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Joint Optimization of Peak Sidelobe Level Suppression of Three-Dimensional Linear Array

Najla Ilyana Ab Majid and **Nik Noordini Nik Abd Malik**

Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia.

*Corresponding author: noordini@utm.my

Abstract: Collaborative beamforming (CB) is a recent technology inspired by antenna array, successfully extending the transmission range and transmission power of a single sensor node in wireless sensor networks (WSNs). However, the random location of sensor nodes that formed virtual antenna array (VAA) yield high peak sidelobe level (PSL) of CB. Thus, previous studies have proposed node selection schemes to further reduce PSL by selecting several sensor nodes to form linear, circular and concentric circular of VAA. Nevertheless, the proposed schemes only suppress the PSL in azimuth direction. Hence, we propose a joint optimization of PSL suppression (JOPS) to mitigate the PSL of beampattern in azimuth and elevation angles by optimizing the inter-element spacing of linear array arranged in three-dimensional spaces. Since the PSL suppression is a complex and non-linear problem, we deployed four optimization algorithms which are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Backtracking Search Algorithm (ICA) and Imperialist Competitive Algorithm (ICA). The performance of the algorithms is compared in terms of PSL reduction and optimization execution time of 10 and 20 linear array. Based on the results, all algorithms managed to reduce PSL of beampattern in both directions compared to uniform linear array (ULA).

Keywords: Wireless Sensor Networks, Metaheuristic Algorithms, Linear Antenna Array

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1. INTRODUCTION

Sensor nodes in Wireless Sensor Networks (WSNs) are usually deployed in harsh environments and have limited computational capacity, storage capacity and battery power due to the cost and size constraint [1], [2]. Thus, a sensor node may drain a lot of energy to transmit data directly to the distant base station (BS) [3]. Collaborative Beamforming (CB) is inspired by the antenna array technologies and has been successfully utilized in conventional WSNs [1], [2], [4]. CB managed to extend the transmission range of a single node and effectively demonstrated the reduction of transmission power of each node [2], [5]. The transmission range of CB is enhanced through the combination of signals from multiple sensor nodes that formed virtual antenna array (VAA) which produce high directional and high gain beams [6].

However, the random location of participating nodes to form VAA severely affects the beampattern of CB [7]. Perturbing the location of static sensor nodes in WSNs does not affect the beampattern properties [8]. Therefore, prior studies have proposed excitation amplitude perturbation schemes of VAA with the aim to minimize peak sidelobe level (PSL) and maximize directivity of CB [3], [6], [8], [9]. Nevertheless, minimizing PSL and maximizing directivity is a complex and non-linear problem which needs to be solved by optimization algorithms. Several optimization algorithms are utilized to optimize the excitation amplitude of VAA such as Genetic Algorithm (GA) [8], [9], Firefly Algorithm (FA) [3] and Gravitational Search Algorithm (GSA) [6]. However, perturbing excitation amplitude is insufficient to suppress PSL of CB.

The random location of CB nodes yields high and asymmetrical sidelobe with wider beamwidth [6]. Hence, a node selection scheme is required to select appropriate sensor nodes to form VAA which further reduces PSL of CB. The sensor nodes are selected based on uniform and non-uniform array optimized by optimization algorithms. Improved Particle Swarm Optimization (ImPSO) is introduced to optimize the inter-element spacing of linear array which is used to select sensor nodes to form virtual linear array [7]. The PSL of selected sensor nodes is further reduced by calculating the approximate amplitude weightage of each node using Least Square Approximation (LSA). Besides, uniform linear array (ULA) [10], uniform circular array (CAA) [11] and uniform concentric circular array (CCAA) [5], [12], [13] are also used in node selection schemes to minimize PSL. Cuckoo Search Algorithm (CSA) [10], Firefly Algorithm (FA) [11], Cuckoo Search Chicken Swarm Optimization (CSCSO) [12] and Variation Particle Swarm Optimization (VPCSO) [5], [13] are deployed to optimize excitation current of selected nodes to further reduce the PSL of CB.

