Biogeography-Based Optimization: A 10-Year Review

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***Abstract*—Biogeography-based optimization (BBO) is an evolutionary algorithm which is inspired by the migration of species between habitats. Almost 10 years have passed since the first BBO paper was published in 2008. BBO has successfully solved optimization problems in many different domains and has reached a relatively mature state. Considering the significant and expanding research on BBO and its applications, we find that the time is right to provide a 10-year anniversary review of the published literature, and also to point out some important avenues of future research. The purpose of this paper is to summarize and organize the literature related to the past 10 years of BBO research. Beginning with a foundation of basic BBO, we review the family of BBO algorithms and discuss BBO modifications, hybridizations, applications in science and engineering, and mathematical theory. Finally, the paper presents some interesting open problems and future research directions for BBO.**

***Index Terms*—Biogeography-based optimization, evolutionary algorithm, hybridization, nature-inspired algorithm, optimization.**

I. Introduction

Nature-inspired algorithms comprise a computer intelligence discipline that has become increasingly popular over the past few decades [1]. They are inspired by natural phenomena and the collective behavior of swarms of ants and bees, flocks of birds, and schools of fish as they search for food and for a better environment. The popularity of nature-inspired algorithms is due to their robust search and optimization ability in solving complex problems. In general, these algorithms can be classified as either evolutionary algorithms (EAs) or swarm-based algorithms. The former begins with a set of candidate solutions (usually generated randomly), iteratively combines the solutions, and implements survival of the fittest until an acceptable solution is reached. Classic examples include genetic algorithms (GAs) [2], evolution strategy (ES) [3] and genetic programming (GP) [4]. Swarm-based optimization starts with a set of individuals, and each iteration a new set of individuals is created based on historical information and other related information. Some algorithms in this category are ant colony algorithm (ACO) [5], artificial bee colony (ABC) [6], cuckoo search algorithm (CSA) [7], [8], firefly algorithm (FA) [9], krill herd (KH) [10], particle swarm optimization (PSO) [11], [12], and others [1].

Biogeography-based optimization (BBO) was introduced in 2008 to solve global optimization problems [13]. It is an evolutionary algorithm that is motivated by the migration of species between habitats. BBO has been demonstrated to be a powerful search technique because it includes both exploration and exploitation strategies based on migration. It is one of the fastest-growing nature-inspired algorithms for solving practical optimization problems. This is a result of its advantages in terms of simplicity, flexibility, and computational efficiency, as well as its stochastic nature, which does not require derivatives of the objective function.

BBO is closely related to other EAs such as GAs and differential evolution (DE) [14], [15]. This has been highlighted in earlier work [13], [16], which showed that in spite of its similarities with other EAs, BBO has distinctive characteristics that give it distinctive behaviors. Because of these distinct properties, it is helpful to maintain the viewpoint of BBO as a unique EA. Another motivation for viewing BBO as a unique EA is that this perspective can encourage the modeling of biogeographical details in BBO, such as the effect of inter-habitat distance on migration; nonlinear migration relationships; the effect of population sizes, mortality rates, and reproduction rates on migration; the influence of predator/prey relationships on population sizes; the effect of different mobility measures of difference species on migration; geographical momentum during migration; and the effect of habitat land area and habitat clusters on migration [1].

The success of BBO has been demonstrated on many problems, including global benchmark functions, economic load dispatch, and others. Studies have shown that the power of standard BBO lies in global exploration, but BBO may get stuck in local optima and thus may not be able to achieve the best global search. This shortcoming leads to modifications, including hybridizations with other heuristics. The main objective of this review is to provide an extensive (though not exhaustive) summary of related work in the 10-year development of BBO, as

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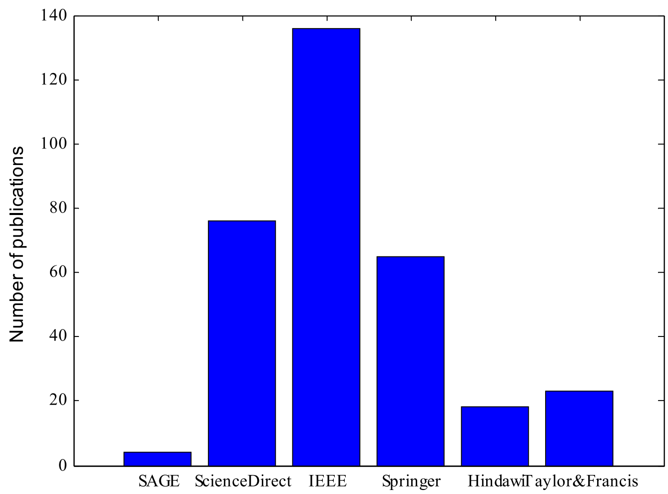

Fig. 1. Number of BBO publications by database.

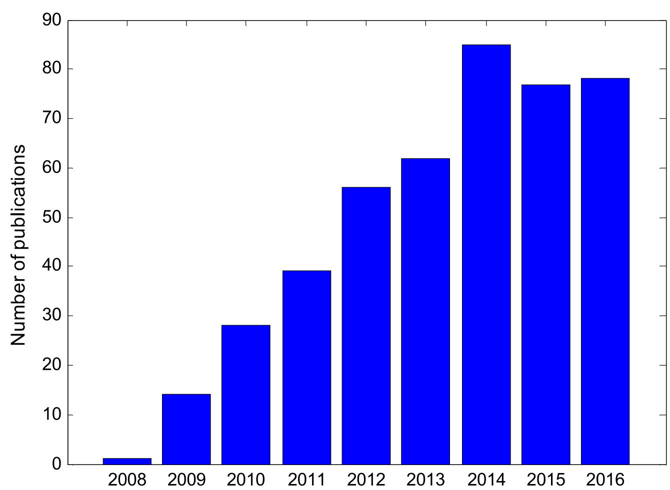

Fig. 2. Number of BBO publications by year.

TABLE I
THE TOP 10 COUNTRIES RANKED BY NUMBER OF BBO PUBLICATIONS

Rank	Country	Num.	Rank	Country	Num.
1	China	111	6	Egypt	6
2	India	98	7	Canada	6
3	USA	42	8	Malaysia	5
4	Iran	16	9	Greece	4
5	Algeria	11	10	France	4

TABLE II
THE TOP 10 JOURNALS RANKED BY NUMBER OF BBO PUBLICATIONS

Rank	Journal	Num.
1	Mathematical Problems in Engineering	8
2	Lecture Notes in Computer Science	8
3	Information Sciences	7
4	Expert Systems with Applications	7
5	Electric Power Components and Systems	7
6	Swarm and Evolutionary Computation	6
7	IEEE Transactions on Power Systems	5
8	Engineering Applications of Artificial Intelligence	5
9	Computers & Operations Research	5
10	Applied Soft Computing	5

TABLE III
THE TOP 5 BBO-RELATED CO-SITED JOURNALS

Rank	Journal	Count
1	IEEE Transactions on Evolutionary Computation	313
2	Information Sciences	106
3	IEEE Transactions on Power Systems	94
4	Engineering Applications of Artificial Intelligence	92
5	Expert Systems with Applications	85

well as to present future challenges and research possibilities. The authors published a recent book with the title "Evolutionary Computation with Biogeography-based Optimization" [17], which summarizes the authors' work on BBO in the past 10 years. This review emphasizes other authors' contributions to BBO in four main areas: modifications, hybridizations, applications and theories. This classification aims to clearly communicate the trends in BBO.

