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The Influence of Artificial Intelligence on Practices in Construction Cost Estimation

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ABSTRACT

The process of cost estimation holds significant importance in the construction sector, serving as a key metric for determining project success. The conventional approach to cost estimation is often marred by human subjectivity and bias, leading to potential inaccuracies. The advent and adoption of Artificial Intelligence (AI), including machine learning (ML) and deep learning (DL) algorithms, are introducing notable technological advancements in the construction industry, particularly in the realm of cost predictions. Despite the ongoing technological changes, the industry still predominantly relies on traditional cost modelling approaches for early estimates, showcasing a hesitation to fully embrace AI applications in this domain. This research delves into the utilization of various ML methods for costing, conducting an exploratory critical review to assess their usage and application in current costing practices. The findings suggest that ML algorithms have the potential to enhance the accuracy and efficiency of cost estimation. However, it is emphasized that while ML can be a valuable tool, it cannot entirely replace the expertise of professionals and is dependent on the availability of relevant data.

KEYWORDS: Artificial Intelligence (AI); Cost Estimation; Machine Learning; Artificial neural network.

1 INTRODUCTION

Every construction project faces a multitude of risks and uncertainties, especially during the early design stages and throughout its life cycle. A significant challenge in this regard is the inherent inaccuracies in cost estimation, where the absence of precise cost data hinders the realization of project objectives. Consequently, cost becomes a pivotal criterion in decision-making across the project's life cycle. Recognized as a crucial preliminary process in construction projects, cost estimation involves predicting the expenses associated with executing the work within the defined project scope. In the initial stages of a project, characterized by uncertainty and numerous ambiguities in the project scope, obtaining accurate input data for cost estimation is particularly challenging [1,2]. The repercussions of overestimation or underestimation during this phase can lead to difficulties in resource allocation and cost overruns. The precision and thoroughness of cost estimation at this juncture are viewed as sensitive matters influenced by various parameters. Notably, the critical task of predicting costs and generating accurate estimates has traditionally relied on the expertise of human professionals. However, this dependence on human input is accompanied by the recognition that experts are susceptible to subjectivity and unconscious bias, potentially influencing the results. Traditionally, this process hinges on the estimator's knowledge and involves making assumptions based on experience and comparisons [3]. Consequently, it is contended that achieving the required level of accuracy in the estimating process through manual means is largely deemed impractical. The emphasis on the significance of employing intelligent techniques to address challenges in cost estimation within the construction sector has been widespread. Intelligent costing methods carry the potential to significantly streamline efforts and reduce time expenditures. The integration of machine learning (ML), a subset of artificial intelligence (AI), is reshaping project delivery in the construction industry, fundamentally altering the tasks performed by construction professionals and influencing construction delivery processes. ML, which aims to replicate human intelligence, is characterized by a computer's ability to learn autonomously, extracting patterns from historical data without explicit programming [1-4].

This facet of AI delves into the structure and functionality of algorithms capable of leveraging and forming assumptions about data, empowering computers to make decisions, recognize speech, and visualize in 3D. There is a burgeoning interest in ML research, particularly in deep learning (DL), a subfield of ML, due to its potential in automating construction processes and enhancing productivity and performance [5,6]. Some studies are specifically focused on how construction processes can benefit from digitization and AI [5]. While machine and deep learning are arguably in their initial stages of implementation in the construction sector, they present opportunities for addressing challenges associated with early cost prediction. AI techniques are now being regarded as a crucial solution to navigate the ambiguity and challenges inherent in cost estimation for construction projects [6]. Consequently, this study delves into the application of ML concerning the practice of construction cost estimating throughout a project's lifecycle [4-7]. It critically analyses the impact of ML techniques on cost estimating practices, scrutinizing the challenges and opportunities that arise. The study aims to offer insights into the current utilization of various AI techniques in costing practices within the construction sector, providing information on strategic future directions and how to leverage emerging opportunities presented by AI [5,6].

