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Cost Control in EPC Public Works Using a System Dynamics Model Embedded with Intuitionistic Fuzzy Reasoning: A Case Study of the Urumqi Civic Center

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Abstract

Cost control in engineering, procurement, and construction (EPC) public works is shaped by interacting drivers, nonlinear feedback, and qualitative judgments. Existing studies usually apply the three relevant method families separately: DEMATEL-ISM maps causal structure but does not propagate hesitation-aware expert judgments into cost trajectories; fuzzy systems represent uncertainty but commonly lack a verified causal hierarchy; and system dynamics (SDs) capture dynamic accumulation but often rely on crisp inputs. The resulting absence of a traceable causal screening to uncertainty to dynamic cost link is the specific gap addressed in this study. We therefore develop a transparent three-stage pipeline combining the Decision-Making Trial and Evaluation Laboratory–Interpretive Structural Modeling (DEMATEL-ISM) method, triangular intuitionistic fuzzy reasoning (TIFR), and SDs. DEMATEL-ISM identifies the causal hierarchy; TIFR represents membership, non-membership, and hesitation in design complexity and human–technology synergy judgments; and SDs evaluate stage-specific cost trajectories. Recalculation from the supplied 17×17 direct influence matrix produced a six-level hierarchy in which senior management decision-making capability and the level of integration occupy the two deepest driving levels. For the Urumqi Civic Center case, the baseline terminal cost absolute percentage error was 0.492%. A coordinated intervention scenario shifted the simulated terminal cost by CNY 12.1243 million (6.1%) relative to the baseline; this is a model-based scenario difference, not an observed project saving. Integration had the largest simulated effects on design and transportation costs, whereas senior management decision-making capability had the largest effects on procurement and construction costs. Security cost curves showed a complementary pattern between managerial capability and workers' professional competence, but no statistical interaction effect is claimed. The framework is intended for within-case scenario comparison and intervention prioritization; multi-project and time-series validation remains necessary.



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Keywords: EPC projects; cost control; system dynamics; triangular intuitionistic fuzzy reasoning

1. Introduction

Against the backdrop of new urbanization and the modernization of the construction industry, public buildings, as core carriers of urban functions [1], are increasing in both scale and complexity and exert a substantial influence on social investment and resource allocation [2]. However, such projects commonly experience cost overruns and schedule

delays, and inadequate cost control has become a major constraint on investment performance. The engineering, procurement, and construction (EPC) delivery model has been widely adopted in the pursuit of high-quality development because it integrates design, procurement, and construction management [3]. Nevertheless, most existing studies treat project cost as a static object and do not fully reveal the complex relationships among cost drivers, the system's feedback mechanisms, or its response to dynamic changes in the external environment. Conventional static and isolated cost control methods cannot adequately characterize or manage this dynamic complexity, resulting in delayed interventions and limiting both the theoretical potential and practical effectiveness of the EPC model in cost control.

Cost management during actual construction is subject to multiple uncertainties, including over- or underestimation of quantities, unbalanced bidding, variations, and claims [4]. Conventional cost accounting is often delayed and distorted and therefore cannot support real-time dynamic cost control. Although cost-value reconciliation (CVR) can improve the timeliness and accuracy of cost management through net-value adjustments, it still focuses on localized static analysis and does not capture nonlinear interactions and dynamic feedback among cost drivers from a system-wide perspective. Under China's dual-circulation development paradigm, cost management is shifting from a static structural perspective to a dynamic systems perspective, with emphasis on supply-demand coordination and the optimization of execution-related drivers [5]. Accordingly, EPC project cost control must address not only the internal cost structure but also the dynamic interactions and feedback mechanisms among internal and external system factors.

System dynamics (SDs), first proposed by Forrester [6], characterize the endogenous dynamics of complex systems through stock-flow structures and causal feedback loops. It is particularly suitable for management problems such as project cost systems, which exhibit nonlinearity, multiple feedback processes, and time delays. In cost control, its application has expanded from cost forecasting to process optimization.

SDs models have been widely applied to cost and operational control. Beyond construction, Taheri et al. [7] represented feedback among time, profitability, and customer satisfaction. Construction cost applications include prefabricated bridge cost management [8], cost-quality trade-offs in lean manufacturing [9], product life-cycle cost simulation [10], green building renovation cost analysis [11], infrastructure PPP value creation [12], and design-stage EPC power-plant cost control [13]. Fuzzy and data-driven approaches address complementary problems: classical fuzzy-set theory [14] and intuitionistic fuzzy sets [15] retain uncertainty in expert judgments; machine learning studies estimate green building cost deviations [16], renovation costs [17], AEC dispute costs [18], and construction-contract dispute outcomes [19]; intuitionistic fuzzy logic combined with SDs supports product life-cycle cost control [20]; integrated DEMATEL-SD has supported project cost prediction [21] and schedule control [22]; and hybrid fuzzy-DEMATEL-SD modeling has been applied to construction social sustainability [23]. These strands show that causal structure, qualitative uncertainty, and dynamic accumulation are each well established, but they are rarely connected in a single reproducible chain for stage-specific EPC public-building cost control. The present case therefore uses an interpretable rule-based approach because the available historical sample is small and several managerial variables cannot be defensibly estimated as precise statistical functions.

The contribution is not the first use of fuzzy reasoning with SDs. Methodologically, the study connects a verified DEMATEL-ISM hierarchy to a hesitation-aware TIFR rule layer and then to five stage-specific SDs cost stocks. Theoretically, it distinguishes deep structural drivers from operational variables and makes their transmission into accumulated costs explicit. Practically, it provides a transparent scenario comparison workflow for a public-

building EPC case. Table 1 compares the closest studies and also makes the boundary of the claim explicit: the contribution lies in this three-stage linkage and its case implementation, not in any individual method or in universal predictive validity.

DEMATEL identifies the direction and strength of causal relationships among interdependent factors, whereas ISM converts those relationships into a multilevel hierarchy. Their combination has been used to distinguish root drivers from direct outcome factors in EPC value creation and building management problems [24,25]. In this study, DEMATEL-ISM is used before dynamic modeling so that the SDs structure and subsequent sensitivity tests focus on the factors with the greatest causal and hierarchical leverage.

Accordingly, this study pursues three objectives: (1) to identify the causal hierarchy and root drivers of EPC public-building cost control using DEMATEL-ISM; (2) to construct an SDs model in which TIFR translates uncertain judgments concerning design complexity and human–technology synergy into simulation parameters; and (3) to validate the integrated model using an actual EPC project and compare the cost effects of alternative control scenarios. The analysis follows the same sequence: DEMATEL-ISM factor identification, SD-TIFR model construction, and case-based validation and sensitivity analysis.

Table 1. Structured comparison with the closest international and hybrid decision-support studies.

Study	Application and Method	Uncertainty/Dynamics	Gap Relative to This Study
Zhang and Han [20]	Product life-cycle cost; intuitionistic fuzzy reasoning + SD	Hesitation-aware fuzzy input and dynamic feedback	No DEMATEL-ISM screening or multi-stage EPC case evaluation
Alsugair et al. [21]	Construction project cost prediction; DEMATEL + SD	Causal structure and dynamic cost forecasting	No intuitionistic fuzzy rule layer or ISM hierarchy
Ajayi and Chinda [22]	Construction schedule control; DEMATEL + SD	Dynamic delay feedback	Schedule rather than multi-stage EPC cost; no hesitation modeling
Rostamnezhad et al. [23]	Construction social sustainability; fuzzy-DEMATEL + SD	Fuzzy causal judgments and dynamics	Different outcome domain; no intuitionistic rule-to-stock linkage
Alnaser et al. [26]	BIM and cost overrun risk; PLS-SEM	Empirical interrelationships among BIM-related risks	No dynamic stock–flow accumulation or fuzzy expert rules
Alshibani et al. [27]	Final construction cost; multi-method fuzzy forecasting	Fuzzy cost uncertainty	No causal hierarchy or SDs feedback across EPC stages
Present study	EPC public-building cost; DEMATEL-ISM + TIFR + SD	Causal hierarchy, hesitation-aware rules, and stage-specific dynamic feedback	Single-case validation; transferability remains to be tested

2. Methodology

2.1. DEMATEL-ISM-Based Identification of Factors Influencing EPC Project Cost Control

2.1.1. Selection of Factors Influencing EPC Project Cost Control

This study addresses the practical problem that actual EPC project costs frequently exceed their targets. Factor identification began with a targeted review rather than a systematic meta-analysis. The China National Knowledge Infrastructure database was searched using ‘EPC project’, ‘cost control’, ‘public building’, ‘system dynamics’, and ‘intuitionistic fuzzy reasoning’. For the revision, publishing and DOI records were updated through 11 August 2026 using the English equivalents together with ‘BIM cost control’, ‘fuzzy cost forecasting’, and ‘hybrid decision support’. Peer-reviewed studies were retained

when they explicitly linked EPC or construction cost to SDs, fuzzy decision methods, BIM, or hybrid causal modeling. Editorials and studies without a construction cost mechanism were excluded. The structured synthesis is reported in Table 1. Factor relevance was then screened through a separate questionnaire administered to design-institute professionals, site-construction practitioners, and university professors, each with at least three years of EPC-related experience. Of 136 questionnaires distributed, 114 were returned, and 108 were valid, giving a return rate of 83.82%, an effective response rate of 79.41%, and a valid proportion of 94.74% among returns. A six-point scale from 0 ('no effect') to 5 ('very strong effect') was used, and a mean score above 3 retained a factor. Cronbach's alpha was not applied because the items are deliberately heterogeneous causal drivers rather than interchangeable indicators of one latent scale. This absence of respondent-level internal-consistency evidence is acknowledged as a limitation. The procedure retained 17 factors across six dimensions [24,25,28], as shown in Table 2. For the DEMATEL stage, the 108 valid respondents rated the directional influence of factor M_i on factor M_j on a four-point scale from 0 ('no influence') to 3 ('strong influence'). For each off-diagonal cell, the arithmetic mean of the 108 ratings was calculated and rounded to the nearest integer using the conventional half-up rule to preserve the original ordinal scale; all diagonal cells were fixed at zero. Thus, $b_{ij} = \text{round}[(1/108) \sum_k x_{ij}(k)]$ for $i \neq j$ and $b_{ii} = 0$. The resulting 17×17 integer direct influence matrix used in the subsequent DEMATEL calculation is supplied in Supplementary Data S1.

Table 2. Influencing factors of EPC cost control.

