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A framework for multi-objective optimisation based on a new self-adaptive particle swarm optimisation algorithm

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ABSTRACT

This paper develops a particle swarm optimisation (PSO) based framework for multi-objective optimisation (MOO). As a part of development, a new PSO method, named self-adaptive PSO (SAPSO), is first proposed. Since the convergence of SAPSO determines the quality of the obtained Pareto front, this paper analytically investigates the convergence of SAPSO and provides a parameter selection principle that guarantees the convergence. Leveraging the proposed SAPSO, this paper then designs a SAPSO-based MOO framework, named SAMOPSO. To gain a well-distributed Pareto front, we also design an external repository that keeps the non-dominated solutions. Next, a circular sorting method, which is integrated with the elitist-preserving approach, is designed to update the external repository in the developed MOO framework. The performance of the SAMOPSO framework is validated through 12 benchmark test functions and a real-word MOO problem. For rigorous validation, the performance of the proposed framework is compared with those of four well-known MOO algorithms. The simulation results confirm that the proposed SAMOPSO outperforms its contenders with respect to the quality of the Pareto front over the majority of the studied cases. The non-parametric comparison results reveal that the proposed method is significantly better than the four algorithms compared at the confidence level of 90% over the 12 test functions.

1. Introduction

Over the last few decades, the multiple-objective optimisation (MOO) has gained great attentions in different areas such as manufacturing optimisation [1,2] and environmental/economic dispatch [3]. Since there may exist conflicts among different objectives in a MOO problem, it is difficult or even impossible to simultaneously optimise all objectives in a MOO problem [4–6]. Therefore, the research of MOO often leads to a problem finding a set of non-dominated solutions [4,7,8]. The issue is that many real-world MOO problems may contain multiple complex and nonlinear objectives and constraints [4–6]. With the complexity and nonlinearity of objectives and constraints, finding a set of good quality non-dominated solutions become more challenging [4–6].

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Thanks to their population-based nature and inherent parallelism, various evolutionary algorithms (EAs) have been proposed for solving different MOO problems. For instances, a novel gradient-based water cycle algorithm (GWCA) with evaporation rate was developed by Alireza et al. in [9]; an adaptive gradient descent-based local search in memetic algorithm was presented to handle the optimal controller design problem by Aliasghar and Alireza in [10]; Li and Zhang developed a new version of multi-objective evolutionary method based on the differential evolution algorithm (MOEA/D-DE) to solve MOO problems with complicated Pareto sets in [11] and a multi-objective memetic algorithm based on decomposition (MOEA/D) was proposed by Tan et al. to solve different MOO problems in [12]. Some other excellent works that concentrate on applying different EAs to tackle with different MOO problems can be found in [3,6,13,14].

As one of the most well-known and preferred EAs, particle swarm optimisation (PSO) has been rapidly and widely applied to solve different single-objective and MOO problems in recent years: a novel adaptive particle swarm optimisation (APSO) algorithm was developed by Alireza and Hamidreza in [15]; Yashar and Alireza proposed a novel fractional PSO-based memetic algorithm (FPSOMA) to solve trajectory control in [16]; a bare-bones multi-objective PSO for the environmental/economic dispatch problem was developed in [17]; a modified binary PSO-based reliability redundancy allocation method was introduced in [18] and a hybrid PSO-based MOO method was proposed to handle the flexible job-shop scheduling problem in [19]. For more works focusing on developing different PSO-based MOO methods, the reader can be referred to [5,20–22].

Nevertheless, since the basic PSO algorithm cannot well balance exploration and exploitation [23,24], the Pareto front searched by the basic PSO may converge to a false Pareto front [5]. This could limit the application of PSO on MOO. It is of great importance to overcome this convergence issue to improve the quality of the Pareto front and consequently enhance the performance of MOO [5,17]. There have been numerous researches focusing on overcoming the typical drawback of the basic PSO [9,16,23–26]. From these studies, it is clearly evident that adjusting the three control parameters, i.e., the inertial weight, the cognitive and social acceleration parameters, is a powerful remedy to the convergence issue in PSO. The three control parameters of PSO influence its exploration and exploitation capabilities and thus determine its convergence property. Therefore, it is essential to address and guarantee the convergence of PSO when adjusting the three parameters for improving PSO [21,27,28]. However, like in most of the stochastic approaches, the stochastic nature of PSO imposes difficulties on the analytical investigation of its convergence [29].

This paper first develops a novel self-adaptive PSO algorithm, called self-adaptive PSO (SAPSO). The main focus of the development is to alleviate the convergence issue of the basic PSO through fine-tuning the three main control parameters. The new self-adaptive strategy proposed adjusts the three control parameters of particles in SAPSO to well balance the trade-offs between exploration and exploitation. In the proposed self-adaptive strategy, the search of particles leverages not only the relative importance between exploration and exploitation over iterations, but also the information of the solution space. As discussed, since the convergence of PSO is a paramount issue in the context of MOO, this paper theoretically analyses the convergence of SAPSO and proposes a parameter selection principle, guaranteeing the convergence of SAPSO.

Then, this paper develops a MOO framework, named self-adaptive multi-objective PSO (SAMOPSO), based on the SAPSO algorithm proposed. Similar to the most currently existing PSO-based MOO approaches, an external repository is designed in the MOO framework to save the non-dominated personal best solutions of particles. For obtaining a well-distributed Pareto front, we introduce a circular sorting method, which is combined with the elitist-preserving approach [4] and updates the external repository.

The performance of the proposed approach is validated through 12 well-known MOO benchmark test functions and a real-world engineering problem. For rigorous verification, the performance of the proposed approach is compared with those of four well-established MOO approaches, namely NSGA-II [4], TV-MOPSO [18], BMOPSO [30] and MOEA/D [31]. The performance comparison is based on five different MOO performance metrics. The simulation results confirm that the proposed approach outperforms its contenders in terms of the quality of the obtained Pareto fronts over the majority of the cases studied. The analysis results of non-parametric statistical comparison also verify that the proposed method performs significantly better than the other four MOO methods with the confidence level of 90% for the 12 benchmark test functions. Furthermore, the computation time of the proposed approach is comparable with those of its counterparts in all the test problems.

The remainder of this paper is organised as follows. Section 2 introduces the proposed SAPSO and investigates its convergence properties. The proposed SAPSO-based MOO framework is described in Section 3. Section 4 performs the numerical simulations and discusses its results. Conclusions of this study are provided in Section 5.

2. Particle swarm optimisation (PSO)

2.1. Review of the basic PSO

Inspired by birds flocking and fish schooling, Kennedy and Eberhart first proposed PSO in 1995. The original aim of the basic PSO algorithm is to reproduce the social interactions among agents to solve some complex optimisation problems [29]. Each agent in PSO is called a particle and associated with a velocity, which is dynamically adjusted depending on its own flight experience and those of its companions. Therefore, each particle is attracted toward a stochastically weighted average of its personal best position and the global best position of the swarm. In the basic PSO algorithm, from iteration k to $k+1$,