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Using a fuzzy clustering chaotic-based differential evolution with serial method to solve resource-constrained project scheduling problems

Min-Yuan Cheng [1], Duc-Hoc Tran *, Yu-Wei Wu [2]

Department of Construction Engineering, National Taiwan University of Science and Technology, #43, Sec. 4, Keelung Rd., Taipei 106, Taiwan

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ABSTRACT

The resource-constrained problem seeks to find the optimal sequence that minimizes project duration under current precedence constraints and resource limitations. This study integrates the fuzzy c-means clustering technique and the chaotic technique into the Differential Evolution (DE) algorithm to develop the Fuzzy Clustering Chaotic-based Differential Evolution (FCDE) algorithm, an innovative approach to solving complex optimization problems. Within the FCDE, the chaotic technique prevents the optimization algorithm from premature convergence and the fuzzy c-means clustering technique acts as several multi-parent crossover operators in order to utilize population information efficiently and enhance convergence efficiency. Further, this study applies a serial method to reflect individual-user priorities into the active schedule and the project duration calculations. The FCDE and serial method are then integrated into a novel optimization model called the Fuzzy Clustering Chaotic-based Differential Evolution for Solving Resource Constrained Project Scheduling Problem (FCDE-RCPSP). Experiments run indicate that the proposed FCDE-RCPSP obtains optimal results more reliably and efficiently than the benchmark algorithms considered. The FCDE-RCPSP is a promising alternative approach to handling resource-constrained project scheduling problems.
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1. Introduction

Project scheduling is an important tool for managing today's complex business and manufacturing systems. Resource-constrained project scheduling is a key challenge for many industrial problems [1]. Project managers widely use the Critical Path Method (CPM) and the Program Evaluation and Review Technique (PERT) to generate schedules that are used in planning and managing large-scale construction projects. These two approaches involve logical dependencies because they assume infinite resource availability. However, assuming infinite resource availability is not reasonable for most real-world construction projects [2].

Using Evolutionary Algorithms (EAs) to analyze resource-constrained problems has attracted increasing attention in recent years [3]. Inspired by the process of natural evolution, EAs have been used successfully to resolve optimization problems in diverse fields [4]. Genetic Algorithms (GAs) are an evolutionary approach used widely to solve the RCPSP [5–7]. The GA searches for the optima in multiple chromosome generations that represent schedules reproduced by crossover and mutation. The internal updating mechanism of chromosomes enables GA to search for the global optima. However, deficiencies in GA performance such as premature convergence and slow convergence have been identified. Particle Swarm Optimization (PSO), an algorithm that simulates bird flocking behavior, has been applied to solve resource-constrained problems [2,8]. Like GA, PSO first initializes a population of random solutions and then updates generations to search for the optima. PSO advantages over GA include relative ease of implementation, faster search process, and more effective performance [9]. Nevertheless, similar to other stochastic search methods, PSO may become trapped in a local minimum and thus may resolve upon a local rather than a global minimum.

The Differential Evolution (DE) [10,11] algorithm is an evolutionary computation technique. DE has drawn increasing interest from researchers, who have explored the capabilities of this algorithm in a wide range of problems. DE is an effective population-based stochastic search engine for global optimization in the continuous domain. DE uses mutation operators, crossover operators, and selection operators at each generation to move its population toward the global optimum. The superior performance of DE over competing algorithms has been verified in many reported research works [10,12,13].

Despite the aforementioned advantages, DE in both its original form and many later variants has several drawbacks. DE does not guarantee convergence to the global optimum. It is easily trapped into the local optima, resulting in low optimization precision or even failure [14]. Further, because a population may not be distributed over the search space, individuals may be trapped in a local solution. Therefore, DE may require more generations to converge toward the optimal or

* Corresponding author. Tel.: +886 92636949.
E-mail addresses: myc@mail.ntust.edu.tw (M.-Y. Cheng), duchoc87@gmail.com (D.-H. Tran), d9305503@mail.ntust.edu.tw (Y.-W. Wu).
[1] Tel.: +886 2 2733 6596; fax: +886 2 27376606.
[2] Tel.: +886 2 27330004; fax: +886 2 27376606.

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near-optimal solution [15]. DE is also subject to various weaknesses, especially if the global optimum is identified in a small number of fitness evaluations. Moreover, although DE is good at exploring the search space and locating the region of the global minimum, it is slow at exploiting the solution [16].

The inherent characteristics of chaotic systems provide an efficient approach to maintaining search algorithm population diversity. Chaos is defined as behavior that is apparently unpredictable and random as exhibited by a deterministic nonlinear system under deterministic conditions. Chaotic systems that are sensitive to small differences in initial system conditions may produce large variances in outcomes. This is a property of instability sometimes referred to as the butterfly effect or Liapunove's sense [17]. Some studies have focused on hybridizing DE with a chaotic algorithm. For example, Jia et al. [14] used a chaotic local search (CLS) with a 'shrinking' strategy. The CLS improves the optimizing performance of the canonical DE by exploring a huge search space in the early run phase to avoid premature convergence and exploiting a small region in the late-run phase to refine the final solutions. Bedri Ozer [15] embedded seven chaotic maps to create the initial population of the DE algorithm. Findings of these studies indicate that coupling emergent results in different areas such as those of DE and complex dynamics may improve the quality of results in some optimization problems.

