Meta-Heuristic Development in Combinatorial Optimization

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Abstract. The quadratic assignment problem is a combinatorial problem of deciding the placement of facilities in specified locations in such a way as to minimize a nonconvex objective function expressed in terms of distance between location and flows between facilities. Due to the non-convexity nature of the problem, therefore to get a ‘good’ starting point is necessary in order to obtain a better optimal solution. In this paper we propose a meta heuristic strategy combined with feasible neighbourhood search to get ‘optimal’ solution. From computational experience in solving some backboard wiring problems, it turns out that the approach proposed is promising.

1. Introducing

Most of good optimization problems that are reviewed in terms of practical and theoretical consist of "best" configuration search variables set so that the goal is achieved (objective). Such problems are divided into two categories, namely, the problem of resolution is real valuable variables, and the problem with the variable is discrete. The problem of optimization with the second category is known as combinatorial optimization problems. The next one in this paper is abbreviated as CO. According to Papadimitriou and Steiglitz (1982) , in the CO problem, it is necessary to find an object from a finite set (or maybe infinit calculated) [1]. This object can be an integer, a subset, a permutation, or a graph structure.

Some of combinatorial problems arise in many practical applications. Some uses include sectors, such as investment portfolio optimization (Bienstock, 1996; Jobst et al., 2001) [2], layout designs in the service and manufacturing sectors (Danna et al., 2005; Sawaya, 2006) [3], integrated and process-controlled design chemistry (Flores-Tlacahuauc and Biegler, 2007) [4], drinking water distribution system (Laird et al., 2006), multiperiod supply chain (Lejeune, 2009; Kaya and Urek, 2016) [5], system energy design (Kim and Edgar, 2014; Yang et al., 2015), Planning construction site layout (Hammad et al., 2016) [6]. Therefore there is an algorithm that is able to solve CO problems efficiently. The algorithm approach to this problem can be classified as an exact or approximate approach. Exact algorithms are guaranteed to obtain optimal solutions in finite time by systematically exploring the settlement space. The exact method for completing CO includes innovative approaches and related techniques that are taken and expanded from solving mixed integer programming (MIP) problems, such as the Outer Approximation (OA) method[7], Branch-and-Bound (B & B) [P. Belotti, 2009; O.K. Gupta and A. Ravindran, 1985; G. Nannicini, P. Belotti., 2009] [8], Extended Cutting
Plane methods [Tamara G. Kolda, Robert M. Lewis., 2003], and Generalized Bender's Decomposition (GBD) [A.M. Geoffrion., 1972] [9], which for resolving CO has been discussed in literature since the early 1980s. These methods generally depend on sequential solutions to related nonlinear programming (NLP) problems. For example, B & B begins by forming pure continuous NLP problems by relaxing the requirements for integrality of discrete variables (often called relaxation). In addition, each node of the B & B tree that appears is a solution of relaxation with a limit that is adjusted to discrete variables. Recently Fernandes et al. (2016) developed a filtered Hooke-and-Jeeves search to complete CO. Vigerske and Gleixner (2017) complete CO in the basic framework of the Branch and Cut method.

However, due to the complete nature of NP from the CO problem, the time needed to grow exponentially for the worst case. To overcome this problem practically, the solution to CO is considered to have met close to the optimal solution in polynomial time. This is the goal of an algorithm approach such as local exploration. The approach algorithm cannot guarantee optimality of completion, but empirically this algorithm often shows "good" results in short computational time, the most used and successful approach algorithm is the local browsing algorithm. This algorithm starts from the completion given and tries to determine the better solution in the surrounding area which is appropriate (through definition) of the solution that has been obtained. If a settlement point is better found, this point replaces the previous dissolution point and local exploration continues.

The most basic local browsing algorithm is called iterative repair. This algorithm works iteratively so that no solution is better found in the area around the point that has been obtained. The ugliness of this algorithm can stop at a local minimum far from the actual optimal point. So to improve its performance, the exploration area needs to be enlarged. Obviously this way will increase the processing time. Another possibility is to start algorithms with new solutions that are randomly formed. But, exploration space contains a large number of locally optimal, so this approach becomes very inefficient for large dimensions.

To prevent this weakness, much of the development of the local browsing algorithm is proposed. These algorithms correct the local browsing algorithm by accepting the worst solution, that is, allowing browsing away from the local optimal, or by producing a good starting point that will lead to better completion. The general scheme for improving local search algorithms is now called metaheuristics [10][11].

2. Methodology

2.1. Metaheuristik

The metaheuristic method was first introduced in 1986, and was described as an excellent alternative search strategy, above the search space in hopes of finding optimal results. Many algorithms have been proposed by researchers in the literature, for example the ant colony optimization method [12], but until now there has been no general accepted definition and a standard reference for the term metaheuristic, but metaheuristics is usually used as a high-level strategy that directs the underlying problem.

