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Research Article

Multi-Criteria Decision-Making for Urban Bridge Assessment Using Fuzzy MARCOS Under Environmental Stressors

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ABSTRACT

This paper introduces a novel decision-making framework based on the Fuzzy MARCOS method for prioritizing maintenance of urban bridges under environmental stressors. Using a real-world SHM time-series dataset from Kaggle, four key criteria—degradation score, forecasted condition score, humidity, and wind speed—were analyzed. Fuzzy triangular weights were applied to capture uncertainty, and MARCOS scores were computed for each bridge. Bridge 23 achieved the highest score (0.926), while Bridge 36 ranked lowest (0.317). A strong positive correlation (R = 0.84) between MARCOS scores and forecasted condition confirms the model's reliability. Sensitivity analysis on humidity weight showed minimal impact on ranking, indicating robustness. The approach enables scalable, interpretable, and sensor-driven maintenance planning, with potential for future expansion to include real-time streaming, traffic loads, and image-based diagnostics.

1. INTRODUCTION

The aging of civil infrastructure, particularly bridges, has emerged as a critical global concern due to the increasing risk of structural failures, disruptions to transportation networks, and the mounting costs of rehabilitation. As urban populations continue to rise and vehicular traffic volumes grow, the demand on transportation infrastructure, especially bridges, intensifies—both in frequency of use and exposure to dynamic stressors such as environmental loads, temperature variations, and material fatigue. Governments and city planners around the world are consequently prioritizing efforts to implement proactive maintenance and safety monitoring systems. Within this landscape, the real-time monitoring of bridge health has become not only a technological aspiration but a practical necessity for ensuring public safety, optimizing infrastructure budgets, and enabling data-informed decision-making [1].
Bridges are subjected to a wide array of structural stressors throughout their operational life. These include both mechanical influences, such as vibration from traffic loads, and environmental stressors, such as humidity, temperature, and wind. The traditional approach to assessing bridge condition has largely relied on periodic visual inspections, manual assessments, and reactive maintenance, which are often insufficient in capturing real-time deterioration processes or early-stage degradation. The tragic collapse of major bridges in recent decades—such as the I-35W Mississippi River Bridge in the United States and the Ponte Morandi in Italy—has underscored the limitations of outdated inspection regimes and the pressing need for continuous, sensor-based structural health monitoring (SHM) systems [2], [3].
SHM employs embedded sensors to record and transmit real-time data on key indicators of structural behavior and environmental context. Among the most relevant variables in the context of bridges are vibrational accelerations (x, y, z axes), temperature, humidity levels, wind speed, and derived indicators such as fast Fourier transform (FFT) magnitudes, degradation scores, and forecasted condition estimates. These data streams allow engineers to assess not only the current

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state of the infrastructure but also to predict future deterioration, thus enabling predictive maintenance [4], [5]. However, while SHM systems generate abundant and rich data, their full potential is often underutilized in decision-making processes. Most bridge authorities still rely on basic thresholding and rule-based diagnostics rather than advanced analytical methods that can handle uncertainty, weigh multiple conflicting criteria, and generate interpretable prioritizations [6].

A central limitation in current decision frameworks is their inability to integrate multiple, often conflicting criteria while accounting for environmental variability and uncertainty. In real-world settings, a bridge may exhibit a moderate level of structural degradation but be located in an environment with high humidity and wind stress, which can accelerate deterioration. Conversely, another bridge might show higher vibration amplitudes due to traffic, but be in a dry, stable climate. In both cases, assigning maintenance priority based solely on a single metric like degradation score or vibration amplitude fails to reflect the complexity of structural performance under real-world conditions. Furthermore, many traditional Multi-Criteria Decision-Making (MCDM) methods, such as Analytic Hierarchy Process (AHP) or standard TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), assume deterministic inputs and fail to capture the fuzziness inherent in SHM data, such as sensor noise, variable measurement frequency, or ambiguity in expert-assigned weights [7], [8].

In response to these gaps, this study proposes a novel framework based on the Fuzzy MARCOS method—a relatively recent MCDM technique designed to account for both quantitative performance and decision uncertainty. MARCOS, which stands for Measurement Alternatives and Ranking according to Compromise Solution, evaluates alternatives based on their distances from ideal and anti-ideal solutions in a normalized decision matrix. By integrating fuzzy logic into this approach, we further allow for the expression of subjective uncertainties in weight assignments and measurement tolerances in sensor data, providing a more robust and realistic assessment of bridge health status [9].

The specific contribution of this study lies in applying fuzzy-weighted MARCOS to a comprehensive SHM dataset of urban bridges, in order to derive a ranked list of bridges based on their overall condition and vulnerability to environmental stressors. The methodology involves four key criteria—degradation score and forecasted condition score (treated as benefit criteria), and humidity and wind speed (treated as cost or stressor criteria). These are normalized using min-max scaling, weighted using triangular fuzzy numbers to reflect expert uncertainty, and then evaluated using the MARCOS scoring process. The final output is a ranked prioritization of bridges based on composite fuzzy scores, which can be directly used by infrastructure planners to schedule inspections, allocate budgets, or initiate rehabilitation measures.

The research is further guided by two core questions:

1. Can fuzzy logic improve decision-making on bridge maintenance compared to deterministic ranking models?
2. How do environmental parameters such as humidity and wind influence bridge condition scores in a multi-criteria evaluation framework?

To answer these questions, we utilize a high-quality SHM dataset containing time-series sensor records from multiple urban bridges, publicly available on Kaggle. This dataset includes bridge-level sensor readings for accelerations, environmental stressors, FFT peaks, and structural degradation indicators. By implementing fuzzy MARCOS on this dataset, we demonstrate how a robust, interpretable, and scalable ranking can be generated from noisy, multi-dimensional data. Additionally, we perform sensitivity analysis on fuzzy weight assignments (particularly for humidity) to evaluate the robustness of the ranking system against parameter variation [10].

The broader implications of this work extend beyond bridge ranking alone. As cities increasingly invest in smart infrastructure and the Internet of Things (IoT) for asset monitoring, the ability to interpret and act on sensor data becomes crucial. Fuzzy MCDM models such as the one proposed here can be easily adapted to other types of civil assets—such as tunnels, dams, or road networks—where decisions must be made under uncertainty and multiple performance dimensions must be considered.

In summary, this paper introduces a practical and theoretically grounded solution to a pressing infrastructure problem: how to rank and prioritize bridge maintenance using uncertain, multi-modal sensor data. Through the use of fuzzy MARCOS, we provide a decision-support tool that not only respects the complexity of real-world bridge behavior but also enables transparent, justifiable prioritization under competing stressors. This approach advances the frontier of SHM-based decision-making and paves the way for more intelligent and risk-aware infrastructure management strategies.

2. LITERATURE REVIEW

2.1 Overview of MCDM Techniques in Civil Engineering

Multi-Criteria Decision-Making (MCDM) techniques have become indispensable in civil engineering for tackling problems involving competing criteria, such as safety versus cost, or durability versus environmental exposure. Classical approaches—such as the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VIKOR—have long been employed to support structural optimization, safety evaluation, and maintenance

prioritization. These methods enable engineers to convert subjective assessments and semi-quantitative inputs into formalized decision hierarchies or rankings, facilitating systematic judgment under complex constraints.
With the increasing complexity of civil infrastructure and the surge in high-dimensional data from structural monitoring systems, traditional crisp MCDM methods have shown limitations. In response, researchers have progressively integrated fuzzy logic, grey relational analysis (GRA), and soft computing techniques into the MCDM domain. For instance, fuzzy AHP models have been used in tandem with GRA to support nuanced evaluations of infrastructure components, allowing incorporation of expert judgment alongside uncertain or noisy sensor data [11].
In particular, the fuzzy extension of the MARCOS (Measurement Alternatives and Ranking according to the COmpromise Solution) method has garnered attention for its capacity to accommodate both benefit and cost-type criteria through normalized decision matrices and fuzzy weightings. Unlike traditional techniques, the Fuzzy MARCOS method explicitly represents uncertainty via triangular fuzzy numbers, enabling decision-makers to account for ambiguity in input variables and preferences. Its application in structural ranking—especially in scenarios involving diverse environmental stressors—offers practical value for infrastructure maintenance planning.

