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A Mamdani Fuzzy Inference System-Based Model for Time and Cost Estimation of Structural Works in Construction Projects

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Abstract

This study addresses the persistent problem of inaccurate time and cost estimation in construction projects caused by uncertainty during the planning and execution phases. Structural works are particularly vulnerable to delays and budget deviations due to factors such as rainfall conditions, labor discipline, planning quality, design changes, and material price fluctuations. Therefore, this study aims to develop a Mamdani Fuzzy Inference System (FIS)-based model for estimating the time and cost of structural works under uncertain project conditions. The research employed a case-based model development design focusing on structural works in a villa construction project. Data were collected from deterministic schedules and budgets, actual project records, expert questionnaires, Focus Group Discussions (FGD), MATLAB simulations, and Microsoft Project integration. The fuzzy model generated Duration Factor and Cost Factor outputs to adjust deterministic baseline values into uncertainty-adjusted fuzzy baselines. The findings showed that the fuzzy model improved estimation accuracy compared to the deterministic baseline. The project duration estimate increased from 346 days to 369.12 days, approaching the actual duration of 377 days, while the cost estimate improved from IDR 3.74 billion to IDR 3.93 billion compared to the actual cost of IDR 4.01 billion. In conclusion, the Mamdani FIS-based model provides a more realistic and adaptive baseline estimation approach for structural construction works under uncertain conditions.

INTRODUCTION

Time and cost estimation is a fundamental component of construction project planning because it determines scheduling, budgeting, resource allocation, and subsequent project control. The project baseline is usually prepared as a deterministic representation of planned work, planned duration, and planned cost. Although this baseline is necessary for contractual and managerial control, its estimates are often prepared when knowledge about the project environment is incomplete. Atkinson (1999) argued that time and cost are among the most widely used project management criteria, but they are also estimates made when the project is least understood. Olawale and Sun (2010) showed that construction time and cost control is inhibited by design changes, risk and uncertainty, complexity, and performance-related issues.

The limitation of deterministic planning becomes more critical in structural works executed under difficult site conditions. The investigated case is a villa project in which earthworks and structural works were carried out on sloping terrain with staged access and sequential construction movement from lower to higher villa levels. In such conditions, rainfall, labour discipline, planning quality, working drawing changes, and material price fluctuation can produce deviations from the deterministic baseline. Recent studies on construction uncertainty also emphasize that limited knowledge during the planning phase and project complexity can affect planning reliability and project outcomes (Kuchta et al., 2023; Lafhaj et al., 2024).

Fuzzy logic has been widely applied to construction management problems because it can transform linguistic judgement and imprecise information into numerical reasoning. Zadeh (1965) introduced fuzzy sets as a way to represent gradual membership rather than crisp binary classification. Mamdani and Assilian (1975) developed a fuzzy rule-based inference approach that is suitable when knowledge can be expressed through IF-THEN linguistic rules. In construction estimation, this capability is useful because expert judgement often contains terms such as high rainfall, poor planning quality, low labour discipline, major drawing change, or high price fluctuation.

Previous fuzzy-based construction studies have contributed to several important areas. Habibi et al. (2018) applied fuzzy logic to improve time and cost estimation based on PERT under uncertainty. Plebankiewicz et al. (2021) reviewed and developed fuzzy models for time, cost, and risk in construction. Ladnykh and Ibadov (2024) used fuzzy modelling to estimate construction duration under risk factors when statistical probability distributions are difficult to define. Canesi and D'Alpaos (2024) applied fuzzy logic to manage construction cost escalation, while Naeni et al. (2011), Desse and Mengesha (2024), and Alshibani et al. (2024) demonstrated fuzzy extensions in earned value analysis and final cost forecasting.

Construction project management continues to face persistent challenges in producing reliable time and cost estimates, particularly because early project planning is often conducted under conditions of incomplete information (Uotila et al., 2020). Time and cost remain two of the most dominant indicators of project performance, yet both are highly vulnerable to uncertainty, changes in site conditions, labor productivity, design revisions, and market fluctuations. In construction practice, deterministic planning is commonly used to establish the project baseline, but this approach often assumes that planned duration and budget will remain stable throughout implementation. In reality, project execution frequently differs from the initial plan, making estimation accuracy a critical issue for contractors, consultants, and project owners.

