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Reconfigurable process-aware factory layout planning: a human-centric multi-objective optimization approach

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ABSTRACT

Factory layout planning is central to manufacturing performance. By aligning productivity with worker well-being, factories can achieve more sustainable operations. Traditional approaches often treat the process sequence as static, limiting adaptability. This article introduces a human-centric approach that treats the process sequence as reconfigurable, enabling dynamic adjustment of resources and equipment across the assembly line. The approach integrates sequence generation with precedence constraints, block layout creation and resource positioning into a unified multi-objective optimization process. A genetic algorithm combined with digital human modelling evaluates proposals in terms of worker well-being, walking distance and area utilization, while ensuring compliance with work-environment regulations. Unlike previous studies, this method integrates reconfigurable sequencing with resource positioning into full assembly-line optimization, validated in an industrial testbed. The findings show how adaptable layouts improve performance and embed human factors and ergonomics into decision making, supporting Industry 5.0 principles of sustainable, human-centric manufacturing.

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1. Introduction

Industry 5.0 emphasizes a shift towards sustainable, resilient and human-centric manufacturing. Building on the technological foundations of Industry 4.0, this vision highlights the importance of aligning digital solutions with worker well-being, social responsibility and adaptability in production environments. In this context, factory layout planning (FLP) is no longer only a matter of logistics and throughput, but a key factor in achieving a balanced and inclusive production system.

Efficient three-dimensional (3D) layout planning is essential for manufacturing system design, directly influencing productivity, material flow, worker well-being and overall resource utilization (Muther and Hales 2015). Traditional layout planning methods often rely on experience and manual adjustments through iterative trial-and-error approaches, frequently using simplified two-dimensional (2D) representations that fail to capture the complexity of real-world manufacturing environments (Klar *et al.* 2022). This current way of working is time consuming and struggles to balance multiple, often conflicting objectives, such as space utilization, task allocation and manufacturing efficiency.

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FLP has been widely studied, with various methods developed primarily to enhance system efficiency through resource allocation and space utilization. Traditional approaches often rely on heuristic or optimization algorithms to improve material flow and increase production throughput.

Heuristic methods offer practical solutions to FLP, particularly for large or complex problems where finding a provably optimal solution is computationally intractable. These methods often rely on constructive or improvement procedures based on established rules or problem-specific knowledge. For example, Rawabdeh and Tahboub (2006) introduced a heuristic approach for computer-aided facility layout. Their method uses algorithms for calculating minimal rectilinear distances and a modified departmental closeness rating. This approach uses an 'adjacency score' that considers the gradual decrease in the importance of closeness as the distance between departments increases. The objective is to maximize a composite score to balance the qualitative aspect of relationship ratings with the quantitative aspect of minimizing distances. Kung and Chern (2009) developed the heuristic factory planning algorithm, a broader approach to factory planning that integrates layout decisions. A key aspect of their heuristic is the identification and prioritization of bottleneck work centres to guide layout generation. Mansour, Afefy, and Taha (2022) proposed a heuristic-based two-stage approach for cellular manufacturing systems, which integrates cell formation and worker assignment with the layout design problem. In their model, the objective function for the layout stage is to minimize the weighted sum of total intercell and intracell movements, operation costs and defect costs.

Optimization-based methods seek to find optimal or near-optimal solutions by formulating the FLP as a mathematical model and employing various algorithmic techniques. These can be further categorized into classical optimization methods and metaheuristics. Classical optimization methods, such as linear programming and mixed-integer programming, can guarantee optimality if a solution is found. However, their application to real-world FLP is often limited by computational demands. Taghavi and Murat (2011) addressed the integrated facility layout design and flow assignment problem using a nonlinear mixed-integer model. Their primary objective was to minimize the total material handling cost. To solve this, they proposed an iterative heuristic that decomposes the problem into facility layout design and product–machine assignment subproblems.

Metaheuristics have become increasingly popular in FLP owing to their ability to find high-quality solutions for complex, large-scale problems in a reasonable amount of time, without guaranteeing global optimality. Pourvaziri *et al.* (2022) focused on robust facility layout design for flexible manufacturing systems. Their approach aims to mitigate the effects of demand volatility by finding a single robust layout that minimizes the total material handling cost over a planning horizon. They employed a design of experiments approach to identify a critical period, and then a hybridized genetic algorithm–tabu search metaheuristic was used to optimize the layout for that period. Klar, Glatt, and Aurich (2023) conducted a comprehensive performance comparison between reinforcement learning and several common metaheuristics, including genetic algorithms, simulated annealing, tabu search and adaptive large neighbourhood search. Their study explicitly focused on a single-objective optimization problem for FLP, aiming to generate high-quality layout solutions based on one primary criterion (*e.g.* minimizing transportation intensity).

The use of multi-objective optimization (MOO) in layout planning and design has gained attention in recent years. For example, Li *et al.* (2023) focus on minimizing logistics costs and carbon emissions in 2D factory layout optimization, while Yao, Li, and Yang (2023) employ a 2D grid method for construction site layout optimization in prefabricated buildings, aiming to balance safety, hoisting duration and economic efficiency. These studies demonstrate that MOO can be effectively applied in 2D environments to support operationally efficient and sustainable layouts.

Although these studies demonstrate the value of heuristic, metaheuristic and MOO methods for exploring layout alternatives, optimization alone is insufficient for evaluating layout feasibility in human-centric assembly systems. Layout decisions influence not only material flow and area utilization, but also task execution, walking distance, reachability and worker well-being. Therefore, optimization-based layout generation must be coupled with simulation-based evaluation methods that can capture the operational and ergonomic consequences of candidate layouts.

A fundamental challenge in FLP is the lack of integration between process planning and resource arrangement. FLP is inherently a MOO problem, where layout proposals represent trade-offs among space utilization, production throughput, material flow efficiency, bottleneck reduction and worker well-being. In reality, the process description and resource arrangement are interdependent; the factory set-up influences the process execution and *vice versa*. However, existing approaches often assume static process descriptions, limiting their adaptability to dynamic manufacturing environments where process flexibility is essential.

A common approach for testing throughput capacity is the use of discrete event simulation (DES) tools, which model manufacturing processes based on predefined task times. While effective for high-level system insights, DES does not inherently account for dynamic spatial constraints, human interactions or real task execution (Klar *et al.* 2024). The task durations are directly affected by workstation configurations, walking distances, material accessibility and worker well-being considerations. Consequently, task durations in DES models are often estimated without accounting for real-world variations due to layout constraints.

At the same time, the role of human factors and ergonomics (HFE) in layout planning has gained increasing attention, particularly through the use of digital human modelling (DHM) tools. These tools enable worker well-being assessments by simulating interactions within a virtual environment. However, their application in large-scale factory layouts remains limited (Dul *et al.* 2012). Previous research has explored worker well-being within work cell design (Hanson *et al.* 2019), but comprehensive approaches that embed HFE into full-factory optimization are still scarce. While hierarchical or cell-based FLP approaches have been proposed in previous work, they typically rely on predefined clusters of interdependent resources or functional areas. In contrast, the modular optimization strategy presented in this study does not assume any fixed grouping of resources. Instead, it operates on bill of process (BOP)-derived task-to-station assignments, where each station is optimized in isolation and later recombined using a validated compatibility logic. This avoids the need for top–down decomposition and allows flexible, bottom–up layout generation.

Despite advances in MOO and simulation techniques, few studies have considered process sequencing as a dynamic input to layout design (Klar *et al.* 2024; Xu, Xu, and Su 2024). Current models largely focus on predefined process flows and fixed task times, overlooking the bidirectional dependency between task execution and layout configuration. Furthermore, human-centric performance indicators, such as walking distance, workload distribution and ergonomic scores, are often excluded. In particular, work by Klar *et al.* (2024) uses reinforcement learning to address factory layout optimization. While their methods are notable for integrating simulation-based evaluation, they operate on fixed process descriptions and do not incorporate worker well-being assessment through DHM. Moreover, their monolithic optimization structures do not allow for station-wise decomposition or modular recombination. In contrast, the approach proposed in this research treats process sequencing as a reconfigurable input, integrates 3D spatial and ergonomic validation, and applies multi-objective evolutionary optimization on the station level, offering greater flexibility and industrial applicability.

Factory layout optimization requires a careful balance between system performance (throughput, capacity and efficiency) and worker well-being (safety, comfort and adherence to regulations). Too often, investment decisions emphasize operational efficiency without sufficient consideration of the impacts on worker safety, system performance and regulatory compliance. This approach can lead to risks, inefficiencies and potential non-compliance with safety standards, resulting in costly redesigns and potential harm to employees.

There is a clear need for a layout planning approach that can adapt task distribution and resource requirements based on spatial constraints, while also integrating human factors into the evaluation. Addressing this gap requires a method that links process flexibility with ergonomic considerations in a structured optimization framework.

In this study, reconfigurable process sequencing is limited to the generation of alternative process sequences and task-to-station allocations that remain feasible under the predefined directed acyclic graph (DAG)-based precedence constraints. It does not refer to unrestricted restructuring

Table 1. Comparison between prior factory layout planning (FLP) approaches and the proposed framework.

Approach	Decision variables	Constraints	Objectives	Validation/main gap addressed
Heuristic/classical FLP (Kung and Chern 2009; Mansour, Afefy, and Taha 2022; Rawabdeh and Tahboub 2006; Taghavi and Murat 2011)	Facility/resource allocation	Mainly 2D spatial constraints	Material flow and handling cost	Analytical or simplified layout checks; fixed/simplified process and layout assumptions
Metaheuristic/MOO FLP (Klar, Glatt, and Aurich 2023; Li *et al.* 2023; Pourvaziri *et al.* 2022; Xu, Xu, and Su 2024; Yao, Li, and Yang 2023)	Resource positions/layout alternatives	Mainly 2D spatial constraints	Cost, flow, emissions and safety	Optimization-based evaluation; mostly 2D or fixed-process layout optimization
Simulation/RL-based FLP (Klar *et al.* 2024; Klar, Glatt, and Aurich 2023)	Resource positions/layout alternatives	Fixed process and simulation constraints	Layout performance metrics	Simulation-based validation, but with fixed process descriptions
Previous DHM-based layout work (Lind *et al.* 2023; Lind, Iriondo Pascual *et al.* 2024; Lind, Elango, *et al.* 2024)	Resource positions and layout parameters	3D spatial and ergonomic constraints	Walking distance, worker well-being and area use	DHM-based validation, but no dynamic BOP generation with station-wise recombination
Proposed framework	Process sequence, task-to-station allocation and resource-layout parameters	Precedence, 3D spatial, collision, reachability, clearance and regulatory constraints	Walking distance, worker well-being and material façade utilization	Integrated process-sequence generation, resource-layout optimization, digital human validation and convergence analysis

Note: MOO = multi-objective optimization; RL = reinforcement learning; 2D = two-dimensional; 3D = three-dimensional; DHM = digital human modelling; BOP = bill of process.

of the assembly process, changes in task content or addition/removal of operations. Rather, the method explores how precedence-feasible process-sequence alternatives affect station-level resource requirements, layout feasibility and human-centric performance.

