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Optimization of Multi-Objective Safety Management System for Wind Power Projects Based on Non-Dominated Sorting Genetic Algorithm

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Abstract: This paper addresses the issues of incomplete safety management systems and the challenge of optimizing multiple safety objectives concurrently in wind power project construction. An approach for solving Multi-objective Optimization Problem (MOP) based on the Non-Dominated Sorting Genetic Algorithm (NSGA) is proposed. First, key safety risk factors in the construction process of wind power projects are systematically analyzed and identified. A multi-dimensional evaluation index system, including personnel safety, equipment safety, environmental safety, and management safety, is established. Next, a mathematical model is developed with safety, cost, and construction period as the optimization objectives. The NSGA-II and NSGA-III algorithms are applied to solve the model. Case study results show that: (1) the proposed MOP model effectively balances the multiple objectives in wind power project construction; (2) compared with traditional methods, the NSGA demonstrates significant advantages in solution efficiency and diversity; (3) the obtained Pareto optimal solution set provides multiple feasible options for engineering decision-making. The research results provide theoretical foundations and practical guidance for safety management in wind power project construction.

Keywords: Wind power projects; Multi-objective Optimization Problem (MOP); Non-Dominated Sorting Genetic Algorithm (NSGA); Safety management; Pareto optimal solutions

1 Introduction

This research addresses the issue of incomplete safety management systems and the difficulty in coordinating the optimization of multiple safety objectives during the construction of wind power projects. By systematically analyzing and identifying key safety risk factors in the construction process, a multi-dimensional evaluation index system is established, which includes personnel safety, equipment safety, environmental safety, and management safety. A mathematical model is built with safety, cost, and construction period as optimization objectives, and NSGA-II and NSGA-III algorithms are used for solving the model.

To achieve optimization of the engineering objectives, many scholars have developed corresponding optimization models for different fields. The introduction of Pareto optimal solutions has led to the emergence of MOP research in various professional fields. Scholars both domestically and internationally have conducted extensive research on the construction of MOP models, solutions, and the selection of optimal solutions. In the field of safety engineering, Ning et al. [1] transformed the construction site layout planning into a MOP and developed a model based on a three-objective ant colony optimization algorithm to solve the MOP problem.

There is a considerable amount of research on MOP in the wind power field, focusing on aspects such as reducing costs [2], improving reliability [3], increasing power generation and reducing load losses [4], improving annual profits [5], and reducing wind abandonment rates. However, research on the safety objectives in wind power engineering is relatively scarce, with more studies focusing on maintenance periods [6] to balance maintenance costs and maintenance activity time.

In past studies, the design of safety objective functions has often failed to fully consider the comprehensive risk factor assessment involved in engineering projects, particularly in complex projects and multi-risk environments. Traditional methods have not conducted in-depth analyses and quantifications of risk factors [7]. This oversight results in the failure to effectively avoid potential risks during the design phase of projects, thereby increasing uncertainty and safety hazards during construction, making the project more risk-prone.

This study takes a wind power project construction in Hebei Province as a case study. Through the comprehensive identification and assessment of risk factors in previous research, the study conducts an in-depth analysis of the impacts of various risk factors. The research particularly considers risks from human factors, equipment, environment, and management. These factors are interrelated and have significant impacts on the overall safety of the project, and thus need to be fully considered in the design of the objective function. By constructing a safety objective function and solving the optimization problem, the study aims to propose a safety balance optimization solution based on comprehensive risk assessment to ensure the optimal balance of safety and stability during the construction process. This process not only provides a theoretical basis for risk control in wind power projects but also serves as a reference for safety management in similar complex engineering projects.

In recent years, with the rapid development of the wind power industry, the scale of engineering projects has continued to expand, and the difficulty and complexity of construction have increased accordingly [8]. However, traditional methods in safety management often focus on the control of single or partial risks and lack a systematic analysis and assessment of the multiple risk factors in complex engineering environments. This limitation leads to the neglect of potential risk factors during project design and implementation, increasing uncertainty and safety hazards during the construction process [9]. Especially in the Hebei region of China, wind power projects are constrained by regional environmental factors, weather conditions, and the diversity of construction equipment, which highlights the importance of safety risk control. Therefore, researching how to systematically identify and assess risk factors in complex environments, and design a reasonable safety objective function based on this, to achieve a safety balance during construction, is a research topic of great theoretical and practical significance.

(1) How to construct and optimize a safety objective function that considers comprehensive risk factors?

Based on the identification and assessment of risk factors, the study needs to design a safety objective function that comprehensively considers human, equipment, environmental, and management factors. This function should possess balance and optimization capabilities to ensure the optimal safety balance between risk control and cost-effectiveness.

(2) How to validate the effectiveness of the optimized safety balance solution in actual wind power projects?

The research will explore how to apply the designed safety objective function in actual wind power projects in Hebei, and verify its feasibility and effectiveness through the optimization solutions obtained. This will provide insights into safety management for other similar complex engineering projects.

