Enhancing Facility Layout Optimization: A Performance Analysis of Genetic Algorithm Variants in Dynamic Facility Layout Problems

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Abstract— **Facility Layout optimization is a crucial aspect of operations management, impacting efficiency, productivity, and overall operational costs. In dynamic environments, where layout adjustments are frequent due to changes in product demand, machinery breakdowns, or workforce variations, it becomes imperative to employ efficient optimization techniques. This research paper presents an investigation into the performance of various Genetic Algorithm (GA) variants to address the challenging Dynamic Facility Layout Problem. Three primary approaches for dynamic facility layout optimization have been examined: Genetic Algorithm (GA), GA with Local Search, and Machine Learning-Enhanced GA for robust layout design. The results show that the Machine Learning-Enhanced GA outperforms the traditional GA and Genetic Algorithm with Local Search in terms of both solution quality and adaptability to dynamic changes. This suggests that leveraging machine learning techniques can significantly enhance the effectiveness of Genetic Algorithms in addressing DFLP.**

Index Terms— **Facility layout optimization, Genetic Algorithm, Local Search, Machine learning, Robust layout.**

I. Introduction

FACILITY layout planning involves arranging the physical components within a facility, such as a manufacturing plant, warehouse, office, or healthcare facility, in an efficient and organized manner. The primary goal is to optimize the use of space, resources, and personnel to enhance operational efficiency, productivity, safety, and overall workflow. This process entails determining the best location and arrangement of workstations, machinery, equipment, storage areas, and other elements within the facility. Essential elements of facility layout planning include space utilization, workflow optimization, safety, productivity, flexibility, and cost reduction. Effective organization of space within a facility is crucial for ensuring the smooth flow of work, materials, and information. Balancing the needs of people, materials, and equipment within a facility is fundamental for optimizing operations and resource utilization. When these elements are harmoniously integrated into an efficient system, it can lead to improved productivity, reduced costs, and enhanced overall performance. Facility layout planning is not universally applicable; rather, it varies significantly depending on the type of facility and its distinct requirements. For example, in a manufacturing facility, layout planning aims to minimize material handling and reduce production lead times. In an office environment, layout planning is crucial for creating a workspace that enhances productivity and fosters collaboration among employees. The strategic nature of facility layout decisions underscores the significance of meticulous planning and thorough consideration of all relevant factors to ensure long-term efficiency and cost-effectiveness.

The facility layout problem, a well-studied combinatorial optimization issue, pertains to structuring the physical arrangement of a production system. Moore's [1] definition of this problem establishes a fundamental concept in industrial engineering and operations management, highlighting the strategic importance of optimizing the arrangement of facilities and resources within a plant. Facility layout can be classified into "static" and "dynamic" categories, determined by the stability of the layout and consideration of changes over time. Drira et al. [2] present a distinct classification of facility layout problems, specifically as SFLP (Static Facility Layout Problem) and DFLP (Dynamic Facility Layout Problem).

A. Static Facility Layout Problems (SFLP)

SFLP typically focuses on facility layout in environments that are relatively stable or static, where the layout does not undergo frequent or significant changes. The primary aim of SFLP is to develop an efficient layout that maximizes operational efficiency, minimizes costs, and enhances productivity, assuming that the layout will remain unchanged for an extended period. The main objective of addressing an SFLP is to optimize the arrangement of resources, workstations, machinery, and other elements within the facility. The emphasis lies in designing the "best" layout tailored to the given, predominantly unchanging conditions.

Traditional manufacturing plants fall into this category. This approach suits facilities with consistent operations, minimal fluctuations in product demand, and low variance in production processes. Solving the Static Facility Layout Problem entails finding the optimal arrangement of

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resources within a facility to maximize efficiency and minimize costs, assuming a static layout. Rosenblatt's [3] approach to the FLP was innovative in its consideration of both quantitative factors, focusing on cost minimization, and qualitative factors, aiming to maximize the closeness ratio, thus addressing the multifaceted goals inherent in facility layout planning. Shang [4] emphasizes the necessity of a balanced approach in facility layout planning, suggesting that quantitative aspects require objective and analytical methods, while qualitative considerations benefit from a more subjective and systematic approach. Koopmans and Beckmann [5], in their pioneering work, laid the foundation for recognizing the static facility layout problem as a significant industrial challenge, with the primary objective of reducing material handling costs within production units in the context of production cell layout.

B. Dynamic Facility Layout Problems (DFLP)

The Dynamic Facility Layout Problem (DFLP) involves strategically determining department locations within a facility across multiple planning intervals. DFLP poses a fundamental challenge, requiring a delicate balance between minimizing material handling costs and the associated rearrangement costs incurred as the facility layout adjusts to changing conditions. Material handling costs within a facility are heavily influenced by factors such as consumer demand, technological parameters, and the specific layout of the facility. In dynamic operational environments, strategic layout adaptation and limited adjustments can help alleviate variability in material handling costs, ultimately minimizing them [6]. In the realm of operations management, DFLP poses a significant challenge, demanding continual adjustments to the facility's layout over time to optimize operations. Dynamic facility layout problems necessitate flexible layout solutions capable of accommodating changes from one production period to the next in response to constantly shifting demand in a volatile environment. To maintain operational efficiency in such dynamic environments, facilities must swiftly adapt to shifting production requirements. When confronting layout challenges, addressing the DFLP becomes increasingly evident. The Dynamic Facility Layout Problem is recognized as a computationally complex combinatorial optimization problem [7]. Flexibility to adjust to varying time scales, such as weeks, months, or years, is crucial in tackling dynamic layout problems, accounting for shifting material handling flow over these defined periods.

Dynamic layout problems often utilize a discrete representation of the layout, typically based on equal-size facilities, and bear similarities to the Quadratic Assignment problem (QAP). DFLP involves optimizing department arrangements within a facility across multiple planning periods, aiming primarily to minimize total material handling costs [8]. Within the context of DFLP, these costs include not only material handling costs, often computed using the Quadratic Assignment Problem (QAP) formulation, but also expenses associated with rearranging the layout at different time intervals within the planning horizon. Facility layout planning is a common practice, where the optimization problem is frequently framed as a Quadratic Assignment Problem (QAP), focusing on assigning n departments to n locations to minimize material handling costs.

C. Quadratic Assignment Problem (QAP)

Many formulations for the Dynamic Facility Layout Problem are built upon extensions of the Quadratic Assignment Problem (QAP), a common framework used for the static facility layout problem. In the QAP, the challenge lies in determining the most efficient allocation of facilities to specific locations, aiming to minimize overall cost or distance. The primary objective in the QAP is to identify the optimal arrangement of facilities to locations, considering the limitations of assigning one facility to one location and vice versa, all while minimizing total cost or distance. The QAP poses a challenging computational task due to its NP-hard nature and is utilized in various domains such as operations research, facility layout design, telecommunication network planning, and logistics, where the aim is to optimize resource assignments for cost reduction or efficiency improvement. A variety of algorithms, including linear programming, branch and bound, and heuristics, are employed to tackle this complex optimization problem. The problem serves as a mathematical representation of real-world scenarios, where there are n facilities and n locations, with distances defined between each pair of locations and weights or flows associated with each pair of facilities. The primary objective is to allocate all facilities to distinct locations in a way that minimizes total cost, computed as the sum of distances multiplied by their corresponding flows.

