Time-Cost Analysis of Trail Bridge Construction in Nepal Using Bromilow Time-Cost Model and General Regression Neural Network

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Keywords

BTC, GRNN, Predictive Accuracy, Time-Cost Modeling, Trail Bridge Construction

Abstract

Timely completion of construction projects is essential for ensuring cost-efficiency and project success, with accurate forecasting of construction duration playing a crucial role. This study examines the relationship between final cost and construction time in trail bridge projects across Nepal, using two modelling approaches: the Bromilow Time-Cost (BTC) Model and the General Regression Neural Network (GRNN).

The analysis covers 254 completed trail bridge contracts implemented by the Suspension Bridge Division (SBD) between fiscal years 2018/19 and 2021/22 across the mountain, hill, and Terai regions. Bridge types include D-type (dismantled), N-type (new), and MN-type (modified new). Data are primarily sourced from official Suspension Bridge Division records, supplemented with interviews with engineers and project managers for validation and contextual understanding

The BTC model was analysed using Microsoft Excel, and the GRNN model using DTREG software. Results show that neither model establishes a statistically significant relationship between cost and duration, with R^2 values below 0.10 across all bridge types. Although GRNN slightly outperformed BTC, predictive accuracy remained limited.

Interview findings identified contextual factors undermining model performance, including fixed-price turnkey contracts, limited qualified contractors, subcontracting, delayed budget releases, frequent regulatory changes, labor shortages, remote material delivery challenges, and environmental and social disruptions.

The study concludes that cost alone is insufficient for predicting construction duration. It recommends incorporating broader explanatory variables and applying advanced or hybrid modelling approaches informed by expert insights to improve timeline forecasting in such settings.

Received: 1 June 2025
Revised: 28 August 2025
Accepted: 4 December 2025

ISSN: 3059 - 9687

I. Introduction

Nepal, a landlocked country situated between China and India, is known for its mountainous landscape, cultural diversity, and challenging geography. Bearing in mind that Nepal has more than 6000 rivers, the Government of Nepal [1] estimated that it contributes over 225 billion cubic meters annually to the Ganges River system. The difficult landscape of hilly and mountainous terrain throughout the country has made most areas unreachable by motorized vehicles or even bicycles. In some cases, entire villages are isolated via road during the monsoon season with limited access to food, healthcare, education, and markets [2].

In these areas, foot trails and mule tracks remain the primary means of transport and communication. Since these foot trails and tracks frequently crosses over the rivers and streams, trail bridges are essential to maintain year-round connectivity. Tuladhar [3] identified foot trails as the most dependable transport option for remote settlements. As a result, trail bridge construction has become an important infrastructure initiative to enhance rural mobility and reduce poverty in geographically scattered communities [4].

In Nepal, the Suspension Bridge Division (SBD) was established in 1964 under the then Ministry of Works and Transport. Since then, SBD has been planning and implementing trail bridges across the country. Since federal dispensations, the ownership and responsibility for constructing these bridges has been shared between local, provincial, and central level governments in a coordinated way. According to the National Trail Bridge Strategy, Nepal requires about 6,500 more trail bridges to meet connectivity needs. In addition, the Ministry of Urban Development (MoUD) has also proposed reducing the maximum allowed detour time to 30 minutes, which is likely to increase this demand [4].

In construction project lifecycle, the length of a contract is critical, especially in agreements between investors, contractors, and subcontractors resulting delay of project consequently causing financial burden and arising of social/political problems. An in accurate construction time estimate leads to disturbance and conflict between the stakeholders [5]. Many studies have tried to estimate the duration of construction taking various factors like cost, building size, number of floors, work amount, available resources, and design details. While these things affect the construction timeline differently depending on the project, cost often turns out to be one of the strongest indicators of how long duration a project will last [6].

For trail bridge projects, accurate time estimation is particularly important due to logistical difficulties and strict funding cycles. It supports better planning, budgeting, and contract management, including the application of incentives and penalties. However, no single accepted method exists for calculating project duration in varied geographic and operational contexts. To address this gap, researchers have tested different predictive tools, such as Artificial Neural Networks [7], reference class forecasting [8], and genetic algorithms [9], to model the relationship between time and cost.