Wind power projects, as a major development direction for clean energy, directly affect the long-term and social benefits of the projects [10]. However, wind power projects involve high-altitude work, complex equipment operations, and frequent weather changes, all of which significantly increase the safety risks during construction and operation [11]. By designing a comprehensive risk assessment and safety objective function, more effective risk management methods can be provided for wind power projects, significantly improving the project's safety level and reducing the probability and frequency of accidents. The safety objective function design method proposed in this paper takes human, equipment, environmental, and management factors into account and constructs a multi-dimensional risk control framework. This innovation provides a new perspective for the theory of risk management in engineering projects and advances the application of engineering safety management theories. Safety accidents in wind power projects often result in high economic costs, including equipment damage, construction delays, and legal liabilities. By optimizing the safety objective function and finding the best balance between cost and safety, the project can minimize risk hazards while controlling costs, ensuring the maximization of project benefits. Therefore, this research not only provides support for safety management in projects but also plays a key role in improving the economic benefits of the projects. This study is dedicated to safety management in wind power projects, ensuring robust construction and operation of the projects. It not only aligns with the national green development strategy but also promotes sustainable development.

2 Theoretical Basis: MOP Theory

Optimization problems generally refer to obtaining the optimal solution of the objective function through certain optimization algorithms. When the optimization objective function is a single one, this is referred to as a Single-Objective Optimization Problem (SOP). When the optimization objective function involves two or more objectives, it is called a MOP. The solution of a MOP is often a set of balanced solutions, unlike the finite solutions of SOP [12].

MOP algorithms can be divided into two major categories: traditional optimization algorithms, including conventional optimization methods, constraint methods, and linear programming methods, such as traditional intelligent optimization algorithms. Essentially, these methods solve multi-objective functions by using SOP methods, i.e., converting multiple objectives into a single objective function. A typical challenge faced by many MOPs is the occurrence of conflicts between objectives. It is impossible to achieve an optimal solution that satisfies all objectives simultaneously. Unlike SOPs, which have finite solutions, MOPs usually generate a set of balanced solutions selected by objective values (which can also be considered as Pareto optimal solutions) [13]. MOPs can be classified into two major categories: evolutionary techniques and population-based techniques. In addition, multi-objective algorithms can also be categorized as hybrid algorithms. In hybrid algorithms, population-based and evolutionary algorithms are combined. Evolutionary techniques form a class of methods that use natural evolution concepts. These techniques allow the generation of a set of trade-off solutions in a single execution and require fewer computational resources to find solutions [14]. Nature-inspired algorithms are widely applied to many optimization problems, particularly addressing various real-world engineering cases. Due to the limitations in solving engineering problems, some methods play an important role in solving optimization problems [15]. MOP refers to the use of related theories such as multi-attribute utility and fuzzy decision-making to optimize multiple interrelated objectives, ultimately obtaining the optimal solution so that each objective reaches a balanced optimal within a certain range. Such solutions are also called Pareto solutions [16]. The solving process of MOP is essentially the search for Pareto optimal solutions.

In 1994, Srinivas and Deb [17] proposed the NSGA, which has several advantages. First, it is unrestricted: the NSGA algorithm has no preset limitation on the shape of the Pareto front. This means that it can adapt to Pareto fronts with various complex shapes, making it widely applicable in practical applications. Second, the flexibility of the objective function: this algorithm imposes no specific requirements or restrictions on the objective functions.

In 2002, Deb et al. [18] improved the NSGA algorithm by proposing the NSGA-II, which includes an elite retention strategy. The advantage of NSGA-II is that it reduces the algorithm's complexity to some extent while ensuring good convergence. The algorithm has an elite retention mechanism and does not require setting a sharing parameter, making it a benchmark evolutionary algorithm in the field of MOP. However, the NSGA-II algorithm also has disadvantages, such as slow search speed and insufficient diversity of solutions.

In 2014, Deb and Jain [19] proposed the NSGA-III, based on NSGA-II. This algorithm employs a fast non-dominated sorting method, significantly reducing the complexity of NSGA; it uses crowding distance and crowding comparison operators to maintain population diversity and introduces an elite strategy to ensure that excellent individuals participate in the evolution of the next generation, thereby improving the algorithm's overall performance [19]. This algorithm was developed to handle optimization problems involving four or more objectives. Compared to NSGA-II, this method performs better. The computational complexity of NSGA-III is the same as that of NSGA-II, but the complexity increases with the number of reference points.

In MOP, genetic algorithms are frequently used, and the precision of the algorithm is high. They are not limited by the search space and can simultaneously seek both global and local optimization when solving high-dimensional problems [14]. When dealing with MOP, genetic algorithms first generate an initial population. After individual fitness screening, the population size is kept constant during the iterative process. The optimization direction of the objective function should align with the direction of individual fitness improvement. Through processes such as selection, crossover, and mutation, the best individuals are retained until the termination conditions are met. The algorithm's termination is typically based on two criteria: (1) stopping after reaching the preset number of iterations, and (2) stopping if the average fitness of the best individuals does not significantly improve after several consecutive iterations. In MOP, because there are often interdependent relationships between objectives, achieving the average optimal solution for all objectives is relatively difficult. Therefore, the Pareto optimal solutions obtained by the algorithm are not absolutely unique but are formed based on the decision-maker's consideration of the relative importance of different objectives.

