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Task-Based Risk Scoring for Early Prediction of Cost and Time Overruns in Construction Projects

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Abstract

Construction projects often experience cost overruns and delay due to the cumulative effect of many risks happening in different activities. Regression-based forecasting, Monte Carlo simulation, and qualitative risk assessment are all well-established techniques, but their integration into a useful and transferable early-stage risk forecasting framework is still lacking. In order to convert expert risk assessments at the activity level into empirically calibrated project-level cost and duration multipliers, this study suggests a task-based risk scoring model. The study combines Monte Carlo simulation of project schedules and costs with expert-based qualitative risk identification organized using a standardized work breakdown structure. Power regression was used to create predictive relationships between baseline estimates and risk-adjusted outcomes using data from four multi-story building projects. Leave-One-Project-Out Cross-Validation (LOPOCV) was used to evaluate the robustness of the model, and Mean Absolute Percentage Error (MAPE) was determined to evaluate the accuracy, confirming low prediction error and strong explanatory capability. Dimensionless cost and duration scores are produced by the framework and can be immediately applied to baseline estimates. The findings show that while high-risk scenarios may increase 25% of project duration and 20% project cost, respectively, even low-risk scenarios may increase project duration and cost by roughly 6% and 7%.

Keywords: *Risk analysis, Risk score, Regression, and Monte Carlo Simulation.*

Introduction

Construction projects are complex processes that require careful management to ensure completion within the planned schedule, while minimizing costs and maintaining acceptable quality standard. Risks frequently lead to cost overruns, schedule delays, and reductions in quality. These issues typically arise due to the complexity of planning, designing, and constructing [1]. Projects that successfully manage risks proactively identify, assess, and mitigate potential consequences [2]. Risk management must be carefully considered when managing construction projects. It is essential to identify the critical risk factors at the preconstruction stage in order to reduce the impact of risks during the execution phase [3]. Risk identification varies across projects. However, when a Risk Breakdown Structure (RBS) is integrated with a Work Breakdown Structure (WBS), the resulting assessment becomes more realistic, structured, and reliable. Another essential part of risk management is quantifying risk factors based on their impact and likelihood. In construction projects, each task may face different risks. By assigning risk factors to individual tasks, an overall project risk score can be computed. This risk score can provide information about the overall project costs and durations based on the risk factors associated with each task. Risks can affect expenditures, time, quality, and safety in a number of ways. For risk factors that impact quality and safety, a robust risk management strategy can be developed and implemented. Similarly, in order to determine the overall project duration and expenses while accounting for these risks, risk factors that affect time and cost should be identified and planned for prior to construction.

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Different tools and techniques can be used for risk analysis, which include historical data, expert opinions, theoretical analysis, and other approaches for risk identification. Analyzing risks can be conducted using both qualitative and quantitative methods [4].

Conventional construction risk management frameworks use expert judgment to identify and rank risks qualitatively. Although these methods are helpful in increasing awareness and promoting communication, they frequently lack a clear link to the overall project cost and schedule forecasting. However, quantitative risk analysis techniques like Monte Carlo simulation rely on specific probabilistic inputs that are usually unavailable in the early phases of planning [5].

In order to maintain their applicability, interpretability, and transferability across different projects, recent research has highlighted the need for hybrid methodologies that integrate qualitative and quantitative techniques. However, many of the existing hybrid models either produce probabilistic results that are impractical for use in making quick decisions or are unduly focused on particular use cases [6, 7].

The objective of this study is to quantify the impact of task-level risks on overall project cost and duration by integrating expert risk assessments with risk propagation across multiple construction case studies. The study aims to identify low, base, and high risk conditions and to formulate regression-based relationships that enable early prediction of risk-induced time and cost overruns to support practical decision-making in construction projects.

Literature Review

Risk Management consists of the chain of steps starting with risk identification, analysis, evaluation, and risk treatment [3, 8, 9]. Barghi [6] explained the steps of risk assessment, which start with planning, identifying, qualitative and quantitative analysis, response planning, and controlling

The initial stage of risk management involves identifying risk factors, which is essential for planning risk controls and mitigation strategies [10]. Numerous studies have developed risk breakdown structures and identified critical risk factors in construction projects [2, 11-16]. Various tools and techniques are discussed in the literature for identifying risk factors, such as brainstorming, expert opinions, experience, checklists, questionnaires, and document reviews [10]. Morano, et al. [17] confirmed that brainstorming was the most used technique for risk identification in projects. A group of consultants can be utilized for brainstorming to identify potential risk factors. In many projects, however, risk assessment may be conducted without the involvement of a consultant. One effective method for identifying risks is through interviews, which can be referred to as expert judgment [18]. Due to the similarity of construction projects, the experienced project manager can use his experience to identify risk factors, as well as use checklist methods to determine the critical risk factors. As a result, past experience and checklists can be counted as another tool and technique for risk determination[10, 19-21].

