Fatigue and damage diagnostics with predictor functions for new advanced materials by Machine Learning

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Abstract: There is an emerging field of new materials highly related to space applications like fibre-metal laminates (DFG FOR3022). Typically, material properties are determined from tensile tests. We investigate approximating predictor functions by Machine Learning (ML) for inelastic and fatigue prediction by history data measured from simple tensile tests within the elastic range of the material. We show some preliminary results from a broad range of materials and outline the challenges to derive such predictor functions by ML.

Related publications:

S. Bosse, *Learning Damage Event Discriminator Functions with Distributed Multi-instance RNN/LSTM Machine Learning*, Proc. of the 5th International Conference on System-Integrated Intelligence Conference, Bremen, Germany, 2020

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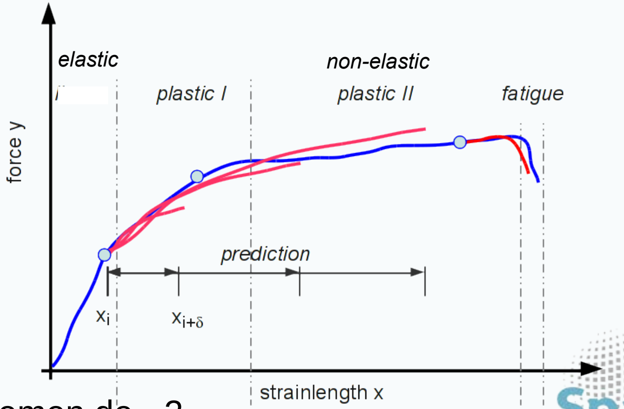
Introduction, Aims and Methods

- Tensile tests (TT) are used to characterise material properties like maximal strength, elastic and non-elastic behaviour
- Commonly, a TT modifies the device under test (DUT) irreversible (destructive method)
- Only one test for each sample is possible!
- Non-elastic behaviour and damage can only be detected from the past
- New hybrid and syntactic foam materials pose non-linear and unexpected behaviour hard to model on functional level

➢ Learning of a set of predictive model functions from strain length- traction force curves using recurrent artificial neural networks (ANN) with Long-short term memory cells (LSTM)

➢ The trained models can be used to predict the future development based on past meas. data:

1. The traction force
2. The strain (length) (inverse problem)



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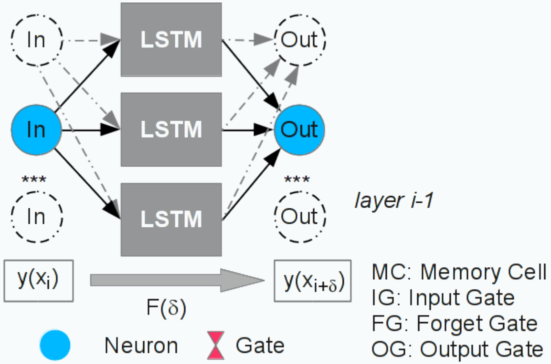
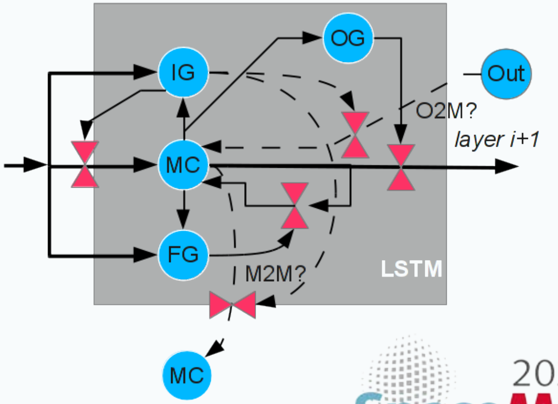
Techniques and Methods

Each predictor function *F* of the set $\mathbb{F}$ is able to predict the target variable at *i*+δ using the past target variable values (measured): $\forall\delta \in \{1,2,..,m\} : y(i+\delta) = F_\delta(y_0, y_1, .., y_i)$

- The ANN consists of an input layer (only one neuron), a hidden LSTM layer (or more), and one output layer (only one neuron)
- The input variable of the network is a sequence of *y* values, i.e., measured forces.
- The output variable of the network is the predicted *y* value for a future *x* point.
- The hidden layer consists of LSTM cells that are connected with the previous and next layer
- The sequence samples must be normalized (equally spaced) with respect to the also measured strain length *x*.





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Preliminary Results and Conclusion

- Input data: TT from 42 experiments of metal sheets with different thermal preparation (Fraunhofer IFAM, Bremen, Lehmhus et al.)
- The maximal prediction error of the predictor function for δ=10 sample points (full scale of measurement is 500 points) is below 10%, with an average of less than 5%.
- The prediction deviates more strongly in curve segments with a high gradient (with spikes, too)
- Higher number of hidden LSTM layers can improve prediction accuracy

Recurrent neural networks are suitable for predicting future development of the traction force and inelastic material behaviour based on past measured force and strain length value sequences.