# Hybrid Neural Network Optimization for Feed Point Determination in Antenna Design

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***Abstract*—In this paper, coaxially feed rectangular microstrip antenna is designed for WIFI communication in accordance with IEEE 802.11a standard between 5.15 GHz and 5.725 GHz. Feeding position of coaxial probe significantly affected antenna characteristics. Optimum feeding point should be selected in 2-D patch plane on the purpose of better antenna characteristics. The model is used to solve the optimization problem. It has three input variables which are antenna parameters as resonance frequency, bandwidth and return loss; on the otherhand, two output such as x and y coordinates of feeding position. Also, error function is updated by proposed artificial intelligence algorithms. Unlike conventional methods, contemporary artificial intelligent algorithms have been proposed for the antenna design. Genetic Algorithm (GA), Spider Monkey Optimization (SMO) and Grey Wolf Optimizer (GWO) are preferred for optimization. According to comparison of these results, optimal antenna for WIFI Protocol is designed.**

***Keywords*— Microstrip Antenna, WIFI Communication, Artificial Neural Network, Artificial Intelligence Algorithm, Optimization.***

## I. INTRODUCTION

In the recent years with the development of the technology, the use of microstrip patch antenna has gradually increased in spacecraft, doppler and navigation radar, satellite communication, mobile radio and guided missiles. Microstrip antennas have several advantages over many known conventional antennas. These advantages are low profile, changeable polarization with feeding position, integrated with solid-state equipment and compatible with co-planar surface [1].

Great strides in the electronics sector provide more functionality and size reduction for especially communication devices. Besides, demands for multiple applications (GPS, GSM, WIFI) in a single device has caused designers to focus more on microstrip antenna. Many applications of artificial neural network and artificial intelligence algorithms exist in literature. The results obtained by using the feedback multilayer perceptron network for the design of the equilateral triangle microstrip antenna were compared with conventional method. The inputs of the artificial neural network are dielectric constant, height, TE and TM modes of the material; on the other hand, resonant frequency is the output of neural network [2]. Microstrip patch antenna was designed for wide band applications with dielectric material thickness of 2 mm. The operating frequency of the microstrip patch antenna with 10.5 to 12 GHz bandwidth was tried to be calculated by the genetic algorithm [3]. Hybrid artificial neural networks techniques and fuzzy logic methods were used to calculate the operating frequencies of microstrip antennas. The hybrid method based on the least squares method with the backpropagation algorithm was performed for dimension optimization of square, circle and triangle microstrip patch antennas [4]. Operating frequency of the microstrip patch antenna with coaxial feed was determined by artificial neural network methods. The inputs of the artificial neural network were the antenna's width and height, and the output was the operating frequencies in the dual band [5]. The bandwidth of the microstrip patch antenna with rectangular geometry was tried to be optimized by using artificial neural network. Error rates of simulation and network results were compared with each other [6]. Forward feedback propagation algorithm is used to optimize and microstrip antenna parameters with square and rectangular pitch are provided. The dimensions of the microstrip antenna were designed as network inputs and the operating frequency was optimized as the network output [7]. A particle swarm optimization algorithm was used to determine the patch sizes of a multi-layer microstrip antenna that can operate in the X and Ku band [8]. A microstrip patch antenna with many slots for wireless communication was designed by multilayer perceptron artificial neural network model [9]. Hybrid artificial neural networks, which is a combination of radial based function and backpropagation algorithm, was used for design of acoupled microstrip antenna. The performance of the hybrid network was compared with other types of network results [10]. Conjugate gradient artificial neural network model was used for determination of the operating frequency in circular microstrip patch antenna [11]. The truncated edges of square microstrip antenna was designed with artificial neural network. Levenberg-Marquardt algorithm with three hidden layers was chosen as an artificial neural network method [12]. Artificial neural networks were used for fractal antenna design.