However, the proposed node selection schemes are solely aiming to suppress peak SLL of CB in azimuth direction. In real applications, considering elevation angle is also important to perform uplink transmission of CB. Thus, we introduced a joint optimization of PSL suppression (JOPS) in azimuth and elevation directions of CB. In this study, JOPS is used to evaluate the PSL yields by sets of inter-elements spacing of linear array optimized by Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Backtracking Search Algorithm (BSA) and Imperialist Competitive Algorithm (ICA).

2. JOINT OPTIMIZATION OF PSL SUPPRESSION

JOPS aims to suppress PSL in azimuth and elevation angles of beampattern by optimizing inter-element spacing of linear array arranged in three-dimensional (3D) space. Figure 1 shows the flowchart of JOPS. The initial inputs of JOPS are number of CB nodes and direction of main lobe in azimuth and elevation. The number of CB nodes determines the number of inter-elements spacing of nodes that need to be optimized. The direction of main lobe specifies the desired beam direction in azimuth and elevation for transmission. In optimization algorithm initialization stage, the initial candidate solutions are generated where each solution consists of a set of inter-elements spacing. The initial candidate solution is known as population. After the initialization stage, the fitness function quantifies how well each solution reduces the PSL. Once the solutions are evaluated, the optimization algorithms modify the solutions iteratively. The modification techniques vary by algorithm. The solutions are modified until termination criteria are met such as maximum number of iterations reached and no significant improvement of solutions over several iterations. The termination criteria are important in an optimization algorithm to define the conditions under which the algorithm will terminate its iterative process, ensuring the algorithm stops at a suitable point to prevent unnecessary computations while aiming for optimal or near-optimal solutions. The final output of JOPS is the set of inter-elements spacing for the linear array that yields low PSL. The set of optimized inter-element spacings are used to plot the beampattern, allowing the evaluation of PSL. The PSL of the plotted beampattern is used to compare between different algorithms.

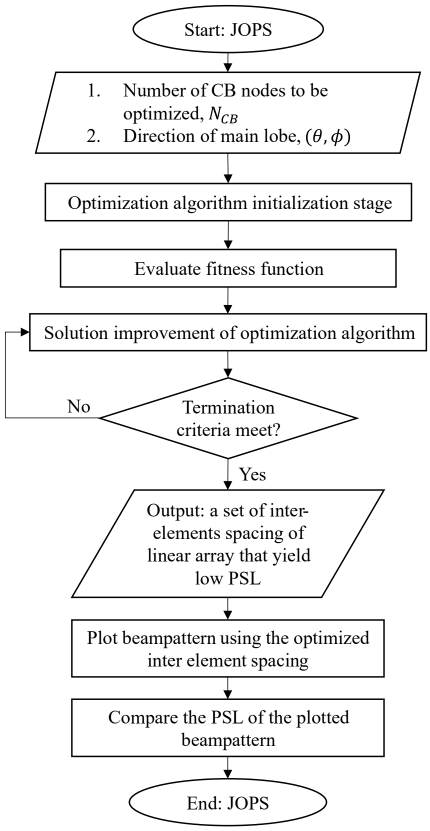

Figure 1. Flowchart of JOPS

2.1 Fitness Function

N isotropic antenna elements are placed along x-axis with beam directed towards BS at (R, θ, ϕ) as shown in Figure 2. Based on the 3D linear array model, array factor is express by [14]:

$$AF(d_n, \phi, \theta) = \sum_{n=1}^{N} I_n e^{j(n-1)(kd_n sin\theta cos\phi + \psi_n)} \quad (1)$$

I_n and ψ_n are the excitation current and phase of each element, respectively. The excitation current of each element is set as 1 in this study. $k = \frac{2\pi}{\lambda}$ is the wave number and λ is the wavelength. The aim of this study is to find a set of inter-elements spacing, d_n that yields minimum PSL of beampattern in both azimuth and elevation directions. The spacing is evaluated by fitness function which is given by:

$$f_{SLL} = \sum_{SLL1}^{MaxSLL} |AF(\phi_{SLL1}, \theta_{SLL1})|_{dB} + \sum_{MinSLL}^{SLL2} |AF(\phi_{SLL2}, \theta_{SLL2})|_{dB} \quad (2)$$