Risk assessment is another stage in risk management. Based on past studies, different tools and techniques can be explained. From the literature review, it is clear that there are two general approaches widely used in project risk analysis: qualitative risk analysis and quantitative risk analysis [22].

Qualitative risk analysis involves prioritizing risks for further examination or action by assessing and combining their probability of occurrence and potential impact. This method, which lays the foundation for quantitative risk analysis, is usually quick and economical. Risk Probability and Impact Assessment, Probability and Impact Matrix, and Expert Judgment are frequently employed techniques in qualitative risk analysis [5, 22-25]. Experts are used in qualitative risk assessment to identify risk variables, estimate their likelihood, and determine their effect. [7, 23]. Ariyanto, et al. [26] and Lv, et al. [27] argued that various techniques can be used to conduct qualitative risk assessments, one of which is expert judgment.

Quantitative risk analysis is a process that mathematically evaluates the impact of identified risks on overall project objectives. This analysis is conducted on risks that have already been prioritized through the qualitative risk analysis process, as these risks are likely to have a significant effect on the project. The primary quantitative techniques in use today are Sensitivity Analysis, Modeling and Simulation, and Decision Trees. Among these, Monte Carlo Simulation is the most preferred method.[5, 22, 28]. In construction projects, risk assessment will be quantitative when the project schedule is added to the analysis [29]. Methods and tools that can be used for conducting quantitative risk assessment include Monte Carlo simulation, fault tree analysis, and sensitivity analysis [5, 30]

Various studies have proposed frameworks and models to enhance the prediction of project costs, duration, and performance in the construction industry. Attalla, et al. [31] introduced a reconstruction framework based on statistical analysis and neural networks, identifying critical performance factors. Kim and Reinschmidt [32] utilized Bayesian inference for cost forecasting, while Babar, et al. [33] integrated risk to estimate completion costs. Du, et al. [34] aimed to improve cost prediction accuracy with Markov chain simulations. Additionally, Rudeli, et al. [35] examined schedule deviations with Markov models, and Jarkas [36] proposed a time-cost model using multiple regression for project duration predictions. Mortaji, et al. [37] created indices for estimating final costs and durations through change point analysis, whereas Lipke, et al. [38] and Leon, et al. [39] utilized various models, including system dynamics, to predict outcomes based on project data. Chen [40] and Ling, et al. [41] employed linear models and regression to increase cost and performance accuracy, respectively. In order to examine construction costs in the face of uncertainty, especially in cases where costs and risk variables are linked, Ökmen and Öztaş [42] put up a novel model based on simulations, known as the correlated cost risk analysis model.

Assaad, et al. [43] quantified the impacts of risks on project performance, developed a comprehensive assessment model, and correlated the system for predicting costs and time upon project completion, employing a multistep research methodology. Lotfi, et al. [44] introduced a new method in machine learning called 3RML, which places an emphasis on project scheduling. This method is robust, resilient, and risk-based. Aldhamad, et al. [45] concluded that simulation modeling has a revolutionary influence on construction project management by providing enhanced tools for planning efficiency, resource allocation, cost calculation, sustainability, and risk management.

Each model should be validated in the literature; different methods can be used for validating models. Taha, et al. [46] developed a risk-driven Artificial Neural Network-based model using Mean Absolute Percentage Error. However, due to the limited number of samples, the model was validated through Leave-One-Project-Out Cross-Validation. Elmousalami [47] classified MAPE as an excellent prediction if it is less than 10%. A MAPE between 10% and 20% is considered a good prediction. MAPE values between 20% and 50% are categorized as acceptable forecasting, while values greater than 50% are deemed inaccurate predictions.

Different regression models can be used to develop a framework; power regression is one of the methods that can be employed for nonlinear regression. Sharma and Chaudhary [48] created a software effort estimating methodology that uses power regression for both object-oriented and procedural applications. They used power regression and then multiplied the effort multipliers to come up with the effort estimate model.

Recently, researchers have proposed hybrid approaches that combine qualitative and quantitative methods[6, 7]. This review reveals a lack of research on how to make transferable, empirically calibrated frameworks that turn qualitative activity-level risk assessments into useful cost and duration adjustment factors for early planning. Another gap that can be highlighted is that most students relied on the risk breakdown structure only, without considering the work breakdown structure. To address this, the present study quantifies risk impacts by assigning expert-evaluated risk factors to construction activities in multi-story building projects. A predictive model is then developed by integrating Monte Carlo simulation with regression analysis, enabling reliable estimation of project duration and cost under different risk conditions.

Research Methodology

Managing project risk involves several steps, each requiring various tools and methodologies. The main objective of this study is to develop a model that helps project managers and estimators predict the risk's impact on the overall project cost and duration. To achieve this objective, different tools and techniques can be used throughout the entire stage of risk analysis. Numerous risk assessment techniques exist [7]. The study tries to use a hybrid methodology that integrates qualitative and quantitative risk assessment. In the following section, the ways that are employed in this study are explained briefly.