Analysis of the error rates of the network results were carried out with the Generalized Regression Neural Networks (GRNN) [13]. Variables such as operating frequencies, gains, directionality, antenna efficiency and radiation efficiency in the dual band were assigned to the inputs of the different artificial neural network based algorithms and height of gap between the ground plane and the dielectric material was computed [14]. The design of microstrip antennas with rectangular and circular patches for wireless communication applications was implemented with particle swarm optimization technique. The inputs of the optimization technique are the operating frequency, the dielectric constant and the height of the dielectric material. [15]. Sathi et al. used to be processed moments matrices optimally with the genetic algorithm, ensuring that the simulation and test results are in harmony with one another in the antenna design [16]. Antony et al. proposed PSO as a design tool in a microstrip antenna array created by a parasitic method. With their design, IEEE 802.11a WLAN achieves a multi-directional radiation pattern and reflection coefficient of <-10 dB in the 5-6 GHz band [17]. Amir et al. calculated resonance frequency and bandwidth in the rectangle microstrip antenna design. Faster and more accurate results were obtained by optimizing the moments method with Bacterial Search Optimization [18]. Arunava et al. applied Cuckoo Search algorithm to increase the bandwidth of the microstrip patch antenna running in the X band [19].

Metaheuristic optimization method have shown a great development and its applications has been carried out in many fields for the last twenty years. Genetic, Differential Evolution, Gravitational Search and Teaching-learning based optimization algorithms are given examples for some commonly used metaheuristic optimization algorithms [20]. In this study, It is introduced that how to design microstrip antenna in Section II. Proposed Artıfıcıal Neural Network algorithm is described in Section III. Genetic Algorithm, Spider Monkey Optimization and Grey Wolf Optimizer, which are based on swarm intelligence and are known as a novel optimization algorithms, are used to determine coaxial feeding position of microstrip antenna for Wi-Fi protocols in Sections IV. The experimental results drawn in Sections V. Section VI inserts the conclusion part.

## II. MICROSTRIP ANTENNA DESIGN

Basic microstrip patch antenna design consists of the three main parts. These are patch plane, dielectric substrate and ground plane. FR4 material ($\varepsilon_r$=2.2) is used in dielectric substrate of proposed microstrip antenna for Wi-Fi protocol. The thickness of this material is determined to be 1.58 mm. The thickness of the copper patches on the dielectric substrate is 38 μm. The operating frequency of the antenna is designed around 5.38 GHz and is suitable for IEEE 802.11a protocol. Patch and ground plane size are designed in accordance with the following formulas in which L, W and $L_g$, $W_g$ represents patch and ground dimension respectively:

$$\varepsilon_{\mathrm{eff}} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left(1 + 12\frac{\mathrm{h}}{\mathrm{W}}\right)^{-0.5} \tag{1}$$

$$\mathrm{W} = \frac{c}{2\mathrm{f}_0\sqrt{\frac{\varepsilon_r + 1}{2}}} \tag{2}$$

$$L_{eff} = \frac{c}{2\mathrm{f}_0\sqrt{\varepsilon_{eff}}} \tag{3}$$

$$\Delta\mathrm{L} = 0.412h\frac{(\varepsilon_{\mathrm{eff}} + 0.3)(w/h + 0.264)}{(\varepsilon_{\mathrm{reff}} - 0.258)(w/h + 0.8)} \tag{4}$$

$$L = L_{\mathrm{eff}} - 2\Delta\mathrm{L} \tag{5}$$

$$L_g = 6h + L \tag{6}$$

$$W_g = 6h + W \tag{7}$$

W×L has been computed as 21.56 × 17.46 $\mathrm{mm}^2$ for patch and on top of that $W_g \times L_g$ has been calculated as 41.8 × 35.6 $\mathrm{mm}^2$ for ground plane. The antenna designed can be excited by coaxial feed as Figure 1. It can be at any position to match with input impedance.

