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A bottom-up multi-objective optimisation approach to dynamic facility layout planning

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ABSTRACT
Dynamic facility layout planning (DFLP) involves determining an appropriate arrangement scheme of the elements making up the production system for each time period into which the planning horizon is divided. When formulating the problem as an optimisation model, using the traditional top-down approach is usual, which firstly determines the block layout (BL) and then the detailed layout (DL) of each work cell. However by this approach, the BL generates area constraints in the detailed phase, which sometimes limit its implementation. In this context, the present paper presents a multi-objective mixed integer non-linear programming (MOMINLP) model that allows the problem to be addressed by considering an alternative approach, known in the literature as the bottom-up approach. The proposed model, called bottom-up mDFLP, considers three objective functions: (1) minimise the total material handling cost (TMHC) and the total rearrangement cost (TRAC); (2) maximise the total closeness rating (TCR) between departments; (3) maximise the area utilisation ratio (AUR). The original MOMINLP is transformed into a more computationally efficient multi-objective mixed integer linear programming (MOMILP) model. The proposed model is applied and validated in a case study of a company in the metal-mechanic sector with 12 departments for three 4-month periods.

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Facility layout; facility planning; multicriteria decision making; non-linear programming; mixed integer linear programming

1. Introduction

Facility layout planning (FLP) refers to the process of finding the best arrangement of all the elements making up the production system in the available physical space, in such a way that certain relevant objectives are fulfilled (Pérez-Gosende, Mula, and Díaz-Madroñero 2021). Of these objectives, better uses of space, equipment and workforce, improving the flow of information, materials and personnel, improving employee satisfaction, job security and the interaction with customers, and flexibility for future changes are prominent (Heizer, Render, and Munson 2019).

Given its importance and its impact on organisations' productivity and competitiveness (Altuntas and Selim 2012; Ku, Hu, and Wang 2011; Navidi, Bashiri, and Messi Bidgoli 2012), FLP is an important research area in the operations management field (Ahmadi, Pishvaee, and Jokar 2017; Al-Zubaidi, Fantoni, and Failli 2021; Anjos and Vieira 2017; Burggraf, Wagner, and Heinbach 2021; Hosseini-Nasab et al. 2018; Kikolski and Ko 2018; la Scalia, Micale, and Enea 2019; Maganha, Silva, and Ferreira 2019; Pérez-Gosende, Mula, and Díaz-Madroñero 2020a; Pérez-Gosende, Mula, and Díaz-Madroñero 2020b; Pérez-Gosende, Mula, and Díaz-Madroñero 2021).

When plant layout is planned in line with the assumption that demand will remain constant over the entire planning horizon, the problem is known as the static facility layout problem (SFLP) (Moslemipour, Lee, and Loong 2017). However in many production systems, the consideration of a single layout may be impractical, because the flow of materials is unlikely to remain constant over time. Instead when demand is seasonal, it is desirable to consider a different plant layout design for each period into which the time planning horizon is divided. In this case, it would be a dynamic facility layout problem (DFLP) in which an optimal layout is adopted for each time period to minimise the total material handling cost (TMHC) and the total rearrangement cost (TRAC) (Turanoğlu and Akkaya 2018; Pournaderi, Ghezavati, and Mozafari 2019; Erik and Kuvvetli 2021). In line with this, Hosseini-Nasab et al. (2018), Pérez-Gosende, Mula, and Díaz-Madroñero (2020a) and Pérez-Gosende, Mula, and Díaz-Madroñero (2021)

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concluded that DFLP has been less addressed in the scientific literature than the SFLP approach.

Traditionally, FLP has been approached by the systematic layout planning (SLP) methodology, which consists of a set of phases that involve plant location to layout implementation (Muther 1961). However, the most addressed phases in the literature about the mathematical optimisation of an FLP problem are the two intermediate phases, known as block layout (BL) and detailed layout (DL). As part of the first phase, the appropriate position of the departments or work centres that make up the production or service system in the available physical space is defined. Subsequently in the DL, the following are defined for each department: the best arrangement scheme for machinery, material depots and workstations; the location of the material pick-up and drop-off points (P/D); the structure of corridors through which materials, means of transport and personnel will circulate is integrated. This hierarchical planning process is traditionally carried out sequentially, and is known as the top-down approach (Meller, Kleiner, and Nussbaum 2004). However, it has been shown that, in practice, layout managers prefer to start with the DL phase and then proceed to the BL, what has been formalised by Meller, Kirkizoglu, and Chen (2010) as the bottom-up approach.

It is important to highlight that developing optimisation models that address both the BL and DL phases simultaneously in the DFLP context has scarcely been addressed, with most contributions in this area mostly made in the modelling of one of these two phases (Pérez-Gosende, Mula, and Díaz-Madroñero 2021). In doing so, the combined use of TMHC and TRAC over the entire planning horizon as a single-objective function of a quantitative nature is common (Hosseini-Nasab et al. 2018; Pérez-Gosende, Mula, and Díaz-Madroñero 2020b). However in real production systems, FLP is a multi-objective problem due to the large number of factors involved in the final decision (Matai 2015; Singh and Ingole 2019; Bozorgi, Abedzadeh, and Zeinali 2015). In this context, the present paper contributes a new MOMINLP model to optimise DFLP with unequal area departments from a bottom-up approach, which considers the DL and BL phases concurrently and dynamically. This model, dubbed bottom-up mDFLP, has been obtained as the main result of the doctoral dissertation by Pérez-Gosende (2022) and aims to bridge a research gap, that of DFLP optimisation integrating BL and DL, which has been identified in the literature, but is barely addressed.

This model has been dubbed bottom-up mDFLP and aims to bridge a research gap, that of DFLP optimisation integrating BL and DL, which has been identified in the literature, but is barely addressed.

The rest of the article is organised as follows. Section 2 describes the literature review that is relevant to the study topic. Section 3 describes the problem to be addressed. Section 4 formulates the MOMINLP model, dubbed as bottom-up mDFLP. Section 5 presents, as part of the model solution methodology, alternatives for its linearisation, and the reduction of the possible symmetry of solutions to reduce the computational effort. As part of this section, the multi-objective solution approach based on the lexicographic method is presented. Section 6 includes the computational results and the model's validation for a real case study. Section 7 discusses managerial implications, and Section 8 describes the study conclusions and future research guidelines.

2. Literature review

In a globalised business environment, the need to consider dynamic conditions in the layout planning process is a requirement, mainly due to the need to readjust production capacity as a consequence of demand fluctuations, and to adopt technological changes in manufacturing systems, increasingly shorter product life cycles and disruptive events in supply chains, among other factors (Dolgui and Ivanov 2021; Chen 2013; Vitayasak, Pongcharoen, and Hicks 2017). Based on this approach, called the multiperiod or DFLP, a layout is designed for each time period into which the planning horizon is divided to minimise the TMHC and TRAC (Turanoğlu and Akkaya 2018; Al Hawarneh, Bendak, and Ghanim 2019; Pournaderi, Ghezavati, and Mozafari 2019). It should be noted that depending on the seasonality of the demand in the concerned industry sector, time periods may be expressed as months, quarters, years, among others.

When planning dynamic facility layouts, departments can be considered to be of equal or unequal area (Feng and Che 2018). The selection of discrete or continuous optimisation models to generate plant layout alternatives is based on this assumption (Allahyari and Azab 2018). The problem of equal-area departments is often addressed by using discrete optimisation models to optimally allocate N departments to a set of N predefined locations (Xiao et al. 2017). Rosenblatt (1986) was the first to formulate DFLP with these characteristics. To solve it, he developed optimal and heuristic procedures based on dynamic programming. However, planning the layout according to the assumption that departments have equal areas when they actually do not, can generate suboptimal solutions with a significantly lower TMHC than what would actually be incurred. Hence the importance of considering the real dimensions of departments according to the operations that will be performed in them. In the cases in which DFLP is formulated by considering departments with different areas, optimisation models that allow the plant layout to be represented in continuous space are normally used (McKendall and Hakobyan 2010; Mazinani, Abedzadeh, and Mohebali 2013), which facilitates the simulation of the operating conditions that come closer to reality. Pérez-Gosende, Mula, and Díaz-Madroñero (2020a) identified that approximately 64% of the reviewed literature works in the DFLP context, and for a time window between 2010 and 2019, considered departments with equal areas, and only the remaining 36% proposed the unequal area approach. This denotes certain underrepresentation of the latter approach in the literature.

