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Multi-Objective Optimization Method of Industrial Workshop Layout from the Perspective of Low Carbon

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Abstract: A crucial measure to accelerate the low-carbon transformation of enterprises in the industrial sector involves stringent control over carbon emissions attributed to logistics and transportation activities. In this study, a multi-objective workshop layout optimization model is developed, aiming to minimize logistics cost per unit area and carbon emissions, and maximize the non-logistics relationship. The objective is to mitigate avoidable transportation-related carbon emissions during enterprise operations, while facilitating the co-development of the enterprise's economy and environment. The model is solved utilizing an enhanced NSGA-II algorithm, with the initial solution set optimized through a combination of system layout design method, dynamic adaptive crossover, and variation strategies. Additionally, the distribution function is introduced to enhance the elite retention strategy and boost the algorithm's search rate. By using an actual case study, the usefulness of the enhanced algorithm is demonstrated, and the plant's initial low-carbon layout is realized in order to advance the enterprises' sustainable growth.

Keywords: workshop layout; multi-objective optimization; enhanced NSGA-II algorithm; systematic layout planning

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1. Introduction

The escalating expansion of carbon emissions presents a formidable predicament, profoundly impacting both the environment and human existence. The imperative to curtail these emissions has garnered global consensus. On 22 September 2020, General Secretary Xi Jinping put forth China's "3060" dual-carbon target, accentuating the primacy of green and low-carbon development as the central theme in industrial transformation. Vitalizing workshop layout optimization emerges as an indispensable approach to realize low-carbonization at its core, enabling proactive scrutiny of carbon emission patterns. Adjustments made to the layout engender alterations in transportation modes and routes, thereby instigating fluctuations in carbon emission levels. Extensive research attests that transportation activities account for a staggering 93% of carbon dioxide emissions stemming from logistics operations, while warehousing activities contribute to the remaining 7% [1]. Concurrently, judicious facility layout design enhances overall operational efficiency and may lead to up to a 50% reduction in total operating costs, as substantiated by Sule [2] and Tompkins [3]. Consequently, effective control over carbon emissions during the design phase, timely feedback on layout adjustments, and meticulous optimization assume pivotal roles in mitigating carbon emissions during the transportation phase while augmenting an enterprise's carbon management prowess.

The Facility Layout Problem (FLP) pertains to organizing facilities in a plant area to achieve an optimal layout that aligns with predefined criteria or objectives, while considering constraints such as facility shape, size, orientation, and pick-up/drop-off points [4]. Factory layout is a part of facility layout, encompassing both overall factory layout and workshop layout [5]. Early in the second decade of the 21st century, research on FLP steadily strengthened, with the number of studies tripling compared to that before 2010. Researchers' interest in FLP has grown due to its practicality and interdisciplinary importance [6]. Perez-Gosende et al. propose a new classification framework for FLP, categorizing it by problem type, method and planning stage, production facility characteristics, material handling system configuration, methods for generating FLP alternative solutions, and evaluation methods. The authors emphasize that existing objective functions can be classified into two types: minimization and maximization, with materials handling cost (MHC) being a key factor for optimizing layout in industrial enterprises [7]. Moreover, some researchers have adopted alternative classification criteria, dividing objectives into qualitative and quantitative aspects [8–10].

In fact, it is widely recognized that layout problems encompass multiple aspects that give rise to conflicting objectives, falling under the category of multi-objective facility layout problems (mFLP) [11]. Over the past few decades, multi-objective facility layouts have been the subject of substantial study and development. Researchers have incorporated various factors and constraints to develop more practical and realistic models for multi-objective facility layouts. Their focus revolves around facility layouts aimed at objectives such as cost reduction, efficiency improvement, and service coverage increase. In the context of the green and low-carbon approach, there is a growing interest in environmental factors and sustainability considerations. Furthermore, in solving multi-objective facility layout problems, scholars are increasingly focusing on identifying the Pareto solution set to emphasize the equilibrium among optimization objectives. Novel multi-objective solution methods and their corresponding advancements are being introduced, including the multi-objective artificial immune system algorithm (MOAIS), the multi-objective ant colony algorithm (MOACO), and the multi-objective simulated annealing algorithm (MOSA). In conclusion, the integration of multi-objective facility layout with multi-objective solution algorithms represents a challenging and state-of-the-art research direction. The current research is currently at a developmental stage, and there are numerous challenges that need to be addressed.

In this paper, we employ the SLP method to analyze the initial data and develop a multi-objective model for workshop layout. The objective functions of this model aim to minimize logistics costs per unit area and carbon emissions while maximizing non-logistics relationships. To solve the multi-objective facility layout problem, we utilize an enhanced version of the NSGA-II algorithm. The effectiveness of the proposed model and algorithm is validated through illustrative examples.

The rest of the paper is structured as follows. Some relevant literature is given in Section 2. A multi-objective workshop layout model is formulated in Section 3. An enhanced algorithm for solving multi-objective problems is described in Section 4. A case study and analysis of the calculations in Section 5 are followed by the main conclusions, future prospects, and corresponding policy recommendations in the final section.

2. Literature Review

Optimizing the design of plant facility layout is an important and complex engineering problem faced by enterprises in the long term. The literature has extensively considered and investigated numerous variations of the FLP, with each variation having a wide range of proposed formulations and objectives. Meanwhile, several approaches have been presented consecutively to achieve effective solutions. This section focuses on two streams of literature on multi-objective facility layout and multi-objective optimization methods.

2.1. Research on Multi-Objective Facility Layout

The optimization objective plays a pivotal role in the facility layout, guiding the overall layout process and evaluating the effectiveness of the final layout solution. The optimization objectives for facility layout problems primarily revolve around reducing distance, time, or cost. Extensive research on layout has revealed that a single objective is insufficient to achieve overall benefits, leading to an increasing number of scholars investigating multi-objective layout problems.

Since Rosenblatt first proposed it as a means to reduce overall material handling costs and enhance the total relationship level, numerous studies on mFLP have been conducted [12]. Matai develops a multi-objective quadratic assignment model that integrates workflow, closeness rating, material handling time, and hazardous movement, all weighted as a unified objective. To tackle multi-objective facility layout problems, an enhanced simulated annealing method is proposed [13]. Pourhassan and Raissi, and Wang et al. employ a multi-objective genetic algorithm to solve a dynamic layout model, aiming to minimize the costs related to unit mobility and material handling [14,15]. Additionally, Liu et al. introduce a multi-objective particle swarm optimization algorithm that incorporates an objective space segmentation method. This approach is used to tackle the multi-objective unequal area facility layout problem, where the optimization objectives included material handling cost, total adjacency value, and shop utilization [16]. Chen et al. develop a multi-objective layout optimization model that considers layout cost per unit area, logistics cost per unit product, and layout entropy as optimization criteria. To solve this problem, they propose a clustered parallel multi-objective genetic algorithm based on Pareto optimization [17]. On the other hand, Jia et al. expand the layout objectives to include reducing the physical labor intensity of workers while optimizing the workshop layout. They establish a workshop layout optimization model from the perspective of human factors by integrating factors such as gender, relative metabolic rate, and logistics considerations [18].

However, existing multi-objectives typically focus on minimizing transport-related functions such as total handling cost, transport time, and transport distance [19]. Generally, layout optimization aims to reduce material handling costs, increase non-logistics relationships, maximize space utilization, or minimize safety hazards. However, the consideration of environmental impact, carbon emissions, and energy consumption is comparatively limited, and the potential for treating environmental objectives as independent optimization targets in facility layout is still ambiguous [20]. The arrangement and scheduling of workshops significantly impact the overall carbon emissions generated during the manufacturing process. By integrating optimization techniques for workshop layout and scheduling, it is possible to achieve additional reductions in total carbon emissions within the manufacturing process [21]. Ren et al. examine the effects of enhancing systematic layout planning (SLP) on reducing warehouse carbon emissions from the standpoint of a low-carbon economy, employing a soft path model as their analytical framework [22]. Li and Guo quantify the total carbon emissions of the remanufacturing process, providing new directions for low-carbon circulation in workshop layout problems [23]. Geng et al. propose a logistics park layout optimization method that considers carbon emissions through combining the STIRPAT model with the enhanced SLP method [24]. Mao et al. employ the FlexSim simulation software to assess and analyze the outcomes of SLP-based layout designs, taking into account carbon emissions and other assembly line-related metrics, with the aim of identifying the most suitable layout optimization strategy [25].