Multi-objective management in engineering projects refers to weighing and comparing the sub-objectives in the objective system, and through the mutual cooperation and coordination of the participating entities in time and space, ultimately achieving a result that satisfies all parties. For example, aiming to improve the management capability of project engineering in green construction [20], an improved NSGA-II algorithm was used to establish a MOP model for engineering projects. In this process, the hill-climbing method was introduced to enhance the search ability of the NSGA-II algorithm. The improved NSGA-II algorithm resulted in a MOP model with strong convergence and distribution, and the iterative curves for duration, cost, and environmental objective functions were all lower than those of the original NSGA-II algorithm, demonstrating better MOP performance.

3 Research Methodology

3.1 General Model of MOP

In general, a MOP with N decision variables and M predefined objectives can be represented by the following mathematical model [21]:

$$
\begin{aligned}
\min / \max f(X) = (f_1(x), f_2(x), \cdots, f_m(x)) \\
g_i(x) \leq 0, \quad i = 1, 2, \cdots, q, \\
h_j(x) = 0, \quad j = 1, 2, \cdots, p, \\
x \in [x_{\min}, x_{\max}], \\
x = (x_1, x_2, \cdots, x_n)
\end{aligned}
\tag{1}
$$

where, x represents the n-dimensional decision variables, $f(X)$ represents the mapping of the decision variables into the objective space, $f_m(x)$ represents the m-th objective function, $g_{(i)}(x) \leq 0$ and $h_{(j)}(x) = 0$ represent the p equality constraints and q inequality constraints, respectively, and x_{min} and x_{max} represent the lower and upper bounds of the decision variables. $minf$ refers to the problem requiring the minimization of the objective function, and $maxf$ refers to the maximization of the objective function.

For a decision vector x^*, if there is no other decision vector $x \neq x^*$ in the decision space that dominates it, then this decision vector x^* is called Pareto optimal, and the objective vector f^* is also Pareto optimal. The surface formed by the objective function values corresponding to all Pareto optimal solutions is called the Pareto front [21].

Figure 1 represents an optimization problem with two objectives, where the arc represents the Pareto front composed of objective function values, and the enclosed region represents the feasible region defined by the relevant constraints of the objective functions. Each point represents a solution of the optimization problem. From Figure 1, we can see that point A is the best on objective function f_2, point B is the next best, and point C is the worst. On the other hand, point C is the best on objective function f_1, point B is next, and point A is the worst. Therefore, there is no dominance relationship between points A, B, and C. However, points D, E, and F have worse values on all objective functions than point B, so they are all dominated by point B.

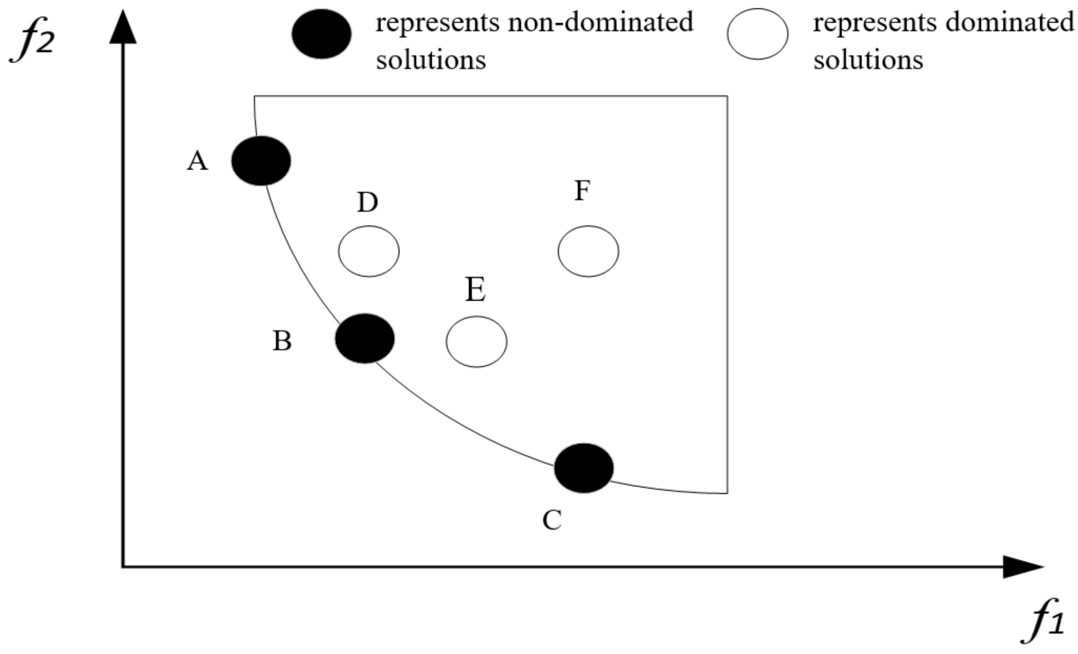


Figure 1. Dominance relation of solutions

In previous studies solving MOPs, methods such as the transformation of multiple objectives into fewer ones, hierarchical sequence method, ideal point method, and multi-attribute utility method have been commonly used. Currently, the most widely used and applied methods are intelligent algorithms, mainly evolutionary-based algorithms and population-based intelligent algorithms [14]. Genetic algorithms are a type of algorithm based on the theory of natural selection. Through processes such as selection, crossover, and mutation, which are similar to biological reproduction, the algorithm iteratively improves, resulting in a more optimal solution for the objectives. This includes NSGA-II, NSGA-III, and multi-objective differential evolution algorithms.

