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CONSTRUCTION SITE LAYOUT PLANNING CONSIDERING TRAVELLING DISTANCE COST AND SAFETY RELATIONSHIPS USING A GENETIC ALGORITHM TECHNIQUE

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Original Scientific Paper

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Efficient planning for construction site layout is pivotal for the successful execution of a project, contributing to enhanced productivity and safety on the site. This involves identifying temporary structures or facilities required to support construction activities, choosing their size and arrangement, and strategic placing within the available space on the site. The problem of site layout planning is a challenging issue in combinatorial optimization, especially as it involves multiple objectives. Its complexity escalates with the increasing number of facilities and constraints. While existing research has proposed various analytical, heuristic, and meta-heuristic approaches to address this problem, many prior studies focused on a limited number of facilities, emphasizing the minimization of travelling distances while neglecting other pertinent cost-related and decision-making factors. This study aims to create practical and effective solutions for site layout by employing a realistic representation that takes into account not just travelling distance but also considers cost and safety relationships. A model for optimization with two objective functions has been developed to minimize travelling distance between facilities in order to minimize cost functions derived from various factors such as construction costs associated with different facility locations and transportation costs between locations, as well as to minimize risks based on the quantitative flow matrix and distance between facilities, as increasing in the frequency of interaction flow between facilities results in a higher probability of collision. In this research, a genetic algorithm (GA) is used as a heuristic optimization approach. A case study was applied to the model to highlight the benefits of the suggested approach, illustrating its effectiveness and comprehensive solutions for construction site layout planning.

Keywords: Construction Site Layout Planning (CSLP); Genetic Algorithm (GA); Temporary Facility (TF.); Fixed Facility (FF.); Access Road (AR.).

INTRODUCTION

The primary objective of construction site layout planning (CSLP) is to create a productive, safe, and secure work environment so that the efficient distribution of resources through site areas increases productivity while decreasing project cost and time (Abdelalim et al., 2019a; Hegazy & Elbeltagi, 1999). Effective site layout planning (SLP) reduces unnecessary movement while also decreasing the overall frequency flow of material handling and labour (Elbeltagi et al., 2004; Ali Mohamed et al., 2020). Proper site layout features may be optimized by selecting the ideal placement for each facility based on relevant activities (Khedr et al., 2021a; Ning et al., 2011; Abd El-Hamid et al., 2023). Furthermore, facilities can be intelligently positioned around the site where labour and equipment move the least, reducing the cost of handling on-site resources (Osman & Georgy, 2005; Abd El-Karim et al., 2017; Afifi et al., 2020A, B). Many site layout planning (SLP) models seek to minimize the total of a weighted distance function (SWDF) to achieve optimisation objectives. This function, denoted $\sum W \cdot d$, assigns weights to

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evaluate the significance or cost of interactions across facilities. There are two ways to determine these weights: (1) Quantitative technique: This technique involves giving weights that represent the cost per unit length ($/m) of transportation between facilities (Zhang & Wang, 2008). It is based on observable parameters related to transportation costs, making weight determination more objective and quantitative. (2) Qualitative technique: In contrast, the qualitative technique distributes weights based on the subjective proximity of facilities (Zhang et al. 1999; El-Samadony et al., 2016; Khedr et al., 2021A, B). It is based on qualitative assessments and subjective judgements about the degree of proximity or connection between facilities. These two techniques provide distinct ways to determine weights for elements impacting transportation costs and facility proximity relationships in the context of site layout planning. The decision between them may be determined by the availability of quantitative data, the needed level of precision, and the specific aims of the site layout optimization. The fundamental drawback of the quantitative technique is the difficulty in precise determination of the cost for each unit of transportation. On the other hand, the qualitative technique has a disadvantage in that the assigned subjective weights cannot accurately represent the true transportation costs.

Furthermore, CSLP optimization entails creating an objective function known as the "safety objective function" that prioritises site safety. This function aims to reduce accidents and address safety concerns such as tower crane placement (Abdelalim 2016; Abd El-Megid et al., 2015; Tam & Tong, 2003; Zhang et al., 1999), hazardous material control (Abune'meh et al., 2016; Xu et al., 2016), intersection reduction (El-Rayes et al., 2005), safety zone definition (Elbeltagi et al., 2004), and noise pollution reduction (Ballesteros et al., 2010; Hammad et al., 2016). By including these goals in the design process, CSLP hopes to achieve a safe and optimized construction site layout.

Construction Site Layout Planning (CSLP) involves strategically arranging temporary and permanent facilities within a construction site to optimize workflow, resource utilization, and safety. Researchers utilize advanced modelling techniques to develop layouts that minimize construction time and costs while maximizing productivity and safety standards. Genetic Algorithm (GA) is a computational optimization technique inspired by natural selection, used to solve complex problems by simulating evolution. It finds applications in various fields to address problems with large solution spaces or non-linear constraints. Temporary facilities (TFs) are crucial for construction projects, providing support functions like site offices and storage areas. Research in TFs focuses on optimizing design and utilization to enhance project efficiency and minimize environmental impacts. While fixed facilities (FFs) are permanent structures providing essential infrastructure for construction projects, with research emphasizing design optimization and sustainability. Access roads (ARs) are vital for site access, and research aims to optimize alignment and materials for safety and efficiency.

Traditional approaches to construction site layout planning often prioritize minimizing travelling distance without fully integrating cost and safety considerations. While minimizing travelling distance is important for efficiency, overlooking cost and safety factors can lead to suboptimal layouts and increased project risks. Existing methodologies lack a comprehensive approach that considers the dynamic interplay between travelling distance, cost, and safety relationships. Therefore, there is a significant research gap in construction site layout planning that fails to address these multi-dimensional challenges effectively. To address the identified research gap in construction site layout planning, this study proposes an innovative approach that considers travelling distance, cost, and safety relationships simultaneously. By utilizing a genetic algorithm (GA) technique, the research aims to optimize layouts that not only minimize travelling distance but also take into account cost implications associated with facility locations and transportation, while simultaneously mitigating safety risks. This integrated approach represents a significant innovation in construction site planning, providing a comprehensive solution to enhance project efficiency and safety. By bridging the gap between traditional methods and the evolving needs of construction projects, this research contributes to advancing the field of construction site layout planning.

LITERATURE REVIEW

The quadratic assignment issue is frequently used to represent site layout optimization with specific safety requirements (Adrian et al., 2015; Singh & Singh, 2010; Abdelalim et al., 2020; Amin Sherif, & Abdelalim, 2023). Various algorithms have been employed to solve this problem, including Genetic Algorithm (GA) (Hu & 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), Ant-colony Optimisation (ACO) (Lam et al., 2007; Wong & See, 2010), Artificial Bee Colony Optimization (Yahya & Saka, 2014), Particle Swarm Optimization (PSO) (Xu & Song, 2014; Zhang & Wang, 2008), Harmony Search Algorithm (Gholizadeh et al., 2010), Cutting Plane Algorithm (Hammad et al., 2017), and Simulated Annealing Algorithm (Singh & Sharma, 2008).

In terms of algorithms that rely on discovering dominant connections between solutions, Yeh (1995) developed the first mathematical optimisation model employing an artificial neural network. Lit & Love (1998) used Genetic Algorithms (GA) to solve the site layout challenge, while Hegazy & Elbeltagi (1999) verified their GA model using a case study from the. Mawdesley et al. (2002) used a sequence-based GA that used Euclidean distance and graph theory to determine the distance between facilities. Cheung et al. (2002) used a steady-state GA model with a rank-based technique for parent selection, whereas Mawdesley and Al-Jibouri (2003) improved their GA model by including several crossover and mutation operators. Osman et al. (2003) used CAD to develop a GA model that took into account the real movement distance for a restricted number of obstacles. Sanad et al. (2008) proposed a GA model that incorporates safety and environmental issues, employs safety zones, and improves distance estimation using the real route technique. Finally, Lam et al. (2009) improved GA by employing the Min-Max Ant System (MMAS) to generate a more effective starting population for the problem.

