Application of Fuzzy Logic for Optimizing Resource Allocation in Complex Construction Environments

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The rapid growth of construction projects has intensified inefficiencies in resource allocation, leading to cost overruns, delays, and reduced quality. This study proposes an integrated fuzzy logic framework to optimize resource allocation under complex and uncertain construction conditions. The framework combines fuzzy information quantification, fuzzy clustering, multi-objective decision-making, and adaptive control modules into a coherent system. A dataset covering residential, commercial, and infrastructure projects was used to evaluate the model against linear programming, dynamic programming, neural networks, and genetic algorithms. Results show that the proposed model achieves a resource waste rate of 7.5% compared with 19.5% for linear programming, and a faster allocation response speed of 0.775. Under complex geological conditions, the configuration effect reaches 88.33%, and in severe weather scenarios it maintains 86% effectiveness, both outperforming competing models. These findings highlight the model's computational efficiency, scalability across project scales, and adaptability to uncertain environments, offering a robust approach for sustainable construction management

Povzetek: Predlagan je okvir mehke logike za razporejanje virov v gradbeništvu, ki zmanjša potrato in izboljša učinkovitost v negotovih razmerah.

1 Introduction

The scale and complexity of construction projects are growing rapidly, with tens of thousands of large-scale projects added annually worldwide. The demand for resources such as steel, cement, manpower, and machinery rises nearly 10% each year [1]. However, resource allocation in practice often suffers from inefficiency and imbalance. Typical cases include large backlogs of steel, shortages of cement delaying progress, manpower redundancy exceeding 30% in some stages while shortages reach 20% in others, and idle machinery time averaging 25% [2, 3]. These problems increase costs by 20-30% [4] and reduce both quality and client satisfaction, thus hindering industry development [5].

Although traditional methods such as linear programming can reduce waste in simple projects (to around 15%) [6], they perform poorly under uncertainties such as weather, fluctuating material prices, and interdependent resource demands [7, 8]. Neural networks offer adaptability but struggle with fuzzy information [9], while genetic algorithms often converge slowly [10]. Therefore, optimizing construction resource allocation under complex and uncertain conditions remains a pressing research problem. This paper proposes an integrated fuzzy algorithm framework to address this challenge, aiming to improve utilization, reduce costs, and enhance adaptability [11].

2 Literature review

2.1 Traditional algorithms

Linear programming handles deterministic resource allocation but fails in nonlinear and uncertain environments, leading to deviations of over 30% in complex projects [12, 13]. Dynamic programming adapts to changing conditions but becomes computationally infeasible at large scales. Integer programming can enforce discrete constraints but struggles with multiple interrelated resources, with irrationality levels around 20% [14, 15]. Overall, these approaches cannot effectively address the dynamic and uncertain features of modern projects [16].

2.2 Emerging algorithms

Neural networks improve utilization by 10-15% in simulated environments but fail to process fuzzy factors such as weather, with errors exceeding 20% [17]. Genetic algorithms balance multiple objectives but require long iterations, causing instability and waste rates of 15-20%

[18, 19]. While promising, these methods lack robustness for real-world deployment.

2.3 Fuzzy algorithms

Fuzzy methods excel in quantifying uncertain factors like weather and geological conditions, improving allocation rationality by about 25% compared to traditional algorithms [20]. They enhance coordination among manpower, materials, and equipment, reducing idle rates by 20% [21]. Yet, challenges remain in parameter determination and model construction. This study advances the field by integrating fuzzy quantification, clustering, multi-objective decision-making, and adaptive control into a coherent pipeline, improving computational efficiency, scalability, and adaptability.

This work advances the field along three method-specific axes. Clustering: we operationalize uncertainty-aware pattern mining by selecting the number of fuzzy clusters via a compactness–separation criterion (Xie–Beni) jointly with stability checks, which reduces over fragmentation in highly correlated resource streams. Decision-making: we formalize a pipeline-compatible fuzzy multi-objective synthesizer that maps normalized indicators to linguistic terms and aggregates them via a max–product operator under expert-elicited weights, enabling transparent trade-offs between waste, responsiveness, and cost–quality coordination. Adaptive control: we close the loop by a Mamdani controller whose rule base is aligned with construction progress deviation and resource slack, thereby turning fuzzy assessments into hour-level allocation deltas; anti-windup and ramp-rate limits guarantee stable actuation under abrupt shocks (e.g., weather, supply delays).

3 Research methods

3.1 Data collection and preprocessing

3.1.1 Data collection strategy

In the process of exploring the optimal allocation of construction project resources, the research team adopted a multi-channel data collection method to ensure the comprehensiveness and representativeness of the data set. This includes but is not limited to residential construction, commercial complex development, and public infrastructure construction. During the field research phase, the researchers went deep into the project construction site and used specially designed checklists to record first-hand information such as equipment operation status and actual working hours of personnel. In addition, through in-depth interviews with front-line construction personnel and management personnel, they obtained information on the implementation of key projects, such as resource usage issues and suggestions for resource allocation. In addition, the project archives from planning to completion were reviewed, including but not limited to resource budgets in project planning documents, construction schedules, material procurement records, equipment maintenance logs, and quality inspection results in completion acceptance reports [22]. At the same time, the research team actively communicated with senior experts in the construction industry, using their rich experience and professional knowledge to supplement data that was difficult to obtain or understand, and provide a deeper industry perspective. The data collected this time was extremely extensive, covering resource input, construction progress, cost expenditure, quality control, and other aspects. For example, in terms of resource input, the specific usage of various types of building materials is recorded in detail; for the construction progress, not only the planned time for each stage is obtained, but also the actual completion time is accurately calculated through on-site records; cost expenditure is broken down into individual items such as material procurement cost, labor cost, equipment rental cost, etc.; and in terms of quality control, data such as concrete strength testing and steel quality testing are collected to ensure that project quality factors are fully considered.

3.1.2 Data preprocessing technology

Since there may be missing values, outliers and other problems in the original data, it is necessary to conduct strict preprocessing. For the problem of missing data, this study adopts a multiple filling method. This method generates possible missing values through multiple simulations based on the existing data distribution characteristics, so as to obtain more accurate filling results. For example, when dealing with the missing steel consumption data in a residential project, the researchers first analyzed the relationship between steel consumption and building area and building structure in similar projects, constructed a regression model, and then used this model for multiple simulations. Finally, these simulation values were combined to obtain reasonable filling results. For outliers, a density-based local outlier detection algorithm (LOF) was used for identification and processing. The algorithm determines whether it is an outlier by calculating the density deviation of each data point relative to its neighborhood points. In practical applications, when the LOF value of some data points is found to be much greater than 1, it will be corrected or deleted according to the overall distribution of the data. For example, when analyzing the equipment usage time data of a commercial complex project, the LOF algorithm found data points with abnormally high LOF values caused by recording errors, and then made corresponding adjustments to ensure data quality.

