Journal of Engineering, Project, and Production Management
2026, 16(3), 2025-202

Optimization of Municipal Construction Project Management Using Multi-Objective IGA

Huafeng Lou
Associate Senior Engineer, Hangzhou Qiantang Urban Construction Group Co., Ltd, Hangzhou, 310020, China, E-mail: huafenglou@outlook.com

Project Management
Received September 12, 2025; revised October 30, 2025; accepted November 4, 2025
Available online April 8, 2026

Abstract: Municipal construction projects play an important role in improving public well-being and promoting economic and social development. Comprehensive project management involves the coordinated integration of key elements such as schedule, cost, quality, and safety. However, current municipal project management often adopts a single-objective optimization approach, overlooking the complexity of multi-objective interactions. To this end, this paper innovatively combines the Ant Colony Optimization (ACO) algorithm, Fuzzy Logic (FL), and Immune Genetic Algorithm (IGA), and proposes a hybrid algorithm for solving multi-objective models of municipal construction projects. Through a structured and collaborative algorithm fusion strategy, it systematically addresses the fuzziness, complexity, and local optimality problems in the multi-objective management of municipal engineering, providing a novel and efficient solution for achieving the global optimal management of the project. Results show that the hybrid algorithm achieves an average accuracy of 98.7%, a data query rate of 99.5%, a spatial complexity of 21.3%, and a computational speed of 17.6 bps. Its overall performance surpasses that of similar algorithms. Meanwhile, the Pareto solutions cover the entire objective space, demonstrating excellent computational efficiency and global optimization ability. Therefore, the hybrid algorithm exhibits outstanding optimization performance and practical applicability, providing a reference for multi-objective optimization (MOO) management in municipal construction projects.

Keywords: Municipal construction, ant colony optimization algorithm, multi-objective management, project optimization, immune genetic algorithm.

DOI 10.32738/JEPPM-2025-202

1. Introduction

Municipal construction projects serve as the core carrier of urban infrastructure development and are crucial for improving public well-being and promoting economic development. Their processes involve multiple objectives, including cost reduction, schedule control, safety management, and quality assurance, and the level of coordinated management among these objectives is directly related to overall project performance (Lafioune et al., 2024). Therefore, achieving dynamic balance among multiple objectives has always been the focus of project management. Currently, municipal project management optimization often relies on single-objective optimization models, thereby ignoring the mutual constraints among objectives. This leads to solutions that cannot meet the multi-dimensional coordination requirements of actual projects (Gong et al., 2025). In addition, traditional optimization algorithms face limitations such as slow convergence and susceptibility to local optima when handling high-dimensional and multi-constraint municipal projects, making them unsuitable for complex environments with many variables (Ooi et al., 2024). The IGA can quickly converge to optimal solutions when handling multiple objectives. The ACO algorithm can avoid local optima, while the Fuzzy Logic (FL) algorithm transforms fuzzy information in municipal projects into computable variables (Wu et al., 2024; Xiao et al., 2025).

Current domestic and international studies on municipal construction project optimization, safety assessment, and project management mainly adopt methods such as single-camera obstacle detection algorithms and weighted clustering, often focusing on single-objective analysis. For example, to achieve automated inspection of municipal facilities and reduce hardware costs, Li and Liu (2025) proposed a single-camera obstacle detection algorithm. They inferred spatial information by estimating object poses in images and used Blender to generate datasets for position estimation. Results showed that the method effectively improved camera utilization on existing inspection equipment. Yang (2025) proposed a digital management approach for construction schedule objectives of municipal infrastructure. The approach used Building

Information Modeling and added interactive modules of digital enterprises. Virtual reality technology converted three-dimensional models of municipal infrastructure into VR models, which could predict construction schedules. Momo et al. (2023) proposed a new convex quadratic programming model that satisfied both design and safety constraints for computing vertical alignment of resources in municipal road construction. This model represented the limit state of a state-based mixed-integer linear programming model, and results indicated that the optimal solution could be obtained in a very short time. Parsons et al. (2024) combined weighted clustering and differential evolution to design a two-stage clustering method for optimizing municipal cleaning routes. They used a three-stage augmented merge algorithm to generate initial solutions, improved the Hill Climbing algorithm to minimize U-turns, and optimized paths with ACO. A case study in Oshawa, Canada, showed improvements across all metrics. Some studies also considered the interactions among multiple objectives in municipal construction. Hussain et al. (2025) applied a relative importance index and mean values to prioritize schedule, budget, and quality indicators. Results showed that the relative importance index ranged from 0.877 to 0.760, and the importance ranking of the indicators was cost, quality, safety, and sustainable construction. These studies provided technical support for target control and optimization management.

IGA was developed by optimizing the traditional genetic algorithm based on biological immune mechanisms. It could quickly find Pareto-optimal solutions when handling multiple objectives and had been applied in various fields. For example, Zhang et al. (2023) combined IGA with the Dendritic Cell Algorithm to build a feature selection and signal classification model. They used adaptive operators to expand optimal grouping paths, and the model could allocate the discovered optimal features to the most suitable signal groups. To address the difficulty of identifying structural edge damage, Zhao et al. (2025) applied IGA for finite element simulation of fixed-end beams and frame structures, tested the vibration performance of fixed-end and cantilever beams, and verified the effectiveness of a two-stage method for edge damage localization and assessment. Results showed that the algorithm performed well in noise robustness and edge damage sensitivity. However, IGA often fell into local optima during global search. ACO could avoid this limitation through pheromone-guided search, while FL could quantify fuzzy variables. Both were commonly applied in multi-objective optimization management. Hossein et al. (2023) combined data-driven modeling and heuristic methods with a metaheuristic ACO and local vaccination algorithm to create an artificial IGA. They used a Random Forest Algorithm to predict process unit products, achieving an accuracy of 99.17%. Changdar et al. (2023) proposed a two-stage ACO combined with a genetic algorithm to solve the single-depot multi-traveling salesman problem in a Type-2 Gaussian fuzzy environment. They generated paths with ACO, optimized features with the genetic algorithm, and reduced Type-2 Gaussian fuzzy travel costs to near crisp values using a critical value reduction method. Zaghba et al. (2025) generated a hybrid model based on FL and proportional-integral algorithms, tuned fuzzy parameters with particle swarm optimization, and handled nonlinear photovoltaic power curves with a rule-based system. Tests showed that the model achieved an overall accuracy of 99.7% and could accurately track the global maximum power point.