Globally, time and cost overruns have been widely reported as recurring problems in construction projects. Gomez-Cabrera et al. (2024) emphasized that causes of overruns are extensively discussed in construction management literature, showing that delays and budget increases are not isolated problems but structural challenges in project delivery. Similarly, Olawale and Sun (2010) identified design changes, risk, uncertainty, complexity, and performance-related issues as key barriers to effective time and cost control. These findings indicate that traditional estimation methods are often insufficient when projects are exposed to uncertain technical, environmental, and managerial factors.

The issue becomes more complex in structural works because this stage usually involves heavy resources, strict sequencing, and high dependency on site conditions. In the case discussed in the manuscript, the construction project involved villa structural works located on sloping terrain, with staged access and sequential construction movement from lower to higher levels (Chawhan & Kamal, 2021). Such conditions increase the possibility of deviation from the deterministic baseline because rainfall, labor discipline, planning quality, drawing changes, and material price fluctuations may directly influence project duration and cost (İlter, 2021; Kermanshachi et al., 2022; Wang et al., 2021). Therefore, structural works require an estimation approach that can accommodate uncertainty more flexibly.

Recent studies have shown that uncertainty during the planning phase can significantly influence project outcomes. Kuchta et al. (2023) explained that uncertainty in public project planning affects decision-making and project performance, while Lafhaj et al. (2024) highlighted that construction project complexity remains a major source of uncertainty. These studies confirm that estimation problems are not merely technical calculations but also involve managerial judgment, contextual conditions, and uncertain variables that are difficult to measure using crisp numerical models.

Fuzzy logic has become one of the promising approaches for addressing uncertainty in construction estimation because it can convert linguistic judgments into numerical reasoning. Zadeh (1965) introduced fuzzy set theory to represent gradual membership rather than rigid binary classification, while Mamdani and Assilian (1975) developed a rule-based fuzzy inference system using IF–THEN linguistic rules. In construction estimation, this approach is relevant because experts often describe project conditions using qualitative terms such as high rainfall, poor planning quality, low labor discipline, major drawing changes, or high material price fluctuation.

Several previous studies from indexed academic literature have applied fuzzy logic to construction time, cost, and risk estimation. Habibi et al. (2018) used fuzzy logic to improve project time and cost estimation based on PERT under uncertainty. Plebankiewicz et al. (2021) developed fuzzy models for construction time, cost, and risk. Ladnykh and Ibadov (2024) applied fuzzy modeling to estimate construction duration under risk factors when statistical probability distributions are difficult to define. These studies demonstrate that fuzzy logic can support more realistic project estimation where uncertainty cannot be fully represented by deterministic assumptions.

Other studies have also confirmed the relevance of fuzzy logic in construction cost management and project control. Canesi and D'Alpaos (2024) applied fuzzy logic to manage construction cost escalation, while Naeni et al. (2011), Desse and Mengesha (2024), and Alshibani et al. (2024) demonstrated fuzzy extensions in earned value analysis and final project cost forecasting. However, many of these studies focus on fuzzy PERT, cost escalation, earned value analysis, or final cost prediction, rather than developing a fuzzy baseline model that simultaneously adjusts deterministic time and cost estimates at the structural work level.

This creates a research gap in the development of an integrated fuzzy baseline estimation model that preserves the deterministic baseline while adding an uncertainty-adjusted layer for structural works. Most previous studies use fuzzy logic either as a forecasting tool or as a general risk model ling technique, but limited attention has been given to generating Duration Factor and Cost Factor as adjustment outputs for deterministic duration and cost. Therefore, a model that integrates Mamdani Fuzzy Inference System, MATLAB calculation, Microsoft Project Baseline1 mapping, and MAPE-based accuracy evaluation provides an important opportunity to strengthen estimation practice.

The urgency of this research lies in the need for more adaptive and realistic estimation tools in construction projects, especially for structural works executed under complex site conditions. When the initial project baseline does not reflect uncertainty, project monitoring may become misleading because actual performance is compared against an overly optimistic plan. By introducing fuzzy adjustment factors, the project team can maintain the original deterministic baseline for contractual reference while also using an uncertainty-adjusted baseline as a more practical benchmark for control and evaluation.

