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REVISITING COST FORECASTING METHODS IN CONSTRUCTION PROJECTS

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Abstract: Accurate cost forecasting is fundamental to construction project management, yet the basis for selecting appropriate forecasting methods across different project conditions remains insufficiently articulated in the literature. This paper presents a structured conceptual review classifying construction cost forecasting methods into five groups: deterministic and rule-based, probabilistic and uncertainty-based, process- and physics-based, data-driven and machine-learning, and hybrid and integrative. A comparative SWOT analysis examines the analytical strengths, weaknesses, opportunities, and threats associated with each method group. A contingency-based method-selection framework is then developed, supported by six testable propositions linking project context, method choice, and expected forecast performance. The central argument is that method selection should be governed by methodological fit with the project context, including in off-site, modular, and industrialised construction, where cost behaviour reflects logistics, and supply-chain dynamics alongside site-based variability.

Keywords: Construction projects; Cost forecasting; SWOT; Method selection; Contingency framework

1. INTRODUCTION

Cost forecasting provides the basis for planning, contingency allocation, and cost control in construction projects (González et al. 2022). Forecast reliability, however, is regularly constrained by incomplete project information, evolving design assumptions, market volatility, supply-chain disruption, and behavioural bias in the estimation process. These conditions indicate that the primary challenge is not simply to improve predictive accuracy, but to ensure that the forecasting methods employed are analytically consistent with the conditions and decision context in which the estimate is prepared (Howell et al. 2010). Research in construction cost forecasting has produced a substantial body of knowledge on the development, application, and comparative performance of different forecasting methods. Conceptual and systematic reviews have helped to organise this literature and clarify the methodological basis of different cost-forecasting approaches, particularly at early project stages where information is limited (Castro Miranda et al. 2022). However, the literature is considerably less explicit about how project context should govern method selection. A method that is appropriate under stable scope and reliable baseline data may be unsuitable where uncertainty is high, information is limited, or project delivery conditions materially affect cost behaviour.

This limitation is significant because construction projects vary in scope definition, data availability, procurement arrangements, and exposure to cost uncertainty. Where these conditions differ, the same forecasting method may produce different levels of reliability because its assumptions may correspond well with one project context but poorly with another. Off-site and modular construction illustrate this point because logistics coordination and early cost commitments may influence cost estimation alongside conventional site-based factors (Choi et al. 2022). This variation supports the need for a contingency-based method-selection framework that explains why particular forecasting methods are more appropriate under particular project conditions.

This paper addresses this limitation by developing a contingency-based account of construction cost forecasting method selection. Rather than treating forecasting methods as competing alternatives, it examines how their suitability depends on project conditions, methodological assumptions, and the intended use of the estimate. The study has three objectives: (i) to classify major construction cost forecasting methods according to their methodological basis; (ii) to evaluate their comparative strengths and limitations through SWOT analysis; and (iii) to develop a contingency-based framework and associated propositions for future empirical assessment across construction project contexts.

2. THEORETICAL FOUNDATION

Contingency theory provides the theoretical basis for explaining why a single managerial approach cannot be assumed to fit all conditions. Its central claim is that managerial decisions are contingent on internal and external circumstances, rather than being governed by one universally applicable method (Garavan and O'Brien 2024). In project management research, this position has been used to challenge one-size-fits-all approaches by emphasising that projects should be examined in relation to their context, since project effectiveness depends partly on the congruence between managerial arrangements and external conditions (Hanisch and Wald 2012). Within construction management, contingency thinking has also been linked to the concept of fit, where performance is understood as a consequence of the correspondence between organisational arrangements and relevant contingencies such as technology, strategy, people, culture, and environment (Deng and Smyth 2013).

In this paper, contingency theory provides the theoretical basis for linking method selection to the conditions under which a cost estimate is prepared. For construction cost forecasting, the key concern is not whether a method is technically advanced, but whether its assumptions correspond with the project information available, the nature of cost uncertainty, and the estimate's decision purpose. This distinction is important because forecasting methods require different types of project information and support different cost-estimation decisions. Methodological fit is therefore used to describe the suitability of a forecasting method to the cost-estimation problem for which it is applied. The typology and framework developed in the following sections build on this position by assessing forecasting methods according to their appropriate conditions of use.