In addition to the methods stated above, Sadeghpour et al. (2004) developed a CAD-based linear programming model for allocation on a visual platform. Gharaie et al. (2006) used ACAD to solve the static layout problem and proposed a partial path replacement (PPR) tool to avoid impractical solutions. Zhang and Wang (2008) proposed the PSO model for solving site layout issues, which included a modified solution space boundary handling (MSSBH) technique. Xu and Song (2014) used PSOM for large-scale projects with various divisions or zones to identify site features using a qualitative index technique. Furthermore, Xu et al. (2016) created a bi-level multi-objective genetic algorithm (BLMOGA) for site optimisation on two levels. RazaviAlavi and AbouRizk (2017) used an integrated simulation-based GA model to optimize the site layout while minimizing the overall layout cost. Finally, Benjaoran and Peansupap (2020) used the PSO model to solve the SLP issue with the "Travel Path Distance Equation." As a result, GA is regarded as user-friendly and suitable for solving large-scale and multi-objective optimization problems.

The genetic algorithm (GA) is a well-known metaheuristic, with widespread use in optimization, design, and practical fields (Albadr et al., 2019). The GA, which functions as a multi-parameter and multi-individual simultaneous optimization approach, is based on the notion of "natural selection and survival of the fittest," which mirrors the processes of heredity and evolution observed in nature. Arqub et al. (2014) used the continuous genetic algorithm to effectively solve second-order boundary value issues, demonstrating its adaptability. Abo-Hammour et al. (2014) broadened the use of genetic algorithms by developing an optimization method, particularly for solving singular boundary value issues. Additionally, Kumar and Cheng (2015) have introduced a novel automated site layout planning framework for crowded building sites based on Building Information Modelling (BIM). Their dynamic technique uses data from a Building Information Modelling (BIM) model to determine the size and dimensions required for each facility. Furthermore, an algorithm, in conjunction with GAs, calculates real trip pathways to produce optimal solutions (layouts). It found that GAs are highly beneficial and easy to use, making them ideal for tackling large-scale issues, particularly in the context of multi-objective optimization.

To address the stated challenges, the constraints of the current safety objective function and the shortcomings of the weighted sum approach in solving multi-objective optimization problems, this study developed a Genetic Algorithm (GA) model. The major purpose of this model is to assist construction site planners during the preconstruction phase by providing a more complete analysis for developing a safe site layout design. The study's specific goal is to improve the layout of temporary facilities (TFs) on building sites by including new safety aspects. The developed model has been tested in a case study to ensure its feasibility and efficacy. The findings of this case study are intended to provide useful advice for developing a safe construction site layout plan in a more scientific and logically rigorous manner. This study supports prior findings in the literature, notably those presented by Medhat et al. (2023), Rizk Elimam et al. (2022), Yousri et al. (2023) and Abdelalim, et al. (2016, 2017, 2018, 2019, 2020, 2021, 2022, and 2023).

RESEARCH METHODOLOGY

The model description will begin with an explanation of the optimization technique that will be used, followed by a portrayal of the location and its facilities. The individual components of the proposed Construction Site Layout Planning (CSLP) model, such as decision variables, objective functions, and constraints, will be explicitly defined. Finally, the concept of travelling distance between facilities will be presented.

Optimization model using GA

This study uses the Genetic Algorithm (GA) as a heuristic optimization strategy, taking inspiration from biology. In Genetic Algorithms (GA), possible solutions are represented as chromosomes composed of genes, with each gene representing the value of a variable under optimisation. A chromosome is essentially a series of genes that has all of the optimisation variables' values. The efficacy of these chromosomes is measured using a fitness function (Gen & Lin 2023; Sanad et al., 2008; Hassanen & Abdelalim, 2022A, B).

The Genetic Algorithm (GA) method begins by randomly producing a population that has a set of chromosomes. Figure 1 depicts the three basic procedures used to find the fittest chromosome: selection, crossover, and mutation. The fittest chromosome is the one with the greatest or lowest value (depending on whether the fitness function is to be minimized or maximized). During crossover, genes are exchanged between two chromosomes at random. The selection of chromosomes for crossing is biased towards the fitter ones, giving them a better chance of being picked. During this process, certain genes from both chromosomes are randomly swapped. To avoid being trapped in a local optimal solution, the procedure incorporates mutation, which involves randomly changing the value of one or more genes. Each cycle produces a new generation of chromosomes, and their fitness is evaluated using the fitness function. One frequent stopping condition for iteration is to establish a maximum number of generations (Li & Love, 2000).

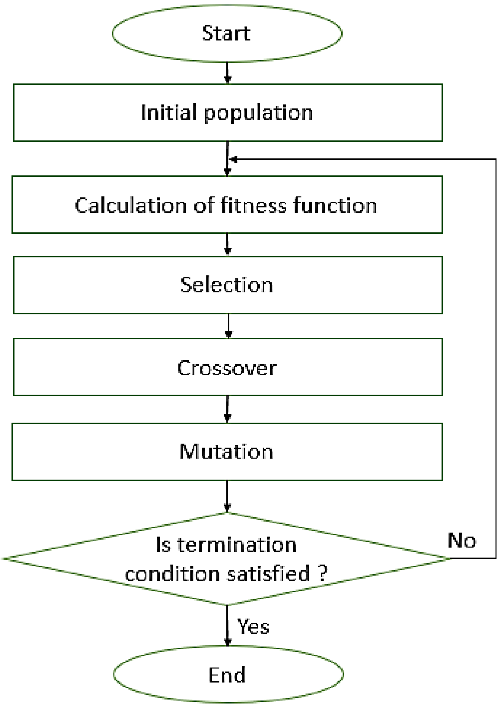


Figure 1: Process of Genetic Algorithm Optimization.

In this study, a chromosome is divided into two major parts that include genes related to site layout and building plan factors. The site layout portion assigns smaller blocks to each facility's variables, such as size, orientation, and location. The number of genes in each smaller block varies according to the facility's parameters. For example, if a facility has a fixed size, a variable position, and a variable orientation, its associated block will include two genes that indicate its location and orientation. The total number of smaller blocks in the site plan section corresponds to the overall number of facilities. Similarly, the building plan section has many genes that correlate to the construction plan variables. The next step is to determine the search domain for these variables. The model takes into account specific constraints and assumptions when it comes to site layout variables. The model incorporates the following assumptions:

- Facilities are presumed to be rectangular.
- The lower-left corner coordinates are utilized to determine probable sites for facilities.
- Facilities can only be oriented between 0 and 90 degrees.
- Facility sizes must be defined by the planner.

These assumptions serve to specify the parameters and constraints within which the variables are optimized throughout the genetic algorithm procedure.

Representation of Site Facilities

Benjaoran and Peansupap (2020) divide site facilities into four types: fixed facilities (FF) (e.g., buildings), access roads (AR), obstacles (OB) (e.g., trees or ancient buildings) and temporary facilities (TFs) (e.g., field offices). Before beginning any project, the size and shape of each facility must be surveyed and predetermined. Fixed facilities (FF) and obstacles (OB) on-site should be represented by four coordinates due to their potential irregular shape, whereas temporary facilities (TF) are represented by their respective positions using the lower-left corner (LC) (e.g., TFi (X1i, Y1i)), as shown in Figure2. These coordinates serve as a reference point for measuring the size and locations of facilities. The lower-left corner (LC) coordinates specify the beginning point of each structure, establishing a uniform foundation for mapping and analyzing the site layout.

Site boundary representation is a graphical portrayal or description of a given site's limit. It specifies the boundaries of the place and aids in understanding its size and geographical context. Typically, site boundary representation may be visualized using the following methods: (1) boundary lines: the site boundary can be depicted by drawing lines on a map to show the borders of the property or (2) Coordinates: Site boundaries can also be represented as coordinate points that designate the site's corners or critical locations, as shown in Figure 2.