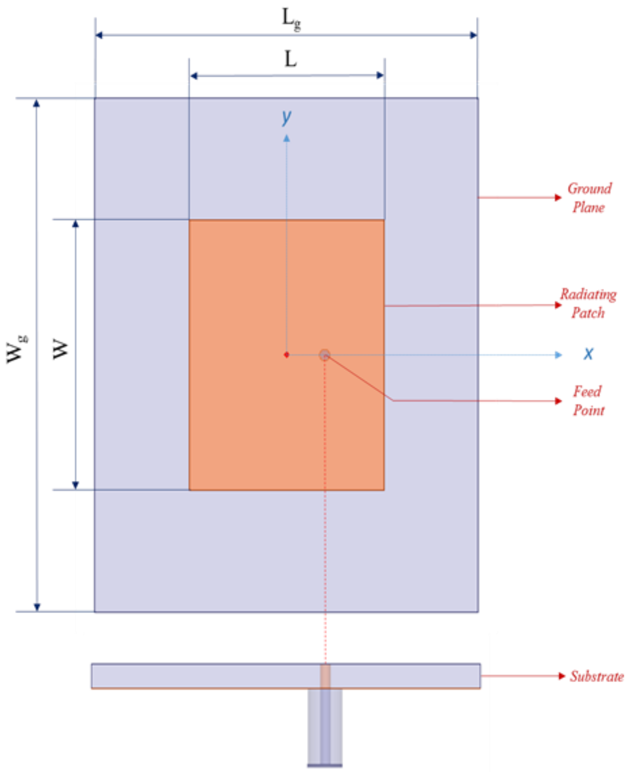


Fig. 1. Top and Side View of Coaxial Feed Microstrip Patch Antenna

Typically, even if $\cos^2(\pi y_0/h)$ formula suggests matching with 50 ohm impedance, there will be some feed position to obtain greater return losses at operation frequency in two-dimensional plane. Hence, utilized hybrid optimization technique is composed of artificial neural network with Genetic Algorithm, Spider Monkey Optimization and Grey Wolf Optimizer in order to estimate feed position.

## III. Artificial Neural Network

Artificial Neural Network (ANN) has ability to learn, use memory the knowledge about the system. Moreover, it can search, reproduce and discover new knowledge without any help. A neural network is a natural propensity for storing experiential knowledge. Also, it can prepares to use when they are needed [21]. ANN is a computer program that simulates biological neural networks. With these features, it can offer effective solutions for optimization, classification, prediction, pattern recognition, memory management and control problems.

## IV. Artificial Intelligence Algorithms

Metaheuristic algorithms are divided into three main groups: evolutionary, physics based and swarm intelligence algorithm. Evolutionary algorithm is an adaptation of evolution events in nature for optimization algorithm. In 1992, Holland proposed genetic algorithm which is the most popular and first algorithm in this branch. Then, Differential Evolution, Biogeography-Based Optimizer, Genetic Programming and Evolution Strategy are some examples of evolution algorithm [22-23]. Physics-based technique is the second subclass of metaheuristic algorithms. This kind of algorithms based on imitate physical rules in nature. Gravitational Search, Charged system search, Artificial Chemical Reaction, Black Hole, Ray, Small-World, Galaxy-based Search and Curved-spaced algorithm are well-known optimization methods [24-31]. Finally, the third main branch of meta-heuristics is the swarm intelligence method. These type of algorithms usually mimics the social behavior of swarm in natural atmosphere. Particle swarm, Ant colony, Artificial Bee Colony and Bat inspired optimization are the main examples of swarm intelligence method [32].

### *A. Genetic Algorithm*

Genetic algorithm (GA) is a heuristics algorithm developed for nonlinear problems [33]. GA could mimic evolutionary processes observed in nature. In the complex multi-dimensional search space, it tries to search for the best solution via the principle of having the best life. Variables of the problem are represented as unique or group of gene in the chromosome. The most important factor in deciding the success of genetic algorithms is the representation of individuals for solving the problem.

Pseudo code of GA is given in Fig. 2. *CP* represents crossing-over point and should be smaller than chromosome size. Mutation rate is abbreviated as *MR*. It is important for diversity in new generation.

**Initialize** the population $X_i$ *(i=1,2,…, n)*

**Initialize** *CP, MR*

**While** (t< Maximum number of iterations)

Exchange the genes at randomly selected *CP*

Perform the mutation process in accordance with *MR*

Calculate the fitness value of each chromosome

Select the better ones for new generation

t=t+1

end **while**

Return $Best\_X_i$

Fig. 2. Pseudo-code of GA

In GA process, chromosomes are randomly generated for initial population. At following iterations, crossing-over and mutation process are performed to obtain a new generation. Crossing-over operation is used to make better solutions from combination of different parts in others. Thanks to random changes in character string, a copy of individuals in the previous generation prevent the transfer to the next generation via mutation process. Then, fitness values are determined for all chromosomes by comparison with each other. The better new ones have fitness value, the more they have chance of survival in the next generation.

### *B. Spider Monkey Optimization*

Spider monkeys have fission-fusion social network which includes temporary subgroups for larger communication structure. Also, fission-fusion social mechanism provides food competition among members of smaller foraging groups. It is necessary to divide into smaller groups in case adequate food supply could not be found by female monkey leader. Although the number of individuals in main monkey groups can be up to 50, the size may be reduced to 3 or 4 [34-37]. The members in all subgroups interact with internal and external individuals about food availability and territorial boundaries.

