WARSAW UNIVERSITY OF TECHNOLOGY Index 351733
FACULTY OF CIVIL ENGINEERING
COMMITTEE FOR CIVIL AND WATER ENGINEERING
POLISH ACADEMY OF SCIENCES ISSN 1230-2945

DOI: 10.24425/ace.2025.155101
ARCHIVES OF CIVIL ENGINEERING
Vol. LXXI ISSUE 3 2025

pp. 311 – 323

Research paper

Multi-objective optimization of construction project management based on an improved genetic algorithm

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Abstract: In construction project management, it is crucial to consider multiple objectives, such as duration and cost, to develop an optimal plan. This paper established a multi-objective optimization model, taking into account the construction period, cost, safety, and quality of projects. A genetic algorithm (GA) was selected as the solution method, and the non-dominated sorting genetic algorithm-II (NSGA-II) was optimized by cat mapping, adaptive crossover, and mutation operators to obtain an improved algorithm for the model solution. Experiments were conducted to evaluate the performance of the designed algorithm. It was found that the improved NSGA-II exhibited superior convergence and diversity when applied to the test functions ZDT1-ZDT3. The mean construction period obtained from the model solution was 124 days, with a cost of 1,204,782 euros. The quality and safety levels achieved were 0.93 and 0.95, respectively, which were significantly better than those obtained by the NSGA-II. These findings demonstrate the reliability of the improved NSGA-II developed in this paper, suggesting its practical applicability.

Keywords: construction engineering, genetic algorithm, multi-objective optimization, NSGA-II, project management

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1. Introduction

As the economy rapidly develops, the construction industry has also developed and made significant contributions to social stability and employment promotion. However, it also faces increasing competitive pressures and new challenges, particularly in project management. Currently, project management methods in the construction industry are relatively singular, lacking comprehensive cost and quality control considerations. Consequently, project management efficiency remains low, impeding enterprises' ability to maximize their interests. Multi-objective optimization in project management involves considering various objectives holistically to make better decisions and achieve greater efficiency and effectiveness. This falls under multi-objective optimization problems (MOP) [1]. As intelligent algorithms continue to advance, an increasing number of methods are being applied to address MOP [2]. For instance, Liu et al. [3] proposed a two-stage multi-objective optimization algorithm for the delivery problem of takeaway riders. This algorithm combined a genetic algorithm (GA) with a large-scale domain search algorithm and demonstrated its reliability through simulation experiments. Zhang [4] focused on the intelligent adjustment of train operation schedules and designed a multi-objective optimization model based on passenger satisfaction. This model was solved using a chaotic firefly algorithm, and its effectiveness was proven through simulation. Erol et al. [5] designed a material optimization model for multilayer self-driven parts, employing a GA for its solution and obtaining feasible designs. Furthermore, Yuen et al. [6] proposed an optimized particle swarm optimization algorithm based on the competitive mechanism. Through experiments on 37 benchmark test problems, they demonstrated the effectiveness of this algorithm for solving MOP. Some research has been conducted on construction project management issues. Hargaden et al. [7] analyzed the role of blockchain technology in construction project management and explored applications of decentralization, peer-to-peer principles, and smart contracts. They pointed out that blockchain technology can significantly improve process efficiency in the construction industry. Mukilan et al. [8] designed an improved particle swarm optimization algorithm to optimize engineering project claim management with the objective functions of project time and cost. Experimental results showed that this algorithm could minimize project costs and time to a maximum extent. Sembiring et al. [9] utilized critical chain project management for scheduling construction projects and discovered through case studies that this approach enables the effective arrangement of project timelines to attain optimal progress. Kannimuthu et al. [10] examined the advantages and disadvantages of single-objective and multi-objective methods in architectural construction planning and concluded from three actual case studies that the single-objective approach is capable of determining superior solutions. GA has good robustness in solving optimization problems [11] and has been successfully applied in parameter optimization [12] and engineering management [13]. However, traditional GA lacks flexibility, and obtaining ideal results for some complex problems is difficult. Therefore, various improvements to traditional GA have emerged [14]. The non-dominated sorting genetic algorithm (NSGA) introduces non-dominated sorting into GA to highlight excellent individuals [15], while NSGA-II is an improved version of NSGA to achieve better convergence and distribution, showing better performance in solving MOP [16]. In this paper, a multi-objective optimization model was established based on the project's duration, cost, safety, and quality. An improved GA was designed to solve this model. The aim is to provide reliable references for optimizing construction project management in practical applications. The research in this article demonstrates the effectiveness of the improved NSGA-II in MOP and provides some theoretical support for considering more objectives in optimizing construction project management.