2 LITERATURE REVIEW

This study adopts an exploratory research approach by systematically identifying publications related to the use of Artificial Intelligence techniques in costing practices within the construction industry. Search queries encompassing AI techniques ('Machine learning,' OR 'Artificial intelligence,' OR 'Artificial Neural Network'), costing practices ('Costing,' OR 'Estimating,' OR 'Cost modelling'), and the construction industry ('Construction Industry,' OR 'AEC industry,' OR 'Architecture Construction and Engineering') were developed and executed on Scopus, Web of Science, and Google Scholar. These databases were selected due to their housing of pertinent publications and their prior utilization in similar studies. Inclusion criteria comprise publications in the English language and are confined to the categories of 'Construction Building Technology' and 'Engineering Civil.' There are no limitations imposed on publication years, and document type restrictions are not applied. The final selection of publications underwent a critical review to identify and compile key findings and lessons learned from these studies. These aggregated insights constitute the foundation for the outcomes of this research.

3 METHODOLOGY

Numerous methods and models are available for generating product costs, with the suitability of each model often contingent on factors such as project type, the information needed for cost estimation, and the specific field of application. In the realm of construction, the choice of cost models is influenced by the project phase and the available data at that point in time. A comprehensive classification system for construction cost modelling methods has been proposed, utilizing a two-category classification system, namely quantitative and qualitative approaches (refer to Figure 1). This classification system categorizes cost modelling techniques based on the level of information required to generate an estimate. For instance, parametric and analytical methods, which involve computational analysis and demand a lower level of granularity to derive costs, are classified under the quantitative category. On the other hand, more subjective methods like intuitive and analogical approaches fall into the qualitative category [1-3]. The subsequent review will delve into the foundational use and applications of these categorized cost modelling methods.

