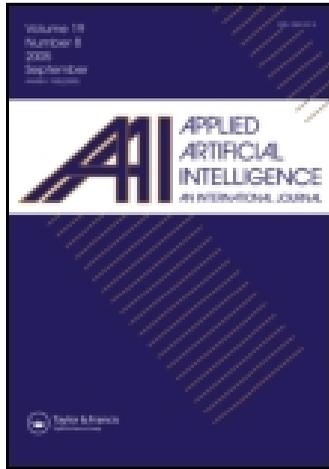


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MULTIOBJECTIVE GAIN-IMPEDANCE OPTIMIZATION OF YAGI–UDA ANTENNA DESIGN USING DIFFERENT BBO MIGRATION VARIANTS

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□ *Biogeography is the study of distribution of biological species, over space and time, among random habitats. Recently developed Biogeography-Based Optimization (BBO) is a technique in which solutions of the problem under consideration are named habitats; just as there are chromosomes in genetic algorithms (GAs) and particles in Particle Swarm Optimization (PSO). Feature sharing among various habitats in other words, exploitation, is made to occur because of the migration operator, whereas exploration of new SIV values, similar to that of GAs, is accomplished with the mutation operator. In this study, the nondominated sorting BBO (NSBBO) and various migration variants of the BBO algorithm, reported to date, are investigated for multiobjective optimization of six-element Yagi–Uda antenna designs to optimize two objectives, viz., gain and impedance, simultaneously. The results obtained with these migration variants are compared, and the best and the average results are presented in the concluding sections of the article.*

INTRODUCTION

An antenna is an electrical device that acts as an interface between free-space radiations and a transmitter (or receiver). The choice of an antenna depends on many factors such as requisite gain, impedance, bandwidth and frequency of operation, and so on. The antenna is simple to construct and has a high gain typically greater than 10dB at VHF and UHF frequency ranges. It is a parasitic linear array of parallel dipoles, one of which is energized directly by transmission line while the other acts as a parasitic radiator whose currents are induced by mutual coupling. Therefore, characteristics of the antenna are affected by all geometric parameters of array.

A Yagi–Uda antenna was invented in 1926 by Yagi and Uda at Tohoku University in Japan (Uda and Mushiake 1954; Yagi 1928). Since its invention, continuous efforts have been put in to optimize its design for desired gain, impedance, Side Lobe Level and bandwidth, requirements using different

optimization techniques based on traditional mathematical approaches (Reid 1946; Bojsen et al. 1971; Cheng 1971, 1991; Shen 1972; Cheng and Chen 1973; Chen and Cheng 1975) and artificial intelligence (AI) techniques (Jones and Joines 1997; Wang et al. 2003; Venkatarayalu and Ray 2004; Baskar et al. 2005, Li 2007, Singh et al. 2007, 2010). In 1949, Fishenden and Wiblin (Fishenden and Wiblin 1949) proposed an approximate design of the Yagi aerials for maximum gain. Ehrenspeck and Poehler have given a manual approach to maximize the gain of the antenna by varying lengths and spacings of its elements (Ehrenspeck and Poehler 1959).

Later, the availability of computer softwares at affordable prices made it possible to optimize antennas numerically. Bojsen et al. proposed another optimization technique to calculate the maximum gain of Yagi-Uda antenna arrays with equal and unequal spacings between adjoining elements in (Bojsen et al. 1971). Cheng et al. have used optimum spacings and lengths to maximize the gain of the Yagi-Uda antenna (Cheng and Chen 1973, Chen and Cheng 1975). Later, Cheng proposed an optimum design of the Yagi-Uda antenna where in the antenna gain function is highly nonlinear (Cheng 1991).

