Research Article

Circular Antenna Array Synthesis Using Multiverse Optimizer

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Antenna array synthesis is one of the most popular topics in the electromagnetic field. Since achieving a desired antenna radiation pattern is a mathematical problem, in the literature, there are various optimization algorithms applied to the synthesis process of different kinds of antenna arrays. In this study, Multiverse Optimizer (MVO) and modified MVO (MMVO) are used to perform circular antenna array (CAA) synthesis. During the exploration, exploitation, and local search phases of calculation, MVO uses three concepts in cosmology; white hole, black hole, and wormhole. Convergence capability of this nature-inspired algorithm is employed for finding optimum amplitude and position values of CAA elements in order to achieve an array pattern with low maximum sidelobe level (MSL) and minimum circumference. The performance of MVO and MMVO was tested on five design examples of pattern synthesis, and the obtained results were compared with ten different algorithms. The simulation results show that MVO and MMVO provide low MSLs with small circumferences.

1. Introduction

In recent days, with the developing technology, devices have started to host more wireless components. The application of wireless technology in all areas of data transfer and communication has accelerated the spread of its use. However, increment in use of this technology brought some drawbacks such as interference and electromagnetic pollution. To overcome this issue and use frequency spectrum much more efficiently, RF components are improved year by year. Antennas, which constitute one of the most important elements of wireless technology, also took part in this improvement. As a result, different antenna types appeared such as wire, horn, dish, and array.

The antenna arrays consist of a combination of multiple antenna elements and they are widely used in communication. Electromagnetic radiation of each element can be constructively or destructively added. Thus, whole array can radiate towards desired direction while minimizing the interference on undesired angles [1]. Thanks to their useful and flexible structure, antenna arrays can provide high gain, high directivity, and high beam steering capability with less

interfering effect. These features of antenna arrays make them popular both in military and civil applications. They are widely used in sonar, radar, navigation systems, cellular systems, and satellite communications.

Antenna arrays take their names according to the geometric shape of overall array structure. Array elements can be positioned on a single line, called linear antenna arrays, or distributed over a plane, called planar antenna arrays. Array structures can be in form of circle and ellipse too. Moreover, by creating nested structures from circular or elliptical arrays, concentric circular and concentric elliptical antenna arrays are achieved.

In this paper, circular antenna array (CAA) is considered for the array synthesis. Unlike the linear antenna arrays, the main lobe of CAA can be directed between 0 and 360 degrees. According to the changes in position, amplitude, and phase of array elements, or changes in circle radius, overall radiation pattern is shaped. However, achieving a desired antenna pattern is a challenging task since the mentioned array parameters have to be calculated. It is seen from the literature that the optimization algorithms can be used to overcome this kind of pattern synthesis problems. The

following can be given as examples of these studies: linear antenna array synthesis using Tabu Search Algorithm (TSA) [2], Harmony Search Algorithm (HSA) [3], and Touring Ant Colony Optimization (TACO) [4]; planar antenna array synthesis using Taguchi Method (TM) [5] and Genetic Algorithm (GA) [6]; elliptical antenna array synthesis using Backtracking Search Optimization Algorithm (BSA) [7]; circular antenna array synthesis using Differential Evolution (DE) Algorithm [8]; and concentric CAA synthesis using BSA [9].

Multiverse Optimizer (MVO), which is a nature-inspired algorithm, was proposed in 2016 [10] and used to solve practical optimization problems in engineering such as welded beam design, gear train design, three-bar truss design, pressure vessel design, and cantilever beam design. In [10], the performance of MVO was compared with GA, Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Gravitational Search Algorithm (GSA). The majority of test results show that MVO outperforms the popular algorithms in the literature. MVO was also used for multiobjective optimal antenna synthesis of microwave wireless power transmission [11].

The main objective of this paper is to compute optimally the amplitudes and positions of CAA elements to achieve low MSL and small circumference using MVO and modified MVO (MMVO). Synthesis process was applied for CAAs with 8, 10, 12, and 20 elements. The obtained results were compared with the results of ten different optimization algorithms: hybrid algorithm (HA) [12] based on Antlion Optimization (ALO) and Grasshopper Optimization Algorithm (GOA), ALO [12], Sequential Quadratic Programming (SQP) [13], Self-Adaptive Differential Evolution (SADE) [13], Biogeography Based Optimization (BBO) [13], GA [14], PSO [15], Firefly Algorithm (FA) [16], Seeker Optimization Algorithm (SOA) [17], and Simulated Annealing (SA) [18].

