QUANT CR FOR TRANSFORMATIVE BRIDGE ASSET MANAGEMENT

Quarterly Progress Report
For the period ending June, 2024

Submitted by:
PI- Bjorn Birgisson
Co-PI – Mi Chorzepa
Research Scientist – Sajib Saha
Research Scientist – Lynn Abdouni
Graduate Student – Adey Sowemimo

Affiliation: Civil Engineering,
School of Environmental, Civil, Agricultural, and Mechanical Engineering
University of Georgia
Athens, GA

Submitted to:
IBT/ABC-UTC
Florida International University
Miami, FL

1. Background and Introduction

The research team aims to develop an artificial intelligence (AI)-powered quantitative condition rating (QUANT CR) model which operates on a low-cost geographic information system (GIS) platform, aiding local and state bridge owners in maintenance, repair, and replacement (MRR) decisions while preserving the established inspection and condition rating practices.

The next generation asset management system leverages the knowledge gained from 50+ years of bridge inspection practices but is predictive, forward-looking, and transformative. QUANT CR embodies insights gained from the understanding of human behavior to better assist bridge owners in decision-making. Thus, we envision QUANT CR will be operated in parallel with the existing bridge condition ratings and provide simple decision aids for bridge owners.

We believe bridge condition ratings can be better predicted by modern machine learning methods, leveraging the historic data, evolving element condition ratings, and detailed defect items. Additionally, deep learning widely used for text recognition enables an analysis of inspectors' narratives describing bridge conditions. Lastly, computer vision and deep generative learning help bridge owners visualize the outcomes of their decisions - MRR actions/inactions, empowering bridge owners. QUANT CR will:

1) Reduce human errors and aid in training bridge inspectors;
2) Close the knowledge gap between predicted and actual bridge performance, noting that it only gets better with time/data;
3) Aid bridge owners in budgetary planning by providing access to performance prediction data and MRR options;
4) Enable the use of technologies such as a drone, autonomously assigning condition ratings and ultimately writing an inspection report that is better [regarding consistency] than one written by a human-writer.

Therefore, this technology is expected to improve bridge inspection outcomes, reduce costs, increase access to performance predictions, aid in MRR decisions, which are essential for asset management at local and state government levels. This innovation will particularly serve to aid rural areas with limited resources.

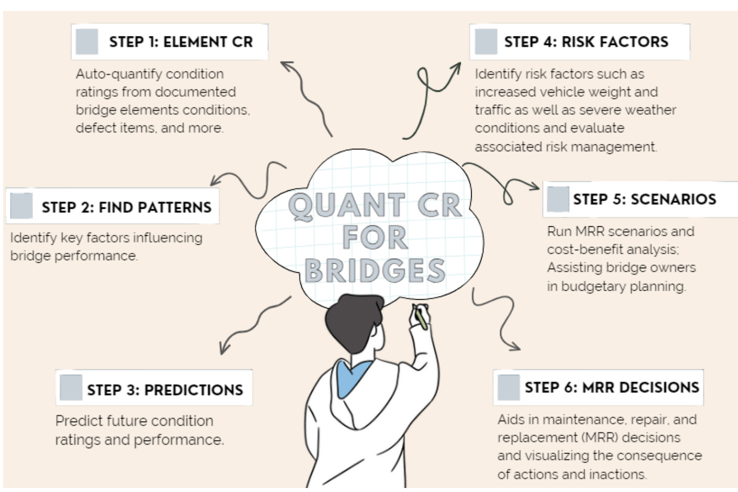


Figure 1. Steps involved in developing a Qaun CR model.

2. Problem Statement

Our bridge infrastructure is at a critical juncture, with over 42% of bridges exceeding 50 years of age and 7.5% classified as structurally deficient [1]. The call for an annual increase in bridge rehabilitation funding by 58% underscores the gravity of this issue [2]. The traditional methodologies of bridge condition assessments—relying heavily on visual inspections and on-site evaluations—are increasingly insufficient due to their resource-intensive nature and can be more efficient and successful, especially when managing disruptive events such as natural disasters. Increasing incidence of extreme weather events, rising sea levels, and climate change present new challenges that current bridge asset owners face in terms of managing their assets. The emergence of automated and heavy trucking poses additional challenges to bridge infrastructure, necessitating a re-evaluation of bridge load permits and condition assessments that account for changes in traffic patterns and vehicle technologies. There is a pressing need to transition from reactive to proactive bridge asset management strategies, which necessitates the development of innovative tools that leverage the vast historical data repositories, such as the National Bridge Inventory (NBI), and integrate them into more detailed bridge element data using modern technologies including AI, machine learning, and geospatial analysis frameworks.

