Research Article

Predicting GPR Signals from Concrete Structures Using Artificial Intelligence-Based Method

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This paper presents the application of an Artificial Intelligence-based method in analyzing the effects of environmental conditions, chloride contamination in concrete, and surface corrosion of rebars on the amplitude of Ground Penetrating Radar (GPR) signals. Six reinforced concrete slabs with different chloride contamination mixtures were fabricated and tested. GPR data were collected under various temperature and ambient humidity combinations. A total of 288 rebar picks were used for training, validation, and testing the proposed Artificial Neural Network (ANN) model. Multiple ANN model configurations with a variation in learning algorithms and the number of nodes in the hidden layer were explored to obtain the optimal model for the nondestructive data. It is shown that the “trainlm” learning algorithm produced the high accuracy prediction of the reflection amplitude of GPR signals. The sensitivity analysis was also conducted with the ANN model to investigate the effects of the input on the output parameters. Results from the sensitivity analysis revealed that the GPR reflection amplitudes were more sensitive to the changes of temperature parameter (TEM) and chloride contamination level (CCL), while they were less sensitive to the variation of ambient relative humidity (ARH) and rust condition on the rebar surface (CSR).

1. Introduction

Ground Penetrating Radar is a geophysical technique using radar pulses for mapping subsurface structure. GPR works by emitting a short pulse of electromagnetic radiation into media and recording the return reflected signal via the receiving antenna. When the electromagnetic waves encounter a buried object or a boundary between two media with different dielectric permittivity, the signals may be reflected or scattered back to the surface. By evaluating the return signals, the subsurface objects, changes in material properties, and voids and cracks can be detected [1]. Figure 1 shows different types of signals produced by a commercial GPR device for three kinds of material, namely, (i) rebar, (ii) an empty plastic conduit, and (iii) a plastic conduit filled with water [2].

The depth range of GPR investigation depends on factors such as the electrical conductivity of the media and the frequency of the transmitted wave. Materials with a high electrical conductivity would attenuate the wave energy

quickly. As a result, the penetration depth would decrease in these materials, and vice versa. The rate of energy attenuation drops with lower frequency waves. Thus, the introduced waves with lower frequencies in the same media would penetrate much higher than that of the higher frequencies. The resolution, however, increases with a higher frequency wave. Thus, the selection of operating frequency is a trade-off between resolution and the penetrating depth.

The application of the GPR method has been extended over recent years in various fields, including archaeology, earth science, nondestructive testing, and environmental remediation. In the nondestructive testing area, GPR is used to detect and pinpoint rebar in concrete [3], to estimate concrete cover thickness and rebar diameters [4, 5], and to monitor the deterioration process in concrete structures [6]. In these applications, the reflection amplitudes were analyzed to identify the target objects using the specialized software. The GPR reflection amplitude, however, was affected by factors such as chloride contaminated concrete,

FIGURE 1: GPR signal for different types of material [2].

rust on the surface of rebar, and the environmental conditions, as suggested in a recent study [7].

Traditionally, the method using the experimental non-destructive test is used to collect data for investigating the effects of chloride content in concrete, surface rust on rebar, and environmental conditions on GPR signals [7–13]. In recent years, an alternative method that can be employed for collecting GPR data is to apply the Artificial Intelligence-based technique. Available data were utilized for training, validating, and testing the proposed ANN model. The successful ANN model could learn from data to establish the nonlinear relationship between the inputs and outputs. Thus, the GPR reflection amplitude can be predicted from the certain input conditions without a need to perform the experimental tests.

Many researchers have successfully applied the ANN model in dealing with various engineering issues [14–22]. For example, Guneyisi et al. [20] employed ANN to predict the flexural overstrength factor of steel beams using 141 experimental records from previously published sources. Results from the study revealed that the ANN model can be used to estimate the capacity of the beam with a high level of accuracy. In another study, Hakim et al. [21] apply ANN to detect the damage of steel girders. It was reported that the ANN model can determine the severity of damage with an error of 6.8 percent.