3.2 Solution with NSGA

The NSGA is an improved version of the genetic algorithm, modifying the selection and reproduction methods. It achieves the objective by performing re-layering based on the dominance and non-dominance relationships of each individual, followed by selection operations. This MOP algorithm was introduced by Srinivas and Deb [17] and is referred to as the first-generation NSGA. The concept of layering is to extract the non-dominated individuals from the population, form a small population (the first non-dominated optimal layer), and assign all individuals in this layer a shared virtual fitness value. After removing these individuals, further non-dominated individuals are extracted from the population, and they form another small population (the second non-dominated optimal layer), with all individuals again assigned a shared virtual fitness value. This process is repeated until the entire population is divided. This is called layering or non-dominated sorting.

NSGA-II [18] is an improvement over the original NSGA algorithm. It uses a fast non-dominated sorting method to reduce computational complexity and algorithm runtime. It also adopts an elitist strategy, combining the parent and offspring populations and performing non-dominated sorting, which expands the search space. During the formation of the next generation of parent populations, individuals with higher priority are selected in order, and among individuals in the same layer, those with smaller crowding distances are preferred. This ensures that high-quality individuals are more likely to be retained. The need for specifying a shared fitness-sharing strategy is replaced with a crowding distance method, which is used as a criterion for selecting excellent individuals in the same layer. This maintains the diversity of the population and allows individuals to undergo selection, crossover, and mutation across the entire range.

The solution process of NSGA-II is as follows:

Step 1: Perform non-dominated sorting on the initial population.

Step 2: Calculate the crowding distance of the sorted population and select the individuals for the next iteration. For individuals with different crowding distances, those in higher layers are prioritized. For individuals in the same layer, those with smaller crowding distances are preferred.

Step 3: After iteration, generate the first generation of offspring by performing crossover and mutation on the parent population.

Step 4: Merge the parent and offspring populations to generate a new parent population.

Step 5: Perform non-dominated sorting on the new parent population and calculate crowding distances to select individuals for the next iteration.

Step 6: Continue iterating, repeating Steps 4 and 5 until the maximum number of iterations is reached.

NSGA-III [20] is another variation of the NSGA algorithm. As the number of objectives in MOP gradually increases, extending beyond one or two objectives, using NSGA-II results in reduced convergence and suboptimal Pareto front solutions. Therefore, non-dominated individuals are selected by generating reference points to expand the application scope of the algorithm.

To obtain the mapping relationship between population individuals and response reference points (i.e., vertical distances), reference points are set to make the direction of evolution between the population and the reference points more aligned, and the reference points are distributed uniformly.

(1) Creation of reference points:

Define a G-dimensional set of reference points $s = (s_1, s_2 \dots s_G)$, where the coordinates of each reference point are:

$$s_j \in \left\{\frac{0}{L}, \frac{1}{L}, \dots, \frac{L}{L}\right\}, \sum_{j=1}^{G} \quad s_j = 1 \tag{2}$$

where, L is the number of segments for each objective.

(2) Calculation of reference point coordinates:

First, construct a combination B of G-1 dimensions, where B$\in \left\{\frac{0}{L}, \frac{1}{L}, \dots \frac{L+G-2}{L}\right\}$;

Next, for $x \in B$, perform the following operations to obtain a new x_{ij}=x_{ij}-$\frac{j-1}{L}$;

Finally, obtain the coordinates for each objective function:

$$\begin{cases} s_{ij} = x_{ij} - 0 j = 1 \\ s_{ij} = x_{ij} - x_{i(j-1)}, 1 < j < G \\ s_{ij} = 1 - x_{i(j-1)}, j = G \end{cases} \tag{3}$$

Finally, the reference count is given by:

$$\text{refCount } = \binom{L+G-1}{L} = C_{L+G-1}^{L} = C_{L+G-1}^{G-1} \tag{4}$$

The advantage of NSGA-III is that it is less likely to get trapped in local optima, is suitable for solving high-dimensional MOPs, and does not require the inclusion of a multi-attribute utility function. To ensure the final Pareto solutions are uniformly distributed, NSGA-III establishes a relationship between the solutions and the reference points. Since the reference points are uniformly distributed, the resulting Pareto solutions are also expected to maintain this characteristic of uniform distribution.

The solution process of NSGA-III is as follows:

First, the input consists of Z^s reference points or the provided expected points Z^a, along with the parent population P_t, and the output is the next generation P_{t+1}.

Step 1: Create an archive storage set S_t, with i=1 indicating the rank.

Step 2: Perform crossover and mutation to generate a new population Q_t.

Step 3: Obtain the combined set of parents and offspring R_t.

Step 4: Perform non-dominated ranking $(V_1, V_2 \ldots)$.