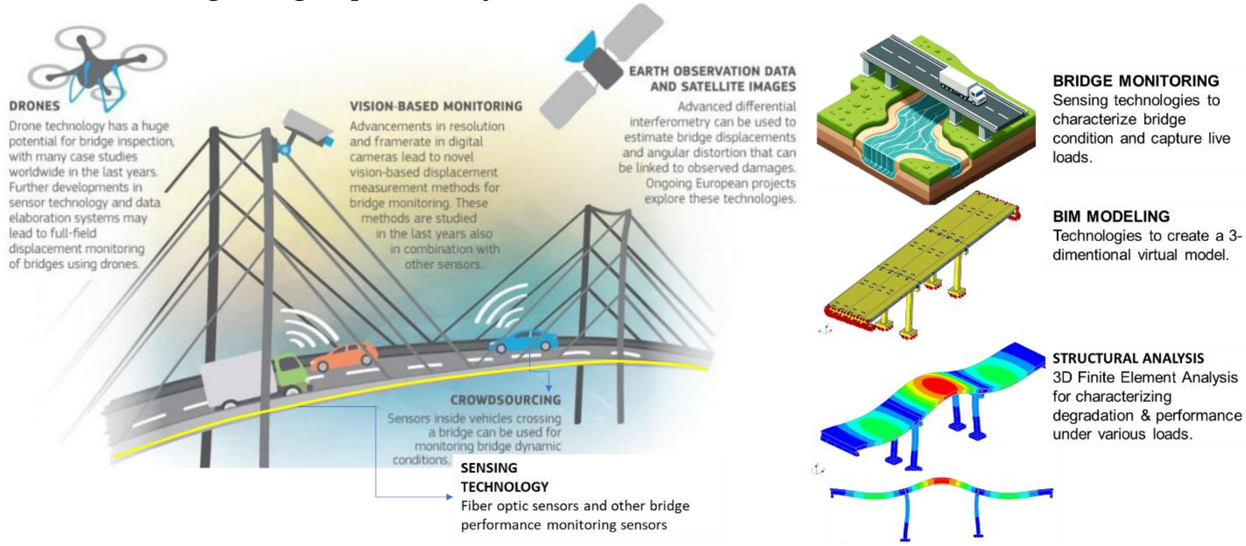


Figure 2. Emerging technologies [3] for bridge performance monitoring and management.

Currently, the AASHTOWare Bridge Management (BrM) is the main tool employed for bridge asset management at state-level; however, this platform is not accessible by local governments. The FHWA's Long-Term Bridge Performance (LTBP) Program's InfoBridge provides excellent resources for all owners but does not serve as an asset management tool. Unfortunately, existing bridge asset management practices fall short in several key areas: they do not sufficiently exploit emerging technologies such as AI to predict future bridge performance and service life based on past and emerging inspection results (refer to Figure 2); they lack comprehensive decision-making frameworks that incorporate a multitude of stressors and scenarios; and they are not adequately tailored to assist local and rural bridge owners with limited resources.

Furthermore, current tools do not fully account for interactions among bridge elements and various types of inter-dependencies that can lead to rapid degradation and cascading failures within the bridge networks, nor do they address the connectivity and sensitivity of the freight network to disruptions. The overarching problem, therefore, is the need for a bridge asset management system that is robust, predictive, and capable of integrating a multitude of data sources. Such a system must be economically viable, user-friendly, and adaptable to the rapidly changing landscape of transportation technology and environmental stressors (refer to Figure 3 for core elements).