In the dynamic industrial manufacturing systems context, the TMHC and TRAC are key factors in obtaining feasible plant layouts (Chen 2013; Balakrishnan et al. 2003; Singh and Ingole 2019). Together they constitute the most widely used quantitative objective function to search for solutions to DFLP (Hosseini-Nasab et al. 2018; Pérez-Gosende, Mula, and Díaz-Madroñero 2020a; Pérez-Gosende, Mula, and Díaz-Madroñero 2021). However when solving any plant layout problem, it might not be necessary to consider quantitative factors with a single objective function to generate satisfactory solutions because, in some industrial and service contexts, qualitative factors like closeness ratings, flexibility or safety may have be of similar or more relevance.

Considering both types of factors simultaneously as part of a mathematical optimisation model usually entails having to find a compromise solution in accordance with the decision maker's preferences (Le, Dao, and Chaabane 2019; Che, Zhang, and Feng 2017). This is because the objectives to be optimised often clash (Ripon et al. 2013), and it is necessary to adopt a multi-objective optimisation approach to tackle these problems (Ripon et al. 2013; Aiello, la Scalia, and Enea 2013). Previously Pérez-Gosende, Mula, and Díaz-Madroñero (2021) identified that only 22% of the articles published between 2010 and 2019 that addressed FLP with a mathematical optimisation model applied a multi-objective approach.

Table 1 shows a review of the scientific literature available in the Web of Science related to DFLP and formulated as a multi-objective optimisation problem, mDFLP, using a time window from 2010 to the present-day. As we see in this table, none of the reviewed papers considers either sequentially or concurrently modelling the BL and the DL as part of the same optimisation problem as our model does. The papers that consider departments of equal area employ the equivalent QAP model, while most of those that contemplate unequal areas use MILP models. Note also that besides our model, only Li et al. (Li, Tan, and Li 2018) apply their formulation to a real-life case study. All the other works opt to look for solutions to mDFLP in classic test problems from the literature or hypothetical case studies. What this shows is that the contributions made to the mDFLP solution have barely been applied in practice. This statement falls in line with Meller, Kirkizoglu, and Chen (2010) when analysing the applicability of FLP research in the industry in a broader context.

In the reviewed literature, both the TMHC and TRAC are common to any DFLP formulation as initially defined by Rosenblatt (1986). However in most cases, the TRAC is considered to be fixed, and related to only the TRAC incurred while interrupting production due to the layout reorganisation work at the beginning of each period. Only a few authors, as in our model, consider the variable rearrangement costs associated with the amount of displacement of a department in the space between one period and another (Abedzadeh et al. 2013; Erfani, Ebrahimnejad, and Moosavi 2020; Erik and Kuvvetli 2021).

Table 1 also shows that the total closeness rating (TCR) is one of the most frequently used objective functions in mDFLP formulation, which is accepted in only in slightly over 53% of the consulted literature. The use of the TCR is based on the fact that the departments with the highest intensity of relationships (whether quantitative or subjective in nature) should be as close as possible in the final arrangement scheme to guarantee the principle of circulation, the workforce's safety and satisfaction, and the minimum distance covered by the flow of materials, means of transport and personnel, among other factors.

For a given spatial arrangement scheme, the TCR value can be calculated as a linear function of the length of the common boundary between each pair of contiguous departments (Ghassemi Tari and Neghabi 2018); like the sum of the adjacency ratings between those cells with a common side (Salmani, Eshghi, and Neghabi 2015); by summing the product of the adjacency ratings by the distance between the centroids of the working cells (Le, Dao, and Chaabane 2019); by summing the product of the adjacency values by the length of the common boundary between them (Bozorgi, Abedzadeh, and Zeinali 2015; Liu et al. 2020); by summing the product of the adjacency values by a factor of adjacency (Jolai, Tavakkoli-Moghaddam, and Taghipour 2012; Emami and Nookabadi 2013; Liu et al. 2018; Huo, Liu, and Gao 2021). In the herein presented model, the latter variant was selected. Its particularity is that, unlike other authors, the adjacency factor is determined as the complement of the proportion representing the distance between the centroids of each department in the direction of the x- and y-axes in relation to the maximum possible distance;

Table 1. Survey of papers addressing mDFLP through mathematical models.

References	Planning phase	Work cell's area	Type of Multi-objective model[a]	Objective function[b]	Practical application	
					Numerical example	Case study
(Jolai, Tavakkoli-Moghaddam, and Taghipour 2012)	BL	Unequal	MINLP	i, ii, x, xi	x	
(Abedzadeh et al. 2013)	BL	Unequal	MILP	i, ii, v, x	x	
(Emami and Nookabadi 2013)	BL	Equal	QAP	i, ii, x	x	
(Samarghandi, Taabayan, and Behroozi 2013)	BL	Unequal	NLP	i, ii, x	x	
(Chen and Lo 2014)	BL	Equal	QAP	i, ii, x	x	
(Bozorgi, Abedzadeh, and Zeinali 2015)	BL	Equal	QAP	i, ii, x, xi	x	
(Kheirkhah, Navidi, and Messi Bidgoli 2015)	BL	Equal	BLPM	i, ii, vi	x	
(Pourvaziri and Pierreval 2017)	BL	Equal	QAP	i, ii, vi, iv	x	
(Tayal and Singh 2018)	DL	Equal	QAP	i, ii, iii, vii, x	x	
(Li, Tan, and Li 2018)	DL	Unequal	MINLP	i, ii, viii, ix, xii		Metalworking company
(Pournaderi, Ghezavati, and Mozafari 2019)	BL	Equal	QAP	i, ii	x	
(Wei, Yuan, and Ye 2019)	DL	Unequal	NLP	i, ii, xii	x	
(Erfani, Ebrahimnejad, and Moosavi 2020)	BL	Unequal	MINLP	i, ii, iii, x, xii	x	
(Erik and Kuvvetli 2021)	BL	Unequal	MINLP	i, ii, vi	x	
(Salimpour, Pourvaziri, and Azab 2021)	BL	Unequal	MINLP	i, xiii	x	
Our model	DL/BL	Unequal	MINLP	i, ii, x, xii		Metalworking company

[a]Type of multi-objective model: MINLP (mixed-integer non-linear programming), MILP (mixed-integer linear programming), QAP (quadratic assignment problem), NPL (non-linear programming), BLPM (bi-level programming model).
[b]Objective functions: (i) minimum total materials handling cost; (ii) minimum total rearrangement cost; (iii) minimum transport time; (iv) minimum work in process; (v) minimum aspect ratio; (vi) minimum costs related to material handling equipment; (vii) minimum risk level associated with the hazardous materials and waste path; (viii) minimum lost opportunity costs; (ix) minimum occupational health/safety risks; (x) maximum closeness rating among departments; (xi) maximum distance requests among departments; (xii) maximum area utilisation ratio; (xiii) minimum dissimilarity of machines in each work cell.

this is defined by the sum of the width and length of the floorspace available for the plant layout.

When planning layout, although achieving the maximum utilisation of the available floor area is particularly important, this objective is not covered very much by the literature in the mDFLP context because it is only considered in three of a total of 15 reviewed papers (Erfani, Ebrahimnejad, and Moosavi 2020; Wei, Yuan, and Ye 2019; Li, Tan, and Li 2018). These authors calculate an area utilisation ratio (AUR), which relates the total area of the departments to the smallest rectangle in which they are circumscribed in the final ordering scheme per period. This forces the model to generate more compact layouts. As the formulation of this approach does not, however, consider the total area available for the arrangement of departments, layouts can be generated with a lot of unused space. Unlike these authors, the proposed model seeks to maximise the average AUR of the entire planning horizon by considering that, during each time period, the ratio between the area occupied by departments and the total available floor area should be come close as possible to unity. This forces the model to generate solutions that make better use of the floor space.

3. Problem statement

The problem under study consists of determining the position, in the available physical space, of a set N of rectangular workcells of different areas required by a production system so that its operations are efficiently performed during a multiperiod planning horizon ($t = 1, \ldots, T$) with no overlapping between them. The different departments in which production or support activities are carried out are called the work cell to group, under the same term, the various forms of work organisation according to the possible process flow structure to be considered in each case, be it job shop, batch shop, assembly line or continuous flow (Ivanov, Tsipoulanidis, and Schönberger 2017). Here a work cell is defined as a space delimited by a physical or imaginary boundary in which the activities necessary for manufacturing processes to normally operate are carried out.

