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GENETIC ALGORITHM OPTIMIZATION OF FACILITY LAYOUTS FOR MANUFACTURING RESILIENCE UNDER DEMAND UNCERTAINTY A SENSITIVITY ANALYSIS STUDY

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A B S T R A C T

The focus of this research paper is on the role of facility layout design influencing manufacturing effectiveness, efficiency, and throughput in uncertain environments. A genetic algorithm-based model has been proposed for optimizing the layout design of a bottled water manufacturing plant with the aim of minimizing material handling costs and increasing efficiency and throughput. Department level location arrangement, material flow association, Manhattan distance, and evolutionary algorithms have been used for designing the optimal layout within a python-based simulation platform. System sensitivity has been analyzed with respect to different levels of demand in the system. The results suggest a significant decrease in material handling costs from 26,500 to 10,600, which is 60% lower than the current scenario. Moreover, the Throughput Index increased from 3.77 to 9.43, indicating a 150% increase in system efficiency and resilience under uncertainty.

1. INTRODUCTION

Today, the concepts of reshoring and regionalization have gained significant traction within the United States because of the weaknesses of the international supply chain exposed due to the pandemic crisis and geopolitical instabilities (Akinbolajo, 2022; Govella, 2022; Kudrenko, 2024). Global manufacturing supply chains have experienced significant disruptions caused by disruptions in transportation, labor, material, and trading policies due to the pandemic situation and other geopolitical factors. These changes have increased concern about the sustainability of offshore manufacturing operations and highlighted the need for developing more sustainable manufacturing strategies such as reshoring and regionalization. These trends are likely to gain more traction in the next few decades, and the focus will be put on increasing supply chain responsiveness, resilience, and manufacturing capacity.

As manufacturing operations transform into more localized and regionalized configurations, there is an increased interest in creating more resilient and flexible manufacturing facilities and related logistics operations. However, it should be noted that many manufacturing and warehouse operations continue to use legacy facility layouts that were created using deterministic approaches, which focused primarily on increasing efficiency and minimizing costs (Mohanavelu et al., 2025; Zuniga et al., 2020). Conventional approaches to designing facility layouts prioritize goals such as reducing material movement and increasing efficiency and productivity. Nevertheless, such approaches rarely provide flexible

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solutions to operational difficulties that occur because of uncertain factors.

During the COVID-19 pandemic, many companies faced issues in adapting their manufacturing operations to the new conditions of operation because rigid facility designs and inefficient material flows did not allow them to implement different strategies aimed at mitigating the effects of the crisis. Bottlenecks, inefficient use of space, travel distance, and rigidity of facility layouts made the process of adaptation more difficult and increased the operational impact of disruptions. The experience of many manufacturers indicates that conventional facility layouts are not suitable for managing manufacturing operations in highly uncertain environments. Thus, modern manufacturing requires a new approach to designing facility layouts that will help to increase the efficiency and resilience of internal facility operations. The current research on facility layouts mostly focuses on modeling the resilience of the supply chain network. Some researchers try to determine how resilience can be modeled in terms of disruptions, recovery costs, service level decline, and increased operating expenses after a disaster (Fattahi et al., 2020). Other researchers investigate the topic of optimizing supply chains for improved reliability by using robust optimization models and stochastic facility networks (Sabouhi et al., 2020; Sarkis et al., 2025; Yılmaz et al., 2023). Although the presented research significantly contributes to developing the science, very little attention is paid to the topic of facility layout resilience.

Facility layout is a crucial step of operations that can significantly affect manufacturing processes because it determines the performance, efficiency, throughput rate, and flexibility of manufacturing. Thus, designing a resilient facility layout becomes crucial since inefficient and rigid facilities will be less likely to withstand operational changes and recover from disruptions quickly. On the other hand, designing resilient facility layouts will enable manufacturing processes to be more sustainable because of increased flexibility and the possibility to change material flows. Genetic algorithms and hybrid AI-based optimization techniques have been widely applied in industrial engineering problems, demonstrating strong performance in handling complex, nonlinear systems (De Oliveira Leite et al., 2026). However, the problem of facility layout design in the face of uncertainty is quite underdeveloped and understudied. There is a strong need to develop new approaches to facility layout design that consider operational uncertainties and the problem of resilience. One of the most promising approaches to solving facility layout problems is Genetic Algorithms. This approach is appropriate for finding efficient and flexible solutions to facility layouts because it helps to handle a complex solution space and find optimal solutions considering multiple constraints. The combination of GA and sensitivity allows evaluating facility layouts under different scenarios, such as transportation delay, demand fluctuations, workforce availability, machine breakdowns, etc.