In the following section, MVO and MMVO are explained in detail. Section 3 includes the CAA geometry and equation of array factor. Section 4 presents results and discussions. Section 5 covers the conclusion part.

2. Multiverse Optimizer

Multiverse theory was proposed by physicists, and MVO is inspired by this theory. It is believed that more than one big bang occurred, and each one of them is resulted with the birth of a universe [19, 20]. The idea behind this theory is the opposite of universe, which states the presence of other universes

in addition to ours. Besides, according to this model, these universes may interact and/or collide with each other.

MVO is based on three concepts in the cosmology: white holes, black holes, and wormholes [10]. Physicists state that the white hole, which is also considered as big bang, is the main component of the birth of a universe [21]. It appeared after the collision of two parallel universes [22]. Black holes are the white holes in reverse and, because of their extremely high gravitational force, they attract everything including light beams [23, 24]. Wormholes can be described as time/space highways where objects are able to travel instantly between two different points of a universe or two different universes too [25].

Basically, MVO converges the target by sending and receiving the objects (variables) between the universes (solutions). This sending/receiving process depends on the inflation rates (fitness values) of the universes calculated over iterations. If a universe has high inflation rate, it is highly probable to have white holes and tends to send object towards other universes. If a universe has low inflation rate, most probably it has a black hole and tends to receive objects. This mentioned process is the exploration step of the algorithm and is represented mathematically as follows [10]:

$$U = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^p \\ x_2^1 & x_2^2 & \cdots & x_2^p \\ \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^p \end{bmatrix}, \quad (1)$$

$$x_i^j = \begin{cases} x_k^j, & r1 < NI(Ui), \\ x_i^j, & \text{otherwise,} \end{cases}$$

where Ui is the i th universe, p is the number of parameters (variables), n is the number of universes (solutions), x_i^j is the j th parameter of i th universe, $r1$ is a random number in $[0, 1]$, $NI(Ui)$ is normalized inflation rate of the i th universe, and x_k^j is the j th parameter of k th universe selected by a roulette wheel selection mechanism.

In the exploitation phase of the algorithm, it is assumed that each universe is using wormholes to transfer the objects through space randomly regardless of inflation rate. Besides, wormholes are used to perform local updates in each universe by establishing a connection to the best universe formed so far. This mechanism is formulated as follows [10]:

$$x_i^j = \begin{cases} \begin{cases} X_j + TDR \times ((ub_j - lb_j) \times r4 + lb_j) & r3 < 0.5 \\ X_j - TDR \times ((ub_j - lb_j) \times r4 + lb_j) & r3 \geq 0.5 \end{cases}, & r2 < WEP, \\ x_i^j, & r2 \geq WEP, \end{cases} \quad (2)$$

where X_j is the j th parameter of best universe formed so far; $r2$, $r3$, and $r4$ are the random numbers in $[0, 1]$; and ub_j and lb_j are used to define upper and lower bound of j th variable, respectively. WEP and TDR are coefficients which are explained below.

WEP stands for the wormhole's existence probability in the universe. In the algorithm, this coefficient is increased linearly over repetitions to emphasize exploitation. WEP is calculated as follows [10]:

$$\text{WEP} = \min + l \times \left(\frac{\max - \min}{L} \right), \quad (3)$$

where, by default, min is defined as 0.2 and max is defined as 1. L indicates the maximum iteration value and l represents the current step of the iteration.

Traveling distance rate (TDR) is also a coefficient. It is used while sending objects through a wormhole to the best universe obtained so far. The formula for TDR is as follows [10]:

$$\text{TDR} = 1 - \frac{l^{(1/p)}}{L^{(1/p)}}, \quad (4)$$

where p indicates the exploitation accuracy and is equal to 6 as a default value.

The pseudocode of the MVO is shown in Figure 1.

