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An artificial immune system based algorithm to solve unequal area facility layout problem

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ABSTRACT

This study introduces an artificial immune system (AIS) based algorithm to solve the unequal area facility layout problem (FLP) with flexible bay structure (FBS). The proposed clonal selection algorithm (CSA) has a new encoding and a novel procedure to cope with dummy departments that are introduced to fill the empty space in the facility area. The algorithm showed consistent performance for the 25 test problem cases studied. The problems with 100 and 125 were studied with FBS first time in the literature. CSA provided four new best FBS solutions and reached to sixteen best-so-far FBS solutions. Further, the two very large size test problems were solved first time using FBS representation, and results significantly improved the previous best known solutions. The overall results state that CSA with FBS representation was successful in 95.65% of the test problems when compared with the best-so-far FBS results and 90.90% compared with the best known solutions that have not used FBS representation.

1. Introduction

The FLP can be defined as the placement of the machines/departments in the plant area. Layout problems are known to be complex and are generally NP-Complete (Sahni & Gonzalez, 1976). Therefore researchers have focused on developing heuristic algorithms that may be construction type, improvement type, hybrid methods (construction and improvement), fuzzy-set-based methods, expert systems and hybrid (analytical and knowledge-based) systems. Further, both construction and improvement types can be categorized as either "conventional" or graph-theory-based Welgama, Gibson, and Al-Hakim (1994). Koopmans and Beckmann (1957) are the first to model the equal area FLP as a quadratic assignment problem (QAP). Since then, many researchers, such as Bazaraa (1975), Burkard and Stratman (1978), Kusiak and Heragu (1987), and Francis, McGinnis, and White (1992) have addressed the importance of QAPs and their relevance to the equal area FLP. Comprehensive reviews of facility layout research are given in Meller and Gau (1996), Singh and Sharma (2006), and Drira, Pierreval, and Gabouj (2007).

Typically, departments have unequal areas in real life cases. Armour and Buffa (1963) proposed the unequal area FLP and applied a pair-wise exchange method to solve the problem without shape constraints. Tong (1991) approached this problem by assuming rectangular departmental shapes placed in bays. The flexible bay structure (FBS) is defined as a continuous layout representation allowing the departments to be located only in parallel bays with varying widths. As stated in Kulturel-Konak, Smith, and Norman (2004), there is no limit on the number, width and content of bays; that's why this representation is called flexible bay. Applications of FBS are seen in Goetschalckx (1992), Tate and Smith (1995), Meller (1997), Peters and Yang (1997), Kulturel-Konak, Norman, Coit, and Smith (2004), Konak, Kulturel-Konak, Norman, and Smith (2006), Chae and Peters (2006), Norman and Smith (2006), and Wong and Komarudin (2010) to list a few.

A sample FBS layout is given in Fig. 1. Departments are located from left to right and from top to bottom (as illustrated with the arrows). In this layout, departments 5 and 6 are in the first bay; 9, 8 and 2 are in the second; 7, 10 and 4 are in the third; 1 and 3 are in the fourth.

There may be various numbers of possible physical layouts, and many locally optimal layouts that are poor compared to the global optimum layout for the unequal area FLP (Tate & Smith, 1995). Therefore, parallel search methods perform better than strictly serial searches and randomized search methods. CSA can exploit and explore the solution space parallel and effectively (Gao, Wang, Dai, Li, & Tang, 2008). Immune systems principles have been applied to solve combinatorial optimization problems from various areas, to name a few, scheduling (i.e., Engin & Doyen, 2004; Hsieh, You, & Liou, 2009; Tsai, Ho, Liu, & Chou, 2007; Zandieh, Ghomi, &

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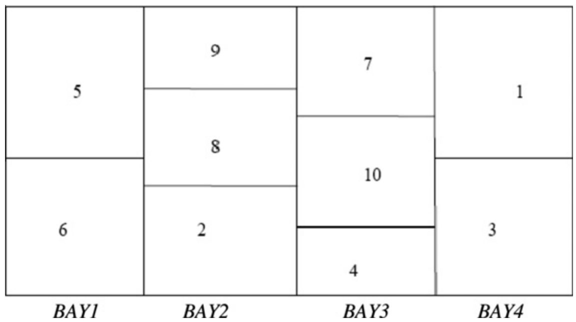

Fig. 1. A sample FBS layout.

