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Research Article

Statistical Assessment of Long-Term Bridge Deterioration Using Field-Measured Structural Response Data

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ABSTRACT

This study aimed to assess the impact of environmental conditions on bridge deterioration by leveraging a comprehensive dataset comprising 1340 records and 15 variables. The dataset included numeric variables such as acceleration, temperature, humidity, wind speed, and categorical variables like bridge and sensor IDs, structural condition, and damage class. Using advanced predictive modeling techniques, we integrated key environmental variables to enhance the understanding of their influence on structural integrity.

Our methodology involved analyzing the dataset to identify patterns of bridge deterioration, focusing on the role of environmental factors as critical determinants of structural health. We employed machine learning algorithms to forecast deterioration over a 30-day period, utilizing forecast scores as a primary outcome measure. The results showed a significant correlation between environmental conditions and bridge degradation, with higher average degradation scores in structures exposed to increased temperatures (mean 25.186°C), humidity (mean 59.836%), and wind speeds (mean 7.602 m/s).

Bridges classified under "Severe" damage exhibited notably higher forecast scores, indicating accelerated deterioration compared to those with "Minor" or "No Damage." These findings suggest that integrating environmental data into predictive models can significantly enhance the accuracy of deterioration forecasts, aiding in the prioritization of maintenance activities.

Our findings suggest that predictive models incorporating environmental variables offer a robust framework for infrastructure management. This approach facilitates data-driven decision-making, enabling more effective maintenance scheduling and resource allocation. Ultimately, the integration of environmental monitoring into bridge maintenance strategies is crucial for optimizing infrastructure resilience and longevity in the face of evolving environmental challenges.

1. INTRODUCTION

The deterioration of infrastructure, particularly bridges, poses significant challenges to both safety and economic efficiency worldwide. As critical components of transportation networks, bridges require continuous monitoring and timely maintenance to ensure their structural integrity and functionality. Environmental factors, cyclic loads, and age-related degradation contribute to bridge deterioration, making it imperative to develop reliable predictive models for assessing their condition. Given the increasing frequency of extreme climatic events and the aging of infrastructure, the need for advanced methodologies to predict bridge health has never been more urgent.

Despite the critical importance of infrastructure maintenance, the field still grapples with significant gaps in predictive accuracy and reliability. Current methods often rely on periodic manual inspections that are labor-intensive and may miss subtle signs of early deterioration. Moreover, traditional models used for deterioration prediction often fail to integrate the full range of environmental and operational variables that influence bridge health. This research addresses these gaps by

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developing a comprehensive dataset comprising 1,340 records and 15 variables, including both numeric and categorical data, to enhance the predictive capabilities of deterioration models.
The objective of this research is to advance the understanding of bridge deterioration processes by integrating a variety of sensor-derived and environmental variables. The dataset includes numeric variables such as acceleration (along x, y, and z axes), temperature, humidity, wind speed, and other metrics like fft_peak_freq and fft_magnitude, which capture vibrational characteristics. Additionally, degradation_score and forecast_score_next_30d offer insights into current and future deterioration states. Categorical variables like bridge_id, sensor_id, structural_condition, and damage_class help contextualize the numeric data, enabling a more nuanced analysis of deterioration patterns across different bridge types and conditions.
The primary research questions guiding this study are: How can multivariate data from sensors and environmental conditions be effectively integrated to improve bridge deterioration predictions? What role do specific environmental factors play in accelerating or mitigating deterioration, and how can these insights inform targeted maintenance strategies? By addressing these questions, this research aims to contribute significantly to the field of infrastructure management.[1][2]
The significance of this research lies in its potential to transform how bridge health is monitored and managed. By leveraging a rich dataset that encompasses both structural and environmental variables, the study seeks to develop more accurate predictive models. These models can enhance inspection schedules, prioritize maintenance activities, and ultimately extend the lifespan of critical infrastructure. Additionally, the research provides a framework for integrating diverse data sources, setting the stage for future advancements in predictive maintenance technologies.[3]
This paper is structured as follows: First, we review the current state of research in bridge deterioration modeling, highlighting existing methodologies and their limitations. Next, we detail the dataset used in this study, describing the variables and their relevance to bridge health assessment. The methodology section outlines the analytical techniques employed to integrate and analyze the data, leading into the results section where key findings are presented. Finally, the discussion interprets the implications of these findings for infrastructure management and future research directions. Through this structured approach, the paper aims to provide a comprehensive understanding of bridge deterioration processes and propose actionable solutions for infrastructure maintenance challenges.[4]

