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MACHINE LEARNING-ENHANCED GENETIC ALGORITHM FOR ROBUST LAYOUT DESIGN IN DYNAMIC FACILITY LAYOUT PROBLEMS

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This paper proposes a new approach for solving dynamic facility layout problems (DFLP) using a genetic algorithm (GA) enhanced with machine learning techniques, namely clustering algorithms. The proposed course aims to design a robust layout that can adapt to changes in the input parameters. Traditionally, the DFLPs are solved using adaptive methods, i.e., the layout from period to period varies. However, in the robust approach, the layout remains the same throughout the different planning periods. The GA is used for generating the solutions, and the machine learning technique is used to cluster the solutions and select the candidate solution to undergo the local search procedure. The proposed approach is tested on a set of benchmark instances and compared with published approaches. The results show that the proposed approach outperforms the existing approaches in terms of solution quality, robustness, and computational efficiency.

Keywords: Robust layout; Facility layout; Quadratic Assignment Problem; Genetic Algorithm; Machine Learning; Dynamic Facility Layout Problem.

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1. INTRODUCTION

To achieve effective functioning of production and service systems, it's essential to have a well-thought-out facility layout in addition to optimal planning and operational policies. Inadequate facility design can lead to various problems, such as decreased productivity, higher work-in-process, extended manufacturing lead times, and chaotic material handling. The objective function of the facility layout problem typically focuses on reducing the Material Handling Cost (MHC), which can account for 20-50% of the total operating cost of the operations within the facility (Chan *et al*., 2004). Efficient facilities planning can result in a 10-30% reduction in the costs associated with MHC, which is considered a non-value-added expense, leading to increased productivity. Efficient initial planning is crucial because implementing changes to an existing layout is a costly and challenging process, making it difficult to achieve without incurring significant expenses. Therefore, designing an efficient facility layout is essential for reducing costs and improving productivity in the long term.

Facility layout design involves identifying the ideal arrangement and placement of departments, cells, or machines within those cells. Typically, the allocation of m departments to m locations with the goal of minimizing the Material Handling Cost (MHC) is modeled as a Quadratic Assignment Problem (QAP). Unfortunately, the QAP is an NP-complete problem, making optimization techniques inefficient for solving problems with more than 30 facilities within a reasonable timeframe. Consequently, heuristic approaches are necessary to obtain satisfactory suboptimal solutions to the facility layout problem.

When the pattern of flow between facilities varies over periods, each period needs to be formulated as a separate QAP. Since the parameters within the QAP change, the optimal solution for one may not be the optimal solution for the other, requiring the facilities to change the positions over periods. Cost is involved in this shifting of facilities, and this possibility of shifting the facilities makes the problem more complex. However, obtaining an optimal solution or at least a near-optimal solution to such problems is important for the profitable operations of organizations in today's business environment.

In an environment marked by competition, markets are often characterized by heterogeneity and volatility. To ensure continued productivity in the face of such volatile demand conditions, manufacturing firms must configure their production processes in a manner that is well-suited to their specific needs. Manufacturing organizations must now possess the capacity

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to create and manage facilities that can quickly and effectively adapt to developing technological advancements and shifting market requirements to achieve success. Consequently, modern manufacturing facilities must exhibit a high degree of flexibility and robustness to respond adequately to significant changes in their operating requirements.

When demand remains relatively constant over time, the approach of the Static Plant Layout Problem (SPLP) has been proven to be an effective method for creating an appropriate layout for a facility. However, when demand is subject to frequent fluctuations, static layout generation approaches may prove to be inefficient at various points during the planning horizon. Changes in product demand, shifts in product mix, the introduction of new products, and discontinuation of existing products are all factors that can render the current facility layout inefficient, leading to increased Material Handling Costs (MHC) and necessitating a change in layout (Afentakis *et al*., 1990; Krishnan *et al*., 2009). In order to maintain an optimal facility layout, it is necessary to continually assess fluctuations in the demand for products and movement between different departments. This highlights the necessity of employing Dynamic Facility Layout Problem (DFLP) strategies to create layouts that can effectively adapt to the evolving requirements of manufacturing plants.

When it comes to addressing the dynamic facility layout problem, there are two main approaches that have been explored: the adaptive/flexible/agile approach and the robust approach. When addressing facility layout problems, the adaptive approach presumes that changes in demand will occur periodically, and with easily movable machines and low rearrangement expenses, the facility layout can adapt to these variations. Conversely, the robust approach presumes that rearrangement costs are exorbitant and aim to reduce the overall expenses of material handling throughout all time frames through a unified layout. To develop layouts for single-period and multi-period problems with multiple production scenarios, the robust approach is frequently used. This approach recommends a single layout for multiple scenarios and periods. Rosenblatt (1986) was the first to model the dynamic facility layout problem, and they used a dynamic programming approach to solve the model for multiple periods. In each stage, the designer resolves a layout design problem that is static in nature for a particular set of options. Lacksonen (1997) proposed a model that could handle both rearrangement and unequal area constraints for the dynamic facility layout problem. The model utilized a pre-processing technique to produce solutions for large-scale problems and incorporated an enhanced branch-and-bound algorithm to generate workable layouts. Finally, Yang and Peters (1998) proposed a flexible machine layout model that includes both material handling and machine rearrangement costs. A rolling horizon planning time window is utilized in this layout design, enabling the facility layout to adapt to changes over time.

A resilient model for DFLP is proposed in the work reported in this paper. A hybrid Genetic Algorithm incorporating machine learning algorithms with a local search into the Genetic Algorithm (GA) is used to solve the robust model for DFLP. The machine learning-based genetic algorithm (ML-GA) proposed in this study has been evaluated using various problems from the existing literature, and the results demonstrate its effectiveness in all cases. Specifically, the robust model has been applied to these problems, and the resulting robust layout solution has been compared to the adaptive layout solution and robust layout solution reported by various authors for the test instances used in the tests. Remarkably, the robust layout strategy yields a solution quality that is nearly equivalent to that of the adaptive layout strategy while avoiding production interruption and relocation. This implies that a robust layout can be defined as one that can efficiently manage fluctuations in product demand across various timeframes within the planning horizon. However, the method of obtaining robust layout for DFLPs are not much explored in the literature. The present work proposes a simple method to obtain robust layouts for DFLPs and presents a GA enhanced with a machine learning-based search algorithm for finding near-optimal solutions for complex DFLPs in a short time.

The rest of the paper is organized as follows: section 2 provides an account of the existing published works on SFLPs and DFLPs. Here, the papers are listed in the literature as per the methods adopted for solving the problem. The research methodology adopted is explained in section 3. Section 4 depicts the experimental results, and section 5 concludes the paper with a discussion of the results obtained.

2. LITERATURE REVIEW

Facility layout design is a critical issue in manufacturing and service industries to achieve efficient utilization of space, reduce material handling costs, and enhance overall operational performance. The problem of facility layout design involves assigning different departments or workstations in a given area to optimize the operational efficiency and productivity of a facility. Various approaches have been proposed to generate layouts, which can be broadly classified into two categories: qualitative and quantitative.

Closeness ratings between departments are utilized in qualitative approaches to determine a suitable layout. The main objective of such approaches is to minimize the material handling cost by arranging the departments or workstations in a manner that reduces the distance between them. In this approach, departments are rated based on their level of interaction, and a layout is generated based on the overall closeness rating. However, these approaches do not consider the specific requirements of the departments, such as space, equipment, and environmental factors, which can limit their applicability in practice.

On the other hand, quantitative approaches aim to minimize the total material handling cost (MHC) between the departments. These approaches consider the specific requirements of each department and the layout of the facility to minimize the MHC while satisfying the constraints. In this approach, the distance between departments is considered, along with other factors such as department size, shape, and orientation. Quantitative approaches are more comprehensive than qualitative approaches, as they consider multiple factors that affect the operational performance of a facility.

The existing methods for the facility layout problem can be categorized into exact, heuristic, meta-heuristic, and hybrid solution approaches. Exact methods provide an optimal solution by exploring all possible layouts, but they are limited to small-size problems due to the computational complexity. Heuristic methods are designed to solve large-scale problems by using a set of rules or procedures that generate near-optimal solutions in a short time. Meta-heuristic methods are based on nature-inspired algorithms that explore the solution space to find a good solution, but they do not guarantee optimality. Hybrid approaches combine the advantages of both heuristic and meta-heuristic methods to improve the quality of solutions and reduce computational time. For a comprehensive review of the existing methods for the facility layout problem, see Kusiak and Heragu (1987), Yaman *et al.* (1993), Singh and Sharma (2006), Drira *et al.* (2007), Sharma and Singhal (2016), Zhu *et al.* (2017), Perez-Gosende *et al.* (2020), Alarcon-Gerbier and Buscher (2022), and Khaleghi and Eydi (2022).

