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Transportation Infrastructure Precast Innovation Center (TRANS-IPIC)

University Transportation Center (UTC)

Optimizing the Planning of Precast Concrete Bridge Construction Methods to Maximize Durability, Safety, and Sustainability
UI-23-RP-05

Final Report

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Executive Summary:

The federal government has enacted in 2021 a $1 trillion infrastructure bill that includes $110 billion in additional funding for repairing and rebuilding aging and deteriorating US bridges and roadways. To maximize the cost-effectiveness of these investments, state DOTs are often confronted with a number of challenges including how to (a) select the most cost-effective construction method from a set of feasible alternatives including conventional cast-in-place, precast bridge elements, precast lateral slide, and precast self-propelled modular transporter; (b) accurately estimate bridge construction cost in the early design phase with limited data; (c) efficiently plan the transportation and installation of precast bridge components; and (d) optimize the impact of important construction decisions on multiple objectives including safety and construction cost. To address these challenges, a research project funded by the Transportation Infrastructure Precast Innovation Center (TRANS-IPIC) was conducted to develop machine learning and multi-objective optimization models to provide state DOTs with much-needed support to accurately estimate and compare construction costs of alternative bridge construction methods during the early design phase with limited data available and optimize the planning of these alternative bridge construction methods during the pre-construction phase to maximize safety of the traveling public and construction workers while minimizing the total cost of planned projects. This report presents the preliminary findings of this research project.

The main tasks of this project include: (1) developing and comparing the performance of six novel machine learning models for predicting the construction cost of conventional and precast accelerated bridge construction methods during the early design phase; and (2) creating a novel multi-objective optimization model to optimize the planning of alternative bridge construction methods during the pre-construction phase to maximize safety of the traveling public and construction workers while minimizing the total cost of planned projects. The educational outreach activities of this project included training a PhD student and sharpening her skills in data analysis, machine learning, and optimization modeling; developing educational modules for construction engineering courses with over 120 annual students; and presenting preliminary research findings at the TRANS-IPIC first workshop and monthly webinar in 2024. The workforce development activities included attending the Transportation Infrastructure Precast Day (TIP Day) at UIUC on November 1, 2024, to explore advancements in precast construction and maintenance, and actively participating in online TRANS-IPIC monthly webinars. The outcome of this research project will be published in four papers including one accepted journal paper, a second journal paper that is currently under review, a third journal paper that will be submitted to a leading journal, and a conference paper that will be published in the proceedings of the ASCE Construction Research Congress in 2025.

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Statement of Problem

The aging and deteriorating conditions of US bridges prompted the federal government to enact a $1 trillion infrastructure bill in 2021 that includes $110 billion in additional funding for repairing and rebuilding US bridges and roadways (White House, 2022). State DOTs need to optimize the use of these investments to accomplish multiple objectives including maximizing durability, safety, sustainability, and mobility while minimizing life-cycle cost. This presents DOTs with a number of challenges including how to (1) select the most cost-effective bridge construction method from a set of feasible alternatives including conventional cast-in-place, precast bridge elements or systems, precast lateral slide, and precast self-propelled modular transporter, for each planned project based on its specific conditions and requirements; (2) accurately predict the cost of these alternative bridge construction methods during the early project phase with limited design data; (3) optimize the planning of transportation and onsite installation of PC elements during the pre-construction phase; and (4) quantify and optimize the impact of important construction planning decisions on multiple objectives including safety and life-cycle cost.

Research Plan/Tasks

Task 1: Develop Machine Learning Models for Estimating Cost of Conventional and Accelerated Bridge Construction Methods During Early Design Phase

This task focused on developing and comparing the performance of six novel Machine Learning models for predicting the construction cost of conventional construction and ABC methods during the early design phase. The six ML models were developed in four main phases that focus on (1) collecting available bridge construction data for conventional and accelerated bridge construction methods; (2) preprocessing the collected bridge construction data to identify, classify, clean, transform, and split all predicted and predictor variables data into training and testing sets; (3) developing six novel ML models for estimating bridge construction cost using Ordinary Least Square (OLS), LASSO Regression (LR), Ridge Regression (RR), Random Forest (RF), Gradient Boosting (GB), and Extreme Gradient Boosting (XGBoost) using the training set; and (4) evaluating and validating the performance of the developed ML models, as shown in Figure 1.

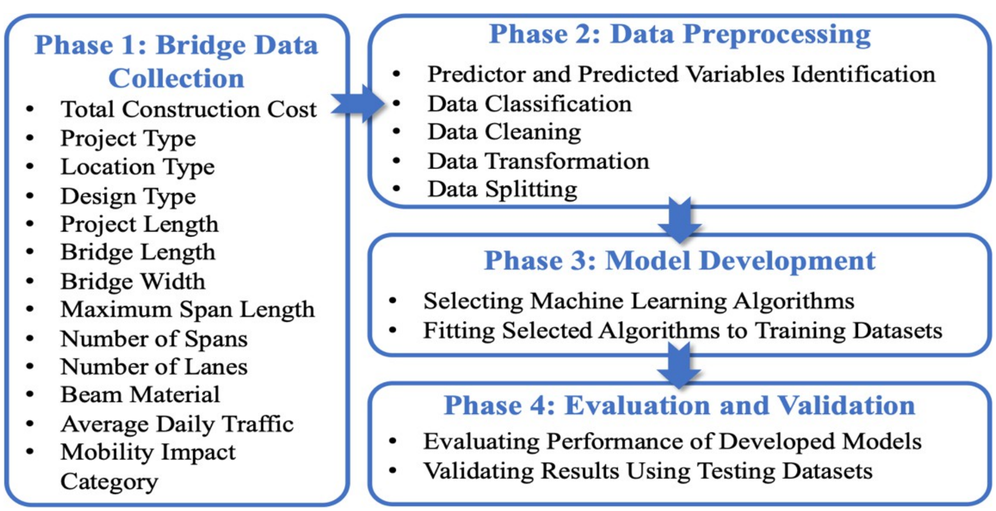


Figure 1. Development phases of machine learning models.