As shown in Figure 1, for each work cell, there is a set Q of feasible detailed layout alternatives that can adopt four possible orientations following a clockwise rotation from its standard orientation as implied in Figure 2.

For each cell design in its standard orientation ($r = 1$), its dimensions in the x- and y-axes direction (l^{s}_{tiqr}), its

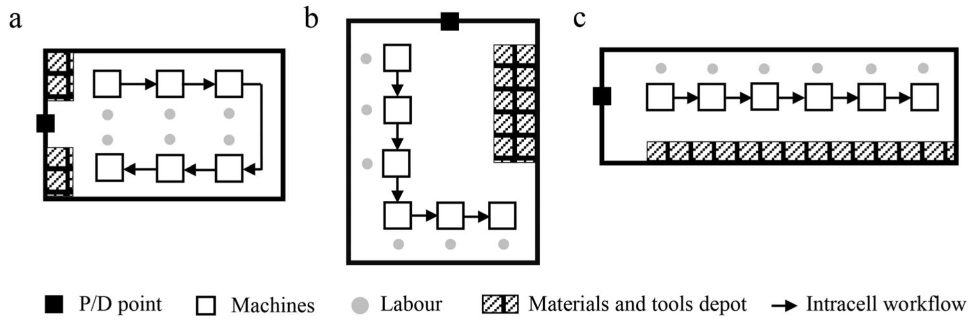

Figure 1. Representation of three alternative DL designs in a standard orientation for a given work cell.

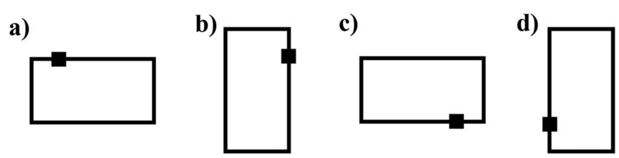

Figure 2. Possible work cell orientations based on clockwise rotation: (a) $r = 1$, (b) $r = 2$, (c) $r = 3$, (d) $r = 4$.

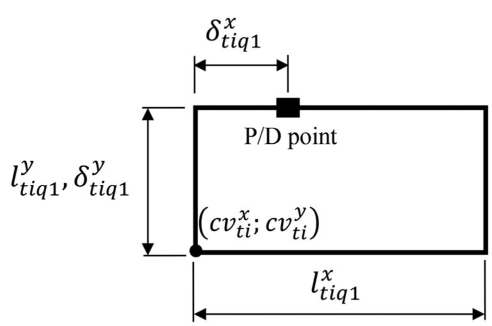

Figure 3. Relevant work cell coordinates and parameters.

Table 2. Obtaining the values of l^s_{tiqr}, and δ^s_{tiqr} in direction $s = x, y$ for any work cell orientation from their value in the standard orientation $r = 1$.

$r = 1$	$r = 2$	$r = 3$	$r = 4$
l^x_{tiq1}	$l^x_{tiq2} = l^y_{tiq1}$	$l^x_{tiq3} = l^x_{tiq1}$	$l^x_{tiq4} = l^y_{tiq1}$
l^y_{tiq1}	$l^y_{tiq2} = l^x_{tiq1}$	$l^y_{tiq3} = l^y_{tiq1}$	$l^y_{tiq4} = l^x_{tiq1}$
δ^{px}_{tiq1}	$\delta^{px}_{tiq2} = \delta^{py}_{tiq1}$	$\delta^{px}_{tiq3} = l^x_{tiq1} - \delta^{px}_{tiq1}$	$\delta^{px}_{tiq4} = l^y_{tiq1} - \delta^{py}_{tiq1}$
δ^{py}_{tiq1}	$\delta^{py}_{tiq2} = l^x_{tiq1} - \delta^{px}_{tiq1}$	$\delta^{py}_{tiq3} = l^y_{tiq1} - \delta^{py}_{tiq1}$	$\delta^{py}_{tiq4} = \delta^{px}_{tiq1}$

area (a_{tiqr}), and the distances (δ^s_{tiqr}) from the lower left cell vertex (cv^s_{ti}) to its P/D point, are known. Some of these parameters and work cell coordinates are shown in Figure 3. Subsequently from the relations described in Table 2, the equivalent of these measures can be obtained for all three remaining orientations.

4. MOMINLP model formulation

The parameters characterising the different DL alternatives for each work cell are fed into the proposed model. The model selects the appropriate DL alternative for each work cell and optimises, according to certain objectives, their relative position in the available physical space in the plant for each time period making up the planning horizon. In this way, the model output simultaneously provides the DL of each work cell, as well as the BL of the facility. However, the fact that for each work cell, a set of DL alternatives needs to be determined in advance to establish an appropriate BL implies that the planning approach considered by the model is, unlike the traditional top-down approach, more in line with a bottom-up approach. To our knowledge, this is the first time that mDFLP has been formulated by this approach.

Of the model's objective functions, we find the work cell closeness rating based on experts' assessments of the relevant qualitative factors that condition the adjacency requirements between each pair of work cells. Quantitative factors, such as the TMHC, the TRAC (considering its fixed and variable components) and the AUR, constitute the other considered objective functions. The notation applied in the model formulation is presented in Table 3.

The model, called bottom-up mDFLP, is based on the following assumptions:

- The firm operates in a dynamic environment where demand is known for each time period
- The material flow intensities between work cells are known for each time period
- The facility's dimensions are known and remain fixed over the entire planning horizon
- The number of work cells required for production processes to operate normally is known
- In each work cell, a finite set of ordering schemes can be generated according to the analyst's preference

Table 3. Notations used in the formulation.

Indices:	
i, j	Workcells ($i, j = 1, \ldots, N$)
q	Alternative workcell designs ($q = 1, \ldots, Q$)
r	Workcell orientation ($r = 1, \ldots, R$)
t	Time periods ($t = 1, \ldots, T$)
s	Direction on the x and y-axes ($s = x, y$)
Parameters:	
F_{tij}	Material flow (t/period) between workcells i and j during time period t (upper triangular matrix)
C_{tij}	Cost to transport materials a unit distance between workcells i and j during time period t (\$/t·m)
FRC_{ti}	Fixed cost of rearranging workcell i at the beginning of time period t (\$)
VRC_{ti}	Variable cost of rearranging workcell i at the beginning of time period t (\$/m)
L^s	Length of the plant floor in direction s (m)
l^s_{tiqr}	Length of workcell i along direction s during time period t according to design q in orientation r (m)
δ^s_{tiqr}	Distance along direction s during time period t from the lower left vertex of workcell i with design q in orientation r to the P/D point (m)
a_{tiqr}	Area of workcell i according to design q in orientation r during time period t (m^2)
v_{tij}	Closeness value (0–5) between workcells i and j during time period t
ce	Cost per extra metre required in the x – and y-axes direction (\$/m)
co	Cost per every underused metre in the x – and y-axes direction (\$/m)
Decision variables:	
dp^s_{tij}	Distance along direction s during time period t between the P/D points of workcells i and j (m)
dc^s_{tij}	Distance along direction s during time period t between the centroids of workcells i and j (m)
l^s_{ti}	Length of workcell i along direction s during time period t (m)
lo^s_{ti}	Clearance distance from workcell i to the floorspace boundary along direction s during time period t (m)
le^s_{ti}	Extra length required for workcell i along direction s during time period t (m)
δ^s_{ti}	Distance along direction s during time period t from the lower left vertex of workcell i to its P/D point (m).
A_{ti}	Area of workcell i during time period t (m^2).
cv^s_{ti}	Lower-left-vertex coordinate of workcell i in direction s during time period t.
cp^s_{ti}	P/D point coordinate of workcell i in direction s during time period t.
p^s_{ti}	Displacement of workcell i in direction s from time period $t-1$ to t (m).
λ_{tij}	Closeness factor between workcells i and j during time period t
$\Delta_{tiqr} =$	$\begin{cases} 1 & \text{If design } q \text{ in orientation } r \text{ is selected for workcell } i \text{ at the beginning of time period } t \\ 0 & \text{Otherwise} \end{cases}$
$\varphi^s_{tij} =$	$\begin{cases} 1 & \text{If workcell } i \text{ precedes } j \text{ in direction } s \text{ during time period } t \\ 0 & \text{Otherwise} \end{cases}$
$\gamma_{ti} =$	$\begin{cases} 1 & \text{If workcell } i \text{ is rearranged at the beginning of time period } t \\ 0 & \text{Otherwise} \end{cases}$