Research Framework

This study conducted the risk assessment in the high-rise buildings, so based on the case study projects, a typical Work Breakdown Structure was developed. The WBS divided the projects into five main categories, which include earthwork, structure, finishing, mechanical, and electrical. Accordingly, a spreadsheet with a list of related risks was created for each task. Through an interview, experts were asked to choose the critical risks for each task based on their experience in order to conduct a qualitative risk assessment. Additionally, they were then asked to estimate the likelihood and impact of the chosen risk factors. The risk factors are used to conduct quantitative risk assessment after determining each risk factor's probability and impact. The risk propagation begins with the assignment of risk factors to each activity schedule, allowing for the subsequent conduct of quantitative risk assessment. Finally, the project risk score in terms of time and cost was then calculated using a Monte Carlo simulation. Figure 1 shows the methodology used in this investigation.

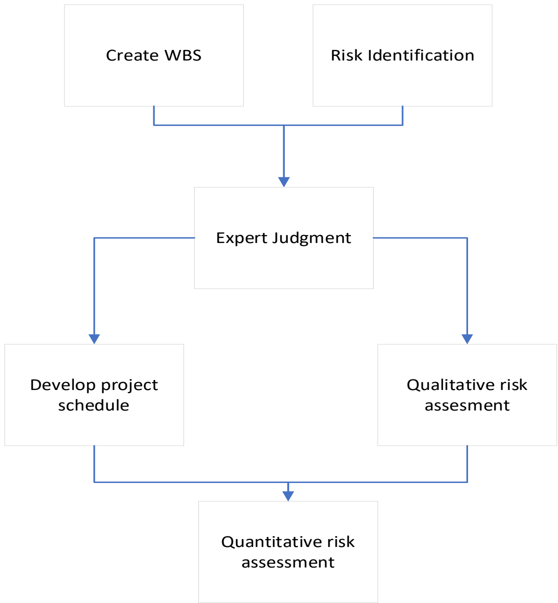

Figure 1. Adopted Method

Qualitative Risk Analysis

The qualitative risk analysis was performed to determine risk probability and impact. For each task, a list of risk factors was established by reviewing various studies related to construction projects, and it was organized in a spreadsheet. The experts were interviewed to identify the critical risk factors along with their probability and impact. The experts were selected based on their experience in high-rise buildings, with each having more than 10 years of experience. The experts were asked to select a risk factor for each task and estimate the probability and impact by choosing one of the following options: very low, low, medium, high, or very high. Before conducting a quantitative risk assessment, the data were converted to a scale referenced in PMBOK, with probability and impact expressed as percentages, as shown in Table 2 [18] .

Table 1. Probability and Impact Scale

Probability	% Probability	Impact	% Impact
Very high	90%	Critical	80%
High	80%	Serious	40%
Medium	50%	Moderate	20%
Low	30%	Minor	10%
Very low	10%	Negligible	5%

Case Study Selection

The case study projects were selected based on the availability of the project schedule and estimated costs. The risk factors assigned to the project schedule were analyzed using Risky Project Professional, and a Monte Carlo simulation was performed. The results for each expert and each project were compiled to determine the project cost score and duration score.

This study selected four projects that are already under construction. The first project consists of a 20-story tower. The original duration is estimated to be 1,073 days, with an original cost of $15,053,415. The second project involves four towers, each consisting of 40 stories, with an original duration of 988 days and an original cost of $81,868,876. The third project comprises 12 towers, each towers have 20 stories, and it is decided to construct in two different phases with an original duration of 2,132 days and an original cost of $249,506,228. The fourth project includes 9 towers, with an original duration of 1,174 days and an original cost of $151,665,040.

Quantitative Risk Analysis

The next step is a quantitative risk assessment. When the risk factors are assigned to the activities in the project schedule, the qualitative risk analysis can be converted into a quantitative risk analysis. The Monte Carlo simulation was applied to four case study projects. Risky Project Professional version 7.2 is used for applying the Monte Carlo simulation to each project, and as a result, three different durations and costs can be identified. For duration, the results will indicate low duration, base duration, and high duration; for cost, the findings will show low cost, base cost, and high cost.

Model Development

The final goal of this study is to develop a model that will assist project managers in predicting project duration and cost while considering risks. The Monte Carlo results for each project and each expert will have three different levels: low, base, and high. The mean score can be calculated using the arithmetic mean for each set of data, which includes the duration at low risk, base risk, and high risk, as well as the project cost at low, base, and high risk. The model can be developed using a non-linear regression technique called power regression, which is based on the following equation[48, 49]:

$$Y = a * X^b \quad (1)$$

While Y is the dependent variable, X is the independent variable, and a and b are constant values.

