Engineering Research Journal

Journal homepage: https://erj.journals.ekb.eg/

Site Layout Planning of Mega Construction Projects

Ahmed Mohammed Abdelalim [1], Ahmed Mohamed Kenawy [2], Khaled Aman [3], Sarah Saeed[4]

[1*] Professor of Construction Management, Founder of PMSC Program, Faculty of Engineering at Mataria, Helwan University, Cairo 11795, Egypt. *Corresponding Author; Email: dr.ahmedabdelalim@m-eng.helwan.edu.ORCID :(https://orcid.org/0000-0003-3359-715X)

[2] M.Sc. Candidate Faculty of Engineering at Mataria, Helwan University, Cairo, Egypt.

[3] Assistant Professor, Beni Sweif Faculty of Engineering, Beni Sweif University, Beni Sweif, Egypt.

[4] Assistant Professor in Civil Engineering Department, Department of Civil Engineering, The Higher Institute of Engineering, El Shorouk Academy, Cairo, Egypt.

*Corresponding author E-mail: dr.aaalim@gmail.com

Abstract

Efficient construction site layout planning is crucial for enhancing productivity and safety. This study addresses the complexities of combinatorial optimization in site layout, which involves strategically placing temporary structures while managing multiple objectives. Existing research has often focused on minimizing travel distances between two facilities, neglecting important factors like costs and safety relationships.

This research develops a model with two optimization objectives: minimizing travel distance between facilities to lower transportation and construction costs traveling distance, and minimizing risks related to interaction frequency between facilities, as increased interaction raises collision probabilities. A genetic algorithm (GA) is employed as the heuristic optimization method.

The study includes a case study to validate the proposed model, demonstrating its effectiveness in providing practical solutions for site layout planning by incorporating cost and safety relationships considerations. By offering a more comprehensive approach, this research aims to enhance decision-making and improve overall project execution on construction site layouts.

Key words: Construction Site Layout Planning (CSLP), Genetic Algorithm (GA), Temporary facility (TF.), Fixed Facility (FF.), Access Road (AR.).

DOI: 10.21608/erj.2025.326158.1119
Received 13 October 2024; Received in revised form 19 December 2024; Accepted 04 January 2025
Available online 01 March 2025

1. Introduction

Most construction sites encounter difficulties primarily due to management considerations rather than technical issues. Effective site-based management plays a crucial role in enhancing cost and time savings during the construction process without necessitating significant additional effort. Site managers are responsible for controlling and maintaining work performance, as well as implementing corrective actions when performance falls short (Elbeltagi & Hegazy, 2001).

A key aspect of successful construction management is site layout, which involves the systematic organization of the construction site to foster a safe and productive working environment. This front-end planning encompasses the optimal use of available site areas and consideration of the overall project timeline. The significance of site layout has gained considerable attention as a means to reduce costs and time while simultaneously improving safety in construction projects (Andayesh & Sadeghpour, 2013). Proper site design not only enhances safety and productivity but also boosts the morale and efficiency of workers and equipment. Conversely, an inadequate layout can lead to inefficient movement of materials and personnel, resulting in various operational challenges (Andayesh & Sadeghpour, 2014).

Construction site layout is about maximizing the effective use of available space to efficiently deploy and relocate temporary facilities while respecting work interrelationships (Farmakis & Chassiakos, 2018). This is particularly important in both crowded urban areas with limited space and larger development projects. In dense environments, it is essential to strategically assign and install temporary facilities to avoid wasting valuable site area (Abotaleb et al., 2016). Conversely, in expansive projects, situating temporary facilities close together can minimize transit times between them (Abotaleb et al., 2016).
Examples of temporary facilities include materials storage spaces, equipment parking lots, access roads, batch plants, fabrication shops, site offices, mess rooms, and maintenance rooms (Abotaleb et al., 2016a; Elbeltagi & Hegazy, 2001; El-Rayes, Asce, & Khalafallah, 2005). In urban construction projects, site space is as critical a resource as labor, materials, or finances due to limited open areas outside construction zones, especially in densely populated cities. Consequently, the effectiveness of construction site layout significantly impacts labor and equipment productivity, project timelines, costs, and overall site safety (Elbeltagi & Hegazy, 2001; El-Rayes, Asce, & Said, 2009).

While site engineers and managers typically rely on personal judgment and prior experience to devise site plans, this experience-based approach can lead to various inefficiencies. Potential pitfalls include incorrect facility allocation—such as placing materials in inconvenient locations that hinder vehicle movement—insufficient access routes, and unsafe conditions created by poor placement of hazardous materials (Abotaleb et al., 2016; El-Rayes, Asce, & Khalafallah, 2005; Mawdesley et al., 2002; RazaviAlavi & AbouRizk, 2017). Therefore, a well-planned site layout is essential for the successful completion of any construction project (Abotaleb et al., 2016).

Site layout planning (SLP) involves several steps: identifying necessary temporary facilities specific to the project, determining their sizes, and selecting their optimal locations on-site to achieve desired objectives (Abotaleb et al., 2016a; Elbeltagi & Hegazy, 2001). Various optimization approaches and models have been developed to address Construction Site Layout Planning (CSLP) challenges. These studies predominantly focus on construction sites with defined boundaries and specific location constraints, examining scenarios such as limited construction zone areas or discrete zones with numerous restrictions (Abotaleb et al., 2016).

This study introduces an adaptable site layout approach for mega construction projects, emphasizing flexible representation of sites and facilities. In the proposed model, facilities are defined as collections of unit areas that can adopt any user-specified shape, allowing for a versatile site form. The model incorporates a flexible genetic algorithm (GA) method for optimal facility placement. Detailed insights into model development and implementation using spreadsheet applications are provided, along with validation through example applications and discussions of potential expansions.

2. Literature Review

The Quadratic Assignment Problem (QAP) is a crucial model in site layout optimization, particularly when addressing specific safety considerations. Numerous studies have explored various algorithms to tackle this optimization challenge. Genetic Algorithms (GA) have emerged as one of the most prevalent methods for solving QAP, demonstrating versatility and effectiveness across various applications (Chuang et al., 2023; Mawdesley et al., 2002; Paes et al., 2017; Papadaki & Chassiakos, 2016; RazaviAlavi & AbouRizk, 2017; Said & El-Rayes, 2013; Wong et al., 2010; Zouein et al., 2002). The flexibility of GA allows it to adapt to diverse layout configurations and project requirements, making it suitable for complex construction environments.

An effective construction site layout plan ensures the optimal utilization of available space, reduced design costs, minimized material relocation during construction, and improved accessibility and safety within the work environment (Wang et al. 2024). Understanding Construction Site Layout Planning (CSLP) necessitates clear definitions of key aspects, including the representation of space, time, and construction elements (Borges et al. 2024).

Beyond Genetic Algorithms, other optimization techniques have been applied to site layout problems. Ant Colony Optimization (ACO) has shown promise in enhancing layout efficiency (Lam et al., 2007; Wong & See, 2010). Additionally, Artificial Bee Colony Optimization has been utilized to address layout challenges with favorable outcomes (Yahya & Saka, 2014). Particle Swarm Optimization (PSO) has also been employed, particularly for larger projects, showcasing its effectiveness in handling multiple zones or divisions within construction sites (Xu & Song, 2014; H. Zhang & Wang, 2008).

In the development of site layout optimization algorithms, early contributions laid the foundation for subsequent advancements. Yeh (1995) introduced a mathematical optimization model utilizing artificial neural networks, while Lit and Love (1998) were among the first to apply Genetic Algorithms specifically to site layout issues. The validation of these models was further enhanced through real-world case studies, as demonstrated by Hegazy and

Elbeltagi (1999). Mawdesley et al. (2002) introduced a sequence-based GA that incorporated graph theory and Euclidean distances to optimize facility placements effectively. Cheung et al. (2002) contributed by applying a steady-state GA with a rank-based selection process for parent generation, while Mawdesley and Al-Jibouri (2003) improved upon these techniques by introducing multiple crossover and mutation operations.

Osman et al. (2003) employed Computer-Aided Design (CAD) technology to develop a GA model that accurately considered movement distances within construction sites. Additionally, Sanad et al. (2008) integrated safety and environmental factors into their GA model, enhancing distance estimation techniques through the use of real route methods. Lam et al. (2009) further advanced GA applications by incorporating the Min-Max Ant System (MMAS) to improve the generation of initial populations for optimization.

