BJES Basrah Journal for Engineering Sciences

Basrah Journal for Engineering Sciences, Vol. 22, No. 1, (2022), 86-92

Original Article

Journal homepage: www.bjes.edu.iq
ISSN (Online): 23118385, ISSN (Print): 18146120

OPEN ACCESS

Design and Optimizing of Compact Ultra-Wide Band Printed Patch Antenna Employing Different Optimization Algorithms Based on Plant Inspiration

Hussein M. Hathal [1, *], Abdulkareem Swadi Abdullah [2], Ramzy S. Ali [3]

[1,2,3] Department of Electrical Engineering, College of Engineering, University of Basrah, Basrah, Iraq
[1] Department of Electrical Engineering, College of Engineering, Mustansiriyah University, Baghdad, Iraq
E-mail addresses: hussein.m.hathal@uomustansiriyah.edu.iq , abdulkareem.abdullah@uobasrah.edu.iq , ramzy.ali@uobasrah.edu.iq
Received: 23 December 2021; Revised: 5 January 2022; Accepted: 11 January 2022; Published: 24 April 2022

Abstract

In this paper, a compact ultra-wide band (UWB) printed patch antenna is designed and optimized using four biologically and plant inspired optimization algorithms. These algorithms are the newly adopted Moss Rose Optimization Algorithm (MROA), Runner Root Algorithm (RRA), Sunflower Optimization Algorithm (SFOA) and Particle Swarm Optimization (PSO). These algorithms are modified in an optimizer software, which merges the attributes of the design of electromagnetic environment of CST Microwave Studio with those of the technical programming environment of MATLAB. A compact (12 × 21.5) mm^2 printed patch antenna has been proposed and simulated over the whole UWB frequency range using these four optimization algorithms. The simulation results show the superiority of the antenna design using MROA, which has the widest covered frequency range, the lowest reflection coefficient and the lowest standing wave ratio.

Keywords: Bio-inspired algorithm, Moss Rose Optimization Algorithm, Particle Swarm Optimization, Runner Root Algorithm, Sunflower Optimization Algorithm, and Ultra-Wide Band (UWB).

https://doi.org/10.33971/bjes.22.1.10

1. Introduction

The optimization is needed in every designing specialty, and issues are various and different. Normally, arrangement techniques are a functioning examination theme. Prior strategies to tackle advancement issues were computationally extraordinary, and turned out to be less helpful as issue sizes expanded. Organically motivated stochastic calculations were acquainted as computationally powerful choices with deterministic methodologies, including the iterative enhancement of alike a populace of arrangements, as in transformative, or a solitary arrangement. They generally utilize randomness and neighborhood looking to discover arrangements [1].

Many researches are presented for designing an ultra-wide band antenna. The design of this type of antenna is based on two methods. The first method, a trial-and-error method is used in finding the optimal dimensions of the antenna that achieve the requirements of the proposed design. The second method, some algorithms are used in finding the optimal antenna dimensions to achieve the desired results. Some related researches for second method will be illustrated below briefly.

In 2014, the optimization process of using algorithms for the design of UWB antennas, in particular genetic algorithm (GA) and particle swarm optimization (PSO) have been presented in [2] for designing a UWB antenna. The results showed that the design antenna had a good radial pattern and gain with a wide performance width of 7.25 GHz over the operating range.

In 2016, a study of a simple, compact, microstrip-fed printed antenna with a triple-band rejected facility was presented in [3]. Researchers used the firefly algorithm (FA) with the Antenna Optimizer software to achieve a better result than PSO. The results show that the proposed antenna design has useful gain and a simple structure, as well as having triple notch band over ultra-wide operating ranges that make it a good candidate for various UWB applications.

In 2016 also, the benefits of optimizing the design of the UWB antenna using the FA are revealed [1]. The FA has given better performance than PSO and GA in the design of the proposed shape antenna. The study showed that the use of optimization algorithms such as GA, PSO, or FA, and since they make no assumptions about design, they can generate optimal data for specific design criteria.

In 2020, a study for a novel design of microstrip with line-feed antenna using modified hybrid of BF-PSO has been presented [4]. The study shows that better results are provided using the modified hybrid method when compared with the classical BF, chaos PSO, IWO, and ABC algorithms.

In 2020, a proposed design of microstrip E-shaped antenna to operate in the broad frequency range using a PSO algorithm has been presented [5]. The working frequency of the proposed microstrip antenna after using the PSO algorithm was obtain an ideal gain according to which the antenna's E-shaped properties. Omni-direction characteristics have been obtained.

