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 (Phase II)
UI-23-RP-05

Quarterly Progress Report
For the performance period ending September 30, 2025

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None

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Project Description:

1. Research Plan - Statement of Problem

The American Road and Transportation Builders Association reported that 36% of all U.S. bridges required major repair work or replacement (ARTBA 2023; FHWA 2024). To address this, the US federal government enacted the Infrastructure Investment and Jobs Act in 2023 that invests over $300 billion in replacing and repairing America's aging roads and bridges (The White House 2023). This presents DOTs with a number of challenges including how to (1) accurately predict the condition of aging conventional cast-in-place and precast bridges to improve their durability and extend their life; (2) analyze and compare during the early design phase the durability, safety, mobility, sustainability, and construction cost of alternative bridge construction methods 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; and (3) quantify and optimize during the preconstruction phase the impact of important construction decisions on multiple objectives including safety, mobility, sustainability, and construction cost, as shown in Figure 1.

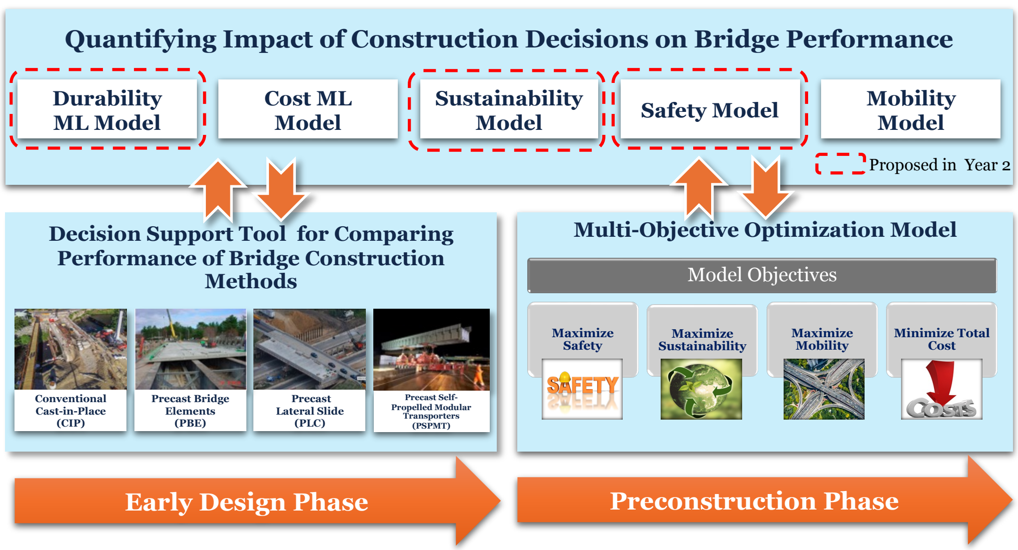

Figure 1. Proposed Decision Support Tool and Optimization Model

2. Research Plan - Summary of Project Activities (Tasks):

Task 1: Develop novel machine learning models to accurately predict the condition rates of both conventional cast-in-place and precast bridges based on a wide range of variables including bridge age, length, design type, average daily traffic, and design load.

Task 2: Create a practical decision support tool (DST) that can be used by DOT planners during the early design phase to analyze and compare the durability, safety, sustainability, mobility, and construction cost of conventional cast-in-place and precast bridges.

Task 3: Expand the developed multi-objective optimization model in the first year to include safety and sustainability to support State DOTs during the preconstruction phase in identifying optimal bridge construction decisions such as delivery day, transportation, and on-site installation of bridge PC modules to enhance safety, sustainability, and mobility while minimizing total construction cost.

Project Progress:

3. Progress for each research task

Task 1 Progress [90% completed]. Last quarter, the research team continued working on the first research task that focused on developing novel machine learning models for predicting the condition rates and deterioration of conventional cast-in-place and precast concrete deck bridges during the early design phase. The development of these models focused on the following four main phases.

a. Data Collection

This phase has been completed and focused on identifying and collecting all data influencing bridge deck condition ratings and deterioration that are available in the National Bridge Inventory (NBI) database (FHWA 2025). The NBI contains data on 624,194 bridges across all 50 U.S. states, with 108 items recorded for each bridge. Although the database includes bridge records from 1697 to 2024, the data collected in this task focused on only bridges that were constructed since 1960. Of these bridges, 61% are concrete cast-in-place deck bridges, 12% are precast concrete deck bridges, 20% are culverts, and 7% utilize other deck materials such as timber, steel, or aluminum, as shown in Figure 2. Since the scope of this study is limited to predicting the condition ratings of concrete deck bridges, only cast-in-place and precast concrete bridges were considered. Accordingly, the collected dataset includes 286,034 bridge projects.