In summary, existing domestic and international research on municipal construction project management has made certain progress, but most studies have ignored the interaction among multiple objectives. IGA demonstrated strong optimization ability in conflicting multi-objective scenarios. However, the current research problem is that existing methods rely heavily on single-objective optimization or simple weighted analysis, ignoring the complex interactions and inherent contradictions between multiple key objectives such as schedule, cost, quality, and safety, resulting in solutions that are difficult to meet the practical needs of multi-dimensional collaborative management in engineering. At the same time, existing methods are difficult to effectively handle and quantify goals with inherent ambiguity and uncertainty, such as “quality” and “safety”, and lack effective mechanisms to convert them into computable variables, thereby limiting the accuracy and practical applicability of optimization models. Therefore, this study develops a comprehensive model integrating schedule, cost, quality, and safety objectives, and proposes a hybrid IGA-ACO-FL algorithm. This approach establishes a multi-objective coordination optimization system based on traditional single-objective management, overcomes the limitations of a single IGA, and improves optimization efficiency and stability in complex project scenarios. It aims to address the challenge of coordinating multiple objectives in municipal construction projects and provides a more scientific and reasonable optimization solution for project management. This study is structured into four parts. The first part systematically analyzes the current situation and challenges of multi-objective management in municipal construction projects, deeply dissects the limitations of existing single-objective optimization methods in dealing with multi-objective collaborative optimization, such as progress, cost, quality, and safety, and at the same time proposes a theoretical basis and methods for solving multi-objective optimization problems. The second part constructs a mathematical model for municipal engineering management that includes four core goals: progress, cost, quality, and safety, and designs the IGA-ACO-FL hybrid algorithm to form a complementary collaborative optimization mechanism. The third part verifies the validity and feasibility of the methods, and the fourth part summarizes the research results.

2. Design of Multi-Objective Optimization Algorithm Based on IGA

2.1. IGA Design for Multi-Objectives in Municipal Construction Projects

In the construction process of municipal projects, schedule, cost, quality, and safety are the key dimensions for optimization. Their interactions jointly determine the overall performance of a project. Therefore, the municipal construction project management model is designed with cost minimization as the primary objective, aiming to find the minimum cost that simultaneously satisfies schedule, quality, and safety objectives. The cost composition is shown in Fig. 1.

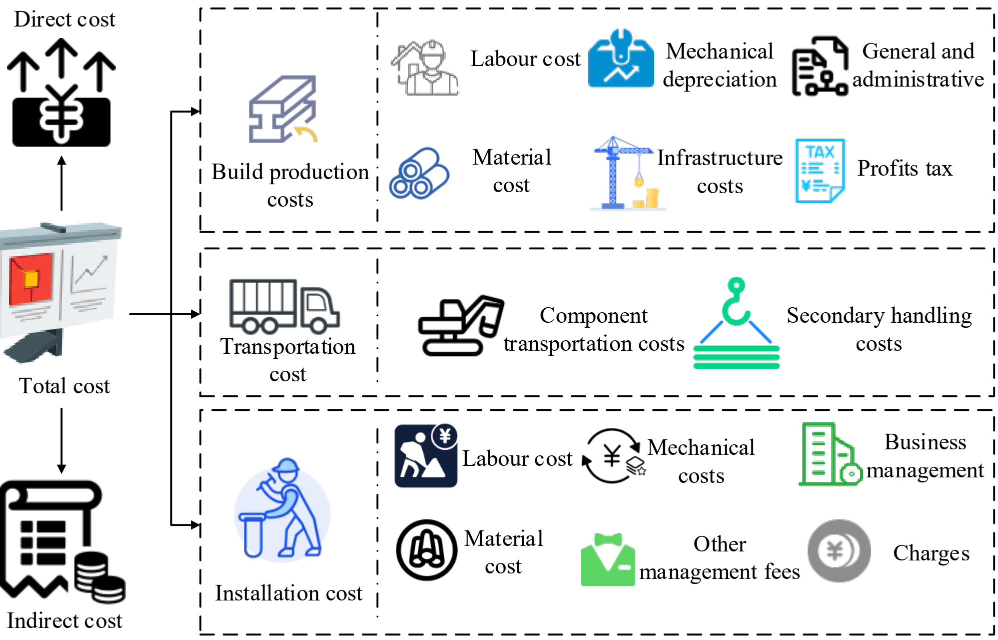


Fig. 1. Composition of municipal construction project management model (Icon source from: https://www.iconfont.cn/)

As shown in Fig. 1, the municipal project cost can be divided into direct and indirect costs. Direct costs include construction production costs dominated by labor, materials, and infrastructure expenses, transportation costs dominated by material handling and facility installation costs. Indirect costs mainly include management fees, financial expenses, and taxes (Olivares et al., 2025). Fig. 1 can help managers identify the cost composition, thereby enabling them to precisely locate controllable cost items during the optimization process and lay the foundation for achieving the core goal of “cost minimization”. In the construction process, the cost objective directly affects the project schedule. Reducing costs may extend the schedule, while compressing the schedule may increase direct costs. The optimal schedule model for cost minimization is expressed in Eq. (1).

$$\begin{cases} \min C = \sum_{i=1}^{N} [C_{in} + r_i \times (T_i - T_{in})^2 + \beta \times T + \pi \times (T - T_C)] \\ s.t. \quad T_{i0} \le T_i \le T_{in} \\ C_{in} \le C_i \le C_{i0} \end{cases} \tag{1}$$

In Eq. (1), C_{in} represents the completion cost of process i under normal working time. T_{in} is the normal working time of process i. T_i is the actual working time of the process. r_i is the incremental coefficient. T represents the actual project completion time. β is the indirect cost rate. T_C is the contract schedule. Increasing costs can improve construction quality, demonstrating a significant positive correlation. The cost-quality optimization model aims to minimize cost while meeting quality standards, as shown in Eq. (2).

$$\begin{cases} \min C_q = \sum_{i=1}^{N} C_i \times \left\{ 0.5 \times [\tan(\frac{\pi}{4}) \times Q_i]^{K_1} \right\} + 0.5 \times [c \times \cot(\frac{\pi}{4}) \times (1 + Q_i)]^{K_2} \\ s.t. \quad T_{i0} \le T_i \le T_{in} \\ Q = \sum_{i=1}^{N} \omega_i In(\alpha_i \times T_i + \beta_i) \ge Q_c \\ Q_{i0} \le Q_i \le 1 \end{cases} \tag{2}$$

In Eq. (2), Q_c represents the contract quality requirement. C_i is the actual cost of process i. Q_i represents the quality level of process i. K_1 and K_2 are cost growth coefficients. Cost and safety objectives also interact. The cost-safety optimization model aims to minimize cost while satisfying safety standards, with the objective function and constraints shown in Eq. (3).

$$\begin{cases} \min C_s = \sum_{i=1}^{n} \eta C_i \times \left\{ 0.3 \times [\tan(\frac{\pi}{2}) \times S_i]^{k_3} \right\} + 0.7 \times (c \times \frac{1}{S_i^2} - 1)^{k_4} \\ s.t. \quad T_{i0} \le T_i \le T_{in} \\ \quad S = [1 - \sum_{j=1}^{m} \omega_i (1 - \mathrm{S}_{nj}{}^{in}) / m] \times S_n \ge S_c \\ \quad S_i = In(\alpha_i \times T_i + b_i) \end{cases} \tag{3}$$

In Eq. (3), C_s represents total safety cost, and S_i is the safety level of process i. Finally, under the conditions of maximizing quality and safety and minimizing cost and schedule, the multi-objective model of cost-schedule-quality-safety is expressed in Eq. (4).

$$\min f(x) = \zeta_1 \times \frac{C}{C_c} + \zeta_2 \times \frac{C_q}{C_{qc}} + \zeta_3 \times \frac{C_s}{C_{sc}} + \zeta_4 \times \frac{T}{T_c} \tag{4}$$

In Eq. (4), ζ_1, ζ_2, ζ_3, and ζ_4 are the weights of project cost, quality, safety, and schedule, respectively, which sum to 1. C_c, C_{qc}, C_{sc}, and T_c represent contract cost, quality cost, safety cost, and schedule cost, respectively. To achieve the optimal combination under multiple objectives in municipal projects, IGA is applied to solve the model. IGA introduces biological immune features into GA. By extensively searching the solution space, it can find optimal solutions under complex interactions of multiple municipal project objectives. The IGA process is shown in Fig. 2.

