A model for time-to-cracking of concrete due to chloride induced corrosion using artificial neural network

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Abstract. To monitor the initiation of concrete cracking beyond the service life of the structure, a novel prediction model of time to cracking of concrete cover using artificial neural network (ANN) was developed in this study. Crack mitigation prevents corrosion and crack development to occur in a more rapid phase that is an essential component in performance-based durability design of reinforced concrete structures. Data available in various literatures were used in the development of the ANN model which is a function of compressive strength, tensile strength, concrete cover, rebar diameter, and current density. The neural network model was able to provide reasonable results in time predictions of cracking of concrete protective cover due to formations of corrosion products. The performance of ANN model was also compared to various analytical and empirical models and was found to provide better prediction results. Even with limitations in the available training data, the ANN model performed well in simulating cracking of concrete due to reinforcement corrosion.

1. Introduction
One vital structural health monitoring concerns in reinforced concrete structures is the corrosion of reinforcement. The abundance of salts in air from a chloride rich environment may be deposited in concrete surfaces and enter gradually through pore spaces. Damage in the passivating film occurs when the amount of chloride ions reached a certain critical level. This condition exposes the rebar to oxygen and water resulting to the onset of reinforcement corrosion. This chloride induced corrosion is one essential factor that contributes to the deterioration of reinforced concrete structures [1]. Corrosion products in this electrochemical process offers volume expansion of up to about 6.5 times the initial rebar volume exerting expansive radial pressure in the surrounding concrete [2]. Cracking and spalling of concrete occur when the force due to the internal stress surpasses the relatively weak tensile strength of concrete. There are numerous ways of monitoring corrosion in concrete that are suitable in assessing the performance and serviceability of concrete structures. Modelling of corrosion development is one of the emerging approaches. Several ideal assumptions were considered to simplify the modelling process for both analytical and numerical studies of corrosion [3]. El Maddawy and Soudki [4] assumed a uniform spatial corrosion distribution, radius of corrosion, and constant radial stress in their study. These assumptions however do not sufficiently describe the actual underlying behavior of corrosion. In one specific parameter considered in the modeling, analytical models showed that the diameter of the bar has an increasing effect in the time-to-cover cracking [5–6]. This however contradicted the majority of the empirical models in the literature due to the insufficiency of assuming a thick-walled cylinder analogy [7–8]. Further for empirical studies for crack development and bond strength models, a limited number of variables were considered and neglected equally important parameters in the modelling such
as porosity of the concrete and crack severity. It is essential to determine the pore space present in the concrete due to the porosity and cracks that will serve as deposition of corrosion products [9]. As a result, the derived models can perform satisfactory prediction ability within the specific framework considered.

Results from various studies showed that the effect of corrosion on the crack development as well as the influence of every concrete component is intricate in nature [4–5,9]. One possible approach to capture the dominant characteristics of such complex system is by using artificial neural network [10]. In such cases of intricate experimental data, ANN is one powerful tool to capture the actual and dominant characteristics involved in the system. Due to its profound adaptability in providing satisfactory projections, the method was found to be convenient and effective in developing models of various nonlinear complex relationships [11–12]. The modelling process using ANN can be done by using actual experimental results instead of adopting simplified ideal assumptions.

In this work, novel prediction model of time-to-cracking of concrete due to chloride induced corrosion using neural network will be developed. No extensive work has been done to generally describe the underlying behaviour of corrosion and the interaction of various factors on the crack development in concrete using ANN. The model can be used to provide baseline information on crack development in concrete to ensure that only initiation phase of corrosion will occur within the service life of the structure. Proper diagnosis and effective preventive measures will be made possible to prolong the service life of concrete structures.

