# OPTIMIZATION OF SIDE LOBE LEVEL AND FIXING QUASI-NULLS IN BOTH OF THE SUM AND DIFFERENCE PATTERNS BY USING CONTINUOUS ANT COLONY OPTIMIZATION (ACO) METHOD 

S. Ali Hosseini and Z. Atlasbaf

Faculty of Engineering
Department of Electrical Engineering
Tarbiat Modares University (TMU)
Tehran, Iran


#### Abstract

In this paper, the optimization of both sum and difference patterns of linear monopulse antennas with low side lobe levels, high directivity and also narrow main beam width are efficiently solved by Continuous Ant Colony Optimization (ACO) Method. The synthesis problem is optimized by defining a suitable cost function which is based on limitation of the side lobe level. In this work, three different parameters are considered to be optimized separately which are the excitation amplitude of each element, the excitation phase of each element and finally the element-to-element spacing. Numerical results of each step, sum and difference patterns, are illustrated in each related part. Finally, we investigate placing some nulls in specific directions to suppress the jamming signals in both sum and difference patterns.


## 1. INTRODUCTION

The two most important parameters in designing a monopulse array antenna are high directivity and the least possible side lobe level. As the matter of fact, to design a high-performance monopulse antenna, large arrays have to be employed to gain a high directivity and also high radiation power; hence the antenna main beam has to contain most of the energy fed into antenna. This means that the sidelobes have to have very low radiation characteristics comparing to main beam. So lowering the side lobe level (SLL) of the antenna is one of the most important optimization parameters.

In [1], Haupt used minimal modifications on both sum and difference patterns to introduce some nulls by assigning a phase shift
or complex factor to each element excitations to make both sum and difference patterns which have to be generated by independent excitation distributions. Rodriguez [2] used Phase-only Control Method and Subarraying [3] to place some quasi-nulls in specific directions while optimizing the side lobe levels of both sum and difference patterns as well. In [4] a Hybrid Real/Integer-Coded Differential Evolution Method is used to optimize both sum and difference patterns of a monopulse antenna. There are several optimization methods inspired by nature which can be applied to both continuous and discrete optimization problems especially for array antenna synthesis such as Genetic Algorithm [5-8], Neural Networks [9], and Simulated Annealing [10], Particle Swarm optimization [11, 12], The Invasive Weed optimization technique [13], Ant Colony Optimization Method [14, 15], Bees algorithm [16] and Clonal Selection algorithm [17].

In this paper, Continuous Ant Colony Optimization (ACO) method has been employed as the introducing method and Genetic Algorithm (GA) is used for comparing the results. Although this method has a very strong ability to solve any NP-hard combinatorial optimization problems [18], there are few optimization works which are done by this method especially in antenna and microwave optimization problems. This Method can be modified for both discrete [19] and continuous optimization problems [20]. In [14], discrete ACO method has been employed to optimize the side lobe level of a Thinned Array Antenna. There is no report on using continuous Ant Colony Optimization method for minimizing the side lobe level of an array antenna and also placing nulls in specific radiation directions so far. Hence in this paper, we used the continuous ACO for minimizing the SLL of the array antenna and placing some quasi-nulls in specific directions and compared the ACO optimization results by GA optimization method as well.

We consider a linear antenna array which is symmetrical about its center. Three different ways are employed to synthesis the array antenna in the case of minimizing the side lobe level of the antenna. To this aim, one option is to have an equally spaced array with specific element amplitude and phase distribution in which the excitation amplitude and phase of each element are the optimization parameters. Another possibility is to vary the position of the elements with uniform amplitude and equal phase.

In most cases, they are required to operate in situations in which intentional or unintentional jamming signals are being received from certain directions [2]. To cancel out these unwanted signals, a practical solution is to put nulls or quasi-nulls in those directions for both sum
and difference patterns. In this case, we employed ACO to place some quasi-nulls in specific directions as well as to minimize the SLL of the antenna.

In this paper, we report the extension of the Continuous Ant Colony Optimization method to design both sum and difference patterns with low side lobe level (SLL), narrow main beam width and also nulls in direction of interferences and compare all the ACO results by Genetic Algorithm Method subsequently. The mathematical formulation of the synthesis problem will be shown in the first part. Then the Continuous Ant Colony Optimization concepts will be discussed in the next part. Afterward the numerical results will be shown in four different categories, optimization of excitation amplitude, phase and element positions and finally placing nulls in direction of jamming signals.