The integration of sensitivity with GA allows investigating multiple operational goals, both traditional goals, such as material handling cost reduction and travel distance minimization, and resilience-related goals such as recovery time, throughput rate, and disruption tolerance. Thus, this methodology is highly relevant for reshored facilities that aim to achieve higher levels of efficiency, resilience, and flexibility of manufacturing operations. Therefore, the study of resilient facility layout optimization is highly relevant and needed today. Thus, this paper will investigate facility layout optimization for resilience and flexibility based on GA technology.

2. LITERATURE REVIEW

2.1 Facility Layout and Simulation-Based Optimization

Indeed, simulation-based optimization has been gaining traction as an optimal technique for designing, assessing, and optimizing the layout of manufacturing facilities amid complex operational dynamics. Traditional manufacturing facility layout optimization approaches often assume deterministic parameters in their analyses based on simplified models that ignore real-life variability. Simulation-based facility layout optimization combines simulation and optimization techniques and uses discrete event simulation models to analyze the performance of facility layouts under realistic production and logistical conditions (Zuniga et al., 2020). The use of DES allows researchers and managers to study how machines, material handling systems, production scheduling, labor allocation, and transportation interact within a production environment characterized by stochastic operations. The utility of DES in studying manufacturing processes cannot be understated because it simulates operations as a series of events happening over time. By applying DES techniques, organizations can explore the impacts of bottleneck situations, machine utilization rates, interruptions, queues, and other variables on their production systems without interrupting the production process itself. This ability is particularly relevant in facility layout optimization because even slight modifications in machine placement, material movement paths, and other elements of facility layouts can have a considerable effect on overall production processes. For this reason, simulation-based optimization techniques have emerged as one of the most useful methods of data-driven facility layout design in manufacturing systems.

A wide range of literature attests to the positive effects of applying DES-based approaches in facility layout redesigns. (Mohanavelu et al., 2025) used a DES-based approach to optimize the facility layout of an assembly production line. By redesigning the layout of the facility based on simulations, the researchers were able to increase machine utilization by 40%, reduce space requirements by 60%, and increase production volume by

75%. Such results confirm the significance of applying simulation-based optimization techniques for designing layouts in manufacturing environments. By assessing multiple possible facility layouts, researchers were able to identify layouts that allowed reducing inefficiencies and promoting smooth workflow in production facilities.
The application of DES-based optimization techniques extends far beyond static facility layout problems. Another example of successful application relates to dynamic facility layout problems in which facility layouts evolve over time based on changes in operational conditions and uncertainty. Specifically, (Guo et al., 2021; Pourhassan & Raissi, 2017) have designed an approach combining simulation techniques with a Non-dominated Sorting Genetic Algorithm II to solve DFLP tasks. By using this approach, researchers managed to minimize not only material handling costs but also transporter interference during multiple planning periods. Integration of simulation and optimization allowed exploring material movement and operation of cost trade-offs in manufacturing systems with changing operational conditions.
Finally, simulation-based optimization can be also used in optimizing complex automated material handling systems that utilize automated guided vehicles (AGVs). (Yang et al., 2023) have proposed an innovative DES-based approach for co-optimizing workshop layouts and material handling routes in AGV systems used in intelligent manufacturing workshops. Through this approach, researchers raised production capacities in workshops by 54%, highlighting the need for combining facility layout optimization with material handling optimization in highly automated manufacturing systems. Because intelligent manufacturing processes entail significant interactions between production layout designs and logistics, DES' approaches remain critical to such manufacturing systems. From the literature review, it becomes evident that simulation-based optimization techniques hold promise for improving manufacturing layouts both in static and dynamic conditions. The use of DES allows modeling real production systems more realistically and optimizing their performance accordingly. In the future, simulation-based optimization approaches can be expected to take a dominant position in industrial layout optimization due to rising complexities of manufacturing processes.

2.2 Genetic Algorithms in Layout Optimization

Indeed, Multi-Objective Genetic Algorithm (GA) techniques have been widely utilized in facility layout optimization as they enable simultaneous optimization of multiple, conflicting objectives, which is essential for designing an effective layout in manufacturing systems with a high level of complexity (Chan et al., 2015; Fan et al., 2024; Klar et al. 2024). As opposed to traditional optimization techniques focused on achieving the best possible performance regarding one single objective, multi-objective optimization algorithms make it possible to evaluate different options based on diverse goals. Such goals may include, among others, material handling costs, adjacency rules, productivity, space utilization efficiency, and design flexibility. A range of previous studies provided clear evidence in favor of the application of multi-objective GA for solving facility layout problems. For instance, (Govella, 2023) offered a framework for optimizing facility layouts based on quantitative and qualitative factors, such as material handling costs and interdepartmental adjacency. Using Pareto-optimality-based optimization, the authors identified multiple potential solutions to be chosen by decision-makers depending on their preferences. Another example relates to (Jannat et al., 2010) study of multi-objective optimization approaches for improving facility performance despite conflictual design objectives. The use of the Pareto optimization method enables the provision of multiple alternatives, which is especially beneficial when planning.
More advanced variants of GA, such as the ones incorporating chaos and being oriented at reconfigurable manufacturing, have been applied in the context of simulation-based layout design. (Zuniga et al., 2020) noted the potential of using such variants in the context of facility layout optimization. For instance, chaos-based GA incorporates nonlinearity into the optimization procedure to reduce the risks of premature convergence. At the same time, reconfigurable manufacturing-oriented GA makes it possible to create adaptable facility designs capable of addressing changing production needs. Apart from applying multi-objective optimization based on GA in the context of manufacturing layout planning, this methodology can also be applied to similar problems in other engineering domains. For instance, the same technique was applied by (Jannat et al., 2010) in wind farm layout optimization to account for multiple objectives, including installation cost and energy generation efficiency. Additionally, GA was used in a study by (Yang et al., 2023) that evaluated multiple low impact development infrastructure designs to optimize cost and environmental performance under real-world conditions. Altogether, previous research suggests that the utilization of multi-objective GA optimization is an effective and versatile solution to various layout problems due to its ability to produce Pareto-optimal solutions, account for qualitative and quantitative objectives, and incorporate dynamic changes in manufacturing operations.

2.3 Disruption and Supply Chain Resilience

Nowadays, supply chain resilience has become one of the key focal areas among scientific studies due to an increasing number of supply chain disruptions occurring at the international level (Azad et al., 2025). (Olagunju et al., 2024) Disruptions may occur in pandemics, geopolitical conflicts, natural events, transport malfunctioning, and supplier failure cases, which highlights a significant vulnerability of interlinked supply chain networks. Therefore, there is a growing need to create robust systems that guarantee operational continuity and allow for efficient supply chain recovery following the occurrence of unforeseen events. Supply chain resilience is regarded as the ability of a supply chain to withstand, adapt to, and recover from disruption with high efficiency to preserve desired levels of performance. Contrary to efficiency-driven traditional supply chain management techniques, resilience approaches focus on flexibility, redundancy, adaptability, and recovery. A recent body of studies has provided novel quantitative tools aimed to enhance supply chain network resilience. For instance, (Fattahi et al., ., 2020) suggest a new definition of supply chain resilience based on the expected increase in operational expenses associated with supply chain recovery after a disruption. Using this approach, the authors created a two-stage stochastic supply chain design model which evaluates supply chain performance in cases of uncertain disruption. Specifically, the first stage of their stochastic model includes making strategic supply chain decisions, and the second stage implies assessing supply chain operational performance post-disruption. Thus, by applying stochastic optimization in terms of resilience analysis, this research is an example of a breakthrough in the field, since it enables organizations to optimize supply chain operations based on resilience evaluation. Apart from quantitative measures of resilience, numerous scholars have suggested various models incorporating different approaches to resilience enhancement in stochastic conditions. For instance, (Sabouhi et al. 2020; Yılmaz et al., 2023) present two-stage stochastic programming model to incorporate several supply chain resilience strategies into network design. Among these strategies, we should mention backup suppliers, extra production capacity, redundant inventories, and flexible transport routing. The goal of using these approaches is to ensure service continuity and preserve the desired level of performance regardless of random disruption events. As mentioned above, the advantage of using stochastic models is that the consideration of several types of disruptions allows for getting a solution which is closer to reality in comparison with a deterministic model. For example, flexible routing and backup sourcing may help mitigate risks associated with disruption of transport routes and supplier companies' failures, whereas extra capacity would help handle rapid changes in demand levels. One should note that the application of stochastic approaches in pharmaceutical and medical supply chains can be vital to the preservation of the desired performance level since such disruptions may directly affect public health and services. There are several studies confirming that integration of stochastic optimization with simulation can improve the reliability and cost-efficiency of these types of supply chain networks compared to classical deterministic network design (Sarkis et al., 2025; Yılmaz et al., 2023) . As seen during the recent years of the COVID-19 pandemic, demic, most supply chains for healthcare products experienced shortages in critical resources including medical devices, medicines, and protective masks owing to the lack of flexibility and redundancy of global sourcing networks. Stochastic simulations allowed studying the effects of various disruption scenarios including uncertain demand fluctuations and transport issues and thus improving performance of the studied networks.