Other reviews and surveys of BBO have also been published in the past few years [18]–[23]. Our review expands on other reviews by providing a much more comprehensive discussion; by organizing the literature in the areas of modifications, hybridizations, applications and theories; and by providing a significant discussion and suggestions for future research in the conclusion.

This review considers various publishers: Elsevier, IEEE, Springer, Taylor & Francis, SAGE, Hindawi, and others. Fig. 1 shows the number of published papers with "biogeography-based optimization" in their titles in different databases, and Fig. 2 shows the chronological distribution of the papers. Table I shows the countries with the most BBO publications, and Table II shows the journals with the most BBO publications. These figures and tables clearly show the breadth, depth, and growth of interest in BBO.

To further analyze the development of BBO, we use CiteSpace software [24], [25], which generates co-occurrence network maps of authors, keywords, and institutions; and co-citation networks of cited authors, cited references, and cited journals, to generate a journal co-citation analysis network. The top 5 BBO-related co-cited journals are shown in Table III. Based on an analysis of publication and co-citation counts, IEEE Transactions on Evolutionary Computation is identified as the core journal for BBO. We also use CiteSpace to generate keyword co-occurrence, which is a useful approach to explore knowledge structure and hot topics, and the top 10 BBO-related keywords are shown in Table IV.

The organization of this paper is as follows. A description of the general structure of BBO is provided in Section II, and the literature review of BBO in relation to modifications, hybridizations, applications and theories are given in Sections III, IV, V and VI respectively. Finally, a discussion of ideas for further development of BBO is outlined in Section VII.

TABLE IV
THE TOP 10 BBO-RELATED KEYWORDS

Rank	Keywords	Count
1	Biogeography-based optimization	176
2	Genetic algorithm	74
3	Algorithm	67
4	Particle swarm optimization	49
5	Differential evolution	46
6	Evolutionary algorithm	34
7	Mutation	24
8	System	24
9	Model	22
10	Design	22

II. BIOGEOGRAPHY-BASED OPTIMIZATION

This section first provides an overview of the scientific foundations of BBO [26] (see Section II-A), and then gives a general description of the standard BBO algorithm (see Section II-B). Finally, it discusses the differences between BBO and other population-based optimization algorithms (see Section II-C).

A. Scientific Foundations

Biogeography describes the distribution and speciation of biological organisms, and is typically viewed as a process that maintains species equilibrium in their habitats. Equilibrium is achieved when the immigration/speciation and emigration/extinction rates are equal. One reason biogeography is typically viewed this way is that this viewpoint was instrumental in the popularization of biogeography in the 1960s [27], [28]. However, since then this perspective has been expanded to include optimality.

Engineers often view stability/equilibrium and optimality/performance as conflicting system characteristics. A simple system is generally more stabilizable than a complicated system, and an optimal system is generally more complicated and less easily stabilized than a simple system [29].

However, in biogeography, equilibrium and performance are two viewpoints that do not necessarily conflict. High performance in biogeography includes diverse and interactive biological populations that can readily adapt to their physical surroundings. Equilibrium implies survival. Experimental studies show that biological communities with complicated interactions are better able to survive than simpler communities [30, p. 82], and these studies have been confirmed by computer simulations [31], [32]. We thus see that in biogeography, stability/equilibrium and optimality/performance are two different viewpoints of the same behavior.

One biogeography example of optimization is Krakatoa, which is an island volcano in the Indian Ocean. An eruption of Krakatoa in 1883 destroyed all life on the island. Subsequent migrations of plant and animal species to the island eventually made the island more habitable for further migrations [33]. The Amazon rainforest is another example of the optimization behavior of biogeography, where both native life forms and their environment are simultaneously optimized [30]. Other examples of the optimization ability of biogeography include Earth's temperature [30]; the composition of Earth's atmosphere [34]; and the mineral content of Earth's ocean [35]. Note that biogeography does not achieve optimality for any specific species, and least of all for humans. Life flourishes on Earth because of Earth's friendliness to life, but not in a way that is oriented toward any particular species.

Biogeography entails positive feedback to a certain point. This characteristic of biogeography is similar to natural selection. When species become fitter, they become better able to survive. The longer that they survive, the better able they can disperse and adapt. Both natural selection and biogeography include this feature of positive feedback. However, the time scale of natural selection (millions and billions of years) is much longer than that of biogeography (hundreds and thousands of years), which suggests the likelihood of better optimization if we use biogeography instead of natural selection to motivate an optimization algorithm (that is, BBO rather than GAs). The premise that biogeography optimizes habitats motivated the introduction of BBO as an optimization algorithm [13].

B. The Structure of Standard BBO

As with any other EA, we begin with an optimization problem and a population of candidate solutions. Candidate solutions are often simply referred to as "solutions" for ease of notation. Each solution is composed of features, or independent variables. A good solution corresponds to a biological habitat that is well suited for life. A poor solution corresponds to a habitat that is poorly suited for life. High-fitness solutions tend to share features with other solutions; that is features tend to emigrate from high-fitness solutions and immigrate to low-fitness solutions. Low-fitness solutions tend to accept shared features from other solutions. Like other EAs, BBO includes two steps: information sharing and mutation. In BBO, information sharing is implemented with migration.

BBO migration is probabilistic. Each solution's migration rate is used to stochastically share features. For solution y_k, its immigration rate λ_k is used to stochastically decide whether or not to immigrate each of its features, one at a time. If a stochastic decision is made in favor of immigration, then a second random decision is made; the emigrating solution y_j is stochastically selected based on emigration rate μ_j. We denote migration as

$$y_k(s) \leftarrow y_j(s) \tag{1}$$

where s is a solution feature index. Migration probabilities are based on deterministic curves, such as those shown in Fig. 3. Nonlinear migration curves are discussed in [36] and below in Section III-A. For the sake of consistency we refer to all possible migration functions as "curves" even though they might be linear as shown in Fig. 3.

Mutation is a probabilistic function that can modify solution features, and can be implemented as in any other EA. The purpose of mutation is to increase diversity among the population.

