Fusion Energy breakout

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Control utilizing high-fidelity physics models

- **Summary:** Develop real-time state control of experimental fusion systems

- **5-10 Year Targets:**
  - ML mapping from simulation parameters to dominant state variables
  - ML mapping from sensor readings to plasma state actuators
  - Physics-informed learning to ensure experiment/simulation ML models follow known physics
  - Interpretability of ML control decisions for experimental physical intuition
  - Online adaptation of ML control models from simulation and experiment

- **Enabling Capabilities:**
  - Design a workflow for creating machine and experiment specific control models
  - Accessible data framework for collaborative research

- **Future Outlook:** Steady-state fusion power plant operation with control
Design optimization

- Design optimization for fusion devices could enable much more attractive reactor design points. Opportunities identified both in plasma physics (e.g., stellarators) and in fusion nuclear technology (plasma facing components, blankets, fuel cycle) including a large range of physics components that need to be included: Plasma physics/ Laser plasma interactions (LPI); Radiation transport; Geometry optimization; Thermal effects; Fluid/kinetic effects

- 5-10 Year Targets:
  - Accuracy and stability of surrogate models of coupled physics
  - UQ/confidence intervals on surrogate models
  - Accurate sensitivities/ gradients/Hessians in parameter/solution space for doing optimization in design space
  - Learning models with sparse (expensive to obtain) simulation and experimental data
  - High dimensional parameter space
Multi-fidelity modeling

● Summary: Dramatically improve predictive models by incorporating multi-fidelity data
  ○ Use machine learning to combine low-fidelity simulation, high-fidelity simulation, and experimental data

● 5-10 year targets
  ○ Demonstrate multi-fidelity model improvement with varied simulations
  ○ Incorporate experimental data with simulated data for best predictions
  ○ Develop theory to estimate data needs
  ○ Develop theory to estimate model capacity and architecture
  ○ Use model inadequacy to drive future simulation or experiment selection
  ○ Perform UQ to measure model improvement and uncertainty reduction
Prediction of transient and/or off-normal events

- Summary: Develop predictive capability for events of interest, for example avoiding disruptions, will be crucial for survivability and monitoring of fusion devices

- 5-10 year targets
  - Long-range dependencies in time sequences need to be learned, especially over long-pulses, new ML architectures needed
  - Be able to combine multi-modalities (multiple diagnostics for different physics)
  - Being able to transfer AI/ML models to next-step devices where training data are rare (transfer learning, etc.)
  - Interpretability of the ML models for learning important physics
  - Training with few labelled data will be necessary (e.g. self- or semi-supervised learning), can also leverage simulation data to enhance.