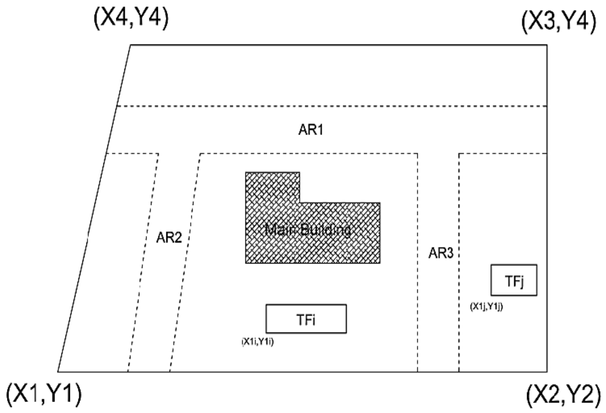


Figure 2: Representation of site boundary and facilities

Decision variables

The decision variables in the Construction Site Layout Planning (CSLP) model provide critical information about a viable site layout, such as the coordinates of the facility's lower-left corner and orientation. The decision variable matrix is represented as (Xi, Yi, Oi) for i = 1-n, where Xi and Yi are the coordinates of the lower-left corner of facilities, Oi is the facility's orientation, and n is the total number of temporary facilities (TFs) to be organized.

Objective functions

The strategic positioning of temporary facilities within a construction site is heavily influenced by the distances between these facilities, all while considering the achievement of pre-defined objective functions. Optimizing the positioning of these facilities on the site is vital to ensure enhanced safety performance, particularly in terms of their potential impact on each other's safety. To accomplish this optimization, a genetic algorithm model has been created, integrating two objective functions: one aimed at improving safety and the other at reducing costs.

Objective Function For total transportation cost

The primary objective function in the problem model is commonly known as the cost function, with its main objective being the minimization of the overall cost associated with travelling between temporary facilities (TFs). Equation (1) represents the mathematical expression of this objective function.

$$\text{Minimize total cost} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} d_{ij} \cdot R_{1ij} \qquad (1)$$

Where d_{ij} = travelling distance between facilities, R_{1ij} = desired proximity weight value between facilities i and j, and n = total number of facilities.

Unit-weighting relationships are significant in indicating the strength of connections between two facilities in the optimization process. Facilities with significant interdependencies or supporting interrelated operations are assigned higher unit weighting relationships, suggesting that they should be positioned near each other. Conversely, facilities with weaker relationships are placed further apart. Previous research by Hegazy & Elbeltagi (1999) and Zouein et al. (2002) found that these unit-weighting relationships are controlled by the proximity or degree of closeness between facility pairs. Ning et al. (2010) propose that proximity levels are influenced by six factors: material flows, information flows, personnel flows, equipment flows, safety and environmental concerns, and user preferences. Quantifying these factors directly poses challenges. In past research, planners have often subjectively assessed proximity levels through pairwise comparisons (Hegazy & Elbeltagi, 1999; Sanad et al., 2008).

In this study, the weighting of proximity relationships between different facilities is implemented by using exponential number scaling based on fuzzy set theory and planner preferences. The proposed model classifies proximity levels between facility pairs into six categories, which are then converted into six unit-weighting relationships, as outlined in Table 1. A strong proximity relationship between two facilities results in a higher unit weighting, suggesting that they should be located in close proximity to each other.

Table 1: Closeness Relationships

Proximity relationship between facilities	Unit weightings
Necessary (A)	65 = 7,776
Especially important (E)	64 = 1,296
Important (I)	63 = 216
Ordinary important (O)	62 = 36
Unimportant (U)	61 = 6
Undesirable (X)	60 = 1

Objective function related to facility safety relationship

The facility safety relationship pertains to the potential risks arising from interactions between different facilities within a construction site. These interactions encompass the flow of various resources, including the frequency of transportation, material movement, personnel mobility, and equipment usage among the facilities. The degree of this relationship can be quantified using metrics such as transportation units per day, the number of employee trips per day, and the quantity of the equipment involved in transfers between the facilities (Ning et al., 2010, 2011).

An increase in the frequency of interaction flows between facilities results in a higher probability of conflicts or collisions among materials, personnel, and equipment. This risk correlates positively with the intensity of contact flows. Furthermore, as resources are required to travel greater distances between facilities, more sites of crossing and overlapping occur along the way. The frequency of road traffic crossing or overlapping is dependent on the distance between facilities, demonstrating a positive link between risk level and distance (El-Rayes et al., 2005). To improve the safety performance of the construction site layout, it is critical to reduce the risk associated with the facility safety relationship, as indicated in Equation (2).

$$\text{Minimize safety relationship} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} d_{ij} \cdot R_{2ij} \qquad (2)$$

Where d_{ij} = travelling distance between facilities, R_{2ij} = value of the facility safety relationship considering quantitative flows of material, personnel, and equipment between facilities i and j; n = total number of facilities.

To evaluate the geographic safety relationship based on different measurement scales for the three quantitative flows (i.e., transportation frequency of resources, personnel flow, and equipment flow), five assessment levels are used. These levels are categorized as VH (very high), H (high), M (medium), L (low), and N (negligible). The assessment rule and corresponding assumed values for each assessment level are outlined in Table 2. The purpose of this assessment is to effectively gauge and classify the risk degree associated with the interactions among facilities in terms of their safety impact.

Table 2: Five Assessment Levels for Quantitative Flow

Assessment Level	Assumed Value
Very High (VH)	243
High (H)	81
Medium (M)	27
Low (L)	9
Negligible (N)	3

Site layout planning constraints

The feasibility approval for any site layout is assessed through a set of constrained functions. The constraints applied to Construction Site Layout Planning (CSLP) involve considerations such as site boundary, overlapping, and inter-facility distance constraints. Each rectangular facility is defined by two coordinates: the lower left corner (LC) and the upper right corner (UC), labelled as (X1i, Y1i) and (X2i, Y2i), respectively, as shown in Figure 3.

The site boundary constraints

The constraint restricts the placement of any facility outside the site border, which is enforced by solving the following equation (3).

$$(X_{1i}, Y_{1i})\ and\ (X_{2i}, Y_{2i}) \Subset [SBACs] \text{ for } i = 1, 2, 3, n \qquad (3)$$

Overlapping constraint

This constraint prevents the occupancy of more than one facility within the given site space. This requirement is imposed for facility I and j with lower left corner (LC) and upper right corner (UC) coordinates represented as (X_{1i}, Y_{1i}), (X_{2i}, Y_{2i}), (X_{1j}, Y_{1j}), and (X_{2j}, Y_{2j}), respectively, by meeting the following equation (4).

$$Max\{[X_{1i} - X_{2j}]\,[X_{2i} - X_{1j}], \\ [Y_{1i} - Y_{2j}]\,[Y_{2i} - Y_{1j}]\} \geq 0 \qquad (4)$$

The inter-facility distance constraint

This constraint requires any pair of facilities to be either close together or far away. This constraint has been introduced to ensure safety and productivity. For example, it guarantees that the site office is located away from the loud workshop and any dust pollution on the premises. The satisfaction of this constraint is expressed through the conditions specified in equation (5).