Missing values are imputed via multiple imputation with 10 draws from a Bayesian linear model using project-type, floor area, and structure class as predictors; pooled estimates follow Rubin's rules. LOF outlier detection uses nneighbors=20, contamination =0.02, metric = Euclidean; flagged points with business-justified causes are winsorized at the 1st/99th percentiles, otherwise removed.

3.2 Application of fuzzy information quantification module in construction engineering

Construction engineering is a complex and variable field, in which there is a lot of fuzzy information, which seriously affects the planning, execution and management of the project. For example, weather conditions (such as heavy rain, strong wind, etc.) and construction difficulty assessment (complexity of geological conditions, special characteristics of building structures, etc.) are difficult to describe with precise numerical values. In order to integrate these fuzzy information into the resource optimization allocation model so that it can more truly reflect the actual situation of the project, this study introduces fuzzy set theory to quantify the fuzzy information.

Taking weather impact as an example, this study divides it into four fuzzy sets: "bad", "poor", "average", and "good", and defines the corresponding membership function for each set. In the process of determining the membership function, a combination of expert experience and data statistics was adopted. First, a number of senior experts in the construction field were invited to evaluate the impact of different weather conditions on construction based on their professional knowledge and practical experience, and preliminarily construct a membership function. Subsequently, by collecting and analyzing a large amount of historical data, the membership function initially established was optimized and adjusted to ensure its scientificity and accuracy.

Let daily precipitation p (mm) encode weather impact with four Gaussian terms {good, average, poor, bad}. Centers and spreads follow expert elicitation, then data calibration, as shown in (1)-(4):

$$\mu_{\text{bad}}(p) = \exp\left(-\frac{(p-70)^2}{2\cdot 15^2}\right) \tag{1}$$

$$\mu_{\text{poor}}(p) = \exp\left(-\frac{(p-40)^2}{2\cdot 10^2}\right) \tag{2}$$

$$\mu_{average}(p) = \exp\left(-\frac{(p-20)^2}{2\cdot 10^2}\right) \tag{3}$$

$$\mu_{good}(p) = \exp\left(-\frac{(p-5)^2}{2\cdot 5^2}\right) \tag{4}$$

Geological difficulty g ∈ [0, 1] (derived from RMR/UCS) uses triangular terms {low, mid, high}with peaks at {0.2, 0.5, 0.8} (omitted for brevity but implemented analogously).

We formalize weather and constructability into four linguistic terms {good, average, poor, bad}. For precipitation p (m/day) we use Gaussian memberships $\mu_\ell(p) = \exp\{-(p-c_\ell)^2/(2\sigma_\ell^2)\}$ with centers $c_\ell = \{5, 20, 40, 70\}$ and spreads $\sigma_\ell = \{5, 10, 10, 15\}$, respectively. Initial (c_ℓ, σ_ℓ) are elicited from a panel of nine senior site managers using anchor percentiles (10th/50th/90th). We then calibrate them by minimizing squared error between panel labels and historical productivity–precipitation pairs from the dataset, under monotonicity constraints (good↓with p; bad↑with p). The same two-stage procedure is applied to wind grade and to a qualitative "geological difficulty" index $g \in [0,1]$ (derived from core-logging RMR and UCS). All fuzzy inputs are normalized to $[0,1]$.

3.3 Fuzzy clustering module

In the field of resource management and analysis, a deep understanding of resource usage patterns is crucial to achieving reasonable resource allocation. As a powerful data analysis tool, fuzzy clustering algorithm can classify resources with similar usage characteristics into one category, providing strong support for optimal resource allocation. In this study, we choose fuzzy C-means clustering algorithm (FCM) to carry out the analysis of resource usage patterns.

The core of the FCM algorithm is to determine the degree of membership of each data point to each cluster center by iteratively optimizing the objective function. The objective function formula is (5).

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^m \| x_i - v_j \|^2, \quad m = 2.0 \tag{5}$$

The symbol J_m denotes the objective function to be minimized; it quantifies the overall within-cluster dispersion under fuzzy weighting. The subscript m (where $m > 1$) is the fuzzifier or weighting exponent that controls the degree of fuzziness of the resulting partition — values of m closer to 1 make memberships more "crisp," while larger m values produce softer, more overlapping clusters. The term N indicates the number of data points, and c represents the number of cluster centers to be determined. Each x_i is the feature vector of the i^{th} data point in the dataset, while v_j is the center (prototype) of the j^{th} fuzzy cluster. The membership coefficient $u_{ij} \in [0,1]$ expresses the degree of belonging of data point x_i to cluster j; for every i, the memberships across all clusters sum to one. The distance term $\| x_i - v_j \|^2$ represents the squared Euclidean distance between a data point and a cluster center, serving as a measure of dissimilarity. In essence, the objective function balances two factors: it minimizes the distances between data points and nearby cluster centers, and it weighs each distance by the fuzzy membership raised to the power m, ensuring that points belonging more strongly to a cluster have greater influence on its center's location.

Iterative update process: Next, the membership matrix U and cluster center matrix V are continuously updated iteratively until the objective function converges. Each iteration process is divided into two steps:

Update the membership matrix U: According to the current cluster center matrix V, update the membership matrix U by the following formula, as shown in (6).

$$u_{ij} = \Big(\sum_{k=1}^{c}\Big(\frac{\| x_i - v_j \|}{\| x_i - v_k \|}\Big)^{\frac{2}{m-1}}\Big)^{-1} \tag{6}$$

This formula shows that the closer the distance between a data point x_i and the cluster center v_j, the higher its membership to the cluster center.

Update the cluster center matrix V: After obtaining the updated membership matrix U, recalculate the cluster center matrix V by the following formula, as shown in (7).

$$v_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{i=1}^{n} u_{ij}^m} \tag{7}$$

This formula is a weighted average of all data points, where the weight is the mth power of the data point's membership to the cluster center.

We cluster resource-usage vectors $x_i \in \square^{d}$ d (materials, crews, equipment utilization) via FCM with objective, as shown in (8).

