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Smarter facility layout design: leveraging worker localisation data to minimise travel time and alleviate congestion

Ayse Aslan[a], Gokula Vasantha[a], Hanane El-Raoui[b], John Quigley[b], Jack Hanson[c], Jonathan Corney[c] and Andrew Sherlock[d]

[a]School of Computing, Engineering and the Built Environment, Edinburgh Napier University, Edinburgh, UK; [b]Department of Management Science, University of Strathclyde, Glasgow, UK; [c]School of Engineering, The University of Edinburgh, Edinburgh, UK; [d]National Manufacturing Institute Scotland, University of Strathclyde, Glasgow, UK

ABSTRACT

This paper introduces a novel methodology leveraging worker localisation data from ultrawide-band sensors to formulate alternative facility layouts aimed at minimising travel time and congestion in labour-intensive manufacturing systems. The system preprocesses sensor data to discern flow patterns between existing stations within the production facility, such as machine tools, workbenches, and stores. This information about the movement of people and materials informs the generation of optimised layouts through scenario-based optimisation. We explored two methods to devise these new layouts: a mixed-integer linear programming method and a simulated annealing metaheuristic, the latter being specifically developed to find high-quality solutions to the quadratic layout design formulation. Both methods employ biobjective formulations, focussing on the minimisation of travel time and the reduction of congestion risk on the manufacturing floor, an aspect often neglected in prior studies. Our methodology, applied to a real-world manual assembly line case study, demonstrated the potential to reduce travel time by a minimum of 32% and alleviate congestion while maintaining significant safety distances between facilities. This was achieved by automatically identifying design features that position high-traffic facilities closely and align them to eliminate movement overlaps.

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1. Introduction

The layout design of manufacturing systems (Anjos and Vieira 2017; Burggräf et al. 2021; Hosseini-Nasab et al. 2018; Pérez-Gosende, Mula, and Díaz-Madroñero 2021) plays a critical role in achieving optimal performance and efficiency. A well-planned layout that aligns with the needs of manufacturing processes and facilitates the easy movement of material and people between stations can lead to enhanced production efficiency and shorter lead times. However, the challenge lies in the cost and disruption associated with modifying layouts, often requiring complete production halts. Therefore, a robust planning approach that considers the total diversity of flow patterns observed in a facility over a significant period of time is an essential input to any process of layout redesign. Factors such as fluctuating demands for product types and workers' dynamic movement patterns in response to environmental changes should be observed and integrated into the layout design. For semi-automated manufacturing systems (Chang and Lin 2015; Kuo, Chen, and Wang 2018; Süer 1996) where human workers undertake tasks at various stations and move between facilities for product transfers, tracking worker movements using localisation sensors, such as Ultra-wideband (UWB) tags, offers valuable insights into flow patterns. This paper presents an innovative methodology that leverages worker localisation data to craft robust layout designs for manufacturing systems reliant on manual labour, providing practical solutions to optimise performance and efficiency.

In proposing a layout design, the primary concern often revolves around reducing material flow distances between facilities to minimise lead times (Anjos and Vieira 2017). In labour-intensive manufacturing, this translates to creating shorter distances that enable workers to move swiftly between facilities. However, focussing solely on distances during layout design may not be enough to facilitate frictionless worker movement during actual operations. Crucially, such layouts often overlook the specific paths workers would take when navigating

CONTACT Gokula Vasantha g.vasantha@napier.ac.uk School of Computing, Engineering and the Built Environment, Edinburgh Napier University, Merchiston Campus, Room C67, 10 Colinton Road, Edinburgh EH10 5DT, UK

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between locations. Worker movements and their chosen paths significantly impact traffic density within the environment, leading to potential congestion hotspots. Besides minimising flow distances, congestion on the manufacturing floor emerges as a vital concern (Butt and Cavalier 1997; Sarkar, Batta, and Nagi 2005; Zhang, Batta, and Nagi 2011). Highly congested areas can result in waiting times, blockages, and even accidents. Consequently, designing a manufacturing layout necessitates considering the congestion risks associated with it. This paper addresses these challenges and proposes methodologies to optimise manufacturing layouts by prioritising efficient worker movement and mitigating congestion risks.

In automated manufacturing systems, congestion management in layout design is often addressed by planning both routing decisions and layout decisions (Zhang, Batta, and Nagi 2011). However, unlike robots or automated vehicles that can adhere strictly to prescribed paths, human workers exhibit a higher degree of flexibility and uncertainty in their movements and chosen paths. Even assuming that human workers tend to favour the shortest paths between locations, the sheer number of potential paths makes it impossible to know the exact routes they will take until the proposed layout is implemented and their actual movements are observed. As a result, prescribing routes to workers may not be preferred by workers and managers in manufacturing systems, where workers have freedom of movement for product and material transfers. Thus, an alternative approach is needed – one that is less intrusive and avoids route prescription while incorporating congestion risks through indirect means based on layout decisions. In this paper, we present a novel worker-centred methodology for generating layouts that focus solely on facility positioning decisions and show how worker movement data supplied by localisation sensors can be integrated to achieve improved layouts. To the best of our knowledge, our study pioneers the incorporation of worker movement data into layout design.

We propose two different methods for generating layouts. Both methods consider the minimisation of flow distance and incorporate congestion risk by assessing the likelihood of congestion based on the relative positioning of facilities. By adjusting the weight parameters of these two objectives, a range of feasible layouts is generated, with the potential to reduce flow distance and/or congestion compared to the current layout, which movement data is observed with. The first is mixed-integer linear programming-based, which can be easily solved to optimality using state-of-the-art solvers such as Gurobi or CPLEX. This linear formulation is made possible by limiting the relative positioning of facilities to be described by only four descriptors and using rectilinear distances. Additionally, we use a quadratic formulation which uses Euclidean distances and identifies the relative positioning of facilities continuously with angles. This quadratic formulation can potentially represent travel distances and congestion risks more accurately. However, it proves too complex to be solved optimally. To discover high-quality solutions for this quadratic formulation, we introduce a simulated annealing metaheuristic, which is benchmarked against four other simulated annealing approaches proposed for similar layout design problems in the literature. Our objective is to assess these two alternative methods, weighing their respective advantages and disadvantages, and determine which one is better suited for achieving high-quality layouts.

Layout design decisions that are based on static flow patterns between facilities neglect the time-dependent aspects of worker movement. Congestion, a spatio-temporal phenomenon, occurs when workers simultaneously pass through the same area (Nanni and Pedreschi 2006; Rempe, Huber, and Bogenberger 2016). To comprehensively assess the performance of proposed layouts in real-world scenarios, evaluations should incorporate these time-dependent aspects. This can be done in two ways. Firstly, one can consider direct implementation in the actual manufacturing environment, where worker movement and travel time between facilities will be observed using sensors over a period of time, allowing for redesign based on the new movement data. However, this approach could be time-consuming and costly if the proposed layout does not yield significant improvements. Secondly, the use of realistic simulation environments to test layouts under simulated worker movement could provide early identification of potential layout shortcomings and preventing the imposition of unsuitable layouts on workers.

To account for time-dependent considerations, we employ simulations to evaluate proposed layouts, calculating various time-based performance metrics such as average travel time between facilities and spatio-temporal congestion measures. Assuming worker preference for shorter paths, we develop a genetic algorithm to find reasonable short paths for human workers, which are then used as possible paths in the simulation for the new layouts. We apply this methodology to a real-world case study involving the assembly line of tricycles, with six workers and seven facilities, utilising UWB sensors to track worker positions (Delamare, Duval, and Boutteau 2020). Our findings demonstrate that our congestion and distance-aware methods successfully identify layouts that significantly outperform the current layout in terms of both travel time and congestion measures.

We summarise our main contributions as follows.

- Methods for facility layout design that demonstrate how worker movement data, supplied by indoor localisation sensors, can be used to improve the current layout in terms of reducing both travel time for workers and congestion risk on the manufacturing floor. This showcases a novel use of sensor data to make manufacturing smarter and more efficient through layout design.
- New approaches to integrate the aspect of congestion risk into facility layout design by considering only the facility location decisions, without controlling the routing decisions.
- Establishment of benchmark against existing simulated annealing meteheuristics proposed for layout design.

The rest of our paper is organised as follows. Section 2 reviews the related literature. Section 3 presents our methodology, explaining how we process localisation data to derive flow patterns between facilities (Section 3.1), using these to generate new layouts (Section 3.2), and evaluating the new layouts under the time-dependent factors (Section 3.3). Section 4 presents our case study where we apply our methodology. Lastly, Section 5 concludes the paper.

2. Related literature

The design of facility layout in manufacturing concerns the strategic placement of facilities used for specific manufacturing operations within the limited space of a manufacturing floor. Businesses strive for a well-designed layout that enables the efficient operation of manufacturing processes, meeting demands at a lower cost, while adequately using floor space and minimising health and security risks for workers (Pérez-Gosende, Mula, and Díaz-Madroñero 2021). In contrast, inefficient layouts can lead to heightened levels of work-in-progress and extended manufacturing lead time (Hosseini-Nasab et al. 2018), as well as bottlenecks and congestion resulting from suboptimal space utilisation (Pérez-Gosende, Mula, and Díaz-Madroñero 2021).

Hosseini-Nasab et al. (2018) provided a detailed classification of such arrangement problems in terms of their evolution (static and dynamic layout), workshop characteristics, problem formulation, and resolution approaches. Based on this classification, the layout design problem addressed in this work is illustrated in Figure 1. The notable observation from this mapping is that the flow patterns are described by prescribed paths such as backtracking and bypassing. However, the sheer number of potential paths workers undertake is not well represented within this categorisation. Consequently, the authors believe that the classification should be expanded to include smart manufacturing based on real-time factory data. The dynamic facility layout problem (DFLP) commonly considers flow over multiple time periods, considering the changes in material flow over time. In contrast, this research focuses on worker's movement over a specific time period.

Given the importance of this design decision, a plethora of optimisation methods have been proposed in the literature to determine the most efficient arrangement of manufacturing facilities (see Burggräf et al. 2021, for an overview of the types of algorithms used); Hasan et al. (2017) for Ant Colony Optimization (ACO) for facility layout problem; Zhu, Balakrishnan, and Cheng (2018) for a review of dynamic facility layout research; Pérez-Gosende, Mula, and Díaz-Madroñero (2020) for sustainability strategies in facility layout; Yelles-Chaouche et al. (2021) for a review on reconfigurable manufacturing systems).

The simplest form of layout design is a quadratic assignment problem, where the potential locations for the facilities are known and enumerated in advance, and the design decisions are made based on a mapping of facilities to these locations. However, even in this simplified scenario, achieving an optimal layout design remains challenging due to the computational difficulty of the quadratic assignment problem (Anjos and Vieira 2017). Consequently, a wide variety of approximate optimisation methods (Renzi et al. 2014) and mathematical modelling formulations (Anjos and Vieira 2017) have been developed to tackle this problem. In the past 10 years, a variety of metaheuristics methods (e.g. genetic algorithms, simulated annealing, particle swarm, tabu search, ant colony and variable neighbourhood search) have been reported for the generation of layouts (Pérez-Gosende, Mula, and Díaz-Madroñero 2021).

For instance, Pillai, Hunagund, and Krishnan (2011) developed a simulated annealing metaheuristic for the design of layouts in cellular manufacturing systems. Salimpour, Pourvaziri, and Azab (2021) utilised a genetic algorithm to solve a multiobjective problem that addressed both cell formation and layout decisions for cellular manufacturing. In some cases, the problems addressed were so complex that they necessitated the development of multi-method solution approaches. For example, Pourvaziri et al. (2021) decomposed the design of a flexible manufacturing system into two subproblems (construction of a robust layout and best routes of products), and employed a metaheuristic to solve the first one, followed by a branch-and-cut algorithm for the latter. Our paper focuses on the continuous formulation

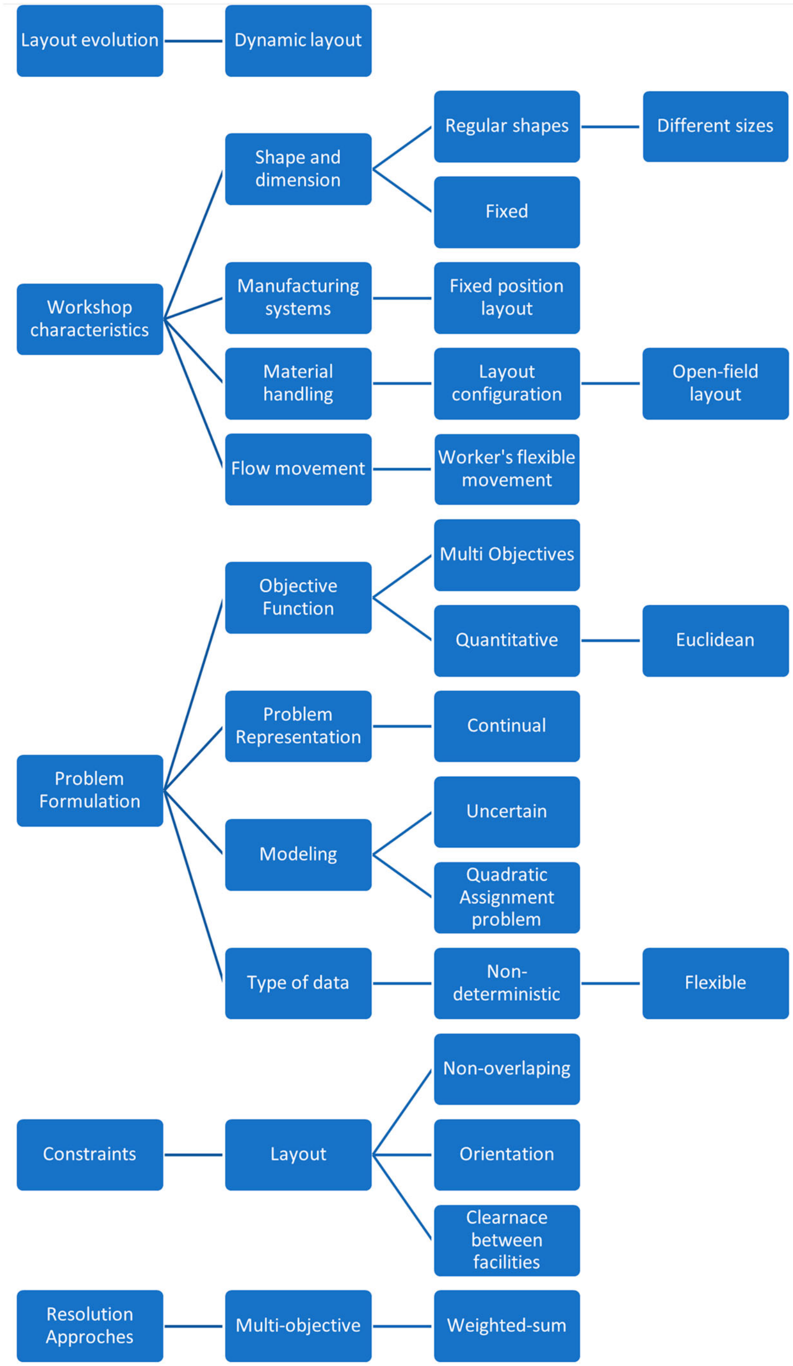


Figure 1. Classification of layout design problems addressed in this work based on Hosseini-Nasab et al. (2018).

of the facility layout problem, where facilities can be placed freely anywhere on the floor. For this computationally challenging problem, we propose two alternative approaches: a mixed-integer linear programming model and a metaheuristic.