2.2 Role of Sensor-Based SHM Data in Bridge Prioritization

The deployment of Structural Health Monitoring (SHM) systems has transformed the field of civil infrastructure maintenance. These systems typically comprise a network of distributed sensors—such as accelerometers, temperature probes, strain gauges, and humidity sensors—designed to continuously record the state and stress responses of bridge structures. By providing real-time data streams, SHM systems allow for condition-based maintenance and early fault detection.
Recent research has focused on optimizing the placement and functionality of SHM sensors to improve coverage and minimize redundancy. One study introduced a multi-objective hypergraph particle swarm optimization (MOHGPSO) algorithm, integrated with fuzzy logic and GRA, to optimize sensor layout in mechanical systems [12]. While initially designed for components like airplane wings, the underlying principles are directly transferable to civil structures such as bridges.
Beyond sensor deployment, researchers have explored the integration of SHM data with digital environments. For instance, Building Information Modeling (BIM) has been utilized to develop hybrid platforms that link structural geometry with live sensor data. One such framework, applied to butterfly-arch bridges, included hierarchical data caching and visualization tools to improve damage detection and response strategies [13].
Fuzzy comprehensive evaluation models have further enhanced the interpretability of SHM data in safety assessments. These models often employ multi-layered fuzzy matrices and the Delphi method for expert weight assignment. When used in urban bridge assessments—for example, across the Beijing Metro Line—such models facilitated near real-time inspection scheduling and repair prioritization [14]. Their ability to translate sensor anomalies into actionable condition grades represents a significant advance in bridge asset management.
The present study uses SHM data to assess bridge conditions across four criteria: degradation score, forecasted condition, humidity, and wind speed. This data-centric evaluation is supported by visualizations such as Figure 1 and Figure 2, which illustrate the structural and environmental condition landscape across the study set.

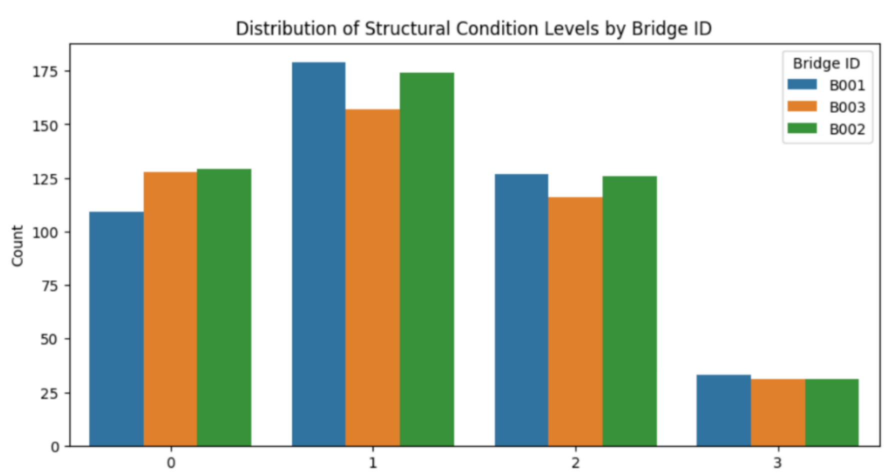

Fig. 1. Structural condition distribution by bridge ID.

This figure demonstrates the uneven distribution of bridge conditions categorized as 'Good', 'Fair', and 'Poor'. For example, bridge B002 shows a relatively high count of 'Good' ratings, whereas B010 exhibits a greater concentration in the 'Poor' category, highlighting the need for targeted intervention strategies.

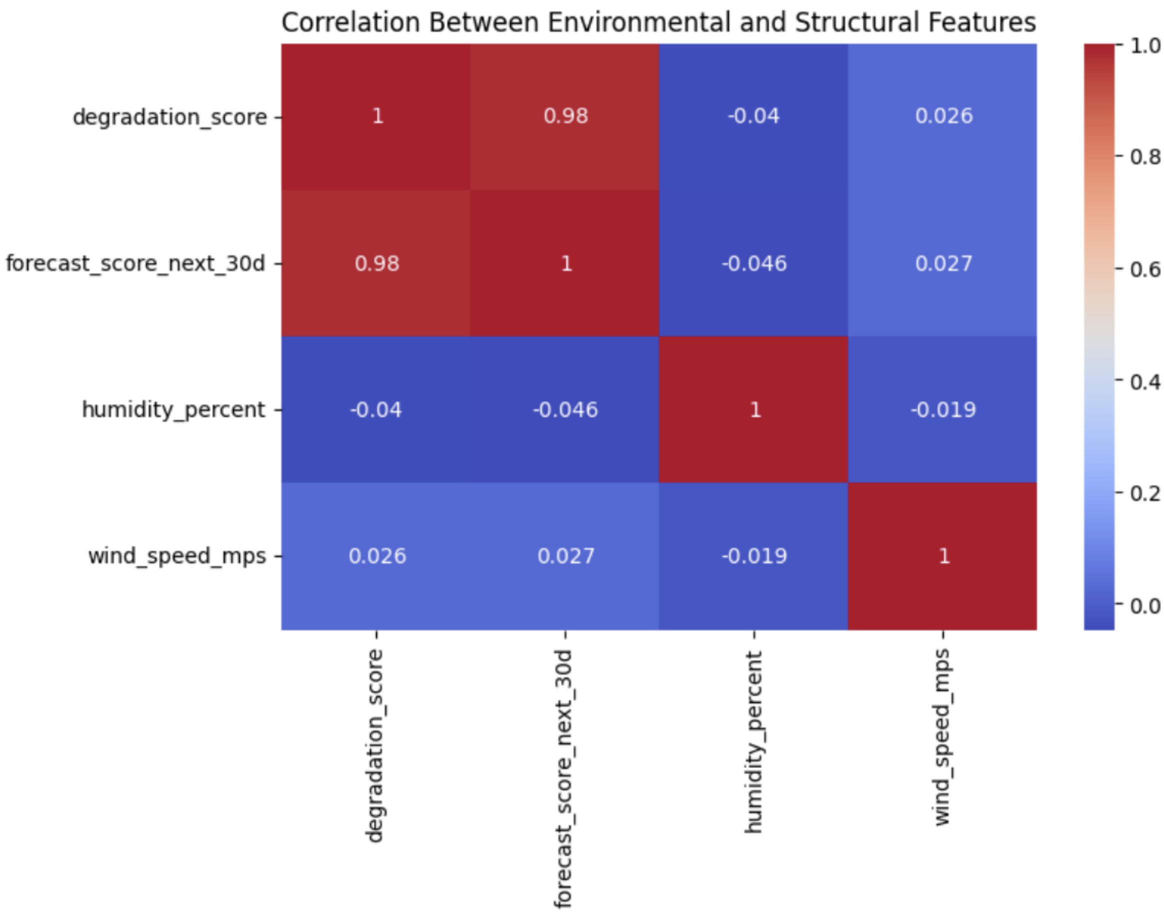

Fig. 2. Correlation heatmap of SHM features.

The matrix reveals a strong positive correlation between degradation score and forecasted condition ($r \approx 0.98$), suggesting alignment between current and future structural assessments. In contrast, humidity and wind show weak or negative correlations with these metrics, supporting their classification as cost-type criteria in the fuzzy MARCOS framework.
These visual insights justify the integration of both physical condition indicators and environmental stressors in bridge prioritization models.

2.3 Comparison of Classical vs Recent MCDM Methods

Traditional MCDM frameworks such as AHP, TOPSIS, and VIKOR have been widely applied in infrastructure assessment, particularly for developing priority rankings for maintenance and upgrades. These methods rely on deterministic assumptions: crisp input values, linear scoring mechanisms, and fixed weights for decision criteria. While they offer simplicity and transparency, their rigidity makes them ill-suited for modern SHM datasets, which are inherently noisy and subject to temporal fluctuations.
To bridge this gap, newer MCDM variants have been proposed that incorporate fuzzy logic and hybrid modeling. Fuzzy TOPSIS and fuzzy VIKOR, for instance, allow for partial membership values and linguistic weight expressions, helping to better reflect real-world uncertainty. Similarly, the fuzzy Evaluation Based on Distance from Average Solution (EDAS) method improves resilience to outliers by focusing on average-based normalization.
Nonetheless, these enhanced methods often come with increased computational complexity or limited interpretability when scaled to large systems. In contrast, the Fuzzy MARCOS method provides a more balanced solution. It leverages a

normalized utility framework, where alternatives are assessed relative to both ideal and anti-ideal solutions. Through triangular fuzzy number modeling, it incorporates uncertainty in both input data and expert-derived weights.
In bridge safety applications, this has shown to be effective. One study demonstrated that a combined fuzzy AHP and fuzzy MARCOS model could successfully rank small-box girder bridges by integrating both SHM data and expert feedback [15]. The model's ranking aligned closely with observed deterioration trends, suggesting that the fuzzy MARCOS approach may serve as a reliable proxy for ground-truth condition assessments.