In fission-fusion social structure, the foraging of spider monkeys have four steps. At the first, monkey groups try to search and find the food foraging. In the second stage, groups' members update their location and calculate the distance from the food sources repeatedly in accordance with their group leader. Also, it is defined as an individual group leaders who have the best position in the group and replaced continuously in order to reach a better position. Therefore, other group individuals can direct in different directions to search for food. Finally, global leader has ever updated its best position under stagnation condition.

In Spider Monkey Optimization (SMO), *Global Leader Limit* and *Local Leader Limit* are two major parameters to help for taking leader decisions. Moreover, maximum group (*MG*) and perturbation rate ($p_r$) are other parameters to control amount of groups and perturbation in current iteration.

SMO has a heuristic process which is based on a trial and error. It starts to initialize population of *N* spider monkeys $SM_i$ (*i=1,2,3…. N)* with *D* dimension vector. *D* denotes the number of variables in optimization structure. $SM_i$ is the *ith* spider monkey in the swarm and generated as:

$$SM_{ij} = SM_{\min j} + U(0,1) \times (SM_{\max j} - SM_{\min j}) \tag{8}$$

$SM_{minj}$ and $SM_{maxj}$ are boundary for $SM_i$ of *jth* direction. *U(0,1)* is a uniformly distributed random number between 0 and 1. The following step is Local Leader phase in which each individual changes the position thanks to experience of local group leader and members. The fitness value is computed every new position of swarm member. If the fitness value of new position is greater than former one, current position is replaced with new one. The position update equation is described as:

$$SMnew_{ij} = SM_{ij} + U(0,1) \times (LL_{kj} - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij}) \tag{9}$$

$SM_{ij}$ is the *ith* SM member in the *jth* dimension, $LL_{kj}$ denotes the *kth* local group leader position. $SM_{rj}$ represents randomly selected kth group member ($r \neq i$). After the *Local Leader phase*, the *Global Leader phase* embarked on a new process. All of the SM's members change their position by using experience of Global Leader. The position update is implemented in this phase via following equation:

$$SMnew_{ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij}) \tag{10}$$

$GL_j$ is the global leader in the *jth* dimension. Next, the new global and local leaders are necessary to be determined again. A member with the best fitness value is proposed for global leader in entire population; on the otherhand, the best fitness values in each group is appropriate candidate for local leaders.

```
Initialize the population SM_i (i=1,2,3.... N)
Initialize MG, p_r, D, Local and Global Leader Limit
While (t< Maximum number of iterations)
Calculate the fitness value
Select the Global Leader and Local Leaders
Perform Global and Local Leader Phase
Perform Global and Local Leader Learning
Perform Global and Local Leader Decision
t=t+1
end while
Return SM_GLOBAL LEADER
```

Fig. 3. Pseudo-code of SMO

### C. *Grey Wolf Optimizer*

Grey Wolf Optimizer (GWO) is one of the novel swarm intelligence method. It is inspired from grey wolves which have 5-12 swarm members. They have a very dominant social hierarchy for concept of search and hunt mechanism.

Grey wolf pack consists of alpha (α), beta (β), delta (δ) wolf and omega's (ω) wolves in Figure 4. Alpha wolf with decisions give the pack directions to hunt. Although some democratic behaviors are observed, alpha has strict authority in the pack. Thanks to strong authority, the pack also has more discipline. At the second best position in the social hierarchy is beta grey wolf. In case of death or aging of the alpha wolf, beta wolf is the best candidate for the leadership in the pack. It has advisory role to alpha wolf and helps to discipline the pack. It is primarily responsible for providing coordination and discipline between the alpha wolf and other members of wolf pack. Delta wolves in the third layer of the hierarchy have the task sharing for scouts, sentinels, elders, hunters and caretakers. They help pack management in groups for the hunting process. Moreover, they take care of the newborn and the older members in the pack. Omega group is in the lowest layer of the social hierarchy. It is required for them to become increasingly powerful and social structure. They provide candidate for the next generation of alpha, beta and gamma wolves [38].