One generation of BBO is depicted in Algorithm 1. The entire population undergoes migration and mutation before any solutions are replaced, which requires the use of temporary population z. The statement In Algorithm 1, "Use λ_k to decide

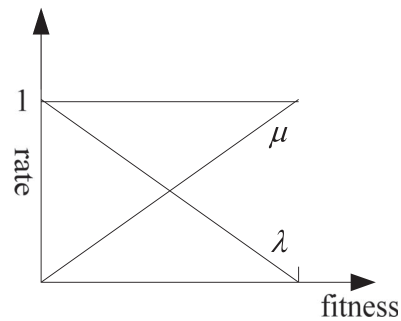

Fig. 3. Linear migration functions. Immigration rate is denoted by λ and emigration rate is denoted by μ.

Algorithm 1: One generation of the standard BBO algorithm, where *N* is the population size, *y* is the entire population of candidate solutions, y_k is the *k*th candidate solution, and $y_k(s)$ is the *s*th feature of y_k.

For each solution y_k set emigration rate μ_k proportional to fitness with $\mu_k \in [0, 1]$.
For each solution y_k set immigration rate $\lambda_k = 1 - \mu_k$.
$z \leftarrow y$.
For each solution z_k ($k = 1$ to N)
  For each solution feature index *s*
   Use λ_k to decide whether or not to immigrate to z_k.
   If immigration was decided then
     Use $\{\mu_i\}$ to select the emigrating solution, denoted as y_j.
     $z_k(s) \leftarrow y_j(s)$.
    End if
  Next solution feature
  Decide whether to mutate z_k.
Next solution
$y \leftarrow z$.

whether or not to immigrate to z_k," can be realized with the following pseudocode, where rand(0, 1) is a random number that is uniformly distributed between 0 and 1:

If $\lambda_k <$ rand$(0, 1)$
Migrate
Else
Do not migrate

The statement "Use $\{\mu_i\}$ to select the emigrating solution" in Algorithm 1 can be realized with the user's favorite fitness-based selection method (because μ_i is proportional to the fitness of y_i) – tournament selection, roulette-wheel selection, etc.

C. *Differences Between BBO and Other Algorithms*

In this section, we point out some differences between BBO and other population-based optimization algorithms, including ABC, DE, FA, GA, PSO, group search optimizer (GSO) [37], and shuffled frog leaping algorithm (SFLA) [38], [39]. Each algorithm has its own unique features that give it a particular flexibility that other algorithms may not have. Their characteristics are summarized in Table V.

In Table V, the column labeled "Biological motivation" indicates the motivating paradigm of each algorithm. For example, PSO is inspired by the swarming behavior of birds, and ABC is inspired by the foraging behavior of bees.

The column labeled "Search domain of original formulation" indicates whether the algorithm was originally proposed for discrete or continuous search domains. For example, SFLA was originally used for discrete search domains, and FA was originally used for continuous search domains.

The row labeled "Convergence speed" indicates whether the algorithm typically has slow or fast convergence. For example, GSO has slow convergence, and DE has fast convergence.

The row labeled "Application of original formulation" indicates the type of problem for which the algorithm was initially developed. For example, SFLA initially obtained good performance for combinatorial optimization problems, and GSO initially showed good performance for multimodal optimization problems.

The availability of these different algorithms provides an attractive set of alternate optimization methods. The variety of algorithms provides the possibility of application to different types of problems, and for useful applications contributions to the algorithm literature.

III. Modifications of BBO

In order to improve performance, different variants of standard BBO have been suggested based on modifications and parameter tuning, and a discussion of these modifications is provided in this section.

A. *Migration-Based Modifications*

The desire to improve BBO performance leads to the modification of migration using biogeography concepts or the evolution operators of other EAs. Ma [36] and Ma *et al.* [40] presented various migration models inspired by the migration behaviors of natural systems to improve BBO for numerical optimization. The authors observed that sinusoidal migration offered the best performance among the set of curves that they studied. To overcome the sensitivity that a particular optimization problem might have to the migration model, Ma *et al.* [41] introduced an ensemble method to combine different migration models. Results showed that this ensemble technique outperformed standard BBO on benchmarks. Motivated by migration theory and those results, Ma *et al.* introduced three variations of BBO [42]. They denoted standard BBO as partial immigration-based BBO, and introduced three new BBO variations, which they called total immigration-based BBO, partial emigration-based BBO, and total emigration-based BBO. Simulation results showed that emigration-based BBO performed best for unimodal problems, while immigration-based BBO performed best for multimodal problems. Christy and Raj [43] improved the performance of standard BBO using predator-prey relationships to solve multi-objective optimal power flow problems. The results of their experiments on the IEEE 30-bus test system showed the effectiveness and robustness of their method. A similar strategy was implemented to solve path planning problems

TABLE V
SUMMARY OF THE DIFFERENCES BETWEEN BBO AND OTHER ALGORITHMS THAT WE STUDY

Algorithm	Year introduced	Biological motivation	Search domain of original formulation	Convergence speed	Application of original formulation
ABC	2005	Foraging behavior of bees	Continuous	Slow	Most optimization problems
BBO	2008	Migration behavior of species between islands	Continuous	Fast	Most optimization problems
DE	1997	Candidate solution vector differences	Continuous	Fast	Multimodal optimization problems
FA	2009	Attraction of fireflies to one another	Continuous	Fast	Multimodal optimization problems
GA	1966	Survival of the fittest	Discrete	Slow	Most optimization problems
GSO	2006	Law of gravity	Continuous	Slow	Multimodal optimization problems
PSO	1995	Swarming behavior of birds	Continuous	Slow	Most optimization problems
SFLA	2003	Leaping behavior of frogs	Discrete	Fast	Combinatorial optimization problems

for a three degree of freedom robot manipulator [44] and for an unmanned combat air vehicle (UCAV) [45].

BBO with covariance matrix based migration was developed by Chen *et al.* [46] to lessen the dependence of BBO performance on the coordinate system of the optimization problem. Computational experiments showed that the proposed method outperformed previous BBO algorithms. Feng *et al.* [47] improved the exploration ability of BBO with orthogonal migration, which was motivated by orthogonal crossover in GAs. The authors observed that their method was capable of locating optimal or near-optimal solutions for benchmark functions. Similarly, Vanita and Deep [48] introduced a Laplacian migration operator based on Laplace crossover in real-coded GAs. Simulation results showed that their method was an efficient and reliable algorithm for solving continuous optimization problems. Another modification embedded polyphyletic migration into BBO to enhance exploration [49]. In this work, the authors utilized features from as many as four candidate solutions to construct a more promising solution. Their results proved the superiority of their method over standard BBO. The same authors [50] combined sinusoidal migration with perturbed and blended migration operators to construct a multi-strategy BBO, and experimental results on four economic dispatch problems showed that their method achieved a good trade-off between exploration and exploitation.