2.2. Research on Multi-Objective Optimization Methods

Since it has been established that the workshop layout problem is a combinatorial optimization problem (COP) with NP-hard characteristics [26], existing solution approaches can be broadly classified into two main categories: process-based methods and algorithm-based methods [27]. Among process-based approaches, the systematic layout planning (SLP) method introduced by Richard Muther (1961) stands out as the most prominent one [28]. However, this method suffers from the disadvantage of being susceptible to subjective influences. Consequently, in recent years, researchers have increasingly explored the integration of SLP with heuristic algorithms as a means to address this issue. Ye and Zhou combine SLP with mixed tabu search and local genetic algorithm to solve the workshop layout model with fixed longitudinal and traverse aisles based on logistics cost and non-logistics relationship closeness as dual objectives [29]. Wang et al. establish a prefabricated plant plan layout optimization model with minimum total material handling distance and maximum layout area utilization, apply SLP initial layout as part of the initial population, and select an artificial bee colony algorithm to solve the model [30].

When employing approximate methods to address facility layout problems, it is common for scholars to aggregate multiple sub-objectives into a composite objective through the application of weighting coefficients. However, the issue of premature convergence often arises as a result of the challenge involved in accurately determining the appropriate weighting coefficients. In comparison, Pareto-based methods directly optimize the multi-objective space and obviate the necessity of transforming multiple objectives. Consequently, multi-objective optimization algorithms capable of solving the Pareto solution set are emerging as the predominant approach for tackling multi-objective problems [17]. For instance, Jiang et al. utilize a multi-objective simulated annealing (MOSA) algorithm to address a facility layout problem driven by transportation lines [31]. Similarly, Zhang et al. employ the differential element cell multi-objective genetic algorithm (DECell) to optimize the layout of a workshop with multiple rows [32]. While all these algorithms are capable of attaining Pareto solutions to a certain extent, it is essential to consider their respective pros and cons within the context of the specific problem when selecting an algorithm.

The NSGA-II algorithm proposed by DEB has been widely used in solving multi-objective optimization problems due to its powerful global search capability, good convergence performance, and fast operation [33]. Despite NSGA-II's elitist characteristics and lack of shared parameters in its design, the algorithm still possesses shortcomings, including excessive reliance on the quality of the initial solution and a predisposition towards local optima [34]. Currently, NSGA-II is widely used for the assignment problem, allocation problem, traveling salesman problem, vehicle routing problem, scheduling problem, knapsack problem, and facility layout problems [35]. Huang et al. utilize the NSGA-II algorithm to solve a multi-objective optimization model for dynamic multiple-period layout problems of unequally sized facilities, with the optimization objectives being the sum of logistics handling and rearrangement costs, non-logistics relationships, and area utilization rate. The authors obtain the Pareto solution set, which overcomes the limitations of traditional weighting coefficients that are difficult to determine and cannot guarantee simultaneous optimization of multiple objectives [36]. Guo et al. employ the NSGA-II algorithm to tackle the facility layout problem involving unequal areas, motivated by two primary factors. Firstly, NSGA-II is an established and reliable algorithm suitable for engineering applications, and its chromosome-based coding structure enables rapid representation of the facility layout. Secondly, the two objectives, namely MHC and CRS, are inherently contradictory [37].

From the related works, it can be said that the multi-objective facility layout problem is still an active area. While the previously mentioned research has expanded the scope of workshop layout optimization studies, several limitations still exist. Firstly, the optimization objectives in workshop layout primarily revolve around maximizing economic benefits, encompassing factors such as area utilization, logistics cost, transportation distance and duration, robustness, and flexibility. However, there is a scarcity of research that focuses on optimizing workshop layout while also taking into account the influence of carbon emissions. Secondly, while the layout process often emphasizes carbon emissions resulting from workshop production processes, there is a dearth of quantitative analysis regarding carbon emissions during transportation. Thirdly, there is potential for further improvement of the NSGA-II algorithm in the domain of layout optimization problems.

In this study, we propose an enhanced version of the NSGA-II algorithm to address the multi-objective facility layout problem. Firstly, we quantify carbon emissions resulting from in-plant transportation in industrial enterprises by considering various influencing factors associated with different transportation modes. In contrast to the conventional focus on material handling costs, we incorporate both the planning and operational stages to establish a logistics cost per unit area target that better reflects the efficient utilization of workshop space. This approach enables us to construct a multi-objective model for workshop layout optimization, which simultaneously minimizes logistics cost per unit area, carbon emissions, and maximizes non-logistics relationships. In terms of algorithmic approach, we enhance the initial population of the NSGA-II algorithm by integrating the SLP method, introducing dynamic adaptive crossover, variant genetic operators, and employing an elite retention strategy based on the distribution function. Additionally, we evaluate the algorithm's convergence and distribution using hypervolume metrics and validate its performance through the utilization of ZDT series and DTLZ series test functions. Ultimately, we apply the proposed model and algorithm to real-world cases.

3. Mathematical Formulation

3.1. Problem Description

The essence of factory workshop layout is to optimize the design objectives as much as possible and determine the specific positions of each workshop within a certain area while satisfying various constraints. Based on current research on workshop layout problems, the following hypotheses are presented:

(1) The details of the shape of each workshop are ignored, and the length and width of each workshop are known in advance.
(2) The workshops are arranged from left to right and from bottom to top in parallel to the axes.
(3) Workshops can be placed in different directions, either horizontally or vertically.
(4) It is assumed that materials are transported from the geometric center of one workshop to the geometric center of the next workshop.
(5) The number of workshops, the area of each functional area, and the freight exchange volume between workshops are known.

Based on the above assumptions and in consideration of improved clarity in description, a coordinate system is established with the bottom-left corner as the origin. This system serves as a reference for calculating the centroid position of the workshop. The X-axis and Y-axis represent the length and width directions, respectively, of the workshop under consideration. The schematic diagram of the workshop layout is illustrated in Figure 1. Accordingly, the constraints can be easily constructed as presented in this section.

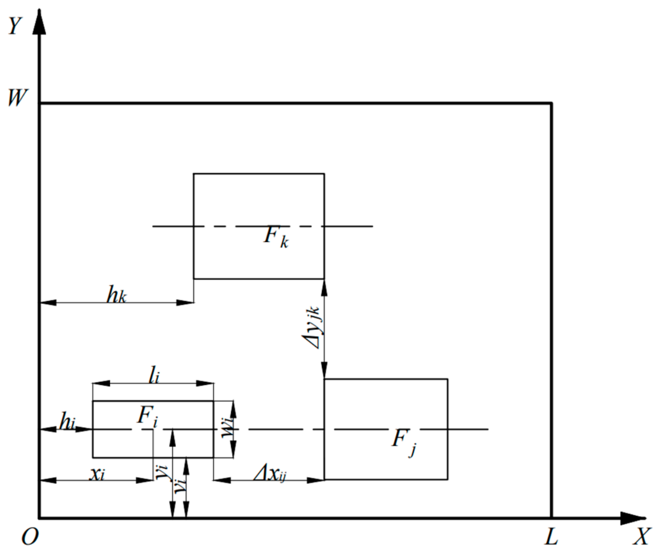


Figure 1. Workshop layout diagram.

First, several parameters and variable notations are defined in Tables 1 and 2, respectively, followed by the establishment of a multi-objective mathematical model for workshop layout from a low-carbon perspective.

Table 1. Parameters and indices.

Parameter	Meaning
F_i	the ith workshop
l_i	length of ith workshop
w_i	width of ith workshop
L	total length of the plant
W	total width of the plant

Table 2. Decision variables.

Decision Variable	Meaning	Domain
x_i	the horizontal distance between the centroid of workshop i and the Y-axis	$[0,\ L]$
y_i	the vertical distance between the centroid of workshop i and the X-axis	$[0,\ W]$
h_i	the length of the ith workshop from the plant boundary	$\left[7.5,\ \frac{L-l_i}{2}\right]$
v_i	the width of the ith workshop from the plant boundary	$\left[7.5,\ \frac{W-w_i}{2}\right]$
Δx_{ij}	the minimum horizontal distance required to be maintained between adjacent workshops i and j	$[10,\ L]$
Δy_{jk}	the minimum vertical distance required to be maintained between adjacent workshops j and k	$[10,\ W]$

3.2. Multi-Objective Function

The workshop layout is mainly based on logistics relationships, supplemented by non-logistics relationships. In line with the low-carbon development needs of current industrial enterprises, this study establishes a multi-objective function with the optimization objectives of minimizing logistics costs per unit area, minimizing carbon emissions, and maximizing non-logistics relationships.