2. A multi-objective optimization model for construction project management

2.1. Multi-objective optimization problem

In most MOPs, it is generally not feasible to achieve an optimal solution that simultaneously meets all objectives. The outcomes obtained from solving MOP are called Pareto optimal solutions [17]. These solutions form a set where at least one objective is optimally satisfied, and the other objectives are also satisfied to varying degrees. Suppose that an MOP can be described by functions:

$$\begin{cases} \min F(x) = \{f_1(x), f_2(x), \ldots, f_m(x)\} \\ s.t. g_j(x) \leq 0, j = 1, 2, \ldots, p \\ h_k(x) = 0, k = 1, 2, \ldots, q \end{cases}, \tag{2.1}$$

where: $x = (x_1, x_2, \ldots, x_n) \in X \subset R^n$ (X: a n-dimensional decision space), referring to a n-dimensional decision vector, $f_1(x), f_2(x), \ldots, f_m(x)$ – optimization objectives, $g_j(x)$ – p inequality constraints, $h_k(x)$ – q equality constraints.

A solution $x \in X$ is usually referred to as a Pareto optimal solution or a non-dominated solution, when and only when $\neg\exists x' \in X : x \prec x'$.

There are two main approaches to solving MOP. One is to decompose the multiple objectives into single objective models, prioritize different objectives, determine the main objective, and search for the optimal solution. However, this method has significant limitations and often fails to achieve optimal decision-making results. The other is to directly solve the MOP using intelligent algorithms such as GA and particle swarm optimization [18]. These algorithms can simultaneously solve the optimization of multiple objectives and are widely used in various applications such as path selection [19] and process optimization [20].

2.2. Multi-objective optimization modeling

In construction project management, the objectives often considered are schedule, cost, and quality. In this paper, in addition to these three objectives, the safety objective is also considered, and the explanation of each objective is as follows.

1. Construction period: it refers to the duration from the start of construction to the acceptance of the project. It is an important indicator to determine whether the project is completed. It is assumed that all processes can only be started after the immediate

predecessor activities have been completed, and the process can not be interrupted. The objective of the construction objective is written as:

$$\min T = \sum_{i \in I} t_i, \tag{2.2}$$

$$s.t. t_{si} \leq t_i \leq t_{li}, \tag{2.3}$$

where: T – the total construction period, I is the set of processes, t_i – the actual construction time of process i, t_{si} – the shortest construction time of process i, t_{li} – the longest time of process i.

2. Cost: it is directly related to project's profitability. The goal is to minimize the cost inputs without affecting other objectives. The cost objective is written as:

$$\min C = \sum_{i=1}^{n} \left[C_i + \beta_i \left(t_i - t_{in} \right)^2 \right] + \gamma T_c \tag{2.4}$$

where: C – the total cost, C_i – the direct cost of process i, β_i – the incremental marginal cost factor, t_{in} – the normal duration time of process i, γ – the indirect cost, and T_c – the total construction period of the project.

3. Quality: each process in the construction project has the corresponding quality requirements. The quality level must be strictly controlled. 0-1 is used to indicate the quality level of each process. It is assumed that the quality under the longest operating time of the process is 1, and the quality gradually decreases as the construction period is compressed. The quality level of process i is written as:

$$Q_i = \ln \left(a_i t_i + b_i \right), \tag{2.5}$$

$$a_i = \frac{e - e^{q_{iI}}}{t_{li} - t_{si}}, \tag{2.6}$$

$$b_i = \frac{e^{q_{iI}} \times t_{li} - e \times t_{si}}{t_{li} - t_{si}}, \tag{2.7}$$

where: e – a natural constant, q_{iI} – the minimum quality requirement of process i. In actual construction projects, the final total quality will be affected by the previous processes. It is assumed that the immediate predecessor activities of process i include $j_1 j_1, \cdots j_m$, then

$$Q_i^{\text{out}} = \left[1 - \prod_{j=1}^{n} \left(1 - Q_j^{\text{out}} \right) \right] \times Q_i. \tag{2.8}$$

