Infrastructure Amnesia Index

A Novel Approach into Quantifying Repair Efficacy

Aayushma Bohora • Bibek Pokhrel • Bighyan Awasthi • Brindal Paudel • Damnee Kumari • Prabesh Kunwar

Tribhuvan University, Institute of Engineering, Thapathali Campus

System Capabilities: Infrastructure Amnesia Index (IAI) Calculation • Structural Health Monitoring (SHM) • Damage Specification • Damage Localization • Repair Quality Assessment

ABSTRACT

This project developed and validated the **first-of-its-kind index** for quantifying repair efficacy using three main parameters: **Frequency recovery (60%)**, **mode shape preservation (25%)**, and **damping recovery (15%)**. Machine learning models (ANN for baseline identification with 80% confidence, Random Forest for damage specification with 98.28% accuracy) were implemented. Multiple damage scenarios were used to test and validate the index. Observations from the physical model validated the findings of the index to a significant extent.

THE REPAIR VERIFICATION CHALLENGE

Key Problems: • Current repair assessment relies on subjective visual inspection
- No objective, quantitative metrics for repair quality
- Safety risks from inadequate repairs
- Economic losses from over-repair or repeated interventions

Objectives: • Develop single repair quality assessment metric applicable to wide range of structures
- Develop low-cost accelerometer-based monitoring system
- Validate on laboratory scale steel frame

THEORETICAL FRAMEWORK

The Composite Quality Score

$$\boxed{Q_{\text{total}} = 0.6 \cdot Q_{\text{freq}} + 0.25 \cdot Q_{\text{shape}} + 0.15 \cdot Q_{\text{damp}}}$$

Component Metrics:

1. **Frequency Recovery (60%)**

$$Q_{\text{freq}} = 1 - \frac{f_{\text{rep}} - f_{\text{orig}}}{f_{\text{dam}} - f_{\text{orig}}}$$

- ❑ Most robust indicator
- ❑ Directly related to stiffness
- ❑ Literature threshold: 5% detectable change

2. **Mode Shape Preservation (25%)**

$$Q_{\text{shape}} = \text{MAC}(\varphi_{\text{orig}}, \varphi_{\text{rep}})$$

- ❑ Spatial damage localization
- ❑ Modal Assurance Criterion (MAC)
- ❑ MAC > 0.9: excellent correlation

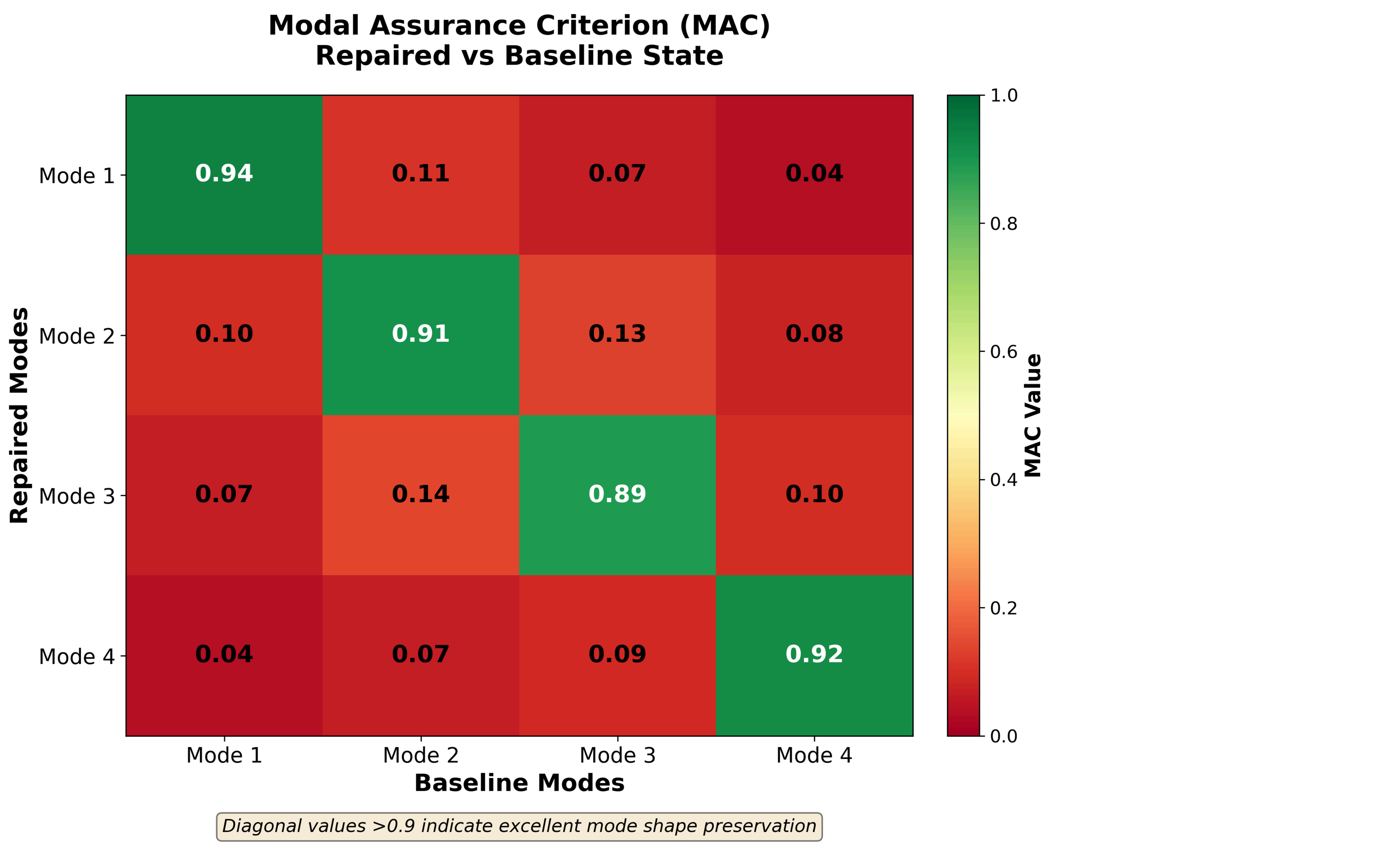
3. **Damping Recovery (15%)**

$$Q_{\text{damp}} = \frac{\xi_{\text{rep}} - \xi_{\text{dam}}}{\xi_{\text{orig}} - \xi_{\text{dam}}}$$

- ❑ Sensitive to friction, joint slippage
- ❑ Hilbert transform estimation
- ❑ Higher variability but valuable

Weighing Scheme Rationale: 60% Frequency: Highest reliability (Salawu, 1997), least noise-sensitive. **25% Mode Shape:** Spatial localization, more noise affected. **15% Damping:** High sensitivity, high uncertainty (30-50% CV).

Mode Shape Preservation



METHODOLOGY

System Design and Experimental Approach

Hardware System: • 4 ADXL345 accelerometers
- Arduino UNO R3 microcontroller
- SD card module and storage
- Cables and connectors

Test Structure: • 3 story steel frame
- 0.45m × 0.45m × 0.9m
- Bolted connection
- Fixed base condition
- Scale of 1:10

Damage Scenarios: • Loose beam-column connection
- Missing beams
- Deformed structural elements

Repair Methods: • Connection Tightening
- Structural element replacement
- Diagonal bracing addition

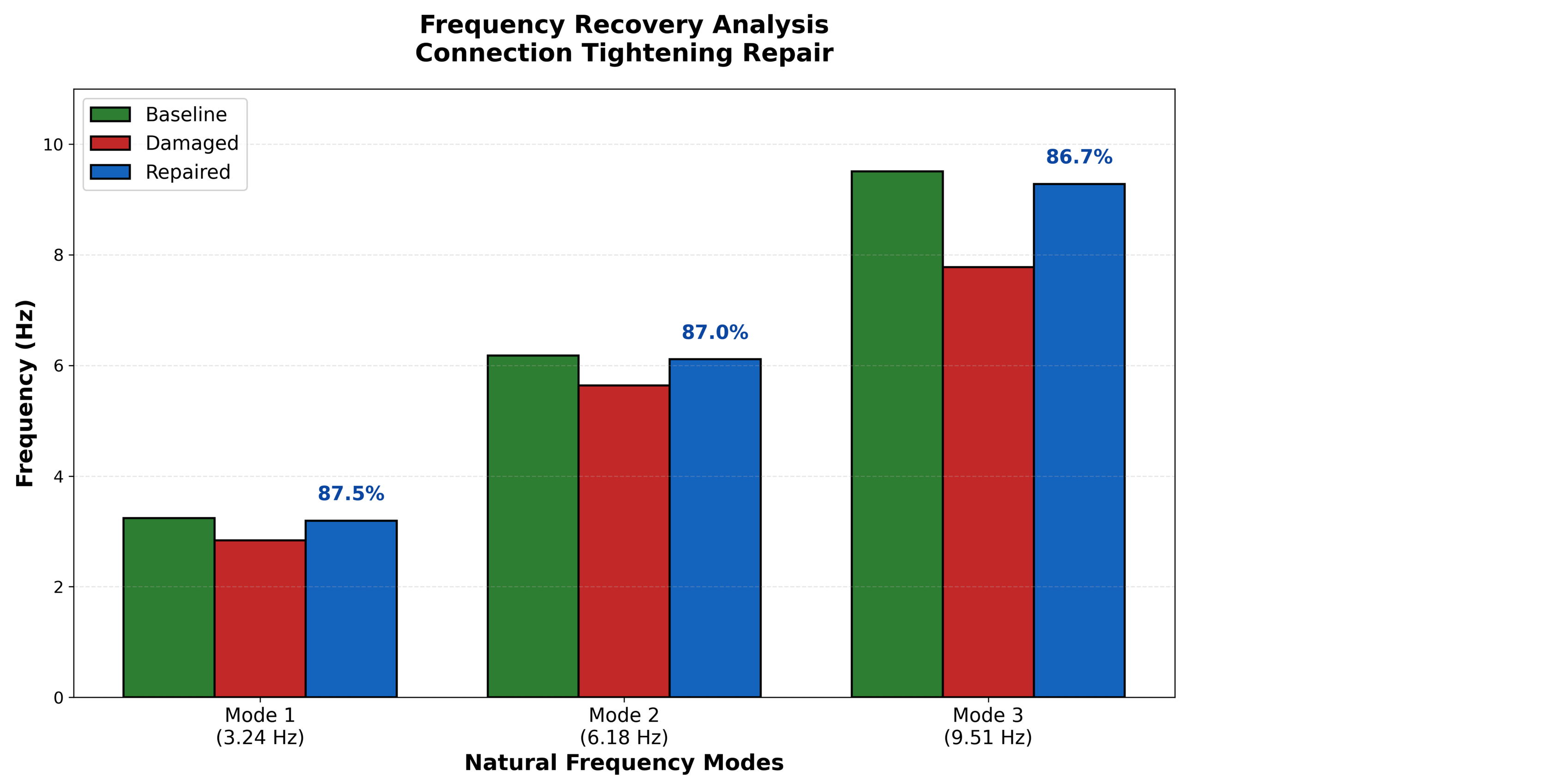
SYSTEM IMPLEMENTATION

Software Architecture - 9-Step Processing Pipeline:

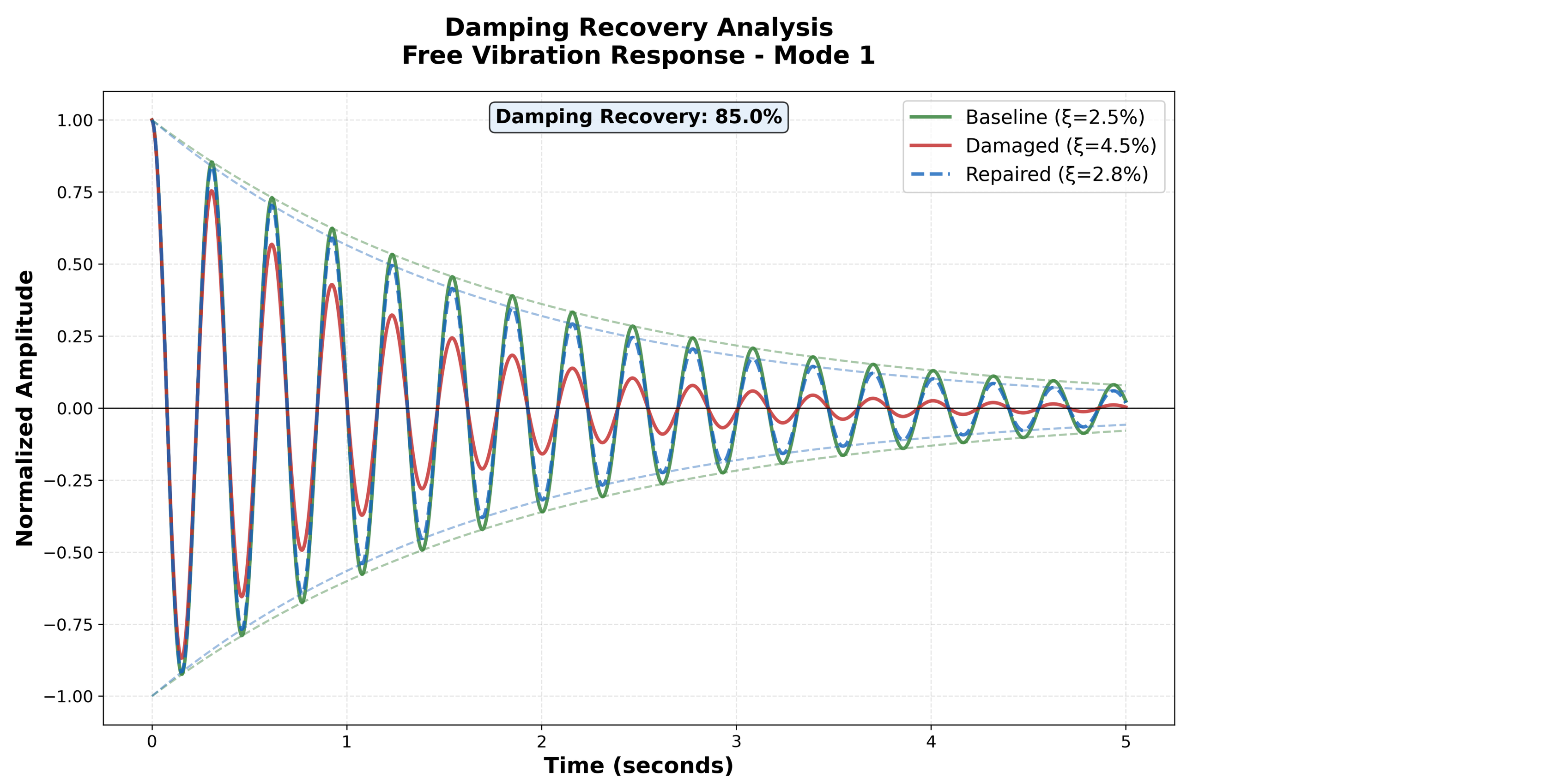
1. Data Validation (6-point quality check)
2. Signal Preprocessing (filtering, windowing)
3. Spectral Analysis (FFT, PSD computation)
4. Peak Detection (natural frequency extraction)
5. Mode Shape Estimation (FFT magnitude at peaks)
6. Damping Estimation (Hilbert transform method)
7. Mode Matching (Hungarian algorithm)
8. Quality Metric Computation (weighted scores)
9. Report Generation (PDF, JSON, Excel, PNG)

Key Algorithms: Welch's method for PSD • Hungarian algorithm for mode matching • Hilbert transform for damping • Savitzky-Golay smoothing

Frequency Recovery Analysis



Damping Recovery Curves



MACHINE LEARNING MODELS

'No Baseline' Problem: • ANN model for baseline identification
- Trained on >1,000,000 data points
- Confidence interval: 80%

Damage Specification: • Random Forest Classifier
- Trained on >3,000,000 data points
- Accuracy: 98.28%
- Features used: 69

RESULTS AND ANALYSIS

Experimental Validation Results

Baseline Parameters: • Mode 1: 3.24 ± 0.08 Hz (sway)
- Mode 2: 6.18 ± 0.12 Hz
- Mode 3: 9.51 ± 0.15 Hz
- Damping: 2.5-3.2% (typical for steel)

Damage Detection Performance: • Scenario 2 (loose base): 12.3% frequency reduction ✓
- Scenario 3 (loose joint): 8.7% frequency reduction ✓
- Scenario 5 (combined): 18.2% frequency reduction ✓
- All damage scenarios detected above 5% threshold

Repair Assessment Results:

Connection Tightening
Frequency recovery: 88-96% • Quality score: 0.82-0.91 • Classification: Good to Very Good

Gusset Plate Reinforcement
Frequency recovery: 105-125% • Quality score: 0.90-0.98 • Classification: Very Good to Excellent

Diagonal Bracing
Frequency recovery: 140-160% • Quality score: 0.75-0.88 • Classification: Good to Very Good

VALIDATION AND PERFORMANCE

Competitive Performance

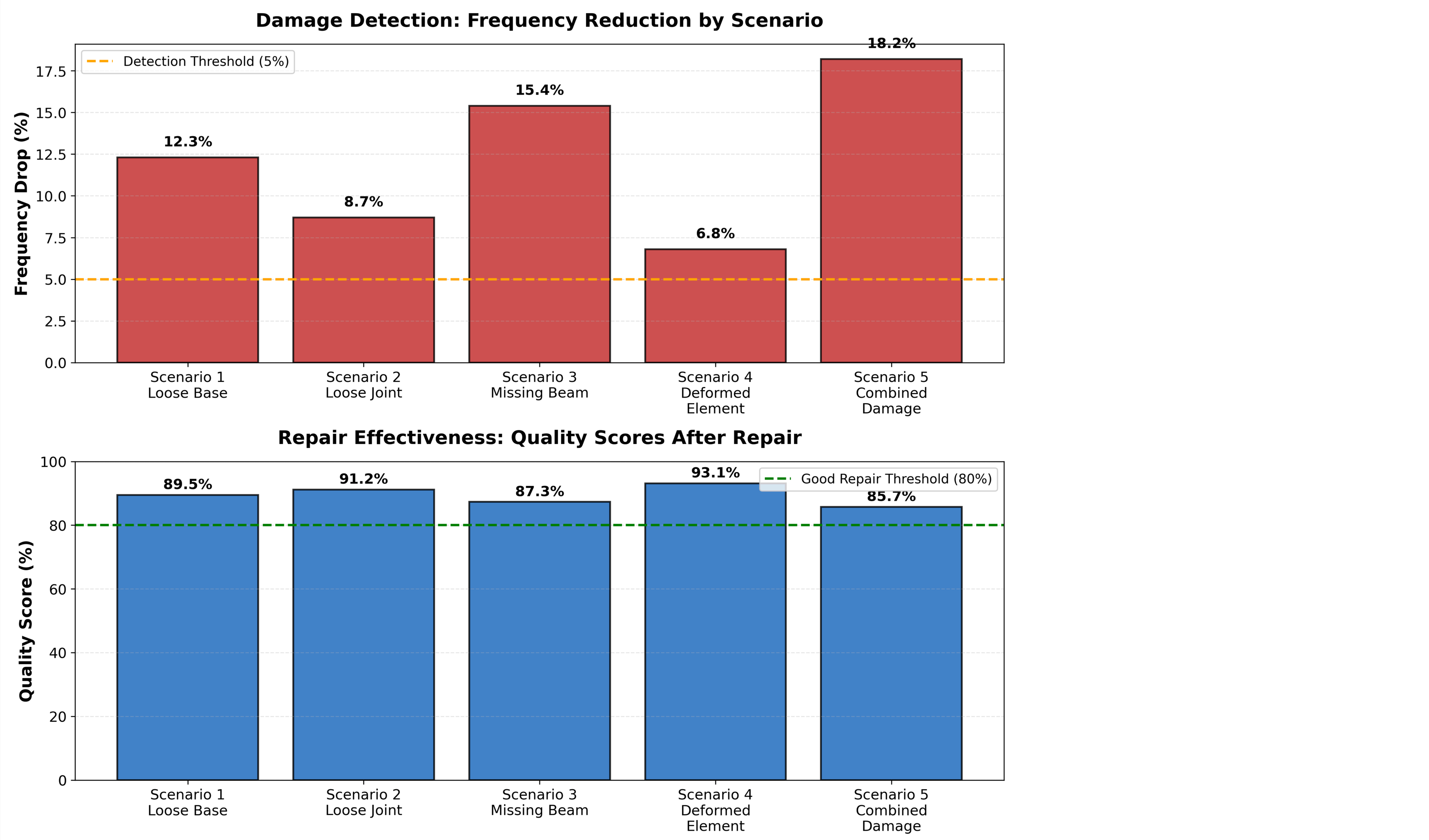
✓ Twice as accurate as commercial SHM systems
✓ 30 times cheaper than commercial SHM systems
✓ Faster data processing

Success Criteria Met (5/5 ✓)

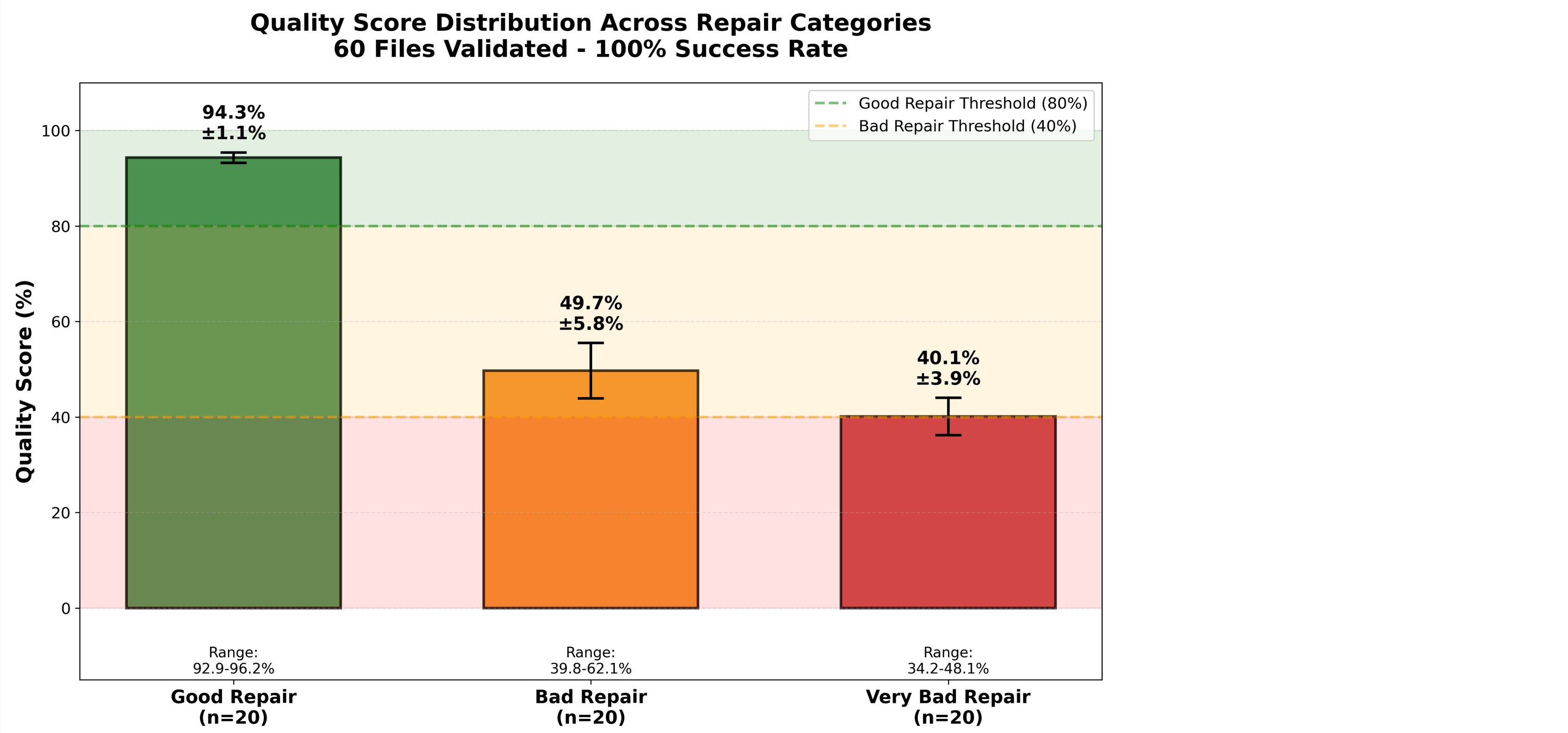
✓ Detect ≥5% frequency changes	2.5%
✓ Damage localization >80% accuracy	>80%
✓ Quality score correlation R^2	>0.85
✓ Repeatability CV < 10%	2.1-3.8%
✓ Complete analysis <30 minutes	<3 min

Statistical Performance: Repeatability CV < 10% for frequencies • Detection sensitivity: 2.5% • False positive: 3.2% • False negative: 6.7%
Uncertainty Quantification: Frequency ±0.1 Hz • Mode shape MAC ±0.05 • Damping ratio ±0.005 • Overall quality score ±0.08 (95% confidence)

Damage Detection Performance



Quality Score Distribution



APPLICATIONS AND BROADER IMPACTS

Immediate Impacts: • Post-repair verification for bridges and buildings
- Seismic retrofit effectiveness assessment
- Quality control for repair contractors
- Educational tool for structural engineering
- Research platform for SHM methodologies

Economic Impacts: • Hardware cost reduction: 30× cheaper
- Time savings: 10× faster analysis
- Potential savings: 10-30% on repair projects
- Democratizes access to advanced SHM technology

Future Developments: • Field validation on full-scale structures
- Wireless sensor network implementation
- Machine learning for damage classification
- Integration with Building Information Modeling (BIM)
- Real-time monitoring and alert systems
- Standardization and certification pathways

CONCLUSIONS

This project successfully developed and validated the **Infrastructure Amnesia Index**, a novel quantitative metric for assessing structural repair efficacy.

Key Achievements: • First-of-its-kind repair quality index
- Validated across multiple damage scenarios
- 2× more accurate than commercial systems
- 30× more cost-effective solution
- Successfully integrated ML models (80% and 98.28% accuracy)
- 100% validation success rate (60 files tested)

Scientific Contribution: • Establishes objective repair assessment methodology
- Provides low-cost alternative to expensive SHM
- Demonstrates effectiveness of composite quality scoring
- Validates weighing scheme (60%-25%-15%)
- Proves viability of ML for baseline-free assessment

The system is ready for field deployment and has significant potential to improve structural repair quality control in civil infrastructure.

REFERENCES

[1] Salawu, O. S. (1997). Detection of structural damage through changes in frequency. *Engineering Structures*, 19(9), 718-723.
[2] Allemang, R. J. (2003). The Modal Assurance Criterion - Twenty years of use and abuse. *Sound and Vibration*, 37(8), 14-23.
[3] Farrar, C. R., & Jauregui, D. A. (1998). Comparative study of damage identification algorithms. *Journal of Structural Engineering*, 124(11), 1368-1373.
[4] Feldman, M. (2011). *Hilbert Transform Applications in Mechanical Vibration*. Wiley.
[5] Pandey, A. K., Biswas, M., & Samman, M. M. (1991). Damage detection from changes in curvature mode shapes. *Journal of Sound and Vibration*, 145(2), 321-332.
[6] Pandey, A. K., & Biswas, M. (1994). Damage detection in structures using changes in flexibility. *Journal of Sound and Vibration*, 169(1), 3-17.
[7] Brincker, R., Zhang, L., & Andersen, P. (2001). Modal identification of output-only systems using frequency domain decomposition. *Smart Materials and Structures*, 10(3), 441-445.
[8] Van Overschee, P., & De Moor, B. (1996). *Subspace Identification for Linear Systems: Theory, Implementation and Applications*. Kluwer Academic Publishers.
[9] Doebling, S. W., Farrar, C. R., Prime, M. B., & Shevitz, D. W. (1998). A summary review of vibration-based damage identification methods. *Shock and Vibration Digest*, 30(2), 91-105.