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16. Abstract The main goal of this project is to provide DOT planners with much-needed support that enables them to analyze and compare the performance of alternative bridge construction methods during the early design phase and optimize their construction decisions during the preconstruction phase. To accomplish this goal, the main tasks of this project focused on: (a) developing novel machine learning models to accurately predict the condition ratings of conventional cast-in-place and precast concrete deck bridges using NBI data; (b) creating a practical decision support tool (DST) to analyze and compare the safety, mobility, sustainability, durability, and construction cost of alternative bridge construction methods during the early design phase; and (c) developing an original muti-objective optimization model for the planning of precast bridge projects to maximize their safety, mobility, and sustainability while minimizing their total construction cost during the preconstruction phase. The developed models and tools enable state DOTs and local agencies to accurately predict deck condition ratings for conventional and precast bridges; select the most suitable construction method for each planned project based on its specific requirements and constraints; and optimize the planning of precast bridge projects to achieve multiple objectives including maximizing safety, mobility, and sustainability while minimizing total construction cost.		
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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 deteriorating condition of U.S. bridges led the federal government to enact the Infrastructure Investment and Jobs Act, which invests over $300 billion in replacing and repairing the nation's aging roads and bridges. This presents state DOTs with several challenges including how to: accurately predict the condition of aging conventional cast-in-place and precast bridges to improve their durability and extend their life; analyze and compare the safety, mobility, durability, sustainability, and construction cost of alternative bridge construction methods for each planned project based on its specific conditions and requirements during the early design phase; and quantify and optimize the impact of important construction decisions on multiple objectives including safety, mobility, sustainability, and construction cost during the preconstruction phase. To address these challenges, a research project funded by the Transportation Infrastructure Precast Innovation Center (TRANS-IPIC) focused on (1) developing six novel machine learning models that can accurately predict bridge deck condition rates for conventional cast-in-place and precast bridges to enable planners to compare and analyze their durability during the early design phase with limited data; (2) creating a practical decision support tool (DST) to analyze and compare the safety, mobility, sustainability, durability, and construction cost of alternative bridge construction methods during the early design phase; and (3) optimizing the planning of precast bridge projects to maximize safety, mobility, and sustainability while minimizing total construction cost during the preconstruction phase.

The outcome of this project has a strong potential to provide planners and decision makers in state DOTs with much-needed support to (i) accurately predict and analyze the durability of conventional cast-in-place and precast concrete deck bridges during the early design phase; (ii) quantify and visualize the performance of alternative bridge construction methods during the early design phase to enable the selection of the most suitable construction method for each planned project; and (iii) generate and analyze optimal trade-offs among multiple and critical precast bridge project objectives including safety, mobility, sustainability, and construction cost.

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1. Problem Description

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 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 (SPMT), 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.

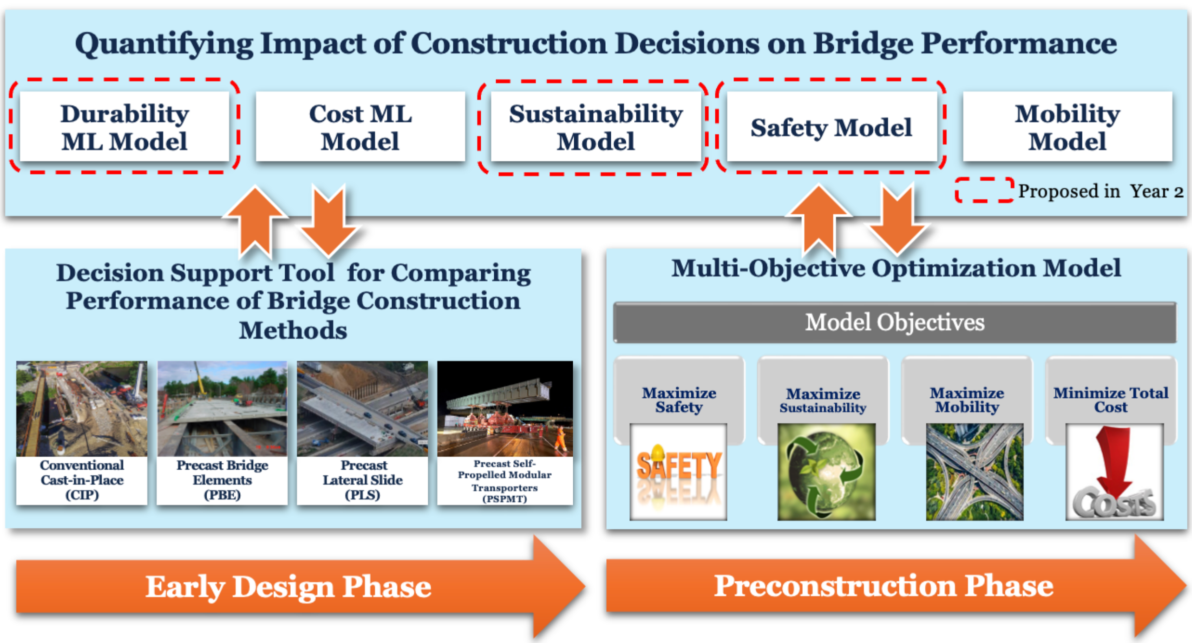


Figure 1. Proposed Decision Support Tool and Optimization Model

To address the aforementioned challenges confronting DOTs, this research project in its second year focused on (i) developing novel machine learning models to accurately predict the condition and durability of 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; (ii) developing practical decision support tool (DST) that can be used by DOT planners during the early design phase to analyze and compare the safety, sustainability, mobility, durability, and construction cost of conventional cast-in-place and precast bridges; and (iii) expand the developed multi-objective optimization model in the first year to provide DOT planners during the preconstruction phase with the added capabilities of maximizing the durability, safety and sustainability of repaired and replaced bridges, as shown in Figure 1. This perfectly aligns with the TRANS/IPIC mission of "*providing gains in durability, safety, and economy as well as reducing environmental impact and resources required for repair and replacement*". Furthermore, this research aligns with TRANS/IPIC goal of "*establishing economic plans for off-site PC manufacturing, shipping, and onsite installation*".