Regarding the application of ANN for GPR-related problems, Dinh et al. [23] applied the ANN method for investigating the effects of concrete cover thickness on rebar reflection amplitude. An ANN model was developed using concrete cover thickness as the input. The output of the model was the GPR reflection amplitude of rebar. Rebar picks were used for training, testing, and validating the proposed ANN model. Results from the study indicated that the ANN model could be employed for evaluating the influence of concrete cover thickness on rebar GPR reflection amplitude with the coefficient of determination value for the entire data set was 0.91.

In recent research, Liu et al. [24] employed a neural network to pinpoint subsurface objects and evaluate the

backscattering properties from GPR data. A single-layer artificial system, called Adaptive Linear Neural Network, was utilized in the study. The inputs were a series of primary functions derived from GPR signals, and the output was the reconstructed GPR data. Numerical GPR data were created and used to train, test, and validate the proposed ANN model. The inverted backscattering intensity with a relative error rate of less than three percent was found in the study. Another approach is using a neural network to process the images produced by GPR devices [25–27].

Many investigators have carried out research to address the GPR-related issues with various approaches [23–27]. Few studies were conducted to develop the relationship between one input with GPR reflection amplitude from rebar using the ANN model [23]. To the best of the authors' knowledge, there are no available publications using the ANN method to establish the GPR signals from rebar with multiple inputs. The primary objective of this research is to fill the knowledge in the application of the ANN method for predicting GPR signals from different input variables. The ANN structure used in this study was constructed with MATLAB R2020a Runtime Environment.

2. Experimental Data

GPR data used in this study were collected on six reinforced concrete slab specimens fabricated at the Advanced Material Testing Laboratory at Marshall University using a GPR device. Four input parameters, namely, chloride contamination level, ambient temperature, surrounding relative humidity, and rust condition on the rebar surface, were examined during the data collection process. The reinforced concrete slabs were fabricated with an identical reinforcement configuration but different chloride contamination concrete levels. GPR data were collected in various temperature and ambient relative humidity combinations inside an environmental growth chamber. The GPR reflection amplitudes from rebar were manually picked from the raw data using commercial software. These steps were described in detail in the subsequent sections.

2.1. Specimen Fabrication. The overall dimensions of all specimens were $36.5 \times 114.3 \times 17.8$ cm (width $\times$ length $\times$ thickness) with specific rebar locations shown in Figure 2. Six noncorroded steel rebars (nominal diameter of 1.58 cm) labeled in numerical order from one (#1) to six (#6) were placed into concrete slab specimens at varying depths. Besides, a precorroded steel rebar at position seven (#7) was placed at the approximate depth as the noncorroded steel rebar at the location six (#6). Specimens were named from SPC1 to SPC6 along with the increase in the percent of chloride content in the specimen (by the weight of concrete) from zero percent (i.e., control specimen, SPC1) to 0.10 percent (in SPC6) with an increment of 0.02 percent. Details of specimens and their chloride content can be found in Table 1.

Specimen name	Chloride (%)
SPC1 (control)	0.00
SPC2	0.02
SPC3	0.04
SPC4	0.06
SPC5	0.08
SPC6	0.10

Temperature (°C)	Relative humidity (%)	Chloride level (%)	Precorroded rebar
5	55	0.00	Yes
10	70	0.02	No
15	85	0.04	
20		0.06	
25		0.08	
30		0.10	
35			
40			

The first GPR data collection procedure was conducted at a combination of a temperature of 5°C and relative humidity of 55%. After completing the first data collection process, the temperature in the chamber was increased from 5°C to 10°C, while the relative humidity was maintained at 55%. This ambient environmental condition remained constant until the next GPR data collection was conducted. The same process was applied for the temperature between

2.3. GPR Reflection Amplitude. The raw GPR data were processed using RADAN7 commercial software [34]. Due to the limitation of the testing devices, the variation in the depth of rebar would not be included in the data collection. The reflection amplitudes from two rebars located at the same depth (rebar #6 and rebar #7) were manually picked, normalized, and converted from data units to decibel (dB) using equation (1). The normalization step was conducted to ensure that the picked GPR amplitude data for steel rebar are comparable [35].

$$\text{Amp}_{\text{db}} = 20 \times \log_{10} \frac{\text{Amp}_{\text{rb}}}{\text{Amp}_{\text{dc}}}, \quad (1)$$

where Amp_{db} is data amplitude in decibels, Amp_{rb} is rebar amplitude in data units, and Amp_{dc} is direct-coupling amplitude in data units.