Travelling Distance

Typically, the distance between facilities is an important factor in establishing the majority of the relevant target functions in site layout planning (SLP). In this study, facility distances were calculated using the Euclidean distance or displacement, with the centroid of the facility shape acting as a reference point. This method allows distances to be calculated based on straight-line measurements or overall shifts between facilities, taking into account the centre point of the facility's shape.

$$(X_{2i} = X_{1j})\ and\ (Y_{2i} - Y_{1j}) = C, \text{ or} \\ (Y_{2i} = Y_{1j})\ and\ (X_{2i} - X_{1j}) = C \qquad (5)$$

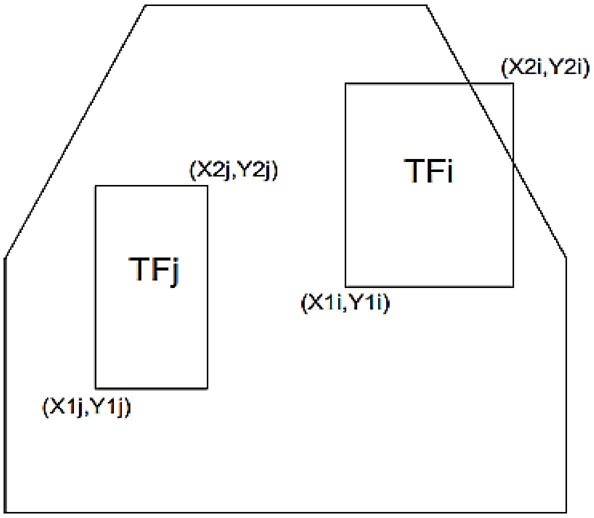


Figure 3: Site layout constrains representation.

To calculate the journey distance using the Euclidean approach for site planning, compute the straight-line distance between two locations in a two-dimensional plane. This may be computed by taking the coordinates of the points and using the Euclidean distance formula, as shown in equation (6). By putting the coordinates into the formula, the distance can be calculated. For example, if we have Point A at (2, 5) and Point B at (7, 9), the Euclidean distance between them is about 6.40 units, as seen in Figure 4.

$$\text{Euclidean distance} = \sqrt{\left(X_a - X_b\right)^2 + \left(Y_a - Y_b\right)^2} \qquad (6)$$

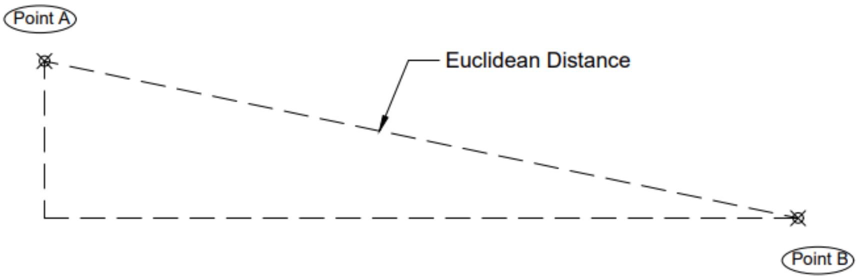


Figure 4: Euclidean distance between two points

SITE LAYOUT PLANNING SYSTEM

The site layout model and Genetic Algorithms (GAs) approach were carried out utilizing a commercial spreadsheet programme to simplify and automate site layout planning. Microsoft Excel was chosen as the software platform for this study due to its easy-to-use interface and powerful programming features. Figure 1 depicts the GA procedure's steps in detail. The process was integrated into a complete site layout design system via Microsoft Excel's macro language. An extensive programming work was required to implement the evolutionary algorithm technique, design a user-friendly interface, and experiment with various components. The resultant workbook includes five worksheets:

1. Main Menu Sheet: This sheet offers a simple interface with buttons to activate different options, depicted in Figure 5.
2. Storage Sheet: Used for storing user input regarding facility data.
3. Preference Matrix Sheet: Contains user-input cells for specifying desired proximity weights and quantitative flow.
4. Site-Map Sheet: Displays a visual representation or drawing of the site.
5. Optimization Model Sheet: This sheet houses all equations and constraints essential for the optimization model.

The system's development involved meticulous coding of the genetic algorithm, creating an interface for user interaction, managing input data, designing the visual representation of the site, and integrating mathematical components necessary for the optimization model all within the Excel workbook structure.

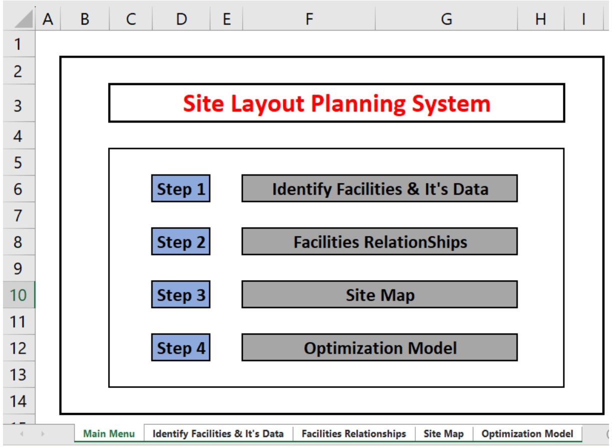
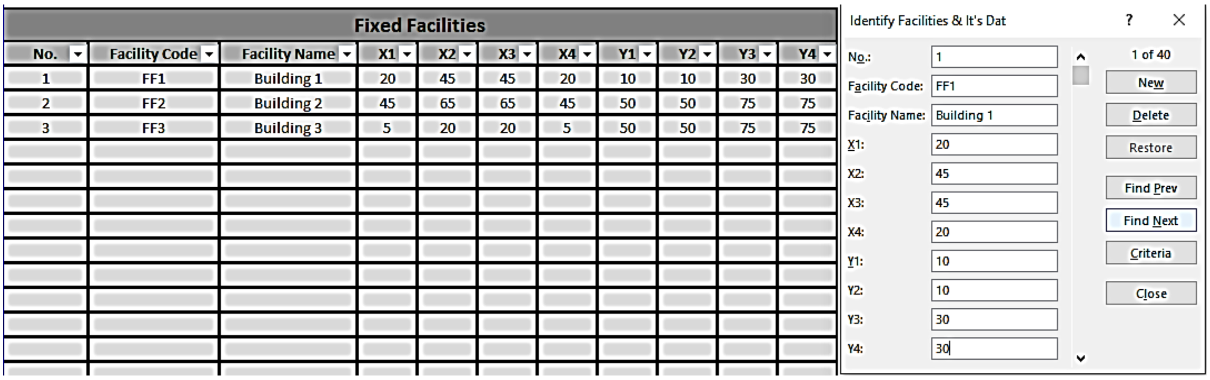


Figure 5: Main Menu

Initially, users need to define both fixed and temporary facilities, providing crucial details for each type. For fixed facilities, the following information is required: facility code, facility name and four coordinates defining the location (as shown in Figure 6). For temporary facilities, the necessary details include: facility code, facility name, dimensions (Length and width), assumed orientation and starting lower-left corner coordinates (LC) (as shown in Figure 7).

Once all facilities are defined, users can input proximity weights, indicating the closeness relationship between each pair of facilities. This information is illustrated in Figure 8. Additionally, the safety relationship is established based on the quantitative flow between facilities, as demonstrated in Figure 9.