1.1 Bridge Data Collection

This phase developed a dataset that was used to train and evaluate the performance of the machine learning models for estimating the construction cost of alternative bridge construction methods during the early design phase. A total of 413 bridges that were constructed between 1992 and 2024 across 29 US states were collected and analyzed (FHWA 2013; FIU 2024; IDOT 2024a; b; UDOT 2024; VTRANS 2017). The dataset includes 202 conventional bridge projects, 168 prefabricated bridge elements projects, 33 lateral slide bridge projects, and 10 self-propelled modular transporter bridge projects, as shown in Table 1. All related bridge data that were reported to have significant impact on bridge construction cost were collected such as bridge length, width, number of spans, maximum span length, average daily traffic, as shown in Figure 1 (Essegbey 2021; Hadi et al. 2016; Juszczyk 2020; Yang and Qiu 2020a). The collected construction cost data was adjusted to 2024 and national average to account for variations in construction year and location using the 2024 RSMeans as shown in Eq. (1) and (2) (Doheny 2023). These adjusted unit cost for the 413 bridge projects were then utilized to calculate the average cost per square foot for each alternative bridge construction method, as shown in Table 1.

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

$$Cost\ in\ Location\ A = Cost\ in\ Location\ B \times \frac{Location\ Factor\ for\ Location\ A}{Location\ Factor\ for\ Location\ B} \tag{2}$$

Table 1. Statistical analysis of unit costs of alternative bridge construction methods.

Bridge Construction Method	Dataset (projects)	Avg. Unit Cost ($/sf)	Min. Unit Cost ($/sf)	Max. Unit Cost ($/sf)	Standard Deviation (ft.)
Conventional Staged	202	346.9	124.8	849.6	116.1
PBE	168	370.7	113.5	856.7	546.1
Lateral Slide	33	1031.3	239.5	1965.4	154.0
SPMT	10	1166.1	321.0	1927.1	681.7

1.2 Data Preprocessing

This phase focused on preprocessing the raw data that was collected in the previous phase for alternative bridge construction methods to ensure its quality and usability. This was accomplished in five main steps that focused on (1) identifying predicted and predictor variables, (2) categorizing predictor variables to categorical and numerical variables, (3) cleaning collected data by detecting and deleting outliers, (4) transforming predictor variables to enhance their performance in the machine learning models, and (5) dividing the transformed data into training and testing sets, as shown in Figure 1.

First, the square foot cost of bridge construction projects was selected as the predicted variable, as it enables the estimation of total bridge costs using bridge length and width, which are readily available during the early design phase. Twelve predictor variables were identified to have an impact on bridge construction cost including construction method, bridge width, bridge length, number of lanes, number of spans, maximum span length, total project length, average daily traffic (ADT), design type, location type, deck material, and mobility impact category (MIC), as shown in Table 2.

Table 2. Types and values for predictor variables.

Predictor Variable	Type	Value
Total Project Length	Numerical	Total project length in feet
Bridge Length	Numerical	Bridge length in feet
Bridge Width	Numerical	Bridge width in feet
Maximum Span length	Numerical	Max span length of the bridge in feet
Average Daily Traffic (ADT)	Categorical	Less than 1,000, 5,000, 10,000, 20,000, 50,000, 100,000, or more than 100,000 vehicles/day
Number of Lanes	Categorical	1, 2, 3, 4, or more than 4 lanes
Number of Spans	Categorical	1, 2, 3, 4, or more than 4 spans
Beam Material	Categorical	Concrete or steel
Design Type	Categorical	Beam, slab, girder, arch, truss, or culvert.
Location Type	Categorical	Urban or rural
Mobility Impact Categories (MIC)	Categorical	Tier 1 (within 1 day), Tier 2 (within 3 days), Tier 3 (within 2 weeks), Tier 4 (within a month), Tier 5 (within 3 months), Tier 6 (longer than 3 months), or 7 (for conventional staged projects)

Second, the identified twelve predictor variables were categorized in two main groups based on their types: numerical and categorical. The numerical variables represent all variables that have measurable quantity including bridge length, bridge width, project length, and maximum span length, as shown in Table 3. The categorical variables represent all variables that can have one of several possible values such as urban or rural location, new or replacement bridge, and steel or concrete beam, as shown in Table 3Table 2. A statistical analysis was conducted on the collected bridge data for these twelve predictor variables to evaluate the comprehensiveness and distribution of the collected dataset, as shown in Table 3 and Figure 2. The flow distribution of bridge construction methods and their subdivision based on the values of each categorical variable is illustrated in Figure 3. For example, the number of prefabricated bridge projects in the dataset is split almost equally between urban (82 projects) and rural (86 projects) locations, as shown in Figure 3 (a). The same figure shows that the dataset includes more conventional bridge projects in urban locations (134 projects) than in rural areas (68 projects). Conversely, the dataset includes more lateral slide and SPMT bridge projects in rural locations, with 19 and 6 projects respectively, compared to 14 and 4 projects in urban areas, as shown in Figure 3 (a).

Table 3. Statistical analysis of numerical predictor variables.