No.	Dimension	Influencing Factor	Description
1	Personnel	Senior management decision-making capability	The level of decision-making and professional competence among senior managers.
2		Workers' professional competence	Workers' levels of technical skill and practical experience.
3		Supplier credibility	The effects of supplier delivery quality, timeliness, and cost-effectiveness on project costs.
4		Workers' work intensity	Work intensity is significantly associated with operational error rates and work efficiency.
5		Owner credibility	Slow technical decision-making and repeated requests for revisions by the owner.
6	Technology	Degree of standardization	The degree of process and procedure standardization has a significant effect on productivity.
7		BIM-based simulation	The use of BIM to simulate transportation and construction activities.
8		Level of integration	The level of integration affects overall cost allocation during the design and transportation stages.

Table 2. Cont.

No.	Dimension	Influencing Factor	Description
9	Environment	Construction site conditions	The completeness of the site's physical conditions and the complexity of its environmental constraints.
10		Natural environmental conditions	The effects of weather conditions and natural disasters on project progress.
11		Transportation distance	The effect of freight transportation distance on transportation costs.
12	Transportation	Multimodal transportation coordination	The effects of rail–water and air–road intermodal transportation on transportation costs.
13		Stockyard arrangement	A rational stockyard layout can prevent damage to finished products and avoid secondary handling of components.
14		Schedule deviation	The difference between actual progress and the baseline schedule.
15	Construction	Accidents	Budgeted cost losses caused by accidents during project execution.
16		Safe and civilized construction	Budgeted expenditures incurred to reduce construction-related environmental pollution and disturbance to local communities.
17	Policy	Relevant national policies	Preferential subsidies for construction projects provided under national policies.

Based on the selected factors, DEMATEL was used to quantify the direction and strength of pairwise influence, after which ISM transformed the resulting causal network into an interpretable multilevel structure. This sequence was selected because DEMATEL alone identifies causal prominence but does not explicitly reveal hierarchical transmission paths, whereas ISM benefits from an empirically grounded influence matrix. Their combination therefore supports both key-factor identification and the subsequent construction of the SDs feedback structure.

2.1.2. Establishment of the Direct Influence and Total Influence Matrices

Let the factors influencing EPC project cost control be denoted by $M = \{M_1, M_2, \dots, M_{17}\}$, $M_i (i = 1, 2, \dots, 17)$. The relationship with $M_j (j = 1, 2, \dots, 17)$ is represented by b_{ij} . A scale of 0, 1, 2, and 3 is used to represent the strength of the influence of M_i on M_j , respectively:

For notation consistency, M_i denotes the source factor, M_j denotes the receiving factor, and b_{ij} is the direct influence assigned from M_i to M_j . Throughout the DEMATEL–ISM analysis, the first subscript denotes the source factor and the second denotes the receiving factor for entries in B, N, F, A, and R.

$$b_{ij} = \begin{cases} 0: & \text{No effect} \\ 1: & \text{Low impact} \\ 2: & \text{Moderate impact} \\ 3: & \text{High impact} \end{cases}$$

The direct influence matrix M for cost control can then be obtained as follows:

$$M = (b_{ij})_{17 \times 17}$$

2.1.3. Establishment of the Total Influence Matrix

Let $B = [b_{ij}]$ denote the 17×17 direct influence matrix and let s be its maximum row sum. The normalized direct influence matrix is $N = B/s$, and the total influence matrix is $F = N(I - N)^{-1}$. For the supplied matrix, $s = \max_i \sum_j b_{ij} = 33$. The calculation used unrounded values of N ; recomputation reproduced the supplied total influence matrix with a maximum absolute difference of 4.997×10^{-6} , attributable to the five-decimal display precision in the workbook.

$$N = B/s, \quad s = \max_{\{1 \leq i \leq 17\}} \sum_{j=1}^{17} b_{ij} = 33 \quad (1)$$

$$F = N + N^2 + N^3 + \dots + N^k = \sum_{k=1}^{\infty} N^k = N(I - N)^{-1} \quad (2)$$

where I is the 17×17 identity matrix. Influencing degree r_i is the sum of row i of F , influenced degree c_i is the sum of column i , centrality is $r_i + c_i$, causality is $r_i - c_i$, and the reported weight is $w_i = (r_i + c_i) / \sum_k (r_k + c_k)$. Positive causality identifies a net cause factor, whereas negative causality identifies a net effect factor. The calculation workbook and intermediate matrices are provided in Supplementary Data S1.

2.1.4. Calculation of Influencing Degree, Influenced Degree, Centrality, and Causality

Based on $F = [f_{ij}]$, the influencing degree $r_i = \sum_j f_{ij}$, influenced degree $c_i = \sum_j f_{ji}$, centrality $r_i + c_i$, causality $r_i - c_i$, and normalized centrality weight w_i were calculated for each factor using Equations (3)–(6).

$$C_i = \sum_{j=1}^n t_{ij} (i = 1, 2, 3, \dots, 17) \quad (3)$$

$$D_i = \sum_{j=1}^n t_{ji} (i = 1, 2, 3, \dots, 17) \quad (4)$$

$$L_i = C_i + D_i \quad (5)$$

$$Z_i = C_i - D_i \quad (6)$$

Here, i and j index the 17 factors; f_{ij} is the total direct and indirect influence of factor M_i on M_j ; r_i summarizes outward influence; and c_i summarizes received influence. Results are presented in Table 3.

Table 3. DEMATEL influencing degree, influenced degree, centrality, causality, and normalized weight.

Factor	C_i Influencing Degree	D_i Influenced Degree	L_i Centrality	Z_i Causality	Weight
M_1	3.216	1.776	4.992	1.441	0.066
M_2	2.322	2.522	4.843	−0.2	0.064
M_3	1.978	2.526	4.504	−0.548	0.059
M_4	2.468	2.013	4.481	0.454	0.059
M_5	2.056	2.356	4.412	−0.3	0.058
M_6	2.494	2.214	4.708	0.28	0.062
M_7	2.139	2.108	4.247	0.031	0.056
M_8	2.897	2.123	5.02	0.774	0.066

Table 3. Cont.

Factor	C_i Influencing Degree	D_i Influenced Degree	L_i Centrality	Z_i Causality	Weight
M_9	2.243	2.325	4.568	−0.081	0.06
M_{10}	2.161	2.239	4.401	−0.078	0.058
M_{11}	2.281	1.97	4.251	0.311	0.056
M_{12}	2.083	2.12	4.203	−0.038	0.055
M_{13}	2.153	2.252	4.405	−0.098	0.058
M_{14}	1.562	2.82	4.382	−1.259	0.058
M_{15}	2.026	2.437	4.462	−0.411	0.059
M_{16}	2.012	2.554	4.565	−0.542	0.06
M_{17}	1.986	1.721	3.708	0.265	0.049

Centrality reflects the overall importance of each influencing factor in the system; a higher centrality indicates a more critical role. A cause–effect diagram of the cost-influencing factors was plotted using centrality on the horizontal axis and causality on the vertical axis (Figure 1). Based on causality, the factors can be divided into two groups. Factors with causality greater than zero are causal factors, and a larger value indicates a stronger driving effect on other factors. Factors with causality below zero are effect factors, and a smaller value indicates weaker autonomy and independence.

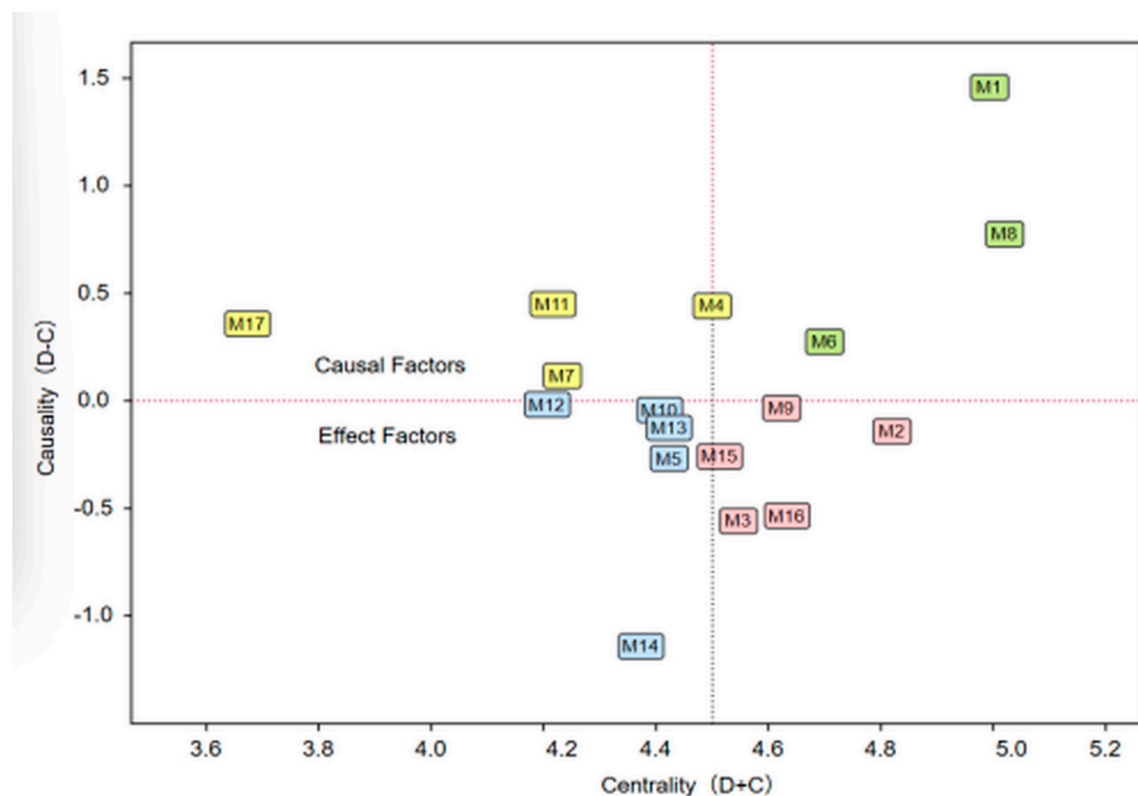


Figure 1. DEMATEL cause–effect diagram. Green labels denote net cause factors; blue and pink labels denote net effect factors and are used only to improve the visual separation of overlapping labels. Centrality measures total system involvement.

2.1.5. Establishment of the Adjacency and Reachability Matrices

The ISM threshold was defined as $\lambda = \bar{f} + \sigma_f$, where $\bar{f}$ and σ_f are the mean and population standard deviation of all 289 entries of the unrounded total influence matrix F . The adjacency matrix A was defined by $a_{ij} = 1$ when $f_{ij} \geq \lambda$ and $a_{ij} = 0$ otherwise.

