International Journal of GEOMATE, July, 2017, Vol.13, Issue 35, pp.87-92
Geotec., Const. Mat. & Env., ISSN:2186-2990, Japan, DOI: http://dx.doi.org/10.21660/2017.35.6683

MODELLING OF CARBONATION OF REINFORCED CONCRETE STRUCTURES IN INTRAMUROS, MANILA USING ARTIFICIAL NEURAL NETWORK

*Richard M. De Jesus[1], Joshua A. M. Collado[2], Jemison L. Go[3], Mike A. Rosanto[4], and John L. Tan[5]

[1]Faculty of Civil Engineering in De La Salle University (Manila), Philippines
[2 - 5]Undergraduate Student of Civil Engineering in De La Salle University (Manila), Philippines

*Corresponding Author, Received: 15 June 2016, Revised: 29 Nov. 2016, Accepted: 25 Dec. 2016

ABSTRACT: Corrosion is a perennial problem in reinforced concrete structures, and is a serious concern due to the deterioration that it causes to reinforced concrete members. Though regarded as having a minor influence to corrosion compared to chloride-induced corrosion, carbonation is becoming a serious threat due to continuous development of cities like Manila. Expectedly, as Manila continues to develop, carbon emission shoots up to alarming proportions, calling out for studies to investigate and mitigate its effect to human health and structures. Artificial Neural Network (ANN) is known for establishing relationships among parameters with unknown dependency towards another variable, similar to the case of carbonation's dependency with age, temperature, relative humidity, and moisture content. Utilizing field-gathered secondary data as training and testing parameter for back propagation algorithm, an ANN model is proposed. Prediction of carbonation depth using ANN Model C421 showed reliable results. Validation of performance of Model C421 was further checked by comparing its prediction with a different set of field-gathered secondary data and results confirmed good agreement between prediction and measured values.

Keywords: Carbonation, Artificial Neural Network (ANN), model C421, reinforced concrete

1. INTRODUCTION

Recent years had shown Philippines' economy rising fast. As of first quarter of 2016, Philippine economy grew close to 7% and considered to be the highest among 11 Asian countries as reported in [1]. The same news agency, on May 16 2016, reported that Philippines is the top performing country in Southeast Asia based on the report of Oxford Business Group (OBG) [1].

According to the Philippine Statistics Authority (PSA), Philippines' gross domestic product (GDP), for the 1st quarter of 2016, was 6.9 percent. It is recorded to be higher than that of China's 6.7% and Vietnam's 5.7% [2].

The country's economic rise is warmly welcomed by Filipinos. But it calls for the country to also grow accordingly with such economic growth. An indicator that the country is lagging behind with this growth, at some areas, is the failure to anticipate overwhelming increase in motor vehicles and its effects, in the past years. As reported by [3], passenger car sale grew from a little over 20,000 in 2005 to over 63,000 in 2015 while that of commercial vehicles grew from over 10,000 to over 30,000 in the same period.

A quantification of effects of increasing car volume, in terms of carbon dioxide (CO2) emission, was presented in the study of [4]. According to this study, the level of CO2 has reached 90.78 million metric tons in 2013. By the beginning of 2015, CO2 emissions has reached 97.91 million metric tons [5].

With this alarming rate of increasing CO2 levels in Metro Manila, it is not only human health that is at risk, but the health of reinforced concrete (RC) structures as well. CO2 penetration in RC structures, known as carbonation, poses a great threat to the structural health as its risk to corrode reinforcing steel bars (rebar) is high. Structures in urban/cities are most vulnerable to carbonation due to high levels of CO2. And to raise the concern farther, only limited studies were done in the country that investigates the effect of CO2 in RC structures, and how fast it contributes to the deterioration of structures. This deterioration happens within RC members are hard to detect from the outside which makes it threat even more alarming.

2. THEORETICAL BACKGROUND

2.1 Carbonation in Reinforced Concrete

Carbonation is a chemical process that involves the reaction of some chemicals in concrete, specifically the cement hydration elements calcium hydroxide ($Ca(OH)_2$), and calcium-silicate-hydrates (C-S-H), with CO_2 from the atmosphere that penetrates into concrete. The chemical reaction produces calcium carbonate ($CaCO_3$) which can potentially lower the passivity of steel bars, hence, contributing to corrosion. This chemical process can be represented by the following chemical equation:

$$CO_2 + Ca(OH)_2 \rightarrow CaCO_3 + H_2O \quad (1)$$

The study of [6] stated that carbonation involves the dissolution of CO_2 with water in the pores of concrete, before reacting with $Ca(OH)_2$, to form carbonic acid ($CaCO_3$). A quantification of how much of CO_2 that penetrates into concrete is attributed to carbonation is explained by [7]. It claimed that only half (50%) of CO_2 reacts with $Ca(OH)_2$. The other half reacts with C-S-H.

