Intelligent Asset Management for Improved Mobility: Technology Transfer for South Carolina

Final Report

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16. Abstract

This report details the implementation of digital twin technology for bridge load rating in South Carolina, focusing on developing a graphical user interface (GUI). Traditional bridge load rating methods are highlighted for their high costs, time consumption, and traffic disruptions. To address these issues, the research team introduced a digital twin approach utilizing drones, fiber optic strain gauges, and acoustic emission sensors to gather data on crack evolution and inherent strain during loading. This data feeds into a high-fidelity finite element model (FEM), forming a digital twin of the bridge. The core of the report is the GUI, which integrates vehicle load assessment, FEM response calculation, model validation, and parameter updating. Key steps include using a machine learning algorithm to assess vehicle load from acoustic emission data, applying this load to the FEM to obtain mechanical responses, and updating the FEM and bridge load rating formula's condition factor based on field monitoring and drone inspection results. Additionally, the report summarizes a workshop on applying digital twin technology in bridge load rating and maintenance, with integration into intelligent asset management platforms like IBM Maximo. The study demonstrates the significant potential of this technology to enhance bridge safety, extend infrastructure lifespan, and reduce maintenance costs through the efficient and user-friendly GUI.

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EXECUTIVE SUMMARY

This report explores the transformative potential of digital twin technology in bridge load rating, surpassing traditional, labor-intensive, and costly methods that often lack accuracy. Conventional infrastructure maintenance heavily relies on manual inspections and static models, which are inadequate to meet the demands of aging infrastructure and increasing traffic loads. Digital twins utilize real-time data from advanced sensors and monitoring systems to update virtual models of physical assets, enabling a more dynamic and precise understanding of bridge conditions. This approach allows for real-time monitoring and proactive maintenance, significantly improving load assessment and extending the lifespan of bridge components.

This study developed a graphical user interface (GUI) for bridges' digital twin load ratings. Developing and utilizing digital twins for bridge load rating includes several steps. First, vehicle loads are assessed using acoustic emission (AE) data captured by sensors installed on the bridge. These data are then applied to a high-fidelity finite element model (FEM) of the bridge to simulate its structural response. The model is continuously updated and validated with actual strain measurements from the bridge to ensure accuracy. Additionally, drone inspections are used to detect surface cracks and other defects and then to update the condition factors in the load rating formula. Finally, all this information is integrated into a GUI, through which users can calculate the bridge's load rating factor.

The study also included a workshop by researchers from the University of South Carolina (USC), Benedict College (BC), IBM, LUNA, and Structural Health Solutions. They collectively discussed the application of digital twin technology in bridge load rating and maintenance. The presentations they made in the workshop are also summarized in this report.

Chapter 1: Introduction

Civil infrastructure, particularly bridges, plays a crucial role in the transportation network, underpinning economic activity and public safety. However, maintaining these structures is a significant challenge due to aging infrastructure, increased traffic loads, and environmental factors that accelerate wear and tear (Costin et al., 2023). In the United States alone, most of the nation's bridges are classified as structurally deficient or functionally obsolete, necessitating frequent inspections and maintenance (Hosamo et al., 2022). While effective to a certain extent, traditional load rating and inspection methods are often labor-intensive, costly, and sometimes less reliable due to their dependence on manual processes and static models (Kaewunruen et al., 2021). To address these challenges, there has been a growing interest in leveraging digital twin technology—a virtual representation of a physical asset that updates in real-time based on data collected from the asset (Yang et al., 2024). By integrating digital twins with advanced field monitoring data, engineers can achieve a more accurate and dynamic understanding of the condition of a structure, leading to better maintenance decisions and enhanced safety (Ramonell et al., 2022).

Digital twin technology involves creating a digital replica of a physical asset, continuously updated with real-time data collected through various sensors and monitoring systems. This digital model mirrors the physical asset's behavior and condition, allowing for real-time performance analysis, prediction, and optimization (Hosamo et al., 2022). In bridge load rating, digital twins can provide a comprehensive and up-to-date picture of a bridge's structural health, enabling more accurate load assessments and proactive maintenance strategies (Ai et al., 2021). The integration of digital twin technology in bridge load rating offers numerous benefits. One of the most significant advantages is the ability to conduct real-time, continuous monitoring of a bridge's condition. This allows for early detection of potential issues and timely interventions, reducing the risk of structural failures and extending the bridge's lifespan (Xue et al., 2022). Moreover, digital twins can provide more accurate load ratings than traditional methods, which often rely on static models and periodic inspections (Dang et al., 2021).

Another key benefit is the potential for cost savings. By automating many aspects of the inspection and load rating process, digital twins reduce the need for labor-intensive manual inspections and the associated costs (Mahmoodian et al., 2021). Additionally, by optimizing maintenance schedules and interventions based on real-time data, digital twins help to prevent unnecessary repairs and extend the life of the bridge components, leading to further cost savings (Shim et al., 2019). Digital twins also enhance the overall safety and reliability of bridge infrastructure. Providing a comprehensive and up-to-date picture of a bridge's condition enables engineers to make more informed decisions regarding maintenance and repairs. This proactive approach to infrastructure management helps mitigate risks and ensure the traveling public's safety (Brenner et al., 2021).

