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Improved differential evolution algorithms for solving generalized assignment problem

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ABSTRACT

This paper presents algorithms based on differential evolution (DE) to solve the generalized assignment problem (GAP) with the objective to minimize the assignment cost under the limitation of the agent capacity. Three local search techniques: shifting, exchange, and *k*-variable move algorithms are added to the DE algorithm in order to improve the solutions. Eight DE-based algorithms are presented, each of which uses DE with a different combination of local search techniques. The experiments are carried out using published standard instances from the literature. The best proposed algorithm using shifting and *k*-variable move as the local search (DE-SK) techniques was used to compare its performance with those of Bee algorithm (BEE) and Tabu search algorithm (TABU). The computational results revealed that the BEE and DE-SK are not significantly different while the DE-SK outperforms the TABU algorithm. However, even though the statistical test shows that DE-SK is not significantly different compared with the BEE algorithm, the DE-SK is able to obtain more optimal solutions (87.5%) compared to the BEE algorithm that can obtain only 12.5% optimal solutions. This is because the DE-SK is designed to enhance the search capability by improving the diversification using the DE's operators and the *k*-variable moves added to the DE can improve the intensification. Hence, the proposed algorithms, especially the DE-SK, can be used to solve various practical cases of GAP and other combinatorial optimization problems by enhancing the solution quality, while still maintaining fast computational time.

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1. Introduction

The generalized assignment problem (GAP) is the problem of assigning *n* different tasks to *m* agents with the objective of minimizing the total assignment cost. GAP was first proposed by Ross and Soland (1975). In the GAP, each task is assigned to only one agent representing a single resource with limited capacity and each task requires a certain amount of a resource used to execute that task. GAP is known to be a Non-Polynomial or NP-hard problem (Fisher & Jaikumar, 1981) and has a wide variety of applications in the real world. As an example, we can find the combination of generalized assignment concepts in problems arising in the vehicle routing problem, traveling salesman problem, location allocation problems, and scheduling problem. Motivated by real life applications, a variety of generalizations of GAP have been proposed, for example, the multi-objective GAP by Subtil, Carrano, Souza, and Takahashi (2010), the dynamic multi-resource generalized assignment problem by Shtub and Kogan (1998), the multi-resource generalized assignment problem with additional constraints by Privault and Herault (1998), the fuzzy assignment problems by Li, Li, Jin, and Wang (2012a), the fuzzy multiple objective generalized assignment problems by Tapkan, ÖZbakıR, and BaykasoğLu (2013), the equilibrium generalized assignment problem by Liu et al. (2012) and the generalized assignment problem with minimum quantities by Krumke and Thielen (2013). Other generalizations of GAP can be found in Cattrysse and Van Wassenhove (1992) and Wang (2002).

To solve the GAP, many different solution methods have been developed by researchers in the past decades. Several exact methods such as branch and price, cutting plane, branch and cut, and branch and bound algorithms have been proposed to solve the problem for its optimal solution (Avella, Boccia, & Vasilyev, 2010; Fisher, Jaikumar, & Van Wassenhove, 1986; Nauss, 2003; Ross & Soland, 1975; Savelsbergh, 1997). However, due to the complexity of the problem, exact methods developed for GAP can solve only small sized instances of up to 200 tasks and 20 agents (Lui et al., 2012). Therefore, efficient approximation methods, i.e., heuristics and metaheursitics, are needed to solve the problem in recent years, especially for large sized problems. Heuristics and metaheursitics have been intensively studied to discover the effective algorithm for solving a large scale GAP. Hence, in this paper, a well-known metaheuristic called the differential evolution algorithm (DE), which is one of the

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evolutionary algorithms, is used to solve the problem and enhance the solution obtained in tractable time. DE was first proposed by Storn and Price (1997) and it has continuously proven to be an effective algorithm to solve both continuous and discrete optimization (Brest, Greiner, Boskovic, Mernik, & Zumer, 2006; Gao, Zhou, Li, Pan, & Yi, 2015; Gong, Cai, & Jiang, 2008; Gong, Cai, & Ling, 2010; Nearchou, 2005, 2007, 2008; Qin, Huang, & Suganthan, 2009). Recently, there have been many researchers expanding the use of DE to solve various combinatorial optimization problems such as the vehicle routing problem, assembly line balancing, vehicle routing with time windows and production flow shop and job shop scheduling (see Cao and Lai, 2010; Dechampai, Tanwanichkul, Sethanan, & Pitakaso, 2015; Fan &Yan, 2015; Mokhtari & Salmasnia, 2015; Nearchou, 2005, 2007, 2008; Onwubolu & Davendra, 2006; Pan, Tasgetiren, & Liang, 2008; Wisittipanich & Kachitvichyanukul, 2011, 2012).

With the success of DE applications in many combinatorial optimization problems, DE was adopted to solve the GAP in this paper. Originally, DE was used to solve many kinds of problems without local search in order to maintain low computational time. To improve the solution for the GAP while still maintaining fast computational time to solve the problem, three local search techniques, shifting, SWAP, and *k*-variable move algorithms, were incorporated into the DE mechanism. The shifting and SWAP algorithms were found in the literature, while the *k*-variable move algorithm was first designed in this paper in an attempt to obtain lower computational time. The performance of the modified DE on this problem might be a good indicator for its ability to solve the GAP and also the complex constrained combinatorial optimization problems. Therefore, in order to show the competitiveness of the proposed approach, it is benchmarked with the well-known heuristics on the problem, BEE (Özbakir, Baykasoğlu, & Tapkan, 2010) and Tabu (Diaz & Fernandez, 2001), that are found in the literature. In view of these shortcomings, our main contributions in this study are not only developing the new local search technique (the *k*-variable move) but also hybridizing all three local search techniques (shifting algorithm, SWAP algorithm, and *k*-variable move algorithm) in the DE algorithms for the GAP with the possibility of keeping low computational time. The remainder of this paper is organized as follows: Section 2 reviews the literature; Section 3 presents the mathematical formulation of the GAP; Section 4 exhibits the proposed heuristic; the computational results are discussed in Section 5, and Section 6 is the conclusion and discussion part of the paper.