2.1 Solution Methods for Facility Layout Problems

Researchers have proposed various methods to solve the facility layout problem. Tam and Li (1991) proposed a heuristic method that considers both quantitative and qualitative factors to generate a layout. Tang and Abdel-Malek (1996) proposed a genetic algorithm to solve the single-row facility layout problem (SFLP) with unequal areas. Foulds *et al*. (1998) proposed a tabu search algorithm to solve the SFLP with equality and inequality constraints. Chan *et al.* (2002) proposed a modified genetic algorithm to solve the SFLP with forbidden regions.

Bock and Hoberg (2007) proposed a hybrid method that combines a genetic algorithm with a local search heuristic to solve the SFLP with constraints such as aisles, walls, and columns. Wilhelm and Ward (1987) proposed a simulated annealing algorithm to solve the facility layout problem with multiple objectives. Mak *et al.* (1998) proposed a genetic algorithm to solve the facility layout problem with unequal areas and multiple objectives.

El-Baz (2004) proposed a hybrid simulated annealing algorithm to solve the facility layout problem with multiple objectives and equality constraints. Hu and Wang (2004) proposed a hybrid genetic algorithm to solve the facility layout problem with constraints such as rectangular shape and adjacency requirements. Rosenblatt (1979) proposed a method that combines qualitative and quantitative factors to generate a layout.

Dutta and Sahu (1982) proposed a method that uses the hierarchical clustering algorithm to group departments based on their interaction and then generates a layout based on the clustering results. Numerous works of literature have focused on combining quantitative and qualitative factors in solving SPLPs. These works use different solution approaches and algorithms to optimize the layout design. Examples of such works include Rosenblatt (1979), Dutta and Sahu (1982), Malakooti and D'Souzas (1987), Soundar *et al.* (1988), Heragu and Kusiak (1990), Catherine and Tothero (1992), Raoot and Rakshit (1993), Meller and Gau (1996), Islier (1998), Sha and Chen (2001), Tuzkaya *et al.* (2005), Ertay *et al.* (2006), and Khilwani *et al.* (2008).

2.2 Solution Methods for Dynamic Facility Layout Problems

From the 1950s to the 1990s, SPLP received significant attention from researchers who conducted extensive research on the subject. However, in recent years, scholars have been focusing on addressing the dynamic facility layout problem (DFLP). Various researchers have proposed new and improved models and algorithms to solve DFLP. In 1986, Rosenblatt (Rosenblatt, 1986) developed a model and solution procedure for DFLP with an adaptive approach for small-sized problems. A review of research on the dynamic layout problem is available in the work of Balakrishnan and Cheng (1998), as well as Ulutas and Islier's (2005) and Konak's (2007) works. The articles classify various algorithms based on whether the departments are of equal or unequal size and the nature of the material flow, whether it's deterministic or stochastic. Numerous researchers, such as Rosenblatt (1986), Balakrishnan *et al*. (1992), and Palekar *et al*. (1992), have developed adaptive, flexible, or agile layouts that can be easily rearranged to meet changes in production requirements. They used exact and heuristic methods to solve the DFLPs. Lacksonen and Enscore (1993), Lacksonen (1997), Kochhar and Heragu (1999), Balakrishnan and Cheng (2000, 2009), Balakrishnan *et al.* (2000), Baykasoğlu and Gindy (2001), Balakrishnan *et al.* (2003), Corry and Kozan (2004), Dunker *et al.* (2005), Lahmar and Benjaafar (2005), Baykasoğlu *et al.* (2001), McKendall and Shang (2006), McKendall *et al.* (2006), and Norman and Smith (2006) are among the other researchers who have contributed to the development of DFLP solution methods.

2.3 Evolutionary Computation Methods for Dynamic Facility Layout Problems

Several researchers have used meta-heuristics, such as simulated annealing, genetic algorithms, and ant colony optimization, to solve the DFLPs. Among them are Kochhar and Heragu (1999), Balakrishnan and Cheng (2000), Baykasoğlu and Gindy (2001), Corry and Kozan (2004), Baykasoğlu *et al.* (2006), and Norman and Smith (2006). Hybrid approaches have also been attempted by Balakrishnan and Cheng (2000), Balakrishnan *et al*. (2003), Dunker *et al*. (2005), McKendall and Shang (2006) and McKendall *et al*. (2006). Some researchers, such as Balakrishnan *et al*. (1992) and Baykasoglu *et al*. (2006), have considered a budget constraint on rearrangement costs in their models. Balakrishnan and Cheng (2009) investigated the performance of various algorithms under different conditions, such as fixed and rolling horizons, shifting costs, flow variability, and forecast uncertainty. Lahmar and Benjaafar (2005) presented a procedure for designing distributed layouts over a multi-period, while Kochhar and Heragu (1999) explored the design of a multiple-floor dynamic facility. Additionally, robust layouts for multiple production scenarios in a single period and multi-period have been developed by several researchers, including Kouvelis *et al.* (1992), Yang and Peters (1998), Benjaafar and Sheikhzadeh (2000), Aiello and Enea (2001), and Pillai and Subbarao (2008). Kouvelis *et al*. (1992) emphasized the importance of robustness for dynamic layout problems and developed an algorithm to generate robust layouts for manufacturing systems. Pillai and Subbarao (2008) presented a genetic algorithm-based solution procedure for forming part families and machine cells that can handle changes in demands and product mixes without any relocations.

Bayliss and Panadero (2023) address the facility location and population assignment problem, where the feasibility is influenced by facility assignments and stochastic arrival times. To tackle this challenge, a novel learning heuristic algorithm is proposed. The algorithm involves two main steps: (1) training a machine learning algorithm using data derived from a queuing model (simulation module) and (2) constructing solutions using the trained machine learning algorithm to rapidly evaluate decisions based on facility completion and population waiting times. To assess the effectiveness of the learn heuristic algorithm, a comparison is made with two other methodologies: exact and simulation-only (Sim heuristic) approaches. Through a series of experiments, various trade-offs between solution cost, completion time, population travel time, and waiting time are explored, showcasing the efficiency and quality of the proposed algorithm.

The effectiveness of a layout in a dynamic environment can be measured by different criteria, and the strategies used to develop robust or adaptive layouts depend on these criteria. Braglia *et al.* (2003) proposed a method using indices to identify whether a robust or agile layout strategy should be preferred. Building upon the single-row machine layout problem case study and an extensive series of experimental trials, the researchers have introduced two analytical metrics: Layout Problem Robustness Index (LPRI) and Layout Configuration Robustness Index (LCRI). These metrics aim to assess, respectively, the resilience of a stochastic layout problem and the robustness of a particular layout configuration when applied to a specific problem. Pillai (Pillai, 2005) explained the general measures of effectiveness used to evaluate layout performance under different conditions, such as the average percentage of cost difference, the percentage of situations where a layout is optimum, the maximum percentage of cost difference, and the robustness indicator. The flexibility of the layout to adjust to shifts in demand is quantified by the robustness indicator, which represents the percentage of cost difference that is equal to or less than a predetermined percentage.

Raman *et al*. (2007) developed a model to measure the effectiveness of layouts in terms of layout flexibility, area utilization, and closeness gap. The notion of a "closeness gap" pertains to the nearness of closely interconnected facilities or departments, with consideration given to the distance that material handling equipment, information, and personnel need to traverse. This approach aims to enhance productivity by measuring these factors.

Pillai and Subbarao (2008) proposed the concept of robust design for cellular manufacturing systems under dynamic demand and used it to develop a robust layout model for DFLP. The proposal was to create a cellular manufacturing system for a typical scenario that would be applicable for all periods within a multi-period planning horizon. The same idea was also extended to the development of a robust design for multi-period layout design. The layout effectiveness measures from Braglia *et al*. (2003) were used to evaluate the suitability of the solution obtained using the suggested robust model for DFLP problems.

Measuring parameters such as layout flexibility, area utilization, and closeness gaps helps improve productivity. Under dynamic demand, the idea of implementing robust design principles in cellular manufacturing systems is a useful approach for developing robust layouts in DFLP. The effectiveness measures proposed by Braglia *et al*. (2003) can be used to evaluate the suitability of solutions obtained using the suggested robust model. An innovative approach has been developed by Pérez-Gosende *et al*. (2023) to tackle the problem using a multi-objective mixed-integer non-linear programming (MOMINLP) model, referred to in the literature as the bottom-up approach. The proposed model, known as bottom-up mDFLP, encompasses three primary objectives: minimizing the total material handling cost (TMHC) and the total rearrangement cost (TRAC), maximizing the total closeness rating (TCR) between departments and maximizing the area utilization ratio (AUR). To enhance computational efficiency, the original MOMINLP has undergone a transformation into a more streamlined form, now referred to as the multi-objective mixed-integer linear programming (MOMILP) model. This modification allows for improved computational speed and optimization in addressing the problem at hand.