2. LITERATURE REVIEW

The study of bridge deterioration has evolved significantly over the past decades, driven by the increasing necessity for accurate predictive models that can inform maintenance and management strategies. At the forefront of this evolution are advanced methodologies that incorporate diverse data sources to enhance the predictive accuracy of bridge health assessments. This literature review explores key theories, models, and frameworks, synthesizes findings from notable studies, and identifies gaps and debates within the field to connect with the current research objectives.[5]
Early models of bridge deterioration were primarily deterministic, relying heavily on historical inspection data and expert judgment. These approaches, while foundational, often lacked precision due to their simplistic treatment of complex variables affecting bridge health. The advent of probabilistic models marked a significant shift, allowing for the quantitative incorporation of uncertainty and variability inherent in environmental and operational conditions[6]. Recent advancements in probabilistic modeling include hierarchical Bayesian frameworks, which enable the fusion of inspection and monitoring data to produce more nuanced deterioration assessments. These frameworks are particularly adept at capturing the probabilistic nature of degradation processes, offering a robust alternative to traditional deterministic models.
The integration of machine learning techniques into bridge deterioration modeling represents another pivotal development. Machine learning models, such as neural networks and decision trees, have been utilized to predict deterioration by analyzing patterns within large datasets. These models excel in handling complex, nonlinear relationships between variables, making them suitable for bridge health assessments where multiple interacting factors are at play[7]. The application of ordinal autoregressive models further enhances predictive capabilities by incorporating temporal dynamics, allowing for the probabilistic prediction of condition levels over time.
Despite these advancements, significant gaps remain in the predictive modeling of bridge deterioration. A critical limitation of many existing models is their inadequate consideration of environmental variables, such as temperature, humidity, and wind speed, which are known to influence structural integrity. Studies have highlighted the importance of incorporating these variables into predictive models to improve accuracy[8]. For instance, research on integrating environmental conditions into machine learning models has demonstrated improved predictions of bridge deterioration, emphasizing the necessity of a holistic approach that considers both structural and environmental factors.
Moreover, the role of vibrational characteristics, captured through metrics like fft_peak_freq and fft_magnitude, is often underexplored in traditional models. These metrics provide valuable insights into the dynamic behavior of bridges, which is crucial for understanding deterioration mechanisms. The current research aims to address this gap by incorporating vibrational data into the predictive framework, thereby enhancing the model's ability to detect early signs of deterioration.[9]

Another area of ongoing debate is the effectiveness of data fusion techniques in bridge deterioration modeling. While the fusion of diverse data sources holds promise for more comprehensive assessments, challenges related to data compatibility, integration, and interpretation persist. Researchers have advocated for the development of standardized frameworks that facilitate the seamless integration of heterogeneous data types, including numeric and categorical variables. The current study's dataset, comprising both numeric variables like acceleration and categorical variables such as structural_condition and damage_class, provides a unique opportunity to explore the potential of data fusion in improving predictive accuracy.[10]

The literature also reveals a growing interest in the development of predictive maintenance strategies informed by advanced modeling techniques. Predictive maintenance, as opposed to traditional reactive approaches, allows for the proactive management of bridge health by optimizing inspection schedules and prioritizing interventions based on predicted deterioration trends. Machine learning and probabilistic models play a critical role in this paradigm shift, enabling the identification of at-risk structures before significant damage occurs.[11]

In conclusion, the review of existing literature underscores the dynamic nature of bridge deterioration research, characterized by ongoing advancements in modeling techniques and data integration. Key contributions include the development of probabilistic and machine learning models that enhance predictive accuracy by incorporating diverse data sources. Despite these advancements, challenges related to the integration of environmental variables and vibrational characteristics persist, highlighting areas for further exploration. The current research seeks to build on these findings by leveraging a comprehensive dataset to develop predictive models that integrate sensor-derived and environmental variables. By addressing existing gaps and synthesizing insights from multiple studies, this research aims to contribute to the development of more accurate and reliable models for assessing and managing bridge health.[12][13][14][15][16]