Metaheuristics is usually a high-level strategy that guides problems underlying specific heuristics to improve their performance, whose main goal is to lead to iterative improvement and gain algorithmic development. Many metaheuristic approaches rely on probabilistic decisions made during the search but the main difference from the search by the metaheuristic method is to be done intelligently [13]. So it can be said metaheuristic is a repetitive master process that guides and modifies subordinate heuristic operations to produce high-quality solutions efficiently. This can manipulate a single solution that is complete (or incomplete) or a collection of solutions in each iteration different from the Heuristic method is a technique designed to solve problems by ignoring whether the solution to the problem can be proven correct or not, but usually produces a good solution or solves easier, faster and simpler problems. The heuristic technique does not have an optimum search algorithm that is definite but has rules that can explore the most promising search space, namely the space for optimum or near optimum solutions [14].
2.2. Genetic Algorithm
Genetic Algorithms are search techniques in computer science to find approximate solutions to search optimization and problems. Genetic algorithms are techniques inspired by evolutionary biology such as inheritance, mutation, natural selection and recombination (or crossover), the genetic algorithm first developed by John Holland in the 1970s in New York, United States. He and his students and coworkers produced a book entitled "Adaption in Natural and Artificial Systems" in 1975. Genetic Algorithms are especially applied as computer simulations where a population of abstract representations (chromosomes) of prospective solutions (called individuals) on an optimization problem will develop into better solutions. Traditionally, solutions are represented in binary as strings '0' and '1', although it is also possible to use different encoding.

2.3. Literature Review
According to Azmi Alazzam and Harold W. Lewis III (2013), suggesting a meta-heuristic approach is not guaranteed to find an optimal solution because it only evaluates a subset of feasible solutions, but this method tries to explore different areas in the search space with smart ways to get near-optimal solutions at lower costs and propose a meta-heuristic algorithm can be used to solve combinatorial optimization problems. Gregory Gutin (2010), Meta-heuristics is a sophisticated algorithm that is intended to find optimal solutions close to a considerable amount of time. The process is longer than local search and it is difficult to analyze theoretically about running time or the surrounding environment, but metaheuristics cannot be compared directly with local search[15]. Arnaud Liefooghe, et al. (2013) proposed a hybrid metaheuristic that combines the evolutionary multi-objective optimization algorithm and the latest single-objective taboo search procedure using functions of achievement variation. And defining metaheuristics in general is an evolutionary algorithm specifically[16]. Stu¨tzle et. al (1999) Metaheuristics is usually a high-level strategy that guides the underlying specific heuristics, more importantly, to improve performance. The main objective is to avoid losses from iterative improvement and, in particular, some offspring by allowing local searches to emerge from local optima. This is achieved by allowing deteriorating movements or generating new initial solutions for local search in a more "smart" way than just providing a random initial solution. Many methods can be interpreted as introducing bias so that high-quality solutions are produced quickly. This bias can be of various forms and can be cast as descent bias (based on objective functions), memory bias (based on previously made decisions) or experience bias (based on previous performance). Many metaheuristic approaches rely on probabilistic decisions made during the search. But, the main difference between pure random search is that in randomness optical optics are not used blindly but in a biased and intelligent form.

Crossover is an operator that allows a combination of genetic material from two or more solutions, Crossover operators in Genetic Algorithms apply a mechanism that mixes genetic material from the parent. The so-called representative string-bit is a n-point crossover. This bisects the solution in position n and alternately assembles it to the new one. For example, if 0010110010 is the first parent and 1111010111 is the second, one crossover point will randomly choose the position, let's assume 4, and produce two candidate solutions descendants of 0010010111 and 1111110010.

Figure 1. Cross over genetic algorithm

3. Results and Discussion
Among the basic estimation methods, we usually distinguish between constructive methods and local search methods. Constructive algorithms produce solutions from zero by adding - to the component of the partial solution that is initially empty, until the solution is complete. This method is usually the
fastest estimate method, but often returns low quality solutions when compared to local search algorithms.

3.1. Metaheuristic classification
In metaheuristic development can be used from various sciences this can be seen from the scientific needs that have been present which are combined with various methods and algorithms. and this paper will use metaheuristic development with a plant propagation algorithm, below is a metaheuristic classification image;

![Metaheuristic Classification Image](image)

**Figure 2. Metaheuristic Classification**

4. Conclusion
a. Determine Regions of Decent Settlement Settlement.
   b. This area is minimized by eliminating (eliminating) regions that do not meet the eligibility requirements for enumeration.
   c. Identification of regions that can provide optimal settlement of optimal counts
   d. From the point obtained in step 2, obtain the direction gradient to the area obtained in step 3
e. Determine how far the movement from that point is so that feasibility is guaranteed.
f. Check the point obtained in step 5, whether it is in an optimal feasible area.
g. If you go to step 8, If it hasn't returned to step 4
h. Continue the movement from the point obtained in step 5 by reducing the area so that the point in step 2 is obtained.
i. Stop.

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