A BRIEF REVIEW OF ARTIFICIAL INTELLIGENCE TECHNIQUES FOR CONCEPTUAL COST ESTIMATION IN CONSTRUCTION PROJECTS

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Conceptual cost estimates, evaluated during a construction project's initiation phase, are fundamental for determining whether to invest in the project, validating its budget, or screening alternatives. Compared to traditional estimation techniques, artificial intelligence (AI) methods proved effective in assessing the nonlinear relationship between project variables and actual cost at completion. Due to the number and variability of available studies, it is not clear which AI techniques are most effective. This study systematically reviews previous works employing AI for conceptual cost estimation, focusing on the techniques adopted and the scorers utilised. The results show a rising trend in AI adoption, including supervised machine learning, knowledge-based, and evolutionary techniques. Performance-wise, the results hint at gradient boosting, random forest, and neural networks proving superior to both genetic algorithms and case-based reasoning techniques, which in turn prove superior to linear models. This review provides a brief overview of possible AI techniques and performance scorers to utilise for conceptual cost estimation in construction projects.

Keywords: Artificial Intelligence; conceptual cost estimate; project management; systematic literature review

INTRODUCTION

The construction industry plays a pivotal role in the global economy. Financially, spending forecasts for 2030 reach $14.4 trillion, representing 14% of global GDP ("Construction Market Report and Strategies To 2032"). Despite this, 28% of construction projects experience cost overruns (Atapattu *et al.,* 2023). These overruns stem from inherent factors, including the competitiveness and fragmentation of the industry project, and external factors, including the pandemic, recent conflicts, and rapid technological changes (Ribeirinho *et al.,* 2020).

Conceptual cost estimates are crucial to project performance. Evaluated during the initiation phase, these estimates provide a quick means of assessing project costs without detailed analysis. Correct estimates help in deciding whether to proceed with

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Ottaviani, F M, De Marco, M, Audisio, A, Wong, J and Belack, C (2024) A Brief Review of Artificial Intelligence Techniques for Conceptual Cost Estimation in Construction Projects *In:* Thomson, C and Neilson, C J (Eds) *Proceedings of the 40th Annual ARCOM Conference,* 2-4 September 2024, London, UK, Association of Researchers in Construction Management, 615-624.

the project, validating its budget, and evaluating possible alternatives (Akintoye and Fitzgerald 2000; El-Sawalhi and Shehatto 2014).

Among standard estimation techniques, parametric modelling is both the most accurate and the most complex. On the one hand, it allows for incorporating multiple variables and relies on empirical evidence inferred from historical data. On the other hand, it also requires selecting a predetermined model and evaluating its parameters, whereas the relationship between project variables and its cost may be heavily nonlinear. This issue is more pronounced in the presence of indirect cost factors - such as complexity, scope definition, site constraints, and bidding characteristics (if any) -affecting the project cost.

According to Costello (2019), artificial intelligence (AI) will automate 80% of project management tasks by 2030. AI is expected to be particularly valuable for cost estimation due to its pattern recognition capabilities. Unlike standard methods, AI can quantify nonlinear relationships between project variables and their cost at completion, including both direct and indirect factors.

Despite the growing number of AI studies, it is still unclear which techniques are best suited to the purpose of conceptual cost estimation in construction projects. Not only is it difficult to correctly assess the performance of an AI technique, but it is also unclear which one is best suited to the specific case, given the project variables at hand.

This objective of this study is to review earlier research on AI techniques for conceptual cost estimation in construction projects. The study aims to collect earlier works, identify techniques used, and compare their perceived performance. The review follows a structured approach based on the PRISMA 2020 framework (Page *et al.,* 2021), adapted to fit the study scope.

The paper is structured as follows. This section outlined the research context, gap, and objectives. The following section explains the steps of the PRISMA 2020 framework. The results section reports the studies analysed, which are then discussed in the next section. Lastly, the Conclusions section summarises the study's key points and limitations, providing directions for future research.