3. METHODOLOGY

3.1 Research Design and Approach

This study employs a quantitative approach to assess long-term bridge deterioration using field-measured structural response data. The methodology is structured around the use of structural response indicators, environmental variables, and predictive modeling to evaluate and forecast bridge conditions. The analysis leverages a dataset comprising 1,340 records with 15 variables, including both numeric and categorical data relevant to bridge deterioration.[17]

3.2 Dataset Structure

The dataset is organized with bridge identifiers, structural condition states, damage classes, and forecast scores serving as the primary categories for analysis. Each record is associated with a unique bridge_id and sensor_id, which facilitate the tracking of structural condition and damage classification. Numeric variables such as acceleration_x, acceleration_y, and acceleration_z are used to compute the Structural Condition Index (SCI), which quantitatively measures the condition of each bridge. Categorical variables like structural_condition and damage_class aid in the discrete classification of bridge health.

3.3 Data Collection Procedures

Data were collected from field sensors installed on various bridges, capturing structural responses and environmental conditions. The sensors measured accelerations along different axes, temperature, humidity, and wind speed, which were averaged over specific intervals to mitigate anomalies and ensure data reliability.

3.4 Variables and Measurements

The Structural Condition Index (SCI) is calculated using Equation 1, where $SCI_i = \Sigma (w_k R_{i,k})$. This equation aggregates weighted structural response indicators ($R_{i,k}$) to produce a continuous measure of the bridge's structural health, facilitating a nuanced understanding of its condition.

$$\mathrm{SCI}_i = \sum_{k=1}^{N} w_k \, R_{i,k}$$

Equation 1. Structural Condition Index (SCI) for bridge i i based on weighted structural response indicators.

3.5 Data Analysis Methods

The SCI values are then converted into discrete damage classes using Equation 2, which categorizes bridges into classes 0, 1, or 2 based on predefined SCI thresholds (θ_1 and θ_2). This classification supports prioritization in maintenance strategies by enabling condition-based comparisons among bridges.

$$D_i = \begin{cases} 0, & \mathrm{SCI}_i \geq \theta_1 \\ 1, & \theta_2 \leq \mathrm{SCI}_i < \theta_1 \\ 2, & \mathrm{SCI}_i < \theta_2 \end{cases}$$

Equation 2. Damage class categorization based on Structural Condition Index thresholds.

The estimation of bridge-specific deterioration rates is accomplished using Equation 8, which calculates λ_i as the mean absolute rate of change in SCI over time. This parameter is critical for understanding long-term degradation trends and informs subsequent predictive analyses.

For short-term forecasting, Equation 7 is utilized to predict the SCI 30 days ahead, considering the estimated deterioration rates. The formula, $\hat{\mathrm{S}}\mathrm{CI}_i(t+30) = \mathrm{SCI}_i(t) - \lambda_i\,\Delta t$, assumes a linear deterioration trajectory within this brief horizon.

$$\widehat{\mathrm{SCI}}_i(t+30) = \mathrm{SCI}_i(t) - \lambda_i\,\Delta t$$

Equation 3. Short-term prediction of bridge structural condition over a 30-day horizon.

$$\lambda_i = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\mathrm{SCI}_i(t) - \mathrm{SCI}_i(t-1)}{\Delta t}\right|$$

Equation 4. Estimation of bridge-specific deterioration rate from historical condition data.

3.6 Environmental Data Processing

Environmental factors, including average temperature (°C), average humidity (%), and average wind speed (m/s), are computed to understand their influence on structural deterioration. These variables are relevant as they can exacerbate or mitigate the deterioration processes by affecting material properties and structural dynamics.

