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Machine Learning Models for Estimating Construction Costs of Conventional and Accelerated Bridge Construction Methods

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ABSTRACT: Accelerated bridge construction methods such as prefabricated bridge elements, lateral slides, and self-propelled modular transporters are increasingly adopted to minimize on-site construction time, reduce traffic disruptions, and improve safety and quality of planned projects. To ensure the cost effectiveness of all bridge construction projects, decision makers need to accurately estimate the costs of alternative bridge construction methods during the early design phase with only limited preliminary design data. This paper presents the development and comparison of three novel machine learning models for early-stage cost estimation of both conventional and accelerated bridge construction methods. The models were developed in four steps that focused on gathering a dataset with 396 historical bridge construction projects utilizing both conventional and accelerated bridge construction methods; preparing collected data by defining predicted and predictor variables, classifying and transforming predictor variables, and splitting the data into training and testing sets; training the models using support vector regressor, random forest regressor, and extreme gradient boosting algorithms; and evaluating and validating the performance of the developed models by comparing their predicted values to the true values. The evaluation and validation results indicate that the Extreme Gradient Boosting model outperformed other machine learning models in the five metrics of coefficient of determination, mean absolute percentage error, mean absolute error, median absolute error, and root mean square error. These enhanced machine learning models are expected to assist bridge planners estimating, comparing, and determining the most cost-effective construction method during the early design phase.

1. INTRODUCTION

The American Road and Transportation Builders Association (ARTBA 2023) and the National Research Council Canada (2024) reported that 36% of the U.S. bridges required major repair or replacement and 11% of Canada bridges were in poor or very poor condition. These bridges pose significant safety hazards and traffic disruptions for the travelling public. To address these challenges, there is a large number of ongoing and planned bridge construction projects to repair and rebuild these bridges using either conventional or accelerated bridge construction methods. In the conventional method, all construction activities are performed on-site. The main advantage of this method is that it can be performed without the need for transporting, lifting, or installing heavy prefabricated components. However, it often requires longer partial or full bridge closures, leading to significant traffic delays and increased safety risks for construction crews, as they remain exposed to roadway hazards over longer construction periods.

To overcome the aforementioned challenges of conventional bridge construction method, Accelerated Bridge Construction (ABC) methods such as Prefabricated Bridge Elements (PBE), Lateral Slides (LS), and Self-Propelled Modular Transporters (SPMT) has been increasingly utilized (Jia et al. 2018). In the PBE

method, major structural components are built offsite then transported, lifted, and installed onsite (FHWA 2005), as shown in Figure 1. In the LS method, the new bridge is built parallel to or under existing one, then moved laterally to replace the old bridge using hydraulic systems and/or cables (FHWA 2013), as shown in Figure 1. In the SPMT method, the new bridge is built offsite then moved to its location using high capacity, highly maneuverable transport trailers (FHWA 2007), as shown in Figure 1. The main advantages of these ABC methods are shorter onsite construction durations and traffic delays, while enhancing safety and quality. However, they require longer planning and design time, and additional cost for specialized equipment (El-Rayes et al. 2023; FHWA 2011).

Figure 1. Alternative Bridge Construction Methods

To select the most cost-effective bridge construction method for planned projects, decision makers need to accurately estimate the costs of alternative bridge construction methods during the early design phase with only limited preliminary design data such as bridge length, width, average daily traffic, location type, number of spans, and maximum span length (Juszczyk 2020; Zheng et al. 2023).

2. LITERATURE REVIEW

To assist bridge planners and decision makers in selecting the most cost-effective bridge construction method for planned projects during the early design phase, various studies were developed that focused on estimating the construction cost of specific bridge components or material. For example, Winalytra et al. (2018) developed predictive models to estimate the construction cost of I-girder superstructure. Kim et al. (2009) developed a model to estimate the superstructure cost of prestressed concrete beam bridges. Fragkakis et al. (2010) estimated the material quantities of concrete foundations and superstructures, then multiplied these by unit prices. Aprianti et al. (2021) introduced a cost model for steel-frame bridges. Creese and Li (1995) estimated the cost of timber bridges. Hadi et al. (2017) developed predictive regression model to estimate the range of construction cost of bridge projects utilizing ABC methods.

Despite the contributions of the aforementioned studies, they are incapable of (1) estimating and comparing the construction cost of alternative bridge construction methods including conventional and accelerated bridge construction methods, and (2) evaluating the performance of different machine learning algorithms in enhancing the accuracy of predicting the construction cost of bridge projects during the early design phase.