Apart from GA, several studies have explored alternative optimization frameworks. Sadeghpour et al. (2004) developed a CAD-based linear programming model that allowed for visual representation of site layouts, while Gharaie et al. (2006) employed AutoCAD to address static layout problems, introducing a partial path replacement tool to circumvent impractical layout solutions. H. Zhang and Wang (2008) proposed a PSO model that incorporated a modified solution space boundary handling technique to improve layout optimization.

The exploration of multi-objective optimization has also gained traction in recent literature, Abdelalim, A.M., et.al. (2021, 2024). Xu et al. (2016) developed a bi-level multi-objective genetic algorithm that enabled more sophisticated site optimization across various layers of project management. RazaviAlavi and AbouRizk (2017) utilized an integrated simulation-based GA model to optimize site layouts while aiming to minimize overall project costs. Additionally, Benjaoran and Peansupap (2020) employed PSO to address site layout planning challenges effectively.

Genetic Algorithms, in particular, have garnered attention for their user-friendly approach and effectiveness in addressing large-scale, multi-objective optimization problems. Their application has extended beyond traditional optimization fields into various practical areas, demonstrating their adaptability (Albadr et al., 2019). Arqub et al. (2014) showcased the use of continuous GA to solve complex boundary value problems, while Abo-Hammour et al. (2014) tailored GA techniques specifically for singular boundary value challenges.

Kumar and Cheng (2015) introduced an innovative framework for automated site layout planning that leverages Building Information Modeling (BIM) to enhance facility sizing and arrangement in congested construction environments. By integrating GAs with BIM, their approach allows for the precise calculation of trip pathways, leading to more optimal site layouts. Construction site layout problems involve not only economic and convenience, but also environmental and safety aspects. Attention also must be given to the worker’s safety in order to improve productivity and avoid the delays that happen to projects (Elbeltagi et al., 2004). Researchers have focused on the need for health and safety regulation. This is due to the high cost associated with worker injuries as well as time lost due to site accidents.

Decisions made during site layout planning are aimed at finding the greatest balance between site safety and overall project cost. One of the main goals of proper site layout planning is to minimize or even avoid accidents on the construction site. In previous literature, safety target features and location constrain have recognized the danger of approaching hazards. Safety considerations are addressed in the form of preferences or restrictions on distances. In the United States, 36% of workplace deaths are due to construction accidents. Therefore, it is important to clearly identify any possible sources of hazards within the site (Benjaoran & Peansupap, 2020). “The U.S Bureau of Labor Static reports an average of one death and 167 injuries per $ 100 million of annual construction spending. The total cost of these accidents reached $8.9 billion or 6.5% of the 137 billion spent annually on industrial, utility, and commercial constructions (Elbeltagi et al., 2004, Abdelalim, A.M., et.al , 2019).
Achieving safety improvements is critical for construction safety management (Ning et al., 2018, Abdelalim, Abd-Elhamed, et.al. 2020, Hassanen, M. A. H., & Abdelalim, A. M. (2022). In 2014, statistics from the Canadian worker’s association showed that 919 workers died on the job, with 25 percent of those deaths occurring in the construction industry (siliker 2016). According to Randolph Thomas et al. (1989), crowded construction sites can result in efficiency losses up to 58% due to restricted access. A University College London study reported that high levels of lost productivity due to the poor site layout planning and conflicts between sub-contractors can lead to up to 20% of accidents on site. Ning et al., (2018) developed a three objective ant colony optimization (ACO)-based model to help planners secure layout plans by analyzing risk factors in derailment during the design phase (Wang et al., 2015).

In summary, the body of literature on site layout optimization reveals a diverse array of algorithms and methodologies, each contributing unique insights and advancements to the field. The development of a Genetic Algorithm (GA) model in this study aims to address limitations in existing safety objective functions and enhance the preconstruction phase of site planning by integrating safety considerations into the arrangement of temporary facilities. This research endeavors to provide a scientifically grounded and logically structured framework for creating safer and more efficient construction site layouts.

3. Methodology of research

The model begins with a comprehensive overview of the Genetic Algorithm (GA) optimization technique, explaining its suitability for solving complex construction site layout planning problems. The GA is a powerful heuristic search method inspired by natural evolutionary processes, which utilizes a population of potential solutions that evolve over successive generations. Each candidate solution represents a possible layout of the construction site, and the GA seeks to iteratively improve the configuration by employing processes such as selection, crossover, and mutation. This optimization process enables the identification of the most efficient construction site layout, considering multiple objectives and constraints.
Following this, a detailed description of the construction site location and its associated facilities is provided. This section outlines key factors that influence the site layout, including

the physical characteristics of the site, accessibility, and the proximity of essential facilities. These facilities may include material storage areas, equipment zones, worker accommodation, administrative offices, construction zones, and safety zones. Understanding the spatial relationship between these facilities is essential for optimizing the overall construction site layout.

The multi-objective optimization problem is then solved using a Genetic Algorithm in Excel's Evolver, where Pareto optimal solutions are obtained by iterating over multiple generations. The algorithm simultaneously aims to minimize both transportation costs and safety relationships, ensuring that the construction site's layout is optimized not only for efficiency but also for the safety and accessibility of the various stakeholders involved. By balancing these competing objectives, the GA produces a set of Pareto optimal solutions, offering decision-makers a range of configurations to choose from based on the trade-offs between cost and safety considerations. This process allows for a more informed, data-driven approach to construction site layout planning, resulting in an overall improvement in project performance.

4. Optimization model using GA

This study utilizes a heuristic optimization approach Known by Genetic Algorithm (GA) as inspired by biological processes. In GA, potential solutions are encoded as chromosomes, which are sequences of genes, with each gene representing a variable that is being optimized. The fitness function is used to measure the effectiveness of these chromosomes (Lin et al., 2023; Sanad et al., 2008).

The GA process starts with the random generation of a population comprised of multiple chromosomes. As illustrated in Figure 1, three key procedures are employed to determine the fittest chromosome: selection, crossover, and mutation. The fittest chromosome is identified based on whether the objective is to maximize or minimize the fitness function.

Genes are randomly exchanged between two selected chromosomes during crossover. The selection process is biased toward fitter chromosomes, increasing their chances of being chosen for crossover. In this step, genes from both chromosomes are randomly swapped. To avoid local optima, mutation is introduced, which involves randomly changing the value of one or more genes. Each iteration results in a new generation of chromosomes, which are then evaluated for fitness using the fitness function. A common criterion for stopping the iterations is to set a maximum number of generations (Li & Love, 2000).

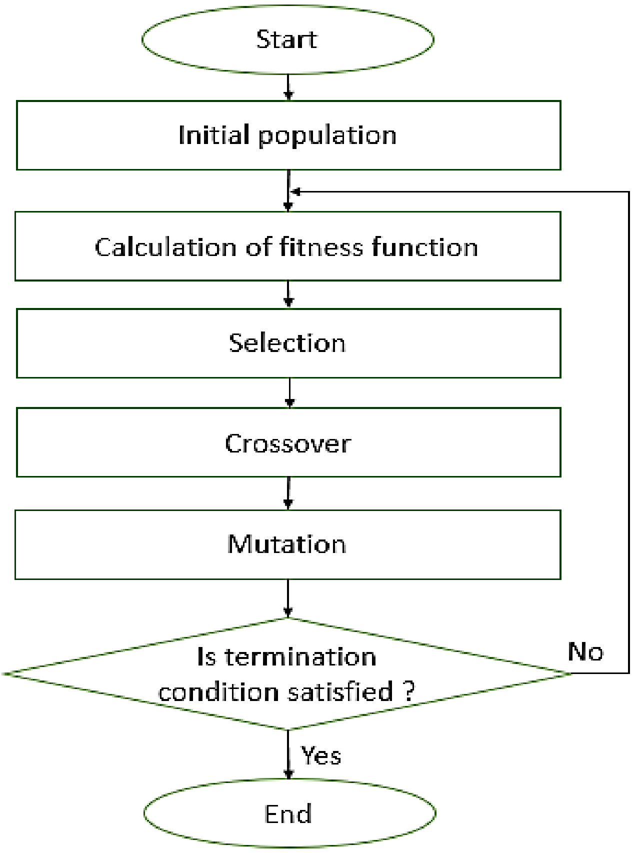

Fig. 1. Optimization Procedures.

5. Representation of Site Facilities

This study develops a methodology for analyzing and representing sites with irregular or non-standard characteristics, defined by user-specified coordinates. It addresses the need for a flexible approach to handle diverse site configurations that do not conform to traditional layouts, such as landscapes, property boundaries, and geographical features. By allowing users to input specific coordinates, the study can generate tailored representations, analyses, or plans suitable for fields like land development, urban planning, geospatial analysis, and environmental assessment.

