Hybrid AI Framework Based on Fuzzy Rough Sets for Two-Dimensional Magnetic Evaluation of Reinforced Concrete Structures

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Abstract

This work presents an intelligent support system for a novel, non-destructive (NDT), 2D method to identify parameters of reinforced concrete (RC) structures. Using association rule analysis (ARA), it detects relationships between signal changes and structure parameter modifications, identifying signal parameters influenced by a single structural parameter. Multitask learning is used to identify concrete cover thickness, reinforcing bar diameter, and steel class. Features are extracted from the three spatial components of magnetic induction via ACO decomposition, which is suited for creating complex databases. Genetic algorithms improve noise resilience in function approximation. Results are shown as Fuzzy Rough Sets. Three vertically placed sensors, combined with AI, enable precise identification of parameters, with changes in one not affecting others.

Keywords: Signal Processing, Fuzzy Logic, Association Rules Analysis ARA, ACO decomposition, Genetic Algorithms GA, Multisensory, spatial analysis MSA, Nondestructive Testing NDT, rebars, Reinforced Concrete.

1. Measuring System and Samples

Magnetic non-destructive testing systems feature a straightforward design, as illustrated in Fig. 1.

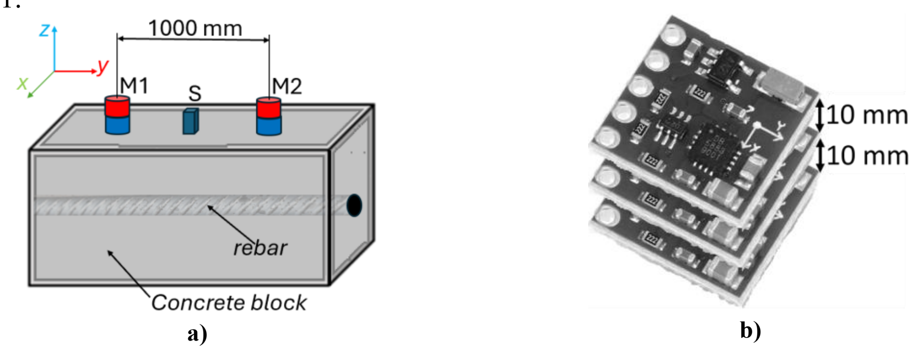

Fig. 1. The system elements: a) positioning elements on the concrete sample: M1 and M2 magnets, and S transducer, b) the magnetic transducer assembled with three HMC5883L sensors placed one on top of the other.

The measurement system has four subsystems: an excitation subsystem, a positioning robot, a magnetic field sensor (HMC5883L), and a data acquisition subsystem. The excitation subsystem placed two stationary neodymium magnets on the sample surface above the rebar (Fig. 1a). The positioning subsystem (XYZ scanner) moved the magnetic sensor (Fig. 1b) perpendicular to the rebar. The sensors captured the magnetic induction components (B_x, B_y, B_z) and sent data to a computer (data acquisition subsystem). Fig. 1a shows the components of the specimen. The sensors are 10 mm apart (Fig. 1b). The 2D measurement compares signals from three sensors at the same distance. The magnets (Fig. 1a) are set in an SPM (same pole magnetization) configuration [1].

The RC structures have three main parameters: concrete cover thickness (h), reinforcing bar diameter (D), and rebar steel class. Samples had h from 20 to 70 mm in 10 mm steps, typically 20-50 mm in RC structures. Two rebar diameters, D_{10} (10 mm) and D_{12} (12 mm), and three alloy classes—AI (max ductility, min hardness), AIII (low ductility, high hardness), and AIIIN (min ductility, max hardness)—were tested.

2. Results

2.1. Association Rules Analysis (ARA) and Identification of Alloy Class

The basics of 2D identification were introduced in [2]. Features of waveforms were extracted using ACO decomposition [3]. Then, association rule analysis (ARA) helps identify how changes in various structural parameters affect the waveform. Examples of ARA usage on signals are presented in [4-6]. For multitask identification, isolating signal features that depend solely on a single parameter can significantly enhance accuracy, thereby making the identification of each parameter independent. ARA helps discover these specific rules. The rules are shown in Table 1.

