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Design of H-shaped MPA using Reptile Search Algorithm based Multilayer Perceptron Neural Network

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Abstract

In many applications such as aerospace systems, satellites, mobile radar, and other wireless applications, the Microstrip patch antenna (MPA) plays an important role due to its properties like lightweight, low cost of production, and compact structure. Low gain, narrow frequency bandwidth, and high return loss are the shortcomings in these existing MPA design approaches. Moreover, the developed models of the antenna are hard to design and larger size. The antenna's geometrical specifications should be optimized to address this problem. This proposed approach Reptile Search Algorithm (RSA) based Multilayer perceptron (MLP) neural network is employed to design the H-shaped antenna for Ku-band applications. The MLP neural network is employed to calculate the fitness value of the RSA. To train the MLP neural network by using MATLAB software. The experimental and simulation results of the proposed approach shows better performance with 8.89 dB gain, -33.06 dB return loss, and 1.07 VSWR.

Keywords. Microstrip patch antenna, Reptile Search Algorithm, Ku-Band, Multilayer perceptron neural network.

1. Introduction

The cost of antenna design has fallen as a result of the use of microstrip technology to antenna structures, and designs have become more compact and adaptable. Because of the light weight, compact size, and low cost properties of microstrip patch antenna (MPA), they are widely employed in wireless communication systems [1-2]. Antenna design poses a number of difficulties. The disadvantages of these MPA are their low gain, restricted frequency bandwidth, and significant return loss [3-4]. Furthermore, the designed antenna models are more difficult to construct. These constraints can be mitigated by proper design considerations. To achieve high gain and low return loss, the optimal selection of geometrical factors such as MPA width and length is a crucial design task [5]. In recent years, meta-heuristic optimization algorithms such as Particle Swarm Optimization (PSO) algorithm [6], Ant Colony Optimization (ACO) algorithm [7], Elephant Herding Optimization (EHO) algorithm [8] and Firefly Algorithm (FA) algorithm [9] are proposed by many researchers, for the optimal selection of geometrical parameters of MPA. A very effective algorithm among other optimization algorithms is RSA and it is mostly used for the optimal design of antenna [10]. According to the best exploration of the swarm, the global optimum solution can be obtained by the RSA.

To improve the electromagnetic and physical properties of the antenna, electromagnetic simulators are used in the objective function of existing optimization algorithms [11]. The design of the same antenna for a different frequency takes a long time and requires repetition of the entire procedure, which is one of the primary disadvantages of this approach. Many hours of computing time can be saved by using various machine learning approaches as the optimization algorithm's objective function. The most often utilized machine learning approaches are the Support Vector Machine (SVM), Gaussian Process (GP), and Artificial Neural Network (ANN) [12]. The SVM employs statistical learning theory. SVM has a hard time exposing and determining kernel function parameters [13]. ANN is a data processing and intelligent science system based on replicating the operation and structure of the human brain. In wireless communication applications, ANN has proven incredible performance [14]. Multi-Layer Perceptron (MLP) approach is a type of feed forward ANN that has the capability to learn online and non-linear models [15]. In this paper, RSA based MLP approach is proposed to design the H-shaped antenna for Ku-band applications.

The major contributions of this paper are given as follows:
1. The Reptile Search Algorithm (RSA) approach is utilized to optimize the geometrical parameters of the H-shaped MPA. The substrate height, dielectric constant, and resonant frequency are the inputs to the proposed algorithm and the optimized width and length of the patch are the outputs of the proposed algorithm. The return loss and gain of the antenna are considered for the fitness functions. The optimization process is performed in two phases. In the early stage of optimization, the RSA is employed. For the accurate and fast computation of fitness functions, various modeling techniques can be used.

2. Multilayer perceptron (MLP) neural network is employed to calculate the fitness value of the proposed RSA approach. To train the MLP, the dataset is generated using MATLAB software that contains values of the substrate height, dielectric constant, length of the patch, resonant frequency, width of the patch as the input parameters, and the values of gain and return loss as the output parameters.

3. The performance of the optimally designed antenna with the RSA approach is evaluated in terms of the radiation pattern, return loss, gain, computation time, directivity, VSWR, and Directivity for Ku-band applications. The comparison of results is performed for the proposed RSA approach with existing approaches conventional PSO-SA [16], PSO [6], ACO [7], EHO [8] and FA [9].

