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Genetic based discrete particle swarm optimization for Elderly Day Care Center timetabling

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ABSTRACT

The timetabling problem of local Elderly Day Care Centers (EDCCs) is formulated into a weighted maximum constraint satisfaction problem (Max-CSP) in this study. The EDCC timetabling problem is a multi-dimensional assignment problem, where users (elderly) are required to perform activities that require different venues and timeslots, depending on operational constraints. These constraints are categorized into two: hard constraints, which must be fulfilled strictly, and soft constraints, which may be violated but with a penalty. Numerous methods have been successfully applied to the weighted Max-CSP; these methods include exact algorithms based on branch and bound techniques, and approximation methods based on repair heuristics, such as the min-conflict heuristic. This study aims to explore the potential of evolutionary algorithms by proposing a genetic-based discrete particle swarm optimization (GDPSO) to solve the EDCC timetabling problem. The proposed method is compared with the min-conflict random-walk algorithm (MCRW), Tabu search (TS), standard particle swarm optimization (SPSO), and a guided genetic algorithm (GGA). Computational evidence shows that GDPSO significantly outperforms the other algorithms in terms of solution quality and efficiency.

1. Introduction

Driven by fertility and mortality reduction, and medical and economic advancements, the rapid aging of the world population has been one of the major global demographic trends [1]. This trend has also increased the demand for age-friendly and affordable healthcare services, including the long-term care, curative care and preventive care. Thus, the quality of healthcare services provided by day-care centers, community care centers and nursing homes gains increasingly significant attention [2]. To ensure the quality of such services, centers should deliver more effective services. However, many care centers suffer from operational inefficiency. Driven by low resource utilization and long waiting lists from manual timetabling, the EDCCs in Hong Kong call for more studies to improve the quality of healthcare services.

The EDCC timetabling problem is the assignment of users (elderly) and the activities of these users to different venues and timeslots depending on the operational constraints of the day care center. Therefore, a feasible solution to this problem can be described by formulating a timetabling assignment which satisfies all hard constraints (constraints that should not be violated under any circumstance) and many soft constraints (constraints that may be violated but with a penalty). The infeasibility value of a solution is the sum of the number of hard constraint violations times a heavy penalty. Infeasibility value plus the sum of the number of soft constraints is the objective value. A solution is better than another solution if this solution has less objective value. *The EDCC timetabling aims to find a feasible solution with smallest objective value and determine which soft constraints suffer most violation.* Timetabling problems are encountered in various situations, such as rostering duties of nurse in hospitals [3–7], scheduling transportation events [8], and constructing timetables for courses or examinations in the education industry [9–15]. The EDCC timetabling has some unique characteristics (e.g. first-come, first-served rule; different service center arrival patterns, and mixed event types in the same room) in contrast to other existing timetabling problems. The details of these differences are discussed in Section 2.1.

Abbreviations: ANOVA, analysis of variance; BCO, bee colony optimization; CSP, constraint satisfaction problem; DPSO, discrete particle swarm optimization; EDCC, Elderly Day Care Center; FSP, flow-shop scheduling problem; GA, genetic algorithm; GDPSO, genetic-based discrete particle swarm optimization; GGA, guided genetic algorithm; JSP, job shop scheduling problem; Max-CSP, maximum constraint satisfaction problem; MCRW, min-conflict random-walk algorithm; NP-hard, non-deterministic polynomial hard; PSO, particle swarm optimization; ROV, ranked-order value; SA, simulated annealing; SPSO, standard particle swarm optimization; TS, Tabu search

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In addition to satisfying hard constraints, if the violations of soft constraints should be minimized, the EDCC timetabling can be defined as an optimization problem that seeks a solution that satisfies the maximum number of constraints and exposes the most violated constraints. Hence, it is formulated with respect to the Max-CSP framework [16]. A typical Max-CSP considers all constraints with same weight, whereas it considers all soft constraints with a same weight but any hard constraint violation with a heavy penalty. The methods to Max-CSP include exact algorithms based on branch-and-bound techniques [16,17] and approximation algorithms based on heuristics, such as the min-conflict [18] and TS [19]. Evolutionary algorithms, such as GA [20] and PSO [21] for solving Max-CSPs, have been examined because of their capacities to resolve successfully difficult problems in various domains.

This study presents a GDPSO to solve the EDCC timetabling problem under the Max-CSP framework. The PSO-based algorithm is proposed because of the following reasons:

- PSO-based algorithms are proven efficient and effective in solving many optimization problems, such as flow-shop scheduling (FSP) [22–26], timetabling [10,13,14], and vehicle routing [27,28].
- PSO has several advantages, including a simple structure, flexibility (immediate accessibility for practical applications), easy implementation, rapid solution acquisition, and high robustness [24].
- An objective of the EDCC timetabling problem is to address the most violated constraints; PSO has been proven as promising in achieving it within a short time because PSO is a one-way information sharing mechanism, where only the local/global best particle provides the best information and all the particles tend to quickly converge into the best solution [29].