Figure 1. A 2 N -element symmetric linear array along $z$-axis.

## 2. MATHEMATICAL FORMULATION

A linear array of $M$ isotropic elements is considered which is positioned symmetrically along the $z$-axis shown in Fig. $1(M=2 N$ and $N$ is an integer number). For this kind of structure the array factor AF $(\theta)$ can be defined by [21]:

$$
\begin{align*}
(A F)_{2 M}(\theta)= & a_{1} e^{+j k \frac{d_{1}}{2} \cos \theta}+a_{2} e^{+j k\left(\frac{d_{1}}{2}+d_{2}\right) \cos \theta} \\
& +\ldots+a_{N} e^{+j\left(\frac{d_{1}}{2}+d_{2}+\ldots+d_{N}\right) k d \cos \theta} \\
& +a_{-1} e^{-j k \frac{d_{1}}{2} \cos \theta}+a_{-2} e^{-j k\left(\frac{d_{1}}{2}+d_{2}\right) \cos \theta} \\
& +\ldots+a_{-N} e^{-j k\left(\frac{d_{1}}{2}+d_{2}+\ldots+d_{N}\right) \cos \theta} \tag{1}
\end{align*}
$$

$$
\begin{equation*}
a_{k}=\left|a_{k}\right| e^{j \varphi_{k}} \tag{2}
\end{equation*}
$$

where, $a_{n}(n=-N \ldots-3,-2,-1$ and $1,2,3 \ldots N)$ are the excitations of each element which can be differ in both amplitude and phase from each other. " $k$ " is the wave number of the medium in which the antenna is located ( $\mathrm{k}=2 \pi / \lambda, \lambda$ is the wavelength), " $d_{i}$ " is the distance between the elements, and $\theta$ defines the angle at which AF is calculated with respect to the direction of the antenna array. For sum pattern, the excitation coefficients are fixed and symmetrical around the center of the array [4]. Under this condition and also by considering the array as an equally spaced one and the excitation phase values are the same for each side, we have $a_{-n}=a_{n}(n=1,2 \ldots N)$. And the main array factor formula (1), for sum pattern, reduced to below:

$$
\begin{equation*}
(A F)_{\text {sum }}(\theta)=\sum_{n=1}^{N} a_{n}^{S} \cos (1 / 2(2 n-1) k d \cos \theta) \tag{3}
\end{equation*}
$$

For difference pattern, the excitation coefficients must be antisymmetric $a_{-n}=-a_{n}(n=1,2 \ldots N)$ [4]. In this case the array factor, for equally spaced array, is reduced as following:

$$
\begin{equation*}
(A F)_{d i f f}(\theta)=\sum_{n=1}^{N} a_{n}^{D} \sin (1 / 2(2 n-1) k d \cos \theta) \tag{4}
\end{equation*}
$$

Since we assume that both patterns are symmetric around array center, only one half of elements are used for pattern synthesis. In (3) and (4) the excitation coefficients may change in both amplitude and phase for each element and the formulas are defined assuming that the array is an equally spaced one. But in a case that the element-to-element spaces are the subject to be optimized the array factor formula, assuming that the excitation amplitudes and phase values are the same for sum pattern and anti-symmetrical for difference pattern, will be changed as following for both sum and difference patterns:

$$
\begin{align*}
& (A F)_{\text {sum }}(\theta)=2 \sum_{n=1}^{N} \cos \left[k\left(\sum_{m=1}^{n} d_{m}-\frac{d_{1}}{2}\right) \cos \theta\right]  \tag{5}\\
& (A F)_{\text {diff }}(\theta)=2 \sum_{n=1}^{N} \sin \left[k\left(\sum_{m=1}^{n} d_{m}-\frac{d_{1}}{2}\right) \cos \theta\right] \tag{6}
\end{align*}
$$

All (3), (4), (5) and (6) are the basis functions for optimization problem which will be discussed in this paper.

