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A multi-population harmony search algorithm with external archive for dynamic optimization problems

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ABSTRACT

Dynamic optimization problems present great challenges to the research community because their parameters are either revealed or changed during the course of an ongoing optimization process. These problems are more challenging than static problems in real-world applications because the latter are usually dynamic, with the environment constantly subjected to change or the size of a problem increasing sporadically. In solving dynamic optimization problems in the real world, proposed solutions should be able to monitor the movement of the optimal point and the changes in the landscape solutions. In this paper, a multi-population harmony search algorithm with external archive for dynamic optimization problems is proposed. Harmony search algorithm is a population-based meta-heuristic optimization technique that is similar to a musical process when a musician is attempting to find a state of harmony. To tackle the problem of dynamism, the population of solutions is divided into several sub-populations such that each sub-population takes charge exploring or exploiting the search space. To enhance the algorithm performance further, an external archive is used to save the best solutions for later use. These solutions will then be used to replace redundant solutions in the harmony memory. The proposed algorithm is tested on the Moving Peak Benchmark. Empirical results show that the proposed algorithm produces better results than several of the current state-of-the-art algorithms.

1. Introduction

Optimization deals with finding the best solution(s) for a given problem, with the goal of minimizing or maximizing the given fitness functions [26]. Optimization problems are encountered in fields such as engineering, planning, scheduling, medicine, and computer science [26]. Optimization problems are categorized as either static or dynamic [26,27]. In static optimization problems, the goal is to find the global optima. In contrast, the goal of dynamic optimization problems is not only to find the global optima but also to monitor the changes that usually occur during the optimization process. Dynamic optimization problems are more challenging than static problems.

Over the years, many population-based methods inspired from natural or biological evolution processes have been applied to solve many real world problems [41,42,44]. Moreover in the last decade, population-based methods were proven

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to be valuable for solving dynamic optimization problems [5–7,11,37] because such methods deal with a population of solutions scattered over the entirety of a search space. This feature helps population-based methods keep track of changes by assigning each solution from the population to a different area in the search space [6].

The most notable challenge in solving dynamic optimization problems is controlling the solution diversity. Thus, the population-based methods proposed in literature are combined with several mechanisms (e.g., memory or multi-population mechanism) to maintain population diversity [8,33], which is the main factor that must be controlled when handling dynamic optimization problems. For example, Branke [8] proposed a multi-population evolutionary algorithm called Self-Organizing Scouts (SOS) to solve the Moving Peaks Benchmark (MPB). In the algorithm, the population was divided and categorized into two subgroups: small and large. The goal of the smaller populations was to keep track of the most promising peaks over time while the larger population continuously searched for new peaks. The proposed algorithm showed positive results when tested on the MPB. Blackwell and Branke [3,4] proposed a multiswarm Particle Swarm Optimization, where the swarm was divided into a mutable interacting subset of swarms. The swarms interacted locally by exchanging information regarding algorithm parameters. They interacted globally based on an anti-convergence mechanism that attempted to remove the worst swarm from its peak and re-initialize it in the search space. Their proposed algorithm obtained excellent results when tested on the MPB. Yang and Li [36] proposed a clustering particle swarm optimizer for the MPB. Their algorithm employed a hierarchical clustering method to locate and track multiple peaks. This method also achieved positive results.

Motivated by the success of the above mentioned methods, the present study proposes a new population-based method based on the Harmony Search Algorithm (HSA) for dynamic optimization problems. HSA is a recently developed population stochastic search algorithm that simulates the rules when a musician is playing music. HSA has been used to successfully solve a number of static optimization problems [17,18,22,30,32,39,43] and, considering its applicability for solving dynamic optimization problems, is a worthwhile endeavor. To employ HSA for dynamic optimization problems, we propose a multi-population-based HSA with external archive (MHSA-ExtArchive). The entire population is divided into several sub-populations based on the quality of solutions. Furthermore, the main role of the external archive is to retain the best solutions as a replacement for the redundant ones in the population.

The proposed algorithm is tested on the well-known MPB problem, which has been widely used by other researchers [1,5,8,12,36]. To verify the effectiveness of our proposed algorithm, its performance is compared with other approaches in the literature. Experimental results show that the proposed algorithm obtains excellent results on a different number of peaks and outperforms others in some instances. The following are the main contributions of this study:

i. It investigates the ability of the HSA to solve a dynamic optimization problem.
ii. It proposes a multi-population-based harmony search algorithm (MHSA) to maintain population diversity.
iii. It integrates the MHSA with an external archive, which saves the best solutions found in the past to replace the redundant solutions in the population in the future.

The remainder of the paper is organized as follows: Section 2 elaborates the details of the algorithm; Section 3 focuses on an experimental study; Section 4 focuses on a computation complexity; and finally, Section 5 presents brief concluding comments.

2. Proposed algorithm

This section gives a detailed account of the basic HSA for dynamic optimization problems, followed by a discussion on the MHSA-ExtArchive.

2.1. Harmony search algorithm

HSA is population-based algorithm proposed by Geem and Kim [16]. It mimics a musician attempting to find a pleasing harmony determined by an esthetic standard. HSA can be represented as an optimization method that seeks a global optimal solution assessed by the fitness function.

Assume that we have three musicians playing different musical instruments, for example, a saxophone, a double bass, and a guitar, with each instrument respectively corresponding to a decision variable (x_1, x_2, x_3). The pitch ranges of each instrument (saxophone = {La, Si, Do}; double bass = {Do, Re, Mi}; guitar = {Mi, Fa, Sol}) correspond to each variable value (x_1 = {1.2, 3.2, 2.1}; x_2 = {3.2, 3.4, 2.8}; and x_3 = {1.7, 3.8, 3.3}). In the optimization process, each musician represents an individual decision variable. Therefore, if the saxophonist selects La, the double bassist selects Do, and the guitarist selects Mi, the new harmony will be (La, Do, and Mi). This new harmony is evaluated by esthetic standards. As in the optimization process, assuming that the selected values for the decision variables are 1.2, 3.2, and 1.7, respectively, then the generated solution will be (1.2, 3.2, and 1.7). This new solution will be measured by the fitness function. HSA consists of the following five steps:

2.1.1. Step 1: Initializing the algorithm parameters

The main parameters of HSA are Harmony Memory Size (HMS), Harmony Memory Consideration Rate (HMCR), Pitch Adjustment Rate (PAR), Bandwidth (*bw*), and Number of Improvisations (NI). HMS represents the number of solution vectors