The final data set consisted of 288 data points (rebar picks); each of them included five properties, namely, temperature (TEM), ambient relative humidity (ARH), chloride level (CLL), corrosion condition on the surface of rebar (CSR), and reflection amplitude from rebar (GRA). The range of the input and output parameters is shown in Table 3. It is worth mentioning that the original values data in the CRS column were not a number. Thus, the values in this column were converted into a readable format for the ANN model. Number 0 was represented for the non-corroded rebar, while number 1 was designated for the corroded rebar.

3. Artificial Neural Networks Methods

An intelligence-based technique, called ANN, was employed in this study to predict the GPR reflection amplitude from the input parameters listed in Table 2. Different types of learning algorithms were examined, and the number of neurons in the hidden layer was investigated to construct the optimal ANN model for the GPR data. Details of these steps are presented in the following sections.

3.1. Network Architecture. ANN is an adaptive data processing system that can learn from the information of the given inputs to generate outputs. An ANN system contains a set of simple neurons working independently and connecting to the others. A neuron collects input values from neurons on the previous layers, calculates an output, and transmits the results to all connected neurons on the next layer. Figure 3 illustrates the structure of a neuron. It consists of four main parts: (i) inputs or information that enters the neuron, (ii) weights and bias, (iii) transferring unit, and (iv) activation and outputs [36].

ANN learns to bridge between input and output through a learning process known as error backpropagation. The process operates by using the errors generated in the network output to adjust the weights in each layer. The error backpropagation includes two reversal processes; one is a feed-forward process, and the other is a backpropagation process. In the feed-forward process, the inputs are used to obtain the outputs with some network errors. The errors are then passed back to the input layers through the backpropagation process. The weights are adjusted during this process to reduce the network errors to an appropriate level.

3.2. Performance Criteria. Performances of the ANN model were assessed based on three factors: coefficient of determination (R^2), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The coefficient of determination measures the correlation between input and output parameters using

TABLE 3: Characteristics of the collected GPR data.

	TEM (°C)	ARH (%)	CLL (%)	CRS	GRA (dB)
1	5	55	0.10	0	-1.47
2	5	55	0.08	0	-0.62
3	5	55	0.06	0	-0.21
—	—	—	—	—	—
—	—	—	—	—	—
286	40	85	0.04	1	-2.95
287	40	85	0.02	1	-2.72
288	40	85	0.00	1	-2.26
Min.	5	55	0	0	-5.16
Max.	40	85	0.10	1	1.04

FIGURE 3: A simple neuron architecture.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (2)$$

where y_i is the i^{th} actual output; $\bar{y}$ is the mean of the actual outputs; $\hat{y}_i$ is the i^{th} predicted outputs; n is the total number of data samples. *MSE* is the average squared difference between predicted outputs and actual outputs. *MSE* can be computed using

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2. \quad (3)$$

Root Mean Squared Error is the square root of Mean Squared Error and can be calculated by

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}. \quad (4)$$

3.3. Choice of Networks. Four parameters, including temperature (TEM), ambient relative humidity (ARH), chloride level (CLL), and corrosion condition on the surface of rebar (CSR), were selected as the inputs for the ANN model, and the GPR reflection amplitude (GRA) was assigned as the output. The dataset was randomly divided into three subsets in which 70% (i.e., 200 data points) of the entire dataset was employed for training model, 15% (i.e., 44 data points) for validation. The remaining 15% (i.e., 44 data points) was utilized for testing the prediction accuracy of the ANN model.

Six popular learning algorithms were used to explore potential ANN models for estimating GPR reflection amplitude. Three assessment categories, namely, training performance (TRP), testing performance (TEP), and validation performance (VAP), were employed to evaluate the performance of the potential ANN models. For each model, ten trials were conducted, and the best performance results were recorded and presented in Table 4. The “trainlm” algorithm (Levenberg–Marquardt) was found to produce the best performance for training, testing, and validation. Thus, the “trainlm” algorithm was selected for the proposed ANN model. The selection was in line with the previous study [37].