3.2.1. Minimal Logistics Cost per Unit Area

Material handling cost is an important factor affecting the efficiency of enterprises, depending on the material flow, handling distance, and unit handling cost between workshops and entrances/exits. There is a certain correlation and uncertainty between the area of the factory and material handling costs. During the planning stage, enterprises pay more attention to the control of land indicators, while during the operation stage, they hope that the logistics cost is as small as possible. Therefore, combining planning and operation to form the logistics cost per unit area can more intuitively reflect the effective utilization value of the workshop area. The smaller the logistics cost per unit area, the higher the utilization rate of the area and the more reasonable the layout.

$$minC_1 = \frac{\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} P_{ij}Q_{ij}D_{ij}}{\max(x_i + \frac{l_i}{2} + l_{oi}) \cdot \max(y_i + \frac{w_i}{2} + w_{oi})} \quad (1)$$

$$D_{ij} = |x_i - x_j| + |y_i - y_j| \quad (2)$$

where P_{ji} is the handling cost per unit distance per unit material between workshops and entry-exit points. Q_{ij} is the logistics volume between workshops and entry-exit points. D_{ij} is the Manhattan distance between workshops and entry-exit points.

3.2.2. Minimal Carbon Emission

In-plant transportation mainly uses a combination of road, rail, and belt transportation, each of which has different characteristics and applicability, and the carbon emissions generated are also very different. In this study, we only focus on the common modes of transportation in the plant and calculate the carbon emission generated by the transportation link in the plant.

At present, the main methods for measuring carbon emissions are the actual measurement method, material balance method, and emission factor method [38]. For measuring carbon emissions from in-plant freight transport, employing the carbon emission factor method is more appropriate, whereby emissions are calculated as the product of the activity level and emission factor associated with each transportation mode.

Carbon Emission from Road Transportation C_d

The carbon emissions from road transportation primarily stem from heavy-duty vehicles employed for freight transport. The amount of carbon emitted by these vehicles is dependent on their fuel consumption, which varies among different vehicle models and is closely related to factors such as transport volume, distance, and load capacity. Therefore, the level of activity in road transportation is calculated using a weight-based fuel consumption measurement model [39], as shown in Equation (3). The carbon emissions generated by road transportation can be expressed as:

$$\mu(Q_{ij}) = \frac{\varepsilon_m - \varepsilon_0}{Q_M} \cdot Q_{ij} + \varepsilon_0 \tag{3}$$

$$C_d = \sum_{i=1}^{n} \sum_{j=1}^{n} \mu(Q_{ij}) \cdot D_{ij} \cdot e_k \tag{4}$$

$$e_k = NCV_k \cdot CEF_k \cdot COF_k \cdot 44/12 \tag{5}$$

where $\mu(Q_{ij})$ is the fuel consumption per unit distance of a freight vehicle transporting a certain material. ε_0 is the fuel consumption per unit distance of an empty freight vehicle, while ε_m is the fuel consumption per unit distance of a fully loaded freight vehicle, with Q_M being the maximum load capacity of the vehicle. e_k is the carbon emission coefficient of the energy source used for on-site road transportation, which is diesel fuel as appropriate. NCV_k is the lower heating value as specified in the "General Rules for Comprehensive Energy Consumption Calculation GB/T 2589-2020". CEF_k and COF_k respectively are the carbon per unit calorific value and the fraction of carbon oxidized of energy consumption as specified in the "Guidelines for the Preparation of Provincial Greenhouse Gas Inventories".

Carbon Emissions from Belt Transportation C_p

Belt transportation is an ideal way to transport bulk raw materials within a factory, as it consumes electricity during transportation and does not directly emit carbon. However, the amount of carbon emissions generated by belt transportation is related to factors such as belt distance, slope, and operating speed. The carbon emissions produced by belt transportation can be expressed as:

$$C_p = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{P}{v} \cdot D_{ij} \cdot e_k \tag{6}$$

where P is the power of the belt conveyor, v is the speed of the belt conveyor, and P/v is the electricity consumption per unit distance of the belt device. The carbon emission coefficient of electricity used for the belt conveyor, e_k is taken as the average emission factor of the regional power grid.

Carbon Emissions from Railway Transportation C_t

Carbon emissions from railway transportation can be calculated based on different forms of traction, including steam locomotives, internal combustion locomotives, and electric locomotives. However, the usage of steam locomotives with high energy consumption has significantly declined since 2005, as reported in the China Statistical Yearbook. Hence, for freight transportation by rail, carbon emissions are primarily attributed to internal combustion and electric locomotives. The fuel consumption per 10,000 ton-kilometers for internal combustion locomotives and the electricity consumption per 10,000 ton-kilometers for electric locomotives can be determined based on the "Key Technical and Economic Indicators of Railway Transportation" in the statistical yearbook.

$$C_t = \sum_{i=1}^{n}\sum_{j=1}^{n} RK_{ij} \cdot EC_{ij} \cdot e_k \tag{7}$$

where RK_{ij} is the turnover volume of goods transported by railway between workshops. EC_{ij} is the energy consumption required to complete the unit turnover volume. e_k is the carbon emission coefficient of diesel or electricity consumed during locomotive operation.

Therefore, the formula for calculating the total carbon emissions generated by material transportation within the factory is as follows:

$$minC_2 = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(\mu\left(Q_{ij}\right) \cdot e_k \cdot D_{ij} + \frac{P}{v} \cdot e_k \cdot D_{ij} + RK_{ij} \cdot EC_{ij} \cdot e_k\right) \tag{8}$$

3.2.3. Maximum Non-Logistics Relationship

The larger the non-logistics relationship value, the closer the connection between workshops. Non-logistics relationships can be expressed as:

$$maxC_3 = \sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij} \cdot c_{ij} \tag{9}$$

where c_{ij} is the non-logistics closeness value between workshops obtained by using SLP, as shown in Table 3. b_{ij} is the closeness correlation factor, which is determined by the actual logistics distance D_{ij} and maximum possible distance between workshops D_{max}, as shown in Table 4. Here, $D_{max} = L + W$, which is determined by the sum of the maximum travel distances in the horizontal and vertical directions.

Table 3. Classification of workshop close relationship.

Relationship	**Letter**	c_{ij}
Absolutely necessary	A	5
Especially important	E	4
Important	I	3
Ordinary	O	2
Unimportant	U	1
Undesirable	X	0

Table 4. Closeness correlation factor.

D_{ij}	b_{ij}
$0 < D_{ij} \leq D_{max}/6$	1
$d_{max}/6 < D_{ij} \leq D_{max}/3$	0.8
$d_{max}/3 < D_{ij} \leq D_{max}/2$	0.6
$d_{max}/2 < D_{ij} \leq 2D_{max}/3$	0.4
$2d_{max}/3 < D_{ij} \leq 5D_{max}/6$	0.2
$5d_{max}/6 < D_{ij} \leq D_{max}$	0

3.3. Constraints

$$\begin{cases} |x_i - x_j| \geq \frac{1}{2}(l_i + l_j) + \Delta x_{ij} \\ |y_i - y_j| \geq \frac{1}{2}(w_i + w_j) + \Delta y_{ij} \end{cases} \tag{10}$$

$$\begin{cases} x_i - \frac{l_i}{2} - h_i \geq 0 \text{ and } x_i + \frac{l_i}{2} + h_i \leq L \\ y_i - \frac{w_i}{2} - v_i \geq 0 \text{ and } y_i + \frac{w_i}{2} + v_i \leq W \end{cases} \tag{11}$$

$$\left(x_i - \frac{l_i}{2}, x_i + \frac{l_i}{2}, y_i - \frac{w_i}{2}, y_i + \frac{w_i}{2} \right) \notin D_k \tag{12}$$

$$\alpha_{ij} = \arctan\left(\frac{h_{ij}}{D_{ij}}\right) \leq \alpha_{\max} \tag{13}$$

Equation (10) represents the spacing constraint, which requires a certain spacing between any two workshops; in other words, the workshops cannot overlap. Equation (11) represents the plant boundary constraint, which means all workshops must be within the red line of the plant, and the workshops should be left at a certain distance from the plant fence. Equation (12) represents the fixed constraint, which shows that certain workplaces must be fixed due to operating requirements or restrictions imposed by a variety of reasons, including the plant's natural conditions, external transportation conditions, and power connection conditions. Equation (13), which represents the belt constraint, states that there must be a minimum height difference between the upper and lower material ports, that the belt conveying angle must not exceed the maximum inclination angle, and that the belt length must be kept to a minimum.