Step 5: Continuously rank the individuals after non-dominated sorting, order them by rank, and store the lower-ranked sets in S_t until the number of individuals in S_t, $|S_t|$, is greater than or equal to the population size C.

Step 6: Assume the last frontier is V_1. If $|S_t| = C$, then the next iteration's initial population $P_{t+1} = S_t$; otherwise, perform reference point-based selection.

Step 7: Set $P_{t+1} = \cup_{J=1}^{l-1} V_j$, where $V_1 = C - |P_{t+1}|$, i.e., the number of l layers in the frontier.

Step 8: Normalize the objective functions and create a reference set.

Step 9: Establish a "mapping relationship" between population individuals and reference points. $\pi(s)$ represents the reference point closest to the population individual, and $d(s)$ represents the distance between the reference point and the individual.

Step 10: Calculate the occurrence count of small niche reference points.

Step 11: Select the least chosen reference points from the small niche and find K population individuals from the V_1 frontier.

This study applies the MOP model to a practical case, using NSGA-II and NSGA-III algorithms to solve the MOP model, obtaining Pareto front solutions, and comparing the performance of the two algorithms.

3.3 Construction of MOP Model

In the process of wind power engineering construction safety, multiple aspects, such as time, cost, and safety management, need to be comprehensively considered. However, these objectives often exhibit certain degrees of inconsistency, making it inevitable to make trade-offs and coordination among them in actual engineering safety construction management, in order to achieve optimal overall benefits.

To assess the coordination of safety objectives in wind power engineering construction, it is necessary to establish a scientific evaluation index system. This system includes measurements of human safety objectives, equipment safety objectives, environmental safety objectives, and management safety objectives, as well as the evaluation of their inter-coordination. The expectations for these four objectives are as follows:

Human Safety Objectives: I. Reduce the risk of human equipment violations, and prevent fatalities and serious injuries. II. Control the risk of unauthorized entry and minimize minor injury accidents. III. Prevent major traffic accidents with significant responsibility, control general traffic accidents, and achieve a zero-traffic-accident goal.

Equipment Safety Objectives: I. Prevent major mechanical equipment failures or malfunctions during construction. II. Prevent major fire accidents.

Environmental Safety Objectives: I. Reduce the risk of sudden environmental changes at the work site. II. Reduce the risks associated with working in areas with heavy sand and unreinforced slopes.

Management Safety Objectives: I. Reduce the risk of insufficient safety management and supervision. II. Reduce the risk of inadequate enforcement of safety and organizational systems. III. Reduce the risk of failure to conduct thorough accident hazard inspections. VI. Reduce the risk of lacking a safety risk grading and control system. V. Reduce the risk of inadequate daily safety inspections.

Based on the established wind power engineering construction safety risk evaluation index system and Eq. (1), the goal values for each safety objective are calculated as follows:

$$max f_1 = \sum_{i=1}^{36} S_{Ci} {*} \omega_{Ci} \tag{5}$$

$$min f_2 = \sum_{i=1}^{36} S_{Ci} {*} p_{Ci} \tag{6}$$

$$minf_3 = \sum_{i=1}^{36} S_{Ci} \cdot t_{Ci} \tag{7}$$

where, S_{Ci} is the safety score for the i-th secondary indicator, which is a variable to be optimized. Due to the special nature of safety production, an 80-point minimum control standard is set, which corresponds to the lower limit of the decision variable, and a full score of 100 points is the upper limit. ω_{Ci} is the weight of the i-th indicator. p_{Ci} is the additional cost required for each 1-point improvement in the i-th indicator. $t_{Ci}$is the additional time required for each 1-point improvement in the i-th indicator.

To obtain reasonable control values for each secondary indicator, the NSGA is used to solve for a balanced control scheme. Both the NSGA-II and NSGA-III algorithms are used to solve this MOP model, obtain the Pareto front solutions, and compare the results of the two algorithms to obtain the optimal solution.

For the Pareto front solutions obtained by the NSGA-II and NSGA-III algorithms, when deriving preferred solutions, the subjective weighting method is often used to calculate the overall objective value. In wind power engineering construction, safety, time, and cost are all essential objectives, and safety is the premise for continued production. Therefore, the focus should be on the balance of decomposed safety objectives.

This study uses the sum of the levels of human safety objectives, equipment safety objectives, environmental safety objectives, and management safety objectives as the base benefit, and the product of the levels as the composite benefit:

$$\mathrm{W} = \frac{1}{\mathrm{n}} \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{Z_j} \tag{8}$$

$$\mathrm{M} = \left(\prod_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{Z_j} \right)^{1/\mathrm{n}} \tag{9}$$

To achieve better balance in the overall performance, the equilibrium index is derived based on the base benefit and composite benefit:

$$H = \frac{M}{W} = \frac{\left(\prod_{1}^{n} Z_j \right)^{1/n}}{\frac{1}{n} \sum_{j=1}^{n} Z_j} \tag{10}$$

where, Z_j represents the evaluation index of the j-th subsystem objective, obtained by normalizing the subsystem objective values from the Pareto front solution set. H represents the equilibrium index. When the base benefit W remains unchanged, the closer the levels of each subsystem objective, the greater the composite benefit M, and the higher the global equilibrium index H. The index H reflects the degree of balance between the subsystems.

