

Article

An Integrated Decision-Support Workflow for Facility Layout Planning

I. Fikry ^{1,2,*} and N. Zamzam ²¹ School of Business & Economics, University of Galway, Lero, H91 WN80 Galway, Ireland² Design and Production Engineering Department, Faculty of Engineering, Ain Shams University, Cairo 11517, Egypt; nessren.zamzam@eng.asu.edu.eg

* Correspondence: ibrahim.fikry@universityofgalway.ie or ibrahim.fikry@eng.asu.edu.eg

Abstract

Facility Layout Planning (FLP) remains a complex task for manufacturers seeking to improve productivity, reduce daily operating costs, and stay competitive in fast-changing markets. Traditional methods such as Systematic Layout Planning (SLP) offer useful guidelines for designing department layouts but still rely heavily on judgment and experience. At the same time, modern optimization and simulation techniques provide valuable quantitative insights. These techniques are often used separately rather than as part of an integrated process. In this work, a hybrid layout-planning approach that combines these techniques is developed and validated through an industrial case study, providing a practical decision-support process for facility layout planning. The process starts with SLP, which develops an initial layout using activity relationship charts, material-flow analysis, and handling-cost estimates. A simulation model then evaluates throughput, machine utilization, and work-in-progress, providing early indications of the layout's real-world performance. A Genetic Algorithm (GA) is used to find improved configurations that reduce distances and costs. The optimized layouts are further tested through simulation. To demonstrate practical use, the framework was applied at a transformer manufacturing plant. It resulted in an approximately 35% reduction in material-handling costs. The results show that the optimized layout reduced material-handling costs from 7062.5 to approximately 4560 L.E. per transformer while increasing monthly throughput by 2.46% (approximately 11 transformers per month). Additionally, a what-if analysis was performed to identify opportunities for improvement, such as increasing production by using an automatic laser-cutting machine. The findings support data-driven decisions in facility layout design and long-term operational planning.

Academic Editor: Cheng-Fu Yang

Received: 5 June 2026

Revised: 9 July 2026

Accepted: 10 July 2026

Published: 21 July 2026

Copyright: © 2026 by the authors. Published by MDPI on behalf of the International Institute of Knowledge Innovation and Invention. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: discrete event simulation; facility planning; genetic algorithm; optimization; SLP

1. Introduction

Facility layout design is one of the most critical decisions in any manufacturing system. It affects how machines and departments are positioned and shapes the behavior of the entire production system. The flow of materials, queue lengths, day-to-day operating costs, and even customer responsiveness are all related to the physical layout [1].

Poorly designed layouts often cause excessive material handling, bottlenecks, and underutilized resources. By contrast, well-optimized layouts can significantly improve efficiency, reduce costs, and increase flexibility [2]. This point is even more important in industries that handle heavy or expensive products. In such settings, even a modest reduction in travel or handling effort can translate into considerable savings over time [3].

Among the various approaches to layout planning, SLP remains one of the most widely used methods. Introduced by Richard Muther in the mid-20th century [4], SLP provides a structured framework for analyzing activity relationships, space requirements, and adjacency needs. SLP enables practitioners to develop feasible layouts that reflect material and non-material flow considerations. This is carried out through relationship charts, activity closeness ratings, and block diagrams.

However, SLP is logical; it is also qualitative and heuristic, relying heavily on expert judgment and the subjective weighting of relationships [5]. This subjectivity often prevents it from guaranteeing globally optimal solutions, especially in large-scale, high-complexity manufacturing environments.

To overcome these limitations, researchers and practitioners have increasingly turned to computational optimization methods, with GA among the most widely applied [6]. GA belongs to the class of evolutionary algorithms inspired by natural selection. It is particularly well-suited to solving combinatorial optimization problems such as facility layout, where the search space is vast and non-linear [7]. Facility arrangements are encoded as chromosomes and evolve through crossover, mutation, and selection. GA can minimize material-handling costs and generate layouts that outperform those from traditional SLP.

A different issue arises when these optimized layouts are evaluated under real operating conditions. Most optimization techniques, including GA, assume stable and deterministic workflows. These assumptions are rarely valid in practice. Breakdowns, fluctuating demand, unbalanced workstations, and variability in processing times all affect actual performance but are difficult to incorporate into a purely mathematical model [8]. This is where Discrete-Event Simulation (DES) becomes particularly valuable.

Software such as FlexSim, Arena, and AnyLogic can model the stochastic variability inherent in manufacturing operations. Simulation enables practitioners to evaluate candidate layouts under fluctuating demand, machine breakdowns, queuing effects, and processing-time variability [9]. It provides a more realistic assessment of system performance across multiple performance indicators, including throughput, cycle time, Work-in-Progress (WIP), and resource utilization.

Although each method—SLP, GA, and DES—has significant strengths, most studies have used them either independently or in partial combinations. Some pair SLP with GA to improve optimization [10,11], or GA with simulation for validation [12]. Studies that systematically integrate all three, SLP for structured qualitative design, GA for optimization, and simulation for dynamic validation, remain limited.

This gap is particularly relevant as manufacturing systems increasingly adopt data-driven decision-support tools. Integrating layout planning, optimization, and simulation gives engineers a systematic approach to evaluating alternative production layouts before implementation.

This study addresses the above gap by proposing and applying an integrated framework that combines SLP, GA, and DES to optimize production layouts in a complex manufacturing system. The approach begins with SLP to establish an initial feasible design. GA is then used to refine this layout by minimizing material-handling costs while accounting for realistic constraints. Finally, the optimized layouts are validated using DES. Specifically, the objectives of this research are:

- To develop and implement an integrated SLP–GA–DES workflow for facility layout planning.
- To evaluate the effectiveness of this framework through application in an industrial case study.
- To derive managerial insights on how integrated data-driven layout planning can improve operational efficiency and support layout planning decisions.

The contributions of this research are both methodological and practical. Methodologically, the study demonstrates an integrated workflow that combines SLP, optimization, and simulation within a unified decision-support process. In practice, the study validates the workflow's applicability through a real-world industrial case, providing manufacturing managers with a practical decision-support approach to improve facility layout.

The paper is organized as follows: Section 2 reviews the literature; Section 3 presents the mathematical model for the problem; Section 4 provides a numerical example with a detailed case analysis; Section 5 presents the case analysis in detail; and finally, Section 6 concludes the paper.

2. Literature Review

The literature review is organized into five subsections that trace the evolution of facility layout methodologies and explain the rationale for the proposed integrated framework. The first subsection discusses SLP, highlighting its value as a structured qualitative approach and its limitations in optimization. The second subsection examines computational optimization methods, with particular attention to GA as a metaheuristic well suited to complex layout problems.

The third subsection focuses on simulation, highlighting how DES captures the dynamic and stochastic behavior of manufacturing systems. The fourth subsection reviews prior attempts to integrate SLP, optimization, and simulation, summarizing their contributions and limitations. Finally, the fifth subsection identifies the research gap that motivates this study, emphasizing the need for a comprehensive framework that integrates SLP, GA, and simulation while accounting for practical constraints, including aisle design.

2.1. SLP in Facility Layout Design

SLP remains one of the most widely used methodologies for facility layout design. It uses activity-relationship charts, space-requirement analysis, and block diagrams to generate feasible layouts. Its strength lies in its simplicity and its ability to integrate both material flow and qualitative factors, such as safety, communication, and supervision [5].

However, SLP is heuristic in nature and relies heavily on subjective judgment, which often prevents it from achieving globally optimal results. Several studies highlight this limitation, showing that while SLP provides a solid foundation, it frequently requires computational methods to refine the results [11,13].

2.2. Optimization Approaches in Facility Layout Design

To address SLP's limitations, researchers have increasingly adopted metaheuristic optimization techniques [14]. Among these, GAs have been widely used for their ability to handle large-scale combinatorial optimization problems. GA represents layout alternatives as chromosomes and evolves them through crossover, mutation, and selection to minimize objectives such as material-handling costs.

Applications include factory layouts [15], make-to-order industries [10], and specialized domains such as ship cabins [16]. Hybrid approaches have also emerged, such as combining GA with Ant Colony Optimization [13], or integrating GA with decision-support methods like

the Analytic Hierarchy Process (AHP) [16]. While these approaches yield improved results, most still overlook practical constraints such as aisle allocation, which is critical in real-world manufacturing [17].

2.3. Simulation in Facility Layout Design

While optimization methods provide reliable solutions, they often fail to capture the dynamic and stochastic nature of manufacturing systems [8]. Simulation enables detailed modeling of variability in process times, machine reliability, breakdowns, and operator availability [9]. It also provides insight into system performance, including throughput, cycle-time distribution, WIP accumulation, and machine utilization.

This has motivated the use of DES tools to evaluate layout performance under realistic operating conditions. FlexSim, in particular, has gained popularity for its object-oriented modeling environment and its ability to integrate material-handling equipment, operator logic, and spatial constraints directly into the simulation [18].

Recent studies highlight that simulation is beneficial for validating optimized layouts and revealing bottlenecks that purely mathematical models may overlook [19]. Another study investigated whether layout optimization should precede simulation or whether simulation should guide layout optimization [20]. However, our study employs simulation in an integrated and iterative manner to effectively enhance system performance.

2.4. Integration of SLP, Optimization, and Simulation

Several studies have explored hybrid approaches to facility layout planning that combine qualitative design methods, optimization algorithms, and simulation. Early research integrated SLP with GA, using SLP to generate an initial layout and GA to refine it. This combination has been widely applied in manufacturing facilities, warehouses, and the shipbuilding industry [11,15].

Other studies have coupled GA with DES to evaluate candidate layouts generated by the optimization algorithm under dynamic operating conditions [12]. SLP has also been integrated with simulation for multi-floor facility layouts [21].

At the same time, more recent studies have investigated simulation-based optimization frameworks considering practical factors such as AGV routing and material transportation [22]. Digital twin-based approaches have also emerged to support layout evaluation and operational planning [23]. These studies demonstrate the benefits of integrating optimization with simulation to improve facility layout decisions.

Despite these advances, several practical challenges remain insufficiently addressed. Many existing studies focus primarily on minimizing material-handling costs while overlooking important industrial constraints such as aisle design, equipment accessibility, and layout feasibility [10,16]. The study by [17], which explicitly incorporated aisle placement into a GA model for an automobile body shop, is among the few efforts to consider these practical requirements. In addition, simulation is commonly used only as a post-evaluation tool, rather than to assess system performance both before and after layout optimization.

As summarized in Table 1, most studies combine SLP with GA or GA with simulation. Despite these contributions, practical considerations such as aisles are rarely modeled, with [17] as a notable exception.

Moreover, simulation is often used solely for post-evaluation, rather than as an iterative tool to assess system performance both before and after optimization. These limitations highlight opportunities for further research on integrated SLP–GA–DES workflows that explicitly incorporate aisle design, industrial feasibility constraints, and comprehensive simulation-based validation.

Table 1. Review of Facility Layout Studies and the approaches used.

Ref.	Hybrid Method	Main Constraints	Objective Type	Performance Measures	Validation
[24]	QFD + FMEA + AHP + DEA + Simulation	Area, budget, ergonomics	Multi-objective	DEA efficiency, AHP score, MH cost	Industrial case + simulation
[21]	SLP + DES	Multi-floor layout, zoning	Single	Total Material Handling Cost (TMHC), space utilization	Industrial case + DES
[10]	GA	Workshop area, production flow	Single	MH distance, convergence	Computational experiments
[12]	Simulation + Metaheuristic	Dynamic demand, relocation	Multi-objective	Total cost, Pareto front	Statistical simulation + case study
[17]	SLP + Improved GA (Pareto-based)	Unfixed main aisle, entrance & exit positions	Multi-objective	MH cost, degree of activity relation	Case study
[25]	SLP + GA	Cabin layout, zoning, safety	Single	Flow distance, space utilization	Case study + simulation
[16]	SLP + GA	Geometric constraints, passages	Single	Flow distance, compactness	Case study
[26]	SLP + Simulation	Aisles, process sequence	Single	Logistics intensity, congestion	Simulation comparison
[13]	SLP + GA-ACO	Storage capacity, picking paths	Single	Picking distance, storage utilization	Simulation + warehouse case
[27]	AHP + DEA + Simulation	Cost, ergonomics, safety	Multi-objective	DEA efficiency, AHP score	Simulation + case study
[11]	SLP + GA	Area, equipment, material flow	Single	Logistics cost, MH distance	Industrial implementation
[15]	SLP + GA	Regional layout, machine allocation	Single	MH distance, runtime	Numerical & case studies
[22]	SBO + AGV Path Planning	AGV routing, congestion	Multi-objective	Travel distance, makespan, delay	Simulation scenarios
[28]	SLP + AHP + NLP	Area, budget, adjacency	Multi-objective	Logistics cost, AHP score	Optimization + case study
Present study	SLP + GA + DES	Non-overlap, aisle restrictions, factory boundaries, production sequence	Single objective + Simulation-based evaluation	TMHC, throughput, machine utilization, GA robustness (20 runs)	Industrial case, DES verification and validation.

2.5. AI-Assisted Decision Support for Manufacturing Systems

Recent advances in AI have expanded the use of computational decision-support techniques across manufacturing systems. AI has been integrated into computer-aided engineering to support analysis, prediction, optimization, and design [29]. AI-assisted methods have been successfully applied to process monitoring, quality prediction, predictive maintenance, production performance forecasting, and FLP [30]. These methods enable more informed and timely operational decisions.

Although the present study does not employ machine-learning techniques, the proposed integration of SLP, GA, and DES follows the same principle of computational decision support by enabling systematic evaluation of alternative facility layouts before physical implementation. Future research could further enhance the proposed workflow by integrating

AI-driven prediction methods, particularly when limited historical production data constrain simulation calibration or scenario generation. In such cases, virtual sample generation and simulation-based synthetic manufacturing data have demonstrated considerable potential [31,32].