3. METHODOLOGY

The main objective of this paper is to develop and compare the performance of three novel Machine Learning (ML) models that can be used by bridge planners and decision makers to accurately estimate the construction cost of alternative bridge construction methods during the early design phase. The models are developed in four steps that focused on (1) gathering available historical bridge construction data for both conventional and accelerated bridge construction methods; (2) preparing collected bridge construction data to guarantee its quality and reliability; (3) utilizing the training dataset in developing novel machine learning models for estimating alternative bridge construction costs using extreme gradient boosting, random forest,

and support vector machine algorithms; and (4) evaluating the performance of the developed models. The following sections provide description of each of these four model development steps.

3.1 Collecting Historical Bridge Data

This step focused on gathering available historical bridge construction data utilizing alternative construction methods to create a dataset that can be used to develop the ML models. This collected dataset includes a total of 396 historical bridge projects, as shown in Table 1. These collected bridge projects consist of 198 conventional bridge projects, 157 prefabricated bridge elements projects, 31 lateral slide bridge projects, and 10 self-propelled modular transporter bridge projects. For each of these projects, all related data that were reported to have an impact on bridge construction cost were collected. For example, Essegbey (2021) identified bridge length, bridge width, number of spans, and location type as key cost factors. Hadi et al. (2016) highlighted the influence of average daily traffic, while Dimitriou et al. (2018) reported that design type and maximum span length have an impact on bridge construction cost.(FIU 2024) noted the importance of mobility impact category, construction method, beam material, and project length. Accordingly, twelve predictor variables were collected for each project including project length, bridge width, bridge length, maximum span length, number of lanes, number of spans, average daily traffic, design type, location type, beam material, and mobility impact category, as shown in Figure 2Click or tap here to enter text.. The RSMeans 2024 was then utilized to adjust collected bridge construction cost to the 2024 and national average to account for variations in construction year and location using Eq. 1 and Eq. 2 (RSMeans 2024).

$$[1] \text{ Current year cost (\$)} = \text{Bridge Cost in Year A} \times \frac{\text{Cost Index for Current Year}}{\text{Cost Index for Year A}}$$

$$[2] \text{ Cost in Location A} = \text{Cost in Location B} \times \frac{\text{Location Factor for Location A}}{\text{Location Factor for Location B}}$$

Table 1. Sample of collected bridge projects

Project ID	Zip Code	Year Built	Method	…	Bridge Width (ft.)	Bridge Length (ft.)	Actual Total Cost ($)	Actual Unit Cost ($/sf)	Adjusted 2024 Unit Cost ($/sf)
043-70908	618	2023	Conventional	…	32.0	273.0	3,830,422.6	438.5	438.0
069-0520	626	2015	Conventional	…	39.2	382.0	3,336,953.9	222.8	345.1
…	…	…	…	…	…	…	…	…	…
Kimberly Br.	988	2008	PBE	…	29.0	42	237,510.0	195.0	368.7
162-72G06	625	2023	PBE	…	40.0	84	2,211,000.0	658.0	666.5
…	…	…	…	…	…	…	…	…	…
Lafayette Br.	551	2015	LS	…	67.0	3435	80,132,545.0	348.2	511.3
LP 345	782	2016	LS	…	359.5	65.0	7,300,000.0	312.4	577.4
…	…	…	…	…	…	…	…	…	…
I-94 2nd Ave.	550	2022	SPMT	…	96.5	314.0	26,000,000.0	858.1	850.9
Phillipson Br.	13	2010	SPMT	…	50.7	120.7	3,250,000.0	531.5	968.8
…	…	…	…	…	…	…	…	…	…

3.2 Preparing Collected Bridge Data

The collected historical bridge data in the previous step was prepared to guarantee its quality and reliability in four sup steps that focused on (1) specifying predicted and predictor variables; (2) grouping predictor

