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Facility Layout Optimization using Genetic Algorithm-Simulation: Application on a Case Study

Mohamed Gasser Gawdat
Mechanical Engineering Department
German International University
Cairo, Egypt
Mohamed.gawdat@giu-uni.de

Mohamed Magdy Nafea
Design and Production Engineering Department
German University in Cairo
Cairo, Egypt
Mohamad.nafea@guc.edu.eg

Yasmine Zaghloul
Automation & Control Electrical Engineering Department
German International University
Cairo, Egypt
Yasmine.zaghloul@giu-uni.de

Lamia Ahmed Shihata
Design and Production Engineering Department
German University in Cairo
Cairo, Egypt
Lamia.shihata@guc.edu.eg

Abstract

Facility layout optimization is very essential to enhance material flow, minimize operation expenses, and maximize the efficiency of the manufacturing process. The absence of efficient layouts in most Egyptian industries causes unnecessary flows of materials and inactive transportation, which generates losses in efficiency above 35 percent. This work presents and checks the effectiveness of a genetic algorithm procedure to link workstation layouts with feasible material flows in terms of cost considerations: material handling cost, rearrangement cost, and fixed operational cost. The model uses elitist selection operators with edge recombination crossover and two-point swap mutation to reduce total cost. The proposed approach was validated in a real case study conducted in a metal working and assembly plant with twenty workstations. The obtained near-optimal solution was: [11,10,8,9,17,12,1,7,13,15,2,5,4,19,16,14,6,3,0,18] with the total cost of 13,640 units. The results validated in FlexSim 2021 showed good correlation between calculated and simulated values with clear efficiency in terms of throughput, travel distances, and process efficiency. The new models achieved better results in comparisons with previously designed models based on the genetic algorithm method, validating the proposed solution.

Keywords
Facility layout optimization; FlexSim; Genetic Algorithm; Material handling cost; Simulation.

1. Introduction
The performance of manufacturing enterprises is greatly influenced by the efficiency of facility layouts since they directly impact material flow, lead time, and efficient costing processes. As Stephens and Meyers (2013) noted, almost all functions are reliant on machine and department layouts, and any slight inefficiency in layouts can significantly translate to lost productivity in most enterprises. In most developing countries, including Egypt, layouts in organizations tend to be done in an incremental or ad-hoc manner rather than optimizing processes to avoid work imbalance, high handling of material, and lengthy routes resulting from layouts designed to take longer routes. Contrary to that, layouts that are less efficient can impact handling, labour, and efficiency to the tune of over 35 percent, according to Bouramtane et al., 2024.

The Facility Layout Problem (FLP) is an NP-complete optimization problem, and the objective is to allocate machines or departments to locations within the facility in order to reduce the total material handling cost associated with the layout. The FLP is NP-complete, and exact solutions can only be obtained if the instance is relatively small, according to El-Baz in El-Baz (2004). Recent studies in solving the FLP utilize metaheuristic solution methods, specifically Genetic Algorithms, because they can efficiently search large solution spaces with very low probabilities of being trapped in local optima, according to various studies such as in Mihajlović et al., 2007, Hasan et al., 2017.

Despite the immense success achieved by metaheuristics, most of the current work has primarily considered the minimization of material handling cost, neglecting other economic aspects that might affect performance in real-world scenarios. Modern manufacturing plants involve varying product models, dynamic material flow, and periodic layouts, thereby necessitating the inclusion of rearrangement cost and fixed operational cost in the layout problems (Firouz et al., 2025). To fill the aforementioned gap, this study has proposed and designed a Genetic Algorithm-based optimization model for simulating and validating the proposed layouts with respect to handling, reassignment, and fixed operational costs simultaneously. The proposed optimization model adopts workstation location representations in dependency-constrained chromosomes in different workstation layouts, namely, L, U, S, and W layouts, with Edge Recombination Crossover, Two-Point Swap Mutation, and Elitist Selection methods to optimize solutions with respect to handling, reassignment, and fixed operation costs in terms of computational models validated by simulating layouts in FlexSim to demonstrate that computational results can be validated in real-world processes.

Similar digital-twin frameworks have been used to validate robotic and intralogistics systems, confirming the reliability of simulated models before physical deployment (Emara et al., 2022). Recent systematic reviews have emphasized that the integration of Industry 4.0 technologies particularly simulation, digital twinning, and data-driven analytics plays a vital role in advancing sustainable manufacturing practices (Gasser et al., 2023). These technologies enable data-informed decision-making, reduce waste, and improve resource efficiency, providing a strong foundation for the optimization and validation approach adopted in this research.