Table 1. Confidence of association rules, scan along the x-axis

	x-axis								
	spatial component B_x			spatial component B_y			spatial component B_z		
	A	C	O	A	C	O	A	C	O
h ↑	↓100	↓100	**(-)100**	↓100	↓100	↓100	↓100	↓100	↑56
D ↑	↑100	↓58	**(-)84**	↑100	↓82	↑100	↓89	↓62	↑100
class ↑	↑94	(-)76	**↑92**	↓52	(-)58	↓57	↑99	(-)61	↑100

ARA revealed that the steel class affects only the offset attribute O for the spatial component of magnetic induction (B_x). Changes in other structural parameters, such as concrete cover thickness (h) and rebar diameter (D), do not affect the outcome, making the identification simple and independent. Patterns for h and D identification still need to be discovered.

Similar analysis can be conducted based on the scans along the z-axis (Fig. 1a), as presented in Table 2.

Table 2. Confidence of association rules, scan along the z-axis

	z-axis								
	spatial component B_x			spatial component B_y			spatial component B_z		
	A	C	O	A	C	O	A	C	O
D ↑	↑100	(-)84	(-)84	↑100	↓100	↑100	↓89	↓100	↑100
class ↑	↑94	↓92	↑92	↓52	↓57	↓57	↑99	↓100	↑100

2.2. Concrete Cover Thickness

Concrete cover thickness is a continuous parameter that affects all three ACO attributes (amplitude, correlation, and offset). ARA analysis reveals that as h increases, the three magnetic induction components decrease proportionally, as illustrated in Fig. 2b. Using all three waveforms (B_x, B_y, B_z) instead of one can strongly improve the quality of the identification. The alloy class and rebar diameter do not affect the shape, allowing for pattern-based, independent identification. The genetic algorithm was used to establish the link between the shape of normalized waveforms (Fig. 7) and h. From these measurements, the cover thickness is determined using Equation (1), which applies to all spatial components. The shape of the B curves was confirmed with numerical simulations.

$$\begin{cases} B_1 = 12.03 \cdot h^{-0,6181} - 0,8814 \\ B_2 = 12.03 \cdot (h+n)^{-0,6181} - 0,8814 \\ B_2 = 12.03 \cdot (h+2n)^{-0,6181} - 0,8814 \end{cases} \tag{1}$$

The B_1 is the amplitude from the sensor closest to the surface (first layer); B_2 is from the sensor 10 mm away (second layer); B_3 is from 20 mm away (third layer); n is the sensor distance (10 mm), and h is the concrete cover thickness. Fig. 2a shows the fit of the approximation to the data.

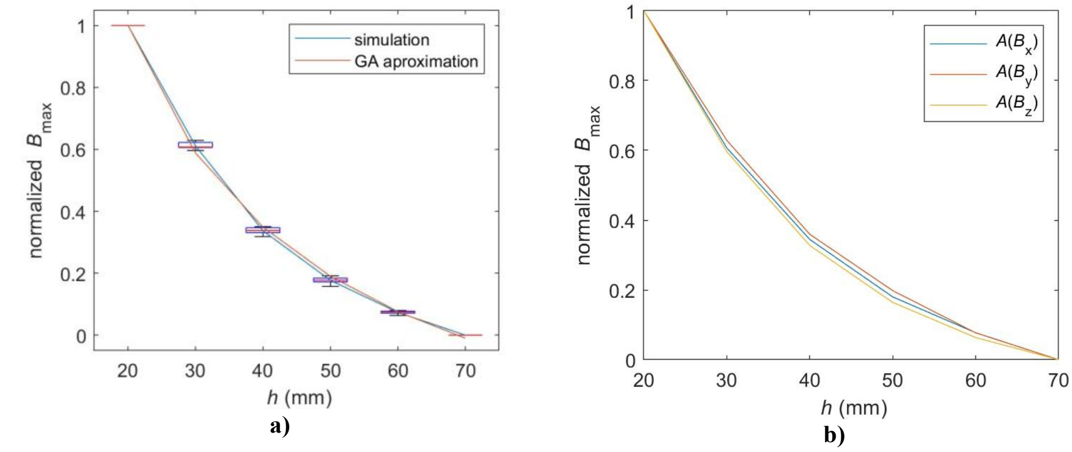

Fig. 2. Normalized relationship between cover thickness and signal amplitude: a) comparison of measurements, simulation results, and approximation, b) comparison of spatial components B.

