Prediction of the flexural behavior of corroded concrete beams using combined method

Hisham Alabduljabbara, James H. Haidob, Rayed Alyousefa, Salim T. Yousifc, Jennifer McConnelld, Karzan Wakile,e, Kittisak Jermsittiparsertg,h,⁎

a Department of Civil Engineering, College of Engineering, Prince Sattam bin Abdulaziz University, Al-kharj 11942, Saudi Arabia
b Department of Civil Engineering, College of Engineering, University of Duhok, Duhok, Kurdistan Region, Iraq
c Department of Civil Engineering, Al-Qalam University College, Kirkuk, Iraq
d Department of Civil and Environmental Engineering, University of Delaware, Newark, Delaware 19716, USA
e Research Center, Sulaimani Polytechnic University, Sulaimani 46001, Kurdistan Region, Iraq
f Department of Computer, College of Science, University of Halabja, Halabja 46018, Kurdistan Region, Iraq
g Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam
h Faculty of Social Sciences and Humanities, Ton Duc Thang University, Ho Chi Minh City, Vietnam

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ABSTRACT
Nationwide statistics on numbers of structurally-deficient bridges coupled with ongoing corrosion processes caused by deicing agents in many climates lead to a demand for better analysis techniques for corrosion-damaged reinforced concrete structural members. Modern computational methods for modeling this behavior such as finite element analysis (FEA) are an ideal tool to fulfill this need. However, these analyses require many inputs that, due to the long timescales over which corrosion occurs, are often prohibitive to obtain through physical testing. In this research, a novel statistical approach using a neural network (NN) model has been constructed to approximate these inputs based on data in the literature from 107 concrete members. Then, outputs from the NN have been introduced into FEA material behavior models for the analysis of corrosion-damaged concrete beams. Load-deflection behavior resulting from such FEA shows good correlation when compared with available experimental data, confirming the accuracy of the NN. Thus, the NN is suggested as a means for obtaining inputs for FEA of corrosion-damaged concrete members.

1. Introduction

The exposure to aggressive environment for long time will lead to degradation in reinforced concrete structure strength due to the deterioration in steel bars. Deicing salts and marine water are considered major sources for steel bar corrosion in concrete constructions [1,2]. The corrosion of reinforcement regards one of the worldwide problems of reinforced concrete elements [3–8]. The corrosion is represented in rust formation which causes spalling and cracking in concrete and consequently decreasing of loading carrying capacity of the structure [9]. High budget larger than one hundred billion US Dollars is annually allocated for repair corrosion deterioration in concrete structures [10].

A number of experimental endeavors have been launched to investigate the effect of corrosion on performance of the concrete beams in the last two decades. Many researchers like [2,3,11] have been conducted experiments to study the behavior of concrete beams with flexural corroded reinforcement in different corrosion modes as electrochemical, humid environment etc. The degradation in reinforced concrete beam strength due to shear reinforcement have been examined in many works such as that provided by Xia et al. [12], Wang et al. [13] and Wang et al. [14].

The flexural strength of corroded reinforced concrete beam has been assessed also in numerical and analytical schemes. Horrigmoe and Hansen [15] used finite element technique in ANSYS program to study the load–deflection relationship of concrete beam reinforced with corroded tension steel bars only. The impact of bond deterioration between concrete and steel was introduced. Reasonable agreement has been observed between numerical and experimental outcomes.

Azher [16] formulated a simplified model composed of two steps depending on experimental data to find the ultimate capacity of beams with corroded reinforcement. Four parameters were considered in the modeling namely material properties, corrosion current density, and...
cross-sectional area of beam and period of corrosion. Finite element outputs have been in good matching with experimental data. Corrosion effect on bond strength in corroded reinforced concrete beams was checked by Berto et al. [17] using frictional and damage type laws. The deterioration of concrete was simulated by a model of coupled mechanical-environmental damage. The researchers proved that the proposed damaged bond model is valid in simulation of failure mechanism.

Wang and Chen [18] developed nonlinear finite element model to simulate the performance of corroded concrete beams. The residual strength of beams were estimated with taking into account rebar corrosion, concrete cover spalling and mid span vertical crack. It was demonstrated that the exposed length of steel bars does not influence on the beam strength. The robustness of corroded reinforced concrete beam structures has been investigated numerically by Cavacoa et al. [17].

