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AI LABS

AI ENABLED NEUTRON FLUX CALIBRATION AND VIRTUAL CALIBRATION IN BOILING WATER REACTORS

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November 1,2023

Introduction

- Accurately capturing the power distribution within a reactor core is vital for ensuring the safe and economical operation of the reactor.
- In boiling water reactors (BWRs), an array of Local Power Range Monitors (LPRM) is used to measure the local flux distribution.
- Problems with this measurement process poses some major challenges:
  - Lack of visibility into local power distribution when an LPRM is bypassed
  - Incorrect or infrequent detector calibrations
  - Premature or overdue replacement of LPRMs that have reached their end-of-life
  - Inaccurate power adaption that has downstream effects on perceived margin to operating limits

Introduction

- For the LPRM system, there is a vast amount of historical data available – a) Processed signals from the LPRM detectors, and b) the corresponding core state-points and the operating conditions of the core.
- In this work, we utilize this data to develop two classes of deep learning models to accurately predict the measured LPRM readings.
- One set of models are useful for real-time predictions, and the other set of models for future offline predictions.

SIGNIFICANT OUTCOMES

- **Projects**
  - **LPRM.ai**
  - **TIP.ai**
  - **RUL.ai**
  - **ThermalLimits.ai**

- **LPRMs** (Local Power Range Monitors) in BWRs
  - Dynamic thresholding for LPRM trip units (reduce the need to bypass an LPRM)
  - More accurate LPRM lifetime estimation (extend replacement intervals) RuL
  - Virtual LPRMs for use when one is in BY/CAL mode (bypassed or being calibrated)
- **TIPs** (Traversing In-core Probes)
  - Trace Alignment
  - Power Adaption
- Thermal Limits Models

AI Enabled Neutron Flux Measurement and Virtual Calibration in Boiling Water Reactors

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ABSTRACT

Accurately capturing the three-dimensional power distribution within a reactor core is vital for ensuring the safe and economical operation of the reactor, compliance with Technical Specifications, and fuel-cycle planning (safety, control, and performance evaluation). Offline (that is, during cycle planning and core design), a three-dimensional neutronics simulator is used to estimate the reactor's power, moderator, void, and flow distributions, from which margin to thermal limits and fuel exposures can be approximated. Online, this is accomplished with a system of local power range monitors (LPRMs) designed to capture enough neutron flux information to infer the full nodal power distribution. Certain problems with this process, ranging from measurement and calibration to the power adaption process, pose challenges to operators and limit the ability to design reload cores economically (e.g., engineering in insufficient margin or more margin than required). Artificial intelligence (AI) and machine learning (ML) are being used to solve the problems to reduce maintenance costs, improve the accuracy of online local power measurements, and decrease the bias between offline and online power distributions, thereby leading to a greater ability to design safe and economical reload cores. We present ML models trained from two deep neural network (DNN) architectures, SurrogateNet and LPRMNet, that demonstrate a testing error of 1.1% and 3.0%, respectively. Applications of these models can include virtual sensing capability for bypassed or malfunctioning LPRMs, on-demand virtual calibration of detectors between successive calibrations, highly accurate nuclear end-of-life determinations for LPRMs, and reduced bias between measured and predicted power distributions within the core.