Therefore, this study aims to develop a Mamdani Fuzzy Inference System-based model for estimating time and cost in structural construction works under uncertainty. The novelty of this research lies in the use of dual fuzzy branches to generate Duration Factor and Cost Factor, the integration of fuzzy outputs into Microsoft Project as Baseline1, and the evaluation of deterministic and fuzzy baselines against actual project data using MAPE. The contribution of this study is expected to support construction practitioners in improving baseline reliability, assist researchers in advancing fuzzy-based construction estimation models, and provide a practical framework for managing uncertainty in structural project planning.

METHOD

Study design, case context, and data sources

This research used a case-based model development design. The case consisted of earthworks and structural works for five villas. The study scope was limited to structural works so that deterministic duration, deterministic cost, fuzzy duration, fuzzy cost, actual duration, and actual cost could be compared consistently. Non-structural work, external packages, indirect costs, overhead, taxes, permits, and unrelated work packages were not included in the accuracy evaluation. The main data sources were deterministic schedule and cost plan, actual schedule and cost records, expert questionnaire results, FGD results, MATLAB fuzzy outputs, and Microsoft Project baseline comparison.

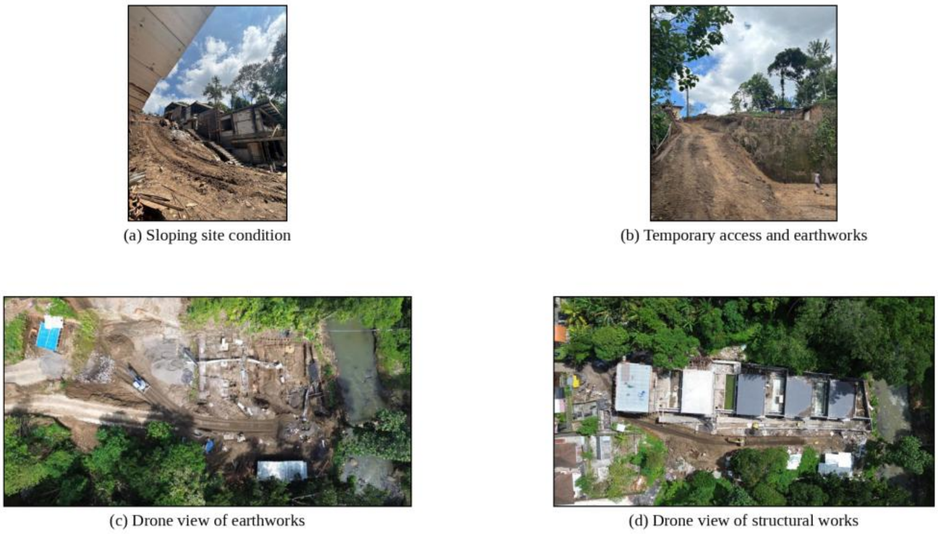

Figure 1. Case project documentation of the investigated structural works.

Research workflow

The research workflow consisted of literature review, RII variable selection, FGD knowledge base development, Mamdani FIS formulation, MATLAB calculation, Microsoft Project Baseline1 integration, and MAPE evaluation.

Figure 2. Research workflow used to develop and evaluate the Mamdani FIS-based model.

Variable selection using Relative Importance Index

The initial uncertainty variables were synthesized from the literature on construction time, cost, productivity, risk, planning, and project control. The variables were screened using the Relative Importance Index. RII was selected because it is commonly used to rank variables collected through structured Likert-scale questionnaires (Boakye et al., 2023). The formula used was:

$$\mathrm{RII} = \frac{\sum \mathrm{W}}{\mathrm{A} \times \mathrm{N}}$$

Where W is the respondent weight, A is the highest scale value, and N is the number of respondents. The final variables were limited to three inputs for the time model and three inputs for the cost model to maintain interpretability and avoid an excessive rule base.

Table 1. Final input variables selected for the fuzzy time and cost models.

Model	Selected input variable	Measured aspect	RII
Time estimation	Weather condition	Rainfall condition	0.89
Time estimation	Project planning	Planning quality	0.88
Time estimation	Labour productivity	Labour discipline	0.87
Cost estimation	Material price	Material price fluctuation	0.97
Cost estimation	Project planning	Planning quality	0.90
Cost estimation	Design change	Working drawing changes	0.89

FGD-based fuzzy knowledge base development

After variable selection, a Focus Group Discussion was used to develop the fuzzy knowledge base. The FGD was not treated as a statistical survey; it transformed expert judgement into operational fuzzy parameters. Focus groups are appropriate when the objective is to obtain structured views, perceptions, and group reasoning around a research problem. In this study, the FGD produced the input domains, output domains, linguistic terms, membership function shapes, rule base, and project input values used by MATLAB.