The recalculated values were $f^- = 0.1317509$ and $\sigma_f = 0.0335064$, giving $\lambda = 0.1652573$ (reported as 0.16526). Thresholds f^- , $f^- + 0.5\sigma_f$, and $f^- + \sigma_f$ retained 129, 80, and 45 directed entries (44.64%, 27.68%, and 15.57% of 289), respectively. After Boolean transitive closure, the mean threshold collapsed the network into two broad levels, the intermediate threshold produced five levels, and the adopted threshold produced six levels. Senior management decision-making capability (M1) remained in the deepest driving level under both stricter thresholds, whereas the mean threshold was too dense to separate the driving structure. This comparison supports the adopted threshold while showing which hierarchy features are threshold-sensitive.

$$Z: \begin{cases} Z_{ij} = 1, t_{ij} \geq \lambda \\ Z_{ij} = 0, t_{ij} < \lambda \end{cases} \quad (7)$$

Let $H = A \vee I$, where $\vee$ denotes the Boolean union, and I is the identity matrix. The reachability matrix R is obtained by Boolean multiplication until stabilization, $H^k = H^{k+1}$. The exact adjacency and stabilized reachability matrices are included in Supplementary Data S1.

$$H = Z + I \quad (8)$$

The stabilized Boolean matrix R records both direct and transitive reachability. Hierarchical partitioning was performed iteratively on the remaining factors; after each top level was identified, those factors were removed, and the reachability and antecedent sets were recalculated for the reduced system.

$$H^{k-1} \neq H^k = H^{k+1} = X \quad (9)$$

The reachability matrix X is thereby obtained.

2.1.6. Development of the Multilevel Hierarchical Model of Influencing Factors

The corrected Boolean reachability calculation yields six levels (Table 4): $L1 = \{M3, M7, M10, M13, M14, M17\}$; $L2 = \{M2, M15, M16\}$; $L3 = \{M5, M6, M9, M12\}$; $L4 = \{M4, M11\}$; $L5 = \{M8\}$; and $L6 = \{M1\}$. Thus, senior management decision-making capability (M1) is the deepest structural driver, and the level of integration (M8) is the second-deepest driver. Workers' professional competence (M2) is an upper operational factor rather than a root factor, although it remains relevant to the security and procurement scenario equations. Figure 2 shows the corrected hierarchy using the transitive-reduction links; all factor codes M1–M17 are consistent with Table 2 and Supplementary Data S1.

Table 4. Corrected ISM reachability, antecedent, intersection sets, and six-level stratification.

Factor	Reachability Set H (Mi)	Antecedent Set K (Mi)	Intersection Set N (Mi)	Level
M ₁	M1, M2, M3, M4, M5, M6, M7, M8, M9, M10, M12, M13, M14, M15, M16	M1	M1	6
M ₂	M2, M7	M1, M2, M4, M5, M6, M8	M2	2
M ₃	M3	M1, M3, M4, M6, M8	M3	1
M ₄	M2, M3, M4, M5, M7, M14	M1, M4, M8	M4	4
M ₅	M2, M5, M7	M1, M4, M5, M8	M5	3
M ₆	M2, M3, M6, M7, M14, M15, M16	M1, M6, M8	M6	3
M ₇	M7	M1, M2, M4, M5, M6, M7, M8	M7	1
M ₈	M2, M3, M4, M5, M6, M7, M8, M9, M10, M13, M14, M15, M16	M1, M8	M8	5

Table 4. Cont.

Factor	Reachability Set H (Mi)	Antecedent Set K (Mi)	Intersection Set N (Mi)	Level
M ₉	M9, M14, M16	M1, M8, M9, M11	M9	3
M ₁₀	M10	M1, M8, M10	M10	1
M ₁₁	M9, M11, M14, M16	M11	M11	4
M ₁₂	M12, M14, M16	M1, M12	M12	3
M ₁₃	M13	M1, M8, M13	M13	1
M ₁₄	M14	M1, M4, M6, M8, M9, M11, M12, M14, M15, M16	M14	1
M ₁₅	M14, M15	M1, M6, M8, M15	M15	2
M ₁₆	M14, M16	M1, M6, M8, M9, M11, M12, M16	M16	2
M ₁₇	M17	M17	M17	1

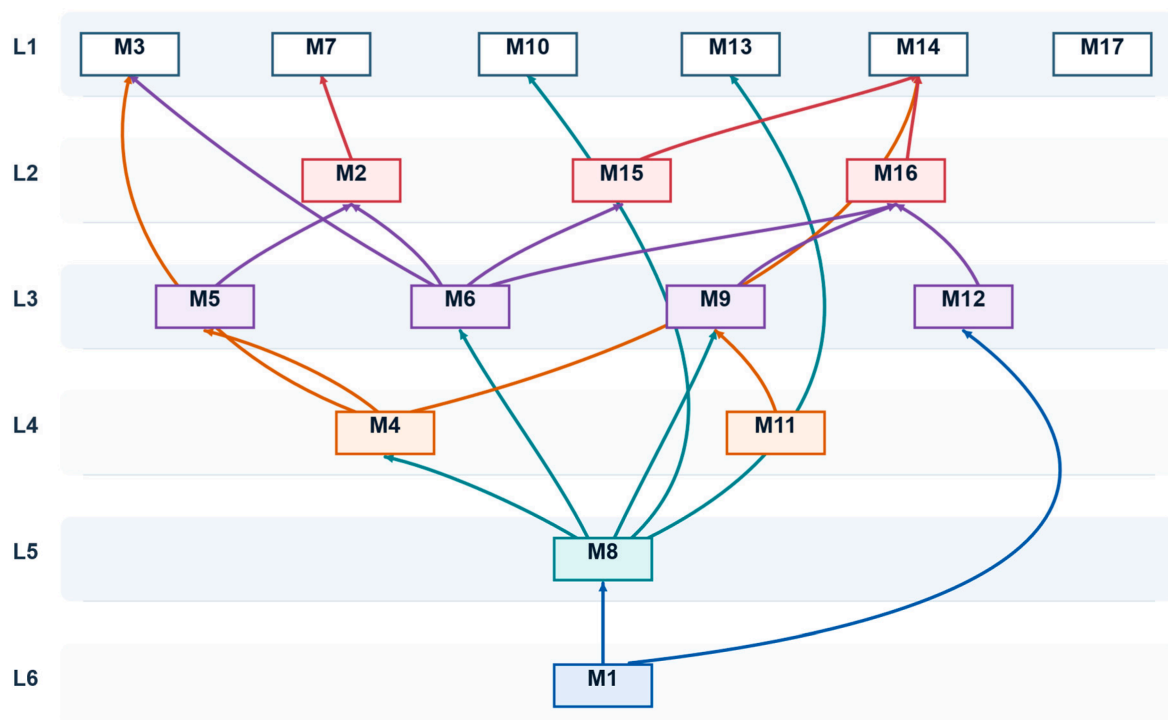


Figure 2. Corrected six-level ISM hierarchy at $\lambda = 0.16526$. Arrows show transitive-reduction influence paths from deeper drivers to higher-level factors; factor definitions are given in Table 2.

2.2. Intuitionistic Fuzzy Reasoning

2.2.1. Triangular Intuitionistic Fuzzy Numbers

Definition 1. An intuitionistic fuzzy set extends a classical fuzzy set by describing objective uncertainty more precisely through two dimensions: membership and non-membership. Let X be a given universe of discourse. An intuitionistic fuzzy set B on X can be expressed as follows:

This definition follows classical fuzzy-set theory [14] and intuitionistic fuzzy-set theory [15].

$$B = \{(x, \mu_B(x), \nu_B(x)) | x \in X\} \quad (10)$$

where $\mu_B(x) \rightarrow [0, 1]$, $\nu_B(x) \rightarrow [0, 1]$ denote the membership and non-membership degrees, respectively, of element x in set B . For any $x \in X$, they satisfy the constraint $0 \leq \mu_B(x) + \nu_B(x) \leq 1$, which ensures that the sum of membership and non-membership does not exceed 1. The quantity $\pi_B(x) = 1 - \mu_B(x) - \nu_B(x)$ is termed the hesitation degree (intuitionistic fuzzy index) of x belonging to B ; for any $x \in X$, $0 \leq \pi_B(x) \leq 1$.

For clarity, $\mu_B(x)$ is the membership degree, $\nu_B(x)$ is the non-membership degree, and $\pi_B(x) = 1 - \mu_B(x) - \nu_B(x)$ is the hesitation degree; the same notation is retained throughout Section 2.2.

Definition 2. *Intuitionistic Fuzzy Set*

$B = \langle (b_1, b_2, b_3); \mu_B, \nu_B \rangle, b_1, b_2, b_3 \in \mathbb{R}$ is an intuitionistic fuzzy number on the real number set [29]. Its membership and non-membership degrees are given by Equations (11) and (12), respectively.

$$\mu_B(x) = \begin{cases} \frac{x-b_1}{b_2-b_1} \mu_B; & b_1 \leq x \leq b_2 \\ \mu_B; & x = b_2 \\ \frac{b_3-x}{b_3-b_2} \mu_B; & b_2 \leq x \leq b_3 \\ 0; & \text{otherwise} \end{cases} \quad (11)$$

$$\nu_B(x) = \begin{cases} \frac{b_2-x+\nu_B(x-b_1)}{b_2-b_1}; & b_1 \leq x \leq b_2 \\ \nu_B; & x = b_2 \\ \frac{x-b_2+\nu_B(b_3-x)}{b_3-b_2}; & x \leq b_3 \\ 1; & \text{otherwise} \end{cases} \quad (12)$$

where μ_B, ν_B represent the maximum membership degree and minimum non-membership degree, respectively. If Definition 1 is satisfied, $B = \langle (b_1, b_2, b_3); \mu_B, \nu_B \rangle, b_1, b_2, b_3 \in \mathbb{R}$ is termed a triangular intuitionistic fuzzy number.

2.2.2. Intuitionistic Fuzzy Reasoning Method

Intuitionistic fuzzy reasoning generally performs separate inferences for the membership and non-membership functions and then applies a truth value, centroid, or weighted average method for defuzzification. Building on previous research, an intuitionistic fuzzy system can be understood as a linear combination of two conventional fuzzy systems [30]. Its output can be expressed in the following intuitionistic fuzzy form:

$$y = (1 - \pi) \cdot y_\mu + \pi \cdot y_\nu \quad (13)$$

where y_μ and y_ν are the crisp outputs obtained by defuzzifying the reasoning subsystems based on the membership and non-membership functions, respectively; π is the overall system hesitation degree and measures cognitive uncertainty in the reasoning process; and $1 - \pi$ is the non-hesitation index, which represents the confidence weight assigned to the membership-function subsystem in decision-making. In particular, when $\pi = 0$, the system reduces to classical fuzzy reasoning. While retaining the structure and intuitiveness of a conventional fuzzy system, this method uses the hesitation mechanism to improve flexibility and interpretability when processing uncertain information.