The proposed GDPSO is in the combination of min-conflict strategy, random walk, genetic operators and one-way information sharing mechanism from PSO. The min-conflict strategy gives greedy heuristic logic to search for better solutions in short time and random walk consists of a succession of random steps. Instead of using the standard update scheme of PSO, it applies the crossover and mutation operator cooperated with min-conflict strategy and random walk to update particles. Compared with swarm optimization algorithms, such as GGA [20] and SPSO [30], GDPSO has fewer parameters to be tuned and quick convergence. In contrast with heuristic methods, such as MCRW and TS [19], GDPSO has stable performance while MCRW may randomly work into a space that violate the hard constraints and provide an unfeasible solution. GDPSO also outperforms TS in terms of solution quality and convergence speed. The main contributions of this article are as follows:

- The presentation of a proposed GDPSO for the EDCC timetabling problem. The experimental results indicate that the proposed GDPSO is deemed superior over other benchmarking methods and also implies its potential in solving the Max-CSP.
- The description and implementation of a Max-CSP-based EDCC timetabling problem. It offers a clear knowledge about which constraint is the most violated one and give the HHC structure suggestions on improvement based on the solution details.

The remainder of this paper is organized as follows. Section 2 reviews the former studies on timetabling and PSO. Section 3 introduces the Max-CSP-based EDCC timetabling problem. Section 4 explains the rationale of the proposed GDPSO. Section 5 describes the experiment design. Finally, Section 6 concludes this study and recommends future research directions.

2. Literature review

2.1. Timetabling problem

Burke and Kingston [31] provided the following generic description of timetabling: "A timetabling problem is defined by four parameters: T, a finite set of times; R, a finite set of resources; M, a finite set of meetings; and C, a finite set of constraints. The problem is to assign times and resources to the meetings so as to satisfy the constraints as far as possible." Timetabling applications have been explored in various forms such as *educational timetabling*, *nurse rostering*, *sports scheduling*, and *transportation timetabling*.

Educational timetabling problems require the allocation of events to timetable periods while satisfying a set of hard constraints and minimizing a set of soft constraints [9–15]. Pillay [32] provided an overview of the research conducted in the school timetabling problem, which summarized its general definition and categorized constraints into seven groups (i.e. problem requirements, no clashes, resources utilization, workload, period distribution, preference and lesson constraints). University timetabling problem can be classified into course timetabling and examination timetabling, between which the substantial difference was summarized by MirHassani and Habibi [33]. For instance, a course has to be scheduled into exactly one room, while several exams share a room or an exam split across several rooms. Critical discussions of the research on educational timetabling in last decades were presented in [32–34], which highlighted the new trends and key achievements.

Nurse rostering problems generate a schedule for each nurse, who has day off patterns, working shifts patterns and different work contracts, to fulfill the collective agreement requirements and hospital staffing demand coverage, while minimizing salary cost and maximizing nurse preferences and quality [3–7]. Burke and Curtois [6] developed a mathematical model for all the instances of nurse rostering problems by applying "regular expression" to incorporate their varying types of constraints (e.g., minimum/maximum consecutive work days, day on/off request, and shift on/off request). Solos et al. [3] proposed a more effective generic variable neighborhood search algorithm to solve seven different nurse rostering instances and summarize these varying types of constraints into two categories: hard constraints (e.g., all shift type demands must be met) and soft constraints (e.g., maximum number of hours worked), most of which were also modeled as an integer programming in [5] and included in [7] when presenting a mathematical formulation for all nurse rostering problem instances with 2 hard and 18 soft constraints in the First International Nurse Rostering Competition (INRC-2010). It is different from the educational timetabling problem mainly because of the demand coverage constraint, which specifies the number of nurses in each skill level [4], salary costs, nurse preferences, and degree of balance among nurses.

Furthermore, the main issue in sports scheduling is determining the date and venue for each tournament game. For example, a round robin tournament requires each team to play against all other teams in a fixed number of times. Moreover, breaks minimization, distance minimization, traveling tournament problem, and carry-over effects minimization can all be considered in sports scheduling, thus, this scheduling is different from the educational timetabling problem. Ribeiro [35] provided an introductory review of fundamental problems in sports scheduling and a survey of applications of optimization methods for solving them.

In terms of train timetabling problems, Cacchiani and Toth [8] presented an overview of the main works on train timetabling and distinguished it into the non-cyclic [36] and cyclic [37] version. Trains with cyclic timetables leave the stations at the beginning or at a specific interval every cycle. For example, if the cycle is one hour, trains leave the stations at the same minute every hour. For