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INTEGRATING EXPERIMENTAL ANALYSIS AND MACHINE LEARNING FOR ASSESSING BOND PERFORMANCE AND CORROSION SEVERITY IN REINFORCED CONCRETE STRUCTURES

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This study presents a comprehensive investigation into the effects of corrosion on bond performance and mechanical properties of steel-concrete interfaces by combining experimental analysis with machine learning techniques. A total of 32 concrete prisms with varying water-cement (w/c) ratios were prepared and subjected to an accelerated corrosion process. Corrosion severity was assessed through visual inspection and weight loss measurements, while mechanical properties were evaluated through the pull-out tests. Experimental results showed that the residual bond load decreased to 77% and 81% for w/c ratios of 0.37 and 0.47, respectively, after accelerated corrosion. Additionally, corroded prisms exhibited significantly reduced residual toughness and stiffness compared to their non-corroded counterparts. To establish a correlation between bond slip and corrosion severity, a machine learning algorithm was developed and implemented. The algorithm achieved an accuracy of 100% for both studied w/c ratios and remarkably low costs after optimization (4.548$\times 10^{-6}$ for w/c ratio of 0.37 and 3.445$\times 10^{-7}$ for w/c ratio of 0.47). This integrated approach provides valuable insights for future infrastructure assessment and maintenance efforts. In conclusion, this study combines laboratory findings with real-world applications. It provides a thorough understanding of the relationship between corrosion and bond performance in reinforced concrete structures. Maintaining the structural integrity and safety of reinforced concrete structures in corrosive environments can be aided by the results of this research.)

Keywords: reinforced concrete, corrosion severity, bond performance, machine learning, accelerated corrosion

1 INTRODUCTION

Reinforced concrete, which consists of steel and concrete, is one of the most critical materials used in construction today. Reinforced concrete has significant benefits, such as low cost and durability, so corrosion is a damage problem that affects them. Corrosion is one of the most significant problems concrete faces, costing approximately $1.8 trillion per year [1]. External elements such as water and exposed concrete are the most significant physical and chemical sources of corrosion. Corrosion is the deterioration of a metal due to its reactivity with the environment. Corrosion often requires metal contact with moisture and air (oxygen). The degradation that occurs throughout the corrosion process is the metal's inclination to revert to its original form before being refined from its primary raw material [2]. Corrosion poses several problems to structures; it makes them dangerous and shortens their lifespan. Therefore, engineers must devise cost-effective and risk-free methods for mitigating corrosion's impact on structures. However, before considering these solutions, understanding how to combat corrosion and what elements regulate it is necessary. In addition, reinforced concrete qualities are influenced by corrosion [3].

Corrosion significantly impacts reinforced concrete due to the loss of several desirable properties, such as strength and bonding between steel and concrete. The bond between concrete and steel is one of the essential properties of reinforced concrete; hence, we will examine the impact of steel on this property through a study of the issue.

Many researchers have investigated the effect of bonding. F. Tondolo.[4] Examined the behavior of bonds with reinforcement corrosion. The test was conducted on RC specimens measuring (120 x 120 x 120 mm) and implanted with a bar (12 mm in diameter and 500 in length). In this study, mass loss tests were undertaken (up to 20 percent of mass weight). Upon reaching a higher degree of corrosion, the results indicated a rapid decrease in residual bond strength, followed by an increase in bond efficiency if the mass loss did not exceed 2%. C. Fang et al. [5] have studied the bonding behavior of corroded reinforcing steel bars in concrete. The pull-out test was done on 24 specimens with dimensions (140 x 140 x 180 mm) and a bar embedded in the concrete with a diameter of 20 mm and a length of 420 mm. Furthermore, testing revealed that a moderate level (about 4 percent) of corrosion significantly impacts bond strength. However, a substantial drop in bond strength occurred when corrosion increased to a higher level (approximately 6 %).

