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Multiple learning particle swarm optimization with space transformation perturbation and its application in ethylene cracking furnace optimization

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ABSTRACT

This paper proposes a new variant of particle swarm optimization (PSO), namely, multiple learning PSO with space transformation perturbation (MLPSO-STP), to improve the performance of PSO. The proposed MLPSO-STP uses a novel learning strategy and STP. The novel learning strategy allows each particle to learn from the average information on the personal historical best position (*pbest*) of all particles and from the information on multiple best positions that are randomly chosen from the top 100*p*% of *pbest*. This learning strategy enables the preservation of swarm diversity to prevent premature convergence. Meanwhile, STP increases the chance to find optimal solutions. The performance of MLPSO-STP is comprehensively evaluated in 21 unimodal and multimodal benchmark functions with or without rotation. Compared with eight popular PSO variants and seven state-of-the-art metaheuristic search algorithms, MLPSO-STP performs more competitively on the majority of the benchmark functions. Finally, MLPSO-STP shows satisfactory performance in optimizing the operating conditions of an ethylene cracking furnace to improve the yields of ethylene and propylene.

1. Introduction

Research on optimization has been highly active in various engineering and science problems, such as in structural design, scheduling, and economic dispatch. As the complexity of the problems increases, traditional optimization algorithms may no longer satisfy problem requirements and consequently entail new effective algorithms. Over the last decades, various meta-heuristic algorithms have been developed as feasible and effective methods for optimization problems. Based on the number of solutions generated in each iteration, meta-heuristic algorithms can be divided into two main categories: individual-based and population-based [1]. For individual-based algorithms, such as Tabu Search (TS) [2] and Simulated Annealing (SA) [3], they start and perform the search process by single solution, thus less computational cost is needed but suffer from premature convergence. In contrary, population-based algorithms can efficiently discourage premature convergence since multiple solutions are involved during the search process. However, the computational cost of population-based algorithms is higher than algorithms with single solution. Many of population-based algorithms, such as Genetic Algorithms (GA) [4], Ant Colony Optimization (ACO) [5], Particle Swarm Optimization (PSO) [6], Artificial Bee Colony (ABC) [7], Gravitational Search Algorithm (GSA) [8], Teaching-Learning-Based Optimization (TLBO) [9–11], and Fruit Fly Optimization (FFO) [12,13], have been successfully implemented in practical problems.

The abovementioned algorithms can solve many challenging real-world problems. However, according to “No Free Lunch” theorem [14], as no single meta-heuristic algorithm is yet able to achieve optimal results for all optimization problems, researchers are currently investing significant efforts to further improve existing algorithms or develop new algorithms inspired by natural phenomena. Some of the recently developed algorithms include Grey Wolf Optimizer (GWO) [15], Ant Lion Optimizer (ALO) [16], Multi Verse Optimizer (MVO) [17], Black Hole (BH) [18], Dragonfly Algorithm (DA) [19], Social Spider Algorithm (SSA) [20], Search Group Algorithm (SGA) [21], Ions Motion Optimization Algorithm (IMO) [22], Charged System Search (CSS) [23], and Moth-Flame Optimization (MFO) [1].

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PSO marks one of the most popular classes of nature-inspired optimizers and has its root in artificial life and social psychology. PSO does not require any information on the gradient of the function to be optimized. It uses only primitive mathematical operators and is conceptually simple. As such, PSO has rapidly progressed in recent years and has been successfully applied in diverse areas of science and engineering, such as in artificial neural networks [24–26], power systems [27–29], electricity markets [30,31], and other fields [32–36]. Similar to other population-based optimization techniques, PSO algorithms are subjected to performance evaluation in terms of two critical criteria, namely, convergence speed and global search ability. Each particle in PSO updates its velocity and position by learning from the personal historical best position (*pbest*) of the particle and the best position (*gbest*) found by the entire swarm so far. Restricting the social learning aspect to only *gbest* causes the original PSO to converge rapidly. However, in multimodal problems, the current *gbest* located at a local optimum may trap the entire swarm and cause premature convergence. The performance of PSO is highly related to particle diversity, especially when attempting to avoid premature convergence and to escape from the local optimum. The performance of PSO has been improved using several PSO variants, including those that resulted from different modifications. These enhancements include tuning the control parameters to balance the local and global search abilities, designing different topologies to replace the traditional global topology, and hybridizing PSO with other search techniques. However, these variants usually preserve swarm diversity at the cost of slow convergence speed or complicated algorithmic structures. Thus, synthetically improving the performance of PSO remains a challenging task in PSO research.

