Enhancing the Identification of Corrosion in Reinforced Concrete Structures Using Association Rules Analysis and the Non-Destructive M5 Method

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Abstract

This study aims to develop a novel AI-driven approach for detecting and evaluating corrosion in reinforced concrete (RC) structures, answering one of the most significant challenges in the construction industry. The research aims to overcome the difficulties of identifying corrosion with limited data. Gathering representative learning databases is challenging due to problems obtaining adequate samples and the high diversity in rebar, concrete, and structural parameters. The research quantitatively analyzes measurements obtained through Magnetic Force Induced Vibration Evaluation (M5), a nondestructive testing (NDT) method. The process is enhanced by employing the specialized Association Rules Analysis (ARA) with a dedicated feature extraction technique. The findings suggest that utilizing a variety of patterns and features enhances the method's identification effectiveness.

Keywords: Nondestructive Testing NDT, Corrosion Detection, Reinforced Concrete, Artificial Intelligence AI, Rebar Corrosion, Association Rules Analysis (ARA)

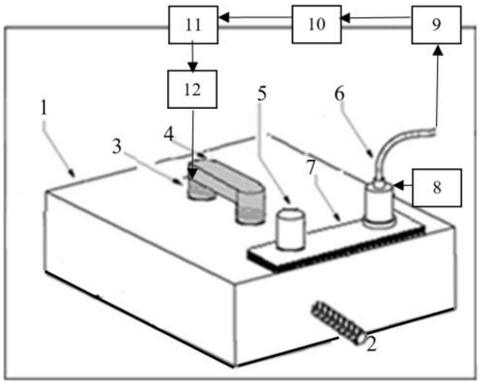
1. Introduction

Rebar corrosion is a significant global problem. Approximately 30% of reinforced concrete structures are currently affected by corrosion. The costs associated with this issue account for roughly 15% of total expenses in residential building operations, resulting in worldwide annual losses of up to $2.5 trillion [2][4]. Most methods currently used for corrosion detection measure carbonation. However, carbonation levels do not directly correlate with the condition of rebars. Structures can remain safe for decades despite significant concrete degradation. Furthermore, these methods may fail to detect corrosion resulting from localized damage [4]. Therefore, the development of direct NDT methods is crucial.

The M5 (Magnetic Force Induced Vibration Evaluation) detects corrosion directly by combining electromagnetic techniques (since concrete doesn't dampen electromagnetic waves) with modal analysis, allowing for the detection of changes in vibration signatures while minimizing the effects of concrete damping [1][4].

2. Measuring System and Samples

The M5 is a modal analysis method that evaluates the bond between rebar and concrete. As corrosion progresses, bond weakening causes changes in resonance. The method's principal operations are described in [4]. The block diagram of the measuring system is shown in Fig. 1.



{1} sample;
{2} rebar;
{3} coil of an electromagnet;
{4} ferrite core of the electromagnet;
{5} magnet;
{6} accelerometer;
{7} physical connection between the magnet and the accelerometer;
{8} conditioning system;
{9} A/D converter;
{10} control computer;
{11} D/A converter;
{12} power amplifier

Fig. 1. The block diagram of the M5 system.

The experiments were conducted using two distinct categories of samples. The category of "laboratory samples" included three standardized cuboidal concrete blocks, each containing a single rebar. The reinforcing bars were coated with wax (that simulated the debonding caused by corrosion) for two of these samples: sample C01 had half of its rebar covered, while sample C02 was fully insulated. In sample C00, the rebar was not covered with any wax.

The second category ("field samples") consisted of unstandardized samples with various parameters from a dismantled bridge slab in Świerkocin, located on the Warta River in Poland. For the experiments presented in this work, three specific groups of specimens were selected: one with corroded rebar (C11), one with non-corroded rebar (C10), and one with loose rebar where complete debonding had occurred due to significant corrosion (C12).

The diameter of the rebars in field samples was 10 mm, which is half the size of those in laboratory samples. The steel alloy also differed significantly; it was made of highly elastic, non-ribbed soft steel, while the laboratory samples consisted of hard, non-elastic materials. A more detailed description of the samples can be found in [4].

3. Methodology

The features of the waveforms were extracted using the Equal Division in the Amplitude Domain (EDA) method, with normalization, as described in [3][5]. The technique was designed for deriving association rules, not for classification [7]. Its main advantage is its ability to extract attributes without prior knowledge of the relationships between waveforms and structural parameters. The pseudocode of the method is shown in Fig. 2. The previous version of the technique was detailed in [5,6]. A rule is expressed as (1):

$$\text{If } (BODY\,[\text{A}]) \text{ Then } (HEAD\,[\text{B}])\ [support,\ confidence] \tag{1}$$

Like the classic Apriori algorithm, the method assumes that interesting rules arise only from frequent item sets, defined as those with support exceeding the researcher-established minimum threshold. However, three significant modifications have been made compared to the classical algorithm:

1. The A encompasses only variables that describe structure/process parameters (Y) in the presented experiment. *BODY* (A) represents the appearance of corrosion, while *HEAD* (B) consists solely of features that describe the examined signal (X) in the presented case, such as the resonance amplitude of specific frequencies.
2. The length of the BODY is constrained to a single element A from Y.
3. Omitting support as a criterion is acceptable, depending on the database architecture.
4. The quality evaluation is introduced (sensitivity).