2.3. Rebar Diameter

The diameter of the rebars affects all ACO parameters of the magnetic induction's spatial components and is a discrete parameter. Identifying it is more challenging than determining the alloy class of the rebars or the thickness of the concrete cover. The pattern found with ARA that allows for independent identification is shown in Fig. 3.

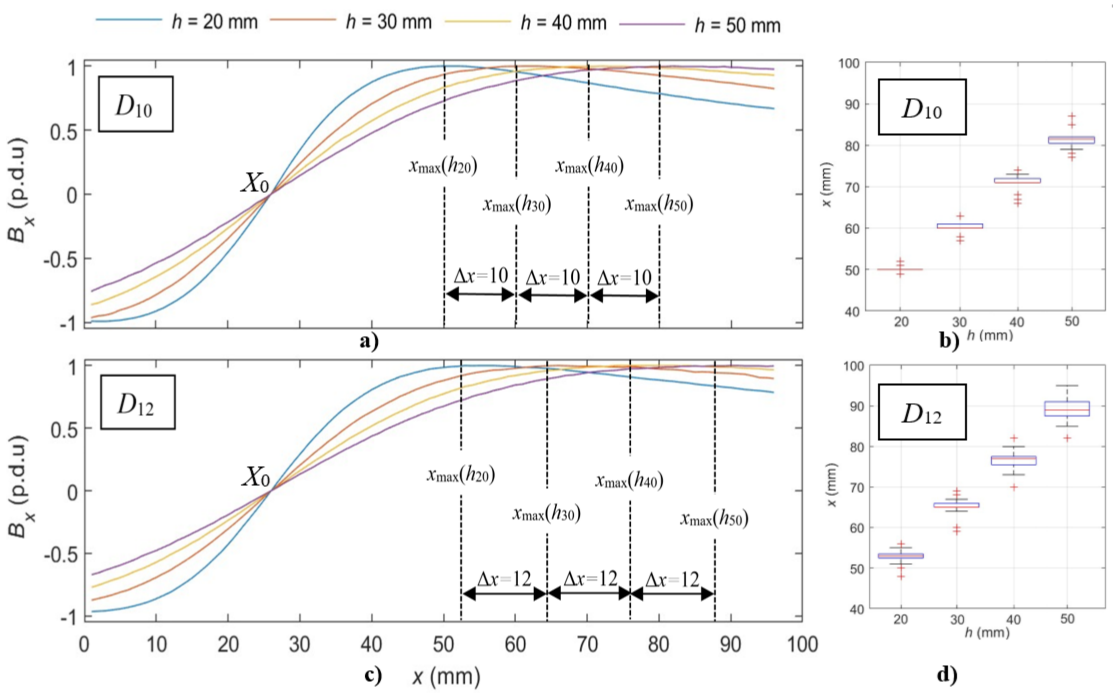

Fig. 3. Two-dimensional identification of rebar diameter: a) D_{10} identification, b) D_{10} relationship between the maximum value position on the x-axis and h, c) D_{12} identification, d) D_{12} relationship between the maximum value position on the x-axis and h.

The two-dimensional identification of rebar diameters also uses signals from sensors placed in different layers. The X_{max} refers to a set of attributes indicating the position on the *x*-axis corresponding to a B_x waveform's maximum value at a specific *h*. For example, $X_{max}(h_{20})$ represents the distance between position X_0, where the waveforms intersect (Fig. 3), and the x position of the maximum value of the waveform measured for $h = 20$ mm. The Δx signifies the difference between successive X_{max} values; for instance, $\Delta x = X_{max}(h_{30}) - X_{max}(h_{20})$ or $\Delta x = X_{max}(h_{50}) - X_{max}(h_{40})$.

As the thickness of the concrete cover increases (or as the sensor moves along the *z*-axis), the position of the maximum value (X_{max}) changes accordingly. This shift follows a linear relationship with *h* (Fig. 3b and Fig. 3d). However, experimental results indicate that the step depends on the diameter of the rebar. The Δx value remains constant at approximately 10 mm for D_{10} (diameter of 10 mm) and 12 mm for D_{12}. Due to the symmetry of the waveforms, a similar relationship can be identified for X_{min}.

