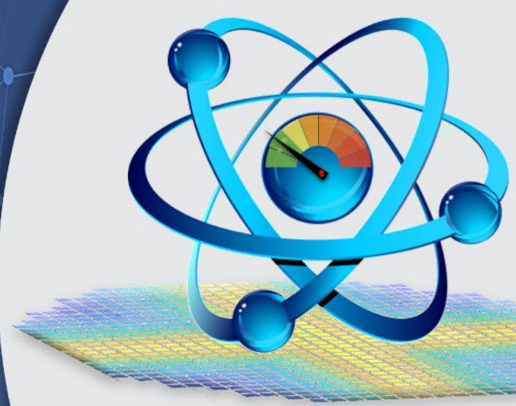
BLUE WAVE AI LABS

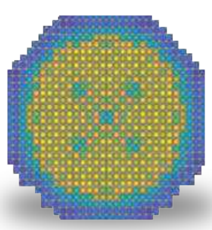
ThermalLimits.ai



A prediction platform for Online Thermal Limits in BWRs

AI Enabled Next-Gen Visibility into Boiling Water Reactors

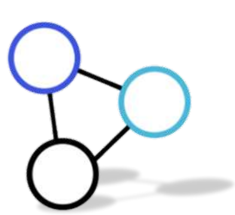
ThermalLimits.ai is a state-of-the-art tool that yields real world, high value results via Machine Learning. It enables powerful predictive capability into crucial operating limits – ensuring compliance with technical specifications, enabling reduced reload fuel costs, and eliminating operational challenges.



Real World

Accurate predictions of core-wide and local behavior are crucial to assuring that targeted margins to the operating limits are maintained. Deviation between measured performance and design predictions can lead to operational challenges, such as unplanned derated conditions, premature coastdown, or increased fuel costs by loading more fuel than required for targeted energy production. Historically, inability to accurately predict online thermal limits from offline methods has challenged core design and cycle management.

While actual operations may at times depart from cycle design basis projections, **there exists an inherent bias between offline and online methods** that stems from the nature of the two systems. Both methodologies rely on a three-dimensional neutronics simulator model to calculate the reactor's power, moderator, void, and flow distributions—from which margin to thermal limits can be determined. However, these calculations are approximations, and the offline quantities determined from them are inexact estimates that lead to uncertainty in thermal limits. Online methods, on the other hand, employ an adaptive process through feedback directly from in-core nuclear instrumentation while the reactor is online.

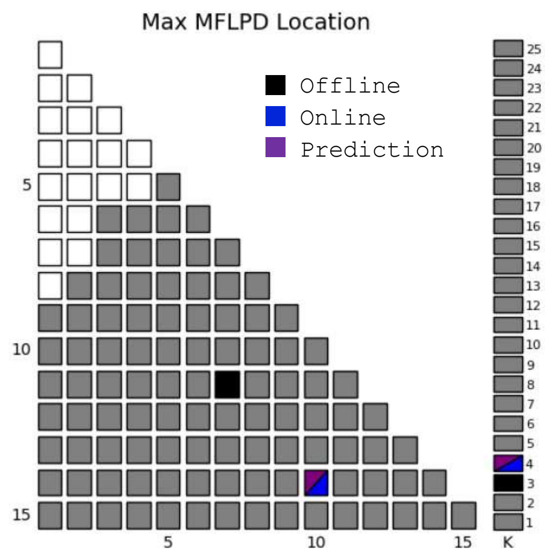


Up until recently, there has been no reliable method to bridge the gap between online and offline methods leading to inaccurate and inconsistent predictions of online thermal limits.