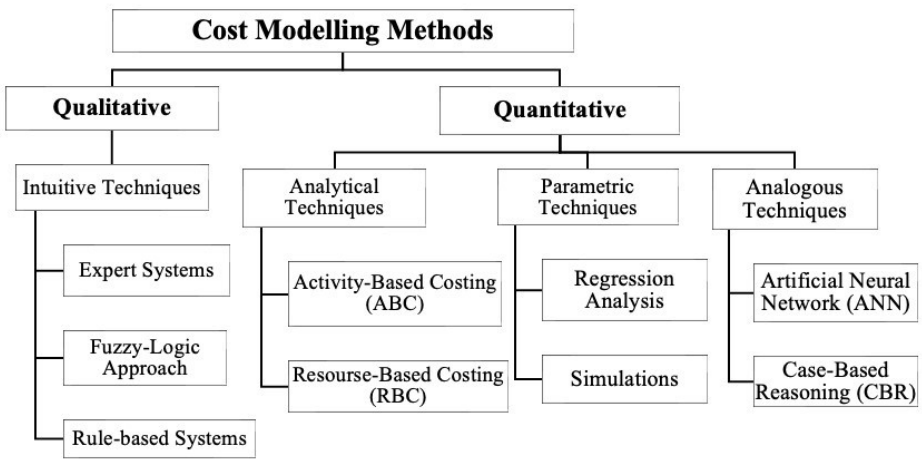

Figure 1: Car modelling methods

3.1 Evolution of cost modelling methodologies

The anticipation of project costs garnered significant attention from the early 1970s to the late 1980s within the construction industry. This heightened interest arose due to the imperative for more precise estimations, given the substantial capital value associated with construction projects and the inherent uncertainties prevalent throughout a project's life cycle. Despite the existence of a few models before this period, the early cost models faced criticism for being less value-driven. This has been attributed to their inability to account for future uncertainties in construction and their inadequacy in generating reliable cost estimates [5-8]. The historical evolution of cost-estimating techniques/tools in the construction industry has progressed through three stages: first, second, and third generations. However, considering the recent technological advancements in the construction sector, there is now a need to introduce a fourth category. As delineated in Table 1, first-generation techniques primarily rely on building functional cost analysis approaches, including Elemental Building Cost (EBC) and activity-based costing (ABC) methods. The RBC method, a prevalent approach in the construction sector, serves as the foundation for construction cost estimating guidelines, such as the RICS new rules of measurements (RICS 2021). The ABC approach represents an advancement over the RBC method, showcasing improved accuracy in tracing the cost per unit of products. Nevertheless, both first-generation models (RBC and ABC) exhibit limitations in terms of cost prediction. This limitation prompted the development of additional tools to address this gap in the early 1970s.

The parametric method, a second-generation approach, uses regression analysis with historical data for cost forecasting, particularly effective in the feasibility stage but may lack accuracy with non-linear relationships. Third-generation tools in the early 1980s introduced Monte Carlo simulation, reducing risk by estimating a cost range. Fourth-generation models, utilizing AI like artificial neural networks and expert systems, offer highly accurate results and faster estimation. Building Information Modelling (BIM) as a fifth-generation approach automates estimations through digital models but has limitations in considering external factors. Recent research explores integrating AI and BIM for enhanced accuracy in construction cost estimation [1].

Table 1: Progressive development of cost Estimation Practices

Timeline	Methods	Strength	Weaknesses	Source
First Generation (Pre - 1960s)	Elemental-Based Costing Activity-Based Costing	Detailed breakdown on cost information Provides information on different levels of analysis. More accurate with ability to track product cost.	Lack of detailed consideration for risk and uncertainties. Not suitable for early development stage. Lacks process view. Not suitable for cost prediction	(Khosrowshahi and Kakat 1996, Akintoye and Fitzgerald 2000). (Günaydin and Doğan 2004, Ayachit *et al.*, 2014)
Second Generation (Early - Late 1970s)	Parametric	Easy to understand due to string mathematical basis. Good at prediction Speed of execution Considerably accurate	Over simplistic and undermine many variables. Inaccuracies when relationship is non-linear	(Khosrowshahi and Kakat 1996, Günaydin and Doğan 2004)
Third Generation (Early 1980s)	Probabilistic Method	Reduces risk with cost estimates	Need advanced user data quantity and quality. Mostly based on the assumption of triangular distribution	(Chou *et al.*, 2009, Chou 2011)
Fourth Generation (Late 1980s)	Network-Based Approaches	Needs less statistical training to perform prediction. Can detect non-linear relationship among variables. Accuracy due to capability developed by numerous training algorithms	Black box method without user understanding Difficult to explain the outcome. Requires large pool of data to be dependable.	(Juszczyk 2017, Elmousalami 2021)
Fifth Generation (Post 2000s)	Building Information Modelling	Speeds up traditional estimating process Ability to link cost information to building model	Based on the quality of the BIM model Cannot automatically identify missing or unmeasured elements	(Wu *et al.*, 2014)

3.2 Influence of ML Techniques on Cost Estimation Practices

Various AI methods have been devised to create machines capable of simulating human cognitive functions. AI systems utilize interconnected sensors to collect data, a process known as data fusion, to integrate and identify potential inferences and characterizations from the data. Machine Learning (ML) is specifically focused on designing computer programs and algorithms with cognitive abilities that enable decision-making traditionally associated with human skills. ML encompasses three categories: supervised learning, unsupervised learning, and reinforcement learning. Some studies categorize ML into shallow learning (using a single layer of neural network nodes) and deep learning (employing multiple layers to process extensive training data) [10,11]. Deep Learning (DL), considered the current state-of-the-art in ML, has demonstrated superior accuracy compared to traditional ML techniques. There is a burgeoning interest in ML research within the Architecture, Engineering, and Construction (AEC) industry, driven in part by the capacity of these technologies to handle the substantial amount of data generated and utilized by construction professionals throughout a project's lifecycle. This interest is also attributed to the potential impact of ML on the cloud-based computing technologies prevalent in the industry. The integration of AI technologies into the AEC sector aims to enhance productivity and efficiency, addressing complexities such as diverse roles and uncertainties related to environmental hazards. While the development of ML and DL is expected to reshape costing practices, human-based methods remain prevalent in construction costing. ML techniques, particularly those dealing with regression, can be applied to solve classification or regression problems in costing practice. Algorithms such as Artificial Neural Networks (ANN), Logistic Regression, Support Vector Regression (SVR), and Deep Neural Networks (DNN) are relevant in this context. The ensuing section provides a brief discussion of these algorithms and highlights studies that have employed them for costing practices in existing literature [12-14].