3. METHODOLOGY

This paper adopts a structured conceptual review approach to organise and synthesise existing knowledge on construction cost forecasting methods (Jaakkola 2020). This approach is appropriate because the study develops a typology, a SWOT-based synthesis, and a contingency-based framework rather than testing a single forecasting model. The review, therefore, focuses on identifying studies that contribute directly to method classification, comparative assessment, and context-based method selection. The literature search was conducted in Scopus using a strategy designed to capture construction cost forecasting studies as well as papers concerned with method classification, review, and framework development. The following search string was applied to titles, abstracts, and keywords:

> *("construction cost estimation" OR "construction cost prediction" OR "construction cost forecasting" OR "construction cost modelling" OR "construction cost modeling" OR "early cost estimation" OR "preliminary cost estimation" OR "conceptual cost estimation" OR "estimate at completion") AND (review OR "literature review" OR "systematic review" OR "state of the art" OR survey OR framework OR classification OR taxonomy OR typology OR method OR technique OR approach*)*

The initial Scopus search returned 483 records. After applying filters for year of publication, document type, language, and subject coverage, 401 records were retained for screening. Title and abstract screening removed studies outside the study scope, including non-construction papers, papers without methodological relevance, and studies with no clear contribution to method classification, comparison, or selection. Full-paper screening then retained studies that directly supported the proposed typology, SWOT synthesis, contingency-based framework, or conceptual propositions. This process produced 21 papers from the Scopus search. These were supplemented by 16 targeted supporting references where additional theoretical, methodological, or contextual support was required. In total, 37 references informed the typology, SWOT analysis, contingency-based framework, and propositions.

The retained literature was analysed in four stages. First, construction cost forecasting methods were classified according to their dominant analytical basis. Second, SWOT analysis was used to examine the strengths, weaknesses, opportunities, and threats associated with each method group (Helms and Nixon 2010; Coman and Ronen 2009). Third, the SWOT synthesis informed a contingency-based framework linking project conditions to suitable forecasting methods. Finally, the framework was used to formulate six propositions, each linking a defined project condition to the forecasting method expected to perform more reliably under that condition.

4. FINDINGS AND DISCUSSION

4.1 Typology

The reviewed literature identifies five method groups in construction cost forecasting. The five method groups are distinguished by the basis on which each method derives and substantiates a cost estimate. Deterministic and rule-based methods draw on predefined cost assumptions, benchmark values, and earned-value measures, giving them a clear role in transparent and auditable forecasting (Barrientos-Orellana et al. 2022; González et al. 2022). Probabilistic and uncertainty-based methods extend the forecast by incorporating cost variability, incomplete information, and outside-view adjustment into the estimation process (Desse and Mengesha 2024; Baerenbold 2023). Process- and physics-based methods locate cost development within project processes, work sequencing, and lifecycle cost formation, rather than depending mainly on prior project records (Liu and Luo 2025; Du et al. 2016). Data-driven and machine-learning methods use structured historical data to estimate non-linear cost associations, although reliability depends on data quality, comparability, and sufficient sample size (Chakraborty et al. 2020; Liu and Lin 2024). Hybrid and integrative methods draw on more than one forecasting method where the estimation problem cannot be adequately addressed by a single method (Abu-Mahfouz et al. 2025; Zhang et al. 2025). This classification is consistent with prior review studies (Castro Miranda et al. 2022; Tayefeh Hashemi et al. 2020; Karadimos and Anthopoulos 2024). However, its purpose here is not only to organise existing methods, but also to establish a basis for assessing their suitability under different project conditions.

4.2 SWOT Analysis

Table 1 presents a comparative SWOT analysis of the five method categories. Strengths and weaknesses refer to the internal analytical characteristics of each method group, while opportunities and threats capture external conditions that may enhance or constrain their use in construction cost forecasting.