Step 1. Intuitionistic Fuzzification

This study adopts triangular membership functions. Parameter values are documented according to their provenance: the human–technology synergy parameterization follows Zhang and Han [20], whereas the case-specific complexity ranges and the 15-rule base are specified through project evidence and the Delphi procedure described in Section 2.3. The non-membership function is defined by the selected membership and hesitation settings.

Step 2. Fuzzy Rule Base and Fuzzy Inference

Intuitionistic fuzzy reasoning must process membership and non-membership information in parallel. To maintain intuitive and structurally clear reasoning, the classical

Mamdani fuzzy inference method is adopted. Specifically, when the system receives an intuitionistic fuzzy premise C (i.e., the proposition “ x is C ”) and an intuitionistic fuzzy rule $C \rightarrow D$ on $X \times Y$ (i.e., “if x is C , then y is D ”), the membership and non-membership degrees of D^* can be inferred using the Mamdani framework [20]:

$$\mu_{D^*} = \bigvee_{y \in Y} (\mu_{C^*} \wedge (\mu_C \wedge \mu_D)) \quad (14)$$

$$\nu_{D^*} = \bigwedge_{y \in Y} (\nu_{C^*} \vee (\nu_C \vee \nu_D)) \quad (15)$$

For a multi-factor, multi-rule case, if there are m factors C and K rules, then D^* is expressed by Equation (16):

$$\mu_{D^*}(y) = \bigvee_{k=1}^K \mu_{D^*}^k(y) = \bigvee_{k=1}^K \left(\bigvee_{\substack{x \in X \\ y \in Y}} \left(\left(\bigwedge_{i=1}^n \mu_{C_i^*}(x) \right) \wedge \left(\left(\bigwedge_{i=1}^n \mu_{C_i} \right) \wedge \mu_D(y) \right) \right) \right) \quad (16)$$

Step 3. Defuzzification

The fuzzy inference result for the membership-function system obtained in Step 2 is defuzzified using the centroid method, and the final result is calculated using Equation (13).

2.3. Embedding the Intuitionistic Fuzzy Reasoning System

The design-stage complexity coefficient is normally estimated from design-revision records for comparable projects, but such records are often unavailable at the initial design stage. An intuitionistic fuzzy reasoning system was therefore used to translate two uncertain inputs—the design complexity coefficient and human–technology synergy capability, which combines personnel competence, technological advancement, and their coordination—into an actual complexity coefficient. Unlike a single crisp score, the intuitionistic representation retains membership, non-membership, and hesitation and therefore records both the experts’ judgment and their residual uncertainty. The input–output mapping is implemented through 15 IF-THEN rules.

For the illustrative implementation, human–technology synergy capability is represented over [15,20] by five linguistic states: low, relatively low, medium, relatively high, and high. The associated triangular intuitionistic-fuzzy parameterization, including the membership, non-membership, and hesitation settings, follows the methodological specification reported by Zhang and Han [20]. It is used as a documented methodological input to the present TIFR system and is not presented as an independently elicited output of the present Delphi panel. Design complexity is represented by [52, 56] and actual complexity by [54, 58], each with low, medium, and high states. The 15 IF-THEN rules map the two inputs to the actual complexity coefficient. Figure 3 presents the complete 5×3 rule matrix. Figures 4 and 5 present, respectively, the unsmoothed and visualization-only smoothed inference surfaces generated from these rules.

The 15 rule assignments and their Round-2 consensus are reported in Supplementary Table S3. The seven-member Delphi panel comprised two senior design-institute engineers, two EPC-contractor cost management heads, two university professors in engineering-construction management, and one representative of a large public-project owner. In Round 1, panelists assessed the 15 input combinations and considered the case-specific design and actual complexity ranges. In Round 2, anonymized summaries were returned for reconsideration. A rule required at least 5/7 agreement for direct acceptance or a second-round simple majority of at least 4/7; all 15 rules reached at least 6/7 agreement. The design complexity interval [52, 56] reflects geometric irregularity and coordination

among at least eight MEP disciplines, and three-star green building requirements. The actual complexity interval [54, 58] reflects design-change notices, design-review frequency, detailed-design workload, and Delphi judgment.

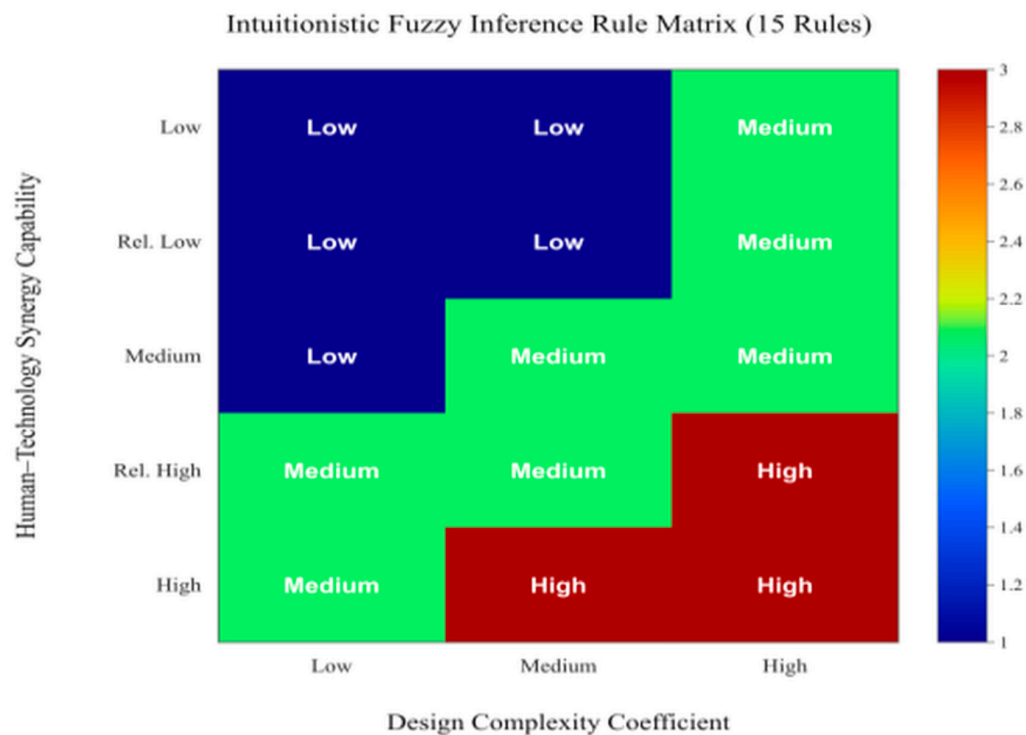


Figure 3. Complete 5×3 intuitionistic fuzzy rule matrix. Each cell maps a human–technology synergy state and design complexity state to a low, medium, or high actual complexity output. Blue, green, and red cells denote low, medium, and high outputs, respectively.

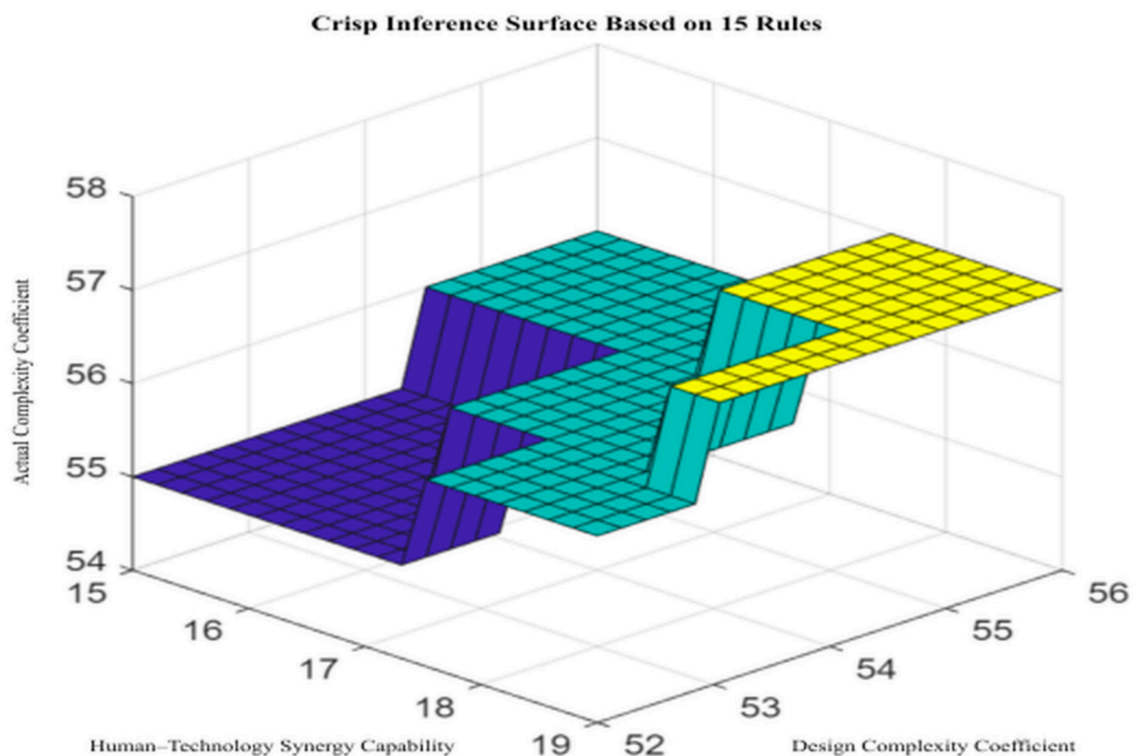


Figure 4. Unsmoothed Mamdani-centroid inference surface generated by the 15 expert-validated rules. The blue–cyan–yellow gradient indicates increasing actual complexity coefficients.