A finite element solution has been implemented within two steps. The first step includes analysis of cross section and the second one is devoted to building a two dimensional model of structure basing on the results of the previous step. Finally, the maximum loading capacity was obtained for corroded members and analysis was displayed the major influence of bond deterioration on the loss of this capacity.

A simplified analytical modeling has been performed by Jnaid and Aboutaha [19] to determine the ultimate flexural strength of corroded concrete beams. Different corrosion rates with decent precision have been included in the model. It was noted that the bond between concrete and steel is the main reason to reduce the flexural strength of beam under low corrosion rate.

The use of artificial neural network could facilitate the determination of the parameters (i.e. concrete compressive strength, area of steel bars, etc.) of the corroded members which are required in their analysis. The examination of flexural behavior of corroded concrete beams with using hybrid model built with computational intelligence and finite element simulation has not been investigated so far. Thus, further researches are considered essential in this direction. The present endeavor develops an analytical method combining neural network and finite element simulation for transformation. Present study involves proposing of NN model for estimating the behavior of corroded reinforced concrete beams with dependence on experimental data. This neural model was provided by using of neural network design toolbox in MATLAB program.

Current neural network model has been constructed using training and testing of experimental data available in the literature [11,26] for 107 corroded concrete members. The range of input data in NN model is given in Table 1 and the distribution of the input values are illustrated in Figs. 2–7. Specific magnitudes of present NN inputs are listed in Table 2.

These experimental data have been separated into two groups in NN model namely training and testing data. Most of researchers have been adopted 90% or more of data for NN model for training [31]. The percentage of training data is selected in present proposing of neural network. The remaining 10% of inputs were used in testing process to neuron can be achieved in the flowchart given in Fig. 1.

In present work, back propagation neural network [24] was used. This network is sorted as simple multi-layered feed forward neural network to relate the parameters within each layer to those in the other layers. Thus, the complex and nonlinear interactions among variables can be grasped in the network by finding adjusted weights of correlation.

Back propagation algorithm was used in current work with gradient descent method [25] to minimize the error in weights associate with training data in neural network. Weights were obtained for correlated neurons layers and consequently find the output as a polynomial function with weighted coefficients. Sigmoid function was adopted in current simulation for transformation. Present study involves proposing of NN model for estimating the behavior of corroded reinforced concrete beams with dependence on experimental data. This neural model was provided by using of neural network design toolbox in MATLAB program.

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### Table 1

<table>
<thead>
<tr>
<th>Item</th>
<th>Maximum value</th>
<th>Minimum value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age of member (corrosion period) in days</td>
<td>9490</td>
<td>0</td>
</tr>
<tr>
<td>Compressive strength of concrete $f_{c'}$ in MPa</td>
<td>63</td>
<td>10.7</td>
</tr>
<tr>
<td>Area of tensile steel bars $A_s$ in mm$^2$</td>
<td>8164</td>
<td>78.5</td>
</tr>
<tr>
<td>Area of compressive steel bars $A_{s'}$ in mm$^2$</td>
<td>2260.8</td>
<td>0</td>
</tr>
<tr>
<td>Yielding stress $f_y$ of tensile steel bars in MPa</td>
<td>585</td>
<td>345</td>
</tr>
<tr>
<td>Yielding stress $f_{y'}$ of compressive steel bars in MPa</td>
<td>891.25</td>
<td>428</td>
</tr>
</tbody>
</table>

### Fig. 2

Distribution of the input 1 (beam age in days) values.
verify the validity of trained neural network model. The technique of multi-layer feed forward with back propagation algorithm has been employed in training. Thus, neural network model was trained using sigmoid transform function [32–34]. In present analysis, a code was prepared in MATLAB and used to train and test the proposed neural network. The consequent final NN network model was used to estimate the magnitude of outputs namely concrete compressive strength and area of steel bars in beam after corrosion.

The outcomes for other beams (i.e. with input values within used range in network but not included in train and test data) were calculated too. Two networks were formulated for finding concrete compressive strength and corroded steel bars area (i.e. tensile or compressive steel bars area) separately. High correlation coefficient (R) presented in Figs. 8–11 is referring to perfect matching between introduced outputs (i.e. regarding training or testing data) and those calculated by best fit linear function.