In 1975, John Holland introduced Genetic Algorithms (GAs) as a stochastic, swarm-based AI technique, inspired by the natural evolution of species, to evolve optimal design of an arbitrary system for a certain cost function. Then many researchers investigated GAs to optimize Yagi-Uda antenna designs for gain, impedance, and bandwidth separately. (Altshuler and Linden 1997; Jones and Joines 1997; Correia, Soares, and Terada 1999; Wang et al. 2003; Venkatarayalu and Ray 2003; Kuwahara 2005; Deb et al. 2002) collectively. Baskar et al. have optimized the Yagi-Uda antenna using Comprehensive Learning Particle Swarm Optimization (CLPSO) and presented better results than other traditional optimization techniques (Baskar et al. 2005). Li has used Differential Evolution (DE) to optimize geometrical parameters of the antenna and illustrated the capabilities of the proposed method with several Yagi-Uda antenna designs in (Li 2007). Singh et al. have investigated another useful, stochastic global search and optimization technique named as Simulated Annealing (SA) to evolve optimal antenna design in (Singh et al. 2007).

In 2008, Dan Simon introduced yet another swarm based stochastic optimization technique based on science of biogeography where features sharing among various habitats, i.e., potential solutions, is accomplished with migration operator and exploration of new features is done with mutation operator (Simon 2008). Singh, Kumar, and Kamal (2010) have presented BBO as a better optimization technique for Yagi-Uda antenna designs.

Du et al. (2009) proposed the concept of immigration refusal in BBO, aiming at improved performance. Ma and Simon (2001) introduced another

migration operator, called blended migration, to solve constrained optimization problems and make BBO convergence faster. Pattnaik, Lohokare, and Devi (2010) have proposed Enhanced Biogeography Based Optimization (EBBO) in which duplicate habitats, created due to migration of features, is replaced with randomly generated habitats to increase the exploitation ability of BBO algorithm.

The various migration and mutation variants of BBO algorithm were explored in Singh and Sachdeva (2012a, b). Nondominated sorting BBO (NSBBO) was proposed and investigated for the performance of multiobjective optimization of gain and impedance simultaneously of the Yagi-Uda Antenna in Singh, Mittal, and Sachdeva (2012b). Further, the performance of NSBBO and NSPSO was compared for simultaneous optimization of gain and impedance of the Yagi-Uda Antenna (Singh, Mittal, and Sachdeva 2012a).

In this article, NSBBO and various migration variants of the BBO algorithm are proposed and investigated to attain multiple objectives, in other words, (1) maximum gain and (2) only resistive impedance of 50Ω , during Yagi-Uda antenna design optimization.

After this brief historical background survey, the remainder of this article is outlined as follows: "Biogeography Based Optimization" is dedicated to BBO algorithms. In the section following that, the Yagi-Uda antenna design parameters are discussed. "Multiobjective Optimization" explains multiobjective problem formulation and the nondominated sorting algorithm. In "Simulation Results and Discussions," simulation results are presented and analyzed. Finally, conclusions and future scope are discussed in the final section.

BIOGEOGRAPHY-BASED OPTIMIZATION

BBO is a population-based global optimization technique inspired from the science of biogeography, that is, the study of distribution of animals and plants among different habitats over time and space. BBO results presented by researchers are better than other Evolutionary Algorithms (EAs) such as Particle Swarm Optimization (PSO), Genetic Algorithms (GAs), Simulated Annealing (SA), and Differential Evolution (DE), and so on (Jones and Joines 1997; Venkatarayalu and Ray 2003; Baskar et al. 2005; Rattan, Patterh, and Sohi 2008).

Originally, biogeography was studied by Charles Darwin (Darwin 1995) and Alfred Wallace (Wallace 2005) mainly as a descriptive study. However, in 1967, the work carried out by MacArthur and Wilson (MacArthur and Wilson 1967) changed this view point and proposed mathematical models for biogeography and made it feasible to predict numbers of species on various islands, mathematical models of biogeography describe migration,

speciation, and extinction of species on 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 as having a high Habitat Suitability Index (HSI) value. However, HSI is analogous to fitness in other EAs whose values depend on many factors such as rainfall, diversity of vegetation, diversity of topographic features, land area, and temperature. The factors/variables that characterize habitability are termed as Suitability Index Variables (SIVs). In other words, HSI is a dependent variable, whereas SIVs are independent variables.