Finally, the regression model will be developed using SPSS and validated using Leave-One-Project-Out Cross-Validation (LOPOCV). This will involve calculating the Mean Absolute Percentage Error (MAPE) [50], as shown in Equation 2.

$$\text{MAPE}=\frac{1}{n}\sum_{i=0}^{n}\left|\frac{Actual(i)-Predicted\ (i)}{Actual\ (i)}\right| * 100 \quad (2)$$

Result and Discussion

The main goal of this study is to convert the risk factors into value in order to help project managers estimate the cost and duration of projects while considering the impact of risks. The process begins with developing a Work Breakdown Structure (WBS) and identifying risk factors. Then, expert engineers were asked to select the critical risks associated with each task, estimating both the probability and impact of these risks. The WBS, along with the response from one of the randomly selected experts, is shown in Table 2.

Table 2. Work Breakdown Structure (WBS) and Expert Response.

Typical Tower Work Breakdown Structure				
WBS Code	Task Name	Risk factor	Probability	Impact
1.1	**Earth Work**			
1.1.1	Excavation	Design changes,	Medium	Moderate
1.1.2	Pile Excavation	Low productivity of equipment,	Medium	Moderate
1.1.3	Back Filling	Site obstacles (access, existing services, size of the location...etc),	Medium	Minor
1.2	**Structure**			
1.2.1	Pile	Difficulty during concrete pouring	Low	Minor
1.2.2	Foundation	Delay in supplying materials (Concrete, steel)	High	Moderate
1.2.3	Column And Shear Wall	Delay in supplying materials (Concrete, steel)	Low	Moderate
1.2.4	Slab	Low productivity of labour,	Medium	Moderate
1.3	**Finishing**			
1.3.1	Lightweight Concrete Block	Low productivity of labour	Medium	Minor
1.3.2	Sand Cement Plaster	Low productivity of labour	Medium	Minor
1.3.3	Gypsum Plaster	Low productivity of labour	Medium	Moderate
1.3.4	Screeding	Low productivity of labour	Medium	Minor
1.3.5	Tile	Material delivery	Low	Minor
1.3.6	Gypsum Board False Ceiling	Low productivity of labour	Low	Minor
1.3.7	Interior Walls And Ceiling Paint	None	Very Low	Negligible
1.3.8	Façade Cement Plastering	Low productivity of labour	Medium	Minor
1.3.9	Aluminum Windows And Doors	Material delivery	Medium	Moderate
1.3.10	Façade Natural Stone	Low productivity of labour	Medium	Moderate
1.3.11	Balcony Glass Balustrade	Material delivery	Medium	Minor
1.3.12	Door	Material delivery	High	Moderate
1.3.13	Kitchen Cabinet Amed	Material delivery	Medium	Moderate
1.3.14	Parquet	Material delivery	Low	Minor
1.3.15	Landscape	Low productivity of labour	Medium	Minor
1.3.16	Podium Cladding	Low productivity of labour	Medium	Moderate
1.3.17	Podium Aluminum Stick Façade	Low productivity of labor	Medium	Minor
1.3.18	Car Park Painting	None	Very Low	Negligible
1.4	**Electrical**			
1.4.1	Inside Building	Design changes,	Medium	Serious
1.4.2	Low Current System	Low Productivity of labor	Medium	Minor
1.4.3	Electrical Substation	Delay in supplying materials	Medium	Minor
1.4.4	(Busbar, Db & Transformer)	Delay in supplying materials	Medium	Moderate
1.4.5	Facade Lighting	Unpredicted technical problems during construction	Medium	Minor
1.4.6	Electrical Works On Basements	None	Very Low	Negligible
1.5	**Mechanical**			
1.5.1	Plumbing	None	Very Low	Negligible
1.5.2	Firefighting	Design changes,	Low	Minor
1.5.3	Ventilation Work	None	Very Low	Negligible
1.5.4	Hvac	Delay in supplying materials	Medium	Minor
1.5.5	Lpg	Site obstacles (access, existing services, size of the location...etc)	Low	Minor
1.5.6	Elevator	Delay in supplying materials	Low	Minor
1.5.7	Lavatory	None	Very Low	Negligible
1.5.8	Firefighting (Basement)	None	Very Low	Negligible
1.5.9	Sewage Treatment Plant	None	Very Low	Negligible
1.5.10	Garbage Chute	Unpredicted technical problems during construction	Low	Minor
1.5.11	Grp Tank	Unpredicted technical problems during construction	Very Low	Minor
1.5.12	Booster & Submersible Pumps	None	Very Low	Negligible
1.5.13	Firefighting Pump	None	Very Low	Negligible
1.5.14	Car Park Ventilation	None	Very Low	Negligible

The quantitative risk assessment result can be determined by assigning risk factors to each task in the four case study projects. Additionally, a distinct Monte Carlo simulation was carried out for every project and expert's outcome. Tables 3, 4, 5, and 6 display the Mont Carlo simulation results, which include the low duration, base duration, high duration, low cost, base cost, and high cost. Equations 2 and 3 were used to compare the modified values to the original data to calculate the project risk score:

Duration Risk Score = Project Duration with Risk / Original Project Duration (2)

Cost Risk Score = Project Cost with Risk / Original Project Cost (3)

Table 3. Monte Carlo Simulation Results for the First Case Study Project.