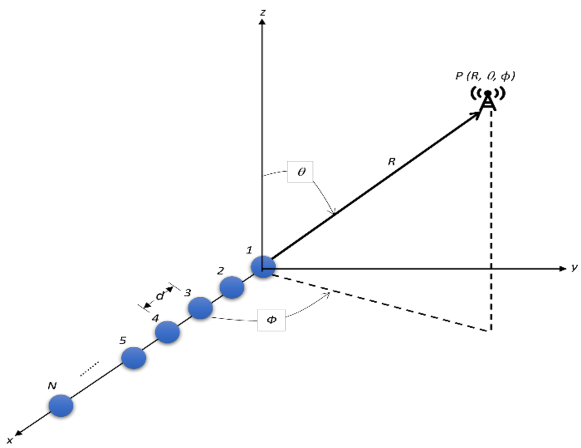

Figure 2. Geometrical linear array in 3D space

ϕ_{SLL1} and θ_{SLL1} are the angles where PSL is minimized in the lower band of azimuth and elevation directions. While ϕ_{SLL2} and θ_{SLL2} are the upper band of PSL minimization in the directions of azimuth and elevation.

2.2 Optimization Algorithms

Optimization algorithms are usually nature-inspired methods and population based which consists of multiple individuals that interact with each other and evolved continuously by iteration [15], [16]. In this study, we deployed GA, PSO, BSA and ICA to optimize inter-element spacing of linear array in 3D.

2.2.1 Genetic Algorithm

GA is inspired by natural selection which utilizes the concept of survival of fittest [17]. Individual in population is represented by chromosome. Initially, a population of n chromosomes are initialized randomly. Each chromosome represents a solution to the optimization problem. The fitness of solution in each chromosome is evaluated using fitness function proposed in this paper. The fitness evaluation is used to select chromosomes to crossover and mutate which produce new offspring. The process of selection, crossover and mutation is repeated on current population until the completion of new population is represented in Figure 3. GA has better global search capability but requires several tuning and select variety of operators [17].

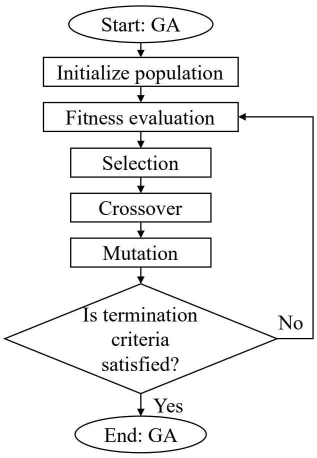

Figure 3. GA operations

2.2.2 Particle Swarm Optimization

PSO is inspired by the social behavior of animals in a swarm which cooperatively find food [18]. During the food searching, the individual in swarm keeps changing the search pattern according to learning experiences of its own and other members. Individual in a population is called a particle which represents a potential solution to optimization problem. The particle population is randomly initialized in D-dimensional search space. Each particle can memorize the optimal position and velocity of the swarm and of its own. The information is combined to adjust the velocity to calculate the new position of the particle. PSO exhibits fast convergence behavior, however, easily to fall into local optimal which hinders the search of high-quality solutions [18] Figure 4 illustrates the flow of PSO in search of near-optimal solutions.

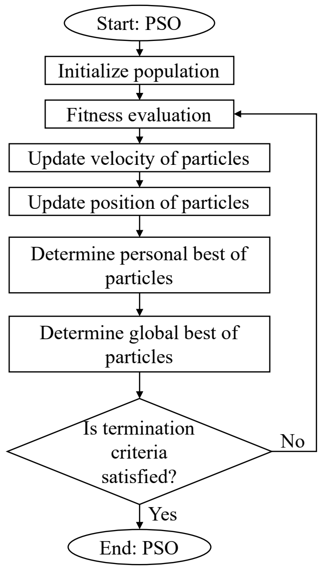

Figure 4. Flowchart of PSO

2.2.3 Backtracking Search Algorithm

BSA is a population-based iterative algorithm. BSA provides strong global exploration capability by generating trial populations to control the amplitude of the search direction matrix [19]. BSA consists of population initialization, selection I, mutation, crossover and selection II. Selection I is used to select population from the current and historical populations, while selection II is used to select the optimal population [19]. The overall process of BSA is represented in the flowchart as shown in Figure 5.