Fuzzy c-means clustering is a soft clustering approach that divides a set of objects into groups or clusters of similarities to accelerate the optimization search in DE. Successful clustering identifies the true natural groupings in the dataset. Fuzzy c-means clustering helps track the evolution of the search algorithm in DE through cluster centers introduced into the populations. In fuzzy clustering, data elements may belong to more than one cluster, with a set of membership levels associated with each element. Membership levels indicate the strength of the association between a data element and a particular cluster. Kwedlo [18] proposed a new version of DE that uses k-means clustering to fine-tune each candidate solution obtained by DE mutation and crossover operators. Wang et al. [19] utilized a clustering technique to improve solution accuracy with less computational effort. Experiments indicate that the new method is able to find near-optimal solutions efficiently.

Hybridization using other algorithms is an interesting direction to further improve DE [20]. Although many methods have been proposed to improve DE, few researchers have studied DE hybridization with clustering techniques and chaotic techniques [20]. An extensive review of the literature done for this study found that fuzzy c-means clustering and chaotic techniques have not yet been used to enhance the performance of DE.

This study uses a hybridization strategy to improve the DE optimizer. This hybridization strategy incorporates the fuzzy c-means clustering technique and the chaotic technique to overcome performance problems inherent to the original DE. Chaotic sequences adopted instead of random sequences, with good results exploited to prevent premature convergence. Further, fuzzy c-means clustering introduces multi-parent crossover operators to population information in order to accelerate algorithm convergence. The remainder of this paper is organized as follows: Section 2 provides a brief overview of the literature related to the new optimization model; Sections 3 and 4 provide a detailed description of the new model; Section 5 demonstrates the performance of the new model using numerical experiments and result comparisons; and Section 6 discusses findings and presents conclusions.

2. Literature review

2.1. Formulating the resource-constrained project scheduling problem

In construction management, resource constrained problems are investigated intensively because of their practical importance. Resource constraint problems address both precedence and resource constraints and are significantly more difficult to resolve than other scheduling problems. Minimizing project duration is the primary objective of the RCPSP [2,8]. Other objectives include minimizing total project cost and leveling resource usage [21–23]. Resources involved in a project may be single or multiple and may be renewable/recoverable (e.g., personnel) or nonrenewable/non-recoverable (e.g., building materials). Preemption means that activities in progress (e.g., frame installing) may be interrupted. Non-preemption means that activities (e.g., concreting) may not be interrupted once in progress. The classical RCPSP that considers renewable resources, non-preemption and the minimizing of project duration is formulated as follows:

$$\min\{\max f_i | i = 1, 2, \ldots, N\} \tag{1}$$

Subject to:

$$f_j - f_i \geq d_i \forall j \in P_i; i = 1, 2, \ldots, N \tag{2}$$

$$\sum\nolimits_{A_t} r_{ik} \leq R_k \ ; \ k = 1, 2, \ldots, K \ ; \quad t = s_1, s_2, \ldots, s_N \tag{3}$$

where N is the number of activities involved in a project and f_i is the finish time of activity $i(i = 1,\ldots,N)$; d_i is the duration of activity i; P_i is the set of activities that have been already scheduled (i.e., predecessors) before activity i may be scheduled to start; R_k is the amount of resource $k(k = 1,\ldots,K)$ available and k is the number of the resource types; r_{ik} is the amount of resource k required by activity i; and A_t is the set of ongoing activities at t; and $s_i = (f_i - d_i)$ is the start time of activity i. Eq. (1) represents the objective. Eqs. (2) and (3) represent precedence constraints and resource constraints, respectively.

2.2. The DE optimization algorithm

Storn and Price first introduced the concept of Differential Evolution (DE) [10,11] as an approach to real-parameter optimization. DE is based on the utilization of a novel crossover-mutation operator, based on the linear combination of three different individuals and one subject-to-replacement parent (or target vector) [24]. The crossover-mutation operator yields a trial vector (or child vector) that competes with its parent in the selection operator. These two terms, trial vector and child vector, are used interchangeably. The selection process is performed via selection between the parent and the corresponding offspring [25]. Fig. 1 depicts the standard algorithm of differential evolution.

In this figure, NP represents the size of the population; $X_{j,i}$ is the jth decision variable of the ith individual in the population; g is the current generation; and D is the number of decision variables. $rand_j(0,1)$ is a uniform random number lying between 0 and 1 and $rnb(i)$ is a randomly chosen index of {1,2,…,D}. Cr is the crossover constant $Cr \in [0,1]$ and F is a mutant factor $F \in [0,2]$. In the original DE algorithm, a user must specify initial values for F and Cr, which are fixed values during the optimization process. Price, et al. [11] suggested an initial value of 0.5 for F and an initial value of 0.9 or 0.1 for Cr, depending on specific problem characteristics.

2.3. Fuzzy c-means clustering

Clustering is a process that decomposes a given dataset into distinctly defined subgroups or clusters. Clustering algorithms may be divided into two main categories: crisp (or hard) clustering algorithms assign each data point to exactly one cluster, while fuzzy clustering algorithms associates each data point with every cluster based on a specific algorithmic degree of membership [26]. Many clustering algorithms have been introduced in the literature. Fuzzy clustering deals efficiently with overlapping clusters and delivers results that are

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