METHOD

The PRISMA 2020 framework consists of three main steps: identification, screening, and inclusion. All authors took part in each step.

For identification, the authors searched the Scopus database on March 18, 2024, using the following query: ("artificial intelligence" OR "machine learning") AND "construction" AND "cost estimate" AND ("conceptual" OR "pre-tender" OR "feasibility"). Subsequently, the retrieved studies underwent screening based on the following eligibility criteria: publication in a peer-reviewed journal or conference proceedings, use of standard English, focus on conceptual cost estimates, and a minimum citation count of ten.

After retrieving the studies, the authors conducted a preliminary screening based on the titles and abstracts. This screening assessed whether the studies met the following criteria: authors applied at least one AI technique to a sample of real or fictitious construction projects, authors provided quantified results using a performance scorer, and studies included a clear description of datasets, methodologies, specific algorithms and procedures, and the rationale for selecting the input and output features. The purpose of this screening was to ensure that the selected studies were methodologically rigorous, relevant to AI-based cost estimation, and provided sufficiently detailed information for further analysis.

This review acknowledges the potential for multiple biases. Information bias may arise from research studies with inaccurate measurements or inaccessible input datasets. Systematic differences between the ground truth and the information recorded during a study might lead to observer bias, which may influence the current review, and the studies analysed. Finally, the focus on demonstrating the improved accuracy of AI techniques for cost estimation may have overlooked studies reporting lower accuracy rates for AI techniques.

FINDINGS

The Scopus query yielded 486 records. After applying the eligibility criteria, 305 records were excluded, resulting in a pool of 181 potential studies. Title and abstract analysis further narrowed the pool to 89 studies. Finally, an in-depth content analysis identified 49 studies that met all inclusion criteria. Table 1 provides the complete list of studies.

Table 1: Identified studies

Study	Studies (continued)	Studies (continued)
G.-H. Kim *et al.*, (2004)	Jafarzadeh *et al.*, (2014)	Juszczyk and Leśniak (2019)
Cheng and Wu (2005)	Jin *et al.*, (2014)	Badawy (2020)
An *et al.*, (2007)	S. Kim and Shim (2014)	Chakraborty *et al.*, (2020)
Cheng *et al.*, (2009)	Fragkakis *et al.*, (2015)	Fan and Sharma (2021)
Cheng *et al.*, (2010)	Shin (2015)	Jiang (2019)
Ji *et al.*, (2010)	Zima (2015)	Karaca *et al.*, (2020)
K. J. Kim and Kim (2010)	Bayram and Al-Jibouri (2016)	Meharie and Shaik (2020)
Koo *et al.*, (2010)	Bayram *et al.*, (2016)	Tijanić *et al.*, (2020)
Koo *et al.*, (2011)	Gardner *et al.*, (2017)	Xue *et al.*, (2020)
Sonmez (2011)	Peško *et al.*, (2017)	Al-Tawal *et al.*, (2021)
Jin *et al.*, (2012)	W.-C. Wang *et al.*, (2017)	Sanni-Anibire *et al.*, (2021)
B. Kim and Hong (2012)	Zhang *et al.*, (2017)	Meharie *et al.*, (2022)
Alqahtani and Whyte (2013)	ElMousalami *et al.*, (2018)	Ujong *et al.*, (2022)
Gulcicek *et al.*, (2013)	Juszczyk *et al.*, (2018)	R. Wang *et al.*, (2022)
S. Kim (2013)	Leśniak and Zima (2018)	Yan *et al.*, (2022)
Ahn *et al.*, (2014)	Aretoulis (2019)	
Bala *et al.*, (2014)	Chandanshive and Kambekar (2019)	

Figure 1 shows the number of studies per year. The figure reveals the number of studies has been increasing since 2011.