Based on the recommendation of the previous study [37], the ANN model with one hidden layer was appropriate for dealing with most of the engineering problems. Thus, the ANN model with one hidden layer was selected for this study. In order to determine the number of neurons in the hidden layer, the ANN models were formed with the number of neurons in the hidden layer being changed from one neuron to 20 neurons with an increment of one neuron. Each model configuration conducted ten trials with identical datasets to obtain the average performance results. The performance of ANN models was then evaluated and plotted in Figure 4 based on the MSE values of the training, validation, and testing.

It can be seen clearly from Figure 4 that the ANN model with 16 neurons generated the best results. Thus, the ANN model with 16 neurons in the hidden layer was picked to be utilized in this study. Table 5 presents detailed information about the chosen ANN model.

4. Prediction of GPR Amplitude

As mentioned above, the GPR reflection amplitude data were predicted based on the four input parameters using the proposed ANN model. The performance of the model was evaluated through the three indications, namely, R^2 , MSE, and RMSE. Alternatively, the performance results were presented in terms of regression plots for training, validation, testing, and overall. In addition, the sensitivity analysis was conducted to evaluate the effects of the single input parameter on the output. Details were described in the subsequent sections.

4.1. Capacity of ANN Model in Predicting GPR Data. Figure 5 shows the performance of the proposed ANN model in the training stage. The performance results of the ANN model for all datasets are presented in Table 6. The ANN model performed well in predicting the GPR reflection signals with the coefficient of determination (R^2) for overall being 0.9958. These numbers for training, validation, and testing were 0.9965, 0.9938, and 0.9941, respectively. Note that the value of R^2 varies between 0 and 1, and the higher the value of R^2 , the better the model. Besides R^2 , MSE and RMSE coefficients were also used in this study to evaluate the performance of the model. MSE value for the overall was 0.122, showing the excellent prediction capacity of the ANN model.

TABLE 4: Performance of the ANN model with different learning algorithms.

Algorithm	TRP	TEP	VAP
trainrp	0.0370	0.0251	0.0302
<i>trainlm</i>	0.0051	0.0047	0.0033
traincgp	0.0314	0.0220	0.0232
traincgb	0.0345	0.0311	0.0213
trainbfg	0.0163	0.0152	0.0142
trainoss	0.0254	0.0201	0.0181

FIGURE 4: Performance of potential ANN models.

TABLE 5: Details of the selected ANN model.

Parameter	Detailed information
Neuron in the input layer	4 (TEM, ARH, CLL, CRS)
Neuron in the output layer	1 (GRA)
Training method	Feed-forward backpropagation
Learning algorithm	trainlm (Levenberg–Marquardt)
Activation function	Sigmoid
Hidden layer	1
Neuron in the hidden layer	16

Figure 6 illustrates the linear regression plots of the ANN model performance for training, validation, testing, and overall. In these figures, the X-axis (i.e., horizontal axis) represents the values from experimental data, and the Y-axis (i.e., vertical axis) presents the prediction values produced by the ANN model. The instances located on the diagonal line indicate a perfect prediction result from the model.

4.2. Errors Assessment. The error histogram for the ANN model in different datasets is presented in Figure 7. It measures the error between predicted values generated from the ANN model and the experimental data. In this graph, the entire error range was divided into 20 vertical bars (bins). The vertical axis (i.e., Y-axis) presents the number of

FIGURE 5: Performance assessment for ANN model. (a) Training state. (b) Best validated performance.

TABLE 6: Performance results of ANN model.

	Training	Validation	Testing	Overall
R^2	0.9965	0.9939	0.9941	0.9958
MSE	0.013	0.024	0.019	0.015
RMSE	0.114	0.155	0.138	0.122
Instances	200	44	44	288

FIGURE 6: Continued.

FIGURE 6: Performance of selected ANN model. (a) Training. (b) Validation. (c) Testing. (d) Overall.

FIGURE 7: Error assessment for selected ANN model.

instances from the dataset in a certain bar. For example, a 9th bin was corresponding to the error of 0.028 dB, and the height of about 48 represented the total number of instances in the training, validation, and testing dataset with that error. The zero-line is related to the zero error on the horizontal axis (i.e., X-axis).