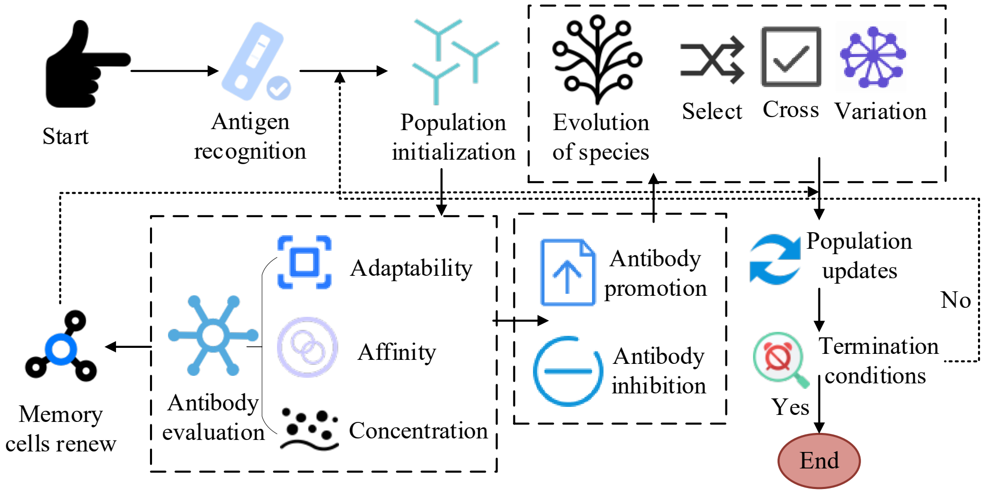


Fig. 2. IGA operation flow chart (Icon source from: https://www.iconfont.cn/)

As shown in Fig. 2, IGA is similar to biological genetic mechanisms. It first sets an initial population for iterative evolution. Individuals undergo selection, crossover, and mutation. Immune evaluation scales such as fitness, affinity, and concentration are calculated. After each iteration, the population is updated. The process continues until the desired number of iterations is reached. The IGA affinity Eq. based on Euclidean distance is shown in Eq. (5) (Zhao et al., 2025).

$$Aij = \frac{\sqrt{\sum_{k=1}^{L} (w_{i,k} - w_{j,k})^2}}{L} \tag{5}$$

In Eq. (5), L is the antibody encoding length. $w_{i,k}$ and $w_{j,k}$ represent the k-th position of antibodies i and j. The antibody concentration calculation operator is derived from affinity, as shown in Eq. (6).

$$Ci = \frac{1}{N} \sum_{j=1}^{N} S_{ij} \quad , \quad S_{ij} = \begin{cases} 1, A_{ij} \ge \lambda \\ 0, A_{ij} < \lambda \end{cases} \tag{6}$$

In Eq. (6), S_{ij} represents the similarity of antibodies i and j. λ is the similarity threshold. Ci is the concentration calculation operator for antibody i. N is the initial population size. Using Ci, the fitness assignment and antibody selection probability are calculated, as shown in Eq. (7).

$$\begin{cases} f_i = \dfrac{\hat{f_i}}{1+\beta \ln C_i} \\ P_i = \dfrac{f_i}{\sum f_i} \end{cases} \tag{7}$$

In Eq. (7), f_i is the adjusted fitness. Higher fitness indicates better individuals. $\hat{f_i}$ is the initial fitness value, and β is the concentration coefficient. P_i is the probability of antibody selection. Higher fitness leads to higher selection probability. The crossover and mutation probabilities of antibodies are calculated as shown in Eq. (8).

$$\begin{cases} P_m = \dfrac{k_i}{1+\exp(\sum(\alpha_i-\alpha_{avg})^2/N)} \\ P_C = k_2 \sin\left[\dfrac{\pi}{2}\dfrac{1}{1+\exp(\sum(\alpha_i-\alpha_{avg})^2/N)}\right] \end{cases} \tag{8}$$

In Eq. (8), P_m and P_C are the crossover and mutation probabilities of antibodies. α_{avg} is the average affinity of the antibody population. After memory cell updates, the optimal iteration solution set under multiple objectives is output. The IGA process for municipal project multi-objectives is shown in Fig. 3.

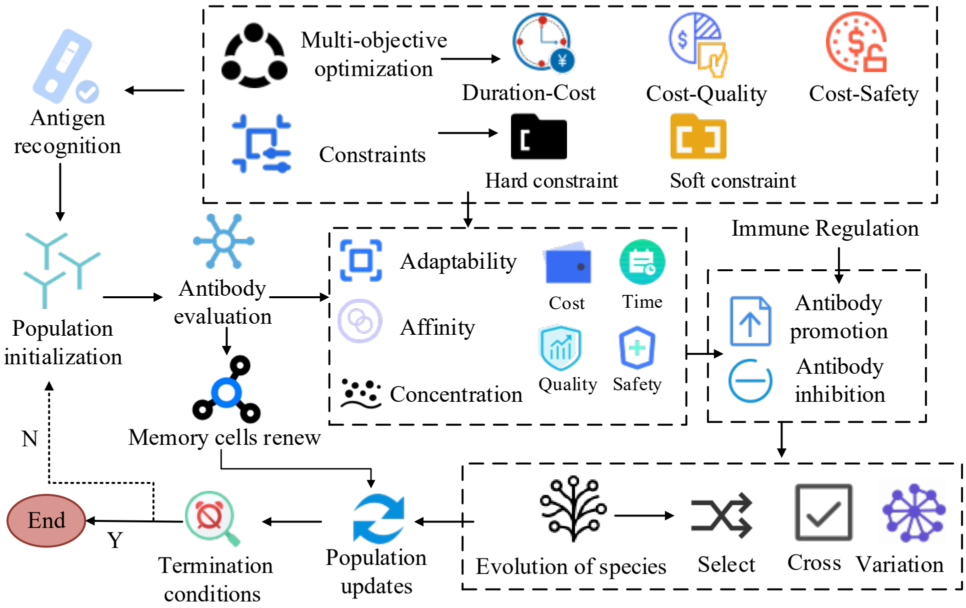


Fig. 3. IGA process based on multi-objective of municipal engineering (Icon source from: https://www.iconfont.cn/)

In Fig. 3, the cost-schedule model, cost-quality model, and cost-safety model together form the multi-objective optimization model of municipal construction projects. They serve as antigens in IGA and generating N initial antibody populations representing different allocation schemes. The objective function calculates affinity, fitness, and concentration to quantify solution quality. Antibodies with high fitness and low concentration undergo immune promotion, whereas those with low fitness and high concentration undergo immune suppression. Selection, crossover, and mutation screen antibodies, replacing the old population with newly evolved antibodies. Iterations continue until the preset number is reached. If fitness meets the threshold, the optimal solution is output; otherwise, iterations continue until the solution satisfies the balance.