The rate of how fast carbonation progresses in concrete is not constant [8]-[9]. This is attributed to continuous hydration of cement particles in concrete and with continuous reaction of CO_2 with $Ca(OH)_2$. With less $Ca(OH)_2$ available, less reaction with CO_2 occurs. The continuous hydration also densifies the microstructure of concrete which lowers the carbonation diffusion rate further.

Several factors were identified to influence carbonation. Major factors were water to cement ratio, degree of hydration, CO_2 concentration of the surrounding air, moisture content, temperature, alkali content, and presence of damaged zones and cracks [10].

This study, however, will only consider age, temperature, relative humidity, and moisture content in modelling carbonation through artificial neural network (ANN) due to availability of data.

Obviously, age is of primary importance in terms of influence to carbonation. With lengthy exposure to CO_2, and extended duration of diffusion of CO_2 in concrete, carbonation depth increases. It is assumed in this study that Fick's law of diffusion which relates carbonation depth with the product of carbonation coefficient and square root of time, is valid.

As temperature increases, the diffusivity of gaseous CO_2 increases [8]. The diffusivity is seen as the rate of CO_2 to react and fully blend with cement hydrating elements. The study further added that the rise in diffusivity can be attributed to increased molecular activity. According to [11], the rise in temperature translates to higher solubility of chemical compounds. This is seen as a process that potentially facilitates the carbonation process faster.

Relative humidity is seen to contribute to carbonation in an opposite manner compared to that of temperature. Higher relative humidity lowers the rate of carbonation according to [8]-[9] due to presence of high moisture in concrete pores. Since diffusivity of CO_2 is lower in water than in air, it is anticipated that CO_2 diffusion in concrete pores lowers with increasing humidity. Moreover, [8]-[9] claimed that thin layer of water covering the pores tend to block the intrusion of CO_2.

2.2 Artificial Neural Network

Artificial Neural Network (ANN) is an effective tool for prediction of behavior or phenomenon. Unlike other tools, it requires no assumption as to how independent variables are affected by a single or multiple independent variables. The only basic requirement it requires is sufficient amount of data. ANN can be seen as a black box where input data are being fed to produce an output data [12]. ANN is efficient and effective in modelling systems influenced by multiple variables with unestablished interrelationships especially with incomplete data [12]. Reference [13] described ANN as made up of large number of highly interconnected processing elements called neurons which work in unison to solve a problem.

Before ANN can establish multi-variable interrelationships and come up with a prediction, it needs to learn the system first which can be achieved by feeding input data with set initial conditions. Reference [12] added that ANN requires no functional relationship among variables since the process is data driven implying that it can adopt to the training data and captures the relationship between the input and output variables.

3. NEURAL NETWORK MODELLING, DATA, AND RESULTS

3.1 Data and its preparation for ANN modelling

A secondary data, based from [14] was utilized for this study for the training of the neural network model. The validation of model was conducted using another secondary data based on the study of [4]. Both studies conducted carbonation test to structures within the same vicinity – Intramuros, Manila.

Normalization of data was performed for these two secondary data. Normalization is to address the wide gap in terms of magnitude between field-measured carbonation data and that of the input variables. The process was done by simply getting the quotient between the data and the maximum value for that particular parameter. This process was implemented to all parameters – age, temperature, relative humidity, moisture content, and carbonation depth. After normalization, all data range from 0 to 1.

3.2 Choosing the ANN architecture

A sample ANN architecture is shown in Figure 1. The first 2 brown circles (a.k.a. neurons) are the inputs and could vary from 1 to N depending on the number of variables considered to influence an output (represented by red circle). The two blue circle in between represents the neurons in the hidden layer.

The arrows connecting the neurons have corresponding weights which change as ANN "learns" the relationship between input and output. This sample ANN architecture represents a feed-forward back propagation network which was adopted in this study.