As can be seen from Figure 7, the errors of the most test samples were between -0.156 dB and 0.167 dB. The negative error value means that the predicted GPR reflection amplitude was smaller than that of the experimental one. A limited number of instances in the training set experienced an error as large as 0.539 dB. The substantial error value might be due to the outliers from the original data. The outliers often generate during data collection processes

because of some unexpected activities such as inadequate calibration in measuring devices, mistakes in the initial setup of data processing, or human errors from the measurement. The performance of the proposed ANN model would increase if these outliers were removed from the input data.

4.3. Study of Inputs and Output Relationship. A sensitivity analysis was performed to investigate the variation of the input parameters to the variation of the output. The sensitivity analysis involves two steps. First, changing one input parameter while keeping others at their nominal values. Second, returning that variable to its nominal value and then repeating the first step for each of the other inputs. In this study, the value of each input variable was sorted into five categories including Low (the smallest value of the input parameter), Mid Low (halfway between Low and Mid), Mid (halfway between Low and High), Mid High (halfway between Mid and High), and High (the biggest value of the input parameter), as listed in detail in Table 7.

The sensitivity analysis was conducted for each input variable by changing its value from Low to High while keeping the values of other input at the Mid. Results from the sensitivity analysis of all input variables were plotted in the form of a parallel coordinate graph, as presented in Figure 8. This graph has five vertical axes positioned from left to right along with the X-axis; each of the axes represents a certain level of the input parameter values, including Low, Mid Low, Mid, Mid High, and High. The value on the vertical axis is the GPR reflection amplitude in decibel.

As can be observed clearly from Figure 8, the GPR reflection amplitudes were sensitive to the change of temperature (TEM) and the chloride contamination level (CLL). Specifically, the GPR reflection amplitude would decrease along with the increase in the TEM variable, and vice versa. The same trend was applied for the variation of the CLL

TABLE 7: Data for sensitivity analysis.

	TEM (°C)	ARH (%)	CLL (%)	CRS
Low	5.00	55.00	0.00	0.00
Mid low	13.75	62.50	0.03	0.25
Mid	22.50	70.00	0.05	0.50
Mid high	31.25	77.50	0.08	0.75
High	40.00	85.00	0.10	1.00

FIGURE 8: Sensitivity analysis result.

parameter. In other words, the GPR reflection amplitude is high when the chloride contamination level in concrete is low. By contrast, the ambient relative humidity variable (ARM) and the rust condition on the rebar surface (CRS) were found to produce a minimal effect on the GRP reflection amplitude. This means that the change in the value of the ARM and CRS parameters would yield a little influence on the output.

5. Conclusions

In this paper, the ANN method was employed to predict the GPR reflection amplitudes from the four inputs, namely, temperature (TEM), ambient relative humidity (ARH), chloride level (CLL), and corrosion condition on the surface of rebar (CSR). A total of 288 GPR data points were collected from a series of chloride contamination concrete slabs under various environmental profiles that were used to train, validate, and test the proposed ANN model. The performance results revealed that the GPR reflection amplitudes could be predicted from the inputs at a high level of accuracy with the coefficient of determination of 0.9958.

The effects of changing inputs on the variation of the output were also conducted in this study. Results from the study indicated that the GPR reflection amplitudes, on one hand, were found to be more sensitive to the temperature changes (TEM) and chloride contamination level (CCL) parameters. The variation of ambient relative humidity

(ARH) and rust condition on rebar surface (CSR) variables, on the other hand, were found to be less sensitive to the output of the proposed ANN model.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Z. W. and H. N. performed review, funding acquisition, and supervision; H. N. performed project administration and provided resources; Z. W., H. N., and T. N. conceptualized the study; T. N. were responsible for methodology and data curation and provided software and wrote the original draft.