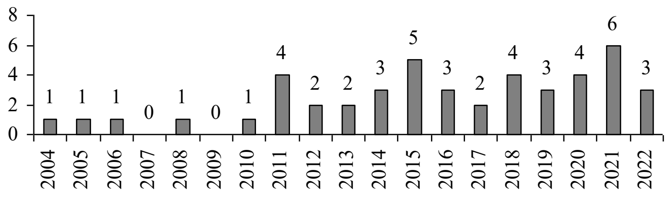

Figure 1: Number of studies by year

The studies analysed count a total of seven AI techniques, which can be divided into three categories: supervised machine learning (ML), knowledge-based, and evolutionary techniques.

ML techniques use labelled data to estimate the values of a model's coefficients. Each technique uses a different model to explain the relationship between the target and independent variables. Linear techniques include multiple linear regression (MLR), while non-linear techniques include neural networks (NN), support vector machines (SVM), k-nearest neighbours (kNN), random forest (RF), gradient boosting (GB) and radial basis function (RBF).

Knowledge-based techniques include case-based reasoning (CBR), which groups historical data into cases and correlates the current problem with experience. Unlike machine learning techniques, CBR does not use mathematical models or pattern recognition to make inferences. This approach relies on comparing new problems with previously solved cases to find solutions.

Evolutionary techniques include genetic algorithms (GAs), which use heuristic-based approaches to solve problems with a significant number of variables that cannot be easily solved in polynomial time. GAs views the trial phase as generating candidate solutions and evaluating the error between them and the expected outcome. This error evaluation is then used to determine which solutions should generate a new batch, iteratively improving towards an optimal solution.

Figure 2 shows the cumulative number of studies employing each technique over time. NN was and still is the most used technique, followed by MLR and then by CBR and GA.

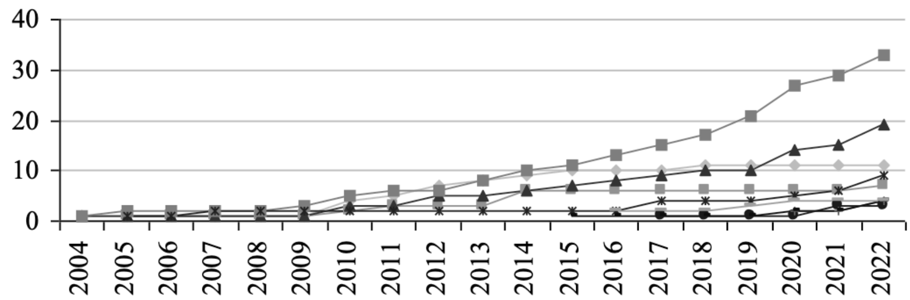

Figure 2: Cumulative number of studies by year by AI technique employed

The studies analysed include a total of seven scorers, categorised into absolute, percentage and squared errors. Absolute errors, which assess the mean accuracy of forecasts, include the mean absolute error (MAE). Percentage errors, which assess the relative accuracy of forecasts, include percentage error (PE), mean percentage error (MPE), absolute percentage error (APE) and mean absolute percentage error (MAPE). Squared errors, which assess the robustness of forecasts to outliers, include mean squared error (MSE) and root mean squared error (RMSE). The analysis shows that MAPE is the most frequently used scorer (19 occurrences), followed by MAE (10), APE and RMSE (6 each). MSE is mentioned in 3 studies, while PE appears in 2. This highlights a predominant focus on mean accuracy metrics (MAPE, MAE) across studies, with less emphasis on outlier considerations (MSE, RMSE).

Table 2 shows the winning probability matrix for the AI techniques. The p_ij value is determined as the ratio of the number of studies in which technique i proved superior to technique j (independently of the scorer used). The Mean column is determined by calculating the average of the rows. Based on the calculated means, GB is the best (.82), followed by RF (.77), NN (.69), GA (.58), and CBR and kNN (.50 each).