B. Mutation-Based Modifications

The attempt to improve BBO has led to modification of the mutation component of BBO, borrowing from the mutation operators of other EAs. In order to improve population diversity and enhance BBO's capacity for exploration, Gong *et al.* [51] integrated three mutation operators into BBO and showed the superiority of their methods over standard BBO. Bansal [52] incorporated polynomial mutation into blended BBO to improve performance. Results confirmed that the proposed approach outperformed standard BBO and other BBO variants. Mutation strategies from DE and chaos theory were used in BBO in [53]. When the performance of the new BBO algorithm was evaluated on model parameter estimation problems of two types of solar and fuel cells, results demonstrated superiority over previous BBO algorithms. Lohokare *et al.* [54], [55] accelerated the convergence of BBO using a modified mutation function in which neighborhood mutation from DE was embedded into BBO. In their study, migration was kept the same as in standard BBO to maintain exploitation, and modified mutation was used to improve exploration. When the authors evaluated the performance of their proposed method on benchmarks and economic load dispatch problems, it was found that their modified BBO outperformed standard BBO. In other research, opposition learning and chaotic maps were employed in BBO to control and synchronize chaotic systems [56]. The modification was aimed at improving the global convergence of BBO. Comparisons with other algorithms demonstrated the effectiveness of the new technique.

C. Other Modifications

Opposition-based learning (OBL) has often been employed in EAs to improve performance. Ergezer *et al.* [57] were the first to use OBL to create oppositional BBO. The authors proved that their method outperformed BBO relative to success rate. In other research, a new opposition-based learning method called quasi-opposition was incorporated in BBO [58] and applied to the optimal power flow problem. Experimental results showed that the new method outperformed other methods relative to convergence rate and global search. Guo *et al.* [59] designed a novel method called backtracking BBO in which a secondary external population was employed to record historical solutions. The secondary population and the regular population were combined to create the next generation's population, which enhanced the algorithm's ability to explore the solution space. Results showed that the method was competitive when solving global optimization benchmark functions. Grouping BBO was developed to solve the location area planning problem by Kim *et al.* [60], in which group migration and mutation approaches were used to preserve population groups. Experimental results showed that their novel approach was robust in finding the best configurations for location area planning with much less computation time than other methods. Zheng *et al.* [61] provided BBO with different topologies (including ring, square, and random) to limit migration, to improve search ability, and to premature convergence. Benchmark results showed that their approach outperformed previous state-of-the-art optimization algorithms.

IV. HYBRIDIZATIONS OF BBO

The popularity of hybrid approaches in optimization is growing as an effective strategy to improve the performance of classical algorithms by combining components from various optimization methods. Studies have shown that BBO performance can be enhanced through the incorporation of techniques from other meta-heuristics. This section provides a review of hybridization approaches in BBO.

A. Hybridization With Local Search Algorithms

Population-based optimization algorithms like BBO often have good global exploration ability. However, they are often not very efficient at local exploitation. In contrast, local search algorithms are efficient at local exploitation but are not effective at exploring the entire search space. Therefore, hybridization of local search with population-based optimization is a promising way to synergize the advantages of both approaches in a single algorithm. The aim of this type of hybridization is to find the right trade-off between global exploration and local exploitation of the problem search space.

Simon *et al.* [62] presented a linearized version of BBO, called LBBO. The authors introduced local search and periodic re-initialization to BBO. Experiments conducted on 45 benchmark functions showed that their method provided competitive performance with state-of-the-art EAs. The method performed especially well for certain types of multimodal problems. Albasri *et al.* [63] proposed hybrid BBO with linear programming for the coordination of directional over-current relays, which is a strongly constrained optimization problem. Experimental results showed the effectiveness and superiority of their method relative to other optimization methods. A new hybrid method called Metropolis BBO was presented in [64]. In this study, the authors enhanced performance by combining BBO with simulated annealing (SA), which has more resistance to premature convergence. They tested their algorithm on 36 benchmarks and showed that the hybrid algorithm significantly outperformed both standard BBO and other EAs. The performance of BBO for solving global optimization problems was improved with local search in [65], which incorporated information from multiple solutions to enhance exploration. The authors verified the performance of their method on 27 benchmark functions and found that their method was highly competitive compared to standard BBO, DE and improved BBO. The attempt to trade off exploration and exploitation for the quadratic assignment problem (QAP) led to the introduction of tabu search in BBO [66]. The authors replaced BBO mutation with tabu search. Experimental results showed their method could find good solutions for benchmark instances from QAPLIB with reasonable computational times. Insertion-based local search and a machine-based decoding strategy were introduced by Yang [67] to enhance exploitation for flexible job shop scheduling. Experiments on well-known benchmarks demonstrated the efficiency of the method.

B. Hybridizations With Other Population-Based Algorithms

This section reviews some significant results related to the hybridization of BBO with other population-based algorithms.

Differential evolution (DE) is the most popular population-based algorithm that has been hybridized with BBO, and many authors have used a hybridization called BBO/DE to solve various optimization problems [68]–[72]. Gong *et al.* [73] was the first to use this hybrid method. The authors carefully studied the performance of their method on 23 benchmark functions and found that it had similar or improved performance relative to state-of-the-art DE methods. Application of this combination of BBO and DE for economic emission load dispatch (EELD) was proposed in [74], [75]. Results showed that the method was effective for solving practical EELD problems. Wireless sensor network power allocation was solved with BBO/DE in [76], where the objective was to minimize the power consumed by a sensor network with a specified performance constraint. The proposed algorithm was demonstrated on several case studies, and results clearly demonstrated that the approach outperformed standard BBO and DE. The same authors modified this hybrid method using a two-stage update strategy to preserve fitter solutions for subsequent generations, and tested the algorithm on benchmark functions [77]. A similar strategy was implemented to design a neuro-fuzzy network for online earthquake victim classification by Zheng *et al.* [78].

BBO is also often hybridized with other population-based algorithms. For example, BBO has been hybridized with evolutionary strategy (ES) [79], ant colony optimization (ACO) [80], particle swarm optimization (PSO) [81], [82], artificial immune algorithm (AIA) [83], harmony search (HS) [84], krill herd (KH) algorithm [85], fireworks algorithm (FA) [86], bacterial foraging algorithm (BFA) [87], and clonal selection algorithm (CSA) [88]. All of these papers successfully demonstrated their algorithms on benchmark functions and real-world applications.

C. Hybridizations With Other Algorithms

Jayaraman and Ravi [89] presented a hybrid of neural networks and BBO for sector-oriented electrical energy forecasting. The authors trained artificial neural networks with BBO to obtain the best weight parameters. They showed that their hybrid method can effectively forecast long-term sector-oriented electrical energy. Similarly, a hybrid algorithm called WPNN-BBO was proposed by Krishnasamy and Nanjundappan [90] to hybridize a weighted probabilistic neural network with BBO for economic dispatch as applied to integrated multiple-fuel and wind power plants. The effectiveness of the proposed approach was demonstrated by comparing results with those of existing methods in the literature. Another novel hybrid method integrated a parallel fuzzy system (PFS) and non-homogenous BBO (NHBBO) for radio access technology (RAT) selection in wireless networks [91], where the PFSs were used to calculate the probability of RAT selection, which was then input to NHBBO. Results demonstrated that the hybrid method was more efficient and more robust than other methods.