2.1. Modified MVO (MMVO). As is stated in No Free Lunch (NFL) Theorem, there is no single algorithm to solve every problem set [26]. Besides, it is realized that the performance of an algorithm can be improved by modifying it and thus the algorithm can be used to solve problems in different fields. Even though the performance of original MVO is good enough to optimize the problems, structure of the algorithm itself is suitable for modifications to improve the convergence. Therefore, in this paper, the exploitation phase of the MVO is changed as follows:

$$x_i^j = \begin{cases} \begin{cases} X_j + \text{TDR} \times ((X_j - x_i^j) \times r4 + x_i^j) & r3 < 0.5 \\ X_j - \text{TDR} \times ((X_j - x_i^j) \times r4 + x_i^j) & r3 \geq 0.5 \end{cases}, & r2 < \text{WEP}, \\ x_i^j, & r2 \geq \text{WEP}, \end{cases} \quad (5)$$

and this modification aims to perform the solution updates locally using the best universe and current universe instead of upper and lower bounds of problem set. Thus, by shortening the exploitation steps, the algorithm is improved and forced to find better amplitude and position values for array elements.

3. Circular Antenna Array

In Figure 2, geometry of a nonuniform CAA is depicted. N isotropic radiators (antenna elements) are placed nonuniformly on a circle of radius a in the x - y plane. The array factor of such structure can be mathematically described as follows [1]:

$$\text{AF}(\theta, \phi) = \sum_{n=1}^N I_n \exp(j[ka \sin(\theta) \cos(\phi - \phi_n) + \alpha_n]), \quad (6)$$

where

$$ka = \frac{2\pi}{\lambda} a = \sum_{i=1}^N d_i, \quad (7)$$

$$\phi_n = \frac{2\pi \sum_{i=1}^n d_i}{ka}.$$

In order to focus the main beam towards the (θ_o, ϕ_o) direction, the excitation phase is written as follows [1]:

```

1. Initialize the universe population U
2. Initialize l, WEP and TDR
3. while l < L
4.   Calculate the fitness for all universes
5.   Sort the universe population and get SU
6.   NI = Normalized fitness values of the universes
7.   for each universe indexed by i
8.     Update WEP and TDR
9.     Black_hole_index = i
10.    for each object indexed by j
11.      r1 = rand([0, 1])
12.      if r1 < NI(Ui)
13.        White_hole_index = RouletteWheelSelection(-NI)
14.        U(Black_hole_index, j) = SU(White_hole_index, j)
15.      end if
16.      r2 = rand([0, 1])
17.      if r2 < WEP
18.        r3 = rand([0, 1])
19.        r4 = rand([0, 1])
20.        if r3 < 0.5
21.          U(i, j) = X(j) + TDR * ((ub(j) - lb(j)) * r4 + lb(j))
22.        else
23.          U(i, j) = X(j) - TDR * ((ub(j) - lb(j)) * r4 + lb(j))
24.        end if
25.      end if
26.    end for
27.  end for
28.  t + 1
29. end while

```

FIGURE 1: Pseudocode of MVO.

FIGURE 2: Geometry of a nonuniform CAA.

$$\alpha_n = -ka \sin(\theta_o) \cos(\phi_o - \phi_n). \quad (8)$$

In the above, I_n and α_n indicate the excitation amplitude and excitation phase of the n th antenna element, respectively. d is used to define the arc distance between the adjacent antenna elements. ϕ_n is the angular position of the n th radiator on x - y

FIGURE 3: Radiation pattern of the optimized 8-element CAA.

plane. θ represents the measured elevation angle from the positive z -axis, and ϕ is used to represent the measured azimuth angle from the positive x -axis. Since the antenna array is placed in the x - y plane, θ is assumed to be 90° . (θ_o, ϕ_o) shows the direction of the main beam of antenna array. In order to simplify the calculations, θ_o is taken as 90° and ϕ_o is taken as 0° . In other words, the main beam is focused along the positive x -axis.

4. Results and Discussion

In this section, the overall performance of MVO and MMVO on CAA synthesis is evaluated in detail. The purpose of performing array synthesis is to achieve a desired antenna pattern. As mentioned in the Introduction, different synthesis processes were applied to different kinds of antenna arrays with different algorithms. The main aim of those works is to get low sidelobe levels, place nulls in desired directions, and increase the gain or directivity of the antenna.