According to Benjaoran & Peansupap (2020), site facilities can be categorized into four types:

1) **Fixed Facilities (FF)**: Permanent structures integral to the site's function, such as office buildings, manufacturing plants, and healthcare centers. These facilities are long-lasting and difficult to relocate.

2) **Access Roads (AR)**: Routes that facilitate transportation and movement within the site, including paved and unpaved roads, pathways, and driveways.

3) **Obstacles (OB)**: Features that may hinder operations or construction, such as natural elements (trees, boulders) and man-made obstructions (old buildings, debris). Proper identification and management of obstacles are vital for safety and planning.

4) **Temporary Facilities (TFs)**: Structures and equipment set up for specific projects or events typically used for a limited time, like temporary offices, portable restrooms, and storage units.

This classification aids in site management, organization, and planning by helping stakeholders assess the presence and impact of various elements on a project.

To determine the locations of fixed facilities and obstacles, four coordinates are established to accommodate their irregular shapes. In contrast, the lower-left corner (LC) coordinates represent the position for temporary facility (e.g., TFi (X1i, Y1i)). These coordinates serve as reference points for measuring facility dimensions and locations, with the LC coordinates defining the starting point of each structure.

Site boundary representation refers to the graphical depiction of a site's limits, helping to define the spatial context. This can be visualized through:

A. **Boundary Lines**: Drawing lines on a map to indicate property edges.

B. **Coordinates**: Using coordinate points to define the corners or key locations of the site.

These methods enhance understanding of the site's extent and facilitate effective planning and management. As shown in Figure 2.

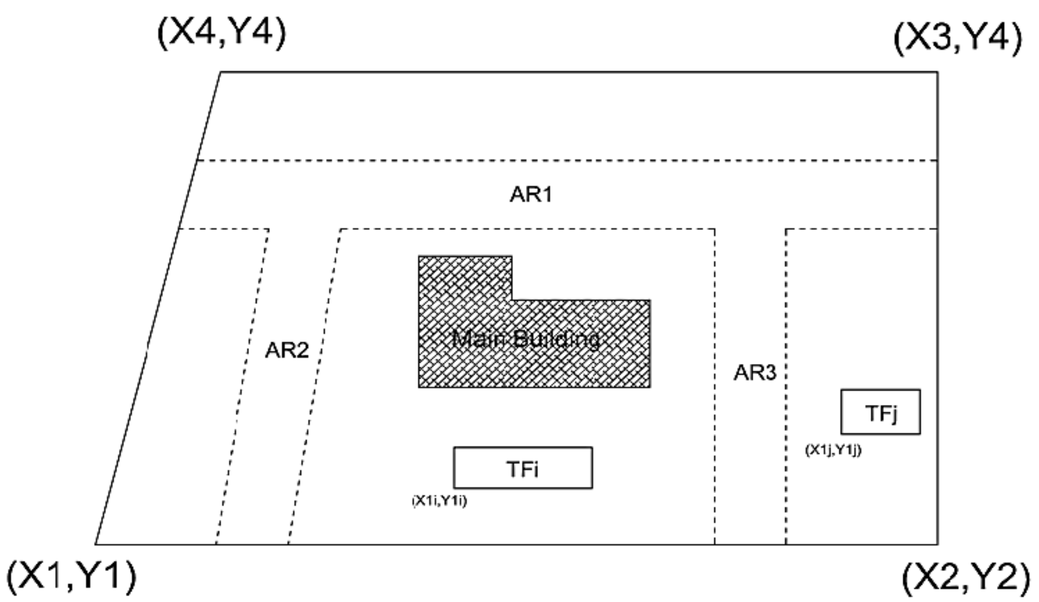

Fig. 2. Site boundary and facilities Representation.

5.1.Decision variables

The decision variables are essential for arranging temporary facilities (TFs) efficiently in Construction Site Layout Planning (CSLP), Each facility is represented by a matrix (Xi, Yi, and Oi):

- Xi: x-coordinate of the lower-left corner of the facility.
- Yi: y-coordinate of the lower-left corner of the facility.
- Oi: orientation of the facility.

The parameter 'n' indicates the total number of temporary facilities, with each facility having unique coordinates and orientation. By adjusting these variables within the CSLP model, planners can optimize the layout to enhance efficiency, minimize costs, maximize resource utilization, and ensure smooth construction operations. The decision variable matrix is crucial for tackling the complex spatial and logistical challenges in site planning.

5.2.Objective functions

The distance between temporary facilities can influence the construction site and the achievement of specific objectives should also be considered. Optimizing the layout of these facilities is key to improving safety effectiveness, particularly regarding their impact on each other’s safety. In this study, a genetic algorithm (GA) model is developed with two main objective functions: to enhance safety and reduce transportation costs.

1. Total transportation cost objective Function

For the model, the main objective function known by “Cost function”, aimed at minimizing the total costs related to travel between temporary facilities (TFs). This objective is mathematically expressed in Equation (1).

$$Minimize\ total\ cost = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{dij} * \mathrm{R1ij} \qquad \text{Equ. (1)}$$

In this case, dij represents the traveling distance between facilities i and j, and $R1ij$ is the desired proximity weight value between these facilities, reflecting their preferred closeness. The variable n stands for the total number of facilities in the system.

Unit-weighting relationships play a crucial role showing the connection strength between facilities during optimization. Facilities with strong Interrelationships or related operations are assigned higher unit weights, suggesting they should be located closer together, while those with weaker connections are placed further apart. Research by Hegazy & Elbeltagi (1999) and Zouein et al. (2002) highlighted that facility proximity influences these relationships. Ning et al. (2010) identified six factors affecting proximity: material, information, personnel, and equipment flows, as well as safety, environmental considerations, and user preferences. However, quantifying these factors is challenging, and previous studies often relied on subjective pairwise comparisons to assess proximity levels.

In this research, the proximity relationships among facilities are evaluated using fuzzy set theory and the preferences of planners through exponential number scaling. As shown in Table 1, unit-weighting relationships are categorized into six unique values based on proximity levels between pairs of facilities. A higher unit weight indicates a stronger proximity relationship between facilities, meaning they should be located closer to each other.

Table 1. Proximity weight relationship

Proximity Description	weightings
Absolutely necessary (A)	7,776
Especially important (E)	1,296
Important (I)	216
Ordinary important (O)	36
Unimportant (U)	6
Undesirable (X)	1

2. Safety relationship objective function

The safety relationship emphasizes evaluating the risks arising from the interactions among various facilities on a construction site. These interactions encompass resource flows, including transportation frequency, materials movement, personnel mobility, and equipment utilization. This relationship can be measured using metrics such as daily transportation units, employee trips per day, and the quantity of equipment engaged in transfers (Ning et al., 2010, 2011).

As the interactions frequency between facilities increases, the risk of conflicts or collisions involving materials, personnel, and equipment also rises, correlating positively with the intensity of these interactions. Additionally, longer distances between facilities result in more crossings and overlaps along transportation routes, increasing the risk of road traffic incidents. The distance between facilities directly influences the frequency of road traffic crossings, demonstrating a positive relationship between risk levels and distance (El-Rayes et al., 2005). Therefore, reducing risks tied to the facility safety relationship is essential for improving safety performance in construction site layouts, as outlined in Equation (2).

$$Minimize\ safety\ relationship = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} dij * R2ij \qquad \text{Equ. (2)}$$

In this context, dij represents the traveling distance between facilities i and j, and $R2ij$ denotes the value of the facility safety relationship. The variable n refers to the total facilities number involved.

To assess safety relationship across different measurement scales, the assessment criteria and the corresponding values for each level are detailed in Table 2. This framework aims to evaluate and categorize the risk associated with interactions among facilities effectively regarding their safety implications.

Table 2. Quantitative Flow Evaluation Levels

Levels	Value
Very high	243
High	81
Medium	27
Low	9
Negligible	3

The safety concern is primarily based on Quantitative Flow Evaluation, which highlights that an increase in the frequency of interaction flows between facilities correlates with a higher probability of conflicts or collisions among materials, personnel, and equipment. This is reflected in elevated quantitative flow values, indicating greater risk.

The intensity of contact flows is directly proportional to the likelihood of such risks. Additionally, as resources are required to travel longer distances between facilities, the number of crossing and overlapping points along the routes increases. The frequency of road traffic crossings or overlaps is influenced by the distance between facilities, thereby establishing a positive relationship between the level of risk and the distance traveled.

