Transportation Infrastructure Precast Innovation Center (TRANS-IPIC)

University Transportation Center (UTC)

Evaluating Prestressed Concrete Beams with Cracks using Machine Learning – Phase II
UB-23-RP-01

Quarterly Progress Report
For the performance period ending June 30

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Collaborators / Partners:
None

Submitted to:
TRANS-IPIC UTC
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TRANS-IPIC Quarterly Progress Report (Section 1 – 7, 5 pages max.):

Project Description:

1. Research Plan - Statement of Problem

   Bridge owners face difficult decisions on whether a bridge should be posted, repaired or replaced when prestressed concrete members have shear cracks due to overloading. The decisions are currently made based on engineering judgment, costly load-testing or time consuming modeling. Guidance is needed to interpret cracks to avoid overly conservative load ratings and to keep bridges operational, without compromising safety and economy. Year 1 of this project developed a tool through machine learning (ML) that relates cracking to the load history of bridge members. This web-based tool can be used by bridge owners, asset managers and inspectors to guide repair decisions. Year 2 of this project will generate the test data required to validate the data-driven tool and to improve its predictions by adding higher-quality data to the existing limited datasets. Integrating higher-quality data into the existing datasets will improve the reliability of the tool's predictions for real-world applications. Additionally, the tool will be expanded to predict changes in the stiffness of a beam due to cracking, which is another indicator for beam health.

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

   Task 1. Stiffness History Prediction: In this task, existing data in the literature on load history and stiffness history are collected, filtered and used to train a Gaussian Process Regression (GPR) algorithm. This newly developed algorithm is integrated with the algorithm for crack width vs load history. The outcome is predictions of stiffness given crack widths.

   Task 2. Pre-test Prediction: Algorithms for crack width vs load history and load history vs stiffness history are used to predict the load history and stiffness corresponding to a set of crack widths for a beam to be tested in Task 3.

   Task 3. High Quality Data Generation: A prestressed concrete beam is designed, fabricated, and tested to collect the data needed to refine and validate the evaluation tools.

   Task 4. Refine Predictions: The data collected in Task 3 is used to re-train and refine the predictions of shear strength, load history and stiffness history of the ML algorithms. The improvement in predictions due to higher quality data is documented.

   Task 5. Post-test Prediction: The web-based evaluation tool is updated. Shear strength, load history, and stiffness history of the tested prestressed beam are predicted to demonstrate the use of the tool, build confidence in the tool, and set expectations for error.

Project Progress:

3. Progress for each research task

   Task 1. Stiffness History Prediction [60% completed to date]: Data on load-displacement relationship of prestressed beams were collected from the published literature. The literature scan identified 47 beams tested under shear with both load-displacement relationship and crack widths documented. The data was reviewed for accuracy and fit for the project. After filtering the dataset to exclude the beams for which displacement was measured at locations other than midspan, there were 41 beams. The dataset was then reviewed for beam failure mode. For the beams that failed prematurely due to strand slippage failure, the part of the load-displacement curve after slippage was excluded from the dataset. For the beams remaining in the dataset, the load-displacement curves were first digitized and smoothened to eliminate jaggedness caused by pauses in testing. The post-peak (negative stiffness) parts of the load-displacement curves were omitted as the beams at this stage would fail rendering any evaluation inconsequential. Tangent stiffness values were sampled from the load-displacement curves at ten equal load intervals from zero to the measured shear strength. This led to 273 data points for shear history vs stiffness history for beams with measured crack widths. Prediction of stiffness using this dataset resulted in a relatively large scatter in results as shown in Fig. 1a. In this figure, stiffness ($K_{applied}$) is normalized by the initial or maximum stiffness (K_{max}).

To reduce the scatter seen in Fig. 1a, the data were further reviewed and filtered by excluding the following four beams from the dataset: 1) two beams with flexure-shear transition failure (not a shear failure), 2) one beam for which failure unexpectedly occurred outside the tested span, and 3) one beam with a seemingly erroneous load-displacement curve. This led to 37 beams with 254 shear history vs stiffness history data points and measured crack widths. As an additional measure to improve scatter in predictions, the following conditions are enforced in post-processing of the results: 1) when the crack width is zero for an unloaded beam (an uncracked beam), the predicted stiffness is the same as the initial stiffness (100% of K_{max}), 2) the predicted stiffness of a cracked beam cannot exceed the initial stiffness of the beam (i.e., 100% of K_{max}). The GPR algorithm is trained using the updated dataset with the additional constraints and the results are shown in Fig. 1b. The scatter and error seen in Fig. 1b are smaller compared to the ones in Fig. 1a due to additional filtering and introduction of constraints.