In this paper, MVO and MMVO algorithms were used to find optimum amplitude and position values of CAA elements in order to achieve low MSL and minimum circumference. The obtained results from both MVO and MMVO were comprehensively compared with the results of ten different algorithms which are GA [14], PSO [15], FA [16], SQP [13], SADE [13], HA [12], ALO [12], BBO [13], SOA [17], and SA [18]. During the optimization, the following fitness function was used:

$$\text{Fitness} = \max \left(20 \log \left| \frac{\text{AF}(\phi_{\text{MSL}})}{\text{AF}_{\text{max}}} \right| \right) + \left| \left(\sum_{i=1}^N d_i \right) - (C) \right|, \quad (9)$$

where ϕ_{MSL} is the angular interval of the sidelobe region that is minimized, AF_{max} is the peak of main beam, and C is the desired circumference. In each iteration step, the difference between the desired circumference and the arc distance summation is taken into account and the algorithm reduces

it while keeping the sidelobe level to a minimum. The fitness function is used for CAA with 8, 10, 12, and 20 elements. In order to observe the real performance of MVO and MMVO and to make a fair comparison, 20 independent runs were performed under the default parameters. All simulations were done by setting the algorithm to 300 iterations with population size of 50 on MATLAB R2016b with a computer that has 2.4 GHz i7 processor and 8 GB RAM.

In the first example, the optimum amplitude and position values of CAA with 8 elements are calculated by MVO and MMVO to get the minimum sidelobe level in the region $\phi = [-180^\circ, -34^\circ]$ and $\phi = [34^\circ, 180^\circ]$. The resultant radiation patterns of MVO and MMVO are shown in Figure 3. Table 1 illustrates MSL and circumference values of the radiation patterns obtained using MVO and MMVO. Table 1 also shows the comparison results of GA [14], PSO [15], FA [16], SQP [13], SADE [13], HA [12], ALO [12], BBO [13], SOA [17], and SA [18]. It can be clearly observed from Table 1 that MSL and circumference values of MVO and MMVO are better than those of GA [14], PSO [15], FA [16], SQP [13], SADE [13], HA [12], ALO [12], BBO [13], SOA [17], and SA [18]. The convergence curves of this example can be seen in Figure 4.

In the second example, the number of array elements is increased from 8 to 10 and the sidelobe region is taken as $\phi = [-180^\circ, -27^\circ]$ and $\phi = [27^\circ, 180^\circ]$. The algorithm has been run 20 times. The patterns of this design example can be seen in Figure 5. The MSL and circumference results of MVO and MMVO are listed in Table 1 in comparison with GA [14], PSO [15], FA [16], SQP [13], SADE [13], HA [12], ALO [12], BBO [13], SOA [17], and SA [18]. As can be seen from this table, the MSL and circumference values achieved by MVO and MMVO are better than those by the other compared algorithms.

The 12-element CAA is the third design example of this part. The best MSL and circumference results are obtained after 20 runs in the $\phi = [-180^\circ, -23^\circ]$ and $\phi = [23^\circ, 180^\circ]$ angular region. The radiation patterns are given in Figure 6. In Table 1, the MSL and circumference values of MVO and MMVO are compared with those of GA [14], PSO [15], FA

TABLE 1: MSL and circumference comparison of algorithms for 8-, 10-, and 12-element CAA.

	Present study		GA [14]	PSO [15]	FA [16]	SQP [13]	SADE [13]	HA [12]	ALO [12]	BBO [13]	SOA [17]	SA [18]
	MMVO	MVO										
N = 8	MSL (dB)	-15.08	-9.81	-10.80	-13.00	-13.16	-12.70	-15.00	-13.71	-12.18	-11.11	-12.00
	$\sum (d) (\lambda)$	4.3810	4.3936	4.4094	4.4931	4.6556	4.6521	4.6505	4.5384	4.5416	4.4070	5.8750
N = 10	MSL (dB)	-14.71	-14.49	-11.03	-12.31	-13.30	-13.02	-13.43	-14.20	-13.52	-12.50	-13.00
	$\sum (d) (\lambda)$	5.8600	5.8653	6.0886	5.9029	6.0700	6.0319	6.0532	5.8821	5.9686	6.1042	8.0214
N = 12	MSL (dB)	-14.70	-14.60	-11.80	-13.68	-14.21	-13.41	-13.19	-14.12	-14.56	-14.11	-13.91
	$\sum (d) (\lambda)$	7.1474	7.1479	7.7724	7.1501	7.2145	7.0841	7.1793	7.2153	7.2661	7.1499	7.9523

FIGURE 4: Convergence curve of 8-element CAA.