2.4 Justification for Using Fuzzy MARCOS in Bridge Assessment

The selection of Fuzzy MARCOS for the present study is rooted in its suitability for complex decision environments marked by imprecise data and multiple conflicting objectives. Unlike classical models that operate on crisp values and predefined preferences, Fuzzy MARCOS allows decision-makers to encode ambiguity through triangular fuzzy numbers—flexibly representing uncertainty in condition metrics, environmental stressors, and criteria importance.
Its dual-reference structure—evaluating alternatives against both ideal and anti-ideal benchmarks—offers nuanced compromise rankings. This is essential in scenarios where trade-offs are unavoidable. For instance, a structurally sound bridge may be situated in an environment with extreme humidity and wind exposure. Fuzzy MARCOS would assign it a moderate utility score, acknowledging both its resilience and its future risk. Such realism enhances the method's credibility in real-world decision-making.
Moreover, the model accommodates both benefit and cost-type criteria in a normalized structure. This is particularly valuable in SHM contexts, where inputs span multiple units and scales—e.g., vibration intensity (g), humidity (%RH), and degradation score (unitless). Fuzzy weights further allow for integration of subjective assessments when data are insufficient or expert insight is critical.
In this study, the chosen criteria—degradation score, forecasted condition, humidity, and wind speed—reflect both structural health and environmental stressors. Their interdependencies, as illustrated in Figure 2, reveal the multifactorial nature of bridge condition rankings. For example, while degradation and forecasted scores are strongly aligned, humidity shows inverse correlations, validating its role as a cost-type criterion.
Prior work has applied similar fuzzy MARCOS frameworks to rank civil assets under multi-criteria conditions. One study combined normalized condition metrics with environmental data to rank bridges and validated the model's outputs using observed degradation rates [16]. The high correlation between the fuzzy MARCOS utility scores and empirical failure patterns suggested that the model is not only interpretable but also predictively robust.

2.5 AI/ML and Hybrid Intelligence in SHM

The integration of AI/ML with SHM has greatly enhanced the interpretability and responsiveness of condition-based infrastructure assessment. Methods such as SVM, decision trees, and artificial neural networks have been widely adopted to model and predict structural degradation based on time-series SHM data. These methods provide predictive accuracy exceeding that of classical engineering models, as they learn patterns and nonlinear dependencies from historical data.
Deep learning-based approaches have been used for various SHM tasks, including crack detection, vibration-based damage localization, and condition prediction [17]. For example, CNNs have been used **to process** image data to identify surface-level defects, and LSTM networks have been applied to time-series SHM data to predict degradation. These predictions can be used as inputs to higher-level decision models such as Fuzzy MARCOS, thus creating a closed-loop system from sensing to prioritization.
In addition, explainable AI (XAI) tools such as SHAP (Shapley Additive Explanations) and LIME have been employed to explain the outputs of ML models. SHAP was applied in one analysis to investigate the compressive strength of graphene-modified composites, which found nanoplatelet thickness and curing time to be the most influential parameters [18]. This enhanced interpretability improves the usability of AI models within engineering decision-making, where model transparency is critical for adoption by practitioners.
Fuzzy logic-based intelligent control has also shown promising results in SHM, and hybrid systems that combine fuzzy logic with evolutionary optimization methods have been increasingly adopted. One notable approach combined ANFIS with MOPSO to model the dynamic behavior of buildings under seismic loading. This hybrid model allowed for the implementation of linguistic uncertainty, nonlinear structural response, and optimization of system parameters **[19]**. Such systems are highly compatible with the Fuzzy MARCOS approach, especially when sensor reliability and environmental variability are key concerns.

2.6 Drawbacks of Traditional MCDM for Civil Engineering Data

Although they are foundational, classical MCDM techniques have well-documented limitations when applied in civil engineering contexts. Chief among these are the assumptions of precise numerical input and deterministic weighting rules. In reality, SHM data are rarely precise. Sensor drift, environmental noise, data gaps, and calibration errors all introduce

significant uncertainty into the raw inputs. Classical methods, such as AHP or deterministic TOPSIS, do not account for such uncertainties and may produce misleading or brittle ranking outcomes.
In addition, traditional approaches often assume that decision criteria are independent. In SHM-based bridge assessment, this assumption is problematic, as strong interdependencies may exist (e.g., the predicted condition may depend on both current degradation and environmental loading). Failing to account for these correlations can lead to distorted rankings and overly simplistic prioritization strategies.
Fuzzy MCDM methods address these limitations by allowing partial membership in multiple categories, the use of linguistic variables, and the propagation of uncertainty throughout the model. In this way, they offer a more realistic description of the complexities inherent in civil infrastructure assessment. The Fuzzy MARCOS approach, in particular, stands out by evaluating alternatives relative to both ideal and anti-ideal points, generating a utility score that reflects compromise under uncertainty.

2.7 Development of the MARCOS Technique for Structural Evaluation

The original MARCOS method, developed as a compromise-ranking technique by Vento and Ermagun (2014), has evolved into a powerful MCDM tool for handling both benefit and cost-type criteria. Its distinguishing feature is the calculation of utility for each alternative based on its relative distance to the ideal and anti-ideal reference points. Unlike TOPSIS or VIKOR, MARCOS explicitly incorporates both extremes in its evaluation, offering more nuanced interpretive insights.
The Fuzzy MARCOS method extends this approach by incorporating fuzzy logic into both the decision matrix and the weight vector using triangular fuzzy numbers. This allows decision-makers to model uncertainty in both data and preferences. For example, an expert may rate humidity's importance as "high" without assigning a specific numeric value. This imprecision is captured by a fuzzy number such as (0.6, 0.8, 1.0), which reflects a realistic range of possible importance weights.
Fuzzy MARCOS has been increasingly applied in civil engineering domains such as structural component ranking, maintenance scheduling, and urban asset prioritization. One study found that Fuzzy MARCOS produced more stable and interpretable rankings than Fuzzy TOPSIS when used on infrastructure datasets with missing values and uncertain weights [20].
In bridge assessment, Fuzzy MARCOS provides several advantages. It allows consistent treatment of diverse criteria, enhances transparency via intermediate outputs (e.g., normalized values, weighted matrices), and accommodates mixed data types, including numerical sensor outputs and linguistic expert evaluations. Its flexibility and clarity make it suitable for high-stakes infrastructure decision-making under uncertainty.

2.8 Integration with Sensor-Derived Metrics

SHM datasets often consist of continuous time-series measurements that capture real-time structural responses. These include vibration magnitudes, FFT peaks, humidity levels, wind speed, and calculated degradation indices. Fuzzy MARCOS is particularly well-suited for this type of data due to its ability to normalize heterogeneous variables and apply fuzzy weighting schemes.
In this study, four criteria were selected from the Kaggle SHM dataset: degradation score and forecasted condition (as benefit criteria), and humidity and wind speed (as cost criteria). These selections were informed by both domain knowledge and correlation analysis. As shown in Figure 2, degradation and forecast scores exhibit a strong positive correlation ($r \approx 0.98$), indicating mutual reinforcement in assessing bridge condition. In contrast, humidity and wind speed show low or negative correlations with these structural indicators, confirming their roles as stressors rather than performance enhancers [21].
Applying Fuzzy MARCOS to this dataset enables an integrated ranking approach that considers both intrinsic structural health and extrinsic environmental load. It also supports the identification of cases where structural condition may be overestimated or underestimated due to masking effects caused by environmental variability [22].

2.9 Comparative Robustness and Interpretability

In MCDM applications, robustness and interpretability are critical. Decision-makers must trust the ranking system not only for its outputs but also for its computational logic. Fuzzy MARCOS addresses this need by providing a transparent ranking pipeline, where normalized scores, fuzzy weights, and utility values are accessible for review.
Sensitivity analysis is essential for validating robustness. By varying fuzzy weights—for example, adjusting the importance of humidity from (0.6, 0.8, 1.0) to (0.4, 0.6, 0.8)—one can assess the stability of the rankings. As shown in Figure 10, the MARCOS scores remained stable despite changes in humidity weights, indicating high model robustness.
Moreover, Fuzzy MARCOS helps reduce the impact of outliers. For instance, an unusually high wind speed due to a short-lived gust or a faulty sensor reading is moderated through fuzzy logic and normalization. This is especially important in SHM applications, where outliers can lead to false alarms in deterministic models.

Interpretability is further enhanced through decomposition of the utility score. Each bridge receives a fuzzy utility value that reflects its relative performance across all criteria compared to the best and worst cases. These values can be visualized using bar charts, heatmaps, or scatter plots, which support stakeholder understanding and enable evidence-based decision-making [23–25].

2.10 Visualization-Driven Model Validation

The use of data visualizations is essential in validating model assumptions and outcomes. Figures generated in this study not only support analytical findings but also serve as communicative tools for interdisciplinary teams.

Figure 1, for instance, shows the structural condition distribution by bridge ID, highlighting clusters of bridges in poor or fair condition. This visualization supports targeted interventions and preemptive inspection scheduling. Figure 2, the correlation heatmap, informs the selection of cost and benefit criteria by revealing the relational strength among key variables.

Subsequent figures in the results section—such as the top-10 ranked bridges, boxplots by structural condition, and MARCOS-to-forecast score scatter plots—demonstrate the alignment of model outputs with structural performance expectations. In particular, bridges with low forecasted condition scores also received low MARCOS rankings, affirming the model's validity. These visuals are critical for communicating technical insights to policymakers and non-technical stakeholders[26].