4 Research Results

Based on the specific survey of the Hebei CL Wind Power Engineering Construction Project, an analysis was conducted to obtain the safety risk evaluation index system for wind power engineering construction, as shown in Table 1. The unit increase cost refers to the additional cost required to increase a safety score by one point, while the unit increase time refers to the additional time required to increase a safety score by one point.

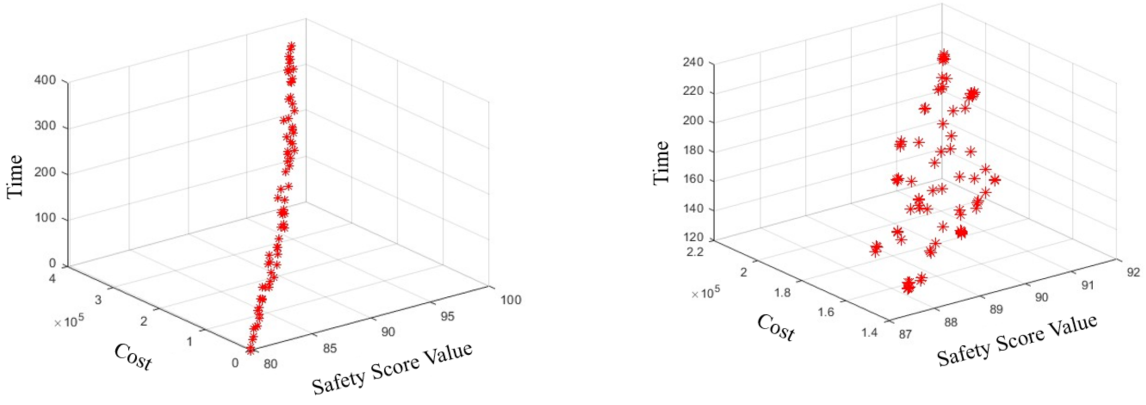
The NSGA-II and NSGA-III algorithms were used to solve the constructed model, with the following settings: 50 iterations, a population size of 40, 36 decision variables, and crossover and mutation coefficients both set to 0.5. The Pareto front solution sets obtained from the model solving process are shown in Figure 2.

According to Table 2, the optimal balanced solution obtained using the NSGA-II algorithm is solution number 3, with corresponding safety score values of 97.0. In Figure 2, the corresponding cost and time values are 3.42×10^5 and 360.0, respectively. The optimal balanced solution obtained using the NSGA-III algorithm is solution number 1, with a safety score of 89.4. In Figure 2, the corresponding cost and time values are 1.6×10^5 and 168.3, respectively. It is evident that the NSGA-III optimization results in lower costs and time values, but with a slightly lower safety requirement, whereas the NSGA-II optimization results in higher costs and time values, but with higher safety requirements.

Table 1. Wind power engineering construction safety risk evaluation index system

Primary Indicator	Secondary Indicator	Weight	Risk Level	Unit Increase Cost	Unit Increase Time
Human Safety Objectives (B1)	Vehicle Operation Error (C1)	0.012	Low Risk	300	1
	Lack of Personal Protective Equipment (C2)	0.034	Medium Risk	500	0.1
	Distance Judgment Error (C3)	0.01	Very Low Risk	100	0.3
	Lack of Safety Skills (C4)	0.017	Low Risk	500	0.2
	Lack of Personnel Qualification (C5)	0.013	Low Risk	500	0.4
	Risk of Unauthorized Entry (C6)	0.036	High Risk	1200	0.5
	Accidental Contact with Live Equipment (C7)	0.017	Low Risk	550	0.3
	Unauthorized Work (C8)	0.015	Low Risk	500	0.25
	Equipment Violation (C9)	0.055	High Risk	600	0.5
	Low Sensitivity to Equipment Changes (C10)	0.016	Low Risk	300	0.1
	Bringing Fire Sources into Wind Farm (C11)	0.027	Medium Risk	1400	0.4
	Storing Flammable Items (C12)	0.027	Medium Risk	650	0.5
Equipment Safety Objectives (B2)	Accidental Climbing of Live Equipment (C13)	0.071	High Risk	600	0.5
	Failure to Install Fire Barriers (C14)	0.031	Medium Risk	1400	0.4
	Transport Failure of Wind Turbine Blades, Tower, and Gearbox (C15)	0.028	Medium Risk	1500	2
	Crane Equipment Failure (C16)	0.042	High Risk	600	0.5
	Dangerous Voltage on Equipment (C17)	0.01	Very Low Risk	200	1.1
	Proximity to Live Parts (C18)	0.018	Low Risk	500	0.3
	Improper Installation of Safety Equipment (C19)	0.031	Medium Risk	300	0.4
	Wind Turbine and Sub-Equipment Failure (C20)	0.033	Medium Risk	1200	0.5
	No Fire Alarm or Extinguishing System Installed (C21)	0.019	Low Risk	1200	0.1
	No Safety Tools or Protective Equipment (C22)	0.04	High Risk	450	0.4
Environmental Safety Objectives (B3)	Unreinforced Sand and Slope Areas (C23)	0.015	Low Risk	300	0.5
	Landslides, Mudslides Blockage (C24)	0.01	Very Low Risk	500	0.2