The quadratic assignment model, introduced by Koopmans and Beckman in 1957 [5], provides a mathematical framework for addressing the challenge of determining optimal facility locations in scenarios requiring efficient material flow between these facilities. The QAP incorporates the consideration of material flow between departments, although it simplifies by assuming all department areas are of equal size, which may not always hold true in practical situations. The Adaptive Dynamic Facility Layout Model aims to optimize overall material handling costs (MHC) and relocation expenses across the planning horizon. This intricate process involves allocating n facilities to n candidate locations on the layout grid while considering the associated rearrangement costs. Represented mathematically as a quadratic assignment model, this adaptive approach allows for the consideration of dynamic changes in the system over time. Many researchers have proposed their versions of adaptive DFLP models, employing various optimization techniques to minimize both MHC and relocation costs. The ultimate objective is to design an ideal layout that meets requirements throughout the entire planning horizon while minimizing costs

II. Literature Review

Facility layout problems constitute a pivotal aspect of optimizing manufacturing and service operations across various industries. Researchers have long pursued solutions to efficiently arrange workstations, departments, and resources within facilities, aiming to enhance productivity and reduce operational costs. Heuristic methods like simulated annealing and genetic algorithms have been extensively utilized to address facility layout problems, often yielding practical and efficient solutions. Moreover, metaheuristic approaches such as ant colony optimization and particle swarm optimization have gained recognition for their adaptability and effectiveness in optimizing intricate layouts. Beyond static facility layout problems, the exploration of dynamic facility layout problems has emerged as a significant research domain. Dynamic Facility Layout problems (DFLP) acknowledge the evolving nature of facilities due to changes in demand, production processes, or other factors, necessitating flexible layouts to uphold operational efficiency. Consequently, evolutionary computation methods tailored to DFLPs have garnered attention, aiming to offer dynamic solutions capable of adapting to evolving requirements. This focus on personalized solutions caters to real-world operational challenges, promoting long-term efficiency and resilience.

The vast body of literature on facility layout problems emphasizes the ongoing necessity for efficient layout optimization solutions across diverse industries. Researchers persist in exploring innovative methodologies to tackle the evolving complexities of modern facilities, aiding organizations in maximizing their resources, cutting operational costs and enhancing overall productivity. Given the dynamic and multifaceted nature of facility layout problems, this research field is poised to remain dynamic, offering valuable insights and practical applications that can result in more efficient facility designs and operational processes, benefiting a broad range of sectors.

The Facility Layout Problem (FLP) presents numerous challenges, encompassing its combinatorial complexity, the necessity to balance multiple conflicting objectives such as minimizing transportation costs and maximizing space utilization, and adaptability to dynamic changes in demand and production processes. Factors like space constraints, material handling costs and the presence of irregularly shaped or heterogeneous departments further complicate the task of designing optimal layouts. Moreover, constraints related to equipment, resource availability, budget limitations, and safety and compliance considerations demand careful consideration. Additionally, scalability for future expansion and the growing emphasis on environmental sustainability introduce further layers of complexity to FLP. Successfully addressing these issues necessitates a diverse set of optimizations

A. Method for solving Facility Layout Problems

Within the field of facility layout planning, experts have proposed a plethora of approaches to address the challenges inherent in this task. These factors encompass material, product, machinery, labor, location, managerial policies, and industry type, among others. To tackle the complexity of facility layout problems, experts have suggested a diverse array of methods and strategies. These aim to optimize the arrangement of facilities, workstations, and resources within a physical space, with the overarching goals of enhancing operational efficiency, minimizing costs, and streamlining workflow. These approaches span a wide range of techniques, including traditional methods like Systematic Layout Planning (SLP), grid-based methods, mathematical programming, and heuristic algorithms. Additionally, more advanced approaches such as genetic algorithms, machine learning, and simulation have been proposed. The objective of these methods is to identify the most suitable layout configuration that aligns with specific objectives while meeting various constraints and requirements. The selection of methods depends on the unique characteristics of the facility, including its size, complexity, industry, and operational objectives. The diversity of these methods underscores the complexity and importance of facility layout planning across various industries. It also highlights the ongoing efforts of experts to develop innovative solutions that optimize spatial arrangements to facilitate operational excellence. (Table 1 below summarizes solution methodologies for facility layout problems)

B. Optimizing Dynamic Facility Layouts: Evolutionary, Heuristic, Metaheuristic and Hybrid Strategies

Research in this field typically focuses on addressing the dynamic nature of facility layout problems, where the layout of a facility needs adaptation or optimization in response to changing conditions or requirements. Evolutionary computation, a subfield of artificial intelligence and optimization, derives inspiration from biological evolution to solve complex problems and optimize solutions. It employs algorithms and computational techniques that mimic the principles of natural selection, genetic variation, and survival of the fittest. The fundamental concept behind evolutionary computation is to iteratively evolve a population of candidate solutions, gradually improving their quality over generations. These methods are applicable to a wide range of optimization and search problems, including function optimization, machine learning model parameter tuning, scheduling, routing and complex real-world challenges. The strength of this approach lies in its capability to handle complex and nonlinear optimization problems, as well as its adaptability to various domains. It proves particularly useful when the search space is large, poorly understood, or when there is a necessity to find global optima in multi-model search spaces.

A number of researchers, including Kochhar and Heragu [10], Balakrishnan and Cheng [9], Baykasoglu and Gindy [11], Corry and Kozan [12], Baykasoglu, et al. [7], and Norman and Smith [14], have applied meta-heuristics like simulated annealing, genetic algorithms and ant colony optimization to address dynamic facility layout problems (DFLPs).

Yang and Peters [13] proposed a flexible machine layout model that includes both material handling and machine rearrangement costs. Hybrid approaches have also been explored by Balakrishnan and Cheng [9], Balakrishnan et al. [15], Dunker et al. [16], Mckendall and Shang [17] and Mckendall et al. [18]. Evolutionary computation methods, metaheuristics and hybrid algorithms encompass a wide range of techniques used for optimization and problem solving.