Respond No.	Low Duration (Day)	Base Duration (Day)	High Duration (Day)	Low Duration Score	Base Duration Score	High Duration Score	Low Cost ($)	Base Cost ($)	High Cost ($)	Low Cost Score	Base Cost Score	High Cost Score
R1	1097	1170	1242	1.02	1.09	1.16	15843688	17237592	18601557	1.05	1.15	1.24
R2	1099	1177	1254	1.02	1.10	1.17	15218191	16104062	16886357	1.01	1.07	1.12
R3	1176	1290	1383	1.10	1.20	1.29	15937567	16734702	17766593	1.06	1.11	1.18
R4	1193	1295	1399	1.11	1.21	1.30	15897514	16870987	17827544	1.06	1.12	1.18
R5	1225	1274	1323	1.14	1.19	1.23	17097767	17771308	18383151	1.14	1.18	1.22
R6	1320	1406	1466	1.23	1.31	1.37	16539494	17318071	17979624	1.10	1.15	1.19
R7	1174	1294	1419	1.09	1.21	1.32	16348275	18354704	20398542	1.09	1.22	1.36
R8	1073	1112	1137	1.00	1.04	1.06	15205652	15487765	15801336	1.01	1.03	1.05
R9	1225	1384	1515	1.14	1.29	1.41	16412151	17018068	17616640	1.09	1.13	1.17
R10	1190	1293	1398	1.11	1.21	1.30	16012864	17081710	18254379	1.06	1.13	1.21
R11	1196	1247	1295	1.11	1.16	1.21	15814119	16484389	17239855	1.05	1.10	1.15
R12	1168	1220	1265	1.09	1.14	1.18	15842848	16226114	16610957	1.05	1.08	1.10
R13	1144	1244	1329	1.07	1.16	1.24	16026675	17088831	18153569	1.06	1.14	1.21
R14	1330	1440	1557	1.24	1.34	1.45	17627058	19376814	21200928	1.17	1.29	1.41
R15	1223	1294	1350	1.14	1.21	1.26	18499852	18878539	19598998	1.23	1.25	1.30

Table 4. Monte Carlo Simulation Results for the Second Case Study Project.

Respond No.	Low Duration (Day)	Base Duration (Day)	High Duration (Day)	Low Duration Score	Base Duration Score	High Duration Score	Low Cost ($)	Base Cost ($)	High Cost ($)	Low Cost Score	Base Cost Score	High Cost Score
R1	988	1094	1204	1.00	1.11	1.22	84539860	89145613	93872334	1.03	1.09	1.15
R2	988	1062	1135	1.00	1.07	1.15	88351201	88351201	94143516	1.07	1.07	1.14
R3	1019	1216	1321	1.03	1.23	1.34	87812777	92078388	96162982	1.07	1.12	1.17
R4	1031	1139	1246	1.04	1.15	1.26	87872562	94760083	101393478	1.07	1.16	1.24
R5	1123	1187	1249	1.14	1.20	1.26	91705304	96756526	101470925	1.12	1.18	1.24
R6	989	1051	1082	1.00	1.06	1.10	86507149	91713751	95989661	1.06	1.12	1.17
R7	1060	1224	1430	1.07	1.24	1.45	90400628	98012981	106310312	1.10	1.20	1.30
R8	989	1051	1115	1.00	1.06	1.13	83217707	85467445	87644036	1.02	1.04	1.07
R9	1132	1253	1435	1.15	1.27	1.45	91363737	95577581	99508043	1.12	1.17	1.22
R10	1000	1116	1211	1.01	1.13	1.23	88214081	94668019	101752791	1.08	1.16	1.24
R11	1000	1090	1167	1.01	1.10	1.18	84458388	90437236	96272271	1.03	1.10	1.18
R12	1060	1145	1211	1.07	1.16	1.23	88965618	92717203	96066822	1.09	1.13	1.17
R13	1007	1119	1202	1.02	1.13	1.22	84660680	88956092	93732117	1.03	1.09	1.14
R14	1031	1251	1494	1.04	1.27	1.51	87575285	97360988	107438131	1.07	1.19	1.31
R15	994	1178	1270	1.01	1.19	1.29	85796815	92807608	98166489	1.05	1.13	1.20

Table 5. Monte Carlo simulation results for the third case study project.