The importance factor [33,35] is dependent on the calculated weight of inputs in training process. According to present importance factors (Figs. 12 and 13) of input variables to predict the outputs in proposed networks, it is observed that concrete compressive strength has the highest effect. A statistical assessment was carried to show the degree of convergence between the formulated expressions (Y) given in Figs. 8–11 and the actual data for concrete compressive strength and corroded steel area. Thus, the mean, standard deviation, variance and

Fig. 3. Distribution of the input 2 (concrete strength in MPa) values.

Fig. 4. Distribution of the input 3 (tensile steel bar area in mm$^2$) values.

Fig. 5. Distribution of the input 4 (compressive steel bar area in mm$^2$) values.

Fig. 6. Distribution of the input 5 (tensile steel bar yielding stress in MPa) values.
median were evaluated for the ratio of outcomes calculated by \( Y \) and the actual values as given in Table 3. Specific predicted outputs of current NN were selected randomly and compared to actual values of these outcomes as illustrated in Table 4. Reasonable matching percentage is observed between the predicted and actual outputs shown in Table 4, with a maximum percent difference of 20% and the majority of the selected data having a percent difference of 5% or less.

### 3. Formulation of nonlinear finite element model

The valid material behavior models are required to be developed in simulation of complicated behavior of reinforced concrete elements [36]. Accordingly, plastic and elastic performance of concrete under tensile and compressive forces should be represented in the model. The analysis of these structures is usually performed with numerical technique like finite element analysis.
In present endeavor concrete damage plasticity model which is available in ABAQUS version 6.14–1 has been used in beam modeling. This model includes the definition for complete compressive and tensile behaviors of concrete in linear and inelastic phases. The effect of corrosion was introduced via calibration process in aforementioned proposed neural network for computing reduced concrete strength and steel bars area after deterioration.

The output of neural network was employed in evolving concrete damage plasticity model. The behavior of concrete under uniaxial compression is considered in current simulation as linear model up 40% (i.e. average value for elastic stress limit given by Wahalathantri et al. [36] of compressive strength and nonlinear curve. This inelastic nonlinear relationship is formulated in term of ascending and descending parts as depicted in Fig. 14. Present nonlinearity equation between compressive stress (i.e. ≥ 0.4fc\') and strain is given as follows [37]:

\[
\sigma = f_c \left[ \frac{k_1 \beta \left( \frac{\varepsilon}{\varepsilon_y} \right)}{k_1 \beta - 1 + \left( \frac{\varepsilon}{\varepsilon_y} \right)^{k_2}} \right] 
\]

Fig. 11. Testing output for present NN for corroded steel bars area in beams.

Fig. 12. Importance factor for each input variables on concrete compressive strength of corroded members.

Fig. 13. Importance factor for each input variables on corroded steel bar area.
The elastic modulus of an object is defined as the slope of its stress–strain curve in the elastic deformation region (Fig. 14), $k_1$ and $k_2$ are coefficients, $\beta$ is a slope, $\varepsilon$ is strain, $\varepsilon_0$ is initial strain in elastic zone, $\sigma$ is stress.

Concerning present uniaxial tension behavior model of corroded concrete, the average value of key points on similar stress–strain curves gave by Naylor and Rasheed [38] and Wahalathantri et al. [36] have been used. Thus, the new tensile behavior curve (Fig. 15) was produced and employed in current modeling in ABAQUS. The linear pre-cracking part of this model is defined by tensile strength ($f_t$) of concrete and its corresponding tensile strain ($\varepsilon_t$) as follows:

$$ f_t = 0.62 \sqrt{f_c'} $$

(4)

$$ \varepsilon_t = \frac{f_t}{E} $$

(5)

The strength of concrete under biaxial compression actions has been magnified by 1.16 which is more than uniaxial compressive strength. Tri-linear model (Fig. 16) has been formulated for steel reinforcement performance under compressive or tensile forces based on average experimental data given by Taha and Morsy [46]. Thus, the plastic