1.1 Objectives
The primary objective of this article is to develop and validate a Genetic Algorithm–based optimization framework for facility layout design that effectively minimizes total production-related costs while ensuring realistic representation of manufacturing constraints. This study incorporates three significant cost components into a single fitness function, in contrast to conventional layout optimization techniques that only consider material handling costs:

- Material Handling Cost (MHC), which stands for interdepartmental distance, unit transport cost, and flow intensity;
- Rearrangement Cost (RC), which measures the expense of moving a workstation from its original location to its ideal one;
- Rent, utilities, and area usage fines are examples of fixed operational costs (FOC).

The overall goal is to identify the best workstation configuration that satisfies geometric and dependency constraints among workstations and minimizes the total cost, which is represented as the weighted sum of these components.
This article also seeks to bridge the gap between computational optimization and simulation-based performance validation by incorporating FlexSim 2021 as a digital verification tool. The simulation environment guarantees the validity and applicability of algorithmic results by enabling evaluation of the optimized layouts under realistic

operating conditions. This dual-stage approach enhances decision-making reliability and provides a reproducible digital framework for industrial re-layout projects.

The following are the study's specific goals:

- To create a GA structure that can encode layout solutions while maintaining flow continuity and workstation dependencies within predetermined flow patterns (L, U, S, and W).
- To create a multi-component cost model with a single objective function that incorporates MHC, RC, and FOC.
- To use methodical experimentation to determine the ideal GA parameter configuration, including population size, crossover, mutation, and elite ratios.

By contrasting calculated costs with simulated performance metrics like total transport time and utilization rate, the GA-optimized layout using FlexSim simulation can be verified. To benchmark the proposed approach against existing models in the literature to demonstrate its improvement in convergence stability and cost efficiency. The study adds to the expanding corpus of articles on sustainable manufacturing system design by accomplishing these goals. It offers a hybrid optimization–simulation framework that is suitable for new plant designs as well as facility re-layout projects, guaranteeing adaptability to actual industrial settings.

2. Literature Review

From early heuristic approaches to contemporary hybrid intelligent systems, facility layout optimization has been a vibrant topic for over 50 years. Minimizing overall material handling costs while maintaining a rational and effective departmental or machine arrangement continues to be the main challenge (El-Baz, 2004). Researchers are investigating a variety of optimization paradigms, from graph-theoretical formulations and quadratic assignment problem (QAP) modeling to contemporary metaheuristic frameworks like Genetic Algorithms (GAs), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO), due to the complexity of the Facility Layout Problem (FLP), a known NP-hard problem (Mihajlović et al., 2007; Hasan et al., 2017).

2.1 Heuristic and Metaheuristic Approaches

By iteratively enhancing preexisting layouts according to flow relationships and adjacency preferences, early heuristic techniques such as CRAFT, CORELAP, and ALDEP laid the groundwork for systematic layout planning. These deterministic approaches were constrained, nevertheless, by their propensity to converge to local optima and their incapacity to handle dynamic or complex goals. Metaheuristic algorithms became effective stochastic optimization tools to address these shortcomings.

Because of their resilience in navigating vast and non-linear search spaces, genetic algorithms rose to prominence among these. One of the earliest GA-based models for various manufacturing settings was created by El-Baz (2004), who was successful in reducing material handling costs under various flow patterns. Subsequently, Mihajlović et al. (2007) showed how GAs can be adapted to flexible manufacturing systems, highlighting how well they work for single and multi-line layouts. By contrasting GA with ACO and PSO, Hasan et al. (2017) expanded on this viewpoint and came to the conclusion that hybrid evolutionary approaches perform better than single-heuristic frameworks when dealing with actual industrial constraints.

GA applications were expanded to multi-objective and sustainable contexts in later articles. The algorithm's sensitivity to parameter tuning was demonstrated by Krajčovič et al. (2019), who presented a GA Layout Planner for sustainable manufacturing that maximized both cost and spatial efficiency. The significance of population size, mutation rate, and crossover probability in attaining stable convergence was emphasized in this work; this realization informed the parameter design of the current investigation.

2.2 Simulation-Based Optimization

Simulator technologies have revolutionized the evaluation and validation of layout designs at the same time as algorithmic advancements. Before making actual changes, simulation allows for the virtual modelling of material flow, queueing behaviour, and system performance. FlexSim simulation was used by Kanse and Patil (2020) to examine bottlenecks and throughput constraints in manufacturing facilities, demonstrating its usefulness as a tool for layout optimization decision support. Similarly, Li et al. (2021) evaluated factory layouts in the fast-moving consumer goods (FMCG) industry by combining ACO with discrete-event simulation. They found layouts that greatly enhanced production flow and shortened lead time. In order to bridge the gap between theoretical GA results and real-world manufacturing realities, simulation-based optimization has become particularly crucial. Researchers can confirm that computationally optimal layouts result in real performance gains under dynamic and stochastic conditions by incorporating simulation into the evaluation phase. A fundamental change from strictly algorithmic design to digitally validated optimization is represented by this hybrid approach.