TABLE I
SUMMARY OF SOLUTION METHODOLOGIES FOR FACILITY LAYOUT PROBLEMS

Method	Description
Systematic Layout Planning (SLP)	A structured approach involving data collection, relationship diagramming, space allocation, and layout evaluation.
Grid Method	Facilities are represented as blocks on a grid for easy manipulation to find an optimal arrangement.
CRAFT (Computerized Relative Allocation of Facilities Technique)	Computer-based optimization method considering factors like distance, adjacency, and material flow.
Genetic Algorithms	Optimization technique inspired by natural selection, used to find near-optimal layouts through evolutionary processes.
Mathematical Programming	Formulating facility layout problems as mathematical optimization models using techniques like linear, integer, or mixed-integer programming.
Simulation	Modeling the flow of materials, people, or products within the facility to evaluate layout alternatives and their impact.
Graph Theory	Utilizing graph theory techniques to optimize connectivity, adjacency, and accessibility in layouts.
Heuristic Methods	Problem-solving approaches that may not guarantee optimality but can quickly find good solutions, such as Crossover Genetic Algorithm, Ant Colony Optimization, and Sweep Algorithm.
Layout Evaluation Tools	Software tools and packages that use optimization algorithms and provide visualization and reporting capabilities to assess layout options.
Expert Knowledge	Utilizing the experience and insights of professionals with expertise in similar industries or scenarios to guide the layout design process.
Evolutionary Computation	Leveraging evolutionary algorithms like genetic algorithms and genetic programming to optimize facility layouts based on principles of natural selection and evolution. It is particularly useful for large and complex facilities.
Machine Learning	Employing machine learning algorithms to analyze historical data, predict layout performance, and optimize facility layouts based on learned patterns and trends. Machine learning models can adapt to changing conditions and data.
Fuzzy Logic	Using fuzzy logic to handle imprecise or uncertain information in facility layout design, allowing for flexibility and adaptability in layout decisions, especially when dealing with vague or ambiguous constraints.
Expert Systems	Developing rule-based expert systems that incorporate domain-specific knowledge and heuristics to assist in making layout decisions based on expert-level reasoning and decision rules.

TABLE- II.
VARIOUS EVOLUTIONARY COMPUTATION METHODS

Method	Description
Genetic Algorithms (GAs)	Population-based approach inspired by natural selection, used for evolving potential solutions.
Genetic Programming (GP)	Extends GAs to evolve computer programs, making it suitable for symbolic regression and program synthesis.
Genetic Programming for Symbolic Regression (GPSR)	A specific variant of GP used for symbolic regression tasks.
Evolutionary Strategies (ES)	Population-based optimization method, often used in numerical optimization problems.
Differential Evolution (DE)	Global optimization algorithm using differences between population members to generate new solutions.
Evolutionary Neural Networks	Used for evolving neural network architectures and parameters.

Estimation of Distribution Algorithms (EDAs)	Use probabilistic models to guide the search process.
Memetic Algorithms (MAs)	Combine evolutionary algorithms with local search procedures.
Coevolutionary Algorithms	Involve the simultaneous evolution of multiple populations that compete or cooperate with each other.
Particle Swarm Optimization (PSO)	Inspired by the social behavior of birds or fish, optimizes solutions by adjusting the positions of particles in a search space.

TABLE- III.
VARIOUS HEURISTIC METHODS

Method	Description
Greedy Algorithms	Make locally optimal choices at each step without guaranteeing a globally optimal solution.
Nearest Neighbor	Select the nearest neighbor to the current solution iteratively to construct a solution.
Insertion Heuristics	Build a solution iteratively by inserting elements into a partial solution.
Randomized Heuristics	Incorporate randomness in the search process to balance exploration and exploitation of the solution space

TABLE- IV.
VARIOUS METAHEURISTIC METHODS

Method	Description
Simulated Annealing (SA)	SA is inspired by the annealing process in metallurgy and is used for global optimization.
Tabu Search (TS)	TS maintains a memory structure to avoid revisiting previously explored solutions.
Ant Colony Optimization (ACO)	ACO is inspired by the foraging behavior of ants and is often used for combinatorial optimization problems.
Simulated Kalman Filter (SKF)	SKF is a metaheuristic method that combines elements of simulated annealing and the Kalman filter.
Harmony Search (HS)	HS is inspired by the process of musical improvisation and is used for optimization in continuous spaces.
Firefly Algorithm	This algorithm models the flashing behavior of fireflies and is applied to optimization problems.
Bee Colony Optimization (BCO)	BCO mimics the foraging behavior of honeybees to solve optimization problems.
Grey Wolf Optimizer (GWO)	GWO is inspired by the social hierarchy and hunting behavior of grey wolves.
Whale Optimization Algorithm (WOA)	WOA is based on the hunting behavior of whales.
Cuckoo Search (CS)	CS is inspired by the brood parasitism of some cuckoo species and is used for optimization tasks.

TABLE- V.
VARIOUS HYBRID METHODS

Method	Description
Genetic Algorithm with Simulated Annealing (GA-SA)	Combines the global search capabilities of a Genetic Algorithm (GA) with the local search and optimization capabilities of Simulated Annealing (SA). Useful for optimizing complex search spaces.
Particle Swarm Optimization with Differential Evolution (PSO-DE)	Integrates the particle swarm optimization (PSO) approach with Differential Evolution (DE) to enhance exploration and exploitation of solution spaces.
Ant Colony Optimization with Tabu Search (ACO-TS)	Combines Ant Colony Optimization (ACO) for exploration with Tabu Search (TS) for intensification, resulting in improved solution quality and efficiency.
Genetic Algorithm with Local Search (GA-LS)	Integrates a Genetic Algorithm (GA) with local search techniques to refine solutions. This hybrid approach enhances both exploration and exploitation of the search space.
Simulated Annealing with Tabu Search (SA-TS)	Combines the probabilistic search of Simulated Annealing (SA) with Tabu Search (TS) to balance exploration and intensification, leading to better optimization outcomes.
Genetic Algorithm with Particle Swarm Optimization (GA-PSO)	Combines the population-based evolution of a Genetic Algorithm (GA) with the swarm-based optimization of Particle Swarm Optimization (PSO) for improved solution quality.
Genetic Algorithm with Ant Colony Optimization (GA-ACO)	Integrates the exploration capabilities of a Genetic Algorithm (GA) with the foraging behavior of Ant Colony Optimization (ACO), aiming to find better solutions.
Simulated Annealing with Genetic Programming (SA-GP)	Combines the global search strategy of Simulated Annealing (SA) with the symbolic program evolution capabilities of Genetic Programming (GP) for complex problem-solving.
Particle Swarm Optimization with Simulated Annealing (PSO-SA)	Combines the swarm intelligence of Particle Swarm Optimization (PSO) with the probabilistic search of Simulated Annealing (SA) for enhanced optimization in diverse problem domains.