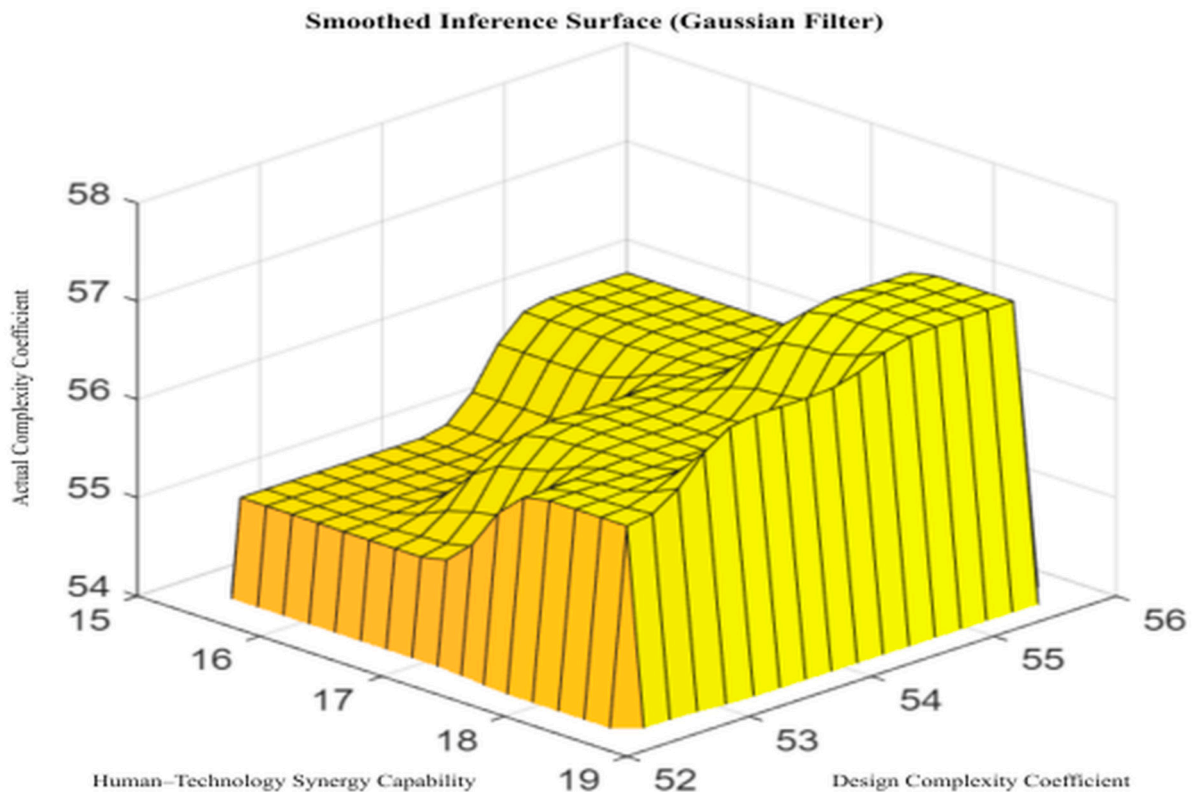


Figure 5. Visualization-only Gaussian-smoothed inference surface using the normalized 3×3 kernel reported in Section 2.3; numerical SDs input uses the unsmoothed inference.

Figure 4 presents the unsmoothed Mamdani-centroid inference surface generated by the 15 rules. Figure 5 is a visualization-only rendering obtained with a normalized 3×3 Gaussian kernel, $[1 \ 2 \ 1; 2 \ 4 \ 2; 1 \ 2 \ 1]/16$ (equivalent to approximately $\sigma = 1$ grid cell). Numerical values passed to the SDs model were calculated from the unsmoothed rule-based inference; therefore, changing or omitting the display filter cannot alter any reported simulation result. The smoothing parameter is reported solely to make the figure reproducible and is not a calibrated model parameter.

2.4. Development of the System Dynamics Model

The TIFR system was embedded in the SDs framework shown in Figure 6. The corrected DEMATEL-ISM hierarchy determined the direction and ordering of structural links. Project records supplied the contract amount, settlement benchmark, schedule timing, and stage-specific cost quantities. Enterprise records and case averages supplied operational constants, whereas the literature and expert judgment supplied behavioral relationships and lookup shapes. Simulations were performed using Vensim PLE 7.3.5 (Ventana Systems, Inc., Harvard, MA, USA). The model contains 92 equation entries and five cost stocks—design, transportation, procurement, security, and construction—whose sum defines total project cost. INITIAL TIME = 0 months, FINAL TIME = 18 months, TIME STEP = SAVEPER = 1 month, and stochastic functions retain fixed seeds for reproducibility. The control indices use a baseline of 0.5 and scenario values of 0.3, 0.5, 0.7, and 0.9. The unsmoothed TIFR output enters the actual complexity coefficient lookup, generates the actual output multiplier, and affects designer salary and baseline defect rate before propagating through the design cost stock. Supplementary Table S1 reports all equations, initial values, units, parameter roles, and data-source categories; Supplementary Table S3 reports the 15 rules; and Supplementary Data S1 reports the DEMATEL-ISM

matrices. Supplementary Tables S1–S5 are consolidated in the Supplementary Materials S1 document, whereas Supplementary Data S1 is the formula-linked calculation workbook.

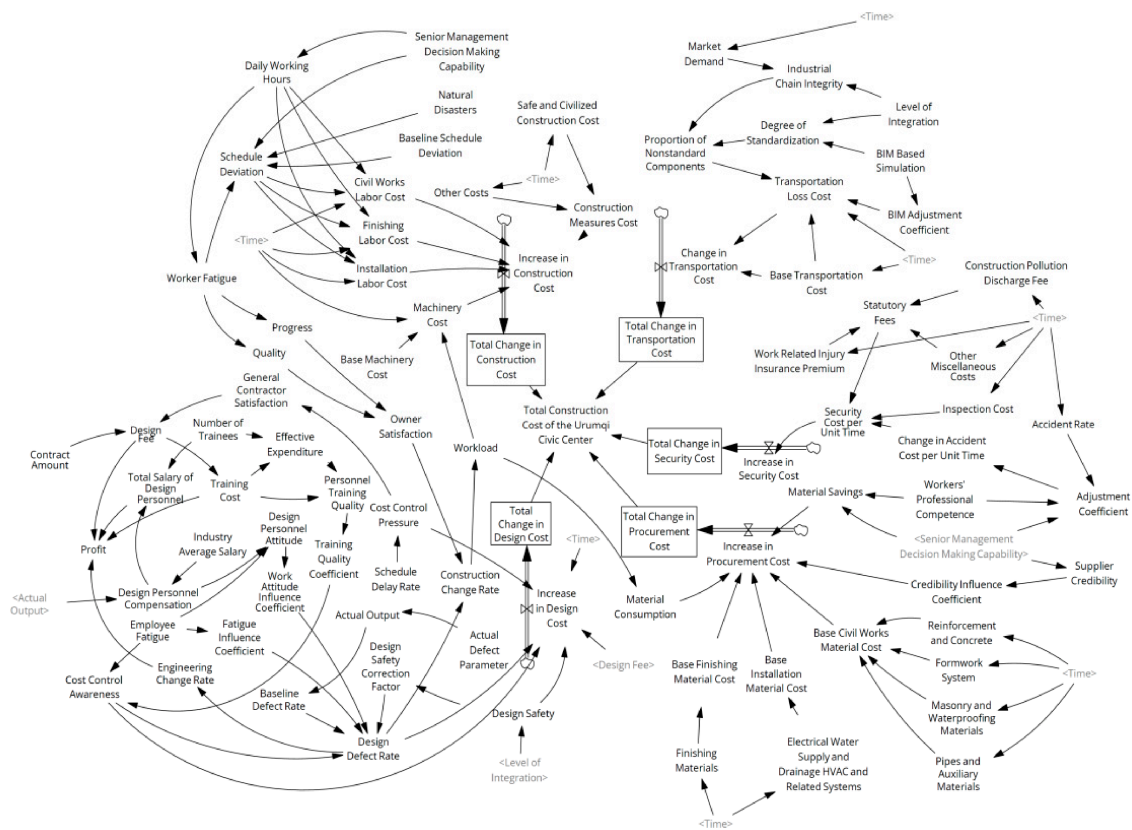


Figure 6. EPC cost control stock–flow model. Five stage-specific cost stocks sum to total project cost; arrows represent the signed model relationships documented in Supplementary Table S1.

3. Results

3.1. Model Validation

Validation used the audited terminal settled cost because a complete audited monthly actual cost series was not available. The baseline simulation produced CNY 199.4926 million at month 18, compared with the settled value of CNY 198.5159 million. The reported error is the terminal absolute percentage error, $APE = |C_{sim}(18) - C_{actual}(18)| / C_{actual}(18) \times 100\% = 0.492\%$. Structural checks confirmed that each of the five cost stocks has a defined inflow, that total cost is exactly the sum of the five stocks, that all scenario runs use the same initial conditions and fixed random seeds, and that the directional responses across 0.3, 0.5, 0.7, and 0.9 are consistent with the signed model relationships. Threshold robustness and fuzzy output local sensitivity are reported separately. These checks support within-case scenario comparison but do not constitute time-series, out-of-sample, or multi-project validation; the model should not be interpreted as a universally calibrated point predictor.

3.2. Effect of the Fuzzy-Derived Actual Complexity Coefficient on Cost Outcomes

A one-factor sensitivity test was conducted by varying the fuzzy-derived actual complexity coefficient from 54 to 58 while holding all other inputs at their baseline values. The corresponding actual output multiplier increased from 1.12 to 1.24, designer salary increased from CNY 8960 to CNY 9920, and total designer salary increased from CNY 1.0752 million to CNY 1.1904 million. As shown in Table 5, the baseline defect rate simultaneously increased from 0.112 to 0.124. Thus, movement across the full fuzzy output interval increased both total designer salary and the baseline defect rate by 10.71%. These results

demonstrate a direct and quantitatively traceable pathway from the intuitionistic fuzzy output to cost-relevant SDs variables; they should be interpreted as local, within-model sensitivity rather than external causal estimates.

Table 5. Local sensitivity of cost-relevant variables to the fuzzy-derived actual complexity coefficient.

Actual Complexity Coefficient	Actual Output Multiplier	Designer Salary (CNY)	Total Designer Salary (CNY)	Baseline Defect Rate
54	1.12	8960	1,075,200	0.112
55	1.15	9200	1,104,000	0.115
56	1.18	9440	1,132,800	0.118
57	1.21	9680	1,161,600	0.121
58	1.24	9920	1,190,400	0.124

3.3. Cost Analysis

3.3.1. Analysis of Total Variation in Design Cost

In the tested model, design cost variation is most responsive to the level of integration (Figure 7). Across the four simulated settings (0.3, 0.5, 0.7, and 0.9), the terminal design cost stock decreases monotonically; the difference between 0.3 and 0.9 is CNY 289,500. This is a within-model scenario difference, not an observed causal effect or realized saving.