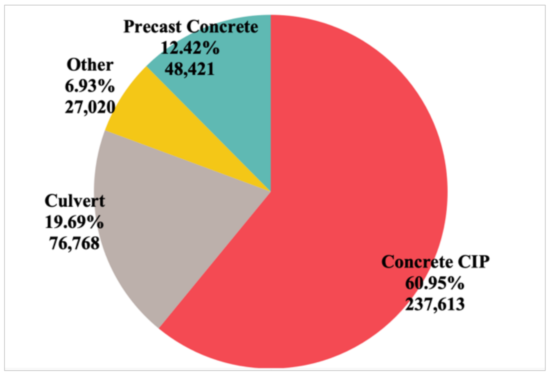

Figure 2. Distribution of NBI Bridges by Deck Type

Based on a comprehensive literature review (Assaad et al. 2020; Bolukbasi et al. 2004; Rashidi Nasab and Elzarka 2023; Srikanth and Arockiasamy 2020; Tolliver et al. 2011; Winoto and Roy 2023), 32 data items were identified to have an impact on the deck condition rating. These items can be categorized into 7 main groups: location, time, dimensions, condition ratings, traffic and load, service and classification, and other/protection, as shown in

Table 1. Some of these items are directly incorporated into the predictive models, while others are used to generate derived variables. For example, the bridge age is calculated based on its construction and maintenance history, as shown in Eq. (1) and (2).

Table 1. Collected data from NBI database

Category	Fields
Location	State Code
Time	Year Built, Year of Improvement, Year Reconstructed, Date of Inspection, Inspection Frequency (Months)
Dimensions	Approach Width (m), Max Span Length (m), Structure Length (m), Deck Width (m), Deck Area (m²), Main Unit Spans (count), Degrees of Skew, Structure Flared (Y/N)
Condition Ratings	Deck Condition, Superstructure Condition, Substructure Condition, Channel Condition
Traffic & Load	ADT (Average Daily Traffic), % ADT Trucks, Design Load
Service & Classification	Service On, Service Under, Structure Kind (Material), Structure Type, Deck Structure Type, Approach Kind, Approach Type
Other / Protection	Work Proposed, Surface Type (Protective System), Membrane Type, Deck Protection

IF Type of Work == Bridge or Deck Replacement:

$$Bridge\ Age = Date\ of\ Inspection - max\ (Year\ Built,\ Year\ Reconstructed,\ Year\ of\ Improvement) \quad (1)$$

Else:

$$Bridge\ Age = Date\ of\ Inspection - max\ (Year\ Built,\ Year\ Reconstructed) \quad (2)$$

b. Data Preprocessing

This phase has been completed and focused on preprocessing the raw data that was collected in the previous phase 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 identifying 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.

First, the deck condition rate was identified as the predicted variable with a numerical value that ranges from 1 to 9. A deck condition rate of 1 and 9 represents a poor and excellent condition rate, respectively. Twenty-four predictor variables were identified to have a potential impact on deck condition rate including bridge age, deck length, deck width, number of spans, maximum span length, degree of skew, deck area, superstructure condition rate, substructure condition rate, channel condition rate, average daily traffic (ADT), percentage of truck in ADT, location (state), service on, service under, design load, deck type, structure material, operating rating, inventory rating, deck protection type, and membrane protection type, as shown in Figure 3.

Second, the identified predictor variables were categorized in two main groups based on their types: numerical and categorical. Numerical variables represent all variables that have measurable quantity such as deck length and width, while categorical variables represent attributes that can take one of several discrete values, such as deck type that can be classified as concrete cast-in-place or precast concrete, as shown in Figure 3.

