = (-x_3, y_0 + \Delta y_1 + \Delta y_2 + \Delta y_3) \tag{36}$$

$$p_9 = (-x_2, y_0 + \Delta y_1 + \Delta y_2) \tag{37}$$

$$p_{10} = (-x_1, y_0 + \Delta y_1) \tag{38}$$

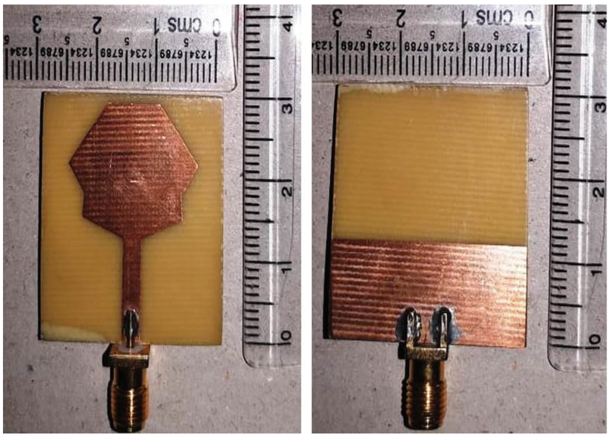
$$p_{11} = (-x_0, y_0,) \tag{39}$$

Though, MATLAB is applied as the key development tool; where HFSS has been utilized to validate the performance of reflection coefficients and radiation characteristics. Additionally, Microsoft VB-script has been used to interface (GSA-QPSO) MATLAB program with HFSS. The simulation environment is designed in such a manner that inputting initial model parameters in Microsoft VB-script, it applied HFSS to estimate the S_{11} parameter, which is subsequently passed to the MATLAB program to assess fitness function and update design parameters, iteratively. Eventually, once updating the coordinate parameters of the target model (Fig. 1), the updated design parameters were fed back to the HFSS through VB-script, and thus it generates the updated S_{11} parameters. This process continued until the obtained S_{11} parameter reached the expected goal. Noticeably, the maximum iteration has been assigned as 500. The proposed research intended to maintain S_{11} parameter below -10 dB within the frequency range of 2.4 to 10.4 GHz. The frequency interval of 0.1 GHz has been considered throughout the targeted WB frequency range.

$$\text{Fitness} = \min\left(\sum_{2.40\ \text{GHz}}^{10.4\ \text{GHz}} S_{11}\right) \tag{40}$$

Thus, maintaining the minimum fitness as per (40), the optimized antenna coordinates have been obtained which resulted in an optimal patch antenna design, serving optimal radiation over 2.4 GHz to 10.4 GHz.

The final optimized coordinates are considered as a proposed antenna. The fabricated model of the MPA design is shown in Fig. 2. The overall simulation and measured results as well as allied inferences are given in the subsequent sections.



(a) Top (b) Bottom

Fig. 2. Dimensions of the fabricated MPA, (a) Patch view and, (b) Ground view

5. RESULTS AND DISCUSSION

This paper focused on improving the computational environment as well as the design aspects of irregular-shaped (polyline) MPA to achieve wider bandwidth. In the proposed model, the efficacy of GSA and QPSO (Delta model with Levy's flight-based particle positioning) has been exploited. Here, the GSA is applied to improve local search efficacy while QPSO helped to achieve global best (gbest) solution. The APBP with the ALA model is applied to enhance the performance with higher fitness value and convergence problem. Accordingly, the obtained results helped to improve the accuracy or the optimality of the design parameters. Further, both GSA and QPSO model have been applied in parallel to solve the aforesaid optimization problem, where GSA helped QPSO to obtain global value (gbest) and velocity optimally. In order to execute the program, 500 generations have been considered as the stopping criteria, while the search space is modeled with six dimensions. This polyline (irregular) shaped patch antenna (Fig.1) has 11 coordinates for identifying a population of 25 agents or particles. In other words, the proposed model is designed in such a manner that it estimates five coordinates with 10 parameters (x1 to x5 and Δy1 to Δy5) to result in an irregular-shaped patch antenna with higher bandwidth. Noticeably, the GSA-QPSO model is regarded as a constrained optimization model, where the limits of x and y are predefined to avoid inappropriate results probability. During simulation, the lower and higher threshold values are maintained for $x_{i=1,2,3,4,5}$ as 0.01 and 14.5, respectively. Similarly, the lower and upper thresholds are kept for $\Delta y_{i=1,2,3,4,5}$ as 0.01 and 5, correspondingly. The target is to achieve a polyline irregular-shaped MPA with a 50 Ω microstrip feed line, where the values of L_f and W_f are fixed which is designed over FR4 substrate with relative permittivity of 4.4. To enable optimal radiation performance, the ground metallization is escaped below the radiator; however, it required a L_g of 11.5 mm.