To make the boundary between the present study and prior work more explicit, Table 1 summarizes representative streams of FLP literature in terms of decision variables, constraints, objectives and validation procedures.

Table 1 shows that the novelty of the present study does not lie in the isolated use of evolutionary optimization, DHM or simulation-based evaluation. Rather, the contribution lies in combining precedence-constrained process-sequence generation, station allocation, station-level resource-layout decision variables, 3D spatial and ergonomic validation, modular recombination and convergence assessment within one workflow.

1.1. Objective of the research

Previous work has explored several steps towards simulation-based and human-centric FLP. These include (1) the integration of safety regulations and planning rules for equipment and resources in industrial contexts (Lind *et al.* 2023); (2) early applications of permutation-based MOO in a logistics-oriented case (Lind, Iriondo Pascual *et al.* 2024); (3) the expansion of decision variables to continuous placement areas in a real battery assembly case; and (4) comparative studies of metaheuristics in an industrial testbed (Lind, Elango *et al.* 2024). Together, these studies demonstrated the feasibility of combining optimization and digital simulation, while also highlighting the limitations of simplified formulations. Building on this progression, the present study advances to full assembly-line optimization, where the process sequence is treated as a reconfigurable input alongside resource positioning, enabling a richer decision space and broader exploration of feasible factory layouts.

The primary objective of this research is to develop and demonstrate an approach that integrates process descriptions as an adaptive input to FLP and design. Unlike conventional methods that assume fixed process sequences, this study introduces a dynamic approach to 3D factory layout optimization that:

- Enables flexible task allocation by adjusting the number of stations and assigning tasks from an assembly list while following a critical sequence; the approach also considers reordering tasks that allow flexibility and subsequently defines the resource needs of the proposed sequence while accounting for spatial constraints.
- Integrates human factors and ergonomics into MOO through simulations with layout and DHM modules, allowing the decision maker to evaluate worker well-being, walking distance, throughput, area requirements and resource utilization.

By addressing these objectives, this research advances human-centric and sustainable manufacturing in alignment with Industry 5.0 principles, providing a structured approach to balance efficiency, worker well-being and spatial constraints in FLP. In doing so, this study contributes to advancing sustainable and adaptive factory systems, where both performance and human well-being are integral to layout decisions.

2. Problem description

Modern FLP faces significant challenges in environments that demand flexibility, efficiency and consideration of human well-being. Traditional approaches often assume static process sequences and predefined resource arrangements, which limits adaptability in dynamic manufacturing settings. In practice, the execution of production processes is tightly coupled with spatial constraints and task allocation strategies, yet most existing methods fail to capture this interdependence.

This section outlines the core problem addressed in this study: how to generate and evaluate feasible layout configurations when both the process sequence and the spatial arrangement of resources must be dynamically adapted. The focus is on understanding the implications of reconfigurable process descriptions, modelled as precedence-constrained task networks, and their influence on station-level task allocation, worker well-being and overall system performance.

2.1. The pedal car and its assembly process

A pedal car was used in this study to demonstrate the FLP and design process. The description of the assembly process of the pedal car is referred to as the bill of process (BOP). A BOP is a structured representation of the tasks required to realize a product, including assembly operations, part retrievals and tool interactions. In this work, the term 'process sequence' is used to denote the BOP-defined order of assembly and retrieval tasks that satisfies the DAG precedence constraints. The BOP is reconfigurable and can vary both in process sequence and in the allocation of tasks to stations. However, all task sequences are subject to precedence constraints, which are modelled as a DAG to ensure that task dependencies are respected. The overall precedence structure used in this study is illustrated in Figure 1.

This precedence structure represents all possible paths to realize the end result of assembling the product, which in this case is a pedal car. Although the DAG in Figure 1 illustrates the task dependencies, it does not capture the full complexity of how these tasks can be distributed across different station configurations. In this study, each BOP variant is generated by splitting the process across two to 19 stations, while still complying with all precedence constraints.

Each generated BOP contains detailed information, including:

- the part or handheld tool involved in each task step (*e.g.* article identifiers, tool requirements)
- the required resources (*e.g.* specific racks or storage units where parts or tools are initially placed)

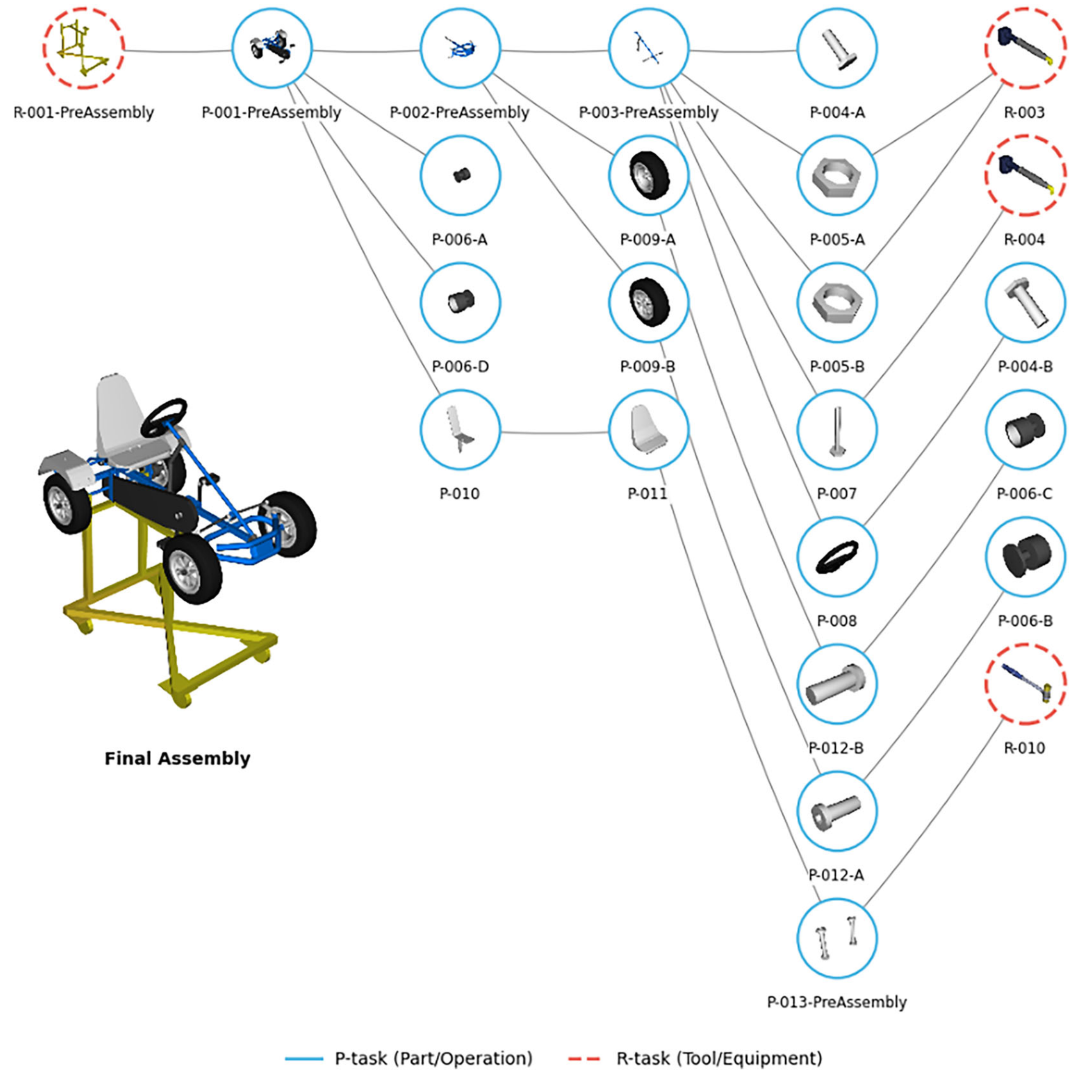

Figure 1. Directed acyclic graph (DAG) representation of task precedence constraints, including both part operations (P-tasks) and required tool interactions (R-tasks).

- the associated activities to be simulated (*e.g.* walking, grasping, placement and assembly operations)
- the assigned worker (represented by a digital manikin with defined anthropometrics)
- the station to which the task is allocated (*e.g.* Station 1, Station 2, *etc.*)

These BOP attributes are not all treated as independent optimization variables. Instead, they are extracted and used at different stages of the workflow. The process sequence and station allocation define the BOP variant and determine which tasks are performed at each station. The part and tool information is used to identify the required resources and to load the corresponding 3D geometries in the simulation environment. The required-resource attribute is then transformed into a station-specific resource list, which defines the set of racks, tools and storage units that must be positioned in the bill of resources (BOR). The associated activities define the simulated operator actions, such as walking, grasping, picking, placing and assembly motions, and are used by Industrial Path Solutions

(IPS) software with Intelligently Moving Manikins (IMMA) to generate motion and extract objective values. The assigned-worker information defines the digital manikin used in the simulation.

Thus, the optimization does not simplify the BOP into a single sequence variable; rather, the BOP acts as a structured input that determines resource requirements, station boundaries, simulation activities and the candidate BOR decision space. To explore the space of valid BOP configurations, Monte Carlo sampling is used. Monte Carlo methods are well established for exploring high-dimensional solution spaces through random sampling and statistical inference (Rubinstein and Kroese 2017). A large number of BOP variants is randomly generated based on the predefined DAG structure. Each BOP respects all precedence constraints and defines a specific task-to-station assignment across a chosen number of stations (ranging from two to 19). Duplicated BOPs are filtered out during each sampling run. The sampling is repeated across multiple sample sizes (*e.g.* 500, 1000, 5000 ...) to estimate the size of the solution space of BOP solutions. During each run, a hash function is used to identify duplicate solutions and ensure that only structurally unique BOPs are retained.

The pedal car assembly line used in this study exists as a physical testbed at Scania's production site in Södertälje, Sweden. The layout currently in use was originally developed using conventional planning practices, relying on expert judgement and experience-based decision making by layout planners. This industrial set-up provides a realistic foundation for both process description and spatial constraints, and enables the simulation-based results to be benchmarked against an expert-designed baseline layout. Notably, the process structure (BOP) of this expert-designed layout is identical to one of the 24 reconfigurable BOP variants generated through the Monte Carlo sampling procedure.

3. Proposed methodology

This section describes the methodology approach used to develop, simulate and evaluate reconfigurable factory layouts under varying process configurations. The proposed approach combines Monte Carlo sampling of precedence-constrained task sequences, which together define the process sequence, 3D resource layout generation, and simulation-based MOO with DHM.