In 2020, a microstrip antenna for ultra-wide band application depending on the moth-flame optimization algorithm is designed [6]. The results found good radiation pattern and directivity. If this method is compared with the earlier methods, constant gain over the band of frequency is got.

In 2021, a novel 3-Dimensions monopole microstrip antenna for biomedical application is proposed [7]. The dimensions of ground and radiating planes are found by using sparrow search algorithm (SpaSA). The proposed antenna was manufactured and the measured S_{11} was found to cover the desired frequency range.

In general, the issue of electro-magnetic improvement has inconsistent and indistinguishable locations, and is merely a calculation in the form of approximation. There are two supportive circumstances of natural heuristics, namely, evading local optima, and adapting to multiple variable issues that are nonlinear. Algorithms derived from the natural process are stimulated and applied to various problems of optimal antenna design. These incorporates Runner Root Algorithm (RRA) [8], Sunflower Optimization Algorithm (SFOA) [9], Particle Swarm Optimization (PSO) [10] and Moss Rose Optimization Algorithm (MROA) [11].

In this paper, the newly adopted Moss Rose Optimization Algorithm (MROA) [11] is compared with Runner Root Algorithm (RRA), Sunflower optimization Algorithm (SFOA) and Particle Swarm Optimization (PSO) in a multi- objective circumstance through a design of a compact UWB printed patch antenna. Section 2 summarizes the main aspects of Moss Rose Optimization Algorithm (MROA). Section 3 reviews Runner Root Algorithm (RRA) and its main equations. Section 4 presents the Sunflower optimization Algorithm (SFOA) and Section 5 discusses Particle Swarm Optimization (PSO). Section 6 presents the design procedure of a proposed compact UWB printed patch antenna with defected ground plane to increase its bandwidth. In Section 7, the optimization processes of the proposed antenna design using the aforementioned optimization algorithms are presented and the obtained results are compared. Conclusions that are extracted from this paper are presented in Section 8.

2. Moss Rose Optimization Algorithm (MROA)

Moss rose optimization is an algorithm that is based on plant inspiration. Using several agents, it will create variable flowering diameters that will find best solution. Each flower is treated as N-dimensional space, which adjusts its diameter depending on several factors such as the clock of sunshine, photochromic creation and the number of hours staying within the sunlight. Each agent tries to modify its diameter using the information of the current diameter, the current flower age, the distance between the best diameter and the current diameter. Each agent monitors its coordinates in the space of the solution associated with the best solution (fitness) of one diameter [11].

The modification of the particle position can be mathematically modelled according the following equations [11]:

1. Create of random variables represent flowering diameters.

$$fd\,(i) = [max - min\,] \times rand\,fd + min \tag{1}$$

where, *rand fd* : are the diameters of roses.
max and *min* are values depend on the application of Fitness function

2. Generate the flowering age parameter that depends on the current diameter and maximum diameter that the flower will reach it. The equation of age is:

$$f\_age = (fd_{max} \times TH) + fd \tag{2}$$

where fd_{max} is the maximum flower diameter, *TH* are the total hours of a day.

3. Calculate the phytochrome parameter, which is depend on the maximum flowering diameter, hours of opining the flower, random hour of morning and minimum flowering diameter. It is given by:

$$phytochrome = fd_{max} \times e^{-(0.27 \times hour - 3)^{oh}} + fd_{min} \tag{3}$$

where,
oh : are the hours of maximum opining flowers.
hour : is random value of time between (7 am and 3 pm).
fd_{min} : is the minimum flower diameter.

4. Calculate the new (*fd*) depending on the following equation:

$$fd_{new} = fd_{old} + phytochrome \times f_{age} \times Pr\,(fd_{best} - fd_{old}) \tag{4}$$

where,
Pr : are the red Photons (in nm).
fd_{best} : is the best flowering diameter that is calculated based on fitness function.

3. Runner Root Algorithm (RRA)

This algorithm is a bio-inspired based algorithm such as artificial bee colony and improved differential evolution. This algorithm received low fitness and less standard deviation when compared to some algorithms, especially when applied to some problems in the field of powerful control theory. There has not been much research applying this method to optimal electrical engineering problems because this algorithm has a variable ability to deal with complex and large-scale problems [12].

