FOA # N00014-22-S-F009 Abstract (Approved for Public Release): Physics-Based Machine Learning Modeling for Platform Design, Acquisition, and Operation

PI: Charbel Farhat, Stanford University

Objectives: The main goal of the proposed transformative research effort is to develop, at the fundamental level, a disruptive Computational Science for building a new generation of numerical models that can accompany a DoD platform from its design, to its acquisition – which includes test & evaluation, as well as maintenance – to its operation; and can enable its predictive rather than preventive maintenance. The research effort will target three different levels of numerical modeling: a lower level pertaining to the material of which a platform is made, or to the environment in which it operates; a middle level relating, among others, to the design, analysis, optimization, and acquisition of the platform; and a higher level targeting its operation, optimal control, and predictive maintenance.

Technical Approach and Significance: At the lower level, the technical approach will be grounded in the enablement of mechanics- and physics-informed deep artificial neural networks (ANNs) for constitutive modeling. At the middle level, it will be anchored in the construction of nonlinear approximation manifolds based on the scalable composition of affine subspace approximations rooted in data compression algorithms and nonlinear approximations of closure errors grounded in deep ANNs, kernel regressors, or finite-dimensional feature maps, to shatter the Kolmogorov barrier to parametric, projection-based model order reduction (PMOR); in a radically reimagined PMOR that embraces models and data of different modalities, and transfer learning; and in innovative methodologies for breaking the curse of dimensionality associated with training PMOR and surrogate modeling in general in high-dimensional parameter domains. At the higher level, the technical approach will leverage data fusion to develop groundbreaking physics-based machine learning (PBML) procedures for extracting from test data, operational data, and/or high-dimensional numerical data, knowledge or information not captured by a deterministic numerical model, and infusing it into a stochastic counterpart to model and quantify model-form uncertainty, perform model updating, and enable transfer learning.

Outcomes: The anticipated outcomes of the proposed transformative research effort will include new paradigms for data-driven constitutive modeling that feature the form-agnostic advantage of purely phenomenological regression models and the physical soundness of mechanistic and thermodynamic models. They will also include disruptive PMOR and other types of PBML methods that could supersede current contenders for the real-time solution of a wide variety of steady (static) and unsteady (dynamic) problems in Computational Physics; can embrace multi-physics models and problem formulations whose settings are dictated by requirements rather than limitations; can handle data of different modalities; and can cope with transfer learning to be able to accompany, for example, a building block approach. The anticipated outcomes will also include seminal probabilistic learning methods that enable numerical models to continually evolve and update themselves in order to better match reality and improve the likelihood of achieving challenging objectives.

Potential Impact: Collectively, the anticipated outcomes highlighted above will revolutionize the modeling and simulation of a DoD platform, its design, acquisition, optimal control, and preventive rather than scheduled maintenance; will enable avant-garde PBML methods that overcome effectively data scarcity; and will bridge the gaps between design, analysis, test & evaluation, operation, and the discovery of operational anomalies. They will also enable the PI and his research team to make significant contributions to the education and training of the workforce in Computational Science, both in the classroom, and by reaching out and collaborating with researchers at DoD laboratories.