- Each alternative ordering scheme for each work cell can adopt four different orientations ($R = 4$) in clockwise rotation
- The work cells, for any arrangement scheme, are rectangular-shaped, have fixed dimensions and must fit in the available area of the plant without them overlapping
- Different alternative arrangement schemes for each work cell do not necessarily have the same area requirement. Consequently, work cells may have different areas
- Each work cell has a single point through which the receipt and dispatch of materials take place. This point is located at cell boundaries (not at the cell centroid)

The proposed optimisation model to address the bottom-up mDFLP is formulated as follows:

Objective functions:

$$\min f_1 = \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j>i}^{N}\sum_{s=\{x,y\}} C_{tij}F_{tij}dp^s_{tij} + \sum_{t=2}^{T}\sum_{i=1}^{N} FRC_{ti}\gamma_{ti} + \sum_{t=2}^{T}\sum_{i=1}^{N}\sum_{s=\{x,y\}} VRC_{ti}p^s_{ti} - co\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{s=\{x,y\}} lo^s_{ti} + ce\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{s=\{x,y\}} le^s_{ti} \quad (1)$$

$$\max f_2 = \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j>i}^{N} v_{tij}\lambda_{tij} + co\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{s=\{x,y\}} lo^s_{ti} - ce\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{s=\{x,y\}} le^s_{ti} \quad (2)$$

$$\max f_3 = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{\sum_{i=1}^{N} A_{ti}}{\prod_{s=\{x,y\}} L^s}\right) + co\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{s=\{x,y\}} lo_{ti}^s - ce\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{s=\{x,y\}} le_{ti}^s \quad (3)$$

Subject to:

$$cv_{ti}^s + l_{ti}^s + lo_{ti}^s = L^s + le_{ti}^s \quad \forall s, \forall t, \forall i \quad (4)$$

$$cv_{ti}^s + l_{ti}^s \le cv_{tj}^s + L^s(1-\varphi_{tij}^s) \quad \forall s, \forall t, \forall i \ne j \quad (5)$$

$$\varphi_{tij}^x + \varphi_{tji}^x + \varphi_{tij}^y + \varphi_{tji}^y = 1 \quad \forall t, \forall i, \forall j > i \quad (6)$$

$$dp_{tij}^s = |cp_{ti}^s - cp_{tj}^s| \quad \forall s, \forall t, \forall i, \forall j > i \quad (7)$$

$$dc_{tij}^s = \left|(cv_{ti}^s + \frac{l_{ti}^s}{2}) - \left(cv_{tj}^s + \frac{l_{tj}^s}{2}\right)\right| \quad \forall s, \forall t, \forall i, \forall j > i \quad (8)$$

$$\lambda_{tij} = 1 - \left(\frac{\sum_{s=\{x,y\}} dc_{tij}^s}{\sum_{s=\{x,y\}} L^s}\right) \quad \forall t, \forall i, \forall j > i \quad (9)$$

$$\sum_{q=1}^{Q}\sum_{r=1}^{R} \Delta_{tiqr} = 1 \quad \forall t, \forall i \quad (10)$$

$$l_{ti}^s = \sum_{q=1}^{Q}\sum_{r=1}^{R} l_{tiqr}^s \Delta_{tiqr} \quad \forall s, \forall t, \forall i \quad (11)$$

$$\delta_{ti}^s = \sum_{q=1}^{Q}\sum_{r=1}^{R} \delta_{tiqr}^s \Delta_{tiqr} \quad \forall s, \forall t, \forall i \quad (12)$$

$$A_{ti} = \sum_{q=1}^{Q}\sum_{r=1}^{R} a_{tiq} \Delta_{tiqr} \quad \forall t, \forall i \quad (13)$$

$$cp_{ti}^s = cv_{ti}^s + \delta_{ti}^s \quad \forall s, \forall t, \forall i \quad (14)$$

$$p_{ti}^s = \left|(cv_{ti}^s + \frac{l_{ti}^s}{2}) - (cv_{t-1,i}^s + \frac{l_{t-1,i}^s}{2})\right| \quad \forall s, \forall i, \forall t > 1 \quad (15)$$

$$\gamma_{ti} = \begin{cases} 1 & \text{If } p_{ti}^s \ne 0 \quad \forall s, \forall i, \\ & \forall t > 1 \text{ or } l_{t-1,i}^x \ne l_{ti}^x \\ 0 & \text{Otherwise} \end{cases} \quad \forall i, \forall t > 1 \quad (16)$$

$$dp_{tij}^s, dc_{tij}^s \ge 0 \quad \forall s, \forall t, \forall i, \forall j \quad (17)$$

$$cv_{ti}^s, l_{ti}^s, cp_{ti}^s, \delta_{ti}^s, p_{ti}^s \ge 0 \quad \forall s, \forall t, \forall i \quad (18)$$

$$A_{ti} \ge 0 \quad \forall t, \forall i \quad (19)$$

$$\Delta_{tiqr} \in \{0,1\} \quad \forall t, \forall i, \forall q, \forall r \quad (20)$$

$$\varphi_{tij}^s \in \{0,1\} \quad \forall s, \forall t, \forall i, \forall j \quad (21)$$

$$\gamma_{ti} \in \{0,1\} \quad \forall t, \forall i \quad (22)$$

The first term in Objective Function (1) measures the TMHC, while the second and third terms allow to respectively obtain the fixed and variable components of the TRAC between the consecutive time periods over the entire planning horizon, namely the total fixed cost of rearranging workcells (TFRC) and the total variable cost of rearranging workcells (TVRC). The fourth and fifth terms of this first function respectively correspond to a penalty for the over- or underutilised length in the x- or y-axis direction while establishing departments in the available physical space. As we can see, these expressions are repeated in Objective Functions (2) and (3). The first term of Objective Function (2) seeks to maximise the total closeness rating between the work cells making up the production system. The closeness ratings used in this work to characterise the adjacency requirements between work cells are presented in Table 4. The first term of Objective Function (3) seeks to maximise the average AUR value among all the periods into which the planning time horizon is divided.

Table 4. Closeness values assigned to closeness requirements.

Closeness requirement	Closeness value	Relation description
Z	$v_{ij} = 0$	It is not desirable for work cells *i* and *j* to be near one another
U	$v_{ij} = 1$	It is unimportant for work cells *i* and *j* to be near one another
O	$v_{ij} = 2$	It is ordinary for work cells *i* and *j* to be near one another
I	$v_{ij} = 3$	It is important for work cells *i* and *j* to be near one another
E	$v_{ij} = 4$	It is especially important for work cells *i* and *j* to be near one another
A	$v_{ij} = 5$	It is absolutely necessary for work cells *i* and *j* to be near one another

Constraint (4) ensures that cells are located within the available floorspace limits of the plant. Constraints (5) and (6) prevent any overlap between work cells, here a cell can only precede another cell in one direction, either in the x-direction or in the y-direction (McKendall and Hakobyan 2010). The distance between the P/D points of each pair of cells is determined by Constraint (7) and the distance between their centroids is obtained by Constraint (8). The closeness factor required to fulfil Objective Function (2) is calculated by Constraint (9). Constraint (10) ensures that, during each time period, for each work cell only a single design alternative is chosen in all its four possible orientations. Constraint (11) defines, for each time period, the length of each work cell in the x- and y-axes direction.

Constraint (12) allows, for each time period, to obtain the distance from the lower left vertex of each work cell to its respective P/D point in the x- and y-axes direction. Constraint (13) allows the area of each department to be obtained for each time period.

The coordinates of the P/D points in the x- and y-axes direction for each time period are calculated by

Constraint (14). Constraint (15) allows to determine the extent to which the work cell has changed position between two consecutive time periods. Constraint (16) ensures that if a work cell has changed its position in the space or along its length in the x-axis direction between two consecutive time periods, then a rearrangement cost is incurred. This constraint can alternatively be expressed by Constraints (23)–(25). The non-negativity restrictions are shown in (17)–(19). Finally, Constraints (20)–(22) restrict the domain of the binary decision variables.

$$p^s_{ti} \leq L^s \gamma_{ti} \qquad \forall s, \forall i, \forall t > 1 \tag{23}$$

$$l^x_{ti} - l^x_{t-1,i} \leq L^x \gamma_{ti} \qquad \forall i, \forall t > 1 \tag{24}$$

$$l^x_{t-1,i} - l^x_{ti} \leq L^x \gamma_{ti} \qquad \forall i, \forall t > 1 \tag{25}$$

5. Solution methodology

5.1. Linearisation approach

The proposed model is non-linear because of the presence of absolute value functions in Constraints (7), (8) and (15). These absolute value functions can be generally linearised in three ways, in order to obtain an equivalent multi-objective mixed integer linear programming model (MOMILP), as shown below for Constraint (7).