Recognising upon the success of simulated annealing in identifying high-quality facility designs in manufacturing contexts (McKendall, Shang, and Kuppusamy 2006), we have chosen a simulated annealing-based metaheuristic. This choice is motivated by its ability to efficiently escape local optima through a probabilistic solution acceptance mechanism, a key advantage for single-solution search methods. For an overview of simulated annealing methods proposed specifically for facility layout design in the literature, we refer the reader to Singh and Sharma (2006).

Layout decisions should take into consideration the uncertainties faced by manufacturing systems, such as changing demand levels or resource unavailability. Layouts that are generated based on deterministic representations of dynamic manufacturing environments can prove unrealistic and unsuitable when implemented in the real-world. It is preferable to have robust layouts that can perform well across a wide range of possible scenarios, rather than optimising for a single idealistic representation of the system. This helps avoid frequent rearrangements, which can be costly and inconvenient for manufacturers and workers (Pourvaziri et al. 2021). To generate robust layouts, it is necessary to consider the uncertainties and the decision variables affected by them. One viable approach is to use random variables to represent problem parameters that are subject to uncertainties. For example, Zha et al. (2017) use fuzzy random variables to formulate uncertain demand levels for products. However, optimisation with stochastic variables is usually a challenging task. To address these challenges, similar to the works of Paydar, Saidi-Mehrabad, and Teimoury (2014) and Pourvaziri et al. (2021), our paper aims to find robust layouts through scenario-based optimisation.

The issue of congestion on the manufacturing floor is significant and directly tied to the layout. As its importance becomes increasingly recognised, researchers have incorporated this concern into their design approaches. The earliest study to acknowledge the importance of congestion is reported by Butt and Cavalier (1997), who investigated a continuous layout design problem with rectilinear distances. In their study, new facilities needed to be placed while considering a number of predefined congested regions where hosting new facilities was not possible. However, travel through these congested regions was permitted at an additional cost per unit distance. The objective was to minimise the crossing of congested regions as much as possible when travelling between facilities. Later, Sarkar, Batta, and Nagi (2005) extended this problem to also include decisions on the dimensions of new facilities. Similar to Butt and Cavalier (1997), they addressed congestion in a static manner by considering congested regions known in advance. One limitation of assuming fixed congested regions is that as new layouts are designed and implemented, congestion may shift on the floor due to the availability of new travel paths between facilities. Therefore, it may be more appropriate to consider congestion as a function of material and worker flow in the proposed layouts.

Recognising this limitation of static congestion consideration, Zhang, Batta, and Nagi (2011) studied layout design decisions in conjunction with routing decisions to control the volume of traffic between facilities and avoid congestion in the links. More recently, Pourvaziri, Pierreval, and Marian (2021) addressed congestion as a dynamic phenomenon resulting from layout and aisle planning decisions. In their work, congestion was incorporated by ensuring that high-traffic aisles were wider. The approaches used in Zhang, Batta, and Nagi (2011), Hosseini et al. (2021), and Pourvaziri, Pierreval, and Marian (2021) are suitable when paths can be restricted, such as in automated systems with vehicles following prescribed paths. However, our paper focuses on manual systems where human workers handle the transfer of materials and products between facilities. Given this distinction, our paper develops innovative indirect approaches to incorporate congestion in layout design without interfering with routing.

The latest research (i.e. published after 2017) in solving the DFLP problem considering congestion, flow movements, production planning, safety, and human factors is summarised in Table 1. Commonly minimising the total material handling cost and the rearrangement cost is considered as an optimisation problem. However, few works have been published considering human factors in the facility layout and production planning optimisation problems (Li, Tan, and Li 2018). Also, the latest research includes sustainability parameters in this layout design problem (Tayal, Solanki, and Singh 2020). Erfani, Ebrahimnejad, and Moosavi (2020) noted that simultaneous optimisation was not concurrently carried out for dynamic facility layout and job shop scheduling.

The significant limitations of most of this research summarised in Table 1 are assumptions related to the certainty of the amount of material flow, identical facility size consideration, restricting the facility orientation, and inflexible routing. Also, congestion related to automated guided vehicles and transporters is considered rather than workers' movements. In particular, the incorporation of real-time data in layout formulation is not elaborately considered in the reviewed literature. Considering the wide variety of computational approaches that have been proposed for a multitude of problem formulations, it is difficult to compare the efficiency of these approaches. However, the most common observations noted from the results are that the efficiency of an industrial process is most effected by the layout in large scale facilities (such as such as many facilities or transporters).

Lastly, we must mention some studies related to domains outside of manufacturing but which share similarities with our layout design approach. Our approach is based on human workers and their observed movement patterns using tracking sensors. Considering the uncertainties in how human workers choose their paths in their work environment, Rezaee et al. (2021) conducted a study on construction site layout planning. They utilised fuzzy representations to model how workers would find their paths, which were then used to evaluate the safety

Table 1. Summary of the latest research on DFLP related to congestion and human factors.

Reference	Objective	Important parameters	Approach used	Results
Pourhassan and Raissi (2017)	Minimise material handling and the relevant costs, and minimise the number of possible interferences among transporters	Known material flow matrix and demand rate for each period; Crowding distance	Simulation and a non-dominated sorting genetic algorithm (NSGA-II) approach	Shown the solutions leading to a reduction in the number of accidents.
Li, Tan, and Li (2018)	Minimise worker's stress, maximise the area utilisation and minimise logistics and re-layout costs.	Logistics factors (distance, handling costs), Human factors (physical and mental stress), and Management factors (reconfigurability, production efficiency)	Artificial bee colony algorithm (ABC)	Compared to PSO and the basic ABC algorithm, the proposed ABC algorithm needs fewer iterations and a shorter running time.
Peng et al. (2018)	Minimise the total material handling cost and the rearrangement cost	Demand uncertainty, transport device assignment	Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO)	The proposed GA performed better than PSO for large-scale instances.
Pourhassan and Raissi (2019)	Minimise total combined rearrangement, material handling and transporting costs	Multiple transporters	Hybrid Genetic and Particle Swarm Optimisation Algorithms	The proposed algorithm performed better with a higher number of facilities.
Pournaderi, Ghezavati, and Mozafari (2019)	Minimise transport and handling equipment cost	Budget constraints, type of material handling system	Multi-Objective Cloud Simulated Annealing Algorithm (MOCSA)	NSGA-II performs better than the MOCSA (except for run-time criterion) and Non-dominated Ranked Genetic Algorithm (NRGA).
Wang et al. (2019)	Minimise total processing time and logistics cost	Number of transportation, interference between facility location and transport path, and assembly time	Placed-Timed Petri Net, reachability graph algorithm and search algorithm	Illustrated the production demand in some period will lead to the optimised facility layout and production planning.
Chen and Tiong (2019)	Minimise work-in-progress in automated guided vehicle (AGV) based modular manufacturing system.	Operation assignment, arrival rate, number of workstations	Queuing theory and simulated annealing	Showed reduction in work-in-progress by identifying the number of workstations.
Tayal, Solanki, and Singh (2020)	Energy-efficient sustainable sub-optimal layout	Energy consumption, CO_2 emission, people's safety and uncertain demand	Big data analytics, Firefly algorithm, data envelopment analysis, and K-mean clustering	Identified U-shaped layouts that consume less energy and emit less CO_2.
Erfani, Ebrahimnejad, and Moosavi (2020)	Minimise material handling cost, machine rearrangement and rotation costs, closeness and farness rating scores of departments, and percentage of unused space	Unequal area, input and output points for each department, transportation delay, machine setup time	Hybrid NSGA-II and Local Search Algorithm	Simultaneous optimisation decreases the mean flow time of jobs by about 10%.
Dridi et al. (2019)	Minimising the total travelled distance	Multiple vehicles, multiple depots, pickup and delivery with time windows, precedence, capacity and time constraints	Particle swarm optimisation	The proposed algorithm reduces the distance by up to 19% in test cases.
Hosseini et al. (2021)	Minimising the sum of material handling costs and machines rearrangement costs	Positions of machines, types of transporters, and sequence of transportation operations	Modified genetic algorithm and cloud-based simulated annealing algorithm	The proposed algorithm is significant for large-sized problems (particularly above 15 facilities and 10 periods of time).
Pourvaziri et al. (2021)	Minimising the material handling costs	Product demand, product routes, critical period	Hybridised genetic-tabu search algorithm	The algorithm performed better than simulated annealing for bigger-sized problems.

risks associated with various layouts. In our simulation-based approach to evaluate the generated layouts, we also rely on modelling likely paths for workers generated by a genetic algorithm. Additionally, we note the study conducted by dos Santos Garcia et al. (2019) who considered clinical layout design based on data obtained by tracking patient visits. Similarly, they employed process mining techniques to analyse this data and extract likely pathways among the facilities.

In summary, the work contributes to facility layout design in two ways: firstly the use of worker movement data provided by indoor localisation sensors and secondly the inclusion of congestion risk along with the objective of reducing flow distance, both without the need to impose specific paths for workers.

3. Methodology

In this section, we present our methodology (coined as FLOW-TD: Facility Layout Optimization using Workplace Tracking Data) for designing a 2D manufacturing layout with length L and width W, based on the observed movement patterns of workers in the initial layout. We represent the manufacturing facilities using the indices $i, j, k \in \mathcal{A} = \{1, 2, \ldots, A\}$. Each facility i is assumed to have a rectangular shape, with longer and shorter sides of lengths L_i^{long} and L_i^{short}, respectively. Furthermore, we use the index $r \in \mathcal{R} = \{1, 2, \ldots, R\}$ to denote the set of workers whose movements are tracked using sensors. The data collected includes their 2D positions on the manufacturing floor over a specific number of periods denoted by $t \in \mathcal{T} = \{1, 2, \ldots, T\}$, such as days or shifts.

Our methodology comprises several steps, which are summarised in Figure 2. The initial step involves processing raw worker movement data using knowledge of the initial layout. This results in generating time-annotated movement patterns for workers, as well as static flow patterns between each pair of facilities (Section 3.1). These flow patterns serve as the foundation for our scenarios outlined in Section 3.2, where we introduce two scenario-based robust optimisation methods for generating layouts. The first method, presented in Section 3.2.1, is based on mixed-integer linear programming. The second method, based on a quadratic formulation, is addressed using a simulated annealing metaheuristic, which we develop in Section 3.2.2. In Section 3.3, we detail our simulation approach for evaluating the performance of the new layouts, as well as the initial layout. This assessment considers the time-dependent aspects of the manufacturing process to gauge congestion through dynamic measures. To assess the new layouts, we must account for the potential paths workers may take within them. We address this by developing a genetic algorithm to determine the new paths. Through this dynamic evaluation,

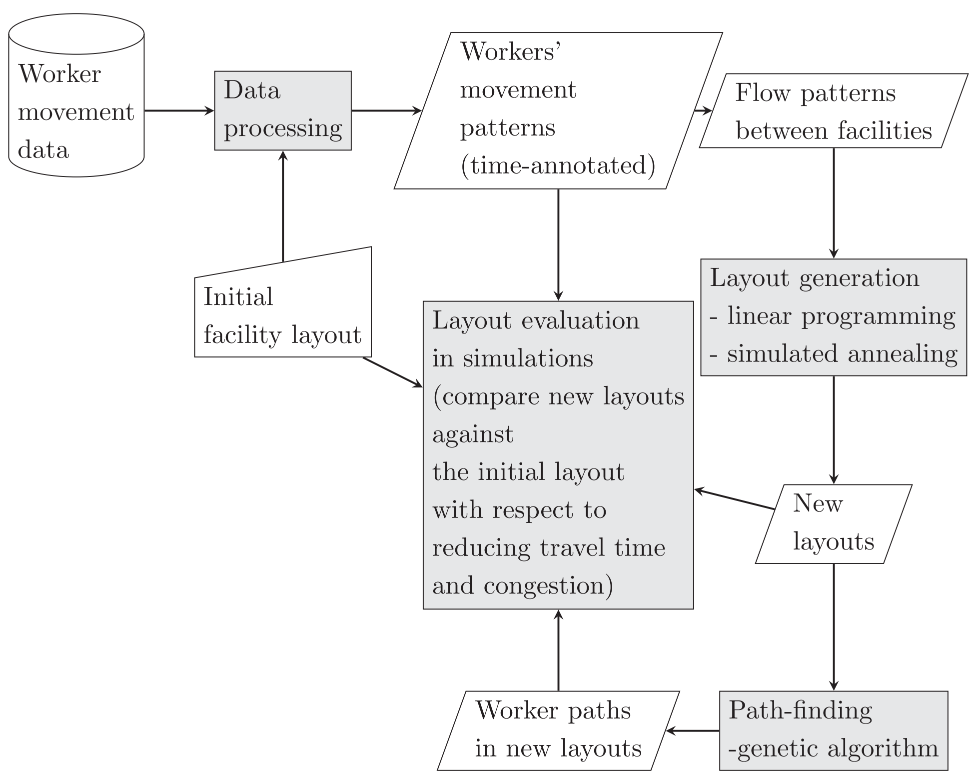


Figure 2. Schematic of Facility Layout Optimization using Workplace Tracking Data (FLOW-TD) components.

we compare the new layouts against the initial layout and quantify the extent to which improvements can be achieved in terms of reducing travel time for workers and alleviating congestion on the floor.

3.1. Data processing

Measurements obtained from movement tracking sensors require some processing before they can be effectively used. For example, this can be necessary to address signal errors and handle missing data. Furthermore, it is worth noting that data mining techniques can be employed to transform sensor data into more meaningful representations for analysis. These techniques aid in eliminating noise, identifying significant patterns, and even predicting likely patterns that may not be directly observed in the data. In our specific case study, rather than directly utilising the raw sensor data, we apply data mining techniques to preprocess the data.