Numerical Variable	Average (ft.)	Min (ft.)	Max (ft.)	Standard Deviation (ft.)
Bridge Length	231.90	21.70	3375.00	339.3
Bridge Width	43.90	8.50	359.50	26.8
Maximum Span Length	81.00	10.00	727.00	58.8
Project Length	819.40	21.70	10261.20	1,036.40

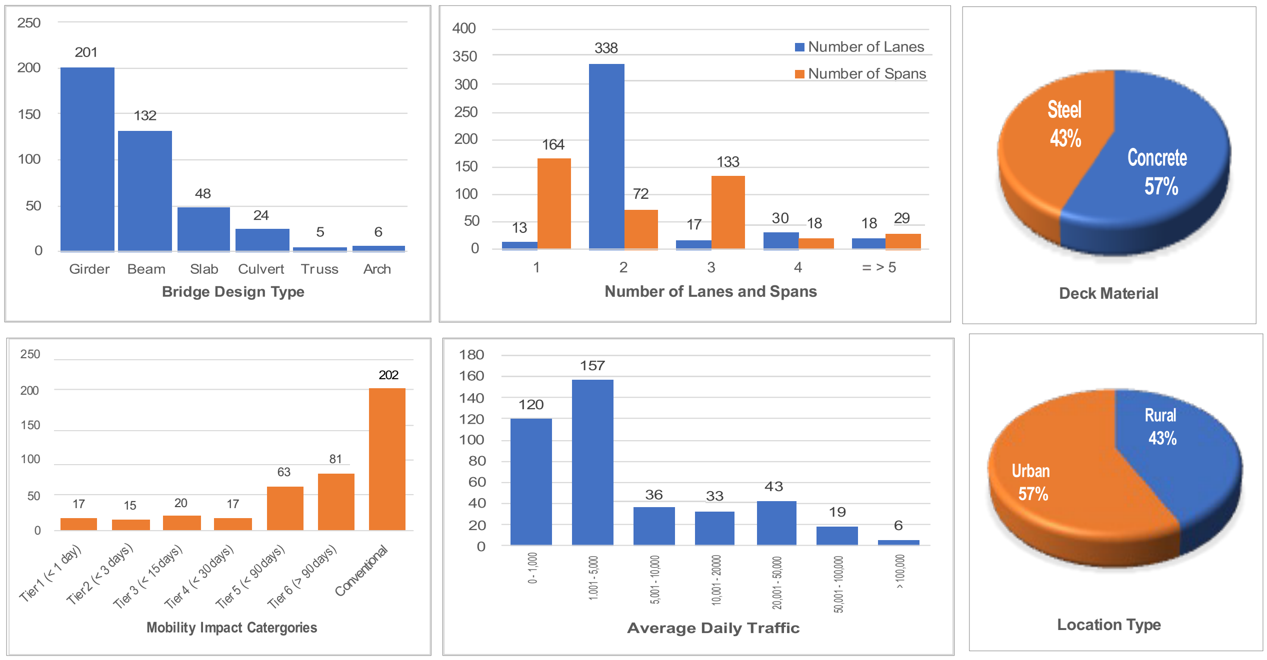
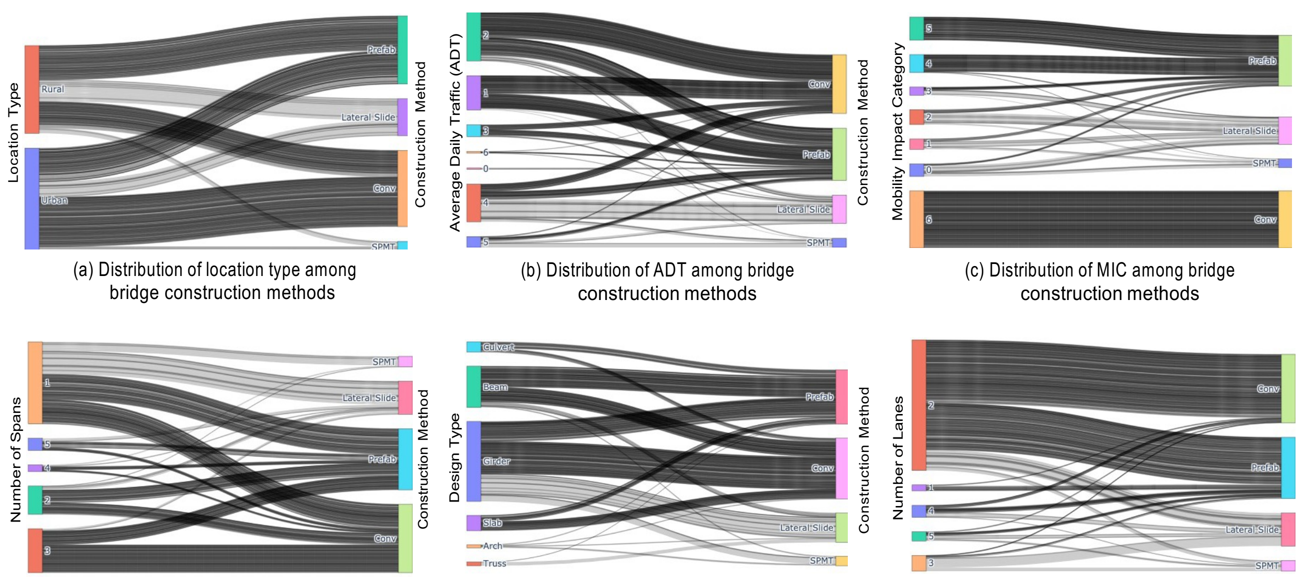


Figure 2. Variability of collected categorical predictor variables by bridge construction methods



(a) Distribution of location type among bridge construction methods

(b) Distribution of ADT among bridge construction methods

(c) Distribution of MIC among bridge construction methods

(d) Distribution of number of spans among bridge construction methods

(e) Distribution of design type among bridge construction methods

(f) Distribution of number of lanes among bridge construction methods

Figure 3. Sankey diagrams of categorical variables by bridge construction methods

Third, the collected dataset was cleaned by detecting and deleting outliers to enhance model performance by reducing noise and minimizing errors caused by these outliers. Frequency distribution histograms were created for each numerical variable to detect outliers, as shown in Figure 4. This cleaning step resulted in the exclusion of 16 outlier bridge projects including 3 conventional construction, 11 prefabricated, and 2 lateral slide bridge projects.

