Measurement of Reinforcement Corrosion in Concrete Adopting Ultrasonic Tests and Artificial Neural Network

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Abstract

Limited research has been performed in testing and measuring the reinforcement corrosion levels using non-destructive tests. This research applied ultrasonic-based non-destructive test and artificial neural network to the diagnosis and prediction of rebar's non-uniform corrosion-induced damage within reinforced concrete members. Ultrasonic velocities were tested by applying ultrasonic to reinforced concrete prisms before and after the rebar corrosion. Input parameters including concrete strength, ultrasonic velocity, and the specimen dimension-related variable were used for the prediction of reinforcement corrosion level adopting artificial neural network models. Using totally 50 experimental observations, Radial Basis Function-based model was found with higher accuracy in predicting corrosion levels compared to Back Propagation-based model. This study leads to future research in high-accuracy non-destructive measurement of reinforcement corrosion in concrete.

Keywords: Reinforcement corrosion; reinforced concrete; non-destructive test; artificial neural network

1. Introduction

Concrete structural damage due to reinforcement corrosion is not uncommon and could be significant [1]. For example, chloride-induced durability problems shorten the service life of concrete structures [2]. The durability of concrete materials under chloride penetration

requires particular attention [3]. However, reinforcement corrosion is not easily noticed. How to identify and measure the rebar corrosion within reinforced concrete structure remains a key issue in the concrete durability research. The commonly adopted non-destructive test approaches for the measurement include half-cell potential method [4] and concrete resistivity method (e.g, Wenner Four-Electrode Method [5]). These existing methods have their own advantages of being easy to operate for on-site tests with simple detection facility. However, both methods can only be used for the probability analysis of rebar corrosion within concrete but are unable to quantify the corrosion level or the corrosion-induced damage, especially for the non-uniform corrosion-induced damage within reinforced concrete. A more effective approach to test the rebar corrosion level would be to separate the rebar from concrete and measure the shape and depth of rebar etch-pits. Nevertheless, the separation of rebar from concrete would cause further structural damage and hence being not feasible. Therefore, it cannot be widely applied. There is hence an urgent need of developing a more applicable and practical measurement technology for the non-destructive test of rebar corrosion within concrete structures.

Ultrasonic measurement can be used to test concrete mechanical properties and internal defects through the elastic wave signals sent to concrete structures. The ultrasonic test implemented in concrete structure is based on the artificial method to generate elastic wave signals, which contains the information of propagation time (or speed), amplitude and frequency. The concrete structure is elastic-viscoplastic, with variations of acoustic impedance among its internal interfaces. The ultrasonic waves have strong reflection, scattering, diffraction, absorption, and waveform distortion when passing through the concrete structure. By extracting the information carried out in the signals and performing inversion analysis, the data of mechanical properties and defect distribution of materials and structures can be obtained.

Huygens-Fresnel Principle [6] can be applied in supporting the ultrasonic measurement by comparing the defect size and the wave length, as the wave path would be different depending on the defect size within concrete structures. The predication of concrete strength by integrating ultrasonic wave and artificial neural network (ANN) has been performed in some existing studies such as Trtnik et al. [7] and Kewalramani and Gupta [8]. However, there has not been sufficient research on applying ultrasonic wave in measuring the rebar corrosion within concrete structures. ANN, as one of the data mining methods that have been widely applied in estimating concrete mechanical properties (e.g., strength) in existing studies such as Chithra et al. [9], Omran et al. [10], Sadowski et al. [11], Wang et al. [12], Wang et al. [13], has not been sufficiently used in the prediction of corrosion level of reinforcement in concrete.