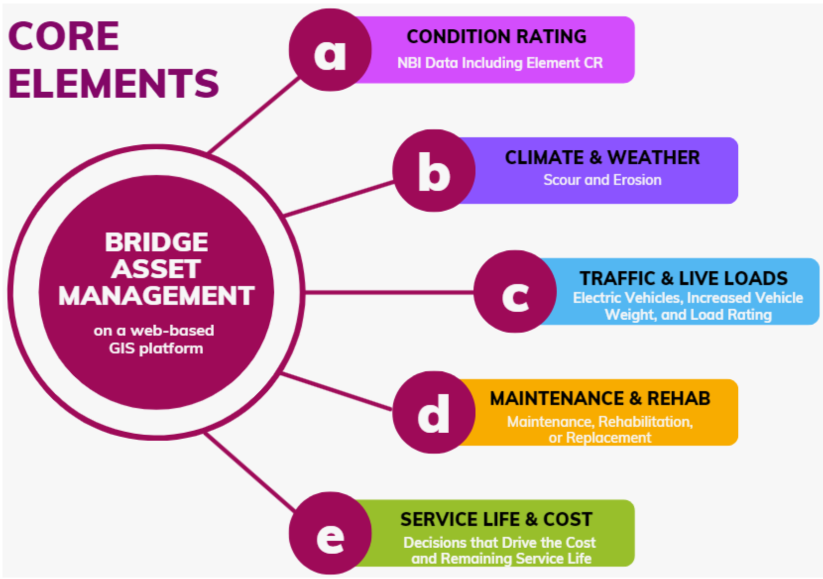


Figure 3. Core Elements for Bridge Asset Management.

The ultimate aim of this project is to equip state and local governments with a tool necessary for long-term bridge asset management, which not only safeguards against current vulnerabilities but also anticipates and mitigates future challenges. To do so, we need a powerful, yet low-cost and easy-to-implement, system that can help local and state bridge owners visualize and understand consequences resulting from their MRR actions or decisions.

Quantitatively computed rating is widely used for equity valuation and management in the financial markets; yet, bridge assets are not valued and quantitatively predicted despite of the significant value they hold.

3. Objectives and Research Approach

This project aims to empower local and state bridge owners to make informed decisions on MRR, optimizing budget plans across various scenarios. Thus, the research approach centers on developing an AI-powered quantitative condition rating (QUANT CR) system and decision analysis tool for bridges, which leverages historical data, including the extensive records of the National Bridge Inventory (NBI)'s element data, Long-Term Bridge Performance Program, bridge MRR scenarios, inspectors' narratives, and ultimately risk management including environmental, traffic, vehicle, and other relevant data to predict long-term bridge performance.

A web-based Geographic Information System (GIS) platform will store and visually represent bridge network assets, providing uniform access to all databases. A hierarchical approach to quantify bridge condition ratings and assigning them to the network analysis tool will improve long-term bridge performance predictions. Deep learning algorithms will analyze historical data and detailed bridge condition narratives to improve the bridge performance predictions at element level. Incorporating the element-level inspection results and detailed defect items is a key task for building a Quant CR model. Text recognition techniques will further interpret inspectors' descriptive reports, transforming qualitative comments into actionable quantitative data.