2.6. Identified Research Gap

The literature identifies three key limitations. First, although SLP provides a structured approach to generating facility layout alternatives, it offers limited quantitative support and cannot systematically identify cost-effective layouts. Second, while GA and other methods effectively minimize material-handling costs, they often simplify or overlook practical industrial constraints, such as aisle design, factory boundaries, equipment accessibility, and spatial feasibility. Third, DES is frequently used only after optimization to validate the final layout, rather than being integrated throughout the decision-support process to support both layout evaluation and scenario analysis.

To address these limitations, this study develops and applies an integrated SLP–GA–DES decision-support workflow and demonstrates its use in an industrial transformer manufacturing case study. The workflow integrates SLP, GA with explicit feasibility checks, simulation-based evaluation of the baseline and optimized layouts, and scenario-based what-if analysis within a unified decision-support process.

Practical implementation constraints, including non-overlapping departments, factory boundaries, and aisle restrictions, are explicitly incorporated during the optimization stage to ensure that the resulting layouts are industrially feasible. The workflow therefore combines the qualitative strengths of SLP with the optimization capability of GA and the performance evaluation capability of DES, providing a structured decision-support process for industrial facility layout planning.

The proposed workflow is illustrated in Figure 1. It begins with SLP, which uses process flowcharts, relationship charts, and space diagrams to generate an initial feasible layout. This baseline layout is then evaluated with DES to assess its operational performance. The layout is subsequently optimized with GA to minimize TMHC while satisfying practical industrial constraints.

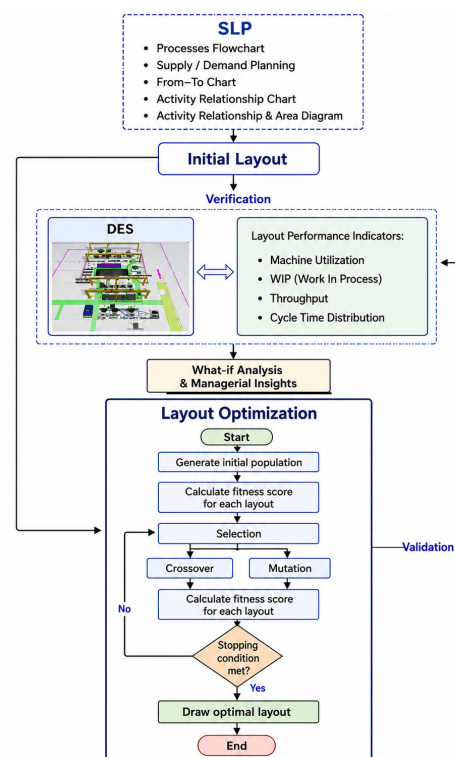


Figure 1. Conceptual framework for facility layout design.

Finally, the optimized layout is re-evaluated through simulation using key performance indicators such as throughput, WIP, cycle time, and machine utilization. The workflow is further extended with scenario-based what-if analyses to explore potential process improvements and support managerial decision-making. By integrating qualitative layout planning, optimization, and simulation-based performance evaluation into a unified decision-support workflow, the proposed methodology supports the development and assessment of industrially feasible facility layouts under realistic manufacturing conditions.

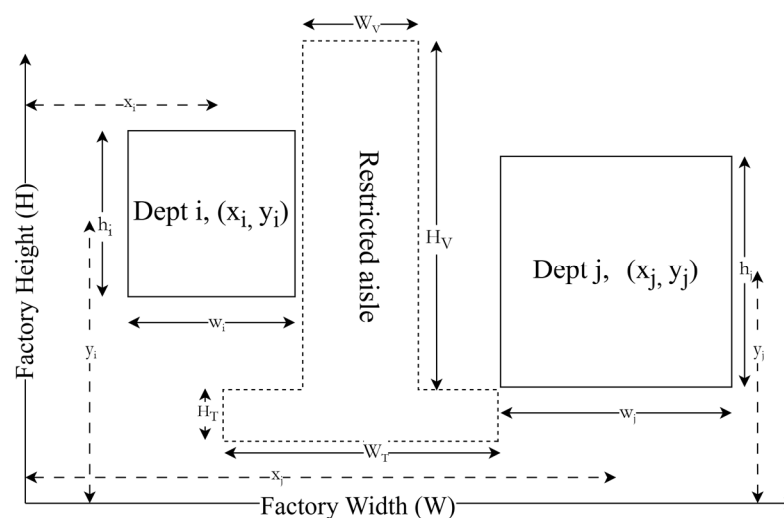
3. Methodology

This section presents the methodology. It is divided into two subsections: the mathematical model and the solution approach for optimizing the facility layout. The first subsection presents the proposed model and defines the layout constraints and objectives. The second subsection discusses the application of GA as an optimization tool to find an optimal departmental arrangement that satisfies the defined spatial and aisle constraints.

3.1. Mathematical Model

The facility layout optimization problem involves determining the optimal arrangement of departments on a manufacturing floor to minimize material-handling costs. It accounts for interdependencies such as material flows between departments, adjacency requirements, and space utilization constraints. The goal is to create a layout that reduces material movement, balances workloads, and minimizes idle time. A mathematical model is provided below to minimize TMHC.

Figure 2 shows the schematic layout used to formulate the model. The factory floor is represented as a rectangle of width W and height H . Each department i and j is represented by a rectangular block, characterized by its width (w_i, w_j), height (h_i, h_j), and centroid coordinates (x_i, y_i) and (x_j, y_j) . Two restricted zones are shown to indicate the aisles required for material movement and operator access. The vertical aisle is defined by its position and dimensions $(X_V, Y_V), (W_V, H_V)$, while the horizontal aisle is defined by $(X_T, Y_T), (W_T, H_T)$, respectively.

**Figure 2.** Schematic representation of the facility layout parameters and variables.

3.1.1. Assumptions

To simplify the layout optimization problem, the following assumptions are made:

- Material flow between departments is uniform and deterministic.
- The factory operates on a single floor with fixed total area dimensions ($W \times H$).
- No operational interruptions or rework are considered.
- Material handling cost per unit distance is constant.
- Environmental factors (temperature, lighting, etc.) are not included.
- All departments have fixed rectangular shapes with known dimensions.
- Aisles are modeled as restricted areas where no department can overlap.

The above assumptions apply only to the mathematical optimization model used by the GA. They simplify the layout optimization problem by considering deterministic material flows and nominal operating conditions. After obtaining the optimized layout, the proposed design is evaluated using DES to assess its operational performance under realistic production conditions, including resource utilization, WIP, throughput, and process bottlenecks. Consequently, the optimization and simulation models serve complementary purposes rather than representing identical system assumptions.

3.1.2. Decision Variables

x_i, y_i : the coordinates of the center of department i .
 x_j, y_j : the coordinates of the center of department j .

3.1.3. Parameters, Sets, and Indices

$i, j \in I$: set of departments.
 w_i : width of department i .
 h_i : height of department i .
 D_{ij} : rectilinear (Manhattan) distance between department centers i and j .
 F_{ij} : material flow between departments i and j .
 C_{ij} : cost per unit distance for transportation between departments i and j .
 X_T, Y_T : coordinates of the horizontal restricted area (aisle).
 W_T, H_T : dimensions of the horizontal restricted area (aisle).
 X_V, Y_V : coordinates of the vertical restricted area (aisle).
 W_V, H_V : dimensions of the vertical restricted area (aisle).
 W : width of the factory floor.
 H : height of the factory floor.

3.1.4. Mathematical Model Formulation

$$\text{Min. TMHC} = \sum_{i=1}^n \sum_{j=1}^n F_{ij} \cdot D_{ij} \cdot C_{ij} \quad (1)$$

$$x_i + \frac{w_i}{2} \leq x_j - \frac{w_j}{2} \quad \forall i, j \in I, i \neq j \quad (2)$$

$$x_j + \frac{w_j}{2} \leq x_i - \frac{w_i}{2} \quad \forall i, j \in I, i \neq j \quad (3)$$

$$y_i + \frac{h_i}{2} \leq y_j - \frac{h_j}{2} \quad \forall i, j \in I, i \neq j \quad (4)$$

$$y_j + \frac{h_j}{2} \leq y_i - \frac{h_i}{2} \quad \forall i, j \in I, i \neq j \quad (5)$$

$$\frac{w_i}{2} \leq x_i \leq W - \frac{w_i}{2} \quad \forall i \in I \quad (6)$$

$$\frac{h_i}{2} \leq y_i \leq H - \frac{h_i}{2} \quad \forall i \in I \quad (7)$$

$$x_i + \frac{w_i}{2} \leq X_T \quad \forall i \in I \quad (8)$$

$$x_i \geq X_T + W_T \quad \forall i \in I \quad (9)$$

$$y_i + \frac{h_i}{2} \leq Y_T \quad \forall i \in I \quad (10)$$

$$y_i \geq Y_T + H_T \quad \forall i \in I \quad (11)$$

$$x_i + \frac{w_i}{2} \leq X_V \quad \forall i \in I \quad (12)$$

$$x_i \geq X_V + W_V \quad \forall i \in I \quad (13)$$

$$y_i + \frac{h_i}{2} \leq Y_V \quad \forall i \in I \quad (14)$$

$$y_i \geq Y_V + H_V \quad \forall i \in I \quad (15)$$

$$x_i, y_i \geq 0 \quad \forall i \in I \quad (16)$$

It should be noted that Constraints (2)–(15) define the feasibility conditions of the layout rather than a mixed-integer mathematical programming formulation. During optimization, these conditions are enforced procedurally through a feasibility-checking routine embedded within the GA.

The objective is to minimize TMHC across all departments, as indicated in Constraint (1). Where $D_{ij} = |x_i - x_j| + |y_i - y_j|$ represents the Manhattan distance between the centers of the departments i and j . Constraints (2)–(5) define the possible spatial relationships required to prevent overlap between departments. During optimization, these conditions are evaluated by the feasibility-checking routine embedded in the GA, which requires only one valid spatial relationship (i.e., left, right, above, or below) for each pair of departments. Constraints (6) and (7) define the factory boundary limits, ensuring that every department lies entirely within the feasible layout area. Constraints (8)–(15) The inequalities guarantee that no two departments occupy the same space by ensuring sufficient separation in both the x- and y-directions. Finally, Constraint (16) imposes non-negativity on the decision variables.

The optimization model considers TMHC as a single objective because material movement is a major operational cost in the transformer manufacturing facility investigated and is directly influenced by department locations. Other performance indicators, including throughput, WIP, cycle time, and machine utilization, are primarily affected by production resources, processing times, and operational policies. Therefore, these indicators were evaluated separately using DES after layout optimization rather than being incorporated directly into the optimization objective. This sequential optimization–evaluation strategy enables the layout to be optimized for material flow while assessing its broader operational impact under realistic manufacturing conditions.

3.2. Solution Approach

Given its combinatorial nature, the facility layout problem is well known to be NP-complete [33], which makes exact optimization methods impractical for larger or more realistic layouts. For this reason, a metaheuristic approach is typically adopted to obtain good-quality solutions within a reasonable time. Among the available techniques, GA has consistently been found to be one of the most effective tools for layout optimization [2].

GA, a population-based search approach inspired by natural selection, can explore an ample solution space while avoiding premature convergence, making it ideal for

complex layout problems. In this study, GA is employed to optimize the department design while meeting spatial and aisle constraints. Figure 3 presents the pseudocode for the developed GA, outlining the main steps of initialization, fitness evaluation, selection, crossover, mutation, and convergence.

Input:

Departments $i \in I$, department dimensions, factory dimensions (W, H)

Material flow matrix F_{ij}

Aisle constraints: $(X_T, Y_T, W_T, H_T), (X_V, Y_V, W_V, H_V)$

GA parameters: population size P , mutation rate μ , max generations G

Output:

Best feasible layout L_{best} and its cost C_{best}

Begin

1. Initialize Population:

Generate P feasible layouts satisfying:

- No overlap between departments
- No overlap with restricted aisles
- Within factory boundaries

2. Evaluate Fitness:

For each layout L in the population:

Compute TMHC:

$$C(L) = \sum_{i=1}^n \sum_{j=1}^n F_{ij} \cdot D_{ij} \cdot C_{ij} \quad (1)$$

Identify L_{best} with the minimum cost

3. While (generation $< G$) and (no convergence)

a. Selection:

Retain the top 50% layouts with the lowest $C(L)$

b. Crossover:

Combine pairs of parent layouts to produce new offspring

c. Mutation:

Swap the coordinates of two departments with probability μ

d. Feasibility Check:

If overlap or constraint violation occurs, regenerate the layout

e. Evaluate Fitness:

Recompute $C(L)$ for all layouts

f. Update L_{best} and C_{best}

4. Termination:

If convergence or max generations reached:

Return L_{best} and C_{best}

End

Figure 3. Pseudocode of the GA for Facility Layout Optimization.

3.2.1. Chromosome Structure

Each chromosome represents a feasible facility layout configuration. A chromosome is encoded as a list of tuples (x_i, y_i) (where the tuple is an ordered pair storing the x- and y-coordinates of the department's centroid) corresponding to the coordinates of each department i . The geometric dimensions (w_i, h_i) are predefined for each department and fixed during optimization. The initial population is created from two sources: layouts produced during the SLP stage, which serve as structured, realistic starting points, and

additional layouts generated randomly to satisfy all geometric and aisle constraints, ensuring diversity in the search space.

3.2.2. Fitness Evaluation

The fitness function measures the TMHC for each candidate layout using Equation (1). Where F_{ij} is the material flow between departments i and j , D_{ij} is the rectilinear distance between their centroids, and C_{ij} is the cost per unit distance. The GA aims to minimize this cost. Layouts that violate constraints are penalized by assigning a high artificial cost, thereby guiding the population toward feasible solutions.

3.2.3. Selection Operator

In each generation, layouts are evaluated based on their fitness scores, and the top half of the population is selected for reproduction. A truncation selection strategy was employed, in which the best-performing 50% of the population were selected for reproduction. This approach favors higher-quality solutions while maintaining diversity through crossover and mutation operators.

3.2.4. Crossover Operator (Uniform Crossover)

The crossover operator combines the spatial attributes of two parent layouts to produce offspring. For each department i , the offspring inherits the position (x_i, y_i) from either parent 1 or parent 2 with equal probability. If the generated child violates feasibility constraints, the feasibility-checking procedure regenerates the layout randomly until it is valid.