Linearisation form 1 (Sherali, Fraticelli, and Meller 2003):

$$dp^s_{tij} \geq cp^s_{ti} - cp^s_{tj} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{26}$$

$$dp^s_{tij} \geq cp^s_{tj} - cp^s_{ti} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{27}$$

Linearisation form 2 (Abedzadeh et al. 2013):

$$dp^s_{tij} = dp^{+s}_{tij} + dp^{-s}_{tij} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{28}$$

$$cp^s_{ti} - cp^s_{tj} = dp^{+s}_{tij} - dp^{-s}_{tij} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{29}$$

$$dp^{+s}_{tij}, dp^{-s}_{tij} \geq 0 \qquad \forall s, \forall t, \forall i, \forall j > i \tag{30}$$

Variables $\boldsymbol{dp^{+s}_{tij}}$ and $\boldsymbol{dp^{-s}_{tij}}$ are artificial variables. They are included in Equations (28)–(30) only as a mathematical strategy to linearise the absolute value function in Constraint (7).

Linearisation form 3 (Poler et al. 2014):

$$dp^s_{tij} = cp^s_{ti} - cp^s_{tj} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{31}$$

$$dp^s_{tij} \leq Dp^s_{tij} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{32}$$

$$-\,dp^s_{tij} \leq Dp^s_{tij} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{33}$$

Of these three forms of linearisation of the absolute value functions, that which results in the shortest computational time to a solution when testing a single-objective and single-period version of the model will be selected.

5.2. Reducing problem symmetry

The bottom-up mDFLP, like many other FLP variants formulated to search for solutions in a continuous space (i.e. when considering unequal-area FLP departments), can generate symmetric solutions. In these cases, for example, if the resulting ordering scheme is rotated 90, 180 or 270 sexagesimal degrees, it provides the same solution. The possibility of a model generating symmetric solutions can considerably increase computational efforts and solution times (Sherali, Fraticelli, and Meller 2003). To avoid this, if the analyst decides to not fix some department in space when running the model on a particular test problem, the inclusion of symmetry breaking constraints (SBC) can be useful (Meller, Kirkizoglu, and Chen 2010; Anjos and Vieira 2017; Sherali, Fraticelli, and Meller 2003).

One of the ways to break symmetry in the FLP variants with a continuous representation is to require the centroid of some key department i' to be located in a specific quadrant of the facility (Meller, Narayanan, and Vance 1998), for instance, the lower left quadrant, as shown in Constraint (34). This symmetry breaking method, called the q-position method in Sherali, Fraticelli, and Meller (2003), has the disadvantage of it losing functionality when the centroid of i' coincides with the centroid of the facility $\left(\frac{L^x}{2}; \frac{L^y}{2}\right)$. To apply this method, key department i' can be that with the highest flow intensity to and from other work cells during the first period of the planning horizon $\left(max_{t=1,(i,j)\epsilon N} \sum_{i\neq j}^{N} F_{tij}\right)$. Possible ties can be broken by considering the cell with the largest area (Meller, Narayanan, and Vance 1998) or the work cell with the largest average area if several detailed design alternatives q are considered per cell.

$$cv^s_{ti'} + \frac{l^s_{ti'}}{2} \leq \frac{L^s}{2} \qquad \forall s, \forall t, \forall i' \tag{34}$$

Another way to break the symmetry of solutions is by applying the p-q position method defined in Sherali, Fraticelli, and Meller (2003). According to this method, two key cells p and q (denoted in the bottom-up mDFLP model as i' and j') are previously selected by the analyst, which forces the first one to be located in a position to the left and below the second one, as shown in Constraints (35)–(36). In DFLP, as the layouts of later periods depend on that obtained for the first one, then the cells with the highest flow intensity between them during the first period of the planning horizon are normally selected ($F_{ti'j'} = \max_{t=1,(i,j)\epsilon N} F_{tij}$) (Abedzadeh et al. 2013). With a tie, the pair with the largest area can be chosen (Sherali, Fraticelli, and Meller 2003), or the largest average area if more than one detailed design alternative is considered per cell. Another way to break the tie is to select the pair of cells that includes that with the smallest index number

(Meller, Kirkizoglu, and Chen 2010).

$$cv^s_{ti'} + \frac{l^s_{ti'}}{2} \leq cv^s_{tj'} + \frac{l^s_{tj'}}{2} \quad \forall s, \forall t, \forall i' \neq j' \tag{35}$$

$$\varphi^s_{tj'i'} = 0 \quad \forall s, \forall t, \forall i' \neq j' \tag{36}$$

Of both these methods for reducing the possible symmetry of solutions, that which results in the shortest computational time to the solution when testing a single-objective and single-period version of the model will be selected.

5.3. Balancing multi-objectives

In solving multi-objective optimisation problems, there is generally no single solution that simultaneously optimises all the objective functions considered when they clash by nature (Rodrigues, Papa, and Adeli 2017). In these cases, decision makers look for a preferred solution as opposed to the optimal solution (Mavrotas 2009; Díaz-Madroñero et al. 2017). In multi-objective problems, the optimality concept is replaced with Pareto optimality. Pareto-optimal solutions, which form the so-called Pareto-optimal set, are those that cannot improve the value of an objective function without deteriorating the performance of at least one of the others (Mavrotas 2009). Thus when faced with a multi-objective problem, the decision maker aims to search for a preferred solution among Pareto-optimal solutions (Aiello, la Scalia, and Enea 2013; Ripon et al. 2013). According to Wang, Olhofer, and Jin (2017), setting up a decision maker's preferences is vitally important because it allows optimisation algorithms to be oriented towards the search for preferred solutions instead of the whole Pareto front.

One of the methods that, a priori, allows a decision maker's preference to be set up in the optimisation process is the lexicographic (LO) method (Romero 2001; Jee, McShan, and Fraass 2007). In this approach, the decision maker assigns a priority order to each optimisation objective according to its importance. Then in that order, a sequence of subproblems is solved that consider only one objective at a time. The optimal value obtained for each objective is then used as a reference to constrain the optimality of the solution in relation to that objective (Jee, McShan, and Fraass 2007; Hathhorn, Sisikoglu, and Sir 2013). As each objective is optimised separately, the LO can handle multi-objectives with different unit scales without them having to be normalised. According to Arora (2017), the LO always provides a Pareto-optimal solution. For all these reasons, in this paper LO is used as a strategy to search for an optimal solution to the proposed bottom-up mDFLP model.

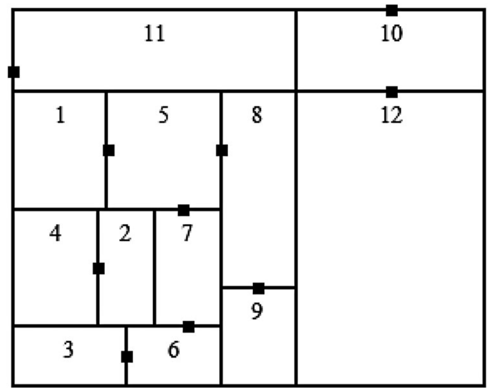

Figure 4. Current layout.

6. Computational results

In this section, we firstly define the characteristics of the real case study to apply and validate the bottom-up mDFLP model. Then we select the form of linearisation of the absolute value functions and the method to generate SBC that has the strongest impact on reducing the computational solution time in a simplified version of the model of a single-objective and single-period nature. Finally, once the final multi-objective model is adjusted, we then search for a Pareto-optimal solution to a real case study ($N = 12/T = 3$) by applying a strategy based on the LO.

The multi-objective bottom-up mFDLP model, along with its single-objective and single-period variants, are coded in MPL 5.0.8.116 and solved using the Gurobi 9.1.2 optimisation solver on a computer with 32 Gb RAM and two Intel® Xeon® E5-2640 v2 microprocessors at a frequency of 2.0 GHz each.