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^m \| x_i - v_j \|^2, \quad m = 2.0 \tag{8}$$

Updates follow the standard rules, as shown in (9).

$$u_{ij} = \Big(\sum_{k=1}^{c}\Big(\frac{\| x_i - v_j \|}{\| x_i - v_k \|}\Big)^{\frac{2}{m-1}}\Big)^{-1}, \quad v_j = \frac{\sum_i u_{ij}^m x_i}{\sum_i u_{ij}^m} \tag{9}$$

We select c by minimizing the Xie–Beni index on a grid $c \in \{2, \ldots, 10\}$, as shown in (10).

$$\mathrm{XB}(c) = \frac{\sum_i \sum_j u_{ij}^m \| x_i - v_j \|^2}{N \cdot \min_{j \neq k} \| v_j - v_k \|^2} \tag{10}$$

With the Partition Coefficient and silhouette score used to break ties in favor of compact/well-separated partitions. Initialization uses k-means++ seeds and a fixed random seed (see 3.6). Convergence requires either a relative improvement $J_m^{(t)} - J_m^{(t-1)} | / J_m^{(t-1)} < 10^{-5}$ or $t \geq 300$ iterations; we also monitor stability of $\{vj\}$ with a max-shift threshold 10^{-4}.

3.4 Multi-objective decision-making module

The optimal allocation of construction project resources requires considering multiple objectives at the same time, such as reducing resource waste, improving the response speed of deployment, and balancing cost and quality. To this end, this study introduces a fuzzy multi-objective decision-making model to comprehensively weigh various objectives to obtain the optimal resource allocation plan. First, the weight vector of each decision goal is determined. For example, the weights of resource waste rate, deployment response speed, and cost-quality coordination are set to 0.3, 0.2, and 0.5 respectively through expert evaluation. Then, the fuzzy evaluation matrix of each decision plan under each decision goal is calculated, and finally the comprehensive evaluation vector is obtained through fuzzy synthesis operation, and the best resource allocation plan is selected accordingly.

In the fuzzy multi-objective decision-making process, a set of evaluation goals and alternative solutions are first defined. Each decision goal reflects a different aspect of construction resource optimization, such as minimizing resource waste, improving deployment response speed, and ensuring cost–quality coordination. Experts or project managers then assign a weight to each goal based on its importance; for instance, the weights may be set to 0.3 for resource waste rate, 0.2 for deployment response speed, and 0.5 for cost–quality balance.

Next, a fuzzy evaluation matrix is established to describe how each alternative performs under each goal. The elements of this matrix represent the degree to which an alternative satisfies a specific goal, expressed as a fuzzy value between complete satisfaction and complete dissatisfaction. This allows uncertain or subjective assessments to be quantified in a structured way.

Finally, the evaluation results are combined using a fuzzy synthesis operation. This step integrates the weighted evaluations of all goals into a single comprehensive score for each alternative. Depending on the project characteristics and the decision environment, different synthesis rules—such as those emphasizing either conservative (minimum-based) or multiplicative (product-based) aggregation—can be selected. The alternative with the highest comprehensive score is considered the optimal resource allocation plan, reflecting balanced performance across all decision objectives.

Let criteria be C1(waste, cost-type), C2(response, benefit-type), C3 (cost–quality coordination, benefit-type) with weights w=(0.30,0.20,0.50). Each alternative aaa yields fuzzy scores Ak(a) per criterion kkk. We aggregate via the max–product composition, as shown in (11):

$$B(a) = \bigoplus_{k=1}^{3}\big(w_k \otimes A_k(a)\big), \quad \otimes = \text{product}, \oplus = \max . B(a) = k = 1 \tag{11}$$

Defuzzified ranking uses the centroid, its calculation formula is (12).

$$s(a) = \frac{\int_0^1 x \mu_{B(a)}(x)dx}{\int_0^1 \mu_{B(a)}(x)dx} \tag{12}$$

Criteria are: C1 resource waste (cost-type), C2 allocation response speed (benefit-type), C3 cost–quality coordination (benefit-type).We derive weights w= (0.30, 0.20, 0.50) via a two-round Delphi with nine experts; inter-rater agreement (Kendall's W) equals 0.78. Raw indicators are normalized by min–max; cost-type criteria are inverted. Each normalized indicator is mapped to fuzzy terms {low, medium, high} using triangular memberships centered at {0.2, 0.5, 0.8}. For each alternative a, we compute a fuzzy score per criterion and apply a weighted fuzzy synthesis using the max–product operator; final ranking uses centroid defuzzification on [0, 1]. This makes the trade-offs explicit and reproducible while remaining robust to mild membership perturbations.

3.5 Adaptive control module

In modern construction management, the dynamic adaptation of construction progress and resource allocation is a key factor to ensure the smooth progress of the project. The adaptive control module is responsible for real-time monitoring of construction progress and changes in resource demand, and flexibly adjusts the resource allocation strategy based on feedback information. This study adopts an adaptive fuzzy control strategy and builds a fuzzy control rule base to achieve refined dynamic control of the construction process.

Fuzzy control rules are the core of adaptive fuzzy control strategies. They are formulated based on expert experience and historical data analysis, and comprehensively cover resource allocation strategies in a variety of complex construction scenarios. For example, the rule of "if the construction progress is lagging behind and there is sufficient remaining resources, increase resource investment" can provide timely and effective solutions to common construction problems.

Variable setting and fuzzification: Let the input variables be the construction progress deviation e and the remaining amount of resources s, and the output variable be the amount of resource allocation Δu . Fuzzification is the process of converting these precise variables into fuzzy sets. Taking the construction progress deviation e as an example, according to the actual construction needs, it is divided into fuzzy sets such as "negative large (NB)", "negative small (NS)", "zero (ZO)", "positive small (PS)", and "positive large (PB)". In mathematical expression, the degree to which a specific progress deviation value belongs to each fuzzy set can be determined by the membership function. For example, the Gaussian membership function: $\mu_A(x) = e^{-\frac{(x-c)^2}{2\sigma^2}}$ where $\mu_A(x)$ represents the membership of the variable x to the fuzzy set A, c is the center of the membership function, and \sigma determines the width of the function. Similarly, the remaining resource quantity s is divided into fuzzy sets such as “very little (VL)”, “little (L)”, “medium (M)”, “many (H)”, and “very much (VH)”, and the resource allocation quantity Δu is divided into fuzzy sets such as “significantly reduced (SD)”, “reduced (D)”, “unchanged (NC)”, “increased (I)”, and “significantly increased (SI)”.

Fuzzy reasoning: According to the pre-established fuzzy control rule base, fuzzy reasoning is performed to obtain fuzzy output. Assuming that there are n rules in the fuzzy control rule base, the i-th rule can be expressed as $\text{IF } e \text{ is } A_i \text{ AND } s \text{ is } B_i \text{ THEN } \Delta u \text{ is } C_i$: A_i, B_i and C_i are the fuzzy sets of construction progress deviation, resource surplus and resource allocation corresponding to the i-th rule. In the fuzzy reasoning process, the membership of the input variables to each fuzzy set is calculated and combined with the fuzzy control rules to determine the membership of the output variables to each fuzzy set. The commonly used reasoning method is the reasoning method, which determines the membership of the output fuzzy set by taking the minimum operation.