3.7 Integrated Deterioration Model

To enhance predictive accuracy, the integrated short-term deterioration prediction model, as described by Equation 5, incorporates both structural and environmental effects. This model, $\hat{\mathrm{S}}\mathrm{CI}_i(t+30) = \mathrm{SCI}_i(t) - \lambda_i\,\Delta t - (\beta_1\overline{T} + \beta_2\overline{H} + \beta_3\overline{V})$, synergizes deterioration trends with environmental influences, offering a comprehensive framework for near-term bridge condition forecasting.

$$\widehat{\mathrm{SCI}}_i(t+30) = \mathrm{SCI}_i(t) - \lambda_i\Delta t - \left(\beta_1\overline{T} + \beta_2\overline{H} + \beta_3\overline{V}\right)$$

Equation 5. Integrated short-term bridge deterioration prediction model incorporating structural response and environmental effects.

3.8 Validity and Reliability Considerations

The methodology emphasizes the robustness of predictive models by integrating diverse datasets and employing rigorous statistical techniques. Consistency in sensor data collection and preprocessing ensures the reliability of the structural and environmental variables used in the analysis.

3.9 Ethical Considerations

The study adheres to ethical guidelines by ensuring data privacy and confidentiality, particularly in managing sensitive infrastructure data. Additionally, efforts are made to minimize the environmental footprint during data collection processes, aligning with sustainable research practices.

In summary, this methodology outlines a systematic approach to evaluating bridge deterioration through advanced modeling that integrates field-measured data and environmental conditions. By employing a comprehensive dataset and leveraging predictive equations, the study aims to enhance the understanding and management of bridge health over time.

4. RESULTS

In this section, we present the results of our analysis on bridge deterioration using the methodological framework described previously. The findings are systematically organized to elucidate the relationships between structural response indicators, environmental variables, and the deterioration rates of bridges. By leveraging the comprehensive dataset and employing advanced predictive modeling, we provide insights into the condition assessment of bridges over time. The following tables will detail the statistical outcomes, deterioration classifications, and predictive accuracy of the models used, offering a quantitative foundation for understanding the efficacy of our proposed integrated deterioration model. This analysis aims to enhance strategic decision-making in bridge maintenance and management.

Table I presents a detailed analysis of bridge conditions, categorized by bridge ID, damage class, structural condition, and a 30-day forecast score. Analyzing the data reveals distinct patterns in deterioration and forecast accuracy. For bridge B003, variations in forecast scores across different damage classes are notable. For instance, when classified as "Minor" damage, the forecast scores fluctuate from 39.903 to 26.91, indicating variability in predicted short-term deterioration. Contrastingly, a "Severe" damage classification for B003 corresponds to a significantly higher forecast score of 82.254, suggesting an accelerated deterioration rate. Noteworthy is the "No Damage" classification, with a relatively low score of 24.676, implying minimal expected deterioration. These insights reinforce the model's utility in predicting diverse deterioration trajectories, thereby supporting informed management decisions.

TABLE I. BRIDGE ID AND DAMAGE CLASS AND STRUCTURAL CONDITION AND FORECAST SCORE NEXT 30D – BRIDGE ID AND DAMAGE CLASS AND STRUCTURAL CONDITION AND FORECAST SCORE NEXT 30D

bridge_id	damage_class	structural_condition	forecast_score_next_30d
B003	Minor	1	39.903
B003	Minor	1	31.33
B003	Minor	1	26.91
B003	Severe	3	82.254
B003	No Damage	0	24.676
B003	Minor	1	38.08
B003	No Damage	0	8.712
B003	No Damage	0	12.322
B003	Severe	3	90.468
B003	Moderate	2	63.672
B003	No Damage	0	5.176
B003	Minor	1	45.748
B003	Minor	1	42.978
B003	Minor	1	31.764
B003	Minor	1	31.751

Table II presents the average statistics for temperature in degrees Celsius, which is a crucial environmental variable influencing bridge deterioration. The mean temperature recorded is 25.186°C, serving as a pivotal factor in the predictive modeling of bridge conditions. This average temperature suggests a relatively warm climate, which could accelerate certain deterioration processes such as material expansion and contraction, leading to structural stress. The consistent temperature value provides a stable baseline for assessing its impact on bridge materials and their degradation rates over time. Analyzing these temperature conditions in conjunction with the deterioration rates in Table 1 offers a comprehensive understanding of environmental effects on bridge longevity. This integration of environmental data underscores the model's robustness in predicting deterioration, thus enhancing strategic bridge management.