To improve traceability, the proposed methodology can be understood as a sequential data flow from process-level modelling to virtual layout evaluation. First, the DAG defines the feasible precedence-constrained task sequences. These sequences are sampled into BOP variants, where each BOP specifies both the task order and the allocation of tasks to stations. The station allocation then determines the station-specific resource requirements, which are translated into BOR decision variables such as resource position, orientation and rack-specific configuration parameters. Each generated BOR candidate is constrained by the corresponding BLOCK_LAYOUT and is validated against geometric and simulation-based constraints, including station boundaries, collision avoidance, front clearance and reachability. Only valid BOR candidates are simulated in IPS IMMA, where the walking distance, Ovako Working Posture Analysis System (OWAS)–Lundqvist index, throughput and material façade utilization are extracted.

These objective values are then used either to rank BOP alternatives using a composite performance index (CPI), described in Section 3.3, or to guide the non-dominated sorting genetic algorithm-II (NSGA-II) evolutionary update for the selected BOP.

3.1. Simulation-based MOO workflow

The entire schematic workflow of the MOO approach is illustrated in Figure 2. To improve the clarity and reproducibility of the proposed workflow, a simplified pseudo-code is presented here. This outlines the main computational steps in the simulation-based MOO approach.

Among the extracted objective values (Step 8) is the worker well-being score, based on the OWAS–Lundqvist index. This index integrates the OWAS (Karhu, Kansi, and Kuorinka 1977) with the Lundqvist Index (Lundqvist 1988), enabling a quantitative assessment and categorization of

(1) **Input:** Define the assembly process using a directed acyclic graph (DAG), representing the bill of process (BOP) with all required precedence constraints.
(2) **BOP sampling:** Apply Monte Carlo sampling to generate a set of feasible BOP variants (task-to-station mappings), ensuring precedence constraints are respected. This step corresponds to the left section in Figure 2.
(3) **Environment preparation for each BOP variant:**
   - Step 1: Import the BOP structure into the digital human modelling (DHM) tool (IPS IMMA), which loads the corresponding 3D geometry.
   - Step 2: Use the BOP station allocation, part/tool information and required-resource attributes to distribute the loaded geometry into stations and derive spatial constraints per station, including:
     - Product space
     - Worker positioning space
     - Material façade space

     These constraints are defined in 3D and comply with Swedish Work Environment Authority regulations (AFS 2020:1).
   - Step 3: Export the spatial constraints as BLOCK_LAYOUT.json to define valid resource placement boundaries.
(4) **BOR generation:** For each BOP, propose resource positions (bill of resources, BOR) using either of the following:
   - Step 4A: Random sampling within each station's block layout.
   - Step 4B: NSGA-II optimization, initialized using random samples, to refine BOR proposals while respecting the spatial boundaries of each station's block layout.
(5) **Simulation and validation of each BOR proposal**:
   - Step 5: Load the BOR configuration into the DHM environment and apply proposed resource positions.
   - Step 6: Perform automated validation, checking for:
     - Collision checks (*e.g.* rack-to-rack, rack-to-worker)
     - Compliance with front clearance and reachability requirements
   - Step 7: For valid solutions, execute simulation and extract objective values otherwise assign 'inf' to all objectives to ensure penalization in the minimization problem.
(6) **Store results**:
   - Step 8: Store all solutions with structured outputs, including:
     - INPUT_BOP.json – process sequence, station allocation, resource requirements, activities, and worker assignment
     - BLOCK_LAYOUT.json – spatial boundaries
     - INPUT_BOR.json – resource positions
     - OBJ_VALUES.json – extracted objective values

     Each solution is evaluated based on:
     - Productivity (walking distance)
     - Worker well-being (OWAS–Lundqvist index)
     - Area efficiency (material façade usage)

worker well-being load based on working postures. Each BOP structure is thus tested through multiple layout configurations (Steps 4–6), with the results stored and used for optimization. This set-up allows systematic performance analysis across BOP variants and facilitates the selection of high-performing candidates for further optimization.

Each BOP structure is then evaluated through multiple layout configurations, referred to as the BOR, using a two-stage approach. First, random sampling (Step 4A in Figure 2) is applied to broadly explore the solution space and identify a diverse set of valid and promising layout configurations. These solutions serve as the initial population for the subsequent MOO step using NSGA-II (Step 4B in Figure 2). This evolutionary algorithm refines the search and approximates the Pareto front by iteratively selecting, recombining and mutating candidate solutions.

To make the transformation from process-level information to layout-level evaluation more explicit, Table 2 summarizes the main methodological stages, the corresponding input transformations, geometric and simulation-based validation steps and outputs.

3.2. Simulation tool

To execute the simulations and calculate objective values, this study uses the software Industrial Path Solutions (IPS) (Göteborg, Sweden, https://industrialpathsolutions.se, accessed on 14 January 2025), together with its DHM module, Intelligently Moving Manikins (IMMA) (Hanson *et al.* 2019), developed by IPS AB. All simulations were conducted using the 2024 release (release 2) of the software.

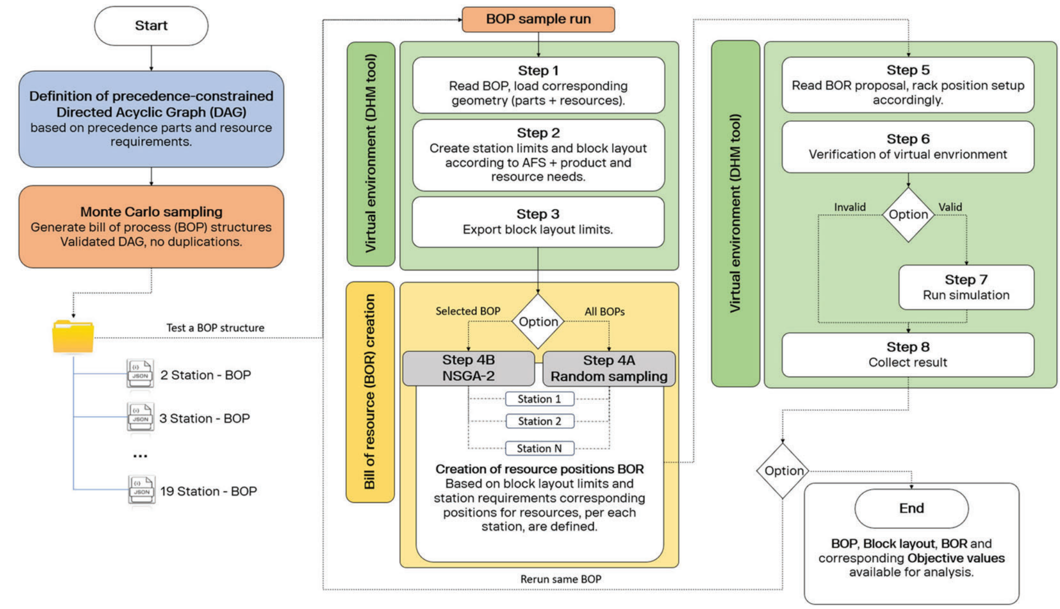

Figure 2. Overview of the proposed simulation-based multi-objective factory layout optimization workflow.

IPS provides an API in the LUA scripting language (Ierusalimschy 2006), which was used to develop custom scripts for automating setting up the layout configurations and simulation process. These scripts manage the exchange of data through JSON files, set up the virtual environment, execute simulations and extract resulting objective values.

In addition, a Python-based program was developed to run the random sampling algorithm and NSGA-II, an evolutionary algorithm commonly used for solving MOO problems (Deb *et al.* 2002). This Python program is responsible for proposing BOR variants, *i.e.* resource positions, while the LUA scripts ensure that these variants are properly loaded, validated and simulated within the IPS environment.

The integration between Python and IPS via JSON files enables automated data exchange between layout generation, simulation and optimization processes. This set-up creates a seamless workflow where IPS handles geometry management, spatial validation, collision detection and compliance checks, while Python manages sampling logic, optimization routines and post-simulation performance analysis.

The spatial constraints and validation routines were defined in collaboration with industrial experts to reflect realistic planning scenarios in final assembly lines.

NSGA-II is used after the initial population of valid solutions has been generated through random sampling. It is then employed to refine the search space and identify Pareto-optimal layout solutions across multiple objectives.

NSGA-II was configured as follows: population size = 200, offspring size = 200, tournament size = 2, crossover probability = 0.8 and mutation probability = 0.01. Simulated binary crossover (SBX) with distribution index $\eta_a = 1$ was used for recombination, while polynomial mutation with distribution index $\eta_m = 20$ was used for perturbation. The number of generations was set dynamically, and the algorithm ran until the hypervolume indicator plateaued. Pareto ranking and crowding distance were used for selection and elitism, following the standard NSGA-II scheme (Deb *et al.* 2002).

On average, 15–25% of offspring generated per NSGA-II generation were rejected during this validation step owing to violations of geometric spatial constraints, collision detection or compliance checks. To maintain compatibility with the optimization framework, these invalid solutions were assigned objective values of 'inf', ensuring that they were automatically ranked poorly in the minimization problem and excluded from selection in subsequent generations.

Table 2. Traceability of methodological stages from bill of process (BOP) generation to bill of resources (BOR) decision variables, geometric and simulation-based validation, and objective outputs.

Stage	Input/transformation	Main constraints/validation checks	Output
BOP generation	DAG is sampled into feasible task sequences that define the process sequence and station allocations	Precedence constraints	BOP variants
Resource derivation	Each BOP defines station-specific operations and required resources	Task-to-station assignment	Resource list per station
Block layout generation	Product, worker, and material façade spaces are generated from 3D geometry	Spatial and regulatory requirements	Station-specific placement boundaries
BOR generation	Required resources are translated into layout variables: position, orientation and rack configuration	Placement limits and rack-specific bounds	Candidate BOR layouts
Feasibility validation	BOR candidates are checked before simulation	Boundary, collision, front-clearance and reachability constraints	Valid or invalid BOR candidates
DHM simulation	Valid BORs are simulated in IPS IMMA	Simulation feasibility	Walking distance, OWAS–Lundqvist index, throughput and façade utilization
Optimization/selection	Objective values are used for CPI-based BOP ranking or NSGA-II update	Invalid candidates are penalized	Ranked BOPs or next generation

Note: DHM = digital human modelling; DAG = directed acyclic graph; 3D = three-dimensional; IPS = Industrial Path Solutions; IMMA = Intelligently Moving Manikins; CPI = composite performance index; NSGA-II = non-dominated sorting genetic algorithm; OWAS = Ovako Working Posture Analysis System.

The collision validation is handled using IPS's built-in geometry engine, which applies bounding-box approximations with a 5 mm tolerance margin. Overlaps between racks or between racks and factory boundaries automatically trigger rejection. Front clearance is checked by requiring at least 0.8 m of free space in front of each pick face, and reachability is verified based on the manikin's kinematic constraints. All of these checks are implemented *via* LUA scripting and applied uniformly across BOR simulations, ensuring consistent enforcement of spatial constraints throughout the optimization process.