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References

- [1] D. J. Daniels, *Ground penetrating radar*, IEE Radar, Sonar and Navigation Series 15 (Ed.). The Institution of Electrical Engineers, London, UK, 2nd edition, 2004.
- [2] GSSI, 2020, <https://www.geophysical.com/whatisgpr>.
- [3] Y. Wang, G. Cui, and J. Xu, "Semi-automatic detection of buried rebar in GPR data using a genetic algorithm," *Automation in Construction*, vol. 114, Article ID 103186, 2020.
- [4] P. Wiwatrojjanagul, R. Sahamitmongkol, S. Tangtermsirikul, and N. Khamsemanan, "A new method to determine locations of rebars and estimate cover thickness of RC structures using GPR data," *Construction and Building Materials*, vol. 140, pp. 257–273, 2017.
- [5] C. W. Chang, C. H. Lin, and H. S. Lien, "Measurement radius of reinforcing steel bar in concrete using digital image GPR," *Construction and Building Materials*, vol. 23, no. 2, pp. 1057–1063, 2009.
- [6] F. Ghodoosi, A. Bagchi, T. Zayed, and M. R. Hosseini, "Method for developing and updating deterioration models for concrete bridge decks using GPR data," *Automation in Construction*, vol. 91, pp. 133–141, 2018.
- [7] W. Zatar, T. T. Nguyen, and H. Nguyen, "Environmental Effects on Condition Assessments of Concrete Structures with Ground Penetrating Radar," Manuscript submitted for publication, 2021.
- [8] J. Hugenschmidt and R. Loser, "Detection of chlorides and moisture in concrete structures with ground penetrating radar," *Materials and Structures*, vol. 41, no. 4, pp. 785–792, 2007.
- [9] S. F. Senin and R. Hamid, "Ground penetrating radar wave attenuation models for estimation of moisture and chloride content in concrete slab," *Construction and Building Materials*, vol. 106, pp. 659–669, 2016.