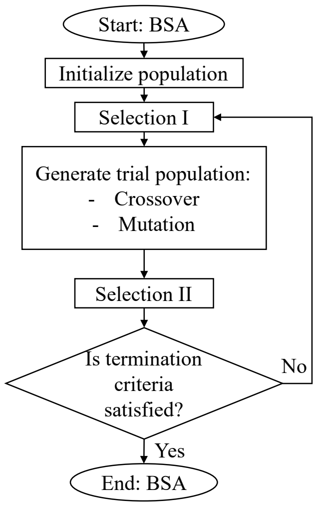

Figure 5. Flowchart of BSA

2.2.4 Imperialist Competitive Algorithm

ICA is inspired by sociopolitical competition among empires where each consists of imperialist and colonies country [20]. Individual populations in ICA are known as country which represents as solution and randomly initialized. Some of the countries are selected to be the imperialists and the remaining countries are assigned to be colonies. The colonies are divided among the imperialists based on their power to form empire. Each empire consists of one imperialist and several colonies. The process continues with assimilation, revolution, imperialistic competition and empire elimination which are illustrated in Figure 6.

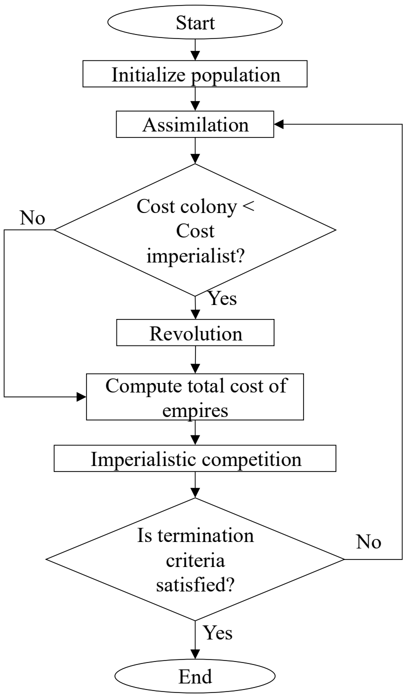

Figure 6. Process of ICA

3. SIMULATION RESULTS

The optimization of inter-element spacing of 10 and 20 linear arrays is simulated using MATLAB. Each algorithm executed 50 times with 1000 iterations. The parameters of WSN environment are tabulated in Table 1. The population size of algorithms is set as 70 throughout the simulations.

Table 1. WSN parameters setup

Parameter	Symbol	Value
BS location	(ϕ, θ)	(70°, 40°)
Number of CB nodes	N	10, 20
Operating frequency	f	150MHz

3.1 Analysis of PSL with Different N

This study simulates 10 and 20 linear arrays arranged in 3D spaces to identify the characteristics of beampattern with the changes of array size. Besides, optimization algorithms may behave differently depending on the problem dimension. Therefore, it is important to evaluate the effectiveness of optimization algorithms with different problem sizes. Figure 7 and Figure 8 show the optimized beampattern of 10 linear arrays in elevation and azimuth angle, respectively. Figure 9 and Figure 10 illustrated the beampattern in elevation and azimuth angles, respectively, optimized by optimization algorithms of 20 linear array. Based on the figures, the beampattern characteristics are different with the changes of array size. The beamwidth of 20 linear array is narrower than beamwidth of 10 linear array.

