Abstract

The conventional creep property extraction method requires a large number of uni-axial tests at different loads, which consumes an intensive amount of time and material resources. It has been a while since indentation experiments have been posed as an alternative to the uni-axial experiments for creep parameter extraction. The theoretical understanding of the indentation behavior under non-linear elastic, plastic, and creep conditions is still far from completion to have an analytical solution to this inverse problem. Artificial Neural Network (ANN) has been successfully employed on numerous inverse problems but has not been explored much in the context of uniaxial creep property extraction from indentation experiments. In the current study, we use fully connected sequential multi-layered ANN trained on Finite Element indentation creep simulations to map the observables (displacement, time) of indentation creep experiments to the corresponding uniaxial creep parameters.

In indentation, the stresses range from a low-stress level well within the elastic regime to high stresses well beyond the material's yield stress in the plastic regime. And as the indentation experiments last for a short time, it is likely that some volume of the material does not reach the steady-state creep regime and creeps in the primary stage for the entire duration of the experiment. Thus, we choose a suitable constitutive creep law ($\epsilon_{creep}=B\,\sigma^n\,t^\alpha$), such that it can capture the entire creep behavior in the wide range of stresses. We then generate training sets by conducting FE simulations with varying creep parameters (B, n, α), keeping the elastic and plastic flow properties of the material fixed. Fixing the elastic and plastic property makes learning with fewer examples easier for the ANN and simplifies the problem of uniqueness (different combinations of material properties (elastic, plastic and creep), giving the same indentation creep behavior: displacement vs. time plot).

The displacement-time curve, the output of constant load and hold FE indentation creep simulation, is fitted (e.g. $d_{creep}=d_0+a\,t^b+c\,e^{(-dt)}$), and the pre-processed fitting parameters (e.g. d_0, a, b, c, d) are provided as inputs to the ANN. We train the ANN using a back-propagation algorithm based on a stochastic gradient descent to map these inputs to the corresponding creep parameters used in the FE simulations. Performance of the ANN is improved by optimizing its architecture using the Bayesian optimization approach and varying the fitting function, the parameters of which are the inputs to the ANN. We evaluate the performance of ANN based on its prediction on the validation set (size - 10% of the

training set) and continue the learning till the mean squared error of this prediction is in the order of 10−3. Finally, we test this trained ANN on indentation creep experiments on Lead and compare its prediction with creep parameters obtained from the uniaxial creep experiments.