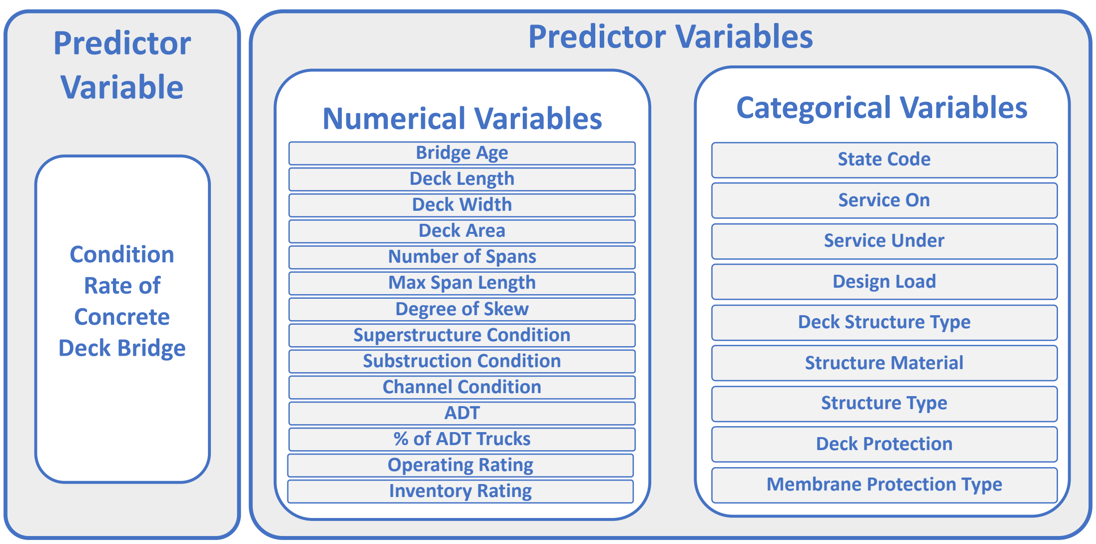

Figure 3. Predictor and predicted variables

Third, the collected dataset was cleaned by identifying and removing outliers to enhance model performance to reduce noise and minimize prediction error. For example, the NBI dataset included bridge projects with a number of spans ranging from 0 to 900. Since only 1,136 out of 286,034 projects either had more than 30 spans or were reported with zero spans, these cases were identified as outliers and excluded. The same procedure was applied to all numerical variables. In addition, the dataset was cleaned by removing data items that were incorrectly entered. For instance, the design load column should contain categorical values from 0 to 9, where each value represents the live load for which the structure was designed (e.g., 1 = MS 9, 2 = MS 13.5). All bridges with non-numeric entries (e.g., A, B, C) for this variable were therefore excluded. In total, this cleaning process resulted in the removal of 20,587 outlier bridge projects.

Fourth, the categorical and numerical variables were transformed to enhance the performance of the machine learning models using the 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, respectively.

c. Model Development

This phase focused on the development of six ML models that can be used to estimate the condition rate and deterioration of conventional and precast deck bridges during the early design phase. These models were developed using six ML algorithms that are widely used for this type of prediction 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.

d. Model Evaluation

The performance of the developed ML 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 Gradient Boosting (GB) model achieved the highest performance with (R^2)values of 94.04%, as shown in Table 2.

Second, the performance of the developed ML models was validated using the testing set by comparing their predicted values to the true values. This validation analysis was conducted using four primary metrics: mean absolute percentage error $(MAPE)$, mean absolute error (MAE), median absolute error $(Med\ AE)$, and root mean squared error $(RMSE)$. The results show that the XGBoost model outperformed the other models in all four metrics of mean absolute percentage error ($MAPE$ = 5.93%), mean absolute error (MAE = 0.36), median absolute error (Med. AE = 0.21); and root mean square error ($RMSE\ =\ 0.55$), as shown in Table 2.

Table 2. Performance of developed machine learning predictive models

Developed ML Algorithms	Training Dataset	Testing Dataset			
	$R2$ (%)	$MAPE$ (%)	MAE	$Med\ AE$	$RMSE$
OLS	47.8	7.51	0.47	0.35	0.63
LR	47.8	7.47	0.46	0.34	0.62
RR	49.04	7.90	0.48	0.36	0.66
RFR	93.43	6.29	0.39	0.25	0.57
GB	**94.06**	6.36	0.40	0.24	0.57
XGBoost	90.42	**5.93**	**0.36**	**0.21**	**0.55**

