

Jan 27, 2022

Intelligent Data-Physics Integration for Electro-Chemo-Mechanical Systems

ABSTRACT:

Advanced engineered systems are getting smart, resilient, integrated – and overall, increasingly complex. Electrochemical energy storage systems such as batteries are a typical example. The fundamental challenge to characterize these systems lies in the tradeoff between the abundance of data and the adequacy of physical laws. At microscales, mechanisms can usually be elucidated, but data are expensive and small in size; at macroscales, physical laws are often hidden in a big dataset that is hard to decipher. Physics- or first-principle-based theories are robust but suffer from the “curse of dimensionality” as the number of variables and degrees of freedom increases. Recently, many data-driven approaches particularly deep learning have shown advantages of dealing with high-dimensional problems, but they are usually agnostic and prone to unphysical failure. Successful characterization of an electro-chemo-mechanical system depends on seeking the intelligent integration of physics-based theories and data-driven approaches. In this presentation, I will demonstrate this methodology with three examples. In the first one, we will see how the curse of dimensionality hinders the implementation of the already-known physics into a mesoscale Li-ion battery cell model. Storing part of the physics into analytical or surrogate models (e.g. deep neural networks) sheds light on efficient large-scale computation to discover the unknowns. In the second example, a PDE-constrained optimization algorithm is developed to inversely “learn” the micromechanics of pure lithium, an important anode material for next-generation batteries. The algorithm is effective to learn the creeping law from localization in conventional tensile specimens, which is commonly treated as noise in human-brain learning. The last example is developing the data-driven safety envelope of Li-ion batteries for macroscopic applications such as EV crashworthiness and battery assessment for reuse or recycling. In all three examples, I will prospect how to further combine the advantages of physics-based and data-driven approaches for intelligent data-physics integration.

BIOGRAPHY:

Dr. Juner Zhu is a Research Scientist working jointly in the Departments of Mechanical Engineering and Chemical Engineering at MIT. He received his Ph.D. degree from MIT Mechanical Engineering in 2019. His thesis entitled “Mechanical Failure of Lithium-ion Batteries” provided a comprehensive study on the mechanical modeling of battery component materials, porous electrodes, and cells. He has published over 30 journal articles with 18 of them on battery modeling. Based on these efforts, Juner co-developed the 2020-2022 phase of the MIT Industrial Battery Consortium and is currently acting as the Executive Director working with eight world-leading companies in the areas of EV, battery, and consumer electronics. During his postdoctoral career, Juner extended his research interests into multiphysics modeling with data-driven methods, including inverse learning, PDE-constrained optimization, and physics-informed neural networks. Juner has considerable industrial experience from his work as a materials engineer at Ford Motor Company and as a battery analyst at Apple. Juner got his B.S. and M.S. degrees from Tsinghua University, where he graduated with top honor (the Presidential Scholarship) for Tsinghua graduate students in 2015.



Juner Zhu

*Research Scientist,
Departments of Mechanical
Engineering and Chemical
Engineering,
MIT*