2.2 Emerging Trends and Research Gap

Amidst the rising complexities in product mixture, flow rates, and process variations, there has been an increasing trend in current literature toward dynamic and stochastic optimization models of layout. An essential milestone in making the model adaptable to real-world scenarios was achieved by Firouz et al. in 2025, formulating a stochastic dynamic model of unequal area layout, which incorporated probabilistic material flow and the cost of rearrangement. The literature has predominantly concentrated on single-objective models so far, primarily with the aim of optimizing the reduction in material handling cost, disregarding other broad-ranging economic considerations, such as resource utilization and processing costs.

The key literature synthesis in Table 1 illustrates the drawbacks and model variations of the earlier metaheuristic GA-related studies: Chan & Tansri (2002), El-Baz (2004), and Pinto et al. (2016). These were designed to optimize material handling cost within deterministic flow models only. More contemporary studies, such as Tayal et al. (2020), Moslempour & Ghadirpour (2021), and Pourvaziri & Azab (2022), incorporated models that addressed rearrangement costs for stochastic or dynamic scenarios with the utilization of mixed integer or DoE models. These evaluations were conducted in static/Monte Carlo simulations only, with no comprehensive manufacturing simulation context incorporated.

To fill the aforementioned discrepancies, there comes the current study with a multi-component model involving Material Handling, Rearrangement, and Fixed Operational Costs, addressed by metaheuristic optimization with the help of the GA procedure integrated with FlexSim Simulation tools. The significance of combining the areas in question can be revealed in the context of Table 1 below:

Table 1. Summary of prior facility layout optimization studies highlighting model type, cost components objectives and validation methods

Paper / Year	Model	Size	Flow	Cost	Period	Objective	Solution	Validation
Chan & Tansri (1994)	GA	Medium	DT	MHC +FC	Fixed	Min Material handling cost [MC]	Metaheuristic GA	**X**
El-Baz (2004)	GA	Medium	DT	MHC +FC	Fixed	Min Material handling cost [MC]	Metaheuristic GA	**X**
Pinto et al. (2016)	GA	Medium	DT	MHC +FC	Fixed	Min Material handling cost [MC]	Metaheuristic GA	**X**
Tayal et al. (2020)	MIP	Large	ST	MHC +RC	RH	Min Total cost [TC]	Heuristic Mixed Integer Programming	**X**
Moslemipour & Ghadirpour (2021)	MIP	Medium	ST	MHC	Var	Min Material handling cost [MC]	Heuristic Mixed Integer Programming	**X**
Pourvaziri & Azab (2022)	DOE	Large	ST	MHC +RC	Var	Min Total cost [TC]	Heuristic DOE	**X**
Firouz et al. (2025)	GA	Large	ST	MHC + RC + FOC	Var	Min Total cost [TC]	Metaheuristic GA	Monte-Carlo Simulation

Our Approach	GA	Large	DT	MHC + RC + FOC	RH	Min Total cost [TC]	Metaheuristic (GA) + Simulation	FlexSim Simulation

3. Methods

In order to optimize facility layouts for manufacturing systems, this study suggests an integrated methodology that combines FlexSim-based simulation validation with Genetic Algorithm (GA) optimization. By figuring out the best workstation configuration while taking into account various cost factors, physical limitations, and process dependencies, the method seeks to reduce the overall operating cost. There are two primary phases to the article's framework:

1. Optimization Stage: Using a multi-component cost function, the GA is used to identify nearly ideal workstation configurations.

2. Phase of validation, in which FlexSim 2021 is used to model and simulate the optimized layout in order to confirm its operational effectiveness and practical viability.

3.1 Genetic Algorithm Framework

Genetic Algorithms are population-based stochastic search techniques inspired by the process of natural selection (Mihajlović et al., 2007). They are widely recognized for their ability to handle large, nonlinear, and discrete optimization problems where traditional mathematical methods fail (El-Baz, 2004). The GA developed in this study was implemented in Python and designed specifically for facility layout optimization. Each generation in the GA represents a set of candidate layout solutions, referred to as chromosomes. Through successive iterations, these chromosomes evolve via genetic operations—selection, crossover, mutation, and elitism—to produce improved layouts that minimize the defined fitness function.