Here, we employ a three-step data processing approach. This approach draws inspiration from the methodology presented in Aslan et al. (2023). In the first step, we preprocess the raw position data to create event logs for each worker. These event logs serve to identify and record the specific activities performed by workers within the described facilities, along with their corresponding start and end times. In creating the event log, we use the initial layout to identify the proximity of workers to facilities. The initial layout provides the rectangles within which each facility resides. By verifying whether a worker's position falls within any of these rectangles at any given time, we can identify manufacturing activities performed by workers. Additionally, we account for the time workers spend inside the rectangle of a specific facility. Employing a filtering parameter β, we only consider stays that last at least β duration as indicative of manufacturing activities being performed.

Mathematically the concept can be described as follows: suppose the position of a worker, denoted as r, is within facility j at time $t-1$, and at time t, this worker is observed at a different facility $i \neq j$. To acknowledge that this worker begins a manufacturing activity in facility i at time t, we must verify that the worker remains within the rectangle of facility i from times $t+1$ to $t+\beta$, thereby constituting a stay lasting at least β. Once this is confirmed, we generate an event in the event log for facility i, attributed to worker r, with a start time of t. The end time of this activity is determined as the last moment $t+\beta$ when the worker's position was still inside facility i. This procedure results in the creation of an event log for each worker. Next, we utilise process mining techniques (dos Santos Garcia et al. 2019) to derive process models from the individual event logs. These process models provide a representation of how each worker moves between different facilities throughout their work shift and also information on mean sojourn times at specific facilities. In the third step, we construct discrete event simulations based on the derived process models and time information, which provide us the processed time-annotated movement patterns. Further details regarding these steps will be case specific. For the case study considered in this paper, we give the details on how these steps are performed in Section 4.1.

Suppose that worker movement patterns are observed through sensors across a set of time periods $t \in \{1, 2, \dots, T\}$ (e.g. days, shifts). By treating these patterns as our scenarios, in the remainder of this paper, we will use the terms 'period' and 'scenario' interchangeably when referring to t as it pertains to these patterns.

We use $s_r^t = ((a_1^{rt}, \tau_1^{rt}), (a_2^{rt}, \tau_2^{rt}), \dots, (a_{N^{rt}}^{rt}, \tau_{N^{rt}}^{rt}))$ to denote the movement pattern of worker r in period t. Here, N^{rt} represents the number of visits performed by worker r in scenario t, while a_l^{rt} and τ_l^{rt} denote the facility visited and the time spent during that visit, respectively. Note that these patterns are time ordered (e.g. worker r visits facility a_2^{rt} next after visiting facility a_1^{rt} first in scenario t) and they are used when evaluating the new layouts in simulations in Section 3.3.

In the generation of new layouts (Section 3.2), where we focus on fixing the locations of facilities, we rely on the static flow patterns between facilities. Specifically, we extract the (static) flow pattern from facility i to facility j by

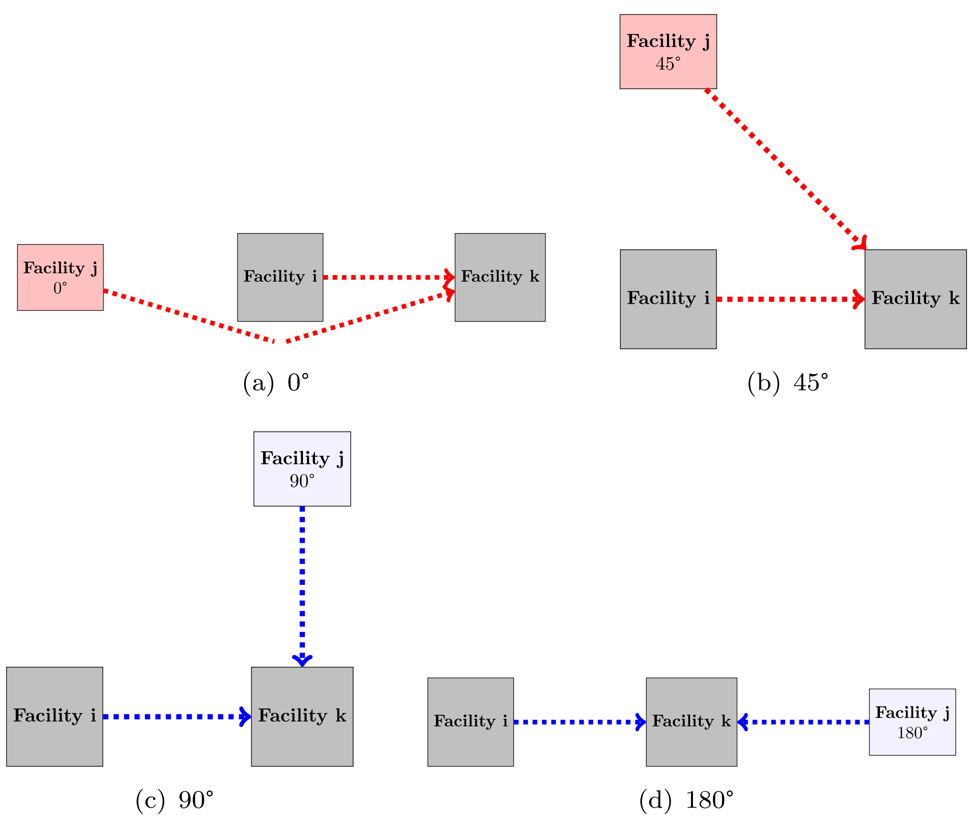
$$F_{ij}^t = \sum_{r=1}^{R} \sum_{n=2}^{N^{rt}} \mathbb{1}_{\{a_n^{rt}=j, a_{n-1}^{rt}=i\}}. \tag{1}$$

3.2. Layout generation procedures

Based on the extracted flow patterns F_{ij}^t, we propose two methods to generate robust layouts that optimise over the patterns observed in all periods. In our approach, we consider the manufacturing floor as a rectangular box with length L and width W. To ensure a feasible layout, all facilities should fit within this box without overlapping each other in either x or y dimensions. Additionally, a safety distance $\delta \geq 0$ needs to be preserved between the facilities. To position each facility i, our formulations determine the x-coordinate ($c_i^x \in [0, L]$) and y-coordinate ($c_i^y \in [0, H]$) of its centroid. In other words, we consider a continuous version of the facility layout design problem, as in Zha et al. (2017) and Salimpour, Pourvaziri, and Azab (2021). We also determine the orientation $o_i \in \{0, 1\}$, which fixes whether the long or short side of the facility will align with the x or y axis, respectively. This consideration for either a vertical or a horizontal orientation is commonly applied in the literature (see Pourvaziri, Pierreval, and Marian 2021; Pourvaziri et al. 2021; Vitayasak and Pongcharoen 2018). Consequently, the lengths of the facility in the x and y dimensions are determined by $l_i^x \in \{L_i^{\text{long}}, L_i^{\text{short}}\}$ and $l_i^y \in \{L_i^{\text{long}}, L_i^{\text{short}}\}$, respectively.

Both of our proposed methods employ a biobjective formulation designed to minimise a weighted combination of two primary objectives: total flow distance (weighted with $w^{\text{dist}} \geq 0$) and congestion potential (weighted with $w^{\text{cong}} \geq 0$) across all periods. The biobjective formulation is chosen to extend beyond layouts that solely focus on minimising flow distances. Instead, it allows for the exploration of multiple layouts by varying the weight settings, thus seeking layouts that strike a balance between minimising flow distances and mitigating congestion potential.

Congestion can arise when multiple flow movements occur simultaneously, resulting in intersections along their paths. However, we face the challenge of not knowing the exact timing of movements or the precise paths workers will take between facilities in the new layouts. Therefore, capturing congestion risk necessitates an indirect and approximate approach. We adopt an approach based on the observation that although the exact paths are unknown, when considering flows from facilities i and j to facility k, if their movements occur concurrently, they must end up in the vicinity of facility k. Consequently, there is a possibility that their movements will overlap, leading to congestion. The congestion risk is particularly significant when facilities i and j are positioned similarly in relation to facility k, indicating a higher likelihood of overlapping movements. Moreover, the congestion risk can increase as the angle between the directions of flows from facilities i and j into facility k becomes narrower. This relationship is illustrated in Figure 3. For instance, when this angle is zero, as shown in Figure 3(a), and facilities i and j are completely aligned relative to facility k, there is a very high probability of flow overlap and congestion. Similarly, even for angles less than 90°s, there remains a substantial risk of congestion. However, as the angle increases, the congestion risk decreases significantly. In summary, while we cannot precisely know beforehand the exact paths and timing of worker movements, we indirectly capture congestion risk by considering the alignment and angle between flows from different facilities into a target facility. By leveraging this information, we can capture the congestion risk and incorporate it as a factor in our layout generation methods.



(a) 0° (b) 45° (c) 90° (d) 180°

Figure 3. Congestion risk for the flow coming from facility i to k and facility j to k as a function of the positioning of facility j and the angle between the direction of these two flows coming into facility k (facility j is coloured blue (in (c) and (d)) when it's location does not cause congestion and red (in (a) and (b)) when it does.). (a) 0°. (b) 45°. (c) 90° and (d) 180°.

Our first layout generation method is based on a mixed-integer linear programming formulation, which can be efficiently solved using a state-of-the-art solver such as Gurobi.[1] To maintain linearity in the formulation, we employ the rectilinear distance function. Additionally, our approach to modelling congestion risk based on flow patterns between facilities is achieved through linear constraints. The primary objective of this method is to minimise overlaps in the relative positioning of facilities, thus reducing congestion risk. To accomplish this, we utilise four positioning descriptors: left, right, below, and above, which help guide the layout optimisation process.

The second method employs a simulated annealing metaheuristic and utilises a quadratic formulation. The use of a quadratic formulation is motivated by two factors. Firstly, we consider Euclidean distances instead of rectilinear distances to better represent actual worker movement in the 2D environment. For instance, workers can walk along the shortest line connecting two facilities when transferring materials, assuming there are no obstacles in between. However, Euclidean distances cannot be expressed through linear constraints. Secondly, instead of restricting the relative positioning descriptors to only left, right, below, or above, we allow for any possible relative positioning scenario. To account for this flexibility, we introduce a continuous variable to model the angle between the directions of different flows entering the same facility. This angle cannot be expressed linearly, resulting in a quadratic formulation. Due to the quadratic nature of the formulation, traditional mathematical programming solvers are not suitable, and a heuristic optimisation approach is necessary. Therefore, we develop a simulated annealing metaheuristic to approximately solve the quadratic formulation. This metaheuristic iteratively explores the search space, gradually reducing the search radius to find high-quality layouts that balance flow distances and congestion risk.

3.2.1. Mixed-integer linear programming model with rectilinear distances

Below we present our mixed-integer linear programming (MILP) formulation to find an optimal facility layout.

$$\text{Minimise} \quad w^{\text{dist}} \sum_{t=1}^{T} \sum_{i,j=1}^{A} F_{ij}^{t} d_{ij}^{\text{rect}} + w^{\text{cong}} \sum_{t=1}^{T} \sum_{k=1}^{A} \sum_{i \neq k, j > i}^{A} F_{ik} F_{jk} \times \left(p_{ijk}^{\text{left}} + p_{ijk}^{\text{right}} + p_{ijk}^{\text{below}} + p_{ijk}^{\text{above}} \right) \tag{2}$$

$$\text{subject to} \quad d_{ij}^{\text{rect}} \geq d_{ij}^{x} + d_{ij}^{y}, \quad \forall\, i,j \tag{3}$$

$$d_{ij}^{x} \geq c_i^x - c_j^x, \quad \forall\, i,j \tag{4}$$

$$d_{ij}^{x} \geq c_j^x - c_i^x, \quad \forall\, i,j \tag{5}$$

$$d_{ij}^{y} \geq c_i^y - c_j^y, \quad \forall\, i,j \tag{6}$$

$$d_{ij}^{y} \geq c_j^y - c_i^y, \quad \forall\, i,j \tag{7}$$

$$l_i^x = L_i^{\text{long}} o_i + L_i^{\text{short}} (1 - o_i), \quad \forall\, i \tag{8}$$

$$l_i^y = L_i^{\text{long}} (1 - o_i) + L_i^{\text{short}} o_i, \quad \forall\, i \tag{9}$$

$$(c_i^x + 0.5 l_i^x) + \delta \leq (c_j^x - 0.5 l_j^x) + M(1 - p_{ij}^{\text{left}}), \quad \forall\, i \neq j \tag{10}$$

$$(c_i^y + 0.5 l_i^y) + \delta \leq (c_j^y - 0.5 l_j^y) + M(1 - p_{ij}^{\text{below}}), \quad \forall\, i \neq j \tag{11}$$

$$p_{ij}^{\text{left}} + p_{ji}^{\text{left}} + p_{ij}^{\text{below}} + p_{ji}^{\text{below}} = 1, \quad \forall i > j \tag{12}$$

$$c_i^x - l_i^x \geq 0, \quad \forall\, i \tag{13}$$

$$c_i^x + l_i^x \leq L, \quad \forall\, i \tag{14}$$

$$c_i^y - l_i^y \geq 0, \quad \forall\, i \tag{15}$$

$$c_i^y + l_i^y \leq W, \quad \forall\, i \tag{16}$$

$$p_{ijk}^{\text{left}} \geq p_{ik}^{\text{left}} + p_{jk}^{\text{left}} - 1, \quad \forall\, i \neq j \neq k \tag{17}$$

$$p_{ijk}^{\text{right}} \geq p_{ki}^{\text{left}} + p_{kj}^{\text{left}} - 1, \quad \forall\, i \neq j \neq k \tag{18}$$

$$p_{ijk}^{\text{below}} \geq p_{ik}^{\text{below}} + p_{jk}^{\text{below}} - 1, \quad \forall\, i \neq j \neq k \tag{19}$$

$$p_{ijk}^{\text{above}} \geq p_{ki}^{\text{below}} + p_{kj}^{\text{below}} - 1, \quad \forall\, i \neq j \neq k \tag{20}$$

The objective function (2) minimises the weighted costs of total flow distance and congestion risk over all periods. Constraints (3)–(7) model the rectilinear distance between facilities. Constraints (8)–(9) impose the lengths of facilities in x and y coordinates based on their orientation. Constraints (10)–(12) imply that facilities should not overlap that any facility i is positioned to the left, right, below or above relative to some another facility j, while also respecting the safety distance δ. In this, we use M, which is a very large scalar to model the if-then constraint. Constraints (13)–(16) impose the physical boundary conditions of the manufacturing floor on each of the facilities. Lastly, constraints (17)–(20) define when overlaps occur in the relative positioning of facilities, which are used in assessing the congestion risk based on the layout.