2.2. Optimization of IGA Municipal Project Multi-Objective Algorithm with ACO and FL

Although IGA has a global search ability in municipal multi-objective management, its local search ability is limited, and the initialization of the population is random. Multiple iterations are required to reach the optimal solution region, leading to low search efficiency and susceptibility to local optima (Jijun and Peng, 2024). ACO simulates ants foraging to find paths, accumulates and updates pheromones, and gradually converges to the optimal path, which accelerates convergence. The pheromone update avoids local optima (Umarani et al., 2025). Therefore, ACO is introduced to compensate for IGA's limitations in municipal multi-objective optimization problems. The optimization process is shown in Fig. 4.

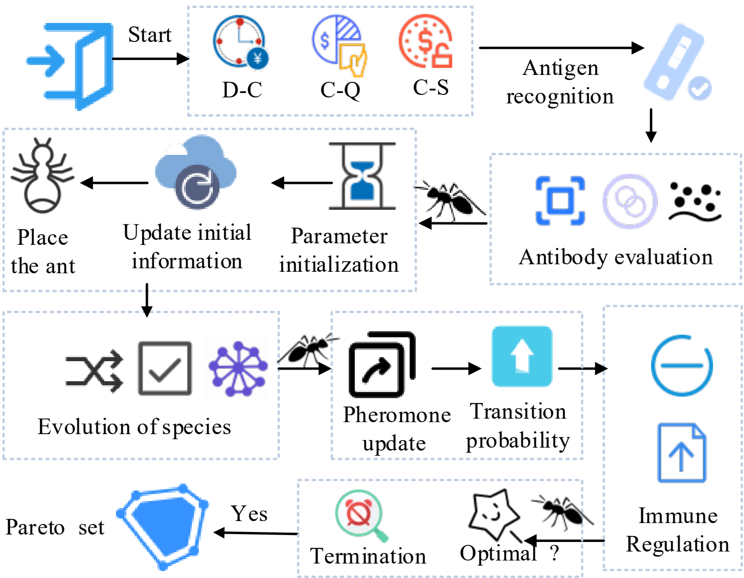


Fig. 4. ACO Optimizing IGA Process (Icon source from: https://www.iconfont.cn/)

As shown in Fig. 4, ACO extends IGA's search paths. The objective parameters serve as IGA antigens, and decision variables are mapped to ant path nodes with initialization information updated. Antibodies generated by IGA through selection, crossover, and mutation operations serve as the initial paths for ACO. Initial solutions and pheromones are generated according to ant transition probabilities. After ants move, pheromones are updated, and IGA solutions undergo local search and antibody evaluation. New paths discovered by ants are incorporated into the IGA population for immune genetic screening. The final solution must satisfy both IGA iteration conditions and ACO optimal criteria. Through the above process, high-quality solution areas can be identified more quickly, significantly improving optimization efficiency and reducing computational time. The ant transition probability is expressed in Eq. (9).

$$p^k{}_{ij}(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N^k{}_i} [\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta} \tag{9}$$

In Eq. (9), $p^k{}_{ij}(t)$ represents the transition probability of ant k from node i to j at time t. α and β are influence factors of pheromone and heuristic function. η_{ij} is the heuristic function. $N^k{}_i$ indicates the set of next nodes available for selection at i station. $\tau_{ij}(t)$ represents the pheromone concentration on the path from i to j at time t. The local pheromone update is expressed in Eq. (10).

$$\tau_{ij}(t) = (1-\rho)\tau_{ij}(t) + \rho \Delta \tau^k{}_{ij}(t) \tag{10}$$

In Eq. (10), ρ is the pheromone evaporation coefficient, and $\Delta \tau^k{}_{ij}(t)$ is the pheromone increment released when k moving from i to j, calculated as in Eq. (11).

$$\Delta \tau^k{}_{ij}(t) = \begin{Bmatrix} \dfrac{Q_1}{L_k} & , if\ k\ goes\ thriugh\ (i, j) \\ 0 & , if\ not \end{Bmatrix} \tag{11}$$

In Eq. (11), L_k represents the sum of path lengths traveled by k, and Q_1 is the sum of pheromones. The global pheromone update after all ants complete the path is shown in Eq. (12).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta \tau^k{}_{ij}(t) \tag{12}$$

In Eq. (12), m represents the total number of ants. Due to the inherent uncertainty of objectives such as safety and quality, municipal project construction faces significant challenges. These objectives are fuzzy and non-quantifiable, making it difficult for IGA alone to model them accurately. FL can quantify abstract objectives and dynamically adjust membership weights (Thenmozhi et al., 2024). Therefore, FL is introduced for further optimization. The process is shown in Fig. 5.

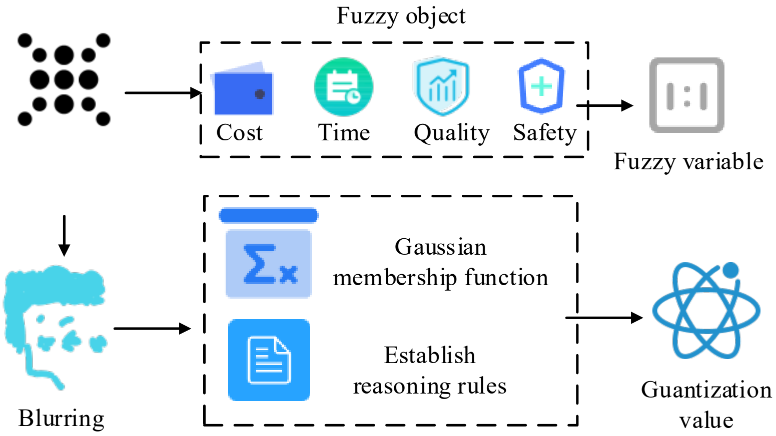


Fig. 5. FL IGA optimization process (Icon source from: https://www.iconfont.cn)

In Fig. 5, FL converts the raw data for multiple objectives, including cost, schedule, quality, and safety, into fuzzy variables. These variables are classified as high/medium/low cost, long/medium/short schedule; excellent/medium/poor quality, and high/medium/low safety. Gaussian membership functions define 0–1 membership degrees to quantify fuzziness. Higher original values correspond to lower membership degrees of objectives like low cost, short schedule, excellent quality, and high safety. This solves the quantification problem of vague concepts such as "excellent quality" and "high safety level" in municipal engineering. By transforming qualitative evaluations into membership degrees between 0 and 1, the algorithm can handle imprecise information like human experts, greatly enhancing the model's ability to address the complexity of real-world scenarios. Inference rules are then established to transform multiple objectives into structured relationships and output membership values. The fuzzification Eq. is expressed in Eq. (13).

$$A_1 : X \to [0,1], x \to A_1(x) \tag{13}$$

In Eq. (13), X represents the set of all x original data. A_1 indicates the fuzzy mapping for X. $A_1(x)$ is the membership function for A_1, with the Gaussian membership function shown in Eq. (14).