Table 1: SWOT analysis of construction cost forecasting methods

Method group	Strengths	Weaknesses	Opportunities	Threats
Deterministic and rule-based	Transparent, auditable, and contractually defensible; produces clear cost-to-complete estimates directly from performance data with established legitimacy in governance and client reporting (Barrientos-Orellana et al. 2022; Narbaev and De Marco 2014a; Swei et al. 2017).	Assumes cost performance stationarity; single-point outputs understate variation under scope change, market disruption, or data sparsity, with limited capacity to represent genuine uncertainty (Kim and Pinto 2019).	Growing adoption of risk-adjusted EAC protocols and structured cost benchmarking in public procurement extends this category's auditability advantage into a wider range of project environments (Narbaev and De Marco 2014a; 2014b).	Increasing project complexity, scope ambiguity, and supply-chain exposure make stable-performance assumptions progressively untenable in a widening proportion of live construction projects.
Probabilistic and uncertainty-based	Explicitly represents uncertainty through distributions, reference classes, fuzzy sets, grey reasoning, and scenario analysis; uniquely supports risk-adjusted contingency allocation and outside-view bias correction (Caron et al. 2013; Baerenbold 2023; Desse and Mengesha 2024).	Depends on calibrated priors, comparable reference data, or expert judgement; poorly specified inputs can produce outputs that appear rigorous but underperform simpler benchmarks.	Progressive development of structured reference-class databases and benchmarking registries for off-site construction is reducing the data constraints that limit practical application of outside-view methods (Mostafa and Hegazy 2019; Dastgheib et al. 2022).	In off-site and novel project types, the absence of established reference-class databases weakens this category's anti-bias capability precisely where optimism bias tends to be most prevalent and consequential.
Process- and physics-based	Captures production mechanisms, feedback dynamics, workflow interactions, and lifecycle processes that statistical methods cannot represent; suited to projects where cost is generated by identifiable production structures rather than historical averages (Liu and Luo 2025; Du et al. 2016).	Requires detailed process information, specialist modelling capability, and significant calibration effort; difficult to apply where design or production information remains limited at the estimation stage.	Growing adoption of digital twins, factory monitoring systems, and logistics tracking in off-site construction directly supplies the parameterisation data that process models require, reducing their primary calibration constraint (Su et al. 2023; Liu and Luo 2025).	Process model accuracy depends on the quality and completeness of project-specific production data; where programmes prioritise delivery speed over data governance, parameterisation requirements may not be met.
Data-driven and machine-learning	Detects complex non-linear cost patterns from large, structured datasets that parametric regression misses by design; ensemble methods and interpretable machine learning are	Performance depends on data volume, quality, and structural comparability; models calibrated in one construction market or project typology may exhibit	Advances in explainable AI and SHAP-based interpretability progressively address the transparency barrier limiting practitioner adoption in audit and contractual forecasting settings	Published accuracy metrics often reflect within-sample optimisation rather than out-of-sample robustness; deployed models that underperform published

	improving transparency and auditability in client-facing cost estimation (Chakraborty et al. 2020; Das et al. 2024; Liu and Lin 2024).	substantial error when applied in structurally different contexts (Zhang et al. 2025).	(Das et al. 2024; Zhang et al. 2025).	benchmarks create credibility and contractual risks that may slow broader adoption.
Hybrid and integrative	Integrates complementary analytical capabilities, encompassing uncertainty representation, pattern recognition, process modelling, and transparency, within a single architecture; suited to multi-condition projects where no single method group is analytically sufficient (Abu-Mahfouz et al. 2025; Zhang et al. 2025; Singh et al. 2025).	Without principled rationale for combining specific methods, hybrid models risk compounding individual error profiles; increased complexity raises the validation burden without guaranteed accuracy gains over well-applied single-method alternatives.	Convergence of gradient-boosting with Bayesian optimisation and Monte Carlo simulation with neural networks enables principled hybrid architectures at lower development cost, extending this category's accessibility beyond specialist research groups (Zhang et al. 2025; Akhbari 2018).	Standardised validation criteria for hybrid construction cost models do not yet exist; apparent superiority over single-method alternatives may reflect dataset-specific optimisation rather than generalised analytical performance (Abu-Mahfouz et al. 2025).