Safety concerns are integrated into the proposed by identifying critical factors and incorporating them into the framework used for decision-making and evaluation. These factors are typically quantified based on site-specific risks, regulations, and historical data. Safety concerns can be estimated through risk assessment techniques such as:

- Hazard identification methods (e.g., HAZOP or Fault Tree Analysis).
- Statistical models based on past incidents and probability assessments.
- Simulation tools that predict potential safety issues under varying conditions.

6. Site layout planning constrains

A site layout feasibility in Construction Site Layout Planning is evaluated using a set of constraint functions that account for factors such as site boundaries, overlaps, and the necessary distances between facilities. Each rectangular facility is defined by two coordinates: the lower-left corner (LC) at (X1i, Y1i) and the upper-right corner (UC) at (X2i, Y2i), as illustrated in Figure 3.

6.1.Site boundary constrains

The constraint prevents facilities from being placed outside the site boundary by applying Equation (3).

$$(X1i, Y1i)\ and\ (X2i, Y2i)\ \Subset\ [SBACs] \qquad for\ i = 1,2,3, n \qquad \text{Equ. (3)}$$

6.2.Overlapping constrain

This constraint prevents more than one facility from occupying the same space within the site. It applies to facilities i and j, defined by their lower-left corner (LC) and upper-right corner (UC) coordinates, represented as (X1i, Y1i), (X2i, Y2i) for facility i and (X1j, Y1j), (X2j, Y2j) or facility j. This requirement is enforced by satisfying the following Equation (4).

$$Max\ \{\ [X1i - X2j]\ [X2i - X1j]\ ,\ [Y1i - Y2j]\ [Y2i - Y1j]\ \}\ \geq\ 0 \qquad \text{Equ.(4)}$$

6.3.The inter-facility distance constrain

This constraint requires that any two of facilities must be either positioned close together or at a safe distance from one another, enhancing both safety and productivity on the site. For example, it ensures that the offices are located away from noisy and areas prone to dust pollution. All of this can satisfied using equation (5).

$$(X2i = X1j)\ and\ (Y2i - Y1j\ ) = \text{C}\ ,\ \ or\ \ (Y2i = Y1j\ )\ and\ \ (X2i - X1j) = \text{C} \qquad \text{Equ.(5)}$$

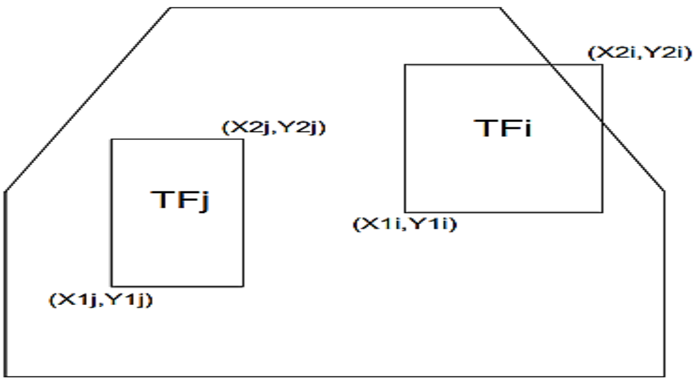

Fig. 3. Site layout constrains Representation.

7. Traveling Distance

In site layout planning (SLP), the distance between facilities significantly impacts various target functions. This study utilizes the Euclidean distance method to calculate distances by referencing the centroid of each facility's shape. This technique facilitates the measurement of straight-line distances between facilities.

To find the distance using the Euclidean method, the distance between two points in a two-dimensional plane is determined using the formula of Euclidean distance, as shown in equation (6). For example, if Point C is at (3, 4) and Point D is at (6, 8), the Euclidean distance between these points is approximately 5.00 units, as demonstrated in Figure 4.

$$Euclidean\ distance = \sqrt{(Xa - Xb)^2 + (Ya - Yb)^2} \qquad \text{Equ. (6)}$$

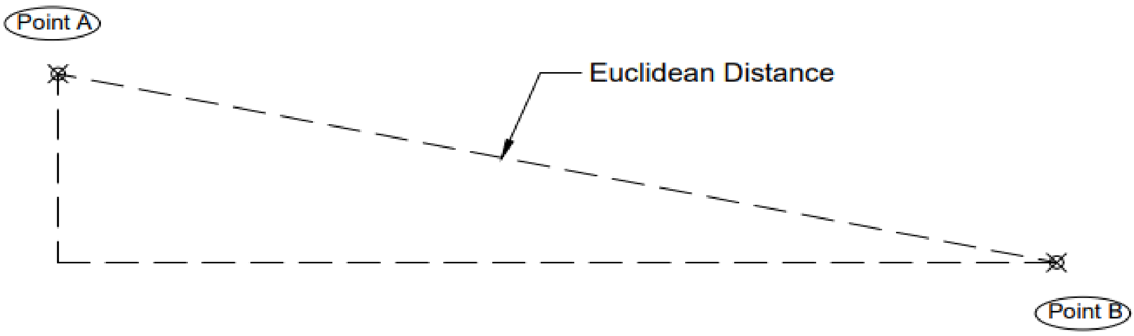

Fig. 4. Euclidean distance

8. CASE STUDY

The case study is vital for validating the proposed Genetic Algorithm (GA) model by allowing for the application and fine-tuning of parameters to achieve optimal construction site layouts. It demonstrates the practical implementation of the model in real-world situations, highlighting its effectiveness.

Analyzing the results from the case study reveals how facility layout influences both cost and safety at the construction site. This understanding aids in developing recommendations to improve safety and reduce costs through efficient temporary facility arrangements.

The insights gained from the case study lead to valuable suggestions for site managers, such as adjusting temporary facility layouts to enhance safety protocols, minimize hazards, and optimize operations. Additionally, cost-saving strategies can be identified by strategically placing facilities to reduce unnecessary movement of resources and personnel, thereby boosting efficiency and productivity.

Overall, the case study not only validates the GA model's effectiveness in practical applications but also offers actionable recommendations to enhance safety performance and cost-efficiency in construction site management.

The case study presented in this paper is a hypothetical example designed for the purpose of demonstrating the application and validation of the proposed Genetic Algorithm (GA) model.

8.1.Case Description

The construction site features a range of facilities, as outlined in Table 3, total number of facilities are fifteen which categorized into two types: fixed and free facilities. Seven of these are classified as fixed facilities, which include the Office for Engineering, parking, WC, three material hoists, and a crane, all positioned in specific and predetermined locations. The office and parking are strategically situated near the entrance of site to enhance accessibility. The material hoists used in transporting construction materials and labor to the building's superstructure, while the crane effectively moves materials across three different buildings. The remaining facilities are classified as free facilities. The algorithm will focus on determining the optimal location considered the objective functions.

Table 3. Construction site Facilities

NO.	Description	Sizes
TF1	Office for Engineering	10 * 5
TF2	WC	3 * 3
TF3	Parking	10 * 10
TF4	Crane	10 * 5
TF5	Storage for inflammable material	5 * 5
TF6	Storage for fire equipment	5 * 5
TF7	Maintenance shop for Equipment	5 * 5
TF8	Woodworking shop	10 * 5
TF9	Metal workshop	10 * 5
TF10	laydown area for Material	10 * 10
TF11	Labor hut	5 * 5
TF12	storage yard for Steel	12 * 7
TF13	Material hoist (for B1)	5 * 5
TF14	Material hoist (for B2)	5 * 5
TF15	Material hoist (for B3)	5 * 5

8.2.Site mapping and facility representation

In this research, all buildings and access roads are defined using four coordinates, while a temporary facility can be represented by only one coordinate (LC) and its dimensions, indicating which of the two dimensions is horizontal and which is vertical. The orientation helps in calculating the other three coordinates.

8.3.Define distance between facilities

In this research, the distance between two facilities is calculated using the "Euclidean distance" equation, measuring the distance from center to center for each pair of facilities. The coordinates of the gravity center can be determined as the intersection point between two diagonals, represented as (Xc, Yc) By using Equation (7), the distance between the facilities can be obtained.

$$dij = \sqrt{(Xci - Xcj)^2 + (Yci - Ycj)^2} \qquad \text{Equ. (7)}$$

8.4.Case study results

The Genetic Algorithm model optimization generates multiple alternative construction site layouts (optimal solutions) that strive to minimize overall transportation costs while considering safety relationships. Figure 5 illustrate the results of the model's solutions obtained from the designated case study. These results highlight the GA's effectiveness in creating layouts that harmonize cost efficiency with safety concerns, illustrating the model's ability to improve site planning through the optimized arrangement of facilities.