One of the most recognized traditional methods is the Bromilow Time-Cost (BTC) model, introduced in 1969, which expresses a mathematical link between project cost and completion time. The accuracy of construction time prediction depends on several factors like the type of project, weather conditions, exchange rates, and contract details [10]. Recently, Artificial Neural Networks (ANNs), especially the General Regression Neural Network (GRNN), have shown promise in handling complex and nonlinear patterns, offering more flexible, data-driven estimates for how long construction might take [11].

However, predicting construction timelines remains complex because factors such a project nature, procurement method, site conditions, resource availability, and local regulations cause significant variation [7]. In Nepal, the Public Procurement Act [12] and Public Procurement Regulation [13] requires project duration estimates to be included in cost projections, yet these rules offer no clear standard for calculating them. Frequent amendments to procurement legislation have further complicated the process of determining and approving time extensions.

Research like Pokhrel et al. [14] shows that agencies such as the SBD often depend on informal, experience-based methods to decide contract durations. This approach can cause inconsistency and inefficiency in completing projects, highlighting the need for more objective, evidence based, and data-driven methods.

Around the world, many time-cost models have been developed, but there's little research specifically focused on trial bridge projects in Nepal's varied and challenging terrain. Most of the prevailing time estimates used by various agencies are based on judgment rather than sound analysis, especially when dealing with fixed-price turnkey contracts. Traditional models like BTC often fail to account for the distinct and intricate factors influencing project durations, particularly in remote areas. While machine learning techniques such as GRNN, show promise, their application in data-scare regions like Nepal remains underexplored. Most past studies have focused primarily on large infrastructure projects like tall buildings or highways, leaving little research on smaller, rural projects like trail bridges. However, recent analyses of health building Dahal, et., [24] and rural roads [25] in Nepal highlight similar inefficiencies in time-cost estimation and contract management, underscoring the need for context-specific models in remote infrastructure. To address this gap, we need to create models tailored to local contexts. These models should consider not only the cost but also practical factors, such as project operations, environmental conditions, and local regulations, to provide more accurate estimates of construction duration.

Ii. Methodology

A. Research Design

Study uses data-driven approach to explore the linkage between construction costs and contract durations for trail bridge projects in Nepal. The main goals were to figure out what factors most influence project timelines, see how well current estimation methods work, and suggest better models that fit Nepal's unique situation.

To achieve, two different methods are compared: the Bromilow Time-Cost (BTC) model, which relies on traditional linear regression, and the General Regression Neural Network (GRNN), a flexible machine learning tool. This comparison helped to determine most appropriate predictions which is best fit in Nepal's specific settings. The evaluation involved descriptive statistics, several error measures (MAE, MSE, RMSE, MAPE), and R^2 values to judge both explanatory and predictive strength.

Key Informant Interviews with engineers, procurement officers, and project managers engaged in trail bridge projects identify weaknesses in current time estimation practices and explain differences between predicted and actual completion times

B. Study Area

The research covered trail bridge projects located across Nepal's three main geographic regions: the mountain, hill, and Terai. All projects considered for the study were implemented under the supervision of the Suspension Bridge Division (SBD), Nepal.

C. Data Source

This study used both secondary and primary data.

- Secondary data was collected from the official SBD archives, including details from 254 completed trail bridge contracts. Information such as bridge type, geographic location, planned duration, and final cost was recorded. Projects completed between fiscal years 2018/19 and 2021/22 were considered to maintain consistency.

- Primary data was gathered through semi-structure interviews with 10 professionals, including Senior Divisional Engineers, Project Chiefs, procurement specialists, and engineers from the Department of Local Infrastructure (DoLI)/Ministry of Urban Development (MoUD). The interviews covered procurement processes, cost and duration estimation methods, and the challenges faced during implementation.