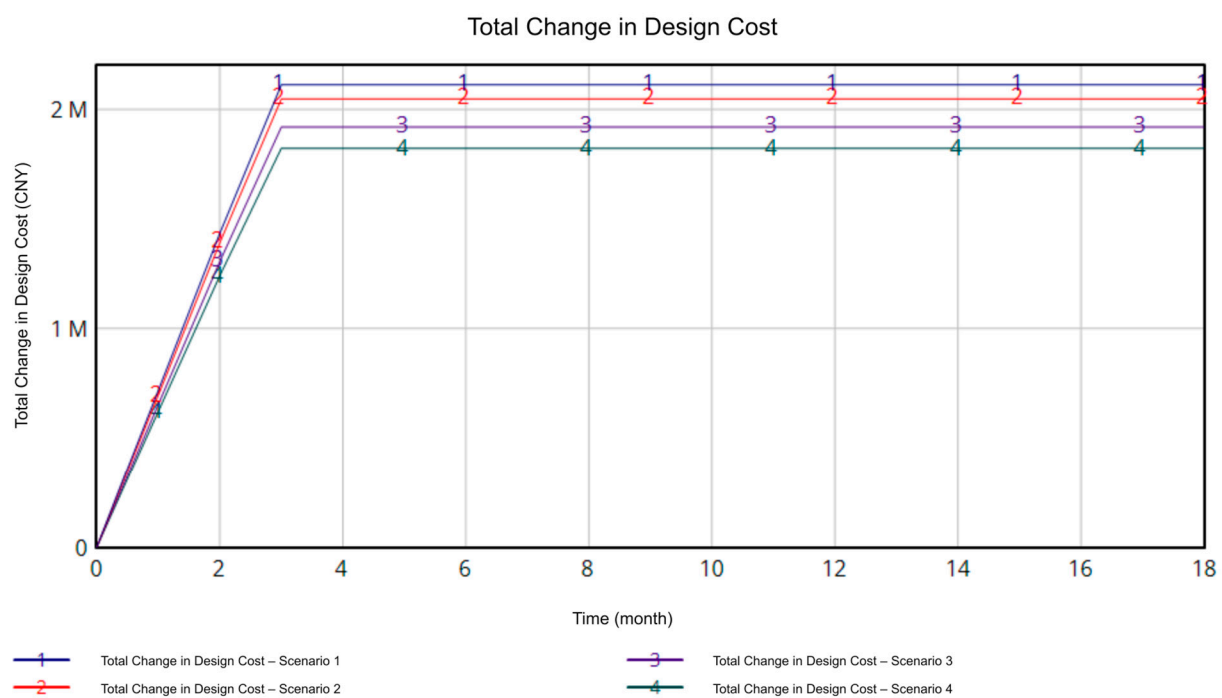


Figure 7. Simulated total change in design cost for level-of-integration settings 0.3, 0.5, 0.7, and 0.9 over months 0–18.

3.3.2. Analysis of Total Variation in Transportation Cost

In the tested model, transportation cost variation is also most responsive to the level of integration (Figure 8). The curves show activity concentrations near months 7 and 14, and the terminal difference between the 0.3 and 0.9 settings is CNY 451,400. This model-based result is consistent with earlier interface coordination and reduced transport mismatch, but it is not direct observational evidence of a realized saving.

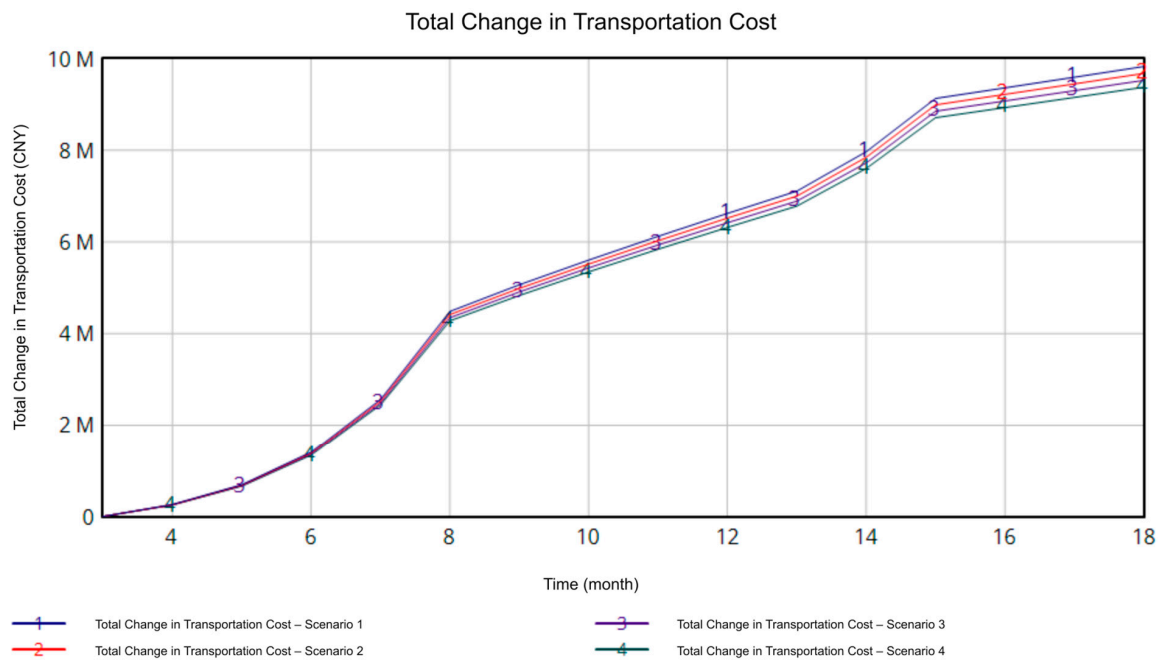


Figure 8. Simulated total change in transportation cost for level-of-integration settings 0.3, 0.5, 0.7, and 0.9 over months 0–18.

3.3.3. Analysis of Total Variation in Procurement and Security Costs

Procurement and security costs were examined using controlled scenario sweeps. One control index was held at 0.3 while the other was varied over 0.3, 0.5, 0.7, and 0.9, with the model's optimized scenario shown as a benchmark (Figures 9–12). This one-factor-at-a-time design identifies conditional curve patterns but does not estimate a statistical interaction coefficient.

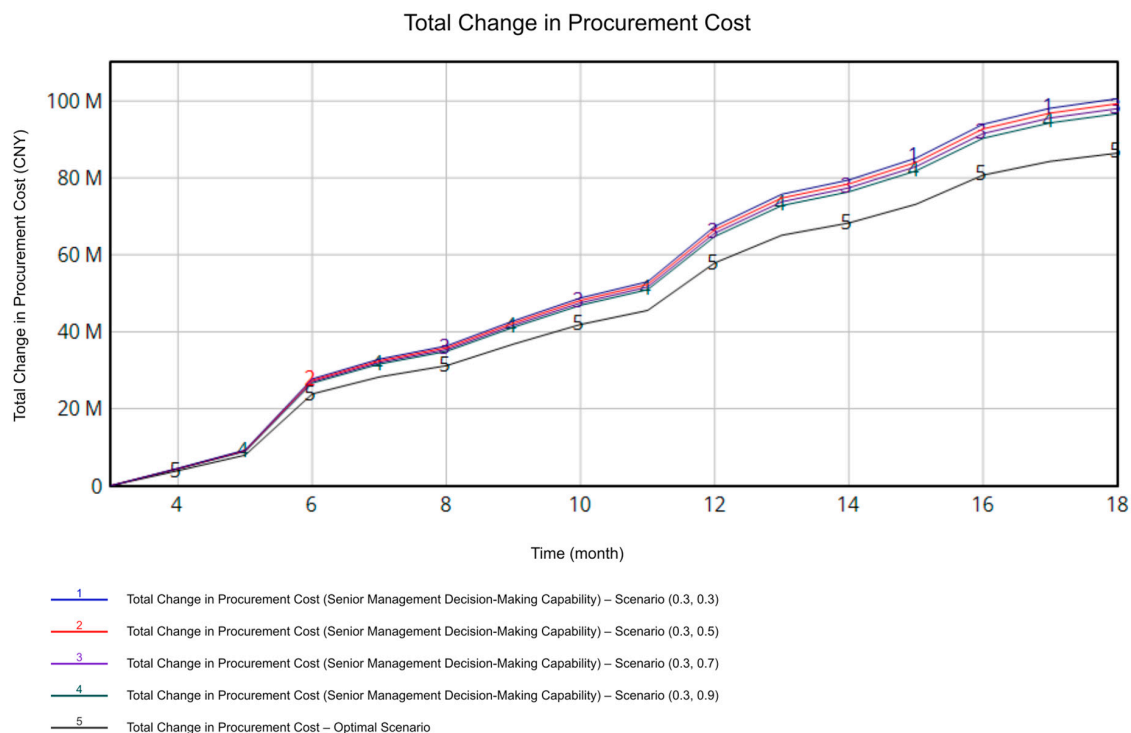


Figure 9. Simulated procurement cost trajectories when senior management decision-making capability is held at 0.3, and workers' professional competence varies from 0.3 to 0.9; the optimized scenario is shown as a benchmark.

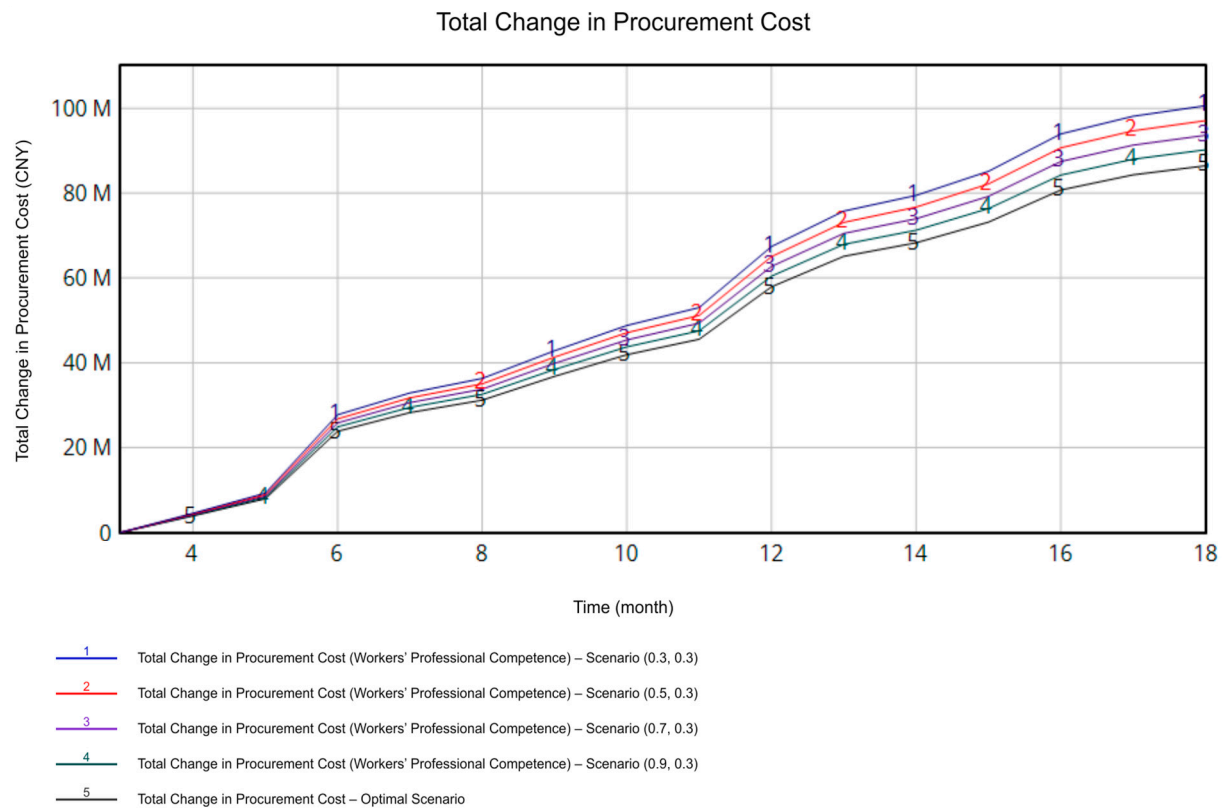


Figure 10. Simulated procurement cost trajectories when workers' professional competence is held at 0.3, and senior management decision-making capability varies from 0.3 to 0.9; the optimized scenario is shown as a benchmark.