In order to simulate the performance, the sweep size or interval band of 0.01 GHz has been taken into account. Recalling the overall research intend where the key emphasis has been made on achieving higher BW under the assign frequency range. In this case, the lower and upper bound of the frequency is maintained at 2.4 GHz and 10.4 GHz, respectively. Thus, the optimal values of the above-stated irregular radiator coordinates are obtained by processing the GSA-QPSO model. Noticeably, to perform coordinate optimization, at first, the GSA-QPSO algorithm is applied which obtains the set of coordinate values (i.e., $x_{i=1,2,3,4,5}$ and $\Delta y_{i=1,2,3,4,5}$) for each iteration. Once obtaining the updated co-ordinate values, it is fed as input to the HFSS through a VB-script which acts as an interface between MATLAB and HFSS. Thus, for each set of radiator's coordinates, HFSS examined corresponding S_{11} values and this process continued till GSA-QPSO reached the stopping criteria. Considering the proposed model to be a population-based stochastic prediction (because both GSA and QPSO use initial populations to estimate sub-optimal solutions), it has been simulated for different test cases. This generated different coordinates, based on which the performance is obtained. To assess relative performance, the proposed model is simulated multiple times and noted the corresponding performance outcomes in terms of S_{11} parameter. The overall proposed model is simulated using MATLAB 2020b with HFSS 18. A few test results for coordinate values by the proposed GSA-QPSO model are given in Table 2.

Table 2. GSA-QPSO optimized MPA design parameters.

Design Constraints	L_f= 12.5 mm W_f=3 mm L_g=11.5 mm ϵ_r=4.4			
Variables	**Threshold (mm)**	**Test Case-1**	**Test Case-2**	**Test Case-3**
x_1	Upper Value= 14.5 Lower Value=0.01	7.089	7.319	7.617
x_2		7.479	7.100	6.748
x_3		8.528	9.680	8.678
x_4		7.391	6.538	5.719
x_5		8.239	6.689	3.594
Δy_1	Upper Value= 5 Lower Value=0.01	0.728	0.408	0.532
Δy_2		1.931	4.613	4.159
Δy_3		2.390	2.702	3.931
Δy_4		2.679	3.171	3.249
Δy_5		4.378	2.828	2.747

Fig. 3 presents the reflection coefficient performance of optimized MPA for three different cases. Because an ideal patch antenna requires maintaining S_{11}<-10dB, perceiving the outcome, it is observed that the anticipated MPA retains S_{11} lower than the aforesaid acceptance range. This pattern can be operated within the assessment frequency band from 2.4 GHz to 10.4 GHz. For instance, the optimized antenna provides the impedance BW in case (1) 8 GHz, ranging from 2.4 GHz to 10.4 GHz, case (2) 8.03 GHz, ranging from 2.38 GHz to 10.41 GHz, and case (3) 8.1 GHz, ranging from 2.34 GHz to 10.44 GHz. In other words, we can say that our proposed MPA can cover the WB or UWB frequencies from 2.4 to 10.4 GHz in these cases.

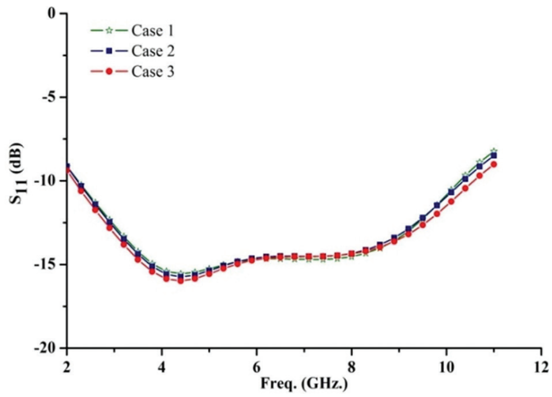


Fig. 3. Reflection coefficient of optimized MPA for different cases.

In the case (3), the optimized MPA provided a wider bandwidth, so this is considered for fabrication and measurement assessment. The final optimized (case 3) MPA is fabricated by a CNC machine, and Agilent's Vector Network Analyzer (VNA) N5247A is used to measure its performance. The fabricated model of MPA is depicted in Fig. 2.