FIGURE 5: Radiation pattern of the optimized 10-element CAA.

FIGURE 6: Radiation pattern of the optimized 12-element CAA.

TABLE 2: MSL and circumference comparison of algorithms for 20-element CAA.

	Varying circumference							Constant circumference							
	Present study							Present study							
	MMVO	MVO	BBO [13]	SADE [13]	SQP [13]	HA [12]	ALO [12]	MMVO	MVO	BBO [13]	SADE [13]	SQP [13]	HA [12]	ALO [12]	Uniform
MSL (dB)	-15.40	-15.11	-13.84	-13.95	-14.87	-14.98	-14.39	-12.62	-12.51	-10.70	-11.30	-11.81	-12.35	-12.15	-6.08
Σ (d) (λ)	10.6024	10.6571	12.3979	12.1851	12.3258	10.7420	13.8948	10	10	10	10	10	10	10	10

FIGURE 7: Radiation pattern of the optimized 20-element CAA.

FIGURE 8: Radiation pattern of the optimized 20-element CAA with 10λ circumference.

TABLE 3: Amplitude and position values of array elements for design examples.

		$[d_1, d_2, d_3, \dots, d_N]$ in λ 's
		$[I_1, I_2, I_3, \dots, I_N]$
Figure 3	MVO	0.3285, 0.6531, 0.2366, 0.6674, 0.6277, 0.7766, 0.7634, 0.3403
	MMVO	0.6649, 0.2609, 0.2650, 0.8362, 1, 0.2546, 0.8236, 0.2229
Figure 5	MVO	0.3233, 0.7422, 0.8153, 0.6103, 0.6470, 0.2177, 0.7008, 0.3244
	MMVO	1, 0.3581, 0.8332, 0.7690, 0.1326, 0.3330, 0.9277, 0.1107
Figure 6	MVO	0.3012, 0.2732, 0.6967, 0.4202, 0.9751, 0.5266, 0.9490, 0.8571, 0.5480, 0.3182
	MMVO	0.8811, 0.1196, 0.2380, 0.4808, 0.6397, 0.7434, 0.4745, 0.2438, 1, 0.1999
Figure 6	MVO	0.1903, 0.1571, 0.9053, 0.4085, 0.9862, 0.5522, 0.9654, 0.4765, 0.8877, 0.3308
	MMVO	0.3621, 0.7931, 0.4929, 0.2722, 0.9545, 0.8882, 0.3011, 0.5697, 1, 0.2856
Figure 6	MVO	0.3204, 0.7554, 0.7360, 0.6310, 0.9008, 0.4192, 0.9589, 0.1723, 0.7213, 0.3601, 0.9386, 0.2339
	MMVO	0.9903, 0.4331, 0.6986, 0.4033, 1, 0.9938, 0.7948, 0.1214, 0.2272, 0.5110, 0.9336, 0.5467
Figure 6	MVO	0.3159, 0.7274, 0.7454, 0.6109, 0.1259, 0.7763, 0.4936, 0.9420, 0.8175, 0.4464, 0.8833, 0.2628
	MMVO	0.6145, 0.3664, 0.6626, 0.1591, 0.1449, 0.9212, 1, 0.7296, 0.2799, 0.4902, 0.6086, 0.6184

TABLE 3: Continued.