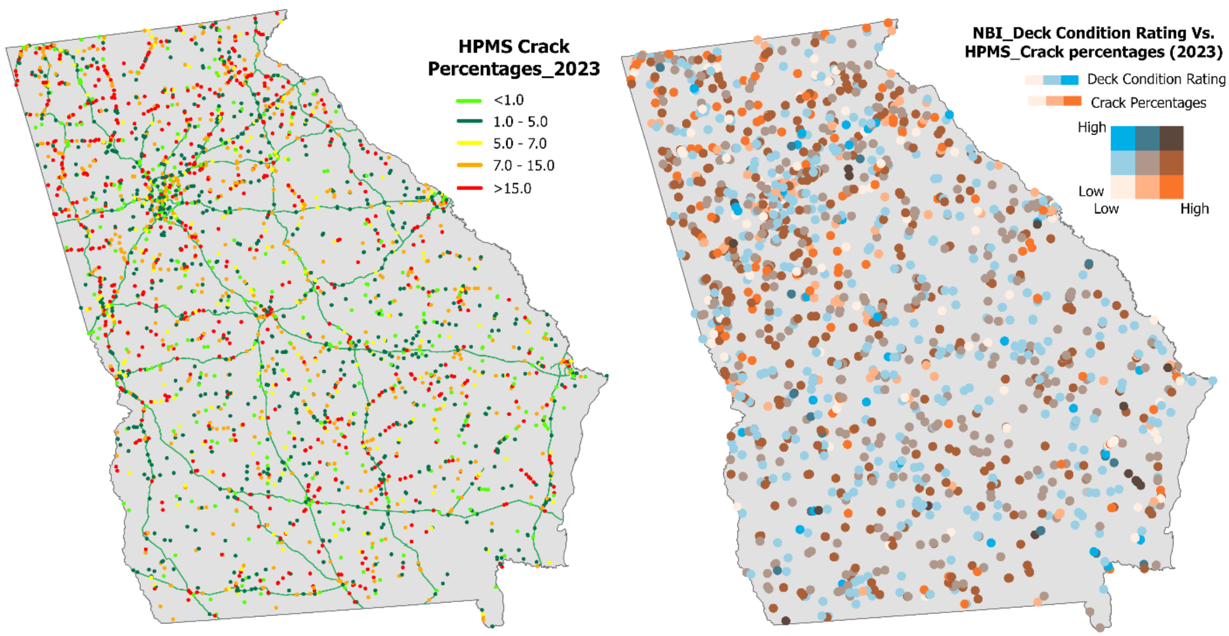
4. Description of Research Project Tasks

The following task is completed during the reporting period.

Task 1 – Acquisition of bridge performance/condition data into geospatial format
In this task, the research team acquires the bridge performance, condition, structural, and traffic data for nationwide bridge network assets from different sources and process into a geospatial data format. In addition to the deck condition data, National Bridge Inventory (NBI) provide data related to operational conditions, functional descriptions, and inspection data in geospatial format. Additionally, Highway Performance Monitoring System (HPMS) database is available and includes detailed roadway and bridge deck surface condition data. Bridge element data is also collected to properly assess element level bridge conditions and effectively manage condition deficiencies.

Description of work performed up to this period:

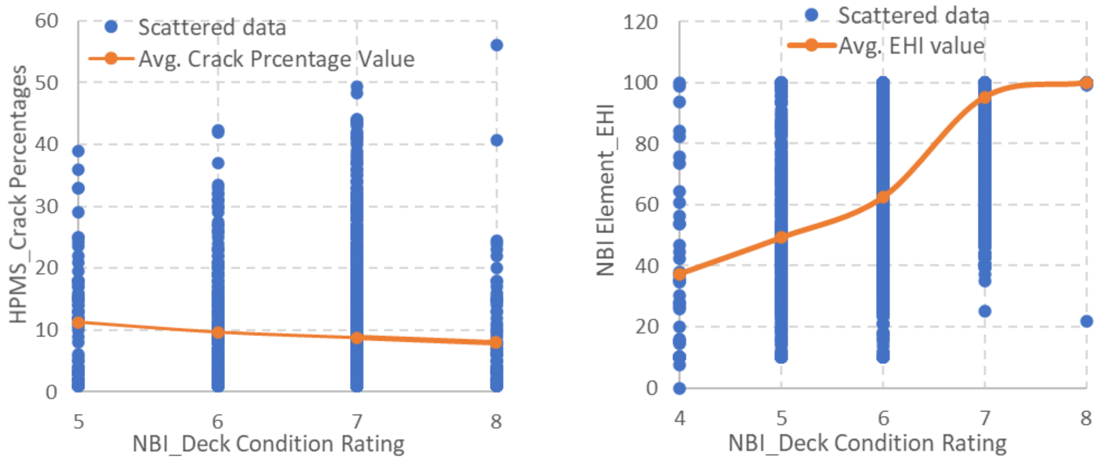
Figure 4 illustrates the mapping of the two (NBI and HPMS) databases within ArcGIS. Figure 5 compares the datasets collected the from HPMS, NBI and NBI Element. The results suggest that the NBI bridge deck condition rating does not have significant correlation with road surface condition (or HPMS) data whereas it is well correlated with the NBI deck element condition ratings.