This study developed a graphical user interface (GUI) for the digital twin load rating of the bridge. Developing and utilizing digital twins for bridge load rating involves several steps. First, vehicle loads are assessed using acoustic emission (AE) data captured by sensors installed on the bridge. This data is then applied to a high-fidelity finite element model (FEM) of the bridge to simulate its structural response. The model is continuously updated and validated using actual strain measurements from the bridge, ensuring its accuracy. Additionally, drone inspections are employed to detect surface cracks and other defects, which are used to update the bridge's condition factor in the load rating formula. Finally, all this information is integrated into a GUI that allows users to calculate the bridge's load rating factor.

The study also included hosting a workshop. Participants comprised the University of South Carolina (USC), Benedict College (BC), IBM, LUNA, and Structural Monitoring Solutions researchers. They collectively discussed the application of digital twin technology in bridge load rating and maintenance.

Chapter 1: Summary of the Developed Graphical User Interface

1.1 Infrastructure Asset Management using Digital Twin Method

The internal program of the developed GUI comprises five steps to ensure accurate bridge load ratings. The first step uses AE signals with a probabilistic machine learning algorithm to assess vehicle load. The second step applies this load to a high-fidelity finite element model (FEM) of the bridge to obtain mechanical responses like displacement and strain. The third step involves validating the FEM by comparing its responses with actual strain measurements from the bridge. In the fourth step, the bridge load rating formula parameters are updated based on drone inspections, focusing on the condition factor. Finally, the fifth, user-operable step involves selecting the bridge and slab, setting the truck type, and integrating all data into the load rating equation to calculate the load rating factor.

1.2 Step 1. Assess Vehicle Load from AE Data

The first step of the internal GUI program is to determine the vehicle load based on the AE signals captured by the AE sensors deployed on-site at the bridge as vehicles pass over. We developed a probabilistic machine learning algorithm for this analysis. This algorithm receives many real-time AE signals generated by passing vehicles and provides an instantaneous result, indicating the probability that the vehicle belongs to different load levels. The load level with the highest probability is then determined as the load of the passing vehicle.

This method was first tested under laboratory conditions. As illustrated in Figure 2.1a, we conducted step loading on a concrete specimen. Moreover, four AE sensors were attached to the specimen (Figure 2.1b). The purpose of this loading was to simulate the load of a passing vehicle. There were five incremental load steps (blue lines in Figure 2.1c, where the one with lowest magnitude represents L1 and with highest magnitude represents L5) and each load step generated numerous AE signals (red dots in Figure 2.1c, where each red dot represents an AE signal). The machine learning model we used was the random forest. The experimental results are shown in Figure 2.1d. For load step L2, 112 AE signals indicated a vehicle load level of L2, 48 indicated an impact force of L3, 21 leaned towards an impact force of L4, and 19 inferred an impact force of L5. Considering all these factors, most decisions supported a load level of L2. Therefore, the model concluded that the applied load level was L2, corresponding with the actual condition. The results of load steps with load levels L3, L4, and L5 were similar to those of load step L2. The model proposed in this study can accurately determine the load.