3.2.5. Mutation Operator (Swap Mutation)

Mutation enhances population diversity by introducing small random changes to the layout. In this study, two departments are randomly selected, and their positions are swapped. Mutation occurs with a predefined probability ($P_m = 0.05$) and is subsequently followed by the feasibility-checking procedure, which rejects infeasible layouts and regenerates feasible ones before fitness evaluation. If the mutated layout results in overlaps or boundary violations, it is regenerated to restore validity.

3.2.6. Feasibility Checking Procedure

During population initialization, crossover, and mutation, every candidate layout is examined using the feasibility-checking procedure. The procedure verifies that:

- departments do not overlap,
- departments remain within the factory boundaries,
- departments do not intersect the horizontal or vertical aisles.

Candidate layouts violating any of these conditions are rejected and regenerated until all spatial constraints are satisfied before fitness evaluation. Figure 4 illustrates an example of the feasibility-checking procedure. Candidate layouts violating the spatial constraints are rejected and regenerated before fitness evaluation, ensuring that only feasible layouts participate in the optimization process.

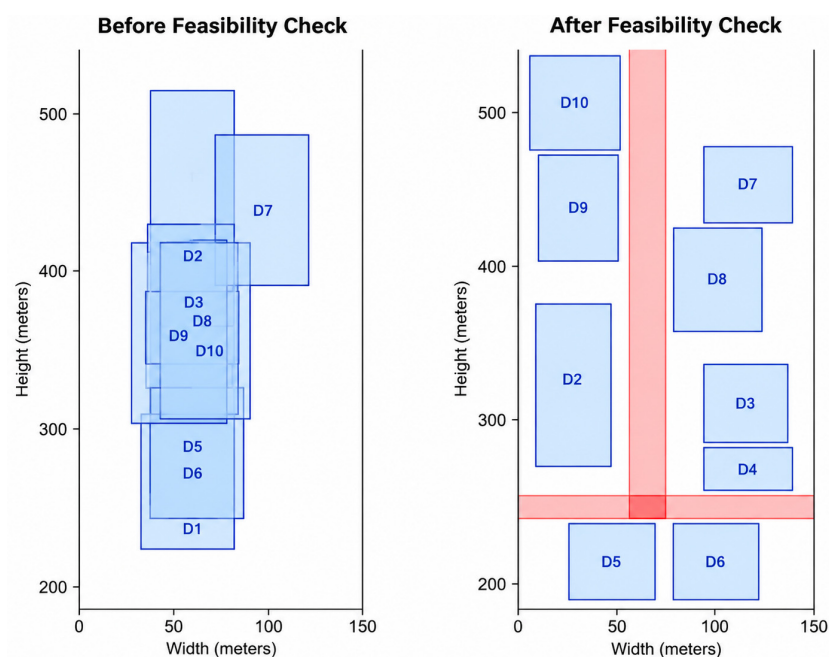


Figure 4. Example of the feasibility-check procedure (D represents the department, and the red zone represents the aisle).

3.2.7. Termination Condition

The GA terminates when either the maximum of 1000 generations is reached or the algorithm converges. The best-performing chromosome at termination represents the near-optimal facility layout.

3.2.8. GA Parameter Settings

Table 2 shows the main algorithmic parameters and operators used in this study. The final settings were selected based on preliminary sensitivity testing and the computational requirements of the case-study layout problem. All computational experiments were performed on a laptop equipped with a 12th Gen Intel® Core™ i5-1235U processor (1.30 GHz) and 8 GB RAM. The GA was implemented in Python 3.x using NumPy, Matplotlib, and Python's built-in random module. No commercial optimization software or specialized optimization solvers were employed. The average computational time was approximately 15 s per independent run.

Table 2. GA parameter and operators.

Parameter	Value/Strategy
Population size	50 individuals
Chromosome representation	encoded as a list of tuples (x_i, y_i)
Initialization	Random feasible placement
Fitness function	Minimize TMHC
Selection strategy	Truncation selection
Elitism	Implicit elitism
Crossover operator	Uniform crossover
Crossover probability	CR = 0.80
Mutation operator	Swap mutation
Mutation rate	MR = 0.05
Constraint handling	Feasibility checking and regeneration
Stopping criterion	50 generations without improvement
Maximum generations	1000

Independent runs	20 runs
Random seed	Seeds 0–19
Computational time	15 s/run on average

4. Numerical Example

A case study was analyzed in a transformer manufacturing facility. Two parallel production streams are required for manufacturing oil transformers. These two streams converge at the final assembly: the active-part stream and the tank-manufacturing stream. The active part stream includes processes such as core cutting, winding, active part assembly, electrical connections, and drying. The tank stream includes fin folding, rib welding, tank assembly, welding, and shot blasting, followed by painting and inspection. Both streams must be synchronized to ensure smooth final assembly of the transformer.

Figure 5 illustrates the complete production flow, as can be seen, it shows two parallel streams (active part vs. tank). As shown, the active part (Stream 1) and the tank (Stream 2) are processed independently before being integrated into the final assembly. While the active part flow is primarily electrical and mechanical, the tank flow involves large, heavy steel structures that require more resources, longer transportation times, and more space for processing and storage.

Although both streams are important, our study focused on the tank manufacturing stream (Stream 2) for four primary reasons:

- The tank stream has a longer cycle time than the active part. The active part's cycle time is nearly equal to the takt time, while the tank stream has a greater processing time, which results in a synchronization imbalance as illustrated in Figure 6.
- This imbalance results in a high level of WIP accumulating in the assembly area. As tank production cannot keep pace with active part manufacturing.
- To meet the demand, the company is outsourcing the shortfall. Figure 7 illustrates how the corporation has outsourced tanks to compensate for its limited in-house tank capacity. Outsourced tanks account for a large share of monthly demand, particularly during peak months (September and October). Outsourcing not only incurs much higher costs but also introduces uncertainty in quality and lead times, leading to on-time delivery issues.
- Finally, the tank stream includes heavy steel structures and extensive welding, which require additional handling effort, crane operations, and aisle access. This highlights the need to optimize tank layout design.

That is why the factory's tank manufacturing stream for oil distribution transformers has been identified as a major bottleneck, unable to meet customer expectations efficiently. This stream, which includes both mechanical and manual activities, has a much lower throughput than the active part production stream.

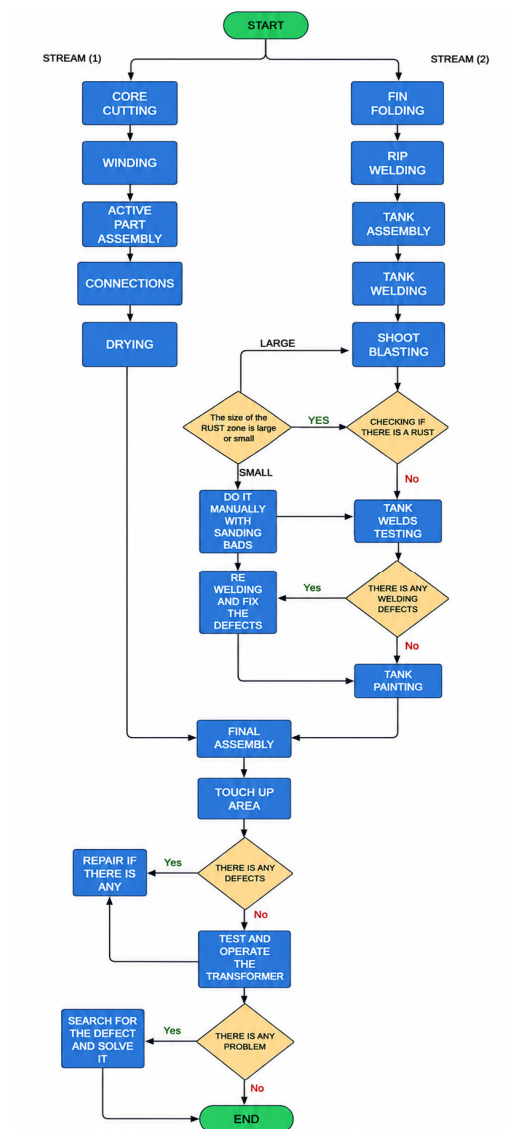


Figure 5. Process flowchart for transformer manufacturing.

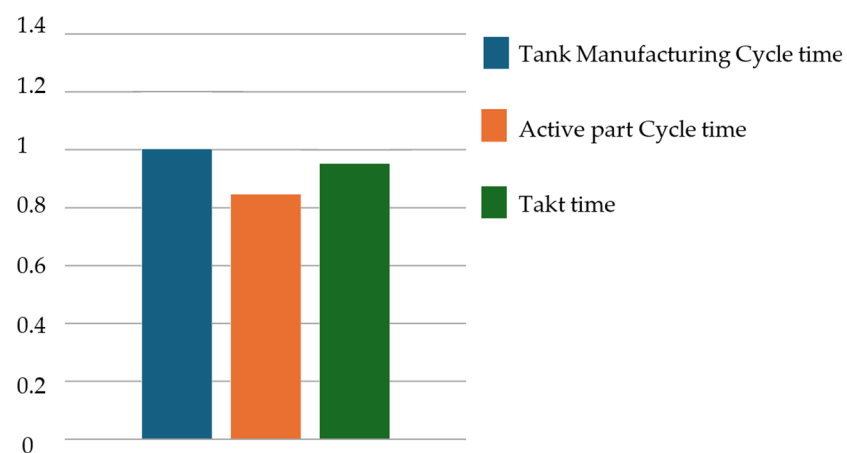


Figure 6. Takt time Vs. Cycle time for the two streams (hours).

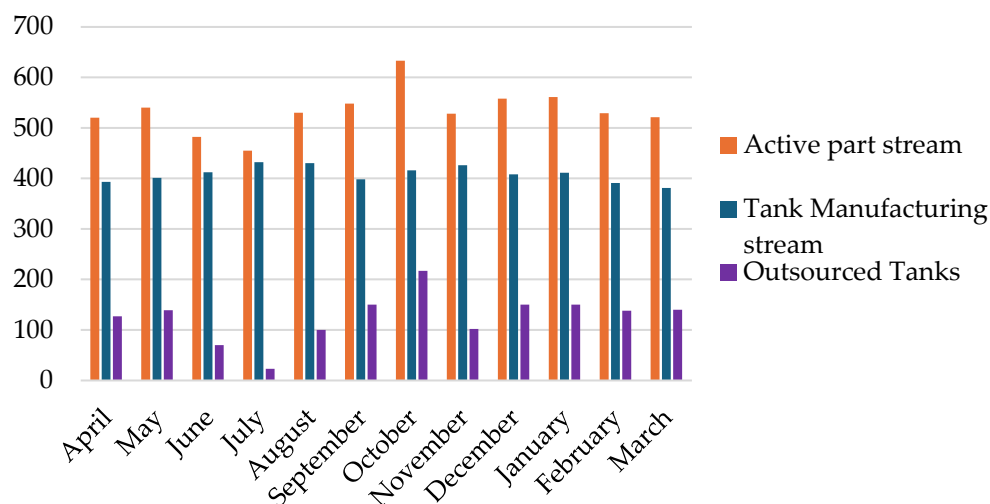


Figure 7. Monthly production of active part stream, tank stream, and outsourced tanks in 2024.

5. Results and Analysis

5.1. SLP Results

The SLP method was applied to develop the initial factory layout. At first, the current production and operational data were analyzed to construct the activity relationship chart, from-to chart, and material flow diagram—shown in Appendix A (Tables A1–A6). These relationships were classified using the standard SLP codes (A, E, I, O, U, X). The relationship diagram is shown in Figure A1. This figure highlights departments, such as raw material storage, welding, and painting, that require proximity due to high material flow.

The layout derived from the SLP analysis was similar to the factory’s current physical layout. The placement of major departments (i.e., fin folding and welding, tank assembly, shot blasting, testing, and painting) closely matched the relationships determined by the SLP closeness codes (A, E, I). The detailed SLP block layout is presented in Appendix A (Figure A2).

Because of this alignment, the existing factory layout was adopted as the initial layout for the optimization and simulation phases (Figure A3). This approach ensured that the GA started with a realistic, feasible starting point, while still allowing improvements focused on material flow and cost reduction. Based on current flow data, the TMHC for the existing setup was calculated at 7062.5 L.E. per transformer. An additional analysis was performed using VisTable (version 3.0) to verify the obtained TMHC, as shown in Appendix A (Figure A4).

5.2. Simulation Model Verification and Validation

5.2.1. Simulation Model Development

The simulation model was developed in FlexSim to replicate the transformer manufacturing process under actual operating conditions. The model incorporated the observed production sequence, machine capacities, operator assignments, crane movements, workstation locations, and material-routing logic. Processing times were obtained from factory production records and directly implemented in the simulation model. Buffers and routing rules were modeled according to the existing production system to provide realistic estimates of throughput, WIP, machine utilization, and cycle time.

The model calculations are based on 7 working hours per shift and 26 working days per month, reflecting the factory's actual production conditions. Table 3 shows the simulation model configuration. Figure 8 shows the simulation model for the initial layout. In addition, Figure 9 shows the simulated monthly throughput of each workstation in the initial layout.

Table 3. Simulation Model Configuration.

