

# Learning Viscoelastic Responses with a Thermodynamic Recurrent Neural Network with Maxwell Encoding

Nicolas Pistenon<sup>1,\*</sup>, Sabine Cantournet<sup>1</sup>, Jean-Luc Bouvard<sup>2</sup>, Daniel Pino Muñoz<sup>2</sup> and Pierre Kerfriden<sup>1</sup>

<sup>1</sup> Mines Paris, Université PSL  
Centre des Matériaux (MAT), UMR7633 CNRS  
91003 Evry, France

<sup>2</sup> Mines Paris, Université PSL  
Centre de Mise en Forme des Matériaux (CEMEF), UMR7635 CNRS  
06904 Sophia Antipolis, France

\* Corresponding author. E-mail address : nicolas.pistenon@minesparis.psl.eu

## ABSTRACT

Neural network methods are increasingly used to build constitutive laws in computational mechanics [1]. Neural Networks may for instance be used as surrogates for micro-mechanical models, whereby evaluating the response of high-fidelity numerical representative volume elements proves prohibitively expensive. Alternatively, Neural Networks may be used whenever traditional phenomenological approaches to constitutive modelling fails, i.e. whenever one fails to find a functional form for the constitutive law that enables to represent the behaviour of the material faithfully over the entirety of possible loading scenarios. One example is the viscoelastic behaviour of polymers, which remains difficult to describe accurately.

The state of the art on these machine learning methods for the prediction of behavioural laws with a dependence on loading history do not show models with both a strong interpolatory, extrapolatory capacity and with a number of data consistent with today's experimental capabilities [2]. To enforce a better bias, one used mechanical knowledge by introducing some mechanical regularisation terms [3], [4] or to considered structural approaches [5].

In this work, we describe a novel Neural Network strategy that combines a Maxwell model, which is extensively used as to describe linear viscoelastic responses, and a Thermodynamic Recurrent Neural Network. The coupling between the phenomenological and data-driven blocks of our model is done in two ways. Firstly, the Neural Network, and more precisely LSTM cells, corrects the response provided by the Maxwell model, which closely resembles the residual connections used in deep learning. Secondly, the Maxwell model acts as an encoding layer that provides hidden variables to the Neural Network, which is meant to avoid relying exclusively on the RNN to encode the history of the material. Both parts of the models are trained concomitantly, using standard back-propagation over differentiable graphs to compute weight sensitivities.

The aim of our study is to obtain a law of non linear viscoelastic polymer material where classical phenomenological approaches fail. During the presentation, we will illustrate both interpolating and extrapolation capabilities of our model in the context of reducing the amount of data according to experimental capabilities.

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