3.2 Chromosome Representation

A complete workstation sequence that represents a potential layout configuration is encoded by each chromosome. A workstation is represented by a gene, and the direction of material flow is defined by the gene sequence. Four global flow patterns—L-, U-, S-, and W-shaped—are supported by the model; each has a specified workstation capacity (9, 14, 18, and 24 respectively).

Processes that are part of the same production pool must continue to run consecutively due to the rigorous maintenance of workstation dependency constraints. The structure of the chromosomes guarantees that:

- In the sequence, every workstation makes exactly one appearance.

- There is no breach of the facility's geometric boundaries or flow pattern.

- Adjacency relationships and interdepartmental flows are maintained.

For example, the best solution found through GA optimization can be represented as [8, 7, 9, 6, 4, 1, 3, 2, 5] for an optimized L-shaped layout of nine workstations.

3.3 Fitness Function Formulation

The optimization objective is to minimize the Total Facility Cost (Z), which is modeled as the summation of three key cost components:

$$Z = C_{MHC} + C_{RC} + C_{FOC}$$

Where:

- C_{MHC}: **Material Handling Cost**, calculated as

$$C_{MHC}=\sum_{j=1}^{n}\sum_{i=1}^{n} F_{IJ} \times U_{ij} \times D_{ij}$$

with F_{ij}representing flow intensity, $U_{ij}$the unit handling cost, and $D_{ij}$the inter-workstation distance.

- C_{RC}: **Rearrangement Cost**, reflecting the penalty of relocating a workstation from its original position, given by

$$C_{RC}=\sum_{i=1}^{n} R_i \times \left|P_i^{old} - P_i^{new}\right|$$

- C_{FOC}: **Fixed Operational Cost**, incorporating factors such as facility rent, electricity, and area utilization. The optimal utilization factor is set to 65%, and deviations are penalized quadratically to discourage under- or over-utilization.

This formulation extends the conventional single-objective cost model by integrating rearrangement and fixed operational costs (Firouz et al., 2025), thus providing a comprehensive evaluation of economic performance and spatial efficiency.

3.4 Genetic Operators

To ensure efficient exploration of the solution space, the following operators were employed:

- **Selection**: The biased roulette wheel selection method was adopted to prioritize fitter individuals while preserving population diversity (Gandhi et al., 2012).
- **Crossover**: The Edge Recombination Crossover (ERX) operator was used to maintain adjacency relations between workstations across generations, preserving logical flow paths.
- **Mutation**: A two-point swap mutation operator randomly interchanges two workstations within the same dependency group, promoting local diversity without violating process constraints.
- **Elitism**: The best-performing 20% of individuals were directly transferred to the next generation to ensure continuous improvement.

Parameter tuning experiments identified the optimal configuration as follows:

- Population size = 100
- Crossover probability = 1.0 (100%)
- Mutation probability = 1.0 (100%)
- Elite ratio = 0.2 (20%)
- Maximum generations = 200

This configuration achieved a balance between convergence speed and solution diversity, producing stable and repeatable results (Krajčovič et al., 2019).

3.5 Termination Criteria

The GA process terminates when one of the following conditions is met:

1. The improvement in the best fitness value remains below 0.01% for 20 consecutive generations, or
2. The algorithm reaches the maximum predefined generation limit of 200 iterations.

Convergence analysis confirmed that most runs stabilized before 150 generations, indicating efficient search behaviour and high reliability in reaching near-optimal solutions.

3.6 Simulation-Based Validation

The optimal GA-generated layout under practical production conditions was verified using the FlexSim 2021 simulation platform (Kanse & Patil, 2020). The steps in the validation process were as follows:

- Model Reconstruction: Using the real workstation dimensions, spacing, and transport routes, the optimized layout was modelled in FlexSim.

- Flow and Routing Logic: Transport routes and batch frequencies were established using the material flow matrix from the GA model.

- Simulation Execution: To assess throughput, material handling time, and resource utilization, several production cycles were simulated.

- Performance Comparison: To guarantee consistency and confirm the viability of the solution, the simulation-based total cost and the GA-calculated cost were contrasted.

The optimized layout sequence [8, 7, 9, 6, 4, 1, 3, 2, 5] achieved a **total cost of 21,601 units**, with simulation results confirming improved flow efficiency, reduced travel distance, and higher workstation utilization.