H. Yalciner et al. [6] conducted an experimental investigation of the binding strength between reinforcement bars and concrete as a function of concrete cover, strength, and corrosion level. The plan included 90 specimens with dimensions (150 x 150 x 150 mm). The characteristics that differed were the extent of corrosion, concrete cover, and strength. In addition, use the pull-out test to identify the bond slip. The results demonstrated that the slip displacement was less for the concrete with the lowest C/D ratio. Moreover, the C/D ratio rose for corroded specimens, although the slip displacement was reduced for the stronger concrete at the same amount of corrosion. E P Kearsley and A Joyce [7] examined the influence of corrosion products on reinforced concrete slabs' bond strength and flexural behavior. The investigation was done on 20 cylinders (100mm in diameter and 200mm in height) with a 10mm-diameter bar implanted. Moreover, 355 in length). The samples were subjected to pull-out and flexural tests. The results indicated that the bond strength of cylindrical specimens (pull-out test) increased for corrosion levels below 2%. The slab specimens corroded to 9 percent and 14 percent (mass loss), and the moment capacity of the slabs decreased significantly.

Effects of Bond Deterioration owing to Corrosion in Reinforced Concrete have been examined by A. Kivell et al. [8]. It was utilized for the following dimensions samples: (140 x 140 x 180 mm). The findings were also determined using the pull-out test. The results revealed a 50% reduction in bond strength combined with a 16% reduction in the average cross-sectional area owing to corrosion. In addition, at the same level of corrosion, less than 16 %, the failure mechanism changes from rupture to progressive sliding, accompanied by a reduction in stiffness. Evaluation of the bond characteristics between concrete and reinforcement as a function of reinforcement corrosion has also been studied by H.S. Lee et al. [9]. The specimens were concrete prisms (104 x 104 mm and length 164 mm). Pull-out test has been used to determine bond stress and the failure mechanism. The results revealed that the pull-out test of corroded specimens and the maximum bond strength of specimens indicated that the specimens were corroded. Decrease according to the percentage of corrosion that increases. In addition, the sample without Lateral reinforcement failed brittlely due to steel corrosion-induced fracture growth.

Many scholarly investigations have been conducted into the use of machine learning techniques within the domain of civil engineering. The findings of these investigations have been advantageous for researchers in the field of civil engineering since they enable prompt and efficient assessment of engineering issues [10]. In the field of civil engineering, the use of computer software, specifically using techniques like the finite element method, is often imperative for the computation of design parameters. Nevertheless, the execution of analysis using this computer program necessitates substantial memory and time resources. The use of machine learning enables the attainment of findings in a prompt and dependable manner. Various aspects of structural engineering are investigated through studies, encompassing confinement coefficients, compressive strength, carbonation, chloride diffusion, failure mode, lateral drifts, long-term deflections, behavior under seismic effects, flexural strength, axial capacity, structural damage, shear stress and plastic viscosity, optimum design, moment capacity, and ductility of diverse materials [10,11,12].

Researchers have used parametric and nonparametric machine learning techniques in civil/structural engineering applications for more than only damage identification. According to reports, machine learning has the ability to forecast and identify corrosion's properties [13,14].

Hence, by the incorporation of experimental research and machine learning methodologies, this investigation offers a comprehensive evaluation of the impact of corrosion on the bonding performance and mechanical properties of steel-concrete interfaces.

2 MATERIALS AND METHODOLOGY

This section presents a concise overview of the methodology employed in this investigation, which integrates experimental analysis with machine learning techniques. The experimental procedure involves casting reinforced concrete prisms, demolding, and curing test specimens, subjecting them to accelerated corrosion, and evaluating their corrosion severity using a pull-out test. Additionally, a machine learning algorithm is developed and implemented to establish a correlation between bond slip and corrosion severity.