Membership function design

The fuzzy model used three linguistic levels for each input and output variable. Trapezoidal functions were used for boundary categories, while triangular functions were used for middle categories. This design keeps the model simple enough for expert validation while allowing overlap between neighbouring categories.

Table 2. Linguistic terms and membership function structure.

Model	Variable	Linguistic terms	Membership function type
Time	Rainfall condition	Low, moderate, high	Trapezoidal, triangular, trapezoidal
Time	Planning quality	Poor, fair, good	Trapezoidal, triangular, trapezoidal
Time	Labour discipline	Low, medium, high	Trapezoidal, triangular, trapezoidal
Time	Duration Factor	Low, moderate, high adjustment	Trapezoidal, triangular, trapezoidal
Cost	Material price fluctuation	Stable, moderate, high	Trapezoidal, triangular, trapezoidal
Cost	Planning quality	Poor, fair, good	Trapezoidal, triangular, trapezoidal
Cost	Working drawing changes	Minor, moderate, major	Trapezoidal, triangular, trapezoidal
Cost	Cost Factor	Low, moderate, high adjustment	Trapezoidal, triangular, trapezoidal

The triangular membership function and trapezoidal membership function were defined as follows:

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ \dfrac{c-x}{c-b}, & b < x < c \\ 0, & x \ge c \end{cases}$$

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ 1, & b < x \le c \\ \dfrac{d-x}{d-c}, & c < x < d \\ 0, & x \ge d \end{cases}$$

Mamdani FIS model and rule base

Two Mamdani FIS branches were developed. The time branch maps rainfall condition, planning quality, and labour discipline into Duration Factor. The cost branch maps material price fluctuation, planning quality, and working drawing changes into Cost Factor. The AND operator was implemented using the minimum operator, rule aggregation used the maximum operator, and defuzzification used the centroid method.

Table 3. Principal representative rules for the time adjustment model.

No.	Rainfall	Planning quality	Labour discipline	Then Duration Factor
T1	Low	Good	High	Low adjustment
T2	Low	Fair	Medium	Moderate adjustment
T3	Low	Poor	Low	Moderate adjustment
T4	Moderate	Good	High	Moderate adjustment
T5	Moderate	Fair	Medium	Moderate adjustment
T6	Moderate	Poor	Low	High adjustment
T7	High	Good	High	Moderate adjustment
T8	High	Fair	Medium	High adjustment
T9	High	Poor	Low	High adjustment

Table 4. Principal representative rules for the cost adjustment model.

No.	Material price fluctuation	Planning quality	Drawing changes	Then Cost Factor
C1	Stable	Good	Minor	Low adjustment
C2	Stable	Fair	Moderate	Moderate adjustment
C3	Stable	Poor	Major	Moderate adjustment
C4	Moderate	Good	Minor	Moderate adjustment
C5	Moderate	Fair	Moderate	Moderate adjustment
C6	Moderate	Poor	Major	High adjustment
C7	High	Good	Minor	Moderate adjustment
C8	High	Fair	Moderate	High adjustment

No.	Material price fluctuation	Planning quality	Drawing changes	Then Cost Factor
C9	High	Poor	Major	High adjustment

Tables 3 and 4 present the principal representative rules used to explain the inference structure. The full operational rule base was implemented in MATLAB for the project data processing workflow.

MATLAB and Microsoft Project integration

The automation structure was developed around an Excel workbook, MATLAB, and Microsoft Project. The workbook stored the work breakdown structure, deterministic baseline values, project input values, membership function parameters, output domains, and rule base. MATLAB read the workbook, constructed the Mamdani FIS objects, evaluated each work group, and generated Duration Factor, Cost Factor, Fuzzy Duration, and Fuzzy Cost. The fuzzy outputs were calculated using the following relationships:

$$FD_i = DD_i \times DF_i$$
$$FC_i = DC_i \times CF_i$$

Where FD is fuzzy duration, DD is deterministic duration, DF is Duration Factor, FC is fuzzy cost, DC is deterministic cost, and CF is Cost Factor for work group i. The fuzzy outputs were then mapped to Microsoft Project as Baseline1. This configuration enables three data layers to coexist: deterministic baseline, fuzzy baseline, and actual project realization.