The Δx attribute is suitable for identifying rebar diameters since it remains unaffected by concrete cover thickness and rebar class. However, the flattening seen near the maximum waveform value and noise can considerably impact the attribute's value. To mitigate noise interference, measurements can be taken multiple times, in various locations simultaneously, or by utilizing both halves (positive and negative) of the waveform. Additionally, using filters is advised.

3. Identification Model

With the implementation of AI methods and 2D measurement techniques, identifying all parameters has become independent, which is extremely important given the lack of learning data. The offset value in the B_x component determines the steel class, while the other parameters depend on the previously discussed 2D relationships. Subsequently, an analysis was conducted based on rough set theory, and a fuzzy system was created by modeling membership functions in alignment with upper and lower approximations, which is more effective for rare data than classic machine learning methods [7]. Example results are presented in Fig. 4.

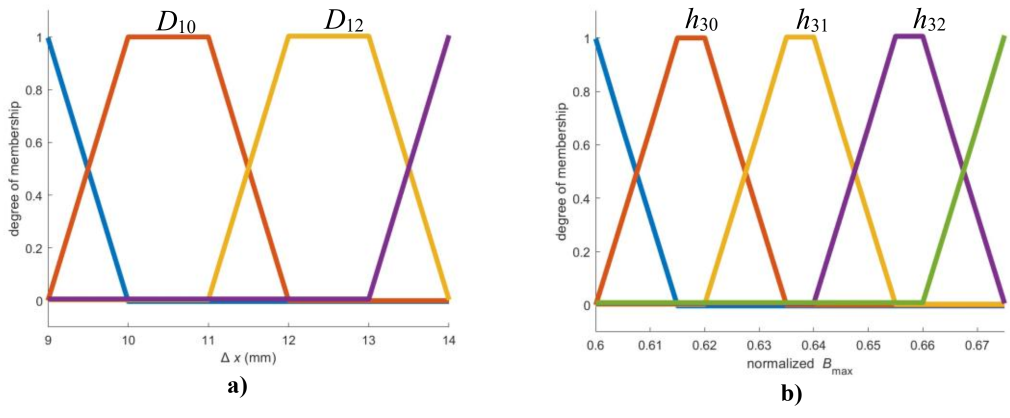

Fig. 4. Example membership functions: a) rebar diameter, b) concrete cover thickness.

Statistical analysis revealed that identifying cover thickness can be more precise than experiments. The standard deviation indicates that identification accuracy could be within 1-2 mm.

The Two-dimensional (2D) analysis enables the integration of scans along the x and z axes (presented in Tables 1 and 2), unlocking entirely new possibilities. The previously discussed identification of cover thickness can be performed across all spatial components of magnetic induction (the least reliable results occur with the B_y component, where noise and distortions significantly impact due to its low amplitude). In this tested case, the confidence level is 100%, indicating that even much thinner cover layers can be detected, and alterations to other structural parameters do not affect the outcome.

In diameter identification, the method demonstrates a confidence level of 93% when considering typical cover thickness, while other parameters, such as cover thickness and rebar class, do not influence the outcome.

4. Conclusions

Artificial intelligence techniques effectively support 2D measurements. ARA association rule analysis identifies measurement features based on a single parameter, enhancing reliability and robustness against unexpected factors. This is vital in NDT, where building a comprehensive database is difficult. Limited training data prompted ACO decomposition, leading to a simple yet effective identification system grounded in fuzzy rough set theory. These methods also minimize noise influence. Further in-depth research is needed to explore their limitations, but the new measurement technique and AI assistance results are promising and yield reliable predictions.

Contributions

Project management and administration—P.K.F.; concept of the 2D method—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—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.; review of the paper—P.K.F., P.M., W.C., and T.S.; consultations about cyvil enginnering—P.M., W.C.; contribution of the authors in %: P.K.F.—94%, P.M.—2%, W.C.—2%, T.S.—2%. All authors have read and agreed to the published version of the manuscript.

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