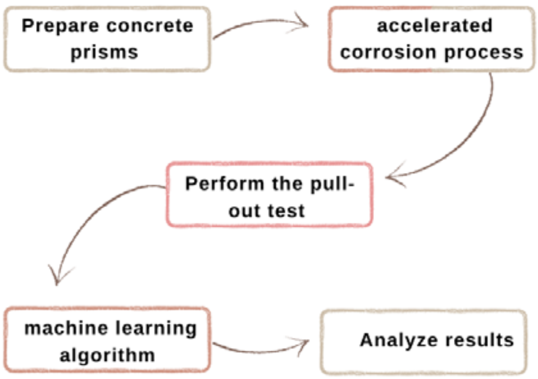


Figure 1. shows a schematic illustration of the experimental program

2.1 Materials

According to ACI-211, two concrete mixtures with water-cement ratios of 0.47 and 0.37 were constructed [15]. For the prisms, specimens were prepared using ordinary Portland cement (Type I) with coarse limestone aggregates and a mix of silica sands. The crushed fine limestone had a maximum aggregate size of 12.5mm (20 percent silica and 80 percent fine aggregate). According to ASTM standard method C136, it was determined that the fineness modulus of the fine limestone was 3.3. According to ASTM standard method C127, the saturated surface dry (SSD) bulk specific gravity (BSG) and the absorption of coarse limestone aggregate were 2.56 and 1.34 %, respectively. According to ASTM standard method C128, the bulk specific gravity (SSD) and absorption of fine limestone aggregate were 2.52 and 3.41 cents, respectively. The comparable results for silica sand were 2.59 % and 0.73 %. Based on ASTM standard C29, the unit weight for coarse aggregate was determined to be 1362 kg/m3 [16]. G60 of steel reinforcement was used in the prism's reinforcements. Table 1 presents the mechanical properties of steel reinforcement.

Table 1. Mechanical properties of steel reinforcement

Size	Grade	Yield Strength, Fy (MPa)	Ultimate Strength, F_u (MPa)	Elongation %
14mm	G60	462	640	16.5

2.2 Test Specimens

According to the ACI code, thirty-two prisms have 10 x 10 x 40cm dimensions. The center of each prism was embedded with a 1 Φ 14mm steel bar. The steel bar consists of two parts, one measuring 28 cm in length and the other measuring 48 cm (inside 24 cm and outside 24 cm). Figure 2 depicts the general configuration of the test specimens and the reinforcement.

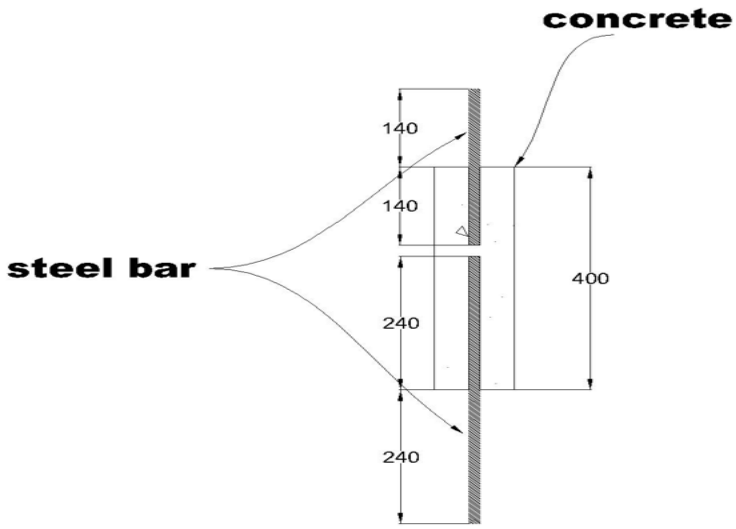


Figure2. General view of the prism used in the study.

As stated in Table 2, the prisms were divided into two groups to achieve the purpose of this study.

Table 2. Details of prism groups

Prism designation	w/c ratio	Number of prisms	Exposure	Testing
Control prism (PN-0.47)	0.47	8	No corrosion	Pull-out
Corroded prism (PC-0.47)	0.47	8	Corrosion	Pull-out
Control prism (PN-0.37)	0.37	8	No Corrosion	Pull-out
Control prism (PC-0.37)	0.37	8	Corrosion	Pull-out

2.3 Casting of concrete specimens

Casting the test specimens required wooden molds with internal diameters of 100×100×400 mm. Before pouring concrete, two 14mm-diameter steel bars were inserted in the center section of the molds. In each batch, eight prisms and three cylinders (100× 200 mm) were cast from concrete mixed using a tilting drum mixer with a batch size of about 0.25 m3. According to ASTM-C143, the slump was studied and found to be around 50 mm. Fresh concrete was poured in three layers into wooden molds, with each layer vibrating on a compacting table. After 24 hours, the specimens were demolded and cured for 28 days using moist burlap. Photos of the above procedures are displayed in Fig. 2.

a) Steel bar inside the wooden mold

b) Specimens cast in each batch

Figure 3. Casting and curing procedure for prisms

Three concrete cylinders (100 by 200mm) were prepared for each batch and tested to determine the compressive strength, which was around 41.6MPa for mixes with w/c =0.47 and 48.3 MPa for mixtures with w/c =0.37. (Fig. 4).