D. Data Analysis

This study examined the relationship between construction costs and project completion times, using both traditional statistical methods and modern machine learning tools. For each bridge, the data included the total cost, actual completion time, and the bridge's category (D-type, N-type, or MN-type). Due to the skewed data, costs and completion times are transformed using natural logarithms to better highlight relative differences. The projects were then split into four groups: one for each type of bridge and one combining all types. Basic statistics like averages, standard deviations, and ranges were calculated to assess the variability in costs and duration across projects.

The first model tested was the Bromilow Time-Cost (BTC) model, which employs a log-linear regression approach to relate project cost to duration. This model was implemented using Ordinary Least Squares (OLS) regression, with R^2 used to measure the proportion of variation in duration explained by cost. As linear models often cannot fully reflect the complexities of construction projects, the General Regression Neural Network (GRNN) was also applied. The GRNN can manage complex, nonlinear, and multi-dimensional relationships without requiring a predefined formula in advance. The BTC model was analyzed using Microsoft Excel, while the GRNN model was developed with DTREG software.

To measure accuracy of models, four key metrics were used: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These measures reveal how far the predicted times deviated from the actual completion times. Separate analyses were conducted for each bridge type and for the combined dataset to evaluate differences across project categories. Finally, a direct comparison between BTC and GRNN was made to determine which provided more reliable predictions for trail bridge construction in Nepal.

To strengthen and interpret the findings, particularly the low R^2 values, the study incorporated insights from the KIIs. The qualitative data was analysed narratively to identify recurring issues and contextual factors influencing construction timelines.

Iii. Results And Discussion

A. Descriptive Statistics of Time and Cost of Bridges

Table I presents the descriptive statistics of project costs for three project types: D-type, N-type, and MN-type. D-type projects have an average cost of 125.17 units, with a standard deviation of 105.02, and costs ranging from 31.64 to 842.20 across 151 samples. Similarly, N-type projects show a higher average cost of 165.00 units and slightly lower variability (SD = 84.45), with values between 10.00 and 410.87 based on 88 observations. In contrast, MN-type projects, based on only 15 cases, have the highest average cost of 614.49 units and the greatest variation (SD = 566.10), with costs ranging from

105.02 to 2463.97. Overall, MN-type projects tend to be more expensive and show greater cost variation compared to D-type and N-type projects.

Table I: Descriptive Statistics of Cost (in '00000 NRs.)

Project Types	Mean	Standard Deviation (SD)	Maximum	Minimum	Number of Samples
D-type	125.17	105.02	842.20	31.64	151
N-type	165.00	84.45	410.87	10.00	88
MN-type	614.49	566.10	2463.97	105.02	15

Table II summarizes the descriptive statistics of project completion time across D-type, N-type, and MN-type projects. D-type projects have an average duration of 740.12 days with a standard deviation of 261.10, ranging from 192 to 1506 days. Similarly, N-type projects show a slightly lower mean of 712.55 days and a comparable variability (SD = 269.48), with durations ranging from 214 to 1499 days. In contrast, MN-type projects, based on 15 observations, have the longest average duration of 908.33 days and the highest variability (SD = 303.92), with time ranging from 563 to 1460 days. Overall, MN-type projects tend to take longer and vary more in duration compared to D-type and N-type projects.

Table II: Descriptive Statistics of Time (in days)

Project Types	Mean	SD	Maximum	Minimum
D-type	740.12	261.10	1506.00	192.00
N-type	712.55	269.48	1499.00	214.00
MN-type	908.33	303.92	1460.00	563.00

B. Assessment of the Bromilow Time–Cost Model

Table III presents the analysis of Bromilow's equation results. The derived parameters include the constant (K), the slope (B), and key performance statistics such as the coefficient of determination (R^2), F-statistics, p-values, and RMSE values. These regression results provide insight into how well project cost predicts construction time across the different bridge types. The summary of regression analysis is presented in Table III.