Fixed Facilities

No.	Facility Code	Facility Name	X1	X2	X3	X4	Y1	Y2	Y3	Y4
1	FF1	Building 1	20	45	45	20	10	10	30	30
2	FF2	Building 2	45	65	65	45	50	50	75	75
3	FF3	Building 3	5	20	20	5	50	50	75	75

Identify Facilities & It's Dat

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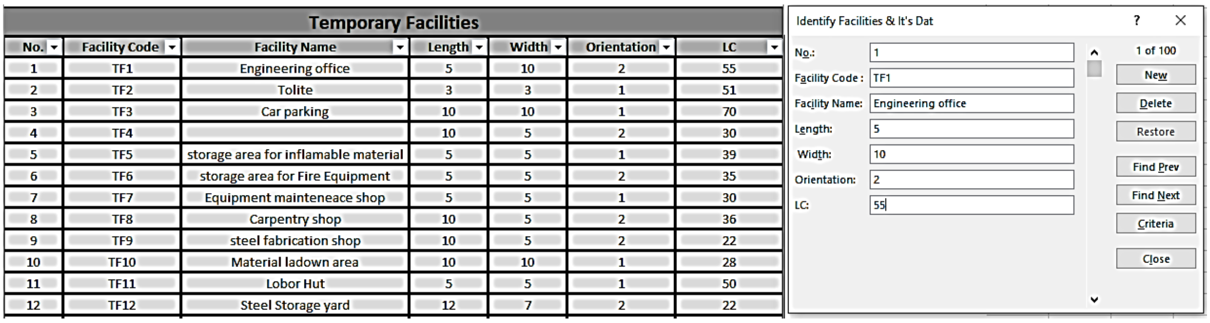
No.: 1
Facility Code: FF1
Facility Name: Building 1
X1: 20
X2: 45
X3: 45
X4: 20
Y1: 10
Y2: 10
Y3: 30
Y4: 30

Figure 6: Input data for Fixed Facility



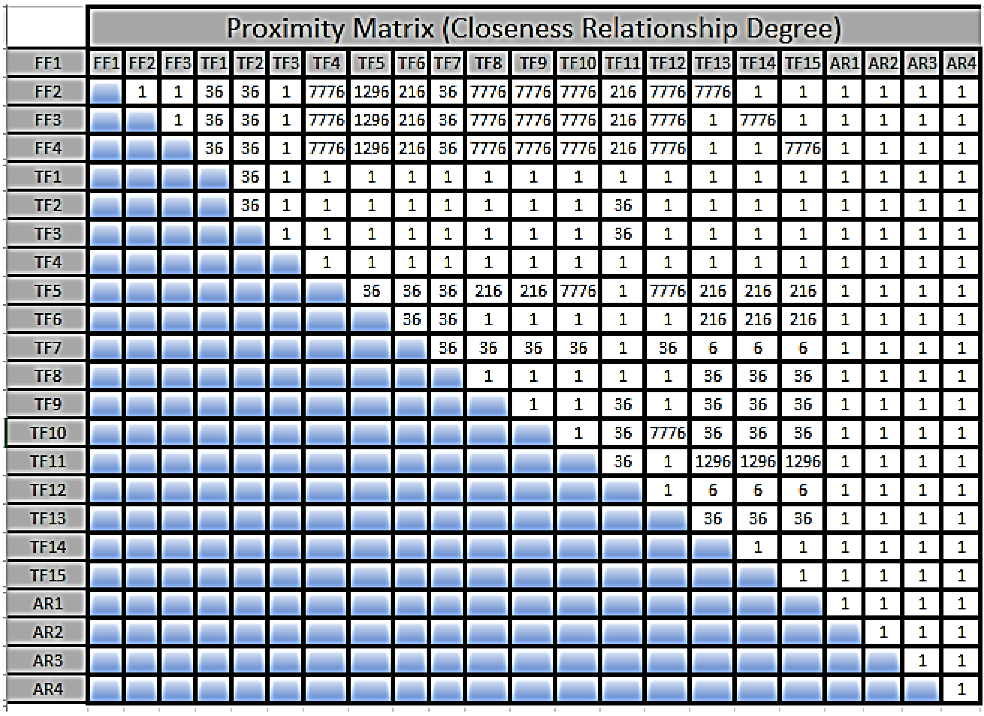
Temporary Facilities

No.	Facility Code	Facility Name	Length	Width	Orientation	LC
1	TF1	Engineering office	5	10	2	55
2	TF2	Tolite	3	3	1	51
3	TF3	Car parking	10	10	1	70
4	TF4		10	5	2	30
5	TF5	storage area for inflamable material	5	5	1	39
6	TF6	storage area for Fire Equipment	5	5	2	35
7	TF7	Equipment mainteneace shop	5	5	1	30
8	TF8	Carpentry shop	10	5	2	36
9	TF9	steel fabrication shop	10	5	2	22
10	TF10	Material ladown area	10	10	1	28
11	TF11	Lobor Hut	5	5	1	50
12	TF12	Steel Storage yard	12	7	2	22

Identify Facilities & It's Dat

No.: 1
Facility Code : TF1
Facility Name: Engineering office
Length: 5
Width: 10
Orientation: 2
LC: 55

Figure 7: Input data for Temporary Facilities



Proximity Matrix (Closeness Relationship Degree)

FF1	FF1	FF2	FF3	TF1	TF2	TF3	TF4	TF5	TF6	TF7	TF8	TF9	TF10	TF11	TF12	TF13	TF14	TF15	AR1	AR2	AR3	AR4
FF2		1	1	36	36	1	7776	1296	216	36	7776	7776	7776	216	7776	7776	1	1	1	1	1	1
FF3			1	36	36	1	7776	1296	216	36	7776	7776	7776	216	7776	1	7776	1	1	1	1	1
FF4				36	36	1	7776	1296	216	36	7776	7776	7776	216	7776	1	1	7776	1	1	1	1
TF1					36	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
TF2					36	1	1	1	1	1	1	1	1	36	1	1	1	1	1	1	1	1
TF3						1	1	1	1	1	1	1	1	36	1	1	1	1	1	1	1	1
TF4							1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
TF5								36	36	36	216	216	7776	1	7776	216	216	216	1	1	1	1
TF6									36	36	1	1	1	1	1	216	216	216	1	1	1	1
TF7										36	36	36	36	1	36	6	6	6	1	1	1	1
TF8											1	1	1	1	1	36	36	36	1	1	1	1
TF9												1	1	36	1	36	36	36	1	1	1	1
TF10													1	36	7776	36	36	36	1	1	1	1
TF11														36	1	1296	1296	1296	1	1	1	1
TF12															1	6	6	6	1	1	1	1
TF13																36	36	36	1	1	1	1
TF14																	1	1	1	1	1	1
TF15																		1	1	1	1	1
AR1																			1	1	1	1
AR2																				1	1	1
AR3																					1	1
AR4																						1

Figure 8: Proximity Weight between facilities

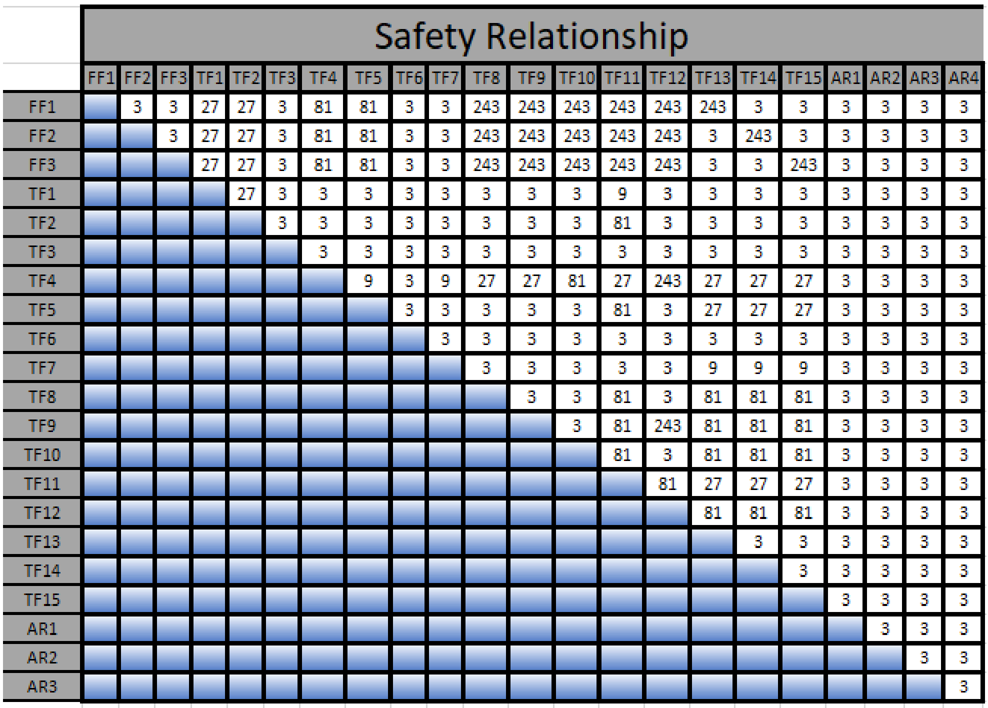
Finally, start genetic algorithm optimization for the model using evolver after assigning variables, constraints and objective functions. The site map automatically draws the site after the optimization process has been finished.