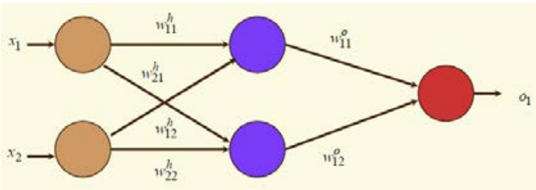

Figure 1. A sample neural network

The neural network architecture adopted in this study considered 4 inputs – age, temperature, relative humidity, and moisture content; while output was set at 1 – carbonation depth. One hidden layer was also considered in this study as more hidden layers tend to make the training and learning with ANN more difficult and complex. The number of neurons in the hidden layer, however, was varied from 1 to 10 based on the recommendation of [15]. Choosing the number of neurons, for the final ANN model, in the hidden layer was based on the following criteria: (1) the training R (Pearson's coefficient) must be 0.80 or higher; (2) the testing R must be 0.90 or higher; and (3) error must be lower than 5% (or 0.05);

Tansig (or log sigmoid) transfer (or activation) function was adopted in the study with Levenberg-Marquadt (LM) as the training algorithm. The rest of the training parameters used were the default values in MATLAB – the software used to execute ANN process.

Comparison of these 3 criteria for 6 considered ANN architecture was summarized in Table 1. Six ANN architectures, of varying number of neurons in the hidden layer (n =1, 2, 3, 4, 5, & 10), were compared based on the above criteria. Based on all 3 criteria, all architectures met the requirements. Ranking of ANN architectures based on the 3 criteria showed that Model C421 was always in the top three (3). Thus, it was decided that Model C421 will represent the modelling of the carbonation depth using ANN.

Prediction of carbonation depth against measured values is shown on Fig. 2 to 7. These show slight deviation between prediction and measured values showing that ANN closely established the relationship between carbonation depth and the carbonation parameters (age, temperature, relative humidity, and moisture content).

Table 1. Comparison of six ANN architecture

ANN Model	error	training R	testing R
C411	0.034	0.811	0.967
C421	0.011	0.942	0.969
C431	0.010	0.949	0.922
C441	0.015	0.912	0.975
C451	0.014	0.923	0.989
C4101	0.016	0.931	0.959

The measured carbonation depths as presented in Fig. 2 to 7 were taken from field-measured carbonation depth.

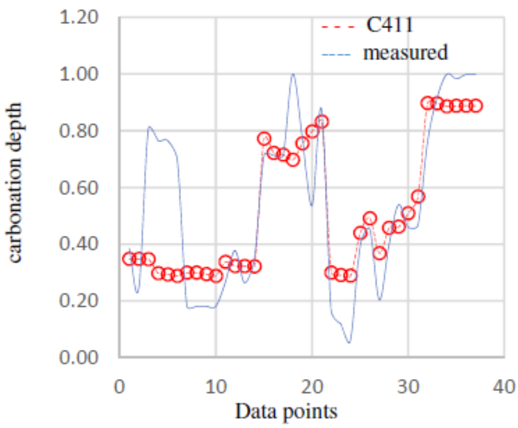

Figure 2. C411 prediction v. actual

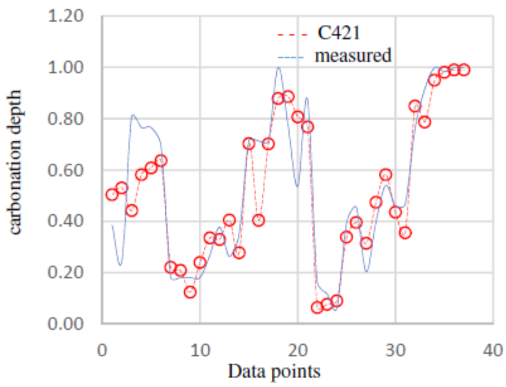

Figure. 3 C421 prediction v. actual

Comparison between measured carbonation depths and the prediction of Model C421, as shown in Fig. 3 showed minimal variation. ANN model C421 is considered to have learned the carbonation behavior via Artificial Neural Network (ANN). How carbonation depth varies with age, temperature,
relative humidity, and moisture content is closely predicted by C421 model.