Non-destructive tests have been applied in the test and evaluation of properties of construction materials, such as bond between concrete layers [11], compressive strength [12], and other types of mechanical properties [15]. However, **limited studies have been performed in applying non-destructive tests to measure reinforcement corrosion level in concrete members in a quantitative approach.** Yeih and Huang [16] adopted ultrasonic testing for the non-destructive detection of concrete reinforcement corrosion, and found certain correlation between the reduction of ultrasonic amplitude and the electrochemical parameters of corrosion. Continued from the research of Yeih and Huang [16], this study aims to apply the ultrasonic test in measuring the corrosion level of non-uniform surfaces of rebar, and to evaluate the accuracy of ultrasonic test-based measurement on reinforcement corrosion level. Radial Basis Function (RBF)-based and Back Propagation (BP)-based models are applied and to be compared of their accuracies in the prediction. The study serves as the initial exploration of non-destructive tests of rebar corrosion level in non-uniform surfaces, leading to further research in establishing

the non-destructive test procedure in measuring steel corrosion within reinforced concrete structures.

2. Experimental program

2.1. Linking reinforcement corrosion level to ultrasonic velocity

The corrosion process of reinforced concrete was defined by Zhao and Jin [17] in terms of three stages, namely: 1) the first stage of free expansion of rust, in which the steel corrosion products fill the rebar/concrete interface voids; 2) tensile stress within concrete cover, in which the concrete cover starts cracking; and 3) cracking within concrete cover, when the cracking continues to be filled with the rust products. Empirical formulas have been established to estimate the rebar corrosion level in concrete structures. Zhao and Jin [17, 18] further proposed empirical formulas to estimate the corrosion depth of reinforcement. Zhao et al [19] used stereoscopic microscope to observe the seriously corroded layer and found that the corrosion depth was not more than $500\ \mu m$. Following Huygens-Fresnel Principle [3], when the corrosion layer size is smaller than the wavelength, the ultrasound would diffract, resulting in a longer receiver signal. In addition, since the acoustic impedance of the air is far lower than that of concrete, sound energy would decrease and the sound duration would increase resulting from the reflecting and scattering of pulse wave at the corrosion surface. Therefore, it is feasible to detect the corrosion level of reinforcement in concrete according to the ultrasonic velocity. The effect of test specimen size described in Fig. 1 in ultrasonic velocity was studied by Zhang and Qiu [20].

2.2. Experimental set-up

Table 1. Mix design details of four different concrete specimens in this study

Specimen Type	Portland Cement (kg/m ³)	Fly ash (kg/m ³)	Granulated blast furnace slag (kg/m ³)	Sand (kg/m ³)	Coarse aggregate (kg/m ³)	Water (kg/m ³)	Water reducer (kg/m ³)	Slump (mm)
C20	182	112	26	757	1045	195	3.52	150
C25	202	87	47	762	1052	185	4.04	150
C30	220	83	58	736	1059	180	4.50	150
C35	245	78	66	695	1086	175	5.06	150

Totally 50 groups of concrete specimens were cast, among them 44 were prisms sized at $100\text{mm}\times100\text{mm}\times400\text{mm}$, and six of them being prisms sized at $150\text{mm}\times150\text{mm}\times550\text{mm}$, each prism was embedded with a hot-rolled round steel rebar with the diameter of 12mm . Cured at the standard laboratory condition for 28 days, specimens were placed in the chloride salt and stray current condition to reach different levels of rebar corrosion. Specifically, two types of corrosion tests were adopted in this study, namely chlorine salt wet-dry cycle and stray current method. In the chlorine salt wet-dry cycle approach, specimens after 28 days' standard curing were soaked and placed in 5% sodium chloride solution for 12 hours, and then oven dried in the temperature of $50\pm1\text{ }^{\circ}\text{C}$ for another 12 hours. This was counted as one wet-dry cycle. The same cycles were repeated to corrode reinforcement in the chloride salt environment; in the stray current condition, concrete specimens after the same 28 days' standard curing were buried in the 5%-sodium-chloride-wetted sand. Rebar was then used as the anode with copper bars as cathodes. They were electrified with a DC power supply to create rebar corrosion in the stray current conditions.

