Recent advances in dynamic facility layout research

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Abstract

It has been nearly two decades since Balakrishnan and Cheng (1998) reviewed the literature in dynamic facility layout. In these intervening years, many advances have been made in modelling as well as in the solution methods. In this study, models and solutions that address the dynamic facility layout problem (DFLP) are examined and categorized. Our review finds that, the recent DFLP models consider more complex design features and constraints. Further, only a few DFLP studies have adopted exact methods, while most of the effective algorithms used are heuristics, metaheuristics and hybrid approaches. Future research directions are also identified.

Keywords: dynamic facility layout; modelling; algorithms; metaheuristics; survey

1 Introduction

This paper reviews recent work in the dynamic facility layout problem (DFLP, also called the dynamic plant layout problem – DPLP) where the facility may be redesigned during the planning horizon due to material flow changes. The DFLP is a relatively new research area compared to the static plant layout problem (SPLP). For a detailed analysis of the early work in DFLP, the reader may refer to Balakrishnan and Cheng (1998).

In the two decades since Balakrishnan and Cheng's (1998) review, significant progress has been made in the complexity of the models as well as in the solution methods. Thus, we feel that it is appropriate to provide an analysis of recent developments, which will give researchers a good understanding of the state-of-the-art in DFLP research. The remainder of the paper is organized as follows. The next section explains the models used by researchers. Section 3 discusses the solution methods applied. Finally, Section 4 summarizes the paper and suggests possible future research directions.

2 Dynamic facility layout modelling

Drira et al. (2007) summarized essential features to characterize facility layout problems (FLP). Based on Drira et al's (2007) framework, the DFLP can be studied from the following aspects: problem formulations including objectives and constraints, and facility characteristics such as the specificities of the manufacturing systems, the facility shapes, and the layout configurations.

2.1 Problem formulations

In the past twenty years, different kinds of mathematical models have been used to formulate DFLP, which include the modified quadratic assignment problem (QAP), mixed integer programming (MIP), graph theoretic models (GT) and so on.

More than half of the DFLP studies are modelled with discrete representation by modified QAP. Generally, in DFLPs formulated by modified QAP, the planar region is divided into a number of rectangular sub-regions with the same size and shape. Each sub-region is assigned to one department, so as to minimize the sum of the material handling cost and rearrangement cost. A typical formulation is shown as follows (Balakrishnan et al. 2003):

$$\min \sum_{t=1}^{P} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} \sum_{l=1}^{n} f_{tik}\, d_{tjl} X_{tij} X_{tkl} + \sum_{t=2}^{P} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} \sum_{l=1}^{n} A_{tijl}\, Y_{tijl} \tag{1}$$

Subject to

$$\sum_{i=1}^{N} X_{tij} = 1; \quad j = 1, 2, \ldots, n; \;\; t = 1, 2, \ldots P \tag{2}$$

$$\sum_{j=1}^{N} X_{tij} = 1; \quad i = 1, 2, \ldots, n; \;\; t = 1, 2, \ldots P \tag{3}$$

$$Y_{tijl} = X_{(t-1)ij}\, X_{til}; \quad i, j, l = 1, 2, \ldots, n; \quad t = 2, \ldots P \tag{4}$$

where f_{tik} is the flow cost from department i to department k in period t; d_{tjl} is the distance from location j to department l in period t; X_{tij} is a 0-1 variable for locating department i at location j in period t; A_{tijm} is fixed cost of shifting department i from j to m in period t ($A_{tijj} = 0$); and Y_{tijm} is a 0-1 variable for shifting department i from j to m in period t. The objective in (1) is to minimize the sum of the material handling cost (first term) and the layout rearrangement cost (second term). Eq. (2) ensures every department to be assigned. Eq. (3) requires every location having a department assigned to it. Eq. (4) assigns Y_{tijm} a value of 1 only when a department has been shifted in the period.

Considering departments with unequal sizes, Kochhar and Heragu (1999) assumed that the facility is divided into a grid of squares of unit area and each department is assigned to one or more unit squares based on its area requirements (see Figure 1). Samarghandi et al. (2013) also considered unequal area and formulated a multi-objective DFLP using modified QAP. Different from Kochhar and Heragu (1999), they assumed that a department can only be placed in certain locations in each period. The formulation is shown as follows (Samarghandi et al. 2013):

$$\begin{aligned} \min z_1 = &\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{m=1}^{N}\sum_{n=1}^{N} c_{imt}\cdot d_{jn}\cdot \pi_{imt}\cdot X_{ijt}\cdot X_{mnt} \\ &+\sum_{t=2}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N} s_i\cdot Y_{ijlt} \end{aligned} \tag{5}$$

$$\begin{aligned} \max z_2 = &\sum_{t=1}^{T}\sum_{a=1}^{A-1}\sum_{b=1}^{B}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(w_{ijt}\cdot V_{iabt}\cdot V_{ja(b+1)t}\right) \\ &+\sum_{t=1}^{T}\sum_{a=1}^{A}\sum_{b=1}^{B-1}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(w_{ijt}\cdot V_{iabt}\cdot V_{j(a+1)bt}\right) \end{aligned} \tag{6}$$

Subject to

$$\sum_{i=1}^{N} X_{ijt} = 1;\quad j = 1,2,\dots,N;\;\; t = 1,2,\dots T \tag{7}$$

$$\sum_{j\in Q_{it}} X_{ijt} = 1;\quad i = 1,2,\dots,N;\;\; t = 1,2,\dots T \tag{8}$$

$$Y_{ijlt} = X_{ij(t-1)}\cdot X_{ilt};\quad 1\le i,j,l\le N;\quad 2\le t\le T \tag{9}$$

$$V_{iabt} = X_{i((a-1)A+b)t};\;\; i = 1,2,\dots,N; \tag{10}$$

$$a = 1, 2, \dots, A; \quad b = 1, 2, \dots, B; \quad t = 1, 2, \dots, T$$

$$X_{ijt} = \begin{cases} 1 & \text{if facility i is assigned to location j in period t} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

The two objectives involved are minimizing total transportation and shifting costs (Eq. (5)) and maximizing closeness rating value (Eq. (6)). In Eq. (5), c_{ijt} is the cost of handling one unit of product from facility i to facility j in period t $(1 \leq t \leq T)$. d_{ij} $(1 \leq i, j \leq N)$ is the distance between location i and j. π_{ijt} $(1 \leq t \leq T, 1 \leq i, j \leq N)$ is the amount of transportation between facility i and facility j in period t. S_i $(1 \leq i \leq N)$ is the shifting cost when facility i is shifted from a location to another passing through periods. In Eq. (6), w_{ijt} $(1 \leq i, j \leq N, 1 \leq t \leq T)$ is the closeness rating value of facilities i and j in period t. In Eq. (8), Q_{it} $(1 \leq i \leq N, 1 \leq t \leq T)$ is the set of locations where facility i can be placed in period t.

Chan and Malmborg (2010) developed a model for dynamic line layout problem considering unequal size work centres, multiple types of material handling devices and stochastic demand. In this model, as the material handling cost is piecewise linear, the robust solutions are obtained by solving an enumeration of the QAP instead of a single QAP. Azevedo et al. (2017) examined reconfigurable multi-facility layout problem considering the location of departments within a group of facilities, and the location of departments inside each facility itself. This dynamic multi-facility layout problem was formulated based on QAP with multiple objectives and unequal areas. In addition to minimizing material handling and rearrangement costs, Pourvaziri and Pierreval (2017) also considered the amount of work-in-process in a dynamic facility layout system. Hence, in their research, the DFLP is formulated by a mathematical model combining a developed QAP and an open queuing network.

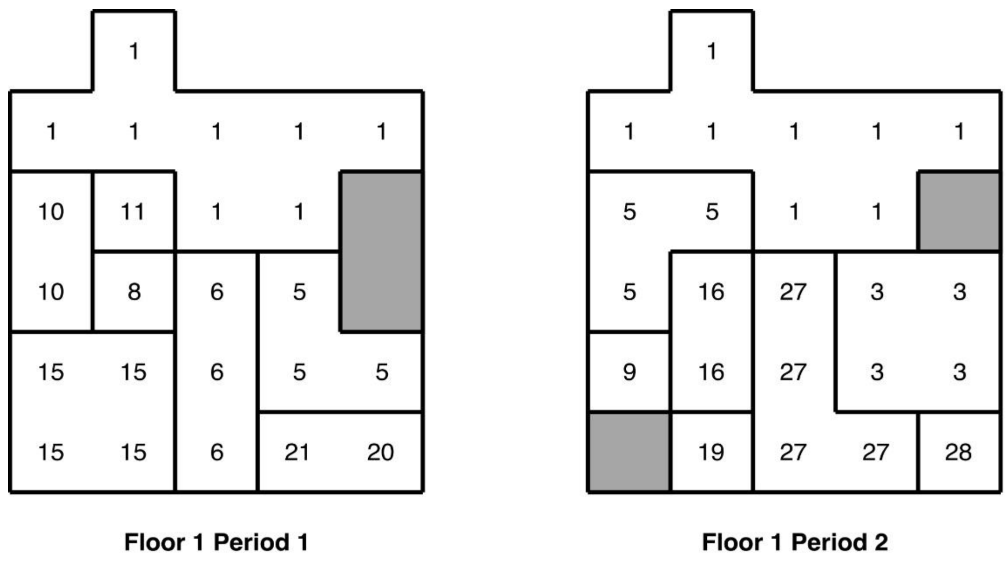

Figure 1 Examples of layouts for one floor in a multi-floor FLP. (Kochhar and Heragu 1999)

Some DFLPs are also formulated with discrete representation considering equal area facilities but through MIP, as the problems they intend to solve are more complicated. These studies often combine DFLP with other system problems or important manufacturing attributes. For instance, Kia et al. (2012) proposed a novel MIP model for the layout design of a dynamic cellular manufacturing system which covers a number of important manufacturing and design features including intra-cell layout, inter-cell layout, multi-rows layout of equal area facilities, alternate process routings, operation sequence, processing time, production volume of parts, purchasing machine, duplicate machines, machine capacity, lot splitting and flexible reconfiguration.

Instead of discrete representation, a number of DFLP studies are formulated with continuous representations by MIP for unequal size facilities, in which the dimensions of facilities do not take integer values and the facilities can be located anywhere on the shop floor (Moslemipour et al. 2012). In these studies, facilities in the plant site are often located by their centroid coordinates. Such DFLP formulations are also suitable for designing a detailed layout where the location of pick-up/drop-off points can also be determined. For example, Jolai et al. (2012) considered a multi-objective DFLP with unequal fixed size departments and pick-up/drop-off locations, and modelled the problem using MIP. In their model, (x_{ti}, y_{ti}) is the centroid coordinate of department i in period t. x'_{tij} and y'_{tij} are horizontal and vertical distances between centroid of department i and department j in period t. The distance between two facilities in period t is then expressed by the following Eq. (12) (Jolai et al. 2012):

$$d_{tij} = x'_{tij} + y'_{tij} = |x_{ti} - x_{tj}| + |y_{ti} - y_{tj}| \tag{12}$$

One of the four objectives considered by Jolai et al. (2012) is to minimize the total material handling cost (Eq. (13)):

$$\text{Minimze:} \quad \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N} C_{tij}\left[\left(x'_{tij} + y'_{tij}\right) + \left(\text{sgn}_{ti} * dp_{ti} + \text{sgn}_{tj} * dp_{tj}\right)\right] \tag{13}$$

In Eq. (13), C_{tij} is the cost of material handling (a unit distance) between department i and department j in period t. The calculation of total material handling cost considers both the distance between two departments i and j and the distance between the department centroid and its pick-up/drop-off location. dp_{ti} represents the distance between the centroid and the pick-up/drop-off location of department i, which depends on o_{ti} (orientation of department i; 0: vertical, 1: horizontal), p'_{ti} and p''_{ti} (Eq. (14) - (15)), and sgn_{ti} is a sign variable which indicates the whether the relative location of departments i and j is positive or negative. DFLPs modelled by MIP are summarized in Table 1.

$$p'_{ti} = \begin{cases} 1 & \text{if pick} - \text{up/drop} - \text{off point is in longer edge} \\ & \text{of department } i \text{ in period } t \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

$$p''_{ti} = \begin{cases} 1 & \text{if pick} - \text{up/drop} - \text{off point is in north} - \text{west edges} \\ & \text{of department } i \text{ in period } t \\ 0 & \text{if pick} - \text{up/drop} - \text{off point is in south} - \text{east edges} \\ & \text{of department } i \text{ in period } t \end{cases} \tag{15}$$

Table 1 DFLPs formulated by MIP.