The quality level of the whole project is written as:

$$Q = Q_n^{\text{out}} = \left[1 - \prod_{i=1}^{n} \left(1 - Q_i^{\text{out}} \right) \right] \times Q_n. \tag{2.9}$$

4. Safety: Safety in construction projects encompasses not only the safety of each process within the construction process but also financial and logistical safety, which poses great complexities. To minimize the occurrence of safety incidents, companies will input safety assurance costs during project implementation. Direct safety costs are incurred to ensure production safety, whereas indirect safety costs are compensation expenses resulting from safety accidents. Assuming that process i has a safety accident occurrence rate of p_i, then its safety level can be written as:

$$S_i = 1 - p_i = 1 - p_{i0}\left(1 - \Delta p_i\right), \tag{2.10}$$

$$\Delta p_i = \Delta p_{i\min} + \frac{\left(\Delta p_{i\max} - \Delta p_{i\min}\right)\left(c_{ig} - c_{igl}\right)}{c_{igh} - c_{igl}}, \tag{2.11}$$

where: p_{i0} – the initial incidence of safety accidents in process i, Δp_i – the rate of reduction in the incidence of safety accidents after investing in security assurance costs, $\Delta p_{i\max}$, $\Delta p_{i\min}$ – the maximum and minimum rates of reduction in the incidence of security accidents after investing in security assurance costs, c_{ig} – the safety assurance cost input in process i, c_{igh}, c_{igl} – the maximum and minimum values of the safety assurance cost input in process i.

In actual construction projects, the final level of total safety is similarly affected by immediate predecessor activities. Assuming that the immediate predecessor activities of process i include $j_1 j_1, \cdots j_m$, then the safety level of this process is written as:

$$S_i^{\text{out}} = \left[1 - \prod_{j=1}^{n}\left(1 - S_j^{\text{out}}\right)\right] \times S_i. \tag{2.12}$$

The level of security for the entire project is written as:

$$S = S_n^{\text{out}} = \left[1 - \prod_{i=1}^{n}\left(1 - S_i^{\text{out}}\right)\right] \times S_n. \tag{2.13}$$

Combining the above objectives, the final multi-objective optimization model of construction project management established in this paper is:

$$\begin{cases} \min T = \sum\limits_{i \in I} t_i \\ \min C = \sum\limits_{i=1}^{n}\left[C_i + \beta_i\left(t_i - t_{in}\right)^2\right] + \gamma T_c \\ \max Q = \left[1 - \prod\limits_{i=1}^{n}\left(1 - Q_i^{\text{out}}\right)\right] \times Q_n \\ \max S = \left[1 - \prod\limits_{i=1}^{n}\left(1 - S_i^{\text{out}}\right)\right] \times S_n \end{cases} \tag{2.14}$$

$$st.\, t_{si} \le t_i \le t_{li}, 0 < Q_i \le 1, 0 < S_i \le 1 \tag{2.15}$$

3. Improved genetic algorithm solution

The GA performs well in both single-objective and multi-objective optimization problem-solving [21]. NSGA-II, built upon GA, stands out for its exceptional performance in addressing MOP [22]. In this paper, the NSGA-II algorithm is also employed to solve the multi-objective optimization model for construction project management, and its steps are as follows.

1. The population is initialized, and the algorithm parameters are set.
2. The initial population is subjected to fast, non-dominated sorting, and the first generation of sub-populations is obtained after crossover and mutation.
3. The offspring and parent populations are merged to create a new population.
4. The new population obtained is subjected to fast, non-dominated sorting. The crowding degree is computed, and appropriate individuals are chosen to constitute a fresh parent population.
5. The above steps are repeated until the termination condition is met.

A few key elements in NSGA-II are listed below.

