Evolutionary Performance Comparison of BBO and PSO variants for Yagi-Uda Antenna Gain Maximization

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Abstract

Bio-geography *Particle Swarm Optimization (PSO) and Biogeography Based Optimization (BBO) are most popular swarm based optimization algorithms those have shown impressive performance over other Evolutionary Algorithms (EAs). Yagi-Uda is one of most widely antenna designs used at High Frequency (HF) and Ultra High Frequency (UHF) due its high gain, low cost and constructional ease. Designing a Yagi-Uda antenna involves determination of wire lengths and their spacing in between them those bear highly complex and non-linear relationships with antenna gain, impedance and Single Lobe Level (SLL) at a particular frequency of operation. In this paper, a comparative study between PSO variants and BBO is presented for optimization of antenna designs for maximum gain. The best antenna designs are tabulated and average of 10 Monte-Carlo simulation runs are plotted for BBO, PSO and its variants for performances in the ending sections.*

Index Terms- Based Optimization, Particle Swarm Optimization, Yagi-Uda Antenna, Antenna Gain.

INTRODUCTION

Antenna is an electrical device which forms an interface between free space radiations and transmitter or receiver. The choice of an antenna depends on various factors such as gain, impedance, bandwidth, frequency of operation, Side Lobe Level (SLL), etc. A Yagi-Uda antenna is a widely used antenna design due to high forward gain capability, low cost and ease of construction. It is a parasitic linear array of parallel dipoles, one of which is energized directly by transmission line while the others act as parasitic radiators whose currents are induced by mutual coupling. The characteristics of Yagi-Uda antenna are affected by all of the geometric parameters of array. It is simple to construct and has a high gain, typically greater than 10dB at VHF and UHF frequency range i.e., 3 MHz to 3 GHz.

A Yagi-Uda antenna was invented in 1926 by H.Yagi and S. Uda at Tohoku University [1] in Japan, however, published in English in 1928 [2]. Since its invention, continuous efforts have been put in optimizing the antenna for gain, impedance, SLL and bandwidth using different optimization techniques based on traditional mathematical approaches [3], [4], [5], [6], [7], [8], [9] and Artificial Intelligence (AI) techniques [10], [11], [12], [13], [14], [15], [16]. In 1949, Fishenden and Wiblin [17] proposed an approximate design of Yagi aerials for maximum gain, however, the proposed was to approximations. In 1959, Ehrenspeck and Poehler have given a manual approach to maximize the gain of the antenna by varying various lengths and spacings of its elements [18].

In 1975, John Holland introduced Genetic Algorithms (GAs) as a stochastic, swarm based AI technique, inspired from natural evolution of species, to optimize arbitrary systems for certain cost function. Then many researchers investigated GAs to optimize Yagi-Uda antenna designs for gain, impedance and bandwidth separately [19], [10], [20] and collectively [11], [21], [22]. Baskar et al. in [13], have optimized Yagi-Uda antenna using Comprehensive Learning Particle Swarm Optimization (CLPSO) and presented better results than other optimization techniques. Li has used Differential Evolution (DE) to optimize geometrical parameters of a Yagi-Uda antenna and illustrated the capabilities of the proposed method with several Yagi-Uda antenna designs in [14]. In [15], Singh et al. have explored another useful, stochastic global search and optimization technique named as Simulated Annealing (SA) for the optimal design of Yagi-Uda antenna.

In 2008, Dan Simon introduced yet another swarm based stochastic optimization technique based on science of biogeography where feature sharing among various habitats, i.e., potential solutions, is accomplished with migration operator and exploration of new features is done with mutation operator [23]. Singh et al. have presented BBO as a better optimization technique for Yagi-Uda antenna designs, in [16]

In 2012, [24] proposed NSBBO and investigated for Multiobjective optimization of Yagi-Uda Antenna Gain and Impedance. [25] Performs the comparisons between NSBBO and NSPSO results. The combinatorial performance of BBO and PSO are illustrated in [26]. Different mutation and migration variants of BBO are explored for optimization of Yagi-Uda Antenna Design in [27], [28], respectively. PSO and BBO are explored for range based localization in [29], [30].