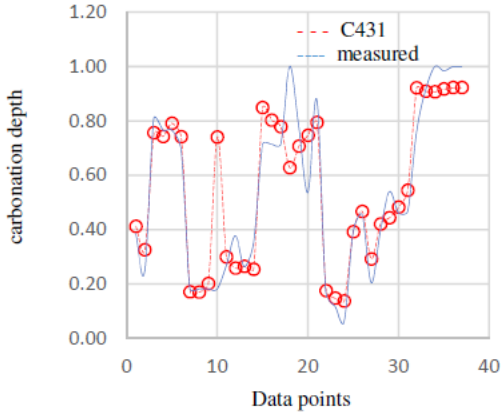

Figure 4. C431 prediction v. actual

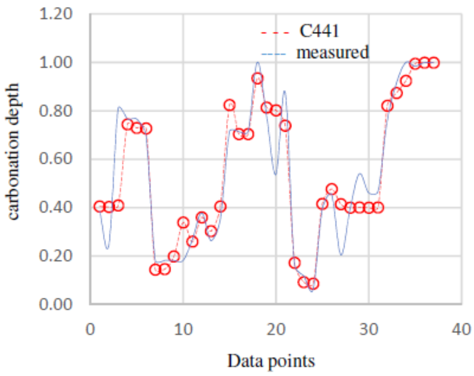

Figure 5. C441 prediction v. actual

Since all models showed close values to measured ones, choosing C421 on the basis of testing R criteria is supported.

Table 2. Initial Biases for C421 Model

Input to hidden	Hidden to ouput
-0.003	0.395
-3.012	

Table 3. Initial Weights for C421 Validation

nodes	Age	Temp	R.H.	m.c.	Depth
1	0.6	0.72	0.078	-1.07	3.30
2	-0.2	-8.97	-1.61	5.00	3.25

Note: nodes refer to hidden nodes, R.H is relative humidity, m.c. is moisture content, and depth is the carbonation depth

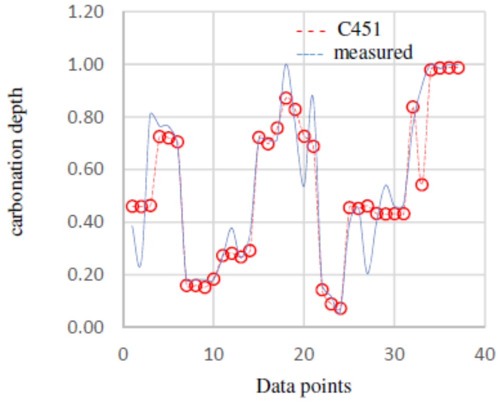

Figure 6. C451 prediction v. actual

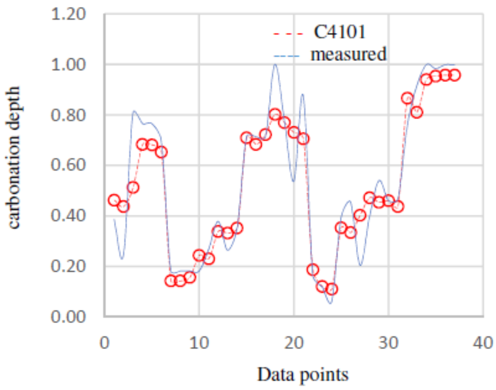

Figure 7. C4101 prediction v. actual

3.3 Validation of ANN Model (Model C421)

To further evaluate the performance of model C421, it is tested against the carbonation data gathered from the study of [4]. Raw data from this study were also normalized, similar to the process adopted for [14]. ANN model C421 were adopted and its optimized weights (shown in Table 3) were set as the initial weights for training the network using MATLAB. Its biases, shown in Table 2, were also adopted.

During validation, C421's training R is 0.9831 while its testing R is 1.0. The results of validation can be seen in Fig. 8. This result confirmed that Model C421 approximates the carbonation prediction with high reliability.

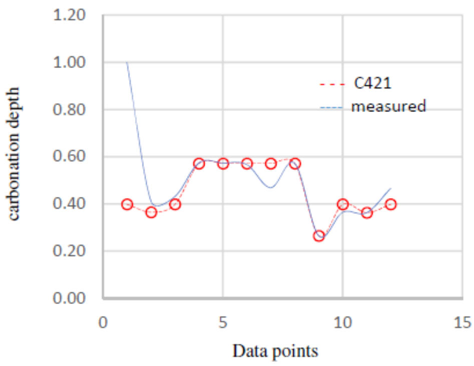

Figure 8. C421 validation

CONCLUSION

The country's remarkable economic growth has been applauded locally and internationally. But some of the environmental effects of a rising economy are treated with less attention. Among these is the alarming increase in CO2 levels in the environment and the potential hazard it poses to reinforced concrete structures due to carbonation.