Table III: Summary of Regression Analysis

Type of Bridge	Ln(K)	K	B	R^2	F-stat	p-value	RMSE
D-type	6.77	871.31	-0.05	0.01	0.91	0.34	0.36
N-type	6.60	735.09	-0.02	0.001	0.09	0.77	0.40
MN-type	6.18	482.99	0.09	0.05	0.72	0.41	0.31
Overall	6.48	651.97	0.01	0.0005	0.12	0.72	0.37

The analysis of the results from Bromilow's equation is shown in Table III. The coefficient of determination (R^2) for D-type, N-type, MN-type, and the combined types of trail bridges are 0.01, 0.001, 0.05, and 0.0005, respectively. Cost explains only 1%, 0.1%, 5%, and 0.05% of the variation in duration for D-type, N-type, MN-type, and the combined bridge types, respectively, with the remainder (99%, 99.9%, 95%, and 99.95%) due to other.

Cost explains only 1%, 0.1%, 5%, and 0.05% of the variation in duration for dismantled, new, modified new, and combined bridge types, respectively, with the remainder due to other factors

In general, the R^2 statistic measures the proportion of variance in the dependent variable that can be explained by the independent variable in the regression model. While no rigid rule dictates an acceptable R^2 value, previous studies have reported considerably higher R^2 values. For example, Guo et al. [15] found BTC model R^2 values between 0.337 and 0.849 across different infrastructure projects, and Jarkas [16] noted acceptable model fits with R^2 exceeding 0.60. In contrast, the R^2 values reported here are well below these benchmarks, indicating a poor model fit for the Nepalese trail bridge cost estimation.

The F-statistic assesses whether the regression model as a whole is statistically significant. A value greater than 1, with a p-value less than 0.05, typically indicates that the model reliably predicts the dependent variable [16], [17]. However, as shown in Table III, the F-values for all bridge types are below 1, and their corresponding p-values are much greater than 0.05. This reinforces that none of the regression models are statistically significant.

The analysis underscores the central role of the intercept in explaining variations in construction time, indicating that a substantial portion of the variance is captured by baseline conditions independent of cost. This suggests that project duration in trail bridge construction may be more strongly influenced by fixed contextual factors such as geographic challenges, mobilization delays, and administrative procedures than by variations in financial expenditure. Although cost exhibits a weak influence on time, the relationship is not statistically significant, implying that cost alone may not serve as a reliable predictor of construction time in this context.

While the Bromilow Time-Cost (BTC) model has been widely validated in infrastructure studies globally, as outlined in Table III, its application to trail bridge projects in Nepal appears inadequate. This finding contrasts with prior studies in Nepal, including those by Basnet [18], Mishra et al. [19], and Pokhrel et al. [14], who reported the model's applicability to road and bridge projects. The divergence may stem from the distinct nature of trail bridge projects, which are typically small-scale, community-based, and executed in remote areas where logistical and environmental factors override financial planning. Notably, similar limitations of the BTC model have been observed in other developing countries. For instance, Ameyaw et al. [20] reported that the BTC model failed to provide reliable predictions for building project durations in Ghana, citing variability in contractor capacity, resource accessibility, and permitting processes as key obstacles.

Table IV: Regression Analysis Results

Type of Bridge		Coefficients	Standard Error	t Stat	P- value
D-type	Intercept	6.77	0.23	28.92	0.000
	Cost variable	-0.05	0.05	-0.96	0.340
N-type	Intercept	6.60	0.35	19.07	0.000
	Cost variable	-0.02	0.07	-0.30	0.770
MN-type	Intercept	6.18	0.69	8.96	0.000
	Cost variable	0.09	0.11	0.85	0.410
Combined	Intercept	6.48	0.16	39.83	0.000
	Cost variable	0.01	0.03	0.35	0.720

C. General Regression Neural Network (GRNN) Assessment

Table V shows that for D-type bridges, the mean of the log-transformed final cost is 4.63 with a standard deviation of 0.58, while the mean log-transformed construction time is 6.54 with a standard deviation of 0.35. For N-type bridges, the mean final cost is 4.95 (SD = 0.61) and the mean construction time is 6.49 (SD = 0.39). For MN-type bridges, the mean cost is 6.15 (SD = 0.72), and the mean time is 6.76 (SD = 0.30). For the combined dataset, the mean cost is 4.83 (SD = 0.70) and the mean time is 6.54 (SD = 0.37).