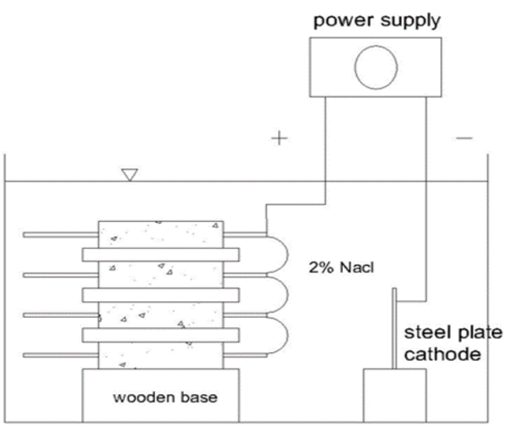
a) Casting and compacting cylinders

b) Capping concrete cylinders

Figure 4. Testing of concrete cylinders

2.4 Corrosion process

The prisms were exposed to an accelerated corrosion process using an electrically impressed DC. The accelerated corrosion process was achieved by applying direct current (DC) to steel bars, which represent the anode within each prism through metallic wires attached to the bars during casting. The cathode was made from a steel plate with dimensions of (800 ×300× 10 mm) that was linked to the cathode wire. A current density of 200 A/cm2 was applied to the prisms. To create an aggressive environment, samples were put in a tank containing a solution with a NaCl content of 3%. The above processes are depicted in photos in Figure 5.



a) general overview

b) Connecting the anode and cathode wires with the device

Figure 5. The accelerated corrosion proces

2.5 Test Setup

The pull-out experiments were conducted utilizing customized universal testing equipment with a capacity of 600kN. The machine was developed precisely to minimize any possible fluctuations in bond strength that may occur during the pull-out tests. The development and customization of this gadget highlights our dedication to maintaining the integrity of our experimental setup and the process of data collecting. In order to achieve accurate regulation and observation of the exerted forces, we used computerized protocols based on displacement control principles. The use of this methodology enabled a systematic and regulated exertion of forces, hence reducing the occurrence of abrupt or irregular variations in load that may potentially undermine the precision of our findings. The careful management of the loading process improves the dependability and replicability of our results. One crucial element of our process included the implementation of a Linear Variable Displacement Transducer (LVDT) onto the steel bar, therefore creating a direct interface with the concrete surface. The use of this device enabled uninterrupted and instantaneous assessments of the relative slip occurring between the steel bar and the concrete matrix. The LVDT enabled the acquisition of slip data, which offered vital insights into the dynamic characteristics of the bond interface, as the applied stress gradually removed the steel bar from its embedded position. Fig 6 shows the pull-out test.

Figure 6. The pull-out test setup

2.6 Machine Learning Algorithm Implementation and Approach

In this study, a machine learning algorithm was developed using the Python programming language, leveraging libraries such as NumPy, Pandas, and Matplotlib for data manipulation, analysis, and visualization. The dataset was imported and preprocessed, creating separate data frames for corroded and non-corroded specimens to facilitate analysis. A scatter plot was generated to visualize the correlation between maximum slippage and ultimate bond load for both corroded and non-corroded specimens.

The input parameters consist of a set of features extracted from both corroded and non-corroded specimens used for both training and testing our machine learning model. These features include a number of physical attributes and corrosion severity indicators relevant to the specimens considered. These features are processed to construct feature vectors. These vectors serve as the input data points for our machine learning model.