6.1. Real-world case study

This section considers datasets from a real manufacturing system. The company under study belongs to the metal-mechanical sector and is engaged in the manufacture of axial flow pumps, turbines, compressors, belt conveyors and tooling. Table 5 shows the identified work cells and their relevant dimensions in the current plant layout ($t = 0$). Figure 4 presents it graphically. In the offices, support processes related to administrative management, logistics and human resources are carried out. Hence these three spaces are considered a single block, which is why they must remain together for safety and organisational reasons.

The production system under study has a seasonal demand characterised by three temporary periods of differentiated demand throughout the calendar year.

Table 5. Relevant dimensions of the work cells in the current layout ($t = 0$).

i	Work cell description	cv^x_{0i}	cv^y_{0i}	l^x_{0i}	l^y_{0i}	A_{0i}	cp^x_{0i}	cp^y_{0i}	δ^x_{0i}	δ^y_{0i}
1	Press shop	4.00	11.00	5.00	6.00	30.00	9.00	14.00	5.00	3.00
2	Polishing area	8.50	5.00	3.00	6.00	18.00	8.50	8.00	0	3.00
3	Threading workshop	4.00	2.00	6.00	3.00	18.00	10.00	3.50	6.00	1.50
4	Sandblasting area	4.00	5.00	4.50	6.00	27.00	8.50	8.00	4.50	3.00
5	Milling workshop	9.00	11.00	6.00	6.00	36.00	13.00	11.00	4.00	0
6	Computer numerical control module	10.00	2.00	5.00	3.00	15.00	13.25	5.00	3.25	3.00
7	Lathe shop	11.50	5.00	3.50	6.00	21.00	13.25	5.00	1.75	0
8	Assembly area	15.00	7.00	4.00	10.00	40.00	15.00	14.00	0	7.00
9	Inspection/packaging area	15.00	2.00	4.00	5.00	20.00	17.00	7.00	2.00	5.00
10	Reception/dispatch area	19.00	17.00	10.00	4.20	42.00	24.00	21.20	5.00	4.20
11	Offices	4.00	17.00	15.00	4.20	63.00	4.00	18.00	0	1.00
12	Warehouse	19.00	2.00	10.00	15.00	150.00	24.00	17.00	5.00	15.00

Table 6. Single-objective and single-period test model alternatives.

	Linearisation form 1	Linearisation form 2	Linearisation form 3
Without SBC	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), (26), and (27)	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), and (28)–(30)	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), and (31)–(33)
q method	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), (26), (27), and (34)	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), (28)–(30), and (34)	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), (31)–(33), and (34)
p-*q* method	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), (26), (27), (35), and (36)	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), (28)–(30), (35), and (36)	Min f_1 s.t.: (4)–(6), (10)–(12), (14), (17), (18), (20), (21), (31)–(33), (35), and (36)

Thus an annual planning horizon is considered, consisting of three 4-month periods ($T = 3$).

The detailed distribution alternatives proposed for each work cell and their relevant dimensions, are presented in Appendix 1. Similarly, this appendix shows the flow intensities between each pair of work cells during each 4-month period, as well as the unit cost of material handling and the proximity ratings identified by a group of seven experts, including operators, supervisors and middle managers, reaching a consensus. So the minimisation of the TMHC and TRAC is considered a priority by the company. The total space available in the plant for spatial distribution is 45 m long × 30 m wide.

6.2. Tightening the model

Before moving on to solve the $N = 12/T = 3$ case study, it is necessary to adjust the model by selecting not only the form of linearisation of the absolute value functions, but also the symmetry breaking method with the strongest impact on reducing computational solution times. To this end, nine variants of single-objective and single-period models are tested for each test problem, which seek to optimise exclusively the TMHC during a single time period for each alternative linearisation of the absolute value functions, without considering symmetry breaking constraints in each case, but they must be contemplated according to the q-position method and the *p*-*q* position method described in Section 5.2. These single-objective and single-period versions of the model are found in Table 6. The results obtained from both the TMHC and the computational solution times are shown in Table 7.

Thus for small problems ($N \leq 6$), using the linearisation form 1 of the absolute value functions is recommended, while employing SBC is discouraged, which allows lower TMHC and shorter run times than other variants. However, utilising SBCs, especially those generated by the *p*-*q* position method, significantly reduce computational times for test instances of seven departments or more, with the best performance achieved when they are combined with linearisation form 2 of the absolute value functions. It is highlighted how using linearisation form 1 provides lower TMHC values than the other alternatives, but leads to longer computational solution times, which makes the model unsolvable (runtime is longer than 24 h) for 10 work cells, even when considering SBC by the *p*-*q* position method.

Accordingly, the recommended bottom-up mDFLP model includes the SBC generated by the *p*-*q* position method and considers linearisation form 2 for the absolute value functions in (7), (8) and (15). In particular, the

Table 7. The TMHC values and computational runtime for the single-objective and single-period test model alternatives.

		Linearisation form 1			Linearisation form 2			Linearisation form 3		
N	SBC	TMHC	Runtime (s)	Gap (%)	TMHC	Runtime (s)	Gap (%)	TMHC	Runtime (s)	Gap (%)
5	No	26.88	0.89[a]	0	32.89	3.85	0	32.89	3.13	0
	q	26.88	3.88	0	32.89	3.64	0	32.89	5.12	0
	p-q	26.88	2.30	0	32.89	1.80	0	32.89	3.66	0
6	No	283.81	3.78[a]	0	352.77	16.78	0	352.77	15.20	0
	q	283.81	13.58	0	352.77	13.38	0	352.77	26.68	0
	p-q	283.81	14.33	0	352.77	10.48	0	352.77	12.94	0
7	No	1331.48	261	0	1507.65	64	0	1507.65	206	0
	q	1331.48	282	0	1507.65	148	0	1507.65	99	0
	p-q	1346.39	62	0	1507.65	19.61[a]	0	1507.65	41.25	0
8	No	2014.32	8711	0	2215.29	4355	0	2215.29	1075	0
	q	2014.32	10,429	0	2215.29	691	0	2215.29	1423	0
	p-q	2014.32	2142	0	2215.29	60[a]	0	2215.29	396	0
9	No	1535.42	86,400[b]	34.7	1728.35	86,400[b]	33.2	1953.16	86,400[b]	24.5
	q	1951.14	86,400[b]	17	2137.25	86,400[b]	17.4	2096.69	86,400[b]	18.9
	p-q	2349.87	44,935	0	2586.53	843[a]	0	2586.53	1481	0
10	*p-q*	1771.90	86,400[b]	24.6	2586.53	2683[a]	0	2586.53	16,243	0
11	*p-q*	–[c]	–[c]	–[c]	2586.53	1357[a]	0	2586.53	9684	0
12	*p-q*	–[c]	–[c]	–[c]	8344.60	4239[a]	0	8344.60	14,337	0

[a]Best computational runtime for each test instance.
[b]Prematurely terminated after 24 h of computation.
[c]Unsolvable after 24 h of computation.

last two would be linearised as illustrated in (37)–(42).

$$d_{tij}^{cs} = d_{tij}^{+cs} + d_{tij}^{-cs} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{37}$$

$$\left(c_{ti}^{vs} + \frac{l_{ti}^{s}}{2}\right) - \left(c_{tj}^{vs} + \frac{l_{tj}^{s}}{2}\right) = d_{tij}^{+cs} - d_{tij}^{-cs} \qquad \forall s, \forall t, \forall i, \forall j > i \tag{38}$$

$$d_{tij}^{+cs}, d_{tij}^{-cs} \geq 0 \qquad \forall s, \forall t, \forall i, \forall j > i \tag{39}$$

$$p_{ti}^{s} = p_{ti}^{+s} + p_{ti}^{-s} \qquad \forall s, \forall i, \forall t > 1 \tag{40}$$

$$\left(c_{ti}^{vs} + \frac{l_{ti}^{s}}{2}\right) - \left(c_{t-1,i}^{vs} + \frac{l_{t-1,i}^{s}}{2}\right) = p_{ti}^{+s} - p_{ti}^{-s} \qquad \forall s, \forall i, \forall t > 1 \tag{41}$$

$$p_{ti}^{+s}, p_{ti}^{-s} \geq 0 \qquad \forall s, \forall i, \forall t > 1 \tag{42}$$

Variables d_{tij}^{+cs} and d_{tij}^{-cs} are artificial variables. They are included in Equations (37)–(39) as a mathematical strategy to linearise the absolute value function in Equation (8). For the same reason, variables p_{ti}^{+s} and p_{ti}^{-s} are included in Equations (40)–(42), this time to linearise the absolute value function in Constraint (15).