3.3. Evaluation and BOP selection strategy

Throughput was excluded as an explicit optimization objective because it was highly correlated with walking distance (Figure 3); including it would not change the Pareto set.

As mentioned in Section 3.1, each valid simulation run generates a complete layout solution, comprising four key files: INPUT_BOP.json, BLOCK_LAYOUT.json, INPUT_BOR.json and OBJ_VALUES.json. These outputs represent a specific combination of task sequence, station layout, resource placement and resulting performance metrics. Owing to spatial constraints, regulatory rules and collision detection enforced by the virtual environment, not all configurations are valid. Consequently, a large number of layout candidates must be explored to identify feasible solutions.

In this study, each BOP was allowed to generate up to 100 valid layout solutions using random sampling. Each solution (BOR) was a complete configuration including all stations. No recombination was performed during sampling.

The Monte Carlo BOP sampling procedure was constrained by the predefined DAG. For each sampled BOP, tasks were assigned to a selected number of stations while preserving all predecessor–successor relationships. A BOP was accepted only if all tasks were assigned exactly once, all

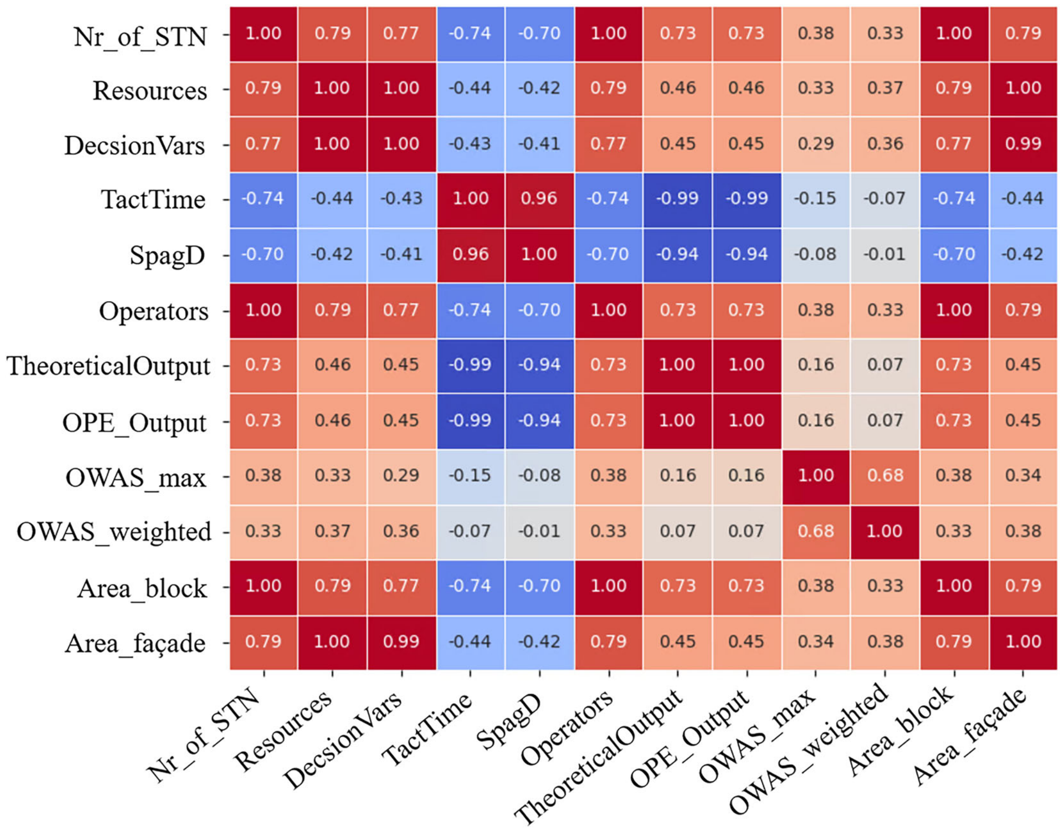

Figure 3. Heatmap of correlation coefficients ($|r| \geq 0.7$) across layout performance metrics for all bills of process (BOPs). The selected composite performance index (CPI) indicators span three distinct domains: productivity, worker well-being and area utilization.

precedence constraints were satisfied and each station contained a non-empty task set. To avoid duplicate BOP variants, each generated BOP was converted into a canonical representation based on the ordered task-to-station assignment and hashed. If the same hash value had already been observed, the BOP was discarded and a new sample was generated. This ensured that only structurally unique BOP variants were retained for subsequent BOR generation.

For one selected BOP, however, the 100 full-line layouts were post-processed to extract station-level solutions. These were then freely recombined across stations within the same BOP, as they shared identical task allocations and block layout constraints. This modular recombination enabled independent station-wise optimization and flexible assembly of new complete layouts. This approach ensured broad coverage of the solution space and increased the likelihood of capturing high-performing layout alternatives. After this exploratory phase, a post-processing procedure was applied to identify the best observed screening result for each BOP based on the selected evaluation objectives. When evaluating layout configurations, any combination of station-level solutions can be assembled into a complete BOR structure, as long as they belong to the same BOP variant. This modular structure enables flexible recombination of stations across generations and allows independent optimization of each station while maintaining global feasibility. Such combinability significantly increases the size of the search space and supports scalable parallelism during both random sampling and evolutionary optimization.

Station-level recombination was only performed within the same BOP variant. Recombined stations therefore shared the same task-to-station allocation, required-resource lists and block-layout definitions, and the resulting full-line BOR was accepted only after the same geometric validation checks had been applied.

This screening result was determined based on performance across multiple evaluation objectives:

- minimum walking distance
- weighted OWAS–Lundqvist index (worker well-being score)
- material façade utilization.

Walking distance was selected as the optimization objective for productivity measures, since it directly influences throughput. Throughput was extracted from the simulations and reported as a performance measure, but was not optimized as a separate objective. For each BOP, the CPI-based screening result was used to represent the best observed trade-off among the selected objectives: walking distance, OWAS–Lundqvist index and material façade utilization. Since the screening step may rely on independently selected station-level results, this value should be interpreted as a comparative BOP-screening score rather than as a claim of global optimality. The selected BOP was then carried forward to the NSGA-II phase, where complete BOR configurations were recombined, geometrically validated, simulated and evaluated at line level.

To facilitate structured cross-comparison between all BOP variants, the CPI was computed by aggregating three globally normalized objectives: total walking distance (reflecting line productivity), weighted OWAS–Lundqvist index (indicating worker well-being) and façade utilization (representing area efficiency). The CPI served as a consistent ranking metric, enabling identification of the most promising BOP configuration (one BOP was selected), which was subsequently refined using NSGA-II.

Each of the three objectives was normalized using min–max scaling across all valid BOR solutions from all BOPs. Specifically, for each objective, the global minimum and maximum values were determined across the entire dataset. Individual values were then transformed to a normalized [0, 1] scale using the formula:

$$\text{normalized\_value} = (\text{value}-\text{min})/(\text{max}-\text{min})$$

The final CPI was calculated as the unweighted sum of the three normalized values:

$$\text{CPI} = \text{norm\_spagd} + \text{norm\_owasl\_index} + \text{norm\_façade}$$

The same global normalization bounds were used for all BOP variants to ensure comparability, and infeasible layouts were excluded from the CPI-based selection. This formulation ensured the equal contribution of each objective to the final index and enabled fair comparison across BOPs. Lower CPI values indicate more favourable trade-offs among productivity, ergonomics and spatial efficiency.

The OWAS–Lundqvist index is a dimensionless score that combines posture frequency and severity levels into a single indicator of worker well-being. In this study, the index is extracted for each BOR simulation and normalized using min–max scaling based on the full set of valid BOR solutions generated from 100 simulations across all 24 feasible BOP configurations. No fixed thresholds are applied; instead, the values are interpreted relative to the best and worst worker well-being outcomes observed in the full solution space. This approach ensures that worker well-being performance is consistently integrated into the composite index without relying on externally defined risk boundaries.

The use of equal weighting for the three normalized objectives in the CPI was selected to provide a neutral and transparent ranking across BOP configurations. Each objective captures a distinct physical dimension, productivity (walking distance), worker well-being (OWAS–Lundqvist index) and area efficiency (façade usage), and was normalized globally across all solutions. As such, no single indicator is inherently dominant, and equal weighting ensures that the ranking does not impose implicit bias towards any one objective. This strategy enables fair comparison and preserves interpretability in the absence of predefined stakeholder preferences.

In practice, the spaghetti diagram (walking) length, OWAS–Lundqvist index and material façade utilization are evaluated at the station level. The final layout is then constructed by combining selected station-level solutions into a full BOR configuration that satisfies the spatial constraints and station boundaries. This modular assembly decomposes the global optimization problem into smaller subproblems. These subproblems can be solved in parallel and recombined into feasible factory layouts, guided by the CPI.

In practical industrial applications, CPI weights do not need to be fixed *a priori* or selected by the researchers alone. Instead, they can be determined jointly by managers, process planners, ergonomists and experts on human factors according to the specific production priorities of the case. For example, a ramp-up scenario may emphasize productivity and walking distance, whereas a workplace redesign driven by ergonomic concerns may assign greater weight to the OWAS–Lundqvist index. The CPI should therefore be interpreted as a transparent decision-support metric whose weighting structure can be adapted to stakeholder priorities rather than as a universal fixed ranking criterion.

Because stations are only recombined within the same BOP and all resources are strictly assigned to individual stations, no resource-sharing conflicts can occur during modular layout assembly. The consistency in task-to-station allocation and identical block layout constraints across stations ensures that recombined layouts are conflict free and geometrically valid by design.

3.4. Offspring generation and evolutionary loop

In the NSGA-II phase, valid BOR solutions from the random sampling phase are used as the initial population P(0). The algorithm uses the same configuration of parameters described in Section 3.2, including population size, crossover and mutation probabilities, and distribution indices for SBX and polynomial mutation. Successive generations [*e.g.* P(1), P(2)] are created using tournament selection, SBX and polynomial mutation. These genetic operators, standard in NSGA-II, are applied at the rack level, modifying x/y positions, rotation around the rack's z-axis (rz) and shelf heights, while preserving rack identity and structural constraints.

To ensure geometric feasibility, each generated offspring undergoes a validation stage in Python before being submitted for simulation in IPS. This validation includes checks for spatial limits (block layout boundaries), interrack overlap, front clearance (ensuring worker accessibility) and rack-specific shelf height constraints. Only offspring passing all checks are exported as complete BOR files and passed to the DHM simulation. Invalid offspring are penalized by assigning infinite objective values, thereby preventing them from being selected for subsequent generations.