Item	Description
Simulation software	FlexSim
Run length	1 month
Warm-up period	10 days
Shift schedule	2 shifts/day
Working days	26 days/month
Process-time distribution	Deterministic
Material routing	According to the production flow in Figure 5
Crane movement	First-come, first-served
Performance measures	Throughput, WIP, utilization, cycle time

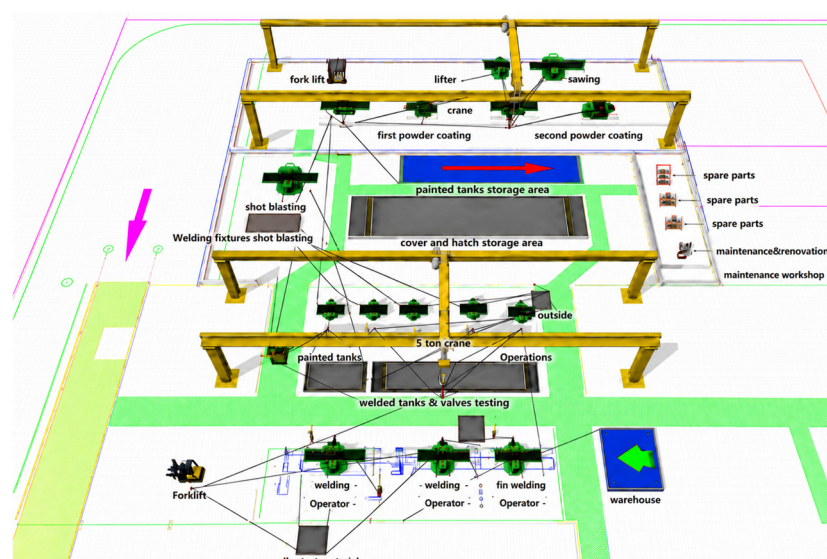


Figure 8. Simulation model for the initial layout.

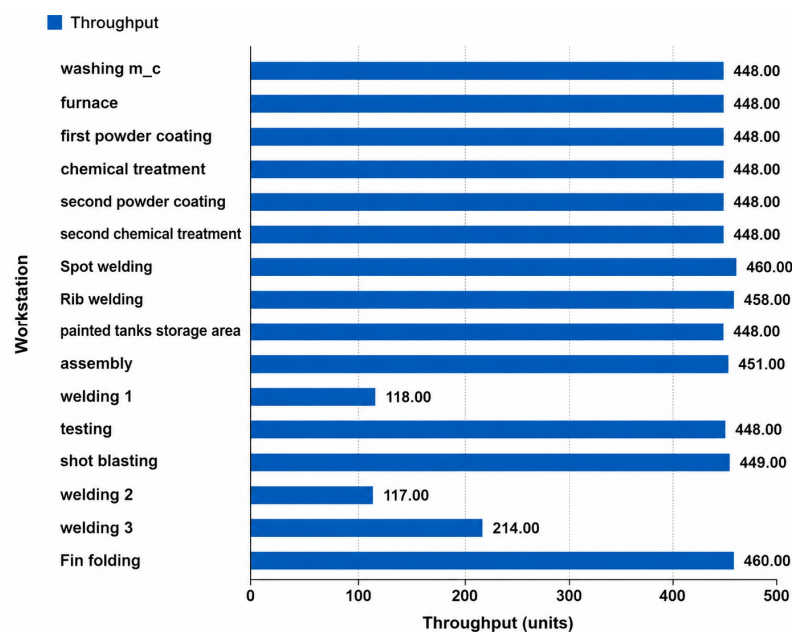


Figure 9. The simulated monthly throughput of each workstation in the initial layout.

5.2.2. Model Verification

The simulation model was verified by ensuring that the implemented logic, process routing, machine capacities, shift schedules, and material flow accurately represented the actual production system. Table 4 summarizes the factory's actual performance, which served as the reference for verifying the simulation model. These exact values were then compared with the simulation results in Table 5. The following equation is used to calculate the error %:

$$\text{Error \%} = \left| \frac{\text{Simulation output} - \text{Actual factory performance}}{\text{Actual factory performance}} \right| \times 100$$

Table 4. Actual factory performance.

Processes	No. of Shifts	Hrs/Month	Actual Processing Time (h)	Hourly Output	Total Output (Units/Month)
fin folding	2	364	0.87	1.14	418
rib welding	2	364	0.835	1.2	436
shoot blasting	2	364	0.77	1.29	469
spot welding (assembly)	1	182	0.37	2.7	491

Table 5. Percentage Error Between Actual Factory Performance and Simulation Model Results.

Processes	Actual Total Output (Units/Month)	The Model Total Output (Units/Month)	Error %
fin folding	418	460	10
rib welding	436	458	5.04
shoot blasting	469	449	4.26
spot welding (assembly)	491	460	6.3

5.2.3. Model Validation

The validation step aimed to assess the simulation model's ability to reproduce the observed behavior of the actual production system by comparing simulation outputs with factory data. The selected processes represent the critical bottleneck and production-

critical operations of the manufacturing line and were therefore chosen for model validation because they have the greatest influence on the overall system performance.

As shown in Table 5, the maximum deviation between the simulation and the actual factory output was 10%, which falls within the $\pm 10\%$ validation criterion commonly adopted in industrial simulation studies [34,35]. Moreover, this threshold is consistent with the factory's quality control specifications, in which deviations of $\pm 10\%$ are considered operationally acceptable and do not affect downstream production or product quality. Therefore, the developed simulation model is considered sufficiently accurate to represent the actual manufacturing system and evaluate alternative facility layouts.

In addition to throughput, current performance was examined using machine utilization profiles and WIP across different workstations. Figure 10 shows the utilization levels of the primary workstations, while Figures 11–14 illustrate the WIP observed before the shot blasting, assembly, welding, and painting processes, respectively. Overall, the validation results indicate that the FlexSim model provides a reliable basis for evaluating layout alternatives and performing post-optimization analysis.

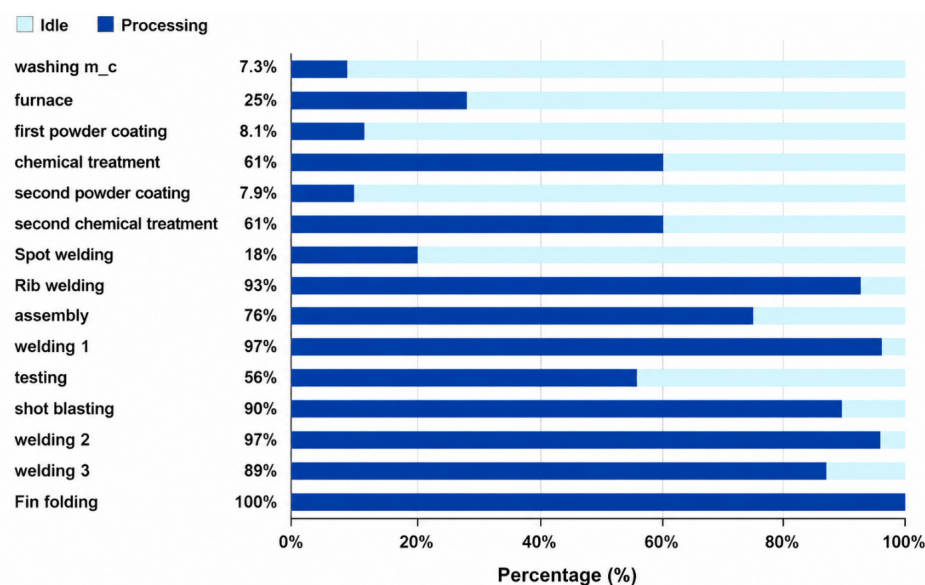


Figure 10. Machine utilization for different stations.

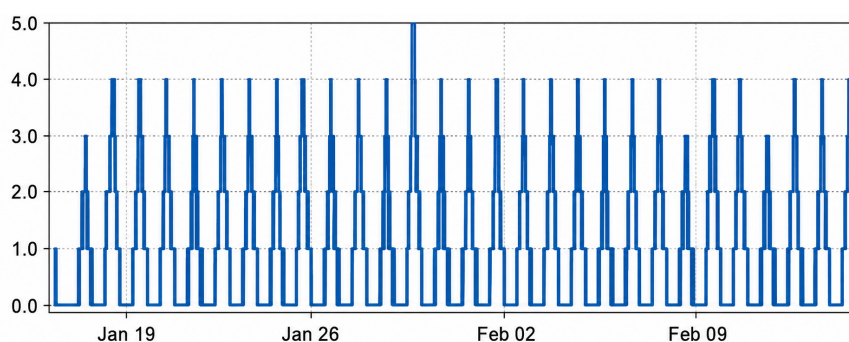


Figure 11. WIP before shot blasting area.

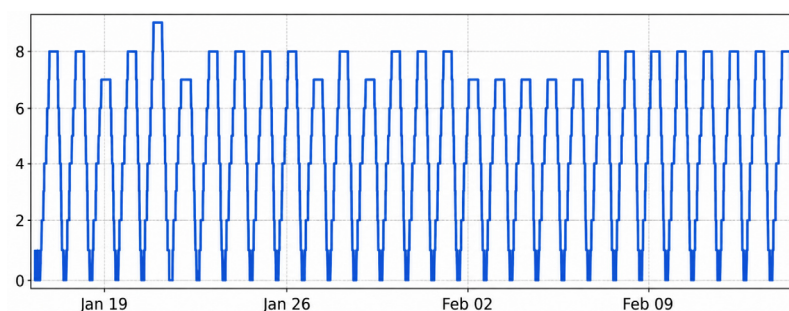


Figure 12. WIP before the assembly area.

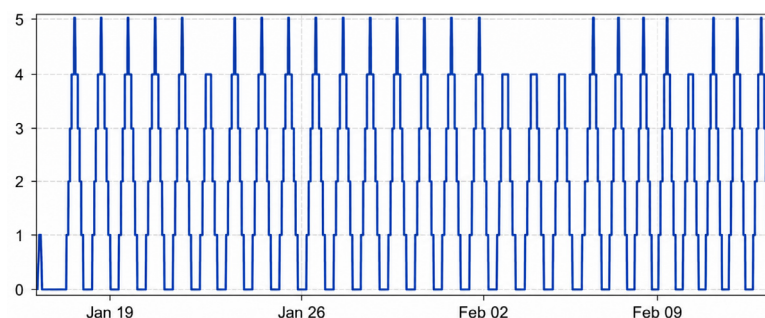


Figure 13. WIP before welding area.

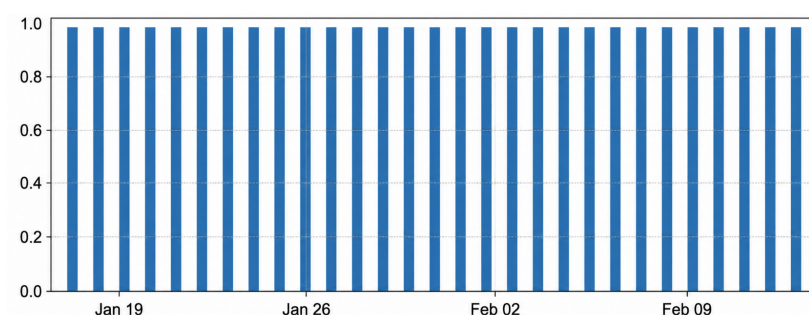


Figure 14. WIP before Painting area.

5.3. GA Results

5.3.1. Optimized Layout

The GA was developed using Python. It was specifically designed to address the features of the transformer manufacturing plant. This algorithm incorporates the previously stated practical layout limitations, such as the requirement for non-overlapping departments, fixed factory perimeters, and restricted T-shaped aisles. To ensure solution diversity while simultaneously promoting convergence, the GA employs a combination of random and systematic search strategies during the evolutionary process.

The input flow matrix used for optimization was identical to that used in the SLP analysis. However, the industrial facility consists of eleven functional areas; only the ten production departments were included as decision variables in the GA optimization. The warehouse serves as a raw-material storage and temporary buffer area located adjacent to the material receiving point. Since its location is flexible and is not part of the production departments whose positions are optimized, it was excluded from the chromosome representation.

Consequently, the GA optimized only the ten production departments. Their corresponding dimensions are listed in Table 6. Figure 15 presents the optimized facility

layout generated by the GA, while Figure 16 illustrates the algorithm's convergence behavior across 20 independent runs.

Table 6. Dimensions of the 10 departments optimized by the GA.

GA ID	Department	Width (m)	Height (m)
D1	Raw Material Area	42.97	172.60
D2	Fin Folding and Rib Welding	42.97	86.30
D3	Welded Ribs	47.50	38.10
D4	Tank Assembly Area	47.50	76.50
D5	Welding Area	47.50	76.50
D6	Shot Blasting	47.50	76.50
D7	Testing Waiting Area	48.00	97.56
D8	Testing Area	38.56	97.56
D9	Painting Area	47.65	97.56
D10	Painted Tanks Storage Area	47.65	97.56

Note: The warehouse functions as a raw-material storage and temporary buffer area. Since its location is flexible and does not affect the internal production flow, it was excluded from the GA optimization. Therefore, the optimization was performed only on the ten production departments.