3.2.2. Simulated annealing metaheuristic for the quadratic formulation

Below we present the quadratic formulation to generate robust facility layouts.

$$\text{Minimise} \quad w^{\text{dist}} \sum_{t=1}^{T}\sum_{i=1}^{A}\sum_{j=1}^{A} F_{ij}^{t} d_{ij}^{\text{euc}} + w^{\text{cong}} \sum_{t=1}^{T}\sum_{k=1}^{A}\sum_{i\neq k}^{A}\sum_{j>i}^{A} F_{ik}F_{jk}a_{ijk}^{\text{cosine}} \tag{21}$$

$$\text{subjectto} \quad \left(d_{ij}^{\text{euc}}\right)^2 \geq d_{ij}^{\text{square}}, \quad \forall\, i,j \tag{22}$$

$$d_{ij}^{\text{square}} = \left(c_i^x - c_j^x\right)^2 + \left(c_i^y - c_j^y\right)^2, \quad \forall\, i,j \tag{23}$$

$$d_{ij}^x \geq c_i^x - c_j^x, \quad \forall\, i,j \tag{24}$$

$$d_{ij}^x \geq c_j^x - c_i^x, \quad \forall\, i,j \tag{25}$$

$$d_{ij}^y \geq c_i^y - c_j^y, \quad \forall\, i,j \tag{26}$$

$$d_{ij}^y \geq c_j^y - c_i^y, \quad \forall\, i,j \tag{27}$$

$$l_i^x = L_i^{\text{long}} o_i + L_i^{\text{short}}(1 - o_i), \quad \forall\, i \tag{28}$$

$$l_i^y = L_i^{\text{long}}(1 - o_i) + L_i^{\text{short}} o_i, \quad \forall\, i \tag{29}$$

$$(c_i^x + 0.5 l_i^x) + \delta \leq (c_j^x - 0.5 l_j^x) + M(1 - p_{ij}^{\text{left}}), \quad \forall\, i \neq j \tag{30}$$

$$(c_i^y + 0.5 l_i^y) + \delta \leq (c_j^y - 0.5 l_j^y) + M(1 - p_{ij}^{\text{below}}), \quad \forall\, i \neq j \tag{31}$$

$$p_{ij}^{\text{left}} + p_{ji}^{\text{left}} + p_{ij}^{\text{below}} + p_{ji}^{\text{below}} = 1, \quad \forall\, i > j \tag{32}$$

$$c_i^x - l_i^x \geq 0, \quad \forall\, i \tag{33}$$

$$c_i^x + l_i^x \leq L, \quad \forall\, i \tag{34}$$

$$c_i^y - l_i^y \geq 0, \quad \forall\, i \tag{35}$$

$$c_i^y + l_i^y \leq W, \quad \forall\, i. \tag{36}$$

$$\left(a_{ikj}^{\text{cosine}} a_{ikj}^{\text{product}}\right) \geq d_{ij}^{\text{square}} + d_{kj}^{\text{square}} - d_{ik}^{\text{square}}, \quad \forall\, i \neq j \neq k \tag{37}$$

$$a_{ikj}^{\text{product}} = \left(2 d_{ij}^{\text{euc}} d_{kj}^{\text{euc}}\right), \quad \forall\, i \neq j \neq k \tag{38}$$

In this formulation, Euclidean distances are modelled through the quadratic constraints (22)–(23). Constraints (24)–(36) are the same as in the linear formulation. Constraints (37)–(38) model the cosine of the angle between two different flows going into the same facility, which we capture by the continuous variables a_{ikj}^{cosine}. In this, we use the so-called law of cosines and use the auxiliary decision variables a_{ikj}^{product}s. Then, in the objective function (21) congestion risk is considered by minimising these cosines. We restrict these variables to be non-negative (see Table 2) so that the congestion risk will be incurred only when the cosine is above zero, namely, when the angle is lower than 90°. Note that cosine is a decreasing function between the range $[0, \pi/2]$ and therefore the congestion risk is considered through the minimisation of the cosines in the objective.

Table 2. Notation summary of the linear and quadratic formulations.

Sets	
$i, j, k \in \mathcal{A} = \{1, 2, \ldots, A\}$	the set of facilities
$r \in \mathcal{R} = \{1, 2, \ldots, R\}$	the set of workers
$t \in \mathcal{T} = \{1, 2, \ldots, T\}$	the set of time periods, scenarios
Parameters	
L	the length of the floor
W	the width of the floor
L_i^{long}	the length of the long side of facility i
L_i^{short}	the length of the short side of facility i
δ	the safety distance parameter
F_{ij}^t	the flow frequency pattern from facility i to facility j in period t
w^{dist}	the weight of flow distance objective
w^{cong}	the weight of the static congestion potential objective
Decision Variables	
$c_i^x \in [0, L]$	x-coordinate of the centroid of facility i
$c_i^y \in [0, W]$	y-coordinate of the centroid of facility i
$l_i^x \in \{L_i^{\text{long}}, L_i^{\text{short}}\}$	the length of facility i along the x-axis
$l_i^y \in \{L_i^{\text{long}}, L_i^{\text{short}}\}$	the length of facility i along the y-axis
$o_i \in \{0, 1\}$	1 if the longer side of facility i is placed on the x-axis, and 0 otherwise.
$p_{ij}^{\text{left}} \in \{0, 1\}$	1 if facility i is positioned to the left of facility j, and 0 otherwise.
$p_{ij}^{\text{below}} \in \{0, 1\}$	1 if station i is positioned below of station j, and 0 otherwise.
$p_{ijk}^{\text{left}} \in \{0, 1\}$	1 if both facilities i and j are positioned to the left of facility k, and 0 otherwise.
$p_{ijk}^{\text{right}} \in \{0, 1\}$	1 if both station i and j are positioned to the right of station k, and 0 otherwise.
$p_{ijk}^{\text{below}} \in \{0, 1\}$	1 if both station i and j are positioned below station k, and 0 otherwise.
$p_{ijk}^{\text{above}} \in \{0, 1\}$	1 if both station i and j are positioned above station k, and 0 otherwise.
$d_{ij}^x \in [0, L]$	the horizontal distance between the centroids of facilities i and j.
$d_{ij}^y \in [0, H]$	the vertical distance between the centroids of facilities i and j.
$d_{ij}^{\text{rect}} \in [0, L + W]$	the rectilinear distance between the centroids of facilities i and j.
$d_{ij}^{\text{euc}} \in [0, \sqrt{L^2 + W^2}]$	the Euclidean distance between the centroids of facilities i and j.
$d_{ij}^{\text{square}} \in [0, L^2 + W^2]$	the square of the Euclidean distance between the centroids of facilities i and j.
$a_{ijk}^{\text{cosine}} \in [0, 1]$	equals 0, when the angle between the direction of flow coming from facility i to facility k and from facility j to facility k exceeds $\pi/2$, otherwise it represents the cosine of this angle.

Solution Encoding and Fitness Calculation: To address the quadratic formulation and search for solutions, we have developed a simulated annealing metaheuristic, which serves as a local search heuristic exploring the decision variable solution space. In this context, a solution $\mathbf{s}$ is defined to encode the positions of facilities (c_i^x and c_i^y variables) and their orientations (o_i variables). Given the assigned values to these variables in a particular solution $\mathbf{s}$, we can determine the corresponding values for the Euclidean distance variables and angle cosine variables. Using Equation (21), we associate an objective value $Obj(\mathbf{s})$ with $\mathbf{s}$, defined as:

$$Obj(\mathbf{s}) = w^{\text{dist}} \sum_{t=1}^{T} \sum_{i=1}^{A} \sum_{j=1}^{A} F_{ij}^{t} d_{ij}^{\text{euc}} + w^{\text{cong}} \sum_{t=1}^{T} \sum_{k=1}^{A} \sum_{i \neq k}^{A} \sum_{j>i}^{A} F_{ik} F_{jk} a_{ijk}^{\text{cosine}}. \quad (39)$$

We incorporate this objective value into the fitness function of $\mathbf{s}$, denoted as $Fitness(\mathbf{s})$. Additionally, we integrate the feasibility aspect into the fitness function since not all values of the decision variables adhere to the layout design constraints. Specifically, the non-overlapping constraints (refer to Equations (30)–(32)) and floor boundary constraints (refer to Equations (33)–(36)) must be satisfied in a feasible solution. Any solution $\mathbf{s}$ that violates these constraints incurs a penalty, assigned a large value w^{infeas} within the fitness function. Thus we have

$$Fitness(\mathbf{s}) = \begin{cases} -Obj(\mathbf{s}) - w^{\text{infeas}}, & \mathbf{s} \text{ is infeasible} \\ -Obj(\mathbf{s}), & \mathbf{s} \text{ is feasible.} \end{cases} \quad (40)$$

We present the pseudocode for our simulated annealing method, named 'the re-operating simulated annealing (ROSA),' in Algorithm 1. The algorithm begins with an initial layout solution $\mathbf{s}^{\text{init}}$. Through iterative exploration, our local search heuristic aims to find high-fitness solutions by generating and evaluating new layouts, up to a specified iteration limit (*n_iter_limit*). Below we describe the components of this iterative method.

Operators: We devise a set of 7 operators that can modify the current solution $\mathbf{s}$ and generate a new solution $\mathbf{s}^{\text{new}}$ for a 2D facility layout. Among these operators, four are shift operators: shift west, shift east, shift north, and shift south. Each shift operator modifies the position of a single facility by moving it along either the x or y dimension. The fifth operator is responsible for changing the orientation of a facility, allowing it to be repositioned with a different alignment. The sixth operator is a swap operator that exchanges the positions of two facilities within the layout. This operator enables the relocation of facilities in relation to one another. Lastly, we have the random operator, which introduces randomness by altering the positions of one or two facilities in both the x and y dimensions. This operator adds variability to the search process, potentially leading to different layout configurations. In the following, we provide a detailed description of each operator.

- **Shift Operators:** Whenever one of these operators is invoked, a facility is selected randomly, and its position is shifted by a random amount. The random shift is determined by uniformly sampling a value from the interval $[0, \delta]$.
- **Change Orientation Operator:** When this operator is invoked, a facility i is randomly selected, and its orientation is modified in the new solution $\mathbf{s}^{\text{new}}$. If the orientation of facility i in the current solution $\mathbf{s}$ is denoted as $o_i = 1$, it will be changed to $o_i = 0$ in $\mathbf{s}^{\text{new}}$. Conversely, if $o_i = 0$ in $\mathbf{s}$, the orientation changes to $o_i = 1$ in $\mathbf{s}^{\text{new}}$.
- **Swap Operator:** When the swap operator is invoked, two facilities i and j are randomly selected, ensuring that $i \neq j$. The positions of these selected facilities are then swapped in the new solution $\mathbf{s}^{\text{new}}$. To determine the orientations of the swapped facilities in $\mathbf{s}^{\text{new}}$, an unbiased random sampling is performed. There is a 0.5 probability that the orientations of the swapped facilities will also be exchanged in the new solution. In other words, if the orientations of facilities i and j in the current solution $\mathbf{s}$ are denoted as o_i and o_j respectively, in $\mathbf{s}^{\text{new}}$ there is a 0.5 chance that o_i will be set to o_j and o_j will be set to o_i. Otherwise, if the random sampling outcome does not result in an orientation swap, the orientations of facilities i and j remain the same as in the current solution.
- **Random Operator:** Each time the random operator is invoked, a facility i is randomly selected. To determine whether to change the position of facility i in the x and y dimensions, two biased random samplings are performed. The biases in the random samplings reflect the lengths of the floor in the x and y dimensions, respectively. If the random sampling indicates that the position of facility i should be changed in the x dimension, a uniform sampling is performed from the interval $[0, L]$ to set the new position of facility i in the x dimension. Similarly, if the random sampling indicates a position change in the y dimension, a uniform sampling is performed from the interval $[0, W]$ to set the new position of facility i in the y dimension. Additionally, with a small probability, another facility j (where $j \neq i$) is chosen to change its position in the same manner as facility i. This process allows for the random alteration of facility positions in the

Algorithm 1 Pseudocode of the re-operating simulated annealing metaheuristic (ROSA)

1: Initialise $n = 0$, $\mathbf{s}, \mathbf{s}^{\text{best}} \leftarrow \mathbf{s}^{\text{init}}$, $Fitness\_best \leftarrow Fitness(\mathbf{s}^{\text{init}})$, $n\_nonimp = 0$, $n\_restart = 0$, $TEMP_0$;
2: **while** $n < n\_iter\_limit$ and $n\_nonimp < n\_nonimp\_limit$ **do**
3: Randomly select an operator from the set of seven operators;
4: Apply the selected operator to $\mathbf{s}$ to form the new solution $\mathbf{s}^{\text{new}}$
5: Toss the re-operate coin;
6: **if** the re-operate coin shows YES **then**
7: go to step 3;
8: **end if**
9: $Fitness\_new \leftarrow Fitness(\mathbf{s}^{\text{new}})$;
10: Calculate $TEMP(n)$ and $P(accept)$ according to Equations (41)- -(42);
11: **if** $Fitness\_new > Fitness\_best$ **then**
12: $\mathbf{s}^{\text{best}}, \mathbf{s} \leftarrow \mathbf{s}^{\text{new}}$, $Fitness\_best, Fitness(\mathbf{s}) \leftarrow Fitness(\mathbf{s}^{\text{new}})$, $n\_nonimprov \leftarrow 0$;
13: **else**
14: $n\_nonimprov \leftarrow n\_nonimprov + 1$;
15: Toss the solution acceptance coin;
16: **if** the acceptance coin is below $P(accept)$ **then**
17: $\mathbf{s} \leftarrow \mathbf{s}^{\text{new}}$, $Fitness(\mathbf{s}) \leftarrow Fitness(\mathbf{s}^{\text{new}})$;
18: **end if**
19: **end if**
20: **if** $n\_nonimprov = nonimp\_restart\_limit$ and $n\_restart < restart\_limit$ **then**
21: Do restart, let $\mathbf{s} \leftarrow \mathbf{s}^{\text{best}}$ and $n \leftarrow n - n\_iterback$ and go to step 3;
22: **end if**
23: $n \leftarrow n + 1$;
24: **end while**
25: **return** $\mathbf{s}^{\text{best}}$ with $Fitness\_best$;

layout, with a slight chance of altering the position of an additional facility.