In this paper, BBO algorithm and PSO variants, viz., *gbest* and *lbest* are investigated to attain maximum gain. After this brief historical background survey, remaining paper is outlined as follows: In Section II, Yagi-Uda antenna design parameters are discussed. Section III is dedicated to BBO algorithm. Section IV explains Particle Swarm Optimization. In Section V, simulation results are presented and analyzed. Finally, conclusions and future scope have been discussed in SectionVI.

Antenna Design Parameters

Yagi-Uda antenna consists of three types of elements: (a) *Reflector*–biggest among all and is responsible for blocking radiations in one direction. (b) *Feeder*–which is fed with the signal from transmission line to be transmitted and (c) *Directors*–these are usually more than one in number and responsible for unidirectional radiations. Figure1 depicts a typical six-wire Yagi-Uda antenna where all wires placed parallel to x-axis and along y-axis. Middle segment of the reflector element is placed at origin, $x = y = z = 0$, and excitation is applied to the middle segment of the feeder element. An incoming field sets up resonant currents on all the antenna elements which re-radiate signals. These re-radiated fields are then picked up by the feeder element that leads to total current induced in the feeder equivalent to combination of the direct field input and the re-radiated contributions from the director and reflector elements.

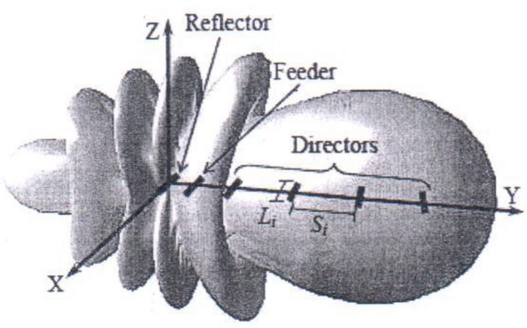

Figure 1. **Six-element Yagi-Uda Antenna**

Designing a Yagi-Uda antenna involves determination of wire-lengths and wire-spacing in between to get maximum gain, desired impedance and minimum SLL at an arbitrary frequency of operation. An antenna with *N* elements requires *2N-1* parameters, i.e., *N* wire lengths and *N-1* spacing, that are to be determined. These *2N-1* parameters, collectively, are represented as a string referred as a habitat in BBO given as(1).

$$H = \lfloor L_1, L_2, \ldots, L_N, S_1, S_2, \ldots S_{N-1} \rfloor \qquad (1)$$

Where L_s are the lengths and S_s are the spacings of antenna elements. An incoming field sets up resonant currents on all the antenna elements which re-radiate signals. These re-radiated signals are then picked up by the feeder elements, that leads to total current induced in the feeder equivalent to combination of the direct field input and the re-radiated contributions from the director and reflector elements. This makes highly non-linear and complex relationships between antenna parameters and its characteristics like gain, impedance and SLL, etc.

Biogeography Based Optimization

As name suggests, BBO is a population based global optimization technique developed on the basis of the science of biogeography, i.e., study of the distribution of animals and plants among different habitats over time and space. BBO results presented by researchers are better than other optimization techniques, like PSO, GAs, SA, DE, etc. [10], [21], [13], [31].

Originally, biogeography was studied by Alfred Wallace [32] and Charles Darwin [33] mainly as descriptive study. However, in 1967, the work carried out by MacAurthur and Wilson [34] changed this view point and proposed a mathematical model for biogeography and made it feasible to predict the number of species in a habitat. Mathematical models of biogeography describe migration, speciation, and extinction of species in various islands. The term island is used for any habitat that is geographically isolated from other habitats. Habitats that are well suited residences for biological species are referred to have high Habitat Suitability Index (HSI) value. However, HSI is analogues to fitness in other EAs whose value depends upon many factors such as rainfall, diversity of vegetation, diversity of topographic features, land area, and temperature, etc. The factors/variables that characterize habitability are termed as Suitability Index Variables (SIVs). In other words, HSI is dependent variable whereas SIVs are independent variables.