4. Enhanced NSGA-II Algorithm

This study reveals the interconnections between three objectives: unit area logistics cost, carbon emissions, and non-logistical relationships. Specifically, elevated unit area logistics costs lead to reduced factory areas, more condensed workshop layouts, shorter product flow distances, and potentially more frequent occurrences of process intersections. These factors can contribute to higher levels of inefficient transportation, including indirect and circuitous routes, which in turn lead to heightened pollution levels and elevated safety risks, consequently diminishing non-logistical relationships. Conversely, lower unit area logistics costs may have the opposite effects. In other words, the goal of layout optimization is to find a balance between logistics cost per unit area, carbon emissions, and non-logistic relationship, thereby providing an optimal layout solution from a comprehensive standpoint. As the NSGA-II algorithm has demonstrated stability and effectiveness in numerous engineering applications, its chromosome encoding structure serves as an effective representation of facility layouts. Given the inherent conflicts among the three objectives, this study enhances the standard NSGA-II algorithm by implementing a combined strategy that integrates randomly generated and partially fixed solutions, introducing adaptive crossover and mutation operators, and incorporating an elite preservation strategy guided by a distribution function. These alterations aim to preserve diversity within the resulting Pareto optimal set and expedite the convergence speed of the algorithm.

4.1. Solution Process

The flowchart of the multi-objective workshop layout algorithm based on the enhanced NSGA-II algorithm is shown in Figure 2.

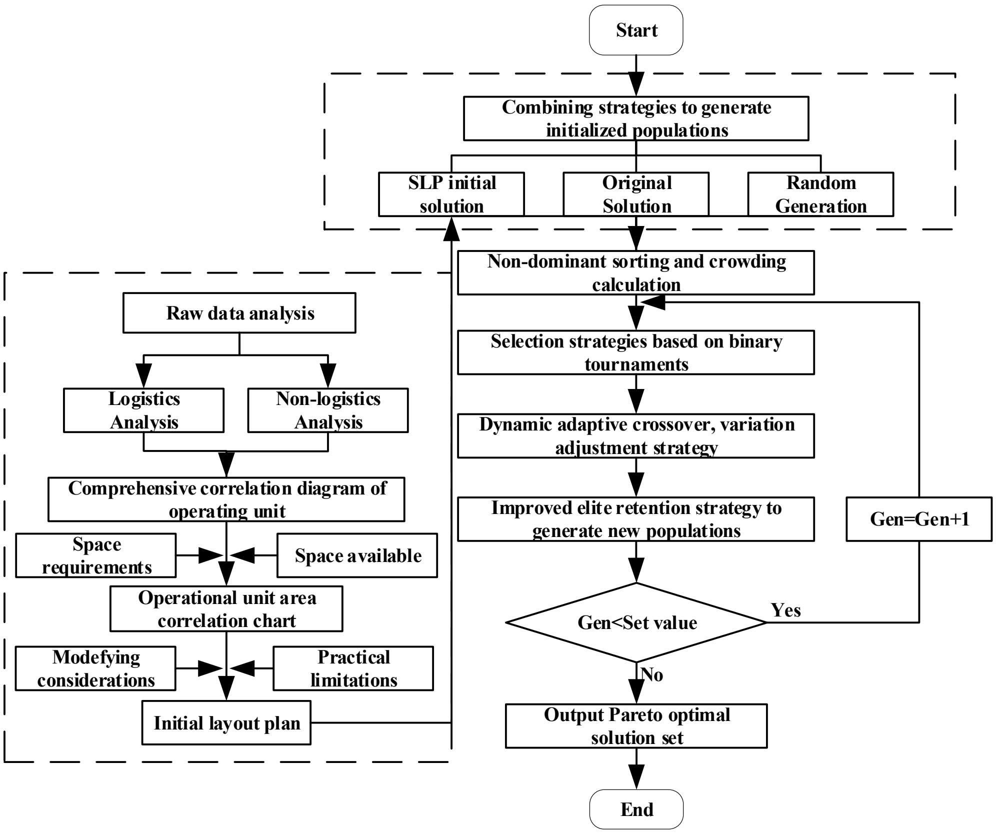


Figure 2. Enhanced NSGA-II algorithm flow chart.

Step 1: An initial population P_t of size N is formed by combining a portion of solutions generated through SLP analysis with the factory's original layout scheme and randomly generated individuals. Non-dominated sorting and crowding distance calculations are performed on all individuals in P_t.
Step 2: Applying selection, crossover, and mutation genetic operators on the parent population P_t to generate offspring population Q_t.
Step 3: By merging P_t and Q_t, a new population R_t of size $2N$ is obtained. Fast non-dominated sorting is conducted on R_t, resulting in various levels of non-dominated fronts $F_1, F_2, \ldots, F_n$.
Step 4: Within each non-dominated front F_i, the crowding distance of each individual is computed. An improved elite preservation strategy is employed to select N individuals and form the new parent population P_{t+1}.
Step 5: The termination condition is evaluated to determine if the evolutionary generation has reached its endpoint. If the condition is met, the loop ends; otherwise, $Gen = Gen + 1$ and the process proceeds to Step 2.
Step 6: Upon completion of the algorithm, the Pareto optimal solution set is obtained.

4.2. Encoding and Decoding

The genetic encoding in this study consists of four parts: workshop placement direction, additional spacing in the workshop and direction, number of rows in workshop layout, and arrangement order per row. It adopts a hybrid encoding method that combines real-number encoding and binary encoding. The basic layout idea is to start from the lower left corner of the factory area and sequentially arrange the workshops along the positive axis direction. If the total length of the arranged workshops exceeds the length of the factory area, a new row will be started along the positive axis direction.

As shown in Figure 3, the chromosome [2,6,5,1,4,3] represents a layout of two rows, with workshops 2, 6, and 5 in the first row and workshops 1, 4, and 3 in the second row.

The layout direction is [0,1,0,0,0,1], where 0 represents horizontal layout and 1 represents vertical layout. The additional spacing in the x and y directions between workshops refers to the extra distance beyond the minimum spacing, that is, the net distance between workshops minus the reserved distance. The reserved distance can be selected according to relevant specifications and actual conditions. For example, the additional distance in the x-direction for Workshop 1 refers to the distance between it and the factory boundary minus the distance required for reserved roads, pipelines, and other installations. The additional distance in the y-direction refers to the distance between Workshop 3 and 6 (outermost) minus the reserved protective distance.

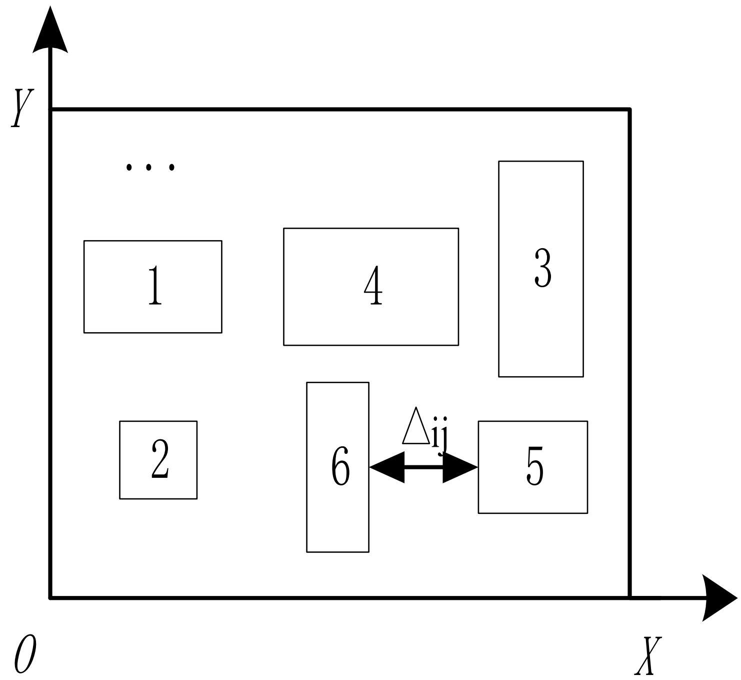


Figure 3. Coding example corresponding workshop layout diagram.

The genetic encoding structure is decoded in a targeted manner. Firstly, the number of rows is determined based on the facility area, spacing, and direction. Then, the order of each row is determined by sorting them from small to large according to their ID numbers. Finally, the length and width of each workshop are outputted, and the maximum width of each row is recorded to obtain the midpoint coordinates of each workshop.