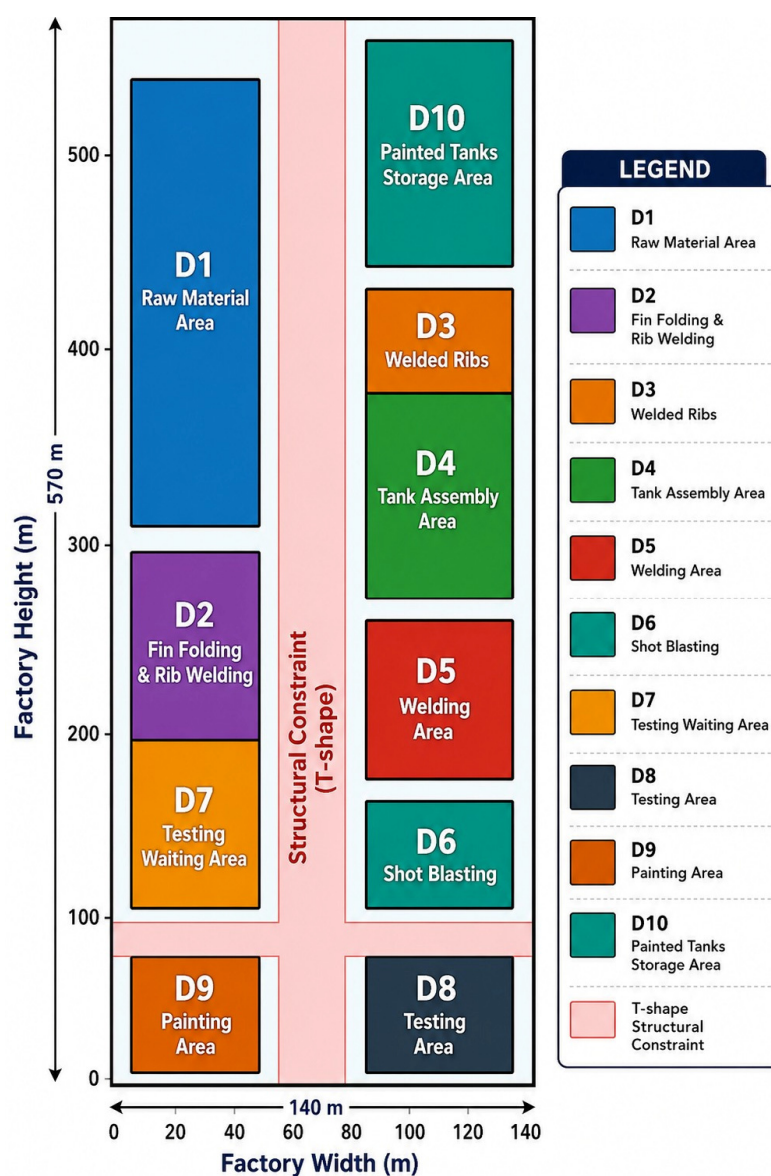
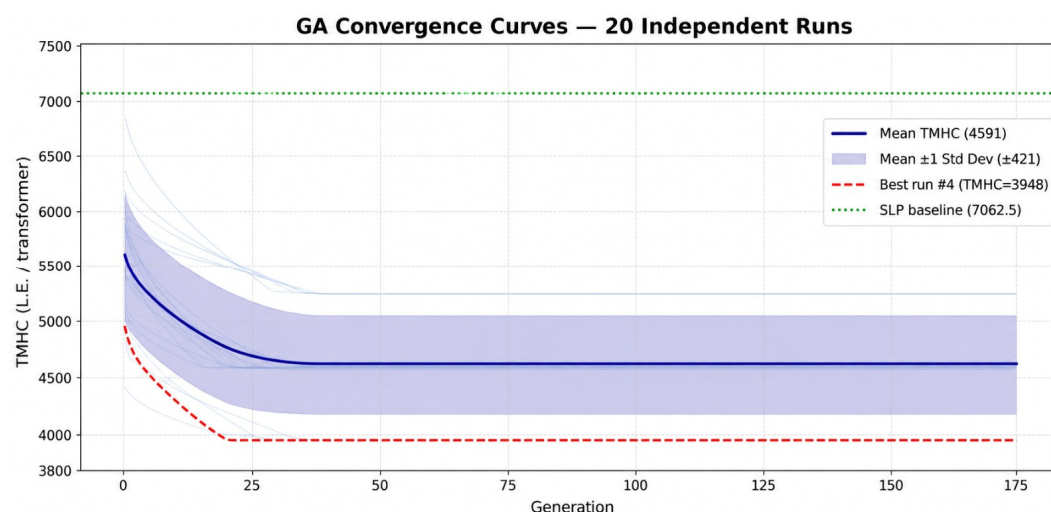


Figure 15. Optimized layout from GA.**Figure 16.** Convergence curves for the proposed GA across 20 independent runs.

5.3.2. Statistical Performance of the GA

Twenty independent optimization runs were performed with different random seeds to assess the robustness and repeatability of the proposed GA while keeping the parameter settings identical. Table 7 summarizes the algorithm's statistical performance.

Table 7. Statistical performance of the GA algorithm.

Metric	Value
Number of independent runs	20
Best TMHC	3948
Mean TMHC	4591
Worst TMHC	5203
Standard deviation	421
Mean convergence generation	125.7

The results demonstrate consistent convergence of the proposed GA across all independent runs. The low standard deviation indicates that the algorithm is robust to random initialization and can repeatedly identify high-quality facility layouts, as shown in Figure 16. It shows the convergence curves for the proposed GA across 20 independent runs, showing the best run, the mean convergence, ± 1 standard deviation, and baseline layouts.

5.3.3. Comparison with Baseline Layouts

To further assess the effectiveness of the proposed GA, its performance was compared with two baseline layouts: the initial SLP layout and randomly generated feasible layouts. Table 8 summarizes the TMHC values together with the corresponding improvements over the baseline methods.

Table 8. Comparison of the proposed GA with the initial SLP and random feasible layouts.

Method	Best TMHC	Mean TMHC	Std. Dev.	Worst TMHC	Mean Improvement vs. SLP (%)	Evaluation
Proposed GA	3948	4591	421	5203	35	20 independent runs
Initial SLP layout	7062.5	—	—	—	Reference	Single layout

Random feasible layouts	4823	5847.3	621.4	7109	17.2	30 random feasible layouts
-------------------------	------	--------	-------	------	------	----------------------------

Compared with the initial SLP layout, Table 8 shows that the proposed GA reduced the mean TMHC by 35%. It also outperformed randomly generated feasible layouts by approximately 21.5%, demonstrating that the improvement is attributable to the optimization process rather than random placement.

5.3.4. Sensitivity Analysis

A sensitivity analysis was performed to investigate the influence of crossover and mutation probabilities on the optimization performance. Figure 17 indicates that a crossover probability of 0.8 and a mutation probability of 0.05 yielded the lowest mean TMHC while maintaining stable convergence and was therefore adopted throughout the study. The selected parameters (CR = 0.80, MR = 0.05) yielded the lowest mean TMHC.

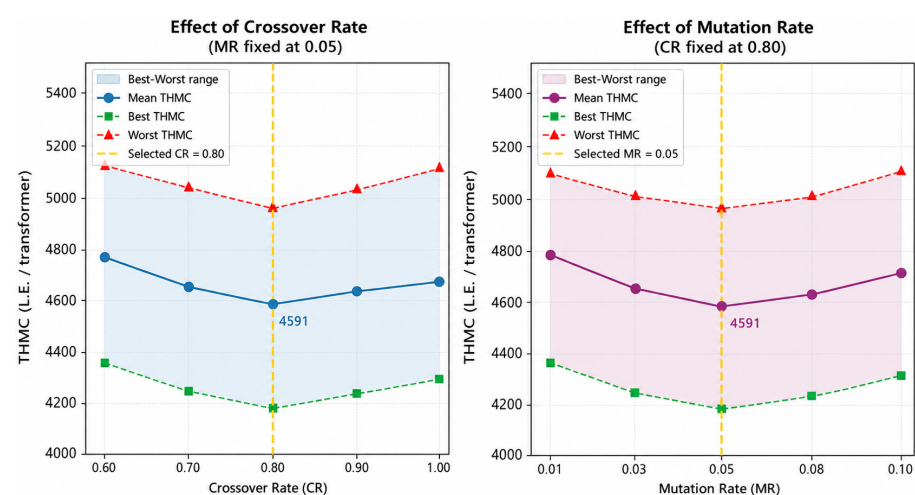


Figure 17. Effect of crossover and mutation rates on GA performance.

Overall, the proposed GA consistently generated high-quality layouts over 20 independent runs and significantly outperformed both the initial SLP layout and randomly generated feasible layouts. The sensitivity analysis further confirmed that the selected crossover and mutation probabilities provided the best optimization performance.

These results demonstrate the robustness and effectiveness of the proposed optimization framework for solving the constrained facility layout problem. Figure 18 presents the final VisTable layout, showing the spatial arrangement and flow paths that minimize TMHC.

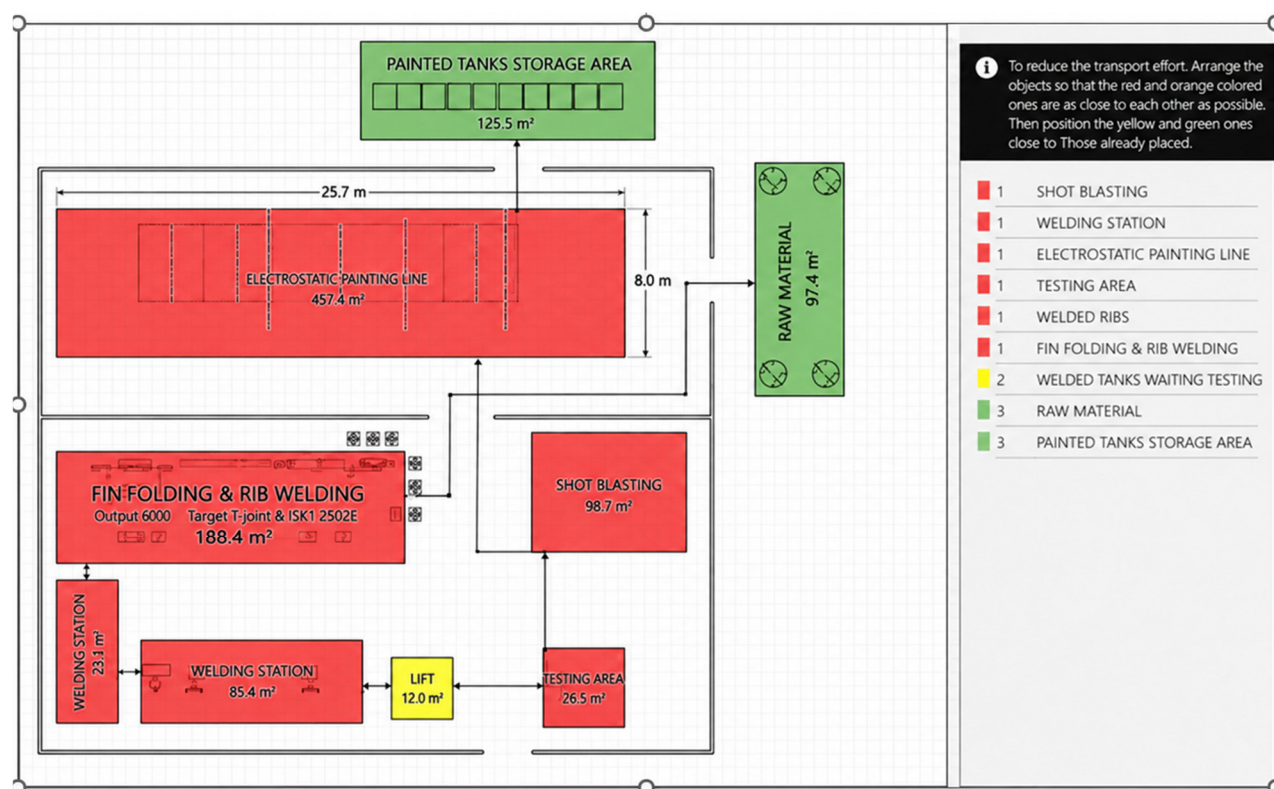


Figure 18. Final layout arrangement using VisTable.

TMHC was then recalculated using the updated inter-department distances (Table 9) and material flows, resulting in a total handling cost of 4560 L.E. per transformer (Table 10). This value differs by less than 1% from the GA solution, confirming the feasibility of the optimized layout. This demonstrates the model's reliability and confirms that the proposed layout is feasible and cost-efficient.

Table 9. The distance matrix of the proposed layout (in meters).

From-To	1	2	3	4	5	6	7	8	9	10	11
1	0	100	0	0	0	0	0	0	0	0	0
2	0	0	2.2	0	0	0	0	0	0	0	0
3	0	0	0	15	0	0	0	0	0	0	0
4	0	0	0	0	2.3	0	0	0	0	0	0
5	0	0	0	0	0	12.2	0	0	0	0	0
6	0	0	0	0	0	0	9.33	0	0	0	0
7	0	0	0	0	0	0	0	2.8	0	0	0
8	0	0	0	0	0	0	0	0	5.4	0	0
9	0	0	0	0	0	0	0	0	0	36.1	0
10	0	0	0	0	0	0	0	0	0	0	10.2

Table 10. TMHC of the proposed layout.

From-To	1	2	3	4	5	6	7	8	9	10	11	Sum
1	0	1899	0	0	0	0	0	0	0	0	0	1899
2	0	0	63	0	0	0	0	0	0	0	0	63
3	0	0	0	778	0	0	0	0	0	0	0	778
4	0	0	0	0	86	0	0	0	0	0	0	86
5	0	0	0	0	0	132	0	0	0	0	0	132
6	0	0	0	0	0	0	262	0	0	0	0	262

7	0	0	0	0	0	0	0	79	0	0	0	79
8	0	0	0	0	0	0	0	0	81	0	0	81
9	0	0	0	0	0	0	0	0	0	1028	0	1028
10	0	0	0	0	0	0	0	0	0	0	153	153
L.E./transformer 4560												

Another observation from the GA analysis indicated a change in the locations of the departments involved in the primary material flow, including the warehouse and the processing stations that follow it. These changes highlighted an opportunity to streamline the production sequence and improve efficiency. Based on the GA-derived flow, a new U-shaped configuration was developed to support one-piece flow and reduce unnecessary transportation. Figure 19 shows the new proposed U-shape layout.

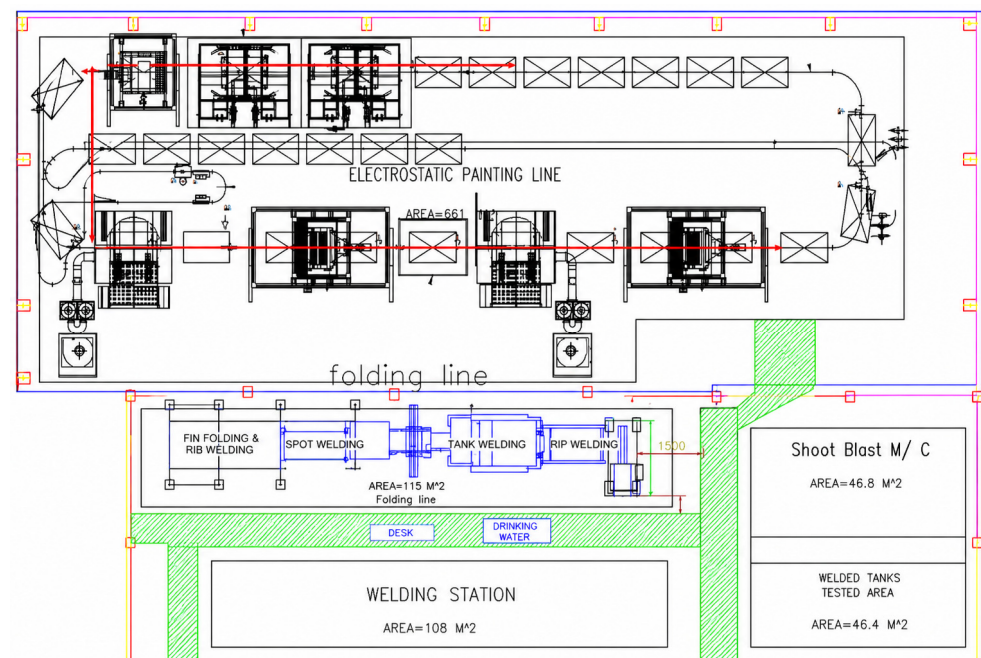


Figure 19. Proposed U-shape layout.