V. Applications of BBO

The literature reports numerous applications of BBO to benchmarks and practical optimization problems. Simon applied the original BBO algorithm to benchmark functions and aircraft engine sensor selection in 2008 [13] and compared performance against seven well-known algorithms. Results proved that BBO outperformed the existing algorithms and could efficiently solve most of the benchmark functions. This section first provides a summary of optimization problem categories: continuous, combinatorial, constrained, multi-objective, and noisy optimization. Then we review the application of BBO to various branches of science and engineering.

A. Optimization

1) Continuous Optimization: Most BBO publications, for example [92]–[96], were applied to well-known continuous benchmark functions. Zheng *et al.* [97] presented a BBO variation called ecogeography-based optimization for continuous optimization, where the population of solutions was regarded as an ecological system. Two novel migration operators – global and local migration – were designed to enhance exploration and exploitation, and mimicked species dispersal. The authors proved that their method outperformed BBO and other EAs. In other research, Shahrzad and Mirjalili [98] employed BBO and chaos theory for solving optimization problems; a chaotic operator was used to improve the performance of BBO relative to both local optima avoidance and speed of convergence. Simulation on 10 benchmark functions showed that their method had highly competitive performance. Laplacian BBO to solve the CEC 2014 continuous optimization benchmarks was developed in [99], where a migration operator based on Laplace crossover in real-coded GAs was introduced to improve performance. Simulations showed that their proposed method was an efficient and reliable algorithm to solve continuous optimization problems. In other research, multi-operator BBO, MOBBO, was used to solve 23 benchmarks with various dimensions and levels of complexity [100]. Simulation results demonstrated that MOBBO outperformed BBO and other EAs.

2) Combinatorial Optimization: BBO has also been used to solve combinatorial problems. Crawford *et al.* [101] adopted BBO to solve the set covering problem (SCP), a classic NP-hard problem, to find solutions that satisfied various criteria with low cost. They discovered that BBO was quite good for such problems. Ergezer and Simon [102] employed oppositional BBO to tackle the traveling salesman problem (TSP). Experiments on TSP benchmarks showed that opposition in BBO improved performance. The introduction of quantum concepts into BBO to solve knapsack problems was presented by Tan and Guo [103], in which multiple quantum probabilities were used to enhance the evolution of probability models towards better solutions. Results on classic 0/1 knapsack problems showed that their modified version was better than original BBO. A similar study that adopted BBO for solving knapsack problems was proposed by Zhao *et al.* [104]. Array thinning is a common discrete-valued combinatorial optimization problem, and Goudos *et al.* [105] designed large thinned arrays using BBO, and results showed that BBO generally performed better than other algorithms.

3) Constrained Optimization: The first application of BBO to constrained optimization was presented by Ma *et al.* [106], who used blended BBO on the CEC 2005 constrained benchmarks. When BBO performance was compared against other optimization algorithms, it was seen that BBO found the best known solutions. The performance of BBO was investigated for constrained problems by using a feasibility-based selection procedure to preserve fitter solutions for subsequent generations [107]. In other research, Long *et al.* [108] employed hybrid BBO to solve constrained optimization problems. Their method was based on an augmented Lagrangian multiplier, and the authors proved that their method had performance comparable to other methods. A similar strategy was implemented to solve the same constrained benchmark functions by Mi *et al.* [109]. Bi and Wang [110] designed a new epsilon constrained BBO algorithm to solve constrained optimization problems. In their work, the epsilon constraint was used with a novel ordering rule to obtain BBO migration rates. The results of the simulation demonstrated that their proposed method had satisfactory performance on 13 well-known constrained benchmark functions. An application of constrained BBO was presented by Shah *et al.* [111] for invariant set computation, which has applications in many constrained control problems. In their study, three such problems, including maximum invariant ellipsoid approximation, maximum invariant semi-ellipsoid approximation, and maximum invariant cylinder approximation, were used to test the constrained optimization ability of BBO. The authors found that BBO outperformed linear matrix inequality method for these problems.

4) Multi-Objective Optimization: Ma *et al.* [112] extended BBO to multi-objective optimization to create biogeography-based multi-objective optimization (BBMO), which made use of the clustering property of the solutions to decompose the problem. The algorithm used non-dominated sorting to improve convergence ability, and employed a crowding metric to ensure Pareto-optimal solution diversity. Computational experiments showed that their method worked better than other methods. Jamuna and Swarup [113] developed multi-objective BBO for the placement of optimal phasor measurement units (PMUs) to make power system networks completely observable. A similar study was conducted on optimal power flow problems [114], and it was found that multi-objective BBO provided promising performance on test problems. Costa *et al.* [115] formulated a multi-objective BBO algorithm by using a predator-prey approach. Optimal design of a brushless DC motor was conducted by the authors to test the performance of their method, and showed that their method was better than existing ones in terms of solution quality and Pareto dominance. Non-dominated sorting BBO, NSBBO, was presented in [116] for tuning a proportional-derivative controller for a six degree of freedom robotic manipulator PUMA 560. Results showed the effectiveness of this multi-objective algorithm for optimizing the control parameters and minimizing the tracking error.

5) Noisy Optimization: Many real-world problems are noisy optimization problems. Ma *et al.* [26] applied BBO to optimize problems for which the fitness function was affected by stochastic noise. The noise interfered with the BBO migration rates, and harmed optimization performance. In their work, the authors analyzed the effect of random noise with a Markov model, and then incorporated fitness re-sampling, which evaluated the fitness of each candidate solution multiple times and averaged the results to ameliorate the effects of noise. The experimental results showed that BBO performed as well as DE, and better than PSO and GA for noisy benchmark functions. The results also showed that re-sampling BBO achieved almost the same performance as Kalman filter-based BBO (KBBO) but required less computational time. Applications of oppositional BBO were presented by Rashid *et al.* [117], [118] for reconstructing human thorax organ boundaries via electrical impedance tomography. In their work, the measurement noise of electrical impedance tomography led to premature convergence. The proposed method was used to estimate the correct solution. The effectiveness of BBO was verified using suitable datasets, and the results of the study showed that their method outperformed the extended Kalman filter. Li and Low [119] presented BBO for online parameter monitoring with low sampling rates for DC-DC converters, in which parameter identification accuracy was degraded due to measurement noise. Simulations and experiments demonstrated that their method improved the parameter estimation under various measurement noise levels.

