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Original Article

BO-WQWO Algorithm for Improving the Efficiency of Uniform Linear Antenna Array

Y. Sahithi[1], P. Siddaiah[2]

[1,2]*Electronics and Communication Engineering, Acharya Nagarjuna University, Andhra Pradesh, India*

[1]*Corresponding Author : yarlagaddasahithi@gmail.com*

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Abstract *- The study explores the use of evolutionary algorithms called Biogeography Optimization – Weighed Quantum Wolf Optimization (BO-WQWO) in antenna array synthesis. Specifically, a network of Uniform Linear Antenna (ULA) using the amplitude control method is employed to investigate the effectiveness of GA using two different methods. The study deploys the novel bio-inspired algorithm, BO-WQWO, which is reviewed compared to traditional BO with the linear migration model. The study aims to minimize the lateral lobes by adjusting the excitation magnitudes of the matrix components. To form dummies in particular directions in the optimized model, a weight parameter is determined based on the cost function. Finally, the effectiveness of the proposed bioinspired algorithm is demonstrated by comparing it to other GA's, such as ACO.*

Keywords *- Biogeography optimization, Weighed quantum wolf optimization, Bioinspired algorithm, Linear antenna array.*

1. Introduction

Habitats are regions with a high concentration of species and are often referred to as islands because they are isolated from the rest of the world. These regions may contain abundant species that are scattered throughout the environment. Biogeography Based Optimization (BBO) is a new method that models habitat space, migration and evolution rates, development, mortality, migration, and mutations of organisms [1]. Suitability Variables (SIV) are single parameters, such as temperature and precipitation, that determine whether a habitat is suitable for living. A high Habitat Suitability Index (HSI) indicates that a habitat is suitable for living, and this index is influenced by SIV [2][3].

Like some other genetic algorithms, BBO employs migration and mutation to transmit information between devices. One distinguishing feature of BBO is that individual parameters such as temperature and rainfall are considered Suitability Variables [4]. Habitats with strong HSI (h=HSI) are favorable to life and have a high habitat relevance score. Those with weaker HSI have lower fitness/health scores [4][5]. Individuals are more likely to find unique features in habitats with higher HSI, which leads to information exchange and an increase in the compatibility score.

Organisms move to different habitats based on the HSI score of the habitat. There are many species within high HSI environments, and while the immigration rate is dropping, the starting cost is increasing, resulting in a stagnation of species diversity [7-9]. Because fewer organisms exist in low HSI environments, immigration into these ecosystems is important, while migration is low. The overall functional assessment of effectiveness or expenditure, which would depend on levels of SIV/characteristics, is used to assess the relevance of these environments [10].

2. Materials and Methods

The BBO technique involves using two different migration models: straight and sinusoidal. Evolutionary rates are also determined for each habitat. Emigration and immigration models are then used to transfer data between habitats in a stochastic manner. The probability of a particular habitat with corresponding immigration and emigration rates is denoted by P with corresponding immigration rate and emigration rates ηi. Each response is changed based on likelihood. When a particular solution HSI chooses to be updated, where 'i' denotes the citizenry's ith answer, the immigrant percentage is utilized to determine whether it should alter the individual suitability component SIV within this remedy if an SIV in a Hi remedy is chosen to be altered, the emigration levels of other Hi responses will be affected. Stochastically determine which one of the answers shall emigrate a randomly chosen SIV to respond Hi.

The BBO ecosystem can be accessed with BBO= (C,ψ, T), and it is designed to solve one optimization problem. The process involves calculating migratory and evolutionary ratios for each habitat, performing habitat alteration and recalibration of the HSI for each habitat, followed by mutagenesis and recalibration of the HSI for each habitat.