4.3. Initial Population

The quality of the initial population has a certain impact on the convergence speed and solution quality of the algorithm. The standard NSGA-II algorithm typically generates the initial population randomly, with poor diversity and no guarantee of individual quality. Therefore, based on existing research, this study incorporates the original layout scheme of the factory and uses a combination strategy to generate initial solutions. A portion of the initial solutions is generated using the SLP method and the original layout, while the remainder is randomly generated, collectively constituting the initial solution set. On the one hand, random solutions are used to ensure diversity of the solutions, and on the other hand, the SLP method is used to generate some solutions with better quality to ensure the convergence speed of the algorithm. Simultaneously, integrating the original layout scheme makes the initial population closer to the actual workshop arrangement.

4.4. Genetic Operator

4.4.1. Selection, Crossover, Mutation

This study adopts the binary tournament selection operator, which selects the next generation individuals based on non-dominated ranks and crowding distances. It prioritizes selecting individuals with lower ranks during the fast non-dominated sorting process, and in cases where the ranks are tied, individuals with higher crowding distances are preferred. The crossover and mutation rates are adjusted dynamically using a strategy that depends on the iteration count. At the early stages of evolution, the rates are increased or decreased appropriately, while at later stages, they are decreased or increased accordingly to enhance the NSGA-II algorithm's adaptability to spatial changes. The formulas for calculating the adaptive crossover and mutation probabilities are as follows:

$$\begin{aligned} P_{\mathrm{c}}(i) &= \min P_{\mathrm{c}} + (\max P_{\mathrm{c}} - \min P_{\mathrm{c}}) \cdot \tfrac{i}{\mathrm{gen}} \\ P_{\mathrm{m}}(i) &= \min P_{\mathrm{m}} + (\max P_{\mathrm{m}} - \min P_{\mathrm{m}}) \cdot \tfrac{i}{\mathrm{gen}} \end{aligned} \tag{14}$$

where gen is the iteration count of the population, while $P_{\mathrm{c}}(i)$ and $P_{\mathrm{m}}(i)$ are the current iteration's crossover and mutation probabilities, respectively.

4.4.2. Elitist Preservation Strategy with the Introduction of Distribution Functions

The standard NSGA-II algorithm's elitist retention strategy involves preserving all high-quality individuals and filling them into the next generation parent population. However, this may lead to rapid convergence or getting stuck in a local optimum, reducing population diversity. To maintain diversity, a distribution function is introduced to limit the number of elites in the parent population. This involves selecting some non-elite solutions by including only a portion of the individuals from the non-dominated front into the next generation. The improved elite selection strategy is shown in Figure 4.

$$n_i = |F_i|^* r_i \; r_i = \mathrm{Rand}(0.8, 1) \tag{15}$$

where $|F_i|$ is the total number of individuals in the ith non-dominated front, n_i is the number of individuals selected from the ith non-dominated front, and r_i is a random real number between 0.8 and 1.

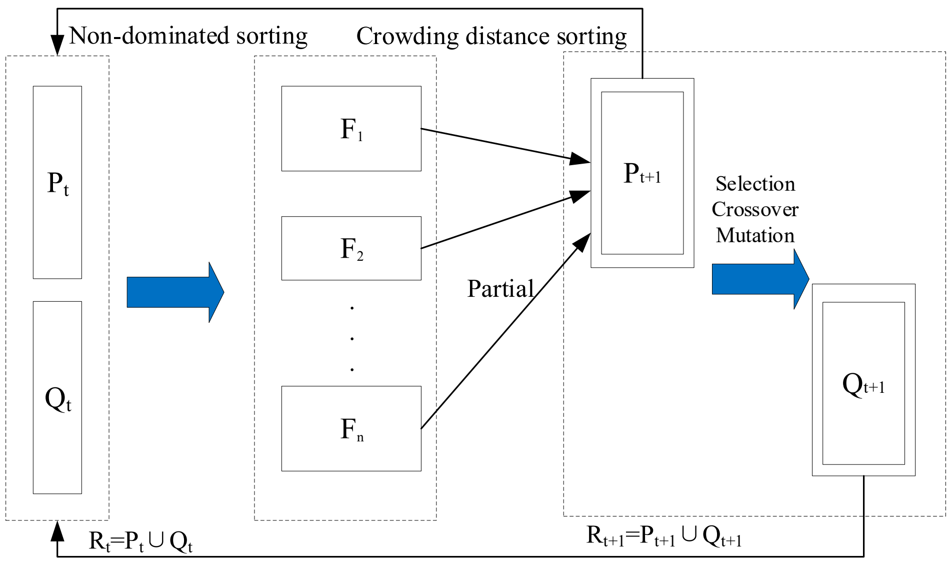


Figure 4. Improved elite selection strategy.

4.5. Algorithm Performance Testing

Performance evaluation metrics are used to measure multi-objective evolutionary algorithms (MOEA), primarily assessing the quality, efficiency, and robustness of the solution set sought by the algorithm, with a particular emphasis on its quality [40]. The widely recognized comprehensive metric Hypervolume (HV), proposed by Zitzler et al., is used to evaluate the performance of multi-objective optimization algorithms. It assesses the extent of coverage of the optimal solution set in the objective space, thereby providing a measure of the solution set's quality, particularly when the Pareto optimal frontier is not known [41]. The metric evaluates both the convergence and distribution of the solution set, and its formula is as follows:

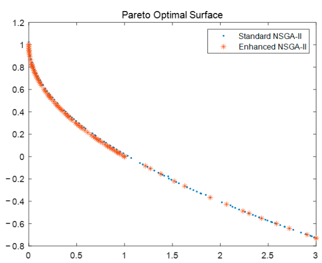
$$HV(S, z^{ref}) = \text{volume}\left(\bigcup_{i=1}^{|S|} v_i\right) \tag{16}$$

where v_i is a hypercube formed by a specific non-dominated solution x and a diagonal reference point z^{ref}, $|S|$ represents the count of non-dominated solution sets. A higher HV value indicates better convergence and more uniform distribution of the algorithm's obtained Pareto front.

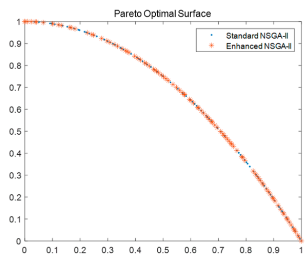
Various DTLZ series functions (DTLZ1, DTLZ2) and ZDT series functions (ZDT1, ZDT2, ZDT3, ZDT4, and ZDT6) were chosen for tests in this study, and the findings are compared to those from the standard NSGA-II test. The running results for HV metrics are obtained by running separately for 30 times with a population size of 100 and 500 iterations. The results are displayed in Table 5. The Pareto front surface of the two algorithms on the test function is shown in Figure 5. The graph of the objective function's evolution over time with the number of iterations is shown in Figure 6. As shown in Table 5, the enhanced NSGA-II algorithm has superior convergence and distribution compared to the original NSGA-II method.

Table 5. The mean and standard deviation of HV on the test functions.

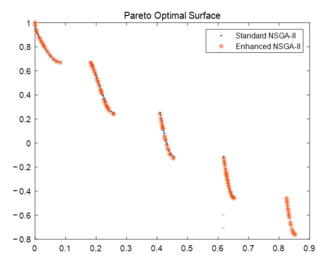
Problem	Standard NSGA-II		Enhanced NSGA-II	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
ZDT1	0.5878	0.2435	0.7453	4.2285×10^{-4}
ZDT2	0.6684	0.2441	0.8610	1.4385×10^{-4}
ZDT3	0.8961	0.0704	0.9219	2.3402×10^{-4}
ZDT4	0.3521	0.1112	0.9298	9.0124×10^{-5}
ZDT6	0.4382	0.3440	0.7902	1.7750×10^{-4}
DTLZ1	0.9986	0.0037	0.9996	2.4614×10^{-5}
DTLZ2	0.9994	4.7660×10^{-4}	0.9995	8.4842×10^{-6}