		$[d_1, d_2, d_3, \dots, d_N]$ in λ 's $[I_1, I_2, I_3, \dots, I_N]$													
Figure 7	MVO	0.2479, 0.4334, 0.9496, 0.7325, 0.6853, 0.5666, 0.9143, 0.5344, 0.1350, 0.3199, 0.1926, 0.4758, 0.7640, 0.2852, 0.4629, 0.7318, 0.5492, 0.9961, 0.5618, 0.1188													
		0.5082, 0.7995, 0.7677, 0.6978, 0.5223, 0.7467, 0.6694, 0.7362, 0.7616, 0.8147, 0.6043, 0.3239, 0.7624, 0.2968, 1, 0.8843, 0.9138, 0.6642, 0.9445, 0.8043													
	MMVO	0.3013, 0.4719, 0.8251, 0.1155, 0.6402, 0.8880, 0.3553, 0.9541, 0.5113, 0.1000, 0.2801, 0.4103, 0.8738, 0.2270, 0.6347, 0.7450, 0.6127, 0.9866, 0.4472, 0.2223													
Figure 8	MVO	0.7599, 0.2832, 0.1555, 0.6541, 0.3102, 0.5869, 0.9399, 0.3185, 1, 0.1036, 0.5827, 0.7808, 0.1381, 0.4406, 0.6412, 0.7885, 0.5329, 0.5145, 0.9146, 0.4414													
		0.1008, 0.1130, 0.4527, 0.4436, 0.9314, 0.2575, 0.2372, 0.3995, 0.8275, 0.9908, 0.3814, 1.0813, 0.9903, 0.3910, 0.3395, 0.8914, 0.4817, 0.4714, 0.1111, 0.1069													
	MMVO	0.5859, 0.5800, 0.9237, 0.6956, 0.7435, 0.8154, 0.3572, 0.7263, 0.9135, 0.7137, 0.9515, 0.7478, 0.7961, 0.7528, 1, 0.6600, 0.9821, 0.3981, 0.7731, 0.5785													
	MVO	0.6364, 0.3793, 0.9334, 0.5274, 0.3513, 0.9207, 0.4730, 0.1859, 0.5125, 0.3305, 0.5517, 0.3355, 0.8594, 0.5929, 0.3201, 0.6699, 0.2335, 0.5339, 0.3883, 0.2644													
		0.7025, 0.7391, 0.2558, 0.3866, 0.8487, 0.5303, 0.2365, 0.7463, 1, 0.8262, 0.1349, 0.9108, 0.1730, 0.7486, 0.6675, 0.2566, 0.7451, 0.2617, 0.6425, 0.6143													
	MMVO

FIGURE 9: Box-and-whisker plots of design examples 1, 2, 3, 4, and 5 for 20 runs.

[16], SQP [13], SADE [13], HA [12], ALO [12], BBO [13], SOA [17], and SA [18]. It is clearly seen from Table 1 that MSL and circumference values of the methods proposed in this study are better than those of the other algorithms except that the circumference value of SQP [13] is slightly better than that of our methods.

In the fourth example, the number of array elements is set to 20 and the sidelobe suppression region is expanded to $\phi = [-180^\circ, -14^\circ]$ and $\phi = [14^\circ, 180^\circ]$. Result comparison of this synthesis example is made in Table 2, and array patterns are shown in Figure 7. According to Table 2, it is evidently seen that the MSL and circumference values obtained by MVO and MMVO are better than those of BBO [13], SADE [13], SQP [13], HA [12], and ALO [12].

In the last example, while suppressing the MSL, the circumference value is fixed to the circumference value of

20-element uniform CAA which is 10λ ($d_i = 0.5\lambda$). After 20 independent runs, -12.51 dB and -12.62 dB MSL are achieved for MVO and MMVO, respectively. The obtained patterns are shown in Figure 8. In Table 2, the MSL results of patterns produced by MVO and MMVO are compared with the results of BBO [13], SADE [13], SQP [13], HA [12], and ALO [12]. It is apparent from Table 2 that MSL values of MVO and MMVO are better than the MSL values of the other compared algorithms.

The amplitude and position values for all design examples are shown in Table 3. Besides, box-and-whisker plots are depicted in Figure 9 to exhibit the overall statistical view of 20 independent runs for each design case. From this figure, improvement in results can be seen as an outcome of modification in the algorithm.

5. Conclusions

In this paper, MVO and MMVO algorithms were presented for the synthesis of CAA. These algorithms were used to calculate the optimum amplitude and position values of the isotropic radiators in the CAA in order to achieve low MSL and minimum circumference. Five different design examples were used to see the overall performance of the MVO and MMVO against ten different optimization algorithms. It was observed that MVO and MMVO have offered minimum sidelobe levels with competitive circumference values. MVO and MMVO can be a good alternative while solving the optimization problems in antenna and electromagnetics.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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