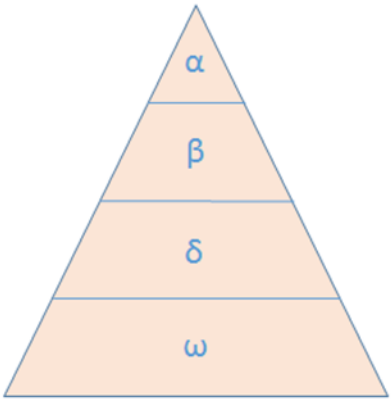


Fig. 4. Social Hierarcy of Grey Wolf

In the GWO, the alpha (α) is the fittest solution in the search space. Then, beta (β) and delta (δ) is assigned as the second and third best solutions. The other solutions are in the omega's (ω) group. We consider the fittest solution as the alpha (α). The hunting mechanism is guided by α, β, and δ. The ω wolves follow and help them. GWO algorithm is basically divided into three main stages such as encircling, hunting and attacking prey.

Grey wolves are coming close and surrounding the prey before hunting. The following formula has been proposed to model mathematically the encircling process in GWO algorithm:

$$\vec{D} = \vec{C}.\vec{X}_p(t)\text{-}\vec{X}(t) \tag{11}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{12}$$

$t$ is the current iteration indices. $A$ and $D$ are indicated coefficient vectors. $X_p$ and $X$ are position vector of prey and a grey wolf in Figure 5.

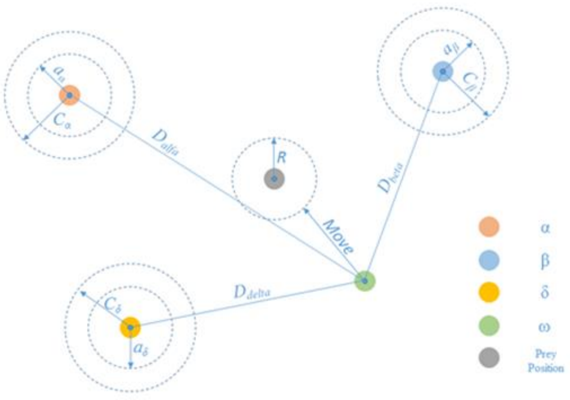


Fig. 5. Position Updates In GWO

The coefficient vectors are calculated as bellows:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{13}$$

$$\vec{C} = 2\vec{r}_2 \tag{14}$$

$a$ is an algorithm component which is linearly changed between 2 and 0. $r_1$ and $r_2$ are random vectors in valid interval [0,1].

The best and latest three solutions are $X_1$, $X_2$ and $X_3$ which are saved as the best position of $\alpha$, $\beta$, and $\delta$. The next final solution $X(t+1)$ is defined as average of alpha, beta and delta position. These expressions are formulated as:

$$\vec{D}_\alpha = |\vec{C}_1.\vec{X}_\alpha\text{-}\vec{X}|,\ \vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta\text{-}\vec{X}|,\ \vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta\text{-}\vec{X}| \tag{15}$$

$$\vec{X}_1 = \vec{X}_\alpha\text{-}\vec{A}_1(\vec{X}_\alpha),\ \vec{X}_2 = \vec{X}_\beta\text{-}\vec{A}_2(\vec{X}_\beta), \vec{X}_3 = \vec{X}_\delta\text{-}\vec{A}_3(\vec{X}_\delta) \tag{16}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{17}$$

In GWO algorithm, alpha, beta and delta are allowed to update their location for right position. At the right iteration, they can attack towards the prey. With the above formulas, grey wolves gradually continue to scan the global space until they reach the optimum solutions in mathematical concept. If A<1, candidate solutions converge towards the prey; otherwise, they diverge from it in Figure 6.

**Initialize** the grey wolf population $X_i$ $(i=1,2,\ldots,n)$

**Initialize** a, A and C

Calculate the fitness of each search agent

$X_\alpha$= the best search grey wolf
$X_\beta$= the second best search grey wolf
$X_\delta$= the third best search grey wolf

**While** (t< Max number of iterations)

Update position of the each search grey wolves by equation

Update **a**, **A**, **C** by equation

Update **D** by equation

Update $\mathbf{X_\alpha}$, $\mathbf{X_\beta}$, $\mathbf{X_\delta}$

t=t+1

end **while**

return $\mathbf{X_\alpha}$

Fig. 6. Pseudo-code of GWO

## V. Proposed Method

ANN consists of multiple neural cells with a combination. Therefore, the concept of the neural cells will help in understanding the entire network. Inputs, weights, biases and outputs are main elements for neural network. Neural networks are separated into the layers such as input, hidden and output layers in Figure 7. Conventional ANN is modified by Artificial Intelligence Algorithms on the propose of update in weights

($W_{i,k,j,o}$) and biases ($B_{I,L1,L2,O}$). In this way, the hybrid network structure optimizes the outputs in lower error rate and processing time.