The habitats with a high HSI tend to have a large population of its resident species, which is responsible for more probability of emigration (emigration rate, μ) and less probability of immigration (immigration rate, λ) due to the natural random behavior of the species. Immigration is the arrival of new species into a habitat or population, whereas 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 becomes extinct, which leads to additional immigration. For sake of simplicity, it is safe to assume a linear relationship between HSI (or population) and immigration and emigration rate and same maximum emigration and immigration probability, that is, $E = I$, as depicted graphically in Figure 1.

The k th habitat values of emigration rate, μ_k , and immigration rate, λ_k are given by Equations (1) and (2).

$$\mu_k = E \cdot \left(\frac{HSI_k}{HSI_{\max} - HSI_{\min}} \right). \quad (1)$$

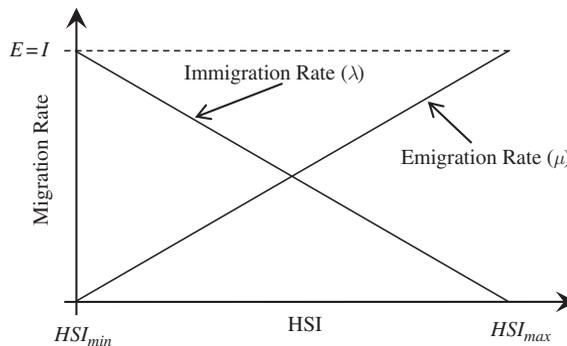


FIGURE 1 Migration curves.

$$\lambda_k = I \cdot \left(1 - \frac{HSI_k}{HSI_{\max} - HSI_{\min}} \right). \quad (2)$$

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

Each habitat, in a population of size NP , is represented by an M -dimensional vector as $H = [SIV_1, SIV_2, \dots, SIV_M]$, where M is the number of SIVs to be evolved for optimal fitness given as $HSI = f(H)$. The following subsections describe the different migration variants of BBO: Standard BBO (Simon 2008), Blended BBO (Ma and Simon 2011), Immigration Refusal BBO (Du, Simon, and Ergezer 2009), and Enhanced BBO (Pattnaik, Lokohare, and Devi 2010).

Standard BBO

Algorithmic flow of standard BBO involves two mechanisms, i.e., migration and mutation; these are discussed in the following subsections.

Migration

Migration is a probabilistic operator that improves HSI of poor habitats by sharing features from good habitats. During migration, the i th habitat, H_i (where $i = 1, 2, \dots, NP$) uses its immigration rate, λ_i given by Equation (2), 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 Equation (1). The process of migration is completed by copying values of SIVs from H_j to H_i at random chosen sites. The pseudocode of the migration operator is depicted in Algorithm 1.

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 in habitats that are, probabilistically, participating less in the migration process. The mutation rate, $mRate$, for the k th habitat is calculated as Equation (3)

$$mRate_k = C \times \min(\mu_k, \lambda_k). \quad (3)$$

Algorithm 1 Pseudocode for Standard Migration

```

for  $i = 1$  to  $NP$  do
  Select  $H_i$  with probability based on  $\lambda_i$ 
  if  $H_i$  is selected then
    for  $j = 1$  to  $NP$  do
      Select  $H_j$  with probability based on  $\mu_j$ 
      if  $H_j$  is selected
        Randomly select an SIV(s) from  $H_j$ 
        Copy these SIV(s) in  $H_i$ 
      end if
    end for
  end if
end for

```

Algorithm 2 Pseudocode for Mutation

```

mRate =  $C \times \min(\mu_k, \lambda_k)$ 
for  $n = 1$  to  $NP$  do
  for  $j = 1$  to number of SIV(s)
    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

```

where μ_k and λ_k are emigration and immigration rates, respectively, given by Equations (1) and (2) corresponding to HSI_k . To reduce fast generation of duplicate habitats, here, C is chosen as 3, to keep the exploitation rate much higher compared to other EAs. The pseudocode of the mutation operator is depicted in Algorithm 2.

Blended BBO

The blended migration operator is a generalization of the standard BBO migration operator and was inspired by blended crossover in GAs (McTavish and Restrepo 2008). In blended migration, an SIV value of the immigrating habitat, $ImHbt$, is not simply replaced by an SIV value of the emigrating habitat, $EmHbt$, as happened in the standard BBO migration operator. Rather, a new solution feature, SIV value, comprises two components as $ImHbt(SIV) \leftarrow \alpha \cdot ImHbt(SIV) + (1 - \alpha) \cdot EmHbt(SIV)$. Here, α is a random number between 0 and 1. The pseudocode of blended migration is depicted in Algorithm 3.