Problem formulation	Authors
MIP with equal areas	Krishnan et al. (2006), Bashiri and Dehghan (2010), Kia et al. (2012), Kia et al. (2013), Kia et al. (2014), Shafigh et al. (2015), Shafigh et al. (2017)
MIP with unequal areas	Yang and Peters (1998), Corry and Kozan (2004), Dunker et al. (2005), McKendall Jr and Hakobyan (2010), Jolai et al. (2012), Abedzadeh et al. (2013), Mazinani et al. (2013), Derakhshan Asl and Wong (2015), Kia et al. (2015), Kulturel-Konak and Konak (2015), Li et al. (2015), Wang et al. (2015), Xu and Song (2015)

DFLP can also be modelled as a graph, which consists of a number of vertices (nodes) and edges. The vertices (nodes) in the graph represent the facilities. The adjacency of each pair of facilities is represented using the edge weight, which is known in advance (Foulds and Robinson 1978). The edge weights can also be used to indicate the benefit or the cost of two adjacent facilities. When the edge weights represent the benefits, the objective considered in the DFLP is to arrange the facilities so as to maximize the total benefits. Dong et al. (2009) and Erel et al. (2003) formulated the DFLP with GT models.

In regard to the data used in the DFLP formulations, given the uncertainties in the problem, some studies formulate the DFLP using fuzzy numbers to model the uncertainties in product market demand (Kaveh et al. 2014), transportation cost (Samarghandi et al. 2013, Xu and Song 2015) as well as the vagueness of the closeness relationship between facilities (Ning et al. 2010, Xu et al. 2016).

Besides the different types of formulation discussed above, Kheirkhah and Bidgoli (2016) proposed a game theoretic model for DFLP to consider the effects of internal and external non-cooperating competitions on the changes in facility layout design over time, which may cause conflicts of objectives for decision makers. Bashiri and Dehghan (2010), Bozorgi et al. (2015) and Tayal et al. (2016) established data envelopment analysis (DEA) models for DFLP to find efficient layouts considering several other criteria in addition to cost. For example, Bashiri and Dehghan (2010) considered three additional criteria besides cost, including adjacency score, shape ratio and flexibility. They used the Global Criteria method to solve the DEA model and selected some efficient solutions for facility rearrangements.

2.2 Objectives

The objectives of FLPs generally include quantitative objectives and qualitative objectives. Quantitative objectives aim at minimizing space cost, material handling cost, rearrangement cost, total flow distance, traffic congestion and shape irregularities etc.. A common qualitative objective considered is maximizing adjacency rate (closeness ratio).

In the DFLP, considering the changes in market demand, product prices and product mix, the planning horizon is divided into multiple time periods (e.g. weeks, months, years). Generally in DFLP, product demand, price and mix are assumed to be deterministic and constant for each period, but change from period to period. The product demand in each period is forecasted using historical data. Forecasts are naturally subject to error. Therefore, to make the model more realistic, some researchers consider the product demand to be stochastic. In these instances, the DFLP becomes the stochastic dynamic facility layout problem (SDFLP). Studies dealing with the SDFLP include papers of Yang and Peters (1998), Krishnan et al. (2008), Ripon et al. (2011a), Moslemipour and Lee (2012), Tayal et al. (2016), Vitayasak et al. (2016) and Tayal and Singh (2016). For DFLPs (including SDFLP), one common method of solving the problem is by using adaptive layout design. In adaptive layout design, the objective is to obtain an optimal layout for each period in the multi-period planning horizon so as to minimizing the sum of material handling and rearrangement costs. Another way is to use a robust approach. In a robust approach, a robust facility layout, which is not necessarily optimal for any particular time period, is selected as the best layout over the entire time planning horizon so that the total material handling cost is minimized (Moslemipour et al. 2012). In recent years, the majority of DFLP studies use adaptive layout design, while some focus on the robust approach which include work by Krishnan et al. (2008) and Pillai et al. (2011). In addition, Yang and Peters (1998) addressed a SDFLP and proposed a flexible machine layout design procedure which chooses robust layout (if the machine rearrangement cost is high), adaptable dynamic layouts (if rearrangement is easy or the production requirements change drastically), or a combination of the two strategies.

Recently, there have been some studies that address multi-objective DFLPs which include more than one objective. Table 2 lists all the studies of multi-objective DFLPs. It is found that in addition to the quantitative and qualitative objectives listed at the beginning of this section, some researchers consider other special objectives like the flexibility of the layout, distance restriction, hazardous score etc.. For example, distance restrictions may be required because the distance between any two departments cannot be too large, or too small, as large distance is a waste while department overlapping can cause great damage to the facilities as well as security problems (Jolai et al. 2012). A ‘hazardous’ score may be relevant since the relationship between the locations may depend on the facilities safety guidelines, type of product and the working environmental conditions so as to reduce the risk of hazard (Tayal and Singh 2016). Specifically, as manufacturing companies become larger and diverse, Tayal and Singh (2016) integrated Big Data Analytics (BDA) into DFLP modelling to handle and evaluate a large set of criteria which can greatly impact the manufacturing time and costs, product quality and delivery performance in optimal layout design. These criteria are identified first, and a survey for generating volume, velocity and variety of Big Data are conducted. A reduced set of criteria are then obtained using BDA. Finally, the reduced set of criteria are used to create a mathematical model with a weighted aggregate objective for a multi-objective SDFLP.

Table 2 DFLP with multiple objectives.

Authors	Objectives
Chen and Rogers (2009)	Minimize the total cost of material flows with consideration of the distances between facility locations Maximize the adjacency scores between the facilities
Bashiri and Dehghan (2010)	All considered criteria (cost, adjacency score, shape ratio and flexibility) are optimized through maximizing sum of Decision Making Units' efficiencies simultaneously
Ning et al. (2010)	Minimize total handling cost of interaction flows between the facilities associated with the construction site layout Minimize the representative score of safety/environment concerns.
Ripon et al. (2011a)	Minimize material handling cost Maximize closeness relationship score

Jolai et al. (2012)	Minimize material handling and rearrangement costs Maximize total adjacency Distance requests
Abedzadeh et al. (2013)	Minimize material handling and rearrangement costs Minimize shape ratio Maximize adjacency rate
Emami and Nookabadi (2013)	Minimize material handling and rearrangement costs Maximize adjacency rate
Samarghandi et al. (2013)	Minimize total transportation and shifting costs Maximize closeness rating value
Chen and Lo (2014)	Minimize material handling and rearrangement costs Maximize closeness rating scores
Bozorgi et al. (2015)	Minimize material handling and rearrangement costs Adjacency and distance requests
Kheirkhah et al. (2015)	Minimize total costs of material handling, buying new material-handling devices, and idle or obsolete material-handling devices Minimize material handling and rearrangement costs
Xu and Song (2015)	Minimize total transportation and rearrangement costs Distance restriction
Tayal et al. (2016)	Minimize material handling and rearrangement costs, flow distance and waste Maximize accessibility and maintenance
Tayal and Singh (2016)	Minimize material handling and rearrangement costs Minimize closeness rating, material handling flow time Maximize hazardous score
Azevedo et al. (2017)	Minimize material handling and rearrangement costs Maximize adjacency rate Minimize unsuitability between departments and locations
Pourvaziri and Pierreval (2017)	Minimize average work-in-progress Minimize empty and full trips of the material handling system

	Minimize machine rearrangement cost

2.3 *Constraints*

Drira et al. (2007) summarized the constraints commonly considered in FLP, which include area constraints (space allocated and facilities' location), position constraints (e.g. non-overlapping, orientation and pick-up/drop-off points) and budget constraints. Among the DFLP studies reviewed in this paper, special constraints considered in the model mainly include non-overlapping constraints, orientation constraints, pick-up/drop-off points constraints, budget constraints and capacity constraints. The capacity constraint considered in the literature usually refers to the limitation on machine capacity (Kia et al. 2013, Kia et al. 2015). The DFLP studies with special constraints are summarized in Table 3.

Table 3 DFLP with different constraints.

Constraints	Authors
Non-overlapping	Yang and Peters (1998), Corry and Kozan (2004), Dunker et al. (2005), McKendall Jr and Hakobyan (2010), Jolai et al. (2012), Abedzadeh et al. (2013), Mazinani et al. (2013), Derakhshan Asl and Wong (2015), Kia et al. (2015), Kulturel-Konak and Konak (2015), Wang et al. (2015), Xu and Song (2015)
Orientation	Yang and Peters (1998), Dunker et al. (2005), Jolai et al. (2012), Abedzadeh et al. (2013), Kia et al. (2015)
Pick-up/drop-off points	Dunker et al. (2005), Jolai et al. (2012), Kia et al. (2015)
Budget	Baykasoglu et al. (2006), Şahin et al. (2010), Azimi and Charmchi (2012), Li et al. (2015)

Capacity	Kia et al. (2013), Kia et al. (2015)

2.4 *Facility characteristics*

Layout problems addressed are also dependent on specific characteristics of the facility studied. Several factors and design issues clearly differentiate the nature of DFLPs addressed, including different manufacturing systems, layout configurations, and facility shapes.

Drira et al. (2007) categorized manufacturing systems into four types based on products variety and the production volumes, which include fixed product layout, product layout, process layout and cellular layout. The fixed product layout is often adopted by industries manufacturing large size products (e.g. ships, aircrafts, etc.), where the product does not move, while different resources and facilities are moved to perform operations on the product. More commonly, products circulate within various production facilities (e.g. machines, workers, etc.). When the manufacturing system has high production volume and low variety of products, facilities are organized according to the order of the successive manufacturing operations, which is called a product layout. When product variety is high or production volume is low, process layout (functional layout) is a common choice, in which resources of the same type (facilities with similar functions) are grouped together. Process layout is often thought to provide the greatest flexibility, but is notorious for its inefficient material-handling and complex scheduling, which can result in long lead times and large work-in-process inventories (Benjaafar et al. 2002). Cellular layout is an alternative to a process layout. In cellular layout, the factory is partitioned into cells, and each cell is dedicated to a family of products with similar processing requirements (Heragu 1994). Although cellular layout can simplify work flow and reduce material handling, it is inefficient when demand for existing products fluctuates or new products are introduced often (Benjaafar et al. 2002). For cellular layout, researchers are generally concerned with not only the inter-cell layout problem, but also the intra-cell machine layout problem. In the recent DFLP studies, Shahbazi (2010) and Yang et al. (2011) specifically focused on process layout problem, and a few other researchers work on cellular layout problems (see Table 4).

Table 4 DFLP for cellular layout.