Solution Acceptance: When a new solution $\mathbf{s}^{\text{new}}$ is generated, its fitness is compared to the fitness of the current solution $\mathbf{s}$. If the fitness of $\mathbf{s}^{\text{new}}$ is better, i.e. $Fitness(\mathbf{s}^{\text{new}}) > Fitness(\mathbf{s})$, the new solution is accepted as the current solution. However, if the fitness of $\mathbf{s}^{\text{new}}$ is not better than that of $\mathbf{s}$, the acceptance of the new solution is determined based on a probability $P(accept)$. This probability is modelled using temperature parameters, which is a common approach in simulated annealing metaheuristics (Kirkpatrick, Gelatt, and Vecchi 1983). As the iterations in the local search progress, the temperature gradually decreases, causing the acceptance probability $P(accept)$ to decrease as well. The initial temperature parameter is denoted as TEMP_0, which remains fixed throughout the process. Additionally, we have a varying temperature parameter $\text{TEMP}(n)$ in iteration n. To control the temperature reduction in iterations (i.e. to have $\text{TEMP}(n+1) < \text{TEMP}(n)$) we employ a logarithmic scheme. The resulting acceptance probability mechanism is as follows.

$$\text{TEMP}(n) = \frac{\text{TEMP}_0}{\log(n+1)} \tag{41}$$

$$P(accept) = \frac{1}{1 - \frac{Fitness(\mathbf{s}^{\text{new}}) - Fitness(\mathbf{s})}{\text{TEMP}(n)}}. \tag{42}$$

Re-operate: To explore the potential of the set of seven operators in different combinations, we introduce a randomised mechanism that allows for the re-application of operators with a certain probability p^{reoper}. Instead of exhaustively considering all possible sequences of operators, this mechanism provides flexibility and diversity in generating new solutions. When applying this randomised mechanism, a sequence of operators is randomly selected and applied to a given solution until a new solution is obtained. However, it is important to strike a balance between exploration and convergence. Applying too many operators or considering solutions that are vastly different from the current one may hinder convergence. To address this, the probability p^{reoper} is introduced, which naturally decreases the likelihood of having very long sequences of operators. For instance, the probability of applying a sequence of two operators is p^{reoper}, while the probability decreases to $(p^{\text{reoper}})^2$ for a sequence of three operators, $(p^{\text{reoper}})^3$ for a sequence of four operators, and so on. This probabilistic mechanism allows for a controlled exploration of different combinations of operators while mitigating the risk of overly long sequences that can generate a new solution that is highly different than the current solution and facilitating convergence.

Restart: To ensure the search progresses efficiently and avoid getting stuck in suboptimal solutions, we employ a restart strategy in our method. When a certain number of iterations pass without finding a better fitness solution, indicated by the variable *n_nonimp*, and this number reaches a predetermined limit *nonimp_restart_limit*, we initiate the restart procedure, unless the restart limit *restart_limit* has been reached. During the restart procedure, the current solution is set to the best solution found thus far, ensuring that valuable progress is not lost. Additionally, to prevent redundancy and promote exploration, the number of remaining iterations is reduced by *n_iterback*. This strategy allows the search process to start afresh from a promising point, potentially enabling the discovery of better solutions that were not reachable within the previous iterations. By incorporating this restart strategy, we maintain an adaptive and dynamic search process that can break free from local optima and continue exploring the solution space for improved layouts.

3.3. Evaluation of layouts in simulations

We assess the effectiveness of generated layouts using time-annotated movement patterns (s_r^t). The goal is to evaluate layouts that we generate based on static flow patterns under time-dependent effects. In this, we focus on two measures: the average time workers spend moving between stations and the level of congestion across the manufacturing floor.

However, the time-annotated patterns alone do not provide information about the exact points in time when movements will be completed and workers will reach their next visited facility in new layouts. This depends on the specific paths workers will take between facilities in a new layout, as well as their walking speed. To simulate these movements, we assume that workers prefer shorter paths to reach their destinations. However, considering that facilities are physical rectangular objects that act as obstacles for walking workers, only paths that do not intersect these objects are feasible, namely, we cannot always use the straight line connecting any two points. Finding the shortest paths among obstacles often involves representing the problem within a discretised grid/mesh environment and utilising algorithms such as A^* (Foead et al. 2021) or Dijkstra's algorithm. However, in this paper, we adopt a different approach inspired by Nazarahari, Khanmirza, and Doostie (2019), where we tackle the problem in a continuous environment, removing the constraint of restricting worker movement to the grid. To address this continuous-space optimisation problem, we develop a genetic algorithm, which is presented in the online supplement.

4. Case study

We present the manual tricycle assembly line process described in Delamare, Duval, and Boutteau (2020) as a case study to illustrate the applicability of our facility layout methodology. The choice of this system is motivated by its labour-intensive manufacturing process, where human workers are tracked using localisation sensors. This allows us to utilise the worker movement data obtained from these sensors to generate flow patterns in accordance with our methodology (refer to Section 3.1). Specifically, we utilise the UWB data from Delamare, Duval, and Boutteau (2020), which provides 2D positions of workers over a 3-hour shift, for our analysis.

In this particular system, six workers ($r = 1, 2, \ldots, 6$) are involved in carrying out six distinct manufacturing tasks. Each task takes place in a designated facility located on the manufacturing floor. Additionally, there is a storage facility that the workers visit to collect materials for the products. Thus, our focus is on optimising the layout of these seven facilities ($i = 1, 2, \ldots, 7$), with the last facility representing the storage area. Table 3 provides a description of these facilities, including their centroid coordinates (c_i^x, c_i^y), orientations (o_i), and initial layout information, in a floor with length $L = 8$ and width $W = 5$. The determination of these parameters is based on the insights derived from Delamare, Duval, and Boutteau (2020). We should note that in Delamare, Duval, and Boutteau (2020), the storage facility is depicted as two small rectangular objects. However, in our paper, we treat this facility as one larger rectangular object. To visualise the initial layout, refer to Figure 4. For reference in the visualisations, we set the coordinate system such that the upper left corner of the floor is denoted as $(0, 0)$, and the bottom right corner as $(5, 8)$.

4.1. Flow patterns from the UWB data and the initial layout

To extract flow patterns from the raw 2D position data obtained from UWB sensors worn by each worker, we employ our three-step data analysis approach.

Table 3. Facilities and their coordinates in the initial layout.

Facility	Task	L_i^{long}	L_i^{short}	Initial Layout (c_i^x, c_i^y)	Initial Layout o_i
1	Lower Frame	1.0 m	0.7 m	(0.5, 5.0)	1
2	Axle	1.0 m	0.7 m	(0.5, 3.0)	1
3	Saddle and Pedalboard	1.0 m	0.7 m	(0.5, 1.5)	1
4	Rear Wheel Axle Unit	1.5 m	1.0 m	(4.25, 1.5)	1
5	Front Wheel Axle	1.0 m	0.7 m	(4.25, 3.0)	1
6	Final Assembly	1.5 m	1.0 m	(4.25, 5.0)	1
7	Material Storage	2.0 m	0.7 m	(2.5, 7.5)	1

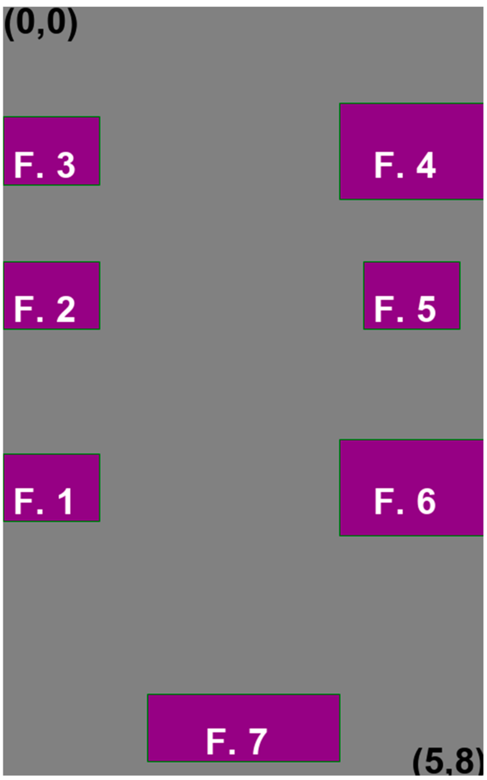


Figure 4. Initial layout (the rectangular object labelled with F. i, $i \in \{1, 2, \ldots, 7\}$) represents facility i.).

First Step: The UWB tags measure position data at a frequency of 100 ms. However, due to obstructions such as metal objects near the workers, there are occasional gaps in the data. To address this, we align the position data using seconds as the time unit. Specifically, we calculate the average of the measurements taken within each second, resulting in positions per second. This averaging process also acts as a smoothing function, reducing measurement errors. In instances where no position measurements are available within a second, we substitute the missing data with the worker's last known position. This approach ensures continuity in the data and prevents abrupt changes in position. Subsequently, we generate event logs for each worker based on their second-by-second positions. To determine the manufacturing activities performed by the workers, we leverage the proximity of workers to the facilities and their duration of stay. However, we filter out short stays since they may not be indicative of actual task performance and could be attributed to measurement errors. For instance, a brief stay near a facility may not signify engagement in a task. To achieve this filtering, we introduce a parameter $\beta > 0$, which we set to 5 seconds in this case study. Using the defined parameter, we consider a worker to be performing a task i at a given time θ if their position was in close proximity to the corresponding facility at any time θ' within the time window $\theta, \theta - 1, \ldots, \theta - \beta$. By applying this filtering, we generate events associated with specific facilities ($i = 1, 2, \ldots, 7$) along with their respective start and end times for each individual worker. The aforementioned data processing steps ensure that we have event logs that capture the relevant manufacturing activities performed by the workers.

Second Step: To derive process models from the event logs of the workers, we utilise process mining techniques (Aslan et al. 2024). There are various algorithms available for discovering process models from event logs, including Alpha Miner, Heuristic Miner, and Inductive Miner. In our study, we employ the implementation of the Inductive Visual Miner in ProM 6.11.[2] The theoretical foundation of this algorithm can be found in Leemans, Fahland, and van der Aalst (2013). The ProM tool offers two filtering hyperparameters, one for activities and another for paths. These filters have a significant impact on the quality measures of the resulting process models, particularly their fitness and complexity. For more detailed information on commonly used quality measures for process models, we refer the reader to dos Santos Garcia et al. (2019). In our paper, we apply a filtering range of 10–30% on the paths and/or activities to obtain process models with a sufficiently high fitness. It's important to note that as the level of filtering increases, the models become simpler, but this may reduce their fitness. The output of the ProM tool is in the form of process models represented using the business process model notation (BPMN) (van der Aalst 2009). Additionally, the tool provides time-related statistical information about the duration of each activity whenever it is executed. Both the process models and the mean activity sojourn time information can be found in the online supplement.

Third Step: We develop discrete event simulation models using the process models obtained from the event logs by taking an approach similar to Aslan et al. (2023). The information extracted from the process models serves as the foundation for constructing a discrete event simulation framework, which represents the process state and the events that transform the state based on transition probabilities. As mentioned in Rozinat et al. (2009), these process models seamlessly integrate into discrete event simulation (see Tamburis and Esposito 2020 for an application in the healthcare domain).

To model the transition probabilities, we utilise the flow sequences and their frequencies directly from the process models. These flow sequences indicate the movement between facilities, and their frequencies are used to determine the transition probabilities. For modelling the transition times, we employ the mean sojourn time information and utilise Exponential distributions. Specifically, we fit Exponential distributions with means based on the obtained mean sojourn times. We would like to emphasise that the Exponential assumption on the duration of activities is commonly adopted in manufacturing (Flapper, Gayon, and Lim 2014; Mouzon, Yildirim, and Twomey 2007). The simulation is implemented in the C++ language, using Visual Studio.

By drawing random samples from the simulation models, we generate 100 work shift patterns ($T = 100$) for each worker. Each scenario t of a worker r provides a time-annotated pattern s_r^t (refer to Section 3.3). To generate the new layouts, we utilise the static data derived from the time-annotated patterns. Specifically, we employ flow patterns F_{ij}^t based on the observed movement patterns, as described in Equation (1). These flow patterns represent the number of times workers move from facility i to facility j in scenario t. The corresponding data can be found in the online supplement.

4.2. Generating new layouts

Once we have obtained the flow patterns observed over 100 scenarios (F_{ij}^ts) for the assembly system, our next step is to explore new layouts as alternatives to the initial layout. To achieve this, we maintain a fixed safety distance parameter, δ, of half a meter, and set w^{dist} to 1. However, we vary the weight assigned to congestion, w^{cong}, to generate a range of new layouts using our two layout generation methods (refer to Section 3.2).

To cover a wide range of scenarios regarding the importance of congestion concern, we consider w^{cong} values of $0.01, 0.1, 1, 10, 100$, where the importance given to the congestion concern is increased with the larger values of w^{cong}. By generating multiple layouts with different weights assigned to congestion, we can assess the layouts based on two important quality measures: reducing the distances travelled by workers and minimising the potential for congestion on the manufacturing floor. By varying only w^{cong}, we can explore the possible layouts that prioritise these two concerns differently in a relative sense.

For generating layouts using the mixed-integer linear programming method, we employ Gurobi 9.0 to find optimal solutions for the linear formulation with rectilinear distances within seconds. In contrast, the simulated annealing metaheuristic approximately solves the quadratic formulation. The success of the simulated annealing metaheuristic in solving the quadratic formulation can be evaluated by the fitness of the layout solutions it discovers. The performance of this metaheuristic can be influenced by its components and parameters. Hence, we conduct experiments to fine-tune the algorithm and gain insights into the effectiveness of the designed components.

Since the simulated annealing method is stochastic, it can converge to different layout solutions due to the random sampling involved in its components, such as probabilistic solution acceptance. To account for this inherent randomness and the rapid convergence of this method, we run the method 20 times, each time using different random seeds. We select the layout with the highest fitness among these runs.

4.2.1. Tuning the simulated annealing metaheuristic to solve the quadratic formulation

We first fix some of the parameters based on offline tuning experiments and let $w^{\text{infeas}} = 10^8$, $n\_iter\_limit = 5000$, $n\_nonimp\_limit = 500$, $\text{TEMP}_0 = 10$, $nonimp\_restart\_limit = 100$, $restart\_limit = 5$, $n\_iterback = 2000$. In these offline experiments, we adopted a design of experiments approach, considering a set of values for each parameter and observing solution quality. Eventually, we fixed their values to the setting that required the least computational intensity (e.g. fewer iterations) while yielding the best observed solution quality. We then focus on the impact of two of the most important components: the effect of the re-operate mechanism governed by the probability p^{reoper} and the neighbourhood operators on the layout cost of the solutions (calculated with Equation (21)) generated by the method.

