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Novel hybrid approach with elite group optimal computing budget allocation for the stochastic multimodal problem

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ABSTRACT

The stochastic multimodal problem commonly arises in the search for efficiency and solution quality in practice. In this study, a hybrid approach is developed for the stochastic multimodal problem. The proposed approach comprises particle swarm optimization (PSO), constriction factor PSO (CPSO), and elite group optimal computing budget allocation (EGOCBA). CPSO or PSO is applied to determine the correct direction in the design space, and EGOCBA is adopted to allocate the appropriate number of samples to each alternative and provide reliable evaluations and identifications to rank particles in the CPSO or PSO procedure. This work improves the searching efficiency of optimal computing budget allocation (OCBA) in the stochastic multimodal problem. Several alternatives referred to as the "elite group," the performance of which is close to that of the current best solution in each swarm, absorb most of the computing budget of OCBA. However, distinguishing the best solution from the elite group is time consuming because of the various local and global optima in the stochastic multimodal problem. Therefore, this study proposes EGOCBA that avoids extra computing costs for the elite group by implementing a new selection procedure. This EGOCBA reserves all the solutions of the elite group and filters them to form an optimal set that contains all the best solutions having an equal mean performance without a significant difference. These tasks are achieved through a confidence interval test in the end of the algorithm. The optimal set can provide more than one best solution to support multiple decisions depending on different decision variables. Two experiments are conducted on stochastic multimodal optimization problem and stochastic resource allocation problem. Experimental results reveal the efficiency and effectiveness of the proposed approach in deriving multiple optimal solutions in a multimodal class and stochastic environment.

1. Introduction

In practical optimization problems, objective functions often lead to multimodal domains [1–6]. These problems have several local or global optima in the design space. Many population-based stochastic optimization algorithms have been designed to address different optimization problems, such as scheduling problem [16], nonlinear resource allocation problem [7], function optimization [8] and vehicle routing problems [9]. Although many studies have proposed improved algorithms for increasing diversity, such as particle swarm optimization (PSO) with adaptive mutation [10], PSO with local search [11] and genetic algorithm with self-adaptive neighborhood scheme and crowding replacement memory [12], improving performance in terms of convergence rate and solution accuracy remains a challenge [13].

The abovementioned problems also involve uncertainty factors that must be considered in the real world [14], such as service time or arrival rate of patients in a healthcare system [15] or manufacturing system, wherein processing time, machine breakdowns, demand, and transportation time might be uncertain [16]. When multimodal optimization is in a noisy environment, determining the optimization solutions is more difficult. Thus, the performance cannot be obtained directly in single run. Monte Carlo simulation, which relies on repeated random sampling to obtain statistic results, is widely employed to solve performance estimation. A few studies for multimodal optimization in noisy environments have been proposed. In [17], a new PSO approach with average neighborhoods for stochastic multimodal function optimization (SMFO) has been proposed. Demonstrating 20 numerical results subject to different level of noises shows that the proposed approach is better than regular PSO in solution quality. An alternative approach, which is considered reliable in dealing with noise in large-scale optimization problems, has also been presented [18]. Although these approaches successfully tackled the multimodal optimization

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problem, determining the sampling method to enhance evaluation efficiency remains a challenge.

Hence, estimating the objective via simulation, which intelligently allocates the number of sampling among potential better alternatives instead of equal allocation in all alternatives is another important topic [19]. Efficiency becomes a key issue when using time-consuming simulation procedures to estimate the performance measure. Accordingly, the "ranking and selection" procedure determines the number of simulation replications for selecting the best design in stochastic environment. Many studies in literature have been conducted [20–25]. Moreover, to enhance simulation efficiency with a given computing budget, Chen and Lee [26] proposed the optimal computing budget allocation (OCBA) technique to optimally allocate the number of simulation replications for all alternatives.

Simulation optimization methodologies are employed to solve problems that are both large and stochastic. In [27], a hybrid nested partition algorithm with OCBA is proposed and its application in discrete resource allocation is presented. The application of OCBA into PSO is considered for function optimization with noise in [28], where a hybrid approach is proposed based on PSO to explore the design space. The role of OCBA is to allocate simulation budget for estimated performance to each particle and finally focus on premature convergence in PSO, which uses hypothesis test to maintain diversity swarm for PSO, to overcome trapping into local optimum. A detailed integration of genetic algorithm (GA) with OCBA [29] and PSO with OCBA [30] as simulation optimization for hybrid flow shop scheduling problem applicable in the semiconductor back-end assembly factory has been presented. In [31], the dispatching rule between an overhead vehicle and machine in automated material handling system in semiconductor manufacturing is determined using PSO with OCBA. This hybrid approach has been proven to be effective and efficient in solving this complicated problem. To solve the stochastic job shop scheduling problem, a hybrid simulation optimization framework based on evolutionary strategy in ordinal optimization combined with OCBA is proposed in [16] to optimize expected sum of earliness and tardiness with given limited simulation runs. Lin and Chiu [32] proposed a hybrid approach called PSO_{OTL} to deal with the premature convergence problem in PSO with OCBA by increasing diversity swarm and reducing the number of replications in the stochastic resource allocation problem.