Table V. Minimal, maximal, mean value, and standard deviation of the predictors and the target variable.

Type of Bridge	Variables	Minimum	Maximum	Mean	SD
D-type	Ln (Final Cost)	3.45	6.74	4.63	0.58
	Ln (Final Time)	5.26	7.32	6.54	0.35
N-type	Ln (Final Cost)	2.30	6.02	4.95	0.61
	Ln (Final Time)	5.37	7.31	6.49	0.39
MN-type	Ln (Final Cost)	4.65	7.81	6.15	0.72
	Ln (Final Time)	6.33	7.29	6.76	0.30
Combined	Ln (Final Cost)	2.30	7.81	4.83	0.70
	Ln (Final Time)	5.26	7.32	6.54	0.37

Table VI presents the performance of the General Regression Neural Network (GRNN) model across different bridge types using the correlation coefficient (R) and coefficient of determination (R^2). The results highlight considerable variation in the model's predictive strength depending on the bridge type.

For D-type bridges, the model yielded an R^2 of 0.025, indicating that only 2.5% of the variability in construction time is explained by the GRNN. Similarly, for N-type bridges, the R^2 was 0.0025, meaning that less than 1% of the variation in time is accounted for. These extremely low R^2 values suggest that the GRNN model fails to capture meaningful patterns in the data for these two categories. Despite a reasonable number of observations, the model's explanatory power is almost negligible. This may be attributed to high variability in project execution, diverse site conditions, or unmeasured contextual factors, such as contractor efficiency, transportation constraints, or localized delays that were not included in the model's input features.

By contrast, for MN-type bridges, the GRNN model showed significantly improved performance, with an R^2 of 0.21, meaning that 21% of the variability in construction time is captured. Although still moderate, this level of explained variance is substantially higher than that of the D- and N-type bridges, indicating a better model fit and more stable pattern of prediction. Interestingly, this improvement occurred despite a smaller sample size for MN-type bridges, suggesting that projects within this category may exhibit more uniform construction characteristics or better-aligned cost-time patterns. The higher R^2 for MN-type bridges implies that the GRNN model may be better suited to capturing relationships in more consistent or standardized project types.

For the combined dataset, which includes all bridge types, the R^2 was 0.04, showing that only 4% of the variability in construction time is explained. This low R^2 underscores the difficulty of generalizing across diverse project types using a single model, as the combined dataset likely introduces heterogeneity in bridge design, site location, construction approach, and logistical challenges. These complexities may weaken the model's ability to learn consistent patterns, further supporting the need for type-specific or stratified models when applying machine learning to construction time prediction.

Table VI: Regression Results of Model for the N, D, MN, & Combined Types of Bridges

Type of Bridge	R	R^2
D	0.16	0.025
N	0.05	0.0025
MN	0.46	0.21
Combined	0.2	0.04

In terms of predictive accuracy, MAPE values further support the relative strength of the model for MN-type bridges. The GRNN achieved MAPE values of 4.44% for D-type, 4.83% for N-type, and a lower 3.29% for MN-type bridges. The combined MAPE was 4.54%, which is well within the 10–20% range generally considered acceptable for good forecasting performance [21]. Notably, although the MN-type bridges had fewer data points, the model yielded both the highest R^2 and the lowest MAPE, indicating better consistency and accuracy for this category.

Several studies have reported the strong performance of GRNN in predicting construction time and cost. For example, Petruseva et al. [7] found GRNN effective for early-stage planning of building projects, while Naik and Radhika [22] reported minimal errors between actual and ANN-predicted outputs. However, these findings differ from the present study, likely due to contextual differences. Unlike standardized building projects, trail bridge construction in Nepal involves remote locations, community-based labor, and logistical challenges, which introduce greater variability. Additionally, the current model used fewer input variables, which may have limited its explanatory power. These factors suggest that while GRNN is promising, its effectiveness depends on project type, data quality, and environmental factors at the construction sites.