Consider the following unconstrained optimization problem:

$$min\, f(x),\ \mathrm{x}_l \le \mathrm{x} \le \mathrm{x}_u \tag{5}$$

where the two vectors x_l, x_u represent the lower and upper limits of variables. When dealing with a restricted optimization issue, conventional methods may be used to transform it to an equal unconstrained problem [7]. RRA starts with a collection of N_{pop} m-dimensional that create vectors randomly in the issue area, each of which serves as a mother plant. For each iteration, all plants that classified as mother excluding one mother (called the best one) create a branch plant randomly named as (daughter) but the best one creates a branch which equal to itself. If $\mathrm{x}^k_{mother}(i)$ represents the position of the original plant (mother) (k = 1, …, N_{pop}) at the iteration i, and $\mathrm{x}^1_{mother}(i)$ represents the best branch plant of the last iteration and $\mathrm{x}^k_{mother}(i)$ (k = 2, …, N_{pop}). Then, the original plants choose between the daughters of the previous iteration based on method of roulette wheel. Therefore, $x^k_{daughter}(i)$ is determined as:

$$x^k_{daughter}(i) = \begin{cases} x^1_{mother}(i) & k = 1 \\ x^k_{mother}(i) + d_{runner} \times r_k, & k = 2, \ldots, N_{pop} \end{cases} \tag{6}$$

where r_k is a vector, whose elements are independent random integers in the range [- 0.5, 0.5] with a uniform distribution, and d_{runner} is a scalar that represents the maximum distance between mother and daughter plants. It is worth noting that, according to Equation (6), the best plant of branch from the last repeating must be recognized both an original and a branch plant in the present repeating. It must note that a new r_k must be created for any calculation of branch plant. The value provided to d_{runner} must be big enough to allow original plants stuck in local min. to escape and search for the optimal universal solution (there location is between x_u - x_l from the present point). As a result, the runners play a critical role in avoiding trapping at local min., which the algorithm is successfully aids in avoiding besieging at these points. When the case is an optimal case with known variable limits, as stated in (5), the value of d_{runnur} must approach the largest entry x_u - x_l. The objective function is assessed in the branch plant position that specified in the (6).

$$\left| \frac{\min_{k=1,\ldots,N_{pop}} f\left(x^k_{daughter}(i)\right) - \min_{k=1,\ldots,N_{pop}} f\left(x^k_{daughter}(i-1)\right)}{\min_{k=1,\ldots,N_{pop}} f\left(x^k_{daughter}(i-1)\right)} \right| \geq tol \tag{7}$$

When one of the branches (at least one plant) results in an important improved performance in the of minimization problem value when it is compared with the finest branch of the last repetition, the universal inspection is still effective according to (7) and the algorithm does not initiate the local search procedure. If the objective functions are designed in such a way that the denominator of Equation (7) has a possibility of being equal to zero, the absolute difference may be utilized instead of the term on the left side of the Equation (7). However, if (7) is not met, the local search should be performed. When designating the best branch plant among those computed in (6) as $x_{daughter,\ best}(i)$ and generate vector when random modification is applied a to the random item of $x_{daughter,\ best}(i)$ as $x_{perturbed,\ k}$, then:

$$x_{perturbed,\ k} = diag\ \{1, 1, \ldots, 1, 1 + d_{rumner}\, n_k, 1, \ldots, 1\} \times x_{daughter,\ best}(i) \tag{8}$$

where n_k (k =1, …, m) is random number normally distribution ($\mu = 0$ and $\sigma = 1$) and $diag\{\ldots\}$ is a diagonal matrix which the k-th repetition is = 1 + $d_{nuner}\ n_k$ and all diagonal values except the k-th iteration is equal to 1. In order to increase the local search, determine $x_{perturbed,k}$ for k = 1 from (8). If $f(x_{perturbed,\ 1}) < f(x_{daughter,\ best}(i))$ then $x_{daughter,\ best}(i) \leftarrow x_{perturbed,1}$ else $x_{daughter,best}(i)$ still constant. Next step, determine $x_{perturbed,k}$ for k = 2 from (8) using the $x_{daughter,best}(i)$ resulted. Also, when $f(x_{perturbed,2}) < f(x_{daughter,best}(i))$, then make that $x_{daughter,best}(i) \leftarrow x_{perturbed,2}$. If the condition is not met. Not make any change on $x_{daughter,best}(i)$. This action will repeat for all of the m variables of $x_{daughter,best}(i)$. The steps of random big local foundation have finished. A random step of small local foundation must be now addressed. This work is carried out in same manner as the previous local foundation with steps of random big local foundation, but only one change being that the following equation is used instead of (8):

$$x_{perturbed,\ k} = diag\ \{1, 1, \ldots, 1, 1 + d_{root}\, r_k, 1, \ldots, 1\} \times x_{daughter,\ best}(i) \tag{9}$$

where d_{runner} is much greater than d_{root} that represents a constant scalar, the final result of steps of random big previous local foundation is $x_{daughter,\ best}(i)$, and r_k (k = 1, …, m) is randomized numbers uniformly distributed between [- 0.5, 0.5]. Note that the two Equations (8) and (9) need not do matrix multiplications (only the entry of $x_{daughter,\ best}(i)$ must be subjected to a randomly change).

