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Residual Useful Life Estimation of Fatigue with Condition-Based Modeling Approach using Long Short-Term Memory Network

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1. Introduction

In general, fatigue life estimation has been carried out using numerous end-of-life data points, which are usually represented on a stress/strain-life (S-N) curve plot [1-3]. One data point on the S-N curve implies one failure time data of a single fatigue test. Therefore, to construct the entire S-N curve with reliable scatter band requires almost hundreds of fatigue tests. However, it may not always be possible to conduct hundreds of expensive and time-consuming fatigue experiments for each and every different testing case. Additionally, aforementioned S-N curve approach disregards data history during the whole fatigue experiment which might have additional information to use.

In this regard, some condition-based modeling approaches were proposed to predict the remaining useful life (RUL) of fatigue in real time by estimating the degradation of the material over time [4, 5] rather than predicting the fatigue life of the material from the beginning. In those condition-based approaches, the long short-term memory (LSTM) network [6] plays an important role in the RUL estimation because it can handle the time-series sequential data without the vanishing/exploding gradient problem.

Therefore, we developed a condition-based fatigue RUL model using a simple LSTM network with a few fatigue test data. In addition, we compared other condition-based modeling approaches without using the LSTM network to investigate whether the LSTM network is really appropriate for this case or not.

2. Fatigue Test Data

Table 1. Fatigue test data (Alloy 52M, strain-controlled).

<table>
<tr><th>Test ID</th><th>Environment</th><th>Strain Amplitude</th><th>Strain Rate</th><th>Fatigue Life</th></tr>
<tr><td>MAH501-1</td><td rowspan="5">300 ℃
In-air</td><td rowspan="3">0.5 %,</td><td rowspan="5">0.1 %/s</td><td>2373</td></tr>
<tr><td>MAH501-2</td><td>3779</td></tr>
<tr><td>MAH501-3</td><td>3831</td></tr>
<tr><td>MAH651-1</td><td rowspan="2">0.65 %,</td><td>1472</td></tr>
<tr><td>MAH651-2</td><td>1367</td></tr>
</table>

Table 1 summarized the testing conditions of the fatigue data. A total of 5 strain-controlled fatigue data were used for the model development. The material of the specimen is Alloy 52M weld. The detailed information of the specimen and the fatigue test were well described in reference [7].

During the fatigue testing, we measured the stress/strain state of the specimen in real time. Figure 1 shows an example of the time-series fatigue data as represented in the hysteresis loop form. In Fig. 1, symbol N implies the number of cycle.

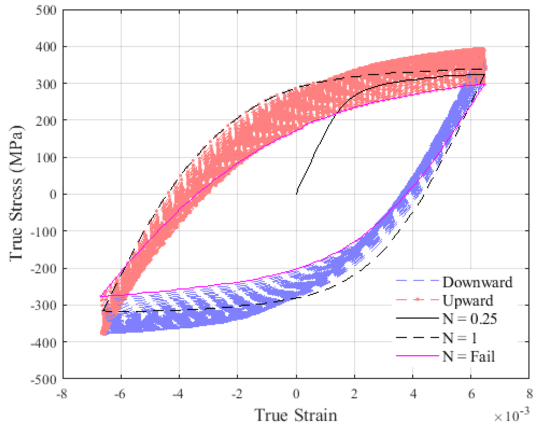

Fig. 1. Example of time-series fatigue data as represented in hysteresis loop form (specimen: MAH651-2).

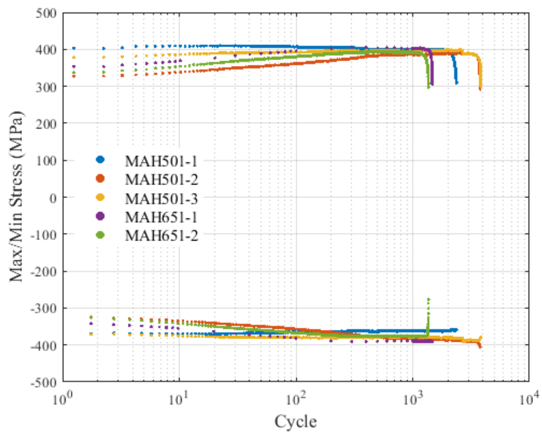

Fig. 2. Cyclic-series maximum/minimum stresses.

It should be noted that the time-series data represented in Fig. 1 shows a repetitive pattern over the cycle. Therefore, it is inefficient to use all the data in Fig. 1 without refinement. We extracted some cycle-series material parameters which represent the each cyclic state of the material. For example, maximum/minimum stress at each cycle can be a candidate (see Fig. 2).