$$\mu(x) = g(x; f, \sigma) = \exp[-\frac{1}{2}(\frac{x-f}{\sigma})^2] \tag{14}$$

In Eq. (14), σ is the standard deviation of the Gaussian function, and f is the mean value. After obtaining the fuzzy variable membership degrees from Eq. (14), fuzzy inference rules are applied to integrate them. If two or more fuzzy variables satisfy the inference rule, the variable with the smaller membership degree is chosen. If two or more variables satisfy one of the inference rules, the variable with the larger membership degree is selected, as shown in Eq. (15).

$$\begin{gathered} \mu_1(x,y) = \min(\mu_A(x), \mu_B(y)) \\ \mu_2(x,y) = \max(\mu_A(x), \mu_B(y)) \end{gathered} \tag{15}$$

In Eq. (15), $\mu_A(x)$ represents the membership degree of variable x in set A, and $\mu_B(y)$ represents the membership degree of variable y in set B. Finally, defuzzification is expressed in Eq. (16).

$$Z = \frac{\sum_{i=1}^{n} z_i \cdot \mu(z_i)}{\sum_{i=1}^{n} \mu(z_i)} \tag{16}$$

In Eq. (16), z_i is the discrete value of the final variable, and $\mu(z_i)$ is its membership value. After defuzzification by FL, IGA can search for more precise, balanced solutions. Therefore, ACO and FL are combined to optimize IGA, constructing the IGA-ACO-FL hybrid algorithm for municipal project multi-objective management. The process is illustrated in Fig. 6.

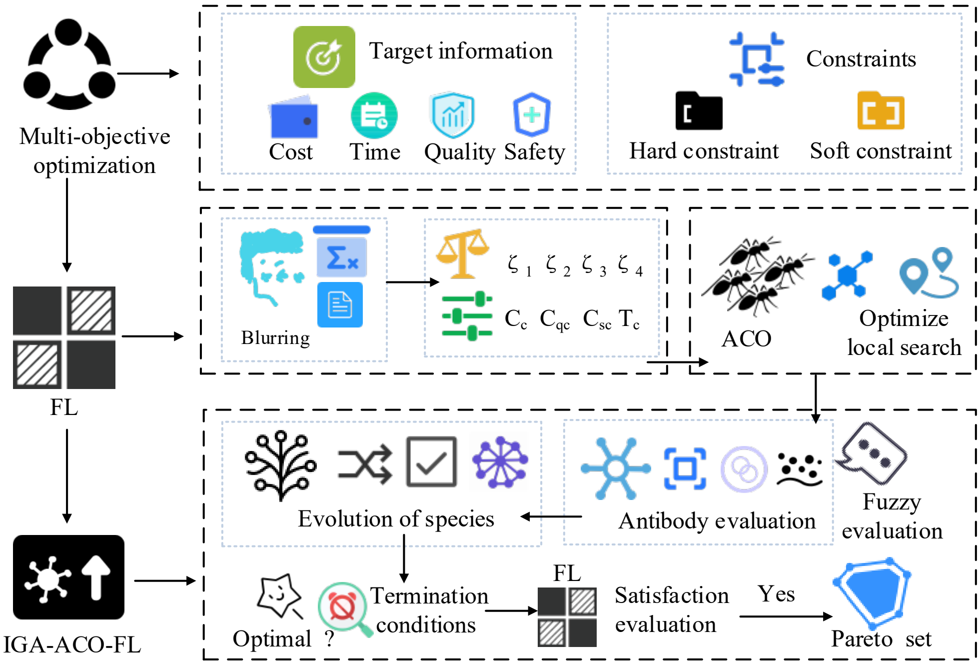


Fig. 6. Operation process of IGA-ACO-FL fusion algorithm (Icon source from: https://www.iconfont.cn)

Fig. 6 illustrates the process beginning with municipal multi-objective optimization requirements, focusing on core objectives of cost, schedule, quality, and safety. Under hard and soft constraints, IGA, ACO, and FL are integrated to solve the multi-objective municipal project management model. First, FL fuzzifies objectives, defines membership degrees, and converts all objectives into quantifiable fuzzy variables. Second, ACO updates pheromones to search paths, calculating total schedule, total cost, overall quality, and safety for each ant. Local fine search is performed on all multi-objective paths. Finally, search results serve as the initial antibody population. IGA evaluates and selects high-quality solutions, performs iterative crossover and mutation, and applies FL for fuzzy evaluation. The process continues until the optimal iteration condition is reached, producing the final optimal solution.

3. Performance Validation of IGA-ACO-FL Project Management Method

3.1. Performance Validation of IGA-ACO-FL Algorithm

To verify the performance of the IGA-ACO-FL algorithm, it was compared with the Adaptive Genetic Algorithm (AGA), the Simulated Annealing Algorithm (SAA), and the Genetic Algorithm Combined with Particle Swarm Optimization (GA-PSO). The experiments were conducted on an i5-12500H CPU processor with a 2.50GHz frequency, 16GB memory, and a 64-bit Windows 11 operating system, using MATLAB R2023b. Iterations were performed up to a maximum of 400 cycles, with the IGA-ACO-FL population size set to 300, mutation probability 0.01, and crossover probability 0.6. The algorithm accuracy and data query rate results are shown in Fig. 7.

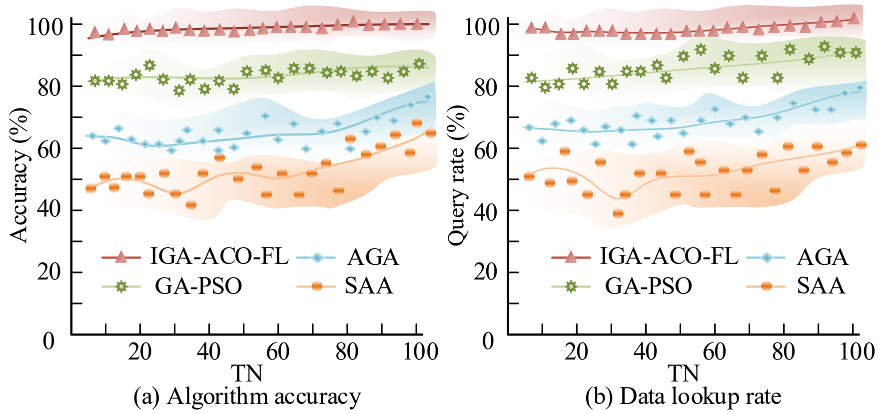
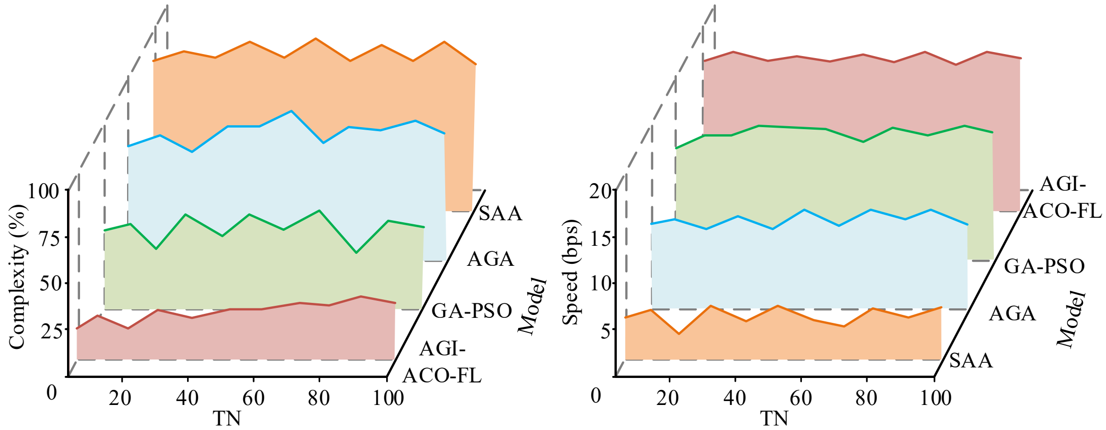