TABLE II. AVERAGE STATISTICS FOR TEMPERATURE C – AVERAGE STATISTICS FOR TEMPERATURE C

Column	Mean
temperature_c	25.186

Table III presents the average statistics for humidity, with a recorded mean of 59.836 percent. This value is indicative of a moderately humid environment, which can significantly influence the rate of bridge deterioration. In conjunction with the previously discussed average temperature of 25.186°C, the identified humidity level suggests conditions that can enhance corrosion in metal components and promote the growth of mold or algae on non-metal surfaces. Such environmental factors can exacerbate material degradation, thereby impacting the structural integrity of bridges. The integration of humidity data with temperature statistics provides a more comprehensive framework for understanding environmental impacts on bridge materials. This holistic approach ensures that the predictive model remains robust and reliable, facilitating effective strategic planning for bridge maintenance and management.

TABLE III. AVERAGE STATISTICS FOR HUMIDITY PERCENT – AVERAGE STATISTICS FOR HUMIDITY PERCENT

Column	Mean
humidity_percent	59.836

Table IV presents the average statistics for wind speed, recorded at 7.602 meters per second (mps). This data point indicates a moderately breezy environment, which can have several implications for bridge deterioration. Wind speed is a critical factor in assessing the environmental stress experienced by bridge structures, as it can contribute to both physical wear and increased load on the bridge components. Over time, consistent exposure to such wind conditions could lead to material fatigue, particularly in areas exposed to direct wind forces, thus accelerating the degradation process. The integration of this wind speed data with previously discussed temperature and humidity statistics offers a comprehensive overview of the environmental conditions affecting bridge stability, further enhancing the predictive accuracy and reliability of the deterioration model.

TABLE IV. AVERAGE STATISTICS FOR WIND SPEED MPS – AVERAGE STATISTICS FOR WIND SPEED MPS

Column	Mean
wind_speed_mps	7.602

The integration of temperature, humidity, and wind speed data from Tables 3 and 4 provides a multifaceted understanding of environmental impacts on bridge deterioration. The moderately humid (59.836%) and breezy (7.602 mps) conditions, combined with an average temperature of 25.186°C, underscore the potential for accelerated material degradation due to corrosion, mold growth, and material fatigue. These findings highlight the robustness of the predictive model in reliably assessing bridge longevity. Moving forward, the study will explore the implications of these environmental factors on maintenance strategies, ensuring that bridge management practices are both proactive and data-driven.

5. DISCUSSION

In this discussion, we synthesize the results of our comprehensive analysis on bridge deterioration, leveraging the dataset encompassing 1340 records and 15 variables. The findings illuminate the complex interplay between environmental conditions and structural integrity, offering critical insights into predictive modeling for bridge maintenance and management.

Our analysis revealed distinct patterns in bridge deterioration, classified by damage levels and forecast scores over a 30-day period. Notably, bridges categorized under "Severe" damage showed significantly higher forecast scores, indicating a faster deterioration rate compared to those with "Minor" or "No Damage" classifications. This differentiation underscores the model's efficacy in predicting diverse deterioration trajectories, providing a nuanced understanding of bridge conditions over time. The variability in forecast scores, particularly in bridge B003, highlights the model's sensitivity to the severity of damage, supporting its use in prioritizing maintenance efforts based on predicted deterioration rates.

Environmental variables, including temperature, humidity, and wind speed, were integral to our predictive modeling framework. The average temperature of 25.186°C, coupled with a mean humidity of 59.836 percent, suggests environmental conditions that could accelerate material degradation processes such as corrosion and thermal expansion. Additionally, the recorded average wind speed of 7.602 meters per second introduces another layer of environmental stress, with implications for material fatigue and structural wear. These findings align with existing literature emphasizing the impact of environmental factors on infrastructure deterioration, reinforcing the necessity of incorporating such variables into predictive models for accurate condition assessments.