CASE STUDY

The case study serves as a means to validate the proposed Genetic Algorithm (GA) model. By applying the model to the case study and adjusting the parameters appropriately, it becomes possible to obtain the best possible results for the construction site layout. Additionally, the case study enables the practical implementation of the model in real-world scenarios. Notably, through analyzing the results, it becomes feasible to understand the influence of facility layout on both safety and cost at the construction site. Using this insight, valuable recommendations can be provided to the site manager for enhancing safety performance and reducing costs by efficiently arranging the temporary facilities.

Case Description

The construction site features various facilities, which can be found in Table 3. There are a total of fifteen temporary facilities, categorized into two types: fixed facilities and free facilities. Among these, seven facilities, including the engineering office, car parking, toilets, three material hoists, and the tower crane, are considered fixed facilities as they are situated in specific, predetermined locations. Specifically, the engineering office and car parking are conveniently positioned near the site entrance. Material hoists play a crucial role in transporting both construction materials and labour to the superstructure of the building. Simultaneously, the tower crane is efficiently employed to transport materials for three distinct buildings. Conversely, the remaining facilities are categorized as free facilities, and their optimal locations are determined through the proposed algorithm's optimization process.



Safety Relationship

	FF1	FF2	FF3	TF1	TF2	TF3	TF4	TF5	TF6	TF7	TF8	TF9	TF10	TF11	TF12	TF13	TF14	TF15	AR1	AR2	AR3	AR4
FF1		3	3	27	27	3	81	81	3	3	243	243	243	243	243	243	3	3	3	3	3	3
FF2			3	27	27	3	81	81	3	3	243	243	243	243	243	3	243	3	3	3	3	3
FF3				27	27	3	81	81	3	3	243	243	243	243	243	3	3	243	3	3	3	3
TF1					27	3	3	3	3	3	3	3	3	9	3	3	3	3	3	3	3	3
TF2						3	3	3	3	3	3	3	3	81	3	3	3	3	3	3	3	3
TF3							3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
TF4								9	3	9	27	27	81	27	243	27	27	27	3	3	3	3
TF5									3	3	3	3	3	81	3	27	27	27	3	3	3	3
TF6										3	3	3	3	3	3	3	3	3	3	3	3	3
TF7											3	3	3	3	3	9	9	9	3	3	3	3
TF8												3	3	81	3	81	81	81	3	3	3	3
TF9													3	81	243	81	81	81	3	3	3	3
TF10														81	3	81	81	81	3	3	3	3
TF11															81	27	27	27	3	3	3	3
TF12																81	81	81	3	3	3	3
TF13																	3	3	3	3	3	3
TF14																		3	3	3	3	3
TF15																			3	3	3	3
AR1																				3	3	3
AR2																					3	3
AR3																						3

Figure 9: Safety Relationships

Table 3: Temporary Facilities for Construction Site

Facility No.	Facility Name	Dimensions	Status
TF1	Engineering office	10 x 5	Fixed
TF2	Toilet	3 x 3	Fixed
TF3	Car Parking	10 x 10	Fixed
TF4	Tower crane	10 x 5	Fixed
TF5	Storage area for inflammable material	5 x 5	Free
TF6	Storage area for fire equipment	5 x 5	Free
TF7	Equipment maintenance shop	5 x 5	Free
TF8	Carpentry shop	10 x 5	Free
TF9	Steel fabrication shop	10 x 5	Free
TF10	Material laydown area	10 x 10	Free
TF11	Labor hut	5 x 5	Free
TF12	Steel storage yard	12 x 7	Free
TF13	Material hoist (for B1)	5 x 5	Fixed
TF14	Material hoist (for B2)	5 x 5	Fixed
TF15	Material hoist (for B3)	5 x 5	Fixed

Site mapping and facility representation

In this research, the site boundary (SB), fixed facilities (FF) (e.g., buildings), and access road (AR) are defined in terms of four coordinates. Additionally, temporary facilities (TFs) are defined in terms of lower-left corner coordinates (LC), which act as a starting point along with their dimensions and orientation. The orientation ranges between 1 and 2, determining which one of the two dimensions is horizontal and which one is vertical, helping to calculate the remaining coordinates of these facilities by adding the length to the starting point.

For example, consider a facility with a total area of 50 m² (10 m × 5 m) and a starting point at (X_{1i}, Y_{1i}) equal to (4, 5) with an orientation of 2. This means the horizontal length is equal to 5 m, while the vertical length is equal to 10 m. The remaining coordinates for the facility can be determined by adding the length to the starting coordinates. The lower right coordinate (X_{2i}, Y_{2i}) can be calculated as follows: ($X_{2i} = X_{1i} + 5$ m $= 4 + 5 = 9$), while ($Y_{2i} = Y_{1i} = 5$).The upper right coordinate (X_{3i}, Y_{3i}) can be calculated as follows: ($X_{3i} = X_{2i} = 9$), while ($Y_{3i} = Y_{2i} + 10$ m $= 5 + 10 = 15$).The upper left coordinate (X_{4i}, Y_{4i}) can be calculated as follows: ($X_{4i} = X_{1i} = 4$), while ($Y_{4i} = Y_{3i} = 15$).

Define the distance between facilities

In this study, the term "facility distance" refers to the Euclidean distance measured between the gravity centres of facilities (GCF). The coordinates of this centre can be determined by finding the intersection point between two diagonals. The gravity centre coordinates are denoted as (Xc, Yc).

After determining the coordinates of the centre of each facility, the distance between two facilities, i and j, can be calculated using equation (7).

$$d_{ij} = \sqrt{\left(X_{ci} - X_{cj}\right)^2 + \left(Y_{ci} - Y_{cj}\right)^2} \tag{7}$$

RESULT OF CASE STUDY

The optimization model utilizing the Genetic Algorithm (GA) identifies alternative construction site layouts (optimal solutions) that meet the dual objectives of minimizing total transportation cost and addressing safety relationships. Figure 10 displays the outcomes of the model solutions obtained for the specified case study.

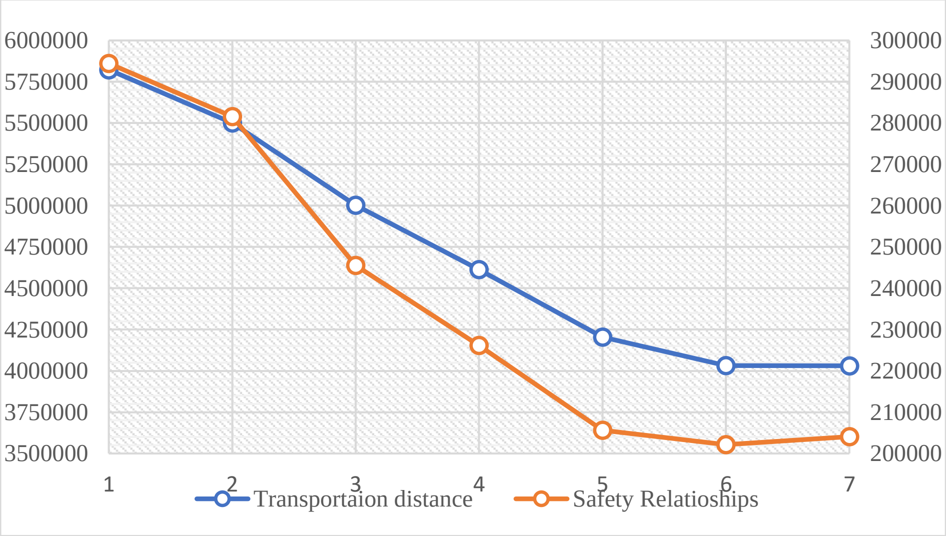


Figure10: The result of site layout alternatives

In an optimization problem with two objective functions, it's common to generate numerous optimal solutions. This arises from the inherent conflict between multiple objectives, making it challenging for a single solution to fulfil the requirements for all objectives simultaneously. In mathematical terms, one solution typically cannot dominate the rest. While a solution may achieve the minimum value for one objective, it may not simultaneously satisfy the other. As a result, the algorithm identified seven optimal solutions in this case. The choice for stopping optimization is based on decision-making by the site manager. The model initially starts to minimize the two objective functions until it reaches a point at which one of them decreases while the other increases. Indeed, safety and cost requirements can differ across various projects, and the design of site layouts is closely tied to user preferences. To define the safety and cost goals for this specific project, input was gathered from site managers. They were tasked with expressing the significance of the two objective functions, allowing them to prioritize and emphasize aspects that are essential for improving the quality of the construction site layout plans. This collaborative approach facilitates informed decision-making regarding the design of the site layout.