Respond No.	Low Duration (Day)	Base Duration (Day)	High Duration (Day)	Low Duration Score	Base Duration Score	High Duration Score	Low Cost ($)	Base Cost ($)	High Cost ($)	Low Cost Score	Base Cost Score	High Cost Score
R1	2132	2418	2681	1.00	1.13	1.26	257398054	271435091	285852760	1.03	1.09	1.15
R2	2146	2310	2492	1.01	1.08	1.17	252193149	268494033	287254992	1.01	1.08	1.15
R3	2269	2497	2696	1.06	1.17	1.26	267076225	280352408	292835842	1.07	1.12	1.17
R4	2198	2517	2856	1.03	1.18	1.34	266557119	288880800	310146681	1.07	1.16	1.24
R5	2344	2540	2692	1.10	1.19	1.26	279004388	294168054	308332714	1.12	1.18	1.24
R6	2156	2334	2415	1.01	1.09	1.13	263427242	279780700	293417509	1.06	1.12	1.18
R7	2228	2653	3112	1.05	1.24	1.46	274462870	297845541	323741096	1.10	1.19	1.30
R8	2138	2237	2324	1.00	1.05	1.09	253524790	260344977	267007917	1.02	1.04	1.07
R9	2276	2478	2706	1.07	1.16	1.27	277992050	290741135	302476619	1.11	1.17	1.21
R10	2192	2520	2849	1.03	1.18	1.34	269607809	289379870	311538641	1.08	1.16	1.25
R11	2182	2377	2616	1.02	1.11	1.23	256916512	275242963	293068833	1.03	1.10	1.17
R12	2240	2335	2426	1.05	1.10	1.14	271432624	283429972	293150453	1.09	1.14	1.17
R13	2182	2389	2577	1.02	1.12	1.21	257543353	270804775	285294635	1.03	1.09	1.14
R14	2223	2571	3188	1.04	1.21	1.50	265861900	301150627	333856130	1.07	1.21	1.34
R15	2176	2693	2938	1.02	1.26	1.38	261295001	281772316	297308102	1.05	1.13	1.19

Table 6. Monte Carlo Simulation Results for the Fourth Case Study Project.

Respond No.	Low Duration (Day)	Base Duration (Day)	High Duration (Day)	Low Duration Score	Base Duration Score	High Duration Score	Low Cost ($)	Base Cost ($)	High Cost ($)	Low Cost Score	Base Cost Score	High Cost Score
R1	1174	1271	1406	1.00	1.08	1.20	155715470	166976313	180652731	1.03	1.10	1.19
R2	1174	1274	1336	1.00	1.09	1.14	153817184	164966764	175375051	1.01	1.09	1.16
R3	1243	1406	1522	1.06	1.20	1.30	163506400	172124164	180630683	1.08	1.13	1.19
R4	1204	1298	1392	1.03	1.11	1.19	162190745	173318510	186854989	1.07	1.14	1.23
R5	1294	1385	1470	1.10	1.18	1.25	168643106	178110009	187078843	1.11	1.17	1.23
R6	1174	1216	1249	1.00	1.04	1.06	159193791	166640028	173741426	1.05	1.10	1.15
R7	1255	1408	1567	1.07	1.20	1.33	164491886	182928590	201540615	1.08	1.21	1.33
R8	1205	1236	1269	1.03	1.05	1.08	153715041	157640666	161727038	1.01	1.04	1.07
R9	1313	1388	1449	1.12	1.18	1.23	165328513	171946970	179888925	1.09	1.13	1.19
R10	1241	1352	1509	1.06	1.15	1.29	160507415	174905066	188392789	1.06	1.15	1.24
R11	1205	1289	1388	1.03	1.10	1.18	157339647	166194654	175061311	1.04	1.10	1.15
R12	1255	1288	1311	1.07	1.10	1.12	162663519	168084714	173266813	1.07	1.11	1.14
R13	1213	1321	1419	1.03	1.13	1.21	159142853	168478613	179246430	1.05	1.11	1.18
R14	1255	1480	1608	1.07	1.26	1.37	173487603	192082715	209382852	1.14	1.27	1.38
R15	1234	1394	1475	1.05	1.19	1.26	158311050	177219539	188057855	1.04	1.17	1.24

The results of the Monte Carlo simulation can be used to determine the overall project risk impact in terms of cost and duration. Based on the arithmetic average of each scenario, the low-risk project duration score will be 1.06. A project with base risk will receive a duration score of 1.16, while the worst-case scenario with high risk will receive a score of 1.25. Using the same formula to assess costs, the average scores for low-cost risk, base-cost risk, and high-cost risk are 1.07, 1.13, and 1.20, respectively.