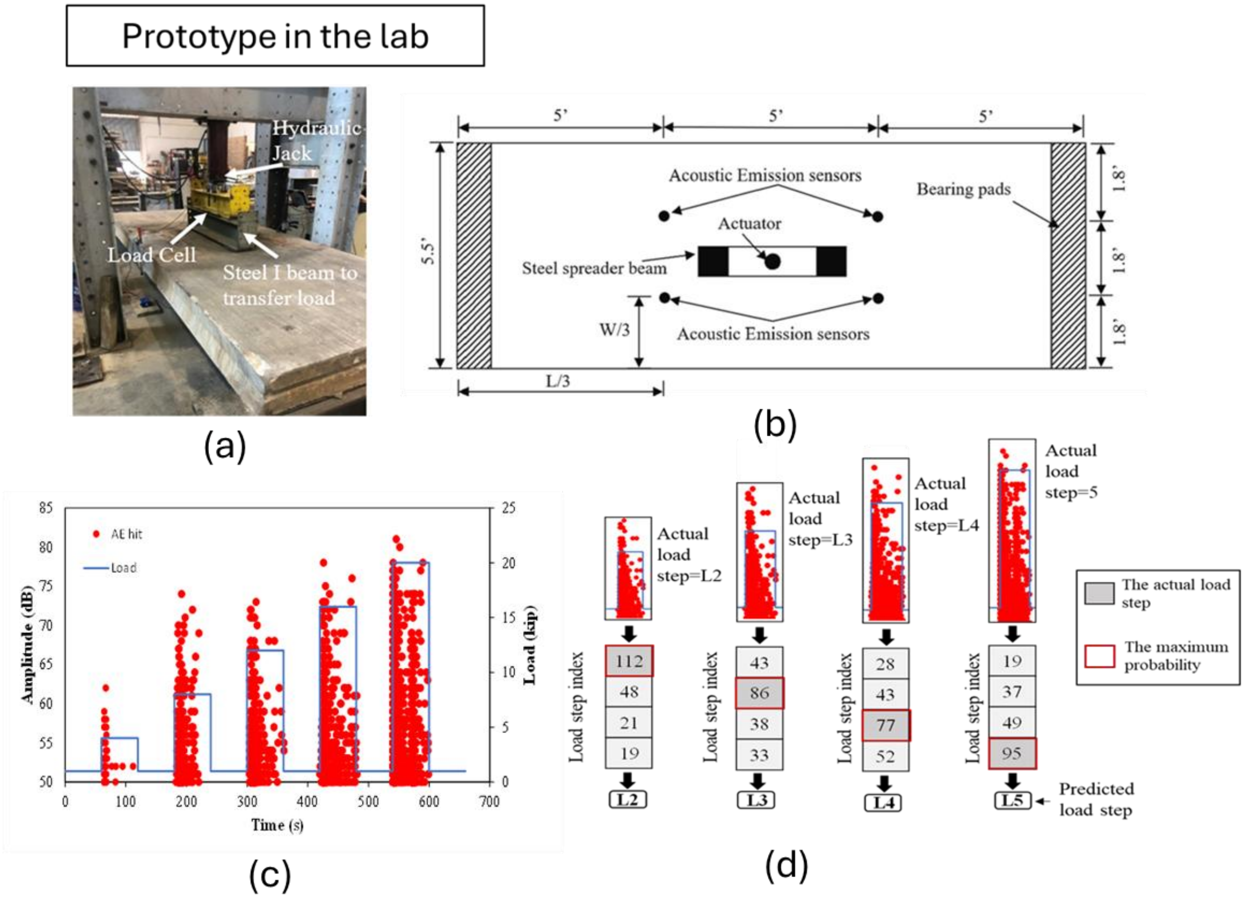


Figure 1.1 Assess load from AE data: (a) experimental setup; (b) specimen and sensor layout; (c) step loading and AE signals; and (d) assessment result

To further evaluate the performance of the proposed method, the experimental dataset underwent a comprehensive guided sampling process. In each iteration, 20% of the data was randomly selected with replacement. This sampling process was repeated 100 times, resulting in 100 different sub-datasets. These sub-datasets were then used as inputs for the proposed model to assess its predictive capabilities. The results obtained from these sub-datasets, particularly those related to the prediction of load levels, are detailed and visually presented in the confusion matrix below (Figure 2.2). The diagonal of the matrix represents the number of correct classifications. As shown, most of the impact energy levels were accurately classified into their corresponding categories. The overall accuracy was 97%. Each load step's precision, recall, and F1 scores were calculated. As illustrated in Figure 2.2, the precision for the four load steps was 100%, 95%, 93%, and 100%, respectively. The recall for the four load steps was 97%, 100%, 98%, and 93%, respectively. The F1 scores for the four load steps were 98.5%, 97.4%, 95.4%, and 96.4%, respectively.

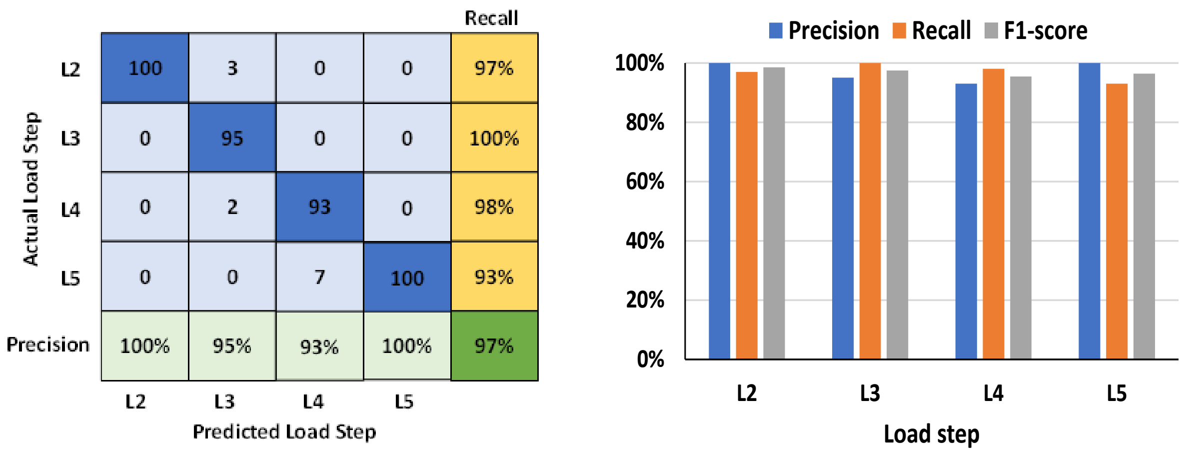


Figure 1.2 Accuracy, precision, recall, and F1-score of the load assessment method

1.3 Step 2. FEM Structural Response of Vehicle Load

The second step of the internal program of the GUI involves applying the vehicle load, determined in the first step, to a high-fidelity finite element model (FEM) of the bridge. This model represents a single span of the bridge. The AE-predicted load is applied to the FEM to obtain the mechanical responses of the bridge, such as displacement and strain. The figure below illustrates an example. Figure 2.3b shows the FEM of a span of the bridge depicted in Figure 2.3a. Figure 2.3c displays the results of the FEM when subjected to the vehicle load.