variables into categorical and numerical variables; (3) transforming predictor variables to improve the performance of ML models; and (4) splitting transformed data into training and testing datasets. First, the predicted variable was specified as the square foot cost of bridge construction projects while twelve predictor variables were specified to have impact on bridge construction cost including total project length, construction method, bridge length, bridge width, number of lanes, maximum span length, number of spans, average daily traffic, location type, design type, deck material, and mobility impact category, as shown in Figure 2. Second, these twelve predictor variables were grouped based on their type into (i) numerical variables such as bridge length, width, project length, and maximum span length; and (ii) categorical variables such as concrete or steel deck, and urban or rural location. Third, each predictor variable was transform based on their type using min-max normalization technique for all numerical variables and one-hot encoding technique for all categorical variables (Daly et al. 2016). Fourth, the transformed data was divided into 80% training and 20% testing datasets. The training dataset was then used to train machine learning models while the testing dataset was used to validate the performance of the developed models.
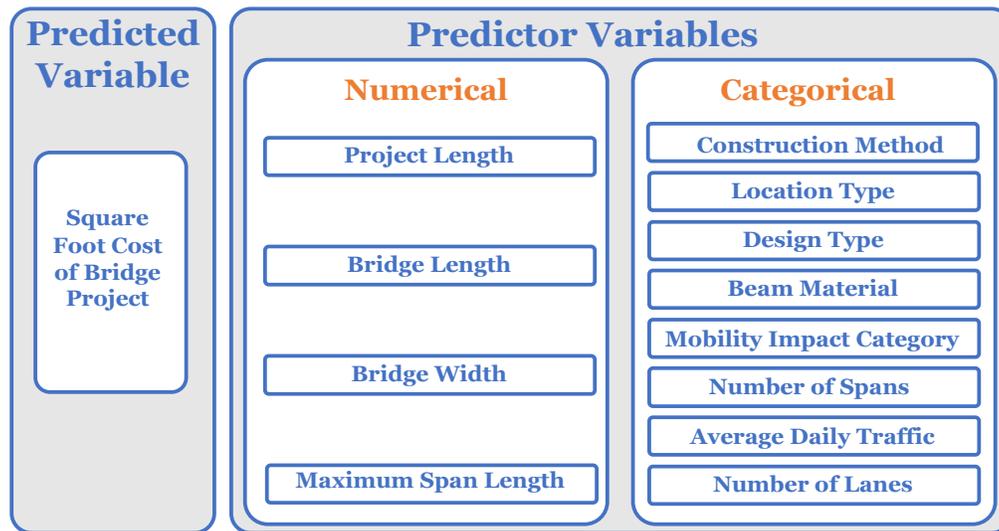

Figure 2. Predicted and Predictor Variables

3.3   Developing Machine learning Predictive Models

The training dataset was used to develop three novel ML models that can be used in predicting the construction cost of alternative bridge construction methods including conventional and accelerated bridge construction methods. The models use twelve design variables that are available during the early design phase such as bridge length, width, and maximum span length, as shown in Figure 2. These models were developed using three machine learning algorithms that are widely used for similar early cost prediction problems: (1) Support Vector Regressor (SVR) (Juszczyk 2020; Meharie and Shaik 2020); (2) Random Forest Regressor (RFR) (Meharie and Shaik 2020; Zheng et al. 2023); and (3) Extreme Gradient Boosting (XGBoost)(Alashari et al. 2023; Zhang et al. 2023). These algorithms were selected based on their strong performance in previous studies and their suitability for modeling nonlinear relationships in small-to-medium-sized datasets, which is common in early design-phase data. Click or tap here to enter text.The SVR model fits a regression function within a specified tolerance while maximizing the margin (Awad and Khanna 2015). The RFR algorithm constructs an ensemble of decision trees in parallel, combining their predictions to enhance accuracy (Breiman 2001). The XGBoost model constructs sequential decision-tree models to correct the errors of previous models and incorporates regularization parameters to avoid overfitting. (Alashari et al. 2023; Chen and Guestrin 2016).

3.4   Evaluating Developed Models

The performance of the developed machine-learning models in predicting the costs of conventional and accelerated bridge construction methods using twelve early-stage design variables was evaluated and

validated based on five main metrics: (i) coefficient of determination (R^2), as shown in Eq. 3; (ii) mean absolute percentage error (MAPE), as shown in Eq. 4; (iii) mean absolute error (MAE) as shown in Eq. 5; (iv) median absolute error (Med AE), as shown in Eq. 6; and (v) root mean square error (RMSE), as shown in Eq. 7. First, the performance of the ML models was evaluated using the training dataset based on their performance in the coefficient of determination (R^2). The results shows that The XGBoost model achieved the highest R^2 of 99.97%, as shown in Table 2. Second, the performance of the developed ML models was validated using the testing dataset by comparing their predicted values to the true values. The outcome of this validation also confirms that XGBoost model outperformed other ML models as it achieved the lowest mean absolute percentage error of ($MAPE$ = 14.97%), mean absolute error (MAE = \$68.43/sf), and median absolute error ($Med.AE$ = \$38.51/sf); and root mean square error (RMSE = \$113.83/sf), , as shown in Figure 3 and Table 2.

$$[3] \; R^2 = \frac{\Sigma(\hat{Y}-\overline{Y})^2}{\Sigma(Y-\overline{Y})^2}$$

$$[4] \; MAPE = Average\left(\frac{|\hat{Y}-Y|}{|Y|}\right) \times 100$$

$$[5] \; MAE = \Sigma_{i=1}^{n}\left(\frac{|\hat{Y}-Y|}{n}\right)$$

$$[6] \; Med.\,AE = median\left(|\hat{Y}-Y|\right.$$

$$[7] \; RMSE = \sqrt{\Sigma_{i=1}^{n}\left(\frac{(\hat{Y}-Y)^2}{n}\right)}$$

Where R^2 is the coefficient of determination, $\hat{Y}$ is the predicted cost, Y is the actual cost, $\overline{Y}$ is the mean of actual costs, and n is number of observations.