3. RESEARCH METHODOLOGY

The work presented in this paper goes through two phases. In the first phase efficiency of the proposed algorithm is proven by solving static layout problem (SPLP) test instances. For this, the QAP instances available in the QAPLIB (Burkard *et al.*, 1997) are used, as QAPs are another representation of SPLPs. In the second phase, the DFLPs are converted into QAP by adding the flow matrices of different periods together to form the flow matrix of the QAP. Then, this QAP is used to find the robust layout for the corresponding DFLP. The details of each of the phases are provided in the following subsections.

3.1 Problem description and formulation for SPLP

When it comes to solving the plant layout problem in a static environment, typically for a single period, the focus is on assigning 'm' facilities to 'm' discrete locations to minimize the assignment cost. This cost is determined by the product of material flow between facilities, the distances between their locations, and the installation cost. However, in order to more accurately reflect the real-world complexity of the problem, the part-handling factor is also considered. This factor takes into account how the characteristics of a component may vary when transitioning from one procedure to another. For example, a part's size, weight, shape, or other attributes may change during assembly operations, and thus, the optimal layout can be different even if the quantitative demand for the part remains unchanged. In order to address this, the part handling factor suggested by Chan *et al*. (2004) is incorporated into the layout design problem.

Solving the plant layout problem requires the consideration of several inputs, such as the number of parts to be produced, demand for each part, machine sequence or route sheet of the parts, part handling factor, and location layout grid. The Quadratic Assignment Problem (QAP) involves determining the flow and distance between facilities, with demand and machine sequence used to calculate the flow. Based on the above-mentioned factors, the flow between the facilities is calculated, which can be used as a single parameter in the modeling of the static layout problems.

3.1.1 Model for SPLP

The mathematical model of static layout problem

$$\text{Minimize } Z_s = \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m}\sum_{l=1}^{m} f_{ik} d_{jl} x_{ij} x_{kl} \tag{1}$$

Subjected to

$$\sum_{i=1}^{m} x_{ij} = 1 \qquad \forall\, j = 1,2,\dots,m \tag{2}$$
$$\sum_{j=1}^{m} x_{ij} = 1 \qquad \forall\, i = 1,2,\dots,m \tag{3}$$

where

$$d_{jl} = \left|x_j - x_l\right| + \left|y_j - y_l\right|, \text{ Euclidean distance between facilities } j \text{ and } l \tag{4}$$
$$x_{ij} = \{0,1\}\ \forall\, i = 1,2,\dots,m \text{ and } \forall\, j = 1,2,\dots,m \tag{5}$$
$$f_{ik} = \text{part flow weight from facility } j \text{ to facility } k$$

$x_{ij} = 1$ if facility i is assigned to location j, 0 otherwise

3.2 Proposed Machine Learning-based Genetic Algorithm (ML-GA) for Layout Formation

The Genetic Algorithm (GA) is a search method that operates on a population of potential solutions, where each member of the population is represented by a feasible solution or chromosome. The GA proceeds through a series of iterative steps designed to improve the quality of the solution. These steps include selection, reproduction, evaluation, and replacement. Through the process of selection, the algorithm identifies the fittest solutions in the population and reproduces them to create new offspring. The offspring are then evaluated for their fitness, and those that are deemed less fit are replaced with new solutions. The algorithm terminates when the population has converged to an optimal solution, as defined by the problem being solved. The flow diagram of the proposed Machine Learning based Genetic Algorithm (ML-GA) is depicted in Figure 1

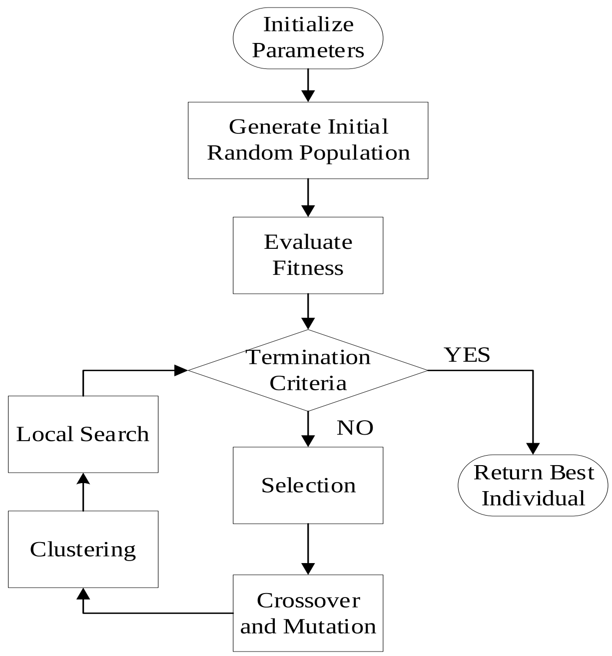

Figure 1. Flow diagram of proposed ML-GA

3.2.1 Model for SPLP

K-Means Clustering represents an Unsupervised Learning technique that organizes unlabeled datasets into distinct clusters. The parameter K determines the quantity of predefined clusters to establish during the process. For instance, if K is set to 2, the algorithm forms two clusters; similarly, for K=3, it generates three clusters, and so forth. The working of the K-Means algorithm is explained in the below steps:

Step-1: Determine the number of clusters, denoted as K.
Step-2: Randomly select K initial points or centroids. These may differ from the points in the input dataset.
Step-3: Assign each data point to its nearest centroid, forming K predefined clusters.
Step-4: Compute the variance and reposition the centroids of each cluster.
Step-5: Iterate through the third step, reassigning each data point to the closest new centroid for its cluster.
Step-6: If any reassignments have occurred, return to step 4; otherwise, STOP.

3.2.2 Local Search

In the proposed algorithm, a machine learning algorithm, namely the K-means clustering algorithm, is used for selecting the individuals which undergo the local search procedure. The population in the GA after the crossover and mutation operations are clustered using the K-means algorithm, and one individual from each cluster is selected randomly to undergo the local search procedure. By employing local search in only one individual in a cluster, it is ensured that repetitive evaluations of the same solutions resulting from the local search of various solutions falling to the same neighborhood are avoided.

The approach employed for local search in this study is the pair-wise exchange (PWX) local search method. This method involves searching through all the potential solutions that result from exchanging two unique elements within the current solution. The PWX local search randomly selects two elements in the parent string and exchanges them (Banzhaf, 1990). For example, consider the parent solution string represented by (1 2 3 4 5 6), and suppose that the second and the fifth assignments are randomly selected, which results in the solution string (1 5 3 4 2 6). If an improved solution is identified, it supplants the original solution, and the PWX local search is repeated recursively with the newly replaced solution at the center. This iterative process persists until a solution is reached where there is no superior alternative within its PWX neighborhood. As such, the recursive variant of the PWX local search method is utilized in this research. Figure 2 depicts the pseudocode for the PWX local search.

The layout model defined above is solved using the proposed ML-GA coded in MATLAB. A program coded in MATLAB for the proposed algorithm was run on the Pentium 4, 2.60 GHz, 2 GB RAM processor. The performance of this solution procedure is tested by solving 92 test instances of sizes ranging from 12 to 50 obtained from the QAPLIB (Burkard, Karisch and Rendl, 1997). Section 4 contains a numerical depiction of the cases and a detailed analysis of the results.

Table 1 presents the operations and parameters employed in the proposed ML-GA for obtaining the robust layout for DFLPs. These operations and parameters used in GA are selected after conducting a pilot study for optimizing the GA.

```
PWX_pseudo_code
{
    do
    {
        a. Select two random positions c1 and c2 in the parent.
        b. Exchange or swap the elements in positions c1 and c2.
    } while solution in b is better
}
```

Figure 2. Pseudocode for PWX local search

Table 1. Selected operations and parameters for the proposed ML-GA

Sl. No.	Parameter / Operator	Value
1	Population Size	*d* × *p* / 2
2	Mutation Probability	0.04
3	Crossover Probability	0.9
4	Termination Criterion	Number of Generations = 10 × *d* × *p*
5	Selection Procedure	Roulette wheel selection
6	Crossover Operator	Single point crossover
7	Mutation Operator	Swap mutation
8	Offspring Insertion Strategy	Parent replacement strategy
9	Clustering Method	K-means clustering
10	Number of Clusters (K)	*d*
11	Local Search Method	Pair-wise Exchange Local Search
12	Fitness value	The inverse of the cost associated with the solution

Note: *d* represents the number of departments, and p represents the number of periods.

3.3 Problem description and formulations for DFLP

The Dynamic Facility Layout Problem (DFLP) deals with designing the optimal layout for a manufacturing system over a planning horizon, which consists of multiple periods. The assumption in the DFLP is that there will be different material flow matrices during different periods of the planning horizon. To solve this problem, adaptive approaches are employed, which involve rearranging facilities and incurring relocation costs. The adaptive DFLP model aims to minimize the combined Material Handling Cost (MHC) and relocation costs throughout the planning horizon. The process involves assigning 'm' facilities to 'm' candidate locations on the layout grid while factoring in the associated rearrangement costs. The mathematical formulation of the adaptive approach is a quadratic assignment model, which considers the dynamic nature of the system over time. Several researchers have proposed adaptive DFLP models that aim to minimize both MHC and relocation costs using various optimization techniques. The ultimate goal is to design an optimal layout that meets the requirements over the entire planning horizon while minimizing costs. Below is a common mathematical representation of the adaptive approach.

