Failure Prediction of Underground Pipeline Based on Artificial Neural Network

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Abstract. Artificial neural network has become a useful tool for many engineering problems. For the prediction and analysis of underground pipeline failure, an ANN model is established as basis of the data of buried pipelines in non-uniform settlement soil. Therefore, the failure of underground pipeline in non-uniform settlement soil is treated as a nonlinear function with several variables. Six influence factors, such as buried depth, wall thickness, pipe diameter, precipitation level, soil modulus of elasticity, and soil density, are considered in this ANN model. The ANN model is a back propagation (BP) network, and model structure is designed based on MATLAB, in which Neuron number in hidden layer and active function are selected. Finally, the accuracy of this ANN model and predictive results are investigated, and some suggestions are offered for the protection of underground pipeline in non-uniform settlement soil.

Introduction

Underground pipeline is obvious frangible to site condition that make the relationship between pipeline and influencing factors very complex and nonlinear [1-4]. Failure probability of underground pipeline in the site condition of non-uniform settlement soil affected by many factors, such as buried depth, wall thickness, pipe diameter, precipitation level, soil modulus of elasticity, soil density, and so on [5-7]. Although there are many researches on the theory and experiment of buried pipeline damage, but most predictive models for pipeline failure is based on statistics [8]. Therefore, we construct a failure prediction model of underground pipeline based on ANN to represent the complex fuzzy nonlinear relation [9-11].

BP network, as the basic ANN, is useful to deal with fuzzy nonlinear relations, and the failure probability of underground pipeline becomes a function in nonlinear relation [12-16]. In this article, the data for underground pipeline failure prediction are obtained by finite element method, and they are divided into training set and testing set. The model is a back propagation (BP) network, and model structure is designed based on MATLAB, neuron number in hidden layer and active function are selected through MATLAB. The calculating results of this predictive model are compared with actual values, and the calculating error is analyzed.
Data of Underground Pipeline

From finite element calculation, it was found that the failure of underground pipeline in non-uniform settlement soil is affected by buried depth, wall thickness, pipe diameter, precipitation level, soil modulus of elasticity, and soil density. The data is shown in table 1, and six influence factors are concluded. Those six influence factors can be treated as a six-dimension vector that is the input variables in MATLAB. The failure probability is represented by axial stress that is treated as a one-dimension vector, and it is the output target variable in MATLAB.

<table>
<thead>
<tr>
<th>No.</th>
<th>buried depth /m (x₁)</th>
<th>wall thickness /m (x₂)</th>
<th>pipe diameter /m (x₃)</th>
<th>precipitation level/m (x₄)</th>
<th>modulus of elasticity/ MPa (x₅)</th>
<th>soil density /kg/m³ (x₆)</th>
<th>axial stress /Mpa (σ)</th>
</tr>
</thead>
<tbody>
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<td>2</td>
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<td>0.8</td>
<td>0</td>
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<td>1750</td>
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<td>3.56</td>
<td>1750</td>
<td>16.532</td>
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<tr>
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<td>3.56</td>
<td>1750</td>
<td>15.081</td>
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<tr>
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<td>3.56</td>
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<td>13.511</td>
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<td>0.8</td>
<td>0</td>
<td>3.86</td>
<td>2600</td>
<td>38.052</td>
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</tbody>
</table>

According to the data in table 1, failure of underground pipeline can be computed based on this artificial neural network model. Obviously, the input variables is a $6 \times 22$ vector, and the output target variable is a one-dimensional vector containing 22 numbers.

**ANN Model**

As a BP network, the predictive model of underground pipeline failure with one hidden layer is expressed as,

$$\sigma_j = \left[ W_{2,0} + W_{2,1} * W_{1,0} \right] x_j \tag{1}$$

In which,

$\sigma_j$=the $j$th value of axial stress,

$W_{2,0}$=the weights matrix between output vector and input vector,

$W_{2,1}$=the weights matrix between output vector and hidden layer vector,

$W_{2,0}$=the weights matrix between hidden layer vector and input vector,

$x_j$=the $j$th value of the $i$th input vector.

Therefore, the training of ANN model can be treated as the calculation of weights matrix. Before the training, the data in table 1 must be normalized, which will affect the convergence speed of ANN.
model during training. Each input vector should be a normalized vector, and a $6 \times 22$ input vector is created for table 1.

The normalization is written as,

$$x_i = \frac{x_i - \text{Min}(x_i)}{\text{Max}(x_i) - \text{Min}(x_i)}$$  \hspace{1cm} (2)

After normalization, we can begin the artificial neural network training.

**Training Function**

The selection of training function is the key of ANN training, if the network error is set as 0.001, the results for this application example data are shown in table 2.

<table>
<thead>
<tr>
<th>Training function</th>
<th>Traindx</th>
<th>Trainlm</th>
<th>Traingd</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iterative number</td>
<td>&gt;1000</td>
<td>87</td>
<td>&gt;1000</td>
</tr>
</tbody>
</table>

It can be found from table 2 that the best function is Trainlm, and the iterative calculation number is 87, this is shown as figure 1. For other training functions, such as Traindx and Traingd, the training results cannot reach the goal with error of 0.001 after 1000 steps’ iterative calculation.

![Figure 1. Training of Trainlm.](image)

In figure 1, convergence speed is very rapid within 10 steps, like a straight line with a steep slope. After 10 times iteration, convergence speed becomes slowly and reaches the error target with iterative number 87.

**Neuron Number in Hidden Layer**

The precision and convergence speed of ANN model are affected by neuron number during training, this is shown in table 3.