The modifications have excluded most generated rules, retaining only those that clarify the relationships between variations in structural parameters and their corresponding changes.

The method's sensitivity can be adjusted by quantizing and discretizing the signal: smaller intervals enhance feature identification, while quantization defines significant changes, indicating when the change is large enough to be considered an increase (↑) or a decrease (↓), rather than no change (-).

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1. START ( (A⊂Y), (B⊂X), k=1);
2. Scan the database part Y to get the pair of instances varying only one parameter;
3. Compare all attributes (part X) from the pairs of records and IF differences of the values
   are diff ≥ sens.min, save results in the database D as (↑), or (↓),ELSE (-);
4. Generate k-itemset candidate (B);
5. For each of the candidates IF supp ≥ supp.min GO TO #6;
6. Add to frequent itemset F;
7. Is the set of k+1 candidates ∅? IF yes GO TO #8, ELSE k++, GO TO #4;
8. For each itemset F IF conf ≥ conf.min GO TO #9;
9. Add to association rules and STOP;
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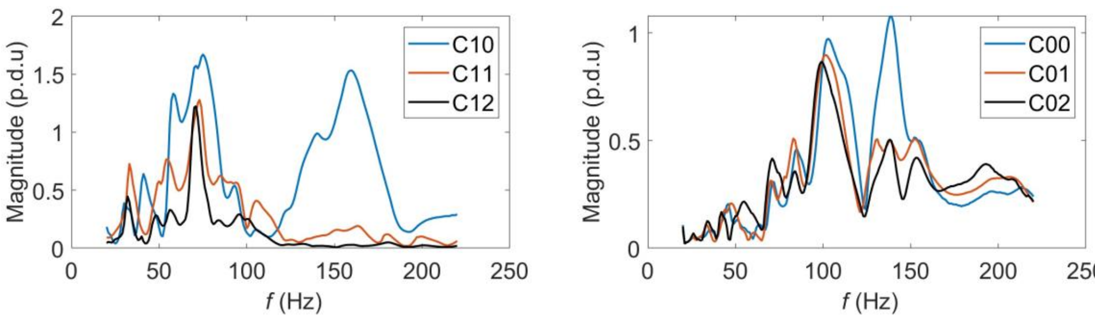
Fig. 2. Pseudocode for the signals association rules extraction algorithm.

4. Results

Example results in Fig. 3 show that corrosion-related debonding reduces frequencies above 120 Hz, but other factors, such as concrete cover thickness, can also cause similar effects. Therefore, association rules should be tested with an algorithm before use.



a) b)

Fig. 3. Example measurement results: a) field samples; b) laboratory samples [4].

To automatically evaluate patterns, signals are characterized using the EDA method, yielding 201 features within the 20–220 Hz range. Normalization decouples amplitude from the shape of the waveform, allowing for the separate analysis of two types of factors. An association rule algorithm (Fig. 2) was used to assess feature usability. The impact of corrosion on amplitude was clear only when other parameters were consistent between the corroded and non-corroded samples. When differences existed in different parameters, the effect on amplitude was less clear.

The Association Rules Analysis (ARA) results of corrosion's impact on amplitude are shown in Fig. 4. ARA detects frequencies where corrosion significantly affects signal power.

Fig. 4a and Fig. 4b show how rebars' corrosion impacts signal amplitudes by comparing uncorroded samples C00/C10 with corroded C01/C11 and debonded C02/C12. Using a 10% sensitivity threshold, uncorroded samples exhibit the highest signal energy, followed by corroded and debonded samples, particularly above 100 Hz.

The results illustrated in Fig. 4a indicate that, for the "field samples", four distinct frequency ranges effectively differentiate the signals from corroded and uncorroded samples. The method's accuracy can be validated by comparing the graph with Fig. 4d, which shows example measurements. Similar observations to those in Fig. 4a are made for laboratory samples (Fig. 4b), but differences between samples were significantly smaller.

The correctness of the results can be verified using Fig. 4d.

Fig. 4c identifies the characteristic frequencies for corrosion changes in both sample sets. Results were obtained by multiplying the confidence values of characteristic frequencies across all cases. Features of frequencies in the 130-150 Hz range can be aggregated to create another helpful identification attribute, alongside signal energy.

