Hybrid modeling via machine learning corrections of numerical process simulations towards experimental measurements for friction surfacing

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Abstract

The combination of data-driven and physics-based modeling can enable the consideration of validated engineering knowledge to increase physical consistency while performing machine learning (ML) regression tasks. A hybrid framework consisting of a physics-based process model for friction surfacing (FS) that shows errors compared to the targeted experimental solution due to inherent simplifications and assumptions is corrected by an ML model to reach that solution. In this presentation, a hybrid framework has been applied to the solid-state processing technique of FS, which produces fine grained coatings with superior corrosion and wear properties. In this regard, a Smoothed-particle hydrodynamics (SPH) model served as the physics based model and a scarce experimental data set based on a Box-Behncken Design of Experiment (DOE) was used to train the ML correction model. This correction task can require less data compared to mapping the complete problem since the correction is often less complex when fundamental relationships are already represented in the physics-based model that is corrected. As a result, the required number of experiments is reduced upon the effective exploitation of the available physics-based model, leading to savings of resources such as materials, energy and time. The development of the correction model is based on dimensionless inputs according to the Buckingham Pi theorem to reduce prediction inaccuracies and increase model generalization. The force, rotation and traverse speed as well as maximum process temperature, feed rate and other parameters are used as dimensionless inputs to train the ML model. The deposition has two dimensions, namely thickness and width. Both dimensions from both experiments and simulations are used to calculate a correction factor k that is the target solution of the ML model. The model was trained to learn the k and the predicted correction factors ˆk is used to correct the simulation thickness and width. A consecutive goal was to replace the SPH simulation model with a data-driven model since it would provide results at a fraction of the time and with a substantial cut in computation cost. These predictions were also corrected to achieve the anticipated results. In that way, a hybrid model composed of a physics-based numerical model and a data-driven ML model is able to predict results that are in very good agreement with experimental measurements of deposition thickness and width.

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