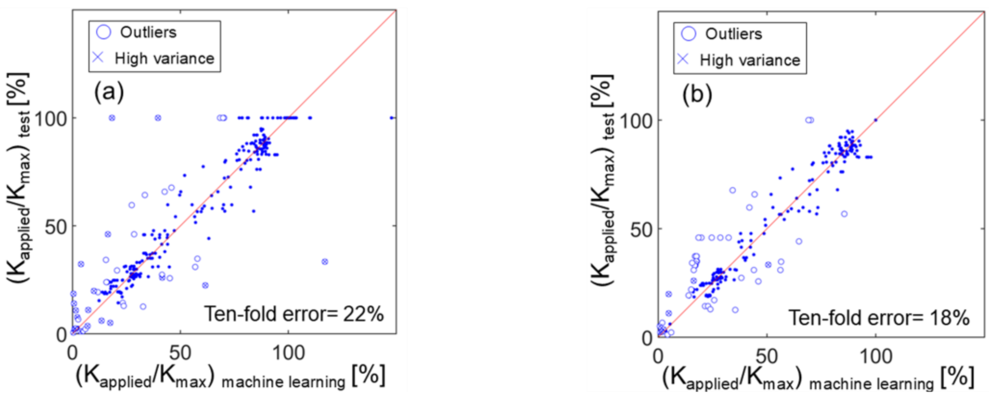

Fig. 1. Stiffness predicted by machine learning and measured by testing (a) before and (b) after additional filtering and introduction of constraints

While the result shown in Fig. 1b is promising, the dataset used to train the algorithm is limited in size (254 data points) as the beams in this dataset must have both crack width and stiffness data. A larger dataset is being created for beams with data on 1) stiffness and load, and 2) crack width and load. This larger dataset will be used to train an alternative GPR algorithm that indirectly correlates crack width with stiffness. The goal is to improve the accuracy of the predictions through a much larger training dataset.

Task 2. Pre-test Prediction [30% completed to date]: A beam design was finalized so that shear failure governs over flexure failure. The beam was modeled using finite element analysis to obtain the flexure cracking, shear cracking, and failure loads. The failure load was also predicted using the machine learning algorithm, the 9th Edition of the AASHTO LRFD Bridge Design Specifications, and ACI 318-19. The shear strength predictions obtained from various methods are compared in Table 1. The variations between predictions are consistent with the uncertainties associated with shear behavior of concrete structures.

Table 1. Strength predictions of various methods for the test specimen

Prediction Method	Predicted Shear Strength
FEA	182 kips
Machine learning	294 kips
AASHTO LRFD Bridge Design Specifications	136 kips
ACI 318-19 Detailed method	164 kips
ACI 318-19 Simplified method	94 kips

In addition, shear history corresponding to a set of crack widths was predicted using GRP for the test specimen as shown in Fig. 2. In this figure, shear history ($V_{applied}$), that is the shear corresponding to a crack width (w_{cr}), is normalized with respect to the shear capacity (V_{max}). Machine learning predicts the first crack to occur when the applied shear reaches at approximately 70% of the shear capacity.

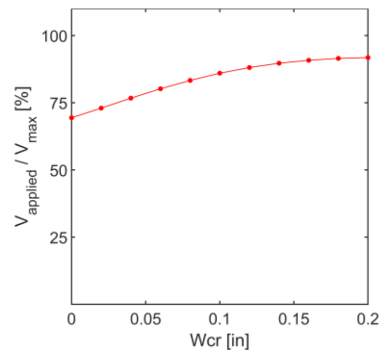

Fig. 2. Pre-test GPR predictions of load history predictions corresponding to crack widths for the test beam

Task 3. High Quality Data Generation [30% completed to date]: A beam was designed so that the expected failure mode is shear and that the capabilities of our Structural Engineering and Earthquake Simulation Laboratory regarding loading and space are not exceeded. This beam will be tested under quasi-static incrementally increasing cyclic loading with crack measurements taken at various intervals. The specimen design was shared with precast concrete manufacturers to obtain feedback and to obtain quotes for fabricating the beam. Three quotes were received that allowed fabrication of one beam. Unavailability of steel forms for specimens suitable for laboratory testing and scheduling challenges at precast plants given the small size of the job were the constraints. The specimen design is shown in Fig. 3.