5.4. Simulation Results of the Proposed Layout

To evaluate how the optimized layout performs under real operating conditions, a simulation model was developed again in FlexSim using the final arrangement. Figure 20 shows the simulated factory environment after applying the optimized layout. The simulation included actual processing times, crane movements, workstation capacities, and material-handling routes.

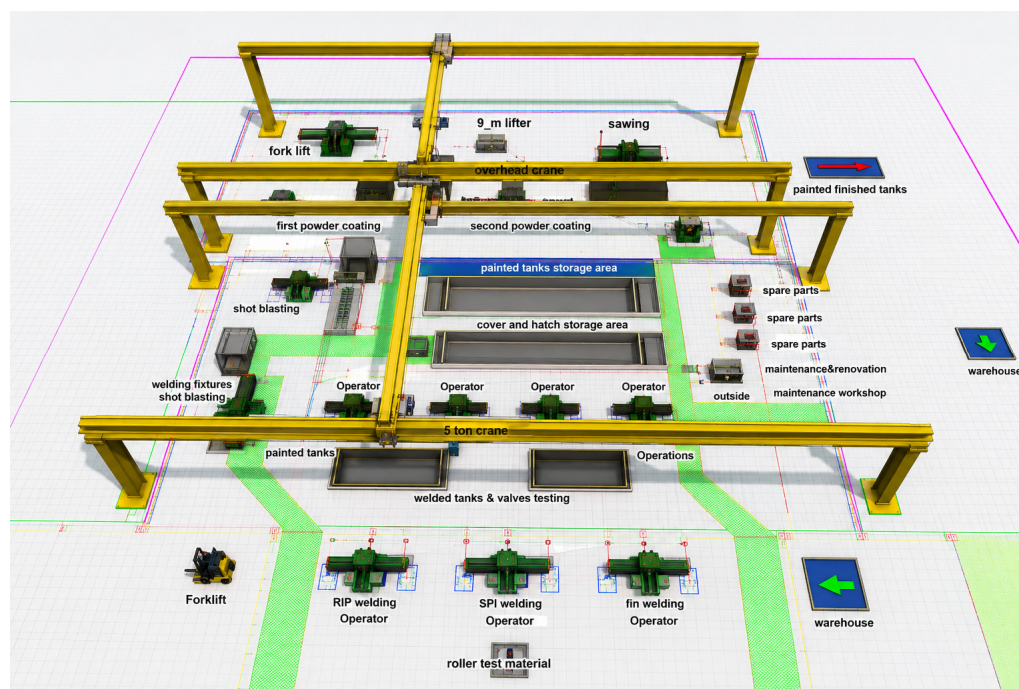


Figure 20. Simulation model for the post-optimization layout.

Figure 21 presents the simulated monthly throughput for each workstation, enabling direct comparison with baseline performance and demonstrating which stations gained the most from the new arrangement. Table 7 compares the plant's initial throughput with the optimized solution.

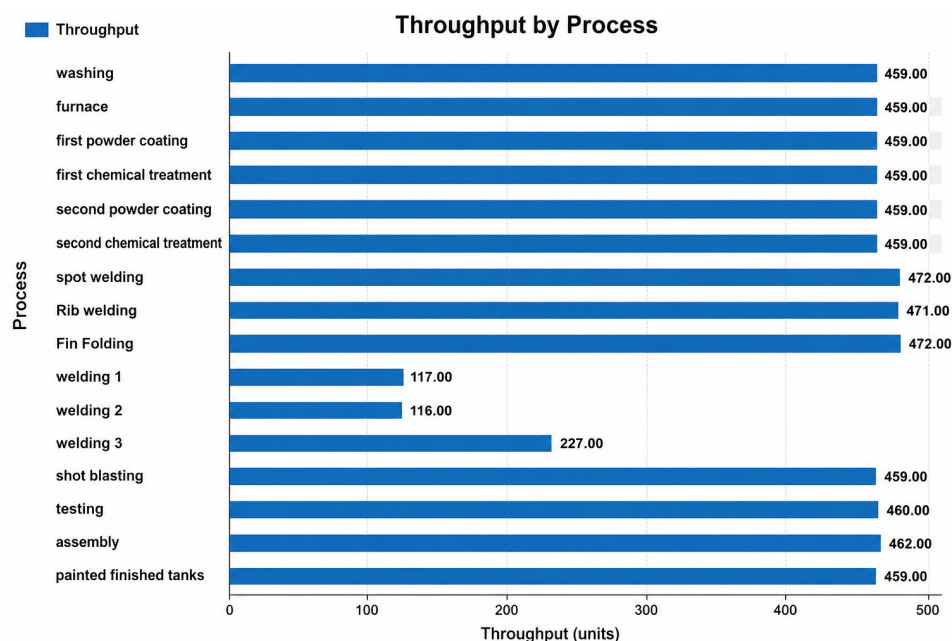


Figure 21. The proposed layout's monthly throughput.

As shown in Table 11, the monthly throughput increased across most stations, with a 2.46% increase in production. This shows a measurable improvement in system performance.

Table 11. Throughput comparison between current and optimized solutions.

Process	Old Solution Throughput (Units)	Optimized Solution Throughput (Units)	Throughput Improvement (Units)
Washing	448	459	+11
Furnace	448	459	+11
First powder coating	448	459	+11
Chemical treatment (1st)	448	459	+11
Second powder coating	448	459	+11
Chemical treatment (2nd)	448	459	+11
Spot welding	460	472	+12
Rib welding	458	471	+13
Painted tanks storage	448	459	+11
Assembly	451	462	+11
Welding 1	118	117	0
Welding 2	117	116	0
Welding 3	214	227	+13
Shot blasting	449	459	+10
Testing	448	460	+12
Fin folding	460	472	+12

Despite the proposed layout reduced the TMHC by 35%, the comparable increase in production throughput was only 2.46%. This difference is expected because GA optimizes the spatial arrangement of departments, reducing transportation distances and material-handling delays. However, the overall production rate remains constrained by processing times, machine capacities, and manual operations at bottleneck workstations, especially the fin-folding and welding stations. Therefore, the layout optimization mainly improves operational efficiency and logistics while only moderately increasing production throughput.

After implementing the optimized layout, machine utilization was further analyzed to identify remaining performance limitations within the system. Figure 22 presents machine utilization for the proposed layout.

From Figure 22, comparing the initial state with the optimized model shows that overall utilization patterns are similar, with slight improvements in assembly and chemical treatment. However, welding stations and fin-folding processes continue to operate near their maximum capacity in both scenarios, confirming that they are the main bottlenecks.

Although the layout optimization improved material flow and reduced handling distances, it could not eliminate bottlenecks caused by long processing times or manual interventions. For this reason, the fin-folding station was selected for further what-if analysis.

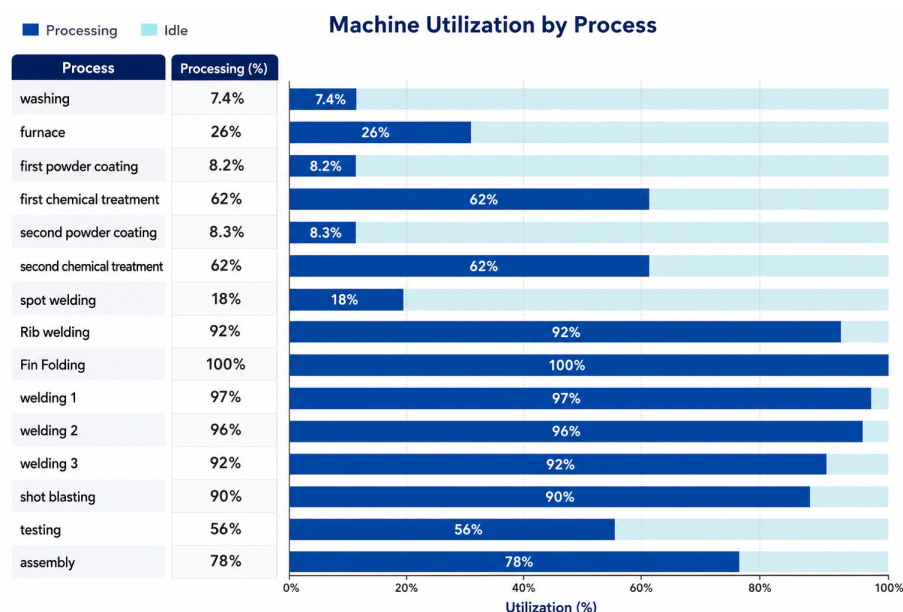


Figure 22. Utilization of the machines for the proposed layout.

5.5. What-If Analysis and Managerial Insights

Based on the utilization results shown in Figure 22, the fin-folding station was identified as a critical bottleneck, operating at near-continuous capacity. Therefore, this subsection focuses on examining the detailed activities of the fin-folding process (Table 12) and evaluating potential improvement scenarios through simulation.

Table 12. Various activities for the fin-folding station.

Activity	Time (min)
Loading the raw material into the m/c	10.77
Adjust the width of the m/c and make the first fin	3.25
Quality check	0.52
Second quality check	5.42
The first side is completed	2.40
The first fin of the second side is completed	0.60
Adjusting the sawing tool	5.82
The second side is completed	1.27
The sawing tool starts to cut	4.15
The external raw material is removed	0.75
Start to make the third side	1.00
Adjusting the saw tool	5.82
Starts to cut	0.53
The first side is cut	0.83
The third side is completed	0.65
Adjusting the m/c system and starting with the fourth side	1.50
Adjusting the cutting tool	5.83
Starts to cut	0.18
The second side is cut	0.68
The fourth side is completed	2.25

From Table 12 and the actual situation in the factory, the following have been found:

- Manual intervention is required after producing several fins, forcing the machine to pause.

- This procedure adds 22.5 min of non-productive time for every batch of four sides.
- Over time, these small pauses accumulate and cause considerable throughput reduction.

5.5.1. Scenario 1—Inserting an Automatic Laser Cutting Machine

A what-if scenario was simulated in which an automated laser-cutting machine replaced the manual cutting process. The processing time used in this scenario was derived from the detailed time study of the fin-folding operation rather than being arbitrarily assumed. The activity analysis identified 22.5 min of planned manual cutting and adjustment time after every four fin sides.

In the proposed scenario, these manual activities were replaced by an automated laser-cutting process with an estimated cutting time of 8.19 min for the same production cycle, operating continuously in synchronization with the fin production rate.

The estimated cutting time was obtained from the engineering design assumptions of the proposed laser-cutting system, which was designed to operate continuously in synchronization with the fin production rate. Consequently, the total processing time of the fin-folding station was reduced from 53.38 min to 39.03 min, and the updated value was used as the simulation input.

The simulation results indicate that although layout optimization reduced material-handling costs, additional throughput improvements require process-level changes. Automating the fin-folding operation therefore complements the layout optimization by addressing one of the primary production bottlenecks. Figure 23 shows the expected throughput for scenario 1.

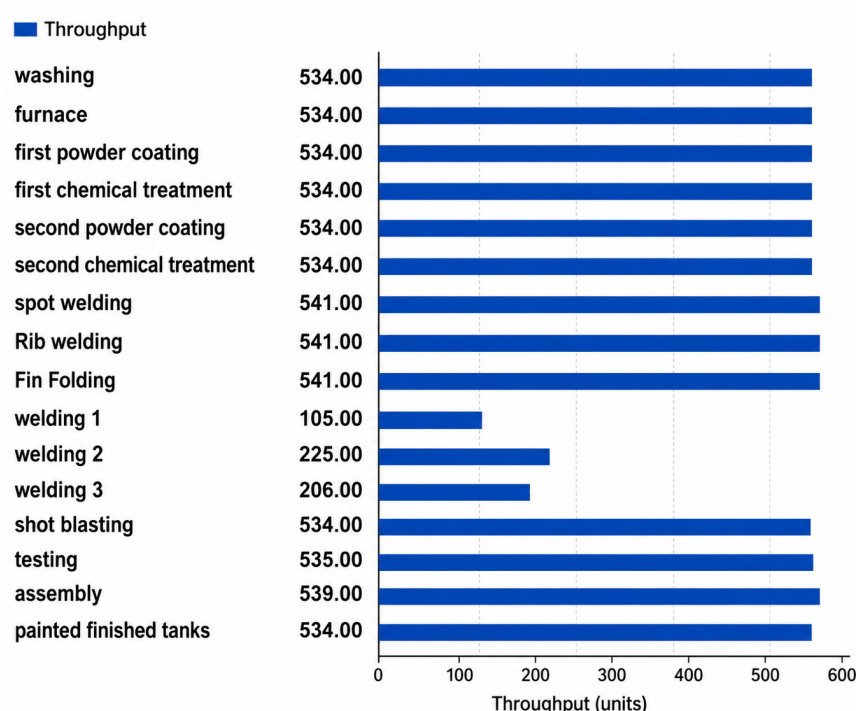


Figure 23. Expected throughput for scenario 1.

From Figure 23, reducing manual interruptions at the fin-folding station increases the throughput of downstream operations, particularly fin folding, rib welding, and spot welding. This confirms that the bottleneck is primarily process-related rather than layout-related, demonstrating that layout optimization alone cannot fully exploit the production capacity without complementary process improvements.