Table 2. Performance of developed machine learning models

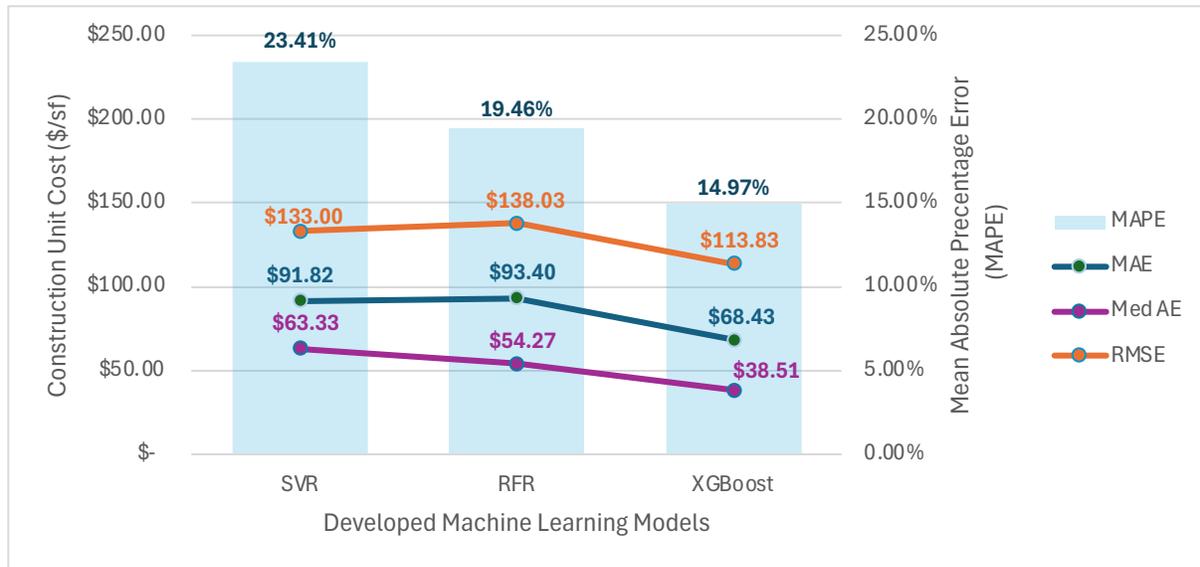| Developed ML Algorithms	Training Dataset	Testing Dataset			
	R^2 (%)	MAPE (%)	MAE ($/sf)	Med AE ($/sf)	RMSE ($/sf)
SVR	84.61	23.41	91.82	63.33	133.00
RFR	90.37	19.46	93.40	54.27	138.03
XGBoost	99.97	14.97	68.43	38.51	113.83

Figure 3. Performance of the developed machine learning models

4. CONCLUSIONS

Three machine learning (ML) models were developed to assist bridge planners in estimating the costs of alternative bridge construction methods including conventional construction and prefabricated bridge elements (PBE), lateral slide (LS), and self-propelled modular transporters (SPMT) using twelve preliminary variables available during the early design phase. The ML models were developed in four main steps that focused on (1) gathering 396 historical bridge construction data for both conventional and accelerated bridge construction methods; (2) preparing collected bridge construction data to ensure its quality and reliability; (3) utilizing the training dataset in developing novel machine learning models for estimating alternative bridge construction costs using Support Vector Regressor (SVR); Random Forest Regressor (RFR); and Extreme Gradient Boosting (XGBoost); and (4) evaluating and validating the performance of the developed ML models. The results of evaluation and validation step showed that the XGBoost model outperformed other models in all metrics as it achieved the highest R^2 of 99.97% and the lowest $MAPE$ of 14.97%, MAE of $68.43/sf, $Med.\ AE$ of $38.51/sf, and $RMSE$ of $113.83/sf. These results are expected to support decision makers and bridge planners in improving the accuracy and reliability of the estimated cost of alternative bridge construction methods during the early design phase.

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