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.

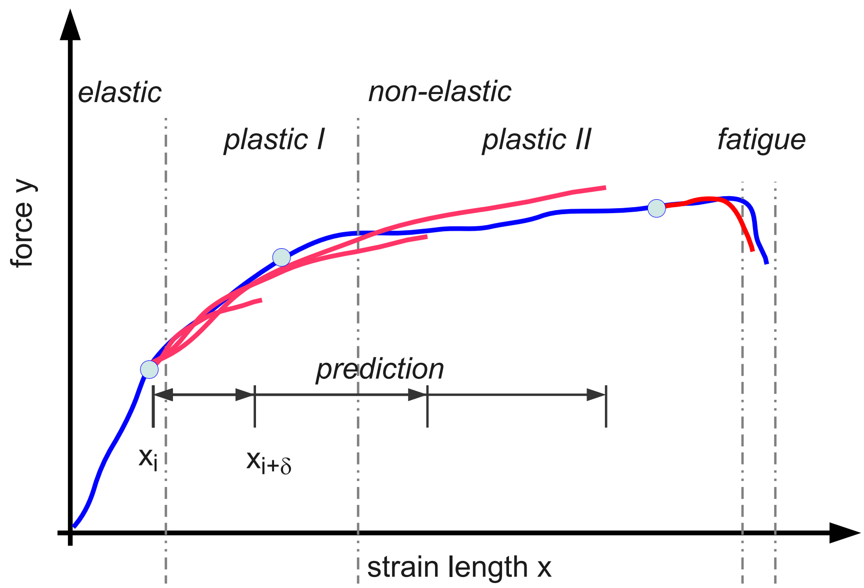
Introduction and Challenges

- Tensile tests (TT) are used to characterise material properties like yield criterion and the work hardening parameters to be identified, the maximal strength, elastic and non-elastic behaviour [1]
- 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 (the event happened)
- New hybrid and syntactic foam materials pose non-linear and unexpected behaviour hard to model on functional level

Aims and Methods

- Learning a set of predictive model functions $F_\delta(Y)$: $Y \rightarrow y_\delta$ with $y_\delta \notin Y$ from strainlength-force curves using recurrent artificial neural networks with Long-short term memory cells (LSTM) [2,3]

- The trained models can be used to predict the future development based on past data of:
    a. The traction force applied to the sample related to the observed strain (length)
    b. The strain (length) related to observed traction force (inverse problem)



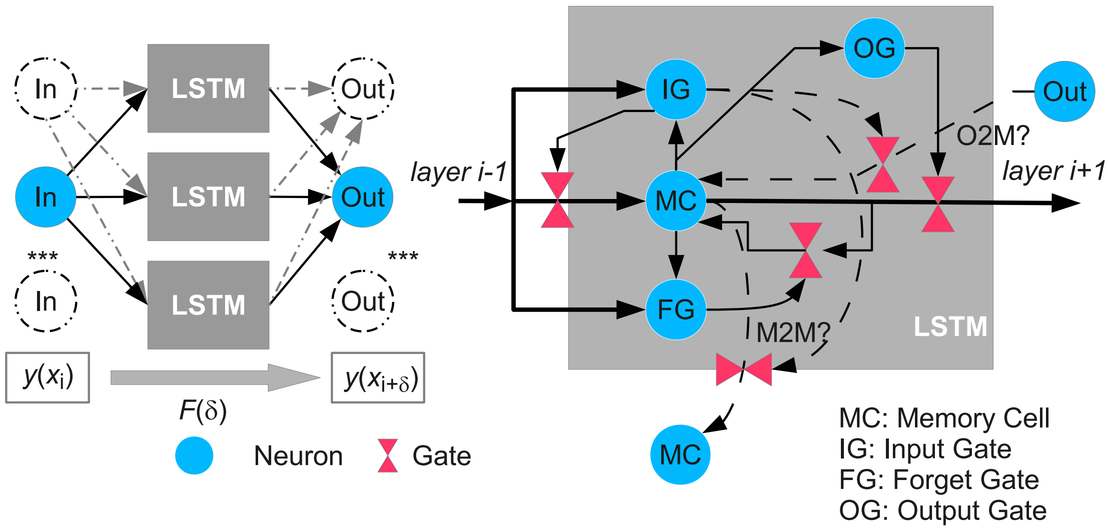
- Each predictor function F of the set $\mathbb{F}$ is able to predict the target variable at i+δ using the past target variable values (measured):

$$\forall \delta \in \{1, 2, .., m\} : y(i + \delta) = F_\delta(y_0, y_1, .., y_i) \tag{1}$$

Machine Learning Network Architecture

- 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 which are connected with the previous and next layer (optional connection between MC in same layer)
- The sequence samples must be normalized (equally spaced) with respect to the also measured strain length x!



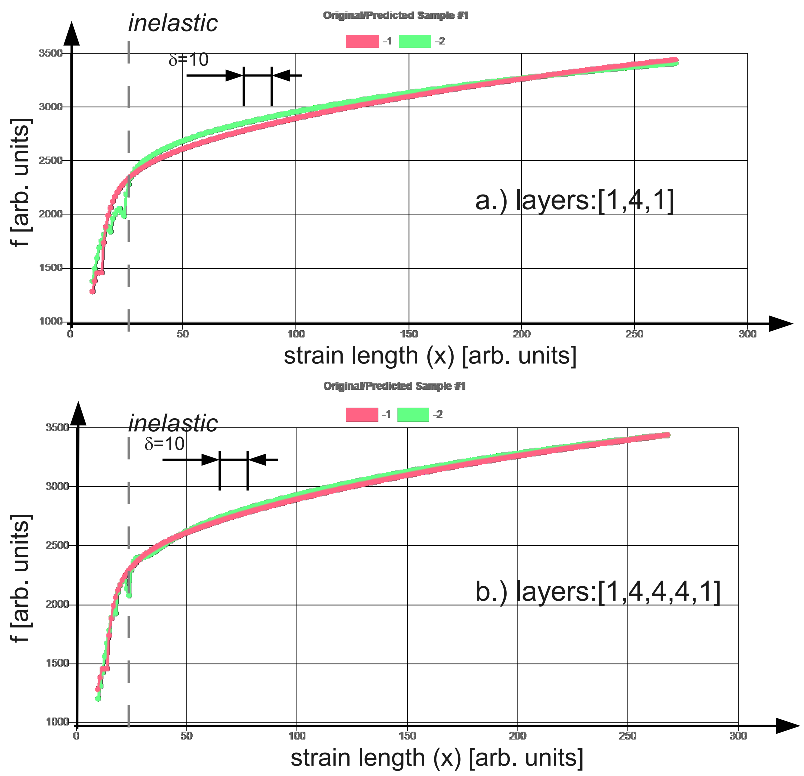
- A modified Neataptic ML framework was used to implement the LSTM-ANN and to perform training and prediction (https://wagenaartje.github.io/neataptic)

Preliminary Results and Conclusion

- Input data: TT from 42 experiments of metal sheets with different thermal preparation (Fraunhofer IFAM, Bremen, Lehmhus et al.)
- Example plots of measured (red line) and predicted x-y curve (green line) for two different network configurations (number of hidden layers) is shown

- 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
- The beginning of the inelastic material behaviour can be predicted

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



References

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