

## Supplementary Materials

### A knowledge-distilled artificial neural network constitutive model for finite element simulation of hot-deformed $\beta$ -C titanium alloy

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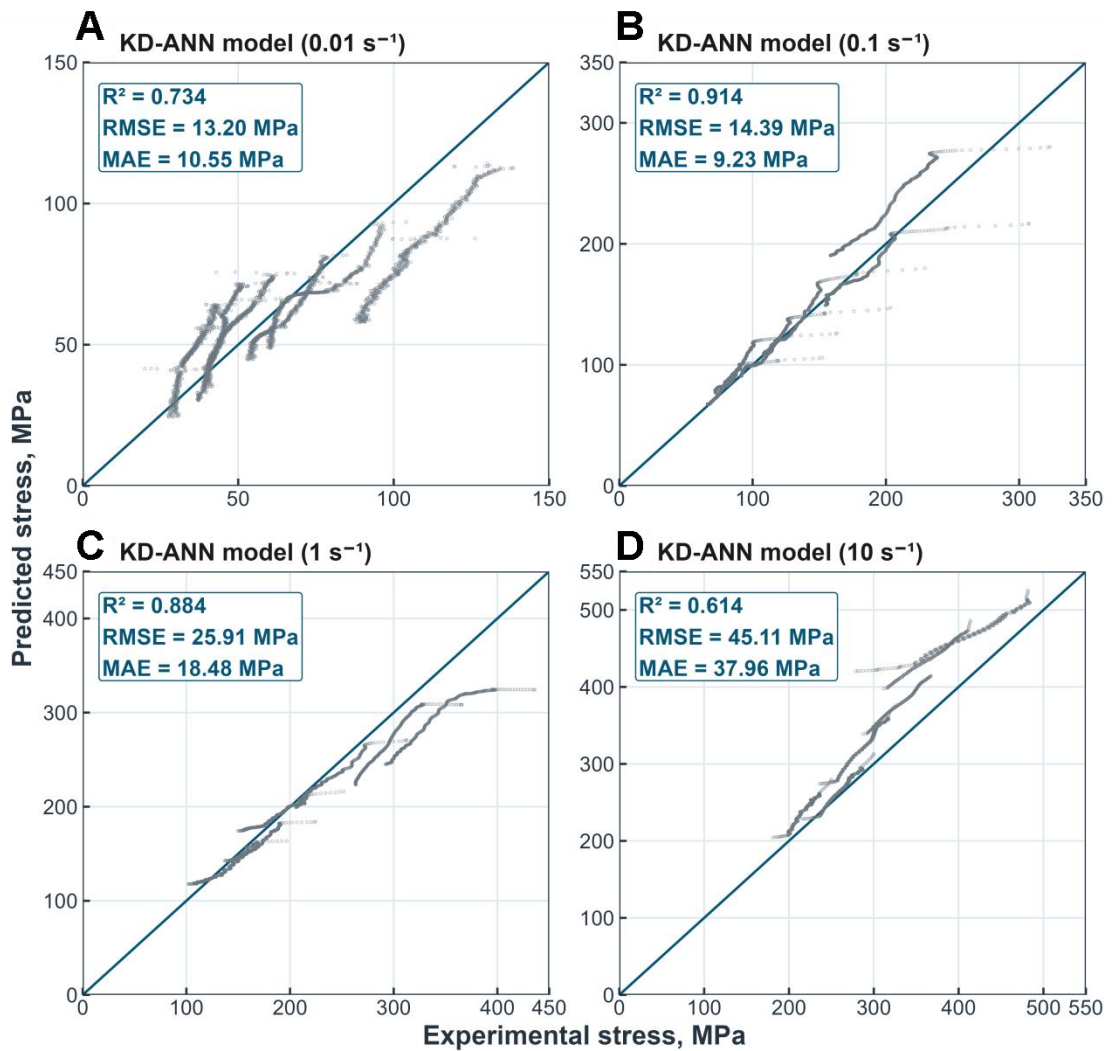
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### Supplementary Material 1:

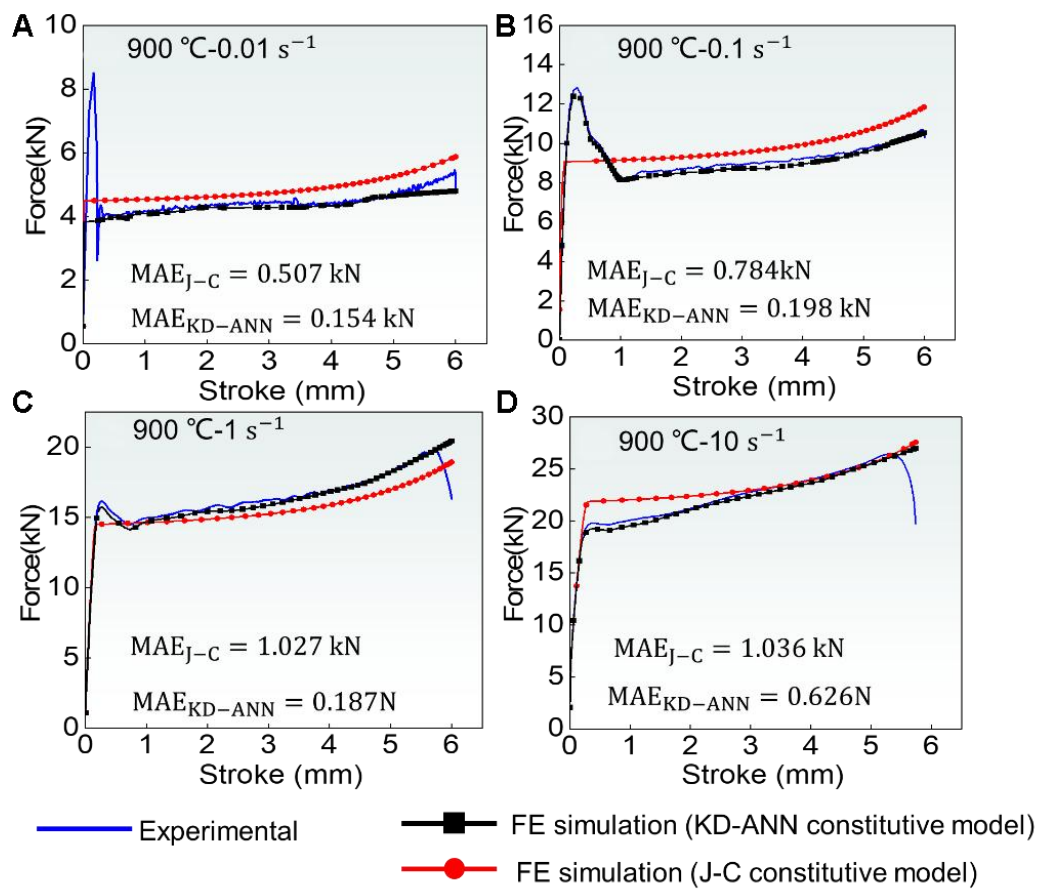
Supplementary Figure 1 shows the KD-ANN predictions under leave-one-strain-rate-out validation. The best agreement is obtained when  $0.1 \text{ s}^{-1}$  is held out ( $R^2 = 0.914$ ,  $\text{RMSE} = 14.39 \text{ MPa}$ ), whereas prediction accuracy decreases at the boundary strain rates. In particular, the held-out  $10 \text{ s}^{-1}$  condition yields  $R^2 = 0.614$  and  $\text{RMSE} = 45.11 \text{ MPa}$ , with a visible tendency to overpredict high stresses. This weaker strain-rate-wise generalization is likely associated with sparse sampling along the strain-rate dimension: only four strain rates, separated by one order of magnitude, are available for learning the rate dependence of flow stress.



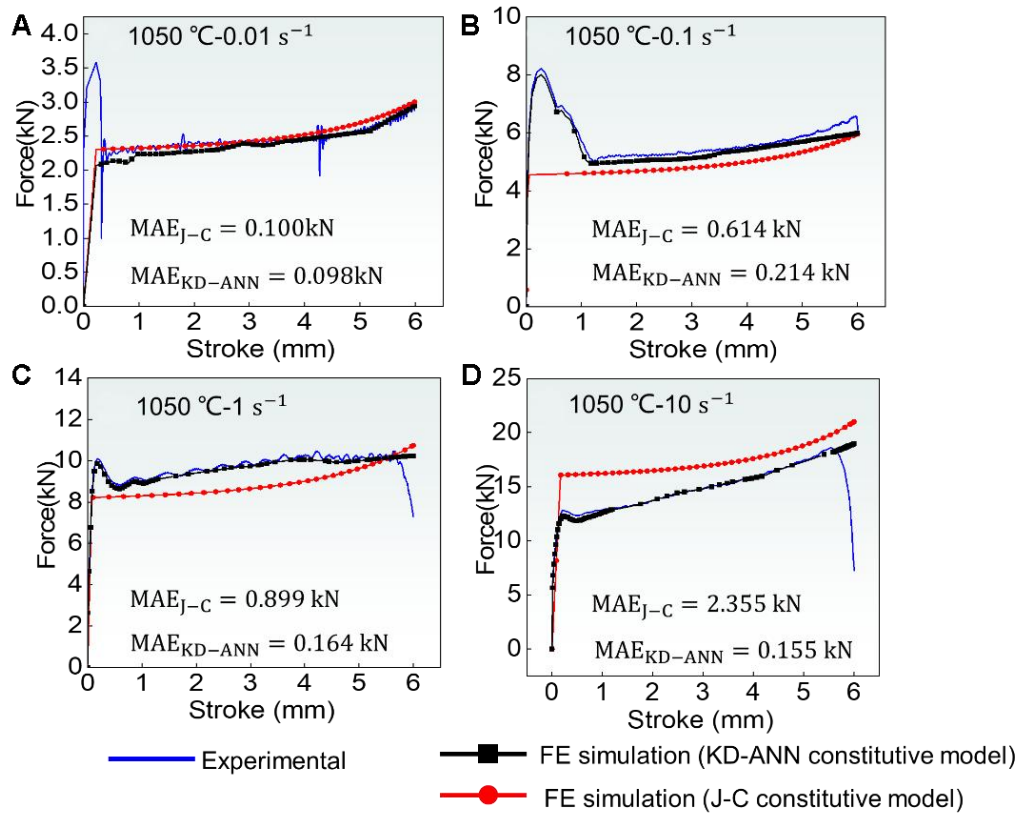
**Supplementary Figure 1.** Experimental versus predicted stresses of the KD-ANN model under leave-one-strain-rate-out cross-validation.

### Supplementary Material 2:

Supplementary Figures 2 and 3 compare the experimental and predicted load–displacement curves at 900 and 1050 °C, respectively. KD-ANN yields a lower MAE than the modified J–C model at each of the four strain rates at both temperatures. The corresponding mean MAEs are 0.291 versus 0.839 kN at 900 °C and 0.158 versus 0.992 kN at 1050 °C. Together with the 800 °C results, these comparisons show that KD-ANN provides closer agreement with the experimental load response across the three examined temperatures.



**Supplementary Figure 2.** Comparison of the experimental load–displacement curves with those predicted by the KD-ANN and modified J–C constitutive models at 900 °C.



**Supplementary Figure 3.** Comparison of the experimental load–displacement curves with those predicted by the KD-ANN and modified J–C constitutive models at 1050 °C.