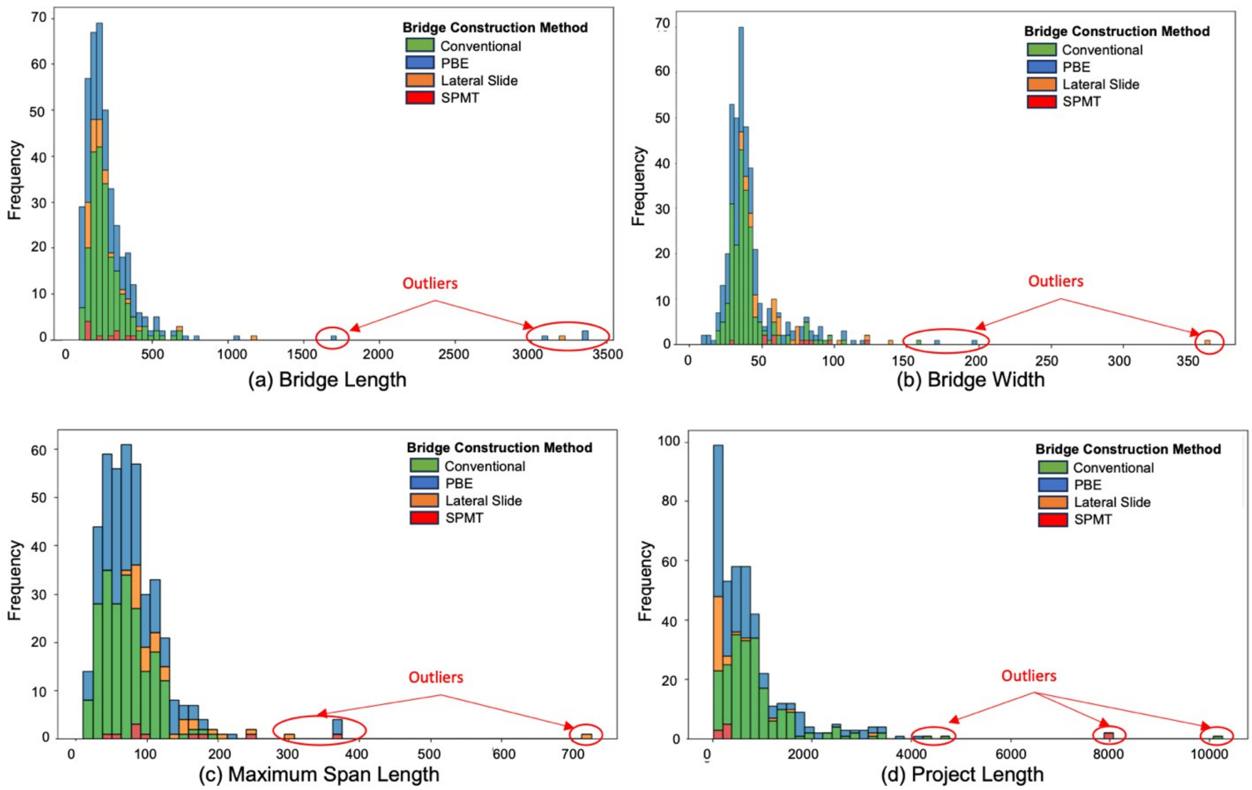


Figure 4. Identifying outliers using histograms of numerical variables

Fourth, the categorical and numerical variables were transformed to enhance the performance of the machine learning models using the using min–max normalization technique for all numerical variables, and the one hot encoding method for all categorical variables (Daly et al. 2016; Hardy 1993).

Fifth, the transformed data were divided into training and testing sets that include 80% and 20% of the cleaned dataset of 397 historical bridge projects, respectively. The stratified train-test split method was utilized to maintain the proportions of bridge projects for each construction method in the original dataset in both the training and testing sets. The training set was utilized to train the machine learning models and evaluate their performance, while the testing set was utilized to validate their performance on unseen data.

1.3 Models Development

This phase focused on the development of six ML models that can be used to estimate the construction cost of conventional and precast accelerated bridge construction methods during the early design phase. These models were developed using six ML algorithms that are widely used for similar cost prediction problems including Ordinary Least Square (OLS), LASSO Regression (LR), Ridge Regression (RR), Random Forest (RF), Gradient Boosting (GB), and Extreme Gradient Boosting (XGBoost). Each model was trained using the training set identified in the previous phase.

To ensure optimal model performance, the hyperparameters of each ML model were tuned using the Genetic Algorithm (GA) optimization technique (Shanthi and Chethan 2023). The GA optimization process aimed to maximize the R^2 value of each model. The GA parameters were set to be population size of 100, total generation of 1000, mutation rate of 0.2, and cross-over rate of 0.6. The optimized hyperparameters values, shown in Table 4, were then used to develop the machine learning models that are described in the following sections.

Table 4. Optimal hyperparameters of developed machine learning models

Machine Learning Model	Hyperparameters Range	Optimal Hyperparameters of Best Performing Model
LASSO Regression	alpha (L1Norm) = 0.01 - 100	alpha (L1Norm) = 0.20
Ridge Regression	alpha (L2Norm) = 0.01 - 100	alpha (L2Norm) = 4.40
Random Forest	estimator = 90-100 max features = 2-38 max depth = 2-38	estimator = 100 max features = 13 max depth = 16
Gradient Boosting	estimator = 90-100 learning rate = 0.1 - 0.990 max depth = 2 - 38 sub sample = 0.01 - 0.99 alpha = 0-1	estimator = 100 learning rate = 0.25 max depth = 30 sub sample = 0.82 alpha = 0.66
XGBoost	estimator = 90-100 learning rate = 0.001 - 0.990 max depth = 2 - 38 sub sample = 0.01 - 0.99 colsample by tree = 0.5 - 1.0 reg lambda = 1 - 30 reg alpha = 0 - 30	estimator = 100 learning rate = 0.56 max depth = 17 sub sample = 0.65 colsample by tree = 0.89 reg lambda = 5.12 reg alpha = 0.19

1.4 Models Evaluation and Validation

The performance of the developed machine learning models was evaluated and validated using the training and testing sets, respectively. First, the performance of the developed models was evaluated using the training set by analyzing their coefficient of determination (R^2) values. This analysis indicates that the GB and XGBoost models acheived the highest performance with R^2 values of 99.99% and 99.97%, respectively, while the R^2 values for the other ML models ranged between 55.85% to 90.3%, as shown in Table 5.