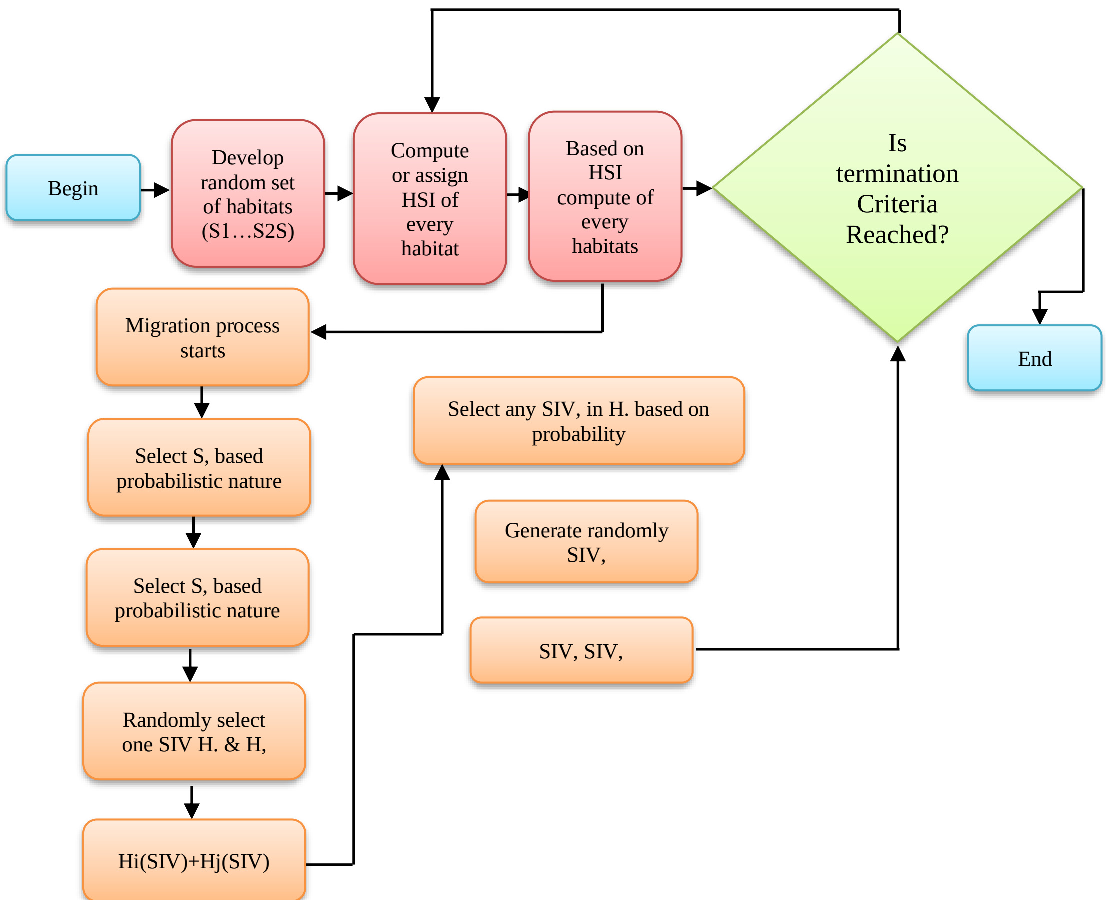

Fig. 1 Flowchart illustrating the BBO technique

3. Proposed Hybrid Bo-Wqwo Method

The BO-WQWO algorithm involves optimizing the suitability of habitats for a given problem. There are two migration models used in BO-WQWO: linear and non-linear. The linear model calculates migration and evolution rates based on the number of subspecies in a habitat. As the number of subspecies in a habitat increases, the rate of immigration decreases, and the rate of emigration increases until they reach equilibrium.

The non-linear model uses a periodic immigration paradigm, where migration and evolution rates are harmonic expressions of the number of organisms in a habitat. During stability, most estimates of the number of organisms are close to their maximum, resulting in increased mobility. To optimize the suitability of habitats using BO-WQWO, the fitness level of each habitat is determined, and the Plutocrats (best-fitting habitats) are kept. Then, a random SIV in a different habitat is chosen for each Plutocrat, and its suitability value is updated to match that of the Plutocrat. This process is repeated for all Plutocrats.

