Enhanced Differential Evolution Based on Adaptive Mutation and Wrapper Local Search Strategies for Global Optimization Problems

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ABSTRACT
Differential evolution (DE) is a simple, powerful optimization algorithm, which has been widely used in many areas. However, the choices of the best mutation and search strategies are difficult for the specific issues. To alleviate these drawbacks and enhance the performance of DE, in this paper, the hybrid framework based on the adaptive mutation and Wrapper Local Search (WLS) schemes, is proposed to improve searching ability to efficiently guide the evolution of the population toward the global optimum. Furthermore, the effective particle encoding representation named Particle Segment Operation-Machine Assignment (PSOMA) that we previously published is applied to always produce feasible candidate solutions for solving the Flexible Job-shop Scheduling Problem (FJSP). Experiments were conducted on comprehensive set of complex benchmarks including the unimodal, multimodal and hybrid composition function, to validate performance of the proposed method and to compare with other state-of-the art DE variants such as jDE, JADE, MDE_pBX etc. Meanwhile, the hybrid DE model incorporating PSOMA is used to solve different representative instances based on practical data for multi-objective FJSP verifications. Simulation results indicate that the proposed method performs better for the majority of the single-objective scalable benchmark functions in terms of the solution accuracy and convergence rate. In addition, the wide range of Pareto-optimal solutions and more Gantt chart decision-makings can be provided for the multi-objective FJSP combinatorial optimizations.

Keywords: Differential Evolution, Wrapper Local Search, Particle Segment Operation-Machine Assignment, Flexible Job-shop Scheduling Problem.

1. Introduction

Optimization algorithms have become a useful technique in all-major disciplines and engineering applications [1–2]. Many practical engineering design or decision making problems involve single-objective or multi-objective optimization. In single-objective optimization, the goal is to find the best design solution as to the minimum or maximum value of the objective function. On the contrary, the multi-objective optimization gives rise to Pareto-optimal solutions [3] because of the interaction among different conflicting objectives. Differential Evolution (DE) algorithm is a population-based and stochastic optimizer first developed by Storn and Price [4]. With the advantages of simplicity, less parameter and robustness, the DE algorithm has been given increasing attention and widely used in many fields, such as data mining [5], structural optimization [6], biogeography [7], and so on [8–9]. DE is considered the most recent studies for solving constrained optimization problems, multi-objective global optimizations, and other complex real-world applications. More details on the state-of-the-art investigation within DE can be found in two surveys [10–11] and the references therein.

For the classical DE, the setting of three control parameters: population size Np, the crossover rate Cr and the scale factor F, is very sensitive to the parameter setting and the choice of the best parameters is always problem-dependent [12]. In addition, for a given specific problem, it may be better to adopt different parameter settings during different generation stages of the evolution than use a single mutation strategy with fixed parameter settings [11]. In 2006, Brest et al. [12] presented a self-adaptive method for DE fixes the population size during the evolution process while adapting the control parameters F_i and CR_i associated with each individual. The jDE reproduces new F_i and CR_i values according to uniform distributions on [0.1, 1] and [0, 1], respectively. And experimental results demonstrated that jDE performs remarkably better than the classic DE/rand/1/bin. Later, Zhang et al. presented "DE/current-to-*p*best" with optional archive and controls *F* and *CR* in an adaptive manner named JADE [13], to track the historical record of success status for mutation factors and crossover probabilities with adaptive parameters in generations, and the external archive to store recently inferior solutions and their difference from current population provides promising directions toward the optimum. In 2012, Islam et al. proposed the MDE_*p*BX [14], which adds a variation to the classical "DE/current-to-best/1" mutation scheme by perturbing the current target vector with the best solution in a group of randomly selected individuals. The crossover operation is performed between the current donor vector and any other individual from *p* top-ranked individuals in the present generation. Simulation results demonstrate that MDE_*p*BX enhances the ability of the basic DE for finding solutions in search space and helps alleviating the tendency of premature convergence or stagnation.

In the recent studies [12–15], various mutation and controll parameters setting strategies have been presented for DE algorithm. Although a number of works can advance the search ability of DE, there is still much room for improving the performance of DE. Motivated by these results, the modified mutation scheme based on MDE_*p*BX, in which the mutation operator can be adjusted dynamically on the solution searching status, is presented to bring several individuals appropriately to find new possible solutions. Meanwhile, a wrapper local search (WLS) strategy via trying to increase or decrease current moving vector by the Cauchy distribution is proposed to improve the local search ability and to balance exploration and exploitation in the search space. Moreover, the proposed hybrid DE framework incorporated with PSOMA method that we previously published to produce feasible solutions for the multi-objective Flexible Job-shop Scheduling Problem (FJSP), is designed for finding optimal solutions of multi-objective FJSP. Competitive experimental results are observed with respect to 15 CEC 2005 benchmark functions for single-objective optimizations, and the three benchmark instances based on practical data were employed as multi-objective FJSP verifications.

The remainder of this paper is organized as follows.

Section 2 describes the typical MDE_pBX, FJSP and external repository. The PSOMA scheme, adaptive mutation method, WLS and the hybrid DE model are presented in Section 3. Experiment and comparison results are provided in Section 4. Conclusions remarks are made in Section 5.

2. Related Works

2.1 Classical Differential Evolution Algorithm

DE algorithm is one of the population-based global optimization algorithms, has two stages including initialization and evolution. After randomly initializs, evolution process evolves from one generation to the next through mutation, crossover and selection operations until the termination criteria are reached. The core of DE algorithm is the mutation operation, which uses a weighted, random vector in each step, to replace the target vector with the better trial vector in the next generation. The main steps of the classical DE are summarized as follows.

2.1.1 Initialization

The DE begins by creating an initial population of target vectors consisting of parameter vectors are denoted by $\vec{X}_{i,G} = [x_{i,G}^1, x_{i,G}^2, \cdots, x_{i,G}^D]^T$, $i = (1, 2, \cdots, N_P)$, where *i* is the index for individuals, *G* indicates the current generation, N_p is the population size, *D* is the dimension of the parameters, and $x_{i,G}^j$ denotes the *j*-th component of the *i*-th individual at the *G*-th generation. The initial individuals are randomly determined within a predefined search space considering the lower and upper bounds of each parameter as follows.

$$x_{i,G}^j = x_{\min}^j + rand(0,1) \times (x_{\max}^j - x_{\min}^j),\ j = (1, 2, \cdots, D) \quad (1)$$

where $x_{\min}^j$ and $x_{\max}^j$ denote the lower and upper bounds, respectively, and $rand(\bullet)$ is a uniformly distributed random number between 0 and 1.