3.3 Case-Based Reasoning (CBR)

Case-Based Reasoning (CBR) is a methodology that utilizes information from past cases, specifically previous projects, to generate cost estimates. It operates as a data mining technique that retains and leverages information, implementing solutions from similar projects to address new challenges. CBR identifies the best-matching example, akin to the current project, to estimate the cost of the new endeavour. Widely applied in construction costing practices, CBR involves storing information on previous projects in a database [13-15]. The system then assesses the characteristics that align with the specifications of the new project, considering changes in systems and assigning a percentage similarity score. Efforts have been documented to enhance the outcomes of CBR, aiming to improve its efficacy. Nonetheless, challenges persist, particularly in determining the appropriate weight values for factors influencing the cost estimation process.

3.4 Regression Algorithm (R)

Various regression algorithms can be applied in costing practices within the construction industry, categorized into single learners and ensembles. Single-learner algorithms encompass linear regression, multiple linear regression, polynomial regression, decision tree regression, and support vector regression. On the contrary, ensemble algorithms include random forest regression, gradient boosting regression, and Bayesian regression.

Ensemble algorithms tend to outperform single learners, while specific algorithms like Support Vector Regression (SVR) exhibit advantages in self-learning and overall generalization performance. However, these algorithms have their limitations. Challenges such as linearity assumptions, susceptibility to overfitting and underfitting, sensitivity to outliers, difficulties in handling categorical variables, and issues related to extrapolation and multicollinearity need to be considered. Despite these limitations, the construction industry can leverage the strengths of both single-learner and ensemble algorithms for effective cost estimation [16].

3.5 Deep Neural Networks (DNNs)

Deep Neural Networks (DNNs) add depth and complexity to standard neural networks, making them particularly adept at capturing intricate non-linear relationships by extracting unique features. In the construction industry, various DNN algorithms can be applied for costing practices. Convolutional Neural Networks (CNNs) prove valuable for automated quantity estimation from images and plans [5]. Recurrent Neural Networks (RNNs) find utility in time series analysis for construction cost forecasting. Generative Adversarial Networks (GANs) contribute by generating synthetic cost data, enhancing accuracy based on historical information. Additionally, transformer networks like ChatGPT, being large language models, can automate cost estimation through textual specifications and project descriptions [10].

Despite the potential benefits, the adoption of DNNs in costing practices faces limitations due to the required data and expertise for model deployment. Published research, such as Wang et al. (2022), has demonstrated the use of DNNs to assess the impact of economic factors on construction costs for public school projects. However, practical applications of this technique in construction costing practices need further exploration to address existing challenges and enhance its widespread implementation.

4 CONCLUSIONS

Researchers in the construction industry focus on accurate cost estimation, with AI and machine learning offering advantages in early estimating due to predictive capabilities. However, deployment in tendering and construction is limited by data scarcity and perceived AI complexity. To improve model accuracy, structured data and sufficient datasets are crucial to address overfitting and underfitting. Opportunities exist for using ANN, regression models, and DNNs in construction costing. While these algorithms enhance efficiency, they cannot replace professionals; domain knowledge is vital for model fitting and effective deployment. Professionals are urged to see these algorithms as tools to leverage, not as competitors.

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