(a) (b)

(a) Percentage of Cracks from the HPMS Database for 2023 Showing Surface Condition Data for Bridge Locations in Georgia; (b) Comparison of Deck Condition Rating from the NBI Database and Percentage of Cracks from the HPMS Database for 2023

Figure 4. NBI and HPMS Database Mapped in ArcGIS.



(a) (b)

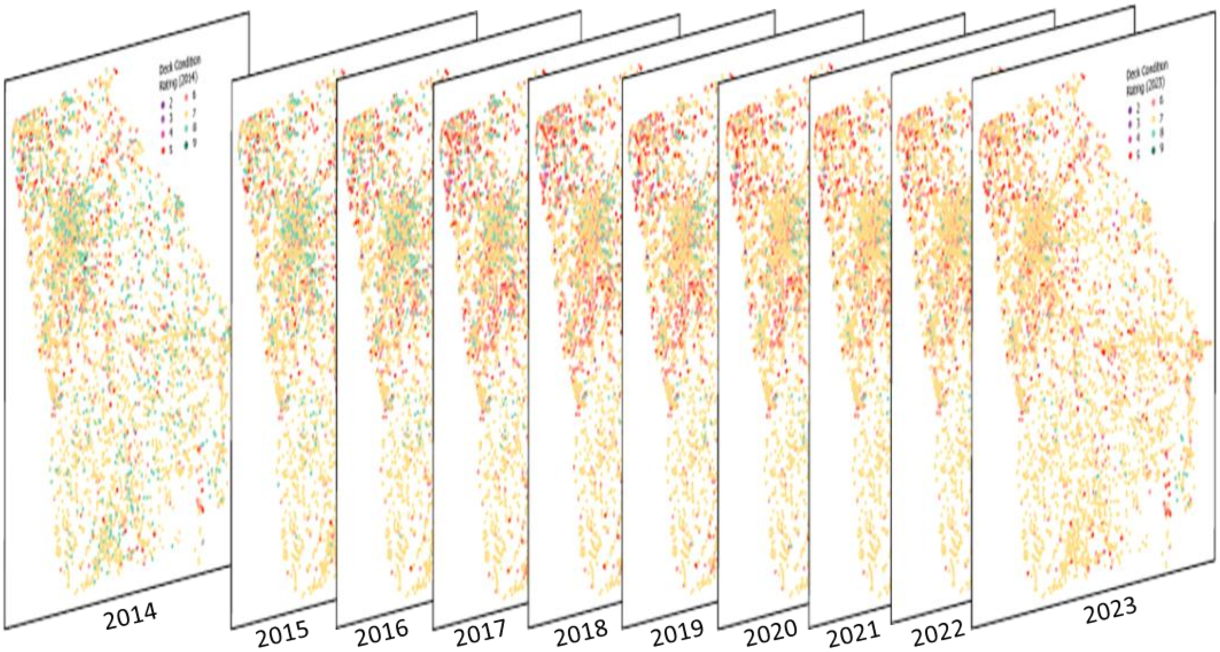
(a) Inverse Relationship Between HPMS_Crack Percentages and NBI_Deck Condition Rating Datasets; (b) Proportional Relationship Between NBI_Element Health Index and NBI_Deck Condition Rating Datasets