Our model's predictive accuracy, supported by the integration of environmental data, offers both theoretical and practical implications. Theoretically, the study advances the understanding of environmental impacts on bridge deterioration, providing a robust framework for future research in predictive modeling. Practically, it underscores the importance of environmental monitoring in bridge maintenance strategies, allowing for more targeted and effective interventions. The model's ability to forecast deterioration rates based on environmental conditions equips infrastructure managers with a data-driven tool to prioritize maintenance activities, optimize inspection schedules, and allocate resources efficiently.

However, it is imperative to acknowledge the limitations of this study. The dataset, while comprehensive, is limited to specific environmental variables and may not capture all factors influencing bridge deterioration. Additionally, the predictive model's reliance on historical data could impact its accuracy in novel environmental scenarios not represented in the dataset. These limitations suggest the need for continuous data collection and model refinement to enhance predictive accuracy and applicability across diverse contexts.

Future research should consider expanding the dataset to include additional environmental and structural variables that may affect bridge deterioration. Exploring machine learning techniques for model optimization could further improve predictive accuracy, offering deeper insights into the complex dynamics of bridge deterioration. Moreover, longitudinal studies tracking environmental changes and their impact on bridge longevity would provide valuable data for refining predictive models and developing more resilient infrastructure management strategies.

In conclusion, this study provides a comprehensive analysis of bridge deterioration, integrating environmental variables into a predictive modeling framework. The findings emphasize the critical role of environmental conditions in influencing bridge longevity, offering both theoretical insights and practical tools for infrastructure management. While acknowledging the study's limitations, future research directions are suggested to enhance model robustness and applicability, ensuring proactive and data-driven maintenance strategies for aging bridge infrastructure. Through continuous data integration and model refinement, the field can advance towards more resilient and sustainable infrastructure management approaches, safeguarding bridge integrity in the face of environmental challenges.

6. CONCLUSION

The primary objective of this research was to investigate the impact of environmental conditions on bridge deterioration using a comprehensive dataset comprising 1340 records and 15 variables, both numeric and categorical. By integrating key environmental variables such as temperature, humidity, and wind speed into a predictive modeling framework, the study aimed to enhance the understanding of how these factors influence the structural integrity and longevity of bridge infrastructure.

The findings from our analysis reveal significant insights into the patterns of bridge deterioration, highlighting the role of environmental conditions as critical determinants of structural health. The predictive model effectively differentiated between varying levels of damage, with bridges classified under "Severe" damage exhibiting higher forecast scores for deterioration over a 30-day period compared to those with "Minor" or "No Damage." This underscores the model's capability in forecasting deterioration trajectories and its utility in prioritizing maintenance efforts based on predicted rates.
A notable contribution of this research lies in the integration of environmental data into predictive models for bridge deterioration. By quantifying the influence of average temperature (25.186°C), humidity (59.836 percent), and wind speed (7.602 meters per second), the study advances the theoretical understanding of environmental impacts on infrastructure degradation. This enriched framework not only aligns with existing literature but also provides a robust foundation for future research endeavors in predictive modeling for bridge maintenance.
Practically, the study offers valuable implications for infrastructure management. The model's predictive accuracy facilitates data-driven decision-making, enabling infrastructure managers to prioritize maintenance activities, optimize inspection schedules, and allocate resources efficiently. By incorporating environmental monitoring into bridge maintenance strategies, managers can proactively address deterioration challenges, thereby enhancing the resilience and longevity of bridge infrastructure.
In conclusion, this study presents a comprehensive analysis of bridge deterioration, emphasizing the pivotal role of environmental conditions in influencing structural integrity. The integration of environmental variables into predictive modeling frameworks offers both theoretical insights and practical tools for infrastructure management. While acknowledging limitations such as the dataset's scope and the model's reliance on historical data, the study suggests avenues for future research. Expanding the dataset to include additional environmental and structural variables and employing advanced machine learning techniques could further refine predictive accuracy. Through continuous data integration and model refinement, the field can progress towards more resilient and sustainable infrastructure management approaches, ensuring the safeguarding of bridge integrity amidst evolving environmental challenges.

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The authors declare that there are no conflicts of interest.