Algorithm 3 Pseudocode for Blended Migration

```

for  $i = 1$  to  $NP$  do
  Select  $H_i$  with probability based on  $\lambda_i$ 
  if  $H_i$  is selected then
    for  $j = 1$  to  $NP$  do
      Select  $H_j$  with probability based on  $\mu_j$ 
      if  $H_j$  is selected
         $H_i(SIV) \leftarrow \alpha \bullet H_i(SIV) + (1 - \alpha) \bullet H_j(SIV)$ 
      end if
    end for
  end if
end for

```

Immigration Refusal BBO

In BBO, if a habitat has a high emigration rate, that is, the probability of emigrating to other habitats is high and the probability of immigration from other habitats is low. However, the low probability does not mean that immigration will never happen. Once in a while, a highly fit solution might receive solution features from a low-fit solution that might degrade its fitness. In such cases, immigration is refused in order to prevent degradation of HSI values of habitats. This BBO variant with conditional migration is termed Immigration Refusal; its performance with a testbed of benchmark functions is encouraging (Du, Simon, and Ergezer 2009). The pseudocode of immigration refusal migration is depicted in Algorithm 4.

Enhanced BBO

The standard BBO migration operator tends to create duplicate solutions, which decreases the diversity in the population. To prevent this diversity decrease in the population, duplicate habitats are replaced with randomly generated habitats. This leads to increased exploration of new SIV values. In EBBO, a clear duplicate operator is integrated in to the basic BBO algorithm to improve its performance. The migration pseudocode of enhanced BBO is depicted in Algorithm 5.

ANTENNA DESIGN PARAMETERS

The Yagi–Uda antenna consists of three types of elements: (1) *Reflector*—largest among all and responsible for blocking radiations in one direction. (2) *Feeder*—fed with the signal from transmission line to be transmitted and

Algorithm 4 Pseudocode for Immigration Refusal BBO

```

for  $i = 1$  to  $NP$  do
  Select  $H_i$  with probability based on  $\lambda_i$ 
  if  $H_i$  is selected then
    for  $j = 1$  to  $NP$  do
      Select  $H_j$  with probability based on  $\mu_j$ 
      if  $H_j$  is selected
        if (fitness( $H_j$ ) > fitness( $H_i$ ))
          apply migration
        end if
      end if
    end for
  end if
end for

```

Algorithm 5 Pseudocode for Enhanced BBO

```

for  $i = 1$  to  $NP$  do
  Select  $H_i$  with probability based on  $\lambda_i$ 
  if  $H_i$  is selected then
    for  $j = 1$  to  $NP$  do
      Select  $H_j$  with probability based on  $\mu_j$ 
      if  $H_j$  is selected
        if (fitness( $H_j$ ) = fitness( $H_i$ ))
          eliminate duplicates
        end if
      end if
    end for
  end if
end for

```

(3) *Directors*—usually more than one in number and responsible for unidirectional radiations. Figure 2 depicts a typical six-wire Yagi–Uda antenna in which all wires are placed parallel to the x -axis and along the y -axis. The 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.

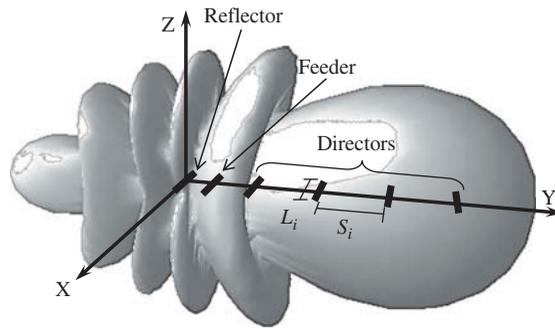


FIGURE 2 Six-element Yagi-Uda Antenna.