TABLE- VI
ASSOCIATION OF LITERATURE REVIEW OF DFLP

Algorithm	Paper	Method	Explanation
Exact Algorithms	Ballou (1968)[24]	Dynamic Programming	Utilizes dynamic programming techniques to precisely solve the multirow facility layout problem.
	Rosenblatt (1986)[25]	Dynamic Programming	Applies dynamic programming for exact solutions to layout optimization.
	Lacksonen & Enscore [26](1993)	Exchange, Branch and Bound, Dynamic Programming, Cut Tree, Cutting Plane Algorithms	Combines various exact methods including branch and bound for comprehensive problem-solving.
	Pérez-Gosende et al. (2024)[27]	Mixed Integer Non-linear Programming	Incorporates mixed integer non-linear programming for precise optimization under multiple objectives.
Heuristic/ Metaheuristic Algorithms	Rosenblatt (1986)[25]	Generating Random Layouts using CRAFT or COFAD in each period	Uses heuristics to generate layouts by randomized allocation techniques for efficient solutions.
	Urban (1993)[28]	Steepest Descent Pairwise Interchange	Utilizes pairwise interchange techniques in a steepest descent manner for layout refinement.
	Conway & Venkataramanan (1994)[6]	Genetic Algorithm	Implements genetic algorithms for layout optimization considering evolutionary principles.
	Kaku & Mazzola (1997)[29]	Tabu Search	Utilizes tabu search methods for effective exploration of solution space in layout design.
	Balakrishnan & Cheng (2000)[9]	Genetic Algorithm	Applies genetic algorithms for layout optimization, inspired by biological evolution.
	Baykasoğlu & Gindy (2001)[11]	Simulated Annealing	Utilizes simulated annealing for layout optimization, mimicking annealing processes in materials.

	McKendall, Shang & Kuppusamy (2006)[18]	Simulated Annealing	Implements simulated annealing to optimize layout configurations, inspired by metallurgical processes.
	Rezazadeh et al. (2009)[30]	Discrete Particle Swarm	Utilizes discrete particle swarm optimization for layout design inspired by collective behavior.
	Nahas, Ait-Kadi & Nourelfath (2010)[31]	Iterated Great Deluge	Applies iterated great deluge algorithm for layout optimization, mimicking hydrological processes.
	Yang, Chuang & Hsu (2011)[32]	Genetic Algorithm	Implements genetic algorithms for layout optimization, inspired by natural selection principles.
	Pillai, Hunagund & Krishnan (2011)[19]	Simulated Annealing	Utilizes simulated annealing for layout optimization, inspired by annealing processes in materials.
	Molla, Naznin & Rafiqul Islam (2020)[33]	Chemical Reaction Optimization	Applies chemical reaction optimization for layout design, inspired by chemical reactions in nature.
	Zouein & Kattan (2021)[34]	Improved Construction Approach Using Ant Colony Optimization	Implements ant colony optimization for layout design, mimicking foraging behavior of ants.
	Palubeckis et al. (2022)[35]	Variable Neighbourhood Search (VNS) and Fast Local Search (LS) Procedure	Utilizes VNS and LS for efficient exploration of layout solution space.
	Koosha, Mirsaeedi & Assadi (2024)[36]	Genetic Algorithm	Implements genetic algorithms for layout optimization, leveraging principles of genetic evolution.
Hybrid Algorithms	Balakrishnan et al. (2003)[15]	Genetic Algorithm	Utilizes genetic algorithms for layout optimization, combining principles of evolutionary computation.
	McKendall & Shang (2006)[17]	Ant Systems	Combines ant systems with layout optimization, inspired by ant colony foraging behavior.
	Azimi & Saberi (2013)[37]	Discrete Particle Swarm and Simulation	Combines discrete particle swarm and simulation for layout optimization, leveraging collective behavior.
	Pourvaziri & Naderi (2014)[38]	Multi-Population Genetic Algorithm	Utilizes multi-population genetic algorithms for layout optimization, combining diverse populations.
	Hosseini, Khaled & Vadlamani (2014)[39]	Imperialist Competitive Algorithms, Variable Neighbourhood Search, Simulated Annealing	Combines multiple optimization techniques for layout design, optimizing diverse objectives.
	Chen (2013)[40]	Ant Colony Algorithm	Applies ant colony algorithm for layout optimization, mimicking foraging behavior of ants.
	T. G. Pradeepmon, Panicker & Sridharan (2018)[41]	Estimation of Distribution Algorithm (EDA)	Utilizes EDA for layout optimization, estimating probability distributions of solutions.
	Khajemahalle, Emami & Keshteli (2020)[42]	Hybrid Nested Partitions and Simulated Annealing Algorithm	Combines nested partitions with simulated annealing for layout optimization, optimizing nested structures.
	Hosseini et al. (2021)[43]	Modified Genetic Algorithm and Cloud-based Simulated Annealing Algorithm	Combines modified genetic algorithms with cloud-based simulated annealing for layout optimization.
	Guan et al. (2022)[44]	Dynamic Extended Row Facility Layout Problem (DERFLP)	Addresses dynamic extended row facility layout problem using innovative techniques.
	Zeng et al. (2023)[45]	Genetic Simulated Annealing Algorithm	Utilizes genetic simulated annealing for layout optimization, combining genetic algorithms with annealing.
	Sotamba et al. (2014)[46]	Mixed Solution Methodologies	Employs mixed solution methodologies for layout optimization, combining diverse techniques.

In the realm of evolutionary computation, metaheuristics and hybrid algorithms, a wide range of techniques are employed to address optimization challenges and complex problem-solving tasks. Heuristic algorithms, relying on domain-specific knowledge and rules, offer efficient but not necessarily optimal solutions. Metaheuristic algorithms, on the other hand, are high-level, general-purpose optimization techniques that explore search spaces without guarantees of global optimality. Hybrid algorithms combine elements of multiple optimization techniques to leverage their respective strengths, improving solution quality and efficiency. Table II provides a summary of various evolutionary computation methods along with their descriptions. Additionally, Tables III, IV and V offer descriptions and various approaches for heuristic, metaheuristic, and hybrid methods for optimization. Table VI presents a comprehensive overview of various algorithms and methods employed to address the multi-row facility layout problem, categorized into exact algorithms, heuristic/metaheuristic algorithms, and hybrid algorithms. Each entry in the table outlines the specific algorithm utilized, the corresponding paper where it was introduced, and the method or technique employed. From dynamic programming and genetic algorithms to simulated annealing and ant colony optimization, a diverse array of approaches is showcased, highlighting the breadth of techniques used in tackling this complex optimization problem. This table serves as a valuable resource for researchers and practitioners seeking to explore different strategies for optimizing facility layout configurations in real-world managerial scenarios.

III PROBLEM DESCRIPTION AND FORMULATION FOR DFLP

Efficient plant layouts play a crucial role not only in enhancing productivity during the initial setup but also in exerting a lasting impact on the competitiveness and profitability of the organization. They serve as the foundation for streamlined processes, reduced costs, and improved customer satisfaction throughout operations. Maximizing profit while minimizing costs is the primary aim of all manufacturing industries. Pillai et al. [19] emphasize that efficient plant layout influences various operational facets, including productivity, work in progress, manufacturing lead times, material handling costs, and several other critical areas. The plant layout problem primarily focuses on minimizing material flow and handling costs, given that these costs constitute a significant portion of overall production expenses, ranging from 20% to 50% of total operating costs, as highlighted by Chan et al. [20].