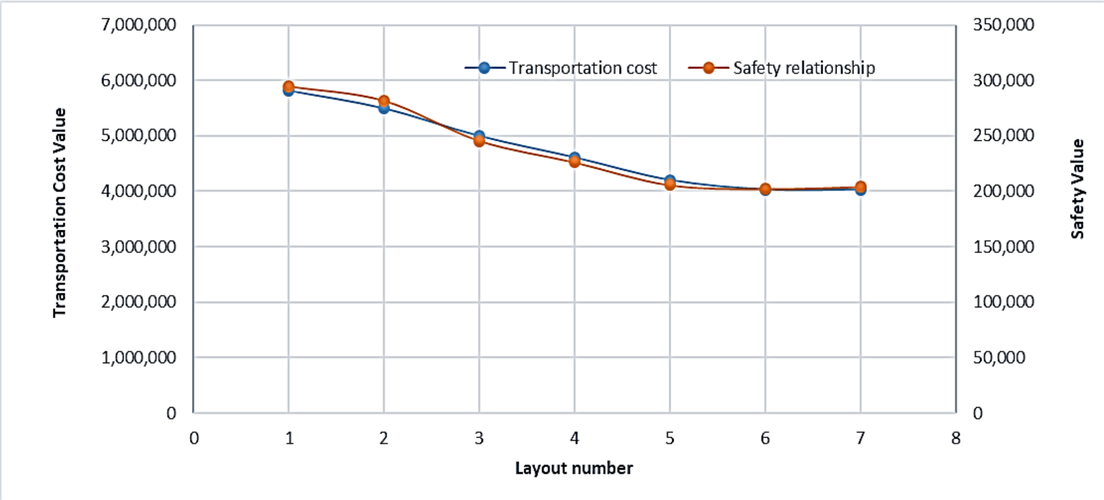

Fig. 5. Result of Case study

In optimization problems with two objective functions, it's common to encounter multiple optimal solutions due to the conflicting nature of these objectives, making it difficult to find a single solution that meets all criteria. Mathematically, it's uncommon for one solution to excel in all areas since optimizing one objective often compromises the other. In this scenario, the algorithm identified seven optimal solutions.

The decision to halt the optimization process depends on the judgment of the site manager. The model starts by minimizing both objectives until it reaches a point where improving one objective results in a decline in the other. Given that safety and cost priorities can differ among projects, user preferences significantly shape the site layout design. To define specific safety and cost targets for the project, feedback from site managers was gathered regarding the relative importance of the two objectives. This collaborative approach enables site managers to prioritize the aspects that are vital for improving the quality of construction site layout plans, fostering informed decision-making in the design process.

The schematic drawings for optimal results of P1, P6, and P7 are presented in detail in Figure 6, 7, and 8, respectively. Furthermore, Table 4 summarizes the optimal outcomes from the construction site layout planning model.

Table 4. The most effective solutions for construction site layout

Objective Functions	P1	P2	P3	P4	P5	P6	P7
Transportation cost	5,822,843	5,501,215	5,001,946	4,613,159	4,203,422	4,032,664	4,030,791
Safety relationship	294,441.3	281,531.3	245,550.9	226,139.5	205,661.5	202,141.7	204,113.9

9. DISCUSSION OF RESULTS

For the three proposed layouts, arrangement P1 (shown in Fig. 6) reflect the highest values for both transportation costs and safety, closely resembling the original layout used at the construction site. In P1, the temporary facilities are intentionally spaced apart from TF4 (crane), TF13 (material hoist 1), TF14 (material hoist 2), and TF15 (material hoist 3), which contributes to a reduced risk level within a designated safety zone. For instance, placing TF10 (laydown area for material) at a distance from TF4 results in longer travel distances, which in turn increases both transportation costs and safety relationship values. Moreover, TF9 (steel fabrication shop), situated at the lower-left corner of the site, is positioned far from TF12 (steel storage area), further affecting travel distances. As a result, the total transportation cost for resources in P1 amounts to a substantial 5,822,843, while the safety relationship value reaches its peak at 294,441.3.

In contrast, layouts P1 and P6 (illustrated in Fig.7) reveal significant differences in the arrangement of temporary facilities (TFs). The layout of P1 features a more spread-out configuration of facilities, yielding a safety relationship value of 294,441.3, while P6 registers a notably lower safety relationship value of 202,141.7. The distance between TF9 and TF10 in P1 results in higher material handling costs, which contributes to elevated resource transportation costs compared to those in P6. Additionally, TF9 is positioned further from TF12 in P1 than in P6, which helps to minimize travel distance in the latter layout. Consequently, P6 achieves a lower overall transportation cost of 4,032,664, thanks to the closer proximity of all TFs, thereby enhancing construction productivity.

In the comparison between layouts P6 and P7 (see Fig.8), TF11 (labor hut) is located away from other facilities in P7, which should ideally be placed closer to facilitate maximum interaction between facilities. Additionally, TF7 (Maintenance shop for Equipment) and TF6 (Storage for fire equipment) in P7 are closer to hazardous facilities than in P6. These factors lead to an increase in the safety relationship value to 204,113.9, even though transportation costs decrease to 4,030,791. However, P7's layout fails to meet the requirements of both objective functions simultaneously, resulting in the selection of construction site layout alternative P6 as a compromise solution.

The case study showcases the developed model's effectiveness in analyzing and optimizing construction site layouts. By quantitatively assessing transportation costs and safety, the model facilitates informed decision-making, ensuring a well-balanced layout selection that aligns with project priorities. In this case, P6 emerges as the preferred layout due to its optimal trade-off between cost efficiency and safety.