Minimize

$$Z = \sum_{t=2}^{T}\sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{l=1}^{m} A_{tijl}Y_{tijl} + \sum_{t=1}^{T}\sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m}\sum_{l=1}^{m} C_{tijkl}\, X_{tij}X_{tkl} \quad (6)$$

Subject to

$$\sum_{j=1}^{m} X_{tij} = 1, \qquad i = 1,2,\dots,m \; and \; t = 1,2,\dots,T \tag{7}$$

$$\sum_{i=1}^{m} X_{tij} = 1, \qquad j = 1,2,\dots,m \; and \; t = 1,2,\dots,T \tag{8}$$

$$Y_{tijl} = X_{(t-1)ij} X_{til}, i,j,l = 1,2,\dots,m, t = 1,2,\dots,T \tag{9}$$

$$X_{tij} = \{0,1\} \; for \; all \; i,j,t \tag{10}$$

$$Y_{tijl} = \{0,1\} \; for \; all \; i,j,l,t \tag{11}$$

where

m = Number of departments and locations.
T = Number of periods.
A_{tijl} = Cost of shifting department *i* from location *j* to *l* in period *t* (where A_{tijj}= 0).
C_{tijkl} = Cost of material flow between department *i* located at location (site) *j* and *k* located at *l* in period *t*.

$$X_{tij} = \begin{cases} 1 \text{ if department } i \text{ is assigned to location } j \text{ at period } t \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{tijl} = \begin{cases} 1 \text{ if department } i \text{ is shifted from location } j \text{ to } l \text{ at the beginning of period } t \\ 0 \text{ otherwise} \end{cases}$$

The primary aim of function (6) is to reduce the total expenses incurred in transferring materials between departments by minimizing both the rearrangement costs and flow costs. To ensure that each location is allocated only one department during each period, constraint set (7) is implemented, while constraint set (8) guarantees that each location is assigned only one department during every period. Additionally, constraint set (9) is utilized to combine the rearrangement costs and material flow costs in situations where a department is moved between locations in consecutive periods. The decision variables are further subjected to the constraints (10) and (11) to satisfy the limitations imposed on them.

3.4 The Proposed robust approach to DFLP

Designing a layout that can accommodate varying flow or demand scenarios during different periods is a challenging issue known as the dynamic layout problem. To address this problem, a robust approach is required. Traditionally, layouts are developed for a single period, assuming that interdepartmental flow remains constant over time. However, this approach may not be suitable in a dynamic environment where demand or flow between facilities varies over time.

To solve this issue, a sturdy solution is put forward, wherein a plan for the anticipated flow or demand scenario is formulated and employed throughout the entire planning horizon, eliminating the need to relocate facilities. This method involves a computational effort of only m!, which is notably less than the adaptive approach that necessitates $(m!)^T$ computational effort.

If relocating facilities is difficult and expensive, the proposed approach is suitable. Additionally, it minimizes the risk of operational disruptions caused by moving facilities over multiple timeframes. To achieve this, a quadratic assignment model is developed to allocate 'm' facilities to 'm' potential locations on the layout grid for each planning horizon period.

Overall, the robust approach to the dynamic layout problem offers a reliable and cost-effective solution to designing a layout that accommodates the expected flow or demand scenario of various periods. It requires less computational effort than other approaches and is ideal for situations where relocation costs are high or operational disruption is a concern.

4. EXPERIMENTAL RESULTS

The data set used for evaluating the performance of the layout formation method consists of data from the QAPLIB (Burkard, Karisch and Rendl, 1997). Data from Balakrishnan and Cheng (2000) are used to demonstrate the performance of a robust layout model.

4.1 Analysis of results of SPLP using the ML-GA method of layout formation

It is necessary to validate the effectiveness of the proposed layout formation method's performance. Standard problem instances from the QAPLIB (Burkard, Karisch and Rendl, 1997) are used for this purpose.

The problem instances obtained from the QAPLIB (Burkard *et al.*, 1997) are mainly used for evaluation. ML-GA was utilized to solve a set of 92 standard problem instances sourced from QAPLIB (Burkard, Karisch and Rendl, 1997). The problem sizes ranged from 12 to 50, and the algorithm was initialized with a random solution value. Each problem was executed 10 times, and the resulting solution values were compared and recorded in Table 2. It is noteworthy that out of the 92 problems, the best-known solution (BKS) was obtained in 77 instances after the 10 runs were performed. The remaining 15 problems reported less than one percentage deviation from the best-known solution. Overall, it can be stated that the proposed ML-GA approach for creating layouts has the potential to yield satisfactory outcomes for layout problems.

Table 2. Results of experiments using ML-GA for solving the SPLPs

Sl. No.	**Problem**	**Size**	**Known Min**	**Solution**			**% Error**		
				Min	**Max**	**Average**	**Min**	**Max**	**Average**
1	bur26a	26	5426670	5426670	5432449	5429210.4	0.0	0.1	0.0
2	bur26b	26	3817852	3817852	3824657	3820631.5	0.0	0.2	0.1
3	bur26c	26	5426795	5426795	5427052	5426836.7	0.0	0.0	0.0
4	bur26d	26	3821225	3821225	3821555	3821316.2	0.0	0.0	0.0
5	bur26e	26	5386879	5386879	5387368	5386927.9	0.0	0.0	0.0
6	bur26f	26	3782044	3782044	3782068	3782046.4	0.0	0.0	0.0
7	bur26g	26	10117172	10117172	10118542	10117309.0	0.0	0.0	0.0
8	bur26h	26	7098658	7098658	7099630	7098755.2	0.0	0.0	0.0
9	chr12a	12	9552	9552	10096	9715.2	0.0	5.7	1.7
10	chr12b	12	9742	9742	10102	9886.0	0.0	3.7	1.5
11	chr12c	12	11156	11156	11662	11337.0	0.0	4.5	1.6
12	chr15a	15	9896	9896	10702	10195.6	0.0	8.1	3.0
13	chr15b	15	7990	7990	9486	8887.0	0.0	18.7	11.2
14	chr15c	15	9504	9504	11366	10454.4	0.0	19.6	10.0
15	chr18a	18	11098	11098	13334	12228.4	0.0	20.1	10.2
16	chr18b	18	1534	1534	1534	1534.0	0.0	0.0	0.0
17	chr22a	22	6156	6194	6412	6330.2	0.6	4.2	2.8
18	chr22b	22	6194	6254	6478	6376.2	1.0	4.6	2.9
19	els19	19	17212548	17212548	17937024	17284995.6	0.0	4.2	0.4
20	esc16a	16	68	68	68	68.0	0.0	0.0	0.0
21	esc16b	16	292	292	292	292.0	0.0	0.0	0.0
22	esc16c	16	160	160	160	160.0	0.0	0.0	0.0
23	esc16d	16	16	16	16	16.0	0.0	0.0	0.0
24	esc16e	16	28	28	28	28.0	0.0	0.0	0.0
25	esc16g	16	26	26	26	26.0	0.0	0.0	0.0
26	esc16h	16	996	996	996	996.0	0.0	0.0	0.0
27	esc16i	16	14	14	14	14.0	0.0	0.0	0.0
28	esc16j	16	8	8	8	8.0	0.0	0.0	0.0
29	esc32a	32	130	130	142	136.2	0.0	9.2	4.8
30	esc32b	32	168	168	192	175.6	0.0	14.3	4.5
31	esc32c	32	642	642	642	642.0	0.0	0.0	0.0
32	esc32d	32	200	200	200	200.0	0.0	0.0	0.0
33	esc32e	32	2	2	2	2.0	0.0	0.0	0.0
34	esc32g	32	6	6	6	6.0	0.0	0.0	0.0
35	esc32h	32	438	438	438	438.0	0.0	0.0	0.0
36	had12	12	1652	1652	1660	1652.8	0.0	0.5	0.0
37	had14	14	2724	2724	2724	2724.0	0.0	0.0	0.0
38	had16	16	3720	3720	3722	3720.2	0.0	0.1	0.0
39	had18	18	5358	5358	5370	5359.2	0.0	0.2	0.0
40	had20	20	6922	6922	6926	6922.6	0.0	0.1	0.0