The population size per station was determined based on the dimensionality of the corresponding decision space, *i.e.* the number of decision variables associated with rack positioning and shelf configuration in each station. Since stations vary in complexity, the population size was aligned with the most complex station to ensure adequate search capacity and avoid premature convergence. This follows standard recommendations in evolutionary optimization, where population sizes are typically scaled relative to the number of decision variables, according to rule of thumb, 10–20 times the number of decision variables (Deb *et al.* 2002).

The files generated in each population P(X) and its corresponding offspring Q(X) are stored in a structured folder hierarchy. This ensures traceability and controlled evolution of candidate solutions. Offspring generated for each station can be recombined across the complete line, allowing full BOR structures to be constructed from independently optimized station-level solutions. The evolutionary loop therefore refines layout configurations while preserving diversity and enforcing geometric feasibility across the non-dominated front.

To assess convergence, the hypervolume indicator (Zitzler *et al.* 2003) is computed after each generation P(X), corresponding to the saved population folders [*e.g.* P(1), P(2), ...]. For each P(X), the non-dominated front is obtained using raw objective values, and the hypervolume is calculated with respect to a fixed reference point in the objective space. A stable or plateauing hypervolume over consecutive generations is used as a practical indicator that the optimization process has converged.

To enable meaningful hypervolume comparison across generations, all objective values used in hypervolume and spacing calculations were normalized using fixed bounds derived from the non-dominated solutions in P(0), P(1) and P(2). This approach ensures a consistent reference frame for evaluating convergence and visualizing the evolution of the Pareto front.

3.5. Summary of the optimization framework

The proposed method combines dynamic process modelling, simulation-based evaluation and evolutionary optimization to support adaptive factory layout design. By integrating Monte Carlo sampling, NSGA-II and DHM-based simulation, the approach explores and refines layout solutions across spatial, operational and ergonomic dimensions. This integrated framework enables informed design decisions that balance performance, compliance and human well-being, in alignment with Industry 5.0 principles.

4. Results

4.1. Monte Carlo sampling of BOPs

Although the Monte Carlo search yielded structurally valid BOPs across a wide range of station counts (from two to 19 stations), only BOPs with three and four stations were physically feasible within the available Scania testbed footprint and were therefore retained for layout optimization.

- The BOPs with a two-station set-up always resulted in infeasible layouts owing to lack of space in the corresponding material façade requirements, *i.e.* violations of spatial requirements for the racks.
- BOPs above four stations exceeded the spatial footprint of the available factory layout, requiring more than 45 m^2 in total area, whereas the maximum permitted was 43 m^2.

Therefore, the final evaluation and optimization were conducted using the physically feasible subset of 24 BOPs: eight BOPs with three-station and 16 BOPs with four-station set-ups.

4.2. BOP selection based on CPI

To enable a consistent and interpretable ranking of BOP configurations, the screening performance of each BOP was first estimated based on random sampling. Specifically, 100 full-line layout proposals were generated for each BOP. For each of the three evaluation objectives, spaghetti diagram length, weighted OWAS–Lundqvist index and material façade utilization, the best performing station-level result was identified independently. These station-level values were then combined into a hypothetical reference for the entire line. Although such a combination of stations may not correspond to any realizable layout, it served as a benchmark for relative performance evaluation within each BOP.

Each layout was then evaluated using the previously defined CPI. The CPI summarizes layout quality as the sum of globally normalized values for the three selected objectives. Lower CPI values indicate better combined performance in terms of productivity, ergonomics and space efficiency.

Since no public benchmarks exist for 3D human-centric FLP, the proposed approach is benchmarked against two meaningful references: (1) the expert-designed layout currently in industrial use; and (2) stochastic sampling of 24 feasible BOPs with 100 layouts each. Together, these represent both state-of-practice and a neutral baseline of feasible process configurations.

To more explicitly isolate the contribution of process reconfigurability, the BOP corresponding to the existing expert-designed layout, 3STN-BOP_9, was treated as a fixed-process baseline. This baseline preserves the existing process sequence and task-to-station allocation, while still allowing resource placement to vary through the same stochastic BOR generation procedure used for the other BOPs. The comparison therefore separates the effect of expert-designed layout planning, automated

Table 3. Weight-sensitivity analysis of the composite performance index (CPI) used for bill of process (BOP) screening.

Approximate walking distance weight (%)	Approximate worker well-being weight (%) (OWAS–Lundqvist index)	Approximate area utilization weight (%)	Top-ranked BOP	CPI score
33	33	33	3STN-BOP_1	0.629
50	25	25	3STN-BOP_1	0.643
25	50	25	3STN-BOP_8	0.771
25	25	50	3STN-BOP_1	0.471
20	20	60	3STN-BOP_1	0.377
20	60	20	3STN-BOP_8	0.857
60	20	20	3STN-BOP_1	0.651
20	40	40	3STN-BOP_1	0.617
40	20	40	3STN-BOP_1	0.514
40	40	20	3STN-BOP_1	0.754

Note: OWAS = Ovako Working Posture Analysis System.

layout generation under a fixed BOP, reconfigurable BOP screening and the subsequent NSGA-II-based layout refinement.

To validate the use of these three objectives as independent performance dimensions, a correlation analysis was performed across all sampled layouts.

As expected, throughput was strongly correlated with walking distance, confirming its role as a derived performance measure rather than an independent optimization objective. Figure 3 further illustrates that the selected objectives span three weakly correlated domains, supporting their combined use in a composite score. In total, 24 BOP configurations were evaluated, each with 100 valid layout proposals. For each BOP, the layout with the lowest CPI was selected as its representative. Among all candidates, the configuration 3STN-BOP_1 achieved the lowest CPI-based screening score of 0.629, making it the top-ranked BOP under the equal-weight CPI decision model. This BOP was therefore selected for further optimization using NSGA-II.

The top three ranked BOPs based on CPI were: (1) 3STN-BOP_1 (CPI = 0.629); (2) 3STN-BOP_8 (CPI = 0.803); and (3) 4STN-BOP_5 (CPI = 1.234).

To assess whether the BOP selection was sensitive to the equal-weighting assumption, an extended weight-sensitivity analysis was performed. In addition to the equal-weight CPI, nine alternative weighting schemes were evaluated by assigning increased or reduced emphasis to productivity, worker well-being and area efficiency. To maintain consistency with the CPI definition used for BOP screening, the weighted CPI was calculated on the same sum-based scale as the original CPI.

As shown in Table 3, 3STN-BOP_1 remained the top-ranked configuration in eight of the 10 tested weighting schemes. The only cases in which another configuration became top ranked were the worker-well-being-focused scenarios, where 3STN-BOP_8 achieved the lowest CPI score. This indicates that 3STN-BOP_1 is robustly among the highest performing BOPs across a broad range of weighting assumptions, while also showing that strong prioritization of worker well-being may influence the final BOP selection.

Among the 24 evaluated BOPs, one configuration, 3STN-BOP_9, corresponds to the process structure of the actual testbed layout currently implemented at Scania, which was designed through conventional planning practices. This confirms that the expert-designed solution is captured within the sampled BOP space. However, this configuration did not rank among the top performers in terms of CPI, nor did it become top ranked under any of the tested weighting schemes. Instead, 3STN-BOP_1 achieved the lowest equal-weight CPI-based screening score and was therefore selected for further optimization using NSGA-II. This selection reflects the ability of the proposed framework to identify layout configurations with higher potential for improved productivity, worker well-being performance and space utilization than the existing expert-based baseline.

4.3. NSGA-II configuration and performance evaluation

To refine layout configurations for the selected BOP (3STN-BOP_1), a station-wise implementation of NSGA-II was performed. Each station was treated as an independent optimization problem, where decision variables included rack positions, orientations and shelf configurations. The most complex station, Station 1, involved 20 decision variables. Following standard recommendations for evolutionary algorithms (Deb *et al.* 2002), a population size of 200 individuals per station was chosen and maintained across all generations. Each generation P(X) produced 200 offspring Q(X) using SBX, polynomial mutation and tournament selection.

The computational cost of the evolutionary phase is primarily determined by the number of candidate BOR evaluations and the time required for DHM simulation. In the initial BOP-screening phase, 100 full-line BOR/layout solutions were generated for each of the 24 feasible BOPs, resulting in 2400 randomly sampled full-line layout evaluations used for CPI-based BOP selection. In the present implementation, one feasible full-line DHM simulation required approximately 15–25 min per complete BOP/BOR layout solution, including all stations in the line. The selected BOP, 3STN-BOP_1, was then further optimized using NSGA-II. In this phase, each station involved 4200 candidate solution tests, consisting of an initial population of 200 solutions and 4000 offspring evaluations over 20 generations. For the selected three-station BOP, this corresponds to 12,600 station-level candidate solution tests before final line-level recombination and validation. If executed sequentially on a single workstation, such a set-up would therefore be computationally prohibitive for larger scale cases. However, the evaluation of candidate solutions within a generation is naturally parallelizable, since each candidate BOR or station-level BOR segment can be simulated independently once generated. Thus, population evaluation can be accelerated by distributing simulation jobs across multiple computers or cluster sessions and collecting objective values before the next generation is formed.

All candidate offspring were geometrically validated before simulation, ensuring compliance with spatial boundaries, collision avoidance, front clearance for operator access and shelf constraints. This ensured that all retained layouts were feasible and could be directly evaluated through DHM-based simulation. This pre-simulation validation reduces the number of computationally expensive DHM evaluations by rejecting infeasible candidates before full simulation.

To evaluate the convergence behaviour of NSGA-II, the hypervolume indicator was used (Figure 4). This metric quantifies the portion of the normalized objective space dominated by the non-dominated front, using a fixed reference point. An increasing or plateauing hypervolume across generations indicates that the optimization process is approaching convergence and discovering better trade-off solutions.

A 1% threshold in relative hypervolume improvement (ΔHV) over two consecutive generations was used as the stopping criterion. For all three stations, the hypervolume increased consistently during the early generations and then stabilized, with ΔHV values falling below 1% over the defined plateau window before or at P(20). This behaviour indicates that the stopping criterion was satisfied and that the final populations had approached a stable, well-distributed Pareto front.

Figure 4 presents the optimization progress for all three stations. The left column shows 3D Pareto fronts with hypervolume bounding boxes comparing the initial population P(0) with the last generation P(20). The right column illustrates the corresponding hypervolume evolution curves across generations P(0) to P(20). Across all stations, the Pareto front shifts and the explored solution space expands from P(0) to P(20), while the hypervolume initially increases and then stabilizes towards P(20), indicating that the search process improved solution quality before satisfying the predefined convergence criterion.

Visual inspection of the Pareto fronts confirmed increasing diversity, while the hypervolume curves showed stabilization according to the predefined $\Delta\text{HV} < 1\%$ criterion. Therefore, generation P(20) was selected as the representative final generation for layout selection and comparative analysis.