The schematic drawings for each of P1, P6, and P7 with the optimal results are displayed in detail in Figures (11-13), respectively. Additionally, Table (4) shows the optimal results for the construction site layout planning model.

Table 4: The optimal results for construction site layout alternatives

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

DISCUSSION OF RESULTS

Among the three potential site layouts, construction site arrangement P1 illustrated in Figure 11 exhibits the highest values for both transportation costs and safety considerations. This layout closely resembles the original configuration utilized at the construction site. In P1, temporary facilities (TFs) are strategically positioned at a considerable distance from TF4 (tower crane), TF13 (material hoist #1), TF14 (material hoist #2), and TF15 (material hoist #3), contributing to a lower risk level within a specific safety zone. The placement of TF10 (material laydown area) far from TF4 (tower crane) results in increased travelling distances, consequently elevating the values of the two objective functions: transportation cost and safety relationships. Furthermore, TF9 (steel fabrication shop), situated at the lower-left corner of the site, away from TF12 (steel storage area), significantly impacts travelling distances. Ultimately, the temporary facilities (TFs) are dispersed with considerable spacing between them, reflecting the maximum values among the alternatives. Consequently, the total transportation cost for resources reaches its high value at 5,822,843, accompanied by the highest safety relationship value of 294,441.3.

When contrasting the layouts of P1 (depicted in Figure 11) and P6 (shown in Figure 12), the allocation of temporary facilities (TFs) is notably more dispersed in P1 compared to P6. As a result, the safety relationship value in P6 is 202,141.7, which is lower than the corresponding value of 294,441.3 in P1. In P1, TF9 (steel fabrication shop) and TF8 (carpentry shop) are positioned at a considerable distance from TF10 (material laydown area), leading to increased material handling costs and consequently a higher resource transportation cost in P1 compared to P6. Meanwhile, TF9 (Steel fabrication shop) in P1 is situated farther away from TF12 (Steel storage area) than in P6, resulting in minimized travelling distance between them in P6. Nevertheless, the overall resource transportation cost is relatively lower in P6, totalling 4,032,664. Furthermore, P6 exhibits a more favourable arrangement where all temporary facilities are situated in close proximity to each other, taking construction productivity into account.

In layouts P6 (see Figure 12) and P7 (see Figure 13), TF11 (labour hut) is located far away from all other facilities in P7. However, this facility should be situated close to the other facilities to ensure maximum flowability between them. Additionally, TF7 (equipment maintenance shop) and TF6 (storage area for fire equipment) are closer to hazardous facilities in P7 compared to P6. All of these factors contribute to an increase in the value of the safety relationship, which reaches 204,113.9, even though transportation costs have decreased to 4,030,791. In the end, in P7's layout, it was not possible to fulfil the requirements of both objective functions simultaneously. The chosen construction site layout represents a compromise solution, specifically opting for construction site layout alternative P6.

COMPARISON OF THE RESULTS

The study by Ning (2018) proposed a tri-objective ant colony optimization (ACO) based model for planning safe construction site layouts. The model aimed to optimize construction site layouts considering three objectives: minimizing construction time, minimizing construction cost, and maximizing safety. By integrating ACO, which mimics the foraging behaviour of ants to find optimal solutions, the model sought to address the complex trade-offs between these objectives in construction site planning. Through their research, Ning (2018) demonstrated the effectiveness of the proposed model in generating layout configurations that simultaneously minimized construction time and cost while maximizing safety levels. By considering safety as a primary objective alongside time and cost, the model aimed to mitigate safety hazards and reduce the likelihood of accidents and injuries on construction sites. Overall, the study's results highlighted the potential of ACO-based models in optimizing construction site layouts to achieve a balance between time, cost, and safety considerations, ultimately contributing to improved project outcomes and enhanced worker well-being.