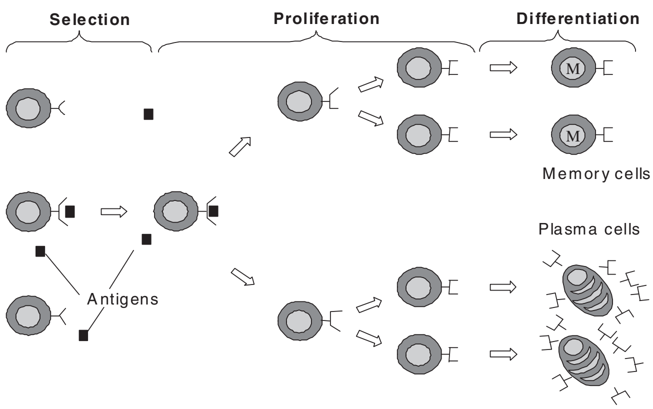

Fig. 2. Clonal selection process in B-cells (De Castro & Timmis, 2002).

Husseini, 2006) and travelling salesman problem (i.e., Gong, Jiao, & Zhang, 2006; Liu, Wang, & Yang, 2009; Masutti & De Castro, 2009). Therefore, this study proposes a novel solution strategy for unequal area facility layout with a new encoding for FBS using CSA principles. Twenty-three known FBS test problems are solved, and two new large size test problems are introduced to FBS literature.

The remaining of the paper is as follows: In Section 2, the features of AIS and CSA are explained. Section 3 provides the general definitions of the FLP with FBS and the new CSA algorithm for FLP with FBS (called CSA-FBS) steps. In Section 4, the performance of the algorithm is tested using the commonly encountered test problems. Finally, Section 5 presents the conclusions and future research directions.

2. Clonal selection algorithm

The natural immune system is known as the defense system. Immune system organs are distributed over the body, and they are not managed from a sole organ unlike in the neural system. Immune systems are very complex in their nature. The efficient mechanisms of the immune systems such as the clonal selection, learning ability, memory, robustness, and flexibility have attracted the attention of researchers (Dasgupta, 1998). AIS algorithms imitate the immune functions, models and principles to solve complex problems (De Castro & Timmis, 2002). The existing theoretical work on AIS is reviewed and detailed in (Timmis, 2008). The application areas of AIS are summarized in Hart and Timmis (2008). Various applications include anomaly detection, optimization problems, clustering/classification, etc. The AIS algorithms in the literature are basically classified as population based (clonal selection, negative selection, and bone marrow) and network based models. CSA, which is one of the population based algorithms of AIS, is based on the clonal selection process in B-cells as illustrated in Fig. 2. B-cells turn to immature lymphocytes at thymus. They are activated when they meet with an antigen. Then, B-cells go through a maturation process in order to recognize different antigens.

Evolution occurs based on the two basic principles of the vertebrate immune system: affinity maturation and receptor editing in CSA (De Castro & Von Zuben, 1999). During proliferation, the antibodies undergo a hypermutation which diversifies the repertoire of the B-cells. After hypermutation processes, receptor editing mechanism is applied where the worst percent of the antibodies in the population is eliminated, and randomly created antibodies are replaced with them. This mechanism allows moving to new search regions in the global search space. For further information about CSA and its increasing number of applications, readers may refer to Brownlee (2007).

Main principles of Evolutionary Algorithms (EAs) and CSA have some common features, although they may have a different biological inspiration. Table 1 summarizes the basic similarities and differences of EA and CSA. Crossover and mutation are the basic tools for creating new solutions for a standard EA (i.e., GA) while hypermutation and receptor editing operators are distinctive for CSA.

In GA, reproductive parents are selected due to their fitness values. A crossover operator is applied, and new offspring are created. Differentiation is mostly achieved by crossover. After applying mutation operator, individuals for the next generation are selected from the whole population. On the other hand, the CSA takes into account the affinity (objective function) values during hypermutation. Mutated antibodies are immediately tested for acceptance or rejection. Hypermutation rates are inversely proportional to the affinity of antibodies. In a standard GA, the mutation rate does not change for different individuals, and is usually considered as a small constant rate for the population. The most remarkable characteristic of the CSA is to use the hypermutation rate as a self-adapting parameter which resembles with the natural immune system.

3. CSA to solve unequal area FLP

In any FLP, in its most general form, a planar region is divided into smaller regions usually named as departments and then the total material handling cost among departments is tried to be minimized. The constraints of the problem may include satisfying the area and shape requirements of the departments and the entire facility. The given facility area can be assumed as one continuous or several continuous spaces (e.g., multiple floors), rectangular or non rectangular shapes, and the departments can be defined as unit squares, rectangular shaped, or irregular shaped. If all departments

Table 1
Similarities and differences between EA and CSA (Dasgupta & Nino, 2008).

Features	EA	CSA
Search space	Set of chromosomes	Set of antibodies
Candidate solutions, individuals	Chromosome	Antibody
Individual representation	Any (strings, real vectors, etc.)	Any
Population size	Fixed	Fixed
Performance measure	Fitness	Affinity
Operators	Chromosome selection, Mutation, crossover	Clone selection, hypermutation
Mutation rate	Small (∼1%)	Big (depends on antibody affinity value)