The study employed regression analysis to create a formula that aids estimators and project managers in project duration and cost estimation. The model was developed by analyzing the Monte Carlo results of fifteen experts from four different projects using SPSS 27. To increase estimation accuracy, this study employed regression analysis to determine a relationship between baseline estimates and risk-adjusted outcomes. The dataset consisted of 180 observations from Monte Carlo simulations (15 experts across 4 projects). The regression results are shown in Tables 7 and 8. In the duration-based analysis, the quadratic and cubic models exhibit the highest R-squared values. The power and linear models also show high R-squared values. However, since the project score is calculated by multiplying the probability by the impact and connecting it to the initial duration, the power model, which yields the highest R-squared value for cost, will be the most useful. The following is the formula for this relationship:

Duration with risks = constant * (Original Duration)^{b1}

Cost with risks = constant * (Original Cost)^{b1}

Specifically, the equation can be expressed as:

Duration with risks = 1.301 * (Original Duration)$^{0.983}$ (4)

Cost with risks = 1.211 * (Original Cost)$^{0.996}$ (5)

Table 7. Model Summary and Parameter Estimates for Duration

Dependent Variable: Duration with risk									
	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.910	1805.259	1	178	.000	21.877	1.140		
Logarithmic	.905	1698.532	1	178	.000	-10831.349	1731.647		
Inverse	.891	1449.653	1	178	.000	3587.415	-2491311.753		
Quadratic	.911	901.071	2	177	.000	349.513	.678	.000	
Cubic	.911	901.272	2	177	.000	272.444	.866	.000	3.481E-8
Compound	.905	1695.755	1	178	.000	618.899	1.001		
Power	.906	1718.121	1	178	.000	1.301	.983		
S	.899	1587.236	1	178	.000	8.454	-1420.350		
Growth	.905	1695.755	1	178	.000	6.428	.001		
Exponential	.905	1695.755	1	178	.000	618.899	.001		
Logistic	.905	1695.755	1	178	.000	.002	.999		
The independent variable is Original Duration.									

Table 8. Model Summary and Parameter Estimates for Cost

Dependent Variable: Cost with risk									
	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.986	12941.906	1	178	.000	234876.346	1.130		
Logarithmic	.849	1004.671	1	178	.000	-1426074884.565	85960193.056		
Inverse	.630	302.573	1	178	.000	209197559.676	-3057201093330093.500		
Quadratic	.986	6435.300	2	177	.000	34666.027	1.135	-1.930E-11	
Cubic	.986	4266.976	3	176	.000	431760.370	1.112	2.224E-10	-6.180E-19
Compound	.858	1074.037	1	178	.000	22957792.340	1.000		
Power	.996	42780.263	1	178	.000	1.211	.996		
S	.926	2216.442	1	178	.000	19.240	-39682050.580		
Growth	.858	1074.037	1	178	.000	16.949	1.128E-8		
Exponential	.858	1074.037	1	178	.000	22957792.340	1.128E-8		
Logistic	.858	1074.037	1	178	.000	4.356E-8	1.000		
The independent variable is Original Cost.									

Different models were developed for the low, base, and high-risk project duration and cost scenarios in order to improve the power regression models' dependability. LOPOCV was used to assess the robustness and generalizability of the model by progressively eliminating each project from the calibration dataset and generating independent predictions. The validation results, which show each model's excellent predictive performance, are shown in Table 9.

Table 9. Leave-One-Project-Out Cross-Validation and MAPE Result

		Model Summary	Parameter Estimates			
	Test Project	R Square	Constant	b1	%Error	%MAPE
Low duration	A	0.989	1.114	0.990	6.10%	5.09%
	B	0.974	1.759	0.930	5.89%	
	C	0.645	0.847	1.033	5.33%	
	D	0.976	1.428	0.958	3.03%	
Base duration	A	0.973	1.133	1.002	5.95%	5.96%
	B	0.961	1.327	0.981	5.23%	
	C	0.496	2.677	0.880	7.37%	
	D	0.969	1.353	0.979	5.27%	
High duration	A	0.938	1.075	1.020	6.36%	9.85%
	B	0.936	1.007	1.029	7.58%	
	C	0.300	6.725	0.758	18.36%	
	D	0.941	1.232	1.003	7.11%	
Low Cost	A	0.995	1.159	0.995	2.68%	2.58%
	B	0.999	1.207	0.993	2.35%	
	C	0.998	1.222	0.993	2.64%	
	D	0.999	1.202	0.994	2.63%	
Base Cost	A	0.992	1.110	1.001	4.27%	3.62%
	B	0.998	1.201	0.997	3.26%	
	C	0.998	1.207	0.997	3.42%	
	D	0.998	1.208	0.996	3.56%	
High Cost	A	0.985	1.155	1.002	5.67%	4.84%
	B	0.997	1.228	0.999	4.39%	
	C	0.996	1.220	0.999	4.50%	
	D	0.997	1.241	0.998	4.79%	

All of the data was subjected to the LOPOCV, and the percentage error was computed independently to verify the validation. Lastly, each formula's percentage MAPE was calculated. The minimum percentage error for the project duration prediction formula that takes low-risk events into account is 3.03%. When Project D, the fourth project, was excluded, this data was acquired. Furthermore, this formula's % MAPE of 5.09% shows excellent prediction because it is less than 10%. Based on this outcome, the following model will be created to forecast project duration while taking low-risk occurrence and impact into account:

$$\text{Duration with Low Risks} = 1.384 * (\text{Original Duration})^{0.962} \quad (6)$$