<table>
<thead>
<tr>
<th>Neuron number</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iterative number</td>
<td>115</td>
<td>105</td>
<td>106</td>
<td>84</td>
<td>89</td>
<td>90</td>
</tr>
<tr>
<td>Network error</td>
<td>0.0312</td>
<td>0.0278</td>
<td>0.0264</td>
<td>0.0152</td>
<td>0.0178</td>
<td>0.0198</td>
</tr>
</tbody>
</table>

From table 3, the neuron number 13 has the fewest iterative number and the least network error. The iterative number is 84 and the network error is 0.0152. The most iterative number is 115 with neuron number 10, also the maximal network error 0.0312. This shows that more is not better, less is also not better for neuron number.

The error of network training is shown in figure 2. In figure 2, the maximum network error is less than 3%, and decreases gradually with the increase of iterative numbers. It shows that the accuracy
and convergence of the model reach the target. Up to now, the modeling of failure prediction for underground pipeline has finished.

Figure 2. Network error with training function Trainlm.

**Results Analysis**

The results of weights matrix are expressed as,

\[
W_{20} = \begin{bmatrix}
0.2146 & -0.5575 & 0.7581 & 0.2313 & -1.7961 & 2.5306 \\
0.0834 & 1.0586 & 0.7702 & 0.9377 & 0.3711 & 0.1124 \\
0.4530 & 0.9079 & 0.1174 & 0.9993 & 0.9959 & -0.2248 \\
1.3399 & 0.1122 & 0.3143 & 0.4927 & -0.1732 & 0.7859 \\
0.6585 & 0.0473 & 0.5313 & 0.4807 & -0.0131 & 0.5576 \\
0.7329 & 0.8447 & 0.5827 & 1.0022 & 0.9153 & 0.1907 \\
0.3451 & 1.2682 & 0.1597 & 1.0339 & 0.5006 & 0.7919 \\
1.4008 & -0.2842 & 0.3730 & -0.2423 & -0.3326 & 1.3506 \\
-0.0857 & -0.6547 & 0.2258 & -0.1492 & -0.5273 & 1.9284 \\
1.3685 & 0.2831 & 0.1663 & 0.0002 & 0.0035 & 0.8689 \\
0.3314 & 0.4289 & 0.6717 & 0.3003 & 0.6651 & 0.0769 \\
0.1793 & 0.7252 & -0.4123 & 0.2851 & 1.2422 & -0.6172 \\
0.6172 & 0.4739 & 0.2074 & 0.9801 & 0.6929 & 0.5348
\end{bmatrix}
\]  \tag{3}

\[
W_{31} = \begin{bmatrix}
0.6956 & 0.5379 & 0.5419 & 0.2906 & 0.3311 & 0.7568 \\
0.0834 & 1.0586 & 0.7702 & 0.9377 & 0.3711 & 0.1124 \\
0.4530 & 0.9079 & 0.1174 & 0.9993 & 0.9959 & -0.2248 \\
1.3399 & 0.1122 & 0.3143 & 0.4927 & -0.1732 & 0.7859 \\
0.6585 & 0.0473 & 0.5313 & 0.4807 & -0.0131 & 0.5576 \\
0.7329 & 0.8447 & 0.5827 & 1.0022 & 0.9153 & 0.1907 \\
0.3451 & 1.2682 & 0.1597 & 1.0339 & 0.5006 & 0.7919 \\
1.4008 & -0.2842 & 0.3730 & -0.2423 & -0.3326 & 1.3506 \\
-0.0857 & -0.6547 & 0.2258 & -0.1492 & -0.5273 & 1.9284 \\
1.3685 & 0.2831 & 0.1663 & 0.0002 & 0.0035 & 0.8689 \\
0.3314 & 0.4289 & 0.6717 & 0.3003 & 0.6651 & 0.0769 \\
0.1793 & 0.7252 & -0.4123 & 0.2851 & 1.2422 & -0.6172 \\
0.6172 & 0.4739 & 0.2074 & 0.9801 & 0.6929 & 0.5348
\end{bmatrix}
\]  \tag{4}

The predictive results of this model are shown in table 4.

<table>
<thead>
<tr>
<th>No.</th>
<th>axial stress /Mpa (σ)</th>
<th>predictive axial stress/Mpa (σ)</th>
<th>Error/(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25.723</td>
<td>26.315</td>
<td>2.3</td>
</tr>
<tr>
<td>2</td>
<td>32.290</td>
<td>32.338</td>
<td>1.4</td>
</tr>
<tr>
<td>3</td>
<td>7.550</td>
<td>7.912</td>
<td>4.8</td>
</tr>
<tr>
<td>4</td>
<td>61.671</td>
<td>59.634</td>
<td>3.2</td>
</tr>
<tr>
<td>5</td>
<td>13.074</td>
<td>13.453</td>
<td>2.9</td>
</tr>
<tr>
<td>6</td>
<td>8.945</td>
<td>9.348</td>
<td>4.5</td>
</tr>
<tr>
<td>7</td>
<td>12.754</td>
<td>12.333</td>
<td>3.3</td>
</tr>
<tr>
<td>8</td>
<td>12.467</td>
<td>12.779</td>
<td>2.5</td>
</tr>
</tbody>
</table>

From table 4, it can be found that the maximal predictive error is 4.8%, which is less than 5%. Therefore, the artificial neural network model can fully satisfy the engineering need. Axial stress of underground pipeline in non-uniform settlement soil can be calculated based on buried depth, wall thickness, pipe diameter, precipitation level, soil modulus of elasticity, and soil density, and the failure of underground pipeline can be analyzed.
Summary

A predictive model for underground pipeline is constructed with double parallel feed-forward neural network. Neuron number in hidden layer and training function are investigated based on MATLAB. Through compare the predictive results with eight groups’ sample data, the results meet well with actual axial stress values. Therefore, ANN is a useful tool for predicting the failure of underground pipeline in non-uniform settlement soil.

Acknowledgement

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References