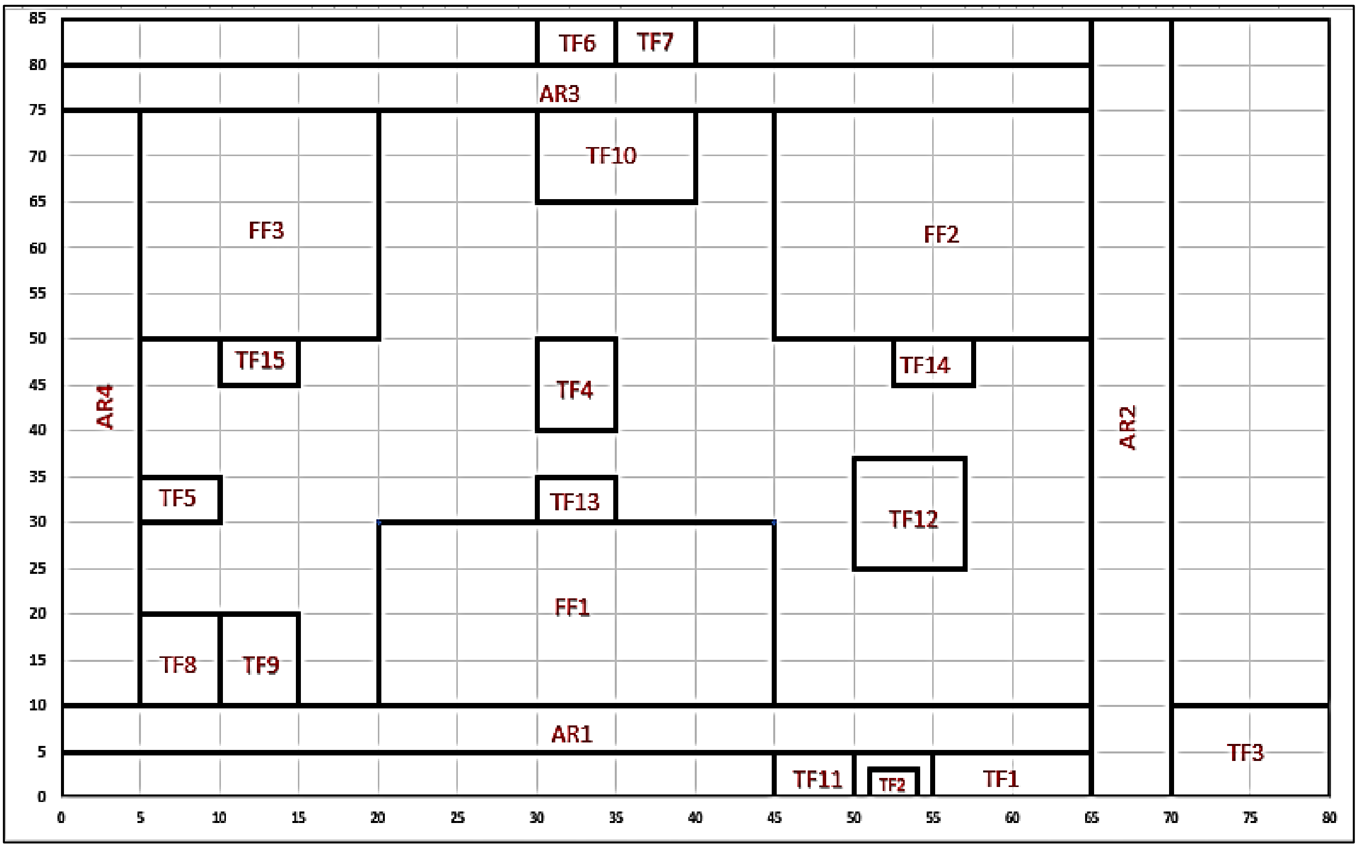

Fig. 6. Layout for P1

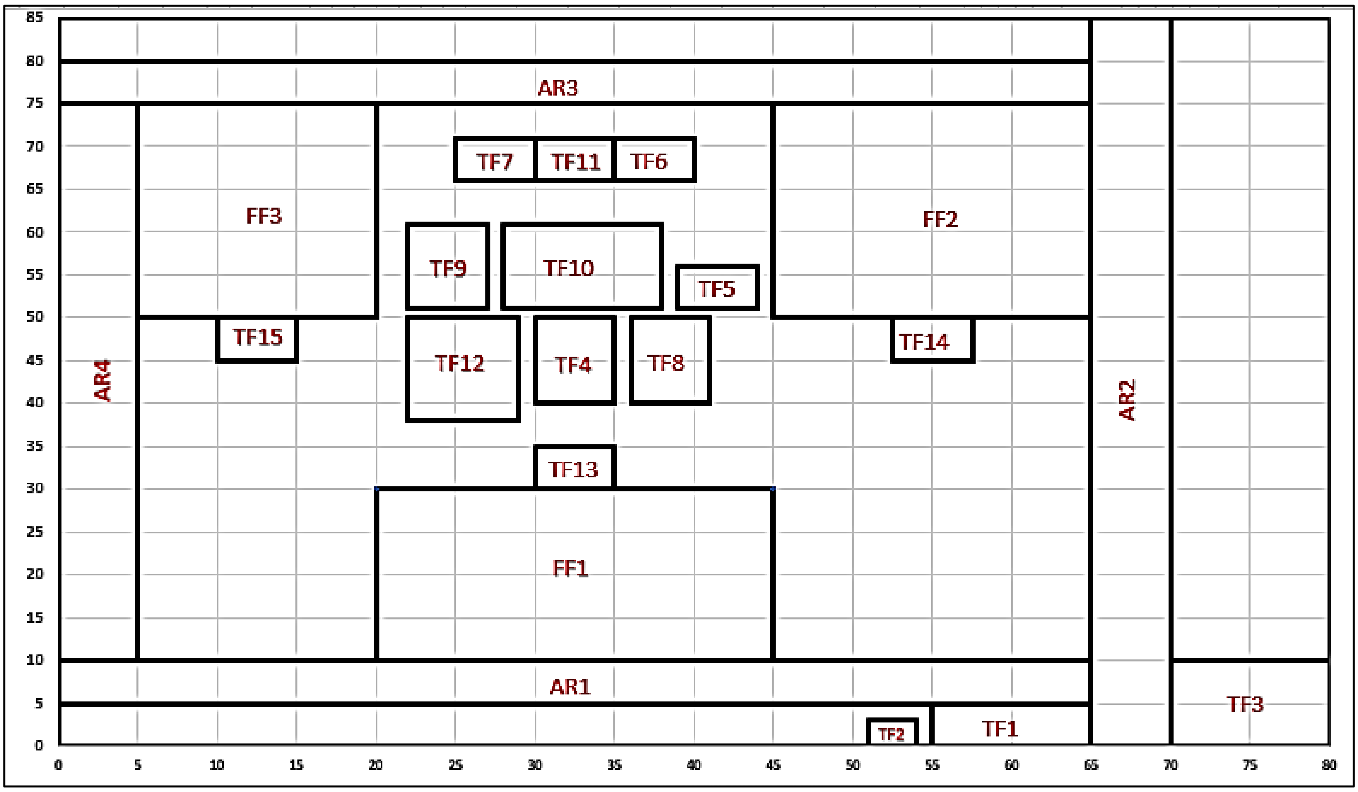

Fig. 7. Layout for P6.

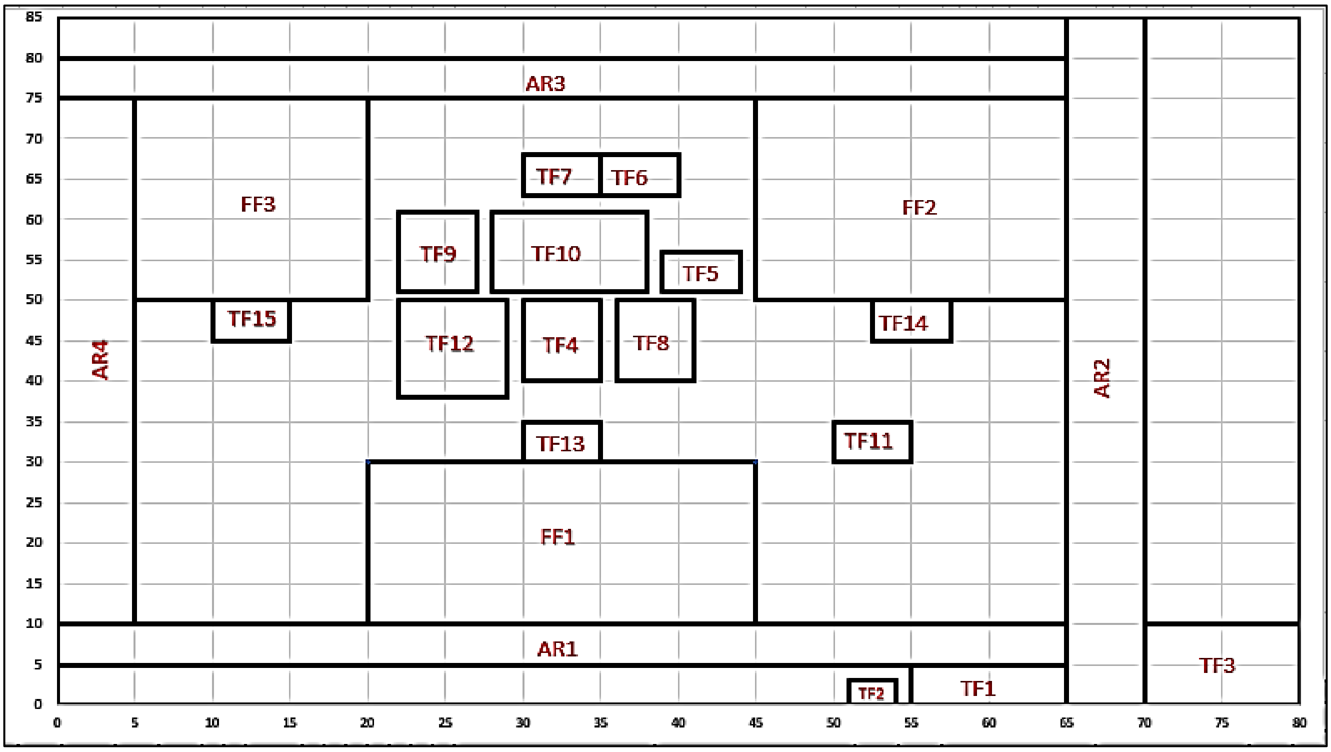

Fig. 8. Layout for P7

10.Comparison of Results

The "Tri-Objective Ant Colony Optimization Model" (Ning et al., 2018) and the "Genetic Algorithm-Based Model for Mega Construction Projects" focus on optimizing construction site layout planning (CSLP) but differ in methodology, objectives, and results as shown in table 5.

Table 5 Comparison of result

P.O.C	Ning et al. (2018)	New model
Objectives	• Optimizes **three objectives**: 1. Geographic Safety Relationship (minimizing proximity risks to hazardous sources). 2. Facility Safety Relationship (minimizing risks from interaction flows between facilities). 3. Total Resource Transportation Costs. • Employs a **tri-objective Ant Colony Optimization (ACO)** algorithm.	• Focuses on **two objectives**: 1. Minimizing total transportation costs between facilities. 2. Minimizing risks arising from interaction flows (facility safety relationships). • Uses a **Genetic Algorithm (GA)** for optimization

Methodology	• ACO incorporates Pareto optimization to provide multiple layout alternatives (Pareto front solutions) and uses dynamic pheromone updates for iterative improvements. • Safety is quantified with both interaction-based and location-based risk measures.	• GA iteratively generates solutions by employing crossover, mutation, and selection to minimize objective functions. • Emphasizes **unit proximity weights** for closeness between facilities and integrates fuzzy set theory to evaluate these relationships.
Results	• The construction site layout is selected through a weighted sum approach, evaluating all relevant objective functions.	• The optimal construction site layout should be selected based on achieving the lowest values for both transportation cost and safety relationship.