Manufacturing System	Authors
Cellular Layout	Chen (1998), Kia et al. (2012), Kia et al. (2013), Kia et al. (2014), Kia et al. (2015), Kumar and Prakash Singh (2017)

Layout configuration is another design issue that impacts the DFLP. Most of the recent models regarding DFLPs are formulated using modified QAP, which is one of the many dealing with multi-row layout problems. The multi-row layout problem locates facilities on several rows and each pair of facilities is separated by their minimum clearances. In particular, Wang et al. (2015) solved a dynamic double-row layout problem. Besides multi-row layout problems, some researchers are interested in single-row layout optimization. Chan and Malmborg (2010) addressed a dynamic line layout problem. Tayal and Singh (2016) focused on optimizing the U-shape facility layout, which is also a type of single-row layout problem. Nowadays, with land supply being insufficient and land being expensive, manufacturers may seek to locate the facilities on several floors, so as to overcome the limitation on available horizontal space in the facility. This leads to the multi-floor FLP. In the multi-floor FLP, both the position on the floor and the level of the floor have to be determined for each facility. Additionally, material flow in multi-floor FLP has two directions, since the products can move both horizontally on a given floor (horizontal flow) and vertically from one floor to another floor at a different level (vertical flow), all of which need to be considered in finding the optimal solution. In the DFLP studies reviewed in this paper, Kochhar and Heragu (1999) and Kia et al. (2014) solved dynamic multi-floor FLPs.

Facility shapes are divided into two types: regular shape (i.e., generally rectangular) and irregular shape. For regular facility shape, the rectangular facility can be defined by fixed dimensions, i.e., fixed length (L_i) and fixed width (W_i), or by its area using aspect ratio. Aspect ratio is usually defined by $a_i = L_i/W_i$, with an upper bound a_{iu} and a lower bound a_{il} such that $a_{il} \leq a_i \leq a_{iu}$. The facility shape is fixed if $a_{il} = a_i = a_{iu}$. In the DFLPs reviewed, a majority of the studies consider a regular rectangular facility with fixed dimensions, while a few studies define facility shape through the aspect ratio (see Table 5).

Table 5 DFLP with aspect ratio.

Regular Facility Shape	Authors
Aspect Ratio	Kulturel-Konak et al. (2007), Bashiri and Dehghan (2010), Abedzadeh et al. (2013), Mazinani et al. (2013), Kulturel-Konak and Konak (2015)

3 Solution methodology

Solution methods for DFLP can be grouped into four categories: exact methods, heuristics, metaheuristics, and hybrid approaches. As the DFLP is NP-hard, exact (optimal) methods are only useful in finding optimal solutions for small-sized problems. In recent years, very few DFLP studies have adopted exact methods, while most of the effective algorithms found in the DFLP literature are heuristics, metaheuristics and hybrid approaches. Studies using different exact methods, heuristics, metaheuristics and hybrid methods are summarized in Table 6.

3.1 Exact methods

The three types of exact methods used in recent DFLP studies are branch-and-bound, dynamic programming and modified sub-gradient.

3.1.1 Branch-and-bound

Branch-and-bound (B&B) is one of the most commonly used tool for solving NP-hard optimization problems. In the B&B algorithm, at each iteration, the current problem is branched into smaller subsets, and the lower bound (in the case of minimization) on the cost of all possible solutions within each subset is calculated. A branch is pruned, if it cannot produce a better solution than the best one found so far by the algorithm. Eventually, the optimal solution (if any) is found when all branches have been pruned. Lahmar and Benjaafar (2005) provided an exact solution based on B&B procedure for small-sized multi-period distributed layout problems, where product mix may vary from period to period and a re-layout can be undertaken at the beginning of each period.

3.1.2 Dynamic programming

In dynamic programming (DP), to solve a DFLP with n-facility and t-period, a very large number $(n!)^t$ of possible solutions must be evaluated to find the optimum solution. For example, we would have to evaluate 1.93×10^{14} possible solutions for a six-facility and five-period DFLP. Hence, DP is used only to solve small-sized DFLPs. Chen (1998) proposed a facility layout model for designing sustainable cellular manufacturing systems with anticipated changes of demand or production process. This model attempts to minimize the total of inter-cell traveling cost, machine cost, and machine installation/removal cost. To solve this problem, DP was employed and a decomposition approach was developed so that the decomposed sub-problems can be solved with less computational effort. Urban (1998) used an incomplete DP algorithm similar to that of Wesolowsky's (1973), so as to find the optimal solution for a special case of DFLP where the rearrangement cost is fixed.

3.1.3 Modified sub-gradient

Ulutas and Saraç (2012) solved a DFLP using the modified sub-gradient (MSG) algorithm for the first time. The MSG algorithm was proposed by Gasimov (2002) for solving a continuous non-linear model. Therefore, to apply the MGS algorithm, the modified QAP model for DFLP was converted into the continuous form first. Since the performance of the MSG algorithm depends on parameters and solver type, the authors also designed computational experiments to determine the appropriate parameter values and the most suitable SNOPT solvers in the general algebraic modelling system (GAMS) software used for solving the problem. The experimental analysis results showed that when suitable parameters are chosen, the MSG algorithm is a promising and competitive algorithm for solving DFLP; and the solver type has more influence on large scale problems.

3.2 Heuristic algorithms

Solving DFLP is a computationally difficult task, exact approaches are often considered not suitable for large-sized problems. As a result, many researchers developed heuristics and metaheuristics to solve large scale DFLPs. Heuristics are also called sub-optimal or approximated approaches, which can produce near-optimal satisfactory solutions in a very low computational time for problems where finding an optimal solution is impossible or impractical.

In addition to the incomplete DP algorithm, Urban (1998) also introduced heuristic methods for problems with larger scale. In addition, upper and lower bounds that dominate all existing bounds were developed for the general DFLP where the rearrangement cost is not necessarily fixed. Yang and Peters (1998) proposed a heuristic procedure based on a construction type layout design algorithm to solve a flexible machine layout design problem over a planning horizon. Balakrishnan et al. (2000) developed an improved dynamic pair-wise exchange heuristic for DFLP. Their heuristic is on the basis of the steepest descent pairwise exchange heuristic proposed by Urban (1993) with two improvements. The first one is using a backward pass instead of the forward pass in Urban's (1993) heuristic because the backward pass will never generate a worse layout than the forward pass (Kulturel-Konak 2007). The second one involves combining Urban's (1993) method with the DP proposed by Rosenblatt (1986). They tested the new dynamic pair-wise exchange heuristic on different problems, and showed improvements on the results published by Urban (1993) in almost every case. Balakrishnan and Cheng (2009) also investigated the performance of this improved dynamic pair-wise exchange heuristic under fixed and rolling horizons, under different shifting costs and flow variability, and under forecast uncertainty. The results showed that rolling horizons have significant effect on the algorithm performance, while forecast uncertainty may not significantly affect the algorithm effectiveness and may be beneficial in some cases. Additionally, it is difficult to identify an algorithm that performs well under all situations (Balakrishnan and Cheng 2009). Ripon et al. (2011a) also developed a modified version of Urban's (1993) heuristic by incorporating a backward pass to solve the multi-objective DFLP under uncertainty that presents the layout as a set of Pareto-optimal solutions.

In addition to an exact method, Lahmar and Benjaafar (2005) offered a decomposition-based heuristic solution procedure for distributed layout design in settings with multiple periods where product demand and product mix may vary from period to period and where a re-layout may be undertaken at the beginning of each period. They showed that the proposed heuristic performs well relative to lower bounds. Also, as a distributed layout is quite robust to uncertainties in the production requirements, optimizing the layout in each period carries significantly less value than it does for process layouts. Chan and Malmborg (2010) developed a simple Monte Carlo simulation based heuristic procedure to identify robust solutions for dynamic line layout problems in which the production facility has unequal size work centres, uses conventional material handling devices and operates under stochastic demand scenarios. Their experimental results showed that robust solutions meeting aspiration levels of material handling cost performance across multiple material flow scenarios can be obtained using a modest volume of random sampling.

Recently, Kumar and Prakash Singh (2017) introduced a novel similarity score-based two-phase heuristic approach which can optimally solve the dynamic cellular layout problem considering multiple products in multiple times to be manufactured within reasonable time. In this two-phase heuristic, first, machines are grouped in cells in Phase I through using a grouping algorithm based on similarity score of machines in the machine–part matrix. In Phase II, an integer programming DFLP is formulated for the cellular layout problem. The proposed heuristic method was able to obtain promising solutions for the tested dynamic cellular FLP in reasonable time.

3.3 Metaheuristics

‘A metaheuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems’ (Dorigo et al. 2006). Since the DFLP is NP-hard, in recent years, a large number of researchers have used efficient metaheuristics to solve the DFLP, especially for large-sized problems. The popular metaheuristics used in DFLP studies mainly include simulated annealing, tabu search, genetic algorithm, ant colony optimization, particle swarm optimization, artificial immune system, and fuzzy system and so on.

3.3.1 Simulated annealing

Simulated annealing (SA) was first proposed by Kirkpatrick et al. (1983) which originates from the theory of statistical mechanics and is based on the analogy between the annealing process of solids and the solution methodology of combinatorial optimization problems (Baykasoğlu and Gindy 2001). SA is relatively easy to implement and is free of local optima in global optimization. However, the quality of the solution obtained by SA depends on the maximum iteration number of the inner loop (cooling schedule) and the initial temperature (Moslemipour et al. 2012). In recent years, SA has been a commonly used metaheuristic for solving DFLP.

After Baykasoğlu and Gindy (2001) first applied the SA to DFLP, McKendall Jr et al. (2006) developed two SA heuristics for DFLP, one is a straightforward adaptation of SA to DFLP, the other combines the first SA method with a look-ahead/look-back strategy. After testing the two SA methods with the data sets taken from the study of Balakrishnan and Cheng (2000), the results showed that the proposed SA heuristics perform well. Ashtiani et al. (2007) proposed a multi-start SA to solve the DFLP. Compared with the SA heuristic developed by Baykasoğlu and Gindy (2001) and the hybrid genetic algorithm presented by Balakrishnan et al. (2003), the results showed that the multi-start SA performs well. Dong et al. (2009) presented a new DFLP with the capability of removing/adding machines in different periods. This new DFLP is defined based on unequal area machines and continual representation, which was converted to a shortest path problem. A shortest path based SA algorithm was proposed to solve this new DFLP. Tests with a case of four periods and 56 machines, showed that the proposed SA algorithm is efficient and effective. Later, Şahin et al. (2010) developed a SA for DFLP considering a budget constraint.

Recently, Pillai et al. (2011) presented a robust model for DFLP. A SA heuristic was proposed to solve the suggested robust model, which performs well in almost all cases of problems from Yaman et al. (1993) and the QAPIB website, except in one case where the result is inferior by 0.07% compared with the optimal value. Kia et al. (2012) established a novel non-linear MIP model integrating cell formation and group layout decisions for a dynamic cellular layout problem. The presented model incorporates several design features including alternate process routings, operation sequence, processing time, production volume of parts, purchasing machines, duplicate machines, machine capacity, lot splitting, intra-cell layout, inter-cell layout, multi-rows layout of equal area facilities and flexible reconfiguration (Kia et al. 2012). A SA technique was developed to solve the model. The solution structure of the SA is presented as a matrix consists of four ingredients fulfilled hierarchically to satisfy constraints. The performance of the proposed SA algorithm is evaluated and compared with the LINGO software using several small/medium-sized problems. The results showed that the proposed SA algorithm could find near-optimal solutions in computational times approximately 100 times less than that of LINGO (Kia et al. 2012). Later, Kia et al. (2015) applied a SA heuristic to another dynamic cellular layout problem, which also integrates cell formation and group layout decisions but considers variability in the number and shape of cells. Kia et al. (2013) proposed a non-linear MIP model for intra-cell layout design of a dynamic cellular manufacturing system, which aims to minimize the total costs of inter-cell material handling, forward and backward intra-cell material handling, setting up routes, machine relocation, purchasing new machines, as well as machine overhead and processing. The proposed model was solved by a SA algorithm whose solution structure was presented as a matrix with six ingredients fulfilled hierarchically to satisfy constraints.