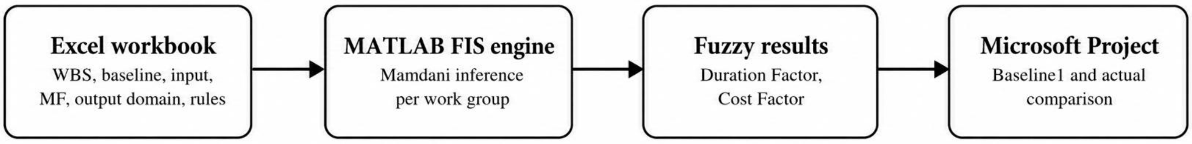

Figure 3. MATLAB to Microsoft Project integration architecture

Accuracy evaluation using MAPE

The deterministic baseline and fuzzy baseline were evaluated against actual data using Mean Absolute Percentage Error. MAPE was selected because its percentage form is easy to interpret in construction planning evaluation. However, the interpretation was limited to closeness against actual data in the investigated case, not universal forecasting superiority. Hyndman and Koehler (2006) noted that forecast accuracy measures can have limitations, and therefore MAPE should be interpreted with awareness of its denominator and context.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Actual_i - Estimate_i}{Actual_i}\right| \times 100\%$$

Results and Discussion

Fuzzy model output and adjustment mechanism

The proposed model produces adjustment factors rather than direct final estimates. This mechanism preserves the deterministic baseline as the planning reference while adding an uncertainty-adjusted baseline. Table 5 explains the interpretation of the main model outputs.

Table 5. Interpretation of fuzzy model outputs.

Output	Function	Interpretation
Duration Factor	Adjusts deterministic duration	A value above 1.00 indicates that fuzzy reasoning extends the deterministic duration.
Cost Factor	Adjusts deterministic cost	A value above 1.00 indicates that fuzzy reasoning increases the deterministic cost.
Fuzzy Duration	Deterministic duration multiplied by Duration Factor	Represents the uncertainty-adjusted duration estimate.
Fuzzy Cost	Deterministic cost multiplied by Cost Factor	Represents the uncertainty-adjusted cost estimate.
Baseline1	Fuzzy baseline in Microsoft Project	Used to compare the fuzzy baseline with actual realization.

This adjustment mechanism is consistent with fuzzy estimation literature, which treats fuzzy logic as a means to represent uncertainty and expert reasoning in numerical outputs. The difference is that the present study applies fuzzy reasoning as a baseline adjustment layer rather than as a full replacement of scheduling or cost planning procedures.

Duration estimation results

Table 6 presents the duration comparison by work group. The duration values for each work group are interpreted as schedule spans, not as additive durations, because several work groups overlap within the project schedule.

Table 6. Duration comparison between deterministic, fuzzy, and actual data.

Work group	Deterministic baseline	Fuzzy baseline	Actual	Fuzzy residual gap
Earthworks	145 days	161.79 days	162 days	0.21 days
Structure Villa 5	183 days	208.35 days	212 days	3.65 days
Structure Villa 4	168 days	193.21 days	195 days	1.79 days
Structure Villa 3	164 days	189.85 days	190 days	0.15 days
Structure Villa 2	183 days	207.88 days	208 days	0.12 days
Structure Villa 1	168 days	191.12 days	191 days	-0.12 days
Total project schedule span	346 days	369.12 days	377 days	7.88 days

