

Active and Passive Acoustic Emission-Based Detection of Corrosion Damage in Steel Rods and Tendons

By

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DECLARATION

I, Sadegh Mahmoudkhani, declare this document to be my own unaided work, and where published sources are used, they are acknowledged.

Abstract

This thesis was focused on two aims: first, using acoustic emission (AE) for corrosion damage monitoring of steel tendons, and second, using AE for corrosion damage monitoring of steel grounding rods.

First, the Fuzzy c-means clustering algorithm was employed to differentiate AEs of breaking wires of steel tendons from environmental and grout crack AEs. The signals were post-processed to simulate different ranges of acoustic attenuation. To optimize the speed and reliability of the clustering algorithm, a Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) was used to find the minimum number of acoustic features needed. The NSGA-II algorithm found 12 combinations of features that resulted in more than 80% wire break detection accuracy. In contrast, less than 3% of grout cracks and 0% of environmental signals were detected as wire breaks. The proposed method has sufficiently low-computational requirements and is reliable and insensitive to attenuation. This work was extended to monitor damage progression in pre-stressed concrete beams exposed to accelerated corrosion. At the termination of the accelerated corrosion experiment, the beam was sliced into sixty-two cross-sections to inspect and correlate corrosion and tendon slippage with AE signals. This work points to the use of AE to track the progression of damage in cases where corrosion has already resulted in tendon fracture and progression is proceeding by loss of bond.

Second, the fuzzy c-means was applied to guided wave pulse-echo detection of corrosion damage in grounding rods. A database of realistic acoustic guided-wave pulse-echo signals was created using accelerated corrosion on steel grounding rods to create corrosion defects with 50% cross-

sectional loss. The rods were covered with different thicknesses of clay to simulate different ranges of acoustic attenuation. The NSGA-II was used to select an optimal acoustic feature set. The defect detection method produced low false positives and achieved a depth resolution of approximately 0.3 m. Monte Carlo analysis showed the proposed method detects >99% of damaged segments as damaged, and 92% of intact segments as intact, with a 90% probability. The proposed algorithm is insensitive to attenuation due to varying soil conditions.

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To my best friend and wife, Mahboubeh...

... and to Silky and Shadow!

Contribution of the Authors

This thesis comprises three papers. All the papers are multi-authored, and Sadegh Mahmoudkhani is the first author of all the papers. The title of the papers and the contribution of the authors are as follow:

Chapter 2: Event identification in acoustic emission from wire breaks in pre-stressing/post-tensioning cables, [Sadegh Mahmoudkhani, Junhui Zhao, Jasmin Cochingco, Aftab Mufti, Douglas Thomson, Submitted to Journal of Civil Structural Health Monitoring, 2023]

D. Thomson, A. Mufti and I developed the idea in this paper. D. Thomson designed the sensor and DAQ system. J. Zhao made the sensor, and J. Cochingco assembled the DAQ. The candidate performed the experiments, programming, and data analysis. D. Thomson and J. Cochingco helped with field data collection. The candidate prepared the manuscript, which was edited and revised by D. Thomson and A. Mufti.

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- Mahmoudkhani, S., Algohi, B., Zhao, J., Ling, H., Mufti, A. & Thomson, D. (2019) “Acoustic Emissions Sensor and Fuzzy C-mean Clustering Based Break Detection in Post-Tensioning Tendons”, IEEE SENSORS 2019, 27-30 October, Montreal, Canada.
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Tensioning Steel Tendons”, 9th International Conference on Structural Health Monitoring of Intelligent Infrastructure, 4-7 August, St. Louis, Missouri, USA.

Chapter 3: Acoustic emission monitoring of pre-stressed concrete beams during accelerated corrosion of pre-stressing tendons, [Sadegh Mahmoudkhani, Junhui Zhao, Jasmin Cochingo, Aftab Mufti, Douglas Thomson, Submitted to 14th International Workshop on Structural Health Monitoring, September 12-14, 2023, Stanford, CA, USA]

D. Thomson, A. Mufti and I developed the idea in this paper. J. Zhao made the sensors, and J. Cochingo assembled the DAQs. The designs of the sensors and DAQs were similar to the previous paper. The candidate performed the experiments, programming, and data analysis. The candidate prepared the manuscript, which was edited and revised by D. Thomson and A. Mufti.

Chapter 4: Acoustic-Guided Wave Detection of Corrosion Pits in Grounding Rods Using Fuzzy C-Means and NSGA-II, [Sadegh Mahmoudkhani, Junhui Zhao, Aftab Mufti, Colin McKenzie, Karim Abdel-Hadi, and Douglas Thomson, Submitted to IEEE Sensors Journal, 2023]

D. Thomson, A. Mufti and I developed the idea in this paper. I performed accelerated corrosion experiments, programming, and data analysis. J. Zhao made sensors and conducted data collection on grounding rods. C. McKenzie and K. Abdel-Hadi provided grounding rods and helpful advice. The candidate prepared the manuscript, which was edited and revised by D. Thomson and A. Mufti.

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Table of Contents

Abstract	iii
Acknowledgments.....	v
Contribution of the Authors	vii
Table of Contents.....	x
List of Tables	xiii
List of Figures	xiv
List of Notations & Abbreviations.....	xvi
1 Introduction.....	1
1.1 Motivation	1
1.2 Objectives	3
1.3 Methodology	5
1.3.1 Fuzzy c-means	5
1.3.2 Non-dominated Sorting Genetic Algorithm (NSGA-II)	6
1.4 Thesis Outline	11
2 Event Identification in Acoustic Emission from Wire Breaks in Pre-Stressing/Post-Tensioning Cables.....	14
2.1 Abstract	14
2.2 Introduction	15
2.3 Materials & Methods.....	20
2.3.1 Tensile Tests	20
2.3.2 Acoustic Emissions from Environmental Sources.....	21
2.3.3 Acoustic emission database	23
2.3.4 Acoustic Features.....	24
2.3.5 Fuzzy C-means Clustering.....	25
2.3.6 Non-dominated Sorting Genetic Algorithm-II (NSGA-II)	26
2.4 Results & Discussions.....	29

2.5	Conclusions	36
3	Acoustic Emission Monitoring of Pre-Stressed Concrete Beams During Accelerated Corrosion of Pre-Stressing Tendons	38
3.1	Abstract	38
3.2	Introduction	39
3.3	Materials & Methods.....	41
3.3.1	The Experimental Set-up	41
3.3.2	Localizing Acoustic Signals	43
3.3.3	Visual Inspection of Tendons After Accelerated Corrosion.....	44
3.4	Results & Discussions.....	45
3.5	Conclusions	48
4	Acoustic-Guided Wave Detection of Corrosion Pits in Grounding Rods Using Fuzzy C-Means and NSGA-II	49
4.1	Abstract	49
4.2	Introduction	50
4.3	Materials & Methods.....	52
4.3.1	The Pulse-Echo Technique	52
4.3.2	Accelerated Corrosion Setup	53
4.3.3	Laboratory Acoustic Testing of Grounding Rods.....	55
4.3.4	Features of Acoustic Signals.....	58
4.3.5	Fuzzy C-means Clustering Algorithm	60
4.3.6	Features Selection using Non-dominated Sorting Genetic Algorithm-II (NSGA-II)	60
4.3.7	Testing of Field-Extracted Grounding Rods.....	62
4.4	Results & Discussions.....	64
4.5	Conclusions	75
5	Conclusion & Future Work.....	76
5.1	Conclusion.....	76

5.2	Future Work	78
References		81

List of Tables

Table 1-1 Domination of sample solutions	7
Table 2-1 The optimal sets of features.....	33
Table 2-2 The overall characteristics of the optimal feature sets	34

List of Figures

Figure 1-1 The non-domination concept.....	7
Figure 1-2 Ranking of solutions	8
Figure 1-3 The crowding distance concept.....	9
Figure 1-4 The Flowchart of NSGA-II	10
Figure 2-1 The experimental set-up for the tensile test of a grouted strand	21
Figure 2-2. The experimental set-up to record environmental noises	22
Figure 2-3 Acoustic features used in this study	25
Figure 2-4 The overall procedure used in the NSGA-II optimized feature selection.....	27
Figure 2-5 The acoustic signal and FFT of a wire break, grout crack and environmental AE.....	29
Figure 2-6 The normalized areas under FFT curves for the database for 15 kHz bands.....	30
Figure 2-7 The peak amplitudes for the database	31
Figure 2-8 The features and the total number of using them in the 200th iteration of the 20 runs for thresholds (Tr.) from 0.001 to 2.251.....	35
Figure 2-9The features and the total number of using them in the 200th iteration of the 20 runs for thresholds (Tr.) from 2.051 to 5.001.....	36
Figure 3-1 The schematic of the pre-stressed beam and the acceleration corrosion set-up; a) Side view, b) top view, and c) Ends of the beam's view.....	42
Figure 3-2 The acceleration corrosion set-up and a corrosion tank.....	43
Figure 3-3 The progress of corrosion over a) 5 days, b) 7 days, and c) 49 days	43
Figure 3-4 A sample of recorded signals, including both saturated and unsaturated signals from the first phase of experiments.	45
Figure 3-5 The localized sources of recorded events and the number of their occurrence.	46
Figure 3-6 Visual signs of a) losing the bond on the left side and b) keeping the bond on the right side between concrete and tendon 1 of the 25th slice.	47
Figure 3-7 The right side of the 30th slice (a), Visual signs of corrosion on the cross-section of tendon 1 on the left side of the 30th slice (b), and corroded wires of tendon 1 from the 30th slice (c).	47
Figure 3-8 Locations with visible a) slipping and b) corrosion.	48
Figure 4-1 The principle of the pulse-echo technique to detect defects in buried grounding rods	53

Figure 4-2 The acceleration corrosion set-up	55
Figure 4-3 The corrosion tank of rod C	55
Figure 4-4 The normalized signal of a 35 kHz pulse launched into rod B covered with 200 g clay	57
Figure 4-5 The 10 time slices of signals and the bins of FFT curves	59
Figure 4-6 The NSGA-II-based feature selection procedure	62
Figure 4-7 The observable defects of the test rods; a) defect I, b) defect II, c) the bent part of rod β , d) area I and e) area II	63
Figure 4-8 The normalized signals of 35 kHz pulses launched into a) rod A, b) rod B, c) rod C and d) rod D covered with 200 g clay.....	65
Figure 4-9 The normalized signals of 35 kHz pulses launched into rod A covered with a) 250 g and b) 350 g clay	66
Figure 4-10 The normalized signals of 35 kHz pulses launched into rod C covered with 350 g clay in the two separate measurements.....	66
Figure 4-11 The number of features selected from each launched frequency for the 16 optimal feature sets	68
Figure 4-12 The results of defect detection on the selection database using the optimal features	70
Figure 4-13 The results of defect detection on the validation database using the optimal features	71
Figure 4-14 The normalized signals of 35 kHz pulses launched into a) rod α , b) rod β and c) rod θ	72
Figure 4-15 The results of defect detection on the test database using the optimal features.....	73
Figure 4-16 The cumulative probabilities of a) intact segments detected as Intact, b) Intact segments detected as Damaged and c) damaged segments detected as Intact for both cases of using the optimal features and all features	74

List of Notations & Abbreviations

AE	Acoustic Emission
ADC	Analog-to-Digital Converter
c	Number of Clusters
DAC	Digital-to-Analog Converter
DAQ	Data Acquisition System
F	Launched Frequency
FFT	Fast Fourier Transform
m	Fuzziness Parameter
NSGA-II	Non-Dominated Sorting Genetic Algorithm-II
u	Membership Value
v	Cluster Centers
W	Weight factor

1 Introduction

1.1 Motivation

The economic and social impacts of aging civil infrastructures is driving the development of rapid, reliable and low-cost structural health monitoring methods (Chang et al., 2003; Williams, 2010; Oughton et al., 2019). Methods that are commonly used for monitoring civil infrastructures include, but not limited to, strain, vibration, acoustic emission, ultrasonic, etc. (Gharehbaghi et al., 2022). Structural health monitoring methods can be used in either passive or active ways (Gharehbaghi et al., 2022). In passive monitoring, the information comes from the variation of the under-inspection structure's physical properties, such as acoustic emissions released from a cracking concrete member. In active monitoring, the information comes from using a simulation in the under-inspection structure, such as using actuators to vibrate a structure. This work focuses on corrosion damage monitoring of steel tendons and rods buried in concrete or soil. Among the existing testing methods for corrosion damage, such as ultrasonic pulse velocity, electrochemical-based techniques, strain monitoring, and electromagnetic-based methods, acoustic emission has promise due to the advantages of cost-effectiveness, high sensitivity, real-time and continuous monitoring, and capability to be used in both passive and active monitoring (Bayane & Brühwiler, 2020; Kot et al., 2021; Gharehbaghi et al., 2022; Verstrynge et al., 2022).

Acoustic emission is widely used in both passive (Kurz et al., 2013; Vidya Sagar & Raghu Prasad, 2013; Behnia et al., 2014; Zaki et al., 2015; H. Li & Ou, 2016; Appalla et al., 2016; Abdullah et al., 2016; Bayane & Brühwiler, 2020; Verstrynge et al., 2022) and active (Miller et al., 2013; Amjad et al., 2015; Mitra & Gopalakrishnan, 2016; J. Li et al., 2017) monitoring of civil

infrastructures. However, in both cases, the variability due to the environment leads to many challenges. One major challenge is the variability in signal strength due to attenuation variation with distance from source to detector and materials. Methods are needed that can detect corrosion defects in high and varying attenuation, and process acoustic signals in the presence of other environmental acoustic signals are notable challenges in applying this method (Ono, 2018). If such a technique can be developed, it will have used in applications such as monitoring corrosion damage progress in steel tendons of pre-stressed/post-tensioned concrete bridges and corrosion damage in steel grounding rods buried in soil.

Pre-stressed/post-tensioned concrete bridges make up more 25% of bridges in the USA alone (National Bridge Inventory (NBI), 2016). Steel tendons, in combination with concrete or grout, are the most commonly used reinforcing materials for prestressed concrete members. Steel, even encased in concrete, corrodes over time, and if the corrosion is sufficient, the stress with the tendons exceeds the breaking strength, and the wires that make up the tendon break (Yuyama et al., 2007; Mangual et al., 2013a; Vélez et al., 2015; Appalla et al., 2016). There were several bridges collapsed in the past years. A well-known recent example is the collapse of the Monte Morandi bridge in 2018 in Genoa, Italy, which killed ten people and left more than 600 people homeless. Post-collapse investigation showed viable showed corrosion pits in the bridge's prestressing tendons (Morgese et al., 2020). Therefore, there is a critical need to detect wire breaks within pre-stressed/post-tensioned concrete structures to ensure safety and optimize the maintenance of aging medium and long-span bridges.

In addition to steel tendons in reinforced concrete systems, steel rods buried in soil are also

employed in power substations as grounding rods. Acoustic methods can also be used as an active method to detect corrosion cross-sectional loss in the rods. There are approximately 70,000 substations alone in North America while 70% of them are more than 25 years old (Williams, 2010). The substations are crucial parts in the distribution of electric power by transforming high voltage power to lower voltages for distribution to final users. A critical element of the substation is the network of rods driven into the ground that provides the electrical ground for the equipment and personnel. As electric substations age, their grounding rod network suffers from corrosion, and the safety of personnel and equipment can be compromised. Since ground rods are buried and are not easily visually inspected for corrosion, the only effective means of inspection involved disconnecting the rods from the grounding network and excavating the rod for inspection, which is a time-consuming and expensive operation. Maintaining the integrity of the ground rods is vital to the safe operation of substations (Fu et al., 2019), and substation failures have a noticeable economical impact (Oughton et al., 2019). Therefore, it is critical to detect if ground rods have corroded to the point where they no longer provide adequate protection to the equipment and operating personnel.

1.2 Objectives

This thesis was prepared to achieve two main objectives. The first goal of the current research was to investigate an innovative solution to monitor wire breaking in pre-stressing/post-tensioning tendons. Specific objectives involved:

1. Laboratory tests to determine the characteristics of acoustic emissions (AE) associated with breaks in the tendons

2. Developing a system suitable for field logging AEs in pre-stressing/post-tensioning bridges
3. Collecting AEs from bridges that come from environmental sources such as truck passages and comparing these with the laboratory AEs associated with wire breaks
4. Deriving AE signal features that are insensitive to signal attenuation
5. Employing artificial intelligence methods to enhance the differentiation of AEs due to wire breaks from other sources of AEs
6. Conducting accelerated laboratory simulation of corrosion damage progression in pre-stressed girders
7. Logging AE events produced during the accelerated corrosion tests.
8. Using post-corrosion dissection of the girder to identify sources of AE from corrosion damage progression in pre-stressed/post-tensioned tendons

The second goal of the current research was to investigate an innovative and insensitive to attenuation solution to monitor corrosion cross-sectional loss in grounding rods. Specific objectives involved:

1. Creating a set of grounding rods for guided wave pulse-echo detection of corrosion. Rods from field recovery, machined pits and corrosion pits created through laboratory accelerated corrosion.
2. Gathering a database of guided wave pulse-echo signals from damaged and undamaged grounding rods with varying levels of signal attenuation.
3. Using artificial intelligence methods to find optimized algorithms to detect and localize the corrosion damage in grounding rods

1.3 Methodology

In this thesis, acoustic emission is used to detect corrosion damage in steel tendons and rods. Fuzzy c-means clustering algorithm is used to differentiate acoustic emissions, and the NSGA-II algorithm is used to select optimal acoustic features to use by Fuzzy c-means. This section explains the details of employing Fuzzy c-means and NSGA-II algorithms.

1.3.1 Fuzzy c-means

Fuzzy C-means, proposed by Dunn (1973) and Bezdek (1980), is a soft clustering algorithm that is widely used in structural health monitoring problems (Shateri et al., 2017; Das & Saha, 2018; Dorafshan & Maguire, 2018; S. Chen et al., 2018; Zeng et al., 2018; Xiao-Mei et al., 2019; Hassan, 2021). Fuzzy c-means minimizes Euclidean distance as a similarity measurement between clusters' centroids and data features to cluster data points (Dunn, 1973; Bezdek, 1980). Similar to other soft clustering algorithms, Fuzzy c-means allows data points to belong to multiple clusters with different degrees of membership to handle uncertainty and overlapping data.

The steps of the Fuzzy c-means algorithm to cluster dataset $X=\{x_1, \dots, x_n\}$ starts with choosing a user-defined number of clusters (c), selecting c random cluster centers (v), and then a user-defined fuzziness parameter (m). This parameter determines the level of fuzziness and is often set to 2. The next step is membership calculation, in which for each data point x_i and each cluster j , compute the membership value u_{ij} , which represents the degree of belongingness of x_i to cluster j . The membership is calculated using the following equation:

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_i - v_j\|}{\|x_i - v_k\|} \right)^{\frac{2}{m-1}}} \quad \text{Equation 1 - 1}$$

After calculating the memberships, the next step is updating the cluster centers using the following equation:

$$v_j = \frac{\sum_{i=1}^n ((u_{ij})^m x_i)}{\sum_{i=1}^n (u_{ij})^m} \quad \text{Equation 1 - 2}$$

If the maximum change between the new and the previous cluster centers is less than a user-defined number, the algorithm is assumed to be converged. A user-defined maximum number of iterations can also define the convergence. Once the algorithm has converged, each data point x_i is assigned to the cluster with the highest membership value u_{ij} . Otherwise, the algorithm goes back to the calculation of memberships with the new centers.

1.3.2 Non-dominated Sorting Genetic Algorithm (NSGA-II)

Non-dominated Sorting Genetic Algorithm- II (NSGA-II) is a popular multi-objective optimization algorithm designed to find solutions for problems with multiple conflicting objectives (Deb et al., 2002). Single-objective optimization methods find an optimal solution within the feasible space of the problem. However, NSGA-II produces a set of optimal solutions, called the Pareto front, that provide a trade-off among objectives.

Non-domination is one of the concepts in the NSGA-II optimization process used to compare a solution with others. Solution A dominates solution B if A is not only no worse than B in all

objectives but also better than B in at least one of the objectives. Otherwise, B is not dominated by A. Figure 1-1 shows an example of domination in which Solution 2 is not dominated by any solution and dominates 5, 7 and 8. Table 1-1 contains the detailed domination of each solution shown in Figure 1-1. A solution not dominated by any solution is called non-dominated, and a set of non-dominated solutions define the Pareto front (shown with the dashed line in Figure 1-1).

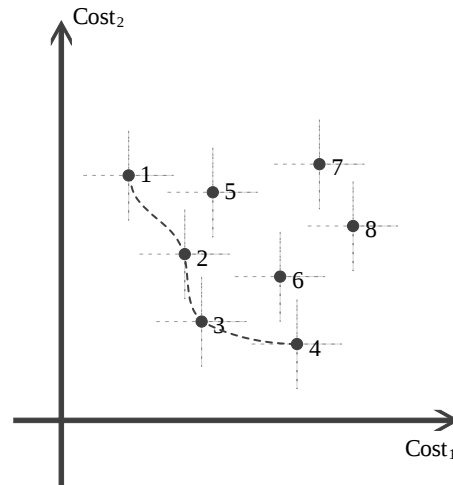


Figure 1-1 The non-domination concept

Table 1-1 Domination of sample solutions

SOLUTION	DOMINATES	DOMINATED BY
1	7	-
2	5, 7 and 8	-
3	5, 6, 7 and 8	-
4	7 and 8	-
5	7	2
6	7 and 8	3
7	-	1, 2, 3, 4, 5 and 6
8	-	2, 3, 4 and 6

In NSGA-II, ranking is used to classify solutions by assigning a rank to each solution based on its dominance. In the ranking procedure, the solutions not dominated by any solution get rank 1, and

are removed from the ranking process. Then, the remaining solutions that are not dominated by any solution get rank 2, and are removed. This process is repeated until all the solutions get a rank. This procedure is also called non-dominated sorting. Figure 1-2 shows the applied ranking on the solutions of Figure 1 and Table 1.

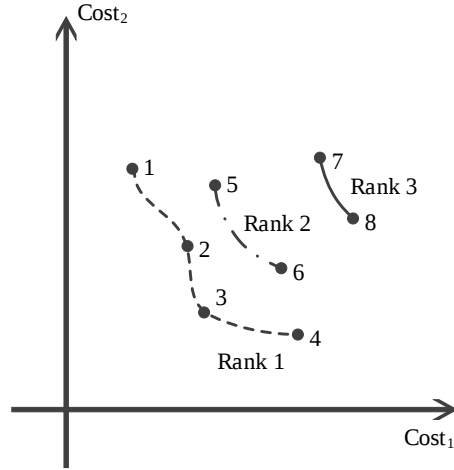


Figure 1-2 Ranking of solutions

Crowding distance (Figure 1-3) is an operator that calculates the density of points around each solution and compares the solutions with the same rank. The crowding distance of i^{th} solution is calculated as follows:

$$\text{Crowding Distance}(i) = \sum_{j=1}^n \frac{\text{Cost}_j(i+1) - \text{Cost}_j(i-1)}{\text{Cost}_j^{\max} - \text{Cost}_j^{\min}} \quad \text{Equation 1 - 3}$$

where j is the number of objectives, and $\text{Cost}_j^{\max}$ and $\text{Cost}_j^{\min}$ are the maximum and minimum values of j^{th} Cost in the rank, respectively. The arrangement of solutions with the same rank in the calculation of crowding distance is based on sorting the solutions according to their cost values.

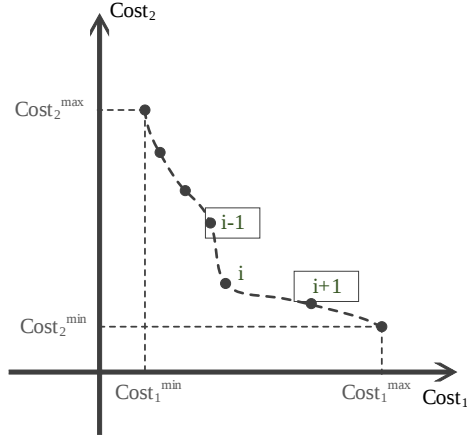


Figure 1-3 The crowding distance concept

Figure 1-4 shows the overall procedure of NSGA-II which is started by randomly choosing N_p members as the initial population. Then non-dominated sorting is applied to the population, and crowding distances are calculated. This population is called the Parents Population. Offspring and mutants are created using Crossover and mutation operations, then merged into Parents Population. Non-dominated sorting is applied to the merged population, and crowding distances are calculated. To select the population of parents for the next iteration of NSGA-II, solutions with the ranks from $r=1:R$ are selected for the population in a way the sum number of solutions from the first rank to the R^{th} rank is less than N_p . The members with the highest crowding distance from $R+1^{\text{th}}$ rank are added to the population to have N_p members in the new Parents Population. After a certain number of user-defined iterations, the members with Rank 1 are exported as the Pareto Front.