The NM-4A type of non-metallic instrument was adopted in this study to test the ultrasonic velocity within the concrete specimen. To prevent the ultrasonic velocity being affecting by the variation of specimens' moisture contents, each specimen was stored indoor under constant room temperature and dried for three days. Each specimen's longitudinal surface was set up with nine test areas. The average ultrasonic velocity was calculated from the nine test areas. Test details, including specimen sections and the nine test zones are described in Fig. 2. The test procedure is illustrated in Fig.3.

Fig.2. Reinforced concrete specimen for ultrasonic tests with details of test specimens (Size units /mm)

Fig.3. Schematic illustration of ultrasonic testing

Before the ultrasonic test had been performed in concrete specimen, the effect of concrete moisture content on ultrasonic velocity was examined. Mix design targeting on C30 ordinary concrete was adopted to cast two standard prisms, with the dimension at $100\text{mm} \times 100\text{mm} \times 400\text{mm}$. Cured at the standard condition on Day 28, the reinforced prism was connected to electrical circuits to achieve different degrees of corrosion severity. Later, following the procedure described by Liu et al. [21], the corroded specimens were immersed

in water for three days to reach full saturation. The saturated specimens were then removed from water, surface dried, and weighted. The specimens were then put in ovens to be gradually dried with lower moisture content. After each drying period, the specimen was removed from the oven, weighted, and retested of the ultrasonic velocity until it reached its constant weight when fully internally dried. The test setup is illustrated in Fig.4.

(a) Specimens being dried

(b) Schematic illustration of ultrasonic testing

Fig.4. Test setup to studying the influence of moisture content on ultrasonic velocity

Data obtained from the test setup described in Fig.4 would then allow the correlation analysis between moisture content and the average ultrasonic velocity.

2.3. Application of artificial neural network to predicting rebar corrosion

Artificial neural network (ANN) was applied in this research to analyzing the rebar corrosion, based on the three following features of ANN [22]: 1) it has strong self-adaptability and is able to capture the corrosion-caused damage in concrete members; 2) it is able to store the damage-related information in the learning stage and compare the predicted data with the measured outcomes; 3) it is robust with its non-linear mapping capacity to establish the relationship between the rust damage related value and the non-destructive parameters. In this study, ANN was modeled using the NeuroSolutions [23] as the tool.

The Back Propagation (BP) and Radial Basis Function (RBF) were the two ANN models that were adopted in this research to link the non-destructive parameters to corrosion levels of rebar in concrete prisms.

BP has been widely applied in the field of civil engineering [24-27]. The topology structure of BP-based network can be described in Fig.5.

Fig.5. topology structure of BP neural network

As displayed in Fig.5, the data samples start from the input layers, passing the hidden layer until they reach the output layer. In Fig.4, ω_{ij} and ω_{ij} represent the connection weightings when data is moving forward from the input layer to hidden layer, and from the hidden layer to the output layer respectively. During the learning and training process, the error would be passed backwards through hidden layer to input layer if the actual output value does not match the expected value. Then the error is spreading to all cells in the input layer illustrated in Fig.5. The error signal serves as a basis for modifying the weighing of

each cell. The weightings will be adjusted through a new cycle by passing the data forward from input to output layers. This kind of cycle can be reprocessed until the error is reduced to a tolerable level, or the learning process has completed certain specified number of cycles. Detailed process of running BP-based models can be found in Buscema [28] and Hecht-Nielsen [29].

RBF's topology structure can be described in Fig.6. Differing from BP, the input layer in RBF only passes information, with the connection weighting at 1.0 . The radial basis function is incorporated in the hidden layer. Linear weightings are adjusted in the output layer. The steps to perform RBF-based network can be found in Billings et al. [30] and Chen et al. [31].

Fig.6. topology structure of RBF neural network

Although RBF has not been widely applied in predicting steel corrosion levels, certain relevant existing studies can be found, such as Chou et al. [32] and Pai et al. [33].

