Prediction of PWSCC Growth Rate for Alloy 600 by Artificial Neural Network

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ABSTRACT : Alloy 600 is used in PWRs for pressure boundary application. Some nuclear plants have experienced primary water stress corrosion cracking(PWSCC) of Alloy 600. The prediction of PWSCC growth rate for Alloy 600 by artificial neural network is performed to evaluate the residual life and integrity of Alloy 600 components. The database for PWSCC growth rate of Alloy 600 is created with data from previous studies. The artificial neural network is constructed by using this database and training algorithm of back propagation. To evaluate the effectiveness of the artificial neural network presented here, comparisons between predicted and observed values are performed. Finally, the effects of influence factors - environmental factors and loading conditions - on PWSCC growth rate are evaluated.

1. INTRODUCTION

Alloy 600 material has been used for primary system pressure boundary penetrations and steam generator tube in many PWR plants. However, some nuclear plants have experienced primary water stress corrosion cracking(PWSCC) of Alloy 600. Accordingly, the prediction of PWSCC growth rate for Alloy 600 is needed in order to evaluate the residual life, performance and integrity of Alloy 600 components because PWSCC has led to the leakage of primary water from Alloy 600 components and the failures of Alloy 600 components in PWR plants. Recently, the studies[1-11] related to this predictive technology have been performing brisker in the field of preventive maintenance of LWR plant components against PWSCC. Jackto et al.[1] studied the effects of different water chemistries on PWSCC growth rate of Alloy 600 at 330°C and Scott[2] developed a model for PWSCC growth rate based on corrosion crack growth kinetics and data from McIlree et al.'s study[3]. Cassagne and Gelpi[4] observed an accelerating factor of between 5 and 10 in growth rates for cold worked materials. Woodman also developed another model for PWSCC growth rate by using the database which didn't account for cold work and verified Scott's crack growth model[5]. Amszallag et al.[6] calculated the crack growth as a function of stress intensity factor for over 200 penetrations in French PWRs which were inspected and Briceno et al.[7] tested Alloy 600 at 325°C and 290°C in refreshed autoclaves with specific water chemistry. Lidar performed the crack growth test for Alloy 600 with a constant active static load with periodic unloading/reloading in a refreshed autoclave with specific water chemistry[8]. Vaillant et al.[9] performed crack growth tests under various loading, temperature and water chemistry conditions. Hunt and Gross[10] developed approximate nominal, upper bound and lower bound curves by using data from McIlree et al.'s study[3] and average crack growth rates for steam generator tubing in Belgian, France and Sweden. Bamford and Foster[11] performed the crack growth measurement tests on Alloy 600 vessel head penetration material
under various loading, temperature and water chemistry conditions and evaluated the effects of material, microstructure, stress intensity factor, holding time and temperature on crack growth rates. However, although there are lots of crack growth rate data for Alloy 600, the various influence factors on crack growth rate can't be exactly evaluated by the existing prediction models.

Artificial neural network[12] has great potential for prediction of material properties used in industry and power plant. Their main benefits are that estimates of material properties are based purely on data and not on preconceptions, and that the network can interpolate effects by learning trends and patterns when data are not available. Accordingly, the studies[13-15] to predict material properties - fatigue life, SCC initiation time and corrosion rate - have been performed by using artificial neural network.

This approach has been adopted to predict PWSCC growth rates and evaluate the various influence factor on ones of Alloy 600 in PWR. The database for PWSCC growth rate of Alloy 600 is created with data from the previous studies[1-11]. Artificial neural network has been also developed to unravel the combined effects of influence factors - materials, environmental factors and loading conditions - on the PWSCC growth rate of Alloy 600 in PWR by using this database and the back propagation algorithm[12]. To evaluate the effectiveness of the artificial neural network presented here, comparisons between predicted and observed values are performed. Finally, the effects of influence factors on PWSCC growth rate are evaluated.

2. ARTIFICIAL NEURAL NETWORK

The training algorithm of artificial neural network adopted for this study is a back propagation. Back propagation describes the learning algorithm. Artificial neural network is composed of many processing elements(Fig.1), called "neurons", that are interconnected and operate in parallel. Also, artificial neural network is created with at least two, but usually three or more, layers of neurons that consist of an input layer, an output layer, and one or two hidden layers.