Task 2 Progress [40% completed]. Last quarter, the research team started the development of a practical decision support tool (DST) designed to assist DOT planners during the early design phase in analyzing and comparing the durability, safety, sustainability, mobility, and construction cost of conventional cast-in-place and precast bridges. The DST will consist of five modules, each designed to evaluate the performance of alternative construction methods in five key objectives: (1) construction cost, using the ML models developed in Year 1 to predict the cost of alternative bridge construction methods (Helaly et al. 2025); (2) durability, using the ML models developed in the first task of Year 2 to predict the condition rating of alternative concrete deck bridges; (3) mobility, by calculating total vehicle delay hours during construction using the FHWA procedure in the Road User Cost Calculator tool (FHWA 2022); (4) safety, by estimating the number of work zone crashes using Safety Performance Functions (SPFs) developed by FHWA and AASHTO (Gayah et al. 2024; Kolody

et al. 2022); and (5) sustainability, by predicting total project greenhouse gas emissions using the FHWA Infrastructure Carbon Estimator methodology (Gallivan et al. 2014). The developed DST is expected to provide DOT planners with a comprehensive framework for evaluating trade-offs among competing objectives during the early design phase, as shown in Figure 1.

Task 3 Progress [100% completed]. The research team developed a multi-objective optimization model to support State DOTs in generating and evaluating optimal trade-offs among four key objectives: maximizing safety, mobility, and sustainability while minimizing the total cost of precast bridge construction projects during the preconstruction phase. The development process involved three main stages: (1) model formulation, which identified all relevant decision variables, objective functions, and constraints; (2) model implementation, which employed the Nondominated Sorting Genetic Algorithm II (NSGA-II) supported by four additional modules; and (3) model evaluation, which analyzed a case study to demonstrate the model capabilities in optimizing the planning of precast bridge construction projects. The outcomes of this task were documented in a manuscript that was submitted to the *ASCE Journal of Construction Engineering and Management* on August 1, 2025.

4. Percent of research project completed

75% of total project is completed through the end of this quarter:

Task 1: 90% completed.
Task 2: 40% completed.
Task 3: 100% completed.

5. Expected progress for next quarter

In the next quarter, the research team will complete the refinement of the developed machine learning (ML) models to further improve their accuracy in predicting the condition rating and deterioration of concrete deck bridge projects. Additionally, the team will finalize the development of the decision support tool (DST) to ensure it is fully functional and capable of comparing and analyzing alternative construction methods during the early design phase. The DST is expected to enable DOT planners to conduct a comprehensive evaluation of bridge durability, safety, sustainability, mobility, and construction cost for conventional cast-in-place and precast bridges.

6. Educational outreach and workforce development

The educational and workforce development (EWD) activities this quarter focused on: (1) continuing to enhance the analytical and research skills of a female PhD student, the lead research assistant, in collecting and analyzing bridge construction data from various databases and developing machine learning and multi-objective optimization models; (2) developing educational modules for two construction engineering courses (CEE 421 and CEE 526), which the PI and Co-PI teach to over 120 students annually; and (3) attending the TRANS-IPIC monthly webinars.

7. Technology Transfer

The research team is currently developing (1) novel machine learning models to predict the condition rates of concrete deck bridge projects during the early design phase; (2) a practical decision support tool (DST) to analyze and compare the durability, safety, sustainability, mobility, and construction cost of conventional cast-in-place and PC bridges during the early design phase, and; (3) a multi-objective optimization model to optimize the planning of bridge projects to maximize safety, mobility, and sustainability, while minimizing the total construction cost.

Research Contribution:

8. Papers that include TRANS-IPIC UTC in the acknowledgments section:

The research team successfully published two papers in leading construction engineering and management journals; a conference paper, which was included in the proceedings of the ASCE Construction Research Congress 2025; and submitted a third manuscript that is currently under review. The publications are as follows:

1. Helaly, H., K. El-Rayes, E.J. Ignacio, and H. J. Joan. (January 2025). “Comparison of Machine Learning Algorithms for Estimating Cost of Conventional and Accelerated Bridge Construction Methods During Early Design Phase” Journal of Construction Engineering and

Management, ASCE. https://doi.org/https://ascelibrary.org/doi/10.1061/JCEMD4.COENG-15934.