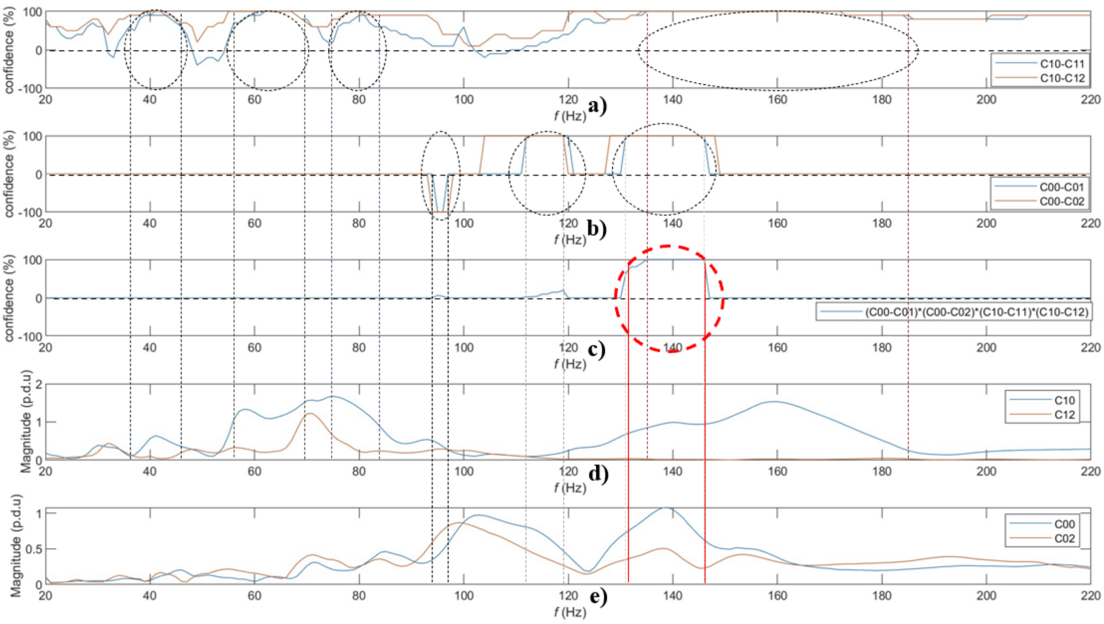


Fig. 4. Changes in signal amplitude when corrosion appears: a) characteristic frequencies – field samples, b) characteristic frequencies – laboratory samples, sensitivity level of a 10%, c) frequencies characteristic for both categories of samples, d) example signals – field samples, e) example signals – laboratory samples.

The quantitative study, which involved comparing records where corrosion was detected with records where corrosion was absent (all possible combinations), revealed that regardless of sample parameters such as concrete cover thickness, reinforcing steel used, or rebar diameter, corrosion consistently causes a significant decrease in signal energy within frequencies of 130–150 Hz range, making these attributes the best indicators of corrosion.

Deeper analysis reveals another interesting relation. When the algorithm sensitivity was set to 10%, a significant difference in the effect of corrosion on the amplitude was observed between frequencies higher and lower than 120 Hz. For the set of higher frequencies, the Confidence coefficient was 100%. This indicates a corrosion damping amplitude (especially between 130 and 150 Hz). In contrast, for lower frequencies (<120 Hz), confidence levels of less than 65% were obtained. Additionally, in the case of corroded samples, with 100% confidence (all cases), the amplitude of 20-119 Hz signals was higher than that of 120-220 Hz, even when the algorithm sensitivity was set to 40%. It indicates that corrosion can be detected based on:

1. The energy of the entire signal.
2. The amplitude of the signal at frequencies 130-150 Hz.
3. The energy of the signal at frequencies 130-150 Hz.
4. By comparing the highest amplitude for frequencies ≥120 Hz to the amplitude of lower frequencies.

5. Conclusions

The proposed method utilizes a novel approach based on association rules and signal feature extraction, employing "equal division in the independent variable domain with normalization." This strategy effectively identifies key components of the signal and converts them into identification attributes. Furthermore, it can be helpful when collecting a representative training set is not feasible.

The method enabled the identification of patterns that allowed corrosion detection only in certain sample types from those that were consistently effective, thus facilitating the selection of the best predictors for identification. In scenarios with limited learning data, using a multi-criteria approach that combines all relevant features is essential. This approach reduces the influence of noise and unknown variables. The proposed method helps select valuable attributes and recognize many beneficial patterns.

Corrosion significantly reduced signal energy across both laboratory and field samples, especially at frequencies above 100 Hz. The 140-160 Hz range emerged as a critical frequency for corrosion detection, exhibiting the most notable amplitude reduction. The results also suggest that debonding in reinforced concrete structures leads to substantial damping of frequencies over 100 Hz.

Even if very promising, the presented results indicate a need for further investigations. The method must be tested on a larger dataset.

Contributions

Project management and administration–P.K.F.; concept of the M5 method – T.C. and P.K.F.; concept of the presented methodology, and algorithms – P.K.F.; concept of the paper – P.K.F.; software development – P.K.F.; hardware development – T.C. and P.K.F.; experiments and measurements – P.K.F.; data curation – P.K.F.; formal analysis – P.K.F.; investigation – P.K.F.; visualization – P.K.F.; writing – P.K.F.; revision –P.K.F., M.M., T.C. and P.M.; contribution of the authors in %: P.K.F. – 90%, T.C. – 6%, P.M. – 2%, M.M. – 2%. All authors have read and agreed to the published version of the manuscript.

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