In summary, the equivalent MOMILP model of the bottom-up mDFLP considers the optimisation of Objective Functions (1)–(3), subject to Constraints (4)–(6), (9)–(14), (17)–(25), (28)–(30), and (35)–(42).

6.3. Bottom-up mDFLP solution

Given the proposed model's multi-objective nature, this paper uses the LO as a strategy to search for a Pareto-optimal solution to the $N = 12/T = 3$ case study. Firstly, according to the characteristics of the manufacturing system and the preference of the company's top management, as part of the LO, the TMHC and TRAC are simultaneously optimised (*f1*). Secondly, the TCR (*f2*) and, finally, the average AUR (*f3*) for the three time periods making up the planning horizon are considered. This order of priority coincides with the frequency of use of these objective functions in the reviewed literature (Table 1). So the following sequence of subproblems is considered in the application of the LO:

Subproblem 1: Optimise the highest priority Objective Function (f_1):

$$\min f_1 = Z_1^*$$

subject to:

Constraints (4)–(6), (9)–(14), (17)–(25), (28)–(30), (35)–(42).

Subproblem 2: Optimise the Objective Function with the second order of priority (f_2):

$$\max f_2 = Z_2^*$$

subject to:

$$f_1 \leq Z_1^* \tag{43}$$

and Constraints (4)–(6), (9)–(14), (17)–(25), (28)–(30), (35)–(42).

Subproblem 3: Optimising the Objective Function with the third order of priority (f_3):

$$\max f_3 = Z_3^*$$

subject to:

$$f_2 \geq Z_2^* \tag{44}$$

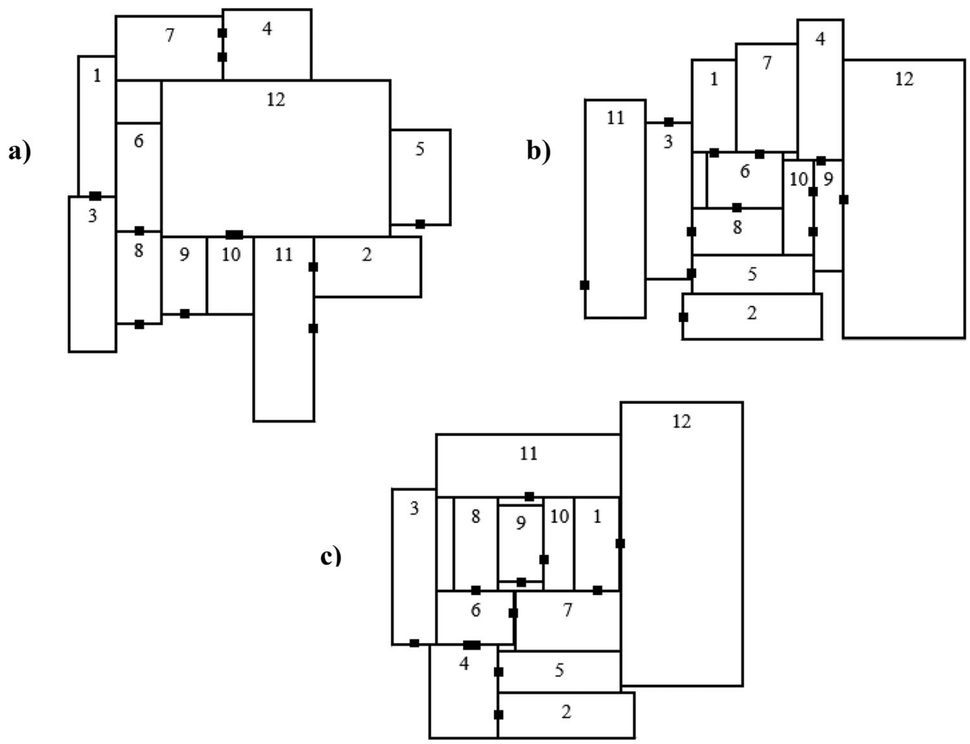

Figure 5. Dynamic layout for each time period: (a) $t = 1$, (b) $t = 2$ and (c) $t = 3$.

and Constraints (4)–(6), (9)–(14), (17)–(25), (28)–(30), (35)–(43).

Once the previous subproblems are successively solved, a dynamic plant layout is obtained. It involves an ordering scheme for each considered time period. The results of the most relevant decision variables for this solution are shown in Appendix 2. The total computational time is 5 h, 44 min and 32 s, which is considered acceptable (Sherali, Fraticelli, and Meller 2003). The representation of the plant layout obtained for each time period is presented in Figure 5.

Similarly, and for comparative purposes, the model is run by fixing the position of the lower left vertex of each work cell, as well as its orientation, over the three time periods by adding Constraints (45) and (46).

$$cv^s_{ti} = cv^s_{t+1,i} \quad \forall s, \forall t, \forall i \tag{45}$$

$$\Delta_{tiqr} = \Delta_{t+1,iqr} \quad \forall t, \forall i, \forall q, \forall r > 1 \tag{46}$$

Once the LO-based sequential optimisation strategy is applied in line with these new constraints, an SFLP solution is obtained; i.e. a single solution for the entire planning horizon. The detailed results of the most relevant variables of this static solution are presented in Appendix 3, while the resulting layout representation is shown in Figure 6.

Table 8 offers the results of the model's objective functions for the three specific cases: (a) the current plant layout; (b) the solution corresponding to the dynamic plant layout; (c) the solution corresponding to the static plant layout. As we can see, both the current layout and the static layout proposal do not incur rearrangement costs. Both the TFRC and TVRC provide a single ordering scheme for the entire planning horizon. Although the dynamic layout solution incurs rearrangement costs, it has lower overall costs than the other alternatives, which represents a 13.59% improvement over the current layout and one of 8.07% over the static proposal. This distribution represents a 3.65% improvement over the TCR of

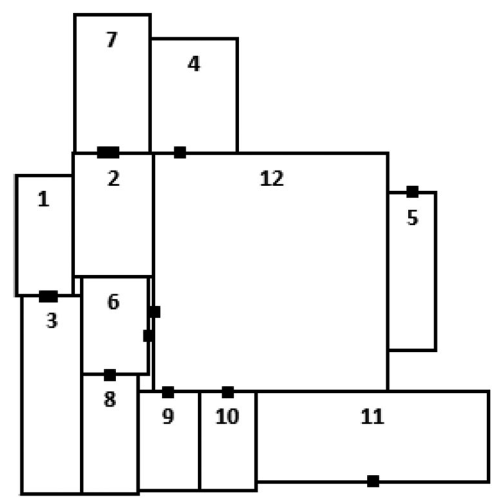

Figure 6. Representation of the static layout for the whole planning horizon.

Table 8. Objective functions results.

OF	OF description	Current layout	Bottom-up mDFLP solutions			
			Dynamic	Improve-ment (%)	Static	Improve-ment (%)
Min f_1	(a) TMHC ($/year)	126984.33	108895.66	14.24%	119972.03	5.52%
	(b) TFRC ($/year)	0.00	600.00	–	0.00	–
	(c) TVRC ($/year)	0.00	231.34	–	0.00	–
	Total costs (a + b + c)	126984.33	109727.00	13.59%	119972.03	5.52%
Max f_2	TCR	306.84	318.035	3.65%	310.123	1.07%
Max f_3	AUR (%)	35.56	30.63	−13.86%	30.05	−15.49%

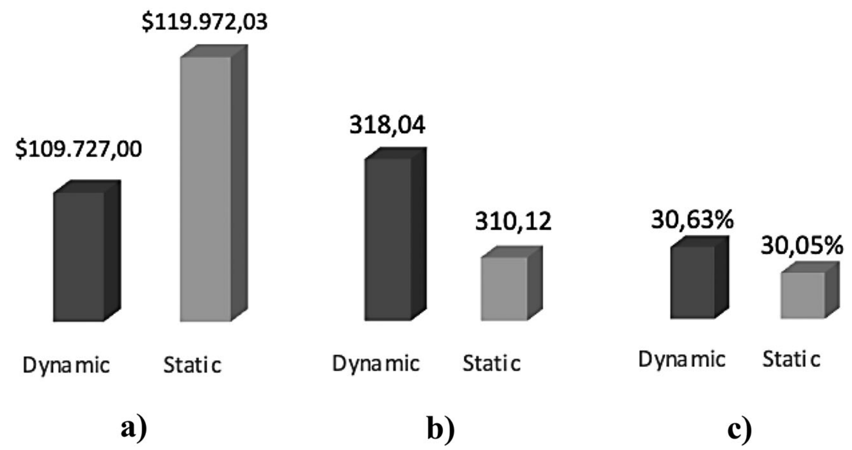

Figure 7. Performance of the dynamic and static layout solutions regarding the model's objective functions: (a) minimise TMHC and TRAC, (b) maximise TCR, and (c) maximise AUR.

the current distribution and one of 2.58% for the static proposal.