Following a local founding, the original plants of the next repetition are selected based on the branch plants of the current repetition using a combination of selection such as roulette wheel and elite. The selection process of elite is as simple as the following:

$$x^1_{mother}(i+1) \leftarrow x_{daughter,\ best}(i) \tag{10}$$

Before choosing the all-remaining original plants of the next repetition based on the method of roulette wheel, the objective of k-th branch ($k = 1, \ldots, N_{pop}$) will determined using the follow:

$$fit\left(x^k_{daughter}(i)\right) = \frac{1}{a + f\left(x^k_{daughter}(i)\right) - f\left(x_{daughter,\ best}(i)\right)} \tag{11}$$

where positive real constant is represented by a. It is worth noting that, according to (11), the best branch obtains highest objective value, that is equivalent to $1/a$, while other branches receive lower objective values. Following the calculation of objective values, the selecting probability of the k-th branches of the current repetition as the original plant of the following repetition, p_k, is computed as:

$$p_k = \frac{fit\left(x^k_{daughter}(i)\right)}{\sum_{j=1}^{N_{pop}} f_{it}\left(x^j_{daughter}(i)\right)} \tag{12}$$

4. Sunflower Optimization Algorithm (SFOA)

A sunflower life cycle is consistent like the needles of a clock; they arise and follow the sun every day. They go in the other way at night to await their departure the next morning. A new algorithm based on flower pollination is proposed in [8]. This hypothesis depends mainly on flowering plants taking into account the biological process of reproduction. The unique behavior of sunflowers in their pursuit of optimal sun orientation is the basis of this study. Pollination was done randomly in this method depending on the shortest distance between Venus I and Venus i + 1. In fact, every part of Venus produces millions of pollen gametes. For simplicity, it will be imposed that each sunflower generates only one pollen gamete and has been reproduced independently. According to the inverse square law radiation, the intensity of the radiation is inversely proportional to the square of distance. His consciousness is that the amount of radiation is reduced to increase the square of distance. For example, doubling the distance reduces radiation by four times. The closer the plant is to the sun, the greater the radiation it receives, and the better it will settle in these places. The opposite is true. Thus, the same idea is selected in this algorithm. Larger steps will be selected to reach the universal solution (sun) as feasible [9]. Q represents the quantity of heat that received by every plant and it is calculated as follows:

$$Q_i = \frac{P}{4 \pi r_i^2} \tag{13}$$

Where P represents the source power and r_i represents the distance between the plant i and current best. The direction of sunflowers to the sun can be modeled as:

$$\vec{s_i} = \frac{X^* - X_i}{\|X^* - X_i\|}, \; i = 1, 2, \ldots, n_p \tag{14}$$

The step of sunflowers on the direction (s) is determined as:

$$d_i = \lambda \times P_i(\|X_i + X_{i-1}\|) \times \|X_i + X_{i-1}\| \tag{15}$$

where (λ) represents the constant determining of the inertial displacement of plants, and P_i ($\|X_i + X_{i-1}\|$) is the pollination probability, that is, sunflowers i pollinate those closest to it (i + 1), resulting in the production of a new individual with a random location that varies in the distance between flowers. Flowers that are closer to the sun will move at smaller steps than distant ones in the search for the best outcome. While moving further away from the sun more regularly, it is important to identify the greatest step that plants can move into so as to avoid the least possible global limit. The maximum step is defined as follows:

$$d_{max} = \frac{\|X_{max} - X_{min}\|}{2 \times N_{pop}} \tag{16}$$

Where X_{min} and X_{max} are the lower and upper limits, and N_{pop} is the plants number for the total population. The new plantation will be:

$$\vec{X}_{i+1} = \vec{X}_i + d_i \times \vec{s_i} \tag{17}$$

At first, the algorithm creates a population, where this population may be even or random. Each individual's estimate helps to choose which of the sunflowers will go towards the sun, in addition to concluding which of these sunflowers will be the highest rated. All other individuals will make random movements in a particular direction to track the sun. The basic steps of SFOA are shown in Fig. 1.