NEUTRON FLUX MEASUREMENT IN BWR'S

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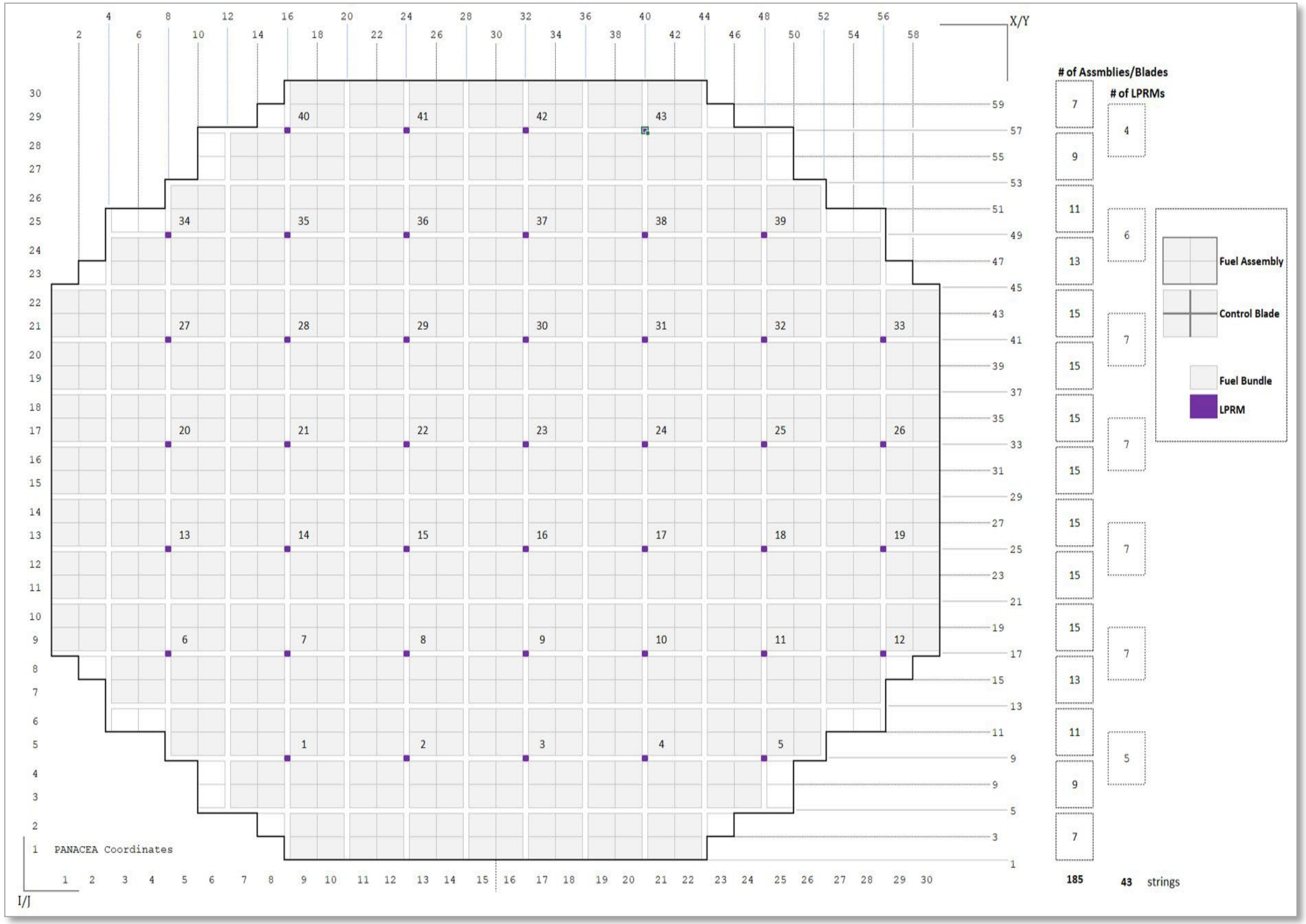
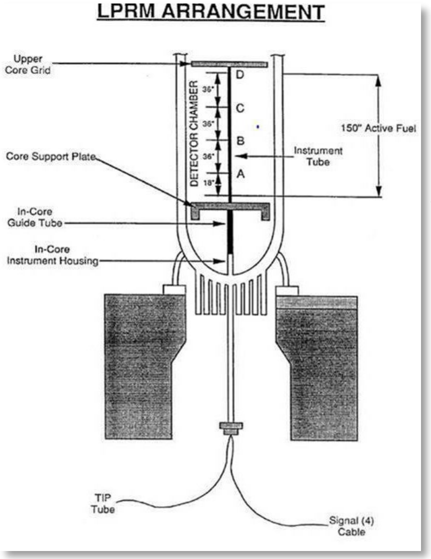
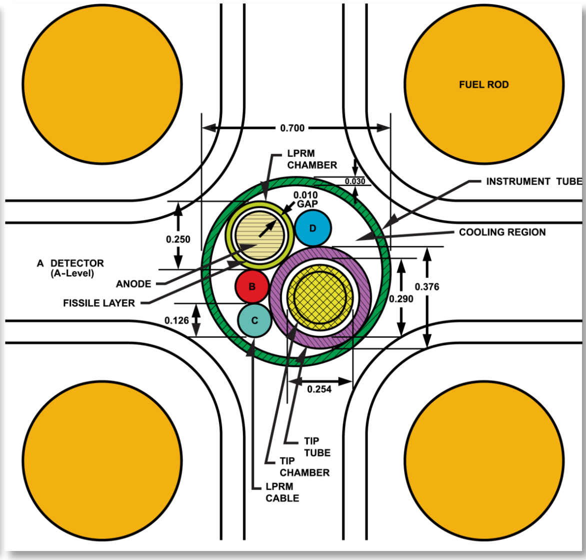
TIP & LPRM Overview