The habitats with a HSI tend to have a large population of its resident species, that is responsible for more probability of emigration (emigration rate, μ) and less probability of immigration (immigration rate,λ) due to natural random behavior of species. Immigration is the arrival of new species into a habitat or population, while emigration is the act of leaving one's native region. On the other hand, habitats with low HSI tend to have low emigration rate, μ, due to sparse population, however, they will have high immigration rate, λ. Suitability of habitats with low HSI is likely to increase with influx of species from other habitats having high HSI. However, if HSI does not increase and remains low, species in that habitat go extinct that leads to additional immigration. For sake of simplicity, it is safe to assume a linear relationship between HSI (or population) and immigration and emigration rates and same maximum emigration and immigration rates, i.e., E = I, as depicted graphically in Figure 2.

For k-th habitat values of emigration rate, μ_k, and immigration rate, λ_k, are given by (2) and (3).

$$\mu_k = E \cdot \frac{HSI_k}{HSI_{\max} - HSI_{\min}} \qquad (2)$$

$$\lambda_k = I \cdot \left(1 - \frac{HSI_k}{HSI_{\max} - HSI_{\min}}\right) \qquad (3)$$

The immigration of new species from high HSI to low HSI habitats may raise the HSI of poor habitats as good solutions are more resistant to change than poor solutions whereas poor solutions are more dynamic and accept a lot of new features from good solutions.

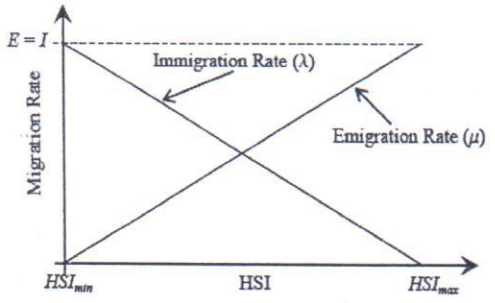

Figure 2. Migration Curves

Each habitat, in a population of size NP, is represented by M-dimensional vector as $H = [SIV_1, SIV_2, \ldots\ldots, SIV_M]$ where M is the number of SIVs (features) to be evolved for optimal HSI. HSI is the degree of acceptability that is determined by evaluating the cost/objective function, i.e. $HSI = f(H)$. Algorithmic flow of BBO involves two mechanisms, i.e., migration and mutation, these are discussed in the following subsections:

A. ***Migration***

Migration is a probabilistic operator that improves HSI of poor habitats by sharing features from good habitats. During migration, *i*-th habitat, H_i (where $i = 1, 2, \ldots\ldots, NP$) use its immigration rate, λ_i given by (3), to probabilistically decide whether to immigrate or not. In case immigration is selected, then the emigrating habitat, H_j, is found probabilistically based on emigration rate, μ_j, given by (2). The process of migration is completed by copying values of SIVs from H_j to H_i at random chosen sites, i.e., $H_i(SIV) \leftarrow H_j(SIV)$. The pseudo code of migration operator is depicted in Algorithm 1.

Algorithm 1 Standard Pseudo Code for Migration

```
for i = 1 to NP do
   Select H_i with probability based on λ_i
   if H_i is selected then
      for j = 1 to NP do
         Select H_j with probability based on μ_j
         if H_j is selected
            Randomly select a SIV(s) from H_j
            Copy them SIV(s) in H_i
         end if
      end for
   end if
end for
```

B. ***Mutation***

Mutation is another probabilistic operator that modifies the values of some randomly selected SIVs of some habitats that are intended for exploration of search space for better solutions by increasing the biological diversity in the population. Here, higher mutation rates are investigated on habitats those are, probabilistically, participating less in migration process. The mutation rate, *mRate*, for *k*-th habitat is calculated as (4) where μ_k and λ_k are emigration and immigration rates, respectively, given by (2) and (3) corresponding to HSI_k. Here *C* is a constant and equal to 3. The pseudo code of mutation operator is depicted in Algorithm 2.