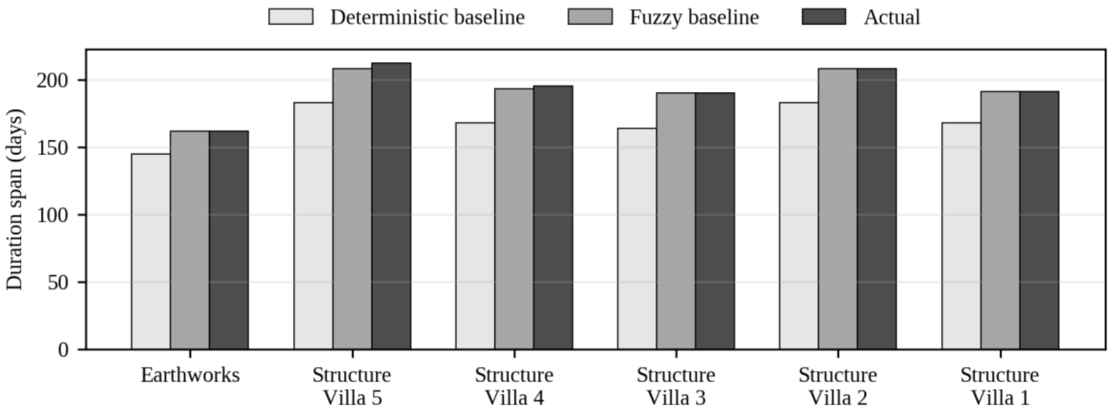

Figure 4. Duration comparison by work group.

The deterministic project duration was 346 days, while the actual duration was 377 days. The fuzzy baseline produced 369.12 days, leaving a residual gap of 7.88 days against actual realization. At the work group level, the fuzzy baseline consistently moved closer to actual duration than the deterministic baseline. This supports the argument that fuzzy logic can improve time estimation when deterministic parameters do not fully capture project uncertainty, as also suggested in the fuzzy PERT and construction duration literature (Habibi et al., 2018; Ladnykh and Ibadov, 2024).

Cost estimation results

Table 7 presents the cost comparison by work group. The total deterministic cost was IDR 3,742,413,165.91, while the actual structural cost was IDR 4,008,706,075.02. The fuzzy model adjusted the cost baseline to IDR 3,932,375,362.79.

Table 7. Cost comparison between deterministic, fuzzy, and actual data.

Work group	Deterministic baseline	Fuzzy baseline	Actual	Fuzzy residual gap
Earthworks	IDR 346,409,156.14	IDR 358,538,573.39	IDR 359,558,297.98	IDR 1,019,724.59
Structure Villa 5	IDR 661,490,107.00	IDR 696,707,203.12	IDR 702,496,165.46	IDR 5,788,962.34
Structure Villa 4	IDR 673,303,719.57	IDR 709,021,780.40	IDR 718,422,647.28	IDR 9,400,866.88
Structure Villa 3	IDR 742,327,997.99	IDR 780,723,517.56	IDR 797,231,152.98	IDR 16,507,635.42
Structure Villa 2	IDR 728,801,197.69	IDR 766,352,277.85	IDR 787,807,416.49	IDR 21,455,138.64
Structure Villa 1	IDR 590,080,987.52	IDR 621,032,010.47	IDR 643,190,394.83	IDR 22,158,384.36
Total project	IDR 3,742,413,165.91	IDR 3,932,375,362.79	IDR 4,008,706,075.02	IDR 76,330,712.23

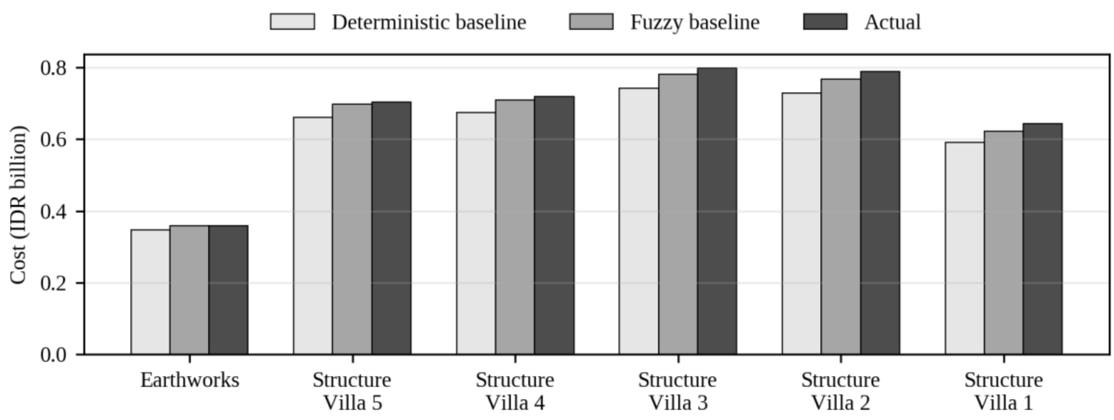

Figure 5. Cost comparison by work group.