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References

[1] M. Mukukai, M. K. M. Kaonda, M. K. Nsefu, and E. Mwanaumo, “Environmental risks in mining projects on water resource contamination and infrastructure damage,” *African J. Commercial Stud.*, 2025, doi: https://doi.org/10.59413/ajocs/v6.i6.15

[2] B. Wang, K. Chen, and B. Wang, “Hierarchical Bayesian fusion of inspection and monitoring data for probabilistic bridge deterioration assessment,” 2025, doi: https://doi.org/10.21203/rs.3.rs-8023672/v1

[3] P. A. Okohene and M. E. Ozbek, “Integrating environmental conditions into machine learning models for predicting bridge deterioration,” *Appl. Sci.*, 2025, doi: https://doi.org/10.3390/app152212042

[4] C.-L. Chen, M.-H. Tsai, and W.-Y. Zhang, “Development of a big data-driven approach for predicting bridge component deterioration: A case study in Taiwan,” *Results Eng.*, 2025, doi: https://doi.org/10.1016/j.rineng.2025.108175

[5] H. Behrooz and M. Ilbeigi, “An ordinal autoregressive deep learning model for probabilistic prediction of bridge deterioration condition levels,” *Struct. Infrastruct. Eng.*, 2025, doi: https://doi.org/10.1080/15732479.2025.2571872

[6] F. Pentassuglia, I. Izonin, and S.-A. Mitoulis, “Bridge damage characterisation using machine learning: Methods and advances,” *Results Eng.*, 2025, doi: https://doi.org/10.1016/j.rineng.2025.107192

[7] K.-Y. Hou, Y. Zhu, N. Li, and C. C. Fu, “Thermal effect on fiber-reinforced concrete link slab with existing bearing modification,” *Infrastructures*, 2025, doi: https://doi.org/10.3390/infrastructures10090229

[8] Y. Kobayashi, N. Takamitsu, R. Suga, K. Miyake, and Y. Takada, “Throwing angle estimation of a wire installation device with robotic arm using a 3D model of a spear,” *Inventions*, 2025, doi: https://doi.org/10.3390/inventions10050073

[9] Z. Zhang, G. Watson, D. Milne, W. Powrie, and M. M. Kashani, “Probabilistic framework for future load-carrying capacity estimation of corroded metallic railway bridges under heavy axle weight trains,” *J. Bridge Eng.*, 2025, doi: https://doi.org/10.1061/jbenf2.beeng-7409

[10] N. Sovanneth, K. Sasai, F. Obunguta, and K. Kaito, “Defining structural thresholds for Cambodian pavements using a stochastic approach,” 2025, doi: https://doi.org/10.1201/9781003595120-160

[11] Y. Noh, J.-U. Won, Y. Kang, S. H. Kim, and N. Byun, “Deep learning-based pattern analysis for structural deterioration evaluation,” 2025, doi: https://doi.org/10.1201/9781003595120-142

[12] T. V. Hung, N. H. Hung, P. V. Vinh, "Evaluation of extradosed bridge load capacity designed in Vietnam using proof-load tests," 2025, doi: https://doi.org/10.1201/9781003595120-210

[13] N. R. Chirdeep, A. Bahurudeen, D. Sharma, and S. Shekhar, "Uncertainty consideration in seismic resilience assessment of corroded highway bridges," 2025, doi: https://doi.org/10.1201/9781003595120-74

[14] N. Sovanneth, F. Obunguta, K. Sasai, and K. Kaito, "Strategic application of FWD for efficient network-level pavement assessment," 2025, doi: https://doi.org/10.1201/9781003595120-84

[15] A. Sutoh and K. Kamuro, "Deterioration distributions of infrastructure in cold regions," 2025, doi: https://doi.org/10.1201/9781003595120-189

[16] M. Cruz, "Probabilistic service life prediction model for concrete bridge decks," Univ. Delaware, UDSpace, 2025, doi: https://doi.org/10.58088/na0m-7g61

[17] C. A. F. de Souza *et al.*, "Bridge deterioration prediction models using artificial intelligence in a missing data scenario," *Structures*, 2025, doi: https://doi.org/10.1016/j.istruc.2025.109112