The overall suitability of each habitat is assessed using a homogeneous probabilistic model, and the best-fitting habitat is designated as the emigration island. The immigration level for each SIV is determined by dividing 1 by the total number of SIVs. For the best-fitting habitat, the immigration rate is 1, while for the others, it is 0.

In summary, the BO-WQWO algorithm involves optimizing the suitability of habitats using either a linear or non-linear migration model. The fitness level of each habitat is determined, and the Plutocrats (best-fitting habitats) are kept. Then, a random SIV in a different habitat is chosen for each Plutocrat, and its suitability value is updated to match that of the Plutocrat. Finally, the overall suitability of each habitat is assessed, and the best-fitting habitat is designated as the emigration island

4. Results and Discussions

4.1. BO-WQWO Technique Mapped to ULA Synthesis

- Step 1: Set up the settings, including the maximum generations, highest migration flows, number of iterations, and highest organisms' identifiers.
- Step 2: Explain the terms immigration and emigration rates.
- Step 3: Create n environments randomly, each representing a feasible solution- population.
- Step 4: Compute the sidelobe of each unique island using

the formula, which involves setting the component width, specifying a θ field, determining the arrays ratio with each intensity stimulation vector, calculating a weighted sum that delivers the greatest SLL, calculating the gap between the actual patterns and the performance in these areas, and calculating the weighting factor to minimize the variations.

- Step 5: Calculate species numbers using HSI measurements.
- Step 6: Determine every island's immigration and emigration rates.
- Step 7: Preserve exceptional ecosystems without alteration.
- Step 8: Choose one island for importation and another for departure based on migrations and evolutionary patterns.
- Step 9: Migrate a set of SIVs randomly depending on the islands chosen in the last stage.
- Step 10: Conduct mutations for every island in a proportionate manner.
- Step 11: Filter the populations, remove duplication and look for viable options.
- Step 12: Proceed to step 4 if the terminating requirements are not satisfied; alternatively, quit.

The wolf optimization algorithm uses a migration operator to transfer information between different wolf packs (i.e., islands) based on the BBO framework. The Wolf Algorithm iterates until a satisfactory solution is found. In the case of a ULA, the algorithm iterates until the array weights converge to a set of values that produce the desired radiation pattern.

