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A Computational Estimation of Cyclic Material Properties Using Artificial Neural Networks

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Abstract

The structural durability design of components requires the knowledge of cyclic material properties. These parameters are strongly dependent on environmental conditions and manufacturing processes, and require many experimental tests to be correctly determined. Considering time and costs, it is not possible to include in the tests all the variables that influence the material behaviour. For this reason, the computational method of the Artificial Neural Network (ANN) can be implemented to support these investigations. This method allows an estimation of the cyclic material properties starting from the static parameters deducted through tensile tests. The results permit a very good approximation of cyclic material properties using just a few specimens in tests, so that the experimental effort can be deeply reduced. The ANN has been implemented in the software called Artificial Neural Strain Life Curves (ANSLC), and has been tested on a large database of steels. In this paper the method of the ANN and the program ANSLC will be presented.

Keywords: artificial neural networks, cyclic properties, structural durability, ANSLC

1. Introduction

Structural durability design of components according to the local strain approach requires information about the cyclic stress-strain curve and the strain-life curve of the materials involved in the process. This information can be provided through experimental tests. During these tests, several specimens must be tested at various strain levels. The strain amplitude is controlled and kept constant, while the number of cycles to failure and the stress amplitude are measured. The results are then plotted in the stress-strain and strain life diagrams, and after a regression through the experimental results, the cyclic material properties of the material are determined. These properties are the parameters of the Ramberg-Osgood (1) and Manson-Coffin-Basquin (2) equations [1-5].

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Nomenclature

E \quad \text{Young’s Modulus}
\varepsilon_a \quad \text{strain amplitude}
\sigma_a \quad \text{stress amplitude}
N, N_f \quad \text{number of cycles to failure}
K' \quad \text{cyclic strength coefficient}
n' \quad \text{cyclic strain hardening exponent}
\sigma_f' \quad \text{fatigue-strength coefficient}
b \quad \text{fatigue-strength exponent}
\varepsilon_f' \quad \text{fatigue-ductility coefficient}
c \quad \text{fatigue-ductility exponent}
R_{p0.2} \quad \text{tensile yield strength}
R_{p0.2}' \quad \text{cyclic yield strength}
R_m \quad \text{ultimate tensile strength}
A_5 \quad \text{engineering strain with gage length } L = 5 \times D (D = \text{diameter of the specimen})
A_{80} \quad \text{engineering strain with gage length } L = 80 \text{ mm}
A_g \quad \text{plastic strain at the maximum stress level}
Z \quad \text{reduction of area}
T \quad \text{temperature}
WR \quad \text{direction of rolling}
K \quad \text{static strength coefficient}
n \quad \text{static strain hardening exponent}
\varphi_e \quad \text{total equivalent plastic strain}

\varepsilon_a = \frac{\sigma_a}{E} + \left(\frac{\sigma_a}{K'}\right)^{1/n'} \quad (1)

\varepsilon_a = \left(\frac{\sigma_f'}{E}\right) \cdot (2N)^b + \varepsilon_f' \cdot (2N)^c \quad (2)

Applying the definition of yield strength to the cyclic curve, the cyclic yield strength can be calculated through (3):

R_{p0.2}' = K' \cdot (0.002)^n \quad (3)

The geometrical meaning of the parameters in (1) and (2) is shown in Fig. 1.
In order to estimate the parameters a variable number of fatigue tests (normally between 8 and 15) is required, and this is expensive and time consuming. Another possible way of determining the cyclic material properties of materials is the analytical one. Literature offers several experimental equations that correlate the cyclic material properties to the static properties derived from the monotonic tensile test or from hardness measurements [6]. These methods are not very accurate, since they are formulated by interpolations of experimental data regarding various material alloys. The third possibility to estimate the cyclic material parameters comes from the use of Artificial Neural Networks [9-13].

2. Artificial Neural Networks and the ANSLC program.

Artificial Neural Networks (ANNs) were developed for the first time in the 50s, together with the birth of the first numerical calculators. They try to emulate the neural system of animals, which have the ability of learning from the events that happen around them, and build up “rules” creating connections between the received inputs and consequent outputs they see. The ANNs consist in nets of fundamental units, called neurons, which take some inputs and process them in order to reproduce some known outputs. This phase, called training, requires therefore a database in which both inputs and outputs are already known. The training process consists in the adjustment of weights with which the neurons combine together the inputs [7].