Moslemipour and Lee (2012) presented a model for dynamic layout design of a flexible manufacturing system in an uncertain environment where the product demands are assumed to be independent normally distributed random variables with a known probability density function and change from period to period. The model also considers the decision maker's attitude about uncertainty in product demands using different confidence levels. A SA method with three different confidence levels was adopted to solve two test problems with 10 parts, 12 machines and two different time periods. Optimal layouts for both of the two test problems were obtained in a reasonable computational time. Li et al. (2015) focused on DFLP for remanufacturing, where a high-level uncertainty exists due to the stochastic returns of used products or components and uncontrollable quality conditions. They proposed a dynamic multi-row layout model and utilized a modified SA approach as the solution method which has a special solution structure with two-stage matrices for remanufacturing layout schemes. Kheirkhah and Bidgoli (2016) developed a game theoretic model for DFLP which considers the effect of an external duopoly Bertrand competition on the facility layout designs under a changing environment. Three algorithms were proposed to evaluate this game theoretic model which include B&B, SA and an imperialist competitive algorithm (ICA). Computational results showed that the proposed SA outperforms other proposed algorithms. Tayal et al. (2016) investigated a sustainable SDFLP considering several quantitative and qualitative criteria, namely material handling cost, rearrangement cost, flow distance, accessibility, maintenance and waste management. The proposed sustainable SDFLP was optimized using various metaheuristic techniques which include SA, chaotic simulated annealing (CSA) and hybrid firefly-chaotic simulated annealing

(Hybrid FA/CSA). The layouts generated by SA, CSA and Hybrid FA/CSA were then used to identify efficient layouts through DEA. Finally, multiple attribute decision making (MADM) techniques and consensus ranking method were applied to rank the efficient layouts considering the aforementioned six criteria. Pourvaziri and Pierreval (2017) presented a DFLP that focuses on reducing not only the material handling and rearrangement costs but also the amount of work-in-process. A cloud-based multi-objective simulated annealing (C-MOSA) which takes advantage of both a Pareto approach and cloud theory was used to find the Pareto-optimal solutions. After comparing the C-MOSA with parallel variable neighbourhood search (PVNS) and non-dominated sorting genetic algorithm (NSGA-II), it showed that the C-MOSA performs better than PVNS and NSGA-II in terms of two performance criteria, mean ideal distance and diversity. Performance of C-MOSA is also acceptable with regard to spacing.

3.3.2 Tabu search

Developed by Glover (1989, 1990), tabu search (TS) is a metaheuristic featured by incorporating two main strategies in local search: adaptive memory and responsive exploration. The basic principle of TS is to prevent cycling back to previously visited solutions through using memory (tabu list) which stores the recent search history; and to accept non-improving moves so as to escape from a local optimum and explore a larger fraction of the search space to find global optimum.

To the best of our knowledge, the first study adopted TS to solve DFLP was by Kaku and Mazzola (1997). In their TS approach, they used pairwise interchange as the local neighbourhood search technique. Their TS heuristic employs two stages. In the first stage, initial solutions are generated using a diversification strategy. In the second stage, neighbourhoods around the promising solutions found in the first stage are searched more intensively. At the end of the second stage, the best layout for DFLP is obtained by the TS heuristic. Compared with some existing heuristics, computational experiment results showed that the proposed TS generates improved solutions for over one third of the test problems. Kulturel-Konak et al. (2007) studied a facility re-layout problem considering unequal area redesign including both fixed facility areas and expanded facility areas. The proposed bi-objective model aims at minimizing material handling cost and re-layout cost was solved by a TS heuristic. In this TS heuristic, the objective function can randomly alternate between the two objectives in each step, thereby eliminating the difficulty of weighting and scaling the two objectives. Test results showed that the proposed TS heuristic is an effective and computationally tractable algorithm. McKendall and Jaramillo (2006) studied the dynamic space allocation problem (DSAP) which can be regarded as a generalization of both the QAP and the DFLP. They used a TS approach and five construction algorithms to solve the DSAP. The five construction algorithms include the first assignment algorithm (FA), the randomized clustering algorithm (RC), the modified first assignment algorithm (MFA) and two modified RC algorithms (MRC I, MRC II). These five construction algorithms are also used to generate initial solutions for the TS heuristic. It was shown that the TS heuristic with MFA, MRC I and MRC II outperformed the TS heuristic with FA and RC with respect to both solution quality and computational time. The proposed TS heuristic also performs better than the SA heuristics presented in the literature. Later, McKendall Jr (2008) developed another three TS heuristics for the DSAP. The first TS is a simple basic TS which is an improvement of the TS in the paper of McKendall and Jaramillo (2006); the second TS is the proposed simple basic TS with diversification and intensification strategies added; the third TS is a probabilistic TS. Tests showed that all the three TS heuristics are efficient techniques for solving the

DSAP, while the TS with diversification and intensification strategies can find new best solutions using less computational time for half of the test problems. McKendall Jr and Hakobyan (2010) presented a continuous DFLP in which the departments have unequal-areas, fixed department shapes and free orientations. A boundary search (construction type) technique (BSH) and a TS (improvement type) technique (TS/BSH) using BSH to generate initial solutions were developed to solve the problem. The computational results showed that TS/BSH heuristic performs well, especially for the large-sized problems. Shahbazi (2010) investigated the DFLP for the case of job shop process and added a new aspect to the problem, which is considering time value of money. To solve this new DFLP, SA and TS heuristics were developed. The computational experiments showed that the proposed TS heuristic performed better than the SA heuristic. McKendall Jr and Liu (2012) developed three TS heuristics for DFLP. Similar to McKendall Jr (2008), the three TS heuristics included a simple basic TS, the proposed simple basic TS with diversification and intensification strategies added and a probabilistic TS. It was shown that the TS with diversification and intensification strategies had the best performance. Bozorgi et al. (2015) determined the most efficient layout for DFLP with equal departments considering three criteria: cost, adjacency rate, and distance requested. For this purpose, a DEA model and a TS heuristic with diversification strategy including frequency-based memory, penalty function and dynamic tabu list size were applied. The local search technique used in the proposed TS heuristic is the steepest descent pairwise exchange heuristic. In the DEA model, cost is a negative criterion which needs to be minimized and is used as the input, whereas adjacency and distance requested are taken as positive criteria and used as outputs. Computational results showed that the proposed TS heuristic performs better than other heuristics developed in relevant literature, and the most efficient layout was obtained.

3.3.3 Genetic algorithm

Genetic algorithm (GA) is a metaheuristic inspired by the evolutionary ideas of natural selection and genetics. GA starts with an initial set of random solutions known as the 'population'. The individual solutions in the population are called 'chromosomes'. The initial population evolves into an optimal solution through successive iterations called 'generations'. In each generation, a new population is created through merging (crossover) and modifying (mutation) chromosomes of the existing population. The selection of chromosomes to crossover and mutate is based on their fitness function (El-Baz 2004). These iterations continue until the GA finds an acceptably good solution (Kia et al. 2014).

Kochhar and Heragu (1999) studied a multiple-floor unequal-area DFLP which is able to respond to production demand and mix changes in a continuously evolving environment. They proposed a GA-based heuristic to solve this problem. Balakrishnan and Cheng (2000) developed a GA with nested loops to solve large-sized DFLPs. In this GA approach, they used point-to-point crossover to increase the search space. To increase population diversity, they utilized mutation and a generational replacement approach. The computational experiment results showed that the proposed GA outperforms the one developed by Conway and Venkataramanan (1994). Krishnan et al. (2008) presented a mathematical model to determine a compromise layout that can minimize the maximum loss in material handling cost for both single and multiple periods. The proposed model is then modified to minimize the total expected loss. A GA approach was developed to solve the proposed models. Results from the case studies showed that the compromise layouts obtained can efficiently reduce maximum loss in material handling cost and minimize the total expected loss.

Yang et al. (2011) adopted a GA approach to solve a dynamic layout planning model considering job order as it significantly affects the moving paths of materials in a job shop manufacturing environment. This study also applies the cost-benefit analysis based on the cost gap between the current layout and the ideal layout obtained by GA. It was suggested that changing the layout can be a good choice when the rearrangement cost is lower than the cost gap. Emami and Nookabadi (2013) presented a multi-objective model for DFLP which aims at minimizing material handling and rearrangement costs and maximizing adjacency rate. They evaluated two classic methods (weighted sum and ε-constraint methods) and three metaheuristic methods including nondominated sorting GA (NSGA-II), differential evolution (DE) and Pareto-simulated annealing (PSA), in which only DE had not been applied to solve the multi-objective DFLP. Using the technique for order performance by similarity to ideal solution (TOPSIS), the best method was selected on the basis of three comparison criteria (i.e. convergence, diversity and runtime). It was shown that metaheuristics outperform classic methods, and NSGA-II and DE are more efficient than PSA. Mazinani et al. (2013) proposed a novel DFLP based on flexible bay structure. In this new DFLP, departments may be free oriented and have unequal areas, which are assigned to parallel bays in a plant floor. A GA was established to solve this problem. After being tested on some problems taken from existing literature, the proposed GA was shown to be effective compared with other algorithms and software. Besides the SA methods discussed previously, Kia et al. (2014) also developed an efficient GA with a matrix-based chromosome structure to solve the multi-floor dynamic cellular layout problem that integrates cell formation and group layout decisions and aims at minimizing the total costs of intra-cell, inter-cell, and inter-floor material handling, purchasing machines, machine processing, machine overhead, and machine relocation.

Vitayasak et al. (2016) solved a SDFLP with heterogeneous-sized resources and rectilinear material flow using three modified Backtracking Search Algorithms (mBSAs), the classic Backtracking Search Algorithm (BSA) and GA. BSA is a new evolutionary algorithm which has a simple structure and a single control parameter. BSA's strategies (two new crossover and mutation operators) for generating trial populations and controlling the amplitude of the search-direction matrix and search-space boundaries make its exploration and exploitation capabilities very powerful (Civicioglu 2013).

3.3.4 Ant colony optimization

The fundamental idea of ant colony optimization (ACO) is on the basis of the social behaviour of natural ants succeed in finding the shortest path from the nest to the food source through following the path with strong pheromone concentration. Pheromone is a volatile chemical substance laid by ants when they move along randomly selected paths. Over time, pheromone on the trail starts to evaporate, thus reducing its concentration. As it takes more time for ants to travel down and back on long paths, more pheromone evaporates, while on short paths, more ants can make the return trip in a given amount of time, thereby increases the density of pheromone and attracts more ants traveling on this path. Eventually, pheromone on the shortest path dominates all other paths, thus most ants are travelling on the shortest path from nest to food source (Corry and Kozan 2004).

Different ACO algorithms have been applied to the DFLP studies in recent years. Corry and Kozan (2004) introduced an ACO algorithm to solve DFLP with fixed shape. The proposed ACO was shown to outperform the heuristically reduced integer programming method used in the study by Yang and Peters (1998). Baykasoglu et al. (2006) used an ACO to solve a DFLP considering the unconstrained and budget constrained cases. This study is the first attempt that applies ACO to DFLP with a budget constraint. Ning et al. (2010) proposed a new solution approach using max-min ant system (MMAS) under the guidance of continuous dynamic searching scheme to solve the multi-objective dynamic construction site layout planning problem through a weighted sum method. Chen and Lo (2014) studied the multi-objective DFLP with distance-based and adjacency-based objectives. They combined ACO with three different multi-objective approaches to solve this problem. The first approach is called ACO-DDML, which couple the ACO with MUGHAL, a weight-sum method for solving FLPs proposed by Dutta and Sahu (1982). The second approach, named ACO-UDML, combines ACO with the additive model developed by Urban (1987). This approach determines the relative importance of the adjacency-based objective to the distance-based objective relying on only one user-defined weight. The third approach ACO-PDML coupling ACO with the Pareto efficiency concept, does not assign weights for multiple objectives but searches for a set of non-dominated solutions. The evaluation results showed that all the three proposed approaches are effective in solving the problem, however none of the them dominates the others for both of the two objectives.