2. Background

Precast bridge elements have been reported by the FHWA (2011) to enhance quality, durability, and reduce onsite construction time. Several studies have been conducted to develop models for predicting bridge condition rates based on bridge age, length, design type, average daily traffic, and design load. For example, Huang (2010) developed a model for predicting the condition and deterioration of Wisconsin bridges. Chyad and Abudayyeh (2020) developed a predictive deterioration model for Michigan's concrete bridge decks. Althaqafi and Chou (2022) estimated deterioration rates for Ohio's bridge components such as decks, superstructures, and substructures. Despite the contributions of these research studies, they are all incapable of accurately predicting the conditions and deterioration of bridges at any state since they were all developed using a limited dataset from a single state and cannot provide reliable estimation in other locations. A number of other related studies have been conducted to support DOTs in the selection of bridge construction methods based on project conditions and requirements. For example, FHWA (2011) developed four flowcharts to identify feasible accelerated bridge construction methods based on planned project characteristics and location. Doolen et al. (2011) developed a decision-making tool to rank bridge construction methods using Analytical Hierarchy Process based on user-specified weights and scores provided by decision makers. Similarly, Jia et al. (2018) developed a multi-criteria evaluation framework to compare and rank bridge construction methods. Despite the contributions of these research studies, they are all incapable of addressing the aforementioned challenges confronting DOTs during the early design and planning phases. Accordingly, there is a pressing need to develop predictive models for accurately estimating the durability and bridge condition of alternative construction methods during the early design phase; and multi-objective optimization model for optimizing the impact of construction decisions on safety, sustainability, mobility, and construction cost during the preconstruction phase, as shown in Figure 1.

3. Research Scope and Objectives

The main goal of this research project is to provide DOTs planners with much-needed support that enables them to analyze and compare the durability, safety, sustainability, mobility, and construction cost of conventional cast-in-place and precast bridges during the early design phase; and optimize bridge construction decisions during the preconstruction phase to advance TRANS-IPIC mission of "*providing gains in durability, safety, and economy as well as reducing environmental impact".* To accomplish this goal, the research objectives of this project are to:

a. Develop novel machine learning models to accurately predict the condition rates of both conventional cast-in-place and precast deck bridges based on a wide range of variables including bridge age, length, design type, average daily traffic, and design load.
b. Create a practical decision support tool (DST) that can be used by DOT planners during the early design phase to analyze and compare the safety, mobility, sustainability, durability, and construction cost of alternative bridge construction methods including conventional cast-in-place and accelerated precast construction methods.
c. Expand the developed multi-objective optimization model in the first year to include maximizing safety and sustainability to support DOTs during the preconstruction phase in identifying optimal construction decisions such as work zone speed limit, crew selection for each bridge activity, and delivery lead days prior to installation day, and the transportation method of each precast element to enhance safety, sustainability, and mobility while minimizing construction cost.

4. Research Description:

Task 1: Develop Novel Machine Learning Models to Predict Condition Rate of Conventional and Precast Bridges during the Early Design Phase

This Task 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.

1.1. Data Collection

This phase 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.

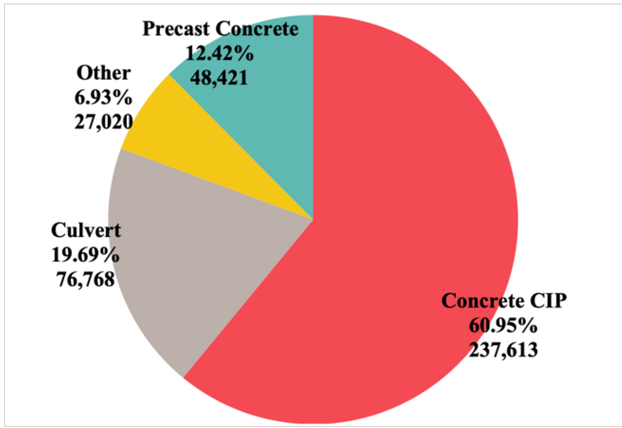


Figure 2. Distribution of NBI Bridges by Deck Type

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 (m^2), 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:

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

Else:

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

1.2. Data Preprocessing

This phase 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.

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.

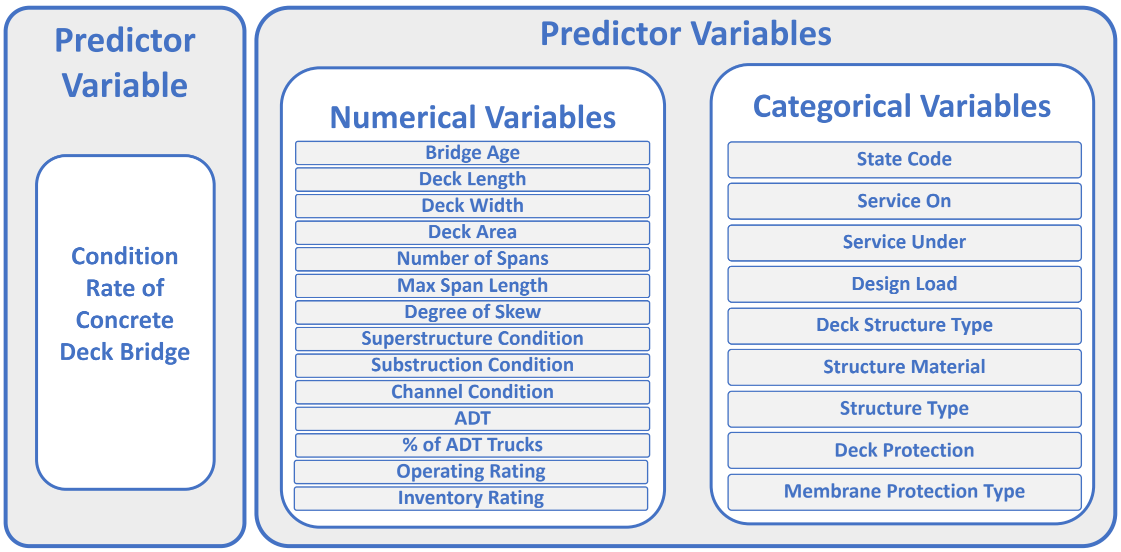


Figure 3. Predictor and predicted variables

1.3. 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.

1.4. 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: Create a practical DST to analyze cost, safety, mobility, sustainability, and durability of alternative bridge construction methods during early design phase.