Sunflower Optimization Algorithm

Initial a uniform/random population of *n* flowers
Find the sun (best solution s^*) in the initial population
Orient all plants toward the sun
while (k < MaxDays)
    Calculate the orientation vector for each plant
    Remove *m* (%) plants further away from the sun
    Calculate the step for each plant
    Best *b* plants will pollinate around the sun
    Evaluate the new individuals
    If a new individual is a global best, update the sun
end while
Best solution found

Fig. 1 Sunflower Optimization Algorithm (SFOA) pseudo code.

5. Particle Swarm Optimization (PSO)

Swarm intelligence, or PSO, is influenced by social psychological theories and provides understanding of social behavior, as well as making a contribution to engineering applications. The proposed algorithm was first defined in 1995 by [13].

It uses agents (particles) that form a swarm that roams the space in search of the best solution. Possible associated Particle is treated as a point in an N-dimensional space that adjusts its "flying" based on its own and other particles' experiences. In order to change its position, each particle uses its current position, its current velocity, the distance between it and its personal best position (*pbest*), and the distance between it and its global best position (*gbest*). In the solution space, every particle keeps track of its location, which are based on the best solution (fitness) achieved so far. This value is known as *p-best*, or personal best. The PSO also keeps track of the best value obtained so far by any particle in the particle vicinity. This value is referred to as the *g-best* value. A random weighted acceleration at each time step serves as the basis for PSO's basic concept of accelerating each particle to its p- best and g-best locations. Particle position adjustments can be mathematically modelled by the following equation:

$$V_i^{k+1} = w\, V_i^k + c_1\, rand_1(\ldots) \times \left(pbest_i - s_i^k\right) + c_2\, rand_2(\ldots) \times \left(gbest_i - s_i^k\right) \tag{18}$$

where,
V_i^{k+1} : velocity of particle i with iteration k.
w : weighting function.
c_1 and c_2 : weighting factors.
rand : random number with uniform distribution between 0 and 1.
s_i^k : current position of particle i with iteration k.
$pbest_i$: personal best of agent i.
$gbest_i$: global-best of the group.

The weighting function is modified based on the following equation:

$$w = w\,Max - \frac{[(w\,Max - w\,Min) \times iter]}{Imax} \tag{19}$$

where,
w Max = maximum acceptable weight.
w Min = minimum acceptable weight.
Imax = number of maximum iterations.
iter = number of the current iteration.

6. Proposed Compact UWB Patch Antenna

A compact UWB printed patch antenna is proposed in this section to operate at the frequency range (4.3 - 13) GHz as shown in Fig. 2. A dielectric substrate FR4 is chosen with dimensions of (12 × 21.5) mm^2, dielectric constant of $\varepsilon_r = 4.4$ and thickness of 1.6 mm. The shape of the radiated patch is chosen as a rectangular one with width (W) and length of (8 mm) and fed by a microstrip line of dimension ($W_f \times L_f$). On the ground plane side, a partial ground plane technique is used in order to increase the antenna bandwidth. It has a length of (L_g) and a width of (12 mm). T-shape slot with horizontal opening of dimensions (S and S_1) and vertical opening of dimensions (L and L_1) is introduced in the defected ground plane. The dimensions of the radiating patch, defected ground plane, and feeder line are the essential boundaries in the antenna configuration that should be optimized based on MROA, RRA, SFOA and PSO. The results obtained from these four algorithms are then obtained and compared.

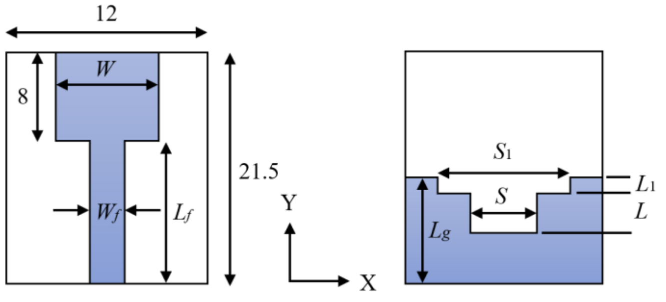

Fig. 2 the proposed UWB printed patch antenna in front sight and back sight.

There is objective to be fulfilled. The antenna should be matched at the frequency range (4.4 - 13) GHz.

$$Ft = \frac{1}{n}\sum_{f_1}^{f_2} p(f) \tag{20}$$

where,

$$p(f) = \begin{cases} -S_{11} & \text{for } S_{11} \geq -10 \\ 0 & \text{for } S_{11} < -10 \end{cases}$$

7. Simulation and Results

In the antenna optimizer, shown in Fig. 3, the simulation steps contain two programs that operated together by instructions.