- [10] A. Tarussov, M. Vandry, and A. De La Haza, "Condition assessment of concrete structures using a new analysis method: ground-penetrating radar computer-assisted visual interpretation," *Construction and Building Materials*, vol. 38, pp. 1246–1254, 2013.
- [11] N. M. Martino, *Quantifying reinforced concrete bridge deck deterioration using ground penetrating radar*, Ph.D. Thesis, Northeastern University, Boston, MA, USA, 2013.
- [12] S. Hong, W. W.-L. Lai, G. Wilsch et al., "Periodic mapping of reinforcement corrosion in intrusive chloride contaminated concrete with GPR," *Construction and Building Materials*, vol. 66, pp. 671–684, 2014.
- [13] A. V. Varnavina, A. K. Khamzin, E. V. Torgashov, L. H. Sneed, B. T. Goodwin, and N. L. Anderson, "Data acquisition and processing parameters for concrete bridge deck condition assessment using ground-coupled ground penetrating radar: some considerations," *Journal of Applied Geophysics*, vol. 114, pp. 123–133, 2015.
- [14] T. T. Nguyen and K. Dinh, "Prediction of bridge deck condition rating based on artificial neural networks," *Journal of Science and Technology in Civil Engineering (STCE)-NUCE*, vol. 13, no. 3, pp. 15–25, 2019.
- [15] T. T. Pham, T. T. Nguyen, L. N. Nguyen, and P. V. Nguyen, "A neural network approach for predicting hardened property of Geopolymer concrete," *International Journal of Geomate*, vol. 19, no. 74, pp. 193–201, 2020.
- [16] K. Prasad, A. K. Gorai, and P. Goyal, "Development of ANFIS models for air quality forecasting and input optimization for reducing the computational cost and time," *Atmospheric Environment*, vol. 128, pp. 1352–2310, 2016.
- [17] T. T. Nguyen, D. H. Pham, T. T. Pham, and H. H. Vu, "Compressive strength evaluation of fiber-reinforced high strength self-compacting concrete with artificial intelligence," *Advances in Civil Engineering*, vol. 2020, Article ID 3012139, 12 pages, 2020.
- [18] E. Hong, Anteneh Mesfin Yeneneh, Tushar Kanti Sen, M. A. Ha, and A. Kayaalp, "ANFIS based Modelling of dewatering performance and polymer dose optimization in a wastewater treatment plant," *Journal of Environmental Chemical Engineering*, vol. 6, no. 2, 2018.
- [19] T. T. Nguyen and K. Dinh, "An artificial intelligence approach for concrete hardened property estimation," *Journal of Science and Technology in Civil Engineering (STCE)-NUCE*, vol. 14, no. 2, pp. 40–52, 2020.
- [20] E. M. Guneyisi, M. D'niell, R. Landolfo, and K. Mermerdas, "Prediction of the flexural overstrength factor for steel beams using artificial neural network," *Steel and Composite Structures*, vol. 17, no. 3, pp. 215–236, 2014.
- [21] S. J. S. Hakim and H. A. Razak, "Structural damage detection of steel bridge girder using artificial neural networks and finite element models," *Steel & Composite Structures*, vol. 14, no. 4, pp. 367–377, 2013.
- [22] T. T. Nguyen, L. T. Ngoc, H. H. Vu, and T. P. Thanh, "Machine learning-based model for predicting concrete compressive strength," *International Journal of Geomate*, vol. 20, no. 77, pp. 197–204, 2021.
- [23] K. Dinh, N. Gucunski, J. Kim, and T. H. Duong, "Improved GPR-based condition assessment of reinforced concrete bridge decks using artificial neural network," *HDKBR Info Magazin*, vol. 5, no. 2, pp. 3–13, 2015.
- [24] T. Liu, Y. Su, and C. Huang, "Inversion of ground penetrating radar data based on neural networks," *Remote Sensing*, vol. 10, no. 5, p. 730, 2018.
- [25] N. Kim, S. Kim, Y.-K. An, and J.-J. Lee, "A novel 3D GPR image arrangement for deep learning-based underground object classification," *International Journal of Pavement Engineering*, p. 1, 2019.
- [26] K. Ishitsuka, S. Iso, K. Onishi, and T. Matsuoka, "Object detection in ground-penetrating radar images using a deep convolutional neural network and image set preparation by migration," *International Journal of Geophysics*, vol. 2018, Article ID 9365184, 8 pages, 2018.
- [27] L. E. Besaw and P. J. Stimac, "Deep convolutional neural networks for classifying GPR B-scans," in *Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XX (Vol. 9454, p. 945413)*, International Society for Optics and Photonics, Bellingham, WA, USA, 2015.
- [28] T. T. Nguyen, T. N. Dao, S. Aaleti, K. Hossain, and K. J. Fridley, "Numerical model for creep behavior of axially loaded CLT panels," *Journal of Structural Engineering*, vol. 145, no. 1, Article ID 04018224, 2018.
- [29] W. Zatar, T. T. Nguyen, and H. Nguyen, Effects of Environmental Conditions and Chloride Contamination on GPR Signals from Reinforced Concrete. Manuscript submitted for publication, 2021.
- [30] Z. Zhang, X. Jin, and W. Luo, "Long-term behaviors of concrete under low-concentration sulfate attack subjected to natural variation of environmental climate conditions," *Cement and Concrete Research*, vol. 116, pp. 217–230, 2019.
- [31] T. T. Nguyen, T. N. Dao, S. Aaleti, J. W. van de Lindt, and K. J. Fridley, "Seismic assessment of a three-story wood building with an integrated CLT-lightframe system using RTHS," *Engineering Structures*, vol. 167, pp. 695–704, 2018.
- [32] H. Min, W. Zhang, and X. Gu, "Effects of load damage on moisture transport and relative humidity response in concrete," *Construction and Building Materials*, vol. 169, pp. 59–68, 2018.
- [33] T. T. Nguyen, "Modeling of CLT creep behavior and real-time hybrid simulation of a CLT-LiFS building," Doctoral Dissertation, University of Alabama, Tuscaloosa, AL, USA, 2017.
- [34] *RADAN 7 [Computer Software]*, Geophysical Survey Systems (GSSI), Salem, NH, USA, 2019.
- [35] K. Dinh, N. Gucunski, J. Kim, and T. H. Duong, "Understanding depth-amplitude effects in assessment of GPR data from concrete bridge decks," *NDT & E International*, vol. 83, pp. 48–58, 2016.
- [36] İ. B. Topçu and M. Sarıdemir, "Prediction of properties of waste AAC aggregate concrete using artificial neural network," *Computational Materials Science*, vol. 41, no. 1, pp. 117–125, 2007.
- [37] M. Nikbin, R. S. Rahimi, and H. Allahyari, "A new empirical formula for prediction of fracture energy of concrete based on the artificial neural network," *Engineering Fracture Mechanics*, vol. 186, pp. 466–482, 2017.