Our machine learning model is designed to predict the probability that a given data point belongs to either the corroded class or the non-corroded class. The output of our model is a probability score that ranges from 0 to 1. This probability score is determined using the sigmoid function, which transforms the raw output of the model into a probability value.

To develop and robustly evaluate our machine learning model, we used a carefully curated dataset containing information on both corroded and non-corroded specimens. Thorough preprocessing steps, including data cleaning and normalization, were performed on the dataset. The dataset was divided into distinct training and testing subsets according to an appropriate split ratio to ensure an unbiased evaluation.

A logistic regression model was utilized to establish a correlation between bond slip and corrosion severity. The model employs a sigmoid function $\sigma(z) = \frac{1}{1+e^{-z}}$, which maps any real-valued number to a value between 0 and 1, representing the probability of a given data point belonging to a specific class. The cost function, denoted as $J(\theta)$, measures the discrepancy between predicted values and actual data points. It is defined as:

$$J(\theta) = (\frac{1}{m}) * \Sigma[-y^i * log(\sigma(X^i * \theta^T)) - (1 - y^i) * log(1 - \sigma(X^i * \theta^T))] \quad (1)$$

where m is the number of data points, y^i is the true label for the $i-th$ data point, X^i is the feature vector for the $i-th$ data point, and θ is the parameter vector. The objective is to minimize the cost function to improve the model's performance.

Gradient descent optimization is employed to minimize the cost function by iteratively updating the parameters (θ) using the gradients calculated from the cost function. The learning rate (α) determines the step size during each iteration. The update rule for gradient descent is as follows:

$$\theta = \theta - \alpha \times \nabla J(\theta) \tag{2}$$

The SciPy library was utilized for the optimization process to find the optimal parameter values. Lastly, a prediction function was developed to classify data points based on their calculated probabilities. The algorithm's performance was assessed by comparing its predictions with the true labels in the dataset, providing an evaluation metric for the logistic regression model.

3 EXPERIMENTAL RESULTS AND DISCUSSION

3.1 Introduction

The results section presents a detailed analysis of the experimental data obtained from the pull-out tests, as well as the outcomes generated by the machine learning algorithm. This section aims to provide insights into the correlation between bond slip and corrosion severity in reinforced concrete structures with varying water-cement ratios. The performance of the logistic regression model is evaluated in terms of its accuracy in classifying corroded and non-corroded specimens.

3.2 Bond-slips response

Figures 7 exhibit the influence of corrosion on the bonding behavior of prisms for two mixes with different water-cement ratios. The prisms with the lowest bond load values were PC-0.37 and PC-0.47. In general, prisms with W/C =0.47 exhibit less slippage than prisms with W/C =0.37.