Geometry & Layout:

- LPRMs strings (4 fission chamber detectors) are installed within instrument tubes in the core
- Large BWR core will have up to 43 strings (172 detectors)
- Replacement of one LPRM requires replacement of entire string
- TIPs are periodically inserted (every few months) within the TIP tube to produce 1-inch integrated power trace along the entire length of active fuel





RESULTS AND ACCOMPLISHMENTS

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LPRM Modeling (virtual sensors)

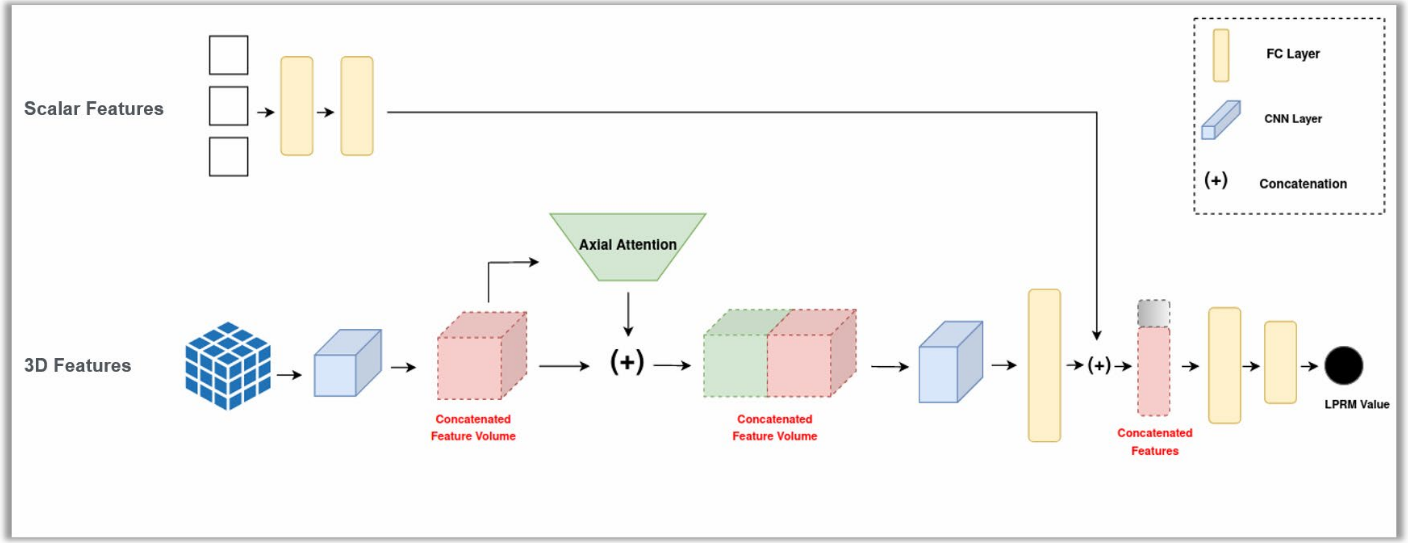
Application

- **Surrogate LPRM Models**
  - **Input:** LPRM String | **Output:** LPRM String
  - **Input:** Multiple LPRM Strings| **Output:** LPRM String

Real-time virtual readings (dashboard),
Virtual calibration

- **Cycle Parameters Model**
  - **Input:** Nodal Power, Rod Variables, Core Flow, Core Power, Thermal Power
  - **Output:** Single LPRM Reading
  - Most robust but complex model, requires block data transfer

~Real-time or future predictions,
Virtual calibration,
Anomaly detection



- Data include:
  - Blade Nodal Depletion Ratio
  - Calculated LPRM Readings (PANACEA)
  - Core Dome Pressure
  - Core Flow
  - Core Inlet Subcooling
  - LPRM Gains
  - LPRM Rejected
  - LPRM Sensitivities
  - Measured LPRM Readings
    - Rod Pattern
    - Thermal Power
    - Cycle Exposure
    - LPRM Mapping
    - Nodal Power

Utilized in Model:

Surrogate LPRMs | Cycle Parameters

- Two Models
  - **SurrogateNet:** A set of models using the **readings of other detectors**. For accurate real-time predictions and virtual readings.
  - **LPRMNet:** A set of models using the **core conditions** and **core parameters** (which are forecastable). For accurate offline and future predictions.