## 3. ANT COLONY OPTIMIZATION THEORY

In this part, it will be presented how the Ant Colony Optimization (ACO) can be used for continuous search domains (Fig. 2) and applied to mixed-continuous optimization problems [20]. Ant Colony Optimization Algorithm was studied from various sources [18$20,22,23]$. Optimization algorithms inspired by the ants' foraging behavior proposed by Dorigo in his PhD thesis in 1992 have been initially used for solving combinatorial optimization problems [20]. Although at first, ACO algorithms were introduced to solve discrete optimization problems; their ability to solve continuous optimization problems attracts an increasing attention.

```
input: An objective function }\mathbb{R}\nif(x):x\in\mp@subsup{\mathbb{R}}{}{n
\tau}\mp@subsup{}{}{i}\leftarrow\mathrm{ initial probability distribution }\mp@subsup{P}{}{i}(\mp@subsup{x}{}{i}),i\in{1..n
while (stop condition not met) do
    {iterate through all m ants}
    for }a=1\mathrm{ to }m\mathrm{ do
        {construction process of ant a}
        s}\mp@subsup{}{}{0}\leftarrow
        for }i=1\mathrm{ to }n\mathrm{ do
            choose value }\mp@subsup{x}{}{i}\mathrm{ randomly according to probability distribution }\mp@subsup{P}{}{i}(\mp@subsup{x}{}{i}
            s}\mp@subsup{}{}{i}\leftarrow\mp@subsup{s}{}{i-1}\cup{\mp@subsup{x}{}{i}
        end for
    end for
    s}\mp@subsup{s}{\mathrm{ Ibest }}{}\leftarrow\mathrm{ iteration best solution
    s}\mp@subsup{\mp@code{G best }}{}{~
    \tau}\leftarrow\mathrm{ pheromone updated based on one or more solutions found
end while
output: Best solution found s}\mp@subsup{s}{\textrm{G}}{\textrm{b}
```

Figure 2. ACO algorithm for continuous domain in [20].
In the continuous domain, a component is a value of $x^{i}$ for $i$ th dimension of the solution $x\left(a<x_{j}<b\right)$ which is an n-element vector in $\Re^{n}$. Rather than using discrete distribution, the continuous PDF $P^{i}\left(x^{i}\right)$ is used as defined below [20]:

$$
\begin{align*}
P^{i}(x) & =G^{i}(x, \omega, \mu, \sigma)=\sum_{j=1}^{k} \omega_{j} \cdot g_{j}\left(x, \mu_{j}, \sigma_{j}\right)  \tag{7}\\
g_{j}\left(x, \mu_{j}, \sigma_{j}\right) & =\frac{1}{\sigma_{j} \sqrt{2 \pi}} e^{-\frac{\left(x-\mu_{j}\right)^{2}}{2 \sigma_{j}^{2}}}  \tag{8}\\
\mu_{j} & =a+(2 j-1) \frac{b-a}{2 *\left(P D F_{\text {Number }}\right)} \tag{9}
\end{align*}
$$

$$
\begin{equation*}
\sigma_{j}=\frac{b-a}{2 *\left(P D F_{\text {Number }}\right)} \tag{10}
\end{equation*}
$$

At first, a number of ants are generated to start searching the domain for each dimension. Each ant starts its journey by choosing a PDF in each dimension according to (11). Then it generates a number according to chosen PDF [20].

$$
\begin{equation*}
p_{j}^{i}=\frac{\omega_{j}^{i}}{\sum_{l=1}^{k^{i}} \omega_{l}^{i}} \tag{11}
\end{equation*}
$$

At next step, the solution found by each ant is evaluated and then all solution found in each step are sorted from the best-iteration solution to the worst one. The most important part of the ACO algorithm is Pheromone (most communication among individuals is based on chemicals called pheromone) updating process which is done when all ants finished their journey and all solutions are evaluated. Pheromone update is a process of modifying the probability distribution used by the ants during the construction process, so that it can guide the ants towards better solutions [20] and finally the best one. This process is formed of two steps:

- First, reinforcing the probability of the best-iteration solution components in each dimension.
- Second, decreasing the weights of the probabilities in the each dimension which give the worst-iteration solution.
The number generating and updating processes will be done continuously until the solution meet the error criteria. In other words if best solution does not change after some iteration, the process will be terminated and the best solution is the best value which optimizes the defined cost function. Fast Convergence to the best global solution is the most important and desirable feature of the Ant Colony Optimization Method.