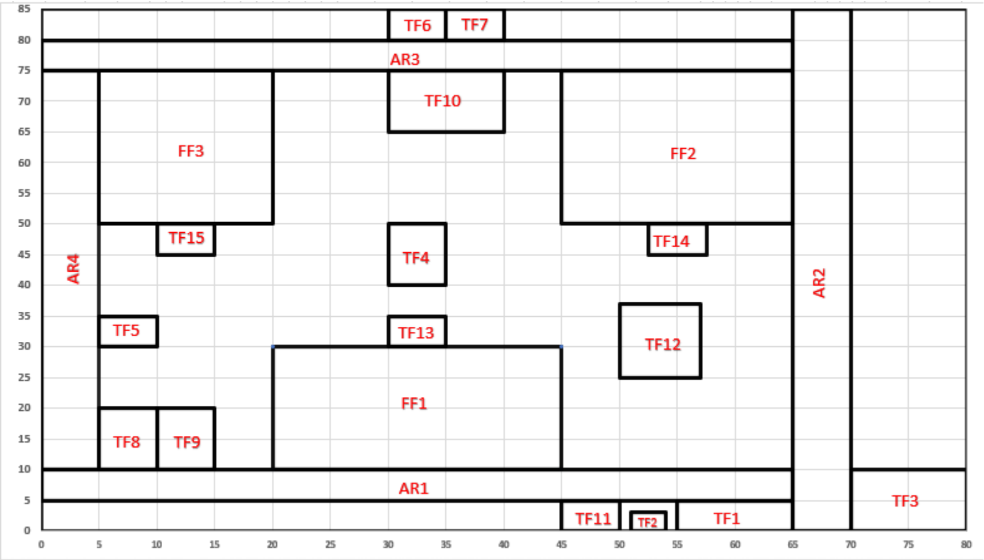


Figure 11: Schematic layout drawing for P1

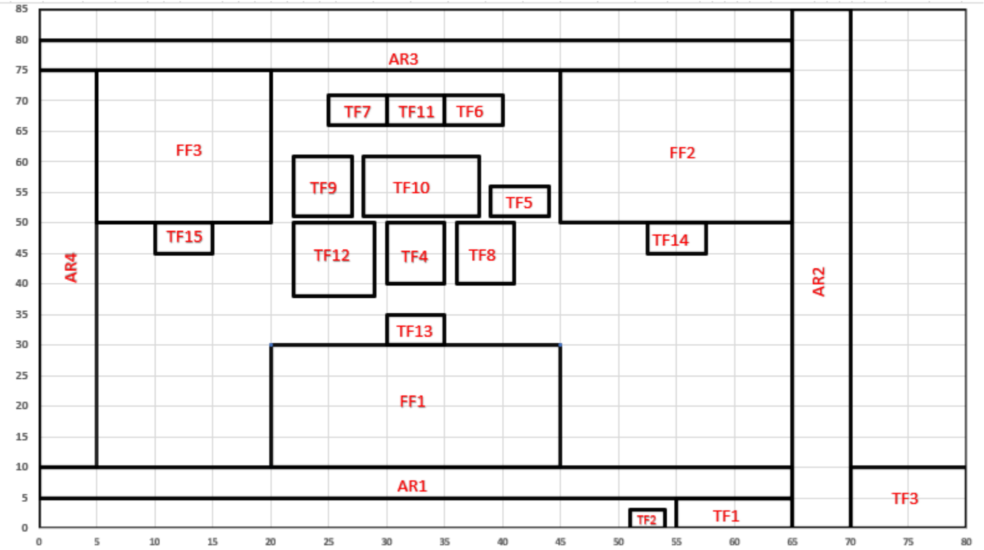


Figure 12: Schematic layout drawing for P6

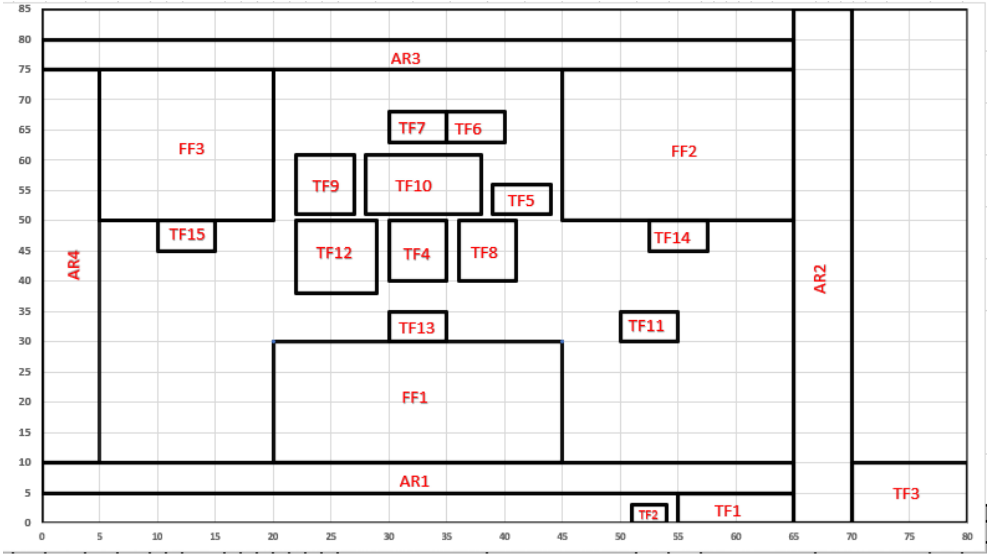


Figure 13: Schematic layout drawing for P7

There are several potential advantages to using Genetic Algorithms (GAs) instead of Ant Colony Optimization (ACO):

1. **Robustness to Local Optima:** Genetic Algorithms are less prone to getting trapped in local optima compared to ACO. This property is advantageous in complex optimization problems where finding globally optimal solutions is crucial.
2. **Handling Multiple Objectives:** GAs are well-suited for handling multiple objectives simultaneously, as they can easily accommodate diverse fitness functions and Pareto optimization techniques. In the context of the paper, which aims to optimize construction time, cost, and safety simultaneously, GAs offer a flexible framework for multi-objective optimization.
3. **Parameter Sensitivity:** GAs typically have fewer parameters to tune compared to ACO, making them easier to implement and less sensitive to parameter settings. This simplicity can streamline the optimization process and reduce the need for extensive parameter calibration.
4. **Scalability:** GAs are often more scalable than ACOs, particularly for large-scale optimization problems with numerous variables and constraints. Their population-based approach enables parallelization and efficient exploration of large solution spaces, which is advantageous for complex construction site layout planning.
5. **Diverse Search Operators:** GAs offer a wide range of genetic operators such as crossover, mutation, and selection, which can be tailored to suit the specific characteristics of the optimization problem. This flexibility allows for diverse exploration of the solution space, potentially leading to more diverse and robust solutions.
6. **Ease of Implementation:** GAs have a straightforward conceptual framework and are relatively easy to implement compared to ACO, which involves complex pheromone-based communication mechanisms. This simplicity can facilitate the development and deployment of optimization models in practical construction planning scenarios.

Genetic Algorithms (GAs) offer several advantages for construction site layout planning. They excel in exploring large solution spaces, making them suitable for complex layout problems with multiple variables and constraints. GAs are robust against getting trapped in local optima and can efficiently handle problems with multiple objectives. Additionally, their adaptability to dynamic environments and potential for parallelization make them valuable tools for optimizing construction site layouts. Overall, GAs present promising opportunities to enhance efficiency, productivity, and safety in construction projects.

CONCLUSION

The optimisation issue in construction site layout planning (CSLP) seeks to develop the best arrangements for locating temporary project facilities inside the construction site borders. This problem may be efficiently addressed using a multi-objective optimization technique, to minimize both the overall distance travelled between facilities and the related transportation costs. Furthermore, the optimization considers facility development costs, site features, and safety concerns raised by the closeness or distance of particular facilities to others.

In this study, an optimization model based on genetic algorithms (GA) is developed to handle construction site layout planning (CSLP) challenges by incorporating transportation and construction costs as well as safety factors. The use of a genetic algorithm for optimization is supported by its capacity to efficiently examine a large number of alternative solutions. The suggested model was tested in a case study, and the findings show that it provides an effective and sensible solution for layout planning, taking into account input parameters and issue constraints. Furthermore, this study provides a practical and scientific method for designing a secure construction site layout, as well as important advice to site managers when making decisions about the organisation of temporary facilities on construction sites.

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PLANIRANJE IZGLEDA GRADILIŠTA UZIMAJUĆI U OBZIR TROŠKOVE PUTOVANJA I BEZBEDNOSNE ODNOSE KORIŠĆENJEM TEHNIKE GENETSKOG ALGORITAMA

Efikasno planiranje rasporeda gradilišta je ključno za uspešno izvođenje projekta, doprinoseći povećanju produktivnosti i bezbednosti na gradilištu. Ovo uključuje identifikaciju privremenih objekata ili objekata potrebnih za podršku građevinskim aktivnostima, odabir njihove veličine i rasporeda. i njihovo strateško postavljanje u okviru raspoloživog prostora na lokaciji. Problem planiranja izgleda lokacije je izazovno pitanje u kombinatornoj optimizaciji, posebno zato što uključuje više ciljeva. Njegova složenost eskalira sa povećanjem broja objekata i ograničenja. Dok postojeća istraživanja predložu različite analitičke, heurističke i metaheurističke pristupe za rešavanje ovog problema, mnoge prethodne studije su se fokusirale na ograničen broj objekata, naglašavajući minimiziranje udaljenosti putovanja dok zanemaruju druge relevantne faktore koji se odnose na troškove i donošenje odluka. Ova studija ima za cilj da stvori praktična i efikasna rešenja za izgled lokacije korišćenjem realnog prikaza, koji uzima u obzir ne samo udaljenost putovanja, već i odnose između troškova i bezbednosti. Razvijen je model za optimizaciju sa dve funkcije cilja kako bi se minimizirala udaljenost između objekata, kako bi se minimizirale funkcije troškova, koje proizilaze iz različitih faktora, kao što su troškovi izgradnje, vezani za različite lokacije objekta i troškovi transporta između lokacija, kao i da se minimiziraju rizici na osnovu kvantitativne matrice protoka i rastojanja između objekata, jer povećanje učestalosti protoka interakcije između objekata dovodi do veće verovatnoće kolizije. U ovom istraživanju, genetski algoritam (GA) je korišćen kao heuristički pristup u optimizaciji. Studija slučaja je primenjena na model, kako bi se istakle prednosti predloženog pristupa, ilustrujući njegovu efikasnost i sveobuhvatna rešenja za planiranje rasporeda gradilišta.

Ključne reči: Planiranje rasporeda gradilišta; Genetski algoritam (GA); Privremeni objekat; Fiksni objekat; Pristupni put.