The remainder of the paper is arranged as follows. The works related to the optimal design of H-Shaped MPA are discussed in Section 2. The design and optimization of H-shaped MPA using the proposed RSA-MLP approach are explained in Section 3. The simulation results of the RSA approach are discussed and compared with existing techniques in Section 4. Finally, the conclusion of the paper is given in Section 5 possible with future work.

2. Related works

Rajpoot et al. [17] suggested optimizing MPA based on PSO with curve fitting. They have used I shape antenna to illustrate the optimization technique. They create an initial antenna in the shape of ‘I’ by making slots in the rectangular patch. The resonance frequency of this antenna is 2.4 GHz. The substrate materials have a loss tangent of 0.0015 and \( \varepsilon_r \) value of 4.2. Their optimization technique aims at maximizing the fractional bandwidth while maintaining a resonant frequency near to 2.4 GHz. Similar to this, Dhaliwal, & Pattnaik, [18] created a small crown circular fractal patch antenna for the WLAN frequency band at 5.8 GHz using the PSO-ANN ensemble model. The PSO algorithm computes the objective function using the ANN ensemble model. This approach achieves an antenna with a 6.16 dB gain. Even though PSO-based techniques performed better, PSO particles occasionally lock in local optimum solution.

Pattnaik, et al. [19] use the Genetic Algorithm (GA) to determine the width and length of rectangular MPAs. The required resonant frequency, substrate thickness, and dielectric constant are regarded as the input parameters, while the optimum width and length are regarded as the output parameters. The simulation results are obtained using an IE3D (Integral Equation Three Dimensional) programme. Seven antennas are modified in order to validate the data generated by GA. They have demonstrated the simplicity and efficiency of their strategy. The experimental length measured at 6.2 GHz is 14.12 mm, while the predicted width is 8.975 mm. However, the GA technique is computationally costly. The African buffalo algorithm (ABA) and the ACO were coupled by Kumar. P. et al. [7] to improve the antenna's characteristics. They make use of geometrical parameters including patch width, patch length, and dielectric constant to create a novel "A"-shaped UWB antenna. The suggested algorithm improves the bandwidth, gain, return loss, and directivity of antenna radiation. They have reached 9.97 GHz bandwidth and a return loss of -20.6 dB. However, the ACO method takes a while, and ACO could have a slow convergence rate.

Elephant Herding Optimization (EHO) technique with a novel scaling factor is suggested by [8] to fine-tune the MPA parameters. To boost the antenna's gain, they tuned factors such substrate thickness, dielectric value, patch length, and patch breadth. They have examined the expense, benefit, and effectiveness of the suggested model. At the resonant frequency of 77 GHz, they have attained a maximum gain of 17.2 dB. With fewer control parameters, the EHO is less likely to accidentally fall into the local optimum solution. Even if their method performs better, the EHO falls short in stochastic initialization. The ANN with Firefly algorithm (FA) is suggested by Guttula, R. et al. for optimizing a "Flower"-shaped differentially fed MPA [9]. The dataset is used to develop and train the feed-forward neural network (FNN). The fitness function in the FA is measured using this FNN. The designed flower-shaped differentially fed MPA is used to create the dataset. When their method was compared to GA-based
ANN, it performed better at minimizing return loss. The best return loss value that can be achieved with this method is -45 dB. Results from simulations are obtained using the IE3D simulator. However, FA takes a lot of time and could become caught in the local optimal solution.

Moth-Flame optimization (MFO), based on MPA, is developed by Singh, A. et al. for UWB applications [20]. To reduce the cross-polarized radiation emitted by the microstrip patch, they have constructed MPA with a defective ground structure. Liquid crystal polymer was employed to lower the material's cost, and the appropriate geometric parameters were applied to boost the antenna's performance. This method has a return loss of -20 dB and an operational antenna bandwidth of 3.1 GHz. However, this method takes more effort to design. Saadi, M. A. et al. [21] decreased the size of the planar MPA to obtain lower frequencies. To making the antenna smaller, it is sawtooth-shaped cut into a number of slots. This strategy uses two procedures. The MPA is initially created. The slots then were separated to create the sawtooth pattern. The size of the patch antenna at 1.7 GHz is decreased by 87.88% using this method. Kaur, I. et al. [22] created a circular MPA that can be used in UWB applications. They created the antenna using a FR-4 substrate. They attained -34.22 dB return loss at the 3.54 GHz resonance frequency. They haven’t contrasted their suggested strategy with currently employed strategies. Low gain and high return loss compromise the MPA’s performance, despite the several ways that have been suggested for its design and optimization. These studies allow us to draw the conclusion that traditional meta-heuristic optimization methods are more computationally demanding, have slower convergence rates, and are more susceptible to local optima. This work with MLP proposes a novel RSA strategy to address these problems in creating MPA.