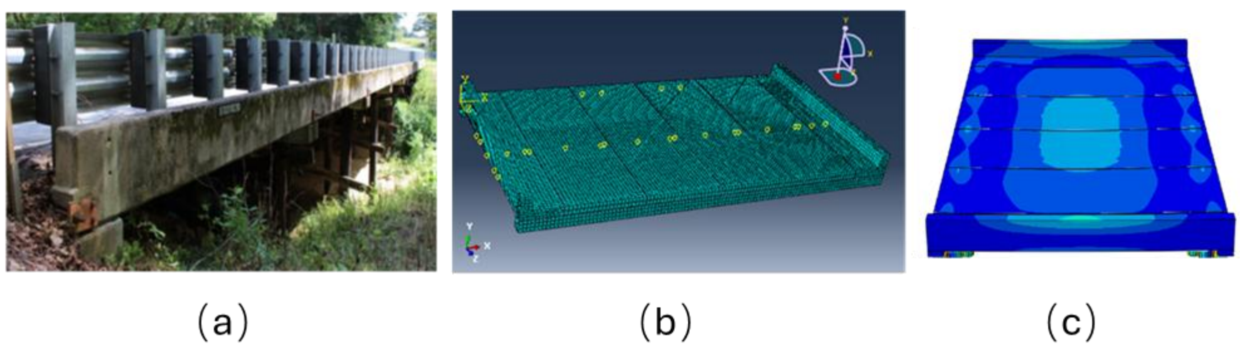
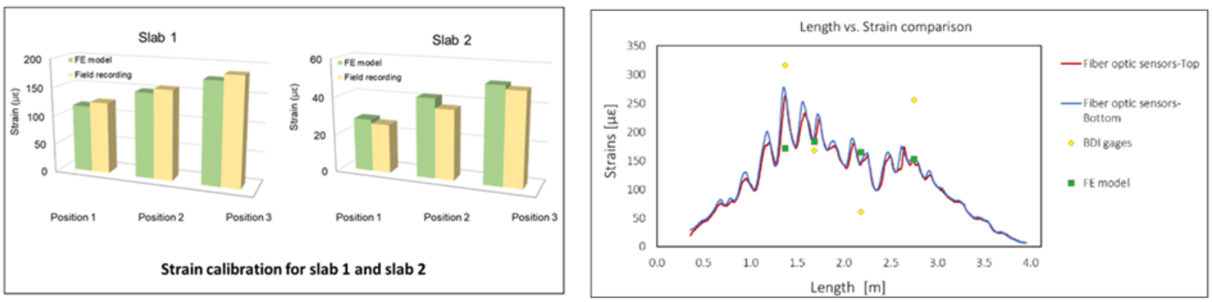


Figure 1.3 FEM of a bridge span: (a) actual bridge; (b) FEM of a span; and (c) structural response from FEM

1.4 Step 3. Update FEM

The third step of the internal program of the GUI is to compare the responses obtained from the FEM in the second step, such as strain, with the actual strain measured on the bridge in order to validate the model. The figure below provides an example. The vehicle load determined in the first step is applied to a high-fidelity finite element model (FEM) of the bridge, representing a single span. The AE-predicted load is applied to the FEM to obtain the mechanical responses of the bridge, such as displacement and strain. The figure below illustrates an example. Figure

2.4a shows a comparison between the strain obtained from the FEM and the strain measured by BDI strain gauges installed on the bridge. Figure 2.4b shows a comparison between the strain obtained from the FEM and the strain measured by fiber optic strain gauges installed on the bridge. It can be observed that the FEM model can accurately simulate the bridge's response to vehicle loads. By periodically validating the FEM results with the long-term strain gauge data, the fidelity of the bridge model can be ensured, guaranteeing that the FEM represents the current state of the bridge.



(a) (b)

Figure 1.4 Update FEM: (a) comparison between the strain obtained from the FEM and BDI gauges; and (b) comparison between the strain obtained from the FEM and fiber optic gauge

1.5 Step 4. Adjust the Load Rating Equation

The fourth step involves updating the bridge load rating formula parameters based on drone inspections. In our study, the primary focus is on updating the condition factor $\emptyset_c$ for the bridge slab. In another project funded by C2M2 (Ziehl et al., 2023; Ai et al., 2024), we developed a method to detect concrete surface cracks and estimate the distance between cracks using drones and computer vision algorithms. This method has been integrated into the GUI. The condition factor can be determined once the crack distances are automatically estimated through drone inspection and computer vision algorithms.

The Bridge Component Inspection Manual provides a systematic assessment of the structural integrity of concrete bridges, with a particular focus on the presence and spacing of surface cracks. Figure 2.5 illustrates the bridge condition rating mechanism, specifically the spacing between surface cracks in concrete bridges. This spacing is a crucial indicator of potential structural damage. The rating system is divided into three conditions: Condition 1 (Good), Condition 2 (Fair), and Condition 3 (Poor). Condition 1 (Good) indicates crack spacing greater than 3.0 feet, suggesting minimal structural issues. Conversely, Condition 3 (Poor) indicates crack spacing less than 1 foot, suggesting significant structural problems.