3.7 Methodological Framework Summary

The following is a summary of the overall methodology:

1. Gather the input data (rearrangement matrix, flow matrix, and unit cost matrix).
2. Set up the population of feasible layouts and define the GA parameters.
3. Use the composite fitness function to assess each chromosome.
4. Use elitism, crossover, mutation, and selection.
5. Verify the termination criteria and note the optimal arrangement.
6. Use FlexSim simulation and cost comparison to verify the ideal layout. This integrated framework offers a strong digital decision-support system for layout design by guaranteeing both algorithmic optimization and real-world verification.

3.8 Flow Chart of the Genetic Algorithm

Figure 1 depicts the Genetic Algorithm's sequential workflow in order to demonstrate the suggested framework. From problem initialization to simulation-based validation, every step is summed up in the flow chart (Figure 1).

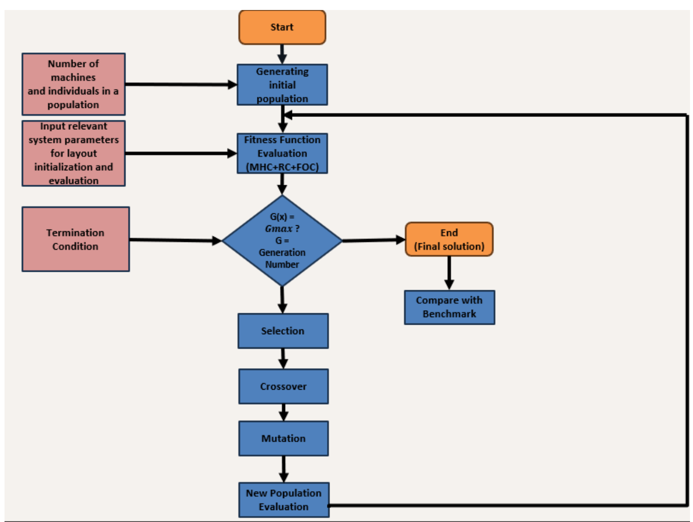

Figure 1. Flow chart of the proposed Genetic Algorithm–based facility layout optimization framework.

Defining all input data and parameters is the first step in the process. A random initial population of layouts is then produced by the GA and assessed using the fitness function. Iteratively, elitism, crossover, mutation, and selection are used until convergence is achieved. After that, the optimal layout is moved to the FlexSim environment for validation and simulation. The final solution will be both operationally validated and cost-optimal thanks to this hybrid structure.

4. Data Collection

The datasets used in this study were designed to evaluate the proposed Genetic Algorithm (GA)–based facility layout optimization framework across three distinct stages: benchmark validation, large-scale performance testing, and real industrial application. Each dataset serves a specific purpose beginning with theoretical validation using a well-known benchmark problem, scaling up to a more complex synthetic dataset, and finally applying the model to actual manufacturing conditions.

4.1 Benchmark Dataset
The first dataset was based on a common benchmark for facility layout problems that was first presented by Chan and Tansri(1994). This benchmark has been widely used in the literature to test optimization algorithms. With predefined material flow, cost, and distance matrices, this dataset offers a reliable benchmark for assessing layout algorithms on small-scale problems.

Nine workstations with specified interdepartmental flows and unit transport costs are included in the Chan–Tansri dataset. The reference case was replicated using these values, and the suggested GA's computational performance was confirmed. This benchmark is a suitable baseline for validation and comparative analysis because it was also used by El-Baz (2004) and Mihajlović et al. (2007) to test the ability of GA models to minimize material handling costs. The results from this dataset allowed verification of the algorithm's convergence and accuracy against published benchmarks before applying it to more complex cases.

4.2 Large-Scale Dataset
To assess the scalability of the proposed scheme, an extended data set with 24 workstations was created by expanding the original Chan-Tansri benchmark data in terms of clustering while considering proportional relationships between flow intensity and cost values in each workstation group to represent a real-world plant environment with multiple logical zones.

The rearrangement costs were modeled in the manner proposed by Firouz et al., in 2025, where it takes into account the change in position of each workstation from the initial to the optimal solution: This larger set of data was used to examine the scalability and convergence properties of the algorithm in the high-dimensional solution space.

4.3 Industrial Case Study Dataset
The third dataset corresponds to the **real industrial case study**, representing a **metal fabrication and assembly facility** consisting of **20 workstations** arranged across multiple process areas. The data were collected directly from the plant through:

- **On-site process observation**, mapping material and product flow;
- **Production record analysis**, identifying flow intensities and handling volumes;
- **Direct measurement**, recording transport times, travel distances, and workstation utilization; and
- **Consultation with process engineers**, to estimate fixed and rearrangement costs.