Primary Indicator	Secondary Indicator	Weight	Risk Level	Unit Increase Cost	Unit Increase Time
Management Safety Objectives (B4)	Severe Weather Conditions (C25)	0.01	Very Low Risk	100	2
	Limited Working Platforms or Space (C26)	0.007	Very Low Risk	300	0.1
	Sudden Environmental Changes at Work Site (C27)	0.027	Medium Risk	1200	0.5
	Toxic and Harmful Gas in Ditches/ Wells (C28)	0.01	Very Low Risk	200	0.2
	Lack of Safety Management Supervision (C29)	0.041	High Risk	500	0.9
	Lack of Safety and Organizational System Enforcement (C30)	0.036	High Risk	500	1
	Lack of Safety Training and Guidance (C31)	0.03	Medium Risk	400	0.9
	Lack of Hazard Inspection (C32)	0.067	High Risk	200	1
	Lack of Safety Risk Grading and Control System (C33)	0.044	High Risk	500	0.5
	Inadequate Daily Safety Inspections (C34)	0.061	High Risk	500	0.5
	Lack of Safety Briefing (C35)	0.02	Low Risk	200	1
	Lack of Personnel (C36)	0.017	Low Risk	200	1



(a) NSGA-II Pareto Front Solution Set

(b) NSGA-III Pareto Front Solution Set

Figure 2. Wind power engineering construction safety risk evaluation index system

Based on the algorithm results, the optimal solution corresponds to the best score values of each safety evaluation secondary indicator, as shown in Table 3. An analysis of the solutions obtained by the two algorithms reveals the following:

(1) Human Safety Objectives: For NSGA-II, the scores for “Vehicle Operation Error (C1)”, “Equipment Violation (C9)”, and “Unauthorized Work (C8)” are higher than those of NSGA-III, with significant differences.

(2) Equipment Safety Objectives: For NSGA-III, the score for “No Safety Tools or Protective Equipment (C22)” is 99.2, higher than NSGA-II’s score of 96.1. For NSGA-II, the scores for “Equipment Transport Failure (C15)”, “Equipment Failure (C20)”, and “Safety Equipment Issues (C19)” are higher.

(3) Environmental Safety Objectives: The scores for this category are quite close between the two methods. NSGA-II performs better in “Sudden Environmental Changes at Work Site (C27)”, while NSGA-III performs better in “Toxic and Harmful Gases (C28)”.

(4) Management Safety Objectives: NSGA-II scores higher for “Lack of Safety Management Supervision (C29)” and “Lack of Hazard Inspection (C32)”, while NSGA-III achieves medium scores for “Safety Training and Guidance (C31)”.

In general, both NSGA-II and NSGA-III demand higher scores for Equipment Safety and Management Safety objectives, with NSGA-II showing higher scores overall. However, NSGA-III slightly outperforms NSGA-II in some specific secondary indicators (C22 and C28).