We begin by examining the impact of the re-operate probability on the quality of the solutions generated for the quadratic formulation by our method. Considering the layout cost incurred from the objective (21), in Figure 5, we present the results where w^{cong} is set to 1, while varying the re-operate probability, p^{reoper}, from the set $\{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6\}$. The figure illustrates that setting high values for this parameter can sometimes impede the success of the method, leading to solutions with notably poor quality. This indicates that employing too many operators in a single iteration, which can drastically alter the current solution, is not a favourable strategy for the method's performance. Conversely, we observe that incorporating the re-operate mechanism with a smaller probability, typically ranging between 0.1

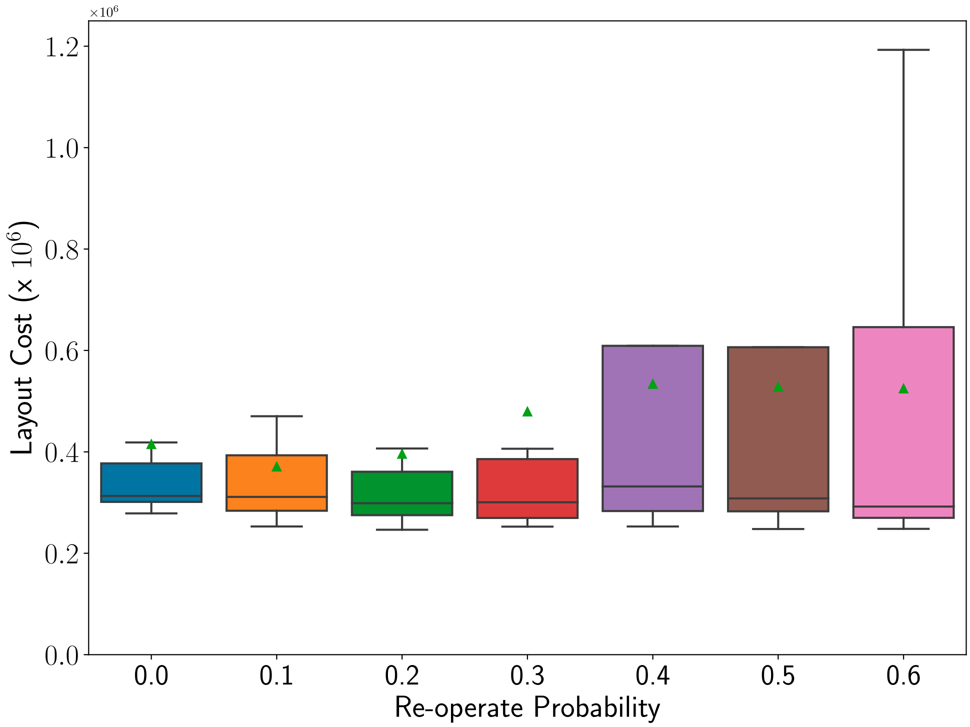


Figure 5. The effect of p^{reoper} (observe that when values exceed 0.3, it leads to significantly higher Q3 values. Additionally, within the set of values $\{0.0, 0.1, 0.2, 0.3\}$, the median and Q1 are higher when $p^{\text{reoper}} = 0.0$.).

and 0.3, offers advantages over not using it at all (i.e. $p^{\text{reoper}} = 0$). Solutions obtained with this range of probabilities tend to exhibit the lowest costs. Based on this performance analysis, we decide to fix the re-operate probability at 0.2 as it strikes a balance between exploring alternative solutions and preserving the overall quality of the layouts.

Next, we investigate the influence of the operators employed in the method's performance. We aim to assess the value of each operator by evaluating its impact under different subsets of operators while considering $w^{\text{cong}} = 1$. In Figure 6, we present the results of this analysis. It is evident from the figure that the four shift operators (shift west, east, south, and north) play a crucial role in achieving high-quality solutions. When these operators are not included, the quality of the solutions significantly deteriorates. The random operator emerges as the second most important operator, contributing significantly to the performance of the method. Additionally, the rotate operator demonstrates its importance by enabling the discovery of more cost-effective solutions. On the other hand, the swap operator appears to have the least impact among all the operators. However, it is noteworthy that including the swap operator still enhances the average performance of the method. Consequently, we conclude that all operators are important and should be included in the simulated annealing method to ensure optimal performance.

4.2.2. Benchmarking the simulated annealing metaheuristic

In this section, we conduct a comparative analysis of ROSA with several other simulated annealing metaheuristics proposed in the literature for the facility layout problem. Since our paper focuses on continuous formulations for generating facility layouts, we primarily consider benchmarks specifically designed for continuous problems.

The first benchmark method is based on the early work by Chwif, Barretto, and Moscato (1998). Their approach employs alternating swap and shift operators across iterations. The shift operator incorporates a parameter that represents a percentage of the maximum polygon height (L) plus the maximum polygon width (W), determining the extent of shift when invoked. In our benchmark experiments, we tune this shift amount parameter to one percent. Additionally, we propose a modified version of the Chwif, Barretto, and Moscato (1998) method by introducing a random sampling approach for determining the shift amount. In this modified version that constitutes our second benchmark, we sample from the interval $[0, \delta]$ using the safety distance parameter δ, aligning it with the shift operator in ROSA.

Our third benchmark method is derived from the recent study by Şenol and Murat (2023). They propose an improved version of the Chwif, Barretto, and

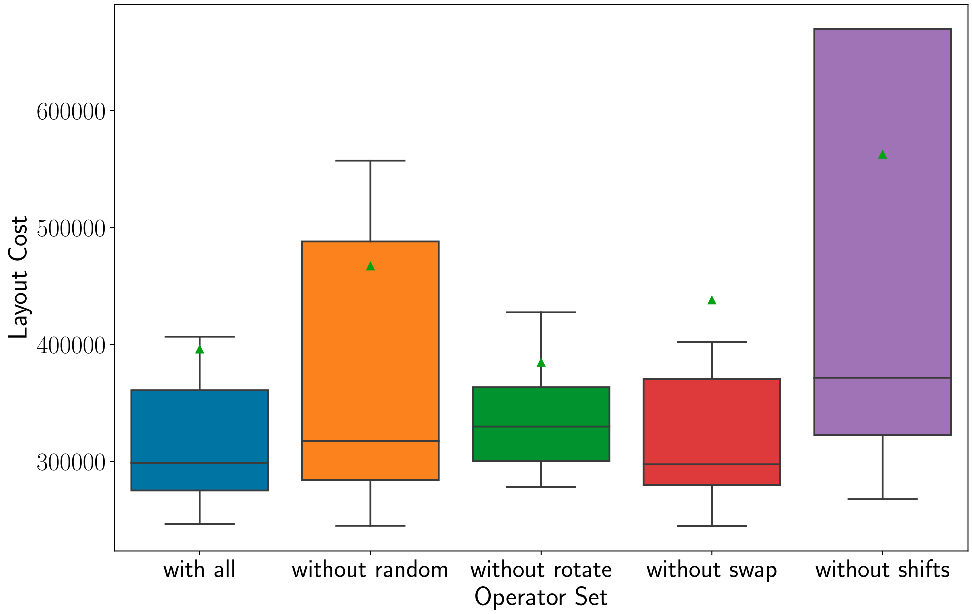


Figure 6. The effect of operators (observe that the medians are significantly elevated when certain operators, particularly the shift, rotate, and random operators, are omitted.).

Moscato (1998) approach, referred to as 'SA-CSR,' as a benchmark for their sequential heuristic in solving the continuous facility layout problem. We implement SA-CSR as a benchmark for ROSA; however, we encountered convergence issues. It was apparent that the problem stemmed from the first step of the neighbourhood generation procedure in SA-CSR. In this step, candidate solutions are generated for the location of each facility by searching for x and y coordinates randomly sampled from the intervals ranging from zero to the maximum polygon width (for the x coordinate) and from zero to the maximum polygon height (for the y coordinate). This extensive neighbourhood search posed convergence problems. To address this issue, we modified the first step of SA-CSR to restrict the search to a close neighbourhood of the facility locations in the current solution. Specifically, for each facility i with current location (x_i, y_i), we perform the search within $[x_i - \delta, x_i + \delta]$ and $[y_i - \delta, y_i + \delta]$. With this modification, SA-CSR successfully converges to improved solutions.

Our fourth and final benchmark is based on the approach proposed by Matai, Singh, and Mittal (2013). Their simulated annealing method is designed for the discrete layout problem, where candidate locations for facilities are predetermined. Consequently, the layout problem is transformed into an assignment problem that maps the facilities to these predetermined locations. It is worth noting that, in terms of solution space size, the continuous problem is significantly more challenging than the discrete problem. As a result, many metaheuristics proposed for the discrete problem only employ the swap operator to explore solutions, as demonstrated in the approach by Matai, Singh, and Mittal (2013). Using only the swap operator may appear limited in terms of solution space coverage for the continuous problem. However, this approach has an advantage in enabling a more greedy search within this restricted neighbourhood to identify the best possible swap move. In the case of n facilities, the number of possible swaps is $(n(n-1))/2$. For instance, one can search through all swap moves, evaluate them, and select the move that yields the most significant improvement. This greedy approach is indeed employed in Matai, Singh, and Mittal (2013). We include this benchmark to gauge the potential of finding an improved layout by solely swapping facility locations in the initial layout. The algorithm utilises a dynamic temperature cooling mechanism based on the average and minimum difference in solution quality across possible swap moves within an iteration. We employ the same parameter values as in Matai, Singh, and Mittal (2013).

Table 4 presents the benchmarking results for various instances with $w^{\text{cong}} \in \{0.01, 0.1, 1, 10, 100\}$. This table displays the rankings of the five considered methods, including ROSA and four benchmark methods from the literature: (i) the method of Chwif, Barretto, and Moscato (1998), (ii) our modified version of the Chwif, Barretto, and Moscato (1998) method, (iii) the method of Şenol and Murat (2023), and (iv) the method of Matai, Singh, and Mittal (2013). For methods that do not achieve the best performance, we provide their relative percentage gap compared to the method that yields the best solution.

Table 4. The Ranking of ROSA and benchmarks with relative percentage gaps to the best performing method (the gap of the method giving the cost value z is found by $100(z - z^*)/z^*$, where z^* is the cost value by the best performing method that gives the smallest cost among all five methods.)

w^{cong}	1st	2nd	3rd	4th	5th
0.01	ROSA	Chwif et al. (1998)	Modif. Chwif et al. (1998)	Şenol and Murat (2023)	Matai, Singh, and Mittal (2013)
	–	0.7%	2.9%	4.9%	58.9%
0.1	Modif. Chwif et al. (1998)	ROSA	Chwif et al. (1998)	Şenol and Murat (2023)	Matai, Singh, and Mittal (2013)
	–	4.4%	5.3%	12.0%	63.1%
1	Modif. Chwif et al. (1998)	ROSA	Chwif et al. (1998)	Şenol and Murat (2023)	Matai, Singh, and Mittal (2013)
	–	0.1%	6.0%	7.4%	98.9%
10	ROSA	Chwif et al. (1998)	Modif. Chwif et al. (1998)	Şenol and Murat (2023)	Matai, Singh, and Mittal (2013)
	–	7.4%	13.6%	14.2%	199.5%
100	Modif. Chwif et al. (1998)	ROSA	Şenol and Murat (2023)	Chwif et al. (1998)	Matai, Singh, and Mittal (2013)
	–	1.7%	26.2%	32.0%	242.9%

Notably, it is evident in Table 4 that the method of Matai, Singh, and Mittal (2013) consistently performs the worst, providing significantly inferior solutions compared to the other methods. This indicates that this method, designed for the discrete layout problem, is not suitable for our continuous layout problem. On the other hand, the best-performing methods are ROSA and our modified version of the method developed by Chwif, Barretto, and Moscato (1998). Both of these methods demonstrate significantly superior performance compared to the method of Şenol and Murat (2023). When comparing the performance of the original method by Chwif, Barretto, and Moscato (1998) to its modified version, we observe that our modification, randomising the shift amount in the shift operator instead of using a fixed amount, proves successful. In two out of the five instances, our method finds the best solution, while in the remaining three instances, the modified version of the Chwif, Barretto, and Moscato (1998) method yields the highest-quality solution. However, considering the gap between the solution qualities obtained by these two methods, we find that ROSA has a slight advantage. Overall, the benchmarking results highlight the strong performance of ROSA compared to the benchmark methods from the literature. This demonstrates the effectiveness of our approach in tackling the continuous facility layout problem.

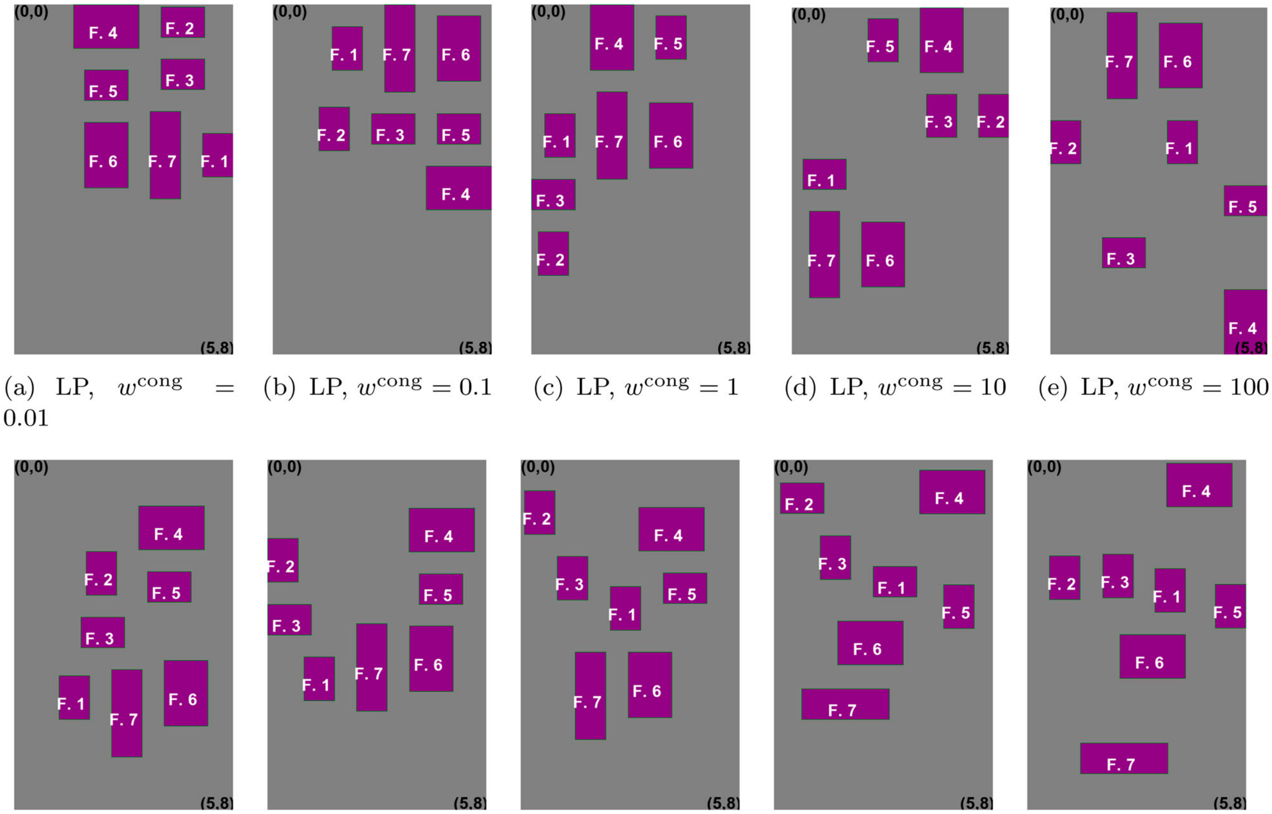
4.3. Evaluating new layouts against the initial layout

We explore a range of new layouts by varying $w^{\text{cong}} \in \{0.01, 0.1, 1, 10, 100\}$ to create layouts with different levels of importance assigned to congestion concerns relative to travel distance reduction, which is held constant at $w^{\text{dist}} = 1$. Figure 7 showcases the layouts generated by two of our methods. Notably, as w^{cong} increases and the avoidance of congestion risks becomes more significant, the facility locations tend to spread out more on the manufacturing floor.