1. Fast non-dominated sorting
   Suppose there is population P with size N and the objective dimension is m. All individuals are traversed, and n_i of each individual is calculated (n_i indicates the number of individuals in the population dominate individual i). Individuals with $n_i = 0$ are stored in non-dominated layer F_1. All individuals in F_1 are traversed, and S_j, the individuals dominated by individual i, is calculated.
   Then, all individuals in S_j are traversed. For any individual k, $n_k = n_k - 1$ is executed. If $n_k - 1 = 0$, n_k belongs to the next non-dominated layer.
   The above operations are repeated until all individuals are sorted.
2. Calculations of crowding degree
   For individual i, its crowding distance is calculated by:

$$i_{\text{distance}} = \sum_{j=1}^{m} \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{\max} - f_j^{\min}}, \tag{3.1}$$

   where: f_j^{i+1}, f_j^{i-1} – the function values of points $i+1$ and $i-1$ on objective function j, $f_j^{\max}$, $f_j^{\min}$ – the maximum and minimum values of objective function j.
3. Elitism strategy
   The i-th population generation, i.e., P_i is regarded as the parent population. Sub-population Q_i is obtained after crossover and mutation. They are merged to generate a new population. Then, the individuals in the population are screened according to the results of the fast, non-dominated sorting and crowding degree until the scale of the new population is N.

To further enhance the diversity and convergence of the algorithm, the NSGA-II is improved in the following two aspects.

1. The population is initialized based on cat mapping, which is an invertible chaotic mapping that has good traversal uniformity and iteration speed [23]:

$$x_{n+1} = (x_n + a y_n) \,(\bmod N)\,, \tag{3.2}$$

$$y_{n+1} = [bx_n + (ab + 1)\, y_n] \,(\mathrm{mod}\, N)\,, \tag{3.3}$$

where: a, b, N – positive integers.

2. To enhance the optimization, adaptive crossover and mutation operators are used:

$$p_c\,(i) = \min p_c + (\max p_c - \min p_c) \times \frac{i}{\mathrm{gen}}, \tag{3.4}$$

$$p_m\,(i) = \min p_m + (\max p_m - \min p_m) \times \frac{i}{\mathrm{gen}}, \tag{3.5}$$

where: i – the current number of generations, gen – the maximum number of generations, max p_c, min p_c – the upper and lower limits of the crossover probability, with values of [0.4, 0.8], max p_m, min p_m – the upper and lower limits of the mutation probability, with values of [0.001,0.01]. The operation process of adaptive crossover and mutation operator is as follows. $p_c\,(i)$ and $p_m\,(i)$ are calculated using the above equations. After determining the positions of genes for crossover and mutation, random numbers are generated and compared with $p_c\,(i)$ and $p_m\,(i)$. If they are smaller than $p_c\,(i)$ and $p_m\,(i)$, crossover and mutation operations are performed.

4. Results and analysis

4.1. Experimental environment and project overview

The experiment was conducted on a Windows 10 system with an Intel(R) Core(TM)i7-10750H 2.6 GHz central processing unit and 16 GB of random access memory. An experiment was conducted using a construction project as an example. Twelve processes were included, as shown in Table 1. The construction period, total cost, quality level, and safety level requirements for this project were no more than 140 days, within 1,261,900 euros, at least 0.8, and at least 0.9. Additionally, the indirect cost per day was estimated at 315.475 euros. The specific parameters for each process are shown in Table 2.

Table 1. Specific processes

Process	**Content**	**Immediate successor activity (the subsequent process following a procedure)**
A	Excavation of foundation pit	
B	Blinding layer	D
C	Base plate	
D	Main part	

Continued on next page

Table 1 – *Continued from previous page*

Process	**Content**	**Immediate successor activity (the subsequent process following a procedure)**
E	Waterproofing	H, I, J, K
F	Backfill	
G	Rough decoration	
H	Doors and windows installation	
I	Pipeline installation	
J	Embedded part	
K	Slotting and piping	
L	Completion	

Note: t_{si}: the shortest construction time of process i, t_{in}: the normal duration time of process i; t_{li}: the longest time of process i; C_i: the direct cost of process i, β_i: incremental marginal cost factor; q_{iI}: the minimum quality requirement of process i; p_{i0}: the initial incidence of safety accidents in process i; $\Delta p_{i\min}$, $\Delta p_{i\max}$: the minimum and maximum rates of reduction in the incidence of safety accidents after investing in security assurance costs.