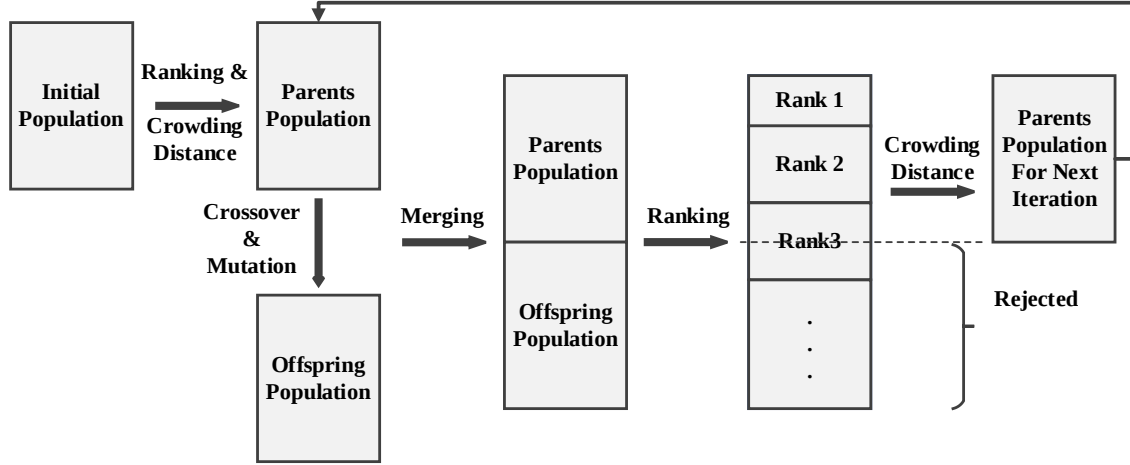


Figure 1-4 The Flowchart of NSGA-II

Binary tournament selection is used to select parents of the crossover population. To select two parents that are used to produce two children (C1 and C2), two members are randomly chosen, and the member with the higher rank is selected as the first parent (P1). If the ranks are the same, the member with a higher crowding distance is selected. The second parent (P2) is chosen with a similar procedure. The simulated binary crossover (Deb and Agrawal, 1995) is used to generate crossovers as follows:

$$C_1 = 0.5[(P_1 + P_2) - \alpha(P_2 - P_1)] \quad \text{Equation 1 - 4}$$

$$C_2 = 0.5[(P_1 + P_2) + \alpha(P_2 - P_1)] \quad \text{Equation 1 - 5}$$

where α is randomly chosen from uniformly distributed random numbers (between zero and one). To generate a mutant, a parent is selected randomly, and the mutant is created using the variations of the parent. Then, a variation of mutation is chosen randomly and is updated by adding σ , the mutation step size, multiplied by a random number (between zero and one).

1.4 Thesis Outline

The thesis is organized into five chapters and includes three papers:

Chapter 1: Introduction

This chapter provides an introduction and summarizes the objective of this thesis.

Chapter 2: Event identification in acoustic emission from wire breaks in pre-stressing/post-tensioning cables, [Sadegh Mahmoudkhani, Junhui Zhao, Jasmin Cochingco, Aftab Mufti, Douglas Thomson, Submitted to Journal of Civil Structural Health Monitoring, 2023]

This chapter includes:

1. Laboratory experiments to study the characteristics of AEs from breaks in the tendons
2. Using acoustic sensors to sense the AEs
3. Developing a system to sense and record AEs in pre-stressing/post-tensioning bridges
4. Collecting other possible AEs in a bridge environment and comparing them with the AEs from wire breaks
5. Post-processing the AEs to make the method insensitive to attenuation
6. Employing Fuzzy c-means and non-dominated sorting genetic algorithm (NSGA-II) to differentiate AEs of wire breaks from other sensed AEs

The contribution of his chapter to the field are:

1. Developing a reliable and fast artificial intelligence-based method that has low-computational costs
2. Developing an insensitive to attenuation analysis method system to differentiate acoustic signals of wire breaks from the other possible acoustic signals present in an operating pre-stressed concrete bridges

Chapter 3: Acoustic emission monitoring of pre-stressed concrete beams during accelerated corrosion of pre-stressing tendons, [Sadegh Mahmoudkhani, Junhui Zhao, Jasmin Cochingco, Aftab Mufti, Douglas Thomson, Submitted to 14th International Workshop on Structural Health Monitoring, September 12-14, 2023, Stanford, CA, USA]

This Chapter includes:

1. Conducting laboratory simulation of corrosion damage in pre-stressed girders
2. Studying AEs before and after corrosion damages in pre-stressed/post-tensioned tendons

The contribution of his chapter to the field are:

1. Dissectioning the girder after accelerated corrosion to identify sources of AE from corrosion damage progression in pre-stressed/post-tensioned tendons

Chapter 4: Acoustic-Guided Wave Detection of Corrosion Pits in Grounding Rods Using Fuzzy C-Means and NSGA-II, [Sadegh Mahmoudkhani, Junhui Zhao, Aftab Mufti, Colin McKenzie, Karim Abdel-Hadi, and Douglas Thomson, Submitted to IEEE Sensors Journal, 2023]

1. Applying guided acoustic wave technique to evaluate grounding rods
2. Conducting laboratory experiments to simulate corrosion damage in grounding rods
3. Covering the rods with different amounts of clay and developing a database with varying levels of attenuation
4. Employing Fuzzy c-means and non-dominated sorting genetic algorithm (NSGA-II) to detect and localize the defects in the rod

The contribution of his chapter to the field are:

1. Developing a reliable artificial intelligence-based method to analyze pulse-echo signals and detect cross-sectional loss in grounding rods
2. Developing a method insensitive to attenuation due to varying soil conditions

Chapter 5: Conclusions

This chapter summarizes this thesis's contribution and main findings and outlines the direction of future work.

2 Event Identification in Acoustic Emission from Wire Breaks in Pre-Stressing/Post-Tensioning Cables

2.1 Abstract

Steel tendons commonly used in pre-stressed/post-tensioned concrete structural systems can lose cross-section due to corrosion, eventually leading to acoustic emission (AE) events when the stress exceeds the breaking strength of the wires that make up the tendons. Reliable differentiation of wire break AE events from traffic or grout crack events is critical for monitoring large structures, even where the distance between sensors may produce highly attenuated signals. In this paper, the Fuzzy c-means clustering algorithm was employed to differentiate AEs released from breaking wires of steel tendons from a database of 13464 AEs, including wire breaks, environmental and grout crack AEs. Wire breaks and grout crack AEs were collected from axial loading tests of grouted tendons in which the load increased until a wire broke. Environmental acoustic signals were collected from a bridge. Then all the collected AEs were gathered in a database and post-processed to simulate attenuation of up to 20 m from source to sensor. To optimize the speed and reliability of the Fuzzy c-means clustering algorithm, an NSGA-II algorithm was used to find the minimum number of acoustic features needed. The NSGA-II algorithm started with 201 possible acoustic features and found 12 combinations of features that resulted in more than 80% wire break detection accuracy. In contrast, less than 3% of grout cracks and 0% of environmental signals were detected as wire breaks. The proposed method is suitable for deployment in a large sensor network

and has sufficiently low-computational requirements for at-the-sensor processing, eliminating the need to send high-frequency sampled data outside the sensor node.

2.2 Introduction

Pre-stressed/post-tensioned concrete is one of the most widely used structural systems in bridge construction, and there are 150,000 prestressed concrete bridges in the USA alone (National Bridge Inventory (NBI), 2016). Unbonded or bonded steel tendons in combination with concrete or grout are the most commonly used reinforcing materials for prestressed concrete members. The composite system relies on tendons, which are pre-stressed or post-tensioned close (80%) to their ultimate strength (Ramadan et al., 2008b; Bakht & Mufti, 2017). Steel, even encased in concrete, corrodes over time, and if the corrosion is sufficient, the stress within the tendons exceeds the breaking strength, and the wires that make up the tendon break (Yuyama et al., 2007; Mangual et al., 2013a; Vélez et al., 2015; Appalla et al., 2016). Moreover, some grouts used to encase tendons have been found to contain excessive levels of chloride that can increase the corrosion rate (FHWA, 2012). Therefore, there is a critical need to detect wire breaks within pre-stressed/post-tensioned concrete structures to ensure safety and optimize the maintenance of aging medium and long-span bridges.

There are various corrosion monitoring methods, including visual inspection, ultrasonic pulse velocity, electrochemical-based techniques, acoustic emission, strain monitoring, impact echo, and electromagnetic-based methods in reinforced concrete structures (Kurz et al., 2013; H. Li & Ou, 2016; Abdullah et al., 2016). Among these methods, acoustic emission showed promising advantages like cost-effectiveness, high sensitivity, and real-time and continuous monitoring

(Vidya Sagar & Raghu Prasad, 2013; Behnia et al., 2014; Zaki et al., 2015; Appalla et al., 2016; Bayane & Brühwiler, 2020; Verstryngge et al., 2022). Pre-stressed/post-tensioned tendons have considerable strain energy stored in them. When a wire in the tendon breaks, this energy is released in various forms, including acoustic energy. This acoustic energy is released in a short pulse lasting 10s of microseconds to a few milliseconds. The pulse will couple into and travels throughout the structure. However, as the acoustic pulse travels through the structure, it will be attenuated (Pritz, 2004). Acoustic sensors attached to the structure can be used to pick up the arrival of these acoustic pulses.

The use of acoustic emission (AE) to detect corrosion damage in prestressed and post-tensioned tendons has been investigated (Yuyama et al., 2007; Kovač et al., 2007, 2015; Ramadan et al., 2008b; Calabrese et al., 2013; Djeddi et al., 2013; Mangual et al., 2013a, 2013b; Vélez et al., 2014, 2015; Appalla et al., 2016). However, several of these works (Kovač et al., 2007, 2015; Ramadan et al., 2008b; Djeddi et al., 2013; Mangual et al., 2013b; Vélez et al., 2014, 2015; Appalla et al., 2016) focused on using acoustic emission to detect and monitor stress corrosion cracking in the tendons. Stress corrosion cracking can occur in steel when corrosion develops in a section under high tensile stress (ACI Committee 222, 2014). In addition, the experiments were conducted in controlled laboratory environments, so the effects of environmental acoustic signals present in operating bridges (such as traffic noise) were not included. In addition, as the experiments were done on small or short-length samples, attenuation's effects on acoustic signals were not investigated.

There are many characteristics of AE signals that aid in identifying the source of the emission. Some of the commonly used features of AE signals are Peak Amplitude, Duration, Rise Time, Counts, Energy, and Power (Ghaib et al., 2018; Bayane & Brühwiler, 2020). The features are described in section 2.3.4 of this paper. In the above-mentioned studies (Kovač et al., 2007, 2015; Yuyama et al., 2007; Ramadan et al., 2008b; Djeddi et al., 2013; Mangual et al., 2013a, 2013b; Vélez et al., 2014, 2015; Appalla et al., 2016), the features were extracted, and then a parametric AE signal analysis approach such as intensity analysis (Fowler et al., 1992) and b-value analysis (Colombo et al., 2003) was employed for AE signals analysis. In complex cases where different types of AEs have similar ranges of parameters (like amplitude or frequencies), the automated application of these techniques is challenging.

Low-grade steels used in reinforced concrete can suffer from general or pitting corrosion damage. In addition, pre-stressing/post-tensioning strands can also suffer from other types of damage, such as hydrogen embrittlement and stress corrosion cracking, fretting fatigue, and corrosion fatigue (ACI Committee 222, 2014). Thus, detecting tendon breaks instead of AE from other sources of damage mechanism is more useful in evaluating the overall safety of a pre-stressed/post-tensioned concrete structure. Yuyama et al. (2007) investigated the application of AE to detect tendon breaks in prestressed concrete bridges in both laboratory and field experiments. In their field experiments, they attached tendons to two bridges, corroded the tendons, and monitored acoustic signals using sensors installed on the girders. The maximum distance between their sensors was 6 m. Similar to the above studies, Yuyama et al. (2007) also used one of the parametric analysis methods to analyze AE signals. Application of the Yuyama et al. method in monitoring a bridge with a 40 m length span requires instrumenting each girder with 8 sensors to limit the distance between the

sensors to 6m. The complexity of installing this number of sensors for a multi-girder, multi-span structure makes the application of this approach challenging. Experimental studies to collect and investigate wire break signals in prestressed girders were done by Käding et al. (2022). In the experiments, wire breaks were initiated by cutting wires until neighbouring wires were overstressed and broke. Sensors attached to the girders were used to collect signals. A database of wire breaks was collected at the end of the experiments. Signals of traffic noise and rebound hammer were also collected and added to the database. In the experiments, the distances between the sensors and the source of wire breaks were quite short, so attenuation's effects on the signals were not studied. Releasing prestressed or post-tensioned wires buried in grout or concrete can also fracture grout or concrete and emit acoustic waves (Shiotani et al., 2013). However, in this study, signals of wire breaks were not differentiated from the cutting process and grout or concrete cracks.

To enhance the automated classification of AE signals and reduce the number of well-trained personnel for AE monitoring, the capabilities of machine learning methods to detect AE signals in different applications such as tendons, plates, and FRP bars have been investigated (Ramadan et al., 2008a; Bonaccorsi et al., 2012; Al-Jumaili et al., 2016; Behnia et al., 2016; Holford et al., 2017; Shateri et al., 2017). Bonaccorsi et al. (2012) and Calabrese et al. (2013) used Self-Organizing Map (Kohonen, 1990) to classify the different phases of stress corrosion cracking in the tendons of a post-tensioned concrete beam. This study was done in a laboratory environment, so the effects of environmental acoustic signals present in bridges were not studied. As attenuation reduces signals' energy, some features of wire break and traffic noise signals, such as amplitude, can be similar in a bridge environment, and the database of AEs is considered an overlapping database.

Mingoti and Lima showed Self-Organizing Map could result in a weak performance in clustering overlapping databases compared with other types of clustering algorithms such as Fuzzy c-means, K-means, and traditional hierarchical clustering algorithms (Mingoti & Lima, 2006). They showed Fuzzy c-means could be a more reliable clustering algorithm for these databases. For example, they showed Fuzzy c-means could result in more than 90 and 88% correct classification rates for databases with 40 and 60% overlapping, respectively. These rates were less than 75 and 50% for Self-Organizing Map and less than 83 and 66% for K-means.

In this work, an automated wire break detection method for pre-stressed/post-tensioned concrete girders was developed. The Fuzzy c-means clustering algorithm was employed to classify AE hits observed in pre-stressed/post-tensioned concrete girders. A diverse database of AE signals was collected to test the method. The AEs of wire breaks and grout cracks were collected from constant rate tensile tests of tendons embedded in grout. Piezoelectric transducers attached to the tendon anchors were used to pick up the released acoustic signals. Then, environmental acoustic signals were collected from a concrete girder bridge with traffic and added to the database of the tensile tests. To provide more robust tests of the clustering method, the signals were post-processed to simulate attenuation of up to 20 m from source to sensor. A Non-dominated sorting Genetic Algorithm (NSGA-II) was used to select an optimized combination of acoustic features to feed into the clustering algorithm.

2.3 Materials & Methods

2.3.1 Tensile Tests

To collect AEs from wire breaks and grout cracks, a static hydraulic testing machine (Instron 300DX) was used to apply a constant rate tensile load on 1.4 m 7-wire strands (bounded in grout) until at least one wire failed. To detect the AE signals, two piezoelectric transducers were attached to the chucks, and a laptop and a DT9816-S data acquisition system (Data Translation, model DT9816-S) with 750 kHz sampling frequency were used to record the AE signals. The transducers were developed by Durham et al. (Durham et al., 2020) and had an approximately 63 kHz resonance frequency and a response range of 1 to 100 kHz. The transducer included two piezoelectric discs (STEMiNC, model SMD15T12S412) placed between two steel rods with a 12 mm radius and 20 mm length. To provide a better acoustic coupling between the chucks and transducers, a layer of couplant gel (Echo Ultrasonics, model Ultrasonix) was used. Figure 2-1 shows the schematic of the experimental apparatus.

A threshold-based algorithm, inspired by the work of Tsamtsakis et al. (1998) and Shateri et al. (2017), was used to extract AE hits from the recorded data. The first step of the algorithm was applying two levels of wavelet transform using Haar wavelet and then calculating the signal envelope using Hilbert Transform. After that, a threshold was applied to the envelope, and the first point that passed up the threshold was considered the start point of the hit. In a time (T) after the start point, the last point passed down the threshold was considered the hit's end. In this research, the threshold and distance T were found via trial-and-error and set to 0.12 and 200 ms, respectively.

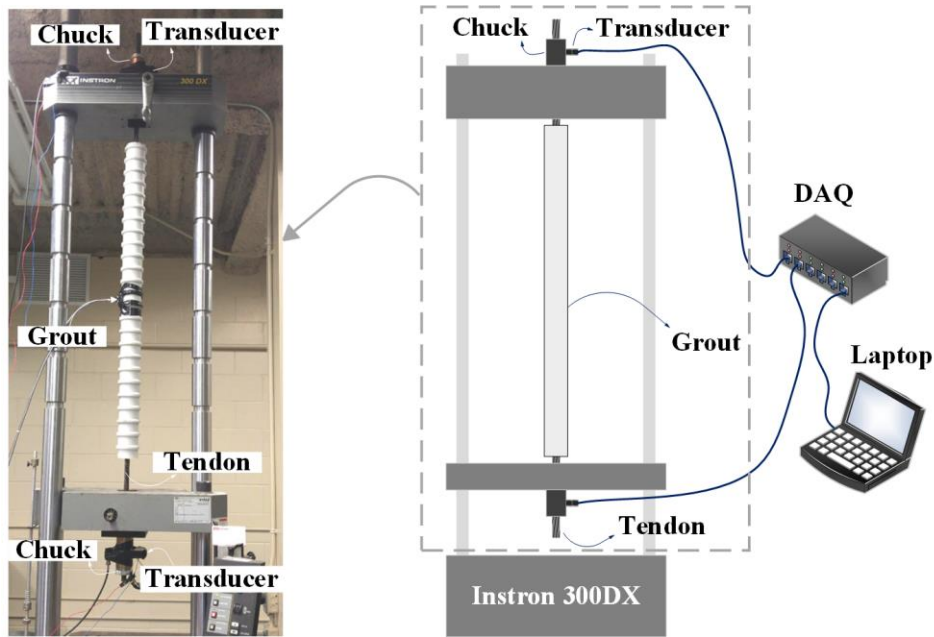


Figure 2-1 The experimental set-up for the tensile test of a grouted strand

2.3.2 Acoustic Emissions from Environmental Sources

Any AE-based wire break detection system will have to detect wire breaks in the presence of signals from environmental sources. Representative environmental signals were gathered for use in testing the wire break detection algorithm. A 6-lane city highway bridge with pre-stressed concrete girders was chosen. The bridge was located in Winnipeg, Canada, was a truck route and had an average 24-hour weekday traffic volume of 78,700. To collect environmental signals, a piezoelectric transducer, an amplifier, and a microcontroller (Teensy 3.6) were used. The geometry of the transducer used in the previous section had variations in acoustic coupling to the concrete and due to rocking on uneven surfaces. The design was modified new to address this issue. The new transducer had a shorter length and also a flanged disk at its base to reduce the rocking problem (see Figure 2-2 for its dimensions). The transducer had a piezoelectric disc (STEMiNC, model SMD15T12S412) bonded to a copper backing mass. Laboratory tests showed the

transducer's resonance frequency was 55 kHz when it was not attached to any surface. When attached to a surface, the resonant behaviour of the transducer was heavily damped, and no resonance was observed below 100 kHz. The transducer was installed on pre-stressed girders near the expansion joints of the bridge. Similar to the tensile tests, a layer of couplant gel (Echo Ultrasonics, model Ultrasonix) was used to improve acoustic coupling between the copper disk and the concrete surface. An op-amp (Analog Devices Inc., model LT1124) was used to provide 100x amplification. Laboratory tests showed the circuit had 100 gain and a bandpass frequency of 1 to 100 kHz. The microcontroller analog-to-digital convertor sampled the incoming acoustic signals. When a threshold was exceeded, 77,000 samples were logged at a 920 kHz sampling frequency. The schematic of the experimental set-up is shown in Figure 2-2. The performance of the circuit was validated by comparing logged sampled data with data acquired using an oscilloscope (Tetronix, model TPS 2024) with the circuit driven by a function generator (Tetronix, model AFG 3021). The logging system is low power and portable for field data logging and in the future will provide an edge processing system in future studies to sense, record and analyze AEs in the field.

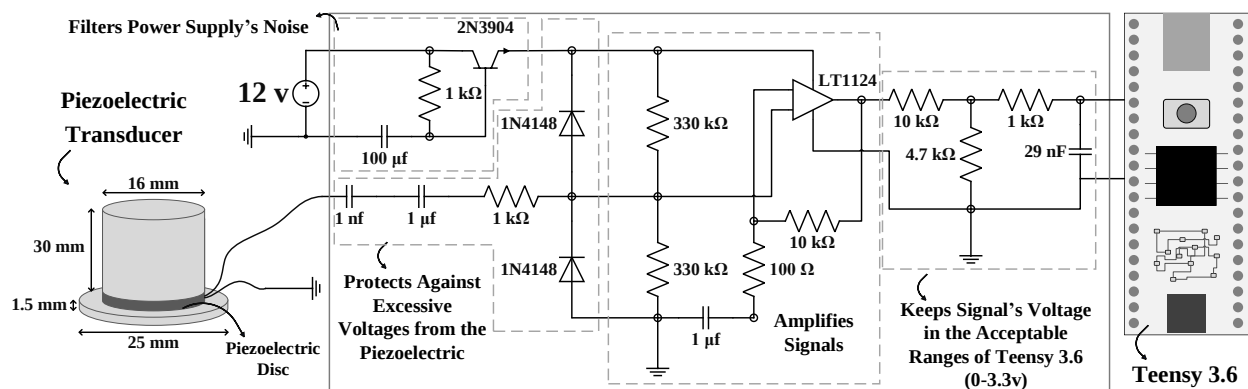


Figure 2-2. The experimental set-up to record environmental noises

2.3.3 Acoustic emission database

The database of collected AE signals included the acoustic signals collected from both the laboratory tensile test and the collected environmental signals. The database contained the AE examples of 123 grout cracks, 14 wire breaks, and 1087 environmental signal examples. In the end application of this method, the AEs will have varying distances to the sensor. Since the attenuation will vary with distance, the effect of attenuation was simulated to produce a more diverse data set. To model the effects of attenuation on the collected signals of wire breaks and grout cracks, the following equation was adopted:

$$Attenuation(dB/m) = \frac{10}{distance} \log \left(\frac{\sum_{i=1}^N Signal_i^2}{\sum_{i=1}^N (W \times Signal_i)^2} \right) \quad Equation 2 - 1$$

where W was a weight factor that simulated the effect of attenuation on the signal's amplitude, and attenuation was assumed 2 dB/m (Mahmoudkhani, Algohi, et al., 2019). The effects of attenuation were modelled using ten distances from 2 to 20 m in 2 m increments. With the effects of attenuation included, the number of AE signals of grout cracks and wire breaks increased to 1353 and 154, respectively. The environmental signals were assumed to have already come from sources of varying distances. However, to improve the robustness of the proposed method, the candidate assumed the primary sources of signals have a 20m distance to the sensor. So, by applying the same equation, the candidate modelled new signals with fewer distances to the sensor. the candidate employed ten distances from 18 to 0m in -2 m increments to increase the number of environmental signals to 11957. It should also be noted that attenuation is dependent on frequency as well (Pritz, 2004).