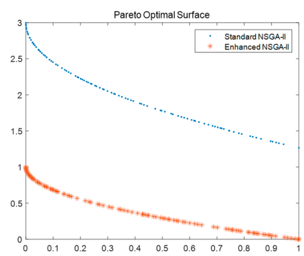
(**a**) ZDT1



(**b**) ZDT2

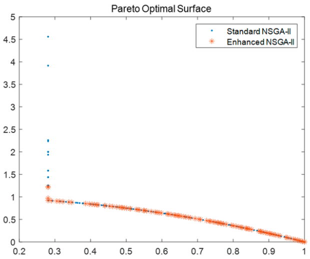


(**c**) ZDT3

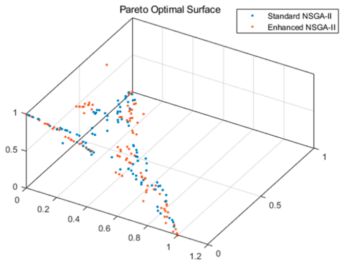


(**d**) ZDT4

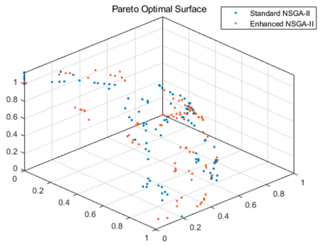
Figure 5. *Cont.*



(**e**) ZDT6

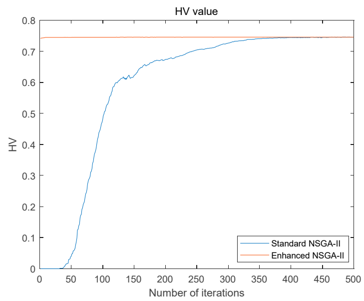


(**f**) DTLZ1

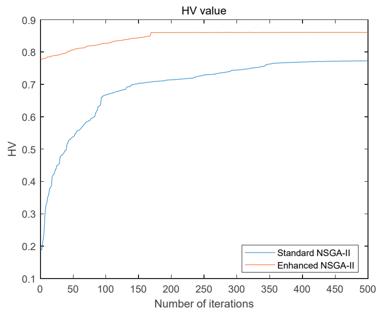


(**g**) DTLZ2

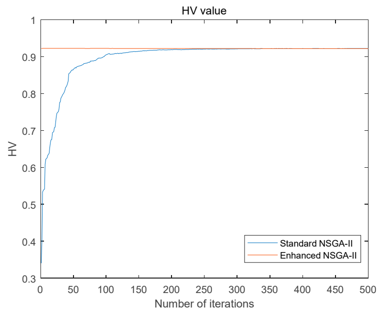
Figure 5. Pareto fronts for the standard NSGA-II algorithm and the modified NSGA-II algorithm on some test functions.



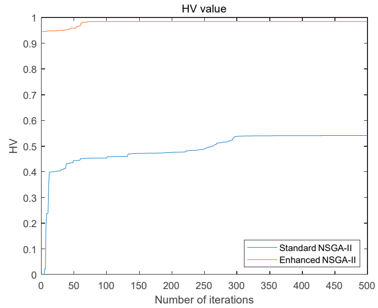
(**a**) ZDT1



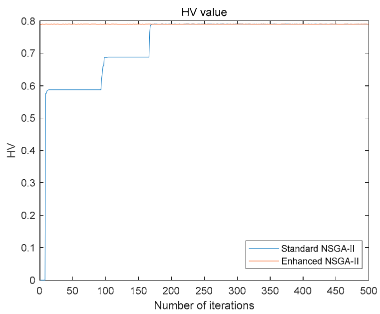
(**b**) ZDT2



(**c**) ZDT3

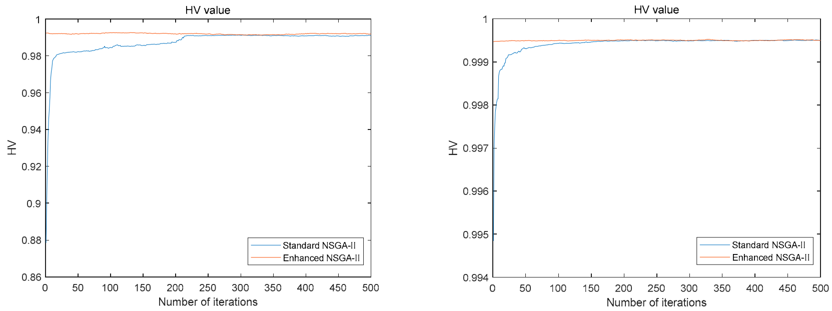


(**d**) ZDT4



(**e**) ZDT6

Figure 6. *Cont.*



(**f**) DTLZ1 (**g**) DTLZ2

Figure 6. Iteration curves for each test function.

5. Illustrative Examples

A certain enterprise is constructing a new dry-process cement production line with a capacity of 4000 tons per day, producing 1.2 million tons of clinker and 1.5 million tons of cement annually. The project site covers an area of approximately 24.97 hectares, with a north–south length of about 700 m and an east–west width of about 450 m. Due to transportation limitations around the project site, it is assumed that the location of the factory gate is fixed at a central coordinate of $(0, W/2)$.

5.1. SLP Method to Obtain A Partial Initial Solution

5.1.1. Division of Work Units

The cement plant workshops can be divided into 12 areas based on the production process and functional zone, with closely related or high-temperature generating workshops being jointly arranged. Additionally, since the original terrain slopes from south to north and the prevailing wind direction is southwest, this study considers the auxiliary raw material storage shed as a fixed workshop while the remaining 11 workshops are treated as units to be arranged. The main workshop area sizes are shown in Table 6.

Table 6. Main workshop area.

Number	Workshop Name	$l_i \times w_i$	Area (m^2)	Number	Workshop Name	$l_i \times w_i$	Area (m^2)
1	Auxiliary feedstock shed	82 × 41	3362	7	Master production area	221 × 90	19,890
2	Auxiliary feedstock prehomogenization yard	159 × 43	6837	8	Clinker storage	64 × 64	4096
3	Raw coal pile shed	120 × 30	3600	9	Cement grinding system	152 × 53	8056
4	Coal prehomogenization yard	192 × 42	8064	10	Cement packing	95 × 59	5605
5	Gypsum mixture shed	128 × 30	3840	11	Auxiliary production facility area	46 × 46	2116
6	Raw material ingredients	58 × 26	1508	12	Pre-plant area	80 × 77	6160

5.1.2. Analysis of Logistics Relationships

Based on the proportions of logistics routes and the proportion of logistics flow undertaken by each workshop, the logistics intensity can be classified into five levels: A, E, I, O, and U. The summary table of logistics intensity for each operational unit is presented in Table 7. Correspondingly, the logistics-related diagrams are depicted in Figure 7.

Table 7. Summary of logistics intensity.

Number	Workshop Operation Unit on	Cargo Flow (million t/a)	Relationship Level	Number	Workshop Operation Unit on	Cargo Flow (million t/a)	Relationship Level
1	1–2	74.25	O	6	6–7	257.4	E
2	2–6	148.5	I	7	7–8	89.1	O
3	3–4	148.5	I	8	8–9	396	A
4	4–7	54.45	O	9	9–10	148.5	I
5	5–9	148.5	I				

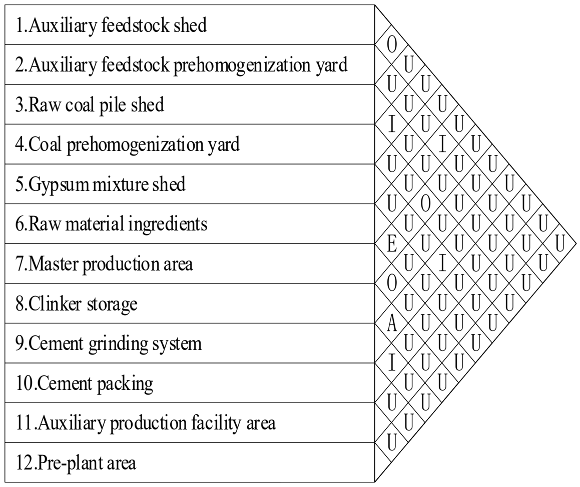


Figure 7. Logistics correlation.

5.1.3. Analysis of Non-Logistics Relationships

The factors influencing non-logistics relationships vary across different types of factories. Considering the specific circumstances of a cement plant, eight influencing factors were selected to construct a table indicating the levels of non-logistics relationships, as shown in Table 8. The non-logistics relationships are illustrated in Figure 8.

Table 8. Each operating unit close degree reason.