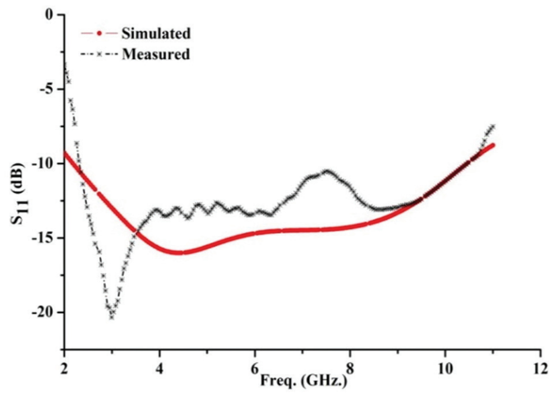


Fig. 4. Reflection coefficient of the final optimized MPA

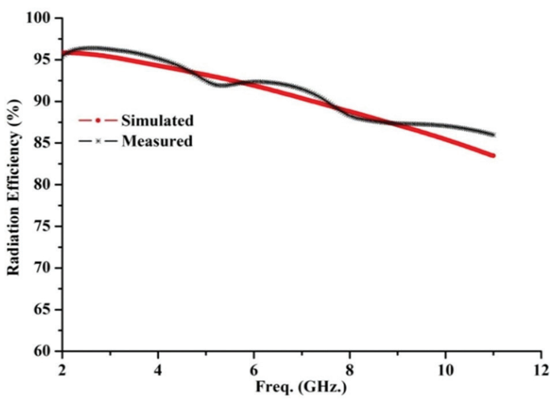


Fig. 5. Radiation efficiency of the final optimized MPA

Simulation and measurement of the final optimized MPA are correlated in Fig. 4 and Fig. 5. Across the entire simulation and measurement frequency range at 2.34 GHz - 10.44 GHz and 2.42 GHz -10.38 GHz, S_{11} is sustained with less than -10 dB. An antenna's radiation efficiency (%) can be compared using Fig. 5 and the corresponding simulations.

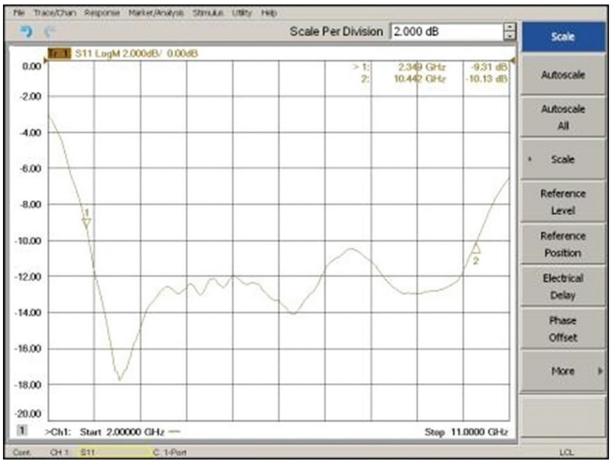


Fig. 6. Reflection coefficient on VNA of the final optimized MPA

The radiation efficiency of an antenna can be determined by comparing the radiated power with the power delivered at its terminals. In this case, the distance between transmitter and receiver is 1.5 meters. Horn antenna (AMkom) is used as a reference antenna, which has a broad frequency range from 1-18 GHz. The details of the experimental method for determining the radiation efficiency of the antenna are given in [52]. As shown in Fig. 5, the measured and simulated radiation efficiency is more than 84% for the whole operational band. When frequencies rise, dielectric loss increases and reduces efficiency. Modeling and simulating over a large BW have led to slightly different outcomes due to fabrication tolerances and software restrictions. The measured outcome of S_{11} on the VNA is presented in Fig. 6. The print of the VNA and anechoic chamber for the projected antenna can be seen in Fig. 7 (a) and (b).