As shown in Table 2.1, the condition factor can be determined based on the Specifications for the National Bridge Inventory. This factor assigns values to the previously discussed condition states: Good, Fair, and Poor. Condition 1 (Good) corresponds to a condition factor of 1.00, indicating the structure is in optimal condition with negligible defects. Condition 2 (Fair) has a condition factor of 0.95, indicating the structural condition is generally acceptable with minor defects. Condition 3 (Poor) has a condition factor of 0.85, indicating significant defects or aging that may threaten the structure's overall integrity.

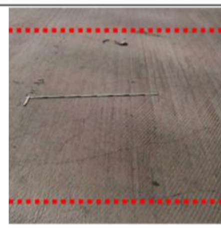
Defects	Condition State 1	Condition State 2	Condition State 3
Cracking	 Spacing greater than 3.0 ft.	 Spacing of 1.0—3.0 ft.	 Spacing of less than 1 ft.

Figure 2.5 Mechanism for grading the condition of bridges

Table 2.1 Criteria to determine the condition factor

Equivalent member structural condition	Condition Factor ($\emptyset_c$)
CS 1 (Good)	1.00
CS 2 (Fair)	0.95
CS 3 (Poor)	0.85

1.6 Step 5. Calculate the Load Rating Factor

The first four steps are internal update procedures within the GUI (updating the FEM based on long-term on-site monitoring strain data and updating the condition factor based on drone inspection). The fifth step is the user-operable step within the GUI. The user selects the bridge and the specific slab on which they want to perform the load rating and sets the type of truck (H-10, H-20, etc.). All this information is then integrated into the load rating equation to calculate the load rating factor. The diagram below illustrates the entire process.

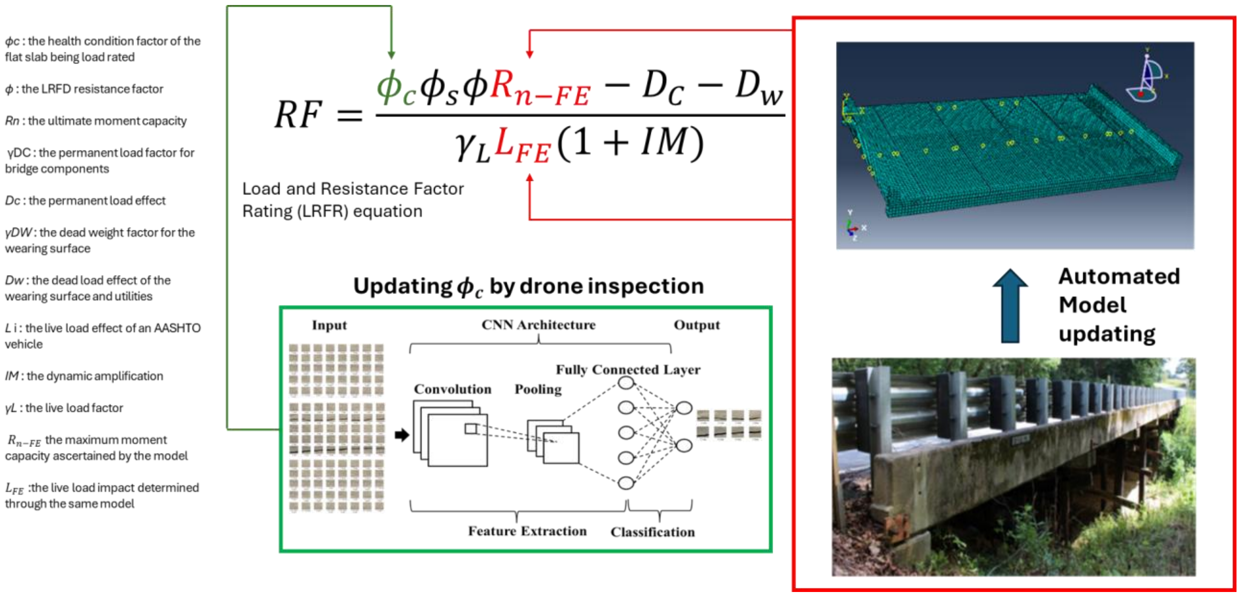


Figure 2.6 The procedure to calculate the load rating factor

1.7 Graphical User Interface

Figure 2.7 displays the designed GUI. Users can input the asset ID to select the bridge for load rating. Once selected, a photo of the bridge (if available) will be displayed on the left. Below, five histograms will be presented, showing key traffic indicators for the asset across different years, including AADT (Annual Average Daily Traffic), SU AADT (Single Unit Truck AADT), CU AADT (Commercial Unit Truck AADT), K factor, and D factor. Users can select the type of truck for the load rating and specify the truck's position. Finally, by clicking the calculate button, the load rating factor will be obtained.