D. Predictive Accuracy of BTC Model and GRNN Model

Table VII summarizes the predictive performance of the Bromilow Time-Cost (BTC) model and the General Regression Neural Network (GRNN) model using key metrics: the coefficient of determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). These metrics provide a comprehensive evaluation of each model's ability to explain variability in construction time and to minimize prediction error across four bridge categories: D-type, N-type, MN-type, and the combined.

Table VII: Summary of R^2 and Error Metrics

Type of Bridge	R^2		MAE		MSE		MAPE		RMSE	
	GRNN	BTC	GRNN	BTC	GRNN	BTC	GRNN	BTC	GRNN	BTC
D	0.025	0.01	0.29	0.29	0.12	0.12	4.44	4.52	0.35	0.35
N	0.0025	0.001	0.31	0.31	0.15	0.15	4.83	4.82	0.39	0.39
MN	0.21	0.05	0.23	0.25	0.07	0.08	3.29	3.69	0.27	0.29
Combined	0.04	0.0005	0.29	0.30	0.13	0.14	4.54	4.57	0.36	0.37

In terms of model explanatory power, R^2 values reveal that the GRNN consistently outperforms the BTC model across all bridge types. For D-type bridges, GRNN achieved an R^2 of 0.025, marginally higher than the 0.01 reported for BTC, indicating both models explain very little of the variation in construction time. Similarly, for N-type bridges, GRNN's R^2 of 0.0025 slightly exceeds BTC's 0.001, yet both values are close to zero, confirming that these models are ineffective in capturing variance for these bridge types.

However, a notable difference appears for MN-type bridges, where GRNN achieves a significantly higher R^2 of 0.21, compared to 0.05 for BTC. This suggests that GRNN explains 21% of the variance in construction time substantially better than BTC's 5% and demonstrates moderate predictive ability for this bridge type. For the combined dataset, the GRNN model again shows stronger performance with an R^2 of 0.04, while BTC yields a near-zero value of 0.0005, indicating its inability to account for variability when bridge types are aggregated.

Despite the overall low R^2 values, which indicate that neither model offers strong explanatory power, the GRNN model provides a clear advantage in terms of variance explanation across all categories, particularly for MN-type and combined datasets. As reported by Pokhrel and Acharya [17], higher R^2 values reflect a model's ability to explain variability in the target variable and signal a better fit. Thus, although modest, GRNN's superior R^2 values indicate improved alignment between predicted and actual construction times compared to BTC.

Error metrics such as MAE, MAPE, and RMSE show that both GRNN and BTC perform similarly for D-type and N-type bridges, with minimal differences (e.g., MAPE ≈ 4.4%–4.8%, RMSE ≈ 0.35–0.39), indicating limited predictive accuracy. In contrast, GRNN outperforms BTC for MN-type bridges across all metrics (e.g., MAPE: 3.29% vs. 3.69%), suggesting better accuracy for more consistent project types. For the combined dataset, GRNN again shows slightly better performance, highlighting its robustness across diverse bridge types. These results support GRNN's relative advantage in construction forecasting while emphasizing the need for additional predictors to improve model performance in complex environments like rural Nepal.

However, both models exhibit low R^2 values across all bridge types, indicating poor explanatory power. While GRNN provides marginally better prediction accuracy, especially in terms of MAPE and RMSE, the overall results suggest that neither model effectively captures the underlying variability in construction time. This highlights the need for more informative predictors and context-specific modeling

E. Exploring the Factors Behind Model Inadequacy

Key informant interviews reveal that the contract duration for trail bridges in Nepal is not determined by a standardized formula. Instead, it is based on cost estimates, location, and past experience, often assigning 1.5 to 2 years irrespective of cost similarity. For example, remote-area bridges may receive 2-year durations despite low cost, while accessible bridges may be limited to 1.5 years, even with higher costs. In the Terai, bridges with the same estimated cost may differ in duration depending on foundation type.