4.3 Contingency-based Framework

Table 2 presents the contingency-based framework for selecting construction cost forecasting methods. For each project context, the framework identifies the method group with the strongest analytical fit and explains the risk of applying a method whose assumptions do not correspond with the forecasting conditions. The framework applies across construction project settings, including off-site construction, where logistics coordination, procurement arrangements, and early cost commitments may affect the reliability of cost estimates.

Table 2: Cost forecasting method selection framework

Project context	Method of best fit	Mechanism and risk of misfit
Stable scope, reliable baseline data, and predictable cost-performance trajectory	Deterministic and rule-based (EVM-based EAC, parametric regression, analogous estimating)	Stable trajectories provide the conditions under which index-based and parametric methods converge reliably; cost and schedule relationships hold over the project lifecycle, and observable performance data directly inform the estimate (Barrientos-Orellana et al. 2022; Narbaev and De Marco 2014a; Swei et al. 2017). Probabilistic methods substituted in stable contexts add distributional specification complexity without commensurate accuracy gain, producing outputs that are harder to audit and defend contractually.
Projects with measurable uncertainty, incomplete information, or weak baseline data	Probabilistic and uncertainty-based (Monte Carlo simulation, Bayesian updating, fuzzy logic, grey models, scenario analysis)	These contexts require representing cost as a range of possible outcomes rather than a point estimate; Bayesian, fuzzy, grey, and simulation-based approaches accommodate incomplete data and distributional uncertainty through principled inference rather than demanding complete historical records (Caron et al. 2013; Al Kailani et al. 2024; Desse and Mengesha 2024; Dastgheib et al. 2022). Applying deterministic methods prematurely forces a single value onto genuinely uncertain conditions, systematically understating contingency requirements and misinforming procurement and investment decisions.
Projects exposed to optimism bias, strategic misrepresentation, or overreliance on internal estimates	Reference-class forecasting and outside-view probabilistic approaches	The forecasting problem here is behavioural rather than informational; cost estimates are distorted at the input stage, a failure that model-level refinement cannot correct. Reference-class forecasting anchors estimates in the empirical distribution of comparable completed projects, providing an outside-view correction that operates independently of project-team assumptions (Baerenbold 2023; Cantarelli et al. 2025; Zani et al. 2024). Deterministic or machine-learning methods applied without outside-view adjustment produce technically coherent estimates that inherit and preserve the original input bias, irrespective of model sophistication.

Projects where cost is substantially driven by production systems, workflow interactions, technical constraints, or lifecycle processes	Process- and physics-based (system dynamics, stochastic process models, discrete-event simulation, lifecycle cost modelling)	The forecasting problem is causal rather than statistical; system dynamics, stochastic process formulations, and discrete-event simulations represent the feedback structures, production rates, and interface interactions that generate cost, in ways that index-based or regression methods cannot replicate (Liu and Luo 2025; Du et al. 2016). EVM-based or regression methods applied to process-driven projects anchor forecasts in historical norms bearing no necessary causal relationship to the mechanisms at work; forecast deviation increases as the project diverges from the historical dataset.
Repeated project types with large, structured, and comparable historical datasets	Data-driven and machine-learning (ensemble models, gradient boosting, neural networks, interpretable ML)	Large, structured datasets create the conditions under which machine-learning models recover complex non-linear cost relationships that parametric regression misses by design; ensemble methods and interpretable approaches improve predictive accuracy while progressively addressing the auditability requirements of contractual and governance settings (Chakraborty et al. 2020; Das et al. 2024; Liu and Lin 2024). Machine-learning models applied to sparse, heterogeneous, or structurally dissimilar data fit distributional artefacts rather than transferable cost relationships, producing lower out-of-sample accuracy than simple parametric baselines (Zhang et al. 2025).
Projects with multi-dimensional forecasting challenges, particularly off-site, modular, and industrialised construction where uncertainty spans manufacturing, logistics, and supply-chain coordination simultaneously	Hybrid and integrative methods (neuro-fuzzy, Bayesian-ML integration, Monte Carlo-ANN, ensemble stacking, process-informed hybrids)	Multi-dimensional contexts require more than one analytical capability simultaneously; hybrid methods are especially suited to off-site projects where primary uncertainty migrates from site-based variability to factory production dynamics, logistics performance, and supply-chain integration that no single-method approach adequately addresses (Abu-Mahfouz et al. 2025; Zhang et al. 2025; Liu and Luo 2025; Govindan Aswin et al. 2024). Site-calibrated single-method approaches applied to off-site projects misattribute cost risk, underweight logistics and manufacturing interactions, and produce systematically biased forecasts regardless of the technical refinement applied to the model.