RESULTS AND ACCOMPLISHMENTS

Performance

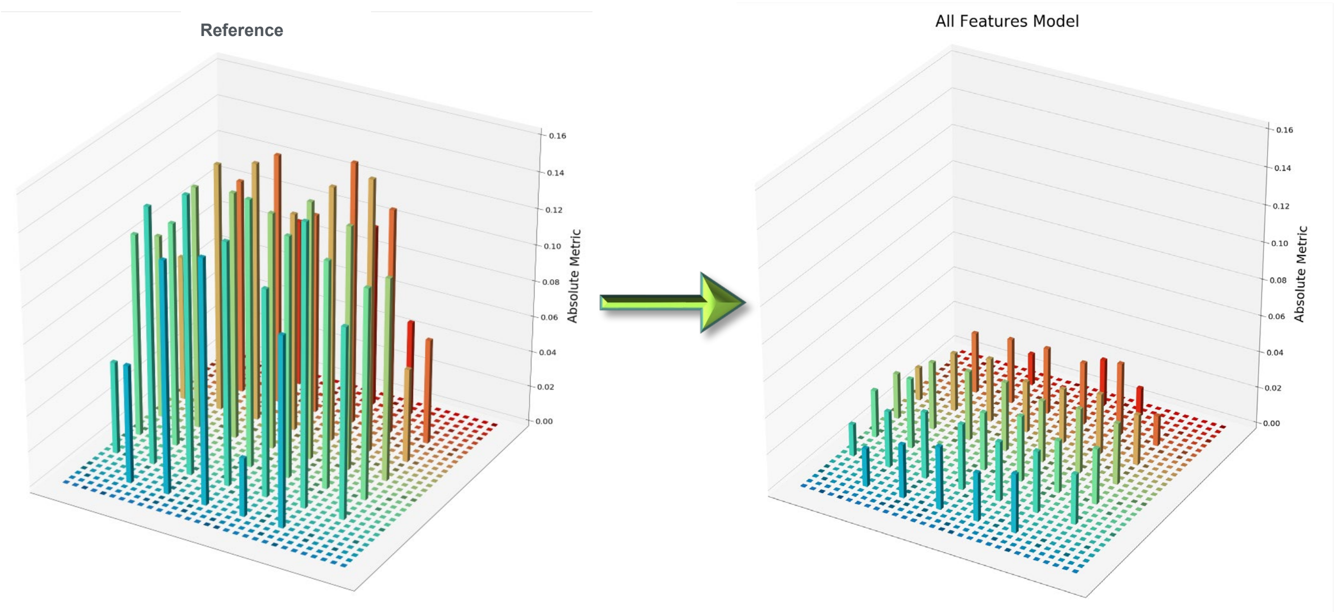
Accuracy:

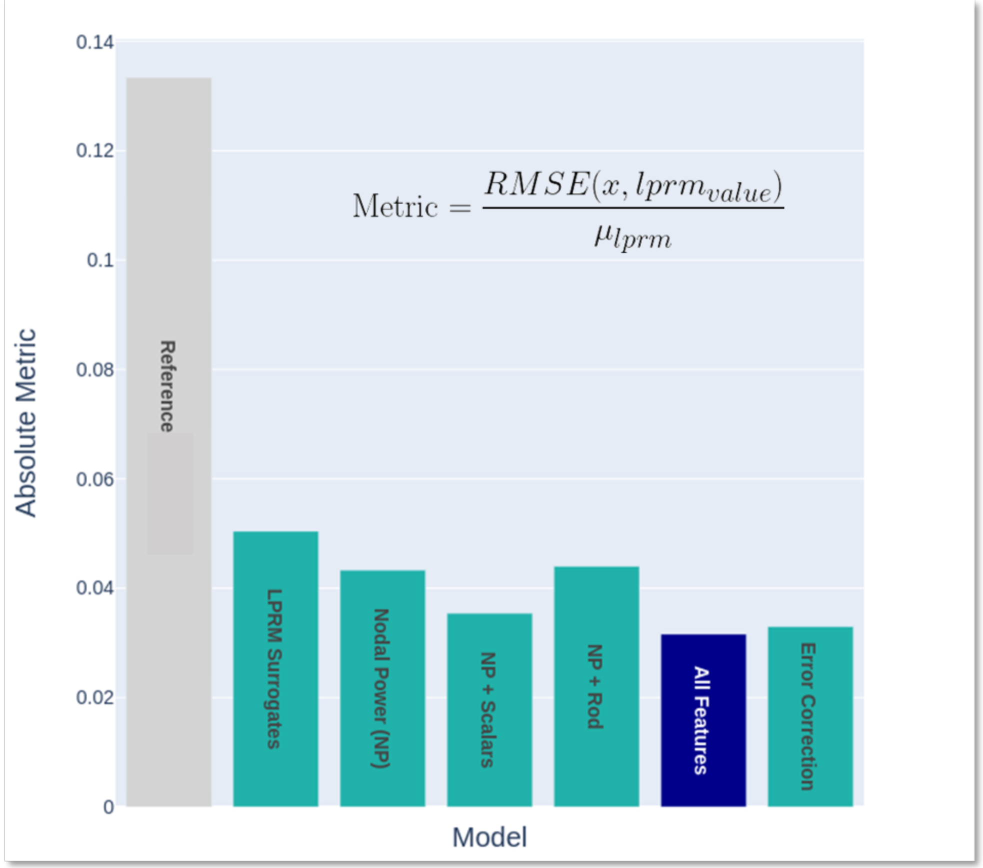
- Virtual LPRMs can predict actual LPRM readings to within $\pm3\%$ on average over all 172 detectors