Table 3
Summary data for NN outputs divided by targets.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Variance</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compression strength, training</td>
<td>1.00</td>
<td>0.0218</td>
<td>0.00047</td>
<td>0.99</td>
</tr>
<tr>
<td>Compression strength, testing</td>
<td>0.94</td>
<td>0.0806</td>
<td>0.00649</td>
<td>0.95</td>
</tr>
<tr>
<td>Area, training</td>
<td>0.97</td>
<td>0.0021</td>
<td>4.5 x 10^-6</td>
<td>0.97</td>
</tr>
<tr>
<td>Area, testing</td>
<td>0.88</td>
<td>0.0015</td>
<td>2.4 x 10^-6</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Table 4
Specific and random predicted values of present NN outputs and their difference to actual data.

<table>
<thead>
<tr>
<th>Difference = ($\frac{\text{predicted value} - \text{actual value}}{\text{actual value}} \times 100$)</th>
<th>Actual value</th>
<th>Predicted value by NN</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>-4.32</td>
<td>37.31</td>
<td>35.70</td>
<td>$f_{c'}$ for corroded beam</td>
</tr>
<tr>
<td>-3.04</td>
<td>11.17</td>
<td>10.83</td>
<td>$f_{c'}$ for beam</td>
</tr>
<tr>
<td>-5.28</td>
<td>27.00</td>
<td>25.58</td>
<td>$f_{c'}$ for beam</td>
</tr>
<tr>
<td>2.62</td>
<td>48.00</td>
<td>49.26</td>
<td>$f_{c'}$ for beam</td>
</tr>
<tr>
<td>0.23</td>
<td>37.00</td>
<td>37.10</td>
<td>$f_{c'}$ for beam</td>
</tr>
<tr>
<td>-3.20</td>
<td>52.84</td>
<td>51.16</td>
<td>$f_{c'}$ for beam</td>
</tr>
<tr>
<td>-20.78</td>
<td>200.98</td>
<td>159.23</td>
<td>Steel area for corroded beam</td>
</tr>
<tr>
<td>-5.42</td>
<td>223.46</td>
<td>211.35</td>
<td>Steel area for beam</td>
</tr>
<tr>
<td>-7.90</td>
<td>78.50</td>
<td>72.31</td>
<td>Steel area for beam</td>
</tr>
<tr>
<td>9.24</td>
<td>196.08</td>
<td>214.20</td>
<td>Steel area for beam</td>
</tr>
<tr>
<td>-21.46</td>
<td>265.00</td>
<td>208.12</td>
<td>Steel area for beam</td>
</tr>
<tr>
<td>-12.16</td>
<td>816.00</td>
<td>717.04</td>
<td>Steel area for beam</td>
</tr>
</tbody>
</table>

Fig. 14. Model of concrete behavior under axial compressive action.

$$ k_2 = \left( \frac{\varepsilon_0}{E} \right)^3, k_1 = \left( \frac{\varepsilon_0}{E} \right)^4 \text{ for 50 MPa} < f_{c'} < 120 \text{ MPa} $$

$$ \beta = 1 \left[ 1 - \frac{f_{c'}}{E\varepsilon} \right] $$

(2)

$$ \varepsilon_0 = 8.9E - 5f_{c'} + 2.114E - 3 $$

(3)

$$ E = \text{modulus of elasticity in MPa}, f_{c'} = \text{compressive strength of concrete after corrosion which is the output of present neural model.} $$

The elastic modulus of an object is defined as the slope of its stress–strain curve in the elastic deformation region (Fig. 14), $k_1$ and $k_2$ are coefficients, $\beta$ is a slope, $\varepsilon$ is strain, $\varepsilon_0$ is initial strain in elastic zone, $\sigma$ is stress.

Fig. 15. Model of concrete behavior under axial tensile action.

Fig. 16. Model of steel bar behavior under axial loading.

Fig. 17. The used elements in present analysis.
The behavior of steel is considered to occur at yielding stress (\(f_y\)) and its corresponding yielding strain (\(\varepsilon_y\)) can be evaluated as:

\[
\varepsilon_y = \frac{f_y}{E} \tag{6}
\]

The concrete is modeled with using 20-noded nonlinear quadratic brick element (Fig. 17) with reduced integration since this element has been used to model the concrete in many researches as the best element for modeling of the concrete with best results in analysis [39,40]. Longitudinal and shear reinforcement has been defined in the model as 3-noded quadratic beam element (Fig. 17) using embedding region interaction constraint. The large deformation phenomenon of beam has been taken into account via geometrical nonlinearity to reach efficient simulation of corroded beam behavior. Geometrical nonlinearity must be introduced in the finite element analysis of corroded concrete beams.

### 4. Applications of finite element and NN

The proposed neural network and developed finite element procedure have been applied in prediction of flexural behavior of the corroded concrete beams given in Table 5. These beams were selected for analysis because the beam parameters that are necessary as inputs in the NN are within the ranges used in the NN development and because these beams are loaded in different transverse loading ways, which allows for evaluating the influence of loading on accuracy, given that this was not a parameter explicitly considered in the development of the NN. Outcomes from the NN for these beams (namely concrete compressive strength and corroded steel bars area) are listed also in Table 5. 20-noded brick elements with maximum size of 50 mm have been used in beam modeling (Fig. 18).

Finite element analysis was performed to simulate the behavior of these beams with consideration of both material and geometrical nonlinearities. Plasticity parameters of the used concrete damage plasticity model for all beams are illustrated in Table 6. The outputs have been evaluated with and without taking into account the effect of large deflection (geometrical nonlinearity). Substantially, there is reasonable matching and underestimation (Figs. 19–22) with using geometrical nonlinearity and linearity respectively between previous experimental

### Table 5

<table>
<thead>
<tr>
<th>Item</th>
<th>Beam designation</th>
<th>Present NN results</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>L3 beam tested by Yi et al. [41]</td>
<td>Concrete compressive strength of corroded beam = 18.192 MPaCorroded tensile steel bars area = 252.5669 mm²Corroded compressive steel bars area = 63.1420 mm²</td>
</tr>
<tr>
<td>2</td>
<td>BS02 beam tested by Yu et al. [2]</td>
<td>Concrete compressive strength of corroded beam = 16.94526 MPaCorroded tensile steel bars area = 130 mm²Corroded compressive steel bars area = 32.50 mm²</td>
</tr>
<tr>
<td>3</td>
<td>BS04 beam tested by Yu et al. [2]</td>
<td>Concrete compressive strength of corroded beam = 17.116 MPaCorroded tensile steel bars area = 130.0707 mm²Corroded compressive steel bars area = 32.51770 mm²</td>
</tr>
<tr>
<td>4</td>
<td>FC-1 beam tested by Wang et al. [42]</td>
<td>Concrete compressive strength of corroded beam = 11.1860 MPaCorroded tensile steel bars area = 163 mm²Corroded compressive steel bars area = 120 mm²</td>
</tr>
</tbody>
</table>

### Table 6

Concrete damage plasticity coefficients.

<table>
<thead>
<tr>
<th>Plasticity parameters</th>
<th>Dilation angle</th>
<th>Eccentricity</th>
<th>Biaxial strength/uniaxial strength</th>
<th>K-factor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>38</td>
<td>0.1</td>
<td>1.16</td>
<td>2/3</td>
</tr>
</tbody>
</table>
and present deflection results.

The toughness (Fig. 23) of beams has been computed as the area under load-deformation curve to quantify the difference between finite element solution and experimental data. The geometrical nonlinearity was dependent in the finite element calculation of beam toughness which is illustrated in Fig. 23. Good agreement has been gained, with consideration of four beams toughness, between the experimental measurements and present FEA outcomes.

5. Conclusions

The back propagation neural network with a single hidden layer of twelve neurons has been applied. Six input parameters have been used in present NN namely corrosion age, concrete compressive strength of uncorroded beam, uncorroded areas of tensile and compressive steel bars and yield stresses of tensile and compressive steel bars. Neural networks have been formulated to correlate these inputs to output parameters of concrete strength and area of steel reinforcement in the corroded beam via separate NN for each output parameter. Nonlinear finite element modeling has been performed to investigate the behavior of corroded concrete beams with depending on NN outcomes. Based on present results of neural networking and finite elements the conclusions can be drawn as hereunder:

- The geometrical nonlinearity was dependent in the finite element calculation of beam toughness.
- Good agreement has been gained between the experimental measurements and present FEA outcomes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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