The main difference between BP and RBF lies in that BP model utilizes the S-type hyperbolic function in its hidden layer. In comparison, RBF is a non-linear network, with its hidden layer utilizing Gaussian function. Both BP and RBF were adopted in the prediction of rebar corrosion levels in this research. Both types of ANN models contain the three layers

(i.e., input, hidden, and output layers). Applied in the predication of rebar corrosion levels, three nodes were included in the input layer for both models, namely compressive strength of concrete specimens (X_1), average ultrasonic velocity (X_2), and the ratio (i.e., $2R/L$) of rebar diameter to test distance illustrated in Fig.1. Four treatment nodes were set in the hidden layer. Rebar corrosion level was set as the single node in the output layer. The Levenberg-Marquardt algorithm was adopted in the data training. The maximum training time was set at 1,000. After the networks were established, data sample could be used for the training. The data sample was divided into training sample and the cross-validation sample. When the training was complete, the error was reduced and eventually approached 0, and corresponding weightings were stored automatically.

3. Results and discussion

3.1. Laboratory observations

Under the laboratory condition, the interfaces between concrete and corroded reinforcements were observed as presented in Fig.7.

Fig.7. Defects of interfaces between corroded reinforcement and concrete

The development of steel corrosion led to defects in the interfaces between reinforcement and concrete as shown in Fig.7. To further identify the defect size of corrosion layers formed in reinforced concrete prisms, the element distribution of the corrosion area was analyzed

adopting scanning electron microscopy (SEM) and electron probe. Adopting C30 specimen as the showcase, the analysis is illustrated in Fig.8.

Fig.8. Linear SEM/EDS analysis of chemical elements in corrosion layer

The black-colored line denoted with *Fe* in Fig.8 represents the rebar, and the red-colored line denoted with *Ca* is concrete. Both lines underwent sudden sharp drops of their element content as it can be seen in Fig.8, indicating the occurrence of corrosion. The length of the overlapping zones of the two lines shows the corrosion depth. It is found from Fig.8 that the corrosion depth was between $80\mu m \sim 200\mu m$, below the maximum depth of seriously corroded rebar at $500\mu m$ according to Zhao et al. [19].

3.2. Effects of moisture contents in ultrasonic velocity

The experimental data of water content corresponding to the ultrasonic velocity is described in Fig.9. Various moisture contents ranging from 0 to 2.5% in concrete were included.

Fig.9. Relationship between ultrasonic velocity and moisture content

Specimens 1 and 2 in Fig.9 represent two different corrosion levels of reinforcement. It can be found from Fig.9 that under both corrosion levels, ultrasonic velocity would not be significantly affected when the moisture content in concrete is not higher than 1.5%. As the moisture content increases from 1.5% in concrete specimens, the ultrasonic velocity would grow more significantly to be 8% higher compared to that when concrete is fully dried. The effect of moisture content in ultrasonic velocity could be due to the heterogeneous feature of concrete structure. Voids and cracking in corroded concrete members are filled with air or moisture. The moisture content in concrete structure would affect the air percentage in concrete, resulting in the change of ultrasonic velocity. As ultrasonic wave travels significantly faster in liquids than in the air, it would be significantly increased when concrete cracking was filled with more moisture. The experimental tests indicated that the moisture content lower than 1.5% could be considered as dry condition when the moisture is not continuously or evenly distributed within concrete internal voids. As a result, the ultrasonic velocity would not be significantly changed. This initial study of moisture content's effect in ultrasonic velocity provides the threshold value that in conducting the ultrasonic tests within concrete structures, concrete should be kept dry with the moisture content below 1.5%.

3.3. Ultrasonic test results

Ultrasonic velocities were tested within different types of specimens under different corrosion levels before and after corrosion. Four typical types of recorded acoustic velocities along the nine locations within the same specimen are showcased in Fig.10.