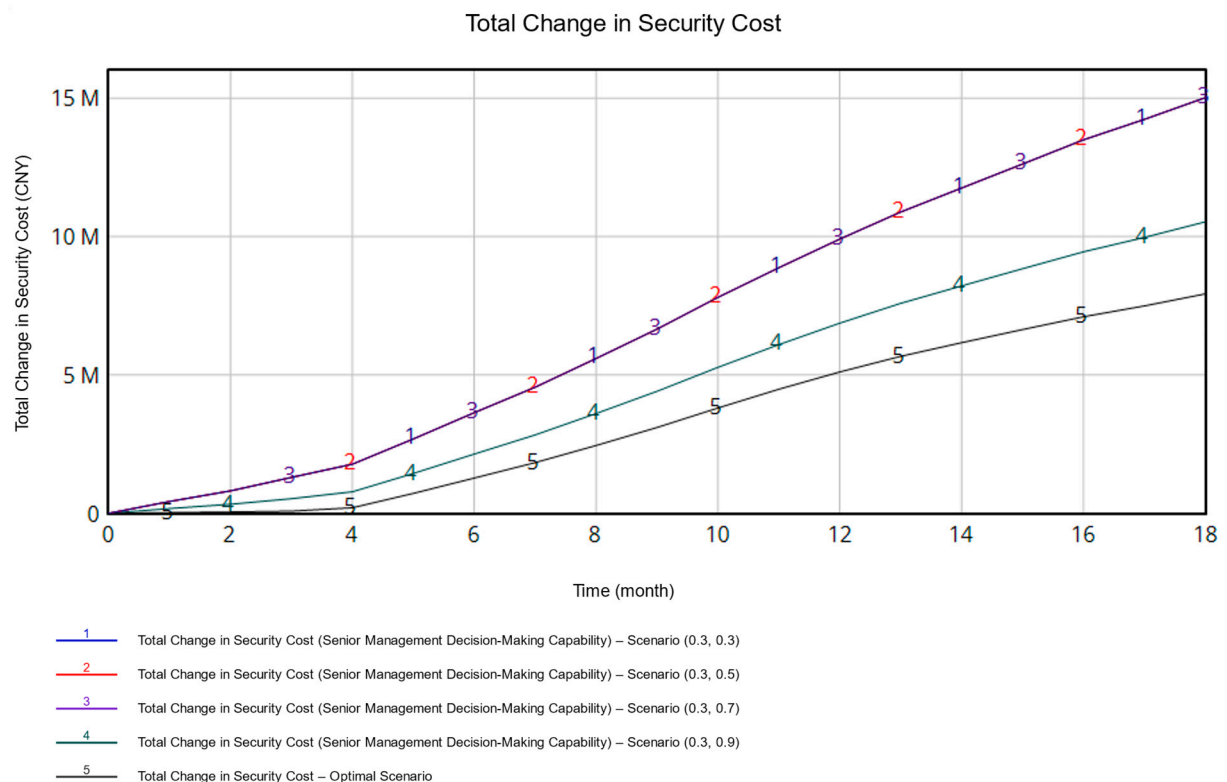


Figure 11. Simulated security cost trajectories when senior management decision-making capability is held at 0.3, and workers' professional competence varies from 0.3 to 0.9; the optimized scenario is shown as a benchmark.

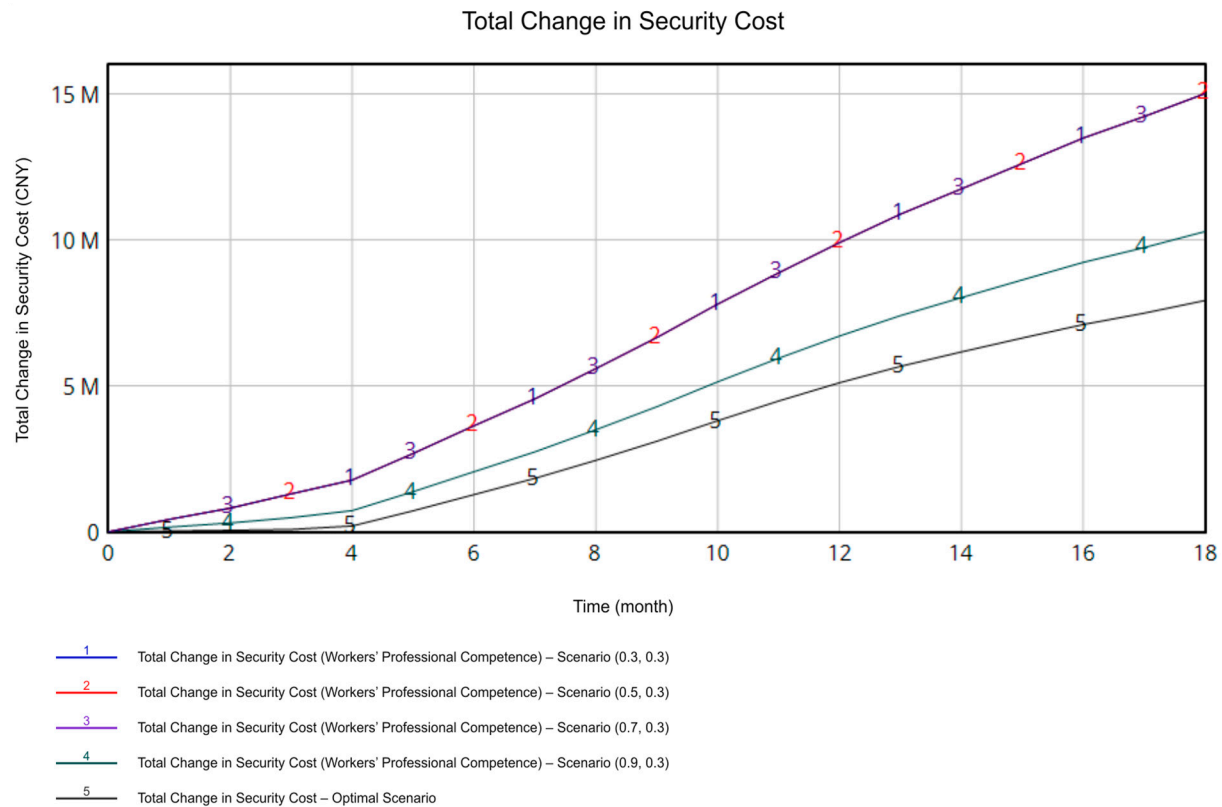


Figure 12. Simulated security cost trajectories when workers' professional competence is held at 0.3, and senior management decision-making capability varies from 0.3 to 0.9; the optimized scenario is shown as a benchmark.

Table 6 shows that, conditional on workers' professional competence, changing senior management decision-making capability produces a procurement cost endpoint range of CNY 10.3918 million; conditional on management capability, changing workers' competence produces a range of CNY 3.9016 million. Management capability therefore has the larger simulated procurement effect. For security cost, the two conditional sweeps show similar endpoint patterns and weak improvement when the other capability remains low. This is evidence of a complementary pattern within the tested equations, not proof of a statistically estimated interaction or a transferable causal effect.

Table 6. Endpoint differences among the simulated parameter scenarios.

Influencing Factors	Parameter Range	Difference (CNY 10,000)	Cost Category Affected	Direction of Influence	Comparative Influence
Workers' Professional Competence Senior Management Decision-Making Capability	0.3 0.3–0.9	1039.18	Procurement Cost	Senior Management Decision-Making Capability ↑ Procurement Cost ↓	Senior Management Decision-Making Capability > Workers' Professional Competence
Senior Management Decision-Making Capability Workers' Professional Competence	0.3 0.3–0.9	390.16	Procurement Cost	Workers' Professional Competence ↑ Procurement Cost ↓	Senior Management Decision-Making Capability > Workers' Professional Competence

Table 6. Cont.

Influencing Factors	Parameter Range	Difference (CNY 10,000)	Cost Category Affected	Direction of Influence	Comparative Influence
Workers' Professional Competence	0.3	472.57	Security Cost	Senior Management Decision-Making Capability ↑	Senior Management Decision-Making Capability ≈
Senior Management Decision-Making Capability	0.3–0.9			Security Cost ↓	Workers' Professional Competence
Senior Management Decision-Making Capability	0.3	448.47	Security Cost	Workers' Professional Competence ↑	Senior Management Decision-Making Capability ≈
Workers' Professional Competence	0.3–0.9			Security Cost ↓	Workers' Professional Competence

Note: ↑ indicates an increase, ↓ indicates a decrease, > indicates a larger comparative influence, and ≈ indicates approximately equal comparative influence.

3.3.4. Analysis of Total Variation in Construction Cost

Construction cost variation is most responsive to senior management decision-making capability in the tested scenarios (Figure 13). Raising the index from 0.3 to 0.9 changes the terminal construction cost stock by CNY 5.3875 million. The result indicates model leverage through resource allocation and change-control equations; it should be interpreted as a simulated scenario difference.