The ANSLC program uses ANNs to correlate the static material properties to the cyclic material properties mentioned above. For this purpose, a quite large database of materials is used. This database is provided by the literature [8]. Inputs of the ANNs are the parameters listed in table 1.

Tab. 1: parameters used as inputs in the ANSLC program.

<table>
<thead>
<tr>
<th>INPUT</th>
<th>E</th>
<th>R_{oL,2}</th>
<th>R_m</th>
<th>A_5</th>
<th>A_g</th>
<th>A_{80}</th>
<th>Z</th>
<th>\varphi_v</th>
<th>WR</th>
<th>T</th>
<th>K</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNIT</td>
<td>GPa</td>
<td>MPa</td>
<td>MPa</td>
<td>%</td>
<td>%</td>
<td>%</td>
<td>%</td>
<td>-</td>
<td>°</td>
<td>°C</td>
<td>MPa</td>
<td>-</td>
</tr>
</tbody>
</table>

Taking this database, there is the interesting chance of using the ANNs for simulating virtual experimental tests, instead of training them directly with the cyclic material properties as outputs. In order to do this, several strain amplitude are selected as reference, and out of this the respective values of N and stress amplitudes are calculated through the material properties read in the database. These values are given as output data in the training phase. A schematic representation of this process is shown in Fig. 3.
Figure 3: simulation of virtual experimental tests using ANNs.

The net is trained and the cyclic material properties are again calculated making the regression through the virtual experimental points [11,13]. As explained in [10,12], the selection of the best performing ANNs is evaluated using two parameters:

- **Bpro**: it shows the percentage of estimations that fall into a predefined tolerance band (in this case 50% of the standard deviation of the materials in the database).
- **Tendency**: represents the percentage of materials whose estimation has the same sign of the original, considering the normalization of the database in the range \{-1, 1\}.

The use of the networks for simulating virtual experimental points has the advantage that these virtual tests can be integrated together with a small number of laboratory tests. The simulated points and the experimental ones can be plotted together in the same diagram, and a single regression through all of them can be made. In this way, the advantage of the experimental tests (higher accuracy in the estimation) and of the use of ANN (lower time and effort) can be used together. In figure 4 an example of merge of real and virtual tests is shown.

Fig. 4: combination of experimental tests with the estimations of ANNs.

3. **Comparison of the results of ANSLC and Uniform Material Law**

Among the methods that were developed in order to give an estimation of the cyclic material properties of materials starting from their static properties, the Uniform Material Law (UML) [6] is probably the most used. Since the purpose of all methods is the estimation of the life-time of a component correspondent to a well determined stress amplitude (derived, for example, from numerical simulations), the comparison is not done directly on the single cyclic parameters, but according to the following procedure (graphically shown in Fig. 5):
A set of different $N$ values is selected. From these values, entering the original strain life curve, the “true” strain amplitudes are determined (step a).

Entering the “true” cyclic stress-strain curve with these strains, the correspondent stress amplitudes are calculated (step b).

The stress amplitudes are then used to calculate the correspondent strain amplitudes, but in this case along the estimated curve (from UML and ANSLC) (step c).

With the so calculated strains, the lifetimes are calculated from the estimated strain-life curves (step d).

In the end, the starting $N$ values and the estimated ones after step d are compared.

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**Fig. 5: procedure for the comparison of the life-time estimations.**

The results are calculated for 10 different $N$ values, going from a minimum of 500 up to $10^7$ cycles. Figure 6 shows the direct comparison of the UML with the ANSLC. The estimated values of $N$ with the two methods are compared to the expected number of cycles for the 225 materials of the database. For each of the 10 selected $N$ values, the percentage of materials for which the estimation of the ANSLC results more accurate is plotted in blue in figure 6. The red bar diagram represents the percentage of values that were better estimated by UML. As shown in the figure, around 80% of the values are more accurately estimated using ANSLC rather than UML.