Sl. No.	Problem	Size	Known Min	Solution			% Error		
				Min	Max	Average	Min	Max	Average
41	kra30a	30	88900	88900	91720	90512.0	0.0	3.2	1.8
42	kra30b	30	91420	91490	92380	91911.0	0.1	1.1	0.5
43	kra32	32	88700	88700	90800	89982.0	0.0	2.4	1.4
44	lipa20a	20	3683	3683	3765	3712.8	0.0	2.2	0.8
45	lipa20b	20	27076	27076	27076	27076.0	0.0	0.0	0.0
46	lipa30a	30	13178	13178	13373	13296.5	0.0	1.5	0.9
47	lipa30b	30	151426	151426	174317	153715.1	0.0	15.1	1.5
48	lipa40a	40	31538	31538	31898	31839.8	0.0	1.1	1.0
49	lipa40b	40	476581	476581	476581	476581.0	0.0	0.0	0.0
50	lipa50a	50	62093	62592	62724	62664.9	0.8	1.0	0.9
51	lipa50b	50	1210244	1210244	1210244	1210244.0	0.0	0.0	0.0
52	nug12	12	578	578	586	582.8	0.0	1.4	0.8
53	nug14	14	1014	1014	1018	1017.2	0.0	0.4	0.3
54	nug15	15	1150	1150	1160	1153.0	0.0	0.9	0.3
55	nug16a	16	1610	1610	1622	1612.4	0.0	0.7	0.1
56	nug16b	16	1240	1240	1240	1240.0	0.0	0.0	0.0
57	nug17	17	1732	1732	1742	1735.0	0.0	0.6	0.2
58	nug18	18	1930	1930	1954	1939.6	0.0	1.2	0.5
59	nug20	20	2570	2570	2574	2572.0	0.0	0.2	0.1
60	nug21	21	2438	2438	2460	2446.4	0.0	0.9	0.3
61	nug22	22	3596	3596	3618	3599.4	0.0	0.6	0.1
62	nug24	24	3488	3488	3526	3506.2	0.0	1.1	0.5
63	nug25	25	3744	3744	3766	3749.8	0.0	0.6	0.2
64	nug27	27	5234	5234	5268	5243.4	0.0	0.6	0.2
65	nug28	28	5166	5166	5230	5196.8	0.0	1.2	0.6
66	nug30	30	6124	6128	6186	6152.2	0.1	1.0	0.5
67	rou12	12	235528	235528	235852	235592.8	0.0	0.1	0.0
68	rou15	15	354210	354210	363604	358824.6	0.0	2.7	1.3
69	rou20	20	725522	725662	741534	732431.2	0.0	2.2	1.0
70	scr12	12	31410	31410	31410	31410.0	0.0	0.0	0.0
71	scr15	15	51140	51140	53182	51935.2	0.0	4.0	1.6
72	scr20	20	110030	110030	112692	110957.6	0.0	2.4	0.8
73	sko42	42	15812	15818	15924	15865.4	0.0	0.7	0.3
74	sko49	49	23386	23454	23516	23481.6	0.3	0.6	0.4
75	ste36a	36	9526	9550	9900	9697.4	0.3	3.9	1.8
76	ste36b	36	15852	15852	16150	15904.6	0.0	1.9	0.3
77	ste36c	36	8239110	8254628	8410990	8296522.6	0.2	2.1	0.7
78	tai12a	12	224416	224416	230704	225044.8	0.0	2.8	0.3
79	tai12b	12	39464925	39464925	39464925	39464925.0	0.0	0.0	0.0
80	tai15a	15	388214	388214	393768	390850.2	0.0	1.4	0.7
81	tai15b	15	51765268	51765268	51866297	51812000.0	0.0	0.2	0.1
82	tai17a	17	491812	494458	502908	499595.8	0.5	2.3	1.6
83	tai20a	20	703482	707178	719654	712619.4	0.5	2.3	1.3
84	tai20b	20	122455319	122455319	123416507	122797905.7	0.0	0.8	0.3
85	tai25b	25	344355646	344355646	366555760	347915081.1	0.0	6.4	1.0
86	tai30b	30	637117113	637117113	651247567	643406828.6	0.0	2.2	1.0
87	tai35b	35	283315445	283315445	289568462	285062874.2	0.0	2.2	0.6
88	tai40b	40	637250948	637250948	653971855	640512285.7	0.0	2.6	0.5
89	tai50b	50	458821517	459081955	465646314	461246979.4	0.1	1.5	0.5
90	tho30	30	149936	149936	151206	150454.0	0.0	0.8	0.3
91	tho40	40	240516	240814	244454	242208.8	0.1	1.6	0.7
92	wil50	50	48816	48824	48926	48881.2	0.0	0.2	0.1

4.2 Analysis of results of Dynamic Facility Layout Problem

In this section, we will discuss the performance evaluation of a robust layout model, which uses data obtained from Balakrishnan and Cheng (2000). The dataset consists of 48 problems, six sizes (6 – departments 5 periods (6d5p); 6 – departments 10 periods (6d10p); 15 – departments 5 periods (15d5p); 15 – departments 10 periods (15d10p); 30 – departments 5 periods (30d5p); and 30 – departments 10 periods (30d10p)) each with eight different scenarios, and the proposed robust model is used to solve the dynamic facility layout problem. To solve this problem, the ML-GA approach is employed, and it is run for ten replications. The results of these replications are presented in Table 4-9.

This analysis demonstrates the effectiveness of the proposed approach in solving dynamic facility layout problems. By using a robust approach, we can develop a single layout that is used throughout the planning horizon, which simplifies the computational process and reduces the need for facility relocation. This approach is particularly useful in situations where facility relocation is difficult, expensive, or disruptive to operations. Additionally, the ML-GA solution procedure provides a reliable and efficient method for finding high-quality solutions to the layout problem. Overall, the results of this analysis suggest that the proposed robust model is an effective approach for solving dynamic facility layout problems in a wide range of scenarios.

In the context of the dynamic facility layout problem, the primary objective is to find the best layout that minimizes the cost over the entire planning horizon. Researchers have proposed two approaches to solve this problem: the adaptive approach and the robust approach. In this paper, the authors compare the results obtained from Balakrishnan and Cheng's data set using the robust approach with the results obtained by several other research papers, including the adaptive approach. The data set contains eight problems in each of the six situations, totaling 48 problems. The proposed robust model for the dynamic facility layout problem uses the ML-GA as a solution procedure and is run for ten replications.

A comparison was made between the outcomes of the robust approach and the adaptive approach. It was found that, even though there were no instances of facility relocation or operational disturbances throughout the planning horizon, the solution values of the robust approach did not significantly differ from those achieved by Balakrishnan and Cheng (2000). Thirteen research papers were considered for the comparison of results, out of which all except one followed the adaptive approach. The ninth paper by Pillai *et al.* (2011) followed the robust approach. Table 3 consolidates the various works used for the performance comparison of the proposed algorithm.

Table 3. Works used for the performance comparison of the proposed algorithm

Sl. No.	Reference	Solution Method	Represented by
1	Conway and Venkataramanan (1994)	Genetic Search	CONGA-1994
2	Balakrishnan and Cheng (2000)	Nested Loop GA	NLGA-2000
3	Balakrishnan *et al.* (2003)	Hybrid GA with Dynamic Programming	HGA-2003
4	Erel, Ghosh and Simon (2003)	Heuristic with Dynamic Programming	DP-2003
5	McKendall *et al.* (2006)	Simulated Annealing	SAII-2006
6	McKendall and Shang (2006)	Hybrid Ant Colony	ACO-2006
7	Baykasoğlu *et al.* (2006)	Hybrid Ant Systems	HAS-2006
8	Şahin and Türkbey (2009)	Hybrid Tabu - Simulated Annealing Heuristic	TABUSA-2009
9	Pillai *et al.* (2011)	Simulated Annealing (Robust)	SA(R) -2011
10	McKendall and Liu (2012)	Hybrid Tabu Search	HTABU-2012
11	Hosseini-Nasab and Emami (2013)	Hybrid Particle Swarm Optimization	HPSO-2013
12	Turanoğlu and Akkaya (2018)	Hybrid Algorithm Based on Bacterial Foraging Optimization	SABFO-2018
13	Zouein and Kattan (2022)	Construction Approach Using ACO	ACOII-2022

The solution values obtained using the robust approach for each size of the problem (i.e., 6d5p, 6d10p, 15d5p, 15d10p, 30d5p and 30d10p) exhibit an average deviation of 2.26-7.45% for the entire planning horizon compared to the best results obtained from the adaptive approach. Furthermore, the results indicate that the deviation is lower for 5-period problems as compared to 10-period problems for all sizes of the problem. Tables 4-9 illustrate the obtained results in detail. The average percentage deviation from best-known solutions (%Diff - BKS) and solutions reported in the paper adopting a robust layout approach (%Diff - Robust) are summarized in Table 10. For the 6d5p problems, the average percentage difference from the optimal solution considering the dynamic layout is 2.26% and considering the robust layout is 0.0%. For the 6d10p problems, the corresponding values are 3.2% and 0.0%. In the case of 15d5p problems, the variation from the dynamic optimal solution is 4.05%, and from the obtained values are the same as that reported by the robust layout. The variation from the dynamic optimal solution is the highest for the 15d10p problems, which is more than 7%. But for the robust approach, the proposed method performs equally good. For 30d5p problems, the difference from the dynamic optimal solution is 2.5%, and in the case of robust layout, the proposed method is able to obtain better results for two test instances. For 30d10p problems, the average percentage variation from the dynamic optimal solution is 4.9%, while considering the robust approach, the proposed method reports the same results.