B. Engineering Applications

1) Applications to Power Systems: Various versions of BBO have been applied to power system problems, which comprise some of the most important areas of engineering practice [120]–[127]. BBO for power management and economic analysis of an autonomous hybrid power system (SAHPS) was discussed in [128], in which the optimization task was to minimize the cost of SAHPS under the constraint of energy availability. Their method demonstrated good convergence and low computational requirements. Bhattacharya and Chattopadhyay [129]–[131] applied various BBO algorithms to tackle complex economic load dispatch (ELD) problems with constraints related to ramp rates, transmission loss, multi-fuel options and disallowed operating zones. The authors concluded that their approach was promising for practical ELD problems. A similar study that adopted BBO for solving optimal power flow problems was presented by the same authors in [132]. In other research, Xiong *et al.* [50] employed multi-strategy ensemble BBO to solve economic dispatch problems in which three migration model extensions were integrated into BBO as motivated by the no free lunch theorem. The authors proved that their method was able to obtain a good trade-off between exploration and exploitation. The same authors [133] published a similar study which employed polyphyletic migration and orthogonal learning in BBO to solve the dynamic economic dispatch problem with valve-point effects. Similar studies were evaluated in [134]–[139], and it was found that BBO showed promising performance on economic and emission dispatch problems. Kumar *et al.* [140] studied the performance of BBO for power management of a wind/photovoltaic hybrid energy plant. Simulation results demonstrated that their algorithm was more effective than other optimization approaches.

2) Applications to Parameter Estimation and Control: BBO is an important optimization tool for parameter estimation and control. Wang and Xu [141] used hybrid BBO to estimate the parameters of a chaotic system, which is an important problem in nonlinear science and computational math. Experiments with chaotic systems demonstrated the effectiveness of the algorithm relative to other methods. Thomas *et al.* [142] adopted BBO for an automotive camshaft timing system where controls based on radial basis functions were optimized for fuel economy, and computational effort was reduced by optimizing the problem parameterization. BBO for security-constrained state estimation for meter placement was presented by Jamuna and Swarup [143], in which optimal and reliable meter locations were obtained, and the effectiveness of BBO was demonstrated for IEEE standard systems. The challenges of electrochemical machining (ECM) were addressed by BBO in [144], where efficient use of ECM was needed to optimize machine parameters. BBO outperformed other algorithms relative to the optimization of system responses and computational effort. A similar strategy was implemented to select the process parameters of electric discharge machining by the same authors [145]. BBO solved block matching motion estimation in [86]. Results showed that their method was faster than traditional methods for scalable video coding with little sacrifice in rate distortion. Huang and Liu [146] proposed BBO to estimate fault sections in power distribution systems. Kaur [147] applied BBO in cognitive radio systems for optimizing transmission parameters under quality of service constraints, and it was shown that BBO outperformed a GA.

BBO of proportional integral derivative (PID) control for nonlinear plants was presented in [148]. Simulations of a mass-spring damper system and an inverted pendulum showed that BBO gave better results than a GA. BBO was used by Kalaivani and Lakshmi [149] to tune PID parameters for active suspension vibration control, and simulation results indicated significant improvement with BBO. Similar strategies were implemented for similar problems in [150], [151]. Type-2 fuzzy logic control (T2FLC) design with BBO was presented by Sayed *et al.* [152]. T2FLC improved the performance of a plant controller. Results showed that the best possible T2FLC was found by modified BBO. Marine dynamic positioning using active disturbance rejection control (ADRC) was proposed in [153], where BBO was employed to optimize ADRC parameters to improve positioning accuracy.

3) Applications to Scheduling Problems: Scheduling is another important application area for EAs [154]–[156]. Lin [157] proposed a hybrid discrete BBO algorithm called HDBBO which combined the Nawaz, Enscore, and Ham (NEH) heuristic with opposition-based learning and BBO for flow shop scheduling. Computational results and comparisons showed the efficiency of their method. Ensemble multi-objective BBO for automated warehouse scheduling was presented in [158], in which a real-world scheduling problem was presented as a constrained multi-objective optimization problem. The authors compared their method to its constituent algorithms and found that it was an effective approach to the warehouse scheduling problem. A railway scheduling application of BBO was presented by Zheng *et al.* [159], which derived a mathematical model that considered multiple stations requiring supplies, source stations for storing supplies, and allocation stations for providing wagons. The aim of the algorithm was to optimize the time required to deliver supplies to targets in an emergency environment. Computational experiments showed that BBO was scalable and robust, and outperformed other optimization algorithms on several problem instances. A similar study was performed on multi-objective supply chain design with uncertain customer demands and transportation costs [160]. Rabiee *et al.* [161] developed a modified BBO algorithm for hybrid flow shop scheduling to minimize mean tardiness under various assumptions, including machine eligibility, unrelated parallel machines, different ready times and sequence-dependent setup times. Computational results indicated that the method outperformed other algorithms relative to the given criteria.

4) Applications to Data Analysis: Multi-objective binary BBO for feature selection in gene expression data was studied by Li and Yin [162]. In their study, multi-objective BBO was used to select informative genes relevant to the classification goal. Results demonstrated that the method compared favorably to PSO and support vector machines. Similarly, Liu *et al.* [163] employed discrete BBO for feature selection in molecular signatures, which is a complex undertaking that is needed to develop efficient cancer diagnoses and classifications. The algorithm was tested on four breast cancer dataset benchmarks. Constrained binary/integer BBO for feature subset selection was demonstrated on the same dataset by Samaneh *et al.* [164]. Fan *et al.* used BBO for protein prediction [165]. In other research, Hammouri and Abdullah [166] employed BBO for data clustering, which is an important data analysis and data mining tool in many fields and applications. Data clustering aims to find homogeneous sets of objects based on the degrees of similarity and dissimilarity of their attributes. The authors showed that BBO was able to obtain results that compare favorably with well-known data-clustering algorithms. A similar strategy was implemented for the same problem by Kumar *et al.* [167].

5) Applications to Network and Antenna Problems: Challenges in wireless sensor network problems, such as optimal power allocation, were solved by hybridizing BBO with DE [76], where the objective was to minimize sensor network power subject to performance constraints. Their method was tested on several problems and was compared to BBO and DE. Mohamed *et al.* [168] employed BBO for distribution system planning of both low voltage (LV) and medium voltage (MV) networks, using both uniform and non-uniform load densities. Simulation results indicated that BBO provided better performance than PSO and GA. Multi-objective BBO with decomposition was presented in [169] for community detection in dynamic networks. In their method, decomposition was used to simultaneously optimize two objectives in dynamic networks: normalized mutual information and modularity. They demonstrated their method on both synthetic networks and real-world networks.