Algorithm 2 Standard Pseudo Code for Mutation

```
mRate = C × min(μ_k, λ_k) where C = 3
for n = 1 to NP do
   for j = 1 to length(H) do
      Select H_j(SIV) with mRate
      If H_j(SIV) is selected then
         Replace H_j(SIV) with randomly generated SIV
      end if
   end for
end for
```

PARTICLE SWARM OPTIMIZATION

PSO is a sociologically inspired optimization technique, since it was initially developed as a tool by Reynolds [35], [36] for simulating the flight patterns of bird flocks, which was mainly governed by three major concerns: *collision avoidance*, *velocity matching* and *flock centering*. On the other hand, the reasons presented for the flocking behavior observed in nature are: *protection* from predator and *gaining-food* from a large effective search-space. The latter reason assumes a great importance, when the food is unevenly distributed over the search-space. It was realized by Kennedy and Eberhart that the bird flocking behavior can be adopted to be used as an optimizer and resulted in the first simple version of PSO [37], [38] that has been recognized as one of the computational intelligence techniques intimately related to EAs. Like EAs, it uses a population of potential solutions called particles that are flown through the search-space with adaptable velocities that determines their movements. Each particle also has a memory and hence it is capable of remembering the best position, in the search-space, ever visited by it. The position corresponding to the best fitness is known as *pbest* and the overall best out of all the particles in the population is called *gbest*.

Consider that the search space is *d*-dimensional and *i*-th particle in the swarm can be represented by $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$, and its velocity can be represented by another *d*-dimensional vector $V_i = (v_{i1}, v_{i2}, \ldots, v_{id})$,. Let the best position ever visited in the past by the *i*-th particle be denoted by $Pi = (pi1, pi2, \ldots, pid)$. Many a times, the whole swarm is subdivided into smaller groups and each group/sub-swarm has its own local best particle, denoted as $P_l = (p_{l1}, p_{l2}, \ldots, p_{ld})$, and an overall best particle, denoted as $P_g = (p_{g1}, p_{g2}, \ldots, p_{gd})$, where g and *l* are particle indices.

A. Global-Best (gbest) PSO model

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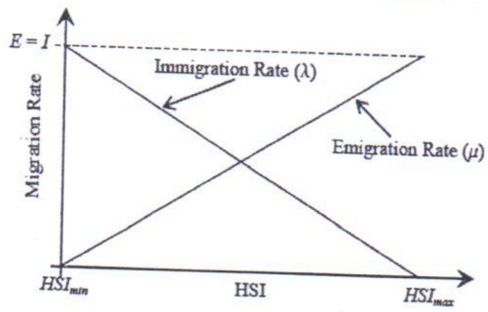

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A. Global-Best (gbest) PSO model

variants. Fairly good results are tabulated in Table I which are obtained during process of optimization

Table I
THE BEST ANTENNA DESIGNS OBTAINED DURING OPTIMIZATION

	BBO		*gbest* PSO		*lbest* PSO	
Element	**Length**	**Spacing**	**Length**	**Spacing**	**Length**	**Spacing**
1(λ)	0.4838	-	0.4856	-	0.4855	-
2(λ)	0.4728	0.1745	0.4746	0.1765	0.4945	0.1623
3(λ)	0.4388	0.2561	0.4414	0.2452	0.4417	0.2423
4(λ)	0.4244	0.3986	0.4289	0.3776	0.4243	0.3931
5(λ)	0.4198	0.4060	0.4204	0.4088	0.4220	0.4271
6(λ)	0.4289	0.3786	0.4245	0.4115	0.4368	0.3381
Best Gain	**13.84 dBi**		**13.84 dBi**		**13.83 dBi**	
***Average Gain**	**13.83 dBi**		**13.82 dBi**		**13.79 dBi**	

Investigation of BBO algorithms for multi-objective Optimization with different migration and mutation variants and different PSO variants both single objective and multi-objective optimization is next our agenda. Further, performance comparison study can be, conducted between NSBBO, NSGA and NSPSO, etc.