On the contrary, the current layout is that with the best AUR, which can be justified by the lower level of priority assigned to this objective function in the LO-based model resolution strategy. It is important to note that a lower AUR solution does not represent any technical or economic operational constraints for the considered planning horizon, but only a lower level of flexibility for future changes.

Finally, it is worth noting that the dynamic bottom-up mDFLP performs better than the static one in all its indicators; i.e. total costs, TCR and AUR (See Figure 7). However, if the company's top management considers that savings in the TMHC represented by the implementation of the dynamic layout solution do not compensate for the possible management effort involved in making changes to both the BL and DL at the beginning of each time period, it can consider the static layout solution to be viable because it does not incur rearrangement costs and guarantees a 5.52% improvement in the TMHC and of 1.07% in the TCR in relation to the current plant layout.

7. Managerial implications

Managerial implications are oriented to provide facility layout planners with a new optimisation model in two versions (dynamic and static), whose solutions in both approaches constitute improvement opportunities in relation to the plant layout to plan or reconfigure. Based on the results of both proposals, companies can assess the costs and benefits of each alternative solution and choose that which best aligns with their strategic planning and favours the performance of their operations. However, the authors of this paper recommend operations managers to consider, in today's globalised business context, the need to organise the elements making up the production system to not be static, but adjustable over time to deal with the continuous readjustments of production capacity as a consequence of fluctuations in demand, and to be able to accommodate technological changes in manufacturing systems as a consequence of products with increasingly shorter life cycles.

The review study shows that the consideration of material handling cost as a single objective function of a quantitative nature, when modelling the DFLP, generates solutions that can compromise the performance of other factors of a qualitative nature; i.e. occupational health and safety, ease of supervision and control, flexibility for future changes, among others. Thus as part of this article, operation managers are encouraged to approach DFLP from a multi-objective perspective by considering both quantitative and qualitative factors.

Approaching DFLP with a bottom-up approach increases the level of layout planning process complexity, generates a longer solution time and forces more data collection and processing efforts (Meller, Kirkizoglu, and Chen 2010). However, by firstly identifying DL alternatives for each department according to specific area needs, and forcing the dimensions of these to remain fixed, this approach ensures a block layout that is more tailored to the manufacturing system's needs.

The bottom-up mDFLP model proposed in this paper (which imposes a penalty for using extra length concerning the width and length of the available floor area and favours underutilised length), as well as the strategy employed in its solution (which consists of dividing the main problem into smaller subproblems using the lexicographic ordering approach), has been shown to obtain pareto-optimal solutions in a reasonable polynomial time for a 12-department manufacturing system. Thus when dealing with FLP in variable demand contexts for production systems of equal or fewer departments, layout planners can rely on the bottom-up mDFLP as a decision support tool to address DFLP as a multi-objective optimisation problem. Management efforts will ensure a solution that allows us to reduce total manufacturing costs, better use the working day by reducing non-value adding transport activities (and consequently improve work productivity), provide a safer working environment for staff and more accessible control and supervision of production, among other qualitative factors of relevance that would otherwise be difficult to quantify and consider.

8. Conclusions

This paper presents an MOMINLP model, called bottom-up mDFLP, which allows the dynamic facility layout problem to be addressed with a bottom-up multi-objective planning approach by considering both quantitative and qualitative objective functions. As far as the authors of this article know, this is the first time that mDFLP is formulated with a bottom-up approach.

The model considers three objective functions: (1) minimising both the TMHC and TRAC; (2) maximising the TCR; (3) maximising the AUR. The model is applied to the case study of a company in the metal-mechanical sector, with 12 departments and a planning horizon composed of three time periods of differentiated demand and material handling costs.

In addition to the bottom-up multi-objective approach that is considered in the model's formulation, other novel elements are proposed to address mDFLP, such as the estimation of both the TCR and AUR. On the one hand, the TCR is obtained by summing the product of the closeness ratings by an adjacency factor that can be interpreted as the complement of the ratio representing the distance between the centroids of each department in the x- and y-axes direction in relation to the maximum possible distance, defined by the sum of the width and length of the surface available for the plant layout. On the other hand, maximising the average AUR of the entire planning horizon is considered to be an objective function by assuming, during each time period, that the ratio between the area occupied by work cells and the total available area of the plant should come as close as possible to unity. This forces the model to generate solutions that better use the available space. This is possible thanks to considering several DL alternatives that do not necessarily have equal areas for each work cell during each time period into which the planning horizon is divided.

Additionally to adjust the original multi-objective model, nine simplified versions of the same model are tested, but they have a single-objective and single-period nature, to determine which formulation strategy generates the least computational effort among three linearisation forms of the absolute value functions and two SBC generation forms. As a result of this experimentation, for problems of six departments or fewer, not using SBC, but employing linearisation form 1 of the absolute value functions in (26)–(27) yields lower TMHC values and shorter computational times than in other variants. However, for instances of seven departments or more, using the SBCs generated by applying the p-q position method combined with linearisation form 2 of the absolute value functions in (28)–(29) significantly reduces the computational time.

Once the proposed model is adjusted, the MOMILP equivalent is obtained, whose resolution employs the LO method as a strategy to balance the three considered objective functions, which allow two pareto-optimal solutions to be obtained for the proposed real case study: (1) a dynamic layout (proposing a different plant layout for each time period); (2) a static layout (proposing a single ordering scheme for the entire planning horizon). The results of the objective functions in each case are compared to the values of the current layout, which leads the dynamic solution to better perform in terms of total costs and the TCR in relation to not only the current layout of the case under study, but also to the AUR for the static layout proposal.

Future research could run the proposed MOMINLP, bottom-up mDFLP model, by considering production systems with more work cells, and resort to other resolution strategies based on deep reinforcement learning. Along the same lines, the use of metaheuristic or matheuristic algorithms is recommended as possible resolution approaches. Additionally, although the proposed model has been inspired in the metal-mechanical sector, there are not restrictions to apply it to other industrial facilities. In fact the proposed model can be applied to case studies from other industrial sectors apart from the metal-mechanical sector herein contemplated. Other future research works could consider uncertainty conditions when estimating the material flow intensity for each time period, and could integrate the system of corridors through which it could circulate throughout the production system. In addition, a larger number of objectives can be incorporated into the model, including the minimisation of occupational health and safety risks, among others. Finally, despite the model being oriented to FLP, new industrial engineering problems can be addressed; for instance, 2D and/or 3D fulltruck loading, where different container types must be placed in a given area by minimising the number of trucks.

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Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article.

Notes on contributors

In memorian of *Pablo Pérez-Gosende* (Matanzas, Cuba, 4 September 1983-Guayaquil, Ecuador, 14 September 2022). Although you are no longer with us, you will never be forgotten. May your memory remain forever on the pages of this article. He obtained his PhD cum laude in Industrial Engineering and Production at Universitat Politècnica de València (2022), Spain. Previously, he graduated cum laude in Industrial Engineering at the University of Matanzas, Cuba (2007), and hold a master's degree in Business Administration, Production and Services Management (2009) from the same institution. He taught production management and engineering in the industrial engineering department at Universidad Politécnica Salesiana (UPS), Ecuador, since 2013–2022, and also he was the research coordinator of this institution at its headquarters in Guayaquil from 2017 to 2022. He was the coordinator of the organising committee for the International Conference on Science, Technology and Innovation for Society (CITIS) in its last five editions (2017–2022) and chaired the technical track of the Ecuadorian Conference on Information and Communication Technologies (TICEC) in its eighth, ninth and tenth editions (2020–2022). His research interests were in production management and engineering.

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