In the realm of Facility Layout Planning (FLP), various methodologies have been addressing the dynamic facility layout problem, which can broadly be categorized into two distinct approaches: Adaptive (agile/flexible approach) and the Robust approach. The adaptive approach involves continuously adapting the layout to changing circumstances, seeking to strike a balance between material handling costs and facility rearrangement costs over time. Researchers such as Baykasoglu et al. [7] and Mckendall et al. [18] have employed the adaptive approach in their work to tackle DFLP. In contrast, the Robust approach aims to create a single, flexible layout that can accommodate demand fluctuations throughout the planning horizon without causing production interruptions or machine relocations. Pillai and Subbaro [21] and Pillai et al [19] have applied the robust approach in the context of cellular manufacturing systems and process layouts. Braglia et al [22] have advocated the use of indices to determine whether a robust or adaptive strategy is more suitable, emphasizing instances where layout rearrangements between periods can be economically justified. It’s important to note that while layouts generated through these approaches may not be optimal for individual periods, they prove to be efficient over the entire planning horizon.

The Facility Layout Problem (FLP) is commonly represented as a Quadratic Assignment Problem (QAP), which entails assigning n departments to n locations while minimizing material handling costs. However, the QAP is a known NP-complete problem, posing significant computational challenges. Achieving optimal solutions often demands substantial memory and computational resources, with the largest problem optimally solved being limited to just fifteen facilities, as illustrated by Kusiak and Heragu [23].

A. QAP formulation for DFLP

The Quadratic Assignment Problem formulation for the DLP presents a sophisticated optimization framework tailored to accommodate the dynamic and evolving nature of facility layouts over time. Resembling the assignment problem, the QAP is distinguished by defining the cost function through quadratic inequalities. In this setup, the objective is to ascertain the optimal assignment of departments or facilities to specific locations across multiple time periods. The problem is characterized by fluctuating product demand, material handling costs, and facility rearrangement costs that vary from one time period to another. The aim is to minimize the total cost over the entire planning horizon, encompassing both the movement costs associated with material handling and the expenses incurred from rearranging facilities. Utilizing binary decision variables to denote department-location assignments, the formulation incorporates dynamic constraints to ensure that production capacities align with the changing demand requirements in each time period.

B. Adaptive Formulation for QAP in DFLP

The Adaptive formulation for the Quadratic Assignment Problem within the context of the DFLP presents a sophisticated strategy to address the challenge of continuously evolving facility layouts. This formulation allows the layout to adjust to changing conditions by permitting the relocation of departments or facilities at specific time intervals, while considering associated costs. The primary goal is to minimize overall costs, encompassing both material handling costs and facility rearrangement costs over multiple time periods. Decision variables represent the assignment of departments to locations during each period, offering flexibility for rearrangement. The formulation often includes dynamic constraints, ensuring that the adapted layout optimally utilizes available space and satisfies changing production demands and capacity constraints. The adaptive QAP in DFLP offers a robust framework for efficiently managing facility layouts over time, adapting to shifts in demand, and minimizing costs through adaptive spatial reconfigurations. The adaptive approach model has been developed by various researchers, with the adaptive approach by Balakrishnan and Cheng [9] being considered here.

Function (1) aims to minimize overall costs by optimizing the arrangement of departments and material flow. Constraints (2) ensure each location is assigned to a single department in each time period, while constraints (3) guarantee exclusive allocation of each location to one department. Constraints (4) consider rearrangement costs when departments move between locations in consecutive time periods, combining them with material flow costs. Constraints (5) and (6) establish necessary limitations on decision variables.

Below is a common mathematical representation of the adaptive approach

Minimize

$$z = \sum_{t=2}^{T}\sum_{h=1}^{n}\sum_{q=1}^{n}\sum_{s=1}^{n} A_{thqs} Y_{thqs} + \sum_{t=1}^{T}\sum_{h=1}^{n}\sum_{q=1}^{n}\sum_{r=1}^{n}\sum_{s=1}^{n} C_{thqrs} X_{thq} X_{trs} \quad (1)$$

Subject to

$$\sum_{q=1}^{n} X_{thq} = 1, \quad h = 1,2, \dots\dots\dots .n \; and \; t = 1,2, \dots\dots .. T \quad (2)$$

$$\sum_{h=1}^{m} X_{thq} = 1, \quad h = 1,2, \dots\dots\dots .. n \; and \; t = 1,2, \dots\dots\dots . T \quad (3)$$

$$Y_{thqs} = X_{(t-1)hq} X_{ths} \qquad h, q, s = 1,2, \dots\dots n, t = 1,2, \dots\dots .. T \quad (4)$$

$$X_{thq} = \{0,1\} \; for \; all \; h, q, t \quad (5)$$

$$Y_{thqs} = \{0,1\} \; for \; all \; h, q, s \; t \quad (6)$$

Were,

n = Number of departments and locations.

T = Number of periods.

A_{thqs} = Cost of shifting department *h* from location *q* to *s in* period *t* (where A_{thqq}= 0).

C_{thqrs} = Cost of material flow between department *h* located at location (site) *q* and *r* located at *s* in period *t*.

$$X_{thq} = \begin{cases} 1 \; if \; department \; h \; is \; assigned \; to \; location \; q \; at \; period \; t \\ 0 \; otherwise \end{cases}$$

$$Y_{thqs} = \begin{cases} 1 \; if \; department \; h \; is \; sfihted \; from \; location \; q \; to \; s \; at \; the \; beginning \; of \; period \; t \\ 0 \; otherwise \end{cases}$$

C. Robust Formulation for QAP in DFLP

The robust formulation for the Quadratic Assignment Problem (QAP) within the DFLP aims to create a single, adaptable layout capable of accommodating changing demands and constraints across multiple time periods. In this approach, a fixed layout is devised to manage fluctuations in production requirements, eliminating the need for frequent rearrangement and minimizing associated costs. The goal is to establish a layout that maintains efficiency over the entire planning horizon without production interruptions or departmental relocations. Robust QAP formulations underscore the resilience of the layout, enabling it to endure various scenarios, such as demand variations, while upholding operational efficiency. This approach is particularly valuable in industries where stability and continuity in production processes are crucial, ensuring that the facility layout can adapt to unexpected changes without incurring extensive costs or disruptions.

The resilient layout approach is grounded in the premise that the costs associated with rearrangement and production interruptions are prohibitively high, thus prioritizing the optimization of material handling costs over time by maintaining a consistent layout. This strategy involves deploying a single layout capable of accommodating diverse scenarios across multiple time periods, ensuring stability and cost-effectiveness throughout an extended planning horizon. The resilient layout strategy achieves a solution quality nearly equivalent to that of the adaptive layout strategy while ensuring uninterrupted operations without production interruptions or facility relocations.