4.2. ULA Synthesis for Minimizing SLL using BBO Model

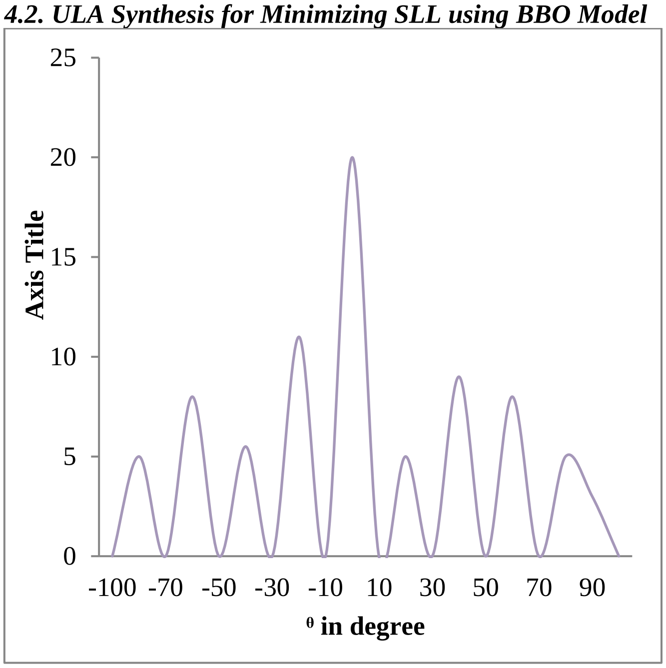

Fig. 2 Optimized Radiation Pattern with minimum side lobe

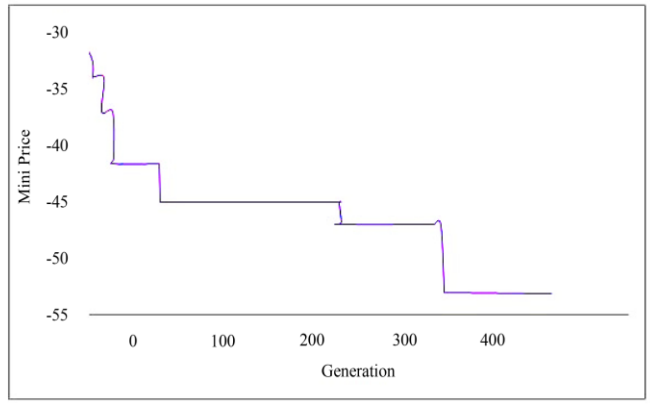

Fig. 3 Curve of Convergence

The scenario research is done in MATLAB on an Intel Pentium dual-core CPU having 1GB RAM operating at 2.80GHz. A 16-element antenna is designed and studied during the first case, which employs the BO model method. The following settings are used: The community is 50, the elitist is 2, and the game has been ongoing for 500 cycles. This program has been executed a total of 25 times. This optimized radiation pattern is shown in Figure 2.

Intermixes were neutralized when they only reside outside the primary beam, which enhances the beamformer's efficiency. Figure 3 shows how soon the converging to -40dB may be reached, i.e., over generations, which is extremely impressive. It proceeds for another few iterations and gradually accumulates to the limit of -53.26dB just at the 375th iteration & stays around until it approaches 500 generations.

4.3 Using BO-WQWO Technique

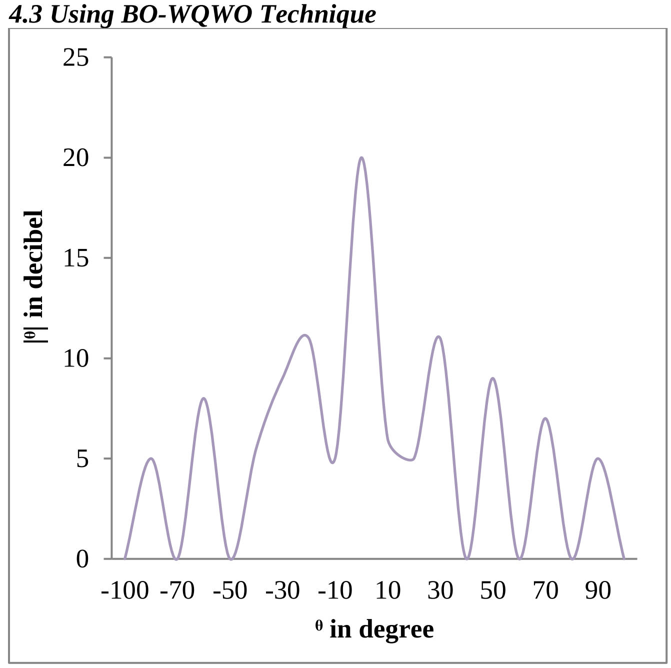

Fig. 4 Optimized Radiation Pattern of BO-WQWO method

BO-WQWO is used with characteristics including a population density of 50, a maximal production of 500, as well as an array of 16 and 24 components. Figure 4 shows the radiation characteristics of a 16-component array.

Using varying numbers of antenna elements, the frequency band & converging curvatures generated utilizing BO-WQWO are examined. Even as several components grow, the addition to the offering becomes more noticeable. Table 1 is a summary of the findings. ULA additionally exhibits unusual behavior based on BO-WQWO. This gap between both the median SLL as well as the greatest SLL just at the end of cycles is smaller for tiny groups of components. Even as the number of items grows larger, the divergence gets more obvious. This demonstrates that a higher number of components can result in a better SLL. Figure 5 shows how this works.

Just after 500 cycles, a significant difference among the mean and median SLL is seen.

Table 1. Proposed BO-WQWO Performance

Size of elements	HPBW (deg)	BWNN (deg)	Number of Side lobes
16	8	30	8
24	4	18	10

Fig. 5 BO-WQWO Convergence curve for a ULA

Table 2. Parameters set for comparison of different EAs

Parameter	Data set
No of the elements in the array	16
Population size	50
Elite count	6
Maximum generations	500

4.4. Comparison of proposed BO-WQWO Techniques with other Existing Algorithms

The overall effectiveness of evolutionary computation like ACO, GA, and other Stud GAs is contrasted to BO-WQWO methods along with BBO-Linear migrating models, & BBO-Sinusoidal migratory prototypes are compared. The research is carried out with variables which are listed in Table 2.

The major goal is to reduce the maximal SLL as much as possible. The highest SLL recorded varies between -53.26dB and -44.32dB. In this evaluation metric, the BO_WQWO algorithm emerged as the strongest performer, outperforming all of the others.

These statistical solutions of optimizing ULA for decreased SLL plus zero controls were matched with various requirements for minimizing maximal SLL and zero controls for interference cancellation, which have now been described in the literature shown in Table 4.

Table 3. Comparison of different EAs

EA	HPBW (deg)	BWnn (deg)	Max No. of Sidelobes
BO-WQWO	8	30	8
BBO-Linear	7.2	32	12
BBO Sinusoidal	5.12	20	14
ACO	5.87	26.62	10
GA	5.12	20.75	14
Stud GA	5.25	21.5	14

Table 4. Element amplitudes normalized according to center elements

Element No.	BBO- Sinusoidal	BBO-Linear	BO-WQWO
±1	1.0000	1.0000	1.0000
±2	0.8280	0.9759	0.9258
±3	0.8065	0.7059	0.7341
y±4	0.7742	0.6824	0.6424
±5	0.4946	0.6353	0.5567
±6	0.4731	0.5176	0.4012
±7	0.4194	0.4824	0.2447
±8	0.3441	0.1529	0.1534

4.5. Theoretical Comparison of BO-WQWO with GA and PSO

Genetic algorithms (GA) utilize survival of the fittest and evolutionary algorithms such as crossing over and mutations. GA populations comprise individuals, who are sets of genes representing optimization variables. After going through all procedures, the best individual is chosen. However, their biggest flaw is a shortage of storage, with the only storage notion being to retain leaders. This causes the search space to shrink, reducing potential consolidation and preventing an appropriate answer due to a lack of greater operators.

In particle swarm optimization (PSO), swarming behavior is determined by factors such as the current location, memories of prior positions, migration speed, and cooperative/social information among species. Obtaining a global answer is easier due to a limited number of variables and relatively straightforward variable adjustment.

The migratory technique in BO-WQWO is a blend of worldwide rearrangement and homogeneous crossovers via GA. During selection or immigration processes, some population characteristics are passed down for generations, which leads to improved efficiency and is a key aspect of BO-WQWO

5. Conclusion

BO-WQWO methods were used to generate low sidelobe levels in the ULA synthesizing challenge. These findings show that suggested ULA synthesizing utilizing BO-WQWO methods has the following benefits: ease of use, fewer testing repetitions, as well as and outstanding quality. In respect of speedier resolution, it surpasses all others. Compared to other BBO methods, the BO-WQWO method performed better in this ULA challenge. The study also compared various EAs, such as ACO, GA, and Stud GA. The results indicate that BO-WQWO oscillatory migrating proposes an effective and appropriate weight matrix. The influence of the variable in the evolutionary algorithm was evaluated, and a reasonable number was implemented. Using a diverse population helped avoid early converging and led to appropriate solutions. This approach can be used for multi-objective optimization, including adaptable genetic changes and other migrating theories for various array shapes.

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