To summarize, existing literature shows that stochastic optimization and stochastic simulation approaches are crucial in terms of improving resilience of supply chains. With the help of these approaches, organizations can enhance their recovery capability, preserve performance, and mitigate the negative effects of disruption.

3. METHODOLOGY

The facility layout optimization problem was formulated with the objective of minimizing total material handling distance while improving production flow efficiency within an existing manufacturing system. The input data included department dimensions, inter-departmental material flow relationships, facility boundary constraints, production sequence, and the current (as-is) layout configuration. The existing facility layout was first used as the baseline representation of the system. A Genetic Algorithm (GA) was then applied to improve this layout by optimizing the spatial arrangement of departments. Each candidate solution was evaluated using a fitness function based on the total weighted Manhattan distance, where lower material handling distance corresponded to higher fitness.

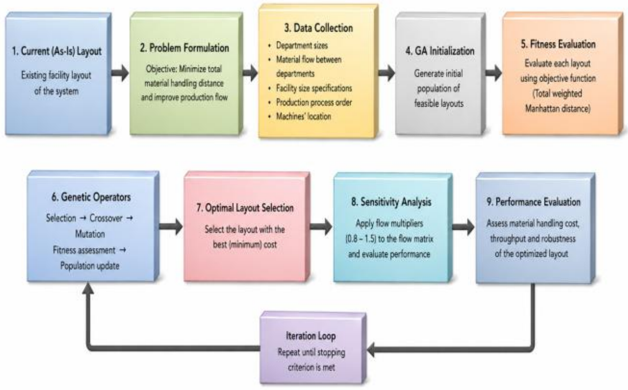

Figure 1. Methodology Process Map

The GA iteratively improved solutions through selection, crossover, mutation, and population updates until convergence was achieved. Finally, sensitivity analysis was conducted using production flow multipliers to evaluate the robustness of the optimized layout under varying demand conditions, assessing performance stability in terms of material handling cost and operational efficiency (Figure 1.).

4. EXPERIMENT

This research looked at the manufacturing process of bottled water within an organization that adopts lean manufacturing practices for the optimization of factory design using a Genetic Algorithm (GA). The core goal of this analysis would be to minimize handling distance, improve the flow of the production process, decrease traffic within the production process, and enhance efficiency of production. The factory occupies a total floor space of 60m by 40m (2,400m²) and operates in two shifts each day. It aims at producing a total of 10,000 units of bottled drinking water each day; each unit containing a volume of 600ml. This factory is deliberately planned to follow lean principles including low WIP, low transportation distance, and smooth flow of products.
The factory involves processes of water treatment, bottle molding, filling, labeling, packaging, storage, and inspection within its manufacturing process. Data was collected manually using a laser measuring instrument and the facility as a built diagram.

