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A dynamic multi-colony artificial bee colony algorithm for multi-objective optimization☆

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ABSTRACT

This paper suggests a dynamic multi-colony multi-objective artificial bee colony algorithm (DMCMOABC) by using the multi-deme model and a dynamic information exchange strategy. In the proposed algorithm, *K* colonies search independently most of the time and share information occasionally. In each colony, there are *S* bees containing equal number of employed bees and onlooker bees. For each food source, the employed or onlooker bee will explore a temporary position generated by using neighboring information, and the better one determined by a greedy selection strategy is kept for the next iterations. The external archive is employed to store non-dominated solutions found during the search process, and the diversity over the archived individuals is maintained by using crowding-distance strategy. If a randomly generated number is smaller than the *migration rate R*, then an elite, defined as the intermediate individual with the maximum crowding-distance value, is identified and used to replace the worst food source in a randomly selected colony. The proposed DMCMOABC is evaluated on a set of unconstrained/constrained test functions taken from the CEC2009 special session and competition in terms of four commonly used metrics EPSILON, HV, IGD and SPREAD, and it is compared with other state-of-the-art algorithms by applying Friedman test on the mean of IGD. The test results show that DMCMOABC is significantly better than or at least comparable to its competitors for both unconstrained and constrained problems.

1. Introduction

In many real-world optimization applications, decision makers (DMs) often have to handle problems with multiple objectives that are conflicting to each other and should be optimized simultaneously, and they are usually called multi-objective optimization problems (MOPs) which are more difficult than one-objective ones since there is no single solution available for them but a set of Pareto-optimal solutions (PS) or non-dominated solutions that represent a trade-off among the objectives.

With the help of some useful techniques, such as objective weighting, method of distance functions or method of min–max formulation, a MOP can be transformed into a single objective problem, and then traditional mathematical programming methods can be applied to deal with it. However, these methods are usually restrained since some objectives may involve noise, discontinuity, concavity and uncertainty in their search space [1]. Alternatively, evolutionary algorithms (EAs) and swarm intelligence (SI) algorithms have been widely extended to find several members of the *PS* of the MOPs in a single run. Among them, Deb's NSGAII [2], Zitzler's SPEA2 [3], Zhang's MOEA/D [4], Tseng's MTS [5], Liu's DMOEADD [6], Liu's LiuLiAlgorithm [7], Kukkonen's GDE3 [8] and Akay's S-MOABC/NS [1] enjoyed more attention.

The island model or multiple-deme model is a very popular scheme used in many EA or SI algorithms [9]. In this model, the algorithms consist of several sub-populations which evolve independently most of the time and exchange members occasionally. The exchange of individuals is called *migration* and often controlled by some parameters [10]. Over the past decades, many algorithms based on island models have been proposed for single-objective optimization problems [11–16]. It was shown by the experimental results that these algorithms not only decreased the processing time but also performed a much broader search than single-population ones.

Recently, modeled as a Markov dynamic system, the island model was theoretically proved to be effective in solving single objective problems [17], and can also be applied to the multi-objective case. In fact, some island model based multi-objective

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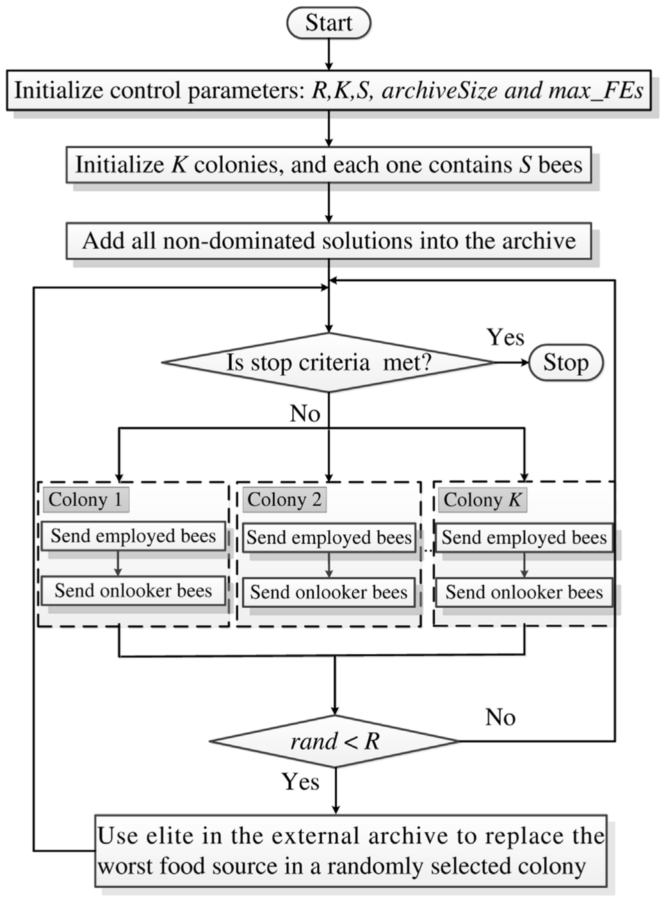
Start
Initialize control parameters: R,K,S, archiveSize and max_FEs
Initialize K colonies, and each one contains S bees
Add all non-dominated solutions into the archive
Is stop criteria met?
Yes
Stop
No
Colony 1
Send employed bees
Send onlooker bees
Colony 2
Send employed bees
Send onlooker bees
Colony K
Send employed bees
Send onlooker bees
rand < R
No
Yes
Use elite in the external archive to replace the worst food source in a randomly selected colony

Fig. 1. The flow chart of the DMCMOABC algorithm.