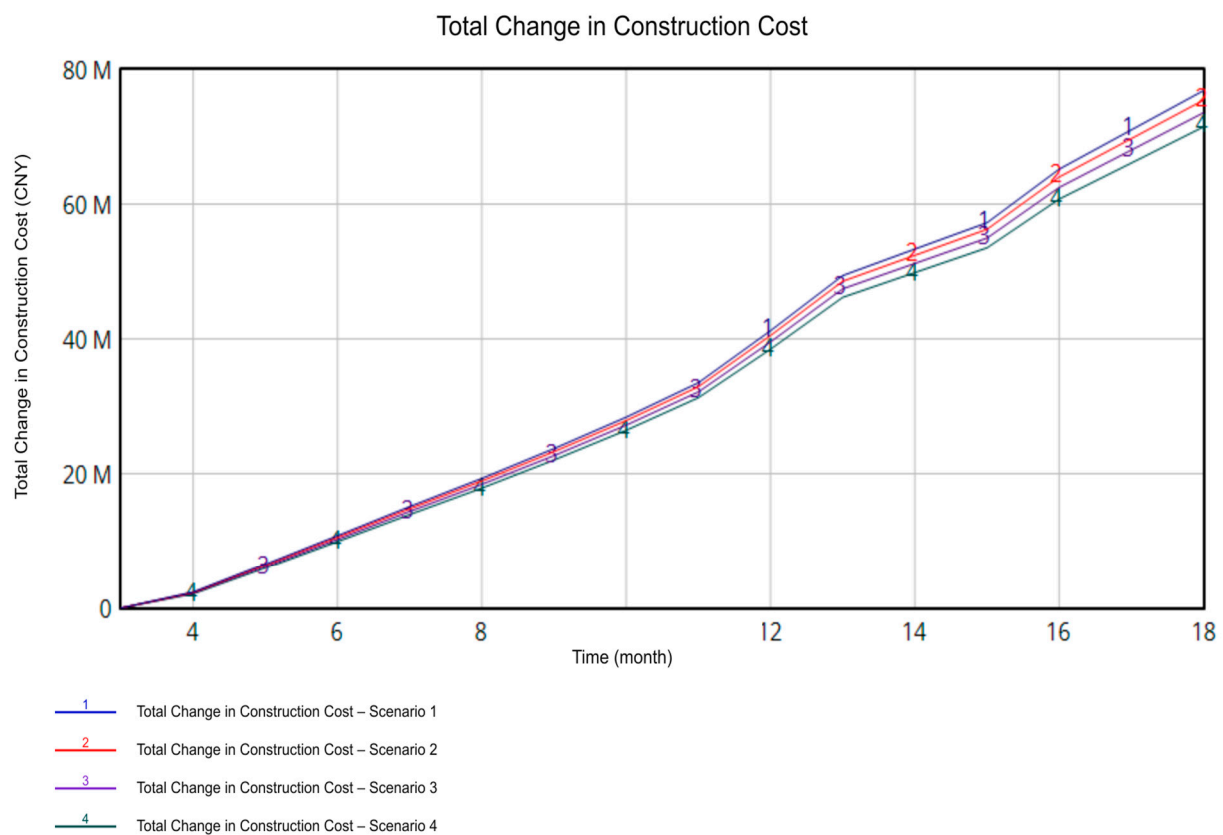


Figure 13. Simulated total change in construction cost for senior management decision-making capability settings 0.3, 0.5, 0.7, and 0.9 over months 0–18.

3.3.5. Trend in Total Cost Variation

The coordinated intervention scenario combines the tested settings for the deepest structural drivers and their modeled transmission paths. Its terminal total is CNY 186.3916 million, CNY 12.1243 million (6.1%) below the CNY 198.5159 million baseline shown in Figure 14. This quantity is a simulated counterfactual scenario difference and must not be interpreted as an actual saving realized by the completed project.

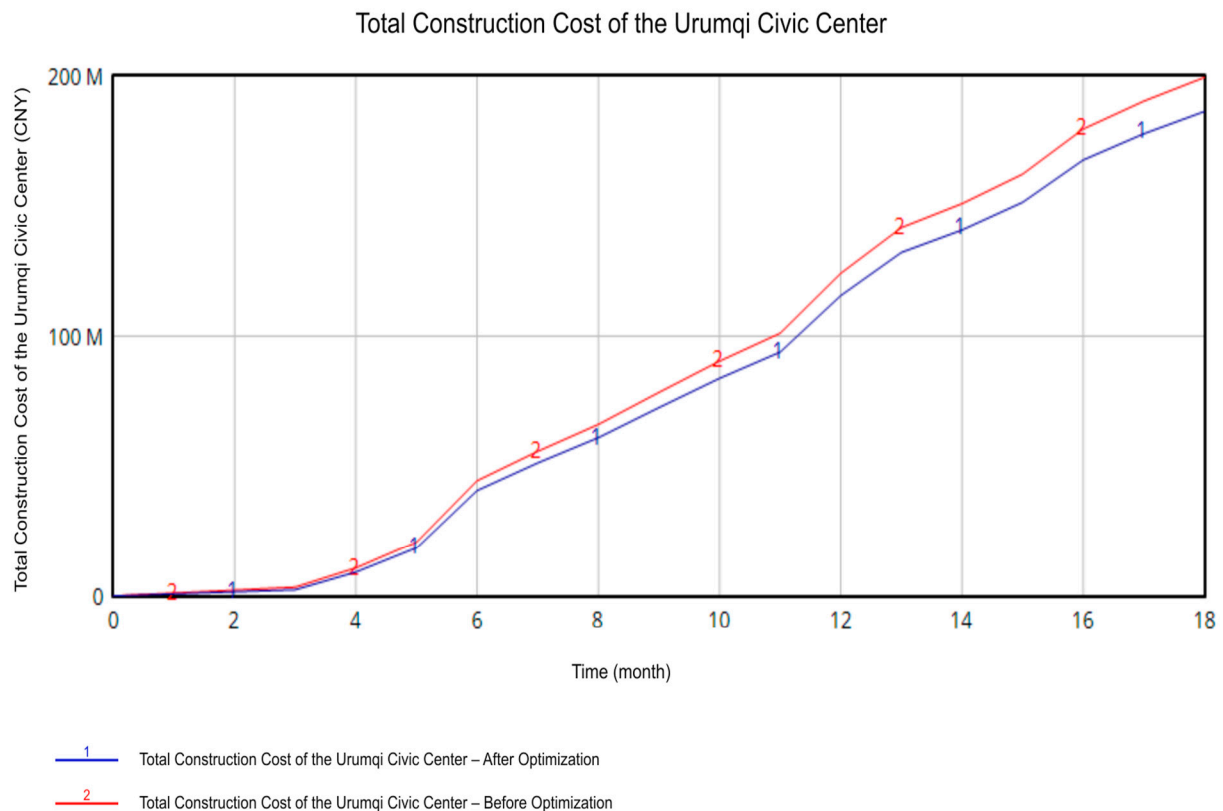


Figure 14. Simulated total project cost before and after the coordinated intervention scenario. The difference is a counterfactual model result rather than an observed project saving.

4. Discussion

The recalculated hierarchy distinguishes structural leverage from operational sensitivity. M1 (senior management decision-making capability) and M8 (level of integration) occupy L6 and L5, respectively, and therefore transmit influence through multiple intermediate factors. M2 (workers' professional competence) lies at L2 and acts closer to operational outcomes. This confirms the general SDs proposition that cost emerges from endogenous feedback [9–13] while refining it: deep causal position and large stage-specific sensitivity are related but not identical properties.

The integration result confirms BIM and coordination studies showing that shared information and interface management can reduce estimation error, change-order risk, and coordination loss [26]. It also extends the DEMATEL-SD cost work of Alsugair et al. [21] by locating integration within an ISM hierarchy and tracing it to separate design and transportation stocks. The mechanism is plausible because earlier interface resolution reduces design revisions and material mismatch, while coordinated logistics reduces duplicated or poorly timed deliveries. The present evidence remains a case-based simulation rather than a cross-project estimate of effect size.

Senior management decision-making capability produced larger procurement and construction endpoint differences than workers' competence. This pattern is consistent

with the role of approvals, supplier selection, contract coordination, resource allocation, and change control, which affect several cost flows simultaneously. By contrast, workers' competence is modeled nearer to execution and security outcomes. The result extends prior DEMATEL-SD schedule findings [22] from delay-control factors to differentiated EPC cost stocks, but it does not imply that workforce competence is generally unimportant.

Security cost curves display a weakest-link or complementary pattern. Improving one capability has limited effect when the other remains low. Management defines safety procedures, inspection intensity, and resources, whereas workers determine implementation quality. Because the analysis uses conditional one-factor sweeps, this pattern should be treated as a model mechanism requiring factorial or longitudinal confirmation. The TIFR contribution is demonstrated directly by traceability: varying the actual complexity coefficient from 54 to 58 changes the multiplier, salary, and baseline defect rate by 10.71%. Relative to Zhang and Han [20], this study adds prior causal-hierarchy identification and five EPC-stage cost stocks. Relative to fuzzy final cost forecasting [27], it adds explicit time-dependent feedback but sacrifices broad statistical calibration.

5. Conclusions

The corrected analysis shows that senior management decision-making capability and the level of integration are the two deepest structural drivers in this case. Scenario sweeps associate integration most strongly with design and transportation stocks and management capability with procurement and construction stocks. Security cost curves show a conditional complementary pattern with workers' competence. The coordinated scenario changes the simulated terminal trajectory by 6.1% relative to baseline; it does not demonstrate an actual realized saving.

Scientifically, the contribution is an interpretable linkage among a verified causal hierarchy, hesitation-aware expert rules, and stage-specific dynamic cost accumulation. Methodologically, the revision supplies the corrected normalization, unrounded-matrix verification, threshold robustness, complete ISM sets, the 15-rule base, and all Vensim equations and settings. The work does not claim that DEMATEL, ISM, TIFR, or SDs are individually novel.

Practically, the model can help EPC owners and contractors compare internally consistent intervention packages: early cross-stage integration, explicit approval protocols for procurement and construction changes, and joint assessment of managerial and workforce capabilities in security management. Its appropriate use is prioritization and scenario learning within a calibrated project context, not universal point prediction.

Limitations are substantial. Validation uses one public-building project and one audited terminal cost rather than a monthly actual cost series; respondent-level direct influence raw scores were not available for a retrospective reliability statistic; fuzzy sets and rules depend on a seven-expert Delphi panel; external price, policy, and macroeconomic shocks are simplified; and the conditional sweeps do not estimate statistical interactions. Future work should conduct preregistered multi-database literature screening, retain respondent-level DEMATEL judgments, validate monthly trajectories across EPC project types and regions, compare against fuzzy forecasting and machine learning baselines, estimate factorial interactions, and calibrate fuzzy parameters from larger historical datasets.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/buildings16173405/s1>, Supplementary Materials S1: Complete Vensim equations and parameters, local sensitivity results, the complete 15-rule TIFR base, DEMATEL–ISM verification and threshold robustness, and validation/reproducibility checks (Tables S1–S5); Supplementary Data S1: Factor mapping; direct, normalized, total-influence, adjacency, Boolean reachability, and hierarchy matrices; threshold-sensitivity calculations; and all 15 TIFR rules.

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