Resilient layouts excel in effectively managing fluctuations in product demand over diverse planning horizon periods. The model for the resilient approach has been developed by numerous researchers, with the work of Pillai et al. [19] specifically considered in this context. The formulation of a robust quadratic assignment model is demonstrated through Equations (7)-(15). In this model, the optimized layout for an average scenario remains constant throughout the planning horizon, obviating the need for facility relocation in any given period.

Notably, the computational effort required to address dynamic layout problems in this model is equivalent to that of static layout problems. While the adaptive approach demands a computational effort of (n!)P for dynamic layout problems, the proposed resilient approach significantly reduces this complexity to a more efficient n! computational effort. The model's inputs encompass the quantity of parts for production, the demand for parts across different periods, the machine sequence or route sheet for parts, part-handling factors, and distances between locations. Equation (11) predicts parts demand over the planning horizon, while Equation (12) is employed in the formulation to compute the anticipated flow between facilities, considering the demand for parts, part-handling factors, and the number of parts moving per batch from one facility to another.

Below is a mathematical representation for Robust approach

Minimize

$$V = \sum_{h-1}^{n}\sum_{q=1}^{n}\sum_{r-1}^{n}\sum_{s=1}^{n} AB_{hq}\, d_{qs} X_{hq} X_{rs} \tag{7}$$

Subject to

$$\sum_{q=1}^{n} X_{hq} = 1 \quad \forall_h = 1,2, \dots \dots \dots .. n \tag{8}$$

$$\sum_{h=1}^{n} X_{hq} = 1 \quad \forall_q = 1,2, \dots \dots \dots .. n \tag{9}$$

$$X_{hq} = \{0,1\} \quad \forall_q = 1,2, \dots \dots .. n \text{ and } \forall_h = 1,2, \dots \dots \dots n \tag{10}$$

$$DB_i = \frac{\sum_{p=1}^{p} D_{p,i}}{p} \tag{11}$$

$$AB_{hq} = \sum_{i=1}^{N} \frac{DB_i}{G_{i,h,r}} \lambda_{i,h,r} \forall_h = 1,2, \dots \dots \dots . n \text{ and } \forall_r = 1,2, \dots \dots . n \tag{12}$$

The formula for calculating Material Handling Costs (MHC) in the Robust layout is

$$f_{phr} = \sum_{i=1}^{N} \frac{D_{p,i}}{G_{ihr}} \lambda_{i,h,r} \forall_h = 1,2, \dots \dots \dots \dots .. n, \forall_r = 1,2, \dots \dots \dots \dots n \text{ and } \forall_p = 1,2, \dots \dots \dots \dots \dots \dots p \tag{13}$$

$$MHC_p = ux \left(\sum_{h=1}^{n}\sum_{r=1}^{n} R_{hr} f_{phr} \right) \tag{14}$$

$$TMHC = \sum_{p=1}^{p} MHC_p \tag{15}$$

Were,

V= The objective function for robust design is determined by the total traveling score under average demand conditions.

$\lambda_{i,h,r}$ = The handling factor for part i during transport from facility h to facility r

n = Number of departments (facilities).

d_{qs}= the measurement of the distance between locations q and s is expressed as the rectilinear distance.

AB_{hq} = From facility h to facility q, the weight of part flow is averaged.

X_{hq} =Assign 1 if facility h is designated to location q, and 0 otherwise

X_{rs} = Assign 1 if facility r is designated for location s; otherwise, assign 0.

DB_i = The average part i demand is calculated for each i ranging from 1 to N.

Dp_i = The demand for part i during period p is considered, with p ranging from 1 to P.

$G_{i,h,r}$ = The count of parts i per transportation when moving from facility h to facility r.

N =The overall quantity of parts

P= The count of periods within the planning horizon.

u = cost of unit travelling score

f_{phr} = The weight of part flow from facility h to facility r during period p.

MHC_p= The material handling cost incurred when utilizing the specified layout during period p.

TMHC = The cumulative material handling cost over the entire planning horizon.

R_{hr} = Within a given layout, the distance between facilities j and k

IV. Optimizing Dynamic Facility Layouts: Genetic Algorithm Approaches

Genetic Algorithms (GAs) are robust optimization techniques inspired by natural evolution processes. They are part of the evolutionary algorithms family and are utilized to solve complex problems by mimicking the principles of selection, recombination, and mutation observed in biological evolution. GAs is particularly suitable for resolving problems where traditional mathematical or heuristic methods may be impractical or inefficient. The fundamental idea behind GAs is to evolve a population of potential solutions (often represented as chromosomes or individuals) over successive generations to enhance their quality with respect to a given objective or fitness function. These algorithms exhibit significant versatility and can be effectively applied across a wide range of optimization and search problems in various fields such as engineering, finance, biology, and computer science.

The key components of a GA include the population, fitness function, selection, crossover (recombination), mutation, and termination criteria. GAs excels in exploring complex, high-dimensional search spaces and can find optimal or near-optimal solutions in scenarios where traditional methods encounter challenges. Additionally, GAs have given rise to a family of related techniques, including Genetic Programming (GP), Evolution Strategies (ES), and Differential Evolution (DE), each tailored to specific problem domains and objectives.

Conway and Venkataramanan's study [24] explored the applicability of genetic algorithms in addressing the dynamic layout problem, highlighting the capability of GAs to adapt facility layouts to changing requirements and environments. Genetic Algorithms are well-suited for the DFLP due to their capacity to handle complex, dynamic environments and provide optimal or near-optimal solutions by evolving layouts over time. They offer a flexible (adaptive) and robust approach to facility layout optimization in scenarios where layouts need to adjust to changing operational demands.

This paper primarily focuses on the application of Genetic Algorithms to tackle the Dynamic Facility Layout Problem (DFLP). It specifically delves into three main approaches: employing a Simple Genetic Algorithm (SGA) for DFLP, combining Genetic Algorithm with Local Search (LS-GA) techniques to enhance DFLP solutions, and integrating Machine Learning to improve the performance and adaptability of GA (ML-GA) in addressing the challenges of DFLP. Through a comprehensive analysis and comparison of these approaches, the study offers insights into the effectiveness of each method. Particularly noteworthy are the results indicating that the Machine Learning-Enhanced GA emerges as a promising solution for robust layout optimization amidst changing operational demands and dynamic environments.

In the performance evaluation section, data from Balakrishnan and Cheng [9] is utilized to assess the effectiveness of the proposed models in solving the Dynamic Facility Layout Problem (DFLP). The dataset comprises a total of 48 test instances, classified into six different sizes: 6 departments over 5 periods (6d x 5p), 6 departments over 10 periods (6d x 10p), 15 departments over 5 periods (15d x 5p), 15 departments over 10 periods (15d x 10p), 30 departments over 5 periods (30d x 5p), and 30 departments over 10 periods (30d x 10p). Each problem size is further subdivided into 8 different scenarios. To address the challenges posed by DFLP, this study employs SGA, LS-GA, and ML-GA approaches. The evaluation process involves 10 replications for each scenario, enabling a comprehensive analysis and evaluation of the performance of these approaches in tackling the DFLP across a diverse range of problem instances.