Designing a Yagi-Uda antenna involves determination of wire-lengths and wire-spacings in between to get maximum gain and desired impedance, and so forth, at an arbitrary frequency of operation. An antenna with N elements requires $2N - 1$ parameters, that is, N wire lengths and $N - 1$ spacings, that are to be determined. These $2N - 1$ parameters, collectively, are represented as a string referred to as a *habitat* in BBO, given as Equation (4).

$$H = [L_1, L_2, \dots, L_N, S_1, S_2, \dots, S_{N-1}], \quad (4)$$

where L_S are the lengths and S_S are the spacing 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 element, which 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 nonlinear and complex relationships between the antenna parameters and its characteristics such as gain and impedance.

MULTIOBJECTIVE OPTIMIZATION

Multiobjective Problems

In single-objective optimization, an optimal solution is easy to obtain as compared to a multiobjective scenario where one solution that could be globally optimal with respect to all objectives may not exist. Objectives under consideration might be conflicting in nature; improvement in one objective could cause declination in other objective(s). One way to solve a multiobjective problem (MOP) is to scalarize the vector of objectives into one objective by averaging the objectives with a weight vector. This process allows a simpler optimization algorithm to be used, however, the obtained

solution largely depends on the weight vector used in the scalarization process. A common difficulty with MOP is the conflicting nature of objectives where no solution that could be globally the best for all objectives is feasible. Thus, a most favorable solution is opted, which offers the least objective conflict.

The solution to multiobjective optimization problems result in Pareto-optimal solutions instead of a single optimal solution in every run. There exists a set of solutions that are the best trade-off solutions, important for decision making and often superior to the rest of the solutions when all objectives are considered; however, inferior for one or more objectives. These solutions are termed as Pareto-optimal solutions or nondominated solutions and others as dominated solutions. Every solution from a nondominated set is acceptable because none of them is better than its counterpart. However, final selection of a solution is done by the designer based on nature of the problem under consideration.

Nondominated Sorting

The problem presented in this article of optimizing an antenna design has two objectives, viz. (1) antenna impedance and (2) maximum antenna gain. Desired antenna impedance, i.e., $(Re + jIm)\Omega$, is formulated as a fitness function, f_1 , given as Equation (5), which is required to be minimized.

$$f_1 = |Re - \text{desiredimpedance}| + |Im|, \quad (5)$$

Whereas, the second objective of gain maximization is also converted into a minimization fitness function, f_2 , given as Equation (6):

$$f_2 = \frac{1}{\text{Gain}}. \quad (6)$$

Suppose every solution, in a swarm of NP solutions, yields f_{1k} and f_{2k} as fitness values (where $k = 1, 2, \dots, NP$), using Equations (5) and (6), that belongs to either a nondominated solution set, P , or a dominated solution set, D . An i th solution in set P dominates the j th solution in set D if satisfies the condition of dominance, i.e., $f_{1i} \leq f_{1j}$ and $f_{2i} \leq f_{2j}$, where both objectives are to be minimized. This condition of dominance is checked for every solution in the universal set of NP solutions to assign it to either P set or D set. Solution members of set P form the first nondominated front, i.e., the Pareto optimal front, and then remaining solutions, those belong to set D , are made to face same condition of dominance among themselves to determine the

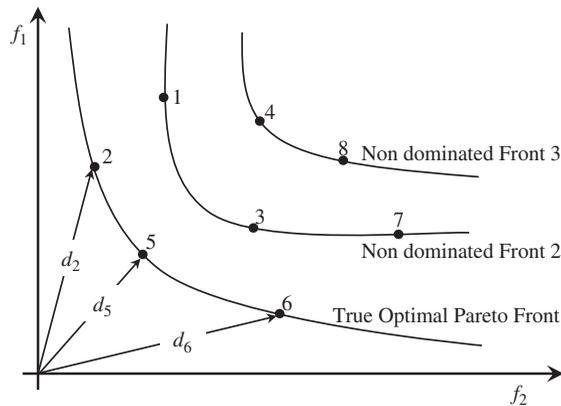


FIGURE 3 Nondominated sorting and Pareto fronts.

next nondominated front. This process continues until all solutions are classified into different nondominated fronts, as shown in Figure 3. Preference order of solutions is to be based on the designer's choice, however, here, Euclidian distance is determined from origin for every member solution in a nondominated front and are selected in ascending order. The pseudocode of nondominated sorting approach is depicted in Algorithm 6.