The fuzzy cost baseline reduced the gap against actual cost from IDR 266,292,909.11 under the deterministic baseline to IDR 76,330,712.23. This result is consistent with studies showing that fuzzy logic is useful for modelling cost uncertainty, including cost escalation, fuzzy earned value analysis, and final project cost forecasting (Canesi and D'Alpaos, 2024; Desse and Mengesha, 2024; Alshibani et al., 2024). In this study, however, the model is not used as a final cost forecasting engine during project execution. It is used to estimate an uncertainty-adjusted baseline before comparison with actual data.

MAPE-based accuracy evaluation

MAPE was used to evaluate estimation closeness. Table 8 shows that both time and cost MAPE decreased after the fuzzy baseline was applied.

Table 8. MAPE comparison of deterministic and fuzzy baselines.

Work group	Time MAPE deterministic	Time MAPE fuzzy	Cost MAPE deterministic	Cost MAPE fuzzy
Earthworks	10.49%	0.13%	3.66%	0.28%
Structure Villa 5	13.68%	1.72%	5.84%	0.82%
Structure Villa 4	13.85%	0.92%	6.28%	1.31%
Structure Villa 3	13.68%	0.08%	6.89%	2.07%
Structure Villa 2	12.02%	0.06%	7.49%	2.72%
Structure Villa 1	12.04%	0.06%	8.26%	3.45%
Total project	8.22%	2.09%	6.64%	1.90%

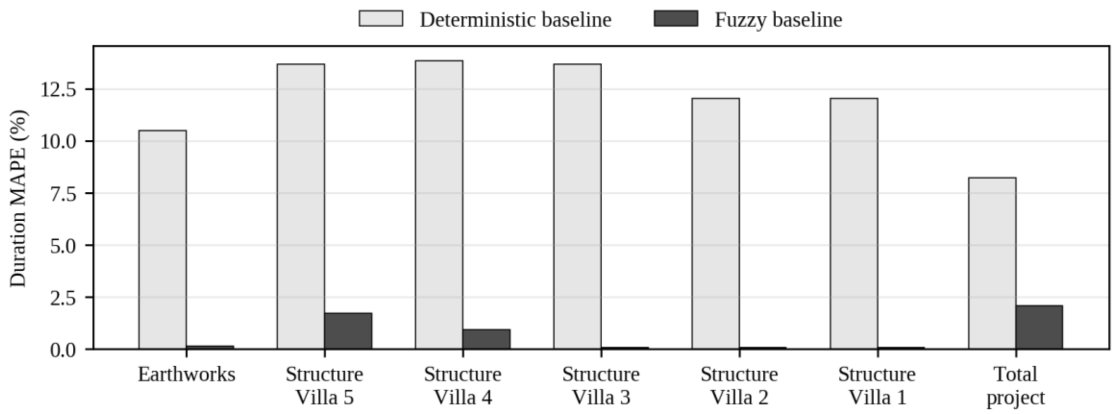

Figure 6. Duration MAPE comparison.

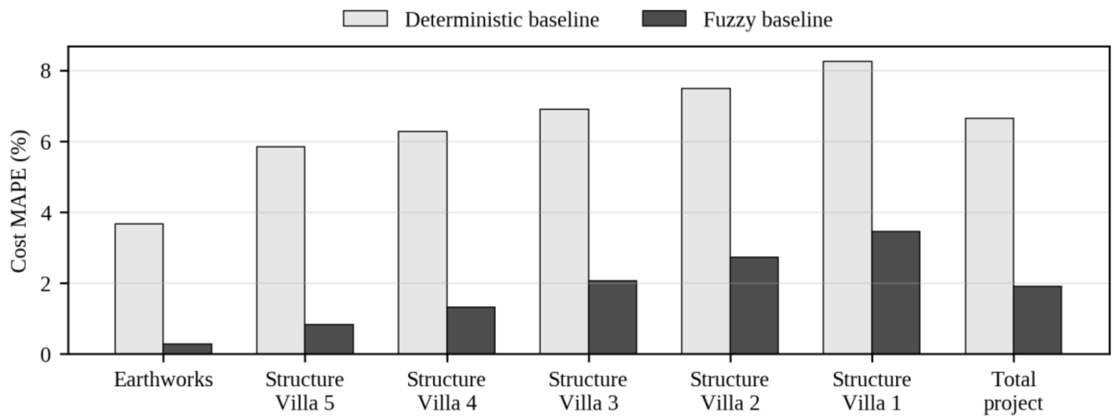

Figure 7. Cost MAPE comparison.