## 4. NUMERICAL SIMULATIONS - PATTERN OPTIMIZATION

In this section, the numerical results of the sum and difference patterns of a 100 -element array which is symmetrical around its center will be illustrated. Three parameters are optimized separately in each step and the sum and difference patterns of each optimization result will be shown subsequently. Finally the optimized parameters for each step will be illustrated all in Table 1.

Table 1. The ACO optimized values for all sections in this paper.

| Elem. NO | Amp. values |  | Phase <br> values |  | $\begin{gathered} \hline \text { Space } \\ \hline \text { S\&D } \end{gathered}$ | Amp. Zero |  | Phase <br> Zero |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Sum | Diff | Sum | Diff |  | Sum | Diff | Sum | Diff |
| 1 | 0.97 | 0.038 | 1.406 | 1.462 | 0.519 | 0.935 | 0.062 | 1.71 | 1.226 |
| 2 | 0.992 | 0.118 | 1.53 | 3.005 | 0.504 | 0.972 | 0.135 | 1.818 | 3.109 |
| 3 | 0.984 | 0.207 | 1.443 | 2.703 | 0.511 | 0.847 | 0.149 | 2.078 | 0.01 |
| 4 | 0.964 | 0.275 | 1.504 | 3.093 | 0.503 | 0.938 | 0.125 | 1.719 | 3.12 |
| 5 | 0.951 | 0.376 | 1.547 | 2.817 | 0.505 | 0.962 | 0.365 | 1.507 | 2.869 |
| 6 | 0.95 | 0.45 | 1.652 | 0.224 | 0.79 | 0.878 | 0.361 | 1.832 | 0.136 |
| 7 | 0.95 | 0.514 | 1.447 | 0.042 | 0.802 | 0.945 | 0.43 | 1.534 | 2.275 |
| 8 | 0.942 | 0.567 | 1.715 | 2.386 | 0.976 | 0.934 | 0.518 | 1.912 | 0.884 |
| 9 | 0.915 | 0.656 | 1.518 | 0.37 | 0.93 | 0.849 | 0.459 | 1.789 | 2.127 |
| 10 | 0.891 | 0.714 | 1.402 | 1 | 0.957 | 0.809 | 0.571 | 1.667 | 2.482 |
| 11 | 0.881 | 0.807 | 1.415 | 3.123 | 0.833 | 0.942 | 0.7 | 1.723 | 3.137 |
| 12 | 0.847 | 0.798 | 1.395 | 1.164 | 0.728 | 0.873 | 0.757 | 1.828 | 0.877 |
| 13 | 0.827 | 0.856 | 1.582 | 1.175 | 0.679 | 0.806 | 0.62 | 1.929 | 1.839 |
| 14 | 0.806 | 0.881 | 1.518 | 1.662 | 0.544 | 0.753 | 0.737 | 1.681 | 1.523 |
| 15 | 0.761 | 0.924 | 1.472 | 1.832 | 0.516 | 0.846 | 0.806 | 1.803 | 1.561 |
| 16 | 0.741 | 0.935 | 1.095 | 1.793 | 0.508 | 0.816 | 0.915 | 1.815 | 1.568 |
| 17 | 0.726 | 0.965 | 1.504 | 1.478 | 0.548 | 0.721 | 0.785 | 1.449 | 1.75 |
| 18 | 0.7 | 0.986 | 0.856 | 1.522 | 0.578 | 0.762 | 0.818 | 1.398 | 1.752 |
| 19 | 0.689 | 0.993 | 0.918 | 1.619 | 0.551 | 0.781 | 0.898 | 2.064 | 1.403 |
| 20 | 0.667 | 0.994 | 1.798 | 1.662 | 0.52 | 0.645 | 0.916 | 1.604 | 1.538 |
