Construction Rework Cost Prediction Using Machine Learning

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Predicting the construction cost of rework (COR) allows for the advanced planning and prompt implementation of appropriate countermeasures. Machine learning (ML) offers a data-oriented solution that can be utilized in different construction project contexts. ML approaches can predict COR by learning the complex patterns within the quality dataset.

Keywords: construction rework ; cost estimation ; machine learning

1. Introduction

A successful construction project is delivered on time and within budget, conforming to the specified quality. To achieve this, potential construction errors and violations are managed by applying an adequate construction quality management (CQM) system. An indispensable procedure within CQM is quality control (QC), which involves ensuring construction activity delivery at a specified standard, appraising its conformance, and maintaining continuous quality improvement. In construction projects, the arrays of errors, omissions, negligence, changes, failures, and violations resulting from poor management, communication, and coordination, or the materialization of potential risks are solved through rework. Thus, it is necessary to put in place a construction QC mechanism that not only prevents the need for rework but also prepares for accepting, acting on, and coping with required rework. Hence, the cost of rework (COR) is an inseparable component of overall construction costs, and its reduction directly improves construction cost and quality performance.

Although construction rework has been addressed in the literature, it remains a widespread [1] and prevalent problem [2][3] and poses a real challenge [4][5][6]. Despite all the advances in philosophies such as lean and total quality management (TQM) in preventing construction errors, COR still accounts for a considerable portion of the total project cost [2][7][8][9] and affects the construction schedule and quality [10]. Construction rework directly impacts the contract value by 5% to 20% [2], which can lead to complete project failure. Measuring COR enables the CQM system to control the construction budget and improve cost performance while allowing construction professionals to better understand the magnitude of the rework, its causes, and decisions on rework prevention measures [9]. Identifying the impact of COR and its sources enables reductions in the amount of rework and improvements in construction cost performance [11]. It is noteworthy that anticipating COR facilitates the utilization of QC techniques, such as Pareto analysis and pie charts. These QC techniques are dynamically used throughout the construction lifecycle to predict the construction rework items with a high-cost impact, which, in turn, allows for the timely adjustment of the associated construction schedule, budget, quality, human resources, and communication plans for the appropriate countermeasures. It is also noteworthy that obtaining COR is a key to understanding the cost of quality (COQ), i.e., the conformance costs, and the nonconformance costs, also referred to as the cost of poor quality (COPQ) [12]. The ability of construction firms to measure COQ is essential for their survival in today's competitive environment [13].

2. Construction Rework

The conventional construction rework procedure based on nonconformities raised within the NCRs is outlined in **Figure 1**.

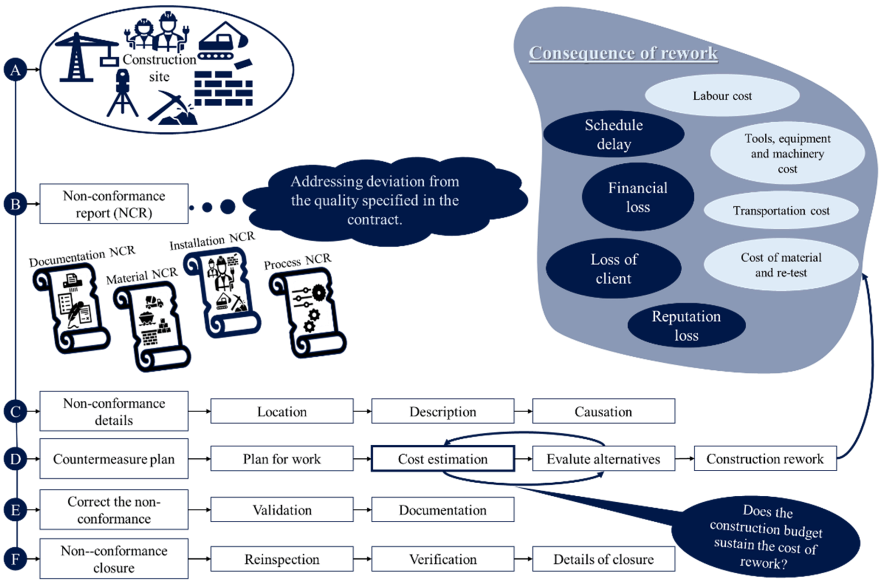

Figure 1. Construction rework procedure outline.

Site accidents, errors, failures, and violations are all causes of delays in the construction schedule and increase costs. Subsequent issues are often raised during the quality inspection of the construction activities performed, whereby the results are recorded in NCRs. The raised nonconformity should be addressed by the contractor, mainly in the form of rework. The topic of construction rework, including its causes, consequences, and prevention measures, has been widely addressed [14][15][16][17] using different terms and interpretations [9], such as quality deviation [18], construction nonconformance [19], defects [20], quality failure [21], and rework [22]. These have all emphasized the importance of factoring in construction rework during the early stages of construction planning in order to mitigate its consequences, which are mainly cost overruns.

3. The Cost Impact of Construction Rework

Despite the attention given to construction cost estimation in the previous research, the prediction of construction cost overrun has received relatively little consideration [23]. Similarly, the estimation of cost overruns resulting from the cost of construction rework has not been adequately addressed. Accordingly, the literature on estimating the cost impact of COR is reviewed here, along with construction cost estimation methods within a broader framework. The associated literature [13][24][25][26] has covered the broader topics of COQ and COPQ. In the literature on CQM, Love and different co-authors have explored construction quality from different perspectives, including construction error [27][28][29][30][31] and rework management [30][32], its impact on construction safety [33][34][35], and cost [9][36]. Hall and Tomkins [37] included the prevention and appraisal costs required to achieve a ‘complete’ COQ for buildings in the UK, while Love and Li [38] extended their earlier work on rework causation to quantify the magnitude of COR for Australian construction projects [39].