Figure 5. Comparison Plots of Data Between HPMS, NBI and NBI Element

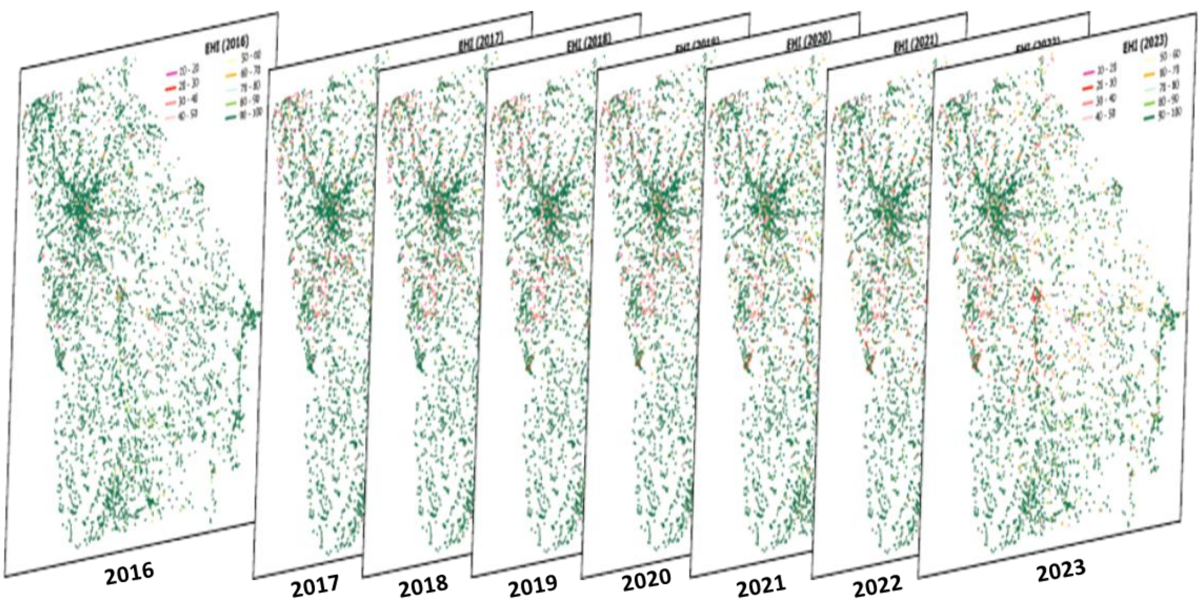
Task 2 – Development of a bridge condition rating prediction model

In this task, to create a Quant CR model, the research team compiled year-by-year bridge deck condition rating datasets collected in Task 1. Figure 6(a) shows the deck condition rating maps from 2014 to 2023 collected from NBI datasets. Similarly, Figure 6(b) illustrates the maps of Element Health Index (EHI) data for all bridges within Georgia from 2016 to 2023, collected from the NBI Element database. In developing the prediction model, we identified 6,283 bridge sections from the NBI dataset and 6,337 bridge sections from the NBI Element dataset for which we obtained consistent year-by-year condition rating and health index data, respectively.

Using the dataset, many-to-many multivariate time-distributed RNN (recurrent neural network) models are selected. RNNs use deep learning algorithms to process sequential data such as bridge condition ratings. The input data shape for a large number of bridges needs to be capable of grouping a sequence of bridge condition ratings by each bridge into a 3D input array, effectively turning the problem into a many-to-many multivariate RNN model. Initially, a flatten layer is used to reduce the 3D input size to fit the 2D input structure provided in a single condition rating prediction model. However, the training losses decreased slightly while the validation losses did not, indicating a scenario typical of overfitting. This suggests that the RNN was memorizing the bridge condition ratings rather than effectively understanding the logic required to predict the correct sequences of future ratings.



(a) Change in Bridge Deck Condition Rating of Georgia from 2014 to 2023 collected from NBI Database



(b) Change in Bridge Element Health Index of Georgia from 2016 to 2023 collected from NBI Element Database

Figure 6. Year-by-year Bridge Deck Condition Rating and Element Health Index Database Mapped in ArcGIS

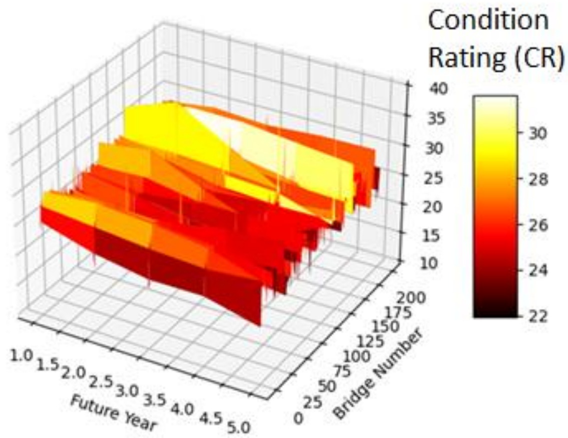


Figure 7. 3D Plot Illustrating the Predicted Condition Rating Data.