Second, the performance of the developed ML models was validated using the testing set by comparing their predicted values to the true values, as shown in Figure 6. This validation analysis was conducted using four primary metrics: (1) mean absolute percentage error (MAPE), (2) mean absolute error (MAE), (3) median absolute error (Med AE), and (4) root mean squared error (RMSE). The results show that (a) the XGBoost model outperformed the other models in the three metrics of mean absolute percentage error ($MAPE$ = 13.90%), mean absolute error (MAE = \$64.28/sf), and median absolute error (Med. AE = \$29.94/sf); and (b) GB model outperformed the other models in the fourth metric of root mean square error (RMSE = \$113.01/sf), as shown in Table 5, Figure 5, and Figure 6.

Table 5. Performance of developed machine learning predictive models.

Developed ML Algorithms	Training Dataset	Testing Dataset			
	R^2 (%)	MAPE (%)	MAE ($/sf)	Med AE ($/sf)	RMSE ($/sf)
OLS	55.82	21.34	123.62	52.98	226.82
LR	56.00	20.54	116.53	51.97	214.89
RR	54.85	20.65	118.50	54.81	215.19
RFR	90.37	19.46	93.40	54.27	138.03
GB	**99.99**	16.99	75.18	57.59	**113.01**
XGBoost	**99.97**	**13.90**	**65.23**	**29.94**	120.29

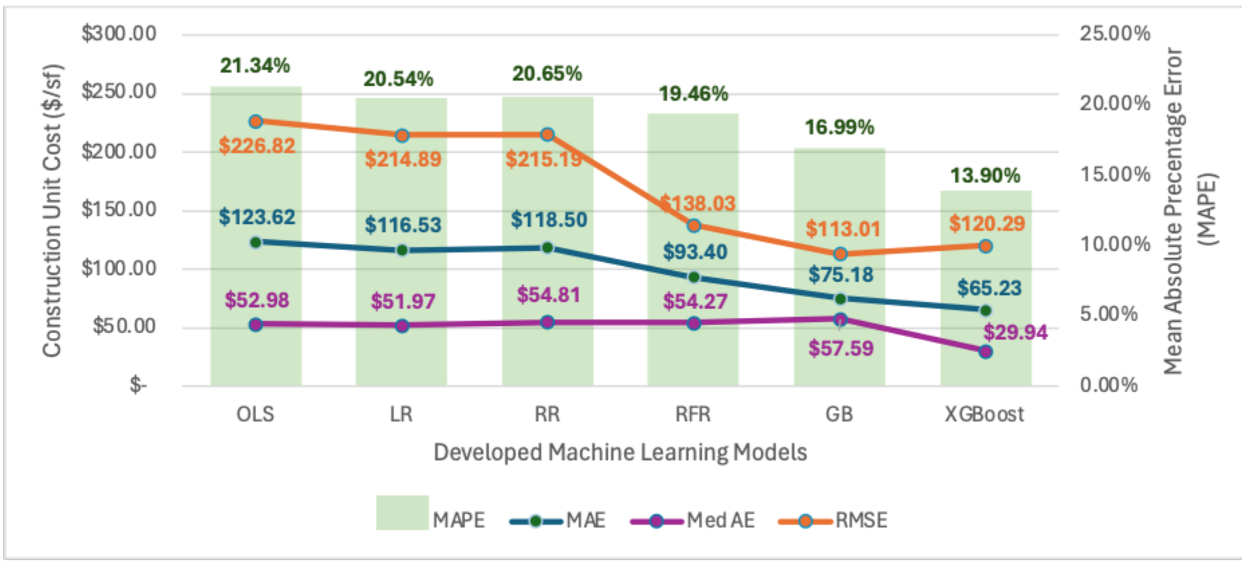


Figure 5. Performance of developed ML models using testing dataset.