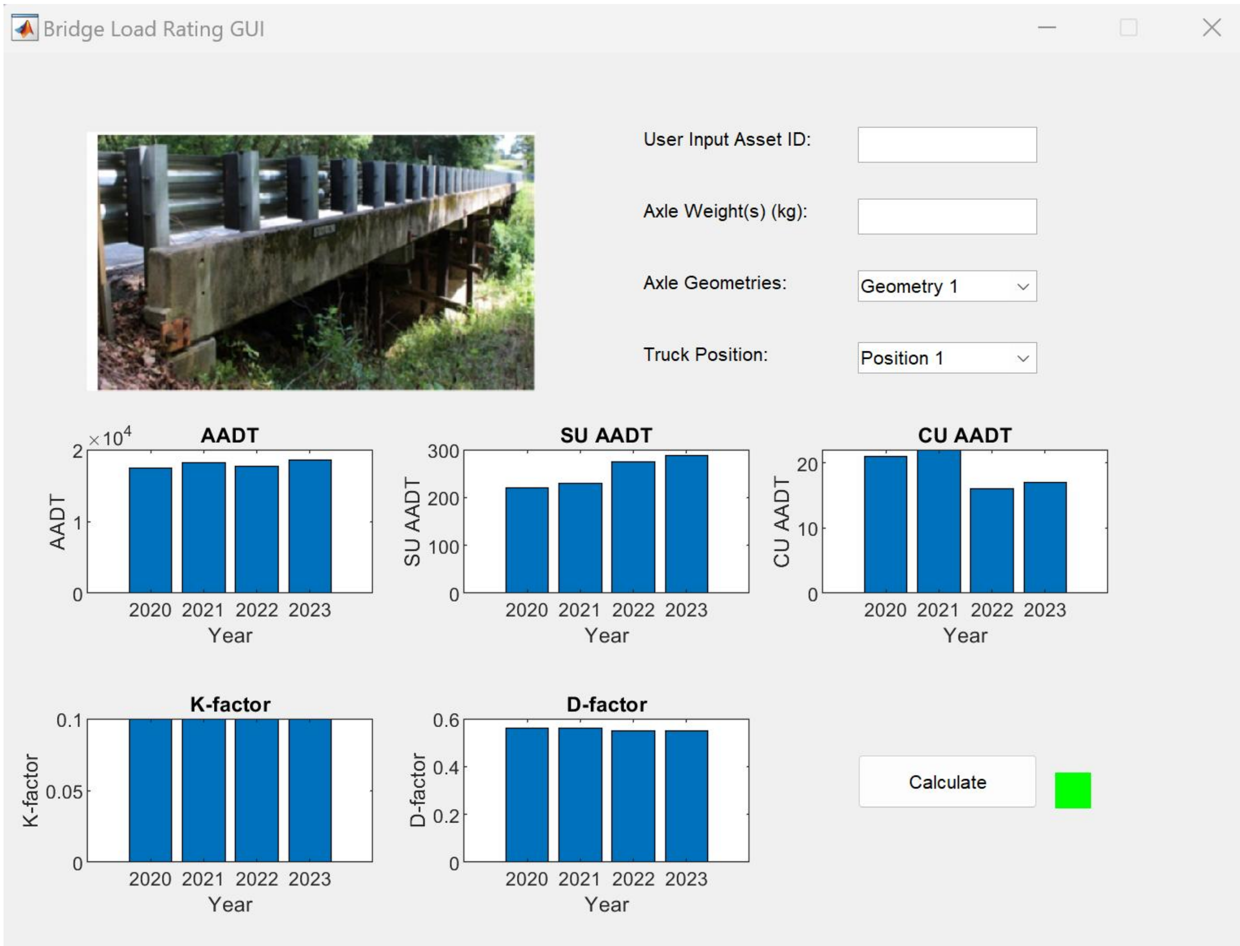


Figure 2.7 GUI of digital twin assisted load rating

Chapter 2: Summary of the Workshop

2.1 Overview of the Workshop

On May 28, 2024, a workshop was held at the McNair Center for Aerospace Innovation and Research for Innovation and Research (Figure 3.1) near the SCDOT headquarters in Columbia, SC. The Center has a state-of-the-art video conferencing room that seats 50 people and multiple break-out conference rooms. The Center is focused on transitioning innovative technologies to industry and is ideal for this event. Meals have been provided to attendees, and travel reimbursements have been provided to selected key participants. IBM, Luna, University of South Carolina, SCDOT, and Structural Monitoring Solutions have given presentations on the C2M2 projects. Sections 3.2 to 3.3 summarize the three representative presentations from the workshop.

Figure 3.1 McNair center for aerospace innovation and research for Innovation and Research

2.2 Presentation from IBM

The presentation by IBM displays IBM's advanced solutions for managing civil infrastructure assets through the Maximo Application Suite. Civil infrastructure remains one of the most asset and labor-intensive industries, so this presentation highlights the pressing need for modern, efficient, sustainable management practices. With a staggering $2.2 trillion backlog on over a million structures and significant portions of roads and bridges in poor condition, traditional infrastructure management methods are proving insufficient. IBM Maximo offers a transformative approach, leveraging innovative technologies to address these challenges effectively.

The key to Maximo's solution is its robust capability to integrate and manage various facets of civil infrastructure maintenance. The suite's features encompass everything from enterprise asset management to condition assessments and predictive analytics. By employing advanced AI models, IoT sensors, and proprietary defect detection algorithms, Maximo can monitor infrastructure health, detect anomalies, and predict potential failures with remarkable accuracy. This proactive approach not only enhances safety and reliability but also significantly reduces maintenance costs and labor hours, addressing the inefficiencies of manual inspections.