Based on the selected layout for Ning 2018, we concluded that the weighted sum may reflect a higher value for transportation costs compared to other layouts. In contrast, the new model can minimize both objective functions without prioritizing one over the other

11.Conclusion

This study developed a Genetic Algorithm (GA) model to optimize Construction Site Layout Planning (CSLP) by addressing two key objectives: minimizing transportation costs and enhancing safety relationships. The model was validated using a case study featuring 15 facilities with fixed and free layouts. The results highlighted seven potential layout alternatives, each balancing transportation cost and safety considerations.

Among the alternatives, layout P6 emerged as the most optimal, achieving a transportation cost of (4,032,664) and a safety relationship value of (202,141.7). This configuration effectively minimized material handling distances and enhanced safety by strategically positioning facilities with high interaction frequencies close to one another. Conversely, layout P1, which resembled the initial site arrangement, exhibited the highest transportation cost (5,822,843) and safety value (294,441.3), demonstrating the inefficiency of dispersed facility placement.

The study demonstrates that GA-based optimization offers a systematic and practical approach to solving multi-objective CSLP problems. By incorporating site-specific constraints and user preferences, the model provides robust solutions that significantly improve both economic and safety performance in construction site layouts.

12.References

1. Abd El-Megid, M. A., Shawki, K. M., & Abdel-Khalek, H. (2015). GA optimization model for solving tower crane location problem in construction sites. *Alexandria Engineering Journal, 54*(3), 519–526. https://doi.org/10.1016/j.aej.2015.05.011

2. Abd-Elhamed, A., Amin, H. E., & Abdelalim, A. M. (2020). Integration of Design Optimality and Design Quality of RC buildings from the perspective of Value Engineering. International Journal of Civil and Structural Engineering Research, 8(1), 105-116.

3. Abdelalim, A. M., Elbeltagi, E., & Mekky, A. A. (2019). Factors affecting productivity and improvement in building construction sites. *International Journal of Productivity and Quality Management, 27*(4), 464-494. https://doi.org/10.1504/IJPQM.2019.101927.

4. Abdelalim, A. M., & Said, S. O. M. (2021). Dynamic Labour Tracking System in Construction Project Using BIM Technology. International Journal of Civil and Structural Engineering Research, 9(1), 10–20.

5. Abdelalim, A.M.; Said, S.O.; Alnaser, A.A.; Sharaf, A.; ElSamadony, A.; Kontoni, D.-P.N.; Tantawy, M. Agent-Based Modelling for Construction Resource Positioning Using Digital Twin and BLE Technologies. Buildings 2024, 14, 1788. https://doi.org/10.3390/buildings14061788.

6. Abotaleb, I., Nassar, K., & Hosny, O. (2016). Layout optimization of construction site facilities with dynamic freeform geometric representations. *Automation in Construction*, *66*, 15–28. https://doi.org/10.1016/j.autcon.2016.02.007

7. Abo-Hammour, Z., Arqub, O. A., Alsmadi, O., Momani, S., & Alsaedi, A. (2014). An optimization algorithm for solving systems of singular boundary value problems. *Applied Mathematics & Information Sciences, 8*(6), 2809.

8. Abune'meh, M., El Meouche, R., Hijaze, I., Mebarki, A., & Shahrour, I. (2016). Optimal construction site layout based on risk spatial variability. *Automation in Construction, 70*, 167–177. https://doi.org/10.1016/j.autcon.2016.06.014.

9. Adrian, A. M., Utamima, A., & Wang, K. J. (2015). A comparative study of GA, PSO, and ACO for solving construction site layout optimization. *KSCE Journal of Civil Engineering, 19*(3), 520–527. https://doi.org/10.1007/s12205-013-1467-6.

10. Albadr, M. A. A., Tiun, S., Ayob, M., & AL-Dhief, F. T. (2019). Spoken language identification based on optimised genetic algorithm–extreme learning machine approach. *International Journal of Speech Technology, 22*, 711-727.

11. Andayesh, M., & Sadeghpour, F. (2013). Dynamic site layout planning through minimization of total potential energy. *Automation in Construction*, *31*, 92–102. https://doi.org/10.1016/j.autcon.2012.11.039

12. Andayesh, M., & Sadeghpour, F. (2014). A comparative study of different approaches for finding the shortest path on construction sites. *Procedia Engineering*, *85*, 33–41. https://doi.org/10.1016/j.proeng.2014.10.526

13. Arqub, O. A., & Abo-Hammour, Z. (2014). Numerical solution of systems of second-order boundary value problems using continuous genetic algorithm. *Information Sciences, 279*, 396-415.

14. Ballesteros, M. J., Fernández, M. D., Quintana, S., Ballesteros, J. A., & González, I. (2010). Noise emission evolution on construction sites: Measurement for controlling and assessing its impact on the people and on the environment. *Building and Environment, 45*(3), 711–717. https://doi.org/10.1016/j.buildenv.2009.08.011.

15. Benjaoran, V., & Peansupap, V. (2020). Grid-based construction site layout planning with Particle Swarm Optimization and Travel Path Distance. *Construction Management and Economics, 38*(8), 673–688. https://doi.org/10.1080/01446193.2019.1600708.

16. Borges, M. L. A. E., Granja, A. D., & Monteiro, A. (2024). A Hybrid Framework for Multi-Objective Construction Site Layout Optimization. *Buildings*, *14*(12), 3790. https://doi.org/10.3390/buildings14123790

17. Cheung, S. O., Tong, T. K. L., & Tam, C. M. (2002). Site pre-cast yard layout arrangement through genetic algorithms. Automation in construction, 11(1), 35-46.

18. Elbeltagi, E., & Hegazy, T. (2001). A Hybrid AI-Based System for Site Layout Planning in Construction. In *Computer-Aided Civil and Infrastructure Engineering* (Vol. 16).

19. Elbeltagi, E., Hegazy, T., & Eldosouky, A. (2004). Dynamic Layout of Construction Temporary Facilities Considering Safety. *ASCE Journal of Construction Engineering and Management*. https://doi.org/10.1061/ASCE0733-93642004130:4534

20. El-Rayes, K., & Khalafallah, A. (2005). Trade-off between Safety and Cost in Planning Construction Site Layouts. *ASCE Journal of Construction Engineering and Management*. https://doi.org/10.1061/ASCE0733-93642005131:111186

21. El-Rayes, K., Asce, M., & Said, H. (2009) *Dynamic Site Layout Planning Using Approximate Dynamic Programming*. https://doi.org/10.1061/ASCE0887-3801200923:2119

23. Farmakis, P. M., & Chassiakos, A. P. (2018). Genetic algorithm optimization for dynamic construction site layout planning. *Organization, Technology and Management in Construction: An International Journal*, *10*(1), 1655–1664. https://doi.org/10.1515/otmcj-2016-0026

24. Gen, M., & Lin, L. (2023). Genetic algorithms and their applications. In Springer handbook of engineering statistics (pp. 635-674). London: Springer London.

25. Gharaie, E., Afshar, A., & Jalali, M. R. (2006, February). Site layout optimization with ACO algorithm. In *Proceedings of the 5th WSEAS international conference on artificial intelligence, knowledge engineering and data bases* (pp. 90-94).

26. Gholizadeh, R., Amiri, G. G., & Mohebi, B. (2010). An alternative approach to a harmony search algorithm for a construction site layout problem. *Canadian Journal of Civil Engineering, 37*(12), 1560–1571. https://doi.org/10.1139/L10-084.

27. Hammad, A. W. A., Akbarnezhad, A., & Rey, D. (2016). A multi-objective mixed integer nonlinear programming model for construction site layout planning to minimise noise pollution and transport costs. *Automation in Construction, 61*, 73–85. https://doi.org/10.1016/j.autcon.2015.10.010.

28. Hammad, A. W. A., Rey, D., & Akbarnezhad, A. (2017). A cutting plane algorithm for the site layout planning problem with travel barriers. *Computers and Operations Research, 82*, 36–51. https://doi.org/10.1016/j.cor.2017.01.005.

29. Hassanen, M. A. H., & Abdelalim, A. M. (2022). Risk Identification and Assessment of Mega Industrial Projects in Egypt. *International Journal of Management and Commerce Innovation (IJMCI), 10*(1), 187-199. https://doi.org/10.5281/zenodo.6579176.