2. Chloride induced cracking models in reinforced concrete

The most common approach in studying corrosion in concrete is by subjecting samples to accelerated corrosion and derived empirical corrosion models using results from experiments. In the study of Andrade et al. [13] the cracking of concrete protective cover of four blocks due to corrosion of rebar was investigated. The evolution of crack widths was observed everyday using strain gauges attached at several locations at the surface of concrete. A current of 100μA/cm$^2$ was applied allowing a sufficiently short experiment within natural values. Results showed that a visible crack of 0.1 mm may be expected for a decrease in the rebar radius of 20μm. The time duration of corrosion initiation as function of initial rebar diameter and corrosion intensity can be expressed as follows:

$$t_i = \frac{0.020 \text{ of diameter}}{\text{mm/year of corrosion}} \text{ (1)}$$

The concrete cover cracking time in a salt contaminated concrete structure is mainly influenced by products of corrosion required to occupy the voids and generate sufficient tensile stress to initiate cracking of concrete cover [5]. The corrosion products and resistance of concrete in cracking are controlled by several equally important factors such as compressive strength and water cement ratio. Considering these factors, Vu et al. [14] developed a set of predictive models for corrosion-induced cracking as shown in the following equations.

$$t_{cr} = k_R x \frac{t_{corr(exp)}}{t_{corr(real)}} t_{cr(exp)} \text{ (2)}$$

In order to minimize the error in the prediction results of the above equations and obtain a more accurate extrapolation of accelerated results to practice, a rate of loading correction factor ($k_R$) was proposed. The models were able to provide satisfactory prediction results in comparison with experimental data. The models further showed that a faster rate of corrosion caused a higher strain rate in concrete and may impart lesser deformations. Thus, applying different corrosion rates will result to distinct crack developments in concrete [15]. In the study of El Maaddawy and Soudki [4], an analytical model was proposed to approximate the time from initiation of corrosion to cracking of concrete cover. The mass loss of steel and the growth of internal radial stress due to corrosion were considered. The
derived model given in equation (3) provided reasonable prediction values compared with experimental results from different studies available in the literature.

\[ t_{cr} = [7117.5(D+2\delta_{cr})(1+\nu+\psi)] \left[ \frac{2C_{cr}}{iE_{cr}} + \frac{2\delta_{cr}E_{cr}}{D(D+2\delta_{cr})(1+\nu+\psi)} \right] \] (3)

Another analytical model considering corrosion resistance factors as a function of bar diameter, concrete tensile strength, and concrete cover was developed by Lu et al [3]. These factors were used to develop a more precise model in predicting the corrosion-induced cracking time of concrete protective cover for concrete structures. After 28 days of curing, samples were immersed in 5% brine solution and subjected to a constant level of impressed current of 3mA/cm² to accelerate corrosion. In developing the analytical model for the overall time from initiation of corrosion to full cracking of the concrete cover \( t_{cr} \), several assumptions were made. The corrosion process is assumed to be uniform around the rebar providing uniform radial expansive pressure and the stresses are induced only by the expansion of the volume of steel due to corrosion. Further, concrete is assumed to be isotropic linear elastic material and is considered as thick-walled cylinder around the steel. Adopting the said assumptions, the time-to-cracking model can be expressed as:

\[ t_{cr} = 234762(d + kc) \sqrt[3]{\left( \frac{0.3 + 0.6 \frac{c}{d} \left[ \frac{f_{cr}}{E_{cr}} \left( \frac{r_{c} + 3} {r_{c} + 3} \right)^{\frac{3}{2}} - \frac{r_{c} + 3}{3} \right] \right)^{2}} - 1 \] (4)

The above equation provided better prediction results against models proposed by Maaddawy and Liu. The analytical model was able to consider residual strength of concrete cover, mechanical characteristics of the volume of rusts, and amount of corrosion products that drifts away the surface of the bar due to porosity and cracks of concrete. Results also showed that the cracking time is influenced by the ratio of concrete protective cover and diameter of reinforcement and the applied current density.

In the process of developing the models however, several ideal assumptions for every study were adopted to simplify the systems involve in the actual conditions of corrosion. This in turn provided prediction results that are satisfactory only to a specific framework of study to which the models were fitted and thus impractical to use in a more general case of corrosion. To address this concern, model prediction of crack development using Artificial Neural Network will be developed. This will provide a broader perspective in understanding the mechanism of corrosion and result to a robust prediction in the time-to-cracking of concrete.