In the proposed method, perceptron structure of artificial neural network is used as objective function in the optimization process. Weights and bias in artificial neural network structure are optimized as objective function. Genetic algorithm, Grey wolf optimizer and spider monkey optimization algorithms are used to update weights and biases in the network structure. The main use of these algorithms is to prevent linerization in the network structure. The reason why the proposed algorithms are used is that the accuracy of each algorithm is different from that of the algorithm. According to mean error function obtained after each iteration, weights and biases of artificial neural network are updated in artificial intelligence algorithms. At the beginning of each algorithm, all weights and biases are randomly assigned. The parameters in optimization algorithms also start randomly at the start. This is to prevent proposed algorithms from reaching local minimum solutions in search space.

In the proposed method, the inputs of the hybrid artificial neural networks are composed of resonance frequency, band width and return loss. The network output is the antenna feed coordinates of the microstrip antenna in 2 dimensions. The proposed method is a supervised algorithm and has training and testing steps. Antenna parameter data was obtained by changing the antenna feed point locations designed using the HFSS program.

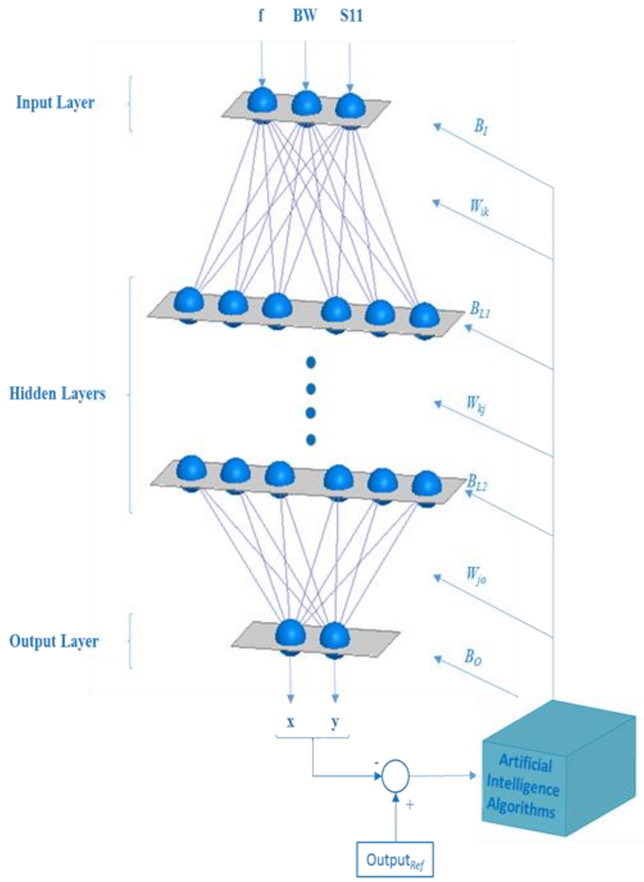


Fig. 7. Hybrid Artificial Neural Network Model

## VI. Results And Discussion

To study the effects of changes in feeding position on the presented geometry, the antenna characteristics are investigated. The optimization algorithms are performed with AMD FX8 AMD 3.5GHz processors. 32GB of RAM with 4 GB of GDDR3 GeForce supported system memory with nVIDIA graphics card is used. Figure 8 indicates the simulation results about antenna design of conventional method and proposed artificial intelligent algorithms for WIFI communication.

In order to train the proposed network, 4075 pieces of data were produced in the patches according to feed points spaced 0.1 mm step. Produced data includes band width, resonance frequency, return loss, x and y axis feed point. The constructed hybrid artificial neural network consists of 10 hidden layers. The weights and biases in these hidden layers are updated with artificial intelligence algorithms instead of the gradient descent algorithm. The input 3 of the network consists of band width, resonance frequency and return loss. At the output, 2-D feed point is tried to be obtained.