This task focused on developing a user-friendly decision support tool (DST) that can be used by bridge planners and decision-makers to predict and compare the construction cost, safety, mobility, sustainability, and durability of alternative bridge construction methods during the early design phase. These alternative bridge construction methods include conventional cast-in-place construction (CIP), precast bridge elements (PBE), precast lateral slide (PLS), and precast self- propelled modular transporter (PSPMT) methods. This DST was developed in six modules that are summarized in the following sections.

2.1. Cost Module

This module focused on utilizing the best-performing machine learning model developed in Year 1 of this project to predict the construction cost of alternative bridge construction methods during the early design phase when data are limited (Helaly et al. 2025). The model utilized the Xtreme Gradient Boosting (XGBoost) algorithm and eleven predictor variables including bridge length, width, project length, maximum span length, number of spans, number of lanes, average daily traffic, deck material, design type, location type, and mobility impact category to estimate the construction cost. The developed XGBoost model achieved coefficient of determination *(R^2)* of 99.97%, mean absolute percentage error (MAPE) of 13.9%, Mean absolute error (MAE) of \$64.28/ft^2, and median absolute error (Med AE) of \$29.94/ft^2 (Helaly et al. 2025).

2.2. Safety Module

This module focused on predicting and comparing the safety score of alternative construction methods using the safety performance functions (SPFs) developed by FHWA and the American Association of State Highway and Transportation Officials (AASHTO) Highway Safety Manual (HSM) (Gayah et al. 2024; Kolody et al. 2022). These SPFs can be used to predict the number of work zone crashes (NWC) based on project duration, work zone length, and average daily traffic, as shown in Eq. (3). The

FHWA SPF coefficients were derived using regression models calibrated on national work-zone crash data for various roadway types. The developed safety module allows users to input project-specific coefficients based on their roadway type and local conditions. It should also be noted that several state DOTs include additional predictors in their SPFs, such as the Illinois DOT that includes speed limit, as shown in Eqs. (4) (Schattler et al. 2020). The module is designed to provide users with the flexibility to include additional predictors as needed.

$$NWC = e^{\alpha} * PD^{\beta_1} * L^{\beta_2} * ADT^{\beta_3} \quad (3)$$

$$NWC_{IL} = e^{-7.049} * PD^{0.904} * L^{0.317} * ADT^{0.486} * e^{-0.0004(S_1 * S_2)} \quad (4)$$

Where NWC is predicted number of work zone crashes, NWC_{IL} is predicted number of work zone crashes in IL, PD is project duration in days, L is work zone length in miles, ADT is average daily traffic, S_1 is speed limit in work zone under normal condition, S_2 is speed limit in work zone during construction, $\beta_1, \beta_2, \beta_3$ are statistical model coefficients, and α is a constant.

<u>2.3. Mobility Module</u>

This module was designed to estimate and compare the mobility scores of alternative bridge construction methods by calculating work zone total vehicle delay time (TVD) using the FHWA procedure in the road user calculator tool (FHWA 2022). The TVD is calculated based on work zone daily delay, detour daily delay and project duration, as shown in Eqs. (5)- (7)

$$Minimize\ (TVD) = (WD + DD) \times \mathrm{P}D \quad (5)$$

$$WD = ADT \times PVW \times WDV = ADT \times PVW \times [\frac{L}{S_2} - \frac{L}{S_1} + SW] \quad (6)$$

$$DD = ADT \times (1 - PVW) \times DDV = ADT \times (1 - PVW) \times [\frac{LD}{S_3} - \frac{L}{S_1}] \quad (7)$$

Where TVD is the total vehicle delay time in hours, WD is work zone daily delay time in hours, DD is detour daily delay time in hours, PD is project total duration in days, ADT is average daily traffic in vehicles per day, PVW is the percentage of vehicle using work zone route, WDV is work zone delay time per vehicle in hours, L is work zone length in miles, S_1 is speed limit in work zone under normal condition, S_2 is speed limit in work zone during construction, SW is stopped time in work zone in hours, DDV is detour delay per vehicle in hours, and LD is detour length in miles, and S_3 is speed limit on detour route.

2.4. Sustainability Module

This module focused on predicting and comparing the sustainability score of alternative bridge construction methods using the FHWA infrastructure carbon estimator methodology to calculate the total work zone traffic congestion emissions (TE) (FHWA 2022; Gallivan et al. 2014). This TE is calculated based on total vehicle miles traveled and emission factors, as shown in Eq. (8)

$$TE = \sum VMT \times EF = \sum [ADT \times PVW \times L \times PD] \times [(PC \times EF_c) + (PT \times EF_T) \tag{8}$$

TE is work zone traffic congestion emissions in kg CO_2e, VMT is total number of vehicle miles traveled within the work zone, EF is average emission factor per vehicle in kg CO_2e per mile, ADT is average daily traffic in vehicles per day, PVW is the percentage of vehicle using work zone route, L is work zone length in miles, PD is project total duration in days, PC is percentage of cars using work zone route, PT is percentage of medium and heavy trucks using work zone route, EF_c is emission factor per car in kg CO_2e per mile, EF_t is emission factor per medium and heavy trucks in kg CO_2e per mile.

2.5. Durability Module

This module was designed to estimate and compare the condition rate of concrete deck bridges constructed using conventional cast-in-place and precast construction methods based on the best-performing machine learning model developed in Task 1 of this project.

2.6. Graphical User Interface Module

This module focused on developing an effective graphical user interface (GUI) to facilitate the use of the developed DST to estimate and compare the performance of alternative bridge construction methods during the early design phase. For each of the aforementioned five modules, the GUI was designed to analyze user specified project input data in order to predict and visualize the performance of alternative bridge construction methods in terms of construction cost, safety, mobility, sustainability, and durability, respectively, as shown in Figure 5, Figure 6, Figure 7, Figure 8, and Figure 9. The individual performances in these five important modules are then aggregated in a single dashboard to support decision makers in analyzing and comparing the performance of alternative bridge construction methods, as shown in Figure 10.

2.7. Case Study

A planned bridge construction project is analyzed as a case study to illustrate the use of the developed DST and demonstrate its capability to quantify the impacts of alternative construction methods on construction cost, safety, mobility, sustainability, and durability. The project has a total length of 500 ft and is located in an urban area of Champaign County, Illinois, with an average daily traffic of 20,000 vehicles/day (80% cars and 20% medium or heavy trucks). The bridge project has a length of 117.0 ft, a width of 33.4 ft, a maximum span length of 28.5 ft, two lanes, four spans, a girder design, and a concrete deck, as shown in Figure 4.