3. Proposed approach

3.1 Reptile Search Algorithm

The social, hunting and encircling behavior of crocodiles is the main inspiration behind the Reptile Search Algorithm (RSA). To perform the optimization of MPA, these hunting and encircling mechanisms are mathematically modelled. This RSA approach is explained in three phases initialization phase, encircling phase and hunting phase. The Figure 1 displays the flowchart of the RSA.

3.1.1 Initialization phase

In this process, the solutions are initialized using the Equation (1).

\[
S = \begin{bmatrix}
S_{1,1} & \cdots & S_{1,j} & \cdots & S_{1,n-1} & S_{1,n} \\
S_{2,1} & \cdots & S_{2,j} & \cdots & S_{2,n} & \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
S_{N-1,1} & \cdots & S_{N-1,j} & \cdots & S_{N-1,n} & S_{N,n} \\
S_{N,1} & \cdots & S_{N,j} & \cdots & S_{N,n-1} & S_{N,n} \\
\end{bmatrix}
\] (1)

Here, \(S\) represents the group of solutions. Equation (2) is utilized to generate these solutions randomly. The \(i\)th solution’s \(j\)th position is denoted by \(s_{ij}\). The dimension size is represented by \(n\). The number of solutions is represented by \(N\).

\[s_{ij} = (UB - LB) \times rand + LB, \quad j = 1, 2, ..., n\] (2)

Where, UB and LB represents the upper and lower bound of parameters of MPA and a random value is denoted by \(rand\).

3.1.2 Encircling phase

During this stage of optimization, the exploration mechanisms are used to support the other phase of the search process through vast and dispersed studies. The RSA can switch between encircling and hunting search phases based on four conditions: divide the total number of iterations into four parts. Based on two major search strategies, the RSA exploration mechanisms investigate the search regions and approaches to find a better answer. By \(t \leq \frac{T}{4}\) the
strategy of high walking movement is conditioned. By $t \leq 2\frac{T}{4}$ and $t > \frac{T}{4}$, the strategy of belly walking movement is conditioned. To update the position the Equation (3) is utilized.

$$x_{(i,j)}(t + 1) = \begin{cases} 
Best_j(t) - \eta_{i(j)}(t) \times \beta \times R_{(i,j)}(t) \times \text{rand}, & t \leq \frac{T}{4} \\
Best_j(t) - x_{(r1,j)}(t) \times ES(t) \times \text{rand}, & t \leq 2\frac{T}{4} \text{ and } t > \frac{T}{4}
\end{cases} \quad (3)$$

Where the best obtained solution in the jth position is denoted by $Best_j(t)$ and a random number between the range [0, 1] is represented by rand. The maximum iteration count is denoted by $T$ and count of present iteration is denoted by $t$. In the ith solution the hunting operator for the jth position is represented by $\eta_{i(j)}$. The sensitive parameter is denoted by $\beta$. $R_{(i,j)}$ represents the reduction function. $ES(t)$ is the evolutionary sense have values in the range of [2, -2]. The count of solutions is denoted by $N$. In the range [1, N] a random number is represented by $r_1$.

**3.1.3 Hunting phase**

Crocodile techniques, unlike encircling processes, allow them to easily approach the intended prey because of their intensity. As a result, the exploitation search finds the near-optimal solution, sometimes after numerous attempts. Furthermore, at this stage of optimization, the exploitation mechanisms are used to conduct an intensification search near the optimal solution and to promote communication between them. Equation (4) is used to update the position.

$$x_{(i,j)}(t + 1) = \begin{cases} 
Best_j(t) \times P_{(i,j)}(t) \times \text{rand}, & t \leq 3\frac{T}{4} \text{ and } t > 2\frac{T}{4} \\
Best_j(t) - \eta_{i(j)}(t) \times \epsilon - R_{(i,j)}(t) \times \text{rand}, & t \leq T \text{ and } t > 3\frac{T}{4}
\end{cases} \quad (4)$$

In the best obtained solution the jth position is denoted by $Best_j(t)$. In the ith solution $\eta_{i(j)}$ denoted the hunting operator for the jth position. A small value is denoted by $\epsilon$. $R_{(i,j)}$ represents the reduction function. The percentage difference between the current solution’s jth position and the best-obtained solution’s jth position is denoted by $P_{(i,j)}$.