To further examine the relationship between the flow patterns between facilities (provided in the online supplement) and the new layouts, we observe that the highest volume of traffic occurs between facilities 4 and 5, facilities 7 and 6, and also between facilities 1 and 7. In Figure 7, we can observe a preference for placing these facilities in close proximity in the generated layouts, particularly when w^{cong} is not excessively high. Furthermore, we notice a tendency to position facility 7 between facilities 1 and 6, both of which experience significant traffic to and from facility 7. This deliberate design choice, emphasised by our congestion-aware layout generation methods, helps prevent the overlap of movements between facilities 6 and 7 with the movements between facilities 1 and 7. Overall, the layouts generated by our methods exhibit a clear consideration for optimising flow patterns and minimising congestion risks, as evidenced by the strategic placement of facilities in relation to their traffic volumes and interaction patterns.

Prior to evaluating them with the time-annotated movement sequences of workers (s_r^t), we determine walking paths for the workers in the new layouts using our genetic algorithm (refer to the online supplement). Considering the positions of workers second by second, we employ this algorithm 42 times to generate paths between every pair of the seven facilities ($A = 7$). Based on the observed average walking speed of workers in the position data, we set the walking speed parameter $\mathbf{v}$ to 0.25. The remaining parameters are tuned as follows: $num\_gens = 100$, $pop\_size =$ 10,000, $pop\_random\_size = 100$, $num\_tournament = 10$, $w^{\text{path\_infeas}} =$ 10,000. The 'Increase Similarity' and 'Seed the Straight Path Angle' procedures are invoked with a probability of 0.5, while the 'Mutation' procedure is called with a probability of 0.1.

By utilising the time-annotated sequences, which provide detailed information on the sequence of facilities visited by workers and the corresponding time spent at each facility, in conjunction with the second-by-second



(a) LP, $w^{\text{cong}} = 0.01$ (b) LP, $w^{\text{cong}} = 0.1$ (c) LP, $w^{\text{cong}} = 1$ (d) LP, $w^{\text{cong}} = 10$ (e) LP, $w^{\text{cong}} = 100$

(f) ROSA, $w^{\text{cong}} = 0.01$ (g) ROSA, $w^{\text{cong}} = 0.1$ (h) ROSA, $w^{\text{cong}} = 1$ (i) ROSA, $w^{\text{cong}} = 10$ (j) ROSA, $w^{\text{cong}} = 100$

Figure 7. Layouts generated by linear programming (LP) and ROSA methods for $w^{\text{cong}} \in \{0.01, 0.1, 1, 10, 100\}$ with safety distance $\delta = 0.5$. (a) LP, $w^{\text{cong}} = 0.01$. (b) LP, $w^{\text{cong}} = 0.1$. (c) LP, $w^{\text{cong}} = 1$. (d) LP, $w^{\text{cong}} = 10$. (e) LP, $w^{\text{cong}} = 100$ (f) ROSA, $w^{\text{cong}} = 0.01$. (g) ROSA, $w^{\text{cong}} = 0.1$. (h) ROSA, $w^{\text{cong}} = 1$. (i) ROSA, $w^{\text{cong}} = 10$ and (j) ROSA, $w^{\text{cong}} = 100$.

paths obtained from the genetic algorithm, we generate the positions of workers in the new layouts for each time step across all scenarios T. To accomplish this, we adopt the following approach: when workers are stationary and engaged in activities at a facility (as indicated by the duration of the current activity in the time-annotated sequence), we fix their positions at the centre of the respective facilities. Conversely, when workers are required to commence movement (signifying the completion of the current activity and the initiation of a new activity at a different facility according to the time-annotated sequence), we determine their positions based on the generated paths until they reach their new destinations.

Subsequently, we employ the simulated position data to evaluate the following travel time and congestion-based metrics for the layouts:

- **Travel Time Metric:** This metric represents the total number of minutes spent by all workers collectively while travelling between facilities during a work shift. It is calculated by summing up the travel times of individual workers across all scenarios and then averaging the result. This metric provides a comprehensive measure of the overall travel efficiency and time expenditure associated with worker movements in the layout.
- **Congestion Metrics:** We employ a spatio-temporal density-based metric (Nanni and Pedreschi 2006) to assess congestion on the manufacturing floor, considering only workers as the moving entities. To evaluate congestion, we partition the floor into square meter subregions and analyse the congestion within these regions over time. This is determined by the number of workers passing through a subregion within the same second. The dynamic congestion measure for each subregion is computed as (number of workers passing) × (number of workers passing − 1). Here, the number of workers passing refers to the total count of workers in motion whose positions fall within the respective subregion at that moment. It is important to note that this congestion measure yields positive values only when there are multiple moving workers passing through the same

subregion simultaneously. This is because a single worker alone does not present congestion-related risks such as collisions. Furthermore, this measure exhibits quadratic growth with increasing density of moving workers, capturing the non-linear impact of density on congestion risks. Based on this spatio-temporal density measure, we use the following two metrics to assess congestion.

- **Congestion Sum Metric:** This metric represents the cumulative congestion measure for all subregions on the manufacturing floor. To calculate this metric, we average the congestion measure for each subregion across all seconds and scenarios. The congestion measure for a subregion captures the density-based congestion within that particular area, considering the number of workers passing through it within the same second. By summing up the congestion measures of all subregions and averaging them over time and scenarios, we obtain a comprehensive assessment of the overall congestion level in the facility layout.
- **Congestion Max Metric:** This metric represents the maximum congestion measure observed among all subregions on the manufacturing floor. To calculate this metric, we compute the congestion measure for each subregion by averaging it across all seconds and scenarios. By identifying the maximum congestion measure among all subregions and averaging it over time and scenarios, we obtain a measure that reflects the highest congestion level experienced in a given facility layout.

In Table 5, we present the evaluation results for the travel time and congestion metrics of the new layouts compared to the initial layout. Both layout generation methods, LP and ROSA, demonstrate success in finding improved layouts compared to the initial one, resulting in significantly reduced travel time for workers and decreased congestion on the manufacturing floor. Notably, the layouts generated with lower weight values for w^{cong} tend to yield the most substantial improvements in both travel time and congestion dimensions.

Comparing the performance of the two layout generation methods, it seems that LP is generally able to find better layouts than ROSA. The quadratic formulation is more comprehensive in measuring the congestion risk than the linear formulation; however, it poses a computational challenge, requiring a heuristic solution approach for which we propose ROSA. On the other hand, the linear formulation uses a restricted measurement of the congestion risk; however, it can be solved to optimality. Each method has different strengths and weaknesses, which can prove to be a better fit than the other in different situations. However, in our case study, we find that using the less comprehensive linear formulation is not too limiting and can achieve better layouts.

The LP method, under the weight value $w^{\text{cong}} = 0.01$, achieves the greatest reduction in travel time, improving upon the initial layout by 55%. Moreover, this layout demonstrates a considerable enhancement in congestion mitigation compared to the initial layout. In fact, all new layouts, except for four, outperform the initial layout across all metrics. These findings highlight the effectiveness of our methods in discovering layouts that not only minimise travel time for workers but also alleviate congestion, underscoring the importance of incorporating congestion considerations in conjunction with flow distances.

To convey the superiority of the LP method when it is used with lower w^{cong} values visually, we present Figure 8 where we show the Pareto front among the initial and new layouts using the travel time and congestion sum metrics.

It is also worth noting that excessively high weight values for w^{cong} can lead to increased travel time, potentially surpassing that of the initial layout. This outcome is intuitive since a higher w^{cong} diminishes the relative importance of minimising flow distances (fixed at $w^{\text{dist}} = 1$) in the layout generation process. As depicted in Figure 7, this phenomenon causes facilities to be more dispersed and segregated in the layouts as w^{cong} increases. Interestingly, this segregation can also exacerbate congestion.

Table 5. Travel time and congestion metrics of the initial and new layouts

Layouts	Travel Time Metric	Congestion Sum Metric	Congestion Max Metric
Initial	80.5	15.36	0.032
LP, $w^{\text{cong}} = 0.01$	**35.7**	5.14	0.025
ROSA, $w^{\text{cong}} = 0.01$	39.6	8.36	0.022
LP, $w^{\text{cong}} = 0.1$	36.9	**4.34**	0.023
ROSA, $w^{\text{cong}} = 0.1$	39.0	15.02	0.022
LP, $w^{\text{cong}} = 1$	40.1	8.1	0.027
ROSA, $w^{\text{cong}} = 1$	45.6	16.29	0.027
LP, $w^{\text{cong}} = 10$	55.8	14.42	**0.021**
ROSA, $w^{\text{cong}} = 10$	79.5	39.0	0.023
LP, $w^{\text{cong}} = 100$	73.5	17.42	0.035
ROSA, $w^{\text{cong}} = 100$	93.5	33.62	0.028

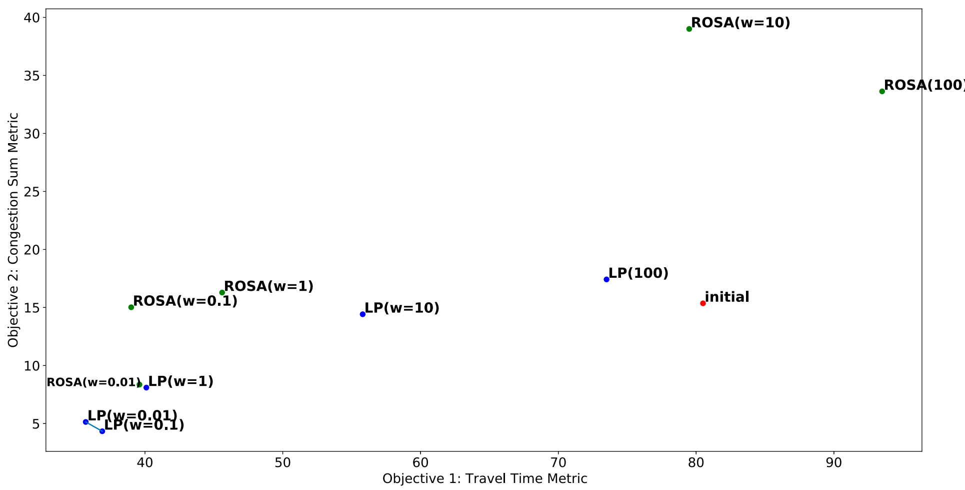
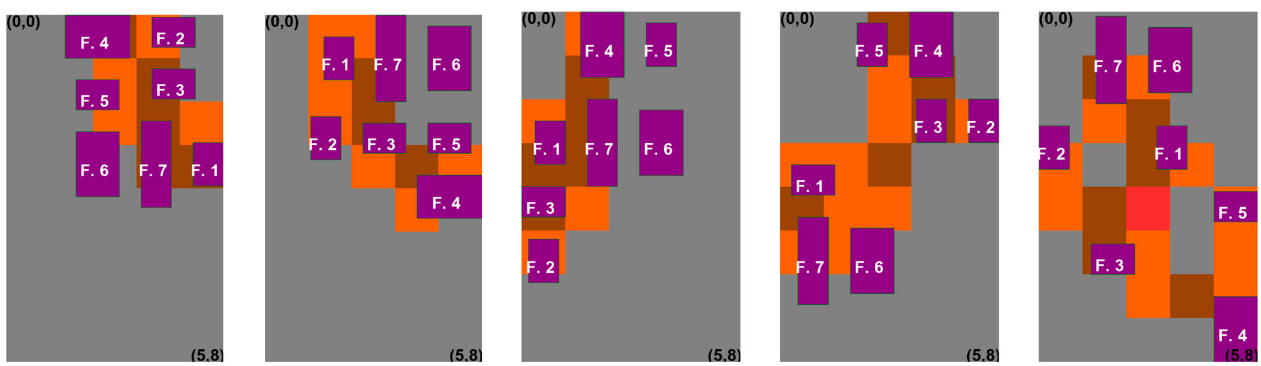
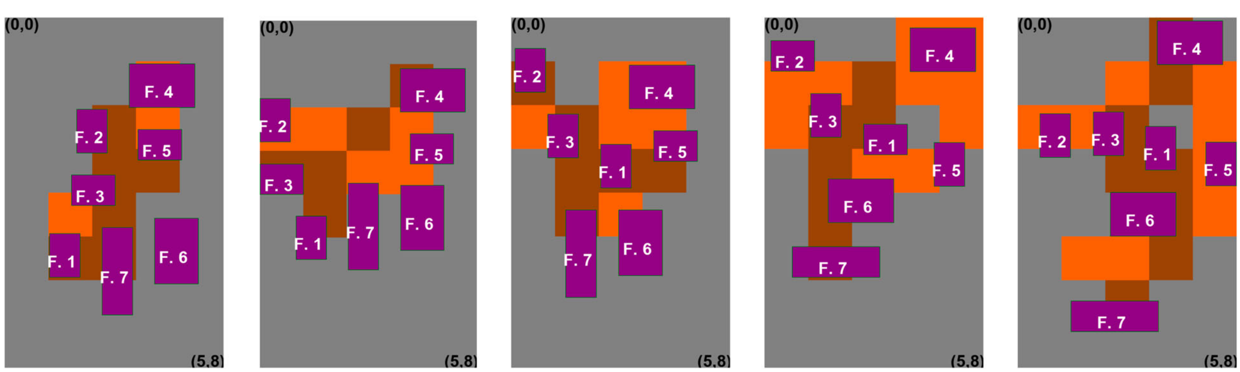


Figure 8. The Pareto front (see the line connecting LP($w^{cong} = 0.01$) and LP($w^{cong} = 0.1$) using the travel time and congestion sum metrics with the initial and new layouts.