Fig. 7. Comparison of algorithm accuracy and data query rate results

In Fig. 7(a), the IGA-ACO-FL algorithm achieved an average accuracy of 98.7%. Its overall accuracy remained stable at the highest level. The next three algorithms ranked as follows: GA-PSO with 81.6%, AGA with 74.5%, and SAA with 60.2%. Data query rate reflects the efficiency of the algorithm's input data detection. In Fig. 7(b), IGA-ACO-FL reached the highest data query rate, with an average of 99.5%, indicating optimal efficiency and comprehensive data retrieval. GA-

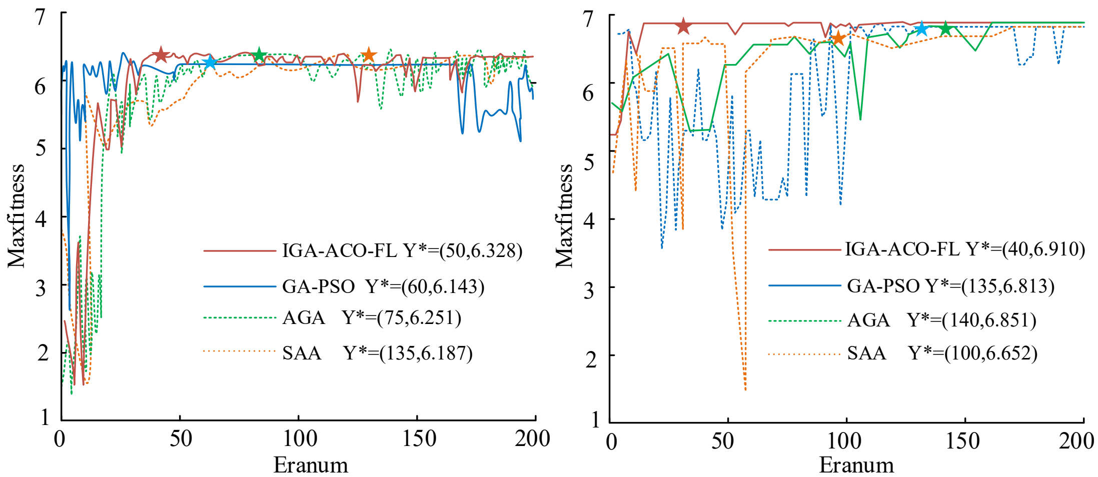
PSO ranked second with an average query rate of 86.8%. AGA and SAA followed, with average query rates of 70.6% and 56.4%, respectively. Overall, IGA-ACO-FL demonstrated the dual advantages of high accuracy and high query rate, which enhanced decision-making confidence and reduced risks caused by data omissions. Next, the space complexity and computation speed of the four algorithms were calculated. Space complexity represents the storage space occupied during algorithm execution, and the results are shown in Fig. 8.



(a) Space complexity (b) Computation speed

Fig. 8. Comparison of space complexity and computation speed

In Fig. 8(a), IGA-ACO-FL had the lowest space complexity, with an average of 21.3%, far below GA-PSO (43.1%), AGA (65.4%), and SAA (83.6%). This indicated that IGA-ACO-FL could run efficiently in memory-limited environments, while other algorithms might be restricted by storage requirements. In Fig. 8(b), IGA-ACO-FL also had the fastest computation speed, with an average of 17.6bps. GA-PSO, AGA, and SAA reached average speeds of 13.5bps, 10.2bps, and 5.8bps, respectively. This demonstrated that IGA-ACO-FL had the highest operational efficiency and was more suitable for time-sensitive tasks. Overall, IGA-ACO-FL combined low space occupation, high computation efficiency, and fast response, providing a multi-optimal solution for municipal project management. To further verify the algorithm's convergence and search capability, two multimodal functions were used for testing, with results shown in Fig. 9.



(a) $Y_1 = \exp(x)\sin(10\pi x)$, $x \in [0,2]$ (b) $Y_2 = \exp(-(x - 0.1)2)\sin^6 5\pi x^{3/4}$, $x \in [0,2]$

Fig. 9. Comparison of algorithm convergence and search capabilities

In Fig. 9, IGA-ACO-FL exhibited smaller fluctuations in later iterations, more stable convergence, and faster convergence speed compared to other algorithms, approaching global maxima more closely. In Fig. 9(a) for test function Y_1, IGA-ACO-FL reached the global optimal value of 6.328 after only 50 iterations, while the other three algorithms required 60, 75, and 135 iterations, with optimal values of 6.143, 6.251, and 6.187, respectively. In Fig. 9(b) for test function Y_2, IGA-ACO-FL reached the optimal value of 6.910 at 40 iterations, whereas the other algorithms reached optimal values of 6.813, 6.851, and 6.652 at 135, 140, and 100 iterations, respectively. Additionally, IGA-ACO-FL showed stable function curves, while other algorithms exhibited significant early-stage fluctuations and multiple local extrema. Overall, IGA-ACO-FL demonstrated superior global search capability and convergence efficiency, avoiding local optima. This ensured that project managers could quickly obtain high-quality and repeatable optimization results when applying the research methods.

3.2. Application Effect of Optimization Management in Municipal Construction Projects

To validate IGA-ACO-FL in municipal project applications, a talent housing project in Zhejiang Province was used as an example. MATLAB was used to solve the multi-objective optimization model. The project had a planned land area of 10,520 m^2 and a total building area of approximately 46,200 m^2. The final optimization algorithm was set with a population size of 100, 300 iterations, a crossover probability of 0.8, and a mutation probability of 0.05. The quantitative results of IGA-ACO-FL for schedule-cost-quality-safety optimization are shown in Table 1.

