

Cycle domain plasticity modeling using machine learning

Nasrin Talebi^{1,*}, Magnus Ekh¹, Knut Andreas Meyer¹

¹ Division of Material and Computational Mechanics, Department of Industrial and Materials Science, Chalmers University of Technology, SE-412 96 Gothenburg, Sweden

A detailed understanding of the influence of long-term accumulation of plastic deformations on fatigue crack initiation behavior of railway rails requires simulating their whole service life, from virgin to highly deformed material states. This involves finite element simulations of rails subjected to many wheel passages, which can result in significant computational time when time domain material models are adopted. One approach to speed up the simulation of many loading cycles is to extrapolate the response by using load sequence extrapolation with error control, as developed by Johansson and Ekh [1]. Alternatively, Suiker and de Borst [2] proposed a cycle domain model to simulate the evolution of maximum plastic deformations in ballasted tracks under many loading cycles. The model framework is based on standard plasticity theory and is formulated as a viscoplastic model [2]. Based on that framework, Li et al. [3] developed a three-dimensional FE simulation tool to predict long-term differential settlement in ballasted tracks to enable fast simulations of many wheel passages.

In this contribution, inspired by [3], we substitute a standard time domain plasticity model, specifically the Chaboche model, with a cycle domain model, where time derivatives of quantities are replaced by their changes per unit cycle N as

$$\frac{d\sigma_{11}}{dN} = E \left(\frac{d\epsilon_{11}}{dN} - \frac{d\epsilon_{11}^p}{dN} \right) \quad (1)$$

where σ_{11} , ϵ_{11} , ϵ_{11}^p , and E are the Cauchy stress, total strain, plastic strain, and Young's modulus, respectively. The proposed approach is to study the cycle domain model for homogeneous virgin (isotropic) material under uniaxial loading and to replace the plastic strain increment per loading cycle $d\epsilon_{11}^p/dN$ with the following expression

$$\frac{d^N \epsilon_{11}^p}{dN} = f_{NN} \left({}^N \sigma_{11}, {}^{N-1} \epsilon_{11}^p \right) \quad (2)$$

where f_{NN} represents a trained neural network based on artificially generated training data. The training data are obtained using the Chaboche model with different strain amplitudes. The neural network architecture is schematically shown in Figure 1. Finally, symbolic regression is adopted to discover an analytical expression for $d^N \epsilon_{11}^p/dN$, and the results are compared against those from the neural network model.

*Corresponding author: nasrin.talebi@chalmers.se

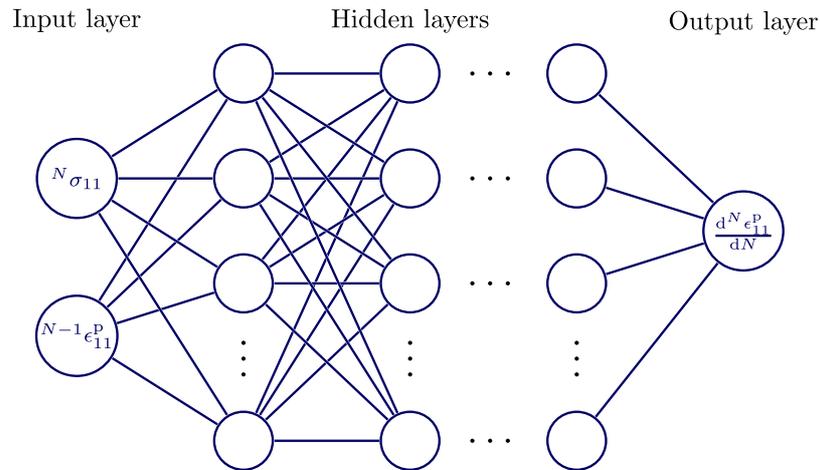


Figure 1: Schematic illustration of the neural network architecture.

References

- [1] G. Johansson, M. Ekh, (2007). On the modeling of large ratcheting strains with large time increments. *Engineering Computations*, 24(3), 221-236.
- [2] S. Suiker, R. de Borst, (2003). A numerical model for the cyclic deterioration of railway tracks. *International Journal for Numerical Methods in Engineering*, 57 (4), 441–470.
- [3] X. Li, M. Ekh, J. C. Nielsen, (2016). Three-dimensional modelling of differential railway track settlement using a cycle domain constitutive model. *International Journal for Numerical and Analytical Methods in Geomechanics*, 40(12), 1758-1770.