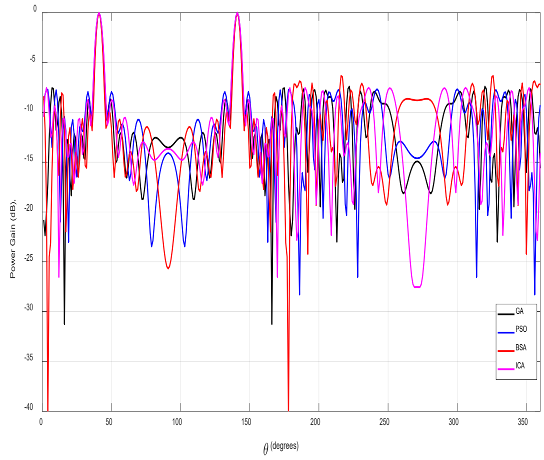

Figure 7. Beampattern in elevation angle (N = 10)

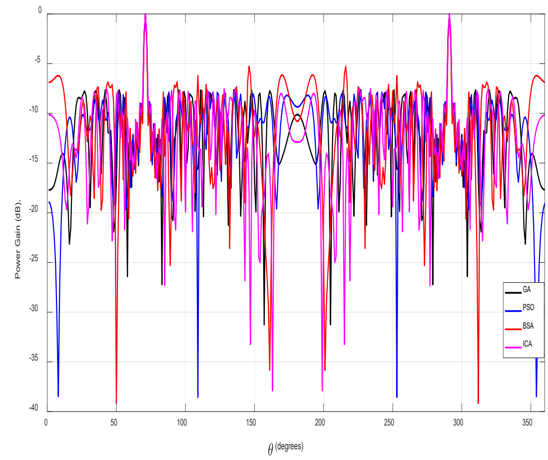

Figure 8. Beampattern in azimuth angle (N = 10)

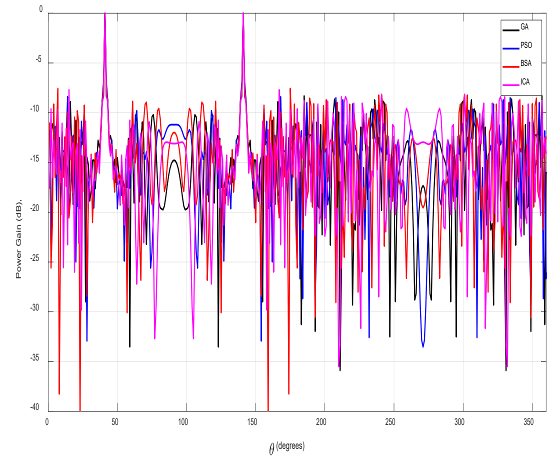

Figure 9. Beampattern in elevation angle (N = 20)

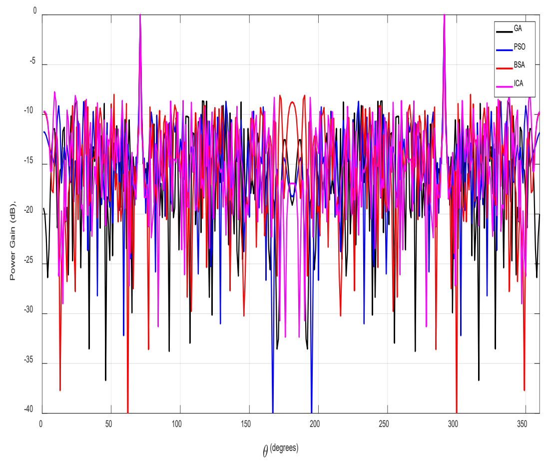

Figure 10. Beampattern in azimuth angle (N = 20)

The PSL reduction obtained by all GA, PSO, BSA and ICA are compared to ULA. The inter-element spacing of ULA is uniform and set as $\frac{\lambda}{2}$. Table 2 tabulates the best, worst and average PSL of 10 nodes along elevation angle optimized by the algorithms. The findings show that PSO achieves the highest improvement of PSL reduction in elevation angle by 170.3% in the best-case scenario, followed by ICA (158.5%) and GA (154.3%). BSA performs the worst with only 129% reduction at best.