There are few studies conducted locally to investigate, and analyze the effect of CO2 intrusion in RC structures. This study was among the initial steps to understand the carbonation phenomenon. Here, CO2 intrusion in concrete, through carbonation depth, is related to age, temperature, relative humidity, and moisture content using feed-forward backpropagation artificial neural network.

ANN model C421 were trained using a secondary data and found close prediction values with measured carbonation depth. This was further validated by comparing the prediction values with measured values from another secondary data. Results showed that model C421 were able to validate the reliability and accuracy of the model as depicted by close values between prediction and measured carbonation depths.

ACKNOWLEDGEMENTS

We thank Engr. Ronaldo S. Gallardo, and his former student thesis advisees, for allowing the use of data from their study in the development (& training) of the ANN model in this paper.

REFERENCES

[1] Jiao, C. (2016, May 16). PH is best economy in Southeast Asia – Oxford Business Group. *CNN Philippines.* Retrieved on June 11, 2016 from http://cnnphilippines.com/business/2016/05/13/ oxford-business-group-economy-philippines-southeast-asia.html

[2] Remitio, R. (2016, May 19). PH is fastest-growing economy in Asia, expands by 6.9% in Q1. *CNN Philippines.* Retrieved on June 11, 2016 from http://cnnphilippines.com/news/ 2016/05/19/philippines-fastest-growing-economy-asia-gdp-q1.html

[3] Punongbayan, J. C., & Mandrilla, K. (2015, August 15). Carmaggeddon: Why are there so many cars in Metro Manila?. *Rappler.* Retrieved on June 11, 2016 from http://www.rappler.com/ views/imho/102701-carmageddon-metro-manila

[4] Collado, J., Go, J.L., Rosanto, M.A., Tan, J.L., and De Jesus, R.M. (2015). Employing Artificial Neural Network in Assessing Various Factors Affecting Carbonation in old structures. *Thesis.* De La Salle University, Manila.

[5] Philippine Carbon Dioxide Emissions. (2013). Retrieved on June 11, 2016 from https:// ycharts.com/indicators/philippines_carbon_dioxide_emissions.

[6] Burkan Isgor, O., and Razanqapur, A. G. (2004). Finite element modeling of couple heat transfer, moisture transport and carbonation processes in concrete structures. Cement and Concrete Composites, 26(1), 57-73.

[7] Park, D. C. (2008). Carbonation of concrete in relation to CO2 permeability and degradation of coatings. Construction and Building Materials, 22(11), 2260-2268.

[8] Talukdar, S., Banthia, N., & Grace, J. R. (2012). Carbonation in concrete infrastructure in the context of global climate change – Part 1: Experimental results and model development. Cement and Concrete Composites, 34(8), 924-930.

[9] Yoon, I. S., Copuroglu, O., & Park, K. B. (2007). Effect of global climatic change on carbonation progress of concrete. Atmospheric Environment, 41(34), 7274-728.

[10] Houst, Y. F. & Wittman, F. H. (2002). Depth profiles of carbonates formed during natural carbonation. Cement and Concrete Research, 32 (12), 1923-1930.

[11] Kolio, A., Pakkala, T. A., Lahdensivu, J., & Kiviste, M. (2014). Durability demands related to carbonation induced corrosion for Finnish concrete buildings in changing climate. Engineering Structures, 62-63, 42-52.

[12] Oreta, A. W. C. (2004). Simulating size effect on shear strength of RC beams without stirrups using neural networks. Engineering Structures, 26(5), 681-691.

[13] Lu, C., & Liu, R. (2009). Predicting carbonation depth of prestressed concrete under different stress states using artificial

neural network. Advances in Artificial Neural Systems,2009,1-8.

[14] Bata, K. J., Beltran, B., Sacaguing, A., & Gallardo, R. (2013). Carbonation profile of old and new reinforced concrete structures in

[15] Hect-Nielson, R. (1989). Theory of back propagation neural networks. Proceedings of the International Joint Conference on Neural Networks, 593-611.