As shown in the equation (20), S_{11} represents the reflection coefficient (in dB), and n is the number of selected samples. The operating bands defined by f_1 and f_2 have values of 4.4 GHz and 13 GHz respectively. The values of parameters needed in the implementation of the four optimization techniques of MROA, RRA, SFOA, and PSO are given in Table 1. The dimension constraints of antenna elements (in mm) are as follows:

$g_1(W, L_g, W_f, L_f, S_1, S, L_1, L) > 0$

Lower bounds:

$(W, L_g, W_f, L_f, S_1, S, L_1, L) = [1, 7, 1, 7, 3, 0.5, 1, 1]$

Upper bounds:

$(W, L_g, W_f, L_f, S_1, S, L_1, L) = [5, 13, 3, 14, 5.5, 2.5\ 3, 6]$

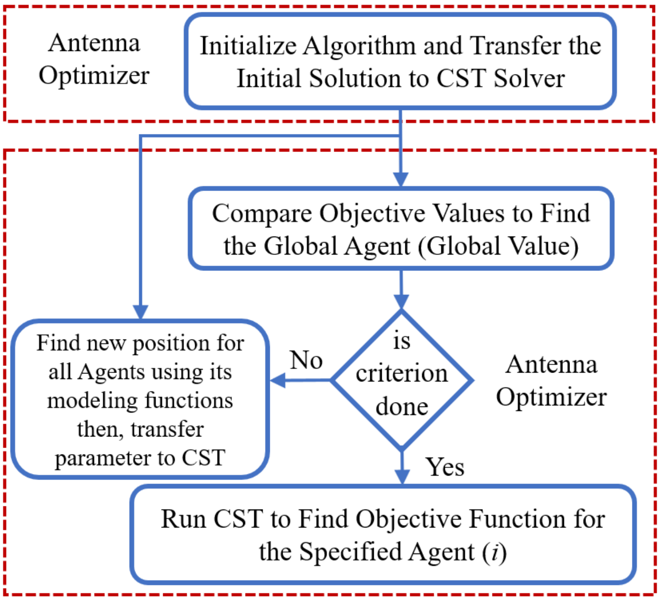

Fig. 3 Antenna Optimizer Simulation Steps.

The optimized values of antenna element dimension based on the four comparative algorithms are illustrated below in Table 2.

The reflection coefficient responses (represented by S_{11}) and voltage standing wave ratio (VSWR) responses of the proposed UWB based on the four optimization algorithms are obtained with the help of CST microwave studio software [11], and shown in Fig. 4 and Fig. 5 respectively.

It is clear from Fig. 4 that the antenna covered frequency range based on the proposed dimensions that found by MROA was found as (4.5 - 13.8) GHz with minimum S_{11} value of about - 37.5 dB at 7.901 GHz. The minimum value of VSWR at 7.091 GHz was found as 1.028.

The range of frequencies obtained using this algorithm is greater than all dimensional designs obtained using other algorithms. The corresponding values of frequency range, minimum S_{11}, minimum VSWR and minimization of objective function (Ft) based on all optimization algorithms are tabulated in Table 3. The smallest elapsed time to find optimal dimensions has been achieved when using MROA algorithm. Table 3 shows the time elapsed for each algorithm.

It is concluded from Table 3 that MROA is superior compared with RRA, SFOA, and PSO. The UWB printed patch antenna designed on the basis of MROA shows compactness, the widest covered frequency range and the lowest values of S_{11}, VSWR, run time, and Ft.

Table 1. Parameters values of the four optimization algorithms.

Algorithm	Parameter	Value
MROA	No. of flower's diameters	50
	Max fd.	4 cm
	Min fd.	0.5 cm
	Red photon value	660 nm
	Clock time	7 am – 3 pm
	No. of iterations	10000
	No. of runs	20
RRA	Number of mother plants	50
	Length of runners	2
	Length of roots	0.01
	Number of variables	10
	No. of iterations	10000
	No. of runs	20
SFOA	Number of sunflowers	50
	Pollination rate, best values	$0.01 < p < 0.10$
	Mortality rate, best values	$0.01 > m < 0.10$
	Survival rate, best values	$0.80 > s < 0.90$
	No. of iterations	10000
	No. of runs	20
PSO	No. of population	1
	Population size	50
	Weight	0.4 - 0.9
	R_1, R_2, C_1, C_2	Random
	No. of iterations	10000
	No. of runs	20

Table 2. Optimized element dimensions of the UWB antenna of the four algorithms (in mm).