As shown in Fig.2, there are five inputs - yielding strength, temperature, stress intensity factor, pH and holding time - and one output, crack growth rate, for this study. There are two hidden layers with the first containing eleven nodes and the second containing nine. The output values of each neuron in the subsequent layers is determined as follows:
- For each pathway in Fig.2, an input value \( O_i \) is multiplied by a weight \( w_{ij} \).
- The products of inputs and weights are added to give a sum \( U_i \).
- The sum \( U_i \) is added to a threshold value \( t_i \).
- An activation function \( F(U_j + t_j) \) is applied, resulting in the output to the next layer \( O_j \).

This process continues at each node and layer until the output for the entire artificial neural network is determined. The output to the next layer is expressed as

\[
O_j = F(\sum O_i w_{ij} + t_j),
\]

\[
F(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}.
\]
The back propagation process trains the network with the output layer and works backwards to the first hidden layer. For each input to the neuron, a new weight \( w_{ij} \) is expressed by

\[
    w_{ij} = w'_{ij} + LR e_i O_i,
\]

where \( w'_{ij} \) is the old weight, \( LR \) is learning rate, \( e_i \) is the error of the output, and \( O_i \) is the input value that corresponds to the weight being adjusted. The learning rate is an important factor because it controls the amount by which the weight is adjusted. For the present study, the learning rate is 0.1.

The error for the output neuron is determined by comparing the output values with a given target value, and is expressed as

\[
    e_i = (1 + O_i)(1 - O_i)(d_i - O_i),
\]

where \( d_i \) is the target value for each output. Eq.(4) can only be determined for the output layer, because there are no target values for the hidden layers. The error for hidden layers is determined from the error \( e_k \) and the old weights \( w'_{ik} \) which correspond to the layer immediately succeeding the current layer, i.e.,

\[
    e_i = (1 + O_i)(1 - O_i) \Sigma e_k w'_{ik}.
\]

This is the most important equation in back propagation artificial neural network because it facilitates learning by the hidden layers.

3. PARAMETER RANGES

The database used to train the artificial neural network contains PWSCC growth rate data obtained from the previous studies[1-11]. It covers an adequate range of
yielding strength, temperature, stress intensity factor, pH and holding time and is composed of the total 1337 data sets, which are classified into 393 data sets from the previous prediction models[2,5,10] and 944 data sets from the other previous studies[1,3,4,6-9]. The distribution of data for various materials, environmental factors and loading conditions is presented in Table 1.

Table 1. Distribution data for various materials, environmental factors and loading conditions.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Range</th>
<th>Occurrence number</th>
<th>Factor</th>
<th>Range</th>
<th>Occurrence number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yielding strength (MPa)</td>
<td>≤200</td>
<td>3</td>
<td>Temperature (°C)</td>
<td>≤290</td>
<td>104</td>
</tr>
<tr>
<td></td>
<td>200&lt; and ≤250</td>
<td>64</td>
<td></td>
<td>290&lt; and ≤300</td>
<td>110</td>
</tr>
<tr>
<td></td>
<td>250&lt; and ≤280</td>
<td>598</td>
<td></td>
<td>300&lt; and ≤310</td>
<td>119</td>
</tr>
<tr>
<td></td>
<td>280&lt; and ≤300</td>
<td>46</td>
<td></td>
<td>310&lt; and ≤320</td>
<td>224</td>
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<tr>
<td></td>
<td>300&lt; and ≤330</td>
<td>160</td>
<td></td>
<td>320&lt; and ≤330</td>
<td>660</td>
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<tr>
<td></td>
<td>330&lt; and ≤380</td>
<td>401</td>
<td></td>
<td>330&lt; and ≤340</td>
<td>69</td>
</tr>
<tr>
<td></td>
<td>380&lt; and ≤430</td>
<td>22</td>
<td></td>
<td>340&lt; and ≤350</td>
<td>15</td>
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<tr>
<td></td>
<td>430&lt;</td>
<td>43</td>
<td></td>
<td>350&lt;</td>
<td>36</td>
</tr>
<tr>
<td>S.I.F.* (MPa√m)</td>
<td>≤20</td>
<td>173</td>
<td>Holding time (hour)</td>
<td>≤0.33</td>
<td>129</td>
</tr>
<tr>
<td></td>
<td>20&lt; and ≤30</td>
<td>414</td>
<td></td>
<td>0.33&lt; and ≤1</td>
<td>328</td>
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<tr>
<td></td>
<td>30&lt; and ≤40</td>
<td>189</td>
<td></td>
<td>1&lt; and ≤100</td>
<td>22</td>
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<td>40&lt; and ≤50</td>
<td>125</td>
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<td>100&lt; and ≤200</td>
<td>17</td>
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<td>101</td>
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<td>200&lt; and ≤300</td>
<td>60</td>
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<td>60&lt; and ≤70</td>
<td>61</td>
<td></td>
<td>300&lt; and ≤900</td>
<td>11</td>
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<tr>
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<td>70&lt; and ≤80</td>
<td>91</td>
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<td>900&lt; and ≤1000</td>
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<td>80&lt;</td>
<td>183</td>
<td></td>
<td>1000&lt;</td>
<td>6</td>
</tr>
<tr>
<td>pH</td>
<td>≤5</td>
<td>37</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5&lt; and ≤6</td>
<td>81</td>
<td>* S.I.F. : Stress intensity factor</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6&lt; and ≤7</td>
<td>1157</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>7&lt;</td>
<td>62</td>
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</tbody>
</table>