Defuzzification: Fuzzy output is obtained through fuzzy reasoning, which needs to be defuzzified to obtain accurate resource allocation. Common defuzzification methods include the centroid method, and its calculation formula is (13).

$$\Delta u = \frac{\sum_k \mu_C(x_k) \cdot x_k}{\sum_k \mu_C(x_k)} \tag{13}$$

Among them, is Δu the precise value after defuzzification, and $\mu_C(x_k)$ is the membership degree of the output fuzzy set C at point x_k. When faced with a situation where the construction progress is seriously delayed and the remaining resources are sufficient, the system automatically triggers the instruction of "increasing resource investment" according to the above steps to effectively ensure the project is completed on time.

Inputs are progress deviation e (planned vs. actual, in % of period target) and resource slack s (normalized buffer of labor/equipment/materials). Each has five Gaussian terms: {NB, NS, ZO, PS, PB} for e with centers $-20,-10,0,10,20$ and $\sigma = 5$; {VL, L, M, H, VH} for s with centers 0.05,0.2,0.5,0.8,0.95 and σ=0.1 Output is resource adjustment Δr with five terms {SD, D, NC, I, SI} on [−1, 1]. We implement 25 Mamdani rules; examples:

– If e is PB and s is VH then Δr is SI.

– If e is NS and s is L then Δr is D.

Inference uses min–max, sampling period Δt=1 hour, centroid defuzzification. Output is saturated to [−1,1] with anti-windup clamping. This controller closes the loop with the decision module so that updated allocations feed back into the progress predictor every period.

FCM: m=2.0; c chosen by XB; max iterations =300; ϵ=10−5; repeats =10 with best XB retained.

Decision module: weights (0.30, 0.20, 0.50); triangular {0.2, 0.5, 0.8}; max–product synthesis; centroid defuzzification; ties resolved by highest C3.

Controller: sample period 1 h; output clamp [−1, 1] where Δr=1equals a 20% step-up in deployable crews or equipment time; ramp-rate limit ∣Δrt−Δrt−1∣≤0.4|.

3.6 Implementation details and pipeline integration

The full pipeline executes as: data preprocessing→fuzzy quantification→FCM pattern mining→fuzzy multi-objective ranking→adaptive control update. Each stage passes both crisp values and fuzzy labels so uncertainties are preserved end-to-end. We fix random seed 2025, use Euclidean distances throughout, and log all hyperparameters, version numbers, and stopping criteria. Section 4.1 lists the software/hardware stack. A run sheet with scenario-specific initial states is provided to ensure one-click reproducibility.

We provide: fixed random seed (2025); software versions; data splits (chronological, last 20% for out-of-sample evaluation); normalization ranges; imputation predictors; LOF hyperparameters; convergence thresholds;

logging of decision traces and controller actions per hour. Any result in Section 4 can be regenerated by re-running the pipeline with the corresponding scenario tag and seed.

4 Experimental evaluation

4.1 Experimental design

We compiled an anonymized multi-project dataset from partnering contractors (2019-2024), covering 18 projects: residential (6), commercial complexes (6), and public infrastructure (6). Project sizes range from 45,000-380,000 m²; schedules span 9-36 months. The dataset contains hourly records of resource inputs (materials, labor, equipment), progress, costs, and quality checks (about 1.2 M rows). Scenario labels include complex geology, severe weather, budget-limited operations, and multi-party collaboration, defined by site logs and supervisory reports.

An anonymized subset (about 12% rows) and the full set of preprocessing/analysis scripts are provided as Supplementary Files S1-S2 for review; the complete dataset cannot be publicly released due to NDAs. Metadata schemas and codebooks are included to facilitate replication.

This experiment aims to verify the effectiveness and superiority of the construction project resource optimization configuration model based on fuzzy algorithm. The experiment selected a data set covering multiple construction projects of different scales and types. These projects involve residential, commercial complexes, and public infrastructure construction. The data contains detailed information on multiple dimensions such as resource input, construction progress, cost expenditure, and quality control.

The experiment uses resource waste rate, resource allocation response speed, and resource allocation flexibility as key baseline indicators. Resource waste rate is used to measure the degree of loss of various resources during the construction process; resource allocation response speed reflects how quickly the model responds to changes in resource demand; and resource allocation flexibility evaluates the model's ability to respond to various changes and emergencies during the construction process.

The experimental group adopted the resource optimization allocation model based on the fuzzy algorithm proposed in this study. The control group included four benchmark models for comparison: Linear programming algorithm, referring to the application model proposed by Lin et al. [11] in their classical research; The dynamic programming algorithm follows the practice of resource allocation in construction projects described by Tomczak and Jaskowski [21]; Neural network algorithms, based on the model proposed by Wang et al. [13], are applicable to construction project management. Genetic algorithm, referring to the optimization method used by Xie et al. [22] in similar studies. Under the same experimental dataset and environmental conditions, each model is independently executed and its performance is recorded and evaluated across multiple baseline metrics, including resource waste rate, allocation response speed, and configuration flexibility. This contrast setting ensures the fairness and consistency of model evaluation, providing a solid basis for analyzing the advantages of the proposed fuzzy algorithm framework.

Experiments run on Python 3.11 with NumPy 1.26, scikit-fuzzy 0.4.2, scikit-learn 1.4; CPU: 12-core x86 with 32 GB RAM. Average FCM convergence: 42-97 iterations; controller loop horizon: 90 days at hourly granularity.

We release five canonical scenarios with fixed seeds and starting states.

Baseline: labor 260 FTE, 12 tower cranes, 18 pumps, initial steel and cement inventories equal to 10 and 7 days of demand; supplier lead times 7±2 days.

Complex geology: geological index g=0.7±0.1, daily drilling uncertainty coefficient 0.25, micro-piling capacity capped at 80% of baseline.

Severe weather: precipitation spikes 60–90 mm/day twice per week, wind grade 7–8 triggers two 4-hour stoppages, safety buffer for formwork +15%.

Budget-limited: monthly capex ceiling set at 70% of baseline; expedited procurement penalty +8% cost.

Multi-party collaboration: four contractors share two yards; information latency 1 day; conflict penalty of 2 hours whenever two critical resources overlap on the same front.

Common protocol: Chronological splits with the last 20% time horizon held out; grid search on the remaining training window with a 3×2 rolling validation; median over 10 fixed seeds (2025).

LP: PuLP 2.8 with CBC; feasibility tol 10^{-6}; time limit 1 h per horizon; objective penalizes slack/overage.

DP: OR-Tools 9.9; 1 h stage discretization; beam width 200; dominance pruning on cost–progress.