| 21 | 0.635 | 0.974 | 1.417 | 1.491 | 0.53 | 0.817 | 0.914 | 1.548 | 1.83 |
| 22 | 0.608 | 1 | 1.437 | 1.417 | 0.573 | 0.582 | 0.962 | 1.792 | 1.642 |
| 23 | 0.584 | 0.936 | 1.776 | 1.559 | 0.504 | 0.629 | 0.917 | 1.328 | 1.514 |
| 24 | 0.524 | 0.932 | 1.914 | 1.181 | 0.533 | 0.581 | 0.923 | 2.351 | 1.916 |
| 25 | 0.51 | 0.858 | 1.557 | 1.275 | 0.567 | 0.692 | 0.859 | 1.408 | 1.759 |
| 26 | 0.482 | 0.841 | 1.389 | 1.502 | 0.631 | 0.528 | 0.813 | 1.657 | 1.618 |
| 27 | 0.477 | 0.855 | 0.215 | 1.325 | 0.535 | 0.575 | 0.923 | 1.991 | 1.608 |
| 28 | 0.43 | 0.803 | 1.056 | 1.297 | 0.694 | 0.564 | 0.746 | 0.878 | 1.763 |
| 29 | 0.406 | 0.774 | 1.481 | 1.331 | 0.591 | 0.569 | 0.875 | 1.478 | 1.706 |
| 30 | 0.367 | 0.725 | 1.056 | 1.467 | 0.53 | 0.527 | 0.862 | 2.06 | 1.798 |
| 31 | 0.328 | 0.68 | 1.906 | 1.334 | 0.516 | 0.463 | 0.759 | 2.131 | 1.566 |
| 32 | 0.3 | 0.632 | 2.843 | 1.459 | 0.588 | 0.37 | 0.745 | 2.859 | 1.764 |
| 33 | 0.292 | 0.6 | 0.308 | 1.516 | 0.695 | 0.444 | 0.762 | 2.838 | 1.701 |
| 34 | 0.267 | 0.534 | 0.406 | 1.673 | 0.563 | 0.473 | 0.581 | 1.272 | 1.771 |
| 35 | 0.257 | 0.497 | 1.974 | 1.711 | 0.667 | 0.305 | 0.644 | 0.166 | 1.631 |
| 36 | 0.2 | 0.465 | 1.669 | 1.215 | 0.709 | 0.349 | 0.616 | 3.07 | 1.496 |
| 37 | 0.238 | 0.386 | 2.913 | 1.201 | 0.896 | 0.297 | 0.607 | 0.661 | 1.956 |
| 38 | 0.18 | 0.346 | 0.002 | 1.479 | 0.891 | 0.34 | 0.573 | 1.094 | 2.678 |
| 39 | 0.164 | 0.356 | 1.955 | 1.511 | 0.926 | 0.329 | 0.464 | 2.571 | 1.474 |
| 40 | 0.137 | 0.305 | 0.846 | 2.145 | 0.865 | 0.176 | 0.418 | 1.631 | 1.434 |
| 41 | 0.14 | 0.263 | 2.12 | 1.32 | 0.888 | 0.29 | 0.454 | 2.37 | 1.151 |
| 42 | 0.11 | 0.222 | 3.141 | 0.947 | 0.958 | 0.36 | 0.487 | 0.59 | 2.082 |
| 43 | 0.097 | 0.212 | 1.522 | 0.809 | 0.93 | 0.251 | 0.357 | 2.276 | 1.947 |
| 44 | 0.102 | 0.173 | 1.248 | 1.177 | 0.988 | 0.167 | 0.241 | 1.194 | 1.453 |
| 45 | 0.054 | 0.129 | 3.125 | 2.116 | 0.962 | 0.188 | 0.377 | 2.724 | 1.172 |
| 46 | 0.067 | 0.131 | 1.157 | 0.948 | 0.972 | 0.152 | 0.204 | 1.566 | 0.992 |
| 47 | 0.041 | 0.099 | 1.072 | 1.69 | 0.979 | 0.146 | 0.28 | 1.841 | 1.522 |
| 48 | 0.062 | 0.063 | 0.823 | 0.014 | 0.987 | 0.327 | 0.302 | 0.899 | 1.997 |
| 49 | 0.031 | 0.067 | 1.623 | 1.811 | 0.83 | 0.236 | 0.251 | 2.178 | 0.375 |
| 50 | 0.033 | 0.049 | 1.506 | 1.082 | 0.933 | 0.127 | 0.211 | 1.585 | 1.715 |