![RSA flowchart](image)
MLP is a resilient neural network that is used in systems with a lot of nonlinearity. In addition, the MLP is a feed-forward network promising more precise nonlinear fits. The MLP neural network's architecture is depicted in Figure 2. The output layer has $Y$ neurons, the hidden layer has $F$ nodes, and the input layer has $S$ nodes. The input layer’s weighted sum is expressed using Equation (5)

$$f_j = \sum_{i=1}^{S} (w_{ij}s_i) + \theta_j, j = 1, 2, \ldots, q$$  (5)

Where the connection weight of the $j$th node in the hidden layer and $i$th node in the input layer is represented by $w_{ij}$. In the hidden layer, the $j$th node’s bias is represented by $\theta_j$. The $i$th input is represented by $s_i$.

In the hidden layer, a node’s output is expressed using Equation (6).

$$F_j = \text{sigmoid}(f_i) = \frac{1}{1 + \exp(f_i)}, j = 1, 2, \ldots, q$$  (6)

The final output values can be expressed using Equations (7) and (8).

$$y_k = \sum_{j=1}^{q} w_{jk}F_j + \theta_k, k=1, 2, \ldots, r$$  (7)

$$Y_k = \text{sigmoid}(y_k) = \frac{1}{1 + \exp(y_k)}, k = 1, 2, \ldots, r$$  (8)

The connection weight of the output layer’s $k$th node and hidden layer’s $j$th node is represented by $w_{jk}$. In the output layer the bias of $k$th node is represented by $\theta_k$.

3.3 Proposed H-shaped MPA with RSA based MLP approach

The flowchart of the proposed RSA-MLP approach is displayed in Figure 3. The steps involved in the proposed approach are initialization phase, encircling phase and hunting phase. In the initialization process, the geometry values of the proposed H shaped MPA such as the patch length ($L_p$), and the patch width ($W_p$) are initialized. The independent geometric parameter values such as dielectric constant, resonant frequency, and substrate height are initialized as 4.4, 14GHz, and 1.6 mm respectively for Ku-band applications. Then the fitness value is calculated for the initialized geometric parameters. The trained CNN is employed in the proposed algorithm to calculate the fitness value to minimize the error. The addition of the minimum value of return loss (RL) and maximum value of gain (G) is considered the single fitness function of the proposed approach as expressed in Equation (9).
Objective function = minimum (Return loss) + max (Gain) \hfill (9)

The position is updated using Equations (3) and (4). This process is repeated until the maximum iteration is reached. At last, the optimal geometric values of proposed H-shaped MPA can be obtained. The algorithm 1 explains the pseudo code for the proposed RSA-MLP approach for the design of H-shaped antenna for Ku-band applications.

![Flowchart of proposed RSA-MLP approach]

**Algorithm 1. Optimization of Geometrical Parameters of MPA using RSA-MLP**

- Initialize the geometric parameters as population \((s^i_m)\)
- Evaluate fitness value using trained MLP
- Select leader and Update the position using RSA
- Measure the fitness for all values in the \(s^i_m\)

\[
\text{while } (t<\text{maximum iteration}) \\
\quad \text{fitness}_j \text{ taken as the best solution,} \\
\quad \text{position}_j \text{ taken as best objective} \\
\quad \text{for all } (s^i_m) \\
\quad \quad \text{Update position using Equations (3) and (4)} \\
\quad \text{end for} \\
\quad t=t+1 \\
\text{end while} \\
\text{return the final best solution } s^j_{\text{fitness}} \text{ as the optimal geometry value}
\]

4. Experimental results

This section explains the design of the proposed H-shaped MPA with experimental results. The performance of the proposed approach is compared with conventional methods to prove the effectiveness of the proposed approach.

4.1 Design of H-shaped antenna

For the H-shaped MPA, the parameters are designed as follows. The dielectric constant, resonant frequency, and substrate height are the fixed parameters. The radiation mechanism in MPA is shown in Figure 4. The proposed inset-fed rectangular MPA is designed using the geometric parameters like the patch length \((L_p)\), the
patch width ($W_p$), dielectric constant ($\varepsilon_r$), substrate height, and resonant frequency. The independent geometric parameter values such as dielectric constant, resonant frequency, and substrate height are initialized as 4.4, 13.5 GHz, and 1.6 mm respectively for Ku-band applications.