Figure 7 illustrates a simple example of the condition rating predictions for 200 bridges over the next four years. The scale of the bridge element condition ratings will be determined later. For a larger dataset, such as 6,000 bridge decks in Georgia, the input data require reshaping the 6,000 rows (representing 6,000 bridges) contained in a dataframe. Initially, 4,800 rows of the training data are reshaped into a 3D input array. The remaining ~1,200 rows are used for validation. The output data return a sequence of 4-year output values (bridge condition ratings), one for each time step.

The input must be three-dimensional to train a condition rating prediction model. This necessitates configuring the last LSTM layer prior to the 'TimeDistributed' layer, which wraps a dense layer in RNN to return sequences. Figure 8 illustrates the input data shape used for the bridge condition rating predictions. Additionally, Facebook's Prophet model will be used for comparison.

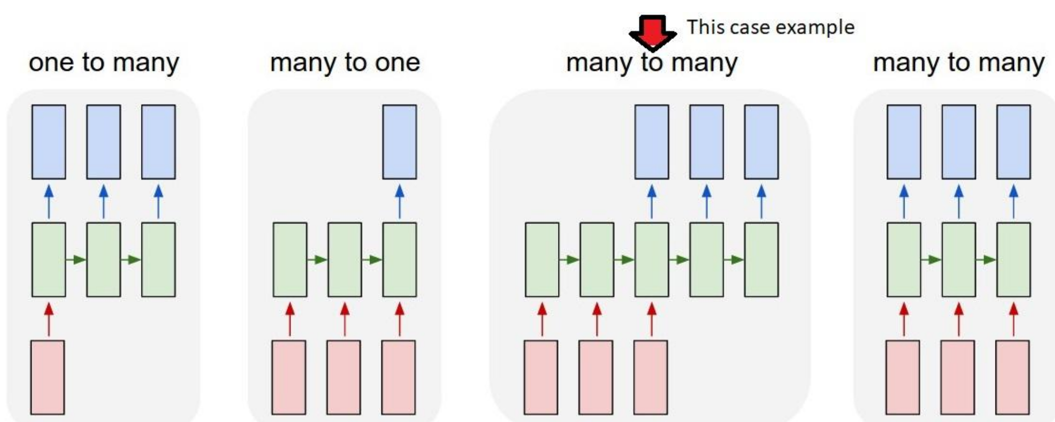


Figure 8. Many-to-Many, One-to-Many, and Many-to-Many RNN Models.

Task 3 – Graph-based network models

Graph-based network models are powerful tools for understanding and solving complex problems in various domains by providing a clear and structured way to represent and analyze the interconnections within a system. During this reporting period, the research team has laid the groundwork to develop graph-based networks of bridges and roadways in Georgia and integrate them using their geographical interdependence. These models will be used to conduct various analyses of the bridge network.

5. Expected Results and Specific Deliverables

This project will create a QUANT CR system that employs artificial intelligence including advanced machine learning algorithms, in order to quantitatively predict condition ratings of bridges, autonomously suggest MRR actions, and ultimately enable writing inspection reports for the next period. The web-based GIS system can run various what-if MRR scenarios and help bridge owners visualize the results. The research team will submit a Technical Report summarizing the methodologies employed to develop a QUANT CR system and data sources.

Description of specific deliverables from this reporting period:

GIS shapefiles and associated databases, specifically year-by-year bridge element condition ratings, have been compiled for Task 2. Additionally, a forward-looking condition rating prediction modeling framework (many-to-many multivariate time-distributed RNN) has been identified.

6. Schedule

Progress of tasks in this project is shown in the table below.

Item	% Completed
Percentage of Completion of this project to Date	33

Table 1 - Gantt chart depicting the timeline.

Months	1-3	4-6	7-9	10-12	13-15	16-18
Task 1						
Task 2						
Task 3						
Task 4						

Notes:

Completed

Task 1 – Acquisition of bridge performance/condition data into geospatial format
Task 2 – Development of a bridge condition rating prediction model
Task 3 – Enhance with a graph-based network model
Task 4 – Verify model and explore benefits from employing other technologies

7. References

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