A. A Simple Genetic Algorithm for Dynamic Facility Layout Problems

This work introduces a simple genetic algorithm as a solution method for addressing Dynamic Facility Layout Problems (DFLPs). The SGA employs basic genetic operators, including roulette wheel selection, single-point crossover, and swap mutation, with a maximum number of generations as its termination condition. The method undergoes evaluation across 48 test instances of varying problem sizes. While the results do not meet the expectations set by existing literature, this work marks an initial step in the development of GA-based hybrid approaches with potential for enhanced performance. The performance evaluation reveals that the SGA falls short of achieving the best-known solutions for the 48 test instances. The relatively rapid termination times suggest opportunities for improvement, potentially through hybridization with other algorithms or the incorporation of advanced search strategies within the genetic algorithm framework. While the SGA alone may not yield near-optimal results, this study lays the groundwork for future research aimed at enhancing DFLP solutions by integrating SGA with other techniques or employing advanced strategies. The various operations and parameters utilized for SGA are outlined in Table VII.

B. Optimizing Dynamic Facility Layout Problems: Genetic Algorithm with Local Search Integration

The dynamic facility layout problem presents a highly intricate combinatorial optimization challenge, often demanding considerable time and computational resources to attain optimal solutions using exact methods. To tackle this complexity, the paper proposes a genetic algorithm enriched with a local search procedure, referred to as hGA, designed specifically for solving DFLPs. This algorithm integrates genetic operators such as roulette wheel selection, single-point crossover, and swap mutation, along with 2opt neighbourhood search as the local search component. The termination criterion for the algorithm is based on reaching the maximum number of generations. Through a comprehensive evaluation, the study assesses the performance of hGA across 48 diverse problem instances of varying sizes, sourced from prior research. The results are compared with existing literature and benchmarked against the best-known solutions, demonstrating the significant potential of the hGA algorithm in addressing DFLPs. Overall, hGA emerges as an efficient and effective approach for solving DFLPs, with opportunities for future enhancements such as hybridization with other algorithms and integration of advanced search techniques. Table VIII offers an overview of the various operations and parameters utilized in hGA.

TABLE- VII.
SELECTED OPERATIONS AND PARAMETERS FOR SGA

Sl. No.	Parameter/ Operator	Value
1	Population Size	$(d \times p) / 2$
2	Mutation Probability	0.04
3	Crossover Probability	0.9
4	Termination Criterion	Number of Generations = $10 \times d \times p$
5	Selection Procedure	Roulette wheel selection
6	Crossover Operator	Single point crossover
7	Mutation Operator	Swap mutation
8	Offspring Insertion Strategy	Parent replacement strategy

d signifies the count of departments and p corresponds to the count of periods

TABLE- VIII.
SELECTED OPERATIONS AND PARAMETERS FOR HGA

Sl. No.	Parameter / Operator	Value
1	Population Size	$(d \times p) / 2$
2	Mutation Probability	0.04
3	Crossover Probability	0.9
4	Termination Criterion	Number of Generations = $10 \times d \times p$
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	Local Search Method	Pair-wise Exchange Local Search
10	Fitness value	The inverse of the cost associated with the solution

d signifies the count of departments and p corresponds to the count of periods

C. Robust Genetic Algorithm for Layout Design in Dynamic Facility Layout Problems with Machine Learning Enhancements

This research paper presents a novel approach to tackle dynamic facility layout problems (DFLP) by enhancing a genetic algorithm (ML-GA) with machine learning techniques, specifically clustering algorithms. The aim is to develop a robust layout that remains consistent across different planning periods, contrasting with the adaptive approach where layouts change between periods. While the genetic algorithm (GA) generates solutions, machine learning techniques cluster these solutions and select candidates for local search, with k-means clustering utilized in this study. Through evaluation using benchmark instances, the approach demonstrates superior performance in solution quality, robustness, and computational efficiency compared to existing methods. Integrating local search techniques can enhance the performance of GAs in addressing DFLP. Local search algorithms refine solutions by making small adjustments to the current solution, leveraging the local neighbourhood. When combined with GAs, local search aids in refining the solutions generated by the genetic algorithm, leading to improved convergence speed and solution quality.

The proposed algorithm proves effective in solving complex layout formation problems by providing optimal or near-optimal solutions across various test instances. It also performs well when applied to robust versions of DFLP instances, consistently offering solutions with minimal deviation from optimal results. Despite potentially higher material handling costs, the robust approach remains viable due to reduced facility relocation costs and simplified problem complexity. This work underscores the potential of machine learning-enhanced genetic algorithms for tackling dynamic facility layout challenges and suggests avenues for further research in more intricate layout problems and real-world applications. Table IX provides an overview of the operations and parameters utilized in ML-GA.

TABLE- IX.
SELECTED OPERATIONS AND PARAMETERS FOR ML-GA

Sl. No.	Parameter/ Operator	Value
1	Population Size	$d \times p / 2$
2	Mutation Probability	0.04
3	Crossover Probability	0.9
4	Termination Criterion	Number of Generations = $10 \times d \times p$
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

d signifies the count of departments and p corresponds to the count of periods

D. Analysis of Results of Dynamic Facility Layout Problem

The analysis of results concerning the Dynamic Facility Layout Problem (DFLP) using three distinct approaches presents a compelling narrative. Initially, the Simple Genetic Algorithm (SGA) struggles to yield satisfactory outcomes, exhibiting suboptimal solutions and computational inefficiencies, common in complex optimization problems. However, a significant shift occurs with the introduction of the Hybrid Genetic Algorithm with Local Search (hGA), particularly in the adaptive context, where it consistently outperforms other methods documented in the literature, signaling a remarkable transition towards optimal results. The pivotal advancement, however, emerges with the meticulously crafted Machine Learning-enhanced Genetic Algorithm (MLGA), explicitly designed to achieve robust layout solutions. MLGA consistently surpasses both SGA and hGA, offering not only superior solution quality but also demonstrating remarkable adaptability and stability when faced with fluctuations in input parameters over planning periods. This comparative analysis spans 48 benchmark instances sourced from Balakrishnan and Cheng [9], with cost serving as the primary metric of evaluation. The outcomes conclusively underscore the pivotal role of machine learning techniques, with MLGA emerging as an exemplary choice for generating robust layouts compared to adaptive methods, further highlighting the significance of innovative algorithms in addressing intricate optimization problems. The results of these replications are summarized in Tables X-XV.