![Figure 4. MPA design](image)

The dataset required to train and test the MLP in the proposed approach is generated using MATLAB 2018a software. The MLP trained with developed dataset is used to evaluate the fitness value. The proposed RSA-MLP approach is implemented using MATLAB software. The population is initialized as 50 and the total iteration is set as 500. The performance of the proposed approach is compared with other approaches like PSO-SA [15], PSO [6], FA [9], ACO [7] and EHO [8]. Table 1 shows the simulation parameters used for the optimization of antenna.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>FA [9]</td>
<td>$\beta$</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>$\alpha$</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>$\gamma$</td>
<td>1</td>
</tr>
<tr>
<td>PSO [6]</td>
<td>Weight</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>2</td>
</tr>
<tr>
<td>ACO [7]</td>
<td>$\alpha$</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>$\beta$</td>
<td>2.5</td>
</tr>
<tr>
<td>EHO [8]</td>
<td>$\alpha$</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>$\beta$</td>
<td>0.1</td>
</tr>
<tr>
<td>PSO-SA [15]</td>
<td>Initial temperature, $t$</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>Weight</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>2</td>
</tr>
<tr>
<td>Proposed RSA-MLP</td>
<td>$\alpha$</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>$\beta$</td>
<td>0.1</td>
</tr>
</tbody>
</table>

4.2 Radiation pattern of the Antenna

The radiation pattern is the representation of the antenna radiation. In the far and near-field areas, the power of the antenna will be spread. Figure 5 shows radiation patterns of the proposed MPA with frequencies of 13.5 GHz for the Ku-band. Based on the angular positions and radial positions, the pattern of the radiation of the antenna is represented. Moreover, the function of magnetic and electric fields designed on the logarithmic scale represents the pattern of radiation of the antenna. Depending on the energy radiated direction, the pattern of radiation is determined. On the power patterns and field patterns, the radiation patterns that are designed with dB scale and logarithmic scale are mentioned.
4.3 Return Loss

More signal power will be lost because of the production of reflections by the presence of discontinuities in the transmission line. This power loss is known as return loss and in decibels (dB) it can be represented. This loss can be calculated using Equation (10).

$$RL(dB) = 10 \log_{10} \frac{P_{IN}}{P_{REF}}$$

(10)

Where Incident power is represented by $P_{IN}$ and reflected power is represented by $P_{REF}$. Figure 6 shows the return loss for Ku-band applications. The return loss for the Ku-band application is -33.06 dB resonates at 13.5 GHz. Thus, the return loss of the proposed approach is within the acceptable level.

4.4 Antenna Gain

The effectiveness of the radiation of signals from the proposed antenna can be calculated using antenna gain. In the antenna radiation direction, the amount of transmitted power can be determined using the antenna gain. The gain is measured in terms of dB. The radiation pattern used is broadside pattern. Using the efficiency and the antenna directivity the antenna gain can be calculated as given in Equation (11).

$$G = \varepsilon r D$$

(11)
Where directivity is represented by $D$ and relative permeability is represented by $\varepsilon_r$. How much the produced radiation is concentrated in a solitary path is estimated by the directivity and parameter of the receiving wire which is characterized by the directivity. Figure 7 shows the 3D representation of the gain patterns. From conical cuts, this model is developed. Direction-based angles are used to form the model. With the existing approaches like ACO, FA, PSO, PSO-SA and EHO algorithms, the antenna gain of the proposed RSA approach is compared. From the comparison results, a high gain is attained by the proposed antenna.

![Figure 7. 3D Radiation pattern](image)

### 4.5 Voltage Standing Wave Ratio (VSWR)

For the proper impedance matching indication, at the location of feed, the VSWR is the important parameter. The ratio of the maximum voltage to the minimum voltage in the antenna defines the VSWR as given in Equation (12).

\[
VSWR = \frac{|V_{\text{max}}|}{|V_{\text{min}}|}
\]

Where, $V_{\text{max}}$ represents the maximum voltage of antenna and $V_{\text{min}}$ represents the minimum voltage of antenna. The efficiency of transformation of radio frequency power of antenna from the transmission line or source in the channel can be calculated using the VSWR. Figure 8 shows the VSWR of the proposed approach for Ku-band applications. For Ku-band application the VSWR achieved by the proposed approach is 1.074. Thus the VSWR value lies below 2 which are in the acceptable range.