2.3.4 Acoustic Features

AE signals are often characterized using an often-used set of features (Unnthorsson et al., 2008; Shateri et al., 2017; Chai et al., 2018). This study uses the commonly used features of Peak Amplitude, Duration, Rise Time, Counts, Energy, and Power. In addition, the candidate has also used Entropy and the areas under the Fast Fourier Transform (FFT) curve in four bins, as they have proven useful for classifying AE signals (Figure 2-3).

The often-used characteristics have been described many times in the literature, but the candidate includes a brief description for completeness. The Peak Amplitude of an AE is the maximum measured amplitude of the voltage. Other features depend on an operator-defined threshold. Rise Time is the time difference between the Peak Amplitude and the first threshold crossing, and, Duration is the time interval between the first and last threshold crossings. Count is the number of times the signal rises through the threshold. To calculate Energy, Power, Entropy, and the areas under FFT, the part of the signal between the first and last threshold crossings is used. The Energy of a signal refers to the area under the squared signal, and, its Power is its Energy per unit of time. Shannon's Entropy, called Entropy in this paper, was proposed By Shannon (1949) to calculate the uncertainty of probability distributions. The detailed calculation process of Entropy that is widely used as an index in damage detection (Unnthorsson et al., 2008; Bai et al., 2014; Chai et al., 2018; Angela & Ercolino, 2019; F. Wang et al., 2019; Karimian et al., 2020; F. Wang et al., 2020) is described in the literature. In this paper, Entropy was calculated in the time domain. As AE signals were discrete phenomena, the histogram of each signal was used to estimate the mass function in the calculation (Chai et al., 2018). The areas under FFT in four bins refer to the area

under the signal's normalized FFT in 15 kHz intervals from 1 to 61 kHz. Each bin's area was divided into the total area of the four bins.

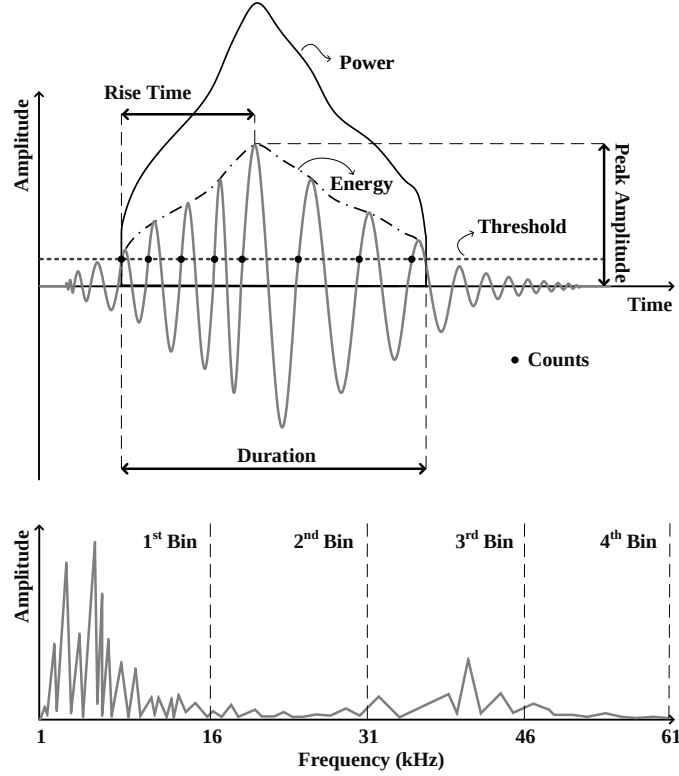


Figure 2-3 Acoustic features used in this study

2.3.5 Fuzzy C-means Clustering

In this work, the Fuzzy c-means algorithm (MATLAB's built-in function) was used to cluster the AEs autonomously based on their features. Clustering algorithms are unsupervised machine learning methods that group unlabeled data based on their similarity into clusters. Fuzzy c-means, proposed by Dunn (1973) and Bezdek (1980), is a low-cost and straightforward clustering algorithm that is widely used in structural health monitoring problems (Shateri et al., 2017; Das & Saha, 2018; Dorafshan & Maguire, 2018; S. Chen et al., 2018; Zeng et al., 2018; Xiao-Mei et al.,

2019; Hassan, 2021). Fuzzy c-means minimizes Euclidean distance as a similarity measurement between clusters' centroids and data features to cluster data points (Dunn, 1973; Bezdek, 1980).

In this work, the number of clusters, the number of iterations, and the minimum desired improvement in objective function were set to 3, 100, and $1e-5$, respectively. Three different criteria were used to evaluate the performance of the algorithm. First, what ratio of wire break signals were classified as wire breaks. Second, what ratio of grout cracks were classified as wire breaks. Third, what fraction of environmental signals were classified as wire breaks.

2.3.6 Non-dominated Sorting Genetic Algorithm-II (NSGA-II)

Non-dominated Sorting Genetic Algorithm (NSGA-II) was used to determine the optimal classification features. In this research, optimal classification features refer to the features that result in the maximum ratio of wire break AEs classified as wire break and minimize the ratios of grout cracks and environmental AEs classified as wire break. It also refers to the minimum number of features that lead to these results. It is important to optimize the choice of feature, as the potential feature set is impractically large. For example, the number of acoustic features can be made very large simply by choosing many different threshold levels. It is computationally costly and impossible to feed all possible combinations of acoustic features into the clustering algorithm. Multi-objective optimization methods can find one or a set of optimal solutions within the feasible space of an optimization problem. NSGA-II, proposed by Deb et al. (2002), is a well-known low-cost multi-objective evolutionary algorithm that is widely used in engineering problems (Abed et al., 2016; Halabian et al., 2016; Yu et al., 2017; Erol et al., 2019; Lin et al., 2019; Gu et al., 2020).

NSGA-II was employed in this study to address the issue of an optimal number of features for wire break detection.

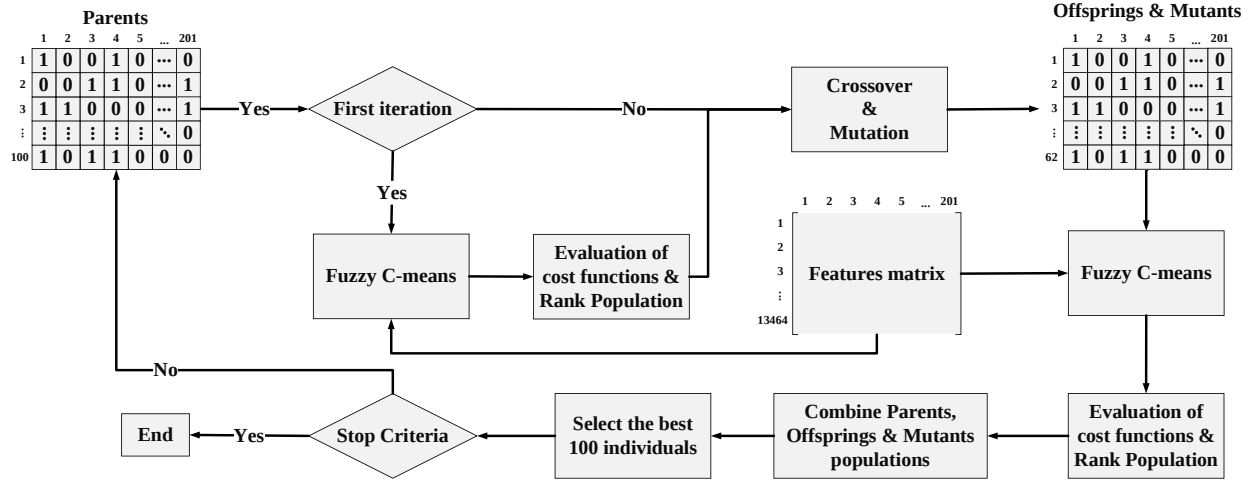


Figure 2-4 The overall procedure used in the NSGA-II optimized feature selection

Figure 2-4 shows the flowchart of the overall procedure used in the NSGA-II optimized feature selection. A detailed description of NSGA-II can be found in Deb et al. (2002). NSGA-II was programmed in MATLAB by the candidate and validated with the examples from Deb et al. (2002). In Figure 2-4, the procedure started with a feature matrix. The matrix contains 201 features. These include peak amplitude and calculating the following features when 20 thresholds (from 0.001 to 5V with 0.25V increments) are applied to each signal (section 2.3.4). These threshold-dependent features are energy, power, count, Entropy, duration, rise time, Area under FFT from 1-16 kHz, Area under FFT from 16-31 kHz, Area under FFT from 31-46 kHz, Area under FFT from 46-61 kHz.

These features are calculated for each acquired signal in the AE database. This yields a matrix with 13464 rows and 201 columns, one row for each AE signal and 201 columns for each corresponding

feature. In this algorithm, each individual represents a subset of the possible features. A one or zero is used to signify if a feature has been chosen for a particular individual. Therefore, each individual has 201 zeros and ones. The first step was started by randomly choosing 100 individuals as the Initial Parents Population, in which each individual has 201 zeros or ones elements. The number of these zeros and ones was equal to the number of features (columns of the features matrix). The zeros mean the individual does not use the corresponding features. Then the individuals were fed into Fuzzy c-means to calculate the three criteria explained in the previous section as the cost functions.

The individuals were evaluated and ranked in the next step by applying non-dominated sorting and calculating crowding distances (Deb et al., 2002). As shown in Figure 2-4, crossover and mutation operations were used to produce offspring and mutants to feed them into the clustering algorithm and then evaluate and rank them. Binary tournament selection and simulated binary crossover (Deb & Agrawal, 1995) were used to select parents and generate offspring, and polynomial mutation (Deb & Agrawal, 1995) was used to create mutants. After that, parents, offspring, and mutants were merged into a population, and the best 100 individuals were selected for the subsequent iterations. This process was repeated until reaching the maximum number of iterations, then members with Rank 1 were exported as the final Pareto Front (final solutions). In this research, the number of parents, offspring, mutants, and the number of iterations were set to 100, 32, 30, and 200, respectively.

2.4 Results & Discussions

The first sets of tests were used to develop the database and identify the AE features of wire breaks. Figure 2-5 shows a wire break signal taken using the procedure outlined in section 2.3.1 and its FFT. As shown in Figure 2-5, the wire break AE signal has the most relative power for frequency content between one and 50 kHz. The Samples of grout cracks and environmental signal and their corresponding FFTs are also shown in Figure 2-5. In comparison with the frequency distribution of the wire break, the grout crack and environmental signals tend to have more normalized magnitude at lower frequencies.

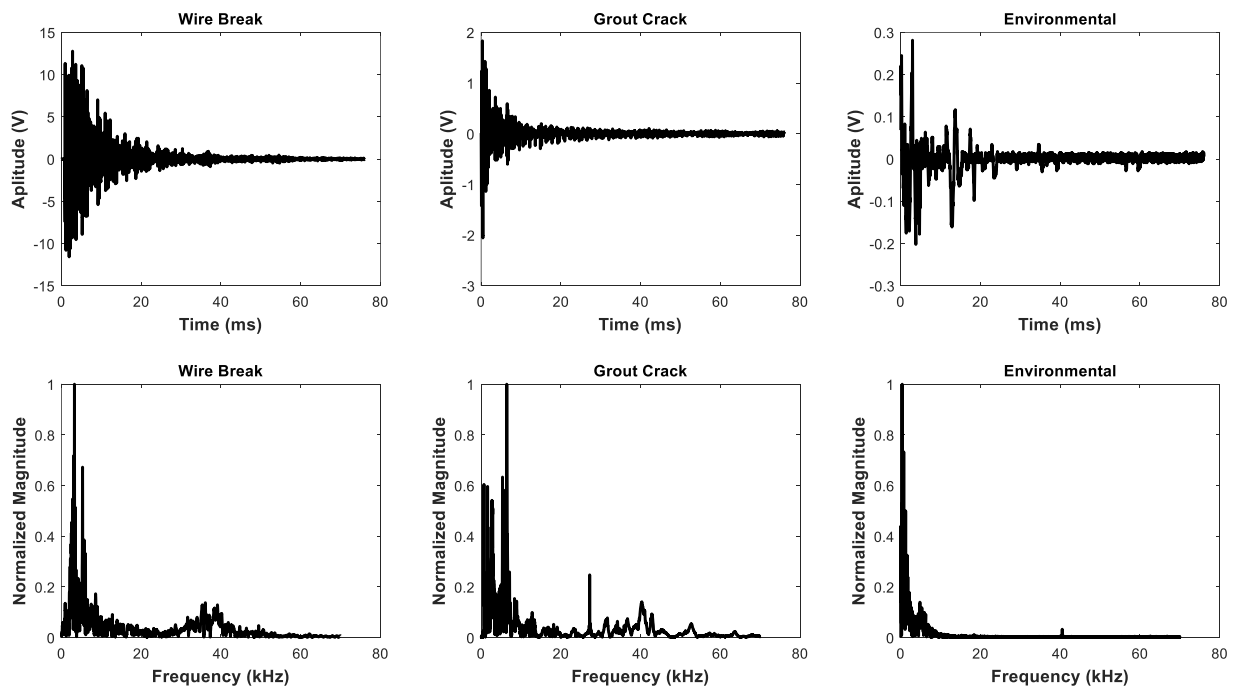


Figure 2-5 The acoustic signal and FFT of a wire break, grout crack and environmental AE

The normalized ratio of areas under FFT curves in certain bands can be a useful feature for AE signal classification. The normalized areas under FFT curves for all the AE signals in the database,

explained in section 2.3.4, utilizing increments of 15 kHz are shown in Figure 2-6. As shown in Figure 2-6, in the band between 31 to 46 kHz, wire break signals are well separated from environmental signals and have minimal overlap with grout cracks signals. This observation resulted in the bands with different widths being explored. However, bands with 15 kHz width showed fewer overlaps, so in the rest of this work, only this bandwidth was used.

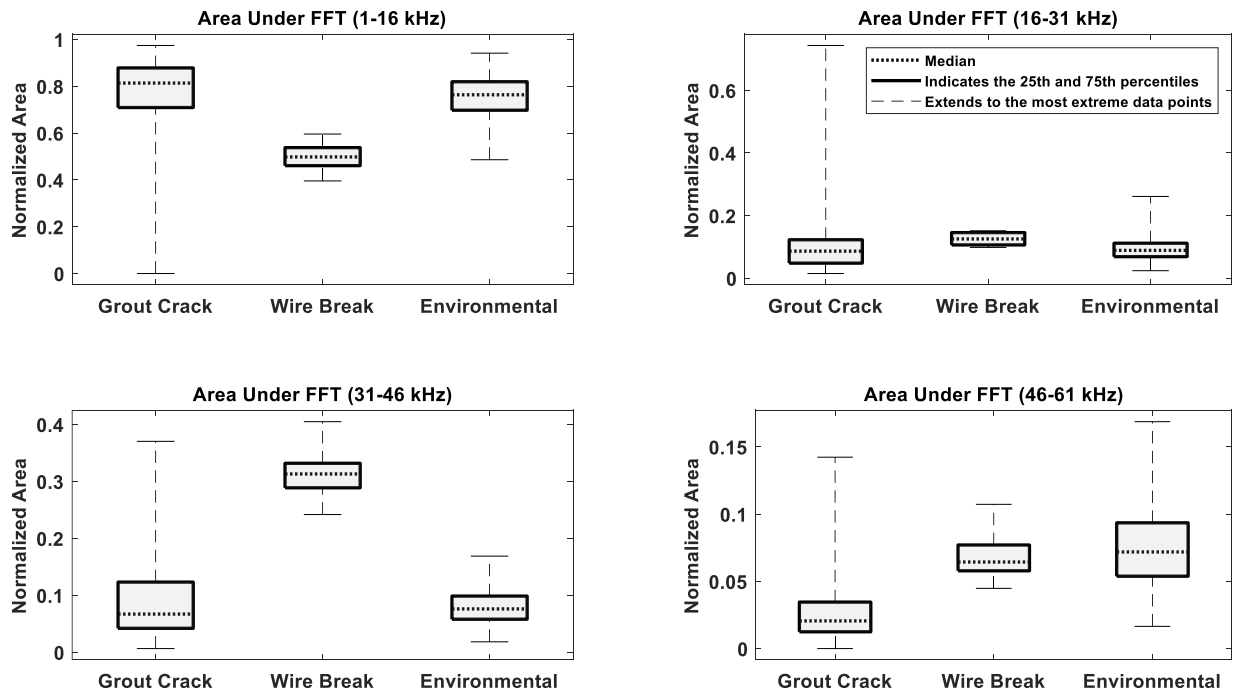


Figure 2-6 The normalized areas under FFT curves for the database for 15 kHz bands

Figure 2-7 shows the variation of peak amplitudes for the database. In practice, acoustic signals are attenuated as they pass through materials. As the distance between the source of emission and the sensor increases, so will the attenuation. Therefore, signal amplitude alone is not a reliable indicator of the source of AE. In this work, the signals in the database have simulated attenuation for distances up to 20 m. As shown in Figure 2-7, the peak amplitudes of wire breaks overlap with

environmental and grout crack signals. Therefore, in this work, the focus is on methods of classification that are insensitive to attenuation.

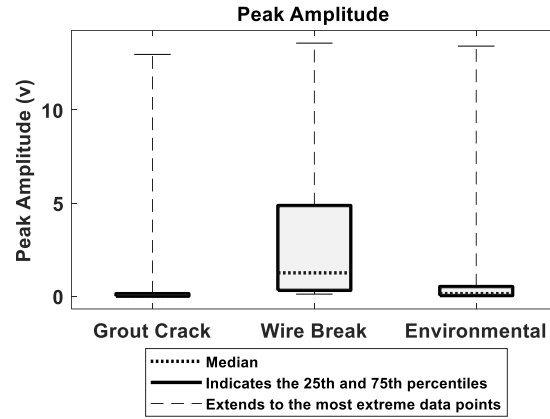


Figure 2-7 The peak amplitudes for the database

The NSGA-II-based algorithm described in section 2.3.6 was used to find optimal sets of features by optimizing the three criteria of section 2.3.5; the ratio of wire breaks' signals classified as wire breaks and the ratios of grout cracks and environmental signals classified as wire breaks. The NSGA-II algorithm relies on random generation and selection operators to sample a large portion of the available solution space. Therefore, the NSGA-II-based algorithm will often produce different outcomes for each run. In many cases, the results will not be acceptable. After several runs, it was observed that it was possible to consistently find solutions with greater than 80% wire break detection accuracy, that simultaneously had less than 3% of grout cracks and 0% of environmental signals detected as wire breaks. The candidate ran the algorithm 20 times with the same number of parents, offspring, mutants, and the number of iterations (100, 32, 30, and 200, respectively). Three out of twenty cases produced the desired results of more than 80% wire break

detection accuracy, while less than 3% of grout cracks and 0% of environmental signals were detected as wire breaks.

The NSGA-II-based algorithm produced 12 optimized feature sets to feed into Fuzzy c-means for wire break detection. By using these optimized feature sets, the Fuzzy c-means algorithm could detect wire breaks with an average 81.06% accuracy. Only an average of 2.69% of grout cracks were misclassified as wire breaks, and none of the environmental signals were classified as wire breaks. The number of features in the acceptable sets was between 10 to 15 features. To ensure the sets had the minimum number of possible features needed to achieve the same or better results, the candidate eliminated features of each set one by one and fed the remaining features into Fuzzy c-means. During this elimination process, the candidate removed the features that had no effect or negative effects on the Fuzzy c-means algorithm. The number of features could be further reduced by a maximum of two features for five feature sets. The final 12 feature sets and their features are listed in Table 2-1. As shown in the table, all features found by the algorithm utilized FFTs with different thresholds and frequency bins.

Table 2-2 shows the number of features, the number of thresholds used in the features, wire break detection accuracy, and false detection ratios for each set. As shown in Table 2-1, several cases only require five calculations of FFT of signals, making this method suitable for deployment in at-the-sensor processing and eliminating the need to send high-frequency sampled data outside the sensor node.

[illegible]

Table 2-2 The overall characteristics of the optimal feature sets

Sets	Number of features	Number of thresholds	Grout cracks detected as wire breaks (%)	Wire breaks detected as wire breaks (%)	Environmental signals detected as wire breaks (%)
1	14	6	2.96	81.17	0
2	13	5	2.66	81.17	0
3	14	7	2.51	81.17	0
4	14	7	2.51	81.17	0
5	15	8	2.73	80.52	0
6	10	5	2.88	81.17	0
7	13	6	2.51	80.52	0
8	13	6	2.81	81.17	0
9	11	7	2.73	81.17	0
10	10	5	2.44	81.17	0
11	10	5	2.88	81.82	0
12	10	5	2.22	81.17	0

In the previous section, a wire break detection rate of 80% was considered acceptable. This implies that there is a probability that several wires might break before a wire break is detected. If an AASHTO 36-in prestressed I girder with 16 seven-wire strands (Tabatabai & Nabizadeh, 2019) loses 25% of its prestressing steel, its initial moment strength drops to Strength I of AASHTO LRFD Bridge Design Specification. In this case, the bridge is operational, but it should be repaired. Based on the limit states concept of AASHTO LRFD, Strength I is related to the load combination of the normal vehicular use of the bridge without wind. Losing 25% of prestressing steel for this girder is equivalent to losing 28 out of 112 wires. In the following, the candidate assumes that missed wire break detection is random. Considering the 81.06% rate of wire break detection, the probability that the proposed method misses all 28 wire breaks is 5.8×10^{-21} . With the same detection rate, the probability that the proposed method misses 10, 15, and 20 wire breaks are 5.9×10^{-8} , 1.4×10^{-11} , and 3.5×10^{-15} , respectively. Therefore, a detection rate of 80.06% has a very

high probability of detecting the majority of wire breaks before there is a significant loss of structural capacity.

The distribution of the final features selected was examined since the NSGA-II uses random starting feature sets, and only a small subset produced acceptable results. The features and the total number of using them in the 200th iteration of the 20 runs are shown in Figure 2-8 and Figure 2-9. The selected features in the last iteration include only FFTs in different bins, Count, and Entropy with different thresholds. Although the feature sets listed in Table 2-1 only include FFT in different bins, the other sets that did not meet the suitable criteria also have FFTs with or without Count and Entropy. Some of the features (11 features) used in the optimal sets were used more than 200 times. The algorithm did not select features such as peak amplitude, Rise Time, Energy, and Power in the last iteration. Count (section 2.3.4) is somewhat sensitive to attenuation and was chosen by the algorithm only 108 times (less than 1% of features made up the last individuals). More than 93% of features occurring in the last iteration are FFTs for different frequency bins. The NSGA-II algorithm can be a powerful tool for selecting optimal feature sets.