2. Helaly, H., K. El-Rayes, and E.J. Ignacio. (February 2025). “Predictive Models to Estimate Construction and Life Cycle Cost of Conventional and Prefabricated Bridges During Early Design Phase.” Canadian Journal of Civil Engineering. https://doi.org/10.1139/cjce-2023-0493.
3. Helaly, H., K. El-Rayes, and E.J. Ignacio. (July 2025). “Machine Learning Models for Estimating Construction Costs of Conventional and Accelerated Bridge Construction Methods” ASCE Construction Research Congress (CRC) 2025, Modular and Office Construction Summit (MOC).
4. Helaly, H., K. El-Rayes, and E.J. Ignacio. (under review). “Multi-Objective Optimization for the Planning of Prefabricated Bridge Construction Projects” Submitted to the Journal of Construction Engineering and Management, ASCE in August 2025.

9. Presentations and Posters of TRANS-IPIC funded research:

None

10. Please list any other events or activities that highlights the work of TRANS-IPIC occurring at your university (please include any pictures or figures you may have). Similarly, please list any references to TRANS-IPIC in the news or interviews from your research.

None

Appendix 1: Research Activities, leadership, and awards (cumulative, since the start of the project)

A. Number of presentations at academic and industry conferences and workshops of UTC findings
   - No. = Four presentations including (1) oral presentation on April 22, during the first day of the TRANS-IPIC Workshop 2025; (2) poster presentation on April 23, during the second day of the TRANS-IPIC Workshop 2025; (3) online presentation during the TRANS-IPIC monthly webinar on May 21, 2025; (4) presentation at the ASCE Construction Research Congress (CRC) 2025, Modular and Offsite Construction (MOC) Summit in July 2025.

B. Number of peer-reviewed publications submitted based on outcomes of UTC funded projects
   - No. = Three peer-reviewed publications submitted based on outcomes of UTC funded projects. Two peer-reviewed papers have been published in (1) *Journal of Construction Engineering and Management, ASCE* in January 2025, and (2) *Canadian Journal of Civil Engineering* in February 2025. A third manuscript was submitted to the *Journal of Construction Engineering and Management, ASCE* in August 2025 and is currently under review.

C. Number of peer-reviewed journal articles published by faculty.
   - No. = Two published peer-reviewed papers that were published in in (1) *Journal of Construction Engineering and Management, ASCE* in January 2025, and (2) *Canadian Journal of Civil Engineering* in February 2025.

D. Number of peer-reviewed conference papers published by faculty.
   - No. = One peer-reviewed conference paper published in the *ASCE Construction Research Congress (CRC) 2025, Modular and Office Construction Summit (MOC)*, July 2025

E. Number of TRANS-IPIC sponsored thesis or dissertations at the MS and PhD levels.
   - No. MS thesis = None
   - No. PhD dissertations = One ongoing PhD dissertation by Hadil Helaly
   - No. citations of each of the above = four citations of the published journal papers listed in Section C.

F. Number of research tools (lab equipment, models, software, test processes, etc.) developed as part of TRANS-IPIC sponsored research
   - Research Tool # 1= six developed machine learning models to estimate the construction cost of conventional and precast bridge projects during the early design phase.
   - Research Tool # 2= multi-objective optimization model to optimize the planning of bridge projects to maximize safety, mobility, and sustainability, while minimizing construction cost.
   - Research Tool # 3= ongoing machine learning models to predict the condition rates and deterioration of bridge projects during the early design phase.
   - Research Tool # 4= ongoing practical Decision Support Tool (DST) to facilitate the use of the developed machine learning models by state DOTs and bridge planners during the early design phase to analyze and compare the durability, safety, sustainability, mobility, and construction cost of conventional cast-in-place and precast bridges.

G. Number of transportation-related professional and service organization committees that TRANS-IPIC faculty researchers participate in or lead.
   - Professional societies
     - No. participated in = One at the ASCE Construction Research Congress (CRC) 2025, Modular and Office Construction Summit (MOC) in July 2025
     - No. lead = None

- Advisory committees (No. participated in & No. led)
  - No. participated in = None
  - No. lead = None
- Conference Organizing Committees (No. participated in & No. led)
  - No. participated in = None
  - No. lead = None
- Editorial board of journals (No. participated in & No. led)
  - No. participated in = None
  - No. lead = None
- TRB committees (No. participated in & No. led)
  - No. participated in = None
  - No. lead = None

H. Number of relevant awards received during the grant year
   - No. awards received = None

I. Number of transportation related classes developed or modified as a result of TRANS-IPIC funding.
   - No. Undergraduate = 3
   - No. Graduate = 4

J. Number of internships and full-time positions secured in the industry and government during the grant year.
   - No. of internships = None
   - No. of full-time positions = None

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