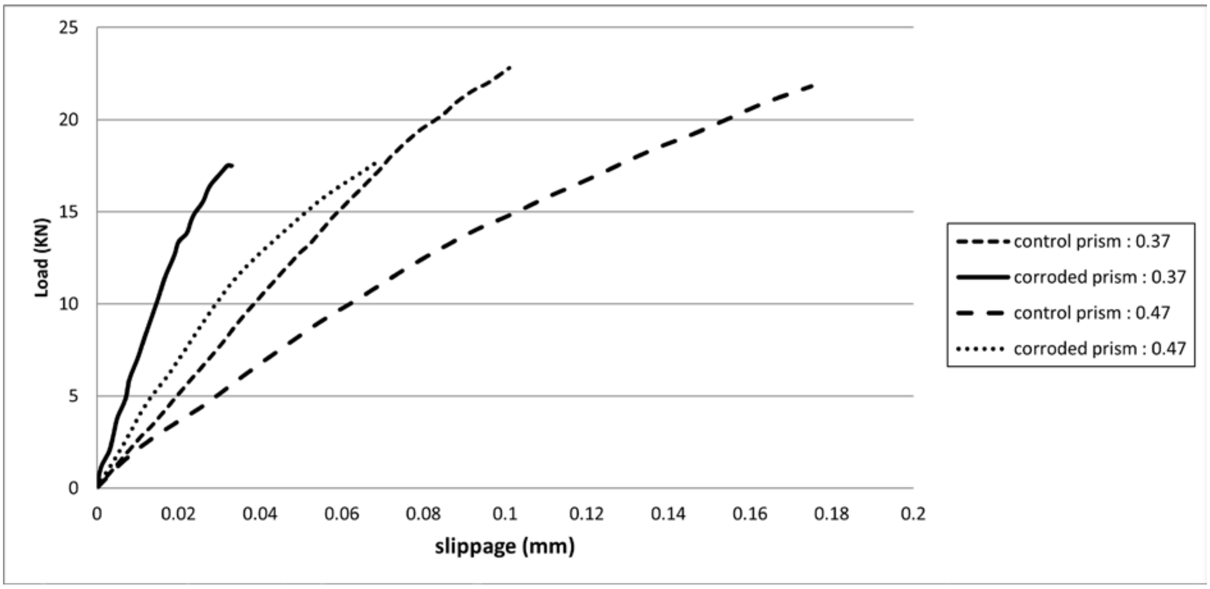


Figure 7. Bond Load-slip curve for prisms with W/C = 0.37 and 0.47

Tables 3 and 4 display the load-slip characteristics of the bond. The tables display the residual bonding capacity for non-corroded and corroded prisms with a W/C value of 0.37. The residual bond load decreased to 77% after accelerated corrosion. Similarly, Table 5 shows the residual bonding capability for the prisms with W/C=0.47. Clearly, after corrosion, the residual bond load decreased to 81 %. The area under the bond-slip curves is used to measure bond toughness. Tables 4 and 5 show the toughness values for two different water-cement ratios. The residual toughness of corroded prisms was much lower than that of non-corroded prisms.

The slope of the initial linear part of the load-deflection curves represents the stiffness of respective prisms. Corroded prisms were less stiff than their non-corroded equivalents.

Table 3. Bond characteristics for the RC prisms with W/C =0.37

case	Prism Designation	Ultimate Bond Load (KN)	Max Slippage (mm)	Toughness (J)	Stiffness (GN/m)
1	Control prism	22.8 (100%) *	0.1 (100%) *	1.26 (100%) *	0.260
2	Corroded prism	17.5 (76.75%) *	0.03 (30%) *	0.34 (27%) *	0.689

*Residual properties

Table 4. Bond characteristics for the prisms with W/C =0.47

case	Prism Designation	Ultimate Bond Load (KN)	Max Slippage (mm)	Toughness (J)	Stiffness (GN/m)
1	Control prism	21.8 (100%) *	0.18 (100%) *	2.18 (100%) *	0.171
2	Corroded prism	17.7 (81.2%) *	0.07 (38.9%) *	0.72 (33%) *	0.378

*Residual properties

3.3 *Performance and Results of the Machine Learning Algorithm*

In this section, we present a comprehensive analysis of the performance of our machine learning algorithm in effectively correlating bond slip of steel-concrete interfaces with corrosion severity for the two different water-cement (w/c) ratios studied. The remarkable performance results of the algorithm underscore its importance in predicting and evaluating bond performance and corrosion severity in reinforced concrete structures. After thorough optimization, the machine learning algorithm achieved remarkably low costs of 4.548×10^{-6} for a w/c ratio of 0.37 and 3.445×10^{-7} for a w/c ratio of 0.47. These results vividly reflect the algorithm's successful ability to minimize discrepancies between predicted and actual data points, indicating its robustness in modeling complex relationships between bond slip and corrosion severity. Furthermore, the 100% accuracy achieved for both w/c ratios is a testament to the algorithm's precision in predicting bond performance and corrosion severity. The consistency of this high level of accuracy confirms the resilience of the algorithm in dealing with varying conditions, further highlighting its potential to provide invaluable insight for infrastructure assessment and maintenance initiatives. Visual representations of the achieved accuracy and predictions can be observed in Figure 8 and Figure 9. These visualizations provide a tangible representation of the algorithm's effectiveness in capturing intricate correlations within the data, thereby increasing the transparency of our results.