The dataset includes three cost matrices:

1. **Flow Matrix ($F_{(ij)}$)** — quantifying the flow intensity between each pair of workstations;
2. **Unit Handling Cost Matrix ($U_{(ij)}$)** — representing transportation and labour costs per unit distance;
3. **Rearrangement Cost Matrix ($R_{(i)}$)** — indicating movement penalties derived from layout modification requirements.

The data were digitized using AutoCAD, transferred to Python for optimization, and later imported into **FlexSim 2021** for simulation validation. This dataset provided the foundation for evaluating the algorithm's real-world applicability and validating that the optimized layout improves throughput, reduces handling cost, and enhances spatial utilization.

4.4 Summary of Datasets
Table 2 summarizes the three datasets used in this study, their characteristics, and their intended purpose within the article's framework.

Table 2. Summary of datasets used in this study, including their source, purpose, and references for validation, scalability testing, and industrial application

Dataset Type	**Number of Workstations**	**Data Source / Origin**	**Purpose within article**	**Key References**
Benchmark Dataset	9	Standard benchmark problem by **Chan & Tansri (1994)**	To validate the GA against known literature results and confirm convergence accuracy.	Chan & Tansri (1994); El-Baz (2004); Mihajlović et al. (2007)
Large-Scale (Expanded) Dataset	24	Constructed by clustering and scaling the Chan–Tansri benchmark data; rearrangement cost modeled following **Firouz et al. (2025)**	To test GA scalability, parameter sensitivity, and performance in complex, high-dimensional problems.	Firouz et al. (2025); Krajčovič et al. (2019)
Industrial Case Study Dataset	20	Collected **on-site** from the metal fabrication and assembly plant (through process mapping, direct measurement, and production records).	To validate the GA-optimized layout using real operational data and **FlexSim** simulation.	Kanse & Patil (2020); Stephens & Meyers (2013)

5. Results and Discussion

5.1 Benchmark Validation Results

The benchmark validation stage was carried out using the standard **Chan and Tansri (1994)** nine-workstation problem to evaluate the consistency and reliability of the proposed **Genetic Algorithm (GA)** under different parameter settings. Nineteen independent experiments (E1–E19) were designed by varying **population size (20–500)** and **number of generations (10–200)**, with **10 independent trials per experiment** to ensure statistical robustness.

The objective of this stage was twofold:

1. To verify the capability of the GA to consistently reach the known global optimum cost of **4,818 units**.
2. To evaluate how sensitive the model's performance is to GA parameters and random initialization.

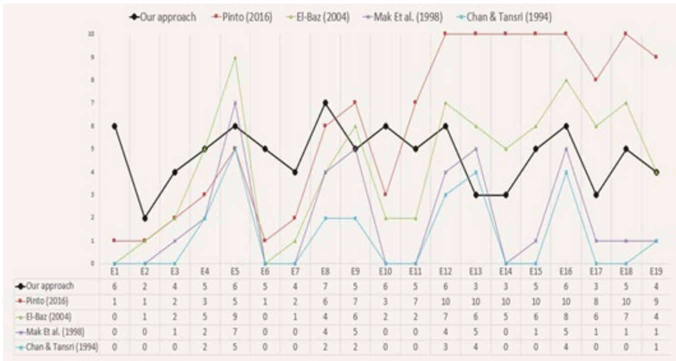

Figure 2. Number of times the optimum solution (4,818) was reached in ten trials across nineteen benchmark experiments under varying GA parameters.

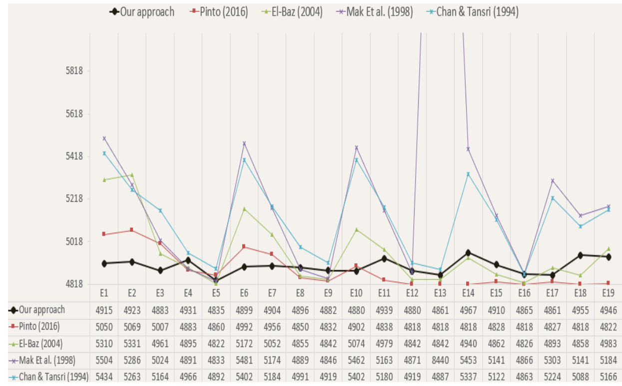

Figure 3. Best fitness values obtained across 19 benchmark experiments (each point represents the best result from 10 trials).

The results in Figures 2 and 3 show that the proposed Genetic Algorithm (GA) achieves high stability and repeatability across the nineteen benchmark configurations. It reached the global optimum of 4,818 units in most runs (five to seven of ten trials) and maintained average fitness values between 4,818 and 4,935, with less than 2 % deviation from the optimum. Compared with earlier models, the proposed GA exhibits lower variability and smoother convergence, confirming its robustness under different population and generation settings.