BBO was proposed by Singh *et al.* [170] to design a Yagi-Uda antenna with a multimodal gain, a challenging problem because of antenna length and spacing dependencies. Experimental results showed that BBO outperformed GA, PSO, and SA. Similar studies that adopted BBO for non-uniform antenna arrays and thinned planar antenna arrays were proposed by the same authors in [171]–[173].

6) Applications to Image Processing: Jasper *et al.* [174] presented BBO with blended migration for natural image enhancement, which is a complex optimization problem in image processing. Experimental results were compared with other approaches and indicated the superiority of BBO. BBO for multi-focus image fusion was presented in [175], where blocks from various images were fused to create a merged image. In their study, the optimal block size was obtained by BBO, and experimental results demonstrated that BBO had good quantitative and visual results. In other research, Gupta *et al.* [176] employed extended BBO for terrain feature classification based on satellite images, and the authors proved that their method was able to extract highly accurate land cover features. A similar study that adopted blended BBO for terrain feature extraction was proposed by Goel *et al.* [177]. Challenges in computer vision problems such as 3D range image modeling were solved by BBO in [178]. Computational experiments were conducted by comparing the performance of BBO with other 3D image registration methods.

7) Applications to Other Problems: There is much literature about the application of BBO to other areas of industrial optimization [179]–[185]. Du and Simon [186] developed a complex system optimization algorithm called BBO/Complex to solve optimization problems with multiple subsystems, multiple objectives, and multiple constraints. Comparisons with three other complex system optimization algorithms on real-world optimization problems showed that BBO/Complex demonstrated good performance. Jalili *et al.* [187] presented a modified BBO method for design optimization of skeletal structures. Numerical results demonstrated that their method was able to obtain competitive results and find optimum designs. Penalty-guided BBO solved reliability redundancy allocation for a series-parallel system under various nonlinear resource constraints [188]. Four reliability redundancy allocation benchmark problems were used to show the competitiveness of their approach. The performance of BBO was investigated for optimal reservoir system operation in [189]. BBO for the optimization of shell-and-tube heat exchanger design was discussed in [190]. Cui *et al.* [191] employed BBO to optimize a polymerization soft-sensor model. Results showed that the optimized model improved the prediction accuracy of conversion rate and velocity. Lastly, BBO has been applied to nonlinear optimization [192], fuzzy differential equations [193], multi-user detection in DS-CDMA systems [194], FIR filter design [195] and makespan and reliability in grid computing systems [196].

VI. Mathematical Theories of BBO

Relative to other population-based optimization algorithms, BBO has obtained significant success. It is not only easy to apply successfully to practical problems in many engineering areas, but it is also supported by significant mathematical analysis. The literature shows that much work has been conducted on mathematical aspects of BBO, which makes it theoretically strong and convincing.

Simon *et al.* [197] derived Markov models for BBO which gave the exact probabilities for all possible population distributions. Furthermore, they provided simulations to verify the models. The same authors also considered the option of elitism in a BBO Markov model [198], and presented analytical and

TABLE VI
MODIFIED VERSIONS OF BBO

Migration-based modifications	Ma [36], Ma *et al.* [40]–[42], Christy and Raj [43], Silva *et al.* [44], Zhu and Duan [45], Chen *et al.* [46], Feng *et al.* [47], Vanita and Deep [48], Xiong *et al.* [49], [50]
Mutation-based modifications	Gong *et al.* [51], Bansal [52], Niu *et al.* [53], Lohokare *et al.* [54], [55], Yang *et al.* [56]
Other modifications	Ergezer *et al.* [57], Roy and Mandal [58], Guo *et al.* [59], Kim *et al.* [60], Zheng *et al.* [61]

TABLE VII
HYBRIDIZATIONS OF BBO

Hybridization with local search algorithms	Simon *et al.* [62], Albasri *et al.* [63], Al-Roomi and El-Hawary [64], Feng *et al.* [65], Wee *et al.* [66], Yang [67]
Hybridization with other population-based algorithms	Rathi *et al.* [68]; Ren and Zhu [69]; Li and Yin [70]; Guha *et al.* [71]; Wang and Wu [72], Gong *et al.* [73], Bhattacharya *et al.* [74], [75], Boussaïd *et al.* [76], [77], Zheng *et al.* [78], Du *et al.* [79], Sinha *et al.* [80], Guo *et al.* [81], Mandal *et al.* [82], Poonam *et al.* [83], Lin [84], Wang *et al.* [85], Zhang *et al.* [86], Lohokare *et al.* [87], Qu and Mo [88]
Hybridization with other algorithms	Jayaraman and Ravi [89], Krishnasamy and Nanjundappan [90], Sangeetha and Aruldoss [91]

numerical comparisons between BBO and GAs based on Markov models [199]. Ma and Simon [200] derived Markov models using different migration models in BBO. Results showed that generalized sinusoidal migration was better than other migration models for the problems that were studied. Simon [201] formulated a BBO dynamic system model that was exact in the limit as population size approached infinity. Simon *et al.* [202] extended standard BBO to distributed learning, called DBBO, and then derived the corresponding exact Markov model. Ma *et al.* [42] investigated mathematical models of variations of BBO, obtained mathematical modeling results, and confirmed the models with simulation. Ma *et al.* [203] also investigated the convergence characteristics of the BBO algorithm for binary problems and showed that they were similar to those of GAs. The advantage of Markov model-based BBO analysis is that when the limit of the generation count reaches infinity, the model reveals the exact probability of arriving at any population given any starting population. Its disadvantage is that the size of the Markov model increases drastically with search space cardinality and population size, which requires large computational efforts and restricts its application to small problems.

Simon [204] presented a simplified BBO algorithm and derived an approximation of the population distribution using random number theory. In that work the probabilistic analysis approximated the number of generations before the best available solution improved, and the average improvement. Ma *et al.* [205] modeled the BBO population dynamics using statistical mechanics theory to describe the population fitness statistics, and confirmed the theory with simulation. The advantage of this method is that it describes the evolution of the statistical properties of the population, rather than trying to exactly predict the evolution of the population. We can use statistical mechanics models of BBO to handle large problems, assuming a knowledge of the cumulants of the fitness distribution and the average fitness correlation within the population. Guo *et al.* [206] utilized a mathematical tool called drift analysis to model the expected value for the first optimum hitting time, and showed that simulation results agreed with the analysis. The advantage of drift analysis is that it reduces the behavior of BBO in a high-dimensional population space to a supermartingale on a one-dimensional space, which is much easier than using the original Markov chain to investigate the expected first hitting time. The same authors [207] also mathematically investigated the impact of migration rates on BBO, and investigated the transition probability matrices of BBO. Simulation results validated their theoretical analysis.

VII. DISCUSSIONS AND CONCLUSIONS

Tables VI–IX summarize the literature review of BBO. The publications in the tables are organized according to algorithmic modifications, hybridizations, applications and theory, as discussed above. The tables show that the growth of BBO is increasing, and every day new BBO publications emerge in various engineering areas. Table X gives BBO web sites and source code for reference and further study.