The research agrees on the negative impact of COR on overall construction cost while attaining varying impact percentages for this according to the demographics and types of evaluated construction projects. Davis et al. [40] found the nonconformance cost to be responsible for over 12% of the total contract value. Love [8][9], through a questionnaire survey on different project types and procurement routes, identified the direct and indirect impact of rework on total construction cost as being 26% and 52%, respectively. Rework costs drag down construction productivity by damaging the associated plans related, for example, to time, cost, and human resources, and this causes financial and reputation loss for the project participants. Hwang et al. [11] evaluated the contribution of COR to the total construction cost of 359 projects, along with its impact on both the client and contractor. They found that construction owners are absorbing twice as much impact from COR than contractors. To reduce the magnitude of this problem, contractors often apply an internal quality control and assurance system, and they also often implement proactive measures to anticipate possible rework and associated costs.

In addition to the negative effects of construction rework, there is a possible positive impact on the project cost and quality. Ye et al. [2] investigated 277 construction projects in China to identify the main areas of rework and showed that active rework can improve construction cost, time, and quality. This study further suggests that by implementing a reward strategy and value management tools, required rework can be identified early, enabling timely decision-making about the rework, time, cost, and quality benefits for the construction project. A statistical evaluation of 78 data points obtained from construction professionals by Simpeh et al. [7] revealed a mean 5.12% contribution of COR to total contract value and a

76% probability of exceeding its average value. This study also found that rework prediction facilitates quantitative risk assessment and, subsequently, the identification of alternative countermeasures for rework prevention. A more recent study by Love and Smith [4] evaluated the literature and put the impact of COR between less than 1% and more than 20% of the total contract value. The literature is not consistent in specifying the conditions according to which the impact of COR should be measured, which hinders its practical implementation. The most recent study stated that the COR can vary from 0.5% to 20% of the total contract value [41]. Thus, these studies have provided in-depth investigations on the cost impact of rework, but they are not consistent when it comes to the magnitude of that impact.

The literature on construction management has recorded different contribution percentages for the impact of COR on overall construction costs. Since studies are conducted on projects of different sizes and types, and within different demographics, the cost impact figures obtained cannot be directly extended to other projects. Although the literature shows the importance of the early identification of COR for improving construction cost performance, the uncertainty about the magnitude of the impact hinders decision-making when selecting the most advantageous countermeasures. Moreover, it is necessary to reach a different COR impact figure for each construction activity in order to prioritize activities with a higher cost impact, since it is not always feasible to implement preventive countermeasures or rework management strategies for all rework items. Furthermore, unless the COR for each work item is measured, it cannot be compared with the rework prevention or control cost.

Thus, to enhance the quality of decision-making and quality planning, as well as to increase the chance of construction project success, it is important to estimate the COR for each work item. To translate the literature results on the impact of COR into the context of different construction projects, ML offers a data-oriented solution that can be utilized in different construction project contexts. ML approaches can predict COR by learning the complex patterns within the quality dataset.

4. ML for Construction Cost Prediction

ML uses historical evidence to offer a reliable solution that facilitates informed decision-making. The literature on ML applications utilizing different types of datasets is growing in various fields [42][43][44][45][46][47][48][49][50][51][52][53][54][55]. Different ML approaches, such as artificial neural network (ANN), deep neural network (DNN), and support vector machine (SVM) is employed due to their ability to understand the complicated, non-linear patterns of real-world datasets. In this regard, the two ML approaches used for the cost estimation of construction projects were ANN [56][57] and SVM [54][58]. Even though other ML approaches, such as k-nearest neighbors (KNN) and decision trees (DT) share similarities with the ANN and SVM algorithms, they have yet to be investigated in the construction management literature [47]. Overall, construction cost estimation studies of more advanced ML approaches are scarce.

The literature on construction quality has mostly focused on quality assurance and quality control, using visual defect detection methodologies for a variety of tasks, including crack identification [59][60], damage localization on wooden building elements [61], and evaluation of pavement conditions [62]. ML approaches have also been used for the identification of rework or defect construction items. To this end, Fan [63] recently constructed a hybrid ML model using association rule mining (ARM) and a Bayesian network (BN) approach to identify quality determinants and gain more effective evaluations of defect risk and its occurrence. In a related study, Kim et al. [64] utilized SVM, random forest (RF), and logistic regression (LR) along with three natural language processing (NLP) methods on 310,000 defect cases from South Korea to assign defect items to the appropriate repair task. Shoar et al. [23] used RF to estimate the COR of engineering services in construction to be used for devising appropriate contingency plans. Their study found using RF as a cost estimator to be an efficient approach for screening and prioritizing from the standpoint of cost overrun within construction projects, and that it can be used to devise related contingency plans.

A study was conducted by Doğan [65] to predict the cost impact of construction nonconformities using case-based reasoning (CBR). His results indicated that the ability of CBR to predict the cost impact of quality problems is higher in construction NCRs. Reviewing the construction management literature, one may say that the development of ML-based cost estimators is still at an early stage. There is a lack of advanced ML approaches, such as ensemble learning methods. Although studies have established the usefulness of these ML methods, they have not elaborated on the robustness of the developed estimators, that is, on the ability to use the systems developed for other datasets. Thus, there is a research gap in the implementation of advanced ML-based techniques for predicting the COR associated with different construction activities.

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