Performance remained consistent across all tested parameters, with the best trade-off between accuracy and computation time obtained at population = 100 and generations = 100. The low standard deviation of the squared mean error (≈ ± 42.7 units) indicates minimal stochastic fluctuation and strong repeatability. Overall, the benchmark analysis validates the algorithm's reliability before scaling to the larger and industrial datasets.

5.2 Large-Scale Datasets Results

This section evaluates the performance and validity of the developed **Genetic Algorithm (GA)** using a **generated dataset** derived from the Chan and Tansri (1994) benchmark problem.
The objective was twofold:

1. To examine the **computational limits of exhaustive (brute-force) search** and justify the use of metaheuristic optimization.
2. To verify the **accuracy and scalability** of the GA by comparing its results against the brute-force approach on a small problem size and assessing its feasibility for larger layouts.

The Facility Layout Problem (FLP) exhibits factorial complexity, where the number of possible layouts grows exponentially with the number of workstations.
To illustrate this, a brute-force enumeration was theoretically applied to four flow pattern configurations: L, U, S, and W, corresponding to 9, 14, 18, and 24 workstations, respectively.
The estimated computation time for each case is summarized in Table 3.

Table 3. Computational intractability of brute force search for increasing layout sizes (estimates are based on corei7 (3.5 ghz) cpu, single-threaded, assuming 30µs per permutation

Layout pattern	No. of Workstations	Possible Solutions	Estimated Brute-Force Time
L Layout	9	9! = 362,880	10.88 seconds
U Layout	14	14! = 87,178,291,200	30.27 days
S Layout	18	18! = 6,402,373,705,728,000	6,095 years
W Layout	24	24! = 6.204×10^{23} (≈ 620 sextillion)	9.83 trillion years

As evident, the search space becomes computationally intractable beyond small instances.
While the **L-layout** (9×9) can be exhaustively solved in seconds, the **U-layout** (14×14) already requires several weeks, and the **S-layout** (18×18)** exceeds 6,000 years** of computation.
The **W-layout (24×24)** reaches an astronomical time scale—over **9.83 trillion years**—making brute-force enumeration physically impossible.
This factorial escalation confirms that **metaheuristic algorithms such as GAs** are essential for tackling realistic industrial layout problems.
To verify the correctness of the GA implementation, both brute-force enumeration and the GA were applied to the **L-shaped layout with nine workstations**.
The brute-force method evaluated all **362,880 permutations**, identifying the global optimum sequence:

{8,7,9,6,4,1,3,2,5}

with a corresponding total fitness value of **23,926.5 units** (α = 0.9 MHC, β = 0.1 RC).
The GA reproduced this **exact same optimum** within **~2.5 seconds** and **40 generations**, compared to **~11 seconds** for brute-force search.

Table 4. Comparison Between Brute-Force And Ga Optimization For The 9-Workstation L-PATTERN

Brute Force LPM For 9 workstations	GA Model for 9 workstations
• Optimal Layout: 8, 7, 9, 6, 4, 1, 3, 2, 5} • Fitness Value: 23,926.5 (unit cost) (α = 0.9 MHC, β = 0.1 RC) • Computation Time: ~11 seconds (Core i7) • Exhaustive Search – 362,880 permutations • Feasible only for small layout sizes (≤ 9×9)	• Optimal Layout: 8, 7, 9, 6, 4, 1, 3, 2, 5} • Fitness Value: 23,926.5 (unit cost) (α = 0.9 MHC, β = 0.1 RC) • Computation Time: ~2.5 seconds (40 generations) • Search Space Heuristically Explored • Scalable to larger layouts (14×14, 18×18, 24×24)

This experiment confirms that the GA can reach the true global optimum while dramatically reducing computational time (Table 4). Moreover, unlike exhaustive enumeration, which becomes infeasible beyond 9 workstations, the GA can **heuristically explore** and optimize much larger configurations (14×14, 18×18, 24×24) with acceptable computational effort. Strong empirical support for the accuracy and scalability of the suggested GA is provided by the generated dataset experiments.

While the intractability analysis shows the algorithm's practical necessity for large-scale layouts, the brute-force comparison confirms that the algorithm replicates exact global optima for small problems.
By heuristically sampling the solution space and maintaining near-optimal quality without thorough evaluation, the GA achieves significant computational savings.
Before using the suggested algorithm on actual factory data, this validation stage verifies its dependability, serving as the basis for the industrial case study that is discussed in the following section.