Table 2. Parameters of each process in this construction project

Process	t_{si}	t_{in}	t_{li}	C_i	β_i	q_i	p_{i0}	Δp_{in}	$\Delta p_{i\max}$
A	12	20	22	13.93	3.12	0.78	0.20	0.08	0.90
B	10	15	20	1.28	3.03	0.82	0.10	0.05	0.85
C	15	18	25	12.94	2.37	0.82	0.08	0.02	0.85
D	20	26	40	52.04	2.78	0.84	0.01	0.02	0.85
E	8	12	15	1.09	2.02	0.80	0.08	0.02	0.80
F	8	13	15	12.17	2.35	0.85	0.15	0.05	0.88
G	5	8	10	0.65	3.21	0.85	0.15	0.08	0.85
H	5	8	10	0.17	1.25	0.88	0.05	0.02	0.80
I	8	13	15	4.43	3.24	0.82	0.10	0.12	0.90
J	5	7	9	0.04	2.87	0.78	0.15	0.12	0.85
K	5	7	8	0.04	2.12	0.78	0.10	0.12	0.85
L	2	2	3	0.06	1.33	0.88	0.05	0.02	0.90

4.2. Improved NSGA-II performance analysis

The performance of the optimized NSGA-II was tested on the multi-objective test functions ZDT1-ZDT3, which are as follows:

1. ZDT1 function

$$\begin{cases} f_1(x) = x_1 \\ f_2(x) = g\left(1 - \sqrt{\dfrac{f_1}{g}}\right) \\ g(x) = 1 + 9\sum\limits_{i=2}^{m} x_i/(n-1) \end{cases} \tag{4.1}$$

$$x_1 \in [0,1] \leq x_i \leq 1, i = 1, 2, \ldots, n \tag{4.2}$$

$F = (f_1(x), f_2(x))$. The minimum values of $f_1(x)$ and $f_2(x)$ were calculated.

2. ZDT2 function

$$\begin{cases} f_1(x) = x_1 \\ f_2(x) = g\left[1 - (f_1/g)^2\right] \\ g(x) = 1 + 9\sum\limits_{i=2}^{m} x_i/(n-1) \end{cases} \tag{4.3}$$

$$x_1 \in [0,1] \leq x_i \leq 1, i = 1, 2, \ldots, n \tag{4.4}$$

$F = (f_1(x), f_2(x))$. The minimum values of $f_1(x)$ and $f_2(x)$ were calculated.

3. ZDT3 function

$$\begin{cases} f_1(x) = x_1 \\ f_2(x) = g(x)\left[1 - \dfrac{f_1(x)}{g(x)} - \dfrac{f_1(x)}{g(x)}\sin(10\pi x_1)\right] \\ g(x) = 1 + 9\sum\limits_{i=2}^{m} x_i/(n-1) \end{cases} \tag{4.5}$$

$$x_1 \in [0,1] \leq x_i \leq 1, i = 1, 2, \ldots, n \tag{4.6}$$

$F = (f_1(x), f_2(x))$. The minimum values of $f_1(x)$ and $f_2(x)$ were calculated.

The convergence and diversity was compared between the NSGA-II and the improved NSGA-II after setting the population size, the maximum number of iterations, and independent running times of the NSGA-II as 100, 250, and 30 [24]. The obtained results are presented in Table 3.

It was seen from Table 3 that the improved NSGA-II exhibited significantly enhanced convergence and diversity compared to the NSGA-II on the ZDT1-ZDT3 test functions, i.e., it could generate more stable and reliable results on multi-objective test functions. These findings validate the effectiveness of the enhancement for NSGA-II. The improvement can enable the algorithm to consistently find a more evenly distributed and reliable Pareto solution set.