2. Related literature

The GAP is a well-known problem. It is one of the widely applied and extensively studied combinatorial optimization problems. Many real life applications can be modelled as a GAP. As a consequence, there has been an increase in GAP research motivated by practical applications. To solve the GAP, various approaches can be found. Exact algorithms have been developed to solve small sized problems. Since the GAP has been shown to be NP-hard, in an effort to find a near optimal solution for the larger, more practical problems, efficient heuristic algorithms including evolutionary algorithms are required for its solution.

The heuristics methods that have been proposed in the literature are generally composed of two steps: (1) construct a set of initial solutions, which can be feasible or infeasible solutions and (2) improve the initial solutions to find better solutions. To construct a set of initial solutions, Lagrangian relaxation is one of the popular techniques widely used (Barcia & Jörnsten, 1990; Jeet & Kutanoglu, 2007; Jörnsten & Näsberge, 1986; Litvinchev, Mata, Rangel, & Saucedo, 2010; Lorena & Narciso, 1996; Narciso & Lorena, 1999; Park, Lim, & Lee, 1998). The construction of the initial solutions can also be built randomly (Diaz & Fernandez, 2001; Liu et al., 2012; Munoz & Munoz, 2012) or by using greedy heuristic information (Munoz & Munoz, 2012; Özbakir et al., 2010). To improve the initial solutions, various heuristics and metaheuristics have been used such as the Genetic algorithm (GA), Tabu Seach (TS), the dynamic Tabu Search algorithm (DTS), Simulated Annealing (SA), Bees algorithm (BA), the Variable Depth Search algorithm, a set partitioning algorithm, the Greedy Randomized Adaptive Search, simple iterative search, and the Cross Entropy algorithm (Amini & Racer, 1994; Cattrysse, Salomon, & Van Wassenhove, 1994; Chu & Beasley, 1997; Diaz & Fernandez, 2001; Higgins, 2001; Liu et al., 2012; Laguna, Kelly, González-Velarde, & Glover, 1995; Shmoys & Tardos, 1993; Narciso & Lorena, 1999; Osman,1995; Özbakir et al., 2010; Romeijn & Romero-Morales, 2000; Trick, 1992; Yagiura, Yamaguchi, & Ibaraki, 1998; Yagiura, Ibaraki, & Glover, 2004 , 2006).

In the past decade, metaheuristic approaches have been applied extensively in various different combinatorial optimization problems, especially for complex and large-scale problems. Recently, there has been significant effort to apply evolutionary computation techniques for combinatorial optimization problems. Among recent evolutionary algorithms (EA) for GAP are those such as TS and SA (see Osman, 1995), GA (see Wilson, 1997; Chu & Beasley, 1997), and the BEE algorithm (see Özbakir et al., 2010).

The DE is one of the most powerful and interesting evolutionary algorithms and is effectively applied to both continuous and discrete optimization problems. DE like the method of GA permits each successive generation of solutions to develop from the previous generations. However, the main difference between the DE and GA is the selection process and the mutation scheme that makes DE self-adaptive. In DE, all solutions have the same opportunity of being selected as parents with independence of their fitness value. DE employs a selection process that the better one of new solution and its parent wins the competition that provides great advantage of converging performance over GA (Hegerty, Hung, & Kasprak, 2009). The application of DE can be found in many research studies. Generally, the classical DE consists of 4 common steps: (1) generate initial solution, (2) perform mutation process, (3) perform recombination process, and (4) perform selection process. However, the convergence of the traditional DE is strongly dependent on the choice of three main control parameters: the mutation scale factor *F*, the crossover constant *Cr*, and the population size *NP*, resulting in easy falling into a local search and slow convergence speed. Choosing proper mutation strategies and control parameters is one of crucial approaches to enhance the performance of DE algorithm. Hence, in 2015, Yan and Fan proposed a self-adaptive DE algorithm with discrete mutation control parameters (DMPSADE) to solve the optimization problem. To assess the performance of the DMPSADE, it was compared with 3 non-DE algorithms and 8 state-of-the-art DE variants by using 25 benchmark functions. The statistical results show that the average performance of DMPSADE is better than that of all other previous studies. For the application of DE in solving the GAP, there have been very few studies, for example, for DE solving the GAP, see Tasgetiren, Suganthan, Chua, and Al-Hajri (2009) and a novel discrete DE (DDE) algorithm for the multi-objective GAP, see Jiang, Xia, Chen, Meng, and He (2013).

Recently, a hybrid approach such as a local search technique is another approach that has become one of the most powerful techniques developed to obtain a better solution than the work applying the classical metaheuristics (Sangsawang, Sethanan, Fujimoto, & Gen, 2015). It can be incorporated into a metaheuristic mechanism for obtaining a better solution to the problem. Neighbourhood search algorithm is one of the efficient local search techniques that can be hybridized with heuristic and metaheuristic algorithms. Generally, the neighbourhood search algorithm can be distinguished into 3 types which are: (1) SWAP algorithm (Diaz & Fernandez, 2001), (2) shifting algorithm (Diaz & Fernandez, 2001; Munoz & Munoz, 2012), and (3) ejection chain neighbourhood (Yagiura et al., 2004; Yagiura et al., 2006). For the SWAP algorithm, if task i is assigned to agent j and task $i + 1$ is assigned to agent $j + 1$, the exchange procedure is just the

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