(a) LP, $w^{cong} = 0.01$ (b) LP, $w^{cong} = 0.1$ (c) LP, $w^{cong} = 1$ (d) LP, $w^{cong} = 10$ (e) LP, $w^{cong} = 100$



(f) ROSA, $w^{cong} = 0.01$ (g) ROSA, $w^{cong} = 0.1$ (h) ROSA, $w^{cong} = 1$ (i) ROSA, $w^{cong} = 10$ (j) ROSA, $w^{cong} = 100$

Figure 9. Congestion across square meter subregions on layouts generated with safety distance $\delta = 0.5$ (any subregion with zero congestion is coloured gray, subregions with congestion between zero and 0.02 are coloured orange, those with congestion between 0.02 and 0.03 are coloured brown and any subregion with congestion of at least 0.03 is coloured red.). (a) LP, $w^{cong} = 0.01$. (b) LP, $w^{cong} = 0.1$. (c) LP, $w^{cong} = 1$. (d) LP, $w^{cong} = 10$. (e) LP, $w^{cong} = 100$. (f) ROSA, $w^{cong} = 0.01$. (g) ROSA, $w^{cong} = 0.1$. (h) ROSA, $w^{cong} = 1$. (i) ROSA, $w^{cong} = 10$ and (j) ROSA, $w^{cong} = 100$.

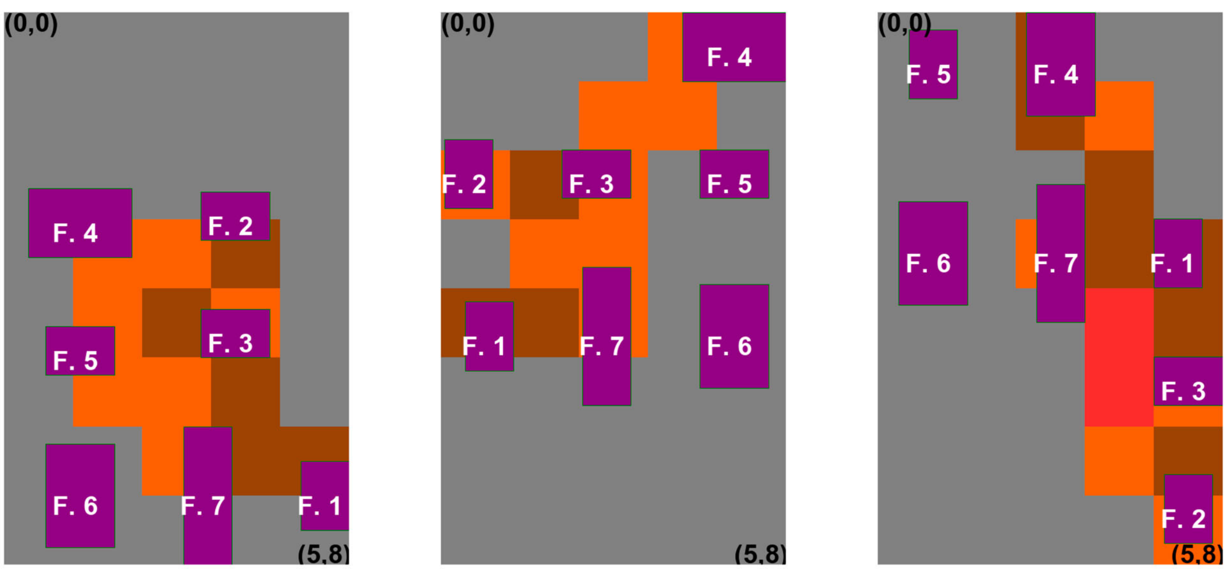
The LP and ROSA formulations aim to reduce congestion potential by minimising the overlap of movements between different facilities when directing them toward a location along the shortest distance. However, achieving this goal necessitates distancing the facilities from each other. Consequently, workers have to travel longer distances, spending more time in motion, which can increase the likelihood of encountering other moving workers. Figure 9 visually demonstrates the congested areas in the new layouts, and it is evident that the number of congested areas may increase as w^{cong} rises. Therefore, to obtain layouts that effectively reduce both travel time and congestion, it is advisable to employ our methods with lower weight values for w^{cong}, resulting in layouts where facilities are reasonably spaced apart.

4.3.1. Evaluation under large safety distance

The layouts illustrated in Figure 9 assume a safety distance (δ) of half a meter. Among these layouts, those generated with lower weight values assigned to w^{cong} have been identified as the most effective, achieving a reduction in travel time of over 50% compared to the initial layout. In this section, we aim to explore the potential for improvement in the new layouts when a larger safety distance of one meter is considered. Our objective is to determine whether our methods can still discover layouts that are significantly superior to the initial layout even when a much larger safety distance needs to be maintained between facilities. To accomplish this, we utilise the linear programming method with $w^{\text{cong}} \in \{0.01, 0.1, 1\}$ and $\delta = 1$, and we present the resulting layouts in Figure 10, along with their corresponding evaluation metrics.

Firstly, it is worth noting that the layouts with a safety distance of $\delta = 1$, as depicted in Figure 10, exhibit a similar structural arrangement to those with $\delta = 0.5$ in terms of the relative positioning of facilities. The key distinction is that now the distances between the facilities are more extensive. Evaluating these layouts reveals significant enhancements compared to the initial layout, with improvements observed in both travel time and congestion metrics for $w^{\text{cong}} = 0.01$ and $w^{\text{cong}} = 0.1$, which achieve a reduction in travel time by more than 32%.

Notably, the layout with $w^{\text{cong}} = 0.01$ in Figure 10(a), which demonstrates the most substantial travel time improvement, bears resemblance to the initial layout (depicted in Figure 4). However, there are two significant positioning modifications in this layout. Firstly, facilities 1 and 6 are positioned in close proximity to facility



(a) LP, $w^{\text{cong}} = 0.01$, Travel Time Metric: 52.7, Congestion Sum Metric: 10.28, Congestion Max Metric: 0.022

(b) LP, $w^{\text{cong}} = 0.1$, Travel Time Metric: 54.4, Congestion Sum Metric: 8.52, Congestion Max Metric: 0.021

(c) LP, $w^{\text{cong}} = 1$, Travel Time Metric: 58.2, Congestion Sum Metric: 16.16, Congestion Max Metric: 0.058

Figure 10. Congestion across square meter subregions on layouts generated with safety distance $\delta = 1$ via LP method under $w^{\text{cong}} \in \{0.01, 0.1, 1\}$ (any subregion with zero congestion is coloured gray, subregions with congestion between zero and 0.02 are coloured orange, those with congestion between 0.02 and 0.03 are coloured brown and any subregion with congestion of at least 0.03 is coloured red.). (a) LP, $w^{\text{cong}} = 0.01$, Travel Time Metric: 52.7, Congestion Sum Metric: 10.28, Congestion Max Metric: 0.022. (b) LP, $w^{\text{cong}} = 0.1$, Travel Time Metric: 54.4, Congestion Sum Metric: 8.52, Congestion Max Metric: 0.021 and (c) LP, $w^{\text{cong}} = 1$, Travel Time Metric: 58.2, Congestion Sum Metric: 16.16, Congestion Max Metric: 0.058.

7, similar to their placement in the initial layout. However, in the new layout, facility 7 is precisely positioned between these two facilities. As mentioned earlier, this design choice offers advantages in terms of preventing movement overlap and also leads to reduced travel time. Secondly, facilities 2 and 3 have exchanged locations, favouring the placement of facility 3 closer to the centre instead of facility 2. In other words, the initial layout can be transformed into the layout depicted in Figure 10(a) through two minor adjustments. This illustrates that even small modifications can yield significant improvements to the initial layout.

5. Discussion and conclusions

This paper introduces two innovative methods for designing facility layouts in labour-intensive manufacturing processes, such as workshops. Unlike automated manufacturing systems that rely on fixed programming for robots, labour-intensive processes involve human workers who exhibit flexible and unpredictable practices. Consequently, the use of integrative optimisation-based facility design approaches proposed for automated systems, which determine both facility locations and manufacturing process-related decisions (e.g. job and route assignments), are not suitable for labour-intensive systems. Instead, this paper proposes less intrusive human-centred methods that focus solely on determining facility locations. By observing workers' movement data, obtained through indoor localisation sensors, we learn from their practices, including their adaptability to changing conditions on the manufacturing floor. This information is utilised to generate scenarios and develop new layouts that are robust to evolving work patterns, while allowing workers to perform tasks according to their own practices.

In facility layout design, we prioritise minimising flow distances, aiming to reduce the distances workers travel when moving between facilities. Additionally, we address the issue of congestion risk in layout generation. Congestion, a spatio-temporal phenomenon where workers occupy the same place simultaneously, cannot be determined solely based on facility locations. To incorporate congestion risk, we employ indirect approaches. We introduce novel methods by identifying potential movement overlaps through the relative positioning of facilities. Our approaches adopt biobjective formulations, considering both minimising travel distances and congestion risk. The first method utilises linear programming, employing rectilinear distances and four descriptors (left, right, above, below) to determine relative facility positioning. This model can be efficiently solved using state-of-the-art optimisation solvers. The second method employs a quadratic formulation that utilises Euclidean distances and angle-based identification of relative positioning. To provide solutions to this formulation, we develop a simulated annealing metaheuristic called ROSA, which we benchmark against four other simulated annealing methods for similar facility layout problems, demonstrating its ability to discover high-quality solutions.

We conducted a real-world case study on a manual assembly line with six workers and seven facilities, where worker movements were tracked using UWB sensors, capturing their 2D positions over a three-hour shift. Our two layout generation methods were applied with varying weight values for congestion risk, resulting in different layouts that balanced the objective of minimising travel distance. We observed that as the weight given to congestion risk increased, facility locations tended to spread out more on the manufacturing floor, leading to increased distances. This outcome is intuitive since avoiding movement overlap necessitates different facility alignments, requiring more floor space. Additionally, our congestion and distance-aware methods successfully placed facilities in close proximity, especially where high traffic volumes occurred, while also discovering designs that completely avoided movement overlap between facilities. These findings demonstrate the effectiveness of our indirect approaches in incorporating congestion risk into facility layouts.

To gain a comprehensive understanding of the performance of the layouts generated by our methods in relation to time-dependent factors, we conducted simulations and evaluated the layouts using time-annotated work patterns and potential worker paths in the new layouts. We employed a genetic algorithm to generate likely paths for workers, enabling evaluation based on time-based measures. Specifically, we considered average travel time and spatio-temporal congestion measures. Our objective was to evaluate the new layouts under these measures and compare them to the current layout, investigating the potential improvement achievable through layout changes. The evaluation revealed that both of our methods produced layouts that outperformed the current layout significantly in terms of both measures. However, we observed that the best layouts were obtained when assigning lower weight values to congestion risk, allowing for congestion risk to be accommodated without excessively spreading out the facilities on the floor.

Both of our methods are able to generate layouts for different number of workers or facilities. Potentially, as the methods have to consider more layout options (as A or/and R increase), the amount of time required to generate the layouts can increase. This can be more of a challenge for our second method, the simulated annealing. However, our linear programming approach will still be able to generate layouts in a matter of seconds even for very large numbers of workers and facilities. Therefore, given that the linear formulation can provide high quality solutions while being more computationally efficient than the simulated annealing, this method can be more advantageous in practice.

Overall, our study highlights a crucial application of location tracking sensors within manufacturing environments, showcasing their capacity to enhance facility layout based on the data they generate. This insight can assist production engineers in making informed decisions regarding the implementation of these sensors, aiding them in assessing the potential value and benefits of such an investment.

Future research can explore alternative approaches to address congestion risks based on facility locations. Additionally, methods can be developed for dynamic facility layout design, especially for flexible systems capable of accommodating layout changes. Leveraging suitable sensor data would enable a more informed approach in this regard. This might involve tracking not only worker movement data but also multi-source sensor data related to workers, materials, equipment, and machines. By doing so, it becomes possible to detect temporal patterns and identify optimal moments for design changes. This, in turn, could lead to significant improvements in reducing travel time for workers and mitigating congestion risks. Adopting such an informed approach might offer advantages over changing the layout at fixed time intervals. One important limitation of our paper is that when aiming to ease worker movement between facilities for a more human-centric facility layout, the weight of the materials workers transfer should also be considered. Future research could incorporate these differences in weights and seek to better facilitate movement for transfers involving heavy materials. Methodologically, the primary limitation of our study lies in our dependence on simulations to assess layouts and our assumption that workers will consistently opt for the shortest paths when moving between stations. However, this assumption may not always align with actual worker behaviour. Future research could address this by integrating behavioural insights from workers into the simulation process, potentially through methods like conducting surveys.

Notes

1. https://www.gurobi.com/
2. https://www.promtools.org/

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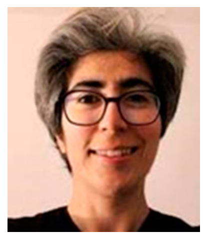
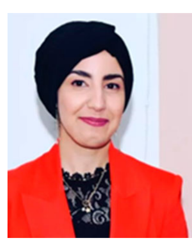
Notes on contributors



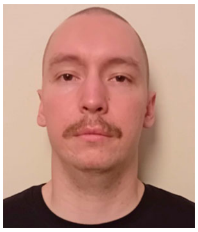
Ayse Aslan was a research fellow in the School of Computing, Engineering and the Built environment at Edinburgh Napier University. She is an applied mathematician specialised in operational research and data science. Her expertise lies in using stochastic modelling, simulation, optimisation, dynamic/sequential decision-making tools, and machine learning techniques to effectively model, analyse, and provide analytical and data-driven decision support for complex real-world problems.

Gokula Vasantha is an associate professor of engineering design and informatics at the School of Computing, Engineering and the Built Environment at Edinburgh Napier University. His interests include predictive engineering design modelling, engineering design informatics, integrated product-service systems, collaborative product development environment, smart manufacturing, modelling and management of engineering design, and crowdsourcing design and manufacturing processes.



Hanane El-Raoui is a lecturer in the department of Management Science at the University of Strathclyde. Her current research interests include behaviour modelling and simulation, organisational safety, risk management.

John Quigley is a Professor in the department of Management Science at the University of Strathclyde, and an Industrial Statistician with expertise in developing and applying statistical and stochastic methods to build decision support models.



Jack Hanson is a research associate at the University of Edinburgh. He completed an MEng in mechanical engineering at Liverpool John Moores University in England in 2017 before completing a PhD in fluid mechanics at the University of Edinburgh. His current research interests include additive manufacture of tuneable metal lattices and the characterisation of human movement in industrial settings.

Jonathan Corney is a Professor of Digital Manufacturing at the University of Edinburgh. His interests include manufacturing applications of crowdsourcing; cloud interfaces for manufacturing, the interactive search of digital media and, the creation of predictive CAD systems by leveraging data analytics.

Andrew Sherlock is a Director of Data-Driven Manufacturing at National Manufacturing Institute Scotland and a Professor of Practice at the University of Strathclyde. His career has focussed on the application of AI, data science and search techniques to design and manufacturing.

Data availability statement

Data available within the article or its supplementary materials. The authors will share source codes of the methods presented in this research article upon request.

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