3.3.5 Particle swarm optimization

Particle swarm optimization (PSO) is a population-based stochastic optimization approach motivated by the analogy with the social behaviour of bird flocking or fish schooling. It belongs to evolutionary computation techniques which shares many similarities with ACO and GA. PSO operates with a population (swarm) of candidate solutions (particles). In PSO, particles fly through a multidimensional search space to find the optimal solution. The position of each particle is considered as a solution for the problem. During the flight, the new position of each particle is guided by the best position found by the particle and the entire swarm's best-known position. Since particles in PSO naturally move in continuous space, it is fundamentally designed to solve continuous problems.

Jolai et al. (2012) dealt with a multi-objective DFLP with unequal sized departments and pick-up/drop-off locations. To solve the problem, they proposed a multi-objective PSO together with two novel heuristics used to preventing departments overlapping and reducing unused gaps between departments. Computational experiment results showed that the average percentage improvements over the initial solutions of the proposed multi-objective PSO ranges between 2% and 24% for the four objectives considered in the problem. Xu and Song (2015) developed a multi-objective position-based adaptive PSO (p-based MOPSO) to solve a multi-objective DFLP with unequal-area departments and fuzzy transportation cost for temporary construction facilities. The main difference between the proposed p-based MOPSO and the standard PSO is in solution representation. The p-based MOPSO uses a position-based solution representation, in which the multidimensional particles with different position values for each dimension are used to represent the candidate solutions (Xu and Song 2015). Kheirkhah et al. (2015) investigated a DFLP which is strongly correlated with the material handling system (MHS) design problem. A novel bilevel model was proposed for this problem, in which the upper objective function minimizes the total costs of material handling between departments, buying new material-handling devices (MHDs) and idle or obsolete MHDs; while the lower level objective function minimizes the total costs of material handling and rearrangement. Two bilevel metaheuristics known as bilevel PSO and coevolutionary algorithm were developed to solve the proposed bilevel model. Compared with the coevolutionary algorithm, the computational results showed that the bilevel PSO gives better average upper level fitness, better rationality and can solve the problem in shorter computational time. Derakhshan Asl and Wong (2015) applied a modified PSO to solve both the static facility layout problem (SFLP) and DFLP with unequal area. In this modified PSO, two local search methods are used. Additionally, the department swapping method is also adopted to prevent local optima and improve the quality of solutions.

3.3.6 Artificial immune system

Artificial immune system (AIS) is an evolutionary computation technique inspired by the principles and processes of the human immune system. Mechanisms and properties of immune system such as the clonal selection, learning ability, memory, robustness, and flexibility make AIS an efficient tool for solving combinatorial problems. The AIS technique that has been applied to the DFLP is the clonal selection algorithm (CSA) which is a population-based algorithm. In CSA, feasible solutions are coded as individuals. CSA starts with a randomly generated population of individuals (antibodies). At each iteration of CSA, first, the affinity value of each antibody is calculated by using the problem's objective function. Then, the antibodies with the best affinity value are selected and cloned. Next, the new generations which are the improved antibodies created by mutating the clones are formed. Finally, a predetermined number of antibodies with low affinity value are replaced by the randomly generated new ones through the receptor editing process. The CSA terminates after replicating a pre-specified number of generations.

Ulutas and Islier (2009) proposed a CSA to solve the DFLP. Test results showed that the proposed CSA achieves the best-known solutions and even better solutions for large-sized problems in nearly 90% of the cases. The CSA also outperforms other methods in the literature with regard to computation time. Later, Ulutas and Islier (2010) adopted the DFLP model proposed by Balakrishnan et al. (2003) (see Eq. (1)-(4)) to solve the dynamic content area layout for internet newspapers. The objective of this layout problem is to minimize the sum of the content dissimilarities (material handling cost) and permanence values (rearrangement cost) for the planning horizons. This layout problem is optimized by CSA as well. Ulutas and Islier (2015) also used the CSA to solve a real-life DFLP in the footwear industry which is prone to seasonal demand changes. To the best of our knowledge, it is the first study of a real-life application.

3.3.7 Fuzzy system

Fuzzy logic uses the whole interval between 0 (false) and 1(true) to describe human reasoning. A fuzzy decision-making system consists of four major components, including fuzzification, knowledge base (including membership functions), if-then fuzzy decision rules, and defuzzification (Moslemipour et al. 2012). Fuzzy logic is an efficient method to cope with uncertainties in DFLP. Ning et al. (2010) and Xu et al. (2016) utilized fuzzy logic to represent the closeness relationship. In their studies, the closeness rating between facilities is divided into five levels described by linguistic words: absolutely important (A), especially important (E), important (I), ordinary (O), unimportant (U) and undesirable (X). Samarghandi et al. (2013) investigated a fuzzy multi-objective DFLP with unequal areas. They modelled the amount of transportation between two facilities using triangular fuzzy numbers. In order to solve this problem, several algorithms including a fuzzy TS, a fuzzy GA, a fuzzy PSO and a fuzzy variable neighbourhood search (VNS) were developed. Kaveh et al. (2014) defined the product demand in DFLP as fuzzy numbers with different membership functions. Therefore, material handling cost, and consequently the total costs are fuzzy numbers as well. The DFLP is then modelled as fuzzy programming through three approaches including expected value model (EVM), chance-constrained programming (CCP) and dependent-chance programming (DCP). As decision makers can only provide a range for average unit cost of materials transportation and the transportation cost fluctuates over time, Xu and Song (2015) modelled the transportation costs between the facilities as fuzzy random variables.

3.3.8 Other metaheuristics

Urban (1998) adopted a greedy randomized adaptive search procedure (GRASP) and an initialized multigreedy algorithm to solve the large-sized DFLP with fixed rearrangement cost. Each iteration in GRASP consists of two phases including randomized construction and local improvement. In the construction phase, an initial feasible solution is randomly selected from a list of the most promising assignments. After a feasible solution is generated, a local search is conducted to identify better solutions in the improvement phase. Finally, at the end of all iterations, the best solution obtained is taken as the final solution. The initialized multigreedy algorithm is similar to GRASP, but appropriate information is transferred between sub-problems in it. The test results showed that for problems with 20 departments or less, the GRASP obtains better solutions than the initialized multigreedy algorithm with slightly higher computational time; while for larger problems, solutions provided by the initialized multigreedy algorithm have better quality, but the GRASP uses shorter computational time.

Ming et al. (2002) developed a symbiotic evolutionary algorithm (SymEA) to solve the DFLP. In this SymEA, a coevolutionary multi-population approach is implemented, hence layouts of a particular period are represented as individuals of a corresponding population. A complete solution, called a symbion, is a combination of individuals in different populations. Symbion is the unit in the evaluation and selection process, top ranked symbia are used to reproduce the population for the next generation. Hence, populations evolve simultaneously and individuals interact both in evaluation and selection process (Ming et al. 2002). In addition, the generational replacement strategy (μ, λ)-selection derived from Evolution Strategies was adopted for refining the symbiotic relationship. It was shown that the proposed SymEA has better performance than other proposed GAs, but is outperformed by a SA algorithm in large-sized problems.

Abedzadeh et al. (2013) solved the multi-objective DFLP using a parallel variable neighbourhood search (PVNS) algorithm and CPLEX 12 optimizer for GAMS 23.3 software. In the proposed PVNS algorithm, six structures, namely ‘swap, reversion, perturbation, insertion, exchange variable and 2-Opt algorithm’ were adopted for producing the neighbourhood around each solution (Abedzadeh et al. 2013). Test results showed that that the proposed PVNS algorithm is more efficient than GAMS software.

Kheirkhah and Bidgoli (2016) evaluated a game theoretic model for DFLP using BB, SA and ICA. ICA is a metaheuristic inspired by the socio-political competition among empires in human social evolution. The proposed ICA has the shortest computation time but cannot get good quality solutions because its performance is largely dependent on the initial solutions.

3.4 Hybrid algorithms

Hybrid algorithms, which combine two or more solving methods together to further enhancing their computational capabilities have drawn increasing attention among researchers in recent years.

GA is commonly considered in hybrid approaches. Balakrishnan et al. (2003) proposed a hybrid GA for DFLP using DP in crossover to create offspring and using a pair-wise exchange heuristic named CRAFT as the mutation method. Compared to other methods, it showed that the proposed hybrid GA performs better than the GA methods developed by Conway and Venkataramanan (1994) and Balakrishnan and

Cheng (2000) as well as a SA. Dunker et al. (2005) developed a hybrid algorithm combining DP and GA to solve DFLP with unequal area. Krishnan et al. (2006) established a new tool called Dynamic From-Between Charts (DFBC) to capture the dynamic inter-departmental relationship and continuously track the flow between machines in DFLP. Besides, they proposed an algorithm which uses a modified Wagner-Whitin (W-W) procedure to select the redesign point and a GA to determine the layout at each step of the algorithm. Lately, since there is increasing use of industrial robots as material handling devices, Ripon et al. (2011b) established a hybrid GA incorporating jumping genes operations and a modified backward pass pair-wise exchange heuristic to solve the DFLP, so as to enhance the production rate and profit, save robot energy usage and extend the life of the robot. The GA with jumping genes operations has better capability of exploration and exploitation because it employs horizontal transmission together with the vertical transmission in the conventional GAs. Experimental results indicated that the proposed hybrid GA performs well in solving DFLP. Pourvaziri and Naderi (2014) developed a novel hybrid multi-population GA for DFLP, which overcomes the shortcomings of the existing algorithms and further improves the performance. In this hybrid GA, the subpopulation is generated using a heuristic procedure which ensures the diversification capability. A powerful SA-based local search is allocated to enhance the intensification capability. They also proposed a novel crossover operator generating only feasible solutions to reduce computational time. Comparing the hybrid multi-population GA with 11 other available algorithms, it showed that the proposed algorithm outperforms all the others. Uddin (2015) developed a hybrid metaheuristic GA-VNS for the DFLP which elegantly integrates the exploration ability of GA and the exploitation ability of VNS together. In the proposed hybrid algorithm, GA is used to ensure diversification capability and VNS local search is applied for intensification. Besides, in VNS, different neighbourhood structures are included to avoid getting trapped into local optimal and expand the search scope.