3.1 Statement of the problem

here are some issues faced by the facility, which include:
1) Excess material movement distance
2) Non-optimum layout of departments
3) Cluttering between workstations
4) Lengthy time in production
5) Low efficiency in throughput

This study aims at achieving a layout of departments which will minimize material moving distance without compromising on the production flow.

3.2 Mathematical Model Objective Function

The objective is to minimize the cost of material handling between various departments.

$$Z = \sum_{i=1}^{n} \sum_{j=1}^{n} F_{ij} . D_{ij}$$

Where:
Z = The cost of material handling
F_{ij} = Material flow between the i and the j department
D_{ij} = The distance between the i and the j department
n = is the total number of departments

Distance Formula
Manhattan distance formula is used here:

$$D_{ij} = | x_i - x_j | + | y_i - y_j |$$

Where:
$x_i - x_j$ = The coordinates of the i department
$y_i - y_j$ = The coordinates of the j department

Constraints
1. Only one location must be assigned for each department:

$$\Sigma_{k=1}^{m} x_{ik} = 1$$

2. Two departments cannot be placed in the same place:

$$\Sigma_{k=1}^{n} x_{ik} = 1$$

3. There should be sufficient space for the department within the plant size:

$$A_i \leq A_a$$

Where:
A_i = The area needed by the i department
A_a = *Available space*

Fitness Evaluation
Each layout solution is evaluated using the objective function:

$$Z = \Sigma F_{ij} . \Sigma D_{ij}$$

Layouts with lower total distance are assigned to better fitness values.

5. RESULTS

The facility layout optimization model was developed in Python programming language using Genetic Algorithm (GA) approach for minimizing material handling costs and maximizing production process efficiency in bottled water manufacturing plant. The model represents physical locations of departments inside a 60 m × 40 m facility considering constraints and objectives of layout.
Python code includes several parts like definition of the plant, department configuration, material flows model, optimization algorithm, visualization, sensitivity analysis, and simulation.
At first stage, plant and department dimensions are defined in the code. The width and height of each department correspond to their actual production functions. Departments included in this model cover: raw water treatment, bottle preform storage, blow molding, rinsing/filling/capping, labeling, shrink wrapping, warehouse/shipping, quality-control laboratory and utilities support area.

Model parameters:
Plant dimensions: 60 m × 40 m = 2400 m^2
Original coordinates of the departments were determined based on a developed factory layout scheme and were used as an initial condition for an optimization algorithm.
Material-flow matrix was used to determine level of interactions between departments depending on production process flow and frequency of material flows: A → C → D → E → F → G, it describes the production

process from water treatment up to warehousing and shipping. To evaluate the performance of each layout we used Manhattan distance for calculating inter-department distances by formula:

$$D_{ij} = | x_i - x_j | + | y_i - y_j |$$

Total material handling cost in each configuration was estimated using the objective function.

$$Z = \sum_{i=1}^{n} \sum_{j=1}^{n} F_{ij} . D_{ij}$$

where:

Z = total material handling cost

F_{ij} = material flow between departments,

D_{ij} = Manhattan distance between departments.

Optimization of layouts was carried out using the Genetic Algorithm. Algorithms generate an initial population consisting of feasible layouts ensuring departments' non-overlapping. Feasibility of layouts was determined through overlap and boundary detection.

Parameters of the GA are listed below:

(a) Population size = 50
(b) Number of Generations = 200
(c) Elite Size = 10
(d) Mutation Method: Random Relocation

Within each generation, layouts with lower material handling cost receive higher fitness values. Only elite layouts remain unchanged, and new layouts are generated due to mutation. Mutation consists of random relocation of departments. As a result, after running GA optimization layouts become more optimal according to the objective function. Visualization and analysis of results were made by creating grids with plots. The original and optimized layout schemes with department labels and sizes were plotted. Sensitivity analysis was performed to estimate the effect of material flows intensity. Multiplier from 0.8 to 1.5 was used for determining the influence of increased production demand on material handling costs. The throughput analysis model was proposed and analyzed. It was suggested that throughput index of a plant is inversely proportional to the total material flow distance: throughput index = constant / distance.