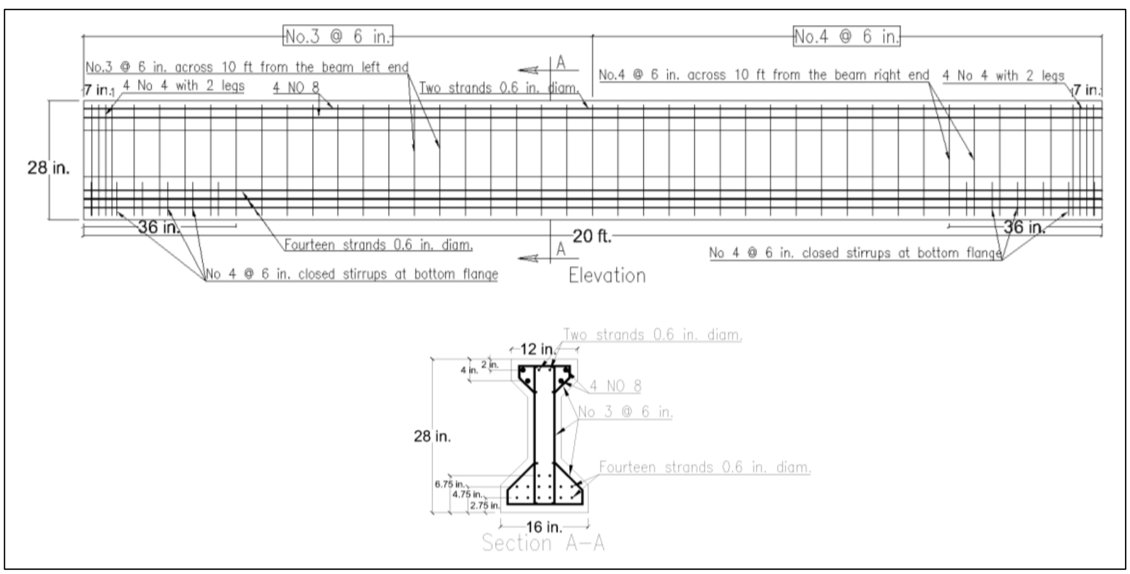

Fig. 3. Beam specimen design

A planning meeting was held with the laboratory staff to plan staffing and equipment needs and scheduling. A loading protocol and an instrumentation plan were developed. A test setup is currently being determined.

Task 4. Refined Predictions [10% completed to date]: Test data from Task 3 is needed to complete this task. Algorithms on strength, crack width vs load history, and crack width vs stiffness are being refined by further filtering the data and post-processing the results as described in Task 1.

Task 5. Post-test Prediction [0% completed to date]: This task requires test data to be collected in Task 3.

4. Percent of research project completed
   This project is 40% completed.

5. Expected progress for next quarter
   In the next quarter, Tasks 1 and 2 will be completed. The focus will be on progressing Task 3 but the completion of this task is dependent on the schedule of precast concrete manufacturers.

6. Educational outreach and workforce development
   The research team presented findings at the meeting of the PCI Northeast Technical Bridge Committee on April 24, 2025 in Sturbridge, MA and online. This meeting is attended by precast concrete manufacturers, consultants, and the Departments of Transportations of New Hampshire, New York, Maine, Massachusetts, Connecticut, Rhode Island, and Vermont.

7. Technology Transfer
   None.

Research Contribution:

8. Papers that include TRANS-IPIC UTC in the acknowledgments section:
   None.

9. Presentations and Posters of TRANS-IPIC funded research:
   Hassan Lasheen, M., Okumus, P., Elhami-Khorasani, N. (2025). "An Enhanced and Implementable Machine Learning-Based Evaluation Tool for Prestressed Concrete Bridges." TRANS-IPIC Workshop, April 22-23, Rosemont, IL.

   Hassan Lasheen, M., Okumus, P., Elhami-Khorasani, N. (2025). "An Enhanced and Implementable Machine Learning-Based Evaluation Tool for Prestressed Concrete Bridges." PCI Northeast Technical Bridge Committee, April 24, Sturbridge, MA and online.

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. = 11

B. Number of peer-reviewed publications submitted based on outcomes of UTC funded projects
   - No. = 1

C. Number of peer-reviewed journal articles published by faculty.
   - No. = 19

D. Number of peer-reviewed conference papers published by faculty.
   - No. =18

E. Number of TRANS-IPIC sponsored thesis or dissertations at the MS and PhD levels.

- No. MS thesis = 0
- No. PhD dissertations = 0
- No. citations of each of the above = 0

F. Number of research tools (lab equipment, models, software, test processes, etc.) developed as part of TRANS-IPIC sponsored research
   - Research Tool #1 (Name, description, and link to tool) = A web-based prestressed concrete girder evaluation tool was developed in year 1. This tool is being expanded in year 2. The tool can be found at https://hassan-lasheen.onrender.com

G. Number of transportation-related professional and service organization committees that TRANS-IPIC faculty researchers participate in or lead.
   - Professional societies
     - No. participated in = 5
     - No. lead = 0
   - Advisory committees (No. participated in & No. led)
     - No. participated in = 1
     - No. lead = 0
   - Conference Organizing Committees (No. participated in & No. led)
     - No. participated in = 1
     - No. lead = 0
   - Editorial board of journals (No. participated in & No. led)
     - No. participated in = 3
     - No. lead = 1
   - TRB committees (No. participated in & No. led)
     - No. participated in = 0
     - No. lead = 0

H. Number of relevant awards received during the grant year
   - No. awards received = 0

I. Number of transportation related classes developed or modified as a result of TRANS-IPIC funding.
   - No. Undergraduate = 0
   - No. Graduate = 2

J. Number of internships and full-time positions secured in the industry and government during the grant year.
   - No. of internships = 0
   - No. of full-time positions = 1

References:

None