These findings suggest that the robust approach is effective in designing a layout for a dynamic environment while minimizing the computational effort. Additionally, the results suggest that the robust approach can yield competitive solutions compared to the adaptive approach in terms of the quality of the solutions for the dynamic facility layout problem.

Table 4. Comparison of the results of the adaptive and robust approaches for the dataset of 8 problems involving 6 departments and 5 periods (6d5p).

	P1	P2	P3	P4	P5	P6	P7	P8	Avg. %dev
CONGA-1994	1,08,976	1,05,170	1,04,520	1,06,719	1,05,628	1,05,606	1,06,439	1,04,485	0.84%
NLGA-2000	1,06,419	1,04,834	1,04,320	1,06,515	1,05,628	1,04,053	1,06,978	1,03,771	0.25%
HGA-2003	1,06,419	1,04,834	1,04,320	1,06,515	1,05,628	1,04,053	1,06,439	1,03,771	0.18%
DP-2003	1,06,419	1,04,834	1,04,320	1,06,509	1,05,628	1,03,985	1,06,447	1,03,771	0.17%
SAII-2006	1,07,249	1,05,170	1,04,800	1,06,515	1,06,282	1,03,985	1,06,447	1,03,771	0.45%
ACO-2006	1,06,419	1,04,834	1,04,320	1,06,509	1,05,628	1,04,053	1,06,439	1,03,771	0.18%
HAS-2006	1,06,419	1,04,834	1,04,320	1,06,399	1,05,628	1,03,985	1,06,439	1,03,771	0.16%
TABUSA-2009	1,06,419	1,04,834	1,04,320	1,06,399	1,05,737	1,03,985	1,06,439	1,03,771	0.17%
SA(R) -2011	1,06,419	1,05,731	1,07,650	1,08,260	1,08,188	1,07,765	1,08,114	1,07,248	2.26%
HTABU-2012	1,06,419	1,04,834	1,04,320	1,06,399	1,05,628	1,03,985	1,06,439	1,03,771	0.16%
HPSO-2013	1,06,419	1,04,834	1,04,320	1,06,399	1,05,628	1,03,985	1,06,439	1,03,771	0.16%
SABFO-2018	1,06,419	1,04,834	1,04,320	1,06,399	1,05,628	1,03,985	1,06,439	1,03,771	0.16%
ACOII-2022	1,06,419	1,03,507	1,04,320	1,06,399	1,05,628	1,03,985	1,06,439	1,03,771	0.00%
BKS	1,06,419	1,03,507	1,04,320	1,06,399	1,05,628	1,03,985	1,06,439	1,03,771	0.00%
ML-GA	**1,06,419**	**1,05,731**	**1,07,650**	**1,08,260**	**1,08,188**	**1,07,765**	**1,08,114**	**1,07,248**	**2.26%**
%Diff - BKS	**0.00%**	**2.15%**	**3.19%**	**1.75%**	**2.42%**	**3.64%**	**1.57%**	**3.35%**	**2.26%**
%Diff - Robust	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	

Table 5. Comparison of the results of the adaptive and robust approaches for the dataset of 8 problems involving 6 departments and 10 periods (6d10p)

	P9	P10	P11	P12	P13	P14	P15	P16	Avg. %dev
CONGA-1994	2,18,407	2,15,623	2,11,028	2,17,493	2,15,363	2,15,564	2,20,529	2,16,291	2.10%
NLGA-2000	2,14,397	2,12,138	2,08,453	2,12,953	2,11,575	2,10,801	2,15,685	2,14,657	0.36%
HGA-2003	2,14,313	2,12,134	2,07,987	2,12,741	2,10,944	2,10,000	2,15,452	2,12,588	0.09%
DP-2003	2,14,313	2,12,134	2,07,987	2,12,741	2,11,022	2,09,932	2,14,252	2,12,588	0.02%
SAII-2006	2,17,251	2,16,055	2,08,185	2,12,951	2,11,076	2,10,277	2,15,504	2,14,621	0.66%
ACO-2006	2,15,200	2,14,713	2,08,351	2,13,331	2,13,812	2,11,213	2,15,630	2,14,513	0.72%
HAS-2006	2,14,313	2,12,134	2,07,987	2,12,530	2,10,906	2,09,932	2,14,252	2,12,582	0.00%
TABUSA-2009	2,14,313	2,12,134	2,07,987	2,12,530	2,10,906	2,09,932	2,14,252	2,12,588	0.00%
SA(R) -2011	2,20,776	2,17,412	2,19,024	2,17,350	2,17,142	2,17,397	2,19,788	2,20,144	3.22%
HTABU-2012	2,14,313	2,12,134	2,07,987	2,12,530	2,10,906	2,09,932	2,14,252	2,12,588	0.00%
HPSO-2013	2,14,313	2,12,134	2,07,987	2,12,530	2,10,906	2,09,932	2,14,252	2,12,588	0.00%
SABFO-2018	2,14,313	2,12,134	2,07,987	2,12,530	2,10,906	2,09,932	2,14,252	2,12,588	0.00%
ACOII-2022	2,14,313	2,12,134	2,07,987	2,12,530	2,10,906	2,09,932	2,14,252	2,12,588	0.00%
BKS	2,14,313	2,12,134	2,07,987	2,12,530	2,10,906	2,09,932	2,14,252	2,12,582	0.00%
ML-GA	**2,20,776**	**2,17,412**	**2,19,024**	**2,17,350**	**2,17,142**	**2,17,397**	**2,19,788**	**2,20,144**	**3.22%**
%Diff - BKS	**3.02%**	**2.49%**	**5.31%**	**2.27%**	**2.96%**	**3.56%**	**2.58%**	**3.56%**	**3.22%**
%Diff - Robust	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	

Table 6. Comparison of the results of the adaptive and robust approaches for the dataset of 8 problems involving 15 departments and 5 periods (15d5p)

	P17	P18	P19	P20	P21	P22	P23	P24	Avg. %dev
CONGA-1994	5,04,759	5,14,718	5,16,063	5,08,532	5,15,599	5,09,384	5,12,508	5,14,839	5.70%
NLGA-2000	5,11,854	5,07,694	5,18,461	5,14,242	5,12,834	5,13,763	5,12,722	5,21,116	6.12%
HGA-2003	4,84,090	4,85,352	4,89,898	4,84,625	4,89,885	4,88,640	4,89,378	5,00,779	0.96%
DP-2003	4,82,123	4,85,702	4,91,310	4,86,851	4,91,178	4,89,847	4,89,155	4,93,577	0.88%
SAII-2006	4,80,496	4,84,761	4,88,748	4,84,414	4,87,911	4,87,147	4,86,779	4,90,812	0.40%
ACO-2006	5,01,447	5,06,236	5,12,886	5,04,956	5,09,636	5,08,215	5,08,848	5,12,320	4.88%
HAS-2006	4,80,453	4,84,761	4,88,748	4,84,446	4,87,722	4,86,685	4,86,853	4,91,016	0.39%
TABUSA-2009	4,80,453	4,84,761	4,89,058	4,84,446	4,87,822	4,86,493	4,86,268	4,90,551	0.37%
SA(R) -2011	5,06,847	5,00,284	5,08,011	5,03,699	5,02,622	4,99,891	5,02,919	5,07,970	4.05%
HTABU-2012	4,80,453	4,84,761	4,88,748	4,84,446	4,87,911	4,86,493	4,86,592	4,90,812	0.38%
HPSO-2013	4,80,453	4,78,310	4,86,987	4,83,813	4,84,968	4,86,493	4,85,384	4,89,150	0.00%
SABFO-2018	4,80,453	4,84,853	4,89,981	4,86,006	4,88,556	4,88,196	4,87,476	4,91,789	0.56%
ACOII-2022	4,80,453	4,84,761	4,88,748	4,84,446	4,87,753	4,86,493	4,86,732	4,90,551	0.37%
BKS	4,80,453	4,78,310	4,86,987	4,83,813	4,84,968	4,86,493	4,85,384	4,89,150	0.00%
ML-GA	**5,06,847**	**5,00,284**	**5,08,011**	**5,03,699**	**5,02,622**	**4,99,891**	**5,02,919**	**5,07,970**	**4.05%**
%Diff - BKS	**5.49%**	**4.59%**	**4.32%**	**4.11%**	**3.64%**	**2.75%**	**3.61%**	**3.85%**	**4.05%**
%Diff - Robust	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	

Table 7. Comparison of the results of the adaptive and robust approaches for the dataset of 8 problems involving 15 departments and 10 periods (15d10p)