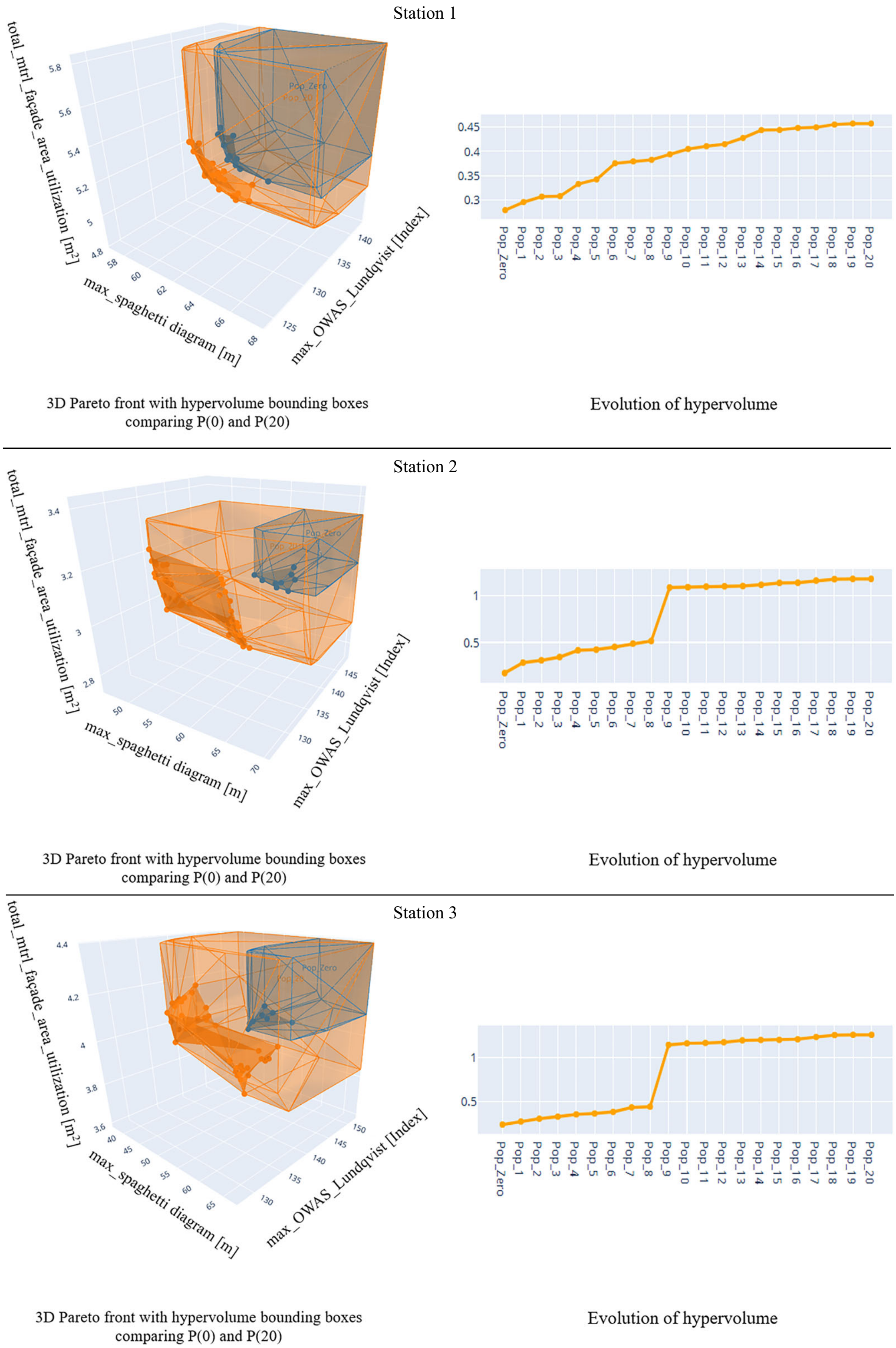

Figure 4. Non-dominated sorting genetic algorithm-II (NSGA-II) optimization progress for the three stations, shown through Pareto-front evolution and hypervolume indicators: (a) Station 1; (b) Station 2; (c) Station 3. Left column: three-dimensional Pareto front with hypervolume bounding boxes comparing P(0) and P(20); right column: evolution of hypervolume.

To complement the hypervolume analysis and better understand trade-offs among objectives, a set of visualizations was produced for each station:

(1) Pairwise scatter plots of objective trade-offs per station (Figure 5). These plots show relationships between the three objectives: spaghetti diagram length (productivity), OWAS-Lundqvist index (worker well-being), and façade utilization (area requirements). Non-dominated solutions are compared with the full population using distinct marker styles to illustrate the location and spread of feasible trade-off solutions.
(2) Line plots of signature solution trends across generations (Figure 6). These charts show how the ideal point, nadir point and average non-dominated solutions changed over generations for each objective. The goal is to track improvement and stability across generations.

For each station, the ideal point was defined as the component-wise minimum objective vector among the non-dominated solutions, while the nadir point was defined as the corresponding component-wise maximum objective vector. The ideal–nadir vector was defined as the line segment connecting these two points in the normalized objective space. From each final front, three signature solutions were extracted for each station: the solution closest to the station-wise ideal point, the solution farthest from the nadir point and the solution closest to the ideal–nadir vector. These representative solutions were carried forward for line-level combination and final evaluation.

4.4. Selecting the end layout configuration

To evaluate the outcomes of the NSGA-II optimization, three signature solutions were extracted from the final generation of each station: the one closest to the ideal point, the one farthest from the nadir and the one closest to the ideal–nadir vector. These solutions were then recombined across stations to form three complete BOR configurations per population. Each resulting layout was geometrically validated, simulated and assessed using the CPI.

The best performing combination, *i.e.* the one with the lowest line-level CPI, was selected and is visualized in Figure 7, which presents the final three-station layout from two perspectives: a global ISO view and a zoomed-in station-level view.

Among all randomly sampled layouts across the 24 evaluated BOP configurations, 3STN-BOP_1 achieved the lowest CPI in the random-sampling screening phase, with a CPI of 0.629, serving as the reference baseline for subsequent optimization. After applying NSGA-II, the refined configuration from generation P(20) achieved a lower CPI of 0.166, a relative improvement of 73.61%. This highlights the capability of the framework to generate layouts with more balanced performance across productivity, worker well-being and area utilization than random sampling alone.

To further isolate the contribution of process reconfigurability, Table 4 compares four levels of layout generation: the expert-designed baseline, automated layout generation under the fixed process structure corresponding to 3STN-BOP_9, reconfigurable BOP screening across the feasible BOP set and the final NSGA-II optimized solution. This comparison distinguishes the effect of automated resource positioning under a fixed process sequence from the additional improvement obtained by allowing precedence-feasible process-sequence and task-to-station alternatives.

The fixed-process automated baseline reduced the CPI from 3.259 for the expert-designed layout to 2.24, showing that automated resource placement improves performance even when the process structure is kept unchanged. However, the reconfigurable BOP screening further reduced the CPI to 0.63, indicating that allowing the process sequence and task-to-station allocation to vary substantially expands the feasible design space. Among the evaluated alternatives, the final NSGA-II optimized solution achieved the lowest CPI of 0.166, demonstrating the combined benefit of process reconfigurability and station-wise evolutionary layout refinement.

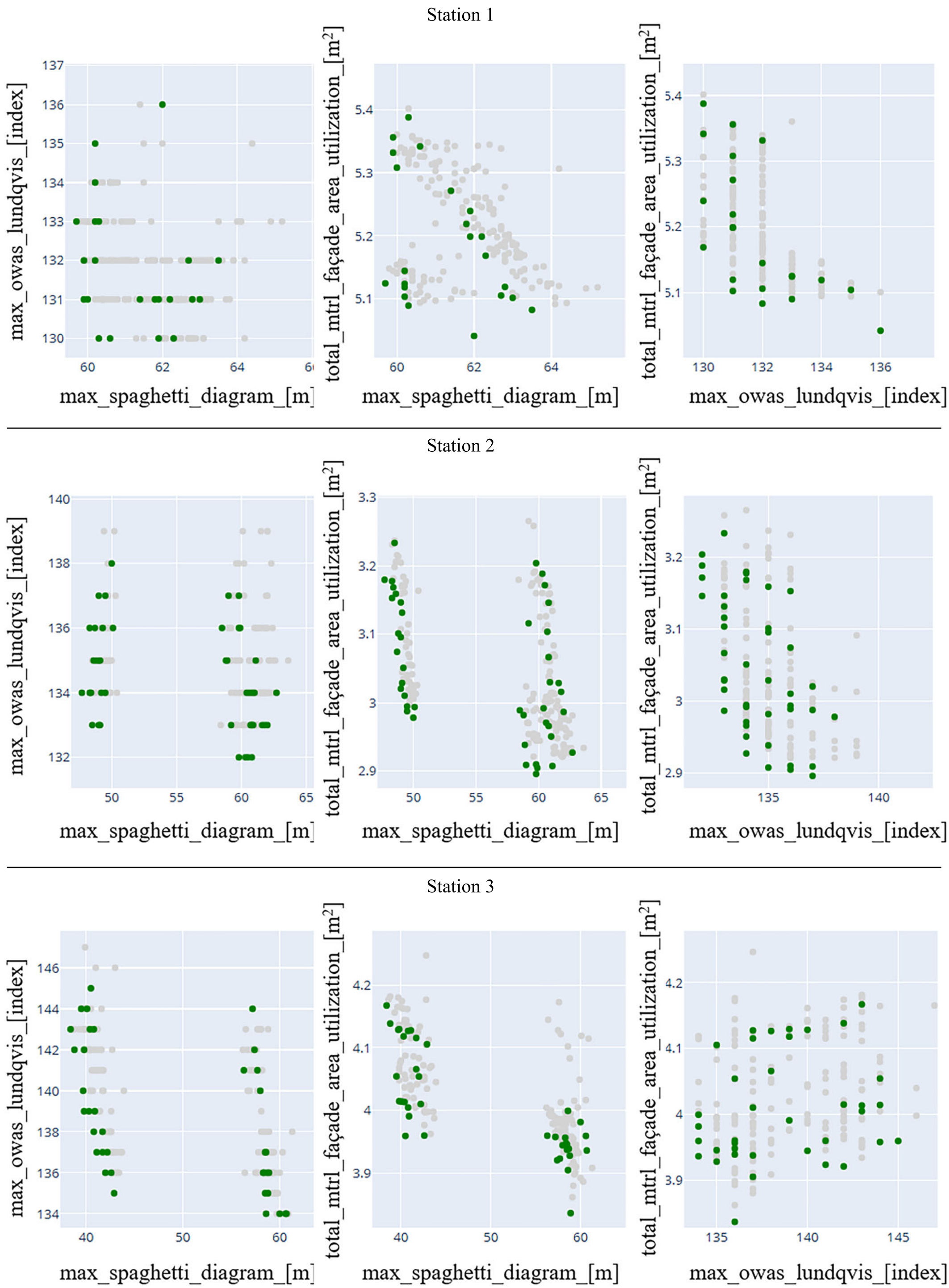

Figure 5. Pairwise scatter plots of objective trade-offs per station: (a) Station 1; (b) Station 2; (c) Station 3.