Existing data cover a yielding strength range of 165.5 to 468MPa, a temperature range of 290 to 363.3°C, a stress intensity factor range of 4 to 100MPa√m, a pH range of 2.5 to 7.4, and a holding time range of 0.0027 to 3214 hour.

4. NEURAL NETWORK ESTIMATES

A database of 1337 data sets is used to train the artificial neural network. Once optimal artificial neural network is designed, the artificial neural network is trained and used to predict crack growth rate for various sets of materials, environmental and loading conditions. The artificial neural network is trained 20 times. Twenty trainings are based on the same data set, but the order in which the data are presented to the artificial neural network for training is varied and the initial artificial neural network weights are randomized to guard against overtraining and to prevent the network from reaching a local minimum solution. The data set that is presented at the start of the training changes the weights more than subsequent data because of this high error. The artificial neural network is considered properly trained when differing initial data
give the same final result.

The results provide insights into the trends that characterize the PWSCC growth rate of Alloy 600 as a function of yielding strength, temperature, stress intensity factor, pH, and holding time. The values predicted by the artificial neural network are compared with experimentally observed values in Fig.3. The predicted crack growth rates show good agreement with the experimental data.

![Fig.3. Comparison between the predicted values by artificial neural network and the observed values from the previous studies[1-11].](image)

5. EFFECTS OF INFLUENCE FACTORS ON CRACK GROWTH RATE

The effects of temperature and stress intensity factor on the PWSCC growth rate of Alloy 600, and those by the previous prediction models[2,11] are shown in Fig.4 and 5, respectively.

As shown in Fig.4, the effect of temperature on crack growth rate of Alloy 600 by the artificial neural network is similar to that by Bamford and Foster[11]. Both indicate that crack growth rate decrease with decreasing temperature.

As shown in Fig.5, the effect of stress intensity factor on crack growth rate of Alloy 600 by the artificial neural network is similar to that by Scott's model[11]. Both indicate that crack growth rate increase with increasing stress intensity factor. Prediction values from artificial neural network are smaller than those from Scott's model[11] in the stress intensity factor range of 15 to 70MPa/√m.

6. CONCLUSIONS

In order to train an artificial neural network, a database of 1337 data sets is utilized. As the optimal artificial neural network is designed, artificial neural network is trained and used to predict the PWSCC growth rate of Alloy 600 for specific sets of material, environmental and loading conditions. The results provide insights into the trends that characterize the crack growth rate of Alloy 600 as a function of yielding strength, temperature, stress intensity factor, pH, and holding time.

The artificial neural network agrees well with the observed values from the previous studies[1-11].
Fig. 4. Effect of temperature on PWSCC growth rate of Alloy 600.

Artificial neural network is a powerful method to predict PWSCC growth rate because the fit of data is completely based on experimental data and the effects by learning trends and patterns can be interpolated into the network in case that complete data sets are not available. The factors that affect crack growth rate can exert synergistic effects on one another. An artificial neural network can detect and utilize these effects in its predictions. Through excellent interpolation, the artificial neural network can make predictions throughout the range of known data by learning how the factors affect PWSCC growth rate. However, lack of data at some ranges makes a difference in confidence level of these ranges. Therefore, additional experiment will be needed to supplement the data in these ranges.

REFERENCES


Monterey, California, August 1991.