Furthermore, the presentation discussed the real-world applications and success stories of IBM Maximo. For instance, it outlines how Sund & Bælt and Autostrade have leveraged Maximo to achieve substantial operational efficiencies, cost savings, and environmental benefits. These case studies illustrate the practical benefits of adopting IBM Maximo, such as extending the lifespan of infrastructure, reducing CO_2 emissions, and ensuring compliance with regulatory standards. By transitioning from reactive to predictive maintenance, organizations can better prioritize their efforts, optimize work schedules, and maintain consistent asset management procedures, ultimately fostering more sustainable and resilient infrastructure systems.

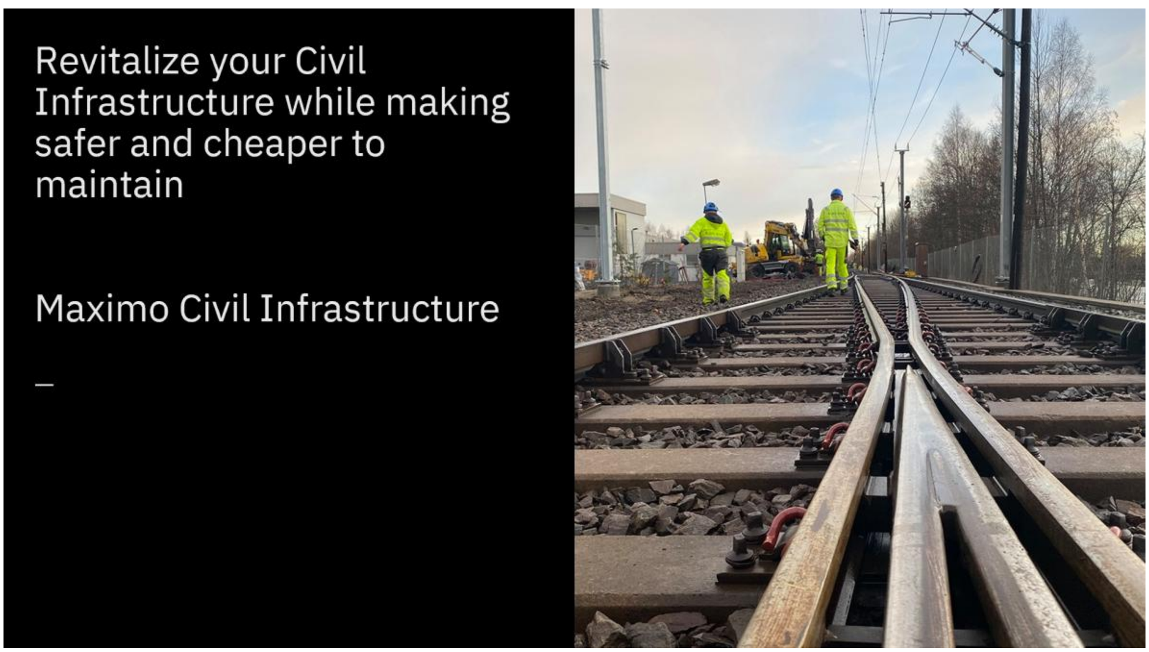


Figure 3.2 Cover of the presentation provided by IBM

2.3 Presentation from the University of South Carolina

The presentation "Assisting Load Rating Testing of Precast Reinforced Concrete Bridge Slab through Digital Twins and Field Monitoring Data" by a researcher from the University of South Carolina studied the application of innovative technology to enhance the assessment and maintenance of bridge infrastructure. As traditional load rating and inspection methods can be labor-intensive, costly, and sometimes less accurate, the integration of digital twin technology represents a significant advancement in civil engineering. This presentation, held at the University of South Carolina's McNair Center on May 28, 2024, aims to illustrate how digital twins, combined with field monitoring data, can revolutionize how we manage and maintain precast-reinforced concrete bridge slabs.

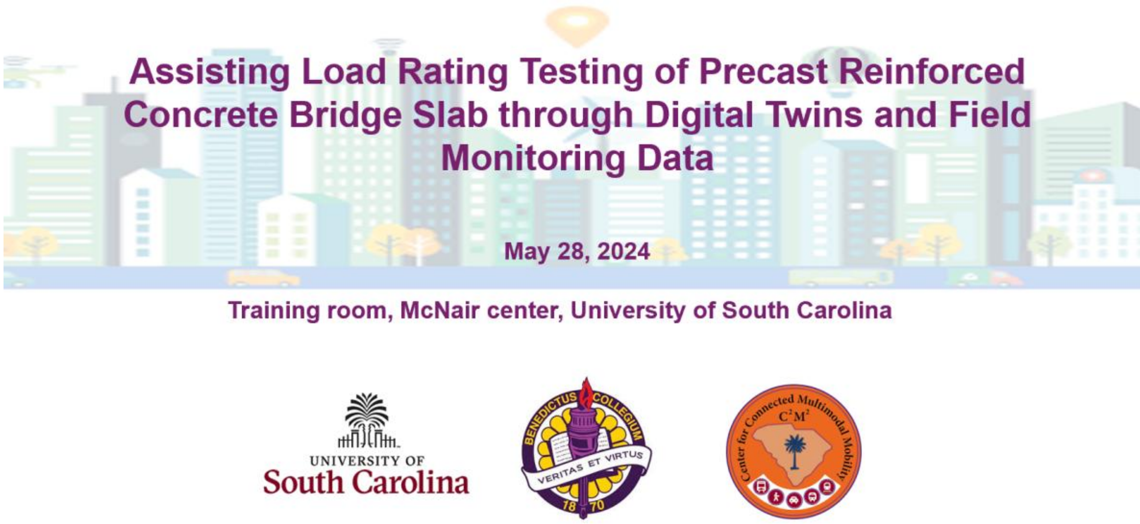


Figure 3.3 Cover of the presentation provided by the University of South Carolina