A. *Suggestions for Future Research*

The development of BBO is diverse and rapidly expanding, but there are still many open research areas. One suggested area for future research is parameter tuning, which is an area that is important for all optimization algorithms. Additional study is needed to tune BBO parameters so that it can more effectively solve a variety of problems. It should also be possible to design automatic schemes so that BBO can adaptively self-tune itself.

Another area for future research is additional mathematical tools for the theoretical analysis of BBO. Table IX shows some previous work in this area, but it is challenging to obtain quantitative results for realistically sized optimization problems using theoretical analyses. Quantitative results such as expected first hitting times for optima, along with theoretical comparisons with other optimization algorithms, could be of great interest to the BBO research community.

Additional research should be pursued to answer the question why BBO works well on certain types of problems, and why it does not work as well on other types of problems. This would

TABLE VIII
APPLICATIONS OF BBO

Optimization	Continuous optimization	Farswan *et al.* [92], Zhang *et al.* [93], Feng *et al.* [94], [95], Wang and Song [96], Zheng *et al.* [97], Shahrzad and Mirjalili [98], Vanita and Kusum [99], Li and Yin [100]
	Combinatorial optimization	Crawford *et al.* [101], Ergezer and Simon [102], Tan and Guo [103], Zhao *et al.* [104], Goudos *et al.* [105]
	Constrained optimization	Ma *et al.* [106], Boussaïd *et al.* [107], Long *et al.* [108], Mi *et al.* in [109], Bi and Wang [110], Shah *et al.* [111]
	Multi-objective optimization	Ma *et al.* [112], Jamuna and Swarup [113], Roy *et al.* [114], Costa *et al.* [115], Chouraqui and Benzater [116]
	Noisy optimization	Ma *et al.* [26], Rashid *et al.* [117], [118], Li and Low [119]
Engineering applications	Power systems	Rarick *et al.* [120], Bhattacharya and Chattopadhyay [121], Ashrafinia *et al.* [122], Jasper and Victoire [123], Kumar and Premalatha [124], Kumar *et al.* [125], [126], Tom and Scaria [127], Bansal *et al.* [128], Bhattacharya and Chattopadhyay [129]–[132], Xiong *et al.* [50], [133], Rajasomashekar and Aravindhababu [134], Roy *et al.* [135]–[138], Kanoongo and Jain [139], Kumar *et al.* [140]
	Estimation and control	Wang and Xu [141], Thomas *et al.* [142], Jamuna and Swarup [143], Mukherjee and Chakraborty [144], [145], Zhang and Yu [86], Huang and Liu [146], Kaur *et al.* [147], Salem and Khelfi [148], Kalaivani and Lakshmi [149], Boghdady *et al.* [150], Sayed *et al.* [151], Sayed *et al.* [152], Wu and Ren [153]
	Scheduling problems	Pu and He [154], Santosa and Safitri [155], Deng *et al.* [156], Lin [157], Ma *et al.* [158], Zheng *et al.* [159], Yang *et al.* [160], Rabiee *et al.* [161]
	Data analysis	Li and Yin [162], Liu *et al.* [163], Samaneh *et al.* [164], Fan *et al.* [165], Hammouri and Abdullah [166], Kumar *et al.* [167]
	Network and antenna problems	Boussaïd *et al.* [76], Mohamed *et al.* [168], Zhou *et al.* [169], Singh *et al.* [170]–[173]
	Image processing	Jasper *et al.* [174], Zhang *et al.* [175], Gupta *et al.* [176], Goel et al. [177], García-Torres *et al.* [178]
	Other problems	Ali and Lee [179], Daoudi, *et al.* [180], Jain *et al.* [181], Xu *et al.* [182], Shafei *et al.* [183], Huang *et al.* [184], Padghan and Mukherjee [185], Du and Simon [186], Jalili *et al.* [187], Garg [188], [193], Haddad *et al.* [189], Hadidi and Nazari [190], Cui *et al.* [191], Zhu [192], Nemade *et al.* [194], Kaur *et al.* [195], Mobini *et al.* [196]

TABLE IX
MATHEMATICAL MODELS OF BBO

Markov models	Simon *et al.* [197]–[199], [202], Ma and Simon [200], Simon [201], Ma *et al.* [42], [203]
Other models	Simon [204], Ma *et al.* [205], Guo *et al.* [206], [207]

TABLE X
BBO WEB SITES AND SOURCE CODE

Web sites	https://en.wikipedia.org/wiki/Biogeography-based_optimization
	http://embeddedlab.csuohio.edu/BBO/
Source code	http://yarpiz.com/239/ypea113-biogeography-based-optimization
	https://www.mathworks.com/matlabcentral/fileexchange/47313
	http://www.alimirjalili.com/Projects.html

provide guidance as to when BBO should be used for certain problems, when it may be better to use other algorithms, and how BBO could be intelligently hybridized for given types of problems.

Additional research should be pursued in the area of effective BBO variations with small population sizes and fast convergence. For many real-world problems a single function evaluation can take several minutes. For other problems a function evaluation could require a physical experiment that takes hours, days, or longer. For these types of problems, EAs such as BBO need to converge within a few hundred function evaluations. How can BBO be modified to obtain good performance with only a few function evaluations?

Additional research should be pursued in the area of BBO hybridization. As reviewed above, BBO has been combined with several other EAs and swarm intelligence algorithms, but there are still other algorithms that have not yet been hybridized with BBO, or whose hybridizations have not yet been explored in any depth.

Another important area for future research is additional applications of BBO. As we have seen from this review, BBO applications are very diverse. The application of BBO to complex optimization problems, including uncertain optimization, many-objective optimization, large-scale optimization, and their combinations, would be of great interest. Many more applications of BBO can emerge with focused research.

Many of these open research questions are common across other fields of computer intelligence. The open questions in BBO research are similar to those in other areas of computer intelligence. Research which is first driven by driven by practical problems, and which is then generalized to broad results and conclusions, has the greatest likelihood to make a strong impact on the field, and so this is the research approach that is recommended for future work in the area of BBO.

B. Summary

This review has summarized the development of BBO during the last 10 years. The review has shown that BBO can be practically applied to virtually any optimization problem domain. BBO has been applied to continuous optimization, combinatorial optimization, multi-objective optimization, constrained optimization, and noisy optimization. BBO is simple, versatile, and flexible, and has proven to be efficient for solving a wide variety of real-world problems. BBO's applications include power system problems, parameter estimation and control, scheduling problems, data analysis, network and antenna problems, image processing and many others. The theoretical foundations of BBO have placed it on a firm mathematical foundation. BBO has proven to be useful to the optimization and engineering community, as well as to researchers who are currently working or will work in these areas.

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