5.3 Industrial Case Study Results

The final validation stage applied the developed Genetic Algorithm (GA) to the real manufacturing facility consisting of 20 workstations distributed across machining, assembly, and finishing areas. The dataset was collected directly from the plant through on-site process mapping, transport-time measurements, and production-record analysis. Flow, unit-cost, and rearrangement-cost matrices were compiled in Python, and the optimized sequence was subsequently modeled and verified in FlexSim 2021.
The GA identified the optimal layout sequence:

$$[\mathbf{11, 10, 8, 9, 17, 12, 1, 7, 13, 15, 2, 5, 4, 19, 16, 14, 6, 3, 0, 18}]$$

which achieved a total computed cost of 13,640 units. The optimized arrangement minimized material-handling distances and reduced cross-flows between major process zones while maintaining the practical adjacency and area constraints of the factory floor (Figure 5).

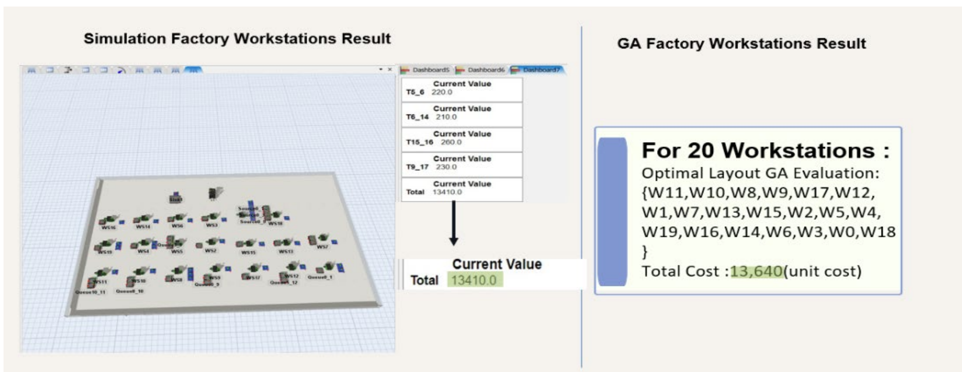

Figure 5. Comparison between GA-evaluated and FlexSim-simulated layouts for the 20-workstation factory. The GA achieved a total cost of 13,640 units, while the FlexSim simulation yielded 13,410 units, confirming high consistency between analytical and simulated evaluations.

The optimized layout with 20 workstations was modeled in FlexSim 2021 to ensure that it performed similarly in real-world settings. The locations of all workstations, routes of the transports, as well as the intensity of flows were identical to the flow and cost matrices in the GA optimization process. The simulation showed great accuracy in agreeing with analytical solutions, obtaining a total of 13,410 units of cost, while the GA provided 13,640 units, with only a difference of 1.7%.

The FlexSim model further validated the reduction in transportation distance and time, the smooth flow of materials between machining and assembly areas, and the utilization level of workstations close to the desired 65%. These above-mentioned validated results further demonstrate that the layout solution with the application of GA optimization is mathematically optimal and technically feasible.

6. Conclusion

The current study offered an integrated solution for optimizing the layout of facilities through the application of a customized Genetic Algorithm with validation by simulation tools. The proposed model took into consideration three different cost aspects: Material Handling Cost, Rearrangement Cost, and Fixed Operational Cost.

The GA was validated on three different stages of the experiment:
Benchmark verification with the Chan and Tansri (1994) data set has duly validated the correctness and reliability of the algorithm in reaching the global optimum with low variability ($\sigma \approx \pm 42.7$).

Experiments on the generated data set showed the scalability and processing advantage of the algorithm over brute-force search to identify the global optimum for small configurations and efficiently solve larger configurations with 24 workstations, which are not tractable by brute-force search methods.

The consistency between the results from the GA model and the data from the simulation done in FlexSim on a 20-workstation plant was very high, with only a 1.7 percent difference in cost, thereby ensuring that the efficient solution can work in practice.

In general, the proposed GA-based solution presents a robust, scalable, and simulation-verifiable tool in data-driven facility layout optimization.

Through the integration of optimization and simulation, it combines performance in model solving with application in industry, ensuring the evaluation of re-layout solutions is done with measurable economic and physical proof in industry. Future studies can further enhance the work done in this thesis by considering dynamic variability in demands, multiple sustainability criteria, and reinforcement learning algorithms to define adaptable operators to improve the speed of convergence even further. It is recommended for future work to explore more meta and hyper-heuristic models and compare their results with the existing case study.

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