SA is another frequently adopted metaheuristic in hybrid methods. Şahin and Türkbey (2009) presented a hybrid algorithm named TABUSA, which adopts both the stochastic nature of the SA and the short-term memory of TS (tabu list) to solve the DFLP. They compared the performance of TABUSA with pure SA and pure TS and showed that the proposed TABUSA is a very effective method to solve the DFLP. Kulturel-Konak and Konak (2015) developed a large-scale hybrid algorithm (LS-HSA) based on the hybridization of SA and MIP to find good solutions for the cyclic facility layout problem (CFLP), which is a special case of DFLP. Wang et al. (2015) combined an improved SA (ISA) with mathematical programming (MP) to generate a hybrid approach (ISA-MP) for solving the dynamic double-row layout problem (DDRLP). In the proposed hybrid algorithm, a mixed solution coding scheme is applied to represent both the combinatorial and continuous aspects of DDRLP, and four operators are devised to enhance the effectiveness of the algorithm. In addition, MP is applied to solutions obtained by ISA so as to further improve the solution quality. Computational experiment results showed that the ISA can find optimal solutions for small-size problems and obtain satisfactory solutions for problems with realistic size. Tayal and Singh (2016) solved a multi-objective SDFLP using a hybrid algorithm (Hybrid FA/CSA) which integrates two metaheuristics, firefly algorithm (FA) and chaotic SA (CSA). In the proposed Hybrid FA/CSA, exploration capability of FA is utilized to get an initial solution and followed by CSA, which exploits the local search space to improve the initial solution. This Hybrid FA/CSA was also used by Tayal et al. (2016) for solving a sustainable SDFLP. Shafigh et al. (2017) proposed a hybrid heuristic algorithm to solve a comprehensive model for distributed layout design with production planning and systems reconfiguration. This hybrid heuristic algorithm is a linear programming (LP) embedded SA with multiple search paths. In this hybrid approach, SA searches over the discrete variables in the problem solution space and the corresponding continuous variables are determined by solving a LP sub-problem using a simplex algorithm. Since there may be infinite combinations of the values for the continuous variables, by solving a LP sub-problem, values that optimally correspond to the integer solution can be obtained easily. Besides, some constraints having continuous variables in their equations may be difficult to satisfy by using stochastic search of the SA alone, but they can be satisfied by solving the LP sub-problem. Computational experiments showed that the proposed hybrid heuristic has very encouraging performance.

Some researchers have built hybrid algorithms based on ACO. McKendall Jr and Shang (2006) modified the hybrid ant system (HAS–QAP) developed by Gambardella et al. (1999) and create three HASs (HAS I, HAS II, HAS III) for DFLP. In HAS I, a random descent pairwise exchange technique is used to improve the initial set of solutions and the set of modified solutions. HAS II uses a SA instead of the random decent pairwise exchange heuristic for local search, which is the only difference between HAS I and HAS II. HAS III is exactly like HAS I except that it adds a look-ahead/look-back strategy to the random decent pairwise exchange heuristic. It showed that all the proposed HASs perform well in computational experiments. Chen and Rogers (2009) investigated a multi-objective DFLP which includes both quantitative (distance-based) and qualitative (adjacency-based) objectives. They proposed an ACO algorithm to solve this problem, which is also expanded from the HAS-QAP developed by Gambardella et al. (1999) with a simple but effective data structure and solution generation mechanism. Yu-Hsin Chen (2013) modified the HAS I and HAS III of

McKendall Jr and Shang (2006) and established two new heuristics named Binary Coded HAS I (BC-HAS I) and Binary Coded HAS II (BC-HAS II). The difference between BC-HAS I and BC-HAS II is that they do not adopt the same local search strategy. BC-HAS I uses a pair-wise exchange heuristic for local search, whereas BC-HAS II adopts the look-ahead/look-back strategy.

Several studies presented hybrid algorithms incorporating more than two techniques. Kaveh et al. (2014) established a hybrid intelligent algorithm combining GA, SA and fuzzy simulation together to solve the three fuzzy models proposed for DFLP. Hosseini et al. (2014) presented a robust and simply structured hybrid algorithm by integrating three metaheuristics, namely, ICA, SA, and VNS, which can solve the DFLP efficiently. In this hybrid algorithms, ICA and VNS are applied for diversification, while VNS and SA are used to ensure intensification capability.

Other hybrid approaches proposed in the literature are summarized as follows. Erel et al. (2003) presented a new hybrid heuristic for DFLP, which has three stages. In the first stage, a set of layouts that are likely to appear in the optimal solution are selected. Since the DFLP can be regarded as a shortest path problem, in the second stage, viable layouts obtained from the previous stage are used to solve this shortest path problem by DP. In the last stage, a local improvement process is included to improve the solutions obtained from the second stage. It was shown that the proposed heuristic can solve large scale DFLP. Azimi and Charmchi (2012) developed a new efficient heuristic algorithm integrating integer programming and discrete event simulation to address DFLP with budget constraint. In this algorithm, the nonlinear DFLP model has been changed to a pure integer programming model. They then used the optimal solution of the linear model in a simulation model to determine the probability of assigning facilities to certain locations. The simulation model obtains near-optimal solution after sufficient number of runs. The test results showed that the proposed heuristic is more efficient in terms of speed and accuracy than the heuristics reported in the paper of Şahin et al. (2010). Rezazadeh et al. (2009) extended the discrete particle swarm optimization (DPSO) developed by Liao et al. (2007) to solve the DFLP. They used the semi-annealing approach, a SA with only the outer loop as the local search technique in DPSO. The performance of the proposed DPSO was compared with other solving methods developed in existing literature including DP, GA, SA, HAS, hybrid simulated annealing (SA-EG), hybrid genetic algorithms (NLGA and CONGA). The results showed that the proposed DPSO performs better than all the other approaches and has a good computational efficiency for larger scale problems. Hosseini-Nasab and Emami (2013) developed a hybrid PSO (HPSO) algorithm to solve DFLP, in which a simple and fast SA is used for local search.

Table 6 Summary of DFLP studies by solution methodology.

Exact Methods	**Authors**
B&B	Lahmar and Benjaafar (2005), Kheirkhah and Bidgoli (2016)
DP	Chen (1998), Urban (1998)
MSG	Ulutas and Saraç (2012)
Heuristics	**Authors**
	Yang and Peters (1998), Balakrishnan et al. (2000), Lahmar and Benjaafar (2005), Balakrishnan and Cheng (2009), Chan and Malmborg (2010), Ripon et al. (2011a), Kumar and Prakash Singh (2017)
Metaheuristics	**Authors**
SA	Baykasoğlu and Gindy (2001), McKendall Jr et al. (2006), Ashtiani et al. (2007), Dong et al. (2009), Şahin et al. (2010), Shahbazi (2010), Pillai et al. (2011), Kia et al. (2012), Moslemipour and Lee

	(2012), Emami and Nookabadi (2013), Kia et al. (2013), Kia et al. (2015), Li et al. (2015), Kheirkhah and Bidgoli (2016), Tayal et al. (2016), Pourvaziri and Pierreval (2017)
TS	Kaku and Mazzola (1997), McKendall and Jaramillo (2006), Kulturel-Konak et al. (2007), McKendall Jr (2008), McKendall Jr and Hakobyan (2010), Shahbazi (2010), McKendall Jr and Liu (2012), Bozorgi et al. (2015)
GA	Kochhar and Heragu (1999), Balakrishnan and Cheng (2000), Krishnan et al. (2008), Yang et al. (2011), Emami and Nookabadi (2013), Mazinani et al. (2013), Kia et al. (2014), Vitayasak et al. (2016)
ACO	Corry and Kozan (2004), Baykasoglu et al. (2006), Ning et al. (2010), Chen and Lo (2014)
PSO	Jolai et al. (2012), Derakhshan Asl and Wong (2015), Kheirkhah et al. (2015), Xu and Song (2015)
AIS	Ulutas and Islier (2009), Ulutas and Islier (2010), Ulutas and Islier (2015)
Fuzzy	Ning et al. (2010), Samarghandi et al. (2013), Kaveh et al. (2014), Xu and Song (2015), Xu et al. (2016)
Others	Urban (1998): GRASP, initialized multigreedy algorithm Ming et al. (2002): SymEA Abedzadeh et al. (2013): VNS Kheirkhah and Bidgoli (2016): ICA
Hybrid	**Authors**
	Balakrishnan et al. (2003), Dunker et al. (2005), Erel et al. (2003), Krishnan et al. (2006), McKendall Jr and Shang (2006), Chen and Rogers (2009), Rezazadeh et al. (2009), Şahin and Türkbey (2009), Ripon et al. (2011b), Azimi and Charmchi (2012), Hosseini-Nasab and Emami (2013), Yu-Hsin Chen (2013), Hosseini et al. (2014), Kaveh et al. (2014), Pourvaziri and Naderi (2014), Kulturel-Konak

and Konak (2015), Uddin (2015), Wang et al. (2015), Tayal et al. (2016), Tayal and Singh (2016), Shafigh et al. (2017)

4 Conclusion and future directions

This paper reviews the DFLP studies published since the survey by Balakrishnan and Cheng (1998) was conducted. At the beginning of this paper, different features of DFLP are discussed in terms of problem formulations, objectives, constraints as well as facility characteristics. Regarding problem formulations, modified QAP and MIP appear to be the most popular forms. Besides, the DFLP is also modelled using GT, game theoretic model and DEA. To address the uncertainties in production, several studies apply stochastic modelling for DFLP, thereby transforming DFLP to SDFLP. In addition, a stream of studies model uncertainties using fuzzy logic. In the past two decades, a number of studies consider multiple objectives in DFLP, including both the conventional quantitative objective (cost minimization) and qualitative objectives such as maximizing adjacency rate, minimizing shape ratio etc., so as to make the problem more realistic. Special constraints are also considered in DFLP modelling, which mainly include position constraints (e.g. non-overlapping, orientation and pick-up/drop-off points), budget constraints and capacity constraints. DFLP studies are also characterized by different manufacturing systems, layout configurations, and facility shapes. For example, a number of researchers focus on cellular layout, while some specifically deal with single-row layout, and some define facility shape using aspect ratio instead of fixed dimensions.

Different solution methods implemented for solving DFLPs are also discussed in details. In recent years, a few researchers used exact approaches to find optimal solutions for DFLP. These methods generally work well on small-sized DFLPs. As recent DFLP studies are trying to capture more specific features in different manufacturing environments, the DFLP models have become more realistic yet more complex in computation. Hence, metaheuristics have become the most widely used approaches (56 out of 77), especially in the last decade (see Figure 2). Among the different metaheuristics adopted, SA is the most popular method followed by TS and GA (see Figure 3).

Further, in the past decade, novel metaheuristics such as PSO, AIS and fuzzy system have been introduced in DFLP research for solving problems with multiple objectives, uncertainties and special constraints. Also, there is increasing interest in hybrid algorithms as they can overcome the weakness of using a pure method by incorporating other approaches so as to enhance computational capability and to improve the solution quality. In hybrid algorithms, the use of GA is frequent, with pair-wise exchange heuristics and SA being commonly used in local search.

Future research in DFLP could include custom objective functions and constraints to depict realistic problems more accurately, such as considering multiple cooperative or conflicting objectives, dynamic transportation costs during a single period (Samarghandi et al. 2013), time-dependent rearrangement cost, departments with variable shapes, new constraints related to facilities or different characteristics for the unsuitability between departments and locations (Azevedo et al. 2017). So far, a number of researchers have already attempted to solve DFLP with multiple floors, unequal area departments, uncertainties in the demand forecast, budget constraint, pick-up/drop-off points, however further exploration of DFLPs with these characteristics are still needed. Incorporating with BDA and DEA in DFLP has been investigated by a few researchers to deal with more complex and realistic problems and determine the most efficient layout. Hence, investigating other analytic methods in the DFLP is also a possible future direction. Besides, the DFLP can also be integrated with more detailed layout configuration for each department at operational level to create powerful decision support systems (Azevedo et al. 2017). Real life circumstance and data (including factory data and big data) may also be considered in the DFLP for future work (Li et al. 2015, Tayal and Singh 2016). In addition, Ulutas and Islier (2010) used the concept of DFLP to solve the dynamic content area layout for internet newspapers, which indicates the possibility of applying DFLP to other relevant problems in the digital age.