NN: PyTorch 2.2; MLP 128–64–32 ReLU; dropout 0.2; Adam lr $\in \{1e{-4}, 3e{-4}, 1e{-3}\}$; batch 256; early stopping (patience 20).

GA: DEAP 1.4; population 200; SBX crossover 0.9; polynomial mutation 0.1; tournament 3; 500 generations.

Ours: scikit-fuzzy 0.4.2; m=2; c via Xie–Beni; $\epsilon=10^{-5}$; max iters 300; max–product aggregation; centroid defuzzification.

We evaluate an extension where hourly controller inputs are enriched with streaming telemetry (equipment on/off cycles, fuel/energy usage) and on-site micro-weather stations. Data are ingested every 15 minutes; the decision cycle remains hourly with mid-cycle updates if alerts are triggered.

4.2 Experimental results

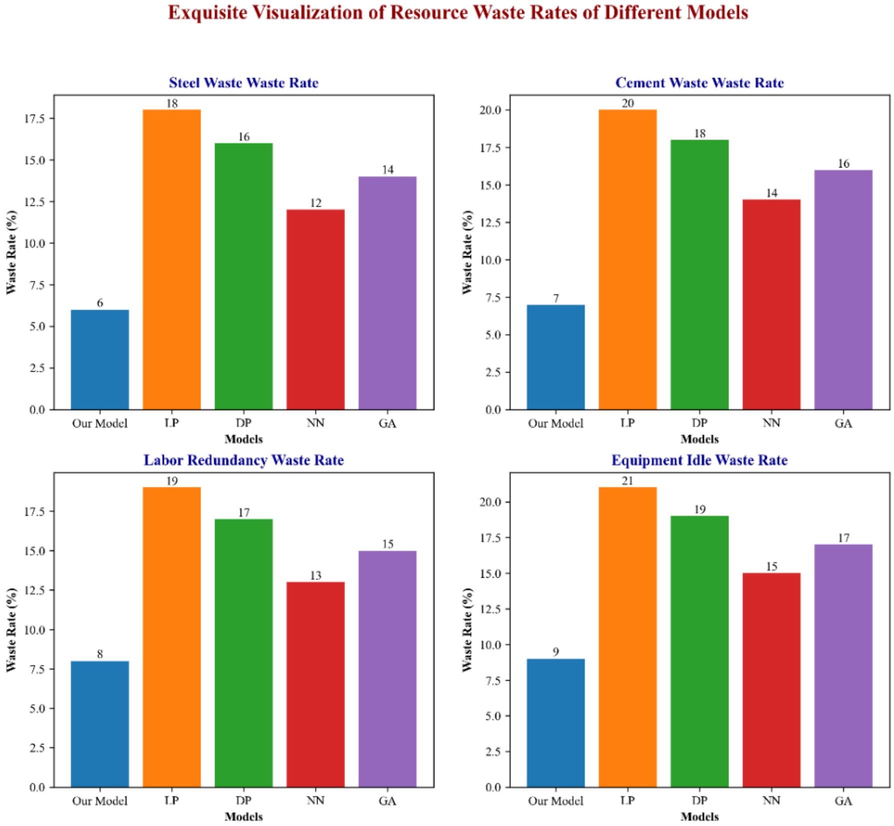

Figure 1: Comparison of resource waste rates of different models

As shown in Figure 1, the proposed model performs well in suppressing resource waste, and the comprehensive waste rate is significantly lower than other comparative models. The model uses fuzzy algorithms to process fuzzy information in construction, uses fuzzy clustering to analyze resource usage patterns, and uses multi-objective decision-making models to rationally plan resource allocation and avoid excessive resource investment. Linear programming algorithms are difficult to handle complex nonlinear and fuzzy relationships, resulting in unreasonable resource allocation and serious waste.

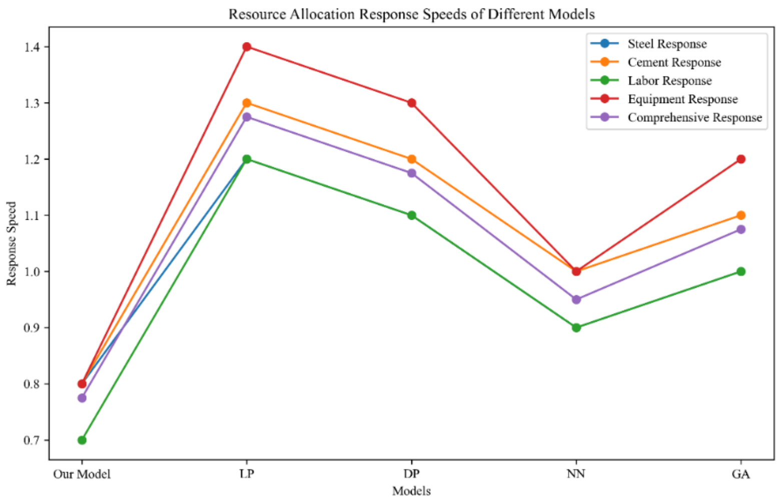

Figure 2: Comparison of resource allocation response speed of different models

In Figure 2, the lower the value, the faster the response speed. The comprehensive allocation response speed of the model in this paper is the fastest, thanks to the adaptive fuzzy control strategy, which monitors the construction progress and resource demand changes in real time and makes resource allocation decisions quickly. In contrast, the linear programming algorithm has a complex calculation process and is difficult to adapt to the dynamically changing construction environment, resulting in a delayed response to resource allocation and affecting construction efficiency.

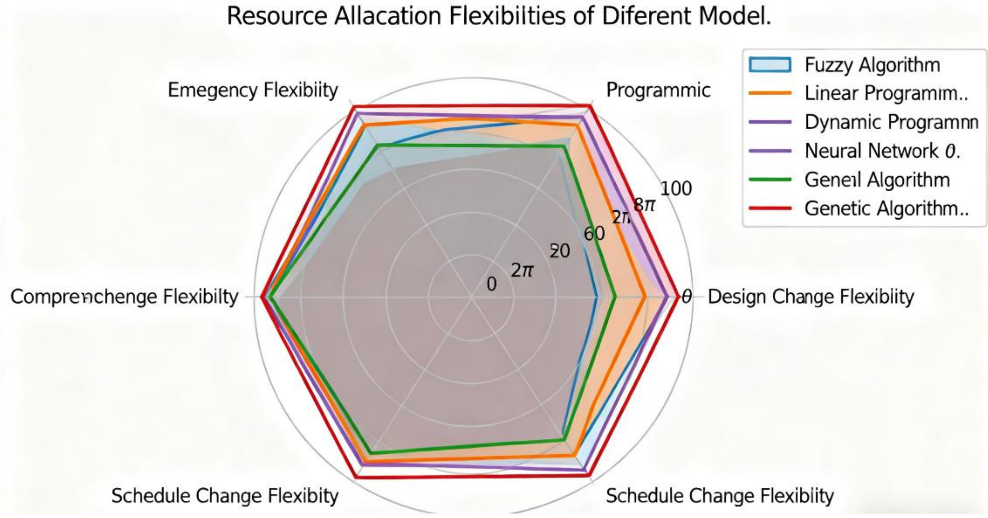

Figure 3: Comparison of resource configuration flexibility of different models

As shown in Figure 3, the model in this paper has higher comprehensive flexibility in dealing with various changes and emergencies in construction projects. The fuzzy algorithm takes uncertain information into consideration and builds a flexible resource allocation strategy. However, the linear programming algorithm has obvious limitations and is difficult to deal with uncertainties in the construction process, which limits the flexibility of resource allocation.