### 4.1. Optimizing the Excitation Amplitude of Each Element

Here, we consider a 100-element equally spaced array antenna in which the distance between elements is $0.5 \lambda$ and all they have identical phase values. As mentioned before the cost function is to reduce the SLL of the antenna to its least possible value and the excitation amplitude of each element is the subject to be optimized in this part. But it has to be mentioned that the excitation amplitude coefficients are still symmetrical around the center of the array and are constrained to lie between 0 and 1 .

Figure 3 and 4 illustrate both sum and difference Patterns of the antenna optimized by ACO method and Genetic Algorithm respectively. The ACO optimized sum pattern has a maximum relative sidelobe level about -50.9 dB and the GA optimized sum Pattern has a SLL of about -28.1 dB . Similarly it is clear that the maximum sidelobe level of difference pattern optimized by ACO is about -48 dB and the SLL of the difference pattern optimized by GA is about -27.35 dB . It can be easily seen that in this section the optimization results of ACO are far better than those of GA.

### 4.2. Optimizing the Excitation Phase of Each Element

Let us now consider a 100-element equally spaced array antenna. The element spacing is $0.5 \lambda$ but in this case all the elements have identical current amplitudes and the excitation phase values are optimized by both ACO and GA methods. The Excitation Phase values for each element are constrained to lie between 0 and $\pi$.

Figures 5 and 6 show the sum and difference patterns optimized by ACO and GA methods respectively. The maximum relative sidelobe level for sum and difference patterns optimized by ACO are -23 dB and -20.8 dB respectively and -20.8 dB and -18.87 dB for the GA optimized patterns. It is obvious that, although the array feed network can become relatively simpler than before but sidelobe levels are increased in both patterns.

### 4.3. Optimizing the Element-to-Element Spacing

In this part, the element-to-element spacing is subject to change while all feeds have identical current phase and amplitude. Same as before, a 100-element array is considered to be optimized to have the least SLL. This kind of array antenna is really desirable because the configuration is really simple and there is no need for a complex feed network since all elements are excited by the same current for sum pattern and fed anti-symmetrical to make difference Pattern.


Figure 3. The ACO optimized patterns for excitation amplitude optimization.


Figure 4. The GA optimized patterns for excitation amplitude optimization.


Figure 5. The ACO optimized patterns for excitation phase optimization.


Figure 6. The GA optimized patterns for excitation phase optimization.

The element spacing values are forced to lie in between $0.5 \lambda$ and $\lambda$. Fig. 7 and Fig. 8 show the sum and difference patterns optimized by ACO and GA respectively. The maximum relative sidelobe levels for the optimized sum Pattern by ACO and GA are -17.4 dB and -16.4 dB and for difference patterns are -17.6 dB and -16 dB respectively.

## 5. NUMERICAL SIMULATIONS - FIXING (QUASI) NULLS IN BOTH SUM AND DIFFERERNCE PATTERNS

In this section, the Ant Colony Optimization method is employed to introduce some nulls in direction of jamming signals. In this work, it is assumed that there are two jamming signal main beams at $\theta=40^{\circ}$ and $80^{\circ}$. The cost function is constructed for maximizing the SLL as well as minimizing the array factor value in both $40^{\circ}$ and $80^{\circ}$ shown in (12).

The Cost Function $=30 * S L L$

$$
\begin{align*}
& +2 *\left|\operatorname{Max}_{d B}-\operatorname{Null}_{\text {Value }-d B}\left(\theta=40^{\circ}\right)\right| \\
& +2 *\left|\operatorname{Max}_{d B}-\operatorname{Null}_{\text {Value }-d B}\left(\theta=80^{\circ}\right)\right| \tag{12}
\end{align*}
$$



Figure 7. The ACO optimized patterns for the element spacing optimization.


Figure 8. The GA optimized patterns for the element spacing optimization.

In the following, two way of fixing nulls in the desired directions by optimizing excitation amplitudes and phase values will be investigated and the results will be shown later.

### 5.1. Optimizing the Cost Function by Optimizing the Excitation Amplitudes

The excitation amplitudes are the subject of optimizing to have the least possible side lobe level as well as two quasi-nulls at $\theta=40^{\circ}$ and $80^{\circ}$ for both the sum and difference patterns. Fig. 9 shows the ACO optimized sum and difference patterns in which two quasi-nulls are introduced at $\theta=40^{\circ}$ and $80^{\circ}$. The side lobe levels of the sum and difference patterns are now -38 dB and -36.4 dB respectively and the quasi-nulls are about -50 dB deep. Fig. 10 illustrates the GA optimized patterns with two quasi-nulls at $\theta=40^{\circ}$ and $80^{\circ}$ and the SLL of -22.50 dB and -21.35 dB for the sum and difference patterns respectively.