Number	Reason
1	continuity of the technological process
2	convenience of material handling
3	ease of personnel communication and management
4	similarity of job nature
5	environmental hygiene requirements (such as dust and exhaust)
6	safety protection requirements (fire prevention, noise prevention, vibration prevention, etc.)
7	power supply requirements
8	material inspection and quality requirements

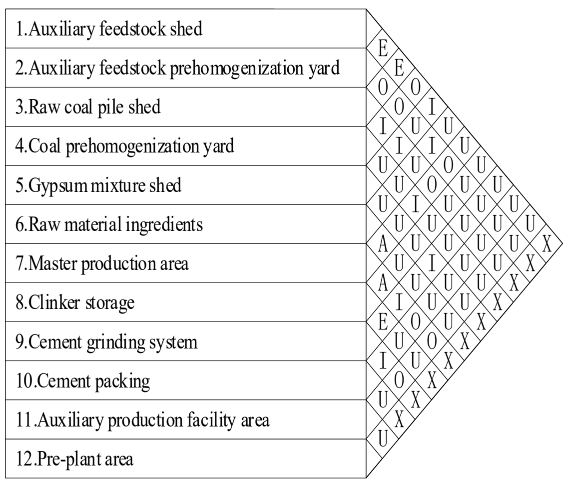


Figure 8. Non-logistics correlation.

5.1.4. Comprehensive Relationship Analysis

When it comes to workshop layout in cement plants, the influence of logistics relationships is significantly greater than that of non-logistics relationships. Adhering to a weighted ratio of $m : n = 2 : 1$, utilizing the assigned values $A = 5$, $E = 4$, $I = 3$, $O = 2$, $U = 1$, $X = 0$ for different levels, the composite relationship level value is determined and a comprehensive interrelationship diagram is depicted as shown in Figure 9.

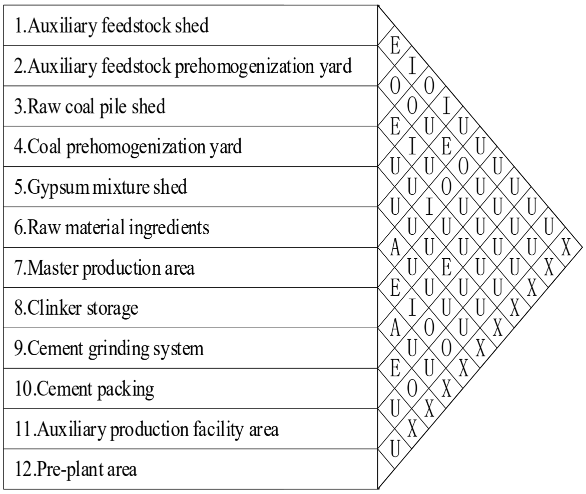


Figure 9. Comprehensive interrelationship diagram.

In summary, the initial layout plan obtained using the SLP method is shown in Figure 10, while the original factory layout plan is shown in Figure 11. The numbers in Figures 10 and 11 represent the 12 workshops in the case, and the workshop names and sizes correspond to the numbers in Table 6. To obtain more reasonable layout results, both initial solutions are reverse-encoded and added to the initial population.

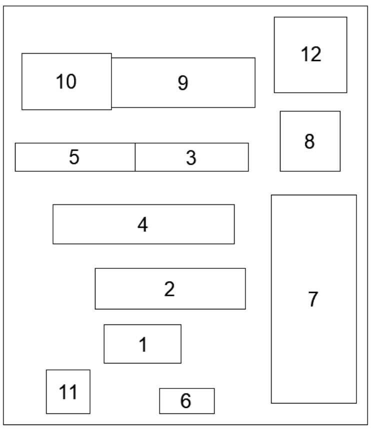


Figure 10. SLP initial layout scheme.

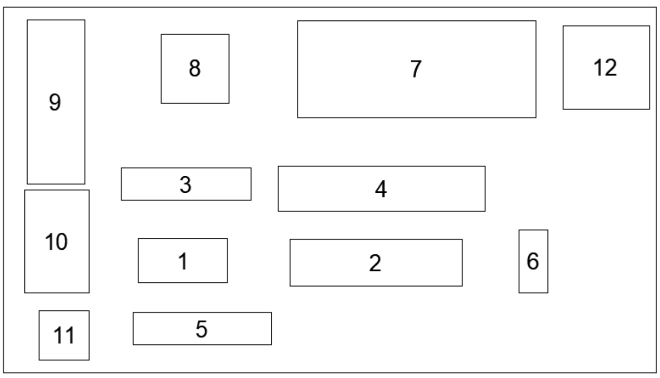


Figure 11. Original layout scheme.

5.2. Algorithm Solution and Result Analysis

5.2.1. Model and Constraint-Related Parameter Settings

Taking into account the fire safety distance between workshops, according to the "Code for Fire Protection Design of Buildings" GB50016-2014 (2018 Edition), a safety distance of 10 m is set horizontally and vertically between workshops. The distance between the workshops and the factory wall is set at 12 m, leaving space for the minimum safe distance between the workshop and the road edge, as well as corresponding pipeline reserves, and the width of the factory's fire access roads. According to the actual production situation of cement factories, the unit cost of belt transportation is taken as 0.5 yuan per ton kilometer, and the unit cost of road transportation is taken as 1.5 yuan per ton kilometer when using a 30-ton truck. The fuel consumption per unit distance in the loaded and unloaded states is 30 L and 16 L, respectively. The speed of the belt conveyor during material transportation is set at 1.5 m/s. According to Equation (5), the carbon emission factor for diesel is calculated to be 3.10 $kgCO_2$. Similarly, when using the national grid average emission factor, the carbon emission factor for electricity is determined to be 0.5810 tCO_2/MWh.

Considering the three aspects of algorithm performance, diversity, and convergence speed, the following algorithm parameters have been set: population size of 150, iteration count of 500, crossover probability of ($\min P_c = 0.2,\ \max P_c = 0.9$), mutation probability of ($\min P_m = 0.01,\ \max P_m = 0.2$).

5.2.2. Results Analysis

After running the program multiple times and eliminating similar layout solutions, we obtain a partial Pareto solution set as shown in Table 9. Within this set, Solution 1 demonstrates superior performance in Objectives 2 and 3, whereas Solution 2 achieves the optimum value for Objective 1. There is no chromosome that simultaneously achieves the optimal values for all three objectives.

Table 9. Partial Pareto solution set.

Number	C_1/(yuan/m^2)	C_2/kg	C_3	Chromosomes
1	0.75	0.79×10^5	105	[1, 2, 11, 3, 4, 5, 6, 8, 7, 10, 9, 12; 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] x_i : 53, 191.5, 306, 79, 245, 100, 222, 101, 253.5, 63.5, 101, 305 y_i : 35, 35, 35, 89, 89, 135, 135, 205, 205, 289.5, 369.5, 369.5
2	0.60	0.84×10^5	103.4	[1, 11, 12, 2, 3, 4, 6, 5, 10, 7, 9, 8; 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] x_i : 53, 129, 297.5, 173.5, 110, 108, 243, 139, 59.5, 228.5, 130, 265 y_i : 52, 52, 52, 123.5, 170, 216, 216, 262, 332, 332, 419, 419
3	0.91	1.09×10^5	100.6	[1, 9, 5, 11, 3, 10, 8, 6, 4, 2, 12, 7; 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0] x_i : 32.5, 187, 104, 222, 72, 193.5, 285, 344, 164, 353.5, 78, 244.5 y_i : 53, 53, 127, 127, 192, 192, 192, 192, 255.5, 255.5, 332, 332
4	0.82	1.06×10^5	101.5	[1, 12, 5, 9, 3, 10, 8, 6, 2, 4, 11, 7; 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0] x_i : 32.5, 171, 87, 88, 260, 62.5, 154, 209, 94.5, 286, 62, 205.5 y_i : 53, 53, 131, 182.5, 182.5, 251, 251, 251, 314.5, 314.5, 391, 391

The evolutionary process of the three objectives with respect to the genetic generation is shown in Figure 12. As the iteration count increases, all objective function values are continuously optimized. After 350 iterations, the objective function values tend to stabilize.

To verify the effectiveness of combining the NSGA-II algorithm with the SLP method, we select a superior solution from the Pareto set for comparison. The layout plan for Solution 1 is shown in Figure 13, numbers 1–12 represent the various workshops present in Table 6 within the cement plant, and a comparison analysis of the objective function values with the original factory layout plan (Figure 9) after adding channels is shown in Table 10. The table illustrates that both the standard algorithm and the enhanced algorithm outperform the original layout plan in terms of objective function values, with a reduction in logistics cost per unit area of 16% and 30%, and a saving of carbon emissions of 19% and 42%, respectively. Nevertheless, the optimization of non-logistics relationships was not as significant. This may be due to the fact that the original layout plan had its entrance and exit located on the southwest side, resulting in a longer distance for raw material transportation and higher carbon emissions.

