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Entropy-based bare bones particle swarm for dynamic constrained optimization

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A B S T R A C T

This paper proposes an entropy-based bare bones particle swarm for solving dynamic constrained optimization problems. The Shannon's entropy is established as a phenotypic diversity index and the proposed algorithm uses the Shannon's index of diversity to aggregate the global-best and local-best bare bones particle swarm variants. The proposed approach applies the idea of mixture of search directions, using the index of diversity as a factor to balance the influence of the global-best and local-best search directions. High diversity promotes the search guided by the global-best solution, with a normal distribution for exploitation. Low diversity promotes the search guided by the local-best solution, with a heavy-tailed distribution for exploration. A constraint-handling strategy is also proposed, which uses a ranking method with selection based on the technique for order preference by similarity to ideal solution (TOPSIS) to obtain the best solution within a specific population of candidate solutions. Mechanisms to detect changes in the environment and to update particles' memories are also implemented into the proposed algorithm. All these strategies do not act independently. They operate related to each other to tackle problems such as: diversity loss due to convergence and outdated memories due to changes in the environment. The combined effect of these strategies provides an algorithm with ability to maintain a proper balance between exploration and exploitation at any stage of the search process without losing the tracking ability. An empirical study was carried out to evaluate the performance of the proposed approach. Experimental results show the suitability of the algorithm in terms of effectiveness to find good solutions for the benchmark problems investigated. Finally, an application is developed where the proposed algorithm is applied to solve the dynamic economic dispatch problem in power systems.

1. Introduction

Dynamic constrained optimization problems (DCOPs) form a class of problems where the objective function or the constraints can change over time. In static optimization problems, finding a global optimum is considered as the main goal. In dynamic environments, the goal is not only to find an optimal solution but also track its trajectory as closely as possible over time. Changes in the environment must be taken into account during the optimization process in such way that these problems are to be solved online [1–7].

In DCOPs, the objective function and the constraints can be combined in three different ways: (1) both the objective function and the constraints are dynamic; (2) the objective function is dynamic and the constraints are static; (3) the objective function is static and the constraints are dynamic. If the objective function changes over time, this can affect the location of the global optimum. For example, it can move from one disconnected feasible subregion of the search space to another one. If the constraints are dynamic, this can affect the structure of the feasible region. For example, the size and the shape of the feasible region and possibly the number of disconnected feasible subregions can change over time. In problems with fixed objective function and dynamic constraints, a change in the feasible region can expose a new global optimum without changing the existing optimum. In addition, DCOPs might also have the common characteristics of constrained problems such as: global optima in the boundaries of feasible regions and multiple disconnected feasible subregions constituting the feasible region. Regardless of the scenario to be considered, DCOPs are difficult problems.

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To deal with DCOPs, optimization algorithms must be able to detect changes in the environment and efficiently respond to the changed environment. Algorithms must be capable of maintaining a good balance between exploration (diversification) and exploitation (intensification). Too much stress on exploration would result in pure global search and slow convergence speed. On the other hand, too much stress on exploitation would result in pure local search and fast loss of tracking ability (traceability).

Nguyen et al. [8] reported an in-depth survey of the state-of-the-art of academic research on evolutionary computation to deal with dynamic optimization problems (DOPs). Richter and Yang [9] developed a comparative study by discussing analytical and evolutionary approaches for DOPs that occur in dynamic programming, optimal control, and evolutionary optimization.

In the literature on dynamic optimization, many algorithms have been designed and tested on dynamic unconstrained optimization problems [10–18]. Most of these approaches have been tested on the moving peaks benchmark problem proposed by Branke [19]. However, new algorithms have been developed recently to solve DCOPs [1–6].

Liu [1] developed one of the first studies in this field and proposed three benchmark problems called DCT 1, 2, and 3, respectively. Liu introduced an approach based on particle swarm optimization (PSO) for DCOPs. The DCT benchmark problems consider the time variable as the only time-dependent parameter. Therefore, the dynamic is created by simply increasing this variable. The performance of the proposed algorithm by Liu was empirically tested on the DCT benchmark problems.

Nguyen and Yao [2–4] studied the characteristics that might make DCOPs difficult to solve by some existing dynamic optimization and constraint-handling algorithms. Nguyen and Yao also introduced a set of benchmark problems, named G24 set, with these characteristics and tested different versions of genetic algorithms (GA) on these problems, including some new variants proposed by the authors themselves. The DCT benchmark problems differ from the G24 benchmark set in the following aspects: (1) the DCT problems only capture linear change, while problems in the G24 set depend on parameters that are time-dependent functions determining how the objective function and the constraint functions change over time; (2) unlike the G24 benchmark set, the DCT problems do not reflect common situations like dynamic objective and fixed constraints, fixed objective and dynamic constraints, and other common properties of DCOPs.