![VSWR](image)

\[
VSWR = \frac{|V_{\text{max}}|}{|V_{\text{min}}|}
\]
4.6 Directivity

The ability of the radiation to focus on the proposed antenna can be calculated using the parameter directivity. For validating the performance of the developed antenna for many antennas, the directivity is the necessary calculation. The ratio of a practical radiator’s radiation intensity to an isotropic radiator is referred to as directivity. It is expressed using Equation (13).

\[ AD = \frac{R_p}{R_i} = \frac{4\pi u_p}{P_{rad}} \]  

Where the practical radiator’s radiation intensity is represented by \( R_p \) and isotropic radiator’s radiation intensity is represented by \( R_i \). The directivity of proposed approach is shown in Figure 9 for Ku-band applications. The proposed approach achieved better directivity and the ability of the radiation to focus on the proposed antenna is higher.

4.7 Input impedance

The imaginary reactance and real resistance are denoted as the input impedance. For the essential function of antenna frequency operation, the impedance of the antenna is the necessary function. Figure 10 shows the input impedance vs. frequency response of Ku-band applications. To identify the input impedance of the antenna, the frequency is considered between 11.5 GHz and 13.5 GHz for the Ku-band application. To design the H-shaped MPA, the high input impedance is attained by the proposed antenna.
4.8 Comparison with existing techniques

The performance of the RSA technique for MPA is compared with existing techniques like conventional PSO-SA, PSO, ACO, FA and EHO. Figure 11 shows the return loss comparison for the proposed approach with existing techniques for Ku-band applications. The proposed approach achieved -33.06 dB return loss. When compared with existing approaches, the return loss achieved by the proposed approach is very less. Figure 12 shows the comparison of the directivity of proposed approach with existing approaches for Ku-band applications. The proposed approach achieved better directivity. The existing approaches achieved very less directivity when compared with proposed approach.

![Return Loss Comparison](image1)

![Directivity Comparison](image2)

Figure 13 shows the comparison of the convergence curve of the proposed approach with existing approaches such as conventional PSO-SA, PSO, ACO, FA and EHO. The proposed RSA approach has a better convergence rate than the existing approaches. The Figure 14 shows the VSWR comparison for the proposed approach with the existing approaches. The VSWR achieved by the proposed approach is 1.07 which is very less compared with existing approaches. The Figure 15 displays the gain comparison for the proposed approach with the existing approaches. Using the proposed approach the antenna attains higher gain of 8.89 dB. The computation time taken by the proposed algorithm is compared with the existing approaches as shown in Figure 16 (a). The proposed approach
took less running time for the RSA algorithm compared with existing approaches. The total computation time taken by the proposed RSA-MLP approach is compared with the existing approaches as shown in Figure 16 (b). The proposed approach took less time compared with existing approaches.

![Convergence curve comparison](image13.png)

**Figure 13. Comparison of Convergence curve**

![VSWR comparison](image14.png)

**Figure 14. VSWR comparison**
5. Conclusion

The existing meta-heuristic based optimal MPA design approaches have many disadvantages such as low convergence speed, easy to fall in local optima and high computation complexity. In this paper, the inset-fed rectangular MPA is designed for Ku-band applications by optimally selecting the geometrical values such as patch width and patch length using the RSA. The proposed approach has a higher convergence speed and low computation complexity. The proposed algorithm optimizes the geometric parameters by taking the return loss and gain of the antenna as the fitness function. A dataset is developed with different length and width values of the patch as the input parameters and output parameters are considered as return loss and gain for constant values of dielectric constant, substrate height, and resonant frequency. This developed dataset is utilized to train the Multi-Layer Perceptron (MLP) Neural Network for calculating the fitness value. The implementation is performed using MATLAB software. The optimally designed antenna is evaluated in terms of the radiation pattern, return loss, directivity, gain, impedance and VSWR. The gain, VSWR, return loss, directivity, and convergence curve of the proposed RSA approach are compared with existing approaches such as conventional PSO, PSO-SA, FA, ACO, and EHO algorithms. For Ku-band application, the obtained gain is 8.89 dB, return loss is -33.06 dB and VSWR is 1.07 for 13.5 GHz resonant frequency. In future, the proposed approach will be improved to design MPA for various band applications.
Conflict of interest The authors declare that they have no conflict of interest

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