Table 3. Results of comparison of convergence and diversity

			ZDT1	ZDT2	ZDT3
NSGA-II	Convergence	Mean value	3.36E-01	6.14E-01	5.56E-02
		Standard deviation	9.41E-02	8.78E-02	1.28E-02
	Diversity	Mean value	6.52E-01	8.50E-01	7.55E-01
		Standard deviation	5.55E-02	1.64E-01	4.05E-02
Improved NSGA-II	Convergence	Mean value	9.92E-04	7.87E-04	4.71E-03
		Standard deviation	1.91E-04	4.98E-05	2.35E-04
	Diversity	Mean value	5.05E-01	5.05E-01	6.12E-01
		Standard deviation	3.85E-02	3.50E-02	2.45E-02

Note: Mean value: $\overline{x} = (x_1 + x_2 + \cdots + x_n)/n$;

Standard deviation: $\sigma = \sqrt{\dfrac{(x_1 - \overline{x})^2 + (x_2 - \overline{x})^2 + \cdots + (x_n - \overline{x})^2}{n}}$;

n: Number of samples.

4.3. Analysis of multi-objective solution results

The multi-objective model of construction project management was solved using the NSGA-II and improved NSGA-II. The population size was 100, and the maximum number of iterations was 500. Some of the solutions are presented in Table 4.

A comparison was made between the results obtained from the NSGA-II and the improved NSGA-II. The mean construction period, cost, quality level, and safety level achieved by the NSGA-II were 128 days, 1,219,800 euros, 0.88, and 0.92, respectively. On the other hand, the improved NSGA-II achieved a mean construction period of 124 days, resulting in a reduction of four days compared to the NSGA-II. Additionally, the cost was reduced by 1.23% to 1,204,782 euros compared to the NSGA-II. Moreover, the quality and safety levels were increased to 0.93 and 0.95, respectively, which were improved by 0.05 and 0.03 compared to the NSGA-II. These findings demonstrated that the solution obtained by the improved NSGA-II yielded better results when tackling the multi-objective model of construction project management.

A detailed analysis of the improved NSGA-II solution reveals a strong relationship between the various objectives in construction project management. When aiming for a short construction period, the project's cost tends to increase while the levels of quality and safety may decrease. A long construction period can lead to reduced project costs and improved quality and safety levels to some extent. Moreover, if the project prioritizes high-quality deliverables and the prevention of safety incidents, the project's construction period will likely be extended, resulting in increased costs. The Pareto solution set obtained through the improved NSGA-II solution offers various options catering to different optimization objectives. Decision-makers can select the most suitable solution based on the specific requirements of the construction project. For instance, Solution 1 may be chosen for execution when prioritizing the shortest construction period, while Solution 2 can be selected when seeking the lowest cost.

Table 4. Partial solutions of the model

Solution	NSGA-II				Improved NSGA-II			
	Construction period/day	Cost/euro	Quality	Safety	Construction period/day	Cost/euro	Quality	Safety
1	120	1,224,140	0.85	0.90	118	1,211,712	0.87	0.92
2	127	1,198,900	0.90	0.90	125	1,192,684	0.92	0.95
3	130	1,236,760	0.87	0.92	128	1,193,852	0.97	0.97
4	128	1,224,140	0.88	0.92	127	1,196,471	0.97	0.96
5	127	1,243,070	0.90	0.92	125	1,198,900	0.95	0.95
6	128	1,230,645	0.89	0.93	125	1,201,519	0.96	0.95
7	127	1,211,712	0.85	0.93	125	1,202,686	0.95	0.94
8	130	1,218,023	0.92	0.92	124	1,211,712	0.95	0.95
9	130	1,211,712	0.90	0.92	124	1,201,519	0.94	0.95
10	137	1,198,900	0.85	0.95	119	1,236,760	0.86	0.97
Mean value	128	1,219,800	0.88	0.92	124	1,204,782	0.93	0.95

5. Conclusions

In this paper, an improved NSGA-II was proposed to address the multi-objective model of construction project management. Through experimental analysis, it was found that the improved NSGA-II performed better than the NSGA-II in terms of convergence and diversity. Moreover, the solutions obtained through the improved NSGA-II exhibited higher quality. In actual construction projects, the improved NSGA-II can provide optimal solutions based on specific requirements, providing some theoretical support for decision-makers.

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Received: 2024-05-13, Revised: 2024-07-25