Fig. 7(a). VNA setup

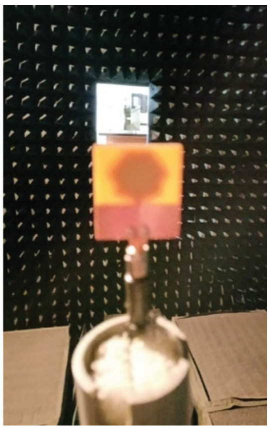
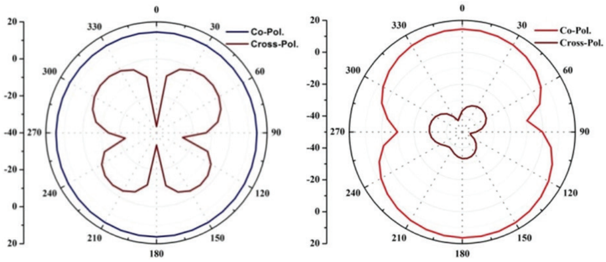
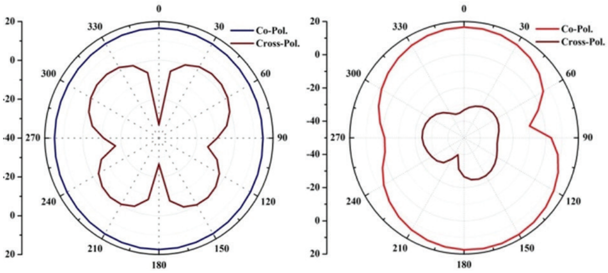


Fig. 7(b). Anechoic chamber

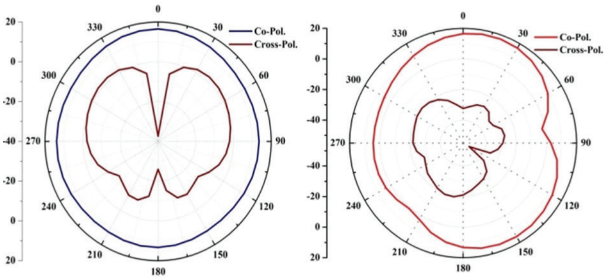
Fig. 8 (a), (b), and (c) displays the simulated two-dimensional radiation profiles of a final projected antenna. The co-polarization and cross polarization for the E and H plane at different operating frequencies of 4.4 GHz, 5.6 GHz, and 8.6 GHz, correspondingly is presented. Co-polarization is the preferred polarization of the wave to be transmitted by the radiator, while cross-polarization is the symmetrical radiation of the preferred polarization of the wave. Essentially, cross polarization is a loss of a signal at the recipient end. Likewise, it is a noise as far as detection is concerned. To reduce the obstruction of the waves, cross-polarization should be less than co-polarization. Generally, 15-20 dB down is adequate, except if the recipient has explicit prerequisites. The undesirable signal can be made adequate until it doesn't influence the detection.



(a) 4.4 GHz



(b) 5.6 GHz



(c) 8.6 GHz

Fig. 8. The radiation pattern of the final optimized MPA at varied resonant frequencies (Left and right side indicate E-plane H-plane, respectively).

In contrast to co-polarization intensities, the cross-polarization intensities are lesser than 14-17 dB and 30-34 dB in the E and H planes. The performance of the radiation pattern of the anticipated MPA is the same as those of a normally printed monopole, so the proposed MPA is appropriate for wide-band applications [2] [5].

6. CONCLUSION

In this paper, the emphasis is made on optimizing both the computational environment as well as the research goal, which is a broader band compatible patch antenna design. This research aimed to optimize the computational environment by implementing a hybrid heuristic concept, named the GSA-QPSO algorithm. Unlike classical heuristic algorithms, in the proposed GSA-QPSO model, QPSO with Levy's flight-based positioning on the one hand enabled optimal estimation, while GSA helped in achieving optimal local search activity. As a result, the GSA-QPSO model assisted in the estimation of appropriate MPA parameters. Noticeably, to further improve accuracy and computational efficiency, the proposed model employed QPSO with APBP and ALA functions. This approach enabled optimal estimation with the suitable set of design parameters while maintaining local minima and convergence avoidance and global optima accomplishment. This mechanism facilitated optimal coordinate parameter estimation for irregular-shaped patch antenna design. The proposed GSA-QPSO model optimized the MPA coordinate parameters in such a manner that it retained higher BW. The proposed model is simulated for the different test cases. This generated different coordinates, regarding which we obtained the performance. In terms of reflection coefficient, three different cases are observed to get optimum coordinate parameters of anticipated MPA. Finally, for case 3, the optimized MPA provided 126.6 % impedance BW with more than 84 % radiation efficiency over the entire operating frequency range from 2.34 to 10.44 GHz. The simulated results are also compared with measured results, which are closer to each other. The performance of the radiation patterns of the anticipated MPA is nearly omnidirectional. It revealed that the proposed MPA can be used for real-world wideband communication drives.

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