SIMULATION RESULTS AND DISCUSSION

As BBO is a swarm-based stochastic optimization algorithm; to present fair analysis, a six-wire Yagi-Uda antenna design is optimized for 10 times using 300 iterations and 50 habitats (particles). The universe of discourses to search optimal values of wire lengths and wire spacings are $0.40\lambda - 0.50\lambda$ and $0.10\lambda - 0.45\lambda$, respectively. However, crosssectional radius and segment size for all wires are kept constant, in other words 0.003397λ and 0.1λ , respectively, where λ is the wavelength corresponding to frequency of operation, 300MHz. The C++ programming platform is used for algorithm coding, whereas method of moments-based software, Numerical Electromagnetic Code (NEC2) (Burke and Poggio 1981), is called, using system command to evaluate antenna designs. Both objectives, gain and impedance, are optimized using two fitness functions, given by Equations (5) and (6).

The average of 10 Monte-Carlo simulation runs are plotted to analyze convergence flow while achieving (1) maximum antenna gain, (2) $Re = 50\Omega$, in other words, resistive antenna impedance of 50Ω , and (3) $Im = 0\Omega$, or, zero reactive antenna impedance, in Figure 4. From the plots, it can be

Algorithm 6 Standard Pseudo Code for Non-dominated sorting

```

for  $s = 1$  to  $NP$ 
     $f_{1s} = |\text{Re-desired imp}| + |\text{Im}|$  and
     $f_{2s} = \frac{1}{\text{gain}}$ 

    end for
 $f = 1$  % Non-dominated front  $f$ 
All solutions in the swarm set  $\in F$ 
if (No. solutions in set  $F \neq 0$ )
     $f = f + 1$ 
    for  $i = 1$  to  $NP$ 
        for  $j = 1$  to  $NP$ 
            if ( $i \neq j$ )
                if ( $f_{1i} \leq f_{1j}$  and  $f_{2i} \leq f_{2j}$ )
                     $j$ -th solution  $\in D_f$ 
                else
                     $j$ -th solution  $\in P_f$ 
                end if
            end if
        end for
    end for
     $F = D_f$ 
end if

```

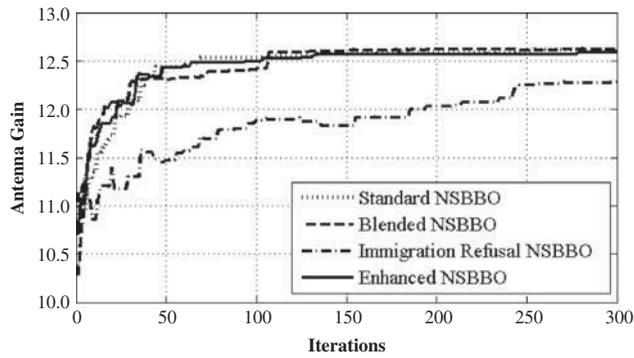
observed that the best compromised solution, during initial iterations, sometimes leads to poor solutions in terms of gain or impedance. However, with increasing numbers of iterations the best compromised solution improves in aggregation that could improve further, if the maximum iteration number is kept high. The best antenna designs obtained during the process of optimization and the average results of 10 Monte-Carlo runs, depicted in [Figure 4](#), after 300 iterations are tabulated in [Table 1](#).