The initial slides provide an overview of the load rating process improved through digital twins. Engineers can achieve a more accurate and up-to-date understanding of a bridge's condition by incorporating drone inspections and automated model updating. Key parameters such as the health condition factor, ultimate moment capacity, and live load effects are continuously monitored and updated, ensuring the bridge's load rating reflects its current state. This proactive approach allows for timely interventions and maintenance, significantly extending the lifespan of the infrastructure.

Subsequent slides detail the methodology behind this innovative approach. The process begins with assessing vehicle loads using acoustic emission data, which replaces traditional weigh-in-motion (WIM) systems and reduces the need for traffic control. This data is then applied to a Finite Element Model (FEM) to simulate the structural response of the bridge. By comparing the actual structural response from field data to the model, engineers can update the FEM to reflect real-world conditions more accurately. This automated model updating process, supported by deep learning algorithms for crack detection and depth prediction, ensures continuous improvement and reliability of the load rating system.

The presentation also includes case studies highlighting digital twin technology's practical application and benefits in bridge load rating. These case studies demonstrate how digital twins can provide more accurate load ratings than traditional methods, ultimately enhancing bridge infrastructure's safety, efficiency, and sustainability. Integrating field monitoring data, advanced analytics, and automated inspections improves the accuracy of load ratings, optimizes maintenance schedules, and reduces operational costs.

In conclusion, the presentation emphasizes the transformative potential of digital twins in civil infrastructure. The industry can move towards more predictive and proactive maintenance strategies by leveraging advanced technologies such as AI, IoT sensors, and automated inspections. This not only ensures the longevity and safety of our bridges but also represents a significant step forward in the field of civil engineering. The presentation aims to inspire and inform practitioners about the benefits and implementation of digital twin technology in their projects.

2.4 Presentation from Structural Monitoring Solutions

This presentation outlined the advanced applications and case studies of structural health monitoring using specialized fiber-optic systems provided by Structural Monitoring Solutions, which collaborates with various agencies and engineering firms. The presentation began with an overview of SHM applications and monitoring technologies, setting the stage for detailed case studies that highlight the effectiveness of these systems in detecting and addressing structural issues in bridges.

The case studies include metal fatigue crack detection on the San Francisco Oakland Bay Bridge, monitoring of cable-stayed and suspension bridges such as the Ben Franklin, Deer Isle, and Anthony Wayne bridges, and post-tensioned and prestressed tendon bridge monitoring, exemplified by the 2022 Roosevelt Bridges CM/GC contract in Florida and the 2020 installation on the HART Rail Bridge in Hawaii. Additional case studies cover projects in VA, PA, FL, SC, NY, CO, Spain, France, and the UK, demonstrating these monitoring systems' global reach and adaptability.

The presentation also introduced new types of fiber-optic sensors, including acoustic, strain gauge, vibration, temperature, and tilt sensors. It highlights innovations such as the new fiber optic distributed strain gauge used on the Roosevelt Bridges, which measures span deflection and twist. These advancements in instrumentation, combined with sophisticated electronics, software, self-diagnostics, real-time analysis, and alarming capabilities, underscore the transformative potential of SHM technologies in ensuring bridge structures' safety, reliability, and longevity.

Chapter 3:
Summary and Conclusions

This final report on technology transfer describes the study on implementing digital twin technology for bridge load rating in South Carolina. The report highlights the shortcomings of traditional bridge load rating methods, including high costs, time consumption, and traffic disruptions. The research team developed a new approach based on digital twin technology to address these issues. This method utilizes drones, fiber optic strain gauges, and acoustic emission sensors to collect data on crack evolution and inherent strain during loading. These data are then applied to a high-fidelity finite element model (FEM), forming a digital twin of the bridge. The report also introduces the development of a graphical user interface (GUI) that integrates vehicle load assessment, FEM response calculation, model validation, and parameter updating. Specific steps include assessing vehicle load from acoustic emission data using a machine learning algorithm, applying the assessed load to the FEM to obtain mechanical responses, validating and updating the FEM with field monitoring data, and updating the bridge load rating formula's condition factor based on drone inspection results. Ultimately, users can select the bridge and specific slab, set vehicle types, and calculate load rating factors through the GUI. The report also summarizes a related workshop discussing the application of digital twin technology in bridge load rating and maintenance and the integration with intelligent asset management platforms like IBM Maximo. The study demonstrates the significant potential of digital twin technology in enhancing bridge safety, extending infrastructure lifespan, and reducing maintenance costs.

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