30. Hegazy, T., & Elbeltagi, E. (1999). EVOSITE: Evolution-based model for site layout planning. *Journal of Computing in Civil Engineering*.

31. Hu, X., & Chuang, Y. F. (2023). E-commerce warehouse layout optimization: systematic layout planning using a genetic algorithm. Electronic Commerce Research, 23(1), 97-114.

33. Ho, S. P., & Liu, L. Y. (2004). Analytical Model for Analyzing Construction Claims and Opportunistic Bidding. *Journal of Construction Engineering and Management, 130*(1), 94-104.

34. Kumar, S. S., & Cheng, J. C. (2015). A BIM-based automated site layout planning framework for congested construction sites. *Automation in Construction, 59*, 24-37.

35. Lam, K. C., Ning, X., & Ng, T. (2007). The application of the ant colony optimization algorithm to the construction site layout planning problem. *Construction Management and Economics, 25*(4), 359–374. https://doi.org/10.1080/01446190600972870.

36. Lam, K.-C., Ning, X., & Lam, C.-K. (2009). Conjoining MMAS to GA to Solve Construction Site Layout Planning Problem. *ASCE Journal of Construction Engineering and Management*. https://doi.org/10.1061/ASCE0733-93642009135:101049

37. Li, H., & Love, P. E. (2000). Genetic search for solving construction site-level unequal-area facility layout problems. *Automation in construction*, *9*(2), 217-226.

38. Li, H., & Love, P. E. (1998). Site-level facilities layout using genetic algorithms. *Journal of computing in civil engineering*, *12*(4), 227-231.

39. Mawdesley, M. J., & Al-Jibouri, S. H. (2003). Proposed genetic algorithms for construction site layout. *Engineering Applications of Artificial Intelligence, 16*(5–6), 501–509. https://doi.org/10.1016/j.engappai.2003.09.002.

40. Mawdesley, M. J., Saad, ;, Al-Jibouri, H., & Yang, H. (2002). Genetic algorithms for construction site layout in project planning. *ASCE Journal of Construction Engineering and Management*. https://doi.org/10.1061/ASCE0733-93642002128:5418

44. Ning, X., Lam, K. C., & Lam, M. C. K. (2010). Dynamic construction site layout planning using max-min ant system. *Automation in Construction, 19*(1), 55–65. https://doi.org/10.1016/j.autcon.2009.09.002.

45. Ning, X., Lam, K. C., & Lam, M. C. K. (2011). A decision-making system for construction site layout planning. *Automation in Construction, 20*(4), 459–473. https://doi.org/10.1016/j.autcon.2010.11.014.

46. Ning, X., Qi, J., Wu, C., & Wang, W. (2018). A tri-objective ant colony optimization-based model for planning safe construction site layout. *Automation in Construction*, *89*, 1–12. https://doi.org/10.1016/j.autcon.2018.01.007

47. Osman, H. M., & Georgy, M. E. (2005). Layout planning of construction sites considering multiple objectives: A goal-programming approach.

48. Osman, H. M., Georgy, M. E., & Ibrahim, M. E. (2003). A hybrid CAD-based construction site layout planning system using genetic algorithms. *Automation in Construction, 12*(6), 749–764. https://doi.org/10.1016/S0926-5805(03)00058-X.

50. Paes, F. G., Pessoa, A. A., & Vidal, T. (2017). A hybrid genetic algorithm with decomposition phases for the Unequal Area Facility Layout Problem. *European Journal of Operational Research, 256*(3), 742–756. https://doi.org/10.1016/j.ejor.2016.07.022.

52. Papadaki, I. N., & Chassiakos, A. P. (2016). Multi-objective Construction Site Layout Planning Using Genetic Algorithms. *Procedia Engineering, 164*, 20–27. https://doi.org/10.1016/j.proeng.2016.11.587.

54. RazaviAlavi, S., & AbouRizk, S. (2017). Site Layout and Construction Plan Optimization Using an Integrated Genetic Algorithm Simulation Framework. *Journal of Computing in Civil Engineering, 31*(4). https://doi.org/10.1061/(asce)cp.1943-5487.0000653.

55. Randolph Thomas, B. H., Sanvido, V. E., Member, A., & Sanders, S. R. (2015.). IMPACT OF MATERIAL MANAGEMENT ON PRODUCTIVITY-A CASE STUDY.

57. Sadeghpour, F., Moselhi, O., & Alkass, S. (2004). A CAD-based model for site planning. *Automation in Construction, 13*(6), 701–715. https://doi.org/10.1016/j.autcon.2004.02.004.

58. Said, H., & El-Rayes, K. (2013). Optimal utilization of interior building spaces for material procurement and storage in congested construction sites. *Automation in Construction, 31*, 292–306. https://doi.org/10.1016/j.autcon.2012.12.010.

59. Sanad, H. M., Ammar, M. A., & Ibrahim, M. E. (2008). Optimal Construction Site Layout Considering Safety and Environmental Aspects. *ASCE Journal of Construction Engineering and Management*. https://doi.org/10.1061/ASCE0733-93642008134:7536

60. Singh, S. P., & Sharma, R. R. K. (2008). Two-level modified simulated annealing-based approach for solving facility layout problem. *International Journal of Production Research, 46*(13), 3563–3582. https://doi.org/10.1080/00207540601178557.

61. Singh, S. P., & Singh, V. K. (2010). An improved heuristic approach for multi-objective facility layout problem. *International Journal of Production Research, 48*(4), 1171–1194. https://doi.org/10.1080/00207540802534731.

62. Tam, C. M., & Tong, T. K. L. (2003). GA-ANN model for optimizing the locations of tower crane and supply points for high-rise public housing construction. *Construction Management and Economics, 21*(3), 257–266. https://doi.org/10.1080/0144619032000049665.

63. Wang, L., Li, J., Ye, Q., Li, Y., & Feng, A. (2024). Automatic planning method of construction schedule under multi-dimensional spatial resource constraints. *Buildings, 14*(12), 3231. https://doi.org/10.3390/buildings14103231

64. Wang, J., Zhang, X., Shou, W., Wang, X., Xu, B., Kim, M. J., & Wu, P. (2015). A BIM-based approach for automated tower crane layout planning. Automation in Construction, 59, 168–178. https://doi.org/10.1016/j.autcon.2015.05.006

65. Wong, C. K., Fung, I. W. H., & Tam, C. M. (2010). Comparison of using mixed-integer programming and genetic algorithms for construction site facility layout planning. *ASCE Journal of Construction Engineering and Management*. https://doi.org/10.1061/ASCECO.1943-7862.0000214

66. Wong, K. Y., & See, P. C. (2010). A hybrid ant colony optimization algorithm for solving facility layout problems formulated as quadratic assignment problems. *Engineering Computations (Swansea, Wales), 27*(1), 117–128. https://doi.org/10.1108/02644401011008559.

67. Xu, J., & Song, X. (2014). Suggestions for temporary construction facilities' layout problems in large-scale construction projects. *Journal of Construction Engineering and Management, 140*(5). https://doi.org/10.1061/(asce)co.1943-7862.0000841.

68. Xu, J., Zhao, S., Li, Z., & Zeng, Z. (2016). Bilevel construction site layout optimization based on hazardous-material transportation. *Journal of Infrastructure Systems, 22*(3). https://doi.org/10.1061/(asce)is.1943-555x.0000303.

70. Yahya, M., & Saka, M. P. (2014). Construction site layout planning using multi-objective artificial bee colony algorithm with Levy flights. *Automation in Construction, 38*, 14–29. https://doi.org/10.1016/j.autcon.2013.11.001.

71. Yeh, I. C. (1995). Construction-site layout using annealed neural network. *Journal of computing in civil engineering*, *9*(3), 201-208.

72. Zhang, H., & Wang, J. Y. (2008). Particle Swarm Optimization for Construction Site Unequal-Area Layout. *ASCE Journal of Construction Engineering and Management*. https://doi.org/10.1061/ASCE0733-93642008134:9739

73. Zhang, P., Harris, F. C., Olomolaiye, P. O., & Holt, G. D. (1999). Location optimization for a group of tower cranes. *Journal of construction engineering and management*, *125*(2), 115-122.

74. Zouein, P. P., Harmanani, H., & Hajar, A. (2002). Genetic algorithm for solving site layout problem with unequal-size and constrained facilities. *ASCE Journal of Construction Engineering and Management*. https://doi.org/10.1061/ASCE0887-3801200216:2143.