In this study, we considered the following 7 cycle-series material parameters: 1) elastic modulus E_N, 2) elastic strain amplitude $\varepsilon_{a,N}^{\mathrm{el}}$. 3) Chaboche type kinematic hardening parameter $C_{1,N}$ [8], 4) Chaboche type kinematic hardening parameter $\gamma_{1,N}$ [8], 5) Plastic strain range $\Delta\varepsilon_N^{\mathrm{pl}}$, 6) Tensile stress amplitude $\sigma_{a,N}$, 7) plastic strain energy PSE_N (i.e., inner area of the hysteresis).

3. Condition-Based Modeling

In the modeling step, the aforementioned 7 cycle-series material parameters are regarded as the inputs. Whereas, the RUL of each cycle (RUL_N) is regarded as the corresponding target. Therefore, in this case, the modeling implies to find the best relation pattern between the 7 cycle-series inputs and 1 corresponding target.

Before the modeling, we performed some input/target pre-processing to enhance the modeling efficiency as follows:

- Discard the input/target data before reaching the maximum tensile stress amplitude.
- Divide input data by each initial value to obtain the relative dimensionless values.
- Standardize the dimensionless input data to have the mean of 0 and the standard deviation of 1.
- Convert the target using the hyperbolic tangent function (see the target equation $T(N)$ in Fig. 3) to focus on the near-failure region (e.g., from 100 cycles before the fatigue life to the fatigue life).

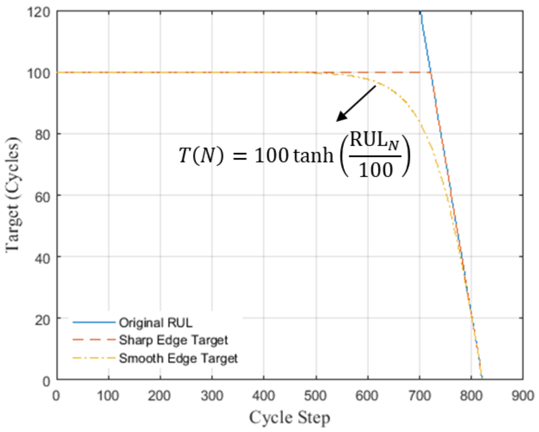

Fig. 3. Example of cycle-series target (specimen: MAH651-2).

As the model form, we considered the 5 functions and networks as follows:

1) Multiple linear regression (MLR)
2) Multiple regression with linear and square terms (MRsq)
3) Multiple regression with linear and quadratic terms (MRquad)
4) Artificial neural network (ANN) regression with 1 hidden layer (36 hidden layer elements, sigmoid activation function)
5) Long short-term memory (LSTM) network regression with 1 hidden layer (36 hidden layer units, hyperbolic tangent activation function)

Both the ANN and LSTM training were carried out using the MATLAB (ver. R2019b) *Deep Learning Toolbox*. The objective function for the training is mean squared error (MSE).

To compare the performance of the aforementioned 5 models, we considered the 5 different training/test cases as shown in Table 2.

Table 2. Model training/test cases.

Case Number	Test Data	Training Data
#1	MAH501-1	Rest of data
#2	MAH501-2	Rest of data
#3	MAH501-3	Rest of data
#4	MAH651-1	Rest of data
#5	MAH651-2	Rest of data

The model performance is estimated based on the root mean squared error (RMSE) of the test data in each case, excluding training data. Table 3 shows RMSEs of 5 models in each training/test case.

Table 3. RMSE of test data in each training/test case.

Case Number	MLR	MRsq	MRquad	ANN	LSTM
#1	12.38	28.28	82.92	24.8	17.3
#2	5.38	7.59	86.56	23.3	8.37
#3	10.80	9.94	13.10	22	4.42
#4	19.14	18.79	22.44	18.5	20.5
#5	39.54	24.16	843.7	19.5	18.4
Avg.	17.45	17.75	209.7	21.62	13.79

From Table 3, it is shown that the average RMSE of the LSTM model is the lowest. This implies that at least for the fatigue data sets used in this work the LSTM model is the best model for predicting the RUL. In general, it is known that the complicated model can easily fall into the overfitting problem. However, it is interesting that the LSTM model does not over-fits even though the LSTM model is actually the most complicated model among the considered 5 models in this study. We suspect that this superiority of the LSTM model is due to the consideration of the sequential data inputs, which the other models (e.g., MLR) do not have.From this result, we can conclude that the LSTM model is suitable for the RUL prediction of fatigue.

4. Conclusions

We developed condition-based fatigue RUL models with 5 strain-controlled Alloy 52M fatigue data in 5 different models. By comparing the RMSE of the test data in each training/test case, it can be concluded that the LSTM model is suitable for the RUL prediction of fatigue.

Acknowledgement

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