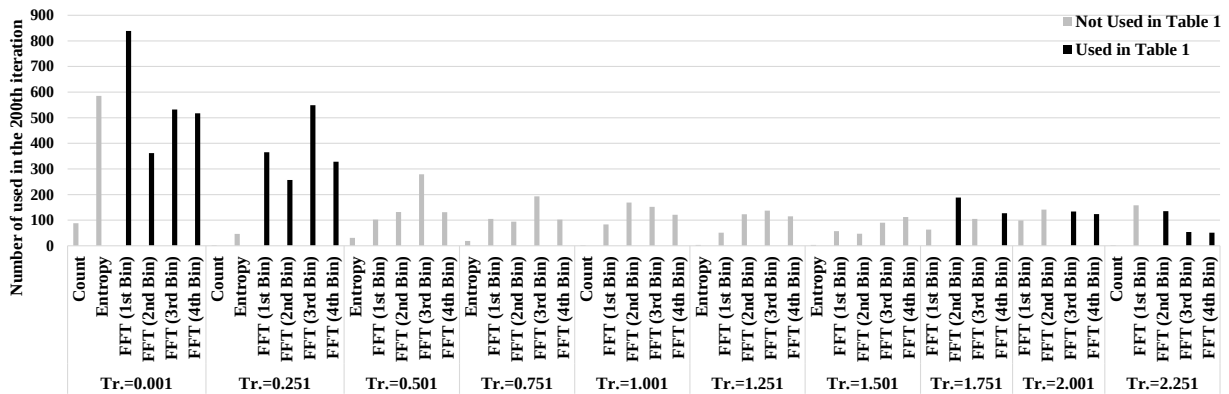


Figure 2-8 The features and the total number of using them in the 200th iteration of the 20 runs for thresholds (Tr.) from 0.001 to 2.251

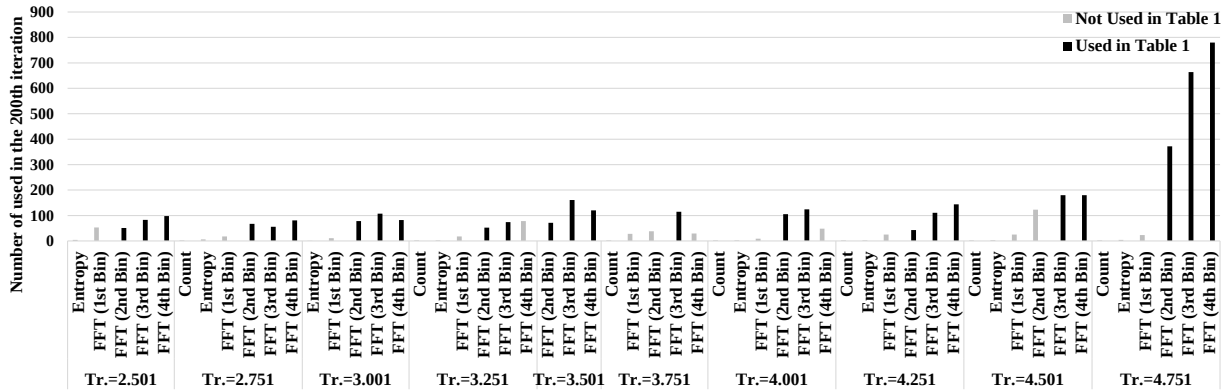


Figure 2-9 The features and the total number of using them in the 200th iteration of the 20 runs for thresholds (Tr.) from 2.051 to 5.001

2.5 Conclusions

In this paper, the candidate developed an automated method to detect wire breaks in pre-stressed/post-tensioned concrete girders using acoustic emission. To differentiate AE hits observed in pre-stressed/post-tensioned concrete girders, the candidate employed the Fuzzy c-means. The candidate collected AEs of wire breaks, grout cracks, and environmental signals present in an operating pre-stressed concrete bridge and post-processed them to simulate the effects of attenuation of up to 20 m from source to sensor. Then, the candidate gathered them into a database of 13464 AEs. To optimize the speed and reliability of the Fuzzy c-means clustering algorithm, the candidate employed an NSGA-II algorithm to find the minimum number of acoustic features needed. The NSGA-II algorithm found 12 combinations of features that resulted in an average of 81.06% wire break detection accuracy. In contrast, an average of 2.69% of grout cracks and 0% of environmental signals were misclassified as wire breaks. For an AASHTO 36-in prestressed I girder with 16 seven-wire strands, the probability that the proposed method does not detect losing 25% of the girder's prestressing steel (dropping its initial moment strength to the Strength I of AASHTO LRFD Bridge Design Specification) is 5.8×10^{-21} . Results show this method is reliable

and suitable for deployment in an extensive sensor network and has sufficiently low-computational requirements for at-the-sensor processing, eliminating the need to send high-frequency sampled data outside the sensor node.

3 Acoustic Emission Monitoring of Pre-Stressed Concrete Beams During Accelerated Corrosion of Pre-Stressing Tendons

3.1 Abstract

Acoustic sensors attached to pre-stressed/post-tensioned bridges are promising tools for monitoring the progression of corrosion damage in pre-stressing/post-tensioning tendons. In this study, acoustic emission signals from a pre-stressed beam containing three pre-stressed tendons that were exposed to accelerated corrosion conditions were studied. A short length of each tendon was exposed, and a tank filled with the NaCl solution was placed over the exposed tendon. Over a period of several months, a corrosion current was driven into the tendons until at least one wire corroded through. Acoustic sensors were attached along the beam and were used to record acoustic emission events during the accelerated corrosion. At the termination of the accelerated corrosion experiment, the beam was sliced into sixty-two cross-sections, each being 5 cm thick. Each slice was inspected to correlate corrosion and tendon slippage with acoustic emission signals. Maps of the estimated origin of acoustic emission signals were compared with the maps of the position of tendon corrosion and slippage. The acoustic emission signals were correlated with the presence of wire fracture due to corrosion on the tendon and with proximity to the end of the beam. The larger emission signals are likely due to the loss of bond between the tendons and concrete, as tendon fracture due to corrosion was not found in any of the cross-sections. This work points to the use of acoustic emission to track the progression of damage in cases where corrosion has already resulted in tendon fracture, and progression is proceeding by loss of bond.

3.2 Introduction

Corrosion damage in pre-stressed/post-tensioned concrete beams and girders is an issue of great concern. The steel tendons of concrete bridges can severely corrode over time and lose cross-sectional area between 70% to 100% (Pape & Melchers, 2011). A low-cost method of monitoring the progression of corrosion damage in these systems is of great interest. As corrosion damage progresses, wire breaks and bond slipping lead to acoustic emission events. Acoustic emission-based monitoring systems show promising results in monitoring the progression of corrosion damage in steel tendons of pre-stressing/post-tensioning girders (Vidya Sagar & Raghu Prasad, 2013; Behnia et al., 2014; Zaki et al., 2015; Appalla et al., 2016; Bayane & Brühwiler, 2020; Verstrynge et al., 2022)

The literature has mainly focused on detecting a particular type of damage in the tendons, such as stress corrosion cracking or hydrogen embrittlement (Kovač et al., 2007, 2015; Ramadan et al., 2008b; Calabrese et al., 2013; Djeddi et al., 2013; Mangual et al., 2013b; Vélez et al., 2014, 2015; Appalla et al., 2016). However, the tendons can suffer from general corrosion, pitting corrosion, fretting fatigue and corrosion fatigue (ACI Committee 222, 2014). Corrosion can induce wire breaks and/or loss of bond between tendons and concrete/grout and consequently decrease the structure's load-carrying capacity (ElBatanouny et al., 2014; Ho et al., 2015; Huo et al., 2019; Verstrynge et al., 2022). Therefore, instead of monitoring the cause of damages or detecting the breaks of wires that make up tendons, tracking the progression of damage can be more practical in evaluating the overall safety of bridges.

Yuyama et al. (Yuyama et al., 2007) and Käding et al. (Käding et al., 2022) conducted experimental investigations on applying acoustic emission to detect tendon breaks in pre-stressed concrete bridges. Yuyama et al. (Yuyama et al., 2007) used accelerated corrosion experiments to produce wire breaks, while Käding et al. (Käding et al., 2022) made the breaks by cutting wires. Breaking or releasing pre-stressed or post-tensioned tendons covered by grout or concrete may fracture grout or concrete and release acoustic emissions (Shiotani et al., 2013). However, Yuyama et al. (Yuyama et al., 2007) and Käding et al. (Käding et al., 2022) did not differentiate between acoustic emission resulting from wire breaks, slipping of the tendon, grout cracking or concrete cracks. Therefore, identifying the cause of acoustic emission is important for developing reliable methods, with minimal false alarms, to monitor damage progression. In this work, acoustic emission from accelerated corrosion in pre-stressed beams yielded was largely attributed to tendon slippage.

In this paper, the candidate conducted accelerated corrosion experiments on a pre-stressed beam with three tendons to study acoustic emission signals released from the beam. The accelerated corrosion experiment was continued over a period of several months until at least one wire from each tendon corroded entirely through. Eight acoustic sensors attached to the beam were used to detect and record acoustic signals during the experiments. At the termination of the experiments, to correlate corrosion and tendon slippage with acoustic emission signals, the beam was sliced into 62 slices each 5 cm thick.

3.3 Materials & Methods

3.3.1 The Experimental Set-up

A 3.15 m long pre-stressed concrete beam with 40 cm width and 27 cm depth was used in this section for the accelerated corrosion experiment (Figure 3-1). As shown in the figures, the beam had three pre-stressing tendons. To record the AEs, present in the beam, eight sensors with DAQs were installed on the beam using epoxy adhesive (Gorilla five-minute epoxy). The location of the sensors is shown in Figure 1. The experiment was done in two phases. In the first phase, an opening around the tendon was created by carefully removing the concrete cover over the tendon using a hammer drill and chisel. Then, a water-tight plastic tank (with a hole the same size as the pit in its bottom) glued putty on top of the pit using plumbing epoxy. The details of the experiment and the mounting of the corrosion tank are shown in Figure 3-2. A stainless steel sheet was used as the cathode, the tendon acted as the anode, and 5% NaCl solution was used as the electrolyte. In the experiments, the corrosion current was 4 mA, and the approximate exposed area of tendons was 120 mm².

The DAQs sampled AE signals at 920 ksamples/s until a threshold was exceeded. Once this threshold was exceeded, the AE signal was sampled for 77,000 samples at 920 ksamples/s and then the sampled data set was stored on an SD card. To set the threshold for each DAQ, the ball impact calibration method was used (McLaskey & Glaser, 2012). A steel ball bearing with a 7 mm diameter was used in the calibration. The ball was dropped from 25 cm height above the sensor and a distance of 10 cm to the sensor. Thresholds were set so that environmental signals would not trigger saving of a sampled data set but would trigger saving a sampled data set when a ball was

dropped. This phase of the accelerated corrosion experiment continued for around five months, and the AE signals collected on the SD card were moved to a laptop once a week. The ball drops were carried out weekly to ensure the ongoing integrity of sensors and DAQs. The DAQ circuit had 100 gain, so the recorded signals were post-processed using MATLAB to compensate for the gain. Figure 3-3 shows the progress of corrosion in the tendon.

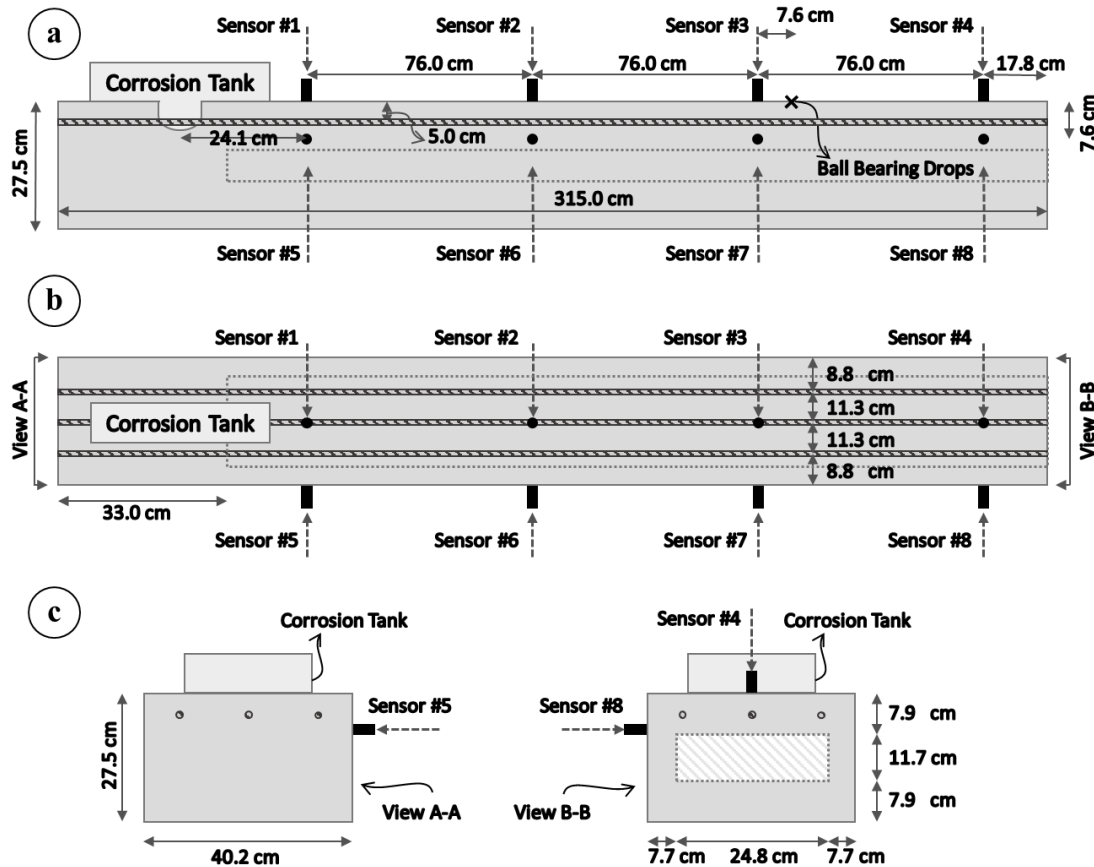


Figure 3-1 The schematic of the pre-stressed beam and the acceleration corrosion set-up; a) Side view, b) top view, and c) Ends of the beam's view.

In the second phase, the corrosion tank of the previous phase was removed, and two pits surrounding the remaining two tendons were created. As in the first phase, corrosion tanks were installed on the tendons. This phase continued as the first stage and also ended after around five

months. Each phase ended when no significant signals were recorded in the preceding month of the experiment.

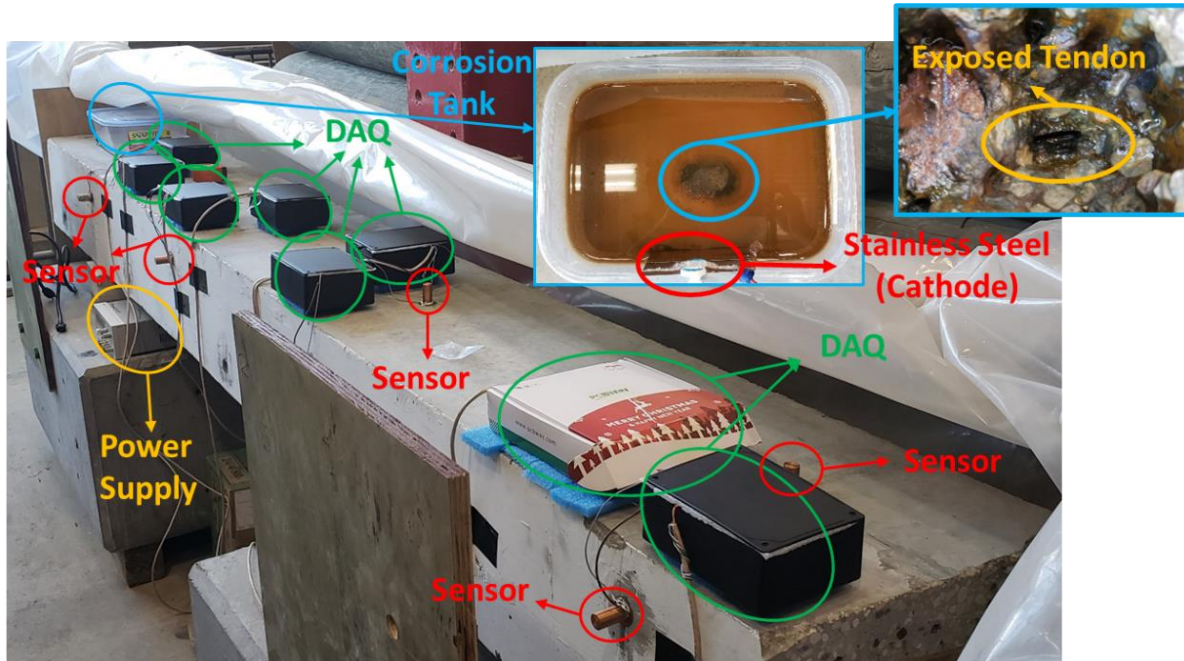


Figure 3-2 The acceleration corrosion set-up and a corrosion tank.



Figure 3-3 The progress of corrosion over a) 5 days, b) 7 days, and c) 49 days

3.3.2 Localizing Acoustic Signals

As the acoustic signals travel through the medium, they are attenuated. The candidate used attenuation between the sensors to localize the source of recorded acoustic signals. For this

purpose, knowing the distance between the sensors, the candidate first estimated the attenuation between the sensors using the ball drop signals. The calculated attenuation was 6.9 dB/m. Then, using the following equation, the candidate localized the sources of recorded events.

$$6.9 = \frac{10}{distance} \log \left(\frac{Power_{sensor\ i}}{Power_{sensor\ j}} \right) \quad \text{Equation 3 – 1}$$

Here, the calculated powers of signals for two sensors were used. In some cases, the DAQ measurements were saturated due to large signal magnitude. In these cases, the signals were only analyzed after the time point when none of the DAQ measurements were saturated. Only the portion of the signal after this maximum saturation time were used to calculate signal power. Figure 4 shows an example of an event with saturated signals. Signals of sensors 1 and 2 (Figure 3-4(a) and Figure 3-4(b)) were saturated, the maximum saturation time among the signals of this event was calculated, then the portion of the signal after this time for all the sensors was used in the calculations.

3.3.3 Visual Inspection of Tendons After Accelerated Corrosion

To visually investigate the condition of the tendons after accelerated corrosion experiments, the candidate has sliced the beam into 62 slices approximately 5cm thick. The cutting process started from the beam's right side (far from the corrosion tanks; see Figure 3-2). Thus, the tendons' cross sections were visible on each piece's right and left sides.

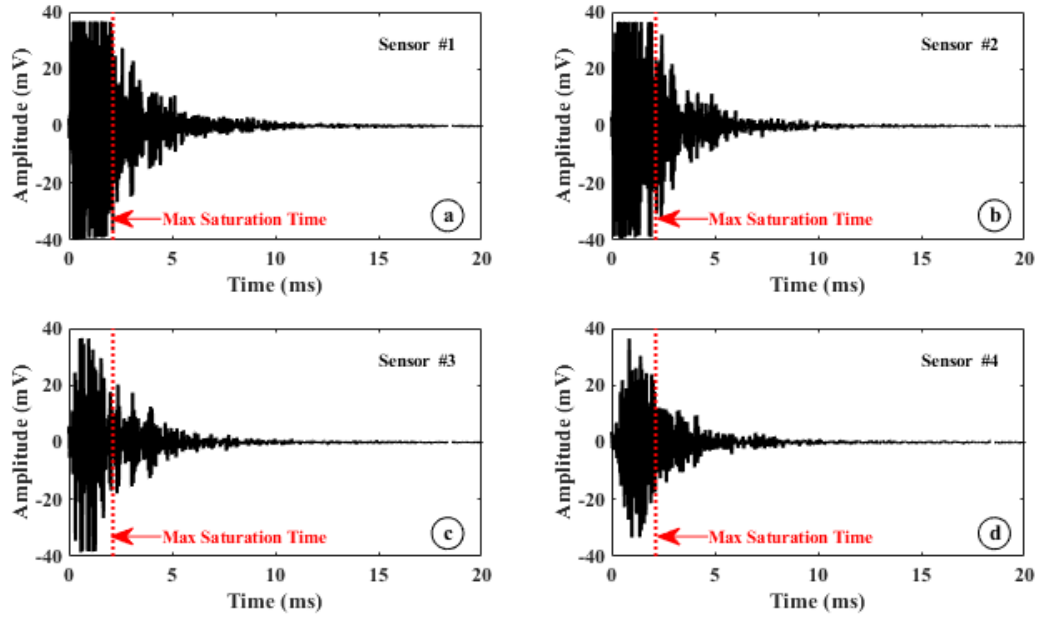


Figure 3-4 A sample of recorded signals, including both saturated and unsaturated signals from the first phase of experiments.

3.4 Results & Discussions

An example of recorded events from the first phase of the experiments is shown in Figure 3-4. The same trends in signals were observed in sensors 1 to 4 and 5 to 8. Therefore, only signals of sensors 1 to 4 were shown in Figure 3-4. As seen, signals sensed by sensors 1 and 2 (Figure 3-4(a) and Figure 3-4(b)) were saturated, while the signals of sensors 3 and 4 (Figure 3-4(c) and Figure 3-4(d)) were not. Therefore, the source of this event is expected to be between sensor 2 and the left end of the beam. Using the signal analysis method of Equation 3-1, the event was estimated to originate between sensors 1 and 2, with a 28 cm distance to sensor 1. Using this same approach, all the AE events were mapped and binned using 31 cm wide bins (Figure 3-5). The location of the most events can be clustered in three areas; first, between the left end of the beam and corrosion pits; second, between the corrosion pits and 20 cm left of sensor 2; third, between sensor 3 and the right end of the beam. Since no wire breaks were found, these are believed to be due to loss of

bond between concrete and tendons near the end of the beam. As the second phase of the accelerated corrosion experiments was done on tendons 1 and 3 simultaneously, therefore, the events were mapped in Figure 3-5 for both tendons simultaneously.

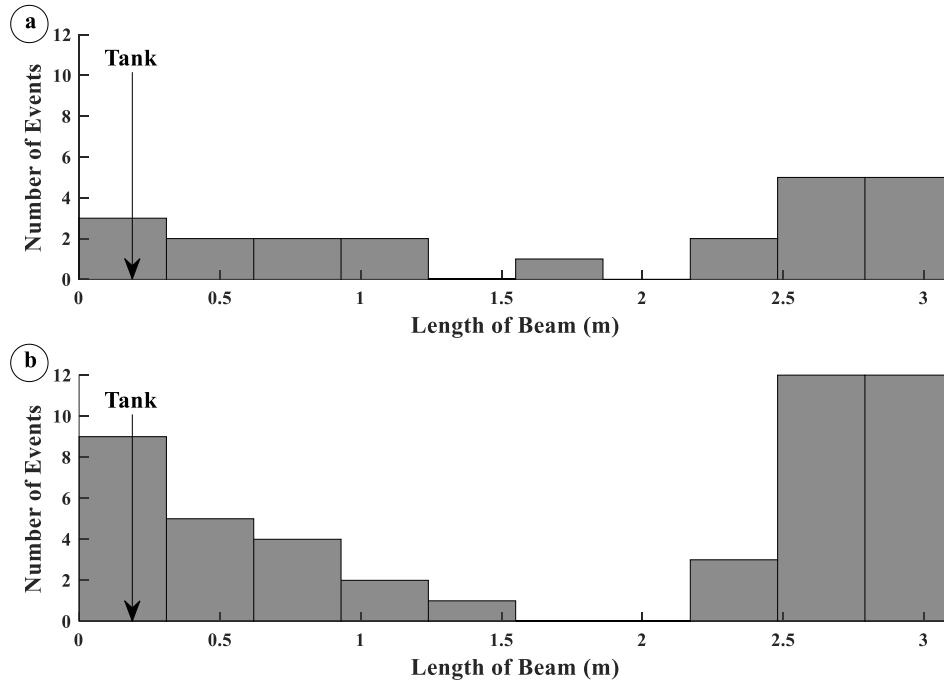


Figure 3-5 The localized sources of recorded events and the number of their occurrence.

Figure 3-6 and Figure 3-7 show two typical examples of slice cross-sections. Figure 3-6 shows tendon 1 on both sides of the 25th slice. As seen, there are signs of losing the bond between the tendon and concrete on the left side. The cutting process was done from right to left, and the candidate has not seen similar signs on the right side of slice 24. Thus the candidate only considered this loss for the left side of tendon 1 in the 25th slice. It should be noted that the slices were numbered from left to right. Figure 3-7 shows the left side of the 30th slice as well as the visual signs of corrosion on the cross-section of tendon 1 on the left side of the 30th slice. The candidate removed the concrete covering the tendon in this slice and found corroded parts on four wires.

Corrosion was more significant on the central wire. The locations of corrosion and slipping tendons were mapped in Figure 3-8. Corrosion was widespread along tendon 2, with higher concentrations near the corrosion tanks for the other two tendons. There was no obvious correlation with regions of corrosion or loss of bond.

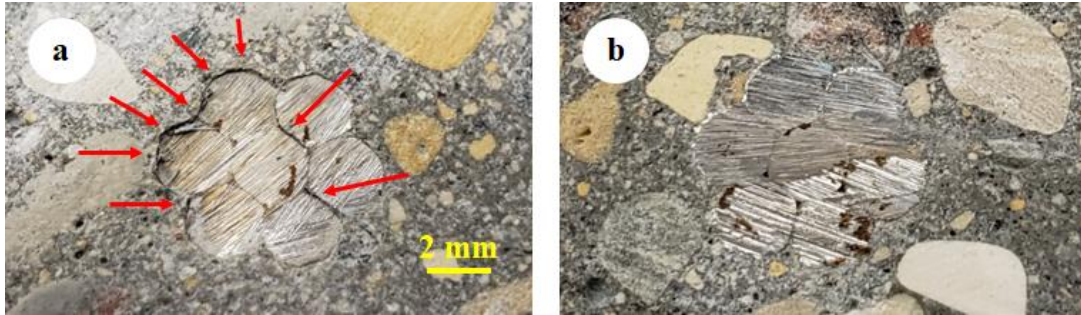


Figure 3-6 Visual signs of a) losing the bond on the left side and b) keeping the bond on the right side between concrete and tendon 1 of the 25th slice.

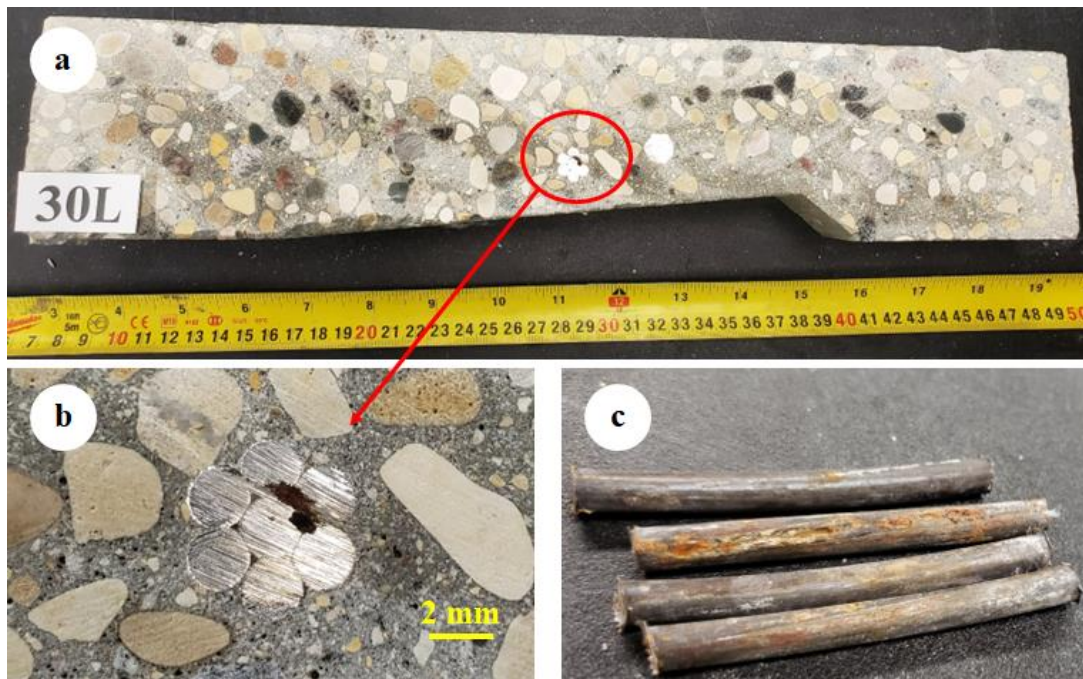


Figure 3-7 The right side of the 30th slice (a), Visual signs of corrosion on the cross-section of tendon 1 on the left side of the 30th slice (b), and corroded wires of tendon 1 from the 30th slice (c).

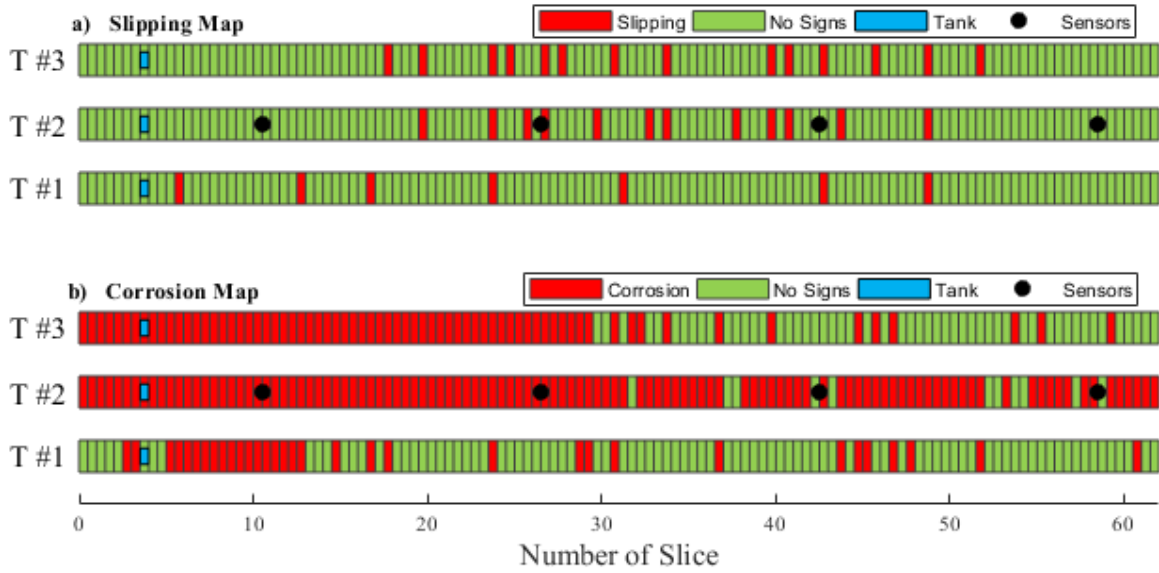


Figure 3-8 Locations with visible a) slipping and b) corrosion.

3.5 Conclusions

In this paper, the candidate used accelerated corrosion experiments to investigate different sources that release acoustic waves when pre-stressing tendons buried in concrete corrode. Acoustic sensors and DAQs were used to detect and record released acoustic waves. The beam was cut into 62 slices in order to inspect the condition of the tendons. The condition of the tendon was not obviously correlated with the origin of the AE signals. The AE signals mechanism is likely the loss of bond between concrete and tendons as wire breaks were not observed. The cumulative number of events within a region is a potential indicator of damage progression. Future work correlating AE event density with loss of structural capacity would be a useful line of study.

4 Acoustic-Guided Wave Detection of Corrosion Pits in Grounding Rods Using Fuzzy C-Means and NSGA-II

4.1 Abstract

In this work, acoustic pulses were launched into ground rods and used to detect loss of cross-section due to corrosion without the need for excavation. These ground rods are a critical element of power distribution substations. The rods are used to establish electrical “ground” for the equipment and personnel. Echos are produced when the launched acoustic pulses reflect from corrosion-damaged sections or the end of the rod. A reliable method to analyze pulse-echo signals to detect cross-sectional loss in grounding rods is crucial. However, variations in soil attenuation and sensor-to-rod coupling make reliable analysis challenging. In this paper, the fuzzy c-means clustering algorithm was applied to signals of guided wave pulse-echo to detect corrosion damage in grounding rods. A database of realistic acoustic guided-wave pulse-echo signals was created using accelerated corrosion on copper-coated steel grounding rods to create corrosion defects with 50% cross-sectional loss. The rods were covered with different thicknesses of polymer clay to simulate field-observed ranges of acoustic attenuation. The Non-dominated sorting Genetic Algorithm (NSGA-II) was used to select an optimal acoustic feature set used by the fuzzy c-mean algorithm. The optimized algorithm is insensitive to attenuation due to varying soil conditions. The defect detection method produced low false positives and achieved a depth resolution of approximately 0.3 m. Monte Carlo analysis showed the proposed method detects >99% of damaged segments as damaged, and 92% of intact segments as intact, with a 90% probability.

4.2 Introduction

Substations play a crucial role in the distribution of electric power by transforming high voltage power to lower voltages for distribution to final users. A critical element of the substation is the network of rods driven into the ground that provides an electrical ground grid for the equipment and personnel.

As electric substations age, their grounding rod network suffers from corrosion, and the safety of personnel and equipment can become compromised. Since ground rods are buried and are not easily visually inspected for corrosion, the only effective means of inspection involved disconnecting the rods from the grounding network and excavating the rod for inspection, which is a time-consuming and expensive operation. There are approximately 70,000 substations alone in North America and 70% of them are more than 25 years old (Williams, 2010). Maintaining the integrity of the ground rods is vital to the safe operation of substations (Fu et al., 2019). In addition, substation failures have a significant economic impact (Oughton et al., 2019). Therefore, it is critical to detect when ground rods networks have corroded to the point where they no longer provide adequate protection to the equipment and operating personnel.

Beyond extraction, very few means are available to detect the progress of corrosion in individual ground rods. Acoustic pulse-echo methods are a promising tool for damage detection in embedded rods, and a number of studies have been reported in the literature. For example, Sharma and Mukherjee used pulse-echo sensors to detect and localize defects of steel reinforcement (Sharma & Mukherjee, 2010), and Lu et al. used guided waves and principal component analysis for damage detection of reinforced concrete beams (Lu et al., 2013). Mustapha et al. (Mustapha et al., 2014)

and Miller et al. (Miller et al., 2013) employed guided waves to monitor reinforced concrete. In addition, the pulse-echo method was used in applications such as monitoring submerged plates (Sharma & Mukherjee, 2015) and steel strands (Farhidzadeh & Salamone, 2015). The acoustic pulse-echo technique also was used to detect cross-sectional loss in steel rods embedded in soil (Shoji & Higashi, 2014; Shoji & Hirata, 2016; Zhao et al., 2019; Durham et al., 2020). However, the detection of corrosion progression in ground rods is challenging due to the varying soil conditions surrounding the rods. For rods surrounded by air, the attenuation of acoustic signals is typically very small, often less than 1 dB/m. When rods are embedded in the soil, the attenuation of acoustic signals is very variable but can be over 6 dB/m. As attenuation varies with soil type and conditions, the classic method of setting a threshold to detect acoustic reflections (used in the literature) is impractical (Papa et al., 2021; Etxaniz et al., 2023). The reliable use of acoustic pulse-echo techniques to detect cross-sectional loss will require insensitive-to-attenuation techniques to detect acoustic pulses.

In this paper, the candidate presented an automated method to detect cross-sectional loss due to corrosion in grounding rods insensitive to signal attenuation. This was accomplished using a genetic algorithm, and a database of variable attenuation signals gathered from laboratory corroded rods with polymer clay coatings to simulate soil. Fuzzy c-means clustering algorithms in combination with features that had some degree of self-normalization, were chosen to minimize the effects of attenuation. The laboratory corroded rods were created using accelerated corrosion methods on copper-coated steel grounding rods to reach 50% cross-sectional loss. 50% cross-sectional loss was chosen as the point at which the rod reached the end of life. The corrosion defects were located at different positions for each rod to create a diverse database of acoustic

pulse-echo signals. Varying amounts of polymer clay were applied to the rods to simulate varying attenuation of soil. The optimal acoustic features to feed into the Fuzzy c-mean were selected using the Non-dominated sorting Genetic Algorithm (NSGA-II).

4.3 Materials & Methods

In this work, the Fuzzy c-means clustering and acoustic pulse-echo technique are used to detect cross-sectional loss due to corrosion in grounding rods. A database of acoustic guided-wave signals from grounding rods with corrosion defects created through accelerated corrosion experiments was used. A Fuzzy c-means algorithm used sets of features extracted from the signals to cluster signals and identify corroded segments. The NSGA-II algorithm was used to find optimal sets of features to use by the clustering algorithm. The NSGA-II algorithm identifies groups of near optimal features. In order to make the final selection the acoustic waves collected from the accelerated corroded rods are divided into two databases. So, half of the acoustic waves (selection database) are used for feature selection using the NSGA-II, and the other half (validation database) is used to validate the outputs of the NSGA-II algorithm and choose the features set for the Fuzzy c-means. The performance of the clustering method, which uses the selected acoustic features, is examined on a database (testing database), including acoustic waves gathered from field extracted grounding rods. This database is not used for the features selection and validation.

4.3.1 The Pulse-Echo Technique

The pulse-echo technique is a non-destructive testing method using acoustic or ultrasonic waves to detect defects in materials (Jeong et al., 2020; Dutta et al., 2021; P. Chen et al., 2021; Park et al., 2021; Wong et al., 2022). The principle of the pulse-echo technique to detect defects in buried

grounding rods is shown in Figure 4-1, in which a transducer emits a wave into a rod and receives the echoes of the wave rebounded from defects and/or the end of the rod. The acoustic pulse can be launched in a number of different modes. The longitudinal mode in steel rods of the type used in this work travels at ~ 5000 m/s. For rods 3m long then the time between the launch of the wave and the echo from the end of the rod is approximately 1.2 ms. The signal from defects will arrive in less time.

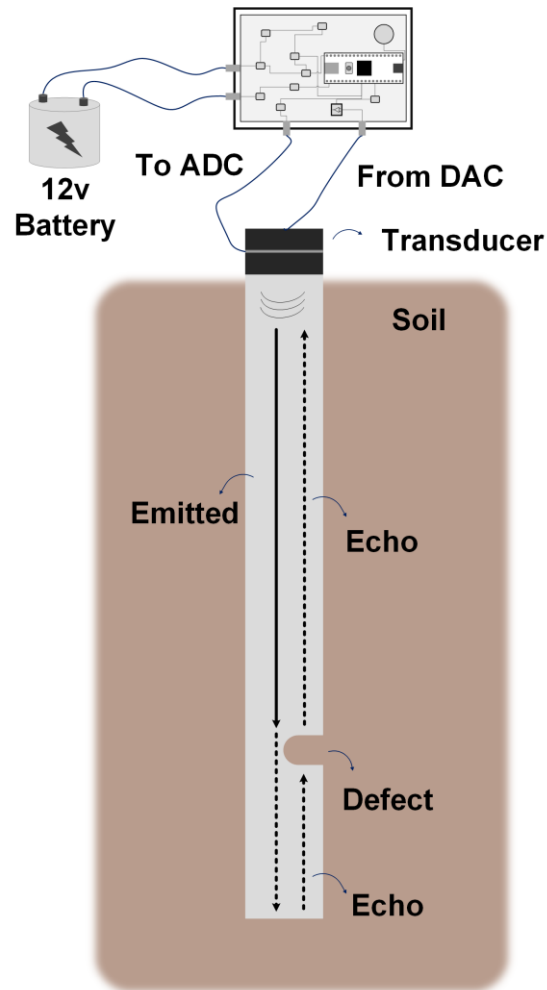


Figure 4-1 The principle of the pulse-echo technique to detect defects in buried grounding rods

4.3.2 Accelerated Corrosion Setup

Copper-coated grounding rods mostly have concentrated and local corrosion damage, while the

shape of corrosion damage (corrosion pit) is non-uniform with a rough surface. This rough and non-uniform surface reflects acoustic waves differently than smooth machinery cuts (Mahmoudkhani, Zhao, et al., 2019). Therefore, the acoustic signal database was collected from rods with corrosion pits created by accelerated corrosion to more closely match signals from actual damage. To prepare three copper-coated grounding rods with 50% cross-sectional loss due to corrosion, an accelerated corrosion set-up was used to corrode them in different locations. Each rod has a corrosion pit, and to have a diverse database, the location of the damage is different for each rod. The candidate named the rods A, B and C, and set the set-up to have a corrosion defect at the middle of rod B. The location of the defect was at three-quarters of the length and a quarter of the length from the cap of the rod, in Rods A and C, respectively. The rods had a length of 3m and a round cross-section. The diameter of rod A was 17.30 mm, while the diameters of rods B and C were 14.30 mm.

Figure 4-2 shows the experimental set-up used to create corrosion pits with shapes more like those expected in the field. The details of one of the tanks are shown in Figure 4-3. As can be seen, a stainless steel sheet, the rod and 5% NaCl solution are used as the cathode, the anode and the electrolyte. The DC power supply with a constant 0.5v voltage and 0.004A current was used to accelerate the corrosion process. To concentrate corrosion to specified locations, a small cut was made in the copper cladding of the rod, and the remaining parts of the rods that were submerged were covered by waterproof plumbing rubber tape. No corrosion was observed under the tape.

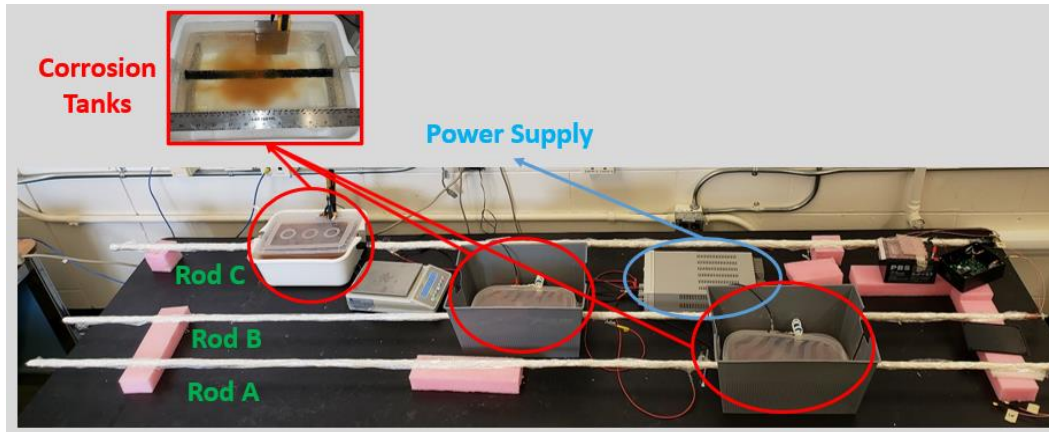


Figure 4-2 The acceleration corrosion set-up

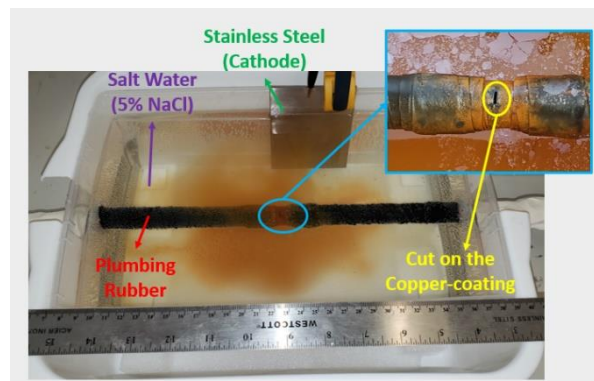


Figure 4-3 The corrosion tank of rod C

4.3.3 Laboratory Acoustic Testing of Grounding Rods

For the analysis, a representative set of acoustic signals for intact and corroded grounding rods with varying levels of attenuation was collected. Three out of four were corroded rods from the previous section (rods A, B and C), and Rod D was an intact grounding rod. The rods had a length of 3 m and a round cross-section. The diameters were 17.3, 14.3, 14.3 and 17.26 mm for rods A, B, C and D, respectively.

The acoustic transducer and signal DAQ device used in this work were developed by Durham et

al. (2020). The acoustic transducer was attached to the cap of the rods and included two piezoelectric discs placed between two steel bars that act as transmission lines (Zhao et al., 2019; Durham et al., 2020). A microcontroller signalled a digital-to-analog converter (DAC) to generate an electrical sinusoidal pulse that was applied to one piezoelectric disc. The electrical signal was transduced by the piezoelectric discs to produce an acoustic pulse.

Once the acoustic pulses were generated, they were coupled into the rod using a layer of Ultrasonix couplant gel between the surfaces of the rod and the transducer. The transducer and rod surfaces were machined to produce a flat and smooth surface between the transducer and the caps of the rods.

The launched acoustic waves travelled in the rods and were reflected from the end of the rod or from defects in the rod. The reflected acoustic pulses then returned to the transducer and produced an echo signal. An analog-to-digital converter (ADC) sampled the received acoustic signals from the second piezoelectric disc at 909k samples per second. For each pulse, 1271 samples or approximately 1.4 ms of data were collected.

Different frequencies have different reflection and transmission characteristics. Therefore, acoustic pulse-echo signals were gathered over a range of frequencies. Each acoustic pulse contained five sinusoidal cycles. For each test, 24 different frequencies in the range from 30 to 84 kHz were measured. The lower frequency limit is due to maintaining a spatial resolution of less than $\sim 0.4\text{m}$, and the higher frequency limit is due to excessive loss.

Significant variation in acoustic loss has been observed in field measurements (Mahmoudkhani,

Zhao, et al., 2019; Zhao et al., 2019). In the laboratory, layers of polymer modelling clay with varying thicknesses were applied to the rods to reproduce the acoustic loss variation observed in the field. To produce acoustic losses similar to the range of signal attenuation observed in the field 200, 250, 300 and 350g was applied uniformly along the length of the rod (Zhao et al., 2019). The range of attenuations was varied from the lowest generally observed in the field to the highest observed in the field. In the field, attenuations from 9 dB to 40 dB or 1.5 to 6.7 dB/m were observed at 35 kHz. Although the diameters of the rods were different in the experiments, the same amounts of clay was applied on them to increase the diversity of the collected AE database. Figure 4-4 shows a sample of recorded signals when a 35 kHz pulse was launched into rod B covered with 200 g polymer modelling clay. As can be seen in the figure, the pulses reflected from the end of the rod and the corrosion defect are clearly detectable.

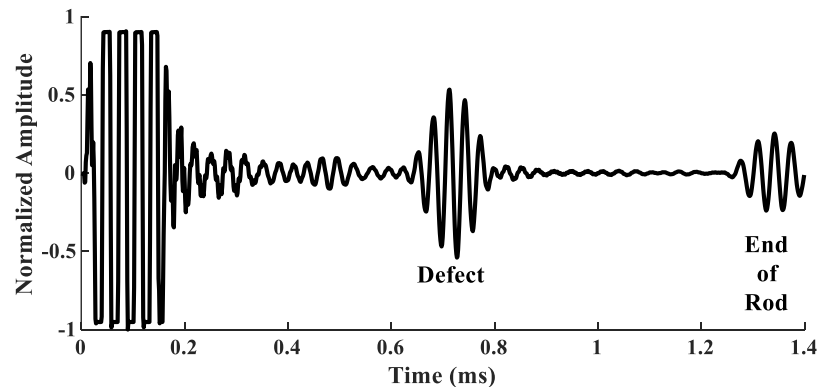


Figure 4-4 The normalized signal of a 35 kHz pulse launched into rod B covered with 200 g clay

Every time a transducer was attached to the cap of a rod, the bonding between the surfaces was slightly different. The reason for this difference was the different pressure between the surfaces and the different thicknesses of bounding gel (Fateri et al., 2015). Therefore to reflect the possible

diversity in signals, the signals were taken with the transducer connected to the rods two separate times for each condition. One time was used for the feature selection database (section 4.3.6), and the other time was used for the validation database.

4.3.4 Features of Acoustic Signals

A spatial resolution of 30 cm was chosen for this work. As a result the signal was segmented into 140 microsecond long blocks (Figure 4-5). For each time segment a number of signal features were chosen that might be expected to change with the defect damage (Jiang et al., 2017; Downey et al., 2018; Pasadas et al., 2020; Liu et al., 2021; T. Wang et al., 2021). To compare different signal patterns and consider the effects of attenuation in their patterns, each of the 24 signals (related to the different launched frequencies) was each normalized. In addition, signal power, signal energy, normalized amplitude, Shannon entropy (Shannon, 1949) and binned normalized Fast Fourier Transform (FFT) curves were calculated for each segment. In this work, the candidate used bins with 10, 15 and 20 kHz widths in the ranges limited between 1 and 100 kHz. For each frequency, the start frequency of the bins was adjusted so that one bin was centered on the launched frequency of the signal (see Figure 4-5). The following equations were used to find the start and end points of the bins:

$$Start = (F - 0.5Width) - Width \times \left\lfloor \frac{F - 0.5Width - 10}{Width} \right\rfloor \quad \text{Equation 4 - 1}$$

$$End = (F - 0.5Width) + Width \times \left\lfloor \frac{F - 0.5Width - 100}{-Width} \right\rfloor \quad \text{Equation 4 - 2}$$

where $\lfloor \cdot \rfloor$ is the floor function, F is the launched frequency, while $Start$ and End are the beginning

and end frequencies of the bins in kHz. To reduce the effects of attenuation, features were normalized using features from the previous time segment. For example, when F and Width are 30 and 10 kHz, the area under the normalized FFT curve for the bin between 15 and 25 kHz calculated for the 5th segment is divided into the area under the normalized FFT curve for the bin between 15 and 25 kHz calculated for the 4th segment. In addition, features were also normalized by dividing by the features calculated for the first segment. In Total, 2024 features were calculated for each time segment of a rod.

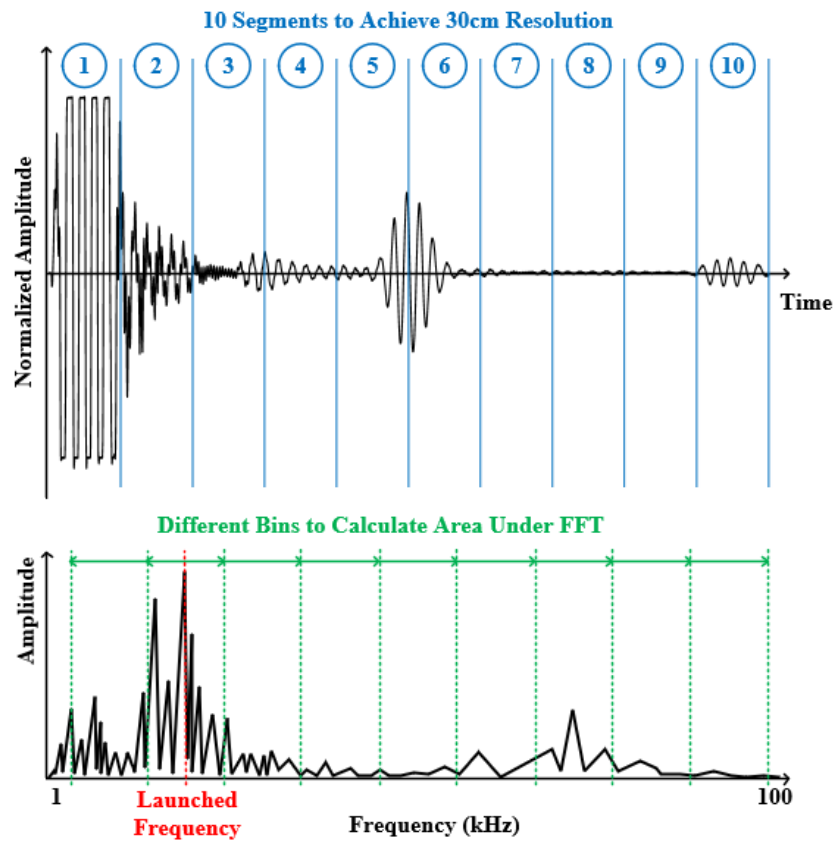


Figure 4-5 The 10 time slices of signals and the bins of FFT curves

4.3.5 Fuzzy C-means Clustering Algorithm

In this work, the Fuzzy c-means clustering algorithm (Dunn, 1973; Bezdek, 1980) was used to identify the damaged segments in the rods using each segment's acoustic features. The Fuzzy c-means algorithm was set to cluster the bins described in the previous section into “Damaged” and “Intact”. The number of clusters, the number of iterations, and the minimum desired improvement in objective function were set to 2, 500, and $1e-6$, respectively. The clustering algorithm were evaluated based on the ratio of damaged segments identified as “Damaged” and the ratio of intact segments identified as “Damaged”. Both these measures were used as cost functions in the NSGA-II.

As can be seen in Figure 4-4 and Figure 4-5, the first two time segments could be saturated with the launched five-cycle sinusoidal pulse. The reason was that the piezoelectric discs used for launching and sensing acoustic waves were at the same place, so the sensing disc could only sense the strong initial launched wave in the first two bins. By increasing the frequency of the launched wave, its length was decreasing and saturated only for the first bin. In this study, the features of the first two segments were not fed into Fuzzy c-means. However, in future studies, the features of the unsaturated second bins will also be fed into the clustering algorithm.

4.3.6 Features Selection using Non-dominated Sorting Genetic Algorithm-II (NSGA-II)

Using different combinations of 2024 features in the Fuzzy c-means algorithm yielded different damage detection outcomes. Selecting an optimal feature set is vital to reaching a suitable damage detection accuracy for the grounding rods. In this work, the well-known and widely used (Cai et

al., 2019; H. Li et al., 2021; N. Li et al., 2021; Feng et al., 2022; Z. Li et al., 2022) Non-dominated Sorting Genetic Algorithm (NSGA-II) (Deb et al., 2002) was used to find an optimal set of features for detecting cross-sectional losses in grounding rods. NSGA-II can find one or more sets of optimal solutions within the feasible space of an optimization problem (Deb et al., 2002).

The flowchart of the NSGA-II-based feature selection is shown in Figure 4-6. The details of the NSGA-II algorithm can be found in (Deb et al., 2002). NSGA-II was programmed in MATLAB R2022a and validated with (Deb et al., 2002). The features matrix is a fixed thing. The feature selection procedure is started with assembling a features matrix. The matrix has 128 rows for each segment of the rods of the database and 2024 columns, one for each feature. The feature selection database has 128 segments; four rods (A, B, C and D) and four levels of clay applied on each rod, and eight segments of each testing case (a rod covered with clay) are used in this paper. Each individual includes a number of features. A one indicates the feature will be included in the Fuzzy c-means clustering, and a zero indicates the feature will not be included. The NSGA-II algorithm begins by creating 1000 parents, each with a vector of 2024 randomly chosen zeros or ones elements. A zero or one indicates if a feature is to be used by an individual in the clustering or not. In the next step, the parents are used by the Fuzzy c-means algorithm for clustering and computing the cost functions explained in the previous section. The first cost function is the ratio of segments identified as “Damaged” compared to actually damaged segments, and the second cost function is the ratio of intact segments identified as “Damaged” compared to the number of intact segments. Then, the parents are ranked and sorted based on the procedures of NSGA-II (Deb et al., 2002). In the next step, 512 offspring and 300 mutants are created using binary tournament selection, simulated binary crossover and polynomial mutation operators (Deb & Agrawal, 1995). Similar to

the parents, offspring and mutants are then fed to Fuzzy c-means and ranked. After that, the populations (parents, offspring, and mutants) are merged into a new population of 1812 individuals. From the population of 1812 individuals and the best 1000 individuals are selected as the parents of the subsequent iteration. After reaching the maximum number of iterations (500 iterations), the individuals with rank 1 (Deb et al., 2002) are considered for use in the final solutions.

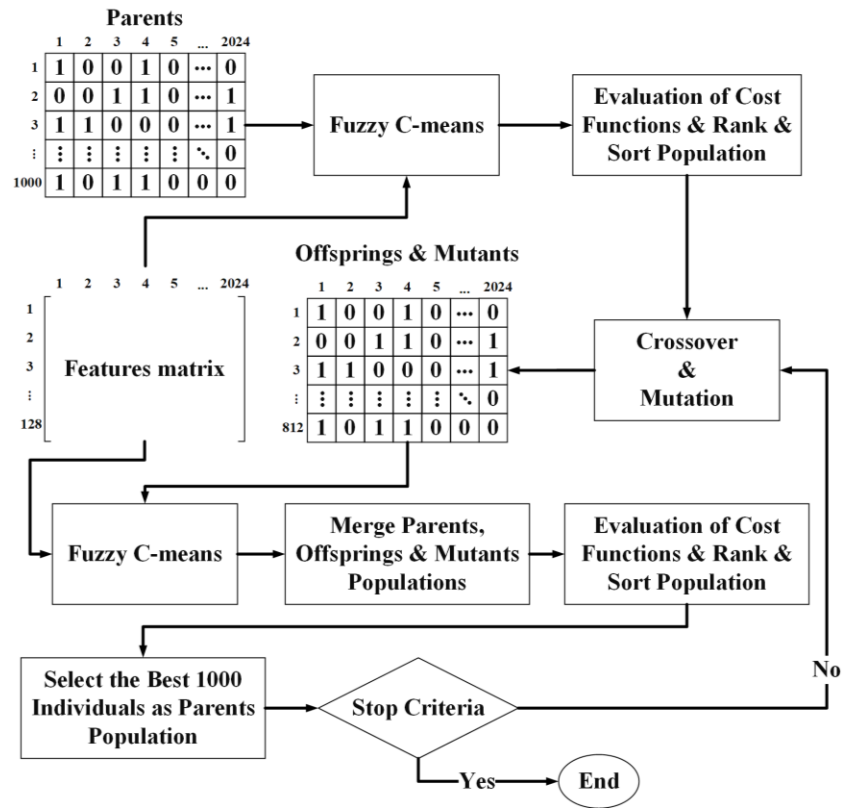


Figure 4-6 The NSGA-II-based feature selection procedure

4.3.7 Testing of Field-Extracted Grounding Rods

To evaluate the performance of the method, the acoustic signals from three 3.06 m long grounding rods extracted from a substation were collected. Rod α and β were copper-coated steel rods, while

rod θ was zinc coated steel.

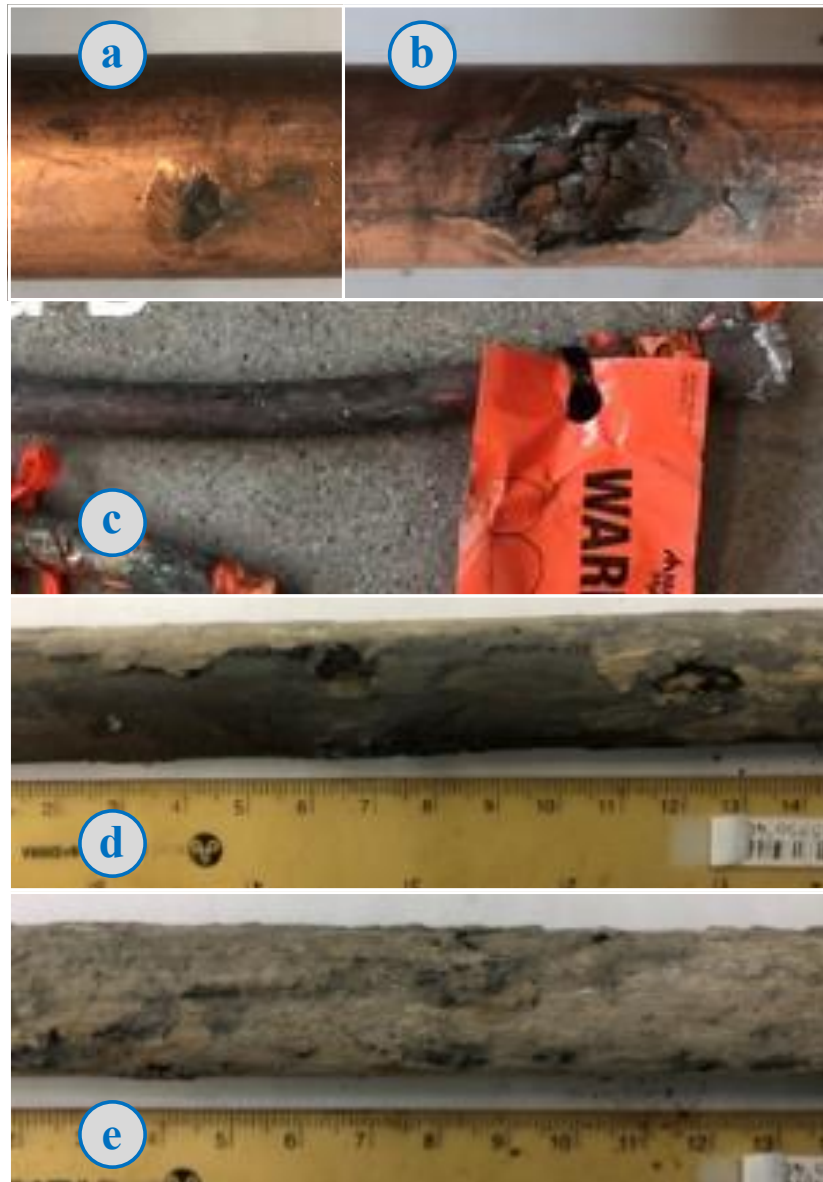


Figure 4-7 The observable defects of the test rods; a) defect I, b) defect II, c) the bent part of rod β , d) area I and e) area II

Rod α had two visible defects at 0.92 m and 2.22 m distances from the cap. The smaller pit (defect I) had a 2×3 mm area and 1mm depth, and the bigger one (defect II) had a 10×20 mm area and 2 to 3 mm deep. Rod β had no noticeable corrosion damage but had a 0.16 m bent part near its cap.

Rod θ had two surface corrosion defects with less than 0.15m length located at around 1.35 m (area I) and 1.88 m (area II) distances from the cap. The defects, areas and the bent part were shown in Figure 4-7. For signal collection, 320, 300 and 300 g polymer clay were applied on rods α , β and θ , respectively, to have a similar attenuation observed for them in the field (Zhao et al., 2019). The caps of the rods were ground smooth using a hand grinder and sandpaper to produce a flat and smooth surface between the transducer and the caps of the rods. The tests were repeated two times. These signals were not included in the selection and validation databases.

4.4 Results & Discussions

The experiments were carried out on zinc or copper-coated steel grounding rods with a range of clay coatings that emulated acoustic losses observed in field measurements. A sample of recorded signals when a 35 kHz wave launched into rods A, B, C and D covered with 200 g clay was shown in Figure 4-8. The pulses reflecting from the rod ends and the defects are clearly visible and detectable. With the transducer mounted at the end of the rod, the wave mode is the longitudinal mode (Zhao et al., 2019). An example of attenuation effects can be seen in Figure 4-9, where 35 kHz waves were launched into rod A covered with 250 and 350g clay. Signals recorded at two different recording times for the same rod are plotted in Figure 4-10 as an example of the variation in received signals for rod C at a launch frequency of 35 kHz and a covering of 350 g clay. Everything has been kept constant in this case, but the transducer contact was different. The signals are largely the same, but some important variations can be observed. If Figure 4-10(a) is compared to Figure 4-10(b), the signals in Figure 4-10(b) have a high-frequency component, especially between 0.2 and 0.6 ms. This example demonstrates some of the signal complexity that makes the unambiguous detection of defects challenging. This example highlights the need to make use of as

much information contained within the signal as possible to minimize misidentification of damage.

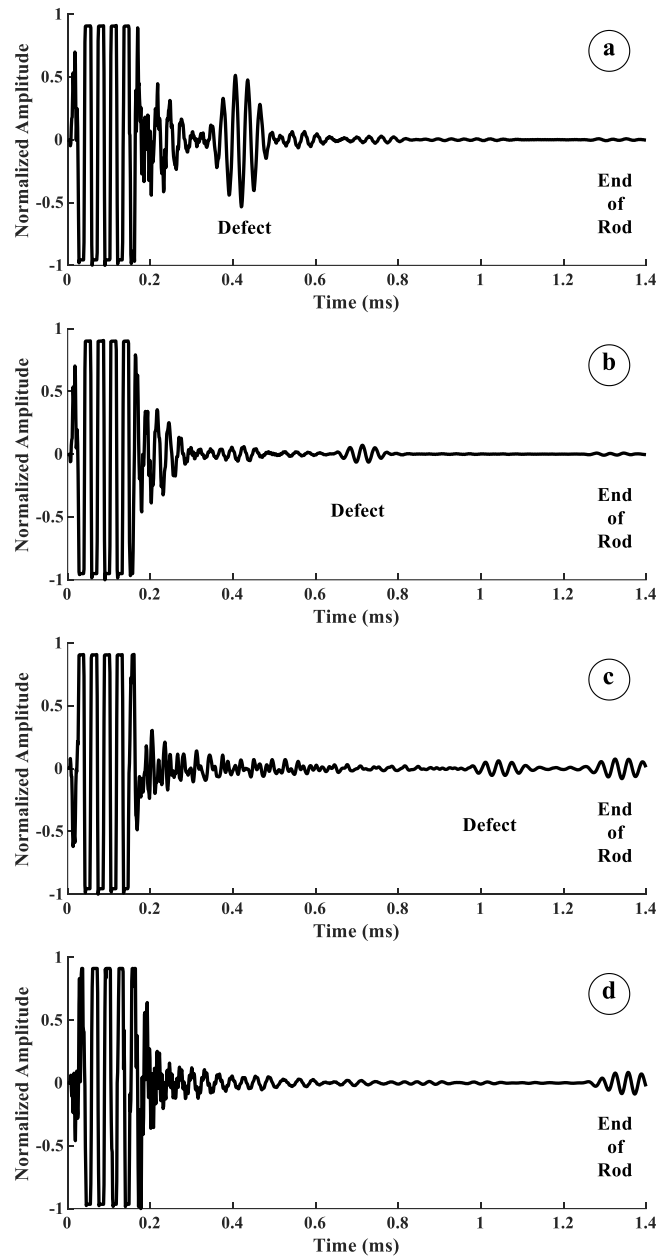


Figure 4-8 The normalized signals of 35 kHz pulses launched into a) rod A, b) rod B, c) rod C and d) rod D covered with 200 g clay

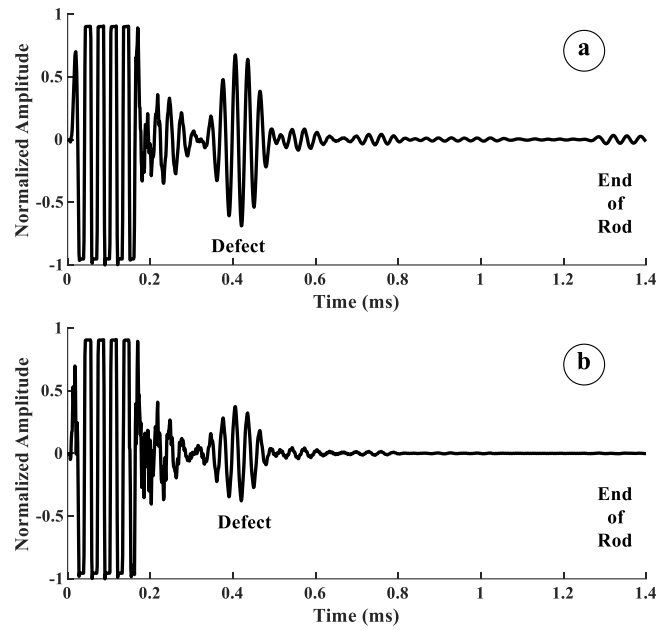


Figure 4-9 The normalized signals of 35 kHz pulses launched into rod A covered with a) 250 g and b) 350 g clay

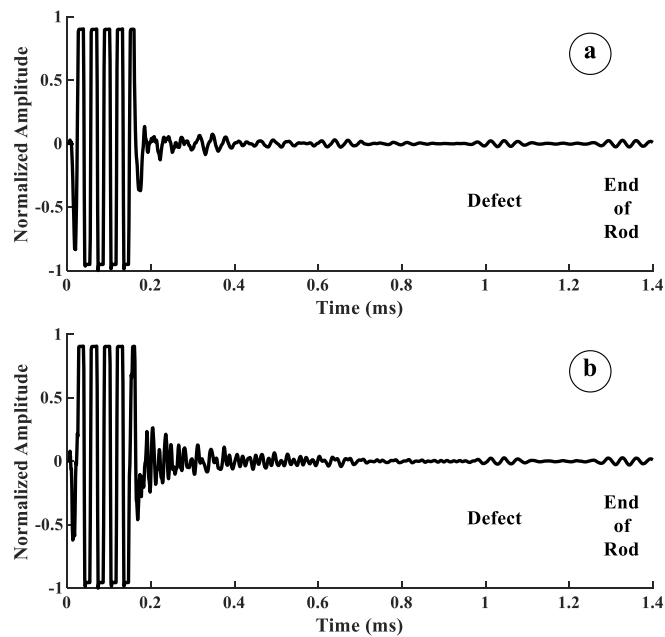


Figure 4-10 The normalized signals of 35 kHz pulses launched into rod C covered with 350 g clay in the two separate measurements

The feature selection algorithm based on NSGA-II (described in section 4.3.6) was used to find the optimal features for damage detection in grounding rods. Two different criteria were used in the optimization process; the ratio of damaged and the ratio of intact segments were detected as "Damaged". The NSGA-II algorithm was designed to explore a large portion of the solution space using random initial parents and Randomness in mutation and crossover operators (Deb & Agrawal, 1995; Deb et al., 2002). Consequently, the results of the NSGA-II-based algorithm could be different for each run.

The candidate ran the feature selection algorithm 30 times with 1000 parents, 512 offspring, 300 mutants, and 500 iterations to consider more possible solutions. The candidate found it possible to detect the end of the rods and the damaged segments of the rods as Damaged. In addition, all intact segments of rod D (the rod with no damage) could be detected as intact. It was possible to detect intact segments of a rod with a corrosion defect (rods A, B and C) as damaged. This level of detection is acceptable as repairing grounding rods is uneconomical, and they are replaced with new rods once they have been identified as damaged. The candidate combined the results of all 30 runs together and selected only the unique individuals. This process produced 615 possible unique feature sets. The 615 feature sets were further refined by going through each feature set and examining the impact of each feature. For each feature set, each feature was evaluated to determine if its inclusion improved the detection performance or not. If the feature did not improve the detection performance, it was eliminated from the feature set. This process continued until all the features in each feature set had been evaluated. At the end of this process, all the duplicate feature sets were eliminated, and only unique sets were retained. This process reduced the final number of feature sets from 615 to 16. Each of the 16 feature sets contained between 376 to 415 features.

On average, for these 16 feature sets, 12 intact segments out of 96 were identified as damaged. In addition, 32 out of 32 damaged and end of the rods' segments were correctly identified.

The features within each feature set were not identical, but they shared some similarities. The differences and similarities can be seen in plots comparing the features chosen. Figure 4-11 is a plot of the selected features for the 16 feature sets. For each frequency, the features normalized using previous segments and the first segment are contrasted. The features using previous segment normalization are favoured. For example, for frequencies between 22.5 and 35 kHz, no features normalized to the first segment were chosen. The patterns can be very similar. Also, between 22.5 and 35 kHz, the number of chosen features is nearly identical. This demonstrates that the NSGA-II algorithm often finds the same feature sets for many frequencies. However, at other frequencies, such as 62 kHz, the number chosen is more variable. Within the 16 feature sets, most features were selected from the features which were normalized to the features of the previous segment (described in section 4.3.4).

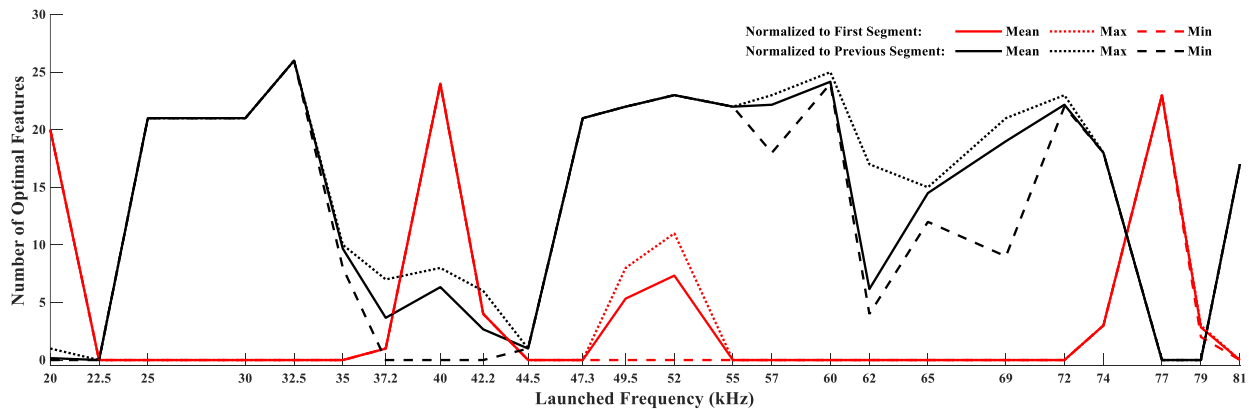


Figure 4-11 The number of features selected from each launched frequency for the 16 optimal feature sets

After further examining the results from the selection database, some feature sets were found to

perform better than others. In only 3 out of 16 feature sets, all segments with corrosion defects and all the rods' ends were detected as damaged, and all intact segments of the rod with no damage (rod D) were detected as intact. Identifying the ends as damaged was beneficial as this could be used to identify rods that were undamaged to the end. So, using these additional criteria, the number of feature sets was reduced to 3.