The current paper proposes a new PSO algorithm, namely, multiple learning PSO with space transformation perturbation (MLPSO-STP). This new PSO variant employs a novel learning strategy and STP to increase the global search accuracy and convergence speed of the algorithm. In specific, each particle in the new learning strategy learns from the average information on *pbest* of all particles and from the information on multiple best positions that are randomly chosen from the top 100*p*% of *pbest*. This learning strategy improves swarm diversity and prevents premature convergence. Moreover, STP increases the chance to find optimal solutions. The performance of MLPSO-STP on 21 well-known benchmark functions with various characteristic features is compared with those of eight PSO variants and seven state-of-the-art metaheuristic search (MS) algorithms. The proposed algorithm performs better than the other tested algorithms in the majority of the test problems.

The monomer ethylene is highly important in the petrochemical industry [37]. Ethylene cracking furnaces are essential process units in ethylene plants; among the equipment used in an ethylene plant, these units have the largest production capacity and the highest energy consumption. Therefore, improving the operating conditions of ethylene cracking furnaces benefits the industry. Aside from ethylene, propylene is also produced using an ethylene cracking furnace. The yields of ethylene and propylene are typical indices of the success of a country's petrochemical industry [38]. Hence, optimizing the operating conditions of a cracking furnace to maximize the yields of ethylene and propylene is highly important to the petrochemical industry. MLPSO-STP exhibits a satisfactory performance on this industrial application.

The article is subsequently organized as follows. Section 2 presents several PSO-related studies. Section 3 briefly introduces the standard PSO algorithm. Section 4 describes our proposed approach. Section 5 provides the experimental settings and results. Section 6 presents the industrial application of the proposed algorithm. Finally, Section 7 concludes this work.

2. Related works

Since the introduction of PSO in 1995 by Kennedy and Eberhart [6], the algorithm has become a popular optimizer and attracted many researchers who have worked on improving its performance in various ways. A brief overview of these variants is presented as follows.

The first area of research concentrates on PSO parameter adaptation strategy. A linearly decreasing inertia weight *w* with a generation number was proposed in [39], whereas a fuzzy adaptive *w* method was proposed in [40]. The concept of varying coefficients was also extended to dynamically update the acceleration parameters in [41]. Clerc and Kennedy [42] proposed the inclusion of a constriction factor in PSO. According to their analysis, adding a constriction factor guarantees convergence and improves the convergence speed. Recently, an adaptive PSO (APSO) has been presented in [43]. The APSO provides four evolutionary states and then uses one equation to adjust the inertia weight, acceleration coefficients, and other algorithmic parameters. Tang et al. [44] proposed a feedback learning PSO with quadratic inertia weight (FLPSO-QIW) by introducing a fitness feedback mechanism to control the parameters. The acceleration coefficients were determined by both generation time and search environment. Mirjalili et al. [45] developed an autonomous group PSO (AGPSO) by utilizing different functions to update the acceleration coefficients and confer particles different behaviors. Hu et al. [46] proposed a parameter control mechanism to adaptively change the parameters and consequently enhance the robustness of PSO with multiple adaptive methods. Xu [47] developed a new strategy wherein the inertia weight is dynamically adjusted according to the average absolute value of velocity. In general, tuning parameters can improve the performance of PSO, but this strategy is largely ad hoc [48].

Another promising line of research aims to increase PSO performance by using different population topologies and learning strategies. Kennedy [49] analyzed the effects of neighborhood topology on PSO and proposed four neighborhood topologies. Suganthan [50] applied a dynamically adjusted neighborhood in which the neighborhood size of a particle gradually increases until it covers all particles. Parsopoulos and Vrahatis [51] combined the global and local versions of PSO and proposed a unified particle swarm optimizer (UPSO). Mendes and Kennedy [52] introduced a fully informed PSO (FIPS), in which the velocity update is not only influenced by the best position in the neighborhood of the particle but also by positions in other neighborhoods. Peram et al. [53] presented a fitness-distance-ratio-based PSO (FDR-PSO) with near-neighbor interaction. Liang et al. [54] introduced a comprehensive learning PSO (CLPSO) for multimodal problems. CLPSO abandons the global best information and updates the velocity of a particle on the basis of the historical best information of other particles in different dimensions. Nasir et al. [55] presented a dynamic neighborhood learning particle swarm optimizer (DNLPSO) that uses the learning strategy of CLPSO but selects the exemplar particle from a dynamic neighborhood. Chen et al. [48] transplanted the aging mechanism to PSO and proposed a PSO with an aging leader and challengers (ALC-PSO), in which the aging mechanism provides opportunities for other particles to lead the swarm and thus provide diversity. Cheng et al. [56] introduced social learning mechanisms into PSO to develop a social learning PSO (SL-PSO). Wang et al. [57] developed MLPSO by increasing the two layers of swarms to multiple layers. Lim and Isa [58] proposed a new variant of PSO with increasing topology connectivity (PSO-ITC). These improvements provide reasonable performance enhancements at the expense of increased complexity.

Hybridization by combining PSO with other search strategies to enhance performance has gained increasing attention.