3. Artificial neural networks

Artificial Neural Networks (ANN) is one essential and convenient way of developing models for highly complicated nonlinear relationships. Due to its profound adaptability to derive outputs from complex or inaccurate data, researchers find this method very useful in providing projections to new situations of interest. ANN is an information processing algorithm adopting the way a biological nervous system like brain synthesizes a certain set of information. The main component of this model is the novel structure of the information processing scheme. It is made up of a large network of highly interconnected processing components considered as the neurons which work as one to address specific problems. Like a biological human being, ANNs learn through a set of observation. An ANN is arranged for a specific application like classification of data or recognition of pattern by means of learning procedure. Learning in biological frameworks includes conformity to the synaptic associations that occur between the neurons. The learning method is a process that can be used to modify and thereby train the neural network, so that an improvement of the network can be achieved to produce a better output for a given input. According to the author David Kriesel [16], ANN could learn by: (1) creating new connections; (2) removing existing connections; (3) updating connection weights; (4) modifying the threshold values
of neurons; (5) varying one or more of the three neuron functions; (6) creating new neurons; and (7) removing existing neurons.

Basically, ANNs have three interconnected layers as shown in figure 1. The first one consists of input neurons which then send the data to the next layer (hidden) which in turn send information to the next layer considered as the output neurons. Each neuron performs a weighted sum of inputs from the neurons connecting to it during the process which is called the activation. The neuron fires if the entirety of information sources surpasses some already set threshold value which is a process called transfer [17]. Feedforward backpropagation learning algorithm is one of the most commonly used algorithm in neural network. The training phase of this method involves forward pass to calculate the output based on the weights, biases, and the inputs of the network. The corresponding errors of the network will be computed in the backward pass in relation to the target outputs. Several number of cycles take place in the training stage of the neural network to meet the threshold of the network. After the network has attained the desired performance of the model, a new set of test data will be used to validate the performance of the model.

Figure 1. Neural network architecture.

Numerous studies were conducted utilizing ANN as the algorithm in the development of the models. In the study of Oreta and Kawashima [11], the proposed models performed well in estimating confined strain and compressive strength of circular columns. The models are dependent on the unconfined compressive strength, column height, core diameter, volumetric ratio of lateral reinforcement, yield strength of transverse rebars, tie spacing, and main steel bar ratio. The rheology of self-compacting concrete is governed by the proportions of material and the admixture dosage introduce in the mixture. In order to optimize the proportions for best workability performance using Genetic algorithm, rheology models were developed using ANN [18]. Models provided satisfactory results in the predicted values in agreement to the results obtained from the experiments. Artificial neural network was also used in the study of Dahou et al [19] to estimate the strength of bond in steel and concrete. The results of the study showed that models derived using ANN provided good prediction results. Parametric analysis of all the parameters in the modelling was conducted to establish the contribution of each material component on the bond performance in reinforced. Upon considering various studies of using ANN, the algorithm is proven to be one excellent tool in developing models using highly complicated data and complex system.

4. Development of time-to-cracking model using artificial neural network

One advantage of using ANN is that it can satisfactory model interactions in complex systems with insufficient amount of data. In the course of this study, a limited number of input-output pairs are available in the literature making ANN the most suitable tool to derive the time-to-cracking of concrete prediction equation. The network consists of five input nodes, one output node, and one hidden layer. For such network specifications, the minimum number of input-output pairs that could provide satisfactory predictions would require data pairs between 12 and 15 [11]. Model development in the neural network architecture in this work adopts a feed forward backpropagation learning algorithm. In this approach, 36 experimental data obtained from the literature are divided into training, testing, and validation sets using the ratio 70:15:15. To avoid overfitting of the model in the data considered, a few number of neurons from 2 to 5 in the hidden layer is considered. An early stopping in the validation is performed to improve further the generalization of the model. Moreover, the least mean squared error
in the validation phase of the simulation is used as indicator in selecting the best model. The time-to-cracking of concrete equation will be a function of compressive strength of concrete (f’c), tensile strength of concrete (ft), concrete cover (cc), bar diameter (d), and current density (i).