Antenna Element	MROA	RRA	SFOA	PSO
W	6.8390	7.0000	5.9204	5.0239
W_f	2.5627	2.0911	2.0971	4.7915
L_f	12.813	13.000	10.485	9.2539
S_1	4.5396	4.9106	5.0873	4.7915
L_1	1.2019	2.7297	1.7755	2.0681
S	2.0734	1.5011	1.7254	1.3821
L	4.2376	3.9616	3.4027	4.0662
L_g	11.026	11.820	11.612	12.021

Table 3. Antenna responses based on the four optimization algorithms.

Value	MROA	RRA	SFOA	PSO
Covered frequency range (GHz)	4.489-13.784	4.455-12.288	5.531-7.835	9.682-15.666
Resonant frequency (GHz)	7.901	5.000	7.000	11.000
Minimum S_{11} (dB)	-37.062	-16.878	-15.99	-30.651
Minimum VSWR	1.028	1.33	1.37	1.06
Minimum Ft	-126.021	-128.425	-127136	-126.687
Elapsed times (s)	36.3038	249.797	41.414	63.669

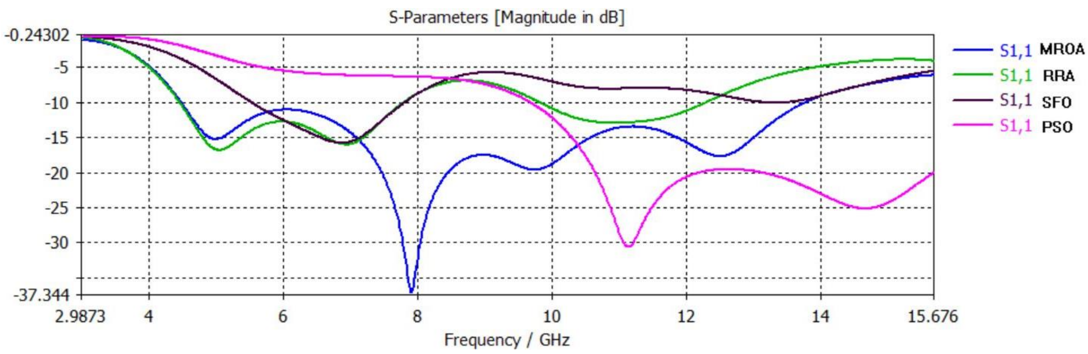

Fig. 4 Antenna S_{11} values for the four optimization algorithms.

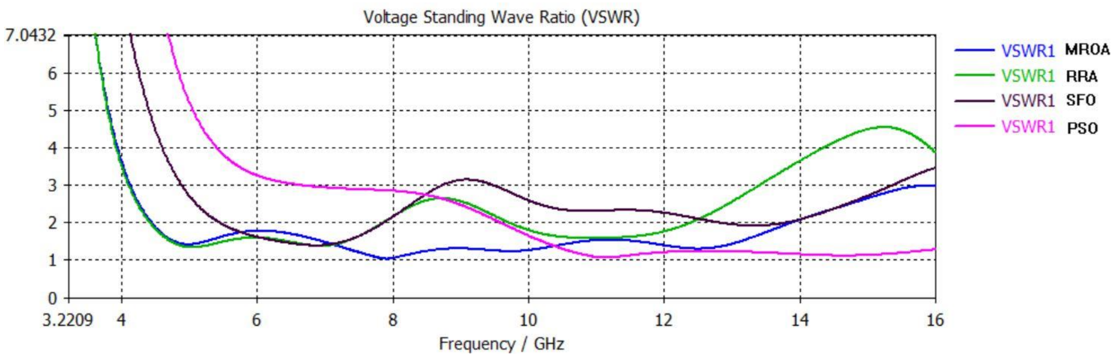

Fig. 5 Antenna VSWR values for the four optimization algorithms.

8. Conclusions

This paper has indicated the advantages of utilizing bio-inspired advancement to improve the design of UWB printed patch antenna. A compact UWB printed patch antenna has been designed and optimized in this paper using four plant inspired optimization algorithms. They are namely: the newly adopted Moss Rose Optimization Algorithm (MROA), Runner Root Algorithm (RRA), Sunflower Optimization Algorithm (SFOA) and Particle Swarm Optimization (PSO). It is shown that antenna design based on MROA accomplished a wideband frequency range of (4.489 - 13.784) GHz for S_{11} < - 10 dB. At a resonant frequency of 7.901 GHz, the antenna design based on MROA also shows the minimum S_{11} value of - 37.062 dB and minimum VSWR value of 1.028. The smallest value of run time is obtained using MROA.