CONCLUSIONS AND FUTURE SCOPE

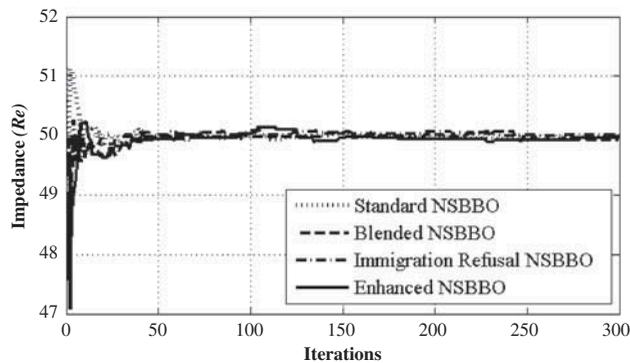
In this article, NSBBO along with different migration variants of the BBO algorithm are investigated for attaining multiple objectives: maximum gain and antenna impedance. The results obtained for multiobjective optimization of the standard NSBBO are found to be better compared to other multiobjective optimization techniques discussed in (Singh, Kumar, H., and Kamal 2010). It can be observed from simulation results that the NSBBO

TABLE 1 The Best Antenna Designs Obtained During Optimization and Average Results after 300 Iterations for 50Ω Impedance

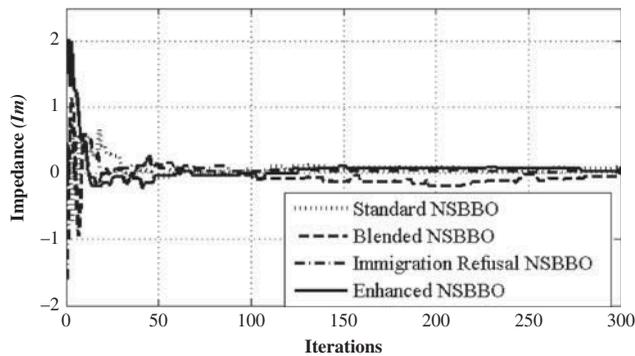
Element	Standard BBO			Blended BBO			IR BBO			EBBO		
	Length	Spacing	Length	Length	Spacing	Length	Length	Spacing	Length	Length	Spacing	
1(λ)	0.4777	—	0.4764	0.4754	—	0.4754	0.4746	—	0.4746	—	—	
2(λ)	0.4700	0.1901	0.4674	0.4652	0.2168	0.4652	0.4653	0.2105	0.4653	0.2111	0.2111	
3(λ)	0.4436	0.1826	0.4428	0.4419	0.1801	0.4419	0.4407	0.1816	0.4407	0.1994	0.1994	
4(λ)	0.4292	0.2912	0.4272	0.4286	0.3032	0.4286	0.4293	0.3068	0.4293	0.2999	0.2999	
5(λ)	0.4239	0.3553	0.4235	0.4250	0.3401	0.4250	0.4233	0.3307	0.4233	0.3349	0.3349	
6(λ)	0.4287	0.3475	0.4272	0.4280	0.3609	0.4280	0.4251	0.3528	0.4251	0.3719	0.3719	
Best Gain	12.70 dBi		12.68 dBi	12.70 dBi		12.70 dBi	12.66 dBi		12.66 dBi			
Best Imp.	50.1265 - j0.0124 Ω		50.1755 - j0.0833 Ω	49.9502 + j0.0612 Ω		49.9502 + j0.0612 Ω	49.9784 - j0.0599 Ω		49.9784 - j0.0599 Ω			
Best Abs Imp.	50.1265Ω		50.1755Ω	49.9502Ω		49.9502Ω	49.9784Ω		49.9784Ω			
Average Gain	12.616 dBi		12.624 dBi	12.282 dBi		12.282 dBi	12.593 dBi		12.593 dBi			
Average Imp.	49.9835 + j0.0902 Ω		49.9532 + j0.00266 Ω	50.00034 + j0.03253 Ω		50.00034 + j0.03253 Ω	49.9755 + j0.08409 Ω		49.9755 + j0.08409 Ω			
Average Abs Imp.	49.9836Ω		49.9532Ω	50.00035Ω		50.00035Ω	49.9756Ω		49.9756Ω			



(a) Antenna Gain Convergence



(b) Resistive Antenna Impedance



(c) Reactive Antenna Impedance

FIGURE 4 Convergence flow for different NSBBO migration variants at 50Ω resistive antenna impedance.

with blended migration presents better convergence flow in terms of achieving gain and only resistive impedance of 50Ω as compared to different variants of BBO over limited 300 iterations. NSBBO has been a good choice for optimizing Yagi-Antenna for multiple objectives and can be tried on other antennas such as antenna arrays as well.

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