As DFLP studies are focusing on more and more complicated and realistic scenarios, efficient solving methods are required. Metaheuristics and hybrid schemes are the most promising approaches for solving complex and large-sized DFLPs. In regard to metaheuristics, researchers can improve current metaheuristics or develop novel metaheuristics techniques to create more effective solutions. For hybrid schemes, combining different algorithms can overcome the drawbacks of a single algorithm type method so as to make it possible for generating good solutions for larger and more practical problems with realistic constraints and objectives. For example, the features of TS such as tabu list, adaptive memory, diversification and intensification may be added to the SA algorithms to obtain better computational results (Şahin and Türkbey 2009). Different local search procedures can also be applied in sophisticated hybrid schemes to develop effective approaches and achieve better solutions in complex DFLPs. Also, the proposed algorithms for DFLPs can be tried on the other well-known combinatorial optimisation problems such as the vehicle routing problem and travelling salesman problem. (Pourvaziri and Naderi 2014, Şahin and Türkbey 2009). Given the nature of today’s business environment where demand may be difficult to predict, the more use of fuzzy methods (Azimi and Charmchi 2012), and game theory (Kheirkhah and Bidgoli 2016) in research would be attractive avenues in increasing realism in DFLP models. Finally, the application of more sophisticated statistical analysis of the results

(Baykasoglu et al. 2006) and the application of design of experiments such as Taguchi methods is also desirable (Ulutas and Islier 2009).

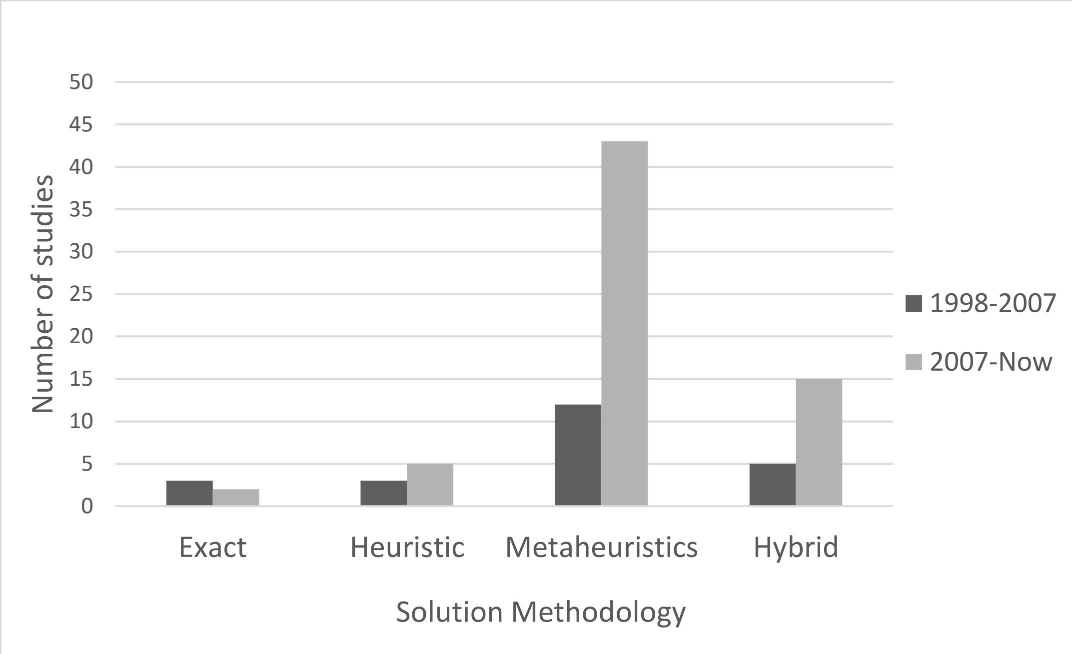

Figure 2 DFLP research classified by solution methodology.

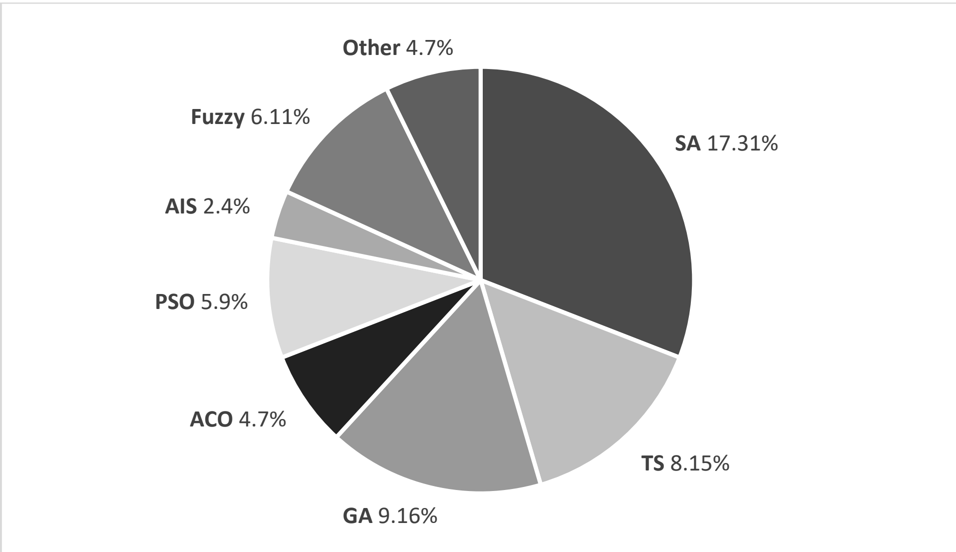

Figure 3 DFLP studies classified by metaheuristics algorithms.

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6 Reference

Abedzadeh M, Mazinani M, Moradinasab N, Roghanian E. 2013. Parallel variable neighborhood search for solving fuzzy multi-objective dynamic facility layout problem. The International Journal of Advanced Manufacturing Technology.65:197-211.

Ashtiani B, Aryanezhad M, Moghaddam BF. 2007. Multi-start simulated annealing for dynamic plant layout problem. J Ind Eng Int.3:44-50.

Azevedo MM, Crispim JA, Pinho de Sousa J. 2017. A dynamic multi-objective approach for the reconfigurable multi-facility layout problem. Journal of Manufacturing Systems. 1//;42:140-152.

Azimi P, Charmchi HR. 2012. A New Optimization via Simulation Approach for Dynamic Facility Layout Problem with Budget Constraints. Modelling and Simulation in Engineering.2012:1-9.

Balakrishnan J, Cheng CH. 1998. Dynamic layout algorithms: a state-of-the-art survey. Omega.26:507-521.

Balakrishnan J, Cheng CH. 2000. Genetic search and the dynamic layout problem. Computers & Operations Research. 5//;27:587-593.

Balakrishnan J, Cheng CH. 2009. The dynamic plant layout problem: Incorporating rolling horizons and forecast uncertainty. Omega. 2//;37:165-177.

Balakrishnan J, Cheng CH, Conway DG. 2000. An improved pair-wise exchange heuristic for the dynamic plant layout problem. International Journal of Production Research.38:3067-3077.

Balakrishnan J, Cheng CH, Conway DG, Lau CM. 2003. A hybrid genetic algorithm for the dynamic plant layout problem. International Journal of Production Economics.86:107-120.

Bashiri M, Dehghan E. 2010. Optimizing a multiple criteria dynamic layout problem using a simultaneous data envelopment analysis modeling. International Journal on Computer Science and Engineering.2:28-35.

Baykasoglu A, Dereli T, Sabuncu I. 2006. An ant colony algorithm for solving budget constrained and unconstrained dynamic facility layout problems. Omega.34:385-396.

Baykasoğlu A, Gindy NNZ. 2001. A simulated annealing algorithm for dynamic layout problem. Computers & Operations Research. 12//;28:1403-1426.

Benjaafar S, Heragu SS, Irani SA. 2002. Next Generation Factory Layouts: Research Challenges and Recent Progress. Interfaces.32:58-76.

Bozorgi N, Abedzadeh M, Zeinali M. 2015. Tabu search heuristic for efficiency of dynamic facility layout problem. The International Journal of Advanced Manufacturing Technology.77:689-703.

Chan WK, Malmborg CJ. 2010. A Monte Carlo simulation based heuristic procedure for solving dynamic line layout problems for facilities using conventional material handling devices. International Journal of Production Research. 2010/05/15;48:2937-2956.

Chen G, Rogers J. Managing dynamic facility layout with multiple objectives. Proceedings of the PICMET '09 - 2009 Portland International Conference on Management of Engineering & Technology; 2009 2-6 Aug. 2009.

Chen GY-H, Lo J-C. 2014. Dynamic facility layout with multi-objectives. Asia-Pacific Journal of Operational Research.31:-1.

Chen M. 1998. A mathematical programming model for system reconfiguration in a dynamic cellular manufacturing environment. Annals of Operations Research. 1998//;77:109-128.

Civicioglu P. 2013. Backtracking Search Optimization Algorithm for numerical optimization problems. Applied Mathematics and Computation. 4/1/;219:8121-8144.

Conway DG, Venkataramanan MA. 1994. Genetic search and the dynamic facility layout problem. Computers & Operations Research. 1994/10/01;21:955-960.

Corry P, Kozan E. 2004. Ant Colony Optimisation for Machine Layout Problems. Computational Optimization and Applications. 2004//;28:287-310.

Derakhshan Asl A, Wong KY. 2015. Solving unequal-area static and dynamic facility layout problems using modified particle swarm optimization. Journal of Intelligent Manufacturing. 2015//:1-20.

Dong M, Wu C, Hou F. 2009. Shortest path based simulated annealing algorithm for dynamic facility layout problem under dynamic business environment. Expert Systems with Applications. 10//;36:11221-11232.

Dorigo M, Birattari M, Stutzle T. 2006. Ant colony optimization. IEEE Computational Intelligence Magazine.1:28-39.

Drira A, Pierreval H, Hajri-Gabouj S. 2007. Facility layout problems: A survey. Annual Reviews in Control.31:255-267.

Dunker T, Radons G, Westkämper E. 2005. Combining evolutionary computation and dynamic programming for solving a dynamic facility layout problem. European Journal of Operational Research. 8/16/;165:55-69.

Dutta KN, Sahu S. 1982. A multigoal heuristic for facilities design problems: MUGHAL. International Journal of Production Research. 1982/05/01;20:147-154.

El-Baz MA. 2004. A genetic algorithm for facility layout problems of different manufacturing environments. Computers & Industrial Engineering. 11//;47:233-246.

Emami S, Nookabadi AS. 2013. Managing a new multi-objective model for the dynamic facility layout problem. The International Journal of Advanced Manufacturing Technology.68:2215-2228.

Erel E, Ghosh JB, Simon JT. 2003. New Heuristic for the Dynamic Layout Problem. The Journal of the Operational Research Society.54:1275-1282.

Foulds LR, Robinson DF. 1978. Graph theoretic heuristics for the plant layout problem. International Journal of Production Research. 1978/01/01;16:27-37.

Gambardella LM, Taillard, xc, Dorigo M. 1999. Ant Colonies for the Quadratic Assignment Problem. The Journal of the Operational Research Society.50:167-176.

Gasimov RN. 2002. Augmented Lagrangian Duality and Nondifferentiable Optimization Methods in Nonconvex Programming. Journal of Global Optimization. 2002//;24:187-203.

Glover F. 1989. Tabu Search-- Part I. ORSA Journal on Computing.1:190.

Glover F. 1990. Tabu Search-- Part II. ORSA Journal on Computing.2:4.

Heragu SS. 1994. Group technology and cellular manufacturing. IEEE Transactions on Systems, Man, and Cybernetics.24:203-215.

Hosseini-Nasab H, Emami L. 2013. A hybrid particle swarm optimisation for dynamic facility layout problem. International Journal of Production Research. 2013/07/01;51:4325-4335.

Hosseini S, Khaled AA, Vadlamani S. 2014. Hybrid imperialist competitive algorithm, variable neighborhood search, and simulated annealing for dynamic facility layout problem. Neural Computing and Applications.25:1871-1885.