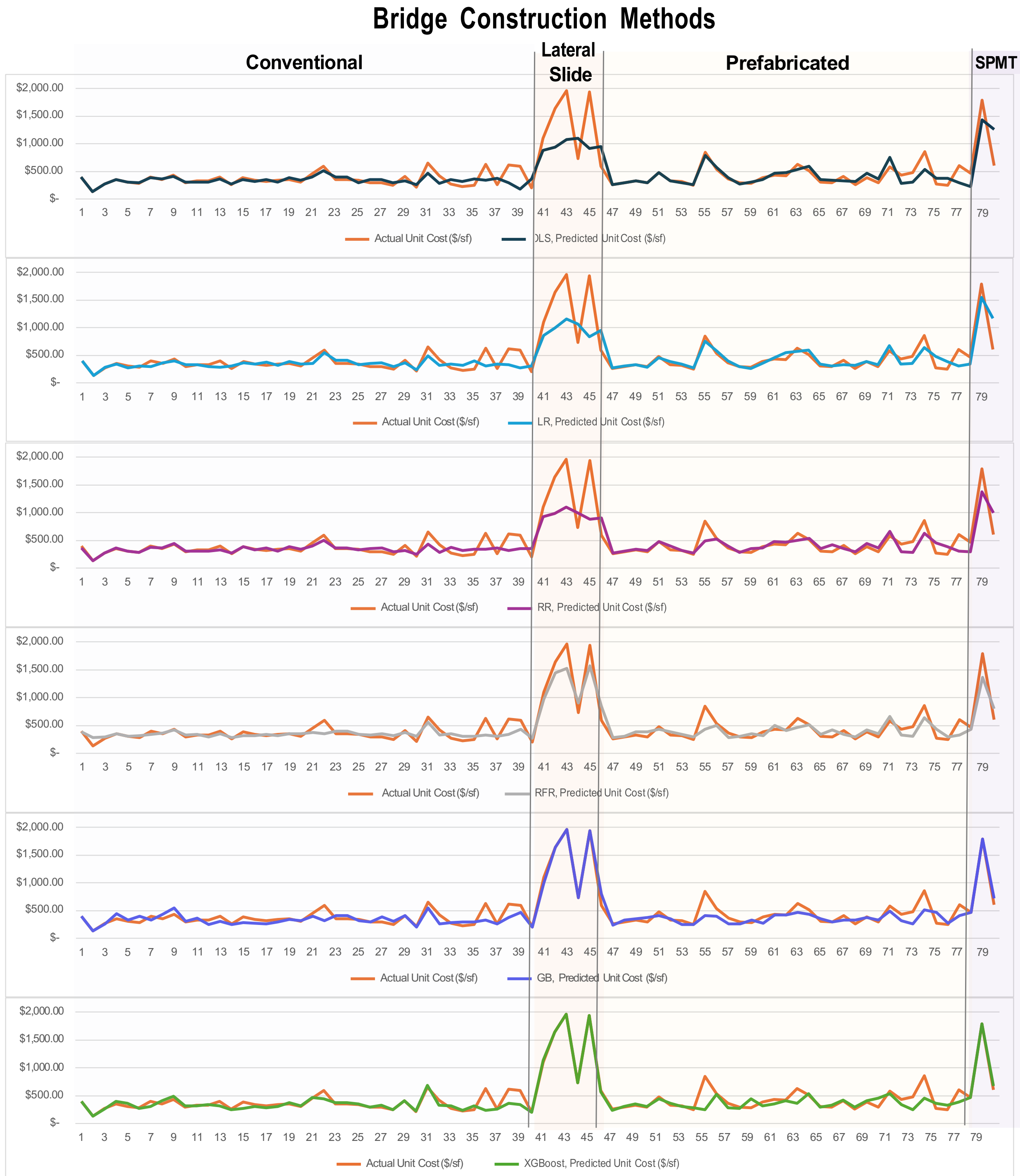


Figure 6. Actual and predicted unit cost for developed ML models using testing set

Task 2: Create Novel Multi-Objective Optimization Model to Optimize the planning of Conventional and Accelerated Bridge Construction Projects

The second task focuses on developing novel multi-objective optimization model to optimize the planning of conventional construction and ABC methods during the pre-construction phase to maximize safety of the traveling public and construction workers while minimizing the total cost of planned projects. The model is developed in four main phases that focus on (i) identifying all decision variables that have a significant impact on the safety and cost of planned bridge projects such as delivery date of PC bridge components to the construction site, size and equipment of each construction crew, use of overtime hours and/or multiple shifts for construction crews, and PC transportation method from prefabrication plant to site; (ii) formulating optimization objectives and constraints; (iii) implementing the optimization model; and (iv) analyzing a case study to illustrate the use of the developed optimization model, as shown in Figure 7.

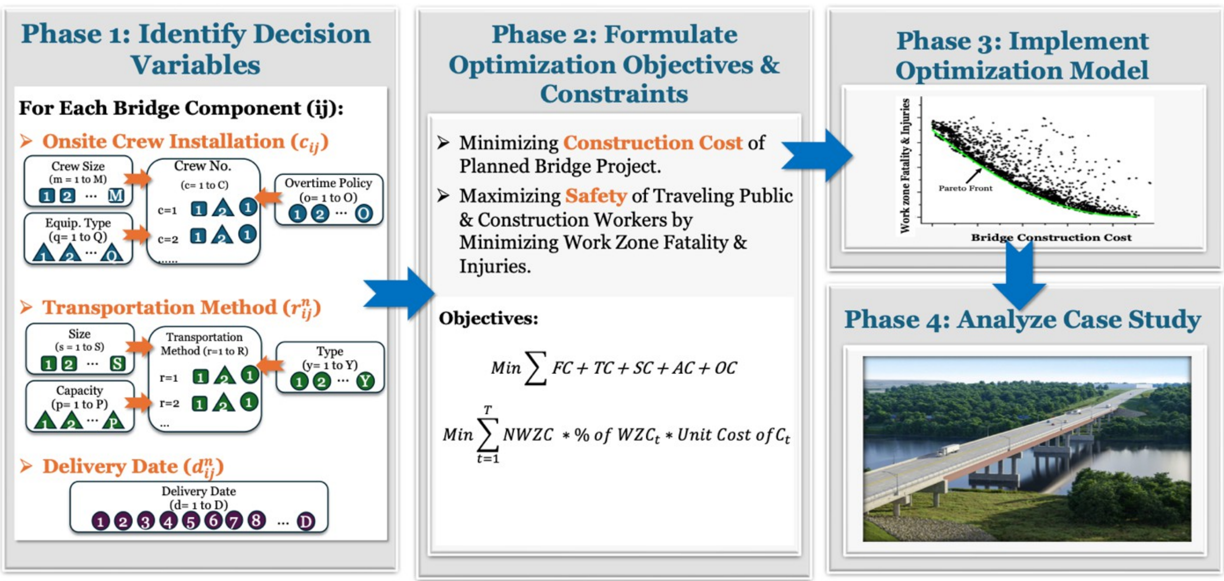


Figure 7. Development phases of the multi-objective optimization model

2.1 Decision Variables

This phase focused on identifying relevant pre-construction planning decisions that have an impact on the cost and safety of planned bridge projects. This includes the decisions of selecting from a feasible set of alternatives: an onsite installation crew (c_{ij}), a transportation method (r_{ij}^n), and a delivery date (d_{ij}^n), as shown in Figure 7. It should be noted that the installation crew decision variable (c_{ij}) represents a combined selection of crew size (*m*), equipment type (*q*), and overtime policy (*p*), as shown in Figure 7. Similarly, the transportation decision variable (r^n) represents a combined selection of transportation type (*y*), size (*s*), and capacity (*p*), as shown in Figure 7.