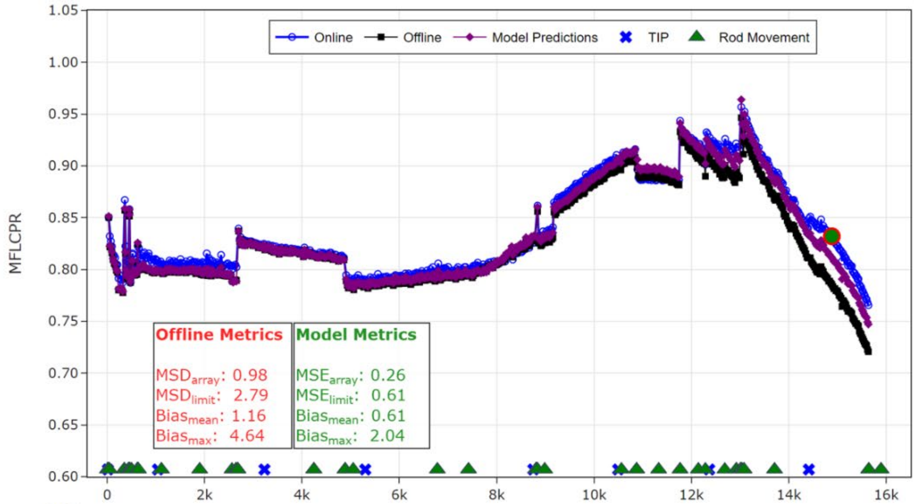
New Methodology

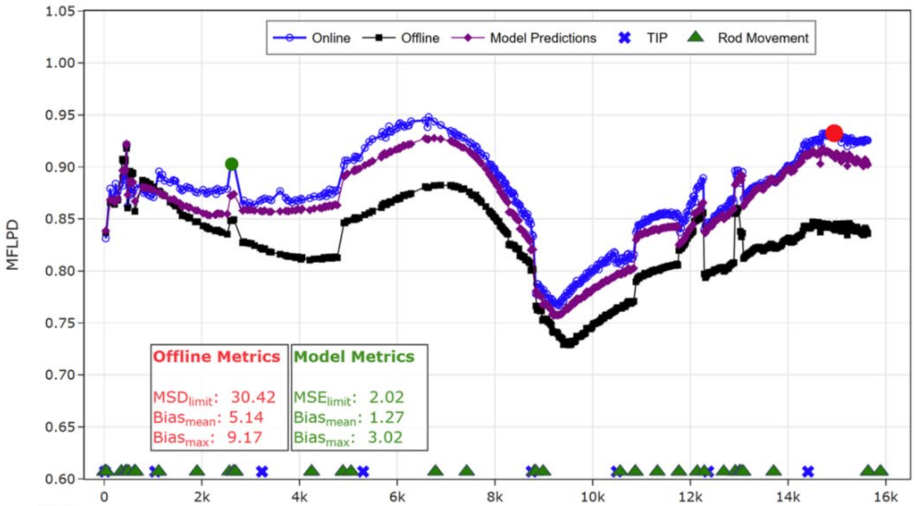
Blue Wave AI Labs is pioneering online thermal limit prediction capability with the creation of **ThermalLimits.ai** to address these deficiencies. Our proprietary physics-informed approach uses machine learning (ML) to leverage historical fuel cycle data, outputs from core simulators, and past online thermal performance to construct a reliable offline surrogate to replace the online feedback provided by the in-core instrumentation.

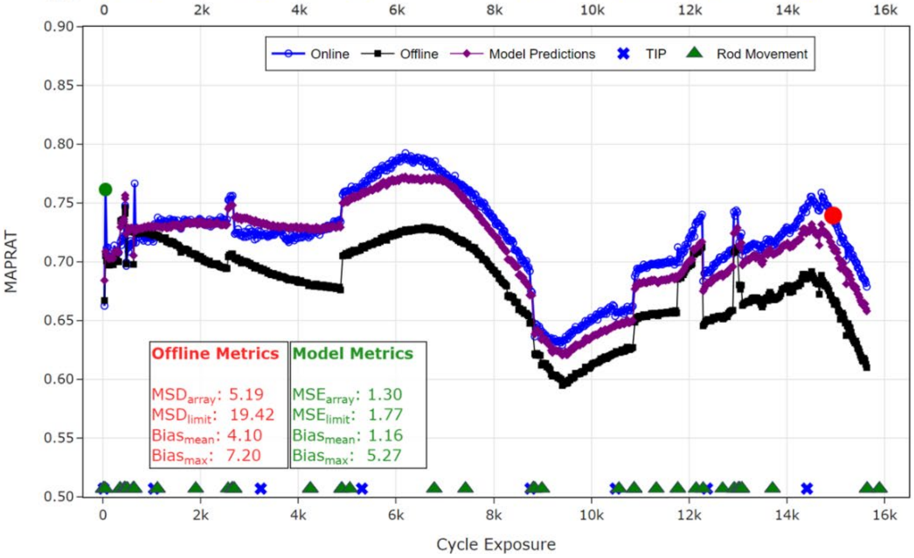
The underlying methodology used to develop these models is the notion of an error-correction deep neural network that leverages the offline nodal or bundle thermal limit array in conjunction with additional offline datasets to train a network that predicts the corresponding online thermal limit nodal or bundle array, thereby enabling predictive capability for online thermal limits from offline nodal power distributions.



Example demonstrating the accuracy between the offline, online, and model predictions for location of max MFLPD.







High Value Results

The predictive capability of ThermalLimits.ai is illustrated above for a typical test cycle for a large BWR. Individual models for each of the MFLPD, MAPRAT, and MFLCPR distributions demonstrate an average reduction in the observed bias by 73% (3.64x) for MFLPD, 46% (1.82x) for MFLCPR, and 67% (3x) for MAPRAT. Moreover, across all fuel cycles independently tested, the maximum bias between online values and model predictions never exceeds 3.9% (for MAPRAT and MFLPD) and 1.5% for MFLCPR.

Features

ThermalLimits.ai is a robust state-of-the-art SaaS application for the nuclear power industry that provides unparalleled accuracy for online thermal limit forecasting in both ***reload core design*** and ***cycle management*** engineering applications. Additional capabilities of these models include:

- An average bias of less than 1% for the max MFLPD and MAPRAT, compared to more than a 4% mean bias for conventional offline methods.
- An average bias of less than 0.39% for MFLCPR, representing a 46% reduction in the bias from conventional offline methods.
- A 2x reduction in mean bias for MFLCPR compared to conventional methods.
- More accurate predictions of the full nodal distributions for MAPRAT and MFLPD, reducing the average nodal bias by more than a factor of two.
- Correct identification of the online most limiting node/bundle location more than 85% of the time, compared to 60% from off-line methods.
- No degradation in model performance when used for mixed cores or during fuel transitions.

With these predictive capabilities, BWR operators can design the most economical and efficient reload cores by eliminating excess design margin, reducing rework, and avoiding operational challenges that often result in power de-rates or increased coastdown lengths.

Requirements for ThermalLimits.ai

Typical situations require approximately three fuel cycles worth of offline and online datasets for a given reactor unit. TheralLimits.ai is compatible with outputs from most vendor and vendor-independent nuclear fuel analysis software and methods.

Energize reload design with the BWnuclear.ai software suite.