	P25	P26	P27	P28	P29	P30	P31	P32	Avg. %dev
CONGA-1994	10,55,536	10,61,940	10,73,603	10,60,034	10,64,692	10,66,370	10,66,617	10,68,216	9.06%
NLGA-2000	10,47,596	10,37,580	10,56,185	10,26,789	10,33,591	10,28,606	10,43,823	10,48,853	6.57%
HGA-2003	9,87,887	9,80,638	9,85,886	9,76,025	9,82,778	9,73,912	9,82,872	9,87,789	0.62%
DP-2003	9,83,070	9,83,826	9,88,635	9,76,456	9,82,893	9,74,436	9,82,790	9,88,584	0.65%
SAII-2006	9,79,468	9,78,065	9,82,396	9,72,797	9,78,067	9,67,617	9,79,114	9,83,672	0.15%
ACO-2006	10,17,741	10,16,567	10,21,075	10,07,713	10,10,822	10,07,210	10,13,315	10,19,092	3.89%
HAS-2006	9,80,351	9,78,271	9,78,027	9,74,694	9,79,169	9,71,548	9,80,752	9,85,707	0.24%
TABUSA-2009	9,78,848	9,77,338	9,81,172	9,71,720	9,76,781	9,68,362	9,78,660	9,82,880	0.08%
SA(R) -2011	10,59,100	10,22,447	10,68,402	10,54,997	10,51,395	10,57,543	10,37,066	10,40,450	7.45%
HTABU-2012	9,81,412	9,78,004	9,83,109	9,71,720	9,77,100	9,71,287	9,78,576	9,83,341	0.19%
HPSO-2013	9,78,588	9,76,208	9,78,027	9,71,759	9,76,119	9,68,539	9,78,519	9,82,964	0.01%
SABFO-2018	9,82,087	9,79,095	9,82,914	9,74,144	9,79,376	9,70,247	9,83,527	9,84,664	0.34%
ACOII-2022	9,79,081	9,77,338	9,81,172	9,71,720	9,76,310	9,67,617	9,78,576	9,84,025	0.08%
BKS	9,78,588	9,76,208	9,78,027	9,71,720	9,76,119	9,67,617	9,78,519	9,82,880	0.00%
ML-GA	**10,59,100**	**10,22,447**	**10,68,402**	**10,54,997**	**10,51,395**	**10,57,543**	**10,37,066**	**10,40,450**	**7.45%**
%Diff - BKS	**8.23%**	**4.74%**	**9.24%**	**8.57%**	**7.71%**	**9.29%**	**5.98%**	**5.86%**	**7.45%**
%Diff - Robust	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	

Table 8. Comparison of the results of the adaptive and robust approaches for the dataset of 8 problems involving 30 departments and 5 periods (30d5p)

	P33	P34	P35	P36	P37	P38	P39	P40	Avg. %dev
CONGA-1994	6,32,737	6,47,585	6,42,295	6,34,626	6,39,693	6,37,620	6,40,482	6,35,776	12.95%
NLGA-2000	6,11,794	6,11,873	6,11,664	6,11,766	6,04,564	6,06,010	6,07,134	6,20,183	7.95%
HGA-2003	5,78,689	5,72,232	5,78,527	5,72,057	5,59,777	5,66,792	5,67,873	5,75,720	1.02%
DP-2003	5,79,741	5,70,906	5,77,402	5,69,596	5,61,078	5,67,154	5,68,196	5,75,273	0.97%
SAII-2006	5,76,741	5,68,095	5,74,036	5,66,248	5,58,460	5,66,597	5,68,204	5,73,755	0.59%
ACO-2006	6,04,408	6,04,370	6,03,867	5,96,901	5,91,988	5,99,862	6,00,670	6,10,474	6.35%
HAS-2006	5,76,886	5,70,349	5,76,053	5,66,777	5,58,353	5,66,792	5,67,131	5,75,280	0.71%

TABUSA-2009	5,74,624	5,68,256	5,72,865	5,66,231	5,57,356	5,66,599	5,67,628	5,73,487	0.48%
SA(R) -2011	5,79,704	5,76,350	5,86,831	5,84,318	5,70,492	5,72,782	5,71,703	5,96,835	2.51%
HTABU-2012	5,74,657	5,67,481	5,71,462	5,64,868	5,55,628	5,65,100	5,66,993	5,73,023	0.31%
HPSO-2013	5,77,248	5,69,175	5,72,105	5,66,124	5,55,551	5,64,804	5,67,131	5,73,755	0.45%
SABFO-2018	5,78,415	5,70,630	5,77,390	5,68,289	5,58,345	5,72,536	5,69,993	5,77,873	1.06%
ACOII-2022	5,73,722	5,66,776	5,65,411	5,64,171	5,54,281	5,64,110	5,64,682	5,72,207	0.00%
BKS	5,73,722	5,66,776	5,65,411	5,64,171	5,54,281	5,64,110	5,64,682	5,72,207	0.00%
ML-GA	**5,79,704**	**5,76,350**	**5,86,831**	**5,84,264**	**5,70,492**	**5,72,782**	**5,71,703**	**5,96,744**	**2.51%**
%Diff - BKS	**1.04%**	**1.69%**	**3.79%**	**3.56%**	**2.92%**	**1.54%**	**1.24%**	**4.29%**	**2.51%**
%Diff - Robust	**0.00%**	**0.00%**	**0.00%**	**-0.01%**	**0.00%**	**0.00%**	**0.00%**	**-0.02%**	

Table 9. Comparison of the results of the adaptive and robust approaches for the dataset of 8 problems involving 30 departments and 10 periods (30d10p).

	P41	**P42**	**P43**	**P44**	**P45**	**P46**	**P47**	**P48**	**Avg. %dev**
CONGA-1994	13,62,513	13,79,640	13,65,024	13,67,130	13,56,860	13,72,513	13,82,799	13,83,610	20.37%
NLGA-2000	12,28,411	12,31,978	12,31,829	12,27,413	12,15,256	12,21,356	12,12,273	12,45,423	7.68%
HGA-2003	11,69,474	11,68,878	11,66,366	11,54,192	11,33,561	11,45,000	11,45,927	11,68,657	1.51%
DP-2003	11,71,178	11,69,138	11,65,525	11,52,684	11,28,136	11,43,824	11,42,494	11,67,163	1.38%
SAII-2006	11,63,222	11,61,521	11,56,918	11,45,918	11,27,136	11,45,146	11,40,744	11,61,437	0.96%
ACO-2006	12,23,124	12,31,151	12,30,520	12,00,613	12,10,892	12,21,356	12,12,273	12,31,408	7.10%
HAS-2006	11,66,164	11,68,878	11,66,366	11,48,202	11,28,855	11,41,344	11,40,773	11,66,157	1.23%
TABUSA-2009	11,61,751	11,60,656	11,55,406	11,44,821	11,25,968	11,43,480	11,45,830	11,64,322	0.96%
SA(R) -2011	11,72,691	11,82,286	11,88,620	11,98,487	11,98,674	12,02,033	12,10,573	12,09,088	4.93%
HTABU-2012	11,59,589	11,57,942	11,54,799	11,43,110	11,23,446	11,41,144	11,45,951	11,60,484	0.79%
HPSO-2013	11,60,388	11,58,243	11,56,198	11,49,753	11,23,673	11,47,935	11,42,031	11,60,658	0.93%
SABFO-2018	11,68,453	11,70,042	11,60,204	11,49,944	11,32,136	11,44,677	11,60,830	11,72,857	1.59%
ACOII-2022	11,57,703	11,56,900	11,52,546	11,41,149	11,19,496	11,40,883	11,44,727	11,06,651	0.04%
BKS	11,57,703	11,56,900	11,52,546	11,41,149	11,19,496	11,40,883	11,40,744	11,06,651	0.00%
ML-GA	**11,72,691**	**11,82,286**	**11,88,620**	**11,98,487**	**11,98,674**	**12,02,033**	**12,10,573**	**12,09,088**	**4.93%**
%Diff - BKS	**1.29%**	**2.19%**	**3.13%**	**5.02%**	**7.07%**	**5.36%**	**6.12%**	**9.26%**	**4.93%**
%Diff - Robust	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	

Table 10. The average percentage deviation from best-known solutions and solutions reported in Pillai, Hunagund and Krishnan (2011)

Sl. No.	Problem Size	Average Deviation from	
		BKS	Robust Layout
1	6d5p	2.26%	0.00%
2	6d10p	3.22%	0.00%
3	15d5p	4.05%	0.00%
4	15d10p	7.45%	0.00%
5	30d5p	2.51%	-0.01%
6	30d10p	4.93%	0.00%

A comparison of the results obtained using the proposed ML-GA algorithm with the results reported in the works using GA-based algorithms are provided in table 11. There is no literature available that uses GA as its solution methodology and approaches the DFLP for obtaining a robust solution. The algorithms based on GA for solving DFLPs follows the adaptive approach. Even with the adaptive approaches, the first two papers report inferior solutions for the DFLPs than that obtained with the robust approach and the algorithm proposed in this work. Only the last paper (Balakrishnan *et al*. (2003)), which proposes a hybrid algorithm and follows the adaptive approach, reports better solutions than the one obtained in the current work. This suggests that the proposed ML-GA algorithm performs good among the GA-based algorithm implementations for solving DFLPs.