Table 1. Comparison of quantitative results of multi-objective optimization

Scheme	Ti (days)	Ci (million yuan)	Qi	Si
A	135	33.81	0.758	0.881
B	143	34.56	0.820	0.903
C	167	36.89	0.852	0.925
D	255	37.23	0.905	0.933
E	301	38.94	0.916	0.962
F	322	40.12	0.957	0.986
G	257	37.10	0.895	0.934
H	178	36.94	0.892	0.933
I	320	40.11	0.933	0.976
J	189	37.21	0.899	0.942

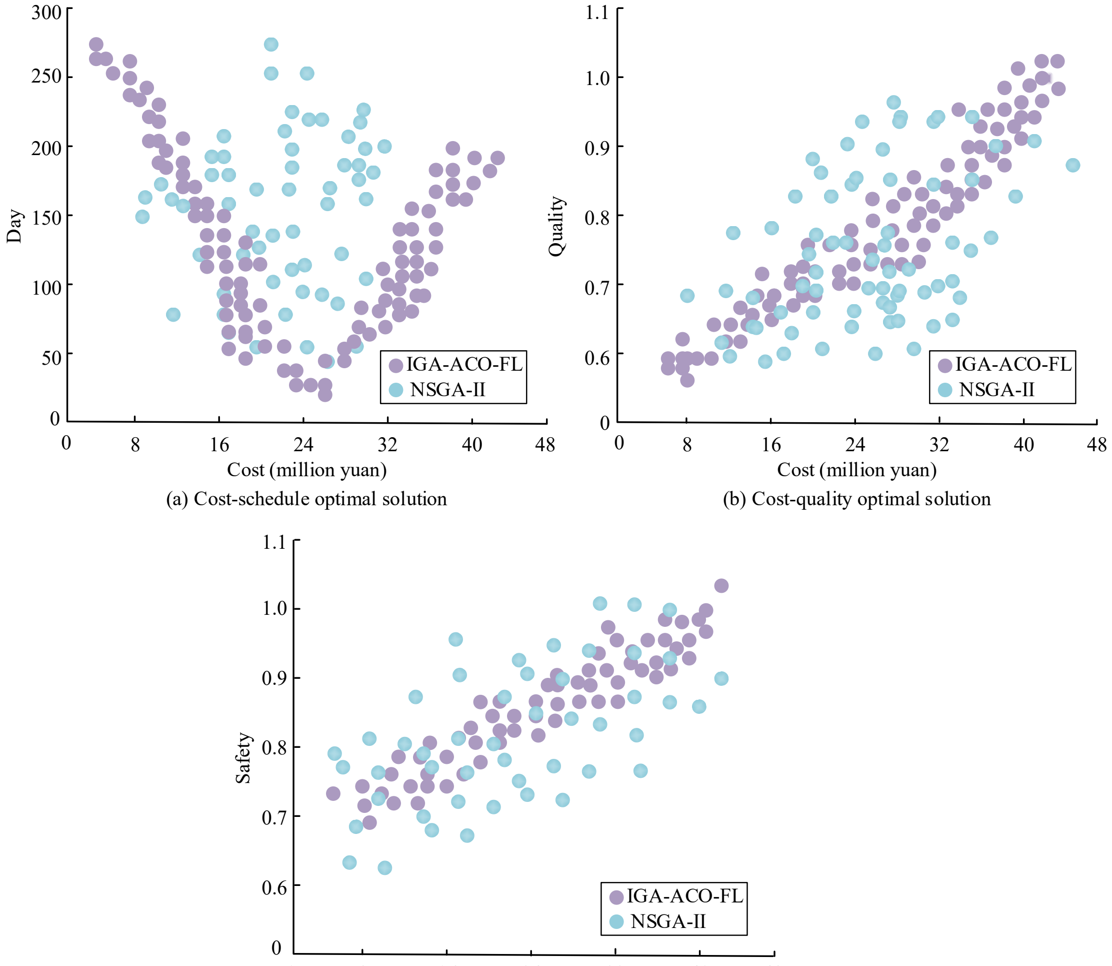
Table 1 reflects the optimal trade-off among different objectives in the municipal construction project. The schedule ranged from 135 to 322 days, the cost ranged from 33.81 to 40.12 million yuan, the quality ranged from 0.758 to 0.933, and the safety ranged from 0.881 to 0.986. This supported managers in making scientific and flexible decisions based on the current primary goals of the project. To visually demonstrate IGA-ACO-FL's solution capability, the Pareto frontier of each generation was recorded using basic project data and compared with the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The Pareto frontiers under schedule-cost, cost-quality, and cost-safety objectives are shown in Fig. 10.

From Fig. 10, IGA-ACO-FL's solution set covered the entire objective space and exhibited good extension along the Pareto frontier. NSGA-II's solutions were relatively sparse and fewer in number, failing to cover the entire solution space, indicating limited exploration and susceptibility to local optima. In contrast, IGA-ACO-FL demonstrated superior convergence and diversity of solutions. For example, in Fig. 10(b), IGA-ACO-FL solutions were closer to the low-cost, high-quality trend, showing an effective balance among objectives. To achieve minimum cost under optimal quality, optimal safety, and minimum schedule, iterative convergence curves were used to show the change of objective function values. The results are shown in Fig. 11.

In Fig. 11(a), IGA-ACO-FL's total cost curve sharply declined in early iterations, quickly eliminating high-cost solutions and approaching the superior solution region. After 50 iterations, the curve stabilized around 36.2 million, and convergence was reached after 60 iterations. In Fig. 11(b), NSGA-II showed a slower cost decline in the first 50 iterations, likely due to dependence on genetic operator search. Its curve stabilized after 200 iterations, with a final cost of 38.3 million. Overall, in the municipal multi-objective model, IGA-ACO-FL achieved lower costs, more precise searches, and a stronger ability to escape local optima.

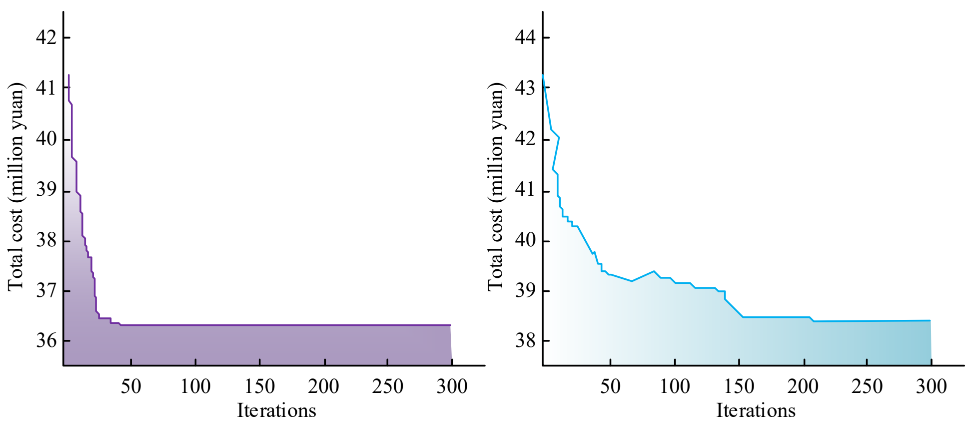
4. Conclusion and Recommendations

To address the limitations of single-objective management in municipal construction projects, a hybrid IGA-ACO-FL algorithm was designed. The FL algorithm fuzzified objectives such as quality and safety, ACO searched for optimal paths using pheromone updates, and IGA applied crossover and mutation to iteratively produce optimal solutions. The study demonstrated that the IGA-ACO-FL algorithm outperformed AGA, SAA, and GA-PSO, achieving an average accuracy of 98.7%, an average data query rate of 99.5%, an average space complexity of 21.3%, and an average computation speed of 17.6 bps. In multimodal function tests, the algorithm reached the global optimum within 50 iterations, demonstrating stable convergence and faster convergence speed. Its Pareto frontier solution set covered the entire objective space, and the algorithm converged after 60 iterations, finding low-cost optimal solutions faster than the NSGA-II algorithm. Therefore, the IGA-ACO-FL hybrid algorithm demonstrated excellent computational efficiency and global search capability. It provides a scientific and efficient solution for multi-objective optimization management in municipal construction projects. In addition, the IGA-ACO-FL hybrid algorithm showed high potential in terms of generalizability. Its methodological framework, which processes uncertain objectives through fuzzy logic, optimizes path search through ant colony algorithms, and ensures global convergence through immune genetic algorithms, could be generally applied to multi-objective optimization problems in various municipal engineering projects. However, the scalability of this algorithm in large-scale municipal systems faces severe challenges: when the project scale expands significantly, decision variables and constraints grow exponentially, algorithm parameters need to be recalibrated, and computational complexity may rise sharply to a prohibitive level. In terms of practical deployment, this algorithm is confronted with multiple implementation obstacles, including fragmentation of existing data systems in municipal departments and lack of unified data quality standards, technical difficulties in integrating with traditional management software, insufficient understanding and acceptance of complex algorithmic decision-making processes by management personnel, and the inherent contradiction between transparency requirements of public project decision-making and the "black box" nature of algorithms.