Fig.10. Comparison of ultrasonic velocities before and after corrosion

Fig.10 displays four examples representing different corrosion levels of reinforcement. All the four examples in Fig.10 demonstrate that ultrasonic velocity was significantly higher in concrete before rebar corrosion. The velocity tested at the nine different areas of the same specimen was generally stable with little variation before corrosion. After the rebar corrosion, the ultrasonic velocity was significantly reduced, and the nine tested velocities within the same concrete specimen had a larger variation. The variation of ultrasonic velocity could be explained by the micro-structure of the concrete specimen. The number and size of defects (e.g., pores and micro-cracks) within concrete structures are relatively small before rebar

corrosion, and the ultrasonic wave would mainly be transmitted with high velocity in a stable way. Following the rebar corrosion, the corrosion products increase creating defects at the concrete-reinforcement interfaces as shown in Fig.11. The final corrosion force leads to concrete cracking and diffraction of ultrasonic wave. The reflection and scattering of ultrasonic waves would then result in significant reductions of velocity according to Wang et al. [34].

Fig. 11. Interface cracking of reinforced concrete due to corrosion expansion

3.4. Results of applying ANN to predicting rebar corrosion rates

Totally 50 observations were used as the data sample in applying BP and RBF models. Among them 45 observations were adopted as the training set, and the rest five were used as the cross-validation set. Fig.12 displays an example of data training.

a) Learning curve

Desired and Output	
Des	Out
5.290000000000	5.785290707936
2.580000000000	2.578098437134
1.030000000000	1.068660923141
7.940000000000	8.966759157537
3.890000000000	4.137865057236

b) Comparing the desired and actual output corrosion rates

Fig.12. Learning curves and predicting the corrosion mass loss ratio of using RBF model

The two ANN models were compared of their performance. Both models were able to complete the data training and predict the rebar corrosion level based on the three input parameters (i.e., X_1 , X_2 , and X_3), where X_1 stands for the design compressive strength pf concrete, X_2 is the average ultrasonic velocity within each observation sample, and X_3 means the ratio of rebar diameter to the test distance (denoted as $2R/L$) as shown in Fig.1. The dependent variable (i.e., corrosion level) was measured by the reinforcement mass loss ratio as shown in Equ.(1).

$$S = \frac{m_o - m_1}{m_o} \times 100\% \quad \text{Equ.(1)}$$

where S denotes the mass loss ratio of reinforcement, m_0 is the mass of the originally non-corroded specimen, and m_1 represents the mass of the corroded specimen after de-rusting. Upon the end of each ultrasonic test in this research, corroded reinforcements were washed using de-rusting solution to remove corrosion products after the corrosion process. The appearances of rebar before and after de-rusting are shown in Fig.13.

Fig.13. Images of reinforcement before and after the corrosion

The removal solution applied in the de-rusting of rebar was prepared by mixing 3% of hexamethylene tetramine with 97% of diluted hydrochloric acid by weight. The relative errors of prediction from the cross-validation sample are listed in Table 2.

Table 2. Corrosion mass loss ratio predicted by neural networks

Data set	X_1	X_2	X_3	Y (Observed)	Y (BP)	Relative error /%	Y (RBF)	Relative error /%
1	C25	3.6220	0.12	5.29	5.36	1.32	5.79	9.45
2	C30	3.8723	0.12	2.58	1.82	29.46	2.58	0.00
3	C35	3.9920	0.12	1.03	1.05	1.94	1.07	3.88
4	C20	3.4557	0.12	7.94	8.30	4.53	8.97	12.97
5	C30	4.1580	0.08	3.89	2.69	30.85	4.14	6.43

It can be found from Table 3 that the RBF model had a superior performance in terms of generally lower relative errors. Several significantly large relative errors were found in the validation sample adopting BP, such as data set 2 and 5 related to C30. The comparison between BP and RBF showed that RBF had the lower standard error. Compared to BP, RBF could better detect the non-linear relationship between the input and output layers with an overall higher prediction accuracy, due to its own advantages in network structure, training algorithms, and usage of network resources, specifically:

- 1) BP network applied weightings from its input layer to the hidden layer. It is not easy to determine the number of hidden layer units in BP network. The network structure will not be changed once it is confirmed in the training process. In comparison, the RBF network utilizes the direct connection between its input and hidden layers, but weightings are applied between its hidden layer and the output layer. RBF is capable of adjusting the number of hidden layer units during the training.
- 2) theoretically, both BP and RBF models are capable of providing the non-linear prediction approach. However, they apply different functions with varied performance of approximation. BP network, with the S-shaped function as the transformation function, uses the approximation of the nonlinear mapping. The RBF network is a network derived from the regular theory. It uses the locally exponentially decaying Gaussian function to locally approximate the nonlinear mapping and has the best approximation Nature according to Zhang [35].

3) the determination of BP neural network weights and thresholds is directly determined by the sum of the squared deviations of each output node. The trained network can only be a compromise between different tasks, and the best effect cannot be achieved for one task. In comparison, the distribution of hidden layer units in RBF network can be decided according to the capacity, category and distribution of training samples. Based on the distribution of hidden layer units, the mapping relationship between input and output can be achieved by adjusting the mapping between the hidden layer's and output layer's units. The impact of different tasks is relatively small, and the network resources can be fully utilized.

It should be noted that the neural network models established in this study of non-destructive test in reinforced concrete specimens serve as initial references in predicting steel corrosion levels. Continuous data training will be performed as the sample size increases. The future work will focus on building a more comprehensive prediction system with more ANN models or data mining methods, as well as further improving the prediction performance.

4. Conclusion

This study aimed to adopt the ultrasonic test as the non-destructive approach in measuring the corrosion level of non-uniform surfaces of rebar within the reinforced concrete structure. Then the artificial neural network was applied in training the experimental data for the prediction of rebar corrosion level. Based on the experimental investigation and the neural network modeling, the following findings can be summarized:

(1) The rebar-concrete interface was observed using scanning electron microscopy (SEM) and electron probe. The corrosion depth in the reinforced prism was identified between $80\mu m \sim 200\mu m$;

(2) The effect of water content in concrete specimens' ultrasonic velocity was studied before conducting the corrosion tests. It was identified that moisture content below 1.5% in concrete would not cause significant increases of ultrasonic velocity. Moisture content over 1.5% would cause more significant increase (i.e., up to 8%) of ultrasonic velocity;

(3) Rebar corrosion would cause significant reductions in ultrasonic velocity in concrete specimens. Compared to the ultrasonic velocity before rebar corrosion, the ultrasonic velocity tested at different zones of the same concrete specimen also tended to vary more significantly. The larger variation of ultrasonic velocity after rebar corrosion was due to the micro-structural perspective in the concrete structure;

(4) two types of artificial neural network models (i.e., BP and RBF) were applied in predicting the rebar corrosion level based on 50 experimental observations. RBF was found outperforming BP in predicting the rebar corrosion level due to the smaller average relative error. The superior performance of RBF was described in comparison to BP in terms of network structure, training algorithm, and network resource usage.

The current study is limited in its data sample size and the types of neural network models. Future research would recruit a larger data sample and more neural models to further explore the application of artificial neural network and other data mining methods in predicting steel rebar's non-uniform corrosion-induced damage in reinforced concrete members. More future research needs to be performed to extend the current study, which only adopted a single rebar in the test specimen. The current study adopted the average velocity of nine test areas within the same specimen to estimate the overall corrosion level of reinforcement. But the current study can lead to future research if different test areas of the same specimen are recorded and input for data analytics. Overall, this research serves as the initial movement towards applying the ultrasonic test as one non-destructive method to estimate reinforcement corrosion level within concrete.

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