The study compared a proposed algorithm to others using Genetic Algorithms (GA) for solving DFLPs. While existing GA approaches are adaptive and change layouts periodically, the proposed method follows a robust approach, maintaining a constant layout. This eliminates facilities relocation costs but raises material handling costs. The savings in relocation costs do not outweigh the increased material handling costs, resulting in a higher total cost. Nonetheless, the robust approach simplifies the problem and only slightly increases the overall cost.

Table 11. Comparison of the results of the proposed ML-GA approach with other GA-based approaches.

6d5p	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**
CONGA-1994	1,08,976	1,05,170	1,04,520	1,06,719	1,05,628	1,05,606	1,06,439	1,04,485
NLGA-2000	1,06,419	1,04,834	1,04,320	1,06,515	1,05,628	1,04,053	1,06,978	1,03,771
HGA-2003	1,06,419	1,04,834	1,04,320	1,06,515	1,05,628	1,04,053	1,06,439	1,03,771
BKS	1,06,419	1,04,834	1,04,320	1,06,515	1,05,628	1,04,053	1,06,439	1,03,771
ML-GA	**1,06,419**	**1,05,731**	**1,07,650**	**1,08,260**	**1,08,188**	**1,07,765**	**1,08,114**	**1,07,248**
%Diff - BKS	**0.00%**	**0.86%**	**3.19%**	**1.64%**	**2.42%**	**3.57%**	**1.57%**	**3.35%**
6d10p	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**
CONGA-1994	2,18,407	2,15,623	2,11,028	2,17,493	2,15,363	2,15,564	2,20,529	2,16,291
NLGA-2000	2,14,397	2,12,138	2,08,453	2,12,953	2,11,575	2,10,801	2,15,685	2,14,657
HGA-2003	2,14,313	2,12,134	2,07,987	2,12,741	2,10,944	2,10,000	2,15,452	2,12,588
BKS	2,14,313	2,12,134	2,07,987	2,12,741	2,10,944	2,10,000	2,15,452	2,12,588
ML-GA	**2,20,776**	**2,17,412**	**2,19,024**	**2,17,350**	**2,17,142**	**2,17,397**	**2,19,788**	**2,20,144**
%Diff - BKS	**3.02%**	**2.49%**	**5.31%**	**2.17%**	**2.94%**	**3.52%**	**2.01%**	**3.55%**
15d5p	**P17**	**P18**	**P19**	**P20**	**P21**	**P22**	**P23**	**P24**
CONGA-1994	5,04,759	5,14,718	5,16,063	5,08,532	5,15,599	5,09,384	5,12,508	5,14,839
NLGA-2000	5,11,854	5,07,694	5,18,461	5,14,242	5,12,834	5,13,763	5,12,722	5,21,116
HGA-2003	4,84,090	4,85,352	4,89,898	4,84,625	4,89,885	4,88,640	4,89,378	5,00,779
BKS	4,84,090	4,85,352	4,89,898	4,84,625	4,89,885	4,88,640	4,89,378	5,00,779
ML-GA	**5,06,847**	**5,00,284**	**5,08,011**	**5,03,699**	**5,02,622**	**4,99,891**	**5,02,919**	**5,07,970**
%Diff - BKS	**4.70%**	**3.08%**	**3.70%**	**3.94%**	**2.60%**	**2.30%**	**2.77%**	**1.44%**
15d10p	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**	**P31**	**P32**
CONGA-1994	10,55,536	10,61,940	10,73,603	10,60,034	10,64,692	10,66,370	10,66,617	10,68,216
NLGA-2000	10,47,596	10,37,580	10,56,185	10,26,789	10,33,591	10,28,606	10,43,823	10,48,853
HGA-2003	9,87,887	9,80,638	9,85,886	9,76,025	9,82,778	9,73,912	9,82,872	9,87,789
BKS	9,87,887	9,80,638	9,85,886	9,76,025	9,82,778	9,73,912	9,82,872	9,87,789
ML-GA	**10,59,100**	**10,22,447**	**10,68,402**	**10,54,997**	**10,51,395**	**10,57,543**	**10,37,066**	**10,40,450**
%Diff - BKS	**7.21%**	**4.26%**	**8.37%**	**8.09%**	**6.98%**	**8.59%**	**5.51%**	**5.33%**
30d5p	**P33**	**P34**	**P35**	**P36**	**P37**	**P38**	**P39**	**P40**
CONGA-1994	6,32,737	6,47,585	6,42,295	6,34,626	6,39,693	6,37,620	6,40,482	6,35,776
NLGA-2000	6,11,794	6,11,873	6,11,664	6,11,766	6,04,564	6,06,010	6,07,134	6,20,183
HGA-2003	5,78,689	5,72,232	5,78,527	5,72,057	5,59,777	5,66,792	5,67,873	5,75,720
BKS	5,78,689	5,72,232	5,78,527	5,72,057	5,59,777	5,66,792	5,67,873	5,75,720
ML-GA	**5,79,704**	**5,76,350**	**5,86,831**	**5,84,264**	**5,70,492**	**5,72,782**	**5,71,703**	**5,96,744**
%Diff - BKS	**0.18%**	**0.72%**	**1.44%**	**2.13%**	**1.91%**	**1.06%**	**0.67%**	**3.65%**
30d10p	**P41**	**P42**	**P43**	**P44**	**P45**	**P46**	**P47**	**P48**
CONGA-1994	13,62,513	13,79,640	13,65,024	13,67,130	13,56,860	13,72,513	13,82,799	13,83,610
NLGA-2000	12,28,411	12,31,978	12,31,829	12,27,413	12,15,256	12,21,356	12,12,273	12,45,423
HGA-2003	11,69,474	11,68,878	11,66,366	11,54,192	11,33,561	11,45,000	11,45,927	11,68,657
BKS	11,69,474	11,68,878	11,66,366	11,54,192	11,33,561	11,45,000	11,45,927	11,68,657
ML-GA	**11,72,691**	**11,82,286**	**11,88,620**	**11,98,487**	**11,98,674**	**12,02,033**	**12,10,573**	**12,09,088**
%Diff - BKS	**0.28%**	**1.15%**	**1.91%**	**3.84%**	**5.74%**	**4.98%**	**5.64%**	**3.46%**

5. DISCUSSION AND CONCLUSIONS

In this research paper, a novel genetic algorithm meta-heuristic based on machine learning is introduced to address layout formation problems. The method's effectiveness is demonstrated through optimal solutions generated for various case studies sourced from the QAPLIB (Burkard *et al.* 1997). Furthermore, the authors have also devised a robust layout procedure that can handle dynamic facility layout problems.

The proposed algorithm uses a machine learning algorithm, namely the k-means clustering algorithm, for enhancing the performance of the simple genetic algorithm. The efficiency of the proposed algorithm is proved using 92 QAP test instances available in QAPLIB (Burkard *et al.* 1997). The size of the problem instances considered varies from 12 to 50, and it is found that the proposed algorithm is effective in solving the QAP to optimality or near optimality. This novet algorithm is then applied to solve the robust versions of the DFLP instances made available by Balakrishnan and Cheng (2000).

The robust layout method produces a layout based on a projected demand scenario or flow matrix for all planning periods. In contrast to the adaptive approach, the robust layout is consistent throughout the entire planning horizon and does not change from period to period. Although this layout may not be ideal for the entire planning horizon, its overall performance will still meet expectations because relocating facilities would require additional effort.

To evaluate the performance of the proposed robust layout approach, the authors applied it to the problems of Balakrishnan and Cheng (2000). The findings demonstrate that 5-period problems of various sizes exhibit lower deviations than 10-period problems. Additionally, the robust approach solution values show an average deviation of 2.26–7.45% among problems of various sizes from the best results of the adaptive approach. Compared with the only robust approach available in the literature, the proposed algorithm provides 0% variation. In fact, in two instances, the proposed algorithm provides better solutions. These results indicate that the proposed robust approach performs well in solving the SPLPs and provides near-optimal solutions without significant computational difficulty.

The authors compared the proposed algorithm with other works using GA for solving DFLPs. The other works using GA are based on the adaptive approach, in which the layout needs to be changed after each period. The proposed work is adopting a robust approach in which the layout remains constant over different periods. This will increase the material handling cost, and the facilities relocation cost will be zero. However, the savings in the relocation cost is less than the increase in the material handling cost, and thus, a robust approach will result in a higher total cost. However, the complexity of the problem is reduced, and the increase in the total cost is minimal.

In conclusion, the proposed machine learning-based genetic algorithm meta-heuristic and the robust layout procedure can be valuable tools for solving facility layout problems in dynamic environments. Future research can explore the application of this approach to more complex layout problems and further investigate its performance in other real-world applications. Also, since the proposed ML-GA algorithm performs good in comparison with other GA-based algorithm implementations, it can be applied for solving the DFLPs following the adaptive approach.

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