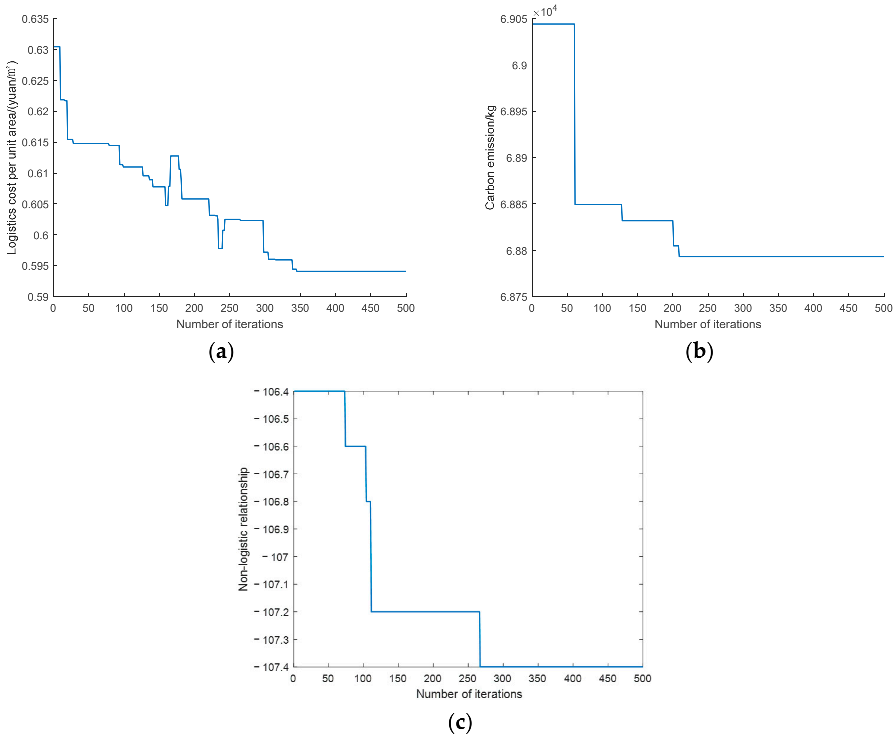


Figure 12. Population evolution iteration diagram. (**a**) Iterative curve of logistics cost per unit area. (**b**) Iteration curve of carbon emissions. (**c**) Iterative curves for non-logistic relationships.

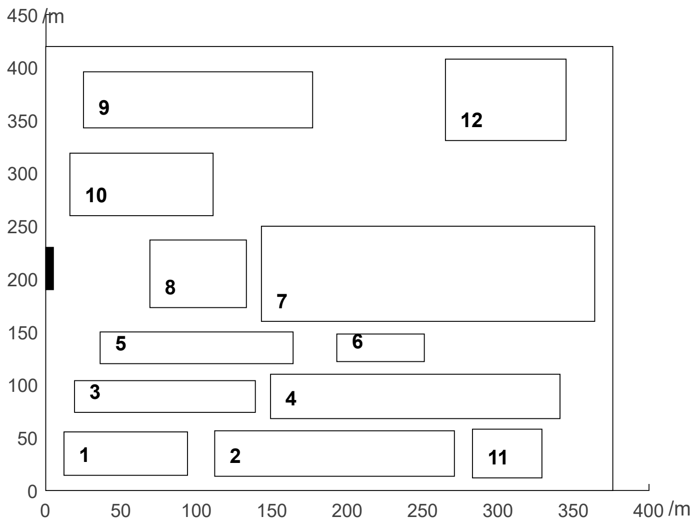


Figure 13. Layout scheme.

Table 10. Algorithm improvement effect comparison.

Optimization Methods		C_1/(yuan/m^2)	C_2/kg	C_3
	Original layout plan	1.08	1.37×10^5	101
	Standard NSGA-II algorithm	0.91	1.11×10^5	102.5
	Enhanced NSGA-II algorithm	0.75	0.79×10^5	105
Optimization effect/%	Standard NSGA-II algorithm-Original layout plan	16	19	1.5
	Enhanced NSGA-II algorithm-Original layout plan	30	42	4

Moreover, to demonstrate the effectiveness of the enhanced NSGA-II algorithm, a Pareto frontier comparison chart is plotted in Figure 14. The results show that the enhanced algorithm can obtain a better set of solutions compared to the standard algorithm, with better performance on all three objectives. Therefore, the proposed algorithm can achieve good results in solving multi-objective workshop layout problems.

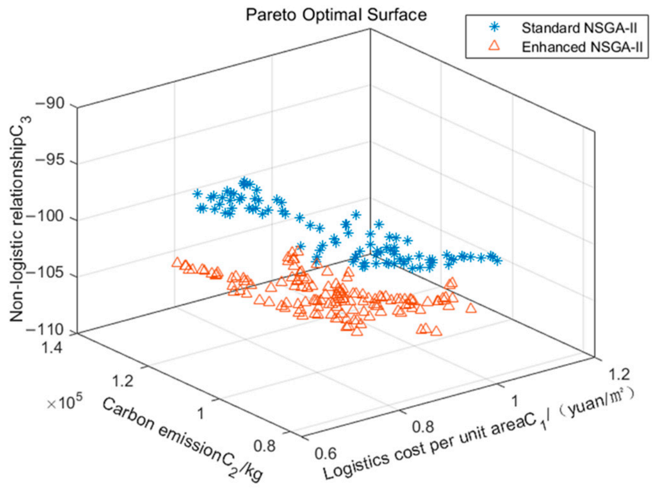


Figure 14. Pareto frontier comparison chart.

6. Conclusions and Policy Implications

With the growing emphasis on sustainable development in industrial enterprises, significant efforts have been devoted to reducing carbon emissions in production processes. However, less attention has been given to the issue of carbon emissions generated during material transportation. From a long-term perspective of enterprise development, achieving low-carbonization is an imperative trend for enhancing market competitiveness. Facility layout is a critical component in the planning of manufacturing systems. To fully unleash the low-carbon potential of enterprises, environmental consciousness is indispensable throughout the planning and design phases. This study proposes a multi-objective optimization method for low-carbon layout of industrial workshops from a low-carbon transportation perspective. The method presented holds general applicability for most industrial enterprises. The primary contributions of this study are as follows:

From a modeling perspective, the first key aspect involves differentiating from the conventional focus on material handling costs. Instead, the integration of planning and operational stages is employed, providing a holistic assessment of the workshop area's effective utilization value in relation to unit logistics cost. Secondly, starting with the influencing factors of carbon emissions under different transportation modes, the quantification of carbon emissions generated by internal transportation in industrial enterprises is incorporated into the objective of minimizing carbon emissions. A multi-objective optimization model for workshop layout, which aims to minimize unit logistics cost, minimize carbon emissions, and maximize non-logistics relationships, is established. Simultaneously, considering the uniqueness of belt transportation, a height difference constraint for belt transportation is introduced to ensure the accuracy of layout solutions.

From an algorithmic perspective, combined with the SLP method, the initial solution set is optimized. Dynamic adaptive crossover and mutation strategies are employed, and an enhanced NSGA-II algorithm with elite preservation strategy using a distribution function is introduced to solve the workshop layout problem. The effectiveness of the proposed model and algorithm is verified through a case study.

In light of the aforementioned conclusions, this study puts forth several policy implications. Firstly, it is impractical for industrial enterprises to solely achieve carbon emissions reduction on their own, as their development is driven by profit motives. Therefore, government intervention becomes imperative. Implementing a carbon emission reward and penalty system within enterprises, imposing penalties for excessive carbon emissions, providing financial and technical support to low-carbon enterprises, encouraging the sharing of low-carbon information, and promoting regional cooperation in digital low-carbon technologies can facilitate the harmonious development of social resources and the environment. Additionally, efforts should be made to establish a digital carbon emission management platform that enables real-time monitoring and facilitates timely adjustments and controls in high-carbon processes. Secondly, in terms of transportation, the use of belt conveyors and clean energy-based transportation methods should be encouraged. Optimization of transportation modes and organization should be prioritized. For transportation with significant emissions, endeavors should be made to minimize inefficient practices such as empty trips and round trips, while increasing the frequency of maintenance and replacement of aging vehicles.

The present study has certain limitations: it solely focuses on the horizontal layout and does not consider vertical optimization taking into account specific topographical variations. Future research could explore incorporating adjustments for terrain slopes into the quantification process of carbon emissions to enhance the accuracy of emission results. Furthermore, by optimizing the placement of entrances and exits, a more comprehensive approach that considers the interplay between horizontal and vertical aspects can be pursued, thereby investigating their mutual influences.

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