To evaluate the impact of optimization using the Genetic Algorithm model, the performance of both layout solutions was compared based on total material handling cost obtained by evaluating the objective function. The total cost of total material handling calculated based on the original layout is: Initial = 26,500, As a result of optimization using the Genetic Algorithm, an improved layout solution was generated with handling cost equal to: Optimized = 10,600. Thus, the optimization process made it possible to achieve improvement of the following magnitude:

Improvement = ((26,500 − 10,600) / 26,500) × 100 = 60%

The large reduction in the cost of total material handling proves that the optimized layout is more effective. In the case of the initial layout, there was too much movement in the process of production since many strongly interacting departments were located relatively far from each other. The presence of warehouses and auxiliary zones increased the need for additional transportation and led to inefficiencies. The optimized layout created an adjacency between departments with frequent exchange of materials, which positively affected process continuity due to reduced distances. In the new arrangement, the departments involved in the production sequence were placed closer to each other, making the left-to-right process flow from treatment of raw water, blow molding, filling, labeling, and packing to warehouse become more natural.

This layout adjustment reduced the required traveling distance and resulted in:

(a) fewer transportation needs,
(b) less forklift movement,
(c) less congestion between stations,
(d) better coordination in production processes,
(e) higher throughput efficiency.

Taking into account that lean manufacturing is aimed at minimizing non-value-added movement, the optimized layout could be considered more effective in this aspect as well. Therefore, the optimization process using the Genetic Algorithm made it possible to increase production efficiency by 60% compared to the manual design process.

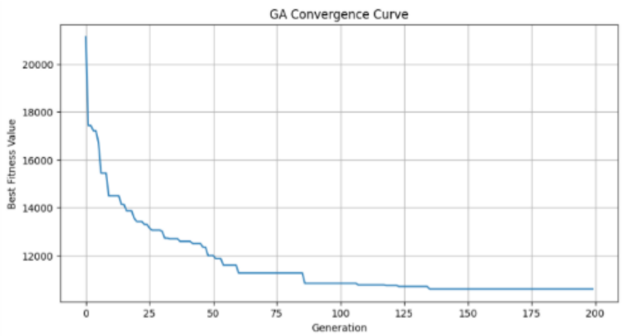

Figure 2. GA Convergence Curve

The GA convergence curve demonstrates progressive improvement in layout optimization across generations (Figure 2). The fitness value decreases rapidly during early generations, indicating significant reduction in material handling costs. The curve gradually stabilizes after approximately 140 generations, showing that the algorithm converged toward an optimal or near-optimal facility layout solution.

A sensitivity analysis was undertaken to determine the effect of changes in production flow intensity on material handling cost in relation to the optimized layout of the facility (Figure 3). Multiplying factors of production flow ranging from 0.8 to 1.5 were used to multiply the material flow matrix with respect to keeping the optimized arrangement of departments unchanged.

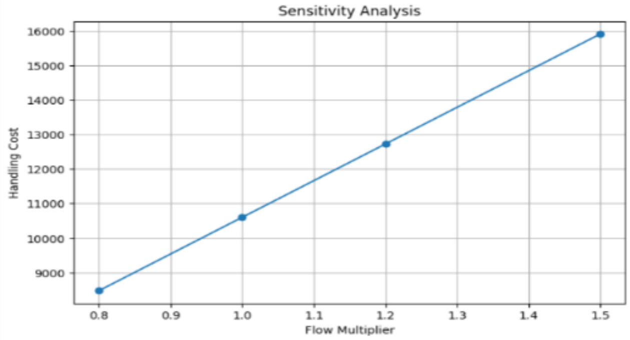

Figure 3. Sensitivity Analysis

The results show that material handling costs vary directly as production flow varies. Material handling cost falls to 8,480 when a flow multiplying factor of 0.8 is considered because there will be a reduction in transport needs at the facility. On the other hand, under standard conditions with a factor of 1.0, a material handling cost of 10,600 will be incurred with the current optimized layout. In case production increases to 1.2 and 1.5, the material handling cost will rise to 12,720 and 15,900, respectively. From the above results, it is clear that the optimized layout is very reliable in terms of being efficient irrespective of the production condition changes. However, increased levels of production lead to higher material handling costs. Nevertheless, the rate of increase in material handling cost will be kept in check by enhanced proximity among highly interacting departments.