Although integrating OCBA with PSO can efficiently allocate the computational cost in the stochastic simulation optimization problem, achieving searching efficiency according to the problem features remains a challenge [34]. Ref. [32] pointed out that metaheuristics may be combined with OCBA to allocate the extra computational cost in local optimum solutions when several alternatives demonstrate similar ideal performances in the design space. These solutions absorb most of the given computational cost in the original OCBA procedure.

In this study, improvement of the allocation rule from the original OCBA procedure was proposed. The new improved rule is called elite group optimal budget allocation (EGOCBA). The concept of EGOCBA is the avoidance of allocating extra sampling to the local optimum in each iteration of the algorithm. These local optima are referred to as the "elite group" in this study. The procedure of EGOCBA is as follows. First, the elite and non-elite groups are determined using a threshold value and selection procedure. Second, the constricted computing budget for the elite group is provided. Third, the allocation rule of OCBA is modified to allocate the simulation budget to the solutions of the non-elite group. Fourth, the elite group is reserved and checked using a confidence interval (CI) test at the termination of the algorithm. After the CI test, the solutions of the elite group form an optimal set. The detailed procedure is introduced in the following section. Compared with the approaches proposed in previous studies [16,28–32], EGOCBA offers fast convergence in the procedure of allocating samples when the swarm contains many solutions with similar and ideal performances in each generation. This approach enhances searching efficiency in allocating the computational cost and offers an opportunity to search for two or more alternatives in stochastic multimodal problems (SMPs).

In this study, two meta-heuristics, namely, constriction factor PSO (CPSO) and PSO combined with EGOCBA, OCBA, and equal allocation (EA) rule, were employed. The corresponding algorithms are called $CPSO_{EGOCBA}$ $CPSO_{OCBA}$, $CPSO_{EA}$, PSO_{OCBA}, PSO_{EGOCBA}, and PSO_{EA}. These algorithms were compared for two experiments: continuing SMFOs and two discrete-based stochastic resource allocation problems (SRAPs). The results show that high efficiency and effectiveness can be achieved with $CPSO_{EGOCBA}$ for SMPs. Given the presence of several constraints in the real world and the fact that the optimal solution cannot be considered from only one optimal solution, $CPSO_{EGOCBA}$ was utilized to obtain multiple global and local optima for users to have numerous choices of optimal solutions.

The rest of this paper is organized as follows. Related studies are introduced in Section 2. Section 3 presents the problems that arise when PSO is combined with OCBA in stochastic multimodal optimization. Section 4 introduces the proposed algorithm. Two experiments and an analysis using a statistical test for a comparison of the six algorithms are presented in Section 5. Section 6 provides the conclusions and future research directions.

2. Related work

2.1. Particle swarm optimization

PSO is a population-based algorithm proposed by Kennedy and Eberhart [35]. This algorithm is inspired by the behavior of communities in nature, such as bird flocking, fish schooling and swarming theory, as well as the simulation of simplified social models. According to the PSO procedure, m particles are required to complete a swarm. We let x_i represent the position of particle i in the design space and the position of particle i is updated at each step by determining its velocity v_i. When particles move, each particle has its own best position called personal best (pbest), which corresponds to the particle best performance obtained so far. The best position is found in the swarm known as global best (gbest). Two core equations can be used to update velocity and position as shown in Eqs. (1) and (2), respectively, where each particle is updated in terms of velocity and position,

$$v_i(t+1) = wv_i(t) + c_1\, r_1\{p_i^*(t) - x_i(t)\} + c_2 r_2 \left\{ p_g^*(t) - x_i(t) \right\}, \tag{1}$$

where w is inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are two independent random numbers with uniform distributions in the range [0,1], P_i^* denotes pbest, and p_g^* represents gbest,

$$x_i(t+1) = x_i(t) + v_i(t+1). \tag{2}$$

Several variants of PSO have been proposed to improve the convergence rate or performance of PSO; these variants include CPSO [36], bare bones particle swarms [37], the fully informed PSO algorithm (FIPS) [38], and comprehensive learning particle swarm optimizer (CLPSO) [39]. These proposed algorithms examine parameter strategies (e.g., inertia weight or learning factor (c1 and c2)). These strategies allow the diversity of the swarm to be enhanced to prevent premature convergence. In this study, CPSO was regarded as another searching algorithm. CPSO is commonly employed to improve fine-tuning parameters and ensure the convergence of PSO; the maximum velocity is not required. Under the constricted factor (CF), the ith velocity of a particle is updated with Eq. (3),