(a) Cost-schedule optimal solution
(b) Cost-quality optimal solution
(c) Cost-safety optimal solution

Fig. 10. Pareto front visualization results



(a) IGA-ACO-FL
(b) NSGA-II

Fig. 11. Iterative convergence curve of minimum cost

Funding

This research received no specific financial support from any funding agency.

Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The author used Grammarly solely for language editing and readability improvement. The author reviewed and verified all content and takes full responsibility for the accuracy and integrity of the manuscript.

Reference

Changdar, C., Mondal, M., Giri, P.K., Nandi, U. and Pal, R.K. (2023). A two-phase ant colony optimization based approach for single depot multiple travelling salesman problem in Type-2 fuzzy environment. *Artificial Intelligence Review*, 56(2), 965-993.

Gong, A., Wang, G., Qi, X., He, Y., Yang, X., Huang, X. and Liang, P. (2025). Energy recovery and saving in municipal wastewater treatment engineering practices. *Nature Sustainability,* 8(1), 112-119.

Hamedi, A.H., Abolghasemi, H., Shokri, S., Nia, H.J. and Moayedi, F. (2023). Integrating Artificial Immune Genetic Algorithm and Metaheuristic Ant Colony Optimizer with Two-Dose Vaccination and Modeling for Residual Fluid Catalytic Cracking Process. *Arabian Journal for Science and Engineering,* 48(12), 16329-16341.

Hussain, S., Hasmori, M.F., Balasbaneh, A.T., Khan, M.W. and Sohu, S. (2025). Contributing Factors to Key Performance Indicators of Saudi Arabian Construction Project Success. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 50(1), 151-167.

Shui, J. D. (2024). Application research on improved genetic algorithm and active disturbance rejection control on quadcopters. *Measurement and Control,* 57(9), 1347-1357.

Lafioune, N., Poirier, E. A., St-Jacques, M. (2024). Managing urban infrastructure assets in the digital era: challenges of municipal digital transformation. *Digital Transformation and Society,* 3(1), 3-22.

Li, J., and Liu, F. (2025). Low-Cost Municipal Facility Obstacle Inspection Algorithm Based on Monocular Camera. *International Conference on Information Technology in Geo-Engineering. Springer, Cham,* 11(3), 97-96.

Liu, J., Li, Y., Li, Y., Zibo, C., Lian, X. and Zhang, Y. (2023). Location optimization of emergency medical facilities for public health emergencies in megacities based on genetic algorithm. *Engineering, construction and architectural management,* 30(8), 3330-3356.

Momo, N. S., Hare, W., and Lucet, Y. (2023). Modeling side slopes in vertical alignment resource road construction using convex optimization. Computer-aided civil and infrastructure engineering, 38(2), 211-224.

Olivares, M. I. J., Sprute, P., and MotyliÅska, M. (2025). Ground Realities: Material Interactions in the Construction of the Buenos Aires Subway. *Technology and Culture,* 66(3), 799-826.

Ooi, J.K., Hoy, Z.X., Hossain, M.U., Zhang, Z., Khan, M., and Woon, K.S. (2024). An integrated multi-objective optimisation framework for municipal solid waste management and emissions trading scheme. *Clean Technologies And Environmental Policy*, 26(5), 1383-1397.

Parsons, T., Seo, J., and Livesey, D. (2024). Municipal street-sweeping area generation with route optimization. International Transactions in Operational Research, 32(3), 1375-1399.

Thenmozhi, M., Umamaheswari, S., Stonier, A.A. and Thangavel, J. (2024). Design and implementation of photovoltaic-assisted dynamic voltage restorer using fuzzy logic controller-based improved SOGI for power quality improvement. *Electrical engineering,* 106(3), 3475-3493.

UmaRani, C., Ramalingam, S., Dhanasekaran, S. and Baskaran, K. (2025). A hybrid machine learning and improved social spider optimization based clustering and routing protocol for wireless sensor network. *Wireless Networks* (10220038), 31(2), 1885-1910.

Wu, L., You, X., Liu, S. (2024). Heterogeneous ant colony algorithm based on selective evolution mechanism and game strategy. *Journal of Supercomputing,* 80(6), 7171-7206.

Xiao, L., Wang, D., Zuo, Q., Yan, X. and Cai, H. (2025). A ZNN-Based Solver with Adaptive Input Range Fuzzy Logic System for Time-Varying Algebraic Riccati Eq. *IEEE Transactions on Fuzzy Systems*, 33(2), 757-766.

Yang, L. (2025). Digital management method of municipal infrastructure engineering construction. Proceedings of The Institution of Civil Engineers. *Proceedings of the Institution of Civil Engineers-Smart Infrastructure and Construction*, 178(1), 62-73.

Zaghba, L., Borni, A., Benbitour, M.K. and Fezzani, A. (2025). Improving photovoltaic energy harvesting systems with hybrid fuzzy logic-PI MPPT optimized by PSO under normal and partial shading conditions. *Electrical Engineering*, 107(4), 4897-4919.

Zhang, D., Zhang, Y., Liang, Y. (2025). A genetic algorithm-based dendritic cell algorithm for input signal generation. *Applied Intelligence*, 53(22), 27571-27588.

Zhao, F., Du, Y., Zhuang, C., Wang, L. and Yu, Y. (2025). An Iterative Greedy Algorithm for Solving a Multiobjective Distributed Assembly Flexible Job Shop Scheduling Problem With Fuzzy Processing Time. *IEEE Transactions On Cybernetics,* 55(5), 2302-2315.

Zhao, J., Zhou, Z., Guan, D. and Gong, L. (2025). Structural edge damage detection based on wavelet transform and immune genetic algorithm. *Scientific Reports,* 15(1), 4376-4376.

Lou Huafeng graduated with a degree in Engineering Management in 2008. Since graduation, he has worked in state-owned enterprises (SOEs) and is currently employed at Hangzhou Qiantang Urban Construction Group Co., Ltd. He holds the professional title of Associate Senior Engineer and serves as Manager of the Engineering Support Department. His key responsibilities include overseeing the construction of municipal projects and pipeline projects (e.g., power supply and water supply systems). His professional honors include the title of “Advanced Individual in Hangzhou Lighting Landscape Engineering” and repeated recognition as an “Advanced Worker” and “Excellent Employee” of the group.