For total project duration, MAPE decreased from 8.22% to 2.09%. For total project cost, MAPE decreased from 6.64% to 1.90%. The results indicate that the fuzzy baseline was closer to actual project realization than the deterministic baseline in the investigated case. The improvement should not be interpreted as proof that the model is universally accurate for all construction projects. It demonstrates improved closeness within a specific structural work case using actual data as the evaluation denominator.

Discussion in relation to previous studies

The findings support the general premise in fuzzy construction estimation research that fuzzy logic can handle imprecise project information more flexibly than crisp values. The time estimation result is aligned with Habibi et al. (2018), who used fuzzy logic to improve time and cost estimation under PERT, and with Ladnykh and Ibadov (2024), who modelled duration under risk factors when statistical uncertainty is difficult to define. The distinction is that the present study does not reconstruct a fuzzy PERT network; it adjusts an existing deterministic schedule through Duration Factor and then stores the fuzzy value as Baseline1.

The cost estimation result is consistent with fuzzy cost research. Canesi and D'Alpaos (2024) used fuzzy logic to manage construction cost escalation, Desse and Mengesha (2024) integrated grey and fuzzy logic within earned value analysis, and Alshibani et al. (2024) developed a fuzzy-based model for forecasting project final cost. The present model differs by focusing on fuzzy baseline estimation before the performance comparison stage. It therefore complements project control models by providing a more realistic baseline for comparison, rather than only forecasting future cost performance.

The role of labour discipline and productivity is supported by Soekiman et al. (2011), Malara et al. (2019), Gunduz and Abu-Hijleh (2020), and Kazerooni et al. (2021), who show that labour productivity and productivity drivers are important to construction performance. In this study, labour productivity is operationalized through labour discipline in the time model because the case project required staged execution and reliable work continuity.

The practical implication is that fuzzy adjustment does not behave like a uniform contingency percentage. Each work group receives an adjustment according to input values and rule activation. The method is compatible with Microsoft Project because the fuzzy outputs can be stored separately as Baseline1, leaving the original deterministic baseline available for contractual or managerial reference.

Practical implication and limitation

For practitioners, the model can be used as a planning review tool before the project baseline is used for monitoring and control. A deterministic baseline can still be maintained for contractual reference, while Baseline1 provides an uncertainty-adjusted benchmark. This is particularly useful in structural works where execution constraints, weather, labour continuity, and design changes can affect the reliability of a fixed initial estimate.

The model has several limitations. First, it was evaluated on one case project and a structural works scope, so cross-project validation is needed before wider generalization. Second, the fuzzy knowledge base depends on expert judgement and the quality of FGD interpretation. Third, MAPE was used because it is easy to interpret, but other error measures may be added in future research. Fourth, the model produces fuzzy baseline estimates and should not be interpreted as a real-time forecasting model unless additional monitoring data are incorporated.

CONCLUSION

This study developed a Mamdani FIS-based model for estimating the time and cost of structural works under uncertainty. The model uses rainfall condition, planning quality, and labour discipline to generate Duration Factor, and material price fluctuation, planning quality, and working drawing changes to generate Cost Factor. These factors are then used to adjust deterministic duration and deterministic cost into fuzzy baseline values. The model improved the closeness of the baseline to actual project realization in the investigated case. The deterministic project duration of 346 days was adjusted to 369.12 days, compared with the actual duration of 377 days. The deterministic cost of IDR 3,742,413,165.91 was adjusted to IDR 3,932,375,362.79, compared with the actual cost of IDR 4,008,706,075.02. The residual fuzzy gaps were 7.88 days for time and IDR 76,330,712.23 for cost. The accuracy evaluation showed that time MAPE decreased from 8.22% under the deterministic baseline to 2.09% under the fuzzy baseline. Cost MAPE decreased from 6.64% to 1.90%. These results indicate that the fuzzy baseline provided a more realistic reference for the investigated structural works case than the original deterministic baseline. The proposed model should be positioned as an uncertainty-adjusted baseline estimation tool, not as a universal forecasting model. Future research should test the model on additional projects, broader work scopes, different site conditions, and additional accuracy metrics. Integration with real-time progress data may also extend the model from baseline estimation into dynamic project control.

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