2.2 Model Formulation

The main objectives of the developed multi-objective optimization model are to (a) maximize safety of both the travelling public and construction workers by minimizing work zone fatality and injury crashes using safety performance functions (Schattler et al., 2020), as shown in

Eq. (3) and (4); and (b) minimize total construction cost of planned bridge project that includes off-site fabrication of PC elements, on-site construction costs as well as the transportation, on-site storage, and assembly of PC elements, as shown in Eq. (5).

$$Min \, \% \sum_{!\#\$}^{''} N * C_{!} * UC_{!} \tag{3}$$

$$N = e^{\%\&.()*} * D^{(.*()} * L^{(.+\$\&} * ADT^{(.),-} * e^{\%(.((()(/!*/'')} \tag{4}$$

Where, N is predicted number of work zone crashes that can be estimated using Eq. (4), $C_{\$}$ is percentage of crash type *t*, *t* is type of crash including fatal, injury, and property damage, $UC_{\$}$ is unit cost of crash type *t*, *D* is work zone duration in days, *L* is work zone length with detour in miles, A*DT* is average daily traffic, S_1 is speed limit in work zone under normal condition, and S_2 is speed limit in work zone during construction.

$$Min \, \% \, FC + TC + SC + AC + OC \tag{5}$$

Where FC is fabrication cost of all PC bridge components, TC is transportation cost of all PC bridge components from fabrication plant to site, SC is onsite storage cost of all bridge components, AC is assembly cost of all PC bridge components, and OC is onsite cost of all bridge components that are not prefabricated.

2.3 Model Implementation

The optimization model will be implemented using multi-objective genetic algorithms due to their ability to efficiently explore and identify near optimal solutions in problems with large search spaces within a reasonable computational timeframe (Abdallah and El-Rayes 2016; Alotaibi et al.2021; Altuwaim and El-Rayes 2021). The model will be implemented using the nondominated sorting genetic algorithms II (NSGA-II) (Deb et al. 2002) and executed with the Distributed Evolutionary Algorithms (DEAP) (Fortin et al. 2012) Python library (vanRossum 2017). The research work in this phase is still ongoing.

2.4 Case study

This phase will focus on analyzing a case study to demonstrate the capability of the developed multi-optimization model in the previous phase in optimizing the planning of conventional construction and precast accelerated bridge construction methods during the pre-construction phase to maximize safety of traveling public and construction workers while minimizing the construction cost of planned projects. This phase is planned to start after the completion of the model implementation phase.

Educational Outreach Activities

The educational outreach activities of this research project include: (1) enhancing the analytical and research skills of a female PhD student, the lead research assistant, in collecting and analyzing bridge construction data from various databases as well as developing machine learning and multi-objective optimization models; (2) developing educational modules for two construction engineering courses (CEE 421 and CEE 526), that the PIs teach with annual enrollments of more than 120 students; and (3) presenting preliminary research findings at the first annual TRANS-IPIC workshop, held at the Big Ten

Office and Conference Center in Rosemont, IL, in April 2024, and during the TRANS-IPIC monthly virtual webinar in August 2024, as shown in Figure 8.

(a) The research team presenting their preliminary findings at the first TRANS-IPIC workshop

(b) The research team with a group of other researchers in the workshop

Figure 8. Research team activities in the first annual TRANS-IPIC workshop in Rosemont, IL

Workforce Development Activities

The research team attended the Transportation Infrastructure Precast Day (TIP Day) that was held at the University of Illinois at Urbana-Champaign (UIUC) on November 1st, 2024, to learn about cutting-edge research for infrastructure PC construction, implementation, and maintenance process. Additionally, the research team actively participated in the TRANS-IPIC Monthly Webinars that were held online.

Technology Transfer Actions

The research team developed (1) six different machine learning models that provide the capability of accurately estimating the construction cost of alternative bridge construction methods including conventional and precast concrete accelerated bridge construction methods during the early design phase; and (2) a multi-objective optimization model for optimizing construction decisions of PC bridges. The research team will develop a plan for sharing the machine learning and optimization models that were created in this research project. Furthermore, the research team plans to develop a user-friendly interface in the second round of funding, if awarded, to facilitate the use of the developed machine learning and optimization models and support their technology transfer.

Papers that Include TRANS-IPIC UTC in the Acknowledgments Section

The outcome of this research project will be published in four papers that include one accepted journal paper, a second journal paper that is currently under review, a third journal paper that will be submitted to a leading journal, and a conference paper that will be published in the proceedings of the ASCE Construction Research Congress, as follows:

1. **First Journal Paper (Accepted):** Helaly, H., El-Rayes, K., Ignacio, E.J., and Joan, H. J. (September 2024) “Comparison of Machine Learning Algorithms for Estimating Cost of Conventional and Accelerated Bridge Construction Methods During Early Design Phase.”

Accepted for publication in the *Journal of Construction Engineering and Management*, ASCE on September 30, 2024.