Figure 9. The ACO optimized patterns for Amp. Optimization with quasi-nulls.


Figure 10. The GA optimized patterns for Amp. Optimization with quasi-nulls.


Figure 11. The ACO optimized patterns for Phase Optimization with quasi-nulls.


Figure 12. The GA optimized patterns for Phase Optimization with quasi-nulls.

Table 2. The comparison between ACO and GA results.

|  |  | Ant Colony Optimi zation Method |  |  |  |  | Genetic Algorithm |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | AMP | Phase | Space | $\begin{aligned} & \text { Zero } \\ & \text { AMP } \end{aligned}$ | Zero Phase | AMP | Phase | Space | $\begin{aligned} & \hline \text { Zero } \\ & \text { AMP } \end{aligned}$ | Zero <br> Phase |
| $\begin{aligned} & \hline \text { SLL } \\ & (\mathrm{dB}) \end{aligned}$ | Sum | -50.9 | -23.0 | -17.4 | -38.2 | -21.2 | -28.1 | -20.8 | -16.4 | -22.5 | -17.9 |
|  | Diff | -48.2 | -20.8 | -17.6 | -36.4 | -18.7 | -27.4 | -18.9 | -16.0 | -21.4 | -14.4 |
| $\begin{gathered} \text { BW } \\ (\mathrm{deg}) \end{gathered}$ | Sum | 4.9 | 2.6 | 1.8 | 3.53 | 2.4 | 3.5 | 2.6 | 1.5 | 4.21 | 2.4 |
|  | Diff | 3.14 | 2.05 | 1.7 | 2.56 | 2.05 | 2.4 | 2.7 | 1.53 | 1.42 | 2 |
| $\begin{gathered} \hline \text { N_40 } \\ (\mathrm{dB}) \end{gathered}$ | Sum | - | - | - | -59.3 | -65.5 | - | - | - | -120 | -39 |
|  | Diff | - | - | - | -50.6 | -65.6 | - | - | - | -45.4 | -46.4 |
| $\begin{gathered} \mathrm{N} \_80 \\ (\mathrm{~dB}) \end{gathered}$ | Sum | - | - | - | -77.1 | -64.5 | - | - | - | -35 | -125 |
|  | Diff | - | - | - | -57.9 | -60.6 | - | - | - | -119 | -122 |
| Iteration | Sum | 1987 | 744 | 219 | 587 | 569 | 2510 | 1040 | 136 | 360 | 464 |
|  | Diff | 1581 | 889 | 219 | 482 | 408 | 2370 | 794 | 136 | 420 | 608 |
| $\begin{aligned} & \hline \text { Time } \\ & (\mathrm{Sec}) \end{aligned}$ | Sum | 410 | 1455 | 391 | 135 | 448 | 502 | 1594 | 177 | 72 | 293 |
|  | Diff | 324 | 1720 | 391 | 112 | 320 | 474 | 1217 | 177 | 84 | 385 |

### 5.2. Optimizing the Cost Function by Optimizing the Excitation Phase values

The excitation phase values for each element are now optimized by ACO to minimize the side lobe level and introduce two quasi-nulls at $\theta=40^{\circ}$ and $80^{\circ}$ and the results are illustrated in Fig. 11. The side lobe levels of the sum and difference patterns are now -21.16 dB and -18.71 dB respectively and the quasi-nulls have at least a 60 dB deep. The GA optimized sum and Patterns with quasi-nulls at the mentioned directions are shown in Fig. 12. The side lobe levels for this case are -17.88 dB for sum pattern and -14.20 dB for difference pattern and the maximum deepness of the quasi-nulls is -40 dB .

## 6. CONCLUSION

In this paper, the optimizations of both sum and difference patterns of monopulse antennas by Continuous Ant Colony Optimization Method have been considered. All the optimized values are shown in Table 1. The method has been checked versus several cost function optimizations. The results confirm that the ACO can find the best optimum value for mixed discrete-continuous problems at relatively a short time and the ACO can guarantee that the results are the best global values comparing with the results shown in Table 2 especially for optimizing the SLL of the array factor only by excitation amplitudes which results very good values for SLL for both sum and difference patterns (about -48.2 dB and -50.9 dB ). Further developments will be aimed at further reviewing the capabilities of the ACO algorithm when applied for different synthesis problems.

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