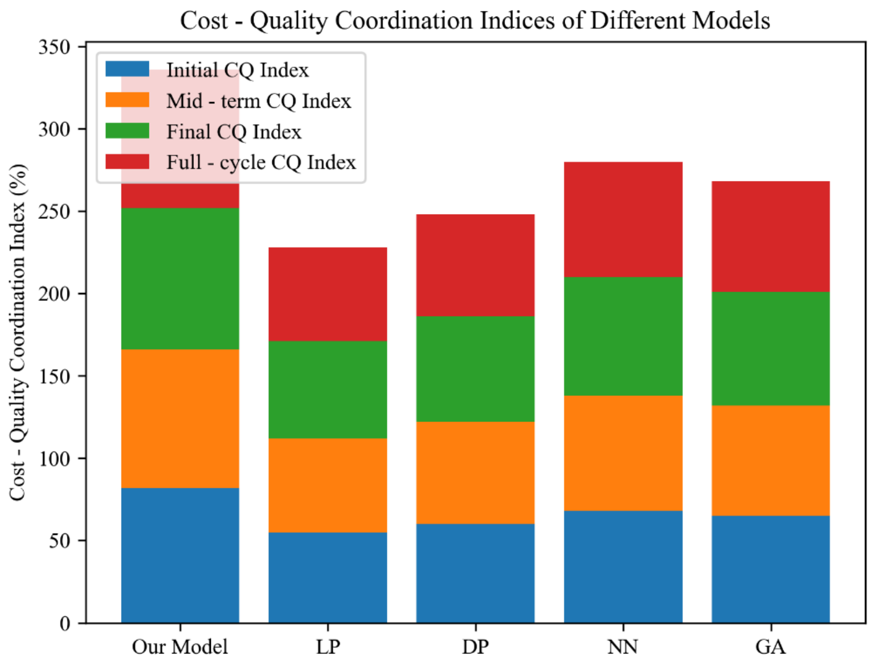

Figure 4: Comparison of cost and quality synergy index of different models

Figure 4 shows that the cost and quality synergy index of the model in this paper is higher than that of other models in the whole cycle. The fuzzy multi-objective decision-making model weighs the cost and quality objectives and achieves the coordinated optimization of the two by adjusting resource allocation. The linear programming algorithm lacks the ability to handle the complex relationship between multiple objectives, resulting in poor cost and quality synergy.

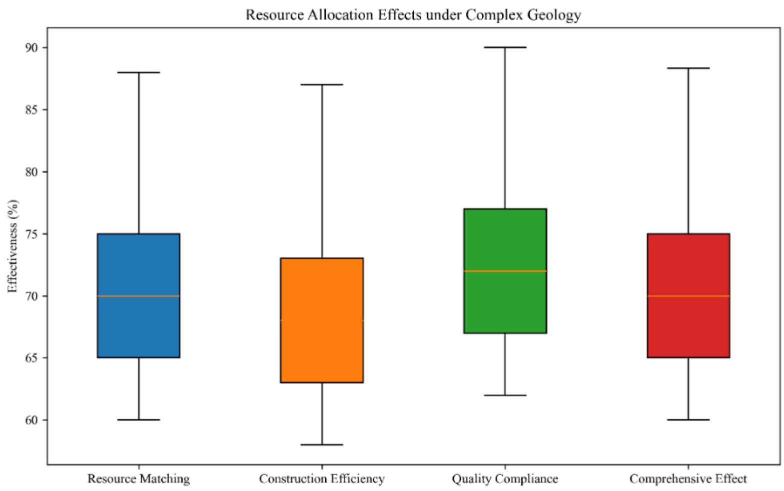

Figure 5: Comparison of resource allocation effects of different models under complex geological conditions

Under complex geological conditions, as shown in Figure 5, the comprehensive configuration effect of the model in this paper is the best. The model uses fuzzy algorithms to quantitatively analyze fuzzy information such as geological conditions and formulate targeted resource allocation plans. Linear programming algorithms cannot accurately handle the uncertainty of geological conditions, resulting in resource allocation that does not match actual needs, reducing construction efficiency and project quality.

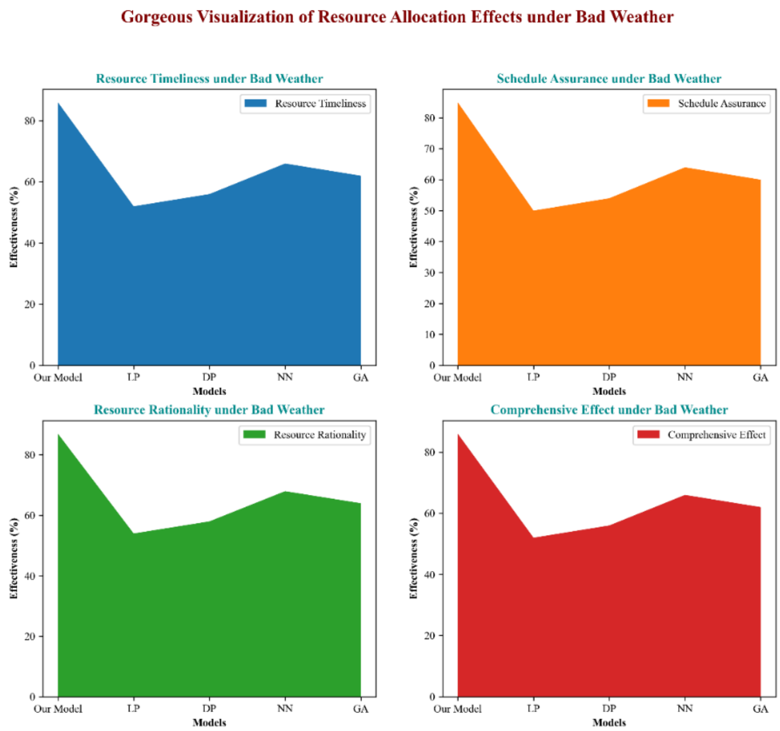

Figure 6: Comparison of resource allocation effects of different models under severe weather conditions

Figure 6 shows the performance of each model under severe weather conditions. The comprehensive configuration effect of the model in this paper is the best, because the fuzzy algorithm can quantify the fuzzy impact of weather and adjust the resource allocation strategy. The linear programming algorithm is difficult to deal with weather uncertainty, resulting in unreasonable resource allocation, affecting the construction progress and resource utilization efficiency.