Jolai F, Tavakkoli-Moghaddam R, Taghipour M. 2012. A multi-objective particle swarm optimisation algorithm for unequal sized dynamic facility layout problem with pickup/drop-off locations. International Journal of Production Research.50:4279-4293.

Kaku BK, Mazzola JB. 1997. A Tabu-Search Heuristic for the Dynamic Plant Layout Problem. INFORMS Journal on Computing.9:374-384.

Kaveh M, Dalfard VM, Amiri S. 2014. A new intelligent algorithm for dynamic facility layout problem in state of fuzzy constraints. Neural Computing and Applications.24:1179-1190.

Kheirkhah A, Bidgoli MM. 2016. Dynamic facility layout problem under competitive environment: a new formulation and some meta-heuristic solution methods. Production Engineering.10:615-632.

Kheirkhah A, Navidi H, Messi Bidgoli M. 2015. Dynamic Facility Layout Problem: A New Bilevel Formulation and Some Metaheuristic Solution Methods. IEEE Transactions on Engineering Management.62:396-410.

Kia R, Baboli A, Javadian N, Tavakkoli-Moghaddam R, Kazemi M, Khorrami J. 2012. Solving a group layout design model of a dynamic cellular manufacturing system with alternative process routings, lot splitting and flexible reconfiguration by simulated annealing. Computers & Operations Research.39:2642-2658.

Kia R, Javadian N, Paydar MM, Saidi-Mehrabad M. 2013. A Simulated Annealing for Intra-Cell Layout Design of Dynamic Cellular Manufacturing Systems with Route Selection, Purchasing Machines and Cell Reconfiguration. Asia - Pacific Journal of Operational Research.30:4_1.

Kia R, Khaksar-Haghani F, Javadian N, Tavakkoli-Moghaddam R. 2014. Solving a multi-floor layout design model of a dynamic cellular manufacturing system by an efficient genetic algorithm. Journal of Manufacturing Systems. 1//;33:218-232.

Kia R, Shirazi H, Javadian N, Tavakkoli-Moghaddam R. 2015. Designing group layout of unequal-area facilities in a dynamic cellular manufacturing system with variability in number and shape of cells. International Journal of Production Research. 2015/06/03;53:3390-3418.

Kirkpatrick S, Gelatt CD, Vecchi MP. 1983. Optimization by simulated annealing. science.220:671-680.

Kochhar JS, Heragu SS. 1999. Facility layout design in a changing environment. International Journal of Production Research.37:2429-2446.

Krishnan KK, Cheraghi SH, Nayak CN. 2006. Solving Dynamic Facility Layout Problems Using Dynamic From Between Charts. IIE Annual Conference Proceedings. 2006:1-6.

Krishnan KK, Cheraghi SH, Nayak CN. 2008. Facility layout design for multiple production scenarios in a dynamic environment. International Journal of Industrial and Systems Engineering.3:105-133.

Kulturel-Konak S. 2007. Approaches to uncertainties in facility layout problems: Perspectives at the beginning of the 21st Century. Journal of Intelligent Manufacturing.18:273-284.

Kulturel-Konak S, Konak A. 2015. A large-scale hybrid simulated annealing algorithm for cyclic facility layout problems. Engineering Optimization. 2015/07/03;47:963-978.

Kulturel-Konak S, Smith AE, Norman BA. 2007. Bi-objective facility expansion and relayout considering monuments. IIE Transactions. 2007/04/30;39:747-761.

Kumar R, Prakash Singh S. 2017. A similarity score-based two-phase heuristic approach to solve the dynamic cellular facility layout for manufacturing systems. Engineering Optimization.1-20.

Lahmar M, Benjaafar S. 2005. Design of distributed layouts. IIE Transactions. 2005/02/23;37:303-318.

Li L, Li C, Ma H, Tang Y. 2015. An Optimization Method for the Remanufacturing Dynamic Facility Layout Problem with Uncertainties. Discrete Dynamics in Nature and Society.2015:1-11.

Liao C-J, Chao-Tang T, Luarn P. 2007. A discrete version of particle swarm optimization for flowshop scheduling problems. Computers & Operations Research. 10//;34:3099-3111.

Mazinani M, Abedzadeh M, Mohebali N. 2013. Dynamic facility layout problem based on flexible bay structure and solving by genetic algorithm. The International Journal of Advanced Manufacturing Technology.65:929-943.

McKendall AR, Jaramillo JR. 2006. A tabu search heuristic for the dynamic space allocation problem. Computers and Operations Research.33:768-789.

McKendall Jr AR. 2008. Improved Tabu search heuristics for the dynamic space allocation problem. Computers & Operations Research. 10//;35:3347-3359.

McKendall Jr AR, Hakobyan A. 2010. Heuristics for the dynamic facility layout problem with unequal-area departments. European Journal of Operational Research. 2/16/;201:171-182.

McKendall Jr AR, Liu W-H. 2012. New Tabu search heuristics for the dynamic facility layout problem. International Journal of Production Research. 2012/02/01;50:867-878.

McKendall Jr AR, Shang J. 2006. Hybrid ant systems for the dynamic facility layout problem. Computers & Operations Research. 3//;33:790-803.

McKendall Jr AR, Shang J, Kuppusamy S. 2006. Simulated annealing heuristics for the dynamic facility layout problem. Computers & Operations Research. 8//;33:2431-2444.

Ming C, Ohkura K, Ueda K, Sugiyama M. A symbiotic evolutionary algorithm for dynamic facility layout problem. Proceedings of the Evolutionary Computation, 2002 CEC '02 Proceedings of the 2002 Congress on; 2002 2002.

Moslemipour G, Lee TS. 2012. Intelligent design of a dynamic machine layout in uncertain environment of flexible manufacturing systems. Journal of Intelligent Manufacturing. 2012//;23:1849-1860.

Moslemipour G, Lee TS, Rilling D. 2012. A review of intelligent approaches for designing dynamic and robust layouts in flexible manufacturing systems. The International Journal of Advanced Manufacturing Technology.60:11-27.

Ning X, Lam K-C, Lam MC-K. 2010. Dynamic construction site layout planning using max-min ant system. Automation in Construction. 1//;19:55-65.

Pillai VM, Hunagund IB, Krishnan KK. 2011. Design of robust layout for Dynamic Plant Layout Problems. Computers & Industrial Engineering.61:813-823.

Pourvaziri H, Naderi B. 2014. A hybrid multi-population genetic algorithm for the dynamic facility layout problem. Applied Soft Computing.24:457-469.

Pourvaziri H, Pierreval H. 2017. Dynamic facility layout problem based on open queuing network theory. European Journal of Operational Research. 6/1/;259:538-553.

Rezazadeh H, Ghazanfar M, Saidi-Mehrabad M, Jafar Sadjadi S. 2009. An extended discrete particle swarm optimization algorithm for the dynamic facility layout problem. Journal of Zhejiang University-Science A.10:520-529.

Ripon KSN, Glette K, Hovin M, Torresen J. 2011a. Dynamic facility layout problem under uncertainty: a Pareto-optimality based multi-objective evolutionary approach. Central European Journal of Computer Science. 2011//;1:375-386.

Ripon KSN, Glette K, Koch D, Hovin M, Torresen J. 2011b. Genetic algorithm using a modified backward pass heuristic for the dynamic facility layout problem. Paladyn.2:164-174.

Rosenblatt MJ. 1986. The dynamics of plant layout. Management Science.32:76-86.

Şahin R, Ertoğral K, Türkbey O. 2010. A simulated annealing heuristic for the dynamic layout problem with budget constraint. Computers & Industrial Engineering. 9//;59:308-313.

Şahin R, Türkbey O. 2009. A new hybrid tabu-simulated annealing heuristic for the dynamic facility layout problem. International Journal of Production Research.47:6855-6873.

Samarghandi H, Taabayan P, Behroozi M. 2013. Metaheuristics for fuzzy dynamic facility layout problem with unequal area constraints and closeness ratings. The International Journal of Advanced Manufacturing Technology.67:2701-2715.

Shafigh F, Defersha FM, Moussa SE. 2015. A mathematical model for the design of distributed layout by considering production planning and system reconfiguration over multiple time periods. Journal of Industrial Engineering International. 2015//;11:283-295.

Shafigh F, Defersha FM, Moussa SE. 2017. A linear programming embedded simulated annealing in the design of distributed layout with production planning and systems reconfiguration. The International Journal of Advanced Manufacturing Technology.88:1119-1140.

Shahbazi E. Mathematical modeling and solution development for "dynamic facility layout problem" in job shop process using meta-heuristic algorithms. Proceedings of the 40th International Conference on Computers and Industrial Engineering (CIE); 2010 25-28 July: IEEE.

Tayal A, Gunasekaran A, Singh SP, Dubey R, Papadopoulos T. 2016. Formulating and solving sustainable stochastic dynamic facility layout problem: a key to sustainable operations. Annals of Operations Research. 2016//:1-35.

Tayal A, Singh SP. 2016. Integrating big data analytic and hybrid firefly-chaotic simulated annealing approach for facility layout problem. Annals of Operations Research. 2016//:1-26.

Uddin MS. 2015. Hybrid Genetic Algorithm and Variable Neighborhood Search for Dynamic Facility Layout Problem. Open Journal of Optimization.4:156-167.

Ulutas B, Islier AA. 2015. Dynamic facility layout problem in footwear industry. Journal of Manufacturing Systems.36:55-61.

Ulutas B, Saraç T. 2012. Determining the parameters of MSG algorithm for multi period layout problem. Journal of Manufacturing Technology Management. 2012/09/07;23:922-936.

Ulutas BH, Islier AA. 2009. A clonal selection algorithm for dynamic facility layout problems. Journal of Manufacturing Systems.28:123-131.

Ulutas BH, Islier AA. 2010. A novel attribute - based dynamic content area layout for internet newspapers. Internet Research.20:135-153.

Urban TL. 1987. A multiple criteria model for the facilities layout problem. International Journal of Production Research.25:1805-1812.

Urban TL. 1993. A heuristic for the dynamic facility layout problem. IIE transactions.25:57-63.

Urban TL. 1998. Solution procedures for the dynamic facility layout problem. Annals of Operations Research.76:323-342.

Vitayasak S, Pongcharoen P, Hicks C. 2016. A tool for solving stochastic dynamic facility layout problems with stochastic demand using either a Genetic Algorithm or modified Backtracking Search Algorithm. International Journal of Production Economics.

Wang S, Zuo X, Liu X, Zhao X, Li J. 2015. Solving dynamic double row layout problem via combining simulated annealing and mathematical programming. Applied Soft Computing. 12//;37:303-310.

Wesolowsky GO. 1973. Dynamic facility location. Management Science.19:1241-1248.

Xu J, Liu Q, Lei X. 2016. A fuzzy multi-objective model and application for the discrete dynamic temporary facilities location planning problem. Journal of Civil Engineering and Management.22:357-372.

Xu J, Song X. 2015. Multi-objective dynamic layout problem for temporary construction facilities with unequal-area departments under fuzzy random environment. Knowledge-Based Systems. 6//;81:30-45.

Yaman R, Gethin DT, Clarke MJ. 1993. An effective sorting method for facility layout construction. International Journal of Production Research. 1993/02/01;31:413-427.

Yang C-L, Chuang S-P, Hsu T-S. 2011. A genetic algorithm for dynamic facility planning in job shop manufacturing. The International Journal of Advanced Manufacturing Technology. 2011//;52:303-309.

Yang T, Peters BA. 1998. Flexible machine layout design for dynamic and uncertain production environments. European Journal of Operational Research.108:49-64.

Yu-Hsin Chen G. 2013. A new data structure of solution representation in hybrid ant colony optimization for large dynamic facility layout problems. International Journal of Production Economics. 4//;142:362-371.