4.4 Conceptual Propositions

The contingency-based framework generates six propositions for future empirical assessment. Each proposition links a defined project condition to the forecasting method expected to provide greater reliability under that condition. Collectively, the propositions provide a clear basis for testing the framework across different construction project settings.

Proposition 1: Where project scope is stable and baseline data are reliable, deterministic and rule-based methods are expected to produce lower forecast deviation than probabilistic methods applied to the same project conditions.

Proposition 2: Where project information is incomplete and cost uncertainty is high, probabilistic and uncertainty-based methods are expected to produce more reliable forecasts than deterministic single-point methods.

Proposition 3: In projects exposed to optimism bias, strategic misrepresentation, or overreliance on internal estimates, reference-class forecasting is expected to reduce forecast deviation more effectively than methods that rely exclusively on project-internal assumptions and data.

Proposition 4: Where cost behaviour is shaped by project processes, work sequencing, or lifecycle cost formation, process- and physics-based methods are expected to produce lower forecast deviation than methods based mainly on historical completed-projects data.

Proposition 5: Where comparable historical project data are sufficiently available, data-driven and machine-learning methods are expected to produce lower final-cost forecast error than simple parametric methods.

Proposition 6: Where the forecasting task involves multiple sources of uncertainty, limited information, and complex project conditions, hybrid and integrative methods are expected to produce lower forecast deviation than single-method approaches.

4.5 Discussion

The typology, SWOT synthesis, contingency-based framework, and propositions collectively show that the choice of cost forecasting method should be judged by methodological fit rather than by the perceived advancement of the technique. The findings indicate that each method group has a different role in supporting cost estimation: some provide transparency, some address uncertainty and bias, some examine how cost develops through project processes, some depend on comparable historical data, and others integrate more than one forecasting method where the forecasting problem is not adequately served by a single method. This interpretation is important because forecast deviation may arise not only from weak data or model error, but also from applying a method under conditions that do not support its assumptions. The framework therefore provides a basis for selecting forecasting methods according to project conditions, while the propositions translate this selection logic into testable claims for future empirical assessment across construction project settings.

5. CONCLUSION

This study has argued that the principal challenge in construction cost forecasting is not the abundance of available methods but the absence of a principled basis for selecting among them. Through a structured conceptual review of 37 studies, the paper classifies major forecasting approaches into five method groups, evaluates their comparative properties through a structured SWOT analysis, and presents a contingency-based method-selection framework linking project conditions to the most analytically appropriate forecasting method. The framework demonstrates that no approach is universally superior; the appropriateness of any method depends on the project context, the nature and degree of uncertainty, data adequacy, transparency requirements, and the decision purpose the estimate is intended to serve. The six propositions advance this contribution by translating the contingency argument into falsifiable predictions that can be tested empirically across different project types, delivery structures, and information environments.

The study makes two principal contributions to the existing literature. The first is a typology-based SWOT synthesis that moves beyond descriptive classification to provide an analytically grounded comparative assessment of each method group's strengths, limitations, and contextual relevance. The second is a prescriptive, context-sensitive selection framework that specifies not only what methods exist, but when and why each is the more appropriate analytical choice. This is of particular relevance to off-site, modular, and industrialised construction, where the systematic application of site-calibrated forecasting methods represents a structurally addressable source of forecast bias. For practitioners, the framework offers a transparent and evidence-based foundation for method selection grounded in project conditions rather than methodological convention alone.

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