When these 3 feature sets were used on the validation data set. With two feature sets, all the defective segments and the end of the rods were detected as damaged in the validation database. However, there were misdetections in the intact segments of the undamaged rod. In one case, one intact segment was misidentified and in the second case two intact segments were misidentified. Only in one of the feature sets, all segments with corrosion defects, and all rod ends were detected as damaged. In addition, in the same feature set, all intact segments were detected as intact. So, this feature set that met the criteria was selected for testing with the field-collected data. The detection results using this feature set on the selection and validation databases are shown in Figure 4-12 and Figure 4-13. As explained earlier, the first two segments of each rod were not included. The figures note the amounts of polymer clay used to encase each rod. Even with different levels of attenuation, segments with corrosion defects and ends of the rods were correctly detected as damaged. Moreover, the undamaged segments of rod D were identified as intact. Detecting segments as damaged could result from the variation in the connection between the sensor and the rod cap, as in Figure 4-10(b), or the variation in the attenuation. Some segments, especially in the middle of rod A, were detected as damaged. This could be due to acoustic pulses that returned at a lower velocity due to mode conversion into flexural modes, for example (Zhao et al., 2019).

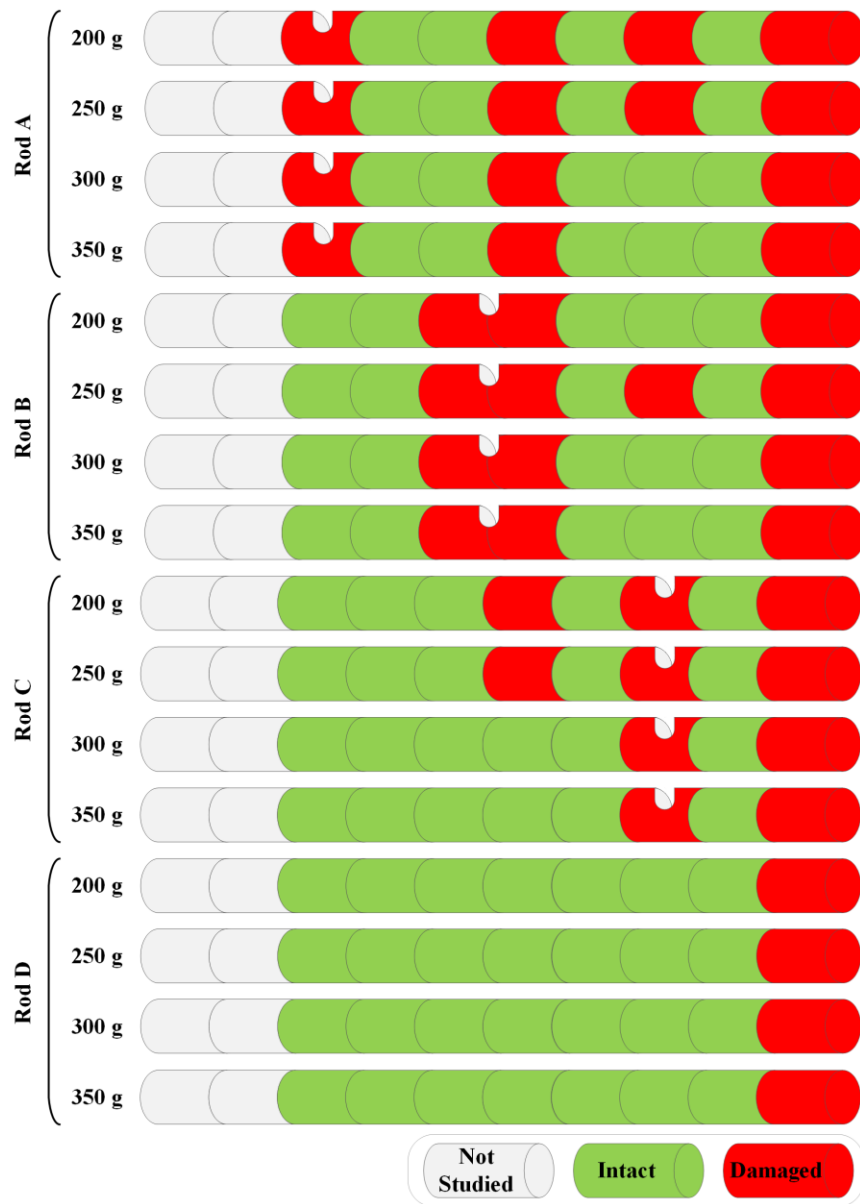


Figure 4-12 The results of defect detection on the selection database using the optimal features

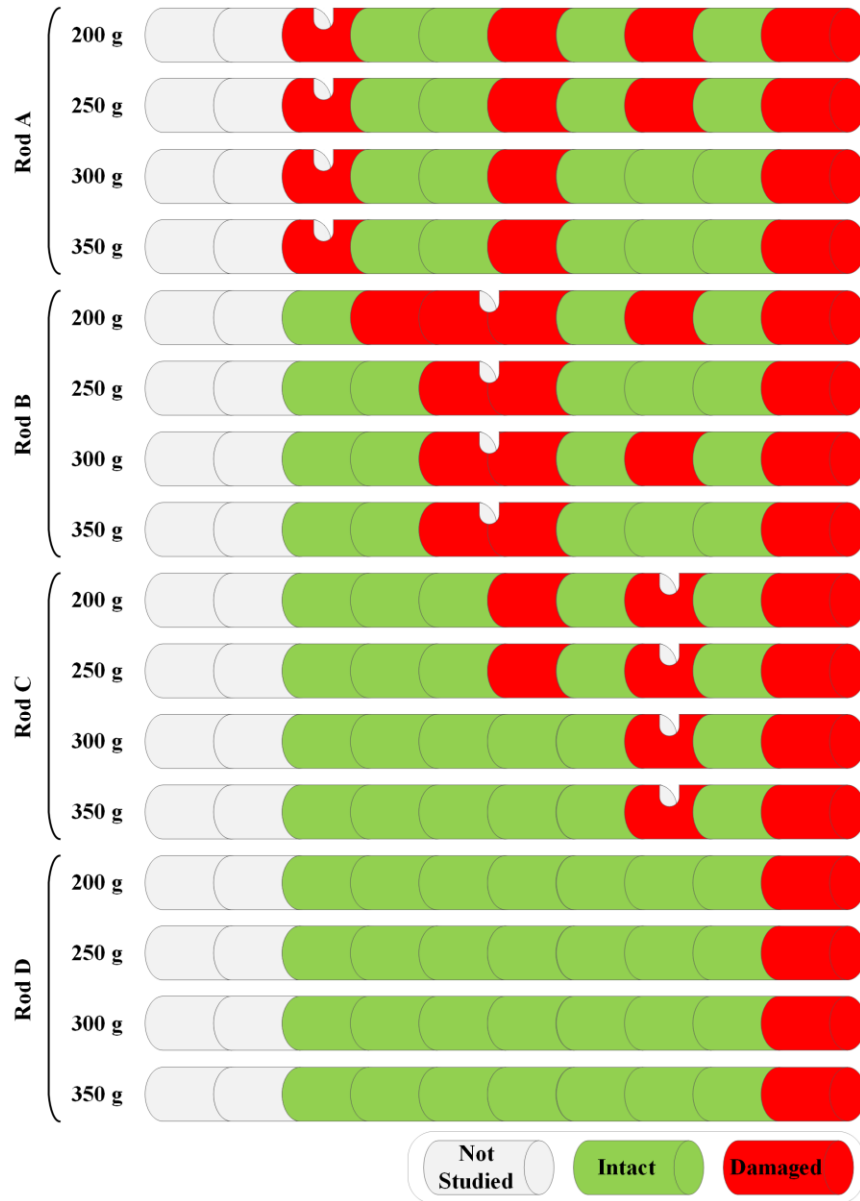


Figure 4-13 The results of defect detection on the validation database using the optimal features

A further test of this feature set was carried out on field-recovered rods. The selected optimal set of features and its corresponding tuned Fuzzy c-means algorithm were also applied to the signals of rods α , β and θ extracted from a substation in Winnipeg, Manitoba. Figure 4-14 Shows examples of recorded signals for 35 kHz pulses being launched into the rods. The rebounds from Defect II, Area I and Area II were noted on the signals. The signal of rod β had a noticeable high frequency

from 0.4 to 0.8 ms. These could be due to mode conversion into torsional modes due to the bent part of the rod shown in Figure 4-7.

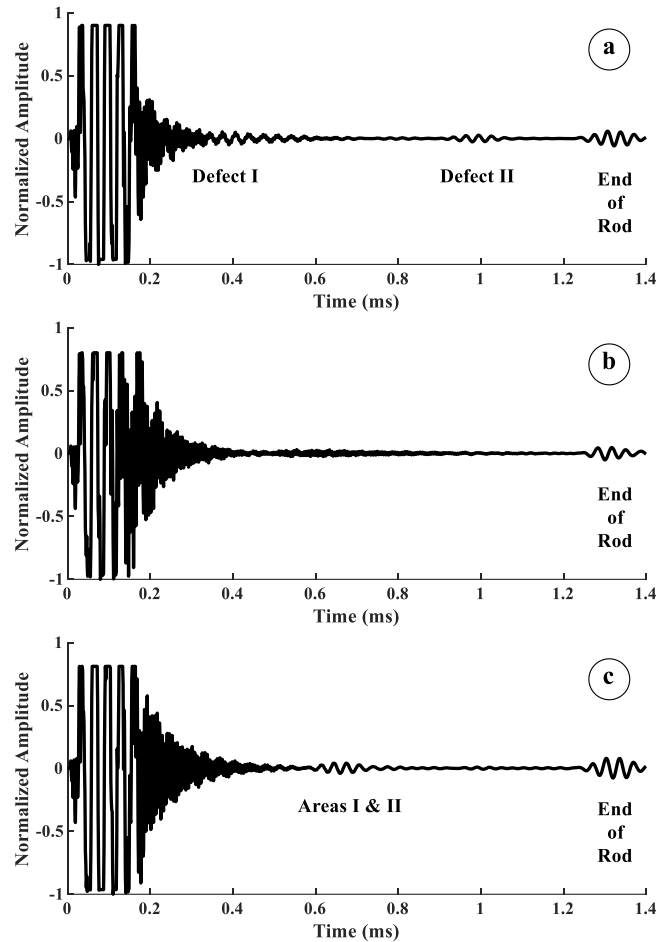


Figure 4-14 The normalized signals of 35 kHz pulses launched into a) rod α , b) rod β and c) rod θ

In the defect detection results in Figure 4-15, the ends of the rods were identified as damaged, and all other segments of rods β and θ were detected as intact. Rod θ had two surface corrosion areas that were not identified as damaged, which agreed with the goal of 50% cross-sectional loss detection. Defect I from rod α was also identified as intact, which agreed with the goal. Defect II was detected for rod α ; however, its location was not detected accurately. Rods A and α had defects

at the same segments (8th segment from the cap), but defect II had around 7 cm distance from the 7th segment while defect of rod A was 15 cm away from its previous segment. This accuracy was acceptable for expected applications where damaged grounding rods will be replaced with new rods.



Figure 4-15 The results of defect detection on the test database using the optimal features

For the selected features set, if all the segments are considered, 0.09% of undamaged segments are identified as damaged, and 0.03% of damaged ones are identified as undamaged. To predict the effect of this on a survey of grounding rods, a Monte Carlo simulation (Rubinstein & Kroese, 2016) was used. The candidate investigated the performance of the tuned algorithm versus the untuned algorithm using a Monte Carlo simulation. The Monte Carlo simulation used 10,000 sets of 64 segments randomly chosen from the selection, validation, and testing databases. Using these randomly selected segments, Fuzzy c-means clustering was carried out using all 2024 features and was compared to clustering using the optimized feature set of 412 features. Cumulative probability curves were plotted in Fig. 16. If a 90% probability threshold is chosen to be used, only 79% of

intact segments would be detected as intact using the full 2024 features. Using the optimized features set, 92% of intact segments would be detected as intact. By using the full features, 37% of intact segments would be identified as damaged. This percentage drops to 15% when using the optimized set. The correctly detection rate for damaged segments is 74% when all the features were used. This detection rate rises to >99% when using the optimized features set. The use of an optimized feature set dramatically improves the correct detection of damaged and intact segments.

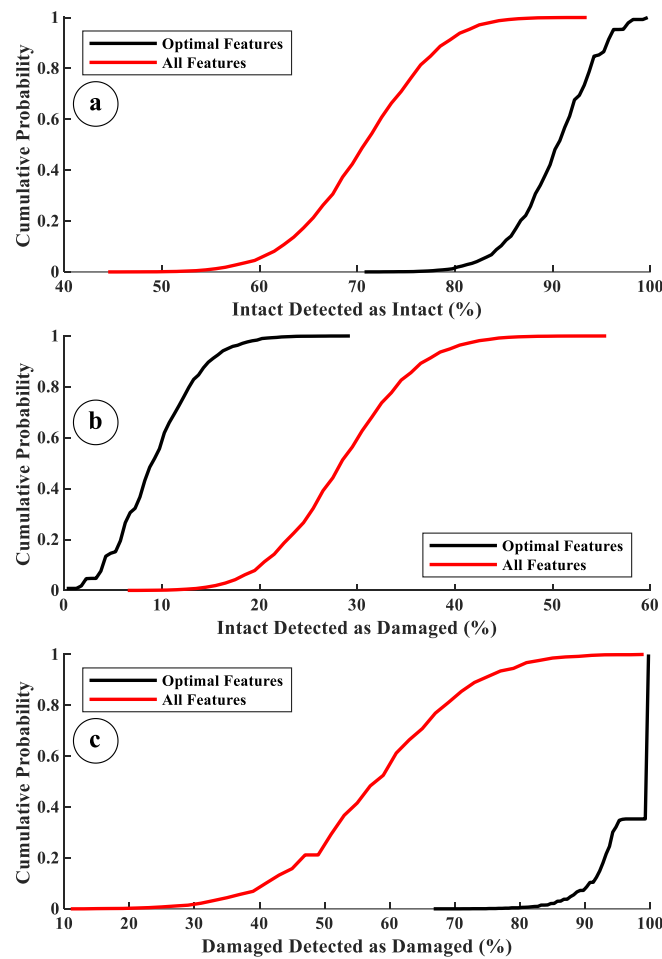


Figure 4-16 The cumulative probabilities of a) intact segments detected as Intact, b) Intact segments detected as Damaged and c) damaged segments detected as Intact for both cases of using the optimal features and all features

4.5 Conclusions

In this work, the candidate developed an automated method using fuzzy c-means clustering and acoustic pulse-echo technique to detect cross-sectional loss due to corrosion in grounding rods. A database of realistic acoustic guided-wave pulse-echo signals was created using accelerated corrosion on copper-coated steel grounding rods to create corrosion defects with 50% cross-sectional loss. The rods were covered with different thicknesses of polymer clay to simulate observed ranges of acoustic attenuation. Starting with a feature set containing 2024 features, a Fuzzy c-mean algorithm in combination with a Non-dominated Sorting Genetic Algorithm (NSGA-II) was used to identify a feature set optimized to identify damaged and intact segments. Using the optimized features set, all rod ends, and the damaged segments were correctly identified. In addition, all intact segments of the intact rods were correctly identified, with no damage were identified as intact. In a Monte Carlo simulation on the entire database, including field-collected rods, the proposed method correctly identified >99% of damaged segments as damaged and 92% of intact segments as intact, with a 90% probability. The addition of further field data is expected to improve the performance of this approach.

The use of pulse-echo in combination with the proposed algorithms is robust, reliable, and insensitive to soil types and conditions to be used with the acoustic pulse-echo technique to detect cross-sectional loss.

5 Conclusion & Future Work

5.1 Conclusion

This thesis aimed to achieve two main objectives. The first goal was to investigate an innovative solution to monitor wire breaking in pre-stressing/post-tensioning tendons. In order to achieve this goal, the author conducted laboratory and field experiments to collect an AEs database of wire breaks, grout cracks, and environmental signals present in operating pre-stressed concrete bridges. Using a Fuzzy c-means clustering algorithm AEs from wire breaks could be differentiated from the other types of AE events. The author also post-processed the database to make the proposed method insensitive to attenuation. The author used the NSGA-II algorithm to find optimal combinations of features to feed into the Fuzzy c-means to enhance the speed and reliability of the method. Using the NSGA-II algorithm, the author found twelve combinations of features that resulted in an average of 81.06% wire break detection accuracy. Using these results, the author found, on average, 2.69% and 0% of grout cracks and environmental signals were misclassified as wire breaks. This level of detection can provide adequate warning for prestressed girders, such as an AASHTO 36-in prestressed I girder with 16 seven-wire strands. This accuracy means the probability that the proposed method does not detect losing 25% of the prestressing steel of an AASHTO 36-in prestressed I girder with 16 seven-wire strands is 5.8×10^{-21} . Losing 25% of its prestressing steel for this girder means dropping its initial moment strength to the Strength I of AASHTO LRFD Bridge Design Specification (In this case, the bridge is operational, but it should be repaired). The author extended this work to monitor damage progression in pre-stressed beams exposed to accelerated corrosion. The author used acoustic sensors and DAQs to detect and record released acoustic waves. At the termination of the accelerated corrosion experiment, the beam was

sliced into sixty-two cross-sections to inspect and correlate corrosion and tendon slippage with AE signals. The author found the condition of the tendon was not obviously correlated with the origin of the AE signals. The author could conclude that the AE signals mechanism is likely the loss of bond between concrete and tendons as wire breaks were not observed. Moreover, the cumulative number of events within a region is a potential indicator of damage progression.

The second goal of the current research was to investigate an innovative and insensitive to attenuation solution to monitor corrosion cross-sectional loss in grounding rods. In order to achieve this goal, the author conducted accelerated corrosion experiments on different locations of copper-coated steel grounding rods. Using accelerated corrosion experiments, the author simulated realistic corrosion defects with approximately 50% cross-sectional loss in the rod. Then, the author collected a database of acoustic signals from the rods using the acoustic guided-wave pulse-echo technique. During signal collection, the author covered the rods with different thicknesses of polymer clay to simulate observed ranges of acoustic attenuation. The author was able to use the Fuzzy c-mean algorithm in combination with the NSGA-II to identify a feature set optimized to identify damaged and intact segments. Using the optimized features set, the author was able to correctly identify all rod ends and the damaged segments. In addition, the author could correctly identify all intact segments of the intact rods and not identify damaged segments as intact. The author conducted a Monte Carlo simulation on the entire database, including field-collected rods. The proposed method correctly identified >99% of damaged segments as damaged and 92% of intact segments as intact, with a 90% probability. The addition of further field data is expected to improve the performance of this approach. Moreover, the use of pulse-echo in combination with the proposed algorithms is robust, reliable, and insensitive to soil types and conditions to be used

with the acoustic pulse-echo technique to detect cross-sectional loss.

5.2 Future Work

This section describes the limitations of this research and the suggested steps to overcome the limitations. As this thesis had two initial goals, each goal's limitations and future work are described separately.

The first goal;

To investigate an innovative solution to monitor wire breaking in pre-stressing/post-tensioning tendons:

Limitations:

1. The process of collecting wire breaks acoustic signals, as well as grout and concrete crack signals, was time-consuming and expensive. So, collecting a database including AEs from structural elements with different shapes, structural designs and strengths will limit the application of the proposed method.
2. The accelerated corrosion experiments showed the complexity of differentiating the mechanisms of AEs generation in a pre-stressing beam. So, collecting a database with all possible AEs and differentiating them will limit the application of this method as well.

Future Work:

To overcome these limitations, I have the following suggestions for future work:

1. Using an anomaly detection algorithm instead of Fuzzy c-means. Anomaly detection is a method to find rare, abnormal, or unexpected patterns in data. It involves collecting and preprocessing data, selecting an appropriate model, and training it on normal instances. The model then identifies deviations from the normal behaviour as anomalies. An anomaly

detection algorithm can be trained by only environmental acoustic emission signals, which are easy to collect. Then the trained algorithm can be used to identify new events different from environmental signals, such as concrete cracks (Goldstein & Uchida, 2016; König et al., 2021; Samariya & Thakkar, 2021; Villa-Pérez et al., 2021).

2. Collecting only environmental signals from newly built operation bridges in different hours, seasons and weather conditions
3. Finding the optimal acoustic features for the anomaly detection algorithm
4. Using the anomaly detection algorithm to non-environmental acoustic signals in bridges and localize
5. Determining the areas where released AEs are clustered
6. Using the cumulative number of anomalous detected AEs in the clusters as an indication of progressing damage
7. Using digital twins to estimate the effect of AE-detected corrosion progression on the predicted structural condition of bridges

The second goal; To investigate an innovative and insensitive to attenuation solution to monitor corrosion cross-sectional loss in grounding rods:

Limitations:

1. Grounding rods are used in substations with different diameters and lengths. However, only grounding rods with 3 m lengths were studied in this thesis.
2. The accelerated corrosion experiments to simulate cross-sectional corrosion loss were a time-consuming process. It is possible to have more than one corrosion defect with diverse levels of loss and location. Therefore, using accelerated corrosion experiments to collect a

diverse database that represents real-world conditions will limit the application of this method.

Future Work:

To overcome these limitations, I have the following suggestions for future work:

1. Conducting accelerated corrosion experiments to simulate different levels of corrosion cross-sectional losses
2. Studying more field-extracted grounding rods for probable locations of corruptions, patterns, length etc.
3. Making different levels of machinery cuts on intact grounding rods
4. Collecting pulse-echo signals from the rods
5. Finding an empirical equation between machinery cuts and corrosion cross-sectional loss
6. Creating a diverse database using grounding rods with machinery cut
7. Feeding the database into the proposed algorithm in chapter 4

References

- Abdullah, A. B. M., Rice, J. A., Brenkus, N. R., & Hamilton, H. R. (2016). Full-scale experimental investigation of wire breakage detection in deviated multi-strand tendon systems. *Journal of Civil Structural Health Monitoring*, 6(2), 217–235.
- Abed, I., Kacem, N., Bouhaddi, N., & Bouazizi, M. L. (2016). Multi-modal vibration energy harvesting approach based on nonlinear oscillator arrays under magnetic levitation. *Smart Materials and Structures*, 25(2), 25018.
- ACI Committee 222. (2014). ACI PRC-222.2-14 Report on Corrosion of Prestressing Steels, American Concrete Institute, Farmington Hills, MI, USA.
- Al-Jumaili, S. K., Pearson, M. R., Holford, K. M., Eaton, M. J., & Pullin, R. (2016). Acoustic emission source location in complex structures using full automatic delta T mapping technique. *Mechanical Systems and Signal Processing*, 72–73(Supplement C), 513–524.
- Amjad, U., Yadav, S. K., & Kundu, T. (2015). Detection and quantification of diameter reduction due to corrosion in reinforcing steel bars. *Structural Health Monitoring*, 14(5), 532–543.
- Angela, D. D., & Ercolino, M. (2019). Acoustic Emission Entropy as a fracture-sensitive feature for real-time assessment of metal plates under fatigue loading. *Procedia Structural Integrity*, 18, 570–576.
- Appalla, A., ElBatanouny, M. K., Velez, W., & Ziehl, P. (2016). Assessing Corrosion Damage in Posttensioned Concrete Structures Using Acoustic Emission. *Journal of Materials in Civil Engineering*, 28(2), 4015128.
- Bai, R. B., Ostachowicz, W., Cao, M. S., & Su, Z. (2014). Crack detection in beams in noisy conditions using scale fractal dimension analysis of mode shapes. *Smart Materials and Structures*, 23(6), 65014.