The study discovered that there is significant variation between projects in the base risk duration prediction model's %MAPE analysis. Project B (5.23%) and Project C (7.37%) had the lowest and highest deviations, respectively. Nonetheless, the average %MAPE of 5.96% shows that the model can make accurate predictions for projects with base-level risks and is within acceptable prediction bounds of less than10%. Accordingly, the predictive relationship for estimating project duration under base-risk conditions is expressed as:

$$\text{Duration with Base Risks} = 1.281 * (\text{Original Duration})^{0.986} \quad (7)$$

The predictive variability was higher for the high-risk duration model, as evidenced by calibration. The least erroneous result was 6.36% with the exclusion of Project A, whereas excluding Project C resulted in maximum error (18.36%), showing that when risk is very high, error compliance increases.

However, the average %MAPE of 9.85% remains below the 10% guideline, and thus it indicates that the model can still give somewhat accurate duration estimates under relatively high-risk conditions. The predictive formula is given as

Duration with High Risks = 1.14 * (Original Duration)$^{1.013}$ (8)

In terms of the low-risk cost prediction model, there is strong evidence by both %MAPE and R^2 in favour of robust performance. The R^2 values are between 0.995 and 0.999 meaning that almost all variation in project cost is explained by the model. The lowest percentage error was in project B (2.35%) and the highest was in project A (2.68%). On the whole, with percent mean absolute percentage error of 2.58%, the study found a very good prediction accuracy, indicating that this MA model is suitable to estimate costs in low-risk environment. The model is expressed as:

Cost with Low Risks = 1.206 * (Original Cost)$^{0.993}$ (9)

The base-risk cost prediction model also demonstrates strong predictive capability. R^2 values range from 0.992 to 0.998, indicating excellent goodness of fit. The minimum error occurred when Project B was excluded (3.26%), while the maximum error was observed for Project A (4.27%). Despite this variation, the overall %MAPE of 3.62% confirms that the model remains highly accurate and well within the 10% acceptability threshold. The predictive formula is as follows:

Cost with Base Risks = 1.200 * (Original Cost)$^{0.997}$ (10)

Evaluation of the high-risk cost prediction model demonstrates strong statistical reliability, with R^2 values ranging between 0.985 and 0.997, indicating that the model successfully explains the vast majority of the variation in project cost, even under elevated risk conditions. The minimum percentage error was obtained when Project B was excluded, yielding a value of 4.39%, whereas the maximum deviation was observed for Project A, with an error of 5.67%. Despite the greater uncertainty associated with high-risk environments, the model achieved an overall %MAPE of 4.84%, reflecting excellent predictive accuracy and confirming its suitability for forecasting project cost under high-risk scenarios. Based on these results, the developed predictive relationship for estimating project cost considering high-risk occurrence and impact is expressed as follows:

Cost with High Risks = 1.227 * (Original Cost)$^{0.999}$ (11)

The power regression models demonstrated low prediction errors and high coefficients of determination in every scenario according to the LOPOCV validation results, demonstrating their robustness and dependability. As a result, power regression can be chosen as the ultimate modeling technique to forecast project duration and cost in low, base, and high risk scenarios.

Conclusion

Risk management is a crucial area in construction projects, as risks can significantly impact time, cost, quality, and safety. Nowadays, it is important to plan effectively in order to consider the risk factors that affect the project's main objectives. This study focuses on the impact of risk in terms of time and cost. This study developed a practical task-based risk scoring framework that employs qualitative expert assessment, Monte Carlo simulation, and regression analysis to determine the impact of risks on project cost and duration. To this end, a two-stage method was employed to collect data using interviews of experts, which qualitatively extracted risk factors. A Monte Carlo analysis was also conducted to translate the risk impact and probability into an overall project risk contribution. A second detail of this study is that the risk factors were established for each task within the project, in accordance with the usual WBS assumption. The arithmetic mean of the Monte Carlo results showed that the project duration score with low risk will be 1.06, which is equivalent to a 6% increase in overall project duration. The project duration base risk score was equal to 1.16, and the project duration risk score with high risk was equal to 1.25. Based on this result, it can be concluded that when risk is not controlled, the project duration might be increased by 25% in the worst-case scenario. Conversely, the results indicated that the risk factors also contributed to cost overruns. The average scores were 1.07 for low-cost risk, 1.13 for base cost risk, and 1.20 for high-cost risk. Finally, based on the data, the study started with qualitative analysis and then conducted quantitative risk assessment, which is used to effectively transform qualitative risk perceptions into measurable adjustment factors at the project level. Through a power regression model, various formulas were developed to predict the impact on project costs and duration. These formulas are designed to assist engineers in calculating project duration and costs while considering risks. Strong model stability and low error values were confirmed by Leave-One-Person-Out Cross-Validation, demonstrating the predictive capability of the power regression models.

For preliminary planning and feasibility assessments, these predictive equations serve as a reliable decision-support tool.

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