Resilient Energy Systems
Mission Campaign

REDLY: RESILIENCE ENHANCEMENTS THROUGH DEEP LEARNING YIELDS

The nation's electrical grid is not infallible to threats leading to interrupted service or physical damage. REDLY is developing scalable methods to provide improved monitoring, prediction, and mitigation of these threats. Our approach focuses on physics-informed machine learning techniques that are robust to missing or falsified data due to cyber activities. Optimization-based methods are being developed to improve and utilize these classifiers and provide rapid mitigation.

THE CHALLENGE

Machine learning methods show significant promise for monitoring, prediction, and mitigation of electrical grid threats. However, many current approaches are based on generalized methods that are not consistent with known physics, especially in areas of limited data. Furthermore, while reliable machine learning classifiers provide valuable situational assessment, they need to be integrated with decision-making tools to provide resilience through mitigation.

APPROACH

This project integrates three elements (see Fig. 1) that leverage existing tools and expertise for improved machine learning and optimization for grid resilience.

1. Development of physics-informed machine learning classifiers for more reliable assessment of grid security.
2. Optimization formulations with grid models and embedded classifiers for improved operation and resilience.
3. Simulation and emulation tools based on industry-accepted environments to capture realistic system behavior for training and testing.

New machine learning approaches and optimization formulations will be made available as open-source software through EGRET and other Sandia tools. This project will utilize the SCEPTRE platform to create virtualized cyber environments with power grid simulations.

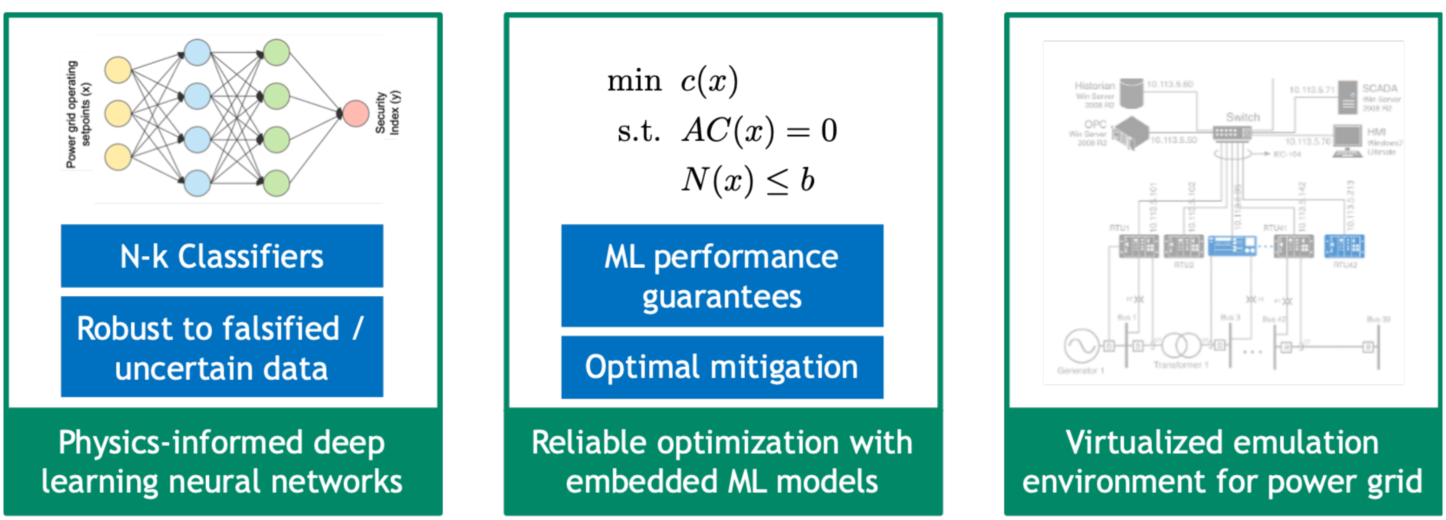

Figure 1: Three-pronged approach integrating emulation with physics-informed machine learning and advanced optimization

EXPECTED RESULTS

Expected results are described in three categories below, and include fundamental advances in machine learning and optimization approaches as well as specific electrical grid applications.

1. **Physics-informed machine learning (ML)**
   - New physics-informed ML approaches that increase accuracy and robustness on out-of-sample scenarios (see Fig. 2)
   - ML classifiers for assessment of N-k security and stability from operating conditions
   - Targeted approaches for efficient sampling of the N-k security and stability boundary
   - ML classifiers that are robust to uncertain and falsified data

2. **Advanced optimization with embedded classifiers**
   - New methods for efficient solution of optimzation problems with embedded artificial neural networks (ANNs)
   - Global optimization techniques to provide rigorous guarantees of model performance
   - N-k compliant economic dispatch integrating optimal power flow with embedded ANN for N-k security and stability
   - Improved resilience and operate-through capabilities with embedded ANNs

3. **Simulation and emulation environment for reliable data generation and testing**
   - Emulation of control and protection hardware with virtualized communication
   - Simulation of falsified and manipulated data with automated system response
   - Data provider and test-bed for ML and optimization methods

EXPECTED IMPACT OF THIS RESEARCH

This project will enhance the security of the electric grid in the face of evolving threats, and make fundamental advances in optimization and machine learning. Expected impacts will include:

1. Industrial impact through new technology available in open-source tools (e.g., EGRET) that can be integrated with independent system operator (ISO) operations for improved monitoring, prediction, and mitigation of different threats.
2. New physics-informed ML techniques with reduced data requirements and improved accuracy on out-of-sample scenarios.
3. New optimization formulations and advanced techniques for problems with embedded ANNs (for surrogates and verification).

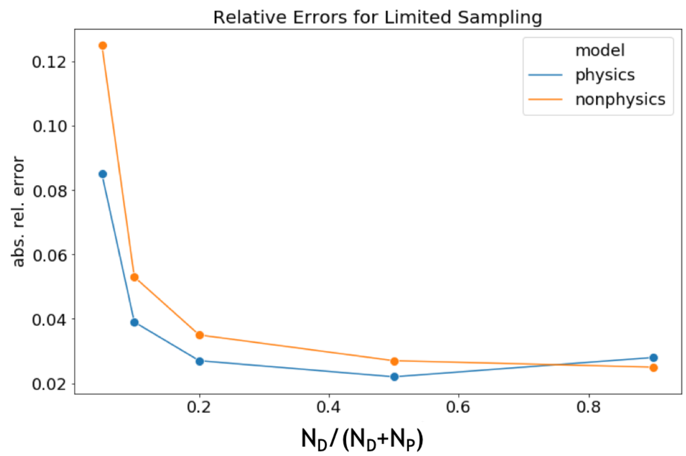

Figure 2: Physics-informed machine learning allows for additional training at points where there is no data, but where known physics apply. This figure shows errors in network outputs as a function of available data.

RESILIENT ENERGY SYSTEMS

Sandia's investment in this project is part of its Resilient Energy Systems portfolio of projects, coordinated R&D that addresses the resiliency of the nation's energy systems and other critical infrastructures to threats.

Deep-learning approaches, coupled with proven modeling and optimization methods, provide an important tool for ensuring resilient energy systems.

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