Despite these practices, projects frequently fail to meet deadlines. Factors contributing to delays include poor planning, inefficient resource use, delayed permits, site-specific challenges, skilled labor shortages, material unavailability, limited contractor capacity, and inadequate funding. External factors such as political instability and adverse weather further compound these issues.

The weak relationship between cost and time and the resulting poor model fit can be attributed to several structural and contextual issues:

- Contract Type: Trail bridges follow turnkey contracts, where cost is fixed, and time extensions do not alter payment, weakening the cost-time linkage.
- Contractor Capacity: Few qualified contractors exist; some misuse mobilization advances or subcontract work to less experienced parties.
- Budget Delays: Insufficient and irregular government funding discourages timely progress.
- Regulatory Loopholes: Frequent changes in construction law allow contractors to exploit extension provisions.
- Labor and Material Shortages: Scarcity of skilled workers and delays in transporting critical materials to remote sites hinder progress.
- Environmental and Social Factors: Difficult terrain, floods, landslides, land disputes, and community conflicts introduce unpredictability into construction timelines.

These findings are consistent with Khadka [23], who identified differing site conditions, labor shortages, and payment delays as key delay factors in trail bridge projects. Similarly, Jarkas [16] found poor contractor performance, client decision delays, and adverse weather to be major causes of project overruns. Comparable inefficiencies in contract management, such as inadequate monitoring and slow decision-making, have been documented in rural road projects [25], contributing to time overruns. In contrast, moderate positive correlations between intended durations and time-cost models were observed in basic hospital constructions [24], suggesting that project type influences model applicability in Nepal's infrastructure sector. Overall, the absence of cost-based contract-time allocation, combined with a range of technical, institutional, and environmental challenges, undermines the validity of cost-time models like BTC and limits the predictive power of GRNN in this context.

Iv. Conclusion

This research examined the link between construction cost and project duration for trail bridges using the Bromilow Time-Cost (BTC) model and the General Regression Neural Network (GRNN). Findings indicate that, although the BTC model is widely applied in Nepal for projects such as bridges and buildings, it is not suitable for forecasting construction timelines in trail bridge works. The model showed a very weak and statistically insignificant correlation between cost and duration. Similarly, the

GRNN model confirmed that cost alone is not a strong predictor of construction time, with low R^2 values pointing to limited explanatory power. However, GRNN produced slightly better prediction results than BTC for all bridge categories. Despite this, neither approach could fully capture the variation in actual completion times, signaling the need for additional predictive variables and more advanced modeling strategies.

Insights from key informants further revealed that trail bridge contract durations are influenced by many factors beyond cost, such as the type of contract, contractor capacity and behavior, funding delays, regulatory conditions, labor and material availability, and site-specific environmental or social issues. Delays often arise from weak planning, inefficient use of resources, shortages of materials or skilled labor, loopholes in regulations, and environmental disruptions. These conditions weaken the cost–time relationship and reduce the effectiveness of predictive models. Based on these findings, the study recommends the development of a more comprehensive framework or set of guidelines that incorporates these diverse influencing factors. Such an approach would help improve the accuracy of contract time estimation and increase the overall efficiency of trail bridge construction in Nepal.

V. Recommendations

Based on the findings, neither the BTC nor the GRNN models adequately explain the relationship between cost and construction time for trail bridge projects in Nepal, making them unsuitable for accurate duration estimation. To improve future modeling, researchers should incorporate additional variables such as location, labor availability, weather, and material supply. Alternative approaches, including advanced machine learning or hybrid models, are recommended. Further studies should stratify data by geographic region and regulatory conditions and examine external factors like economic conditions and policy changes to develop more accurate and context-specific predictive models.

Vi. Acknowledgement

The authors express their gratitude to the Suspension Bridge Division, Ministry of Urban Development, Nepal, for providing access to the archival data on 254 completed trail bridge contracts, which formed the basis of this study. Their cooperation and support were instrumental in facilitating this research.

Vi. Declarations

The authors declare no competing interests.

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