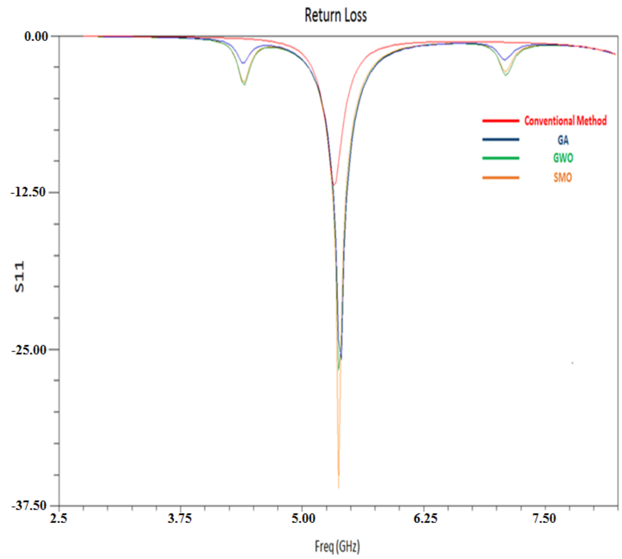


Fig. 8. Results of Antenna Design

The feeding points of the antenna were separately determined via GA, SMO and GWO algorithms in order to obtain the most appropriate return loss, operating frequency and bandwidth. Computing feeding positions were respectively (1.3230, 4.7317), (1.7770, 4.5424) and (1.8330, 4.6262) for GA, SMO and GWO. The results in Table 1 were obtained when the design parameters for the feed points were arranged and antenna parameters were examined.

TABLE I. Antenna Parameters Of Each Design

Analyzing the data shown on Figure 8, some technical parameters of the antenna such as operating frequency, return loss and bandwidth were extracted from Table 1. According to the values given in Table 1, there are significant differences between conventional and other design methods. The best return loss and the widest bandwidth are obtained by antenna design of SMO algorithm. If we examine the resonance frequencies obtained from the design methods, they are all very close together. The resonance frequencies obtained from the methods according to the order given in Table 1 are 5.32, 5.4, 5.37 and 5.37 GHz. When these frequencies are examined, it is observed that the proposed antenna is suitable for the IEEE 802.11a (5.15-5.725 GHz) standard. Taking into account the return loss, the conventional method has performed quite poorly with -11.89 dB. If we think that bandwidth is calculated starting from -10 dB, conventional method design seems to be quite inadequate. For the proposed optimization algorithms GA, GWO and SMO, return losses are -25.8998 dB, -26.6732 dB and 36.0399 dB, respectively. Return loss of the antenna designs of GA and GWO algorithms are close to each other. The SMO algorithm alone showed the highest design performance with a return loss of -36.0399 dB. The return loss of the SMO algorithm is about -24 dB lower than the return loss obtained by conventional methods, and is about -10 dB lower than GA and GWO. The return loss is affected by the feeding point changes in µm level when the feeding points of the mm level obtained from the algorithms are taken into consideration. Finally, when bandwidths are examined, conventional method has the lowest bandwidth at 40 MHz. The highest bandwidth belongs to SMO algorithm with 560 MHz. Furthermore, the results of the operating frequency for all designs are appropriate for IEEE 802.11a WIFI standard with 5.15 GHz and 5.725 GHz. On the otherhand, SMO optimization design with optimal antenna feeding point location is determined as 1.8330 mm in x axis and 4.6262 mm in y axis.

## VII. CONCLUSION

In this study, the hybrid artificial neural network models are proposed to be designed antenna structure. The proposed models are more effective compared to conventional methods. Artificial intelligence algorithms with neural network are performed in feed position determination. Artificial intelligence methods are used for minimization mean squared error between computing and reference output value in training process. Therefore, appropriate weights and biases are tried to be obtained for test data set. Finally, desired parameters are defined by suitable algorithms. When results are analyzed, it is observed that hybrid algorithms have better return loss and wider bandwidth for WIFI communication than conventional method. Especially, Spider Monkey Optimization has the greatest performance on antenna characteristics. In future studies, this type of hybrid neural network model can be used in full antenna design in order to obtain desired antenna performance.

| **Design Methods** | **Resonance Frequency (GHz)** | **Return Loss (dB)** | **Bandwidth (MHz)** |
|---|---|---|---|
| Conventional Method | 5.3204 | -11.8998 | 40 |
| GA | 5.4033 | -25.8998 | 550 |
| GWO | 5.3756 | -26.6732 | 550 |
| SMO | 5.3756 | -36.0399 | 560 |


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