- Bakht, B., & Mufti, A. (2017). Evaluation of One Hundred and One Instrumented Bridges, Report for SIMTReC – Centre for Structural Innovation and Monitoring Technologies Inc., Winnipeg, MB, Canada.
- Bayane, I., & Brühwiler, E. (2020). Structural condition assessment of reinforced-concrete bridges based on acoustic emission and strain measurements. *Journal of Civil Structural Health Monitoring*, 10(5), 1037–1055.
- Behnia, A., Chai, H. K., Ranjbar, N., & Jumaat, M. Z. (2016). Damage detection of SFRC concrete beams subjected to pure torsion by integrating acoustic emission and Weibull damage function. *Structural Control and Health Monitoring*, 23(1), 51–68.
- Behnia, A., Chai, H. K., & Shiotani, T. (2014). Advanced structural health monitoring of concrete structures with the aid of acoustic emission. *Construction and Building Materials*, 65(Supplement C), 282–302.
- Bezdek, J. C. (1980). A Convergence Theorem for the Fuzzy ISODATA Clustering Algorithms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-2(1), 1–8.
- Bonaccorsi, L., Calabrese, L., Campanella, G., & Proverbio, E. (2012). Artificial Neural Network Analyses of AE Data during Long-Term Corrosion Monitoring of a Post-Tensioned Concrete Beam. *Journal of Acoustic Emission*, 30.
- Cai, X., Wang, P., Du, L., Cui, Z., Zhang, W., & Chen, J. (2019). Multi-Objective Three-Dimensional DV-Hop Localization Algorithm With NSGA-II. *IEEE Sensors Journal*, 19(21), 10003–10015.
- Calabrese, L., Campanella, G., & Proverbio, E. (2013). Identification of corrosion mechanisms by univariate and multivariate statistical analysis during long term acoustic emission monitoring on a pre-stressed concrete beam. *Corrosion Science*, 73, 161–171.
- Chai, M., Zhang, Z., & Duan, Q. (2018). A new qualitative acoustic emission parameter based on Shannon's entropy for damage monitoring. *Mechanical Systems and Signal Processing*, 100(Supplement C), 617–629.
- Chang, P. C., Flatau, A., & Liu, S.-C. (2003). Health monitoring of civil infrastructure. *Structural Health Monitoring*, 2(3), 257–267.
- Chen, P., He, X., & Wang, X. (2021). Ultrasonic Measurement of Axial Stress Using High-Frequency Cylindrical Guided Wave. *IEEE Sensors Journal*, 21(5), 6691–6697.

- Chen, S., Zhou, S., Chen, C., Li, Y., & Zhai, S. (2018). Detection of double defects for plate-like structures based on a fuzzy c-means clustering algorithm. *Structural Health Monitoring*, 18(3), 757–766.
- Colombo, I. S., Main, I. G., & Forde, M. C. (2003). Assessing damage of reinforced concrete beam using " b-value" analysis of acoustic emission signals. *Journal of Materials in Civil Engineering*, 15(3), 280–286.
- Das, S., & Saha, P. (2018). Structural health monitoring techniques implemented on IASC–ASCE benchmark problem: a review. *Journal of Civil Structural Health Monitoring*, 8(4), 689–718.
- Deb, K., & Agrawal, R. B. (1995). Simulated binary crossover for continuous search space. *Complex Systems*, 9(2), 115–148.
- Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2), 182–197.
- Djeddi, L., Khelif, R., Benmedakhene, S., & Favergeon, J. (2013). Reliability of acoustic emission as a technique to detect corrosion and stress corrosion cracking on prestressing steel strands. *Int. J. Electrochem. Sci*, 8(6), 8356–8370.
- Dorafshan, S., & Maguire, M. (2018). Bridge inspection: human performance, unmanned aerial systems and automation. *Journal of Civil Structural Health Monitoring*, 8(3), 443–476.
- Downey, A., Sadoughi, M., Laflamme, S., & Hu, C. (2018). Incipient Damage Detection for Large Area Structures Monitored With a Network of Soft Elastomeric Capacitors Using Relative Entropy. *IEEE Sensors Journal*, 18(21), 8827–8834.
- Dunn, J. C. (1973). A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters. *Journal of Cybernetics*, 3(3), 32–57.
- Durham, N., Zhao, J., Bridges, G., & Thomson, D. (2020). Acoustic guided wave detection of grounding rod corrosion: equivalent circuit model and implementation. *Smart Materials and Structures*, 29(5), 55040.
- Dutta, C., Kumar, J., Das, T. K., & Sagar, S. P. (2021). Recent Advancements in the Development of Sensors for the Structural Health Monitoring (SHM) at High-Temperature Environment: A Review. *IEEE Sensors Journal*, 21(14), 15904–15916.
- ElBatanouny, M. K., Mangual, J., Ziehl, P. H., & Matta, F. (2014). Early corrosion detection in prestressed concrete girders using acoustic emission. *Journal of Materials in Civil*

- Engineering, 26(3), 504–511.
- Erol, A., von Lockette, P., & Frecker, M. (2019). Multi-objective optimization of a multi-field actuated, multilayered, segmented flexible composite beam. *Smart Materials and Structures*, 29(2), 24001.
- Etxaniz, J., Aranguren, G., Gil-García, J. M., Sánchez, J., Vivas, G., & González, J. (2023). Ultrasound-based structural health monitoring methodology employing active and passive techniques. *Engineering Failure Analysis*, 107077.
- Farhidzadeh, A., & Salamone, S. (2015). Reference-free corrosion damage diagnosis in steel strands using guided ultrasonic waves. *Ultrasonics*, 57, 198–208.
- Fateri, S., Lowe, P. S., Engineer, B., & Boulgouris, N. V. (2015). Investigation of Ultrasonic Guided Waves Interacting With Piezoelectric Transducers. *IEEE Sensors Journal*, 15(8), 4319–4328.
- Feng, Y., Ji, R., Hong, Z., Wang, J., Song, J., Gao, L., Hao, X., & Tan, J. (2022). Analytical Optimization of the Bearing Voltage of Motor Considering the Thickness of Insulating Coating: An Improved Equivalent Circuit Model. *IEEE Sensors Journal*, 22(19), 18567–18579.
- FHWA. (2012). ACTION: Elevated Chloride levels in SikaGrout® 300 PT Cementitious Grout. Report for Federal Highway Administration, Washington DC, USA.
- Fowler, T. J., Blessing, J. A., & Conlisk, P. J. (1992). New direction in testing: Third International Symposium on Acoustic Emission from Composite Materials, Paris (France), 17–21 Jul. 1989, pp. 16–27. ASNT (1989). *NDT & E International*, 25(1), 43–44.
- Fu, Z., Wang, X., Wang, Q., Xu, X., Fu, N., & Qin, S. (2019). Advances and challenges of corrosion and topology detection of grounding grid. *Applied Sciences*, 9(11), 2290.
- Ghaib, M., Shateri, M., Thomson, D., & Svecova, D. (2018). Study of FRP bars under tension using acoustic emission detection technique. *Journal of Civil Structural Health Monitoring*, 8(2), 285–300.
- Gharehbaghi, V. R., Noroozinejad Farsangi, E., Noori, M., Yang, T. Y., Li, S., Nguyen, A., Málaga-Chuquitaype, C., Gardoni, P., & Mirjalili, S. (2022). A Critical Review on Structural Health Monitoring: Definitions, Methods, and Perspectives. *Archives of Computational Methods in Engineering*, 29(4), 2209–2235.

- Goldstein, M., & Uchida, S. (2016). A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data. *PloS One*, 11(4), e0152173.
- Gu, X., Li, J., & Li, Y. (2020). Experimental realisation of the real-time controlled smart magnetorheological elastomer seismic isolation system with shake table. *Structural Control and Health Monitoring*, 27(1), e2476.
- Halabian, A. M., Zafarani, M. M., Soheilipour, M. S., & Behbahani, S. (2016). Optimal semi-active control of seismically excited MR-equipped nonlinear buildings using FLC and multi-objective NSGAII algorithms considering ground excitations. *Journal of Civil Structural Health Monitoring*, 6(3), 561–586.
- Hassan, S. (2021). Investigation of Machine Learning Methods for Structural Safety Assessment under Variability in Data: Comparative Studies and New Approaches. *Journal of Performance of Constructed Facilities*, 35(6), 4021090.
- Ho, S. C. M., Ren, L., Labib, E., Kapadia, A., Mo, Y.-L., Li, H., & Song, G. (2015). Inference of bond slip in prestressed tendons in concrete bridge girders. *Structural Control and Health Monitoring*, 22(2), 289–300.
- Holford, K. M., Eaton, M. J., Hensman, J. J., Pullin, R., Evans, S. L., Dervilis, N., & Worden, K. (2017). A new methodology for automating acoustic emission detection of metallic fatigue fractures in highly demanding aerospace environments: An overview. *Progress in Aerospace Sciences*, 90(Supplement C), 1–11.
- Huo, L., Cheng, H., Kong, Q., & Chen, X. (2019). Bond-Slip Monitoring of Concrete Structures Using Smart Sensors—A Review. *Sensors*, 19(5), 1231.
- Jeong, H., Cho, S., Shin, H., Zhang, S., & Li, X. (2020). Optimization and Validation of Dual Element Ultrasound Transducers for Improved Pulse-Echo Measurements of Material Nonlinearity. *IEEE Sensors Journal*, 20(22), 13596–13606.
- Jiang, T., Kong, Q., Peng, Z., Wang, L., Dai, L., Feng, Q., Huo, L., & Song, G. (2017). Monitoring of Corrosion-Induced Degradation in Prestressed Concrete Structure Using Embedded Piezoceramic-Based Transducers. *IEEE Sensors Journal*, 17(18), 5823–5830.
- Käding, M., Schacht, G., & Marx, S. (2022). Acoustic Emission analysis of a comprehensive database of wire breaks in prestressed concrete girders. *Engineering Structures*, 270, 114846.
- Karimian, S. F., Modarres, M., & Bruck, H. A. (2020). A new method for detecting fatigue crack initiation in aluminum alloy using acoustic emission waveform information entropy.

- Engineering Fracture Mechanics, 223, 106771.
- Kohonen, T. (1990). The self-organizing map. *Proceedings of the IEEE*, 78(9), 1464–1480.
- König, F., Sous, C., Ouald Chaib, A., & Jacobs, G. (2021). Machine learning based anomaly detection and classification of acoustic emission events for wear monitoring in sliding bearing systems. *Tribology International*, 155, 106811.
- Kot, P., Muradov, M., Gkantou, M., Kamaris, G. S., Hashim, K., & Yeboah, D. (2021). Recent Advancements in Non-Destructive Testing Techniques for Structural Health Monitoring. *Applied Sciences*, 11(6), 2750.
- Kovač, J., Leban, M., & Legat, A. (2007). Detection of SCC on prestressing steel wire by the simultaneous use of electrochemical noise and acoustic emission measurements. *Electrochimica Acta*, 52(27), 7607–7616.
- Kovač, J., Legat, A., Zajec, B., Kosec, T., & Govekar, E. (2015). Detection and characterization of stainless steel SCC by the analysis of crack related acoustic emission. *Ultrasonics*, 62(Supplement C), 312–322.
- Kurz, J. H., Laguerre, L., Niese, F., Gaillet, L., Szielasko, K., Tschuncky, R., & Treysse, F. (2013). NDT for need based maintenance of bridge cables, ropes and pre-stressed elements. *Journal of Civil Structural Health Monitoring*, 3(4), 285–295.
- Li, H., & Ou, J. (2016). The state of the art in structural health monitoring of cable-stayed bridges. *Journal of Civil Structural Health Monitoring*, 6(1), 43–67.
- Li, H., Zhong, Z., Shi, J., Li, H., & Zhang, Y. (2021). Multi-Objective Optimization-Based Recommendation for Massive Online Learning Resources. *IEEE Sensors Journal*, 21(22), 25274–25281.
- Li, J., Lu, Y., Guan, R., & Qu, W. (2017). Guided waves for debonding identification in CFRP-reinforced concrete beams. *Construction and Building Materials*, 131, 388–399.
- Li, N., Yan, J., Zhang, Z., Martínez-Ortega, J.-F., & Yuan, X. (2021). Geographical and Topology Control-Based Opportunistic Routing for Ad Hoc Networks. *IEEE Sensors Journal*, 21(6), 8691–8704.
- Li, Z., Zhang, L., Cai, Y., & Ochiai, H. (2022). Sensor Selection for Maneuvering Target Tracking in Wireless Sensor Networks With Uncertainty. *IEEE Sensors Journal*, 22(15), 15071–15081.

- Lin, J.-F., Xu, Y.-L., & Zhan, S. (2019). Experimental investigation on multi-objective multi-type sensor optimal placement for structural damage detection. *Structural Health Monitoring*, 18(3), 882–901.
- Liu, L., Chen, L., Wang, Z., & Liu, D. (2021). Early Fault Detection of Planetary Gearbox Based on Acoustic Emission and Improved Variational Mode Decomposition. *IEEE Sensors Journal*, 21(2), 1735–1745.
- Lu, Y., Li, J., Ye, L., & Wang, D. (2013). Guided waves for damage detection in rebar-reinforced concrete beams. *Construction and Building Materials*, 47, 370–378.
- Mahmoudkhani, S., Al-Gohi, B., Zhao, J., Mufti, A., Klowak, C., Whitmore, D., Furgal, J., & Thomson, D. (2019). Characterization of Acoustic Emission from Wire Breaks In Post-Tensioning Steel Tendons. *Proceedings of the 9th International Conference on Structural Health, Monitoring of Intelligent Infrastructure: Transferring Research into Practice*.
- Mahmoudkhani, S., Algohi, B., Zhao, J., Ling, H., Mufti, A., & Thomson, D. (2019). Acoustic Emissions Sensor and Fuzzy C-mean Clustering Based Break Detection in Post-Tensioning Tendons. *2019 IEEE SENSORS*, 1–4.
- Mahmoudkhani, S., Zhao, J., Durham, N., Mckenzie, C., Abdel-Hadi, K., Mufti, A., & Thomson, D. (2019). Algorithms for Guided Wave Detection of Corrosion in Ground Rods. *Structural Health Monitoring* 2019.
- Mangual, J., ElBatanouny, M. K., Ziehl, P., & Matta, F. (2013a). Acoustic-Emission-Based Characterization of Corrosion Damage in Cracked Concrete with Prestressing Strand. *ACI Materials Journal*, 110(1).
- Mangual, J., ElBatanouny, M., Ziehl, P., & Matta, F. (2013b). Corrosion Damage Quantification of Prestressing Strands Using Acoustic Emission. *Journal of Materials in Civil Engineering*, 25(9), 1326–1334.
- McLaskey, G. C., & Glaser, S. D. (2012). Acoustic Emission Sensor Calibration for Absolute Source Measurements. *Journal of Nondestructive Evaluation*, 31(2), 157–168.
- Miller, T. H., Kundu, T., Huang, J., & Grill, J. Y. (2013). A new guided wave–based technique for corrosion monitoring in reinforced concrete. *Structural Health Monitoring*, 12(1), 35–47.
- Mingoti, S. A., & Lima, J. O. (2006). Comparing SOM neural network with Fuzzy c-means, K-means and traditional hierarchical clustering algorithms. *European Journal of Operational Research*, 174(3), 1742–1759.

- Mitra, M., & Gopalakrishnan, S. (2016). Guided wave based structural health monitoring: A review. *Smart Materials and Structures*, 25(5), 53001.
- Morgese, M., Ansari, F., Domaneschi, M., & Cimellaro, G. P. (2020). Post-collapse analysis of Morandi's Polcevera viaduct in Genoa Italy. *Journal of Civil Structural Health Monitoring*, 10(1), 69–85.
- Mustapha, S., Lu, Y., Li, J., & Ye, L. (2014). Damage detection in rebar-reinforced concrete beams based on time reversal of guided waves. *Structural Health Monitoring*, 13(4), 347–358.
- National Bridge Inventory (NBI). (2016). Tables of frequently requested NBI information: Deficient Bridges by Superstructure Material.
- Ono, K. (2018). Review on structural health evaluation with acoustic emission. *Applied Sciences*, 8(6), 958.
- Oughton, E. J., Hapgood, M., Richardson, G. S., Beggan, C. D., Thomson, A. W. P., Gibbs, M., Burnett, C., Gaunt, C. T., Trichas, M., & Dada, R. (2019). A risk assessment framework for the socioeconomic impacts of electricity transmission infrastructure failure due to space weather: An application to the United Kingdom. *Risk Analysis*, 39(5), 1022–1043.
- Papa, I., Lopresto, V., & Langella, A. (2021). Ultrasonic inspection of composites materials: Application to detect impact damage. *International Journal of Lightweight Materials and Manufacture*, 4(1), 37–42.
- Pape, T. M., & Melchers, R. E. (2011). The effects of corrosion on 45-year-old pre-stressed concrete bridge beams. *Structure and Infrastructure Engineering*, 7(1–2), 101–108.
- Park, H. J., Akasaka, S., Tasaka, Y., & Murai, Y. (2021). Monitoring of Void Fraction and Bubble Size in Narrow-Channel Bubbly-Flows Using Ultrasonic Pulses With a Super Bubble-Resonant Frequency. *IEEE Sensors Journal*, 21(1), 273–283.
- Pasadas, D. J., Baskaran, P., Ramos, H. G., & Ribeiro, A. L. (2020). Detection and Classification of Defects Using ECT and Multi-Level SVM Model. *IEEE Sensors Journal*, 20(5), 2329–2338.
- Pritz, T. (2004). Frequency power law of material damping. *Applied Acoustics*, 65(11), 1027–1036.
- Ramadan, S., Gaillet, L., Tessier, C., & Idrissi, H. (2008a). Assessment of the stress corrosion cracking in a chloride medium of cables used in prestressed concrete structures by the

- acoustic emission technique. *Measurement Science and Technology*, 19(11), 115702.
- Ramadan, S., Gaillet, L., Tessier, C., & Idrissi, H. (2008b). Detection of stress corrosion cracking of high-strength steel used in prestressed concrete structures by acoustic emission technique. *Applied Surface Science*, 254(8), 2255–2261.
- Rubinstein, R. Y., & Kroese, D. P. (2016). *Simulation and the Monte Carlo Method: Third Edition*. In *Simulation and the Monte Carlo Method: Third Edition (Third)*. Wiley.
- Samariya, D., & Thakkar, A. (2021). A Comprehensive Survey of Anomaly Detection Algorithms. *Annals of Data Science*.
- Shannon, C. E. (1949). Communication Theory of Secrecy Systems*. *Bell System Technical Journal*, 28(4), 656–715.
- Sharma, S., & Mukherjee, A. (2010). Longitudinal guided waves for monitoring chloride corrosion in reinforcing bars in concrete. *Structural Health Monitoring*, 9(6), 555–567.
- Sharma, S., & Mukherjee, A. (2015). Ultrasonic guided waves for monitoring corrosion in submerged plates. *Structural Control and Health Monitoring*, 22(1), 19–35.
- Shateri, M., Ghaib, M., Svecova, D., & Thomson, D. (2017). On acoustic emission for damage detection and failure prediction in fiber reinforced polymer rods using pattern recognition analysis. *Smart Materials and Structures*, 26(6), 65023.
- Shiotani, T., Oshima, Y., Goto, M., & Momoki, S. (2013). Temporal and spatial evaluation of grout failure process with PC cable breakage by means of acoustic emission. *Construction and Building Materials*, 48, 1286–1292.
- Shoji, M., & Higashi, Y. (2014). Fundamental study on guided wave testing of cylindrical bars embedded in soil. 2014 IEEE International Ultrasonics Symposium, 1404–1407.
- Shoji, M., & Hirata, A. (2016). Ultrasonic guided wave testing of anchor rods embedded in soil. 2016 IEEE International Ultrasonics Symposium (IUS), 1–4.
- Tabatabai, H., & Nabizadeh, A. (2019). Strength and Serviceability of Damaged Prestressed Girders (No. 0092-17-02) (U. of W.--M. D. of C. and E. Engineering (ed.)). <https://rosap.nrl.bts.gov/view/dot/50646>
- Tsamsakis, D., Wevers, M., & De Meester, P. (1998). Acoustic emission from CFRP laminates during fatigue loading. *Journal of Reinforced Plastics and Composites*, 17(13), 1185–1201.

- Unnthorsson, R., Runarsson, T. P., & Jonsson, M. T. (2008). AE entropy for the condition monitoring of CFRP subjected to cyclic fatigue. *Journal of Acoustic Emission*, 26, 262–269.
- Vélez, W., Matta, F., & Ziehl, P. (2014). Acoustic Emission Intensity Analysis of Corrosion in Prestressed Concrete Piles. In *AIP Conference Proceedings* (Vol. 1581).
- Vélez, W., Matta, F., & Ziehl, P. (2015). Acoustic emission monitoring of early corrosion in prestressed concrete piles. *Structural Control and Health Monitoring*, 22(5), 873–887.
- Verstrynge, E., Van Steen, C., Vandecruys, E., & Wevers, M. (2022). Steel corrosion damage monitoring in reinforced concrete structures with the acoustic emission technique: A review. *Construction and Building Materials*, 349, 128732.
- Vidya Sagar, R., & Raghu Prasad, B. K. (2013). Laboratory investigations on cracking in reinforced concrete beams using on-line acoustic emission monitoring technique. *Journal of Civil Structural Health Monitoring*, 3(3), 169–186.
- Villa-Pérez, M. E., Álvarez-Carmona, M. Á., Loyola-González, O., Medina-Pérez, M. A., Velazco-Rossell, J. C., & Choo, K.-K. R. (2021). Semi-supervised anomaly detection algorithms: A comparative summary and future research directions. *Knowledge-Based Systems*, 218, 106878.
- Wang, F., Chen, Z., & Song, G. (2020). Monitoring of multi-bolt connection looseness using entropy-based active sensing and genetic algorithm-based least square support vector machine. *Mechanical Systems and Signal Processing*, 136, 106507.
- Wang, F., Ho, S. C. M., & Song, G. (2019). Monitoring of early looseness of multi-bolt connection: a new entropy-based active sensing method without saturation. *Smart Materials and Structures*, 28(10), 10LT01.
- Wang, T., Cao, J., & Pei, L. (2021). A Novel Underground Pipeline Surveillance System Based on Hybrid Acoustic Features. *IEEE Sensors Journal*, 21(2), 1040–1050.
- Williams, H. (2010). Transmission & distribution infrastructure. White Paper, Harris Williams & Co Ltd, Richmond, VA, Summer.
- Wong, V.-K., Hu, Y., Tham, Z. W., Chen, Y. F., Liu, M., Lim, K. E., Park, S. J., Cui, F., & Zhang, L. (2022). Measurement of Elastic Constant Matrix of Carbon Fiber Composites With an Ultrasonic 2D-Array Transducer. *IEEE Sensors Journal*, 22(6), 5562–5570.
- Xiao-Mei, Y., Ting-Hua, Y., Chun-Xu, Q., Hong-Nan, L., & Hua, L. (2019). Automated

Eigensystem Realization Algorithm for Operational Modal Identification of Bridge Structures. *Journal of Aerospace Engineering*, 32(2), 4018148.

Yu, J., Dong, X., & Zhang, Z. (2017). A novel model of magnetorheological damper with hysteresis division. *Smart Materials and Structures*, 26(10), 105042.

Yuyama, S., Yokoyama, K., Niitani, K., Ohtsu, M., & Uomoto, T. (2007). Detection and evaluation of failures in high-strength tendon of prestressed concrete bridges by acoustic emission. *Construction and Building Materials*, 21(3), 491–500.

Zaki, A., Chai, H. K., Aggelis, D. G., & Alver, N. (2015). Non-destructive evaluation for corrosion monitoring in concrete: A review and capability of acoustic emission technique. *Sensors*, 15(8), 19069–19101.

Zeng, Y., Yan, Y., Weng, S., Sun, Y., Tian, W., & Yu, H. (2018). Fuzzy clustering of time-series model to damage identification of structures. *Advances in Structural Engineering*, 22(4), 868–

Zhao, J., Durham, N., Abdel-Hadi, K., McKenzie, C. A., & Thomson, D. J. (2019). Acoustic guided wave techniques for detecting corrosion damage of electrical grounding rods. *Measurement*, 147, 106858.