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A novel hybrid evolutionary approach for capturing decision maker knowledge into the unequal area facility layout problem

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ABSTRACT

Introducing expert knowledge into evolutionary algorithms for the facility layout design problem can provide better solutions than the mathematically optimal solutions by considering qualitative aspects in the design. However, this approach requires the direct intervention of a designer (normally called the decision maker) in the evolutionary algorithm that guides the search process to adjust it to his/her preferences. To do this, the designer scores each of the most representative designs of the population to avoid fatigue. The selection of the solutions to be presented for human assessment is crucial, so a small number of solutions that represents the characteristics of the population must be selected without losing the variability of the solutions. The novel hybrid system proposed in this study consists of an interactive genetic algorithm that is combined with two different niching methods to allow interactions between the algorithm and the expert designer. The inclusion of niching techniques into the approach allows for the preservation of diversity, which avoids presenting similar solutions to the designer in the same iteration of the algorithm. The proposed approach was tested using two case studies of facility layout designs. The results of the experiments, which successfully validate the approach, are presented, compared and discussed.

1. Introduction

The placement of facilities in a plant, which is often referred to as the *facility layout problem*, is known to have a significant impact on manufacturing costs, work in process, lead times and productivity (Drira, Pierreval, & Hajri-Gabouj, 2007). Where to locate facilities and the efficient design of those facilities are important and fundamental strategic issues in any manufacturing industry (Singh & Sharma, 2006). Well laid out facilities contribute to the overall efficiency of operations and can reduce total operating costs by between 20% and 50% (Tompkins, White, Bozer, & Tanchoco, 2010).

Depending on the features that are considered, several problems are included in the field of facility layout design (FLD) (Kusiak & Heragu, 1987). In particular, the novel proposal presented in this article focuses on the unequal area facility layout problem (UA-FLP) as described by Armour and Buffa (Armour & Buffa, 1963), who formulated the UA-FLP as a rectangular plant layout that is composed of unequal rectangular facilities that should be arranged in an effective way.

FLD problems can be modeled using linear integer programming, mixed integer programming (Izadinia, Eshghi, & Salmani, 2014) and Graph Theoretic methods (Heragu & Kusiak, 1991). However, because the number of facilities limits the application of optimal methods, suboptimal methods have been used to solve more complex problems. Several techniques have been applied, such as the branch and bound method (Solimanpur & Jafari, 2008) and graph theory (Kim & Kim, 1995). Recently, researchers have focused on meta-heuristic methods, such as tabu search (McKendall et al., 2006; Scholz, Petrick, & Domschke, 2009), simulated annealing (Şahin, Ertoğral, & Türkbey, 2010), the ant system (Komarudin & Wong, 2010, 2012a) and genetic algorithms (GAs) (Aiello, Scalia, & Enea, 2013; Goldberg, 1989). The latter methods have been commonly used in UA-FLP (García-Hernández, Arauzo-Azofra, Pierreval, & Salas-Morera, 2009; Michalewicz, Dasgupta, Riche, & Schoenauer, 1996).

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In general, the problem of designing a physical layout involves the optimization and consideration of certain objectives (mainly, the material flow) (Aiello, Scalia, & Enea, 2012) and criteria. However, Babbar-Sebens and Minsker (2012) stated that these optimization approaches may not appropriately describe all of the important qualitative information that is considered to be essential by a human expert who is involved in the design phase (e.g., engineers). However, it is difficult to take into account these qualitative features using a classical heuristic or meta-heuristic optimization system (Brintup, Ramsden, & Tiwari, 2007). Supposedly, the most reasonable way to consider all of these features in the selection process is to personally include the decision maker (DM) in the process (Brintup et al., 2007), which provides additional advantages such as eliminating the requirement of specifying all of the desirable information about the facility design in advance, offering the DM the ability to learn about his/her own preferences, and stimulating the users creativity (García-Hernández, Pierreval, Salas-Morera, & Arauzo-Azofra, 2013).

Brintup, Takagi, Tiwari, and Ramsden (2006) highlighted the fact that interactive evolutionary computation (IEC) can greatly contribute to improving the optimized design by involving users in searching for a satisfactory solution. However, in real-world optimization problems, we are sometimes not satisfied with only one optimal solution. In this sense, GAs often lack the ability to find multiple optima. Many authors have used niching methods to solve this problem, which can maintain a diverse population and are not as prone to converging prematurely as simple GAs (Yu & Suganthan, 2010).