References

[1] H. J. Mohammed, F. Abdulsalam, A. S. Abdulla, R. S. Ali, R. A. Abd-Alhameed, J. M. Noras, Y. I. Abdulraheem, A. Ali, J. Rodriguez, and A. M. Abdalla, "Evaluation of genetic algorithms, particle swarm optimisation, and firefly algorithms in antenna design", 2016 13th International Conference on Synthesis, Modeling, Analysis and Simulation Methods and Applications to Circuit Design, (SMACD) 2016. https://doi.org/10.1109/SMACD.2016.7520747

[2] H. J. Mohammed, A. S. Abdullah, R. S. Ali, Y. I. Abdulraheem, and R. A. Abd-Alhameed, "Performance Comparison of Particle Swarm Optimization, and Genetic Algorithm in the Design of UWB Antenna", Journal of Telecommunications, Vol. 27, Issue 2, pp. 22-26, 2014. http://hdl.handle.net/10454/8680

[3] H. J. Mohammed, A. S. Abdullah, R. S. Ali, R. A. Abd-Alhameed, Y. I. Abdulraheem, and J. M. Noras, "Design of a uniplanar printed triple band-rejected ultra-wideband antenna using particle swarm optimisation and the firefly algorithm", IET Microwaves, Antennas and Propagation, Vol. 10, Issue 1, pp. 31-37, 2016. https://doi.org/10.1049/iet-map.2014.0736

[4] N. Gupta, J. Saxena, and K. S. Bhatia, "Optimized metamaterial-loaded fractal antenna using modified hybrid BF-PSO algorithm", Neural Computing and Applications, Vol. 32, pp. 7153-7169, 2020. https://doi.org/10.1007/s00521-019-04202-z

[5] Y. Yulindon, N. A. Samsudin, and R. Efendi, "Optimization of E-shaped microstrip patch antenna using particle swarm optimization (PSO) for wideband application", International Journal of Intelligent Engineering and Systems, Vol. 13, No. 4, pp. 305-315, 2020. https://doi.org/10.22266/IJIES2020.0831.27

[6] A. Singh, R. M. Mehra, and V. K. Pandey, "Design and Optimization of Microstrip Patch Antenna for UWB Applications Using Moth–Flame Optimization Algorithm", Wireless Personal Communications, Vol. 112, pp. 2485-2502, 2020. https://doi.org/10.1007/s11277-020-07160-1

[7] M. B. Bicer and E. A. Aydin, "A novel 3D printed curved monopole microstrip antenna design for biomedical applications", Physical and Engineering Sciences in Medicine, Vol. 44, pp. 1175-1186, 2021. https://doi.org/10.1007/s13246-021-01053-8

[8] F. Merrikh-Bayat, "The runner-root algorithm: A metaheuristic for solving unimodal and multimodal optimization problems inspired by runners and roots of plants in nature", Applied Soft Computing, Vol. 33, pp. 292-303, 2015. https://doi.org/10.1016/j.asoc.2015.04.048

[9] G. F. Gomes, S. S. da Cunha, and A. C. Ancelotti, "A sunflower optimization (SFO) algorithm applied to damage identification on laminated composite plates", Engineering with Computers, Vol. 35, No. 2. pp. 619-626, 2019. http://dx.doi.org/10.1007/s00366-018-0620-8

[10] J. Robinson and Y. Rahmat-Samii, "Particle swarm optimization in electromagnetics", IEEE Transactions on Antennas and Propagation, Vol. 52, Issue 2, pp. 397-407, 2004. http://doi.org/10.1109/TAP.2004.823969

[11] H. M. Hathal, R. S. Ali, and A. S. Abdullah, "A Novel Metaheuristic Moss-Rose-Inspired Algorithm with Engineering Applications", Electronics, Vol. 10, Issue 16, 2021. https://doi.org/10.3390/electronics10161877

[12] T. T. Nguyen, T. T. Nguyen, A. V. Truong, Q. T. Nguyen, and T. A. Phung, "Multi-objective electric distribution network reconfiguration solution using runner-root algorithm", Applied Soft Computing, 2016. https://doi.org/10.1016/j.asoc.2016.12.018

[13] J. Kennedy and R. Eberhart, "Particle swarm optimization", Proceedings of ICNN'95 - International Conference on Neural Networks, Vol. 4, pp. 1942-1948, 1995. https://doi.org/10.1109/ICNN.1995.488968