5.5.2. Economic Considerations

Although a detailed economic evaluation is beyond the scope of this study, the proposed laser-cutting scenario was also assessed from an industrial perspective. According to the factory's preliminary business assessment, automating the fin-folding process would reduce manual intervention, eliminate reliance on equipment that has been in service for more than 30 years, and increase production capacity to meet target demand.

In addition, improving the fin manufacturing process would reduce dependence on imported corrugated walls, which currently require approximately 10 weeks of lead time and incur higher procurement costs. The factory's internal business assessment estimates the investment cost of the proposed machine at approximately USD 1,525,000 (excluding installation costs), with a projected additional annual revenue of approximately USD 451,200.

These preliminary estimates suggest that the proposed investment is industrially feasible; however, a comprehensive financial evaluation, including installation costs, maintenance, operating expenses, payback period, and return on investment, should be conducted before full-scale industrial implementation.

5.6. Discussion and Future Perspectives

Despite the proposed framework demonstrating promising results for the transformer manufacturing case investigated, its applicability depends on the availability of reliable production data, including processing times, material flows, and operational constraints.

In the meantime, the numerical results are specific to the presented case study; the proposed SLP–GA–DES workflow is based on well-established principles of facility layout planning, optimization, and simulation that can be adapted to other discrete manufacturing environments with comparable production data. Previous studies have identified limited historical manufacturing data as a major challenge for simulation calibration, scenario generation, and bottleneck diagnosis.

Recent research has also shown that DES can generate representative synthetic manufacturing data to support data-driven prediction when real production data are insufficient [32,36]. Building on these developments, future research could integrate data-driven predictive models into the proposed SLP–GA–DES workflow to improve simulation calibration, scenario generation, and operational decision-making when historical production data are limited, thereby enhancing the transferability and robustness of the proposed methodology across diverse manufacturing settings.

6. Conclusions

In this paper, an integrated decision-support workflow based on SLP, GA, and simulation was applied to improve the operational efficiency of manufacturing facilities. The proposed workflow provides a structured approach to improving facility layout, enabling the identification of opportunities for operational improvement. To test its real-world applicability, the model was applied to a transformer manufacturing facility.

An initial layout was developed using SLP, then improved by GA to enhance the flow of materials and processes. The results showed that the proposed design could reduce material-handling waste and shorten transfer times. The results demonstrate the effectiveness of the proposed workflow, which integrates qualitative planning, optimization, and simulation-based validation into a unified decision-support process, resulting in measurable improvements in throughput and reductions in production costs.

Simulation was first used to evaluate the initial layout and subsequently to validate the optimized layout under realistic operating conditions. This enabled experimentation with

different scenarios and prediction of performance without disrupting actual production. Furthermore, a what-if analysis was conducted to assess the facility's potential to meet demand targets. Overall, the integrated application of SLP, optimization, and simulation provided an effective decision-support workflow for facility layout planning.

The results demonstrate the effectiveness of the proposed workflow for the investigated industrial case study, yielding measurable reductions in material-handling costs and modest improvements in production throughput. Although the proposed workflow is intended for offline facility layout planning rather than real-time operation, it provides a structured foundation for future data-driven manufacturing applications.

By integrating live production data from sensors, Manufacturing Execution Systems (MES), or Industrial Internet of Things (IIoT) platforms, the simulation model could continuously reflect the current production state, supporting more informed operational decision-making. These capabilities demonstrate the proposed workflow's potential in future digital manufacturing environments.

Although the proposed workflow integrates generally applicable planning, optimization, and simulation techniques, its validation in the present study is limited to a single transformer manufacturing case. Consequently, further validation across different industrial sectors and production systems is required to establish its broader generalizability. In addition, the current optimization model assumes deterministic operating conditions.

Future research should integrate stochastic optimization and simulation by incorporating machine failures, processing-time variability, operator availability, and demand uncertainty into a unified decision-support framework to represent real manufacturing environments better.

Furthermore, integrating real-time production data with AI-assisted predictive analytics could enable physically interpretable production forecasting, bottleneck diagnosis, and adaptive decision support for facility layout planning. Extending the proposed workflow from a broader supply chain perspective also represents a promising direction for future research.

Author Contributions: Conceptualization, I.F.; methodology, I.F.; software, I.F.; validation, I.F. and N.Z.; formal analysis, I.F. and N.Z.; investigation, I.F. and N.Z.; resources, I.F.; data curation, I.F.; writing—original draft preparation, I.F.; writing—review and editing, I.F. and N.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This publication has emanated from research jointly funded by Taighde Éireann—Research Ireland under Grant Number 13/RC/2094_2, and co-funded by the European Union under the Systems, Methods, Context (SyMeCo) programme Grant Agreement Number 101081459. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the European Research Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

Data Availability Statement: The data used in this study were obtained from the transformer manufacturer. All the data are included in the manuscript.

Acknowledgments: During the preparation of this manuscript/study, the authors used ChatGPT (GPT-5.6) to improve the clarity, grammar, and academic style of the text and to assist with minor graphical editing. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

FLP	Facility Layout Planning
SLP	Systematic Layout Planning
GA	Genetic Algorithm
DES	Discrete Event Simulation
AHP	Analytic Hierarchy Process
ACO	Ant Colony Optimization
WIP	Work-in-Progress
MCDM	Multi-Criteria Decision Making
NLP	Non-Linear Programming
DEA	Data Envelopment Analysis
TMHC	Total Material Handling Cost
MES	Manufacturing Execution Systems
IIoT	Industrial Internet of Things

Appendix A

Appendix A presents the detailed data and diagrams used in the SLP phase to develop the initial factory layout. These include quantitative flow matrices, cost data, and diagrams supporting relationship and layout development. Table A1 lists the departments considered throughout the study.

Table A2 presents the material flow matrix, showing the number of units transported between each pair of departments. The SLP analysis considers all eleven functional areas in the factory, including the warehouse. During the subsequent GA optimization, the warehouse was excluded from the optimization variables because it serves as a flexible raw-material storage and temporary buffer area. Consequently, the GA optimized only the ten production departments.

Table A3 provides the corresponding rectilinear distances (in meters), while Table A4 reports the transportation time calculated using a handling speed of 40 m/min. These matrices quantify the interaction intensity between departments and determine the cost impact of their relative placement.

Table A5 lists the cost per minute associated with each production area. These values were used in calculating the TMHC. Using the flow, distance, and cost data, the TMHC matrix was computed and is shown in Table A6. The TMHC for the existing configuration is 7062.5 L.E. per transformer.

Table A1. Department numbering used throughout the study.

ID	Department
1	Warehouse
2	Raw material area
3	Fin folding and rib welding
4	Welded ribs
5	Tank assembly area
6	Welding area
7	Shot blasting
8	Testing waiting area
9	Testing area
10	Painting area
11	Painted tanks storage area

Table A2. Material flow matrix (No. of units).

From-To	1	2	3	4	5	6	7	8	9	10	11
1	0	6	0	0	0	0	0	0	0	0	0
2	0	0	1	0	0	0	0	0	0	0	0
3	0	0	0	4	0	0	0	0	0	0	0
4	0	0	0	0	4	0	0	0	0	0	0
5	0	0	0	0	0	1	0	0	0	0	0
6	0	0	0	0	0	0	1	0	0	0	0
7	0	0	0	0	0	0	0	1	0	0	0
8	0	0	0	0	0	0	0	0	1	0	0
9	0	0	0	0	0	0	0	0	0	1	0
10	0	0	0	0	0	0	0	0	0	0	1

Table A3. Distance matrix (m).

From-To	1	2	3	4	5	6	7	8	9	10	11
1	0	143	0	0	0	0	0	0	0	0	0
2	0	0	2	0	0	0	0	0	0	0	0
3	0	0	0	21.5	0	0	0	0	0	0	0
4	0	0	0	0	2.33	0	0	0	0	0	0
5	0	0	0	0	0	12.2	0	0	0	0	0
6	0	0	0	0	0	0	26	0	0	0	0
7	0	0	0	0	0	0	0	30.7	0	0	0
8	0	0	0	0	0	0	0	0	9.34	0	0
9	0	0	0	0	0	0	0	0	0	36.1	0
10	0	0	0	0	0	0	0	0	0	0	13.1

Table A4. Time taken between stations (min).

From-To	1	2	3	4	5	6	7	8	9	10	11
1	0	9.53	0	0	0	0	0	0	0	0	0
2	0	0	2.20	0	0	0	0	0	0	0	0
3	0	0	0	8.60	0	0	0	0	0	0	0
4	0	0	0	0	3.92	0	0	0	0	0	0
5	0	0	0	0	0	1.22	0	0	0	0	0
6	0	0	0	0	0	0	2.60	0	0	0	0
7	0	0	0	0	0	0	0	3.07	0	0	0
8	0	0	0	0	0	0	0	0	1.93	0	0
9	0	0	0	0	0	0	0	0	0	3.61	0
10	0	0	0	0	0	0	0	0	0	0	1.31

Table A5. Cost per minute for each area.

Area	Cost/Time (L.E./min)
Fin folding	284.7
Rib Welding	129.6
Tank assembly	93.3
Welders	107.8
Tank testing	150.2
Shoot blasting	281
Warehouse	126.3
Painting	284.7
Tanking	262

Table A6. TMHC.

From-To	1	2	3	4	5	6	7	8	9	10	11	Sum
1	0	2714		0	0	0	0	0	0	0	0	2714
2	0	0	56	0	0	0	0	0	0	0	0	56
3	0	0	0	1114	0	0	0	0	0	0	0	1114
4	0	0	0	0	86	0	0	0	0	0	0	86
5	0	0	0	0	0	131	0	0	0	0	0	131
6	0	0	0	0	0	0	730	0	0	0	0	730
7	0	0	0	0	0	0	0	862	0	0	0	862
8	0	0	0	0	0	0	0	0	140	0	0	140
9	0	0	0	0	0	0	0	0	0	1027	0	1027
10	0	0	0	0	0	0	0	0	0	0	196	196

L.E./transformer 7062.5

The closeness relationships among departments were evaluated using the SLP codes (A = Absolutely necessary, E = Especially important, I = Important, O = Ordinary, U = Unimportant, and X = Undesirable). These relationships are visualized in the activity relationship diagram. Figure A1 illustrates the diagram generated during the SLP analysis. At the same time, Figure A2 illustrates the conceptual block layout generated from the SLP procedure. It reflects the logical arrangement recommended by the SLP, based on workflow, material movement, and the importance of adjacency.

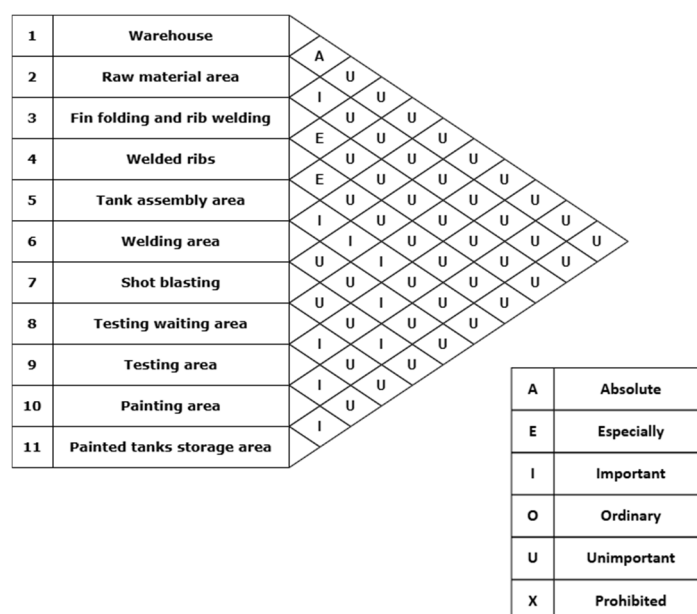


Figure A1. Activity relationship diagram (ARD) developed using the SLP closeness ratings (A, E, I, O, U, and X).

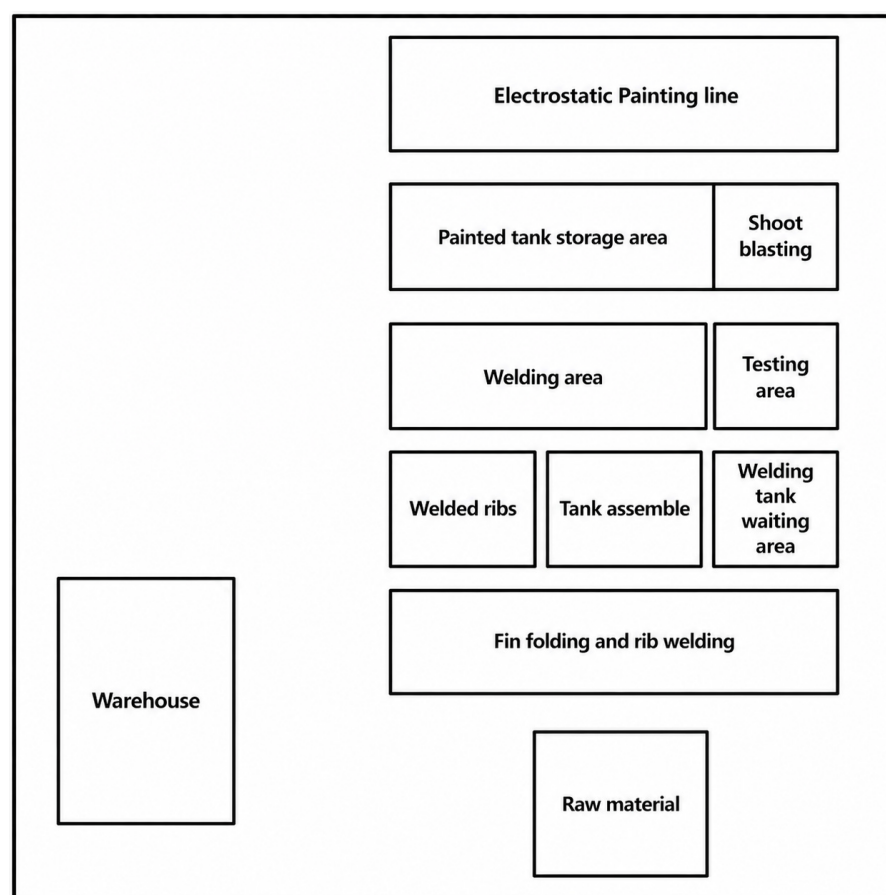


Figure A2. Initial conceptual block layout generated during the SLP phase, before optimization.