  → **This represents 4x reductions in uncertainty from current state-of-practice**

- This is with a model trained from 1 Reactor unit
- Currently expanding training set to several multi-unit generating stations

  → **This will drive down uncertainty even further**





PROJECT OVERVIEW

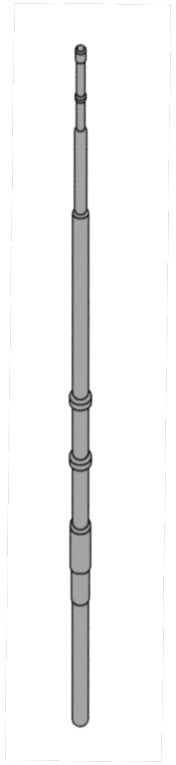
LPRM Monitoring Calibration, and EOL Determination Methodology

Objectives

- Provide Virtual Measurements
  - Offline / bypassed LPRM readings (redundancy)
  - Anomaly detection (early failure indication)
  - Increased effective service life
- Enable Virtual Calibration of LPRMs
  - On-demand
  - Quick calibration for new LPRMs
  - Improved nodal flux characterization
- Improve RUL determinations & Replacement Schedule
  - Higher accuracy
  - Reduce premature LPRM replacement
- Streamline bookkeeping and workflow
  - Easy review of detector history (interactive UI)
  - Visual insights (layout / heatmaps / graphs)

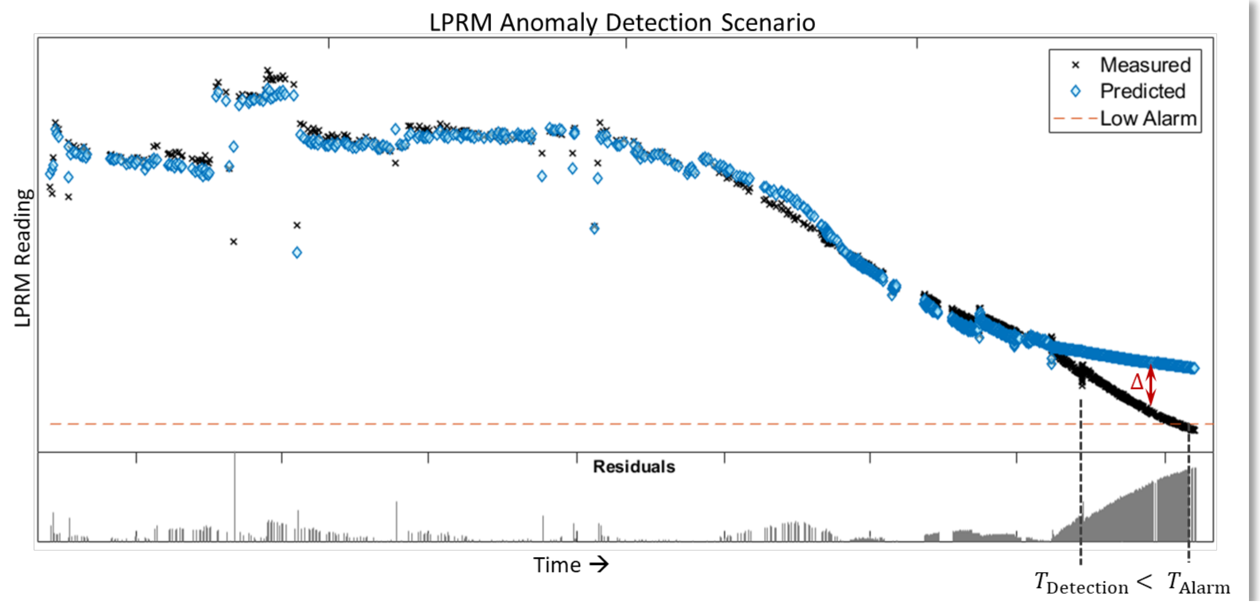
Problem statement: The LPRMs are critical for monitoring the thermal neutron flux within a boiling water reactor (BWR). Their reliability and accuracy are crucial to accurately assess thermal limits and monitor the core. Problems include:

- Infrequent calibrations leading to periods of inaccurate readings
- Lack of visibility when an LPRM goes offline / bypassed
- Premature replacement due to inaccurate end-of-life (EOL) determination



MODEL APPLICATION REGIMES

Two main regimes: on-line diagnostics and future (necessarily off-line) forecasting



TIP

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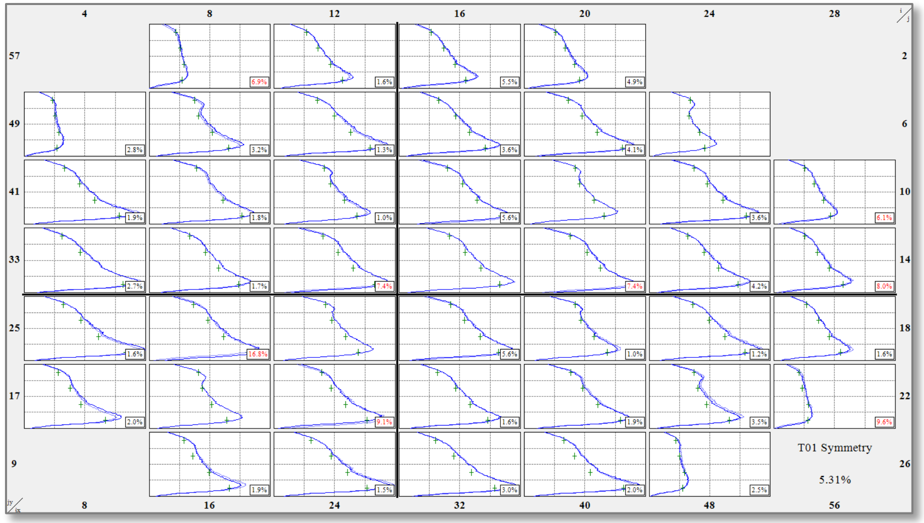
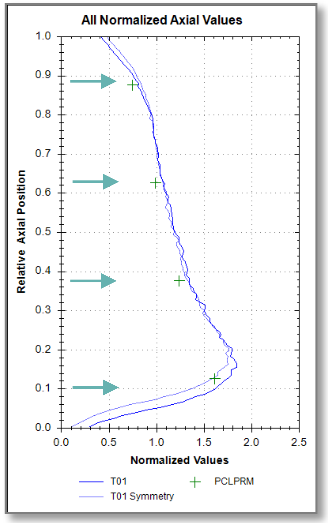
TIP Alignment Methodology and Flux Adaptation

Objectives

- ML Detection of when auto alignment is performed incorrectly
  - Historical trace review for past few cycles
  - Tool integration into customer process for identification of issues going forward
- Develop new methodology for high fidelity TIP trace adaptation
  - Train classifiers to more accurately adjust and adapt TIP traces than the current state-of-practice
  - Correct misaligned traces
- Detect other spurious TIP data for increased visibility by Reactor Engineering
  - Use to validate LPRM calibrations from TIP traces

Problem statement: The auto TIP alignment feature (in fuel vendor software) occasionally incorrectly shifts the local flux profile (by more than a full node) resulting in higher thermal limits (e.g. MFLPD). Higher thermal limits challenge operations due to inadequate margin and may result in a power derate if a limit is reached.