Table 2: AI Techniques Winning Probability Matrix

i\j	CBR	GA	MLR	NN	SVM	kNN	RF	GB	RBF	Mean
CBR	—		1.00	.00						.50
GA		—	1.00	.33	1.00			.00		.58
MLR	.00	.00	—	.08	.60	.00	.00	.33		.14
NN	1.00	.67	.92	—	.67	1.00	.25	.25	.80	.69
SVM		.00	.40	.33	—	.50	.00	.00		.21
kNN			1.00	.00	.50	—				.50
RF			1.00	.75	1.00		—	.33		.77
GB		1.00	.67	.75	1.00		0.67	—		.82
RBF				.20					—	.20

DISCUSSION

The systematic review, despite its limited scope, yielded several significant insights. Firstly, it revealed an increasing interest in AI techniques for conceptual cost estimation, underscoring three categories: supervised ML, knowledge-based, and evolutionary techniques. Among supervised ML techniques, MLR and NN emerged as the most attempted at. In terms of performance, the results suggest that GB, RF and NNs outperform GAs and CBR techniques. This is due to the nonlinear techniques handling complex relationships between project variables (Cheng *et al.,* 2010). However, they are highly sensitive to input data. More data can enhance the number of relations identified and modelled, but increasing input factors also raises complexity. Furthermore, their black-box nature the interpretation and justification of their decisions, posing challenges in contexts requiring transparency (Tayefeh Hashemi *et al.,* 2020).

In contrast, CBR technique offer a more transparent approach. Although it relies on extensive historical data (like ML), it updates by incorporating new cases, calculating similarity indices, and storing these new cases for future estimates (G.-H. Kim *et al.,* 2004). Unlike ML techniques, CBR ensures transparency, enabling users to investigate and correct the solution process (Duverlie and Castelain 1999). This transparency cannot be matched by parametric approaches or black-box algorithms.

The review also highlighted the benefits of hybridising AI techniques. Overall, genetic algorithms are more effective in optimising other algorithms, such as CBR and NNs, rather than functioning as standalone solutions. GA optimises regression pipelines by aiding in feature selection and hyperparameter tuning, which can enhance overall model accuracy. However, the relatively limited number of studies on evolutionary techniques suggests a potential bias.

All the above considerations must be viewed in light of the study's constraints. Focusing on a single database and imposing a minimum citation count may have excluded recent research and innovative methodologies. Additionally, relying solely on article text limits a comprehensive assessment of efforts to optimise individual model performance. Future studies should aim to incorporate a wider range of sources and consider alternative methodologies to provide a more holistic understanding of the field.

CONCLUSIONS

This literature review explored the application of AI techniques for conceptual cost estimation within construction projects. The use of AI in cost estimation aligns with the industry's demand for improved project managements. As AI continues to evolve and gain popularity, it is expected to transform project management, enabling project managers to focus on higher-value tasks and improving project success rates. Consequently, further research and practical implementation of AI techniques in construction projects are essential to harness the full potential of these technologies.

Algorithms such as NNs and CBR have the potential to revolutionise cost estimation by offering improved accuracy and adaptability. However, these techniques display high sensitivity to their structure and training, with results varying widely based on indexing and feature selection. This sensitivity underscores the need for careful consideration in the application and development of these models.

The review identifies several promising areas for future research. Addressing the identified biases could enhance the robustness of systematic reviews in this domain. Expanding the range of literature sources and including newer publications could reveal additional insights and emerging methodologies. Broadening the scope to compare AI-based techniques with probabilistic or simulation-based estimation methods would also provide valuable contributions to the field. Moreover, conducting empirical studies to directly test and benchmark various AI approaches for pre-tender cost estimation in real-world construction settings could be highly beneficial for the industry.

This review highlights promising areas for future research. Further investigation into overcoming the identified biases could enhance the robustness of systematic reviews in this domain. Moreover, considering an expanded range of literature sources and the inclusion of newer publications could reveal additional insights and emerging methodologies. Expanding the scope of analysis to compare AI-based techniques with newer probabilistic or simulation-based estimation methods would also provide a valuable contribution. Finally, conducting an empirical study to directly test and benchmark various AI approaches for pre-tender cost estimation in a real-world construction setting could be highly beneficial for the industry.

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