Table 2. Pareto front solution set and balance calculation

Scheme	NSGA-II					NSGA-III				
	B1	**B2**	**B3**	**B4**	**H*100**	**B1**	**B2**	**B3**	**B4**	**H*100**
1	30.48	17.68	6.32	25.28	85.906	33.8	20.16	7.01	28.43	**85.888**
2	31	17.87	6.37	25.48	85.816	34.07	20.14	6.94	28.63	85.615
3	36.72	21.52	7.66	31.09	**85.907**	34.29	20.35	6.98	28.91	85.586
4	37.35	21.72	7.75	31.31	85.867	33.95	20.08	6.85	27.84	85.601
5	37.23	21.64	7.72	31.27	85.836	34	20.13	6.91	28.66	85.554
6	30.81	17.79	6.35	25.4	85.847	34.58	20.23	6.92	28.61	85.422
7	35.4	20.49	7.15	30.16	85.358	34.07	20.25	6.89	28.44	85.563
8	32.54	18.68	6.62	26.36	85.733	34.57	20.24	6.92	28.68	85.4
9	36.24	21.18	7.37	30.54	85.549	34.03	20.16	6.83	28.7	85.376
10	35.41	20.66	7.2	30.17	85.471	33.92	20.17	6.92	28.38	85.664
11	36.93	21.17	7.54	31.03	85.576	34.21	20.19	6.92	28.67	85.518
12	30.68	17.9	6.35	25.61	85.861	34.1	20.12	6.9	28.8	85.484
13	36.32	20.86	7.42	30.57	85.576	33.9	20.16	6.94	28.53	85.691
14	34.59	20.18	7.13	29.06	85.754	34.7	20.29	6.9	28.54	85.357
15	31.46	18.06	6.42	26.52	85.558	34.13	20.11	6.88	28.65	85.45
16	36.9	21.35	7.6	30.87	85.747	34.39	20.34	6.93	28.96	85.434
17	35.28	19.42	7.07	29.22	85.265	34.28	20.14	6.92	28.83	85.466
18	35.8	20.78	7.28	30.49	85.457	34.28	20.15	6.95	28.59	85.563
19	37.22	21.53	7.62	30.92	85.699	34.58	20.23	6.92	28.63	85.419
20	31.68	18.34	6.53	27.03	85.635	34.29	20.19	6.91	28.83	85.432
21	34.89	19.86	7.24	29.34	85.791	34.38	20.28	6.89	28.52	85.444
22	35.1	20.47	6.99	29.66	85.212	34.72	20.3	6.9	28.58	85.34
23	33.07	18.63	6.6	26.89	85.375	33.92	20.13	6.88	28.56	85.541
24	37.13	21.53	7.68	31.18	85.788	33.99	20.16	6.95	28.45	85.689
25	31.46	18.2	6.45	26.87	85.567	34.18	20.15	6.85	28.18	85.474
26	36.18	20.84	7.52	30.69	85.781	34.28	20.23	6.92	28.59	85.525
27	36.75	21.11	7.56	30.9	85.676	33.89	20.26	6.83	28.25	85.517
28	35.85	20.53	7.44	29.65	85.902	34.42	20.09	6.92	28.63	85.455
29	35.77	20.15	7.37	30.47	85.575	33.93	20.11	6.89	28.17	85.631
30	31.74	18.27	6.5	26.25	85.715	33.97	20.13	6.88	28.13	85.621
31	33.28	19.13	6.78	27.9	85.554	34.12	20.22	6.94	28.35	85.66
32	34.45	19.69	6.83	28.53	85.208	34.57	20.27	6.92	28.68	85.403
33	34.05	19.62	7.04	28.55	85.78	34.25	20.25	6.94	28.73	85.552
34	34.28	19.57	7.08	28.09	85.883	34.3	20.26	6.86	28.48	85.408
35	31.18	17.93	6.41	26.4	85.638	33.94	20.11	6.89	28.17	85.63
36	32.94	18.79	6.7	27.42	85.548	33.99	20.13	6.89	28.56	85.549
37	37.14	21.57	7.64	31.21	85.725	34.08	20.13	6.94	28.05	85.723
38	30.48	17.68	6.32	25.28	85.906	34.33	20.22	6.88	28.51	85.427
39	33.29	19.45	6.73	27.76	85.524	34.28	20.23	6.92	28.57	85.529
40	30.95	17.9	6.43	26.13	85.83	33.89	20.26	6.82	28.28	85.503

Table 3. Best scores for each secondary safety evaluation indicator

Primary Index	Secondary Index	NSGA-II	NSGA-III
Human Safety Goals (B1)	Vehicle Operation Error (C1)	96.4	81.9
	Personal Protection Deficiency (C2)	97	84.9
	Distance Judgment Error (C3)	92.9	86.7
	Safety Work Skill Deficiency (C4)	93.9	83.4
	Personnel Qualification Deficiency (C5)	96.8	90.1
	Risky Entry (C6)	94.6	88.3
	Electric Shock (C7)	93.4	88.4
	Unauthorized Work (C8)	95	82.2
	Equipment Violation (C9)	99.6	90.7
	Low Sensitivity to Equipment Changes (C10)	89	81.6
	Bringing Fire into Wind Farm (C11)	91.6	84.6
	Storing Flammable Materials (C12)	99.5	93.1
	Climbing Live Outdoor Equipment (C13)	99.5	90.7
	No Fire Isolation (C14)	94.7	93.5
Equipment Safety Goals (B2)	Wind Blade, Tower, Gearbox Transport Failure (C15)	99.4	91.2
	Crane Equipment Failure (C16)	99.3	93.7
	Hazardous Voltage (C17)	97.3	91.7
	Proximity to Live Equipment (C18)	93.8	89.6
	Non-Compliant Safety Equipment Installation (C19)	96.6	93.8
	Wind Turbine and Accessory Failure (C20)	98.9	86.5
	No Fire Alarm or Extinguishing System (C21)	95	88.9

5 Conclusions

For the multi-objective characteristics of wind power engineering safety management issues, this study considered three aspects: time, cost, and safety management, and evaluates the coordination of various safety objectives in wind power engineering construction, including the measurement of human safety objectives, equipment safety objectives, environmental safety objectives, and management safety objectives. The specific situation of the Hebei CL wind power engineering construction project was analyzed. In this study, the NSGA-II and NSGA-III algorithms were used to solve the constructed model, and the results of the two algorithms were compared. The following conclusions can be drawn: First, there is a clear inverse relationship between safety score value and cost, time, i.e., the higher the safety score, the more time and cost are required; the equilibrium of each indicator after the decomposition of the safety dimension of each solution set was calculated, and the equilibrium optimal solution was obtained. Among these, the NSGA-III optimization results in lower cost and time values, but the safety requirements are slightly lower. The optimal solution's corresponding variable values and the best scores of each safety evaluation secondary indicator were obtained. The solutions of both algorithms show that the requirements for equipment safety objectives are high and that management in this area needs to be strengthened. The conclusions help the organizers and leaders of the Hebei CL wind power engineering construction project in making scientific decisions, benefiting the smooth implementation of the project and the realization of the engineering project's safety objectives.

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Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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