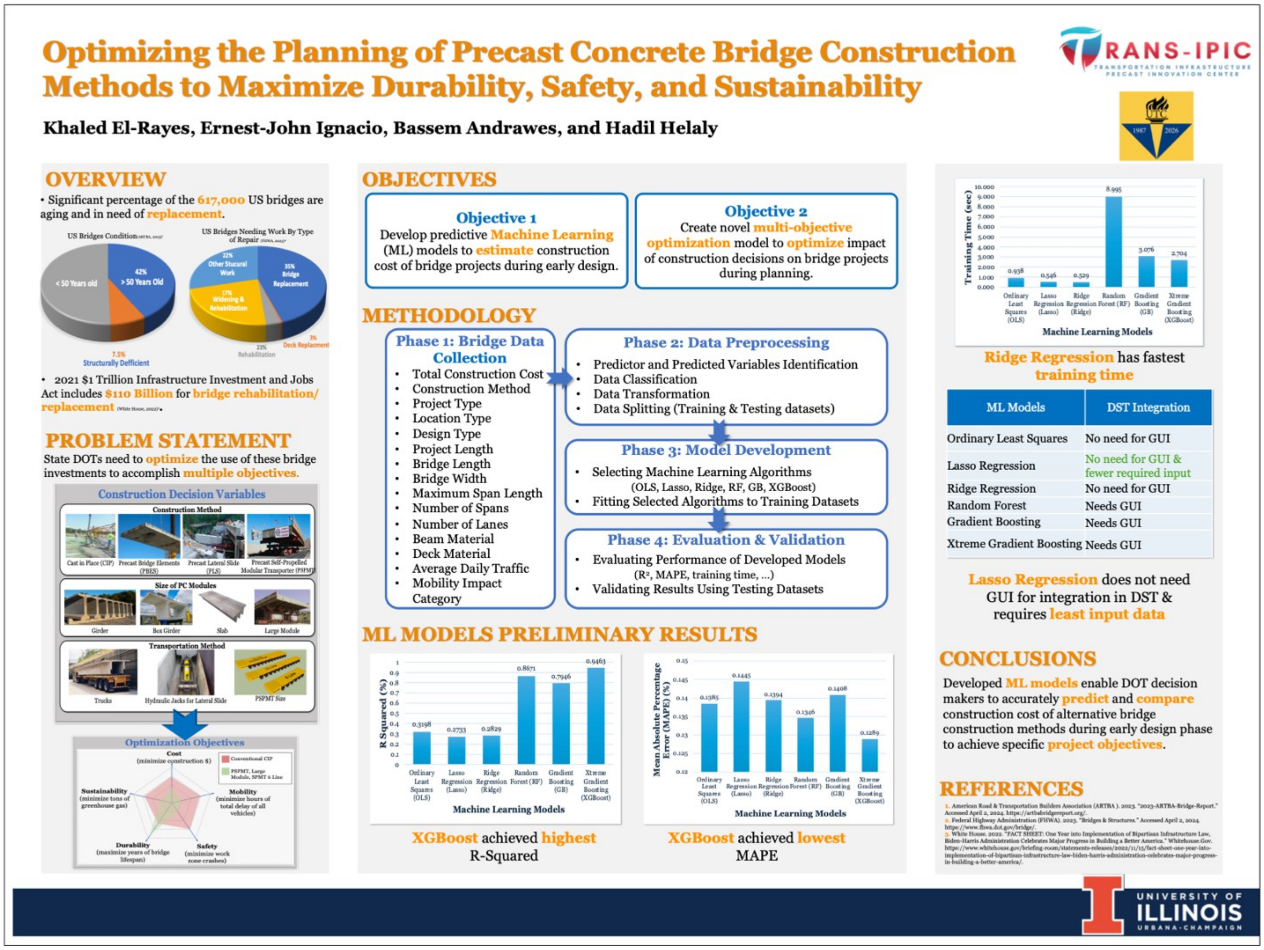
2. **Second Journal Paper (Under 2nd Review):** Helaly, H., El-Rayes, K., and Ignacio, E.J. (Under 2nd Review) "Predictive Models to Estimate Construction and Life Cycle Cost of Conventional and Precast Bridges During Early Design Phase." Submitted to *Canadian Journal of Civil Engineering*, CSCE, for 2nd Review on September 10, 2024.
3. **Third Journal Paper (In Progress):** Helaly, H., El-Rayes, K., and Ignacio, E.J. (In progress) "Optimizing the Planning of Conventional and Accelerated Bridge Construction Projects during the Pre-Construction Phase."
4. **Conference Paper (Submitted):** Helaly, H., El-Rayes, K., and Ignacio, E.J. (July 2025) "Machine Learning Models for Estimating Cost of Conventional and Accelerated Bridge Construction Methods." Abstract submitted to the *ASCE Construction Research Congress (CRC) 2025, Modular and Office Construction Summit (MOC) 2025,* November 2024.

Presentations and Posters of TRANS-IPIC Funded Research

The research team presented their preliminary research findings at the first annual TRANS-IPIC workshop, held at the Big Ten Office and Conference Center in Rosemont, IL, in April 2024 (see Figure 9), and during the TRANS-IPIC monthly online webinar in August 2024, as follows:

• El-Rayes, K., Ignacio, E.J., Andrawes, B., and Helaly, H., April 2024. "Optimizing the Planning of Precast Concrete Bridge Construction Methods to Maximize Durability, Safety, and Sustainability." Poster presented at the first Annual TRANS-IPIC Workshop, Rosemont, IL.

• El-Rayes, K., Ignacio, E.J., Andrawes, B., and Helaly, H., August 2024. "Optimizing the Planning of Precast Concrete Bridge Construction Methods to Maximize Durability, Safety, and Sustainability." Presentation at the Monthly TRANS-IPIC Virtual Webinar. https://mediaspace.illinois.edu/media/t/1_58gfc5g2



ML Models	DST Integration
Ordinary Least Squares	No need for GUI
Lasso Regression	No need for GUI & fewer required input
Ridge Regression	No need for GUI
Random Forest	Needs GUI
Gradient Boosting	Needs GUI
Xtreme Gradient Boosting	Needs GUI

Figure 9. Poster presenting preliminary results of this TRANS-IPIC research project (El-Rayes et al., 2024)

Any other Events or Activities that Highlights the Work of TRANS-IPIC Research that Occurred at Your University

None

Any Mentions/References to TRANS-IPIC in News or Interviews from Your Research

None

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