Table 2. PSL in elevation angle (N = 10)

Algorithms	Best PSL (dB)	Worst PSL (dB)	Average PSL (dB)
GA	-7.40	-6.41	-6.96
PSO	-7.86	-6.12	-7.25
BSA	-6.66	-2.29	-4.73
ICA	-7.52	-6.59	-7.05
ULA	-2.91		
ULA	-3.28		

Table 3 shows the best, worst and average PSL of 10 nodes along azimuth angle optimized by GA, PSO, BSA and ICA. PSO shows the highest improvement (141.5%) in the best-case scenario for PSL reduction in azimuth angle. GA and ICA perform similarly, while BSA shows a significantly lower improvement by 30.5%.

Table 3. PSL in azimuth angle (N = 10)

Algorithms	Best PSL (dB)	Worst PSL (dB)	Average PSL (dB)
GA	-7.75	-6.99	-7.35
PSO	-7.92	-6.82	-7.55
BSA	-5.76	-2.25	-4.28
ICA	-7.50	-2.23	-5.71

All algorithms significantly outperform the ULA in reducing PSL of 10 nodes, with PSO demonstrating the lowest average PSL across elevation and azimuth angles. BSA shows the worst performance among other algorithms with higher worst-case PSL values.

Table 4 tabulates the PSL in elevation angle of 20 nodes obtained by the algorithms. The results show that PSO manages to achieve the highest improvement of PSL in elevation angle by 184.8%, followed by GA (179.5%) as compared to ULA. ICA and BSA exhibit slightly lower performance yet show significant improvement over ULA.

Table 4. PSL in elevation angle (n=20)

Algorithms	Best PSL (dB)	Worst PSL (dB)	Average PSL (dB)
GA	-8.41	-4.61	-7.00
PSO	-8.57	-4.50	-7.15
BSA	-8.33	-4.08	-6.71
ICA	-8.05	-4.62	-6.76
ULA	-3.01		

Table 5 shows the PSL in azimuth angle of 20 nodes obtained by GA, PSO, BSA and ICA. Based on the results, GA achieves the highest improvement by 189% in the best-case scenario, followed by PSO, BSA and ICA.

Table 5. PSL in azimuth angle (n=20)

Algorithms	Best PSL (dB)	Worst PSL (dB)	Average PSL (dB)
GA	-9.05	-7.68	-8.33
PSO	-8.74	-7.09	-8.01
BSA	-8.01	-4.67	-6.37
ICA	-7.85	-4.54	-6.52
ULA	-4.79		

The algorithms exhibit better PSL improvement for 20 nodes compared to 10 nodes. GA and PSO provides the best results, especially PSO which yields lower PSL across most scenarios.

Table 6 and Table 7 tabulate the inter-element spacing of 10 and 20 nodes optimized by different algorithms. PSO and GA manifest more balanced inter-element spacing distributions, while ICA and BSA show more extreme variations. The findings suggested that the balanced inter-element spacing generally leads to smoother and more predictable beampattern and reduces PSL. However, the extreme variations in inter-element spacing lead to irregular beampattern which may increases PSL.

Table 6. Inter-element spacing obtained by the algorithms (N = 10)

Algorithms	Inter-element spacing, d_n
GA	0.69, 0.90, 0.61, 0.65, 0.84, 0.70, 0.73, 0.85, 0.74, 0.61
PSO	0.85, 0.79, 0.60, 0.74, 0.75, 0.51, 0.78, 0089, 0.65, 0.68
BSA	0.90, 0.50, 0.63, 0.59, 0.57, 0.57, 0.93, 1.00, 0.98, 0.52
ICA	0.72, 0.84, 0.56, 0.50, 0.92, 0.50, 0.78, 0.50, 0.77, 0.52

Table 7. Inter-element spacing obtained by the algorithms (N = 20)

Algorithms	Inter-element spacing, d_n
GA	0.81, 0.74, 0.77, 0.86, 0.72, 0.80, 0.84, 0.89, 0.66, 0.72, 0.74, 0.88, 0.80, 0.59, 0.74, 0.60, 0.78, 0.98, 0.77, 0.65
PSO	0.55, 0.65, 0.78, 0.77, 0.60, 0.73, 0.74, 0.68, 0.72, 0.71, 0.55, 0.77, 0.68, 0.76, 0.90, 0.89, 0.66, 0.94, 0.72, 0.71
BSA	0.68, 0.70, 0.50, 0.95, 1.00, 0.50, 0.83, 1.00, 0.81, 1.00, 0.50, 0.54, 0.71, 1.00, 0.89, 0.70, 0.50, 0.54, 0.50, 0.89
ICA	0.61, 0.71, 0.79, 0.66, 0.76, 0.71, 0.52, 0.82, 0.64, 0.63, 0.77, 0.74, 0.72, 0.74, 0.61, 0.73, 0.84, 0.95, 0.82, 0.72