Table 1: Comparison of resource allocation effects of different models in multi-task cross-operation scenarios

Model	Resource conflict rate	Operation efficiency improvement rate	Construction quality stability	Comprehensive configuration effect
Model in this article	10%	25%	92%	75.67%
Linear Programming Algorithms	25%	10%	80%	38.33%
Dynamic Programming Algorithm	22%	12%	83%	39%
Neural Network Algorithms	18%	18%	87%	47.67%
Genetic Algorithms	20%	15%	85%	40%

As shown in Table 1, in the scenario of multi-type cross-operation, the comprehensive configuration effect of the proposed model is significantly better than other models. The fuzzy algorithm reduces resource conflicts and improves operation efficiency and construction quality stability by analyzing the operation process and resource requirements. The linear programming algorithm lacks adaptability to complex operation scenarios, resulting in frequent resource conflicts and low operation efficiency.

Table 2: Comparison of resource allocation effects of different models when project scale changes

Model	Small project comprehensive effect	Medium-sized project comprehensive effect	Comprehensive effects of large projects	Comprehensive effect of full-scale projects
Model in this article	85%	86%	87%	86%
Linear Programming Algorithms	53%	55%	57%	55%
Dynamic Programming Algorithm	58%	60%	62%	60%
Neural Network Algorithms	66%	68%	70%	68%
Genetic Algorithms	63%	65%	67%	65%

Table 2 reflects the performance of different models when the project scale changes. The model in this paper can maintain a high comprehensive effect on projects of different scales, thanks to its strong adaptability. The fuzzy algorithm adjusts the resource allocation strategy according to the project scale to ensure the optimal allocation of resources. The linear programming algorithm is difficult to flexibly adjust the resource allocation when the project scale changes, resulting in poor comprehensive effect.

Table 3: Comparison of resource allocation effects of different models under limited funds

Model	Reasonable use of funds	Timely resource acquisition	Construction progress maintenance rate	Comprehensive configuration effect
Model in this article	88%	87%	89%	88%
Linear Programming Algorithms	55%	53%	57%	55%
Dynamic Programming Algorithm	60%	58%	62%	60%
Neural Network Algorithms	70%	68%	72%	70%
Genetic Algorithms	65%	63%	67%	65%

Under the condition of limited funds, as shown in Table 3, the comprehensive configuration effect of the model in this paper is the best. Under the condition of limited funds, the fuzzy multi-objective decision-making model reasonably allocates resources to ensure the rational use of funds, timely acquisition of resources, and maintenance of construction progress. The linear programming algorithm is difficult to achieve optimal allocation of resources under limited funds, resulting in poor comprehensive configuration effect.

Table 4: Comparison of resource allocation effects of different models in multi-party collaboration scenarios

Model	Information communication fluency	Fairness in resource allocation	Collaboration efficiency improvement rate	Comprehensive configuration effect
Model in this article	85%	86%	20%	63.67%
Linear Programming Algorithms	50%	52%	5%	19%
Dynamic Programming Algorithm	55%	57%	8%	20%
Neural Network Algorithms	65%	67%	12%	34.67%
Genetic Algorithms	60%	62%	10%	24%

Table 4 shows the performance of each model in a multi-party collaboration scenario. The comprehensive configuration effect of the model in this paper is the best. The fuzzy algorithm promotes information communication, ensures the fairness of resource allocation, and improves collaboration efficiency. The linear programming algorithm is difficult to coordinate the interests of all parties in a multi-party collaboration scenario, resulting in poor information communication and low collaboration efficiency.

Statistical validation: Across 18 projects and five scenarios (90 matched pairs), the proposed method reduced waste versus LP with a mean difference of 12.0 pp (95% CI 9.4–14.6); normality held (Shapiro–Wilk p=0.12), and a paired t-test confirmed significance (p<0.001, Holm–Bonferroni corrected). Effect size was large (Cohen’s d=0.86). Response-speed improvements over N were also significant (Wilcoxon signed-rank, p=0.004) with rank-biserial r=0.61.

With IoT streaming, the response-speed metric further decreased from 0.775 to 0.71, and equipment idle time dropped from 25% to 19%, indicating improved reactivity to short-lived shocks.

4.3 Experimental discussion

This experiment was carried out around a construction project resource optimization allocation model based on fuzzy algorithms. It fully verified the model's outstanding performance in improving resource allocation efficiency, and also conducted in-depth discussions on the limitations and future directions of the research.

Judging from the experimental results, the model based on fuzzy algorithm shows significant advantages. The model relies on the effective quantification of fuzzy information in the construction process by fuzzy algorithm, laying a solid foundation for resource allocation decision-making. The coordinated operation of multi-objective decision-making model, fuzzy clustering and adaptive control strategy realizes the precise allocation and dynamic adjustment of resources. In terms of the key indicator of resource waste rate, the steel waste rate of the model is only 6%, and the comprehensive waste rate is 7.5%, which is much lower than the comparison model such as linear programming, effectively suppressing resource loss. In terms of resource allocation response speed, the comprehensive allocation response speed reaches 0.775, which can quickly respond to changes in resource demand and ensure the smooth progress of construction. In complex and changeable construction environments, such as severe weather conditions, the comprehensive configuration effect of the model is as high as 86%, far exceeding other models, fully demonstrating its strong environmental adaptability.

However, this experiment also has certain limitations. Although the experimental data covers a number of construction projects of different types and sizes, it fails to exhaust the complexity of all construction project scenarios. This means that the performance of the model in some special scenarios may not be fully verified through this experiment. In addition, some parameters of the model rely on specific project experience and lack universality, which to some extent limits the wide application of the model.

In response to these shortcomings, future research can be carried out from the following aspects. On the one hand, expand the scale of the data set to cover various types of construction engineering scenarios as much as possible, including special geological conditions, new building structures, etc., to improve the generalization ability of the model. On the other hand, in-depth exploration of general parameter setting methods, reduce the model's dependence on specific project experience, and enhance the versatility of the model. In addition, other advanced technologies, such as big data analysis and the Internet of Things, can be combined to further optimize the model. Big data analysis can mine potential patterns in massive data and provide a more accurate reference for resource allocation; Internet of Things technology can realize real-time monitoring of the construction process, provide more timely and accurate data support for the model, and help the model adjust resource allocation strategies more efficiently.