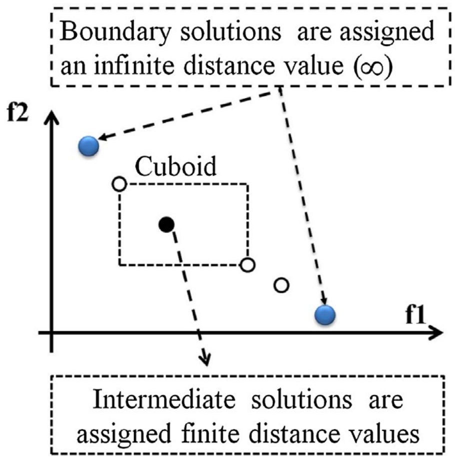
Boundary solutions are assigned an infinite distance value (∞)
f2
Cuboid
f1
Intermediate solutions are assigned finite distance values

Fig. 2. Crowding distance calculation diagramed in a two-dimensional objective space.

evolutionary or SI-based algorithms have already been proposed. Montaño et al. [18] introduced a novel island model based multi-objective evolutionary algorithm: pMODE-LD+SS, where differential evolution (DE) operators were used and two parallel schemes were designed to improve effectiveness as well as efficiency. Cheshmehgaz et al. [19] proposed an effective multiple multi-objective evolutionary algorithms (MOEAs) by using a novel island model where a central island was assisted by multiple VIP islands and a sophisticated immigration strategy was designed to exchange information. Shang et al. [20] suggested a multi-population cooperative coevolutionary algorithm (MPCCA) for Capacitated Arc Routing Problem (CARP). In this algorithm, multiple subpopulations are used to search different objective subregions simultaneously and share individuals with their adjacent subpopulations cooperatively. Zhang et al. [21] proposed a multi-objective parallel evolution algorithm (MPEA) where the migration frequency is dynamically changed according to the diversity of the parent solutions. The algorithm was applied to effectively solve flight assignment problems. Some other island model based multi-objective algorithms can be found in Refs. [22–25].

Some of the above algorithms (e.g., [18,20,25]) divide the whole objective space into several sub-regions by a set of uniformly distributed weight vectors or direction vectors. Then each sub-region is assigned with a sub-population. However, it is not always easy to generate a set of uniformly distributed weight/direction vectors, especially when high-dimensional objective space is considered, and the generation of these vectors needs a recursive procedure [25]. The migration strategy used in most of these algorithms is static, i.e., a sub-population only exchanges individuals with its adjacent sub-populations in terms of the used topological structure. Meanwhile, some immigration strategies (e.g., [18,23–25], etc.) involve frequent re-division operations (central re-collection and re-distribution of all solutions from/to sub-populations [19]). This may be a main drawback since a re-division in distributed systems may affect the efficiency of the algorithm when a high level of parallelization is expected. Contrarily, this paper suggests a new island model where each island is equivalent and shares individuals with other islands dynamically. In this model, the migration is realized by using an elite pool (also known as the archive where non-dominated solutions are stored during the search process) and an island exchanges individuals with all other islands randomly. What is more, the proposed model involves no central re-collection, re-division and re-distribution operations.

Based on the proposed island model, a dynamic multi-colony multi-objective artificial bee colony algorithm (DMCMOABC) is suggested in this paper. For each island, the artificial bee colony (ABC) algorithm first proposed by Karaboga [26], is selected as the

```
Send employed bees in each colony
1.  For $i \leftarrow 1$ to $FN$
2.      For $\vec{X}_i$, randomly select a neighbor $\vec{X}_k$
3.      Calculate the position $\vec{V}_i$ by using $\vec{X}_i$ and $\vec{X}_k$ with Eq. (4)
4.      Work out $\vec{F}(\vec{V}_i) = (f_1(\vec{V}_i), f_2(\vec{V}_i), \ldots, f_M(\vec{V}_i))$
5.      /* Select a candidate between $\vec{V}_i$ and $\vec{X}_i$
          by using domination comparator */
6.      If $(\vec{V}_i \prec \vec{X}_i)$ // $\vec{V}_i$ dominates $\vec{X}_i$
7.          $\vec{X}_i \leftarrow \vec{V}_i$; $\vec{F}(\vec{X}_i) \leftarrow \vec{F}(\vec{V}_i)$
8.          archive.add $(\vec{V}_i)$
9.      ElseIf $(\vec{V}_i \triangleq \vec{X}_i)$ // $\vec{V}_i$ and $\vec{X}_i$ are non-dominated
10.         If (archive.add $(\vec{V}_i)$ = true)
11.             $\vec{X}_i \leftarrow \vec{V}_i$; $\vec{F}(\vec{X}_i) \leftarrow \vec{F}(\vec{V}_i)$;
12.         Else
13.             Do nothing
14.         End If
15.     Else $(\vec{X}_i \prec \vec{V}_i)$ // $\vec{V}_i$ is dominated by $\vec{X}_i$
16.         $\vec{V}_i$ is discarded
17.     End If
18. End For
19. Call computeFitness() to get fitness value of each food source
End of Send employed bees
```

Fig. 3. The pseudo code of *send employed bees*.