Few studies have incorporated human expert knowledge into the FLD process. Quiroz, Louis, Banerjee, and Dascalu (2009) suggested an approach to handle collaborative design issues in constructing floor plans. Zhao, Li, Yang, Abraham, and Liu (2014) proposed an approach for packing problems that consisted of a human–computer cooperative particle swarm optimization-based immune algorithm. Although they considered the designer knowledge in their approach by asking him/her for possible preliminary designs, the algorithm does not allow the designer to evaluate the solutions that are obtained by the algorithm. Additionally, this approach does not allow the designer to change his/her initial preferences to new ones that could appear during the process. Moreover, in this approach, the designer must know his/her preferences perfectly before the beginning of the computing process, which could be difficult because these preferences may be unclear at this point. García-Hernández et al. (2013) presented a proposal to consider qualitative features in UA-FLP. Although it improved upon previous methods, the algorithm was mainly focused on introducing designer knowledge by means of his/her evaluation of representative solutions that were selected from the entire population using a clustering method. Unfortunately, the selection method resulted in a lack of diversity in the population, so similar solutions were frequently presented to the DM in the same algorithm iteration and during the entire process. This caused fatigue for the DM, which led him/her to evaluate inappropriate solutions (which had been evaluated previously) and unnecessarily extended the duration of the design process. This was pointed out in the conclusions of this study, where the authors introduced the necessity of investigating new ways to avoid tiring the DM. To provide a solution to this problematic issue, it is necessary to determine a better way to preserve the population diversity. It could be interesting to explore the possibilities of introducing new selection techniques to improve the set of solutions that will be shown to the DM while not allowing the same solution to appear more than once in the same evaluation set. Moreover, to the best of our knowledge, no studies have addressed the UA-FLP and are able to provide solutions that satisfy the DMs qualitative preferences while preserving the population diversity.

This article presents a novel hybrid evolutionary algorithm (HEA) for incorporating human expert knowledge into the UA-FLP. This approach consists of an interactive genetic algorithm that is combined with two niching methods to allow interactions between the algorithm process and the expert human designer while preserving the diversity of the population of solutions.

The remainder of this article is organized as follows. The problem is formulated in Section 2. Section 3 provides an explanation of the computational models that are used in our proposed method. Section 4 details how the suggested new HEA works. In Section 5, the methodology is tested, and the obtained results are analyzed. Finally, concluding remarks and future work are presented in Section 6.

2. Problem formulation

The UA-FLP was proposed by Armour and Buffa (1963). It considers a rectangular plant with fixed dimensions, $W\ (width) \times H\ (height)$, and a set of facilities that each has a required area (A_i), where the sum of the facility areas must be less than or equal to the total plant area; see Eq. (1). The aim is to allocate the facilities in the plant based on a given optimization criterion subject to the non-overlapping restriction of the facilities.

$$\sum_{i}^{n} A_i <= W \times H \tag{1}$$

Many authors have taken into account quantitative criteria or constraints for the UA-FLP, including material handling costs, adjacency requests, distance requirements or a desired aspect ratio. However, as was discussed in the previous section, other qualitative features could be considered by the DM in the facility layout design. These features are difficult to consider with an optimization method because they are difficult to quantify, change depend on the design case and are frequently unknown at the beginning of the process. This study specifically emphasizes these qualitative features. Thus, the aim of this proposal is to find solutions that satisfy the DM's preferences, which could differ greatly between DMs. For example, the DM's preferences could be those proposed by García-Hernández et al. (2013), which are:

- The distribution of the remaining space in the plant layout. The DM may prefer designs in which the remaining space is dispersed all over the plant (for example, for use as storage areas), or in which all of the remaining space is aggregated in a particular location.
- The facility placement. This aspect implies the DM's preference about the location of a certain facility in the layout, which could be at the top, bottom, center or corner of the plant.
- The orientation that the DM prefers for a facility to match the sequence of the production process. For example, the DM may want the longest side of a facility to be parallel to the right side of the plant.
- Locations that are not desired for a certain facility to avoid certain factors (e.g., noise, bad smells, humidity) that exist in the plant.
- Any other subjective preference that the DM considers to be necessary in the final facility layout design.

3. Bio-inspired systems

This section describes the bio-inspired computational models (Helmy, Fatai, & Faisal, 2010) that have been applied in our novel approach to solve the UA-FLP based on qualitative features.