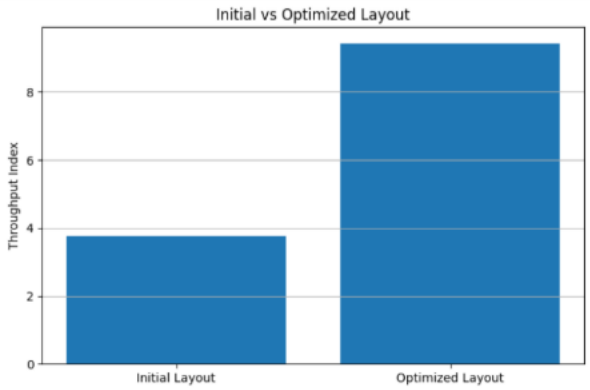

Figure 4. Throughput Index

From the above findings, one can see that there was a considerable improvement in the performance of the system because of the facility layout optimization process. The Throughput Index, which can be described as the measure of the efficiency of the material flow and production rate within the system, improved from 3.77 in the initial stage to 9.43 in the optimized stage (Figure 4). This clearly shows that there was a great level of efficiency gained in the process, most likely due to reduction in travel distance, better workstation sequencing, and reduction in material handling. Throughput improvement of 150% implies that there is a possibility of having more output in the same period when the system is operating at the optimal point as compared to the baseline point. Therefore, this means that the facility has the potential to double its initial output without adding any further resources to the process.

6. DISCUSSION

The research conducted shows that using the combination of a genetic algorithm (GA) with sensitivity-based analysis provides an excellent method for optimizing the design of facilities in terms of its operation and layout. The main aim of the present research was to overcome the weaknesses of traditional static layout planning methods and suggest an alternative way of designing facilities which would be both efficient and flexible/resilient.

In particular, the optimized layout was shown to provide a significant drop in the material handling cost of the factory. The cost decreased from 26,500 to 10,600 (a 60% improvement). Thus, it can be concluded that the GA successfully managed to optimize the interaction between departments by reducing transportation costs and improving the continuity of the production process. Indeed, the new layout better represents the natural flow of work (starting from water treatment to packaging and warehousing) and reduces unnecessary interdepartmental transportation by avoiding inefficiency inherent in the previous layout.

Concerning the question of resilience, the sensitivity analysis shows that the optimized layout proves to be consistent in terms of its performance when the production level changes (i.e., it varies from a flow multiplier of 0.8 to 1.5). The cost associated with material handling increases when the output rises; however, the growth appears to be relatively steady and slow, indicating that the system becomes more robust in face of production changes. In other words, the optimized layout allows for overcoming the problem mentioned in the introduction, according to which the lack of attention to operational aspects of facility design was observed. As concerns throughput, the analysis provided showed that the optimized layout was successful in terms of efficiency. The throughput Index improved by 150% and became equal to 9.43, while in the previous situation, it was 3.77. This means that optimization helped to improve throughput efficiency and reduce the time needed for completing the production process.

7. CONCLUSION

In this study, a Genetic Algorithm-based Optimization Framework is presented for improving the efficiency and robustness of facility layout design in a bottled water manufacturing system. The proposed approach tackles the challenge of inefficiencies in and lack of adaptability of facility layouts by using material flow analysis, spatial optimization, and uncertainty assessments. As shown by the results, the optimized facility layout reduces the total cost of material handling by 60% from 26,500 to 10,600, alongside increasing throughput by 150% based on the Throughput Index, which goes from 3.77 to 9.43. This implies that optimizing spatial relationships between high material flow departments increases efficiency and reduces unnecessary costs. Additionally, sensitivity analysis reveals that the optimized facility layout maintains robustness under different levels of production demand, indicating its flexibility and adaptability. This is crucial for addressing the problem described in the introduction regarding the development of facility layouts that can cope with production demand variations and uncertainties. In conclusion, applying Genetic Algorithms offers a viable framework for creating efficient, flexible, and robust facility layouts. The approach is especially relevant for modern manufacturing systems where uncertainties, demand variations, and disruptions are common. Future research can further develop the model by considering stochastic disruptions, multi-criteria optimization, and adaptive layout design.

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