Notably, the spatial order of departments produced by this conceptual layout closely aligned with the facility's current physical configuration. The material movement paths across the facility are illustrated in Figure A3.

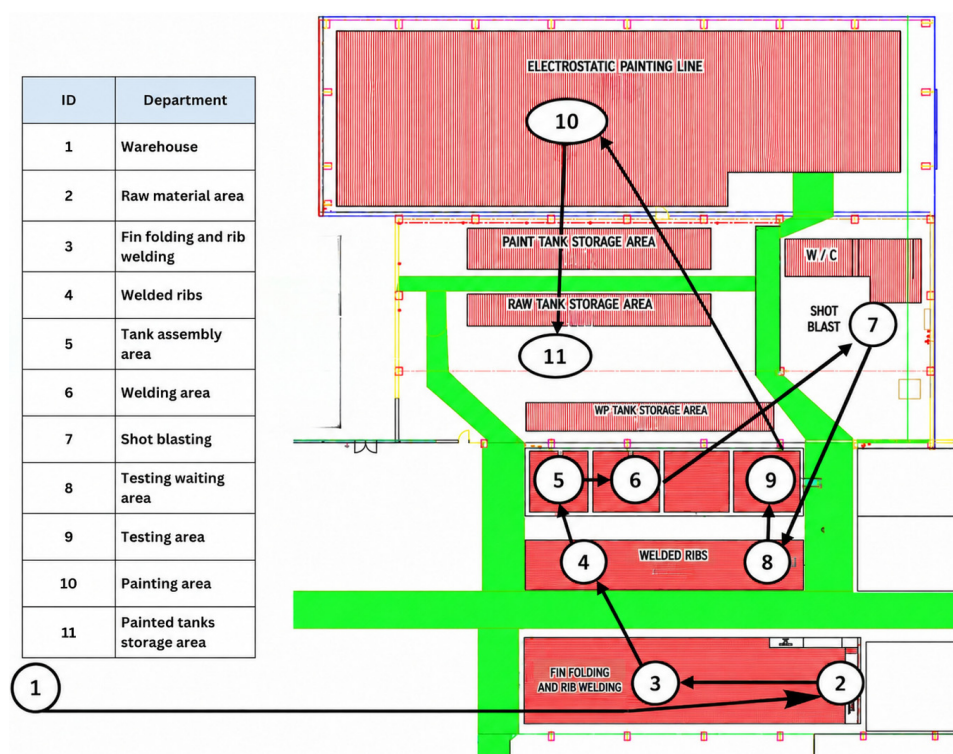
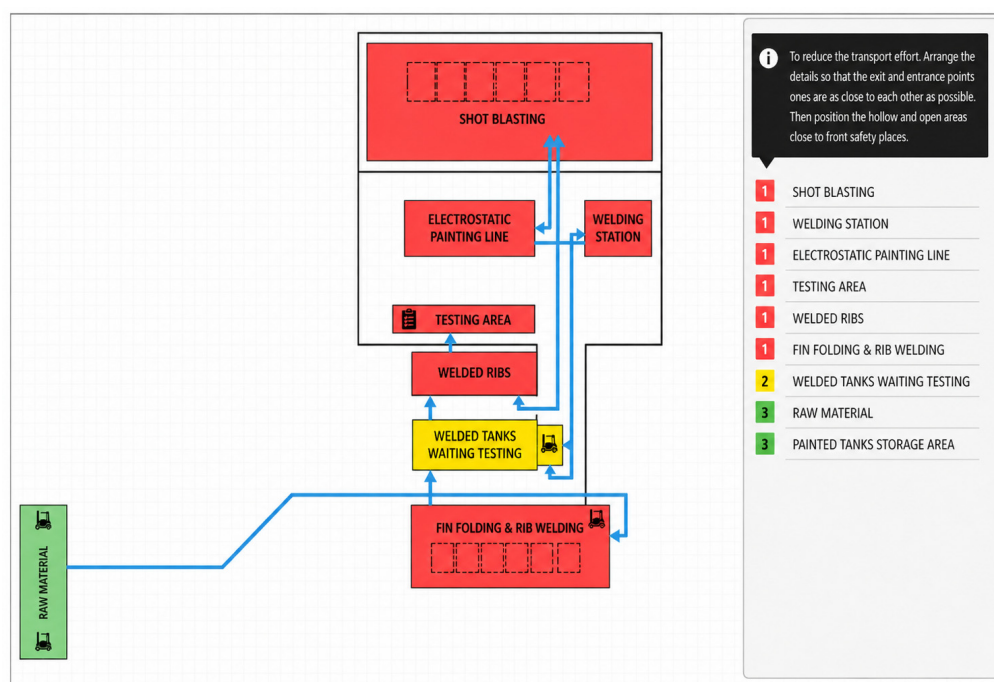


Figure A3. Material flow within the facility.

Figure A4 provides a visualization generated with VisTable to verify the accuracy of the obtained TMHC. Therefore, the existing factory layout was adopted as the initial layout for the GA optimization and DES verification stages. This ensures that the optimization process begins with a realistic baseline that already satisfies most qualitative SLP constraints.

**Figure A4.** Factory's layout using VisTable.

References

- Salins, S.S.; Zaidi, S.A.R.; Deepak, D.; Sachidananda, H.K. Design of an Improved Layout for a Steel Processing Facility Using SLP and Lean Manufacturing Techniques. *Int. J. Interact. Des. Manuf. (IJIDeM)* **2024**, *18*, 3827–3848.
- Hasan, H.-N.; Sepideh, F.; Taghi, F.G.S.M.; Fakhrzad, M.B. Classification of Facility Layout Problems: A Review Study. *Int. J. Adv. Manuf. Technol.* **2018**, *94*, 957–977.
- Patil, S.B.; Kuber, S.S. Productivity Improvement in Plant by Using Systematic Layout Planning (Slp)-A Case Study of Medium Scale Industry. *Int. J. Res. Eng. Technol.* **2014**, *3*, 770–775.
- Muther, R. *Systematic Layout Planning*; Cahnerns Books: Boston, MA, USA, 1973.
- Chien, T. An Empirical Study of Facility Layout Using a Modified SLP Procedure. *J. Manuf. Technol. Manag.* **2004**, *15*, 455–465.
- Gen, M.; Lin, L.; Zhang, H. Evolutionary Techniques for Optimization Problems in Integrated Manufacturing System: State-of-the-Art-Survey. *Comput. Ind. Eng.* **2009**, *56*, 779–808.
- Azadivar, F.; Wang, J. Facility Layout Optimization Using Simulation and Genetic Algorithms. *Int. J. Prod. Res.* **2000**, *38*, 4369–4383.
- Azadeh, A.; Moradi, B. Simulation Optimization of Facility Layout Design Problem with Safety and Ergonomics Factors. *Int. J. Ind. Eng.* **2014**, *21*, 209–230.
- Sokolowski, J.A.; Banks, C.M. *Principles of Modeling and Simulation: A Multidisciplinary Approach*; John Wiley & Sons: Hoboken, NJ, USA, 2011.
- Wang, Y.; Li, Y.R.; Zhou, Y.Q. Research on the Facilities Layout Planning in MTO Manufacturing Industry Based on Genetic Algorithm. *Adv. Mat. Res.* **2014**, *842*, 695–702.
- Zhu, L.; Wang, R.; Zhao, Z. Factory Layout Optimization Based on Systematic Layout Planning and Genetic Algorithm. In *Proceedings of the International Conference on Algorithms, Microchips and Network Applications*; SPIE: Bellingham, WA, USA, 2022; Volume 12176, pp. 106–114.

12. Pourhassan, M.R.; Raissi, S. An Integrated Simulation-Based Optimization Technique for Multi-Objective Dynamic Facility Layout Problem. *J. Ind. Inf. Integr.* **2017**, *8*, 49–58.
13. Zhao, D.; Yang, J.; Zhou, H. Layout Design of Warehouse Based on Systematic Layout Planning and GA-ACO Algorithm. In *Proceedings of the 2020 Chinese Automation Congress (CAC)*; IEEE: New York, NY, USA, 2020; pp. 7101–7104.
14. Kia, R.; Baboli, A.; Javadian, N.; Tavakkoli-Moghaddam, R.; Kazemi, M.; Khorrarni, J. Solving a Group Layout Design Model of a Dynamic Cellular Manufacturing System with Alternative Process Routings, Lot Splitting and Flexible Reconfiguration by Simulated Annealing. *Comput. Oper. Res.* **2012**, *39*, 2642–2658.
15. Yang, Y.; Yun, L.; Fan, H.; Jin, M. An Algorithm of Factory Layout Problem Based on SLP and GA. In *Proceedings of the International Conference on Wireless Communications, Networking and Applications*; Springer: Berlin, Germany, 2022; pp. 498–508.
16. Su, S. Cabin Placement Layout Optimisation Based on Systematic Layout Planning and Genetic Algorithm. *Pol. Marit. Res.* **2020**, *27*, 162–172.
17. Liu, Y.; Xu, J. Optimization on Production Line Layout of Automobile Body Shop. In *Proceedings of the 2017 International Conference on Service Systems and Service Management*; IEEE: New York, NY, USA, 2017; pp. 1–6.
18. Guerra-Zubiaga, D.A.; Aksu, M.; Richards, G.; Kuts, V. Integrating Digital Twin Software Solutions with Collaborative Industrial Systems: A Comprehensive Review for Operational Efficiency. *Appl. Sci.* **2025**, *15*, 7049.
19. Akpan, I.J.; Offodile, O.F. The Role of Virtual Reality Simulation in Manufacturing in Industry 4.0. *Systems* **2024**, *12*, 26.
20. Aleisa, E.E.; Lin, L. For Effective Facilities Planning: Layout Optimization Then Simulation, or Vice Versa? In *Proceedings of the Proceedings of the Winter Simulation Conference*; IEEE: New York, NY, USA, 2005; pp. 1381–1385.
21. Hosseini, S.S.; Mirzapour, S.A.; Wong, K.Y. Improving Multi-Floor Facility Layout Problems Using Systematic Layout Planning and Simulation. In *Proceedings of the International Conference on Advances in Information Technology*; Springer: Berlin, Germany, 2013; pp. 58–69.
22. Yang, C.; Liu, S.; Xu, Z. A Simulation-Based Optimization Method for Facility Layout Considering the AGV Path. In *Proceedings of the Journal of Physics: Conference Series*; IOP Publishing: Bristol, UK, 2023; Volume 2430, p. 012019.
23. Yao, W.; Gao, G.; Li, Y.; Ding, T.; Zhang, Z. Research on Digital Design and Simulation of Factory Based on SLP. In *Proceedings of the International Conference on Mechanical Design and Simulation (MDS 2022)*; SPIE: Bellingham, WA, USA, 2022; Volume 12261, pp. 1279–1285.
24. Shahin, A.; Poormostafa, M. Facility Layout Simulation and Optimization: An Integration of Advanced Quality and Decision Making Tools and Techniques. *Mod. Appl. Sci.* **2011**, *5*, 95.
25. Li, J.; Guo, H.; Zhang, S.; Wu, X.; Shi, L. Optimum Design of Ship Cabin Equipment Layout Based on SLP Method and Genetic Algorithm. *Math. Probl. Eng.* **2019**, *2019*, 9492583.
26. Xu, X. SLP-Based Technical Plant Layout Planning and Simulation Analysis. In *Proceedings of the IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2020; Volume 772, p. 012020.
27. Ketabi, S.; Ghandehari, M.; Khoshkrodi, M.P. Facility Layout Problem by Integration of AHP and Computer Simulation with DEA. *Int. J. Serv. Oper. Manag.* **2021**, *39*, 262–282.
28. Singla, V. An Integrated Systematic Layout Planning, Analytical Hierarchy Process and Nonlinear Programming Approach to Facility Layout Design. *Int. J. Oper. Res.* **2025**, *52*, 128–145.
29. Zhao, X.-W.; Tong, X.-M.; Ning, F.-W.; Cai, M.-L.; Han, F.; Li, H.-G. Review of Empowering Computer-Aided Engineering with Artificial Intelligence. *Adv. Manuf.* **2026**, *14*, 103–143.
30. Hu, F.; Wang, C.; Wu, X. Generative Artificial Intelligence-Enabled Facility Layout Design Paradigm. *Appl. Sci.* **2025**, *15*, 5697.
31. Chen, Z.; Lv, Z.; Di, R.; Wang, P.; Li, X.; Sun, X.; Xu, Y. A Novel Virtual Sample Generation Method to Improve the Quality of Data and the Accuracy of Data-Driven Models. *Neurocomputing* **2023**, *548*, 126380.
32. Chan, K.C.; Rabaev, M.; Pratama, H. Generation of Synthetic Manufacturing Datasets for Machine Learning Using Discrete-Event Simulation. *Prod. Manuf. Res.* **2022**, *10*, 337–353.
33. Vitayasak, S.; Pongcharoen, P.; Hicks, C. A Tool for Solving Stochastic Dynamic Facility Layout Problems with Stochastic Demand Using Either a Genetic Algorithm or Modified Backtracking Search Algorithm. *Int. J. Prod. Econ.* **2017**, *190*, 146–157.
34. Law, A.M.; Kelton, W.D.; Kelton, W.D. *Simulation Modeling and Analysis*; Mcgraw-Hill: New York, NY, USA, 2007; Volume 3.

35. Sargent, R.G. Verification and Validation of Simulation Models. *J. Simul.* **2013**, *7*, 12–24.
36. Lopes, P.V.; Silveira, L.; Guimaraes Aquino, R.D.; Ribeiro, C.H.; Skoogh, A.; Verri, F.A.N. Synthetic Data Generation for Digital Twins: Enabling Production Systems Analysis in the Absence of Data. *Int. J. Comput. Integr. Manuf.* **2024**, *37*, 1252–1269.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.