Aragón et al. [5] investigated the behavior of an adaptive immune system for solving DCOPs. The approach proposed by Aragón and co-authors is called dynamic constrained TCell (DCTC) and it is an adaptation of an existing algorithm, which was originally designed to solve static constrained problems. The performance of DCTC was compared with respect to two GA-based approaches tested on the G24 benchmark set.

Pal et al. [6] introduced a new approach for DCOPs, combining the gravitational search algorithm (GSA) with a modified version of the repair method (GSARepair). GSARepair was also tested on the G24 benchmark set and its performance was compared with respect to several GA-based approaches tested on this benchmark set.

Li and Yang [20] presented a review of different approaches based on PSO for DOPs. In fact, PSO has been applied as an effective tool to solve many global optimization problems: there are variants of PSO for unconstrained optimization [21–28] and for constrained optimization [29–32]. However, there are difficulties to apply PSO to solve DOPs. The difficulties lie in two important aspects: diversity loss due to convergence and outdated memories due to changes in the environment. The second difficulty can be solved by re-evaluating particles over time. However, it is hard to solve the diversity loss issue due to the difficulty of balancing the exploration and exploitation during the search process. Hence, to address the diversity loss issue, different kinds of approaches have been proposed to enhance the performance of PSO in dynamic environments. As mentioned, Li and Yang [20] discussed several approaches based on PSO for dynamic optimization and categorized the main ideas in different groups in terms of their main characteristics: diversity maintaining schemes, multi-population schemes, adaptive schemes, and hybrid schemes. Memory schemes to tackle diversity loss have rarely been studied in PSO, since each particle in the swarm has its own memory.

Bare bones PSO (BBPSO) is a variant of PSO originally introduced by Kennedy [33] for unconstrained optimization. BBPSO uses a probability distribution (for instance, a normal distribution) to update the position of a particle instead of adding a velocity in the current position as is done in PSO. The parameters of the distribution are defined in terms of the information contained into the memory of the particle, operating as a self-adaptive mechanism to select a new position in the search space. BBPSO has been investigated by many researchers and new variants have been proposed [25,34–39]. In fact, BBPSO is a swarm algorithm that has shown potential to solve optimization problems in static environments, but until recently it has not been adapted to deal with DCOPs.

This paper proposes an entropy-based BBPSO for solving DCOPs. The Shannon's entropy [40] is established as a phenotypic diversity index and the proposed algorithm uses the Shannon's index of diversity to aggregate the global-best and local-best bare bones particle swarm variants. The proposed approach applies the idea of mixture of search directions, using the index of diversity as a factor to balance the influence of the global-best and local-best search directions. High diversity promotes the search guided by the global-best solution, with a normal distribution for exploitation. Low diversity promotes the search guided by the local-best solution, with a heavy-tailed distribution for exploration. This dynamic rule works as a mechanism to maintain and introduce diversity during search process. A constraint-handling strategy is also proposed. It treats the objective function and the constraints separately using a ranking method with selection based on TOPSIS (technique for order preference by similarity to ideal solution) [41,42] to obtain the best solution within a specific population of candidate solutions. This constraint-handling strategy balances the objective function against the degree of constraint violation in such a way that neither of them is dominant. Mechanisms to detect changes in the environment and to update the particles' memories are also implemented into the proposed algorithm. The mechanism to detect changes in the environment is based on a fixed set of detectors uniformly distributed in the search space [43,44]. The population of detectors differs fully from particles that constitute the swarm, which means that our mechanism is not based on performance drop. When a change in the environment is detected, a random-immigrants scheme acts to introduce diversity. Part of the swarm is replaced with randomly generated particles and this strategy acts only on the first iteration of the changed environment. Re-evaluation of fitness values and the ranking method combined with TOPSIS are used to update the particles' memories.

In summary, the proposed algorithm, named as EBBPSO-T, is endowed with mechanisms to maintain and introduce diversity, handling constraints, detect changes in the environment, and update memories. It is important to emphasize that these mechanisms do not act independently. They operate related to each other to tackle problems such as: loss of diversity, outdated memories, and loss of tracking ability. The main contribution of this paper is to provide an adaptation of the BBPSO to deal with DCOPs using an estimator of the Shannon's index of diversity as a decisive factor to maintain the proper balance between diversification and intensification at any stage of the search process without loss of traceability. The usage of the selected estimator is motivated by a discussion about