Table The p-values indicate a significant difference between the PSL obtained by the optimization algorithms and the ULA for both 10 and 20 nodes. Lower p-values show that the optimized results offer superior PSL reduction. The results show that all optimization algorithms exhibit highly significant improvements over ULA as the p-values are extremely lower than 0.05. However, the magnitude of PSL improvement varies for all algorithms. GA and PSO show much stronger significance in reducing PSL, indicating that the solutions obtained by both algorithms are significantly better than ULA. ICA performs well in reducing PSL along elevation angle but shows inconsistencies in azimuth angles. BSA has relatively higher p-value which showcasing its less consistency in PSL reduction.

Table 8. Significant difference of PSL yield by ULA and optimization algorithms (N = 10)

Algorithms	p-value	
	Elevation	Azimuth
ULA/GA	1.9e-112	1.4e-132
ULA/PSO	2.1e-98	2.7e-112
ULA/BSA	5.8e-24	2.5e-14
ULA/ICA	4.5e-108	5.7e-18

Table 9. Significant difference of PSL yield by ULA and optimization algorithms (N = 20)

Algorithms	p-value	
	Elevation	Azimuth
ULA/GA	2.1e-54	3.4e-87
ULA/PSO	6.1e-54	1.0e-79
ULA/BSA	1.9e-52	3.0e-27
ULA/ICA	1.4e-55	2.2e-27

Overall, PSO consistently provides the lowest PSL across 10 and 20 nodes, suggesting it as the best for PSL reduction. GA exhibits the most stable algorithm, followed by PSO. BSA and ICA shows higher variations in PSL reduction especially along azimuth angle, making them less reliable in some cases. Besides, GA and PSO shows the highest significant improvement of PSL reduction as compared to ULA by more than 170% in most cases. ICA performs well in reducing PSL along elevation angle but less consistent in azimuth angle, while BSA exhibits inconsistent performance in some cases.

3.2 Optimization Execution Time

Optimization execution time directly impacts computational resources and time constraints. Some optimization algorithms have higher computational complexity than others, leading to longer execution times. Besides, the increasing problem dimensionality leads to longer execution times. Table 8 tabulated the execution time of optimization algorithms in optimizing 10 and 20 linear arrays. Based on the results, BSA exhibits the fastest execution time, followed by ICA, GA and PSO. The simple nature of BSA gives low complexity and fast execution time, however, leading to converging into sub-optimal solution due to lack exploration of highly complex problems. In time-sensitive applications, prioritizing fast execution may be preferable. Nevertheless, investing more time in computationally intensive algorithms to obtain higher-quality solutions is important in critical applications where accuracy is supreme.

Table 10. Execution time of optimization algorithms

Algorithms	Execution time (s)	
	N=10	N=20
GA	99.1	201.0
PSO	133.2	217.0
BSA	19.0	47.3
ICA	96.3	132.6

4. CONCLUSION

This paper introduces JOPS to jointly suppress the PSL of beampattern in elevation and azimuth angles. JOPS is used to evaluate the inter-element spacing of 10 and 20 linear arrays arranged in 3D spaces optimized by GA, PSO, BSA and ICA. The results show that all algorithms managed to yield beampattern with lower PSL than ULA. Besides, GA outperforms other algorithms in terms of PSL suppression, however, exhibit longer execution times. While BSA executes the optimization faster with lowest PSL reduction than other algorithms. The trade-off between execution time and solution quality depends on the complexity of algorithms. The decision between speed and solution quality depends on the specific needs of the application. Thus, careful consideration of trade-off is important to achieve the desired balance between efficiency and effectiveness in optimization tasks.

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