After isolating the contribution of process reconfigurability in Table 4, Table 5 provides a more detailed comparison between the initial best sampled solution for 3STN-BOP_1 and the final NSGA-II optimized layout. While both are based on the same BOP structure, with identical task-to-station

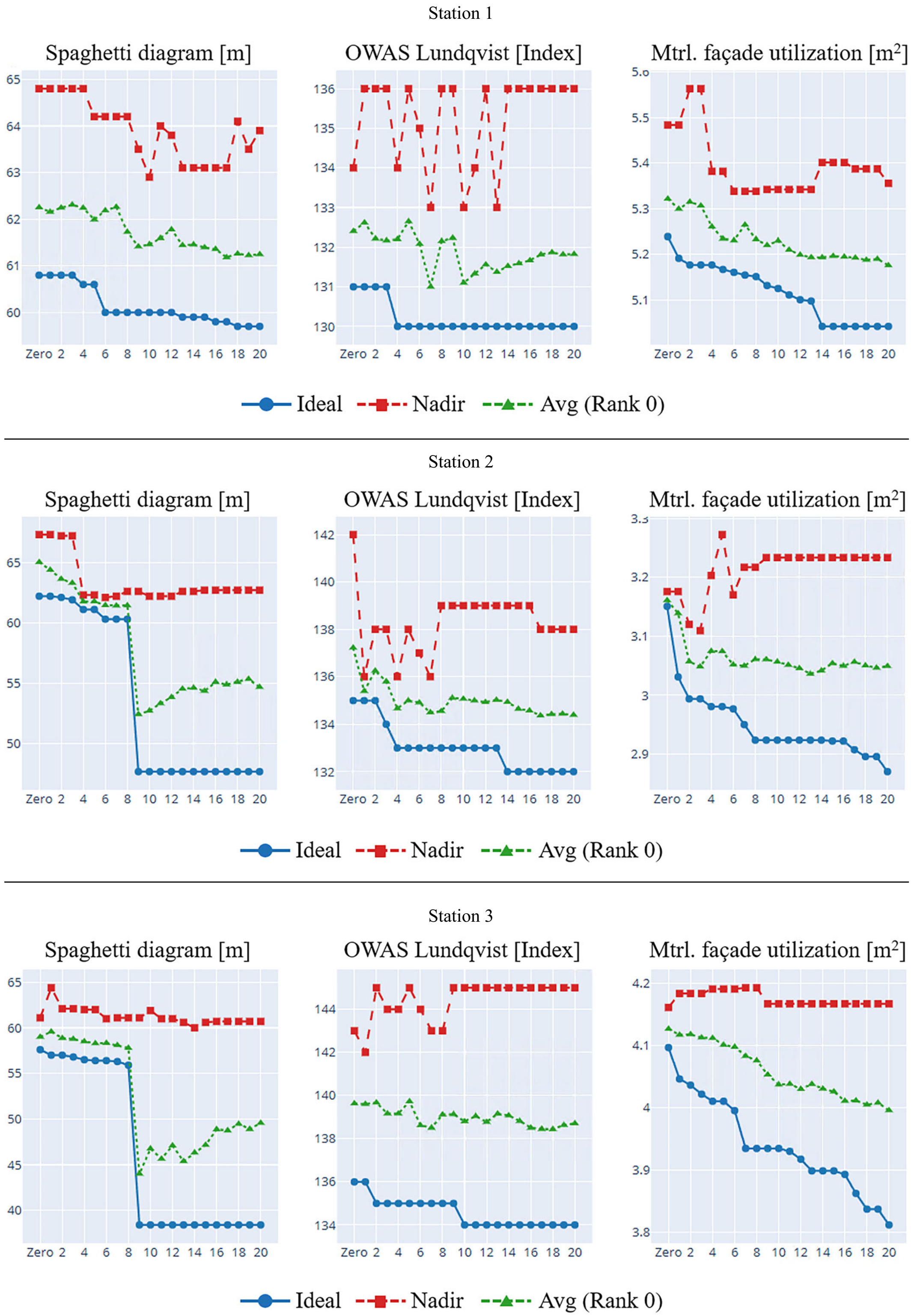

Figure 6. Evolution of representative solution indicators across generations: (a) Station 1; (b) Station 2; (c) Station 3. OWAS = Ovako Working Posture Analysis System.

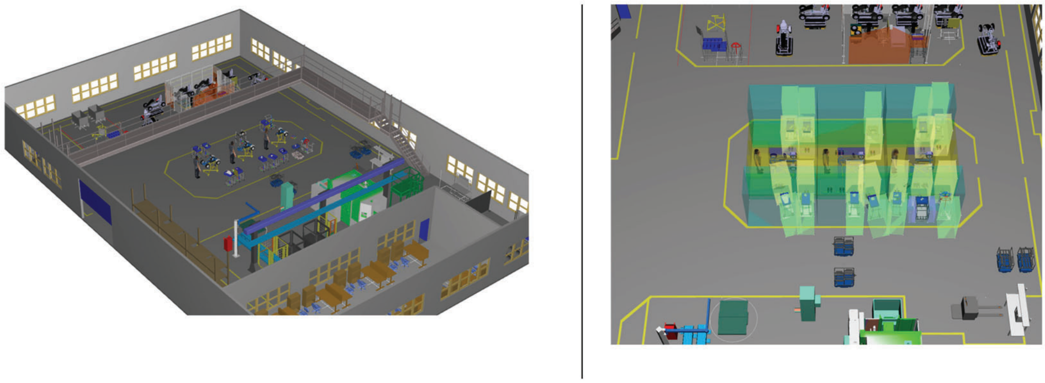

Figure 7. (a) Selected full-line layout in the three-dimensional factory context (ISO view); (b) zoomed view of selected three-station line configuration with visualized racks, station limits, rules and regulation boundaries.

Table 4. Quantitative comparison of expert-designed, fixed-process, reconfigurable-process and non-dominated sorting genetic algorithm-II (NSGA-II) optimized layout alternatives.

Comparison level	Process structure	Layout generation	CPI
Expert-designed baseline	Same as 3STN-BOP_9	Expert-designed/experience-based	3.259
Fixed-process automated baseline	3STN-BOP_9	100 stochastic BOR layouts	2.24
Reconfigurable BOP screening	3STN-BOP_1	100 stochastic BOR layouts	0.629
Proposed final solution	3STN-BOP_1	NSGA-II optimized BOR layout	0.166

Note: CPI = composite performance index; BOP = bill of process; BOR = bill of resources.

Table 5. Comparison between the selected non-dominated sorting genetic algorithm-II (NSGA-II) solution from P(20) and the best randomly sampled reference solution.

	Best NSGA-II solution	Best randomly sampled reference solution
Population	P(20)	100 random sampling
Solution tests (nr)	4200	100
Number of stations (nr)	3	3
Required resources (nr)	12	12
Decision variables (nr)	STN 1: 20; STN 2: 12; STN 3: 18	STN 1: 20; STN 2: 12; STN 3: 18
Throughput (s)	141.158	141.277
Bottleneck station	STN 1	STN 1
Max. spaghetti diagram (m)	60.00	62.20
Theoretical max. output (units/year)	63,758	63,704
OWAS–Lundqvist index	131	135
Façade utilization (m^2)	12.448	12.486

Note: The theoretical maximum output is calculated based on the achieved throughput of each solution and assumes an annual opening time of 2500 h. This standardizes the productivity comparison between configurations. It translates throughput into annual throughput under consistent operational conditions. OWAS = Ovako Working Posture Analysis System.

assignment and resource requirements, the evolutionary approach optimizes the spatial positioning of resources. This refinement produced modest but consistent improvements across the individual raw indicators: a lower OWAS–Lundqvist index, shorter walking distance and slightly lower façade utilization. The larger improvement is observed in the CPI, which reflects the combined effect of these normalized objectives.

In addition to the layout solutions generated by the optimization framework, the expert-designed state-of-practice layout currently implemented at Scania's physical testbed was evaluated. This expert-designed configuration was developed independently of the optimization process, using conventional planning practices based on planner experience and iterative adjustments. Notably, its underlying process structure matches 3STN-BOP_9, one of the Monte Carlo-generated BOP variants. However, the resource placement was configured by expert planners through conventional experience-based planning, without the use of simulation-based optimization.

When evaluated using the same objective metrics and normalized reference intervals (derived from all 24 BOPs and their respective 100 randomly sampled layouts), the expert-designed layout yielded the following results:

- maximum spaghetti diagram: 79.10 m (normalized: 0.711)
- weighted OWAS–Lundqvist index: 141 (normalized: 1.600)
- façade utilization: 16.61 m^2 (normalized: 0.947)
- CPI: 3.259
- throughput: 181.609 s.

For comparison, the best NSGA-II optimized layout achieved a CPI of 0.166. This illustrates the substantial improvement potential of the proposed optimization framework over traditional layout planning, even when the task-to-station allocation remains identical.

5. Discussion

This study introduces a novel and modular approach for FLP and design that tightly integrates reconfigurable process sequencing, spatial resource optimization and digital human simulation. Unlike conventional approaches that assume fixed process sequences and monolithic optimization, the proposed method decomposes the global optimization problem into station-level subproblems that can be evolved independently using evolutionary optimization algorithms, such as NSGA-II, and then recombined into complete layouts. If only resource position is optimized for fixed process sequences, the potential remains constrained. The results in this study show that only a physically feasible subset of 24 BOP variants remained within the brownfield footprint, confirming that reconfigurability is essential in practice. This modular strategy supports parallelism, increases solution diversity and enables traceable refinement across multiple generations.

The scalability of the proposed framework depends on the number of stations, the number of resources per station and the computational cost of DHM-based simulation. The station-wise decomposition reduces the dimensionality of the optimization problem by avoiding a monolithic full-line search. It also allows candidate evaluations to be distributed across stations, generations or simulation instances. In the current implementation, early feasibility validation is already used to reject geometrically infeasible BOR candidates before full DHM simulation. For larger industrial applications, scalability can be further improved by extending these pre-simulation feasibility checks, increasing the degree of parallel execution for station-level or candidate-level simulations, and introducing surrogate-assisted evaluation for computationally expensive simulation outputs. These strategies support the extension of the framework from testbed-scale validation towards larger production-line applications while preserving the same underlying BOP/BOR optimization logic.