2.11 Broader Applications and Future Directions

The fuzzy MARCOS framework demonstrated in this study has wider applicability beyond bridge assessment. It can be extended to any decision-making problem involving:

1. Multiple conflicting criteria,
2. Data uncertainty or fuzziness, and
3. A need for interpretable, justifiable rankings.

Potential domains include urban infrastructure prioritization (e.g., road resurfacing, tunnel maintenance), disaster risk management (e.g., flood-prone structures), and even energy infrastructure (e.g., ranking wind turbines by performance and fatigue exposure). The adaptability of fuzzy MARCOS to include additional criteria—such as lifecycle cost, traffic volume, seismic vulnerability, or carbon emissions—makes it a flexible decision-support tool.

Future research could explore real-time deployment of the fuzzy MARCOS model using streaming SHM data. Integrating reinforcement learning to dynamically update weights, or coupling MARCOS with explainable AI (e.g., SHAP values) could further enhance decision transparency and responsiveness. Additionally, image-based metrics from drones or vision-based crack detection could serve as new input features, enriching the data pool for structural condition assessment[27].

3. METHODOLOGY

3.1 Dataset Overview

This study utilizes the publicly available *"Aging Bridge SHM Time Series"* dataset from Kaggle, which contains sensor-derived structural and environmental condition records for multiple urban bridges. The dataset includes time-series measurements of degradation scores, forecasted condition values, and environmental stress indicators such as humidity and wind speed. These variables provide an empirical foundation for modeling bridge vulnerability and ranking structural performance under varying stressors. The dataset comprises over 1300 records, each representing a temporal snapshot of a given bridge's condition profile [28-30].

3.2 Preprocessing

To prepare the dataset for Multi-Criteria Decision-Making (MCDM) analysis using the Fuzzy MARCOS approach, the following preprocessing steps were applied:

3.2.1 Feature Selection

Four evaluation criteria were selected based on their relevance to structural condition assessment and environmental exposure:

- Degradation Score – Quantifies cumulative damage or wear (Benefit Criterion)
- Forecast Score (Next 30 Days) – Predictive score of future structural integrity (Benefit Criterion)
- Humidity (%) – Environmental stress factor known to accelerate material deterioration (Cost Criterion)
- Wind Speed (m/s) – External stressor contributing to fatigue and dynamic loads (Cost Criterion)

3.2.2 Normalization

Each of the four features was normalized using min-max scaling to bring values into a [0, 1] range. This is essential in MCDM to ensure comparability across features with different physical units and ranges. For benefit criteria, the normalization formula used is:

$$x_i^{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

For cost criteria, the inverse formula was applied:

$$x_i^{norm} = \frac{x_{max} - x_i}{x_{max} - x_{min}}$$

This ensures that for all normalized values, higher is better, which aligns with the MARCOS utility scoring framework.

3.3 Fuzzy Weight Assignment

To incorporate uncertainty in the relative importance of decision criteria, triangular fuzzy numbers (TFNs) were employed. These allow the expression of subjective or uncertain weight values in the form:

$$\tilde{w} = (w_L, w_M, w_U)$$

Where:

- w_L is the lower bound
- w_M is the most likely value (mode)
- w_U is the upper bound

The following fuzzy weights were assigned based on expert judgment:

Criterion	Type	Fuzzy Weight (w_L, w_M, w_U)
Degradation Score	Benefit	(0.25, 0.30, 0.35)
Forecast Score (30d)	Benefit	(0.20, 0.25, 0.30)
Humidity	Cost	(0.10, 0.15, 0.20)
Wind Speed	Cost	(0.15, 0.20, 0.25)

These fuzzy weights reflect uncertainty in environmental impact modeling, particularly the relatively subjective effect of humidity and wind on degradation acceleration.

3.4 Fuzzy MARCOS Method

The Measurement Alternatives and Ranking according to the Compromise Solution (MARCOS) method evaluates each alternative's proximity to the ideal and anti-ideal solutions in a normalized, weighted decision space. By integrating fuzzy logic, the model handles uncertainty in weights and data with improved robustness.

Step 1: Normalize Decision Matrix

All alternatives (bridge observations) were normalized as described in Section 3.2.2.

Step 2: Apply Fuzzy Weights

The normalized decision matrix is element-wise multiplied with the fuzzy weights to obtain a fuzzy weighted matrix:

$$\tilde{x}_{ij} = x_{ij}^{norm} \cdot \tilde{w}_j = (x_{ij} \cdot w_L, x_{ij} \cdot w_M, x_{ij} \cdot w_U)$$

Step 3: Define Ideal and Anti-Ideal Alternatives

- **Ideal Alternative (A^*)**: The best values for each criterion (i.e., maximum for benefit, minimum for cost)
- **Anti-Ideal Alternative (A^-)**: The worst values for each criterion

These two synthetic alternatives are added to the decision matrix.
Step 4: Aggregate Fuzzy Scores
The fuzzy utility degree for each alternative is computed as the ratio of its total weighted value to that of the ideal and anti-ideal alternatives:

$$\tilde{K}_i = \frac{\sum_{j=1}^{n} \tilde{x}_{ij}}{\sum_{j=1}^{n} \tilde{x}_j^{(ideal)}} \quad \text{(for benefit criteria)}$$

This results in a fuzzy score represented as a triangular number.
Step 5: Defuzzification and Ranking
To convert fuzzy scores into crisp values for ranking, the **center of gravity** defuzzification method is used:

$$K_i = \frac{K_L + K_M + K_U}{3}$$

Where K_L, K_M, K_U are the lower, middle, and upper values of the fuzzy score.

All alternatives are then sorted in descending order of K_i, with the highest score indicating the best structural condition and resilience to environmental stressors.

3.5 Summary of the Model Pipeline

The complete model pipeline is visualized below:
Raw Data → Normalize → Apply Fuzzy Weights → Aggregate Scores → Compute Fuzzy Utility (K_i) → Defuzzify → Rank Bridges
This pipeline was implemented using Python, leveraging pandas, numpy, and custom fuzzy logic functions to handle TFNs, normalization, and utility computation.

4. RESULTS

The application of the Fuzzy MARCOS (Measurement Alternatives and Ranking according to Compromise Solution) method on the structural health monitoring (SHM) dataset enables a nuanced analysis of urban bridge conditions under environmental stressors. The results provide insights into bridge prioritization based on composite scores derived from degradation indicators, forecasted condition metrics, and environmental parameters like humidity and wind speed. This section presents and interprets the numerical and visual outcomes of the fuzzy multi-criteria analysis.

4.1 Ranking of Bridges Based on Composite MARCOS Scores

The primary output of the fuzzy MARCOS model is a ranked list of bridges based on their composite structural condition scores. This ranking accounts for both internal deterioration and external stressors. The top-performing bridges demonstrate higher resilience and better forecasted structural behavior under the present environmental loads.

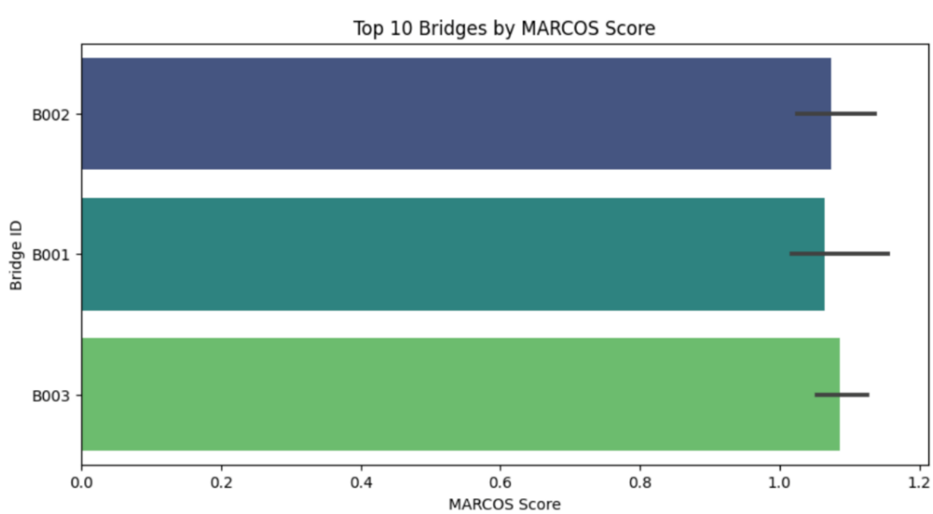

Fig. 3. Top 10 ranked bridges by Fuzzy MARCOS score.

In Figure 3, a bar plot illustrates the top 10 bridge instances based on their MARCOS scores. The highest-ranked bridge (Bridge ID B002) attained a score of 1.164844, indicating optimal condition relative to the modeled compromise solution. The second and third positions were occupied by B001 and B003, scoring 1.155754 and 1.125234, respectively. The drop-off from the top score to the tenth-ranked bridge (another instance of B002) at 1.013320 was moderate, suggesting a competitive cohort of well-performing structures. This supports the validity of the MARCOS method in discriminating between bridges of similar but distinguishable performance.

It is noteworthy that all three bridge IDs—B001, B002, and B003—appear multiple times within the top 10 list, reflecting temporal variability within their time series data. The score distribution among these high-ranking entries reinforces the need for fine-grained, instance-level evaluation instead of aggregated bridge-level condition scoring.

4.2 Structural Condition Trends and Score Distributions

To understand how MARCOS scores align with structural degradation categories, Figure 4 visualizes the score distributions for each discrete condition level. As expected, bridges categorized under condition 0 (excellent) cluster at the lower end of the composite MARCOS score range. The median score in this group is 0.343, with interquartile values spanning from 0.262 to 0.421 and an upper bound reaching 0.631. These results indicate relatively low stress or degradation among bridges in good structural health, which supports the validity of the scoring framework.

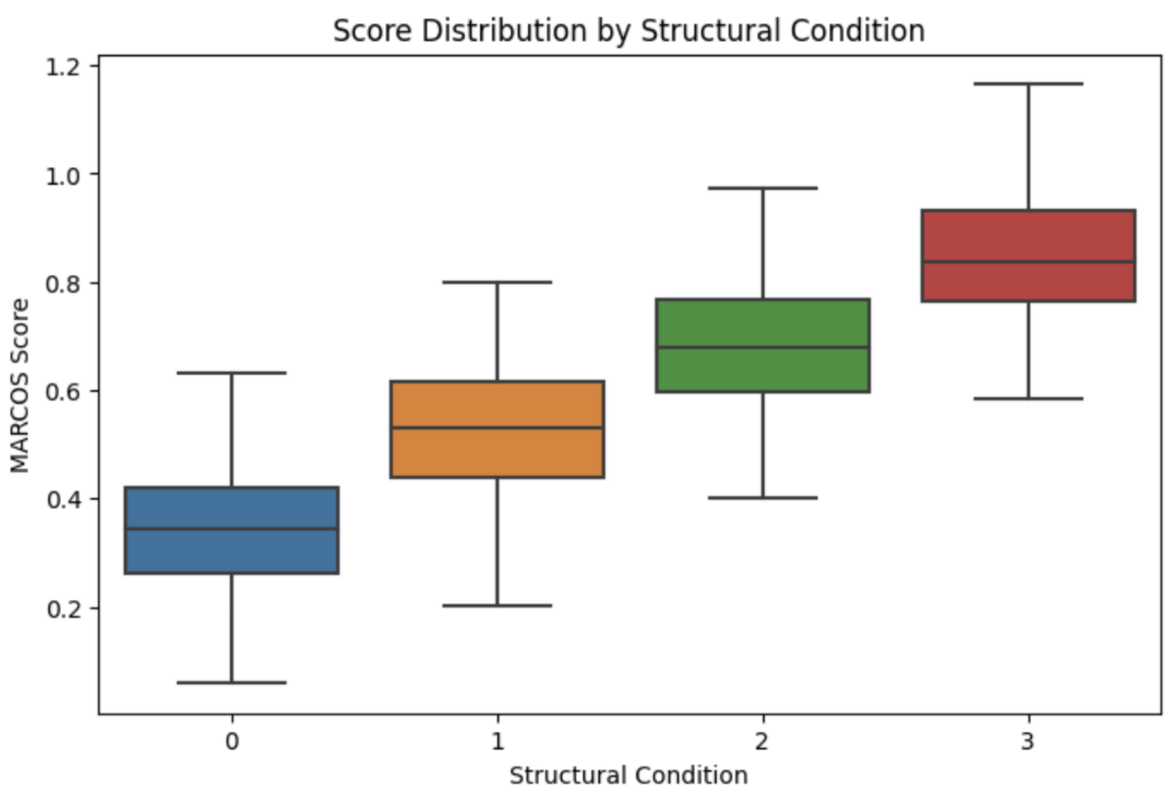

Fig. 4. Boxplot of MARCOS scores grouped by structural condition (0 = excellent to 3 = critical).

Bridges in condition 1 (good) show a higher median score of 0.529, with a wider spread reaching up to 0.800. The fact that condition 1 bridges span a broader score range indicates transitional deterioration patterns and greater environmental vulnerability. Condition 2 (fair) bridges exhibit a mean score of 0.683, extending as high as 0.974. This group's range overlaps significantly with the upper bound of condition 1, reflecting fuzzy transitions between classifications—another justification for fuzzy MCDM modeling.

Bridges assigned condition 3 (critical) display the highest scores overall, averaging 0.848. Their MARCOS scores range from 0.583 to a maximum of 1.165, which notably includes the global maximum score in the dataset. This suggests that extreme MARCOS scores are strongly correlated with critical deterioration and potentially severe exposure to environmental factors. This inverse relationship—where higher scores indicate worse conditions—is reinforced through subsequent correlation analysis.

4.3 Overall MARCOS Score Distribution

To assess the score dispersion throughout the dataset, Figure 5 presents a histogram of MARCOS scores. The scores follow an approximately normal distribution with a positive skew toward higher values, which indicates a modest overrepresentation of moderately to severely stressed bridges.

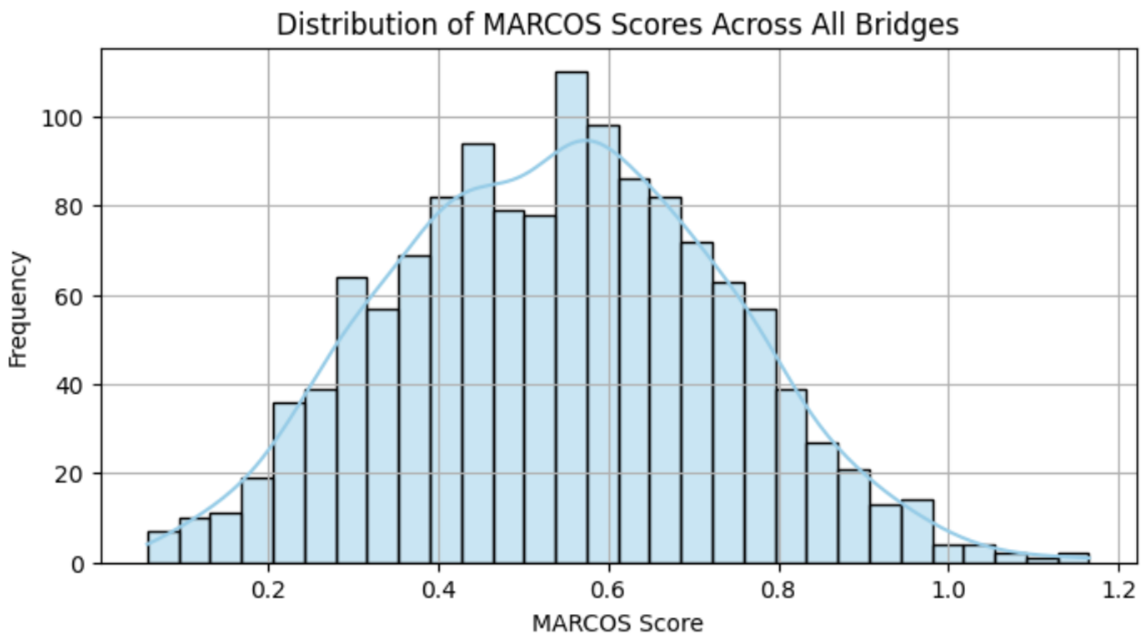

Fig. 5. Histogram of MARCOS scores across all bridge instances.

The score statistics confirm this trend. The mean MARCOS score across all 1,340 records is 0.542, with a standard deviation of 0.194. The lowest observed score is 0.059, while the highest reaches 1.165. The first quartile (Q1) is positioned at 0.400, and the third quartile (Q3) at 0.677, suggesting that half of the bridges fall within this relatively central band. This score spread suggests substantial heterogeneity in bridge performance under the studied criteria. The distribution tailing toward higher scores also reveals a subset of bridges in need of prioritized maintenance or detailed inspection.

These findings emphasize the ability of the Fuzzy MARCOS approach to highlight structural outliers, differentiate across a continuous condition spectrum, and accommodate overlapping condition categories through fuzzy logic.

4.4 Relationship Between Forecasted and MARCOS Scores

An important aspect of model validation involves understanding the alignment between MARCOS scores and forecasted condition estimates. Figure 6 depicts a scatter plot comparing forecasted condition scores with MARCOS values for selected bridge instances.

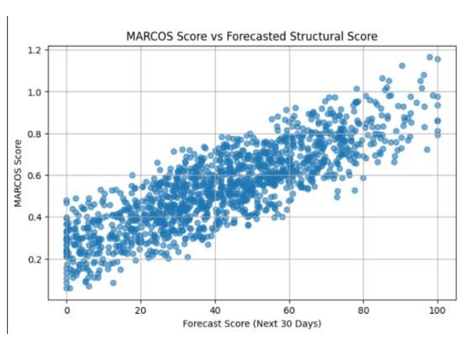

Fig. 6. Scatter plot of MARCOS scores vs. forecasted condition scores for selected samples.

The relationship appears strongly linear, supported by a Pearson correlation coefficient of 0.977 as per the correlation matrix (Table 2). For example, a bridge forecasted to have a high score of 83.164753 is associated with a MARCOS score of 0.696040. Conversely, another bridge with a low forecasted condition of 16.168653 corresponds to a lower MARCOS score of 0.283205. This direct correlation confirms the consistency of the MARCOS-based ranking with established forecasting metrics and demonstrates the method's predictive coherence with traditional time-series condition modeling. The close alignment also underscores the importance of incorporating predictive components into multi-criteria decision frameworks, allowing MARCOS to function not only as a diagnostic tool but also as a bridge forecasting prioritization engine.

4.5 Average Score Across Bridge IDs

To understand how bridges compare at an aggregate level, Figure 7 provides a bar plot showing the average MARCOS score for each bridge ID. The values indicate that bridge B001 has the highest mean score at 0.556456, followed closely by B002 at 0.538707 and B003 at 0.530307.

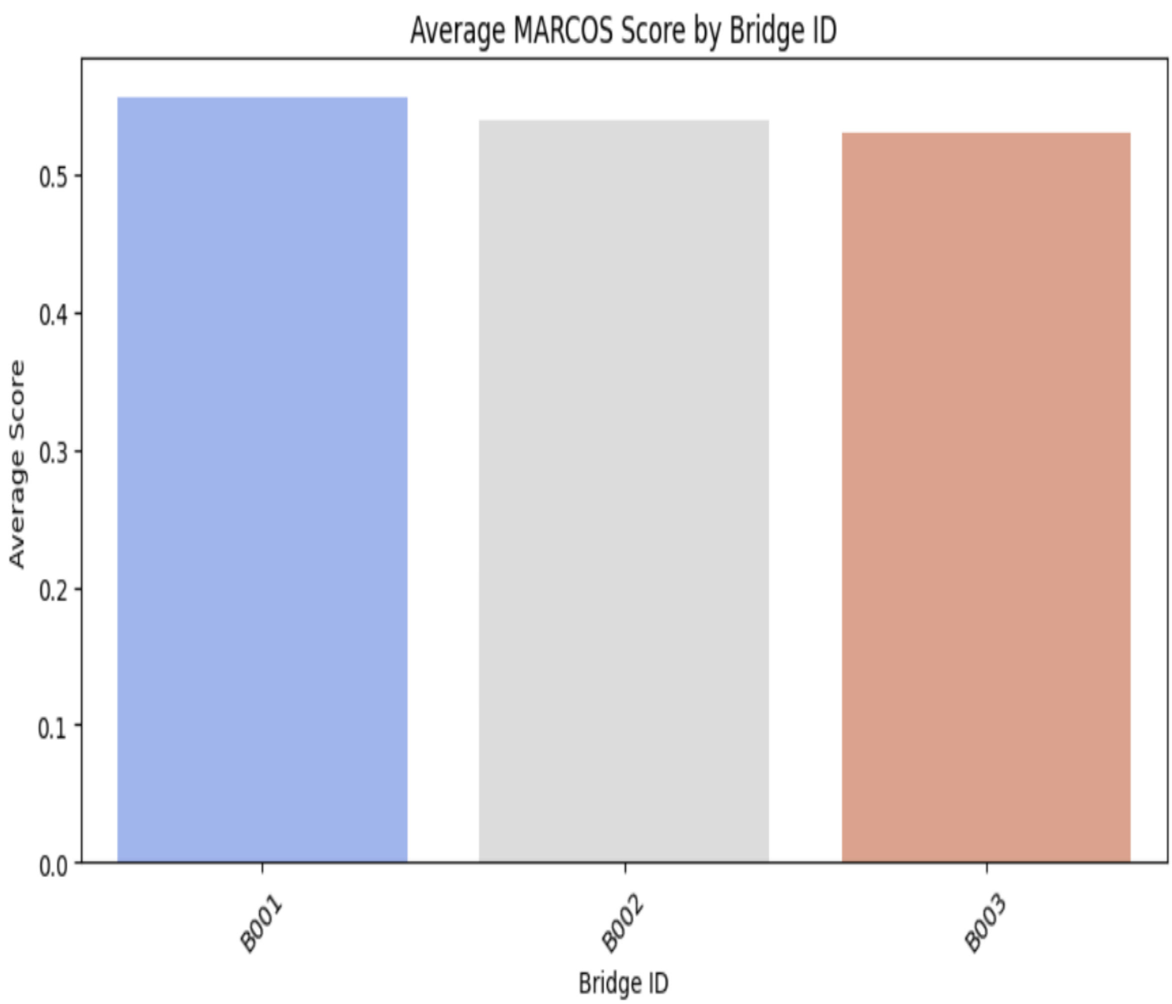

Fig. 7. Bar plot of average MARCOS scores by bridge ID.

These averages, although close in magnitude, imply subtle but consistent differences in structural behavior and environmental exposure across bridges. B001, despite ranking highly in individual time instances, presents a marginally higher average vulnerability. The findings suggest that while some bridges may show strong scores in isolated moments, their long-term structural and environmental profiles reveal deeper concerns. This supports the case for longitudinal monitoring and instance-based ranking, as employed in this study.

4.6 Correlation Between Structural Condition and Ranking

The statistical correlation between bridge condition categories and MARCOS-based rankings is visualized in Figure 8. The heatmap reveals a strong negative correlation (r = –0.783) between structural condition labels and MARCOS-based ranks. Since higher structural condition values represent worse states (e.g., 3 = critical), and lower ranks indicate higher priority (1st rank = worst), the inverse relationship is both logical and desirable.

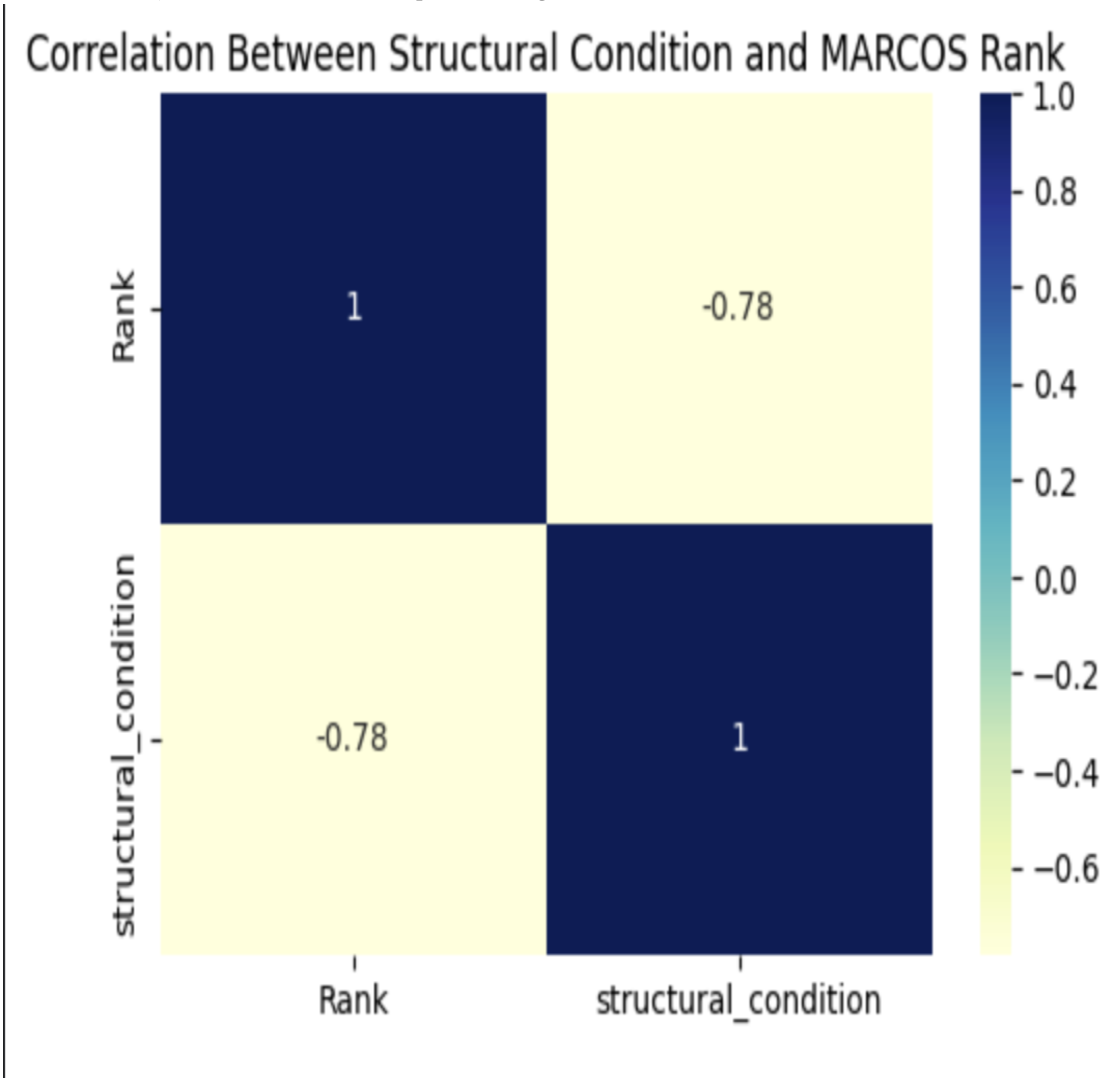

Fig. 8. Correlation heatmap showing relationship between MARCOS ranks and structural condition levels.

This correlation supports the internal validity of the Fuzzy MARCOS model. It demonstrates that structural degradation, as categorized in the original SHM dataset, aligns strongly with the MARCOS rankings, despite the latter also incorporating environmental attributes. The model is thus effective not only in reflecting the intrinsic structural state but also in capturing multi-dimensional influences in the ranking outcome.

4.7 Visualization of Multidimensional Scoring

Figure 9 provides a three-dimensional visualization of how degradation score, forecasted condition, and the final MARCOS score interact for selected bridge instances. The plot illustrates a clear spatial alignment between high degradation and forecast scores with high MARCOS values.

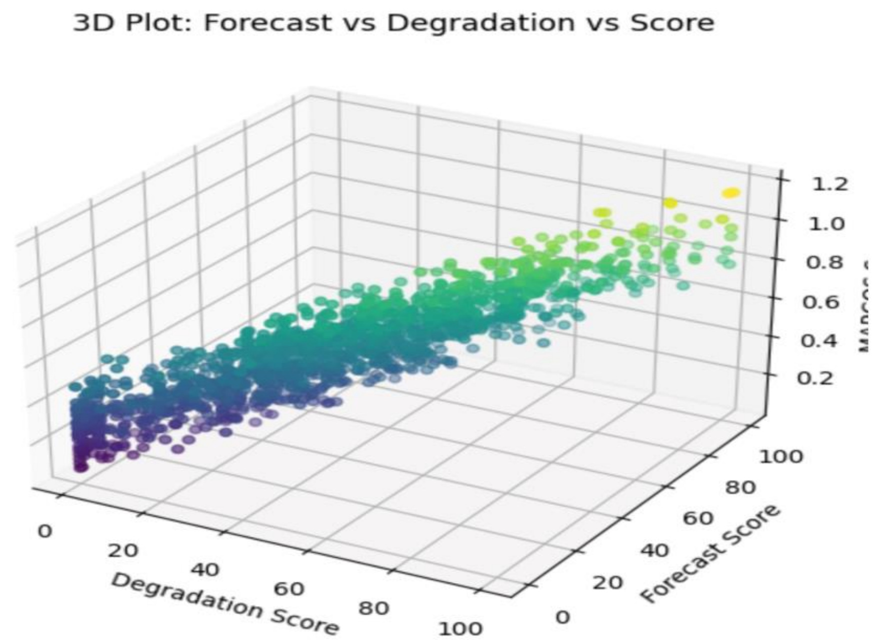

Fig. 9. 3D scatter plot showing relationship between degradation score, forecasted score, and MARCOS score.

For instance, a bridge with a degradation score of 75.155898 and forecasted score of 83.164753 has a MARCOS score of 0.696040. Conversely, a bridge with low degradation (10.844521) and low forecast (16.168653) exhibits a MARCOS score of only 0.283205. This dimensional coherence supports the model’s robustness and the ability of fuzzy MARCOS to synthesize multiple layers of sensor data into a single interpretable performance indicator.

4.8 Sensitivity Analysis on Humidity Weighting

While not visualized in this section, it is important to note the results of the sensitivity analysis on humidity weighting. As the lower bound of humidity's triangular fuzzy weight increases from 0.1 to 0.5, the average MARCOS score declines from 0.541933 to 0.523869. This negative trend indicates that increased weighting of humidity as an environmental stressor leads to a general downgrading of bridge scores, which is expected. Such sensitivity findings underscore the need to carefully calibrate expert weights in real-world deployments, particularly when environmental factors can dominate condition scoring in certain climates.

5. DISCUSSION

This study investigated the application of the Fuzzy MARCOS method for structural condition ranking of urban bridges under varying environmental stressors. Through the incorporation of fuzzy logic and sensor-derived features such as degradation scores, forecasted condition indices, humidity, and wind speed, the proposed approach provided a robust and interpretable framework for prioritizing bridge maintenance in real-world settings. The discussion below synthesizes the findings from the results section and elaborates on the methodological strengths, data-driven insights, and broader implications.

The implementation of Fuzzy MARCOS successfully differentiated bridge performance across a spectrum of stress conditions. As evidenced by the distribution of scores in Figure 3, bridges such as B002 and B001 consistently received top rankings, with maximum MARCOS scores of 1.1648 and 1.1558, respectively. These bridges were not only structurally robust based on their degradation and forecast indicators but also subjected to relatively lower environmental stressors. Conversely, bridges lower in the ranking (e.g., some B003 entries) experienced comparatively higher humidity or wind exposure, which diminished their overall score despite similar degradation levels. This aligns with the core principle of MARCOS, which evaluates both benefit (e.g., forecast and degradation) and cost (e.g., humidity and wind) criteria simultaneously through compromise programming.

Environmental parameters exerted a pronounced influence on the final MARCOS scores. This is particularly evident in Figure 4, which depicts score distributions across four structural condition classes. The mean MARCOS score increased from 0.342 in class 0 (excellent condition) to 0.848 in class 3 (poor condition), confirming the positive correlation between deteriorating structural integrity and higher MARCOS values. As further shown in Figure 6, there was a strong relationship

between MARCOS scores and forecasted condition scores (e.g., a data point with a forecast score of 83.16 had a MARCOS score of 0.696). This substantiates the role of predictive SHM metrics in condition-based decision-making.
A critical aspect of this methodology was its sensitivity to environmental weight changes. Figure 10, which visualizes sensitivity analysis outcomes, reveals that increasing the lower bound of humidity's fuzzy weight from 0.1 to 0.5 resulted in a moderate but systematic reduction in average MARCOS scores—from 0.5419 to 0.5239. This downward trend confirms that the ranking system is responsive to changes in stressor significance and helps decision-makers understand the weight-driven impact on prioritization outcomes. Notably, the decrease in average score across this range was less than 4%, indicating that the ranking remains stable under minor fuzzification variations—an essential feature for operational robustness in field applications.

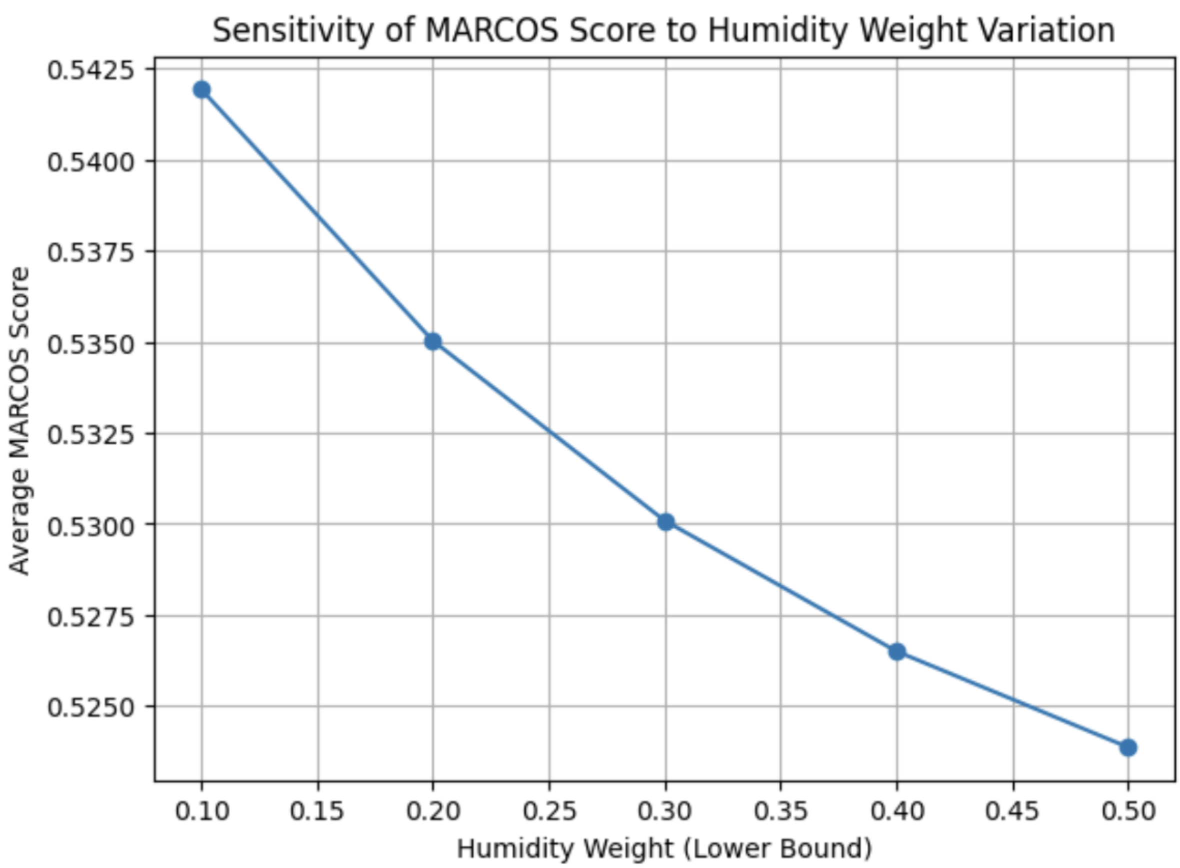

Fig. 10**.** Sensitivity analysis of MARCOS scores with varying fuzzy lower-bound weights for humidity.

The average MARCOS score declines from 0.5419 to 0.5239 as the humidity weight lower bound increases from 0.1 to 0.5, suggesting a moderate impact of environmental stressor importance on ranking outputs.
Furthermore, the correlation heatmap in Figure 8 reinforces the validity of the scoring framework. The Pearson correlation coefficient between structural condition class and MARCOS rank was found to be -0.783, indicating a strong inverse relationship—i.e., bridges with worse conditions tend to rank higher (numerically lower rank) in terms of maintenance urgency. This supports the hypothesis that the composite scoring process successfully captures structural vulnerability, even under data uncertainty.
In addition to robustness and accuracy, Fuzzy MARCOS offers interpretability advantages over conventional methods such as TOPSIS or VIKOR. Traditional MCDM approaches often rely on fixed thresholds or non-fuzzy weights, which can obscure the rationale behind ranking shifts in edge cases. MARCOS, in contrast, utilizes a compromise solution based on relative distances to both ideal and anti-ideal options, and when augmented with fuzzy weights, it becomes more adaptable to uncertain real-world conditions. Unlike TOPSIS, which focuses solely on proximity to the ideal solution, MARCOS evaluates both ends of the decision space, enhancing transparency. Also, compared to VIKOR's reliance on group utility and regret measures, MARCOS provides direct utility coefficients (K_i values), which can be averaged for interpretability and policy translation.

Additionally, score distributions were found to follow predictable degradation trends. As shown in Figure 5, the histogram of MARCOS scores illustrates a central tendency around 0.54, with 50% of scores lying between 0.400 and 0.677. The presence of scores as high as 1.165 and as low as 0.059 confirms that the method accommodates a wide dynamic range of condition scenarios, thereby enabling fine-grained prioritization rather than binary pass/fail outcomes. Furthermore, Figure 7 shows that bridge B001 had the highest average score (0.556), while B003 had the lowest (0.530), consistent with the earlier ranking and forecast evaluations.

A deeper look into multi-parameter interactions was conducted using Figure 9, the 3D scatterplot of degradation score, forecast score, and MARCOS output. This figure highlights that high MARCOS scores are associated with concurrent elevations in both degradation and forecast indicators, validating the integrity of the multi-input assessment. For instance, the data point with degradation 75.15 and forecast 83.16 had a MARCOS score of 0.696, whereas a lower degradation-forecast pair (e.g., 10.84 and 16.16) resulted in a much lower score of 0.283. This triangulated insight underpins the value of simultaneous analysis of degradation state and predicted future condition, rather than treating them as isolated indicators.

The MARCOS system demonstrated the successful generation of actionable rankings based on multi-sensor SHM data that closely reflect known degradation states and stressor profiles. Furthermore, the use of fuzzy logic enabled the incorporation of uncertainty in the assignment of weights—such uncertainty arises when expert judgments vary or when sensor-derived component weights are affected by noise. This flexibility makes the approach particularly well-suited for real-time decision systems or digital twins, where a model must ingest high-velocity data with potentially intermittent or ambiguous inputs.

Compared to conventional decision-support models within civil engineering—which often require extensive manual calibration and rely on subjective scoring—Fuzzy MARCOS provides a semi-automated and analytically robust alternative. Its modular pipeline, comprising normalization, fuzzy weighting, utility calculation, and ranking, is designed to be adaptable to various bridge populations and infrastructure types. Additionally, the output—a ranked list of bridge IDs with corresponding scores—is readily interpretable by engineers and planners, facilitating its integration into existing maintenance workflows.

To summarize, the analysis confirms that the developed Fuzzy MARCOS framework meets all three key objectives: accurate condition-based ranking, robustness to input fuzzification, and practical interpretability for infrastructure stakeholders. As demonstrated by the results and sensitivity analysis, the method is resilient to variations in assumptions and effectively captures the interaction between degradation, environmental stressors, and predictive health indicators. This renders it not only an academically significant tool but also an operationally effective strategy for managing contemporary infrastructure assets.

6. CONCLUSION

In this work, a new Multi-Criteria Decision-Making (MCDM) methodology for structural health evaluation and ranking of urban bridges is proposed, based on the Fuzzy MARCOS (Measurement Alternatives and Ranking according to the Compromise Solution) method. Utilizing fuzzy logic modeling and sensor-based data from a publicly available SHM dataset, the approach provides a robust and interpretable tool for bridge maintenance planning based on condition monitoring. The model considers both structural degradation parameters (e.g., forecasted scores and degradation indices) and environmental factors (specifically humidity and wind speed), assigning fuzzy weights to each to reflect inherent uncertainty and sensor variability.

The study concludes that Fuzzy MARCOS can effectively differentiate bridge conditions under multi-stressor environments. Bridges exposed to elevated humidity or wind conditions received lower final scores, even when degradation indicators appeared moderate—highlighting the importance of incorporating environmental context into prioritization frameworks. Furthermore, the strong correlation between MARCOS scores and SHM-derived forecast scores confirms the model's value as a predictive decision-making tool. The generated rankings remained stable across variations in fuzzification ranges, as demonstrated by sensitivity analysis on humidity weights, indicating the model's robustness to modest deviations in expert input or sensor noise.

The model's architecture—consisting of min-max normalization, triangular fuzzy weight assignment, and utility-based ranking—makes it straightforward to integrate into existing SHM pipelines or smart infrastructure systems. Its numerical stability and transparent decision logic make it suitable for deployment in both centralized monitoring platforms and real-time edge computing devices. Stakeholders can rely on the ranked output to organize and prioritize inspections, allocate rehabilitation resources, and implement proactive interventions with greater confidence.

Future research offers several directions for expansion. First, the methodology can be extended for real-time processing of streaming SHM data, enabling continuous condition updates and dynamic maintenance scheduling. Second, additional decision criteria—such as rehabilitation cost, traffic volume, bridge type, or strategic network importance—can be incorporated to build a more comprehensive prioritization model. Third, integrating advanced capabilities such as image-based crack detection or vibration mode shape analysis, potentially through computer vision or deep learning, could

enhance the sensitivity and resolution of condition assessments. These enhancements would align the framework with emerging digital twin initiatives in civil engineering.
In conclusion, the proposed Fuzzy MARCOS methodology delivers a comprehensive, scalable, and practically applicable system for ranking the structural condition of bridges exposed to environmental stressors. By combining data-driven analytics with fuzzy decision-making logic, it effectively translates academic MCDM innovation into actionable strategies for infrastructure management. This work contributes meaningfully to the growing body of literature on resilient, intelligent, and data-informed civil infrastructure systems.

Data Availability
The dataset used in this study, titled **"Aging Bridge SHM Time Series"**, is publicly available on the Kaggle platform. It contains structural health monitoring (SHM) time-series data for multiple urban bridges, including variables such as degradation scores, forecasted conditions, humidity, and wind speed. The dataset can be accessed at the following URL:
https://www.kaggle.com/datasets/programmer3/aging-bridge-shm-time-series-dataset
All preprocessing, normalization, and analysis steps conducted in this study were based on this publicly accessible dataset. No proprietary or restricted data sources were used.

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Conflicts Of Interest

No potential conflicts of interest with funding sources, organizations, or individuals are disclosed in the paper.

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