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**Fig. 6: comparison between ANSLC and UML.**
In order to quantify the accuracy of the methods, the relative error in the estimations of $N$ with UML and ANSLC is calculated for all materials. The errors are clustered in ranges with a step of 5%, and the percentage of materials whose estimation falls in each range is counted. A summary of these results is presented for UML in Fig. 7a and Tab. 2, and for ANSLC in Fig. 7b and Tab. 3. The diagrams report in the axis of abscissas the original $N$ values. In the ordinate, the percentage of estimations falling in each range is plotted with different colours. Taking for example $N = 500$ and error $\pm 5\%$, both diagrams and tables show that just 5% of the materials estimated with UML fall in this range, while the percentage raises to 23% in the case of ANSLC.

Fig. 7: a) accuracy of estimations with UML; b) accuracy of the estimations with ANSLC.

Tab. 2: accuracy of the estimations of the life-time $N$ with UML.

<table>
<thead>
<tr>
<th>Reference number of cycles</th>
<th>5·10^2</th>
<th>1·10^3</th>
<th>5·10^3</th>
<th>1·10^4</th>
<th>5·10^4</th>
<th>1·10^5</th>
<th>5·10^5</th>
<th>1·10^6</th>
<th>5·10^6</th>
<th>1·10^7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative error in the estimation of $N$</td>
<td>± 5%</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>± 10%</td>
<td>10</td>
<td>7</td>
<td>9</td>
<td>11</td>
<td>7</td>
<td>6</td>
<td>8</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>± 15%</td>
<td>15</td>
<td>12</td>
<td>16</td>
<td>17</td>
<td>11</td>
<td>10</td>
<td>10</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>± 20%</td>
<td>22</td>
<td>19</td>
<td>20</td>
<td>16</td>
<td>14</td>
<td>14</td>
<td>11</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>± 25%</td>
<td>26</td>
<td>28</td>
<td>23</td>
<td>26</td>
<td>20</td>
<td>18</td>
<td>16</td>
<td>12</td>
<td>12</td>
</tr>
</tbody>
</table>

Tab. 3: accuracy of the estimations of the life-time $N$ with ANSLC.

<table>
<thead>
<tr>
<th>Reference number of cycles</th>
<th>5·10^2</th>
<th>1·10^3</th>
<th>5·10^3</th>
<th>1·10^4</th>
<th>5·10^4</th>
<th>1·10^5</th>
<th>5·10^5</th>
<th>1·10^6</th>
<th>5·10^6</th>
<th>1·10^7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative error in the estimation of $N$</td>
<td>± 5%</td>
<td>23</td>
<td>24</td>
<td>33</td>
<td>32</td>
<td>23</td>
<td>18</td>
<td>16</td>
<td>15</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>± 10%</td>
<td>42</td>
<td>43</td>
<td>51</td>
<td>54</td>
<td>46</td>
<td>36</td>
<td>27</td>
<td>23</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>± 15%</td>
<td>54</td>
<td>52</td>
<td>61</td>
<td>63</td>
<td>57</td>
<td>52</td>
<td>38</td>
<td>34</td>
<td>29</td>
</tr>
<tr>
<td></td>
<td>± 20%</td>
<td>62</td>
<td>66</td>
<td>69</td>
<td>70</td>
<td>65</td>
<td>62</td>
<td>47</td>
<td>44</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>± 25%</td>
<td>67</td>
<td>75</td>
<td>76</td>
<td>75</td>
<td>71</td>
<td>67</td>
<td>58</td>
<td>53</td>
<td>46</td>
</tr>
</tbody>
</table>
The quality of the estimations with ANSLC is considerably higher, considering for example that an average of 55-60% of the estimations lays the range ± 25% against the average of 15 - 20% with the UML.

4. Conclusion

The Artificial Neural Networks can be successfully used to estimate the cyclic material properties of materials, once the static properties are provided. The simulation of virtual experimental tests with the Artificial Neural Networks offers the opportunity of integrating these results with a reduced number of experimental tests. In comparison with the largely used Uniform Material Law, the results of the estimation with the ANSLC program, even without including the support of real experimental tests in the regression, show a considerably higher accuracy in the life-time estimation. The ANSLC works rather well in the estimation of N in the range $1 \cdot 10^3$-$1 \cdot 10^5$, which corresponds to the transition zone between the elastic and the plastic behaviour, while it is slightly worse in the estimation of N in the pure elastic range.

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References:


