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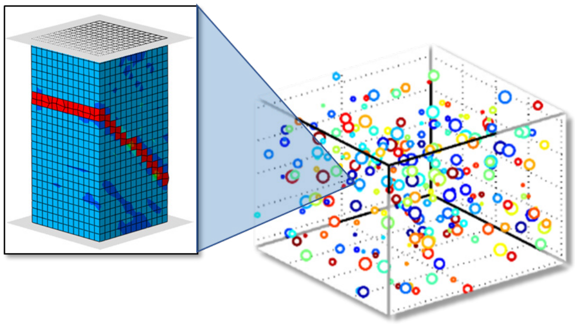
Artificial Intelligence & Machine Learning Capabilities

Overview



FEMs are sampled from material parameter space and used to build VAE-based ANN for calibrating material properties to sparse test data.

ATA Engineering (ATA) is actively applying artificial intelligence (AI) to engineering problems using machine learning (ML) approaches. The rapid development of increasingly powerful and accessible tools for ML coupled with the ability to scale computing power offers unprecedented potential for solving problems in engineering that may appear intractable using more traditional approaches.

ATA has been integrating ML techniques into our existing engineering workflows, as well as within novel methods developed internally, to extend our capabilities and fill critical technology gaps. A recognized leader in methods development, technology commercialization, and knowledge transfer, ATA is frequently contracted to provide customized solutions and cutting-edge tools and has successfully leveraged our expertise in AI to deliver results. We have conducted AI/ML research and development with academic institutions like UC San Diego and in government-funded Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs. Our familiarity with a variety of ML tools, our expertise across a range of engineering domains, and the results we have delivered make us uniquely qualified to help with your next-generation engineering applications.

Research Areas

- Enhancing the efficiency of complex finite element analysis (FEA) by replacing computationally expensive contact simulation with fast-running ML-trained metamodels in the Abaqus FEA solver, reducing the computational cost of analyzing post-damage submarine hatch performance. The approach is applicable to any FEA method that uses an iterative process to determine contact between surfaces.
- Employing symbolic regression to derive target terms in modified Reynolds-averaged Navier–Stokes (RANS) turbulence closure models to enable more-efficient computational fluid dynamics (CFD) simulation of high-speed flight systems; symbolic regression was used to provide interpretability of models and ease of integration into existing CFD code.
- Developing and refining an ML-based workflow for statistical calibration of high-fidelity composite material finite element models (FEMs), wherein probabilistic predictions are achieved by inferring a distribution of material parameters consistent with test data mean and scatter using Markov chain Monte Carlo (MCMC) methods and a fast-running ML surrogate model.
- Building a variational autoencoder (VAE)-based artificial neural network (ANN) pipeline for calibrating underdetermined material model parameters to limited test data, which produces a simulation model that can replicate test behavior. Inverse models are trained to map stress-strain curves to a consistent distribution of parameters through a latent space learned by a VAE.
- Developing a physics-constrained Bayesian neural network technique for predicting the remaining useful life of lithium batteries. Such an approach could be used to forecast evolution of other self-accelerating phenomena, such as corrosion and crack growth.
- Developing an approach for obtaining a physically interpretable data-driven model of a structural dynamics system (i.e., a digital twin) by enforcing structure-preserving properties of an ensemble of neural networks that learn the kinetic and potential energies and Rayleigh dissipation terms from observed responses. The digital twin can be used to identify damage in a non-observable region of a deployed structure based on response measurements outside the region of interest.
- Using a physics-constrained ensemble of neural networks to reconstruct the nonlinearity of forces acting on an isolated region of an as-built and as-deployed structure as a deviatoric force term acting on an idealized system; this approach can be used to monitor a deployed system as its state evolves.
- Developing an ML-based image segmentation pipeline to model as-built laminated composites based on numerical reconstruction of X-ray computed tomography data. This tool enables material characterization based on their as-built condition, helping the end-user make cost-effective decisions for repair limits and disposition of non-conforming composite components.