In order to develop a prediction model for time-to-cracking of concrete, experimental data will be used from the studies of Maaddawy et al. [4], Alonzo et al. [8], Andrade et al. [13], Vu et al. [14], Rasheeduzzafar et al. [20], Cabrera et al. [21], Mangat et al. [22], Torres et al. [23], and Al-Harthy et al. [24]. In their studies, the following main variables were considered and found to be affecting the time-to-cover cracking of concrete: (1) compressive strength of concrete (f’c); (2) rebar diameter; (3) Elastic modulus of concrete; (4) concrete cover; (5) tensile strength of concrete; (6) current density; (7) thickness of the porous zone and (8) molar mass of corrosion products.

5. Results and discussion

5.1 Artificial neural network model for time-to-cracking of concrete due to chloride induced corrosion

A neural network topology having 5 predictors, 2 neurons in the hidden layer, and 1 output node is denoted as N 5-2-1 model. The number of neurons in the hidden layer was varied between 2 to 5 neurons resulting to 4 distinct neural network topologies. After a series of simulations of the different ANN architectures, N 5-5-1 model having 5 neurons in the hidden layer emerged as the best model as shown in table 1. The model provided the least error and the highest correlation coefficients in training, testing, and validation among all models considered. By these results, the derived model was able to learn satisfactory from the limited number of data used.

Table 1. Summary of errors and pearson coefficient of different neural network models.

| ANN Model | MSE   | R    |
|-----------|-------|------|
| N 5-2-1   | 187.665 | 94.541 |
| N 5-3-1   | 134.902 | 95.088 |
| N 5-4-1   | 194.592 | 94.333 |
| N 5-5-1   | 102.334 | 96.473 |

The deduced optimum structure of N 5-5-1 contains five normalized nodes in the input layer, one normalized node in the output layer, and five nodes in the hidden layer. With this structure, the simulation resulted to weights and biases of the input and output layers as shown in Table 2. The relative importance of each predictor to the output of the model is also determined using the causal inference procedure developed by Garson [25].

Table 2. Connection weights and biases of N 5-5-1 model

| Hidden Nodes | d   | cc  | i   | f’c  | ft   |
|--------------|-----|-----|-----|------|------|
| 1            | 0.77146 | -2.72990 | 0.17963 | 1.87840 | -0.05219 | -3.25630 |
| 2            | 2.29090 | -0.53898 | 1.13320 | -0.17699 | -0.45675 | -1.35000 |
| 3            | 0.46558 | -2.04980 | 0.92636 | 2.59410 | 0.024711 | -1.17520 |
| 4            | 1.74460 | -1.65500 | 0.42828 | 2.78140 | 0.006931 | -1.34720 |
| 5            | 2.21750 | -0.88298 | 0.73104 | -0.39535 | 0.126500 | 2.02370 |
| Biases       | 1.83620 | -1.66320 | -2.55700 | 2.23560 | -0.76576 | -0.28052 |
| Rel. Impt. (%) | 29.71 | 27.90 | 13.28 | 26.25 | 2.86 |

The derived model has the ability to estimate the cracking time of concrete cover using the given values of the five independent parameters. The predicted values of the model are compared with the experimental results obtained from different studies. The values are plotted with the experimental values on the horizontal axis and the estimated values on the vertical axis as shown in figure 2. The values obtained are highly correlated as describe by the correlation coefficient R=0.96. Roughly 90% of data
points in the plot almost lie on the perfect line with average error of 14 hrs in the predicted values. Further, an average ratio of 1.01 is observed between the experimental and estimated values indicating a desirable performance in the prediction of the ANN model. The rebar diameter, concrete protective cover, and compressive strength of concrete emerged as main contributors in the crack resistance of concrete as described by their high relative importance values.

To evaluate the predictive capacity of the derived model relative to the models available in the literature, the experimental and predicted values are also calculated using the existing models. Figure 3 shows the results of the different models and a perfect prediction is represented by a point lying on the 45° line. The closer the point to the line, the better will be the predicted value. The plot reveals a wide scatter of points due to significant deviations from the perfect line. It can be seen clearly that the existing models generally perform well only within the data considered in the framework of their study. Different models seem to be unfit to predict experimental data that were not used in the calibration of the models. In the proposed ANN model however, a vast majority of points in the plot almost lie on the line. The ANN model exhibited the best correlation R among all the models considered and perform well in almost all experimental values obtained from various literature. The ratio of experimental to predicted values are also computed for all the models for further comparison. The prediction performance can be classified as satisfactory if the ratio is close to 1.0. In all the equations considered, the model of Maaddawy gave the least desirable ratio of 0.34 while the proposed ANN model provided the most desirable average ratio of 1.01. With these results, the derived ANN model emerged as the best performing model in this study.

5.2 Parametric study of the proposed ANN model
The sensitivity of the derived model in each variable considered is tested by varying one parameter at a time while all other predictors remain constant. It is evident in figure 4 that the increase in the cover, compressive strength, and tensile strength of concrete offered increase in time for the concrete cover to crack due to rebar corrosion. There is a gradual improvement in the cracking time of concrete between 45 mm to 70 mm of concrete cover while a significant jump in the cracking time is observed for covers beyond 70 mm. At low compressive strengths of concrete from 20 MPa to 35 MPa, the cracking time is roughly constant while sudden increase in cracking resistance is gained for 40MPa to 70 MPa. Among the three predictors that directly enhance the cracking resistance of concrete, the tensile strength parameter offered the least contribution in the model. An observable cracking time change is achieved between 1 MPa to 2 MPa of tensile strength. These observations are reasonable since these parameters
enhanced the resistance of the concrete to cracking. The greater the concrete strength and cover, the stronger will be the sample in resisting internal radial stress develop in concrete due to reinforcement corrosion.

![Graphs showing the relationship between concrete cover, compressive strength, tensile strength, and predicted time](image1)

**Figure 4.** Effect of concrete cover, compressive strength and tensile strength on the cracking time of concrete.

On the other hand, the two other variables offered indirect relationship with the model. As the rebar diameter and current density increases, the cracking time of concrete decreases as described in figure 5. A drastic change can be observed for high values in both predictors and this relationship is consistent with the findings in other studies. Higher current densities offer faster growth of corrosion resulting to a rapid development of internal pressure in the interface of rebar and concrete. This pressure in turn will eventually surpass the tensile capacity of concrete in a shorter period of time resulting to cracking of the cover of concrete. Lastly for the diameter of steel, a greater surface area of steel will be exposed to corrosion for larger diameter of reinforcements. Since the volume of rust is 5-6 times greater than the volume of the parent metal, radial tensile stress is more excessive for larger rebar diameters.
6. Conclusions

The cracking time of concrete cover due to rebar corrosion is influenced by multiple factors in complex non-linear interactions. Because artificial neural network (ANN) is suitable in developing models of highly convoluted relationships with limited number of observed data, this study employed the power of ANN to develop a model for time-to-cracking of concrete due to chloride induced corrosion. The derived N 5-5-1 model was found to give satisfactory prediction results in simulating the cracking time of concrete cover. Using a limited set of data, the model was able to capture the dominant contribution of each variables in the cracking of concrete and performed well against the other existing models in the literature considered in this study. Among all the variables considered in the modeling, the compressive strength of concrete, rebar diameter, and concrete cover turned out to be the main influencing variables in the resistance of concrete to cracking. The model can be used as a rapid and reliable way of estimating crack development in concrete which can be utilized as baseline information in selecting appropriate interventions for sustainable design.
7. References

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