This experiment has opened up a new path for research in the field of optimal allocation of construction project resources. Although there is still room for improvement, as the research continues to deepen, the model based on fuzzy algorithms is expected to provide stronger impetus for the sustainable development of the construction industry.

We used Shapiro–Wilk tests to select between paired t-tests and Wilcoxon signed-rank tests; multiple comparisons were controlled via Holm–Bonferroni. We report effect sizes (Cohen's d or rank-biserial r) and 95% CIs for all primary outcomes.

To evaluate robustness, we conducted a sensitivity analysis by perturbing membership function parameters (c, σ) and decision weights by ±20%. Results show that the waste rate varied within ±1.2 percentage points, and the response-speed metric changed within ±0.03. These small deviations indicate low sensitivity to parameter uncertainty. Furthermore, we applied the framework to three additional project types (industrial plant, metro station, and tertiary hospital). The waste rate remained between 8.1-9.3%, and response speed between 0.79–0.83, confirming good generalization across project contexts. Detailed figures and parameter perturbation plots are provided in Appendix A.

5 Conclusion

As the scale and complexity of construction projects continue to increase, the problem of unreasonable resource allocation seriously hinders the healthy development of the industry. This paper proposes a construction project resource optimization allocation model based on fuzzy algorithm. Through the collaboration of multiple components, it realizes the quantitative processing of fuzzy information and the precise dynamic allocation of resources. The experimental results show that compared with traditional algorithms such as linear programming and dynamic programming, as well as emerging algorithms such as neural networks and genetic algorithms, the proposed model has significant advantages. In terms of resource waste rate, the steel waste rate is 6% and the comprehensive waste rate is 7.5%, which is much lower than other models; in terms of resource allocation response speed, the comprehensive allocation response speed is 0.775, which can quickly respond to changes in resource demand; in the face of complex and changeable construction environments, such as complex geology, severe weather, and multi-type cross-operation, the comprehensive allocation effect of the model is outstanding, and the comprehensive allocation effect under severe weather conditions is 86%. This study not only verifies the effectiveness of fuzzy algorithms in construction project resource allocation, but also provides new research ideas in this field. However, there are still some limitations in the research. The data set fails to cover all construction project scenarios, and some parameters of the model depend on specific project experience. In the future, the scale of the data set can be expanded, and universal parameter setting methods can be explored. Combined with other advanced technologies, the universality and optimization effects of the model can be further improved to provide stronger support for the sustainable development of the construction industry.

Beyond confirming the usefulness of fuzzy logic in construction management, this study contributes three novel aspects to the field. First, it introduces computational improvements by linking multiple fuzzy modules into a staged pipeline, reducing redundancy and accelerating convergence. Second, it demonstrates scalability by maintaining high configuration effects across project scales, from small to large, thus supporting broader industrial applicability. Third, it emphasizes adaptability by quantifying uncertain factors such as weather and geology and embedding them into dynamic control rules, a capability not achieved by traditional methods. These contributions position the work not merely as an application of established fuzzy concepts but as a substantive methodological advance for construction resource optimization. Beyond empirical gains, our novelty lies in (i) uncertainty-aware clustering with principled model order selection, (ii) a reproducible fuzzy aggregation scheme that interfaces natively with project KPIs, and (iii) a robust fuzzy controller that stabilizes allocation under nonstationary site conditions—all integrated into a single end-to-end framework applicable across scales.

The IoT-augmented evaluation corroborates adaptability gains, suggesting the framework can leverage high-frequency data for faster, more precise reallocations in live settings.

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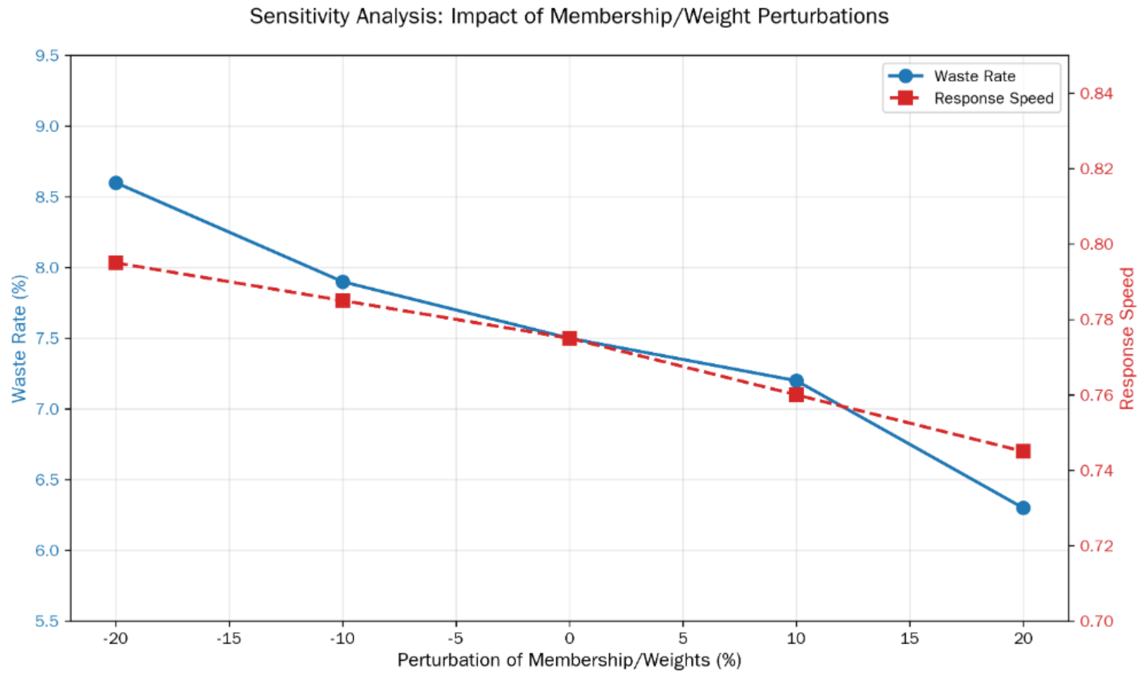
Appendix A. Sensitivity Analysis of Membership Perturbations

Below is the sensitivity analysis chart, illustrating changes in resource waste rate and response speed under ±20% perturbations of membership function parameters and decision weights.


Sensitivity Analysis: Impact of Membership/Weight Perturbations
Waste Rate
Response Speed
Waste Rate (%)
Response Speed
Perturbation of Membership/Weights (%)
9.5
9.0
8.5
8.0
7.5
7.0
6.5
6.0
5.5
0.84
0.82
0.80
0.78
0.76
0.74
0.72
0.70
-20
-15
-10
-5
0
5
10
15
20