The pedal car assembly case at the Scania testbed is deliberately bounded in product scale, but it should not be interpreted as a trivial optimization problem. Even for a product with a limited number of articles and assembly tasks, the combination of precedence-feasible process sequences, task-to-station allocations and station-level BOR alternatives creates a very large combinatorial search space. In the present case, BOP variants were generated across a wider range of station counts, but the available footprint of the physical Scania testbed, represented in the virtual factory model, restricted the feasible subset to three- and four-station configurations. This restriction was not introduced to simplify the optimization problem; rather, it resulted from the available Scania testbed footprint, where configurations with more than four stations exceeded the permitted factory area and two-station configurations could not accommodate the required material façade. This illustrates a central motivation for the proposed method: even when many process alternatives are theoretically possible, only a small subset may be feasible once spatial and ergonomic constraints from the intended implementation environment are applied. The case therefore serves as a physically grounded virtual testbed for systematic BOP/BOR exploration before any potential physical implementation. The low proportion of feasible BOPs should therefore be interpreted less as a failure of the method and more as an indication of the restrictive nature of real spatial constraints in brownfield layout planning. However, it also highlights the need for stronger feasibility pre-screening when applying the approach to larger problem instances.

In heavy manufacturing contexts, additional non-geometric hard constraints may further restrict the feasible design space. These could include, for example, electrical and pneumatic service interfaces, floor-bearing or foundation-load limits, anchoring requirements, lifting-device access, safety zones around high-energy equipment and constraints related to material supply systems. Gravity- or orientation-dependent assembly requirements are partly aligned with the existing DAG formulation, since any mandatory ordering of tasks can be encoded as precedence constraints. If such requirements also impose restrictions on product orientation, lifting direction or access paths, they can be represented as additional orientation or access constraints in the BOP and BOR validation logic. Such constraints are not fundamentally incompatible with the proposed framework, but they were outside the scope of the present implementation. They could be incorporated by extending the BOP, BOR and BLOCK_LAYOUT data structures with additional resource-specific attributes and feasibility rules. For example, resources requiring compressed air or electrical supply could be restricted to feasible service zones, floor-load constraints could be represented as maximum allowable load per floor region and lifting-device access could be represented as additional access-space constraints. The addition of such constraints would increase the dimensionality and coupling of the problem, and is therefore identified as an important direction for future research.

The main contribution of this article is not the use of NSGA-II. General-purpose search methods such as simulated annealing, tabu search or particle swarm optimization could, in principle, be applied: the optimizer generates decision variables, while the simulation environment evaluates 3D clearance, reachability, worker well-being, productivity (walking distance) and area utilization with regulatory checks. NSGA-II was selected because of its maturity and transparency; however, the principal novelty lies in the 3D human-centric problem formulation and the station-wise decomposition with recombination.

The comparison between the NSGA-II optimized layout and the expert-designed state-of-practice layout currently implemented at Scania illustrates the limitations of conventional layout planning practices. Although the expert-designed configuration was developed with significant domain knowledge and practical experience, it exhibited substantially higher values for walking distance, worker well-being risk (OWAS–Lundqvist index) and façade utilization when evaluated using the same objective metrics and normalized reference intervals. This confirms that traditional methods, while effective in capturing contextual knowledge and operational feasibility, often lack the systematic optimization capabilities necessary to achieve truly balanced trade-offs across multiple performance dimensions. Stakeholders may apply their own weightings to reflect specific priorities. The CPI was deliberately designed as a neutral, equally weighted index to avoid bias. However, as discussed in Section 3.3, CPI weights can be adapted to stakeholder priorities rather than being treated as fixed universal values. The weight-sensitivity check showed that the selected BOP remained top-ranked in eight of the 10 tested weighting schemes and ranked second in the worker well-being-focused scenarios. This indicates that the CPI-based selection is relatively robust under moderate weighting variations, while also confirming that stakeholder-specific preferences may influence the final ranking. Future applications could therefore incorporate alternative multi-criteria decision-making or robust ranking approaches when explicit stakeholder preferences or data-driven weighting schemes are available.

The fixed-process baseline further clarifies the specific contribution of process reconfigurability. When the process structure is kept identical to the expert-designed layout, the search is restricted to layouts compatible with 3STN-BOP_9. By contrast, allowing the process sequence and task-to-station allocation to vary enabled the framework to identify 3STN-BOP_1 as a more promising process-layout configuration. This indicates that the improvement is caused not only by automated resource positioning, but also by expanding the feasible design space through precedence-constrained process reconfiguration.

Overall, the proposed simulation-based optimization framework enables the generation and evaluation of a large number of layout alternatives, each validated against spatial constraints and worker well-being criteria. This allows not only for reproducible performance comparisons, but also for data-driven improvements beyond what manual planning can typically achieve. The integration of simulation, DHM and an evolutionary search represents a shift towards more transparent and measurable layout design, which can augment rather than replace human expertise in industrial decision making.

While the IPS IMMA-based DHM simulations do not explicitly model physiological fatigue, they function as a proactive screening tool for identifying posture-related risks and spatial access constraints early in the design phase. This reflects standard industrial practice, where virtual assessments of worker well-being are conducted prior to physical implementation. Future work may include empirical validation using motion-capture data or operator observations to further enhance the credibility and ergonomic relevance of the simulation results.

Furthermore, by applying hypervolume-based convergence analysis across generations $[\mathrm{P}(X)]$, the method offers a robust evaluation of the search process, ensuring that the optimization converges to a diverse and well-distributed set of Pareto-optimal layouts. The integration of DHM and simulation-based objectives further distinguishes the approach, allowing worker well-being indicators, walking distances and area utilization to directly influence layout decisions.

This study contributes an integrated framework that combines (1) dynamic BOP generation *via* precedence-constrained DAGs, (2) modular station-wise evolutionary optimization with recombination into BOR structures, and (3) convergence metrics and digital human simulation within a unified 3D layout planning and design approach. The resulting system is not only theoretically grounded, but also practically implementable, offering structured decision support for sustainable, human-centric manufacturing aligned with Industry 5.0 principles.

5.1. Future work

While this study focused on optimizing factory layouts based on a single product with reconfigurable process structure, an important direction for future research is the extension towards multi-product systems. In real-world assembly environments, multiple product variants often share the same production line, each with distinct or partially overlapping task sequences and resource requirements.

Integrating multiple BOPs into the optimization framework would introduce new layers of complexity, such as concurrent task allocation for different products, scheduling compatibility across variants and layout robustness to product mix variation. Addressing these challenges would require hybrid strategies that combine sequencing flexibility, real-time scheduling and adaptive layout configurations. Moreover, the optimization process may need to shift towards robust or scenario-based formulations that account for product mix variability and uncertainty in production demands.

The current modular structure and task-to-station allocation logic is well-suited for such extensions, as the method treats each BOP as an independent optimization problem and supports scalable recombination of validated stations. This positions the approach for adaptation to more complex and heterogeneous manufacturing environments.

It should also be acknowledged that layout optimization is only one part of decision making in factory set-up practice. Managerial factors such as re-layout downtime, relocation costs and operator learning curves concern how to implement a chosen layout, rather than which layout is best. These aspects are therefore better treated as complementary analyses alongside the presented optimization framework, enabling decision makers to balance performance improvements with implementation effort.

Another possible direction of research is to reduce the computational complexity of FLP by applying knowledge about the validity of BOPs and BORs extracted during the random sampling process. In this study, many of the generated BOPs, and the subsequent BORs, were found to be infeasible after simulation, which is a computationally expensive process. By applying data-mining techniques to an initial set of randomly generated configurations, it may be possible to identify patterns that distinguish feasible from infeasible BOPs and BORs. These patterns can then be used to predict the feasibility of new configurations. By associating each prediction with a confidence value, an automated heuristic can be implemented to decide whether to simulate a configuration or discard it without simulation. Such an approach could significantly reduce runtime and the evaluation burden associated with a large number of configurations, as is common in complex multi-product systems. Future research could explore stakeholder-informed weighting strategies for the CPI, allowing domain experts to prioritize specific objectives such as worker well-being or area utilization depending on context. Alternatively, sensitivity analyses could be conducted to assess how different weighting schemes affect BOP rankings and layout recommendations.

Such an extension would further align the method with the principles of Industry 5.0, where adaptability and human-centred flexibility are essential for sustainable manufacturing.

Benchmarking was conducted against an expert-designed layout and extensive stochastic baselines; future work may extend this by adding cross-site case studies to broaden external validity. The methodology was developed in close collaboration with industrial partners (Scania CV AB and Volvo CE). All spatial constraints, simulation parameters and manikin configurations were defined based on real-world factory planning practices, ensuring practical relevance and alignment with industry standards.

6. Conclusion

This study presents a novel simulation-based method for optimizing factory layouts that integrates dynamic process descriptions, spatial resource constraints and human-centric performance metrics. By treating the BOP, including the process sequence and station allocation, as a variable input and combining Monte Carlo sampling with NSGA-II-based evolutionary optimization, the approach enables the generation and evaluation of thousands of feasible layout configurations. The framework supports decision making across multiple objectives, including system productivity, ergonomic safety and area efficiency.

From 24 evaluated BOP configurations, one (3STN-BOP_1) was identified as the most promising using a globally normalized CPI. This BOP was then refined using a station-wise NSGA-II loop, allowing scalable optimization while maintaining layout validity. The proposed approach ensures spatial feasibility through block layout validation, and aligns with Industry 5.0 principles by integrating DHM for evaluating worker well-being.

The method is implementable with existing commercial software, and demonstrates how adaptive, multi-objective layout planning can be made practical for real-world production environments. It provides a blueprint for how factory layouts can be optimized not only for throughput but also for worker health and spatial utilization, which are often overlooked in traditional planning tools. This work contributes a practical pathway for transitioning from static to adaptive, human-centred layout planning, and offers a robust optimization backbone for next-generation smart factories. For industrial layout planners, the method enables early validation of HFE aspects (productivity, worker well-being and spatial constraints), systematic reduction of walking distances and reproducible comparisons between layout alternatives. In the Scania testbed, the NSGA-II refinement reduced the CPI from 0.629 for the best randomly sampled layout of the selected BOP to 0.166, corresponding to a 73.61% improvement in the composite index.

Author contributions

CRediT: **Andreas Lind:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Visualization, Writing – original draft, Writing – review & editing; **S. Bandaru:** Conceptualization, Funding acquisition, Validation, Writing – review & editing; **L. Hanson:** Conceptualization, Formal analysis, Methodology, Validation, Writing – review & editing; **R. Salman:** Conceptualization, Software, Writing – review & editing

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Data availability statement

Pseudo-code for the optimization loop is included in Section 3.1. Example JSON files and schemas (BOP, BOR, BLOCK_LAYOUT and objective-value files), together with a minimal test BOP, will be provided upon reasonable request to the corresponding author. IPS/IMMA project files cannot be shared owing to licensing restrictions, but all input/output schemas are documented to support reproducibility.

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