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Metropolis biogeography-based optimization

Ali R. Al-Roomi*, Mohamed E. El-Hawary[1]

Department of Electrical and Computer Engineering, Dalhousie University, 1459 Oxford Street, Halifax, NS B3H 4R2, Canada

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ABSTRACT

Biogeography-based optimization (BBO) is a new population-based evolutionary algorithm (EA). Although the exploitation level of BBO is good researchers found some weaknesses in its exploration. This study proposes a new hybridization between BBO and simulated annealing (SA) to enhance its performance. In this proposed algorithm, the inferior migrated islands will not be selected unless they pass the Metropolis criterion of SA and so the new algorithm is called MpBBO. The performance of MpBBO is evaluated using 36 benchmark functions with five different cooling strategies of SA and then compared with the original and essentially modified BBO models. The results show the exponential, inverse, and inverse linear cooling strategies provide best solutions, but they are the slowest. Among these three strategies, the exponential cooling rate can compromise between the solution quality and CPU time compared with the others. Also, the inverse cooling rate is competitive and wins when the mutation stage is completely disabled. The F-test and T-test show that MpBBO has significant differences. Further, it has been observed, through sensitivity analysis, that MpBBO behaves like BBO and SA. The parameters of SA and BBO can affect the performance of MpBBO, which has more immunity against trapping into local optimums. Moreover, the superiority of MpBBO appears when it is compared with non-simplified migration-based BBO models as well as other hybrid/non-hybrid EAs.

1. Introduction

The biogeography-based optimization (BBO) algorithm was presented by Dan. Simon in 2008 [46], and it is considered as a one of meta-heuristic population-based evolutionary algorithms (EAs) that can converge to the location of the global optima. The first appearance of this stochastic-based optimization algorithm was with a simplified linear migration model, where its performance was evaluated based on 14 benchmark functions, and then tested to solve a real sensor selection problem for aircraft engine health estimation. The BBO algorithm proved itself as a very competitive technique as compared with the other EAs [46]. Although this global optimization method has good exploitation, it lacks exploration [16,17,26,42]. Some of these inherent weaknesses have been addressed and solved in [3]. However, the performance of the migration stage is still poor.

* Corresponding author. Tel.: +1 9029894589.
E-mail addresses: alroomi@al-roomi.org (A.R. Al-Roomi), ElHawary@dal.ca (M.E. El-Hawary).
[1] Tel.: +1 9024736198.

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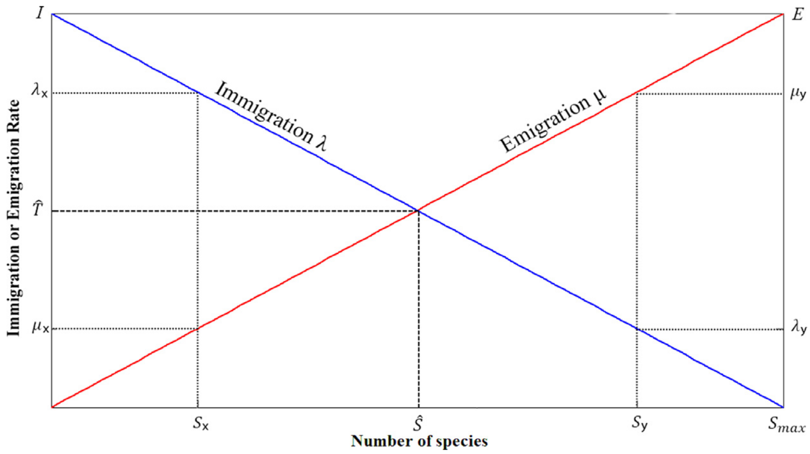

Fig. 1. Simplified equilibrium model of a biota of a single island.

1.1. Literature review

Two approaches have been applied in the literature to improve BBO performance: modifying the main structure of the BBO algorithm itself [11,29,31,32,42,48,50], or hybridizing it with other EAs [12,17,33,34].

In [11], the immigration refusal stage was used to prevent any low island suitability index (*ISI*) island to be selected as a source of modification for the poor islands. Thus, the good individuals will not be ruined, because the poor islands are not selected as a source of modification. However, this approach will also reduce the exploration level, because the low *ISI* islands may contain some good features that may guide the algorithm to converge to the optima. This algorithm has some weaknesses similar to the simplified partial migration based BBO (SPMB-BBO) that are covered in [2], where reliance only on the best individuals does not guarantee escaping from the local optima.

In [12], the Opposition-Based Learning (OBL) was employed in BBO to improve its searching process, and thus the new algorithm is referred to as Oppositional BBO (OBO). The idea behind the OBO algorithm is to compare between the actual decision variables and their opposites, where the better one is used in the population. Based on that, the search space can be more explored.

Other researchers [19,29,31,32] mainly focused on the equilibrium species count $\hat{S}$, because at this point the probability P_i and the mutation m_i reach their highest and lowest possible values, respectively; see Fig. 1. Different migration models have been used for their investigations, where some of these models are described by naturalists [10,27,35,36,38]. In [31], the constant and linear rates were used for λ_i and μ_i with a bias θ as a minimal emigration rate. This research was further expanded in [29], where other functions such as trapezoidal, quadratic, and sinusoidal were employed, and it was found that the sinusoidal migration model achieved the best overall performance. After that, the study of the effects of successional changes on the immigration rate [39] was involved to improve the performance of the sinusoidal BBO algorithm. The controllable model, called generalized sinusoidal (GenSin), was presented with satisfactory results [32]. This work was analyzed again in [19] and proposed two new analysis-based models.

The Gaussian, Cauchy, and Lèvy mutation operators were used in a real-coded BBO (RCBBO) [16]. These suggested variations increase the population diversity, which in turn raise the algorithm exploration level.

In [42], a new suggested algorithm called Enhanced BBO (EBBO) was presented. When the migration process is completed, some of the modified islands could become similar, which reduces the features diversity of the newly generated candidate solutions. To prevent this, a new clear duplication operator with random mutation was introduced.

The Blended BBO (BBBO) in [33] also has the ability to solve the preceding problem. BBBO is equipped with a blended crossover operator of the genetic algorithm (GA). Thus, the emigrated features will not fully take the place of the old features available on the poor island. Instead, the new features (or design variables) are a mixture of the poor and good island features with percentage ratio. This work was extended in [18] by using five different operators motivated from the variation of crossover in GA.

In [21], the BBO algorithm was hybridized with the flower pollination by artificial bees (FPAB) to classify a satellite image. The BBO algorithm itself does not inherently have the clustering property. For that, FPAB and BBO are respectively used as clusters and optimal solution finders.

Other hybridization techniques have been reported in [17,25,51]. The most interesting study is [17], where it combines the good exploration of the differential evolution (DE) algorithm with the good exploitation of the BBO algorithm in one algorithm called hybrid DE/BBO algorithm. The study given in [26] uses the same concept to accelerate the rate of convergence of the BBO algorithm.