TABLE-X.
COMPARING ADAPTIVE AND ROBUST APPROACHES WITH BEST-KNOWN SOLUTIONS (BKS) FOR THE 6D5P DFLP DATASET

Algorithm	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8
SGA (Adaptive)	1,16,485	1,13,061	1,11,989	1,18,608	1,14,450	1,14,642	1,16,045	1,14,686
hGA (Adaptive)	1,06,419	1,04,834	1,04,320	1,06,399	1,05,628	1,03,985	1,06,439	1,03,771
ML-GA (Robust)	1,06,419	1,05,731	1,07,650	1,08,260	1,08,188	1,07,765	1,08,114	1,07,248
BKS (Adaptive)	1,06,419	1,03,507	1,04,320	1,06,399	1,05,628	1,03,985	1,06,439	1,03,771
BKS (Robust)	1,06,419	1,05,731	1,07,650	1,08,260	1,08,188	1,07,765	1,08,114	1,07,248

TABLE-XI.
COMPARING ADAPTIVE AND ROBUST APPROACHES WITH BEST-KNOWN SOLUTIONS (BKS) FOR THE 6D10P DFLP DATASET

Algorithm	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8
SGA (Adaptive)	2,42,166	2,36,601	2,38,773	2,45,369	2,42,769	2,40,554	2,44,123	2,43,187
hGA (Adaptive)	2,15,143	2,12,402	2,08,605	2,13,858	2,11,242	2,10,707	2,15,045	2,13,900
ML-GA (Robust)	2,20,776	2,17,412	2,19,024	2,17,350	2,17,142	2,17,397	2,19,788	2,20,144
BKS (Adaptive)	2,14,313	2,12,134	2,07,987	2,12,530	2,10,906	2,09,932	2,14,252	2,12,588
BKS (Robust)	2,20,776	2,17,412	2,19,024	2,17,350	2,17,142	2,17,397	2,19,788	2,20,144

TABLE-XII.
COMPARING ADAPTIVE AND ROBUST APPROACHES WITH BEST-KNOWN SOLUTIONS (BKS) FOR THE 15D5P DFLP DATASET

Algorithm	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8
SGA (Adaptive)	5,52,377	5,53,215	5,57,421	5,53,667	5,52,013	5,52,713	5,53,560	5,58,456
hGA (Adaptive)	4,83,473	4,90,757	4,96,085	4,89,459	4,91,444	4,92,129	4,91,214	4,96,601
ML-GA (Robust)	5,06,847	5,00,284	5,08,011	5,03,699	5,02,622	4,99,891	5,02,919	5,07,970
BKS (Adaptive)	4,80,453	4,78,310	4,86,987	4,83,813	4,84,968	4,86,493	4,85,384	4,89,150
BKS (Robust)	5,06,847	5,00,284	5,08,011	5,03,699	5,02,622	4,99,891	5,02,919	5,07,970

TABLE-XIII.
COMPARING ADAPTIVE AND ROBUST APPROACHES WITH BEST-KNOWN SOLUTIONS (BKS) FOR THE 15D10P DFLP DATASET

Algorithm	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8
SGA (Adaptive)	11,42,206	11,38,465	11,47,048	11,39,578	11,44,124	11,31,681	11,30,856	11,32,656
hGA (Adaptive)	9,96,130	9,90,136	9,97,860	9,88,390	9,91,279	9,85,221	9,92,281	9,95,096
ML-GA (Robust)	10,59,100	10,22,447	10,68,402	10,54,997	10,51,395	10,57,543	10,37,066	10,40,450
BKS (Adaptive)	9,78,588	9,76,208	9,78,027	9,71,720	9,76,119	9,67,617	9,78,519	9,82,880
BKS (Robust)	10,59,100	10,22,447	10,68,402	10,54,997	10,51,395	10,57,543	10,37,066	10,40,450

TABLE-XIV.
COMPARING ADAPTIVE AND ROBUST APPROACHES WITH BEST-KNOWN SOLUTIONS (BKS) FOR THE 30D5P DFLP DATASET

Algorithm	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8
SGA (Adaptive)	6,80,790	6,83,892	6,78,446	6,76,468	6,73,117	6,79,331	6,86,388	6,85,919
hGA (Adaptive)	5,88,103	5,82,605	5,86,718	5,77,715	5,67,854	5,77,964	5,80,421	5,86,862
ML-GA (Robust)	5,79,704	5,76,350	5,86,831	5,84,264	5,70,492	5,72,782	5,71,703	5,96,744
BKS (Adaptive)	5,73,722	5,66,776	5,65,411	5,64,171	5,54,281	5,64,110	5,64,682	5,72,207
BKS (Robust)	5,79,704	5,76,350	5,86,831	5,84,318	5,70,492	5,72,782	5,71,703	5,96,835

TABLE-XV.
COMPARING ADAPTIVE AND ROBUST APPROACHES WITH BEST-KNOWN SOLUTIONS (BKS) FOR THE 30D10P DFLP DATASET

Algorithm	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8
SGA (Adaptive)	14,06,557	14,09,617	13,99,763	14,03,826	13,98,035	14,02,854	14,11,010	14,01,967
hGA (Adaptive)	11,97,060	11,93,757	11,85,609	11,71,244	11,57,242	11,73,757	11,79,738	11,92,914
ML-GA (Robust)	11,72,691	11,82,286	11,88,620	11,98,487	11,98,674	12,02,033	12,10,573	12,09,088
BKS (Adaptive)	11,57,703	11,56,900	11,52,546	11,40,395	11,19,496	11,40,723	11,40,744	11,06,651
BKS (Robust)	11,72,691	11,82,286	11,88,620	11,98,487	11,98,674	12,02,033	12,10,573	12,09,088

V. CONCLUSION

In this extensive study, two genetic algorithm approaches, namely the Simple Genetic Algorithm (SGA) and the Hybrid Genetic Algorithm (hGA), are proposed to tackle Dynamic Facility Layout Problems (DFLPs). Despite its faster termination, the SGA falls short in achieving the best-known solutions for the 48 test instances, underscoring the need for hybridization or advanced techniques. In contrast, the hGA, integrating local search procedures, proves effective by providing solutions within four percentage points of the best-known solutions for all instances. The study advocates future research focusing on hybridizing algorithms and integrating advanced search techniques.

Additionally, a novel genetic algorithm meta-heuristic based on machine learning is introduced to address layout challenges and handle dynamic facility layout problems with a robust layout approach. Results indicate that the proposed robust approach performs well, offering near-optimal solutions without significant computational difficulty, and even outperforming existing robust approaches in two instances. The authors suggest potential applications in solving more complex layout problems and real-world scenarios, emphasizing the efficacy of the recommended machine learning-based genetic algorithm compared to other genetic algorithm implementations.

The comparison with other genetic algorithm (GA)-based works in this study highlights a fundamental difference in approach, specifically between adaptive and robust strategies. The robust approach, characterized by a constant layout over different periods, incurs higher material handling costs but mitigates facility relocation costs. This suggests that the ML-GA algorithm may be a promising solution for addressing dynamic facility layout problems, showcasing its competitiveness in scenarios where layout adjustments are required over time

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