Project Information			
Project Name	SN 082-0166		
Prepared By	Bridge Planner		
Location	Champaign County	State	Illinois
Current Date (mm/dd/yy)	1/15/26	ZipCode	622
Planned Construction Year (yyyy)	2025	Predicted Inflation Rate from 2025	1.05

Project Specifications			
Bridge length(ft.)	117.00	Bridge Width (ft.)	33.40
Project Length (ft.)	500.00	Max Span Length (ft.)	28.50
No of lanes	2	No of Spans	4
Design Type	Girder	Location Type	Urban
Deck Material	Concrete	Annual Average Daily Traffic (AADT)	20,000
Percentage of Cars	80%	Precentage of Medium or Heavy Trucks	20%

1.Project Input Data | 2.Construction Cost Module | 3.Safety Module | 4.Mobility Module | 5.Sustainability Module | 6.Durability Module | 7.Summary | Values

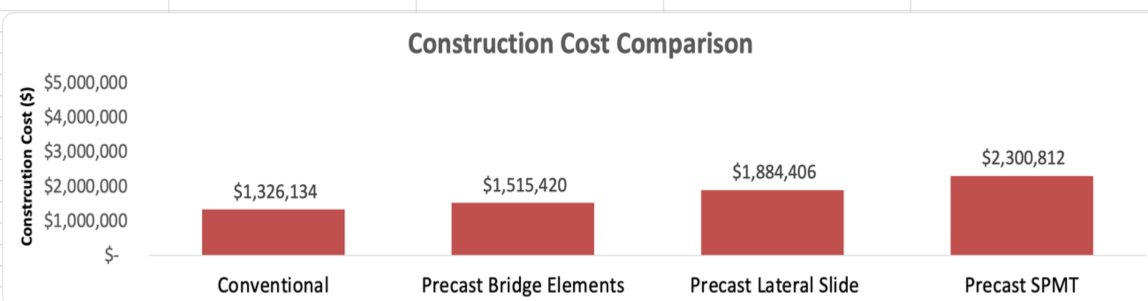
Yellow Text Input Data   Blue Dropdown List

Figure 4. DST project information input data

The DST was used to estimate and compare the construction cost of alternative bridge construction methods as \$339/f^2 for conventional cast-in-place, \$388/f^2 for precast bridge elements, \$482/f^2 for precast lateral slide, and \$589/f^2 for precast SPMT construction method, as shown in Figure 5.

Predicted Construction Cost Module				
Construction Method	Conventional	Precast Bridge Elements	Precast Lateral Slide	Precast SPMT
Mobility Impact Category	Not Reduced (Conventional)	Tier 5 (within 3 months)	Tier 3 (within 2 weeks)	Tier 2 (within 3 days)
Predicted Cost/Sf	\$ 339	\$ 388	\$ 482	\$ 589
Predicted Total Construction Cost	\$ 1,326,134	\$ 1,515,420	\$ 1,884,406	\$ 2,300,812

Run Predictive Models

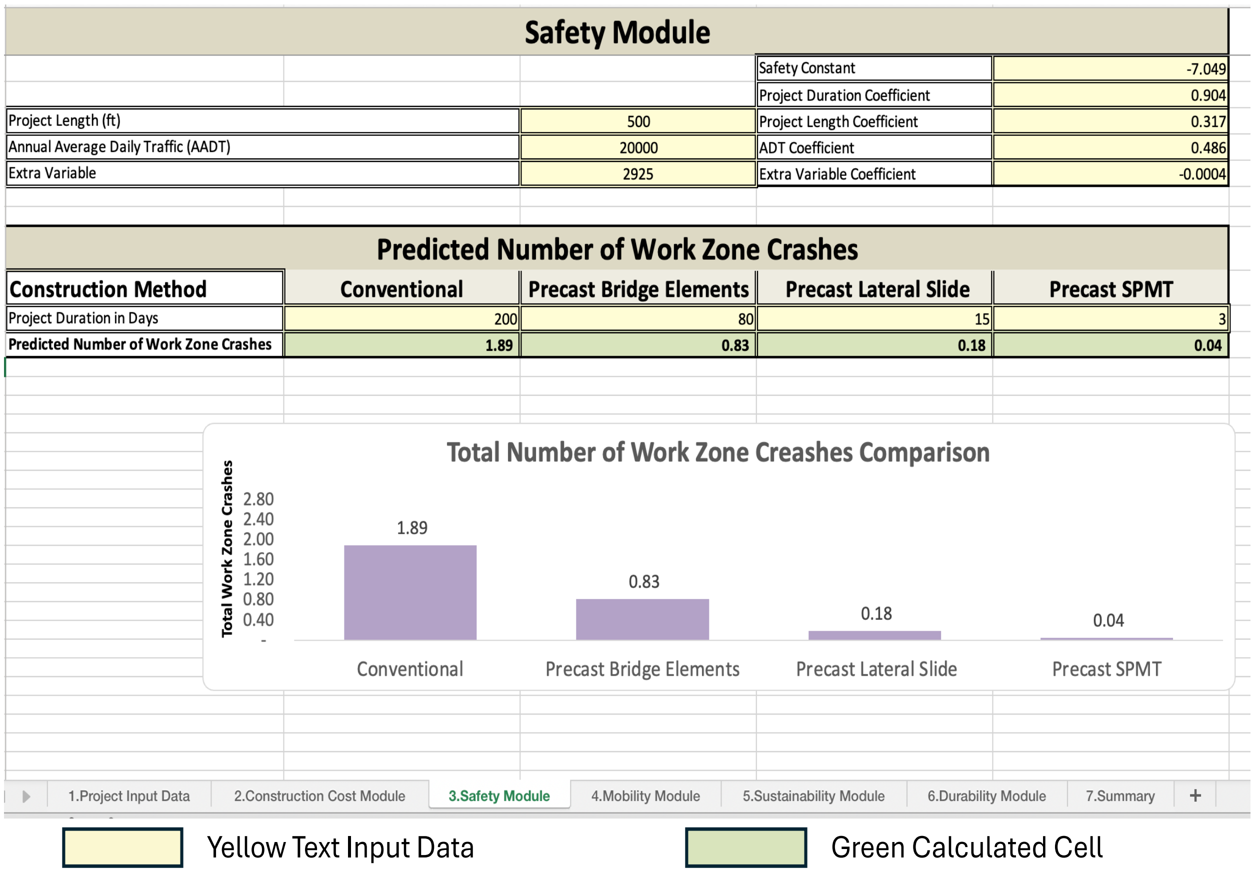


1.Project Input Data | 2.Construction Cost Module | 3.Safety Module | 4.Mobility Module | 5.Sustainability Module | 6.Durability Module | 7.Summary