REFERENCES

[1] S. Uda and Y. Mushiake, Yagi-Uda Antenna, Maruzen, *Ed. Maruzen Company, Ltd, 1954*.

[2] Yagi, "Beam Transmission of Ultra Short Waves," *Proceedings of the Institute of Radio Engineers*, vol. 16, no. 6, pp. 715–740, 1928.

[3] G. Reid, "The Gain of an Idealized Yagi Array," *Journal of the Institution of Electrical Engineers-Part IIIA: Radiolocation*,, vol. 93, no. 3, pp. 564–566, 1946.

[4] Bojsen, H. Schjaer-Jacobsen, E. Nilsson, and J. Bach Andersen, "Maximum Gain of Yagi–Uda Arrays," *Electronics Letters*, vol. 7, no. 18, pp. 531–532, 1971.

[5] K. Cheng, "Optimization Techniques for Antenna Arrays," *Proceedings of the IEEE*, vol. 59, no. 12, pp. 1664–1674, 1971.

[6] L. C. Shen, "Directivity and Bandwidth of Single-band and Doubleband Yagi Arrays," *IEEE Transactions on Antennas and Propagation*,, vol. 20, no. 6, pp. 778–780, 1972.

[7] Cheng and C. Chen, "Optimum Element Spacings for Yagi-Uda Arrays," *IEEE Transactions on Antennas and Propagation*,, vol. 21, no. 5, pp. 615–623, 1973.

[8] Chen and D. Cheng, "Optimum Element Lengths for Yagi-Uda Arrays," *IEEE Transactions on Antennas and Propagation*,, vol. 23, no. 1, pp. 8–15, 1975.

[9] K. Cheng, "Gain Optimization for Yagi-Uda Arrays," *Antennas and Propagation Magazine*, IEEE, vol. 33, no. 3, pp. 42–46, 1991.

[10] [E. A. Jones and W. T. Joines, "Design of Yagi-Uda Antennas using Genetic Algorithms," *IEEE Transactions on Antennas and Propagation*,, vol. 45, no. 9, pp. 1386–1392, 1997.

[11] J. Wang, K. F. Man, C. H. Chan, and K. M. Luk, "Optimization of Yagi array by Hierarchical Genetic Algorithms," *IEEE*, vol. 1, pp. 91–94, 2003.

[12] N. Venkatarayalu and T. Ray, "Optimum Design of Yagi-Uda Antennas Using Computational Intelligence," *IEEE Transactions on Antennas and Propagation*,, vol. 52, no. 7, pp. 1811–1818, 2004.

[13] S. Baskar, A. Alphones, P. N. Suganthan, and J. J. Liang, "Design of Yagi-Uda Antennas using Comprehensive Learning Particle Swarm Optimisation," *IEEE*, vol. 152, no. 5, pp. 340–346, 2005.

[14] Y. Li, "Optimizing Design of Antenna using Differential Evolution," *IEEE*, vol. 1, pp. 1–4, 2007.

[15] U. Singh, M. Rattan, N. Singh, and M. S. Patterh, "Design of a Yagi-Uda Antenna by Simulated Annealing for Gain, Impedance and FBR," *IEEE*, vol. 1, pp. 974–979, 2007.

[16] U. Singh, H. Kumar, and T. S. Kamal, "Design of Yagi-Uda Antenna Using Biogeography Based Optimization," *IEEE Transactions on Antennas and Propagation*,, vol. 58, no. 10, pp. 3375–3379, 2010.

[17] R. M. Fishenden and E. R. Wiblin, "Design of Yagi Aerials," *Proceedings of the IEE-Part III: Radio and Communication Engineering*, vol. 96, no. 39, p. 5, 1949.