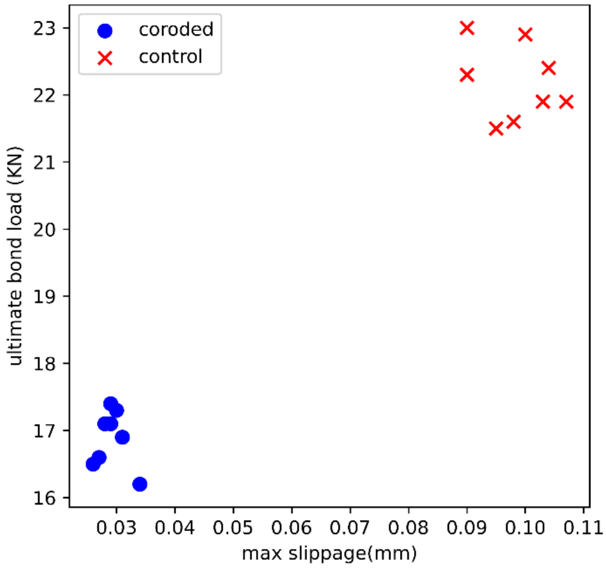


Figure 8. The correlation between maximum slippage and ultimate bond load for control and corroded prisms at 0.37

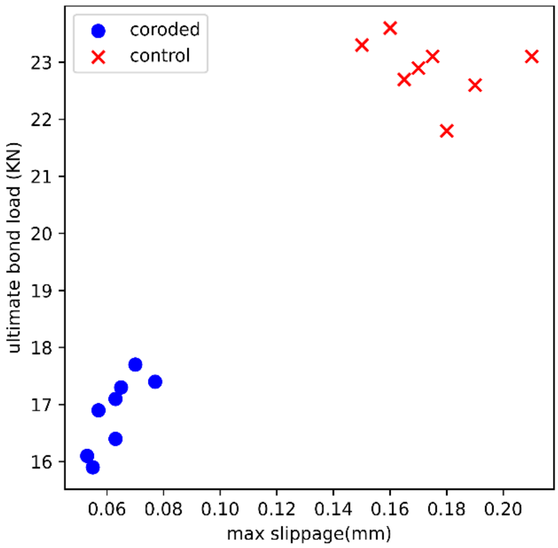


Figure 9. The correlation between maximum slippage and ultimate bond load for control and corroded prisms at 0.47

4 CONCLUSION

In summary, this research effectively integrated experimental methodologies with machine learning algorithms to examine the influence of corrosion on the bonding characteristics and mechanical attributes of steel-concrete interfaces. The experimental findings indicate that the residual bond load and stiffness of corroded prisms were drastically diminished in comparison to their non-corroded counterparts. Additionally, the residual toughness of corroded prisms exhibited a considerable decrease. The aforementioned results underscore the need to comprehend the impacts of corrosion on reinforced concrete buildings in order to guarantee its durability and security. Concurrently, a unique machine learning technique was methodically devised and executed to ascertain a link between the bond slip of steel-concrete surfaces and the degree of corrosion. The algorithm presented in this study proposes an innovative methodology for quantifying and predicting the complex correlation between bond performance and corrosion, a longstanding issue in prior research efforts. The algorithm's outstanding performance is especially notable, as it achieves a stunning 100% accuracy for both the water-cement (w/c) ratios that were investigated. The algorithm's high level of predicted accuracy highlights its dependability and promise as an advanced tool in the area of structural analysis. Significantly, the machine learning method that has been proposed demonstrates noteworthy practicality in real-world contexts. By facilitating the connection between controlled laboratory experiments and the intricate nature of real-world infrastructure, this approach provides engineers and stakeholders with a dependable method to evaluate the structural soundness of constructions exposed to corrosive surroundings. The process of translating research findings into practical insights is in perfect harmony with the current focus on evidence-based decision-making in the field of infrastructure maintenance and management. Furthermore, the use of machine learning methodologies in conjunction with empirical data signifies a significant advancement in understanding the intricate correlation between corrosion and bond performance. The integration of several disciplines provides a more comprehensive comprehension that exceeds traditional ways of analysis. The integration of data-driven analysis with empirical observations results in a more detailed understanding of the fundamental processes that regulate the behavior of steel-concrete interfaces in corrosive environments.

5 ACKNOWLEDGMENT

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