Green Calculated Cell   Blue Dropdown List

Figure 5. Construction cost comparison

To enable bridge planners to quantify the impact of these alternative bridge construction methods on the safety of the travelling public and construction workers, the DST was then used to compare the number of work zone crashes that were predicted using Eq.s (3) and (4), as shown in Figure 6. The resulting values are 1.89 crashes for conventional cast-in-place, 0.83 crashes for precast bridge elements, 0.18 crashes for precast lateral slide, and 0.04 crashes for precast SPMT construction method, as shown in Figure 6.


Safety Module

		Safety Constant	-7.049
		Project Duration Coefficient	0.904
Project Length (ft)	500	Project Length Coefficient	0.317
Annual Average Daily Traffic (AADT)	20000	ADT Coefficient	0.486
Extra Variable	2925	Extra Variable Coefficient	-0.0004

Predicted Number of Work Zone Crashes

Construction Method	Conventional	Precast Bridge Elements	Precast Lateral Slide	Precast SPMT
Project Duration in Days	200	80	15	3
Predicted Number of Work Zone Crashes	**1.89**	**0.83**	**0.18**	**0.04**

Figure 6. Number of work zone crashes comparison

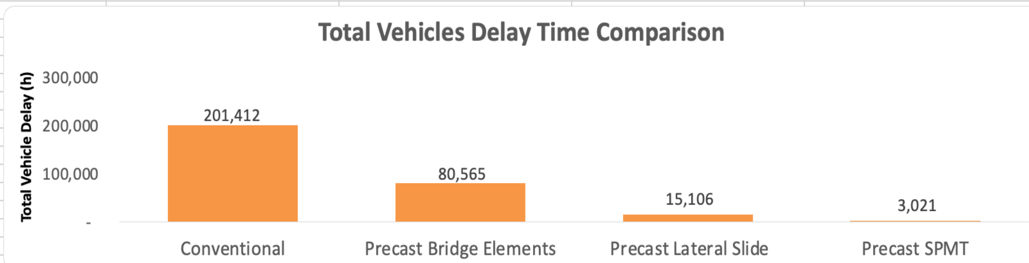
The developed DST was also utilized to quantify the impact of alternative bridge construction methods on traffic mobility by comparing the total vehicles delay time using Eq.s (5) - (7), as shown in Figure 7. The calculated total vehicles delay time is 201,412 h for conventional cast-in-place, 80,565 h for precast bridge elements, 15,106 h for precast lateral slide, and 3,021 h for precast SPMT construction method, as shown in Figure 7.

Mobility Module

Project Length (ft)	500
Annual Average Daily Traffic (AADT)	20000
Percentage of Vehicles using Work Zone Route	50%
Speed Limit in Work Zone under Normal Condition (mph)	65
Speed Limit in Work Zone during Construction (mph)	45
Speed Limit on Detour Route (mph)	55
Stopped Time in Work Zone (min)	5
Detour Length (m)	1

Predicted Total Vehicles Delay Time (TVD)

Construction Method	Conventional	Precast Bridge Elements	Precast Lateral Slide	Precast SPMT
Project Duration in Days	200	80	15	3
Work Zone Daily Delay Time (h)	840	840	840	840
Detour Daily Delay Time (h)	167	167	167	167
Predicted Total Work Zone Vehicle Delay Time (h)	**201,412**	**80,565**	**15,106**	**3,021**



1.Project Input Data | 2.Construction Cost Module | 3.Safety Module | 4.Mobility Module | 5.Sustainability Module | 6.Durability Module

Yellow Text Input Data   Green Calculated Cell

Figure 7. Total vehicles delay time comparison

The DST was then utilized to compare the total work zone traffic congestion emissions to quantify the impact of alternative bridge construction methods on project sustainability using Eq. (8), as shown in Figure 8. The resulting values are 129,394 kg CO_2e for conventional cast-in-place, 51,758 kg CO_2e for precast bridge elements, 9,750 kg CO_2e for precast lateral slide, and 1,941 kg CO_2e for precast SPMT construction method, as shown in Figure 8.