[18] H. Ehrenspeck and H. Poehler, "A New Method for Obtaining Maximum Gain from Yagi Antennas," *IRE Transactions on Antennas and Propagation*,, vol. 7, no. 4, pp. 379–386, 1959.

[19] Altshuler and D. Linden, "Wire-antenna Designs using Genetic Algorithms," *Antennas and Propagation Magazine*, IEEE, vol. 39, no. 2, pp. 33–43, 1997.

[20] D. Correia, A. J. M. Soares, and M. A. B. Terada, "Optimization of gain, impedance and bandwidth in Yagi-Uda Antennas using Genetic Algorithm," *IEEE*, vol. 1, pp. 41–44, 1999.

[21] N. V. Venkatarayalu and T. Ray, "Single and Multi-Objective Design of Yagi-Uda Antennas using Computational Intelligence," *IEEE*, vol. 2, pp. 1237–1242, 2003.

[22] Y. Kuwahara, "Multiobjective Optimization Design of Yagi-Uda Antenna," *IEEE Transactions on Antennas and Propagation*,, vol. 53, no. 6, pp. 1984–1992, 2005.

[23] D. Simon, "Biogeography-based Optimization," *IEEE Transactions on Evolutionary Computation*,, vol. 12, no. 6, pp. 702–713, 2008.

[24] S. Singh, E. Mittal, and G. Sachdeva, "NSBBO for gain-impedance optimization of yagi-uda antenna design," *proceedings IEEE, WICT* pp. 856–860, 2012.

[25] ——, "Multi-objective gain-impedance optimization of yagi-uda antenna using NSBBO and NSPSO," *International Journal of Computer Applications*, vol. 56, 2012.

[26] S. Singh, S. Tayal, and G. Sachdeva, "Evolutionary performance of BBO and PSO algorithms for yagi-uda antenna design optimization," *proceedings IEEE, WICT*, pp. 861– 865, 2012.

[27] S. Singh and G. Sachdeva, "Mutation effects on bbo evolution in optimizing yagi-uda antenna design,"*proceedings, IEEE, EAIT*, pp. 47–51, 2012.

[28] ——, "Yagi-uda antenna design optimization for maximum gain using different bbo migration variants," *International Journal of Computer Applications*, vol. 58, 2012.

[29] S. Singh, Shivangna, and S. Tayal, "Article: Analysis of different ranges for wireless sensor node localization using pso and bbo and its variants," *International Journal of Computer Applications*, vol. 63, no. 22, pp. 31–37, February 2013, published by Foundation of Computer Science, New York, USA.

[30] S. Singh, Shivangna, and E. Mittal, "Range based wireless sensor node localization using PSOand BBO and its variants," *proceedings IEEE, CSNT*, 2013.(communicated).

[31] M. Rattan, M. S. Patterh, and B. S. Sohi, "Optimization of Yagi-Uda Antenna using Simulated Annealing," *Journal of Electromagnetic Waves and Applications*, 22, vol. 2, no. 3, pp. 291–299, 2008.

[32] A.Wallace, "The Geographical Distribution of Animals," Boston, *MA: Adamant Media Corporation*, vol. Two, pp. 232–237, 2005.

a. Darwin, "The Orign of Species," New York : gramercy, vol. Two, pp. 398–403, 1995.

[33] R. MacArthur and E. Wilson, *The Theory of Island Biogeography*. Princeton Univ Pr, 1967.

[34] R. C. Eberhart, Y. Shi, and J. Kennedy, "Swarm intelligence," 2001.

a. W. Reynolds, "Flocks, herds and schools: A distributed behavioral model," vol. 21, no. 4, pp. 25–34, 1987.

[35] Kennedy and R. Eberhart, "Particle swarm optimization," vol. 4, pp. 1942–1948, 1995.

[36] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," pp. 39–43, 1995.

[37] J. Burke and A. J. Poggio, "Numerical Electromagnetics Code (NEC) method of moments," NOSC Tech. DocLawrence Livermore National Laboratory, Livermore, Calif, USA, vol. 116, pp. 1–131, 1981.