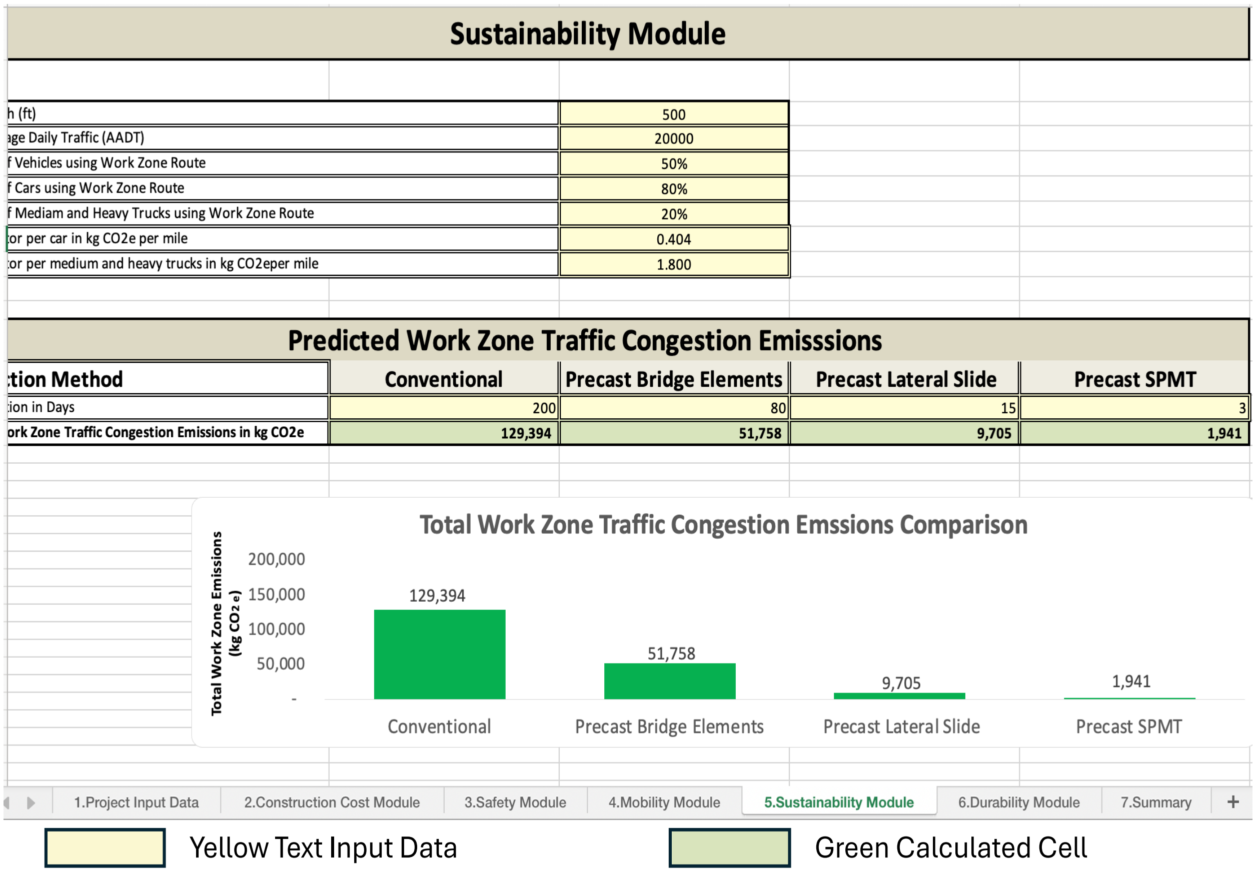


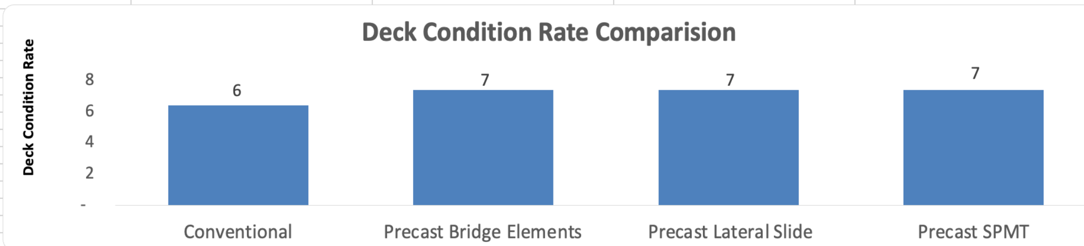
Figure 8. Total work zone traffic congestion emissions comparison

The durability module was then applied to estimate and compare the predicted deck condition rating for each construction method over the analysis period, as shown in Figure 9. The predicted ratings are 6 for conventional cast-in-place and 7 for precast bridge elements, precast lateral slide, and precast SPMT construction method, as shown in Figure 9.

Durability Module			
Superstrucure Condition Rate	6	Design Load	MS 22.5 / HS 25
Substructure Condition rate	7	Service on	Highway
Channel Condition Rate	7	Service Under	Highway, with or without pedestrian
Operation Rating Method	Load Factor (LF)	Operation Rating	60
Inventory Rating Method	Load Factor (LF)	Inventory Rating	50
Type of Membrane	None	Degree Skew	10
Deck Protection Type	Epoxy Coated Reinforcing	Bridge Age	30

Run Predictive Models

Predicted Deck Condition Rate				
Construction Method	**Conventional**	**Precast Bridge Elements**	**Precast Lateral Slide**	**Precast SPMT**
Predicted Number of Work Zone Crashes	6	7	7	7



1.Project Input Data | 2.Construction Cost Module | 3.Safety Module | 4.Mobility Module | 5.Sustainability Module | 6.Durability Module | 7.Summary

Yellow Text Input Data   Blue Dropdown List   Green Calculated C

Figure 9. Deck Condition Rate Comparison

Finally, the DST integrates the outputs from the five modules into a single dashboard, allowing decision makers to view predicted values for cost, safety, mobility, sustainability, and durability side by side and to visually compare the overall performance of the alternative bridge construction methods, as shown in Figure 10.

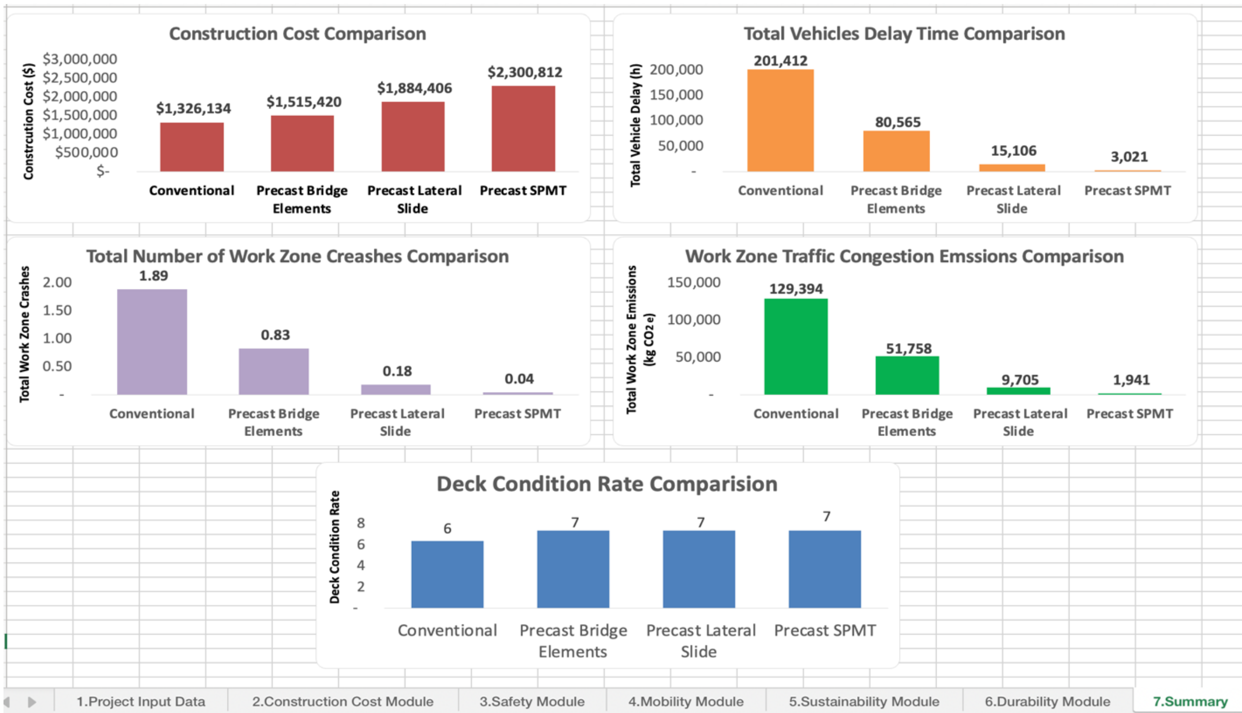


Figure 10. Bridge Construction Methods Dashboard Comparison

Task 3: Expand the multi-objective optimization model in Year 1 to add safety and sustainability as preconstruction objectives, in addition to cost and mobility.

This task focused on expanding the developed multi-objective optimization model in Year 1 to include maximizing safety and sustainability in addition to maximizing traffic mobility and minimizing total construction cost to support State DOTs identifying optimal construction decisions during the preconstruction phase. The development of the optimization model focused on the following three main stages, as shown in Figure 11.

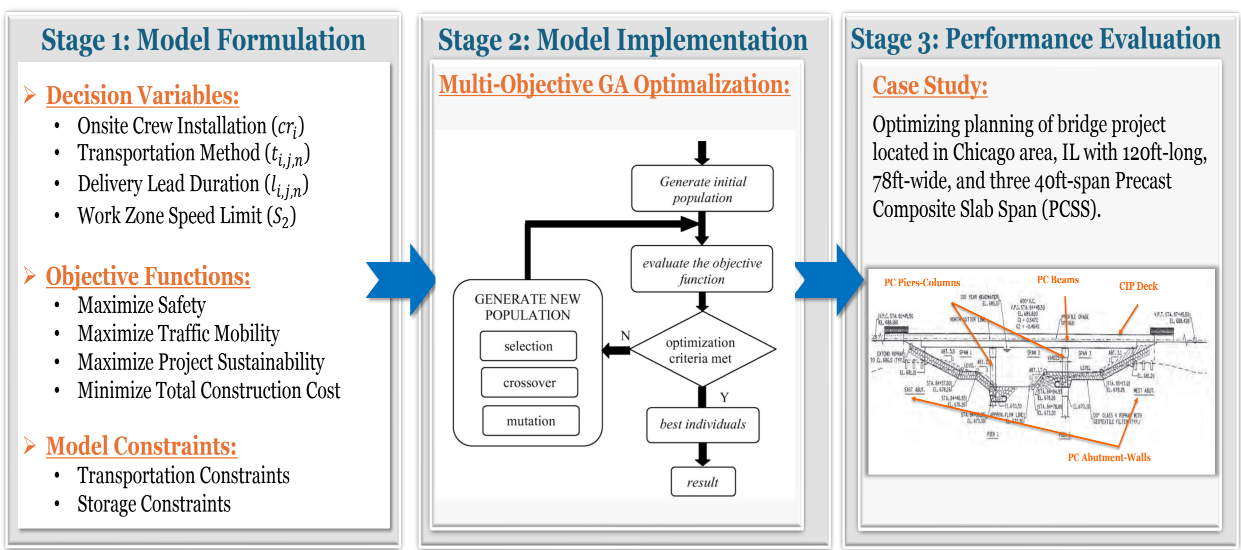


Figure 11. Development stages of multi-objective optimization model

3.1. Model Formulation

This stage focused on formulating a novel multi-objective optimization model for identifying optimal construction planning decisions for precast bridge construction projects. This was achieved in three main steps that focused on: (i) identifying all relevant decision variables including work zone speed limit (S_2), crew selection (Cr_i) for each bridge activity i, and delivery lead days ($l_{i,j,n}$) prior to installation day, and the transportation method ($t_{i,j,n}$) of each precast element n of section j in activity i; (ii) formulating objective functions to maximize safety, mobility, and sustainability while minimizing total construction cost; and (iii) modeling all practical constraints related to the transportation and onsite storage of precast elements.

3.2. Model Implementation

This stage focused on implementing the optimization computations of the formulated model. This was executed in Python using the Nondominated Sorting Genetic Algorithm II (NSGA-II) and four supporting modules: (a) scheduling module that generates a construction schedule to comply with crew availability, job logic, and crew work continuity; (b) transportation module that creates a practical and cost-effective plan for transporting all precast bridge elements to the construction site with the least number of truck trips and transportation cost; (c) cost module that calculates the cost of each generated solution based on the formulated cost objective function; and (d) performance module that estimates safety, mobility, and sustainability scores.

3.3. Performance Evaluation

This stage focused on analyzing a case study of a bridge construction project in Illinois to evaluate the performance of the developed optimization model and demonstrate its capabilities in optimizing the planning of precast bridge construction projects. In this case study, the model generated a set of 35 optimal solutions, where each represents a unique and optimal trade-off among the four optimization objectives, as shown in Figure 12.

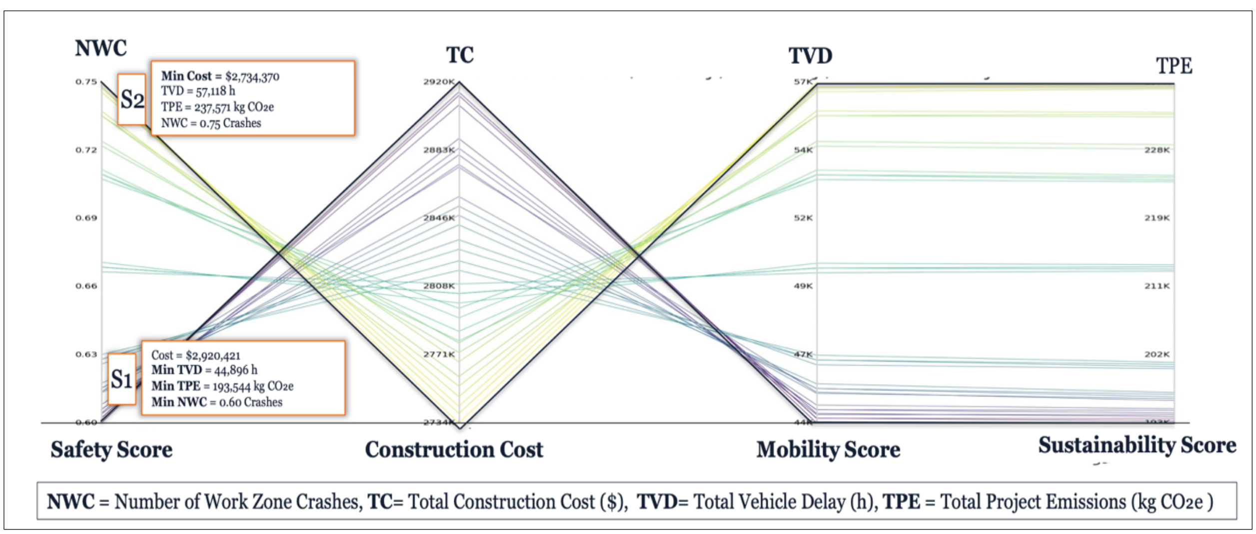


Figure 12. Parallel coordinates plot of optimization objectives

5. Project Results

This main findings of this project and its key deliverables include: (1) six novel machine learning models for predicting the condition ratings of conventional cast-in-place and precast concrete deck bridges; (2) a practical decision support tool (DST) that quantifies and compares cost, safety, mobility, sustainability, and durability of alternative bridge construction methods during the early design phase; and (3) a multi-objective optimization model that generates optimal trade-offs among cost, safety, mobility, and sustainability for precast bridge projects during the preconstruction phase.

First, the research team utilized the National Bridge Inventory (NBI) database to develop and compare six machine learning (ML) algorithms for predicting the condition rating of concrete deck bridges constructed using conventional cast-in-place and precast methods. The evaluated ML algorithms in this analysis included Ordinary Least Squares (OLS), LASSO Regression, Ridge Regression, Random Forest (RF), Gradient Boosting (GB), and Extreme Gradient Boosting (XGBoost). Model development followed four phases: data collection, data preprocessing, model development, and model evaluation. The evaluation results showed that the XGBoost model outperformed the other ML models in terms of mean absolute percentage error (MAPE), mean absolute error (MAE), median absolute error (Med. AE), and root mean squared error (RMSE), as summarized in Table 2.

Second, the research team developed a user-friendly DST to predict and compare the construction cost, safety, mobility, sustainability, and durability of alternative bridge construction methods during the early design phase. The DST consists of six modules: cost, safety, mobility, sustainability, durability, and a graphical user interface. The cost module utilized the best-performing machine learning model developed in Year 1 to predict construction cost for each method. The safety module utilized the FHWA Safety Performance Functions to calculate work zone crashes. The mobility module utilized the FHWA Road User Cost procedure to calculate total vehicle delay time. The sustainability module utilized the FHWA Infrastructure Carbon Estimator methodology to calculate total work zone traffic congestion emissions. The durability module used the best-performing ML model from Task 1 to predict deck condition ratings for cast-in-place and precast concrete bridges. The graphical user interface was designed to facilitate the use of the developed DST and enable its users to compare and visualize the performance of alternative bridge construction methods during the early design phase, as shown in Figure 4 - Figure 10. Applied to a representative bridge case study, the DST showed that accelerated precast bridge construction methods substantially reduce expected work-zone crashes, user delay, and emissions; achieve higher predicted deck condition ratings while requiring higher initial construction cost.

Third, the research team expanded the Year-1 multi-objective optimization model to include safety and sustainability as preconstruction objectives, in addition to cost and mobility. The optimization model was developed in three main stages: formulation, implementation, and performance evaluation, as shown in Figure 11. The formulation stage focused on identifying all relevant decision variables, formulating the four objective functions, and modeling practical constraints. The implementation stage utilized the Nondominated Sorting Genetic Algorithm II (NSGA-II) with four supporting modules to perform the optimization computations. In the performance evaluation stage, a bridge construction case study was analyzed to assess the performance of the developed optimization model and demonstrate its capabilities in optimizing the planning of precast bridge construction projects. The model generated a set of trade-off plans that balance cost, safety, mobility, and sustainability, demonstrating its ability to support data-driven planning of precast bridge construction projects, as shown in Figure 12.

6. Conclusions and Recommendations

The scope of this project focused on three main research tasks to provide DOT planners with much-needed support that enables them to analyze and compare the performance of alternative bridge construction methods during the early design phase and optimize their construction decisions during the preconstruction phase. To accomplish this goal, the first research task developed six machine learning models for predicting deck condition ratings of conventional cast-in-place and precast bridges during the early design phase. The second research task developed a user-friendly Decision Support Tool (DST) to quantify and compare the cost, safety, mobility, sustainability, and durability of alternative construction methods during the early design phase. The third research task expanded the multi-objective optimization model from Year 1 to provide DOT planners with the capability of optimizing precast bridge project decisions during the preconstruction phase in order to maximize safety, mobility, sustainability while minimizing total construction cost.

Despite the significant contributions of this research project, future research can focus on expanding the optimization model developed in the third task of this project to: (1) consider and optimize additional decision variables that affect project performance, such as lane-closure time, detour routes, and work-zone configurations; (2) expand the scope of the optimization framework to enable the analysis of multiple projects at a district and/or state level; and (3) integrate the model into a user-friendly interface to facilitate its practical use by agencies and practitioners.

7. Practical Application/Impact on Transportation Infrastructure:

The outcome of this project has a strong potential to be implemented by state DOTs and local agencies. They are expected to provide planners and decision makers in these agencies with much-needed support to (1) accurately predict and analyze the durability of conventional cast-in-place and precast concrete deck bridges during the early design phase; (2) quantify, compare, and visualize the performance of alternative bridge construction methods during the early design phase in terms of their construction cost, work-zone safety, user delay, congestion emissions, and durability in order to select the most suitable construction method for each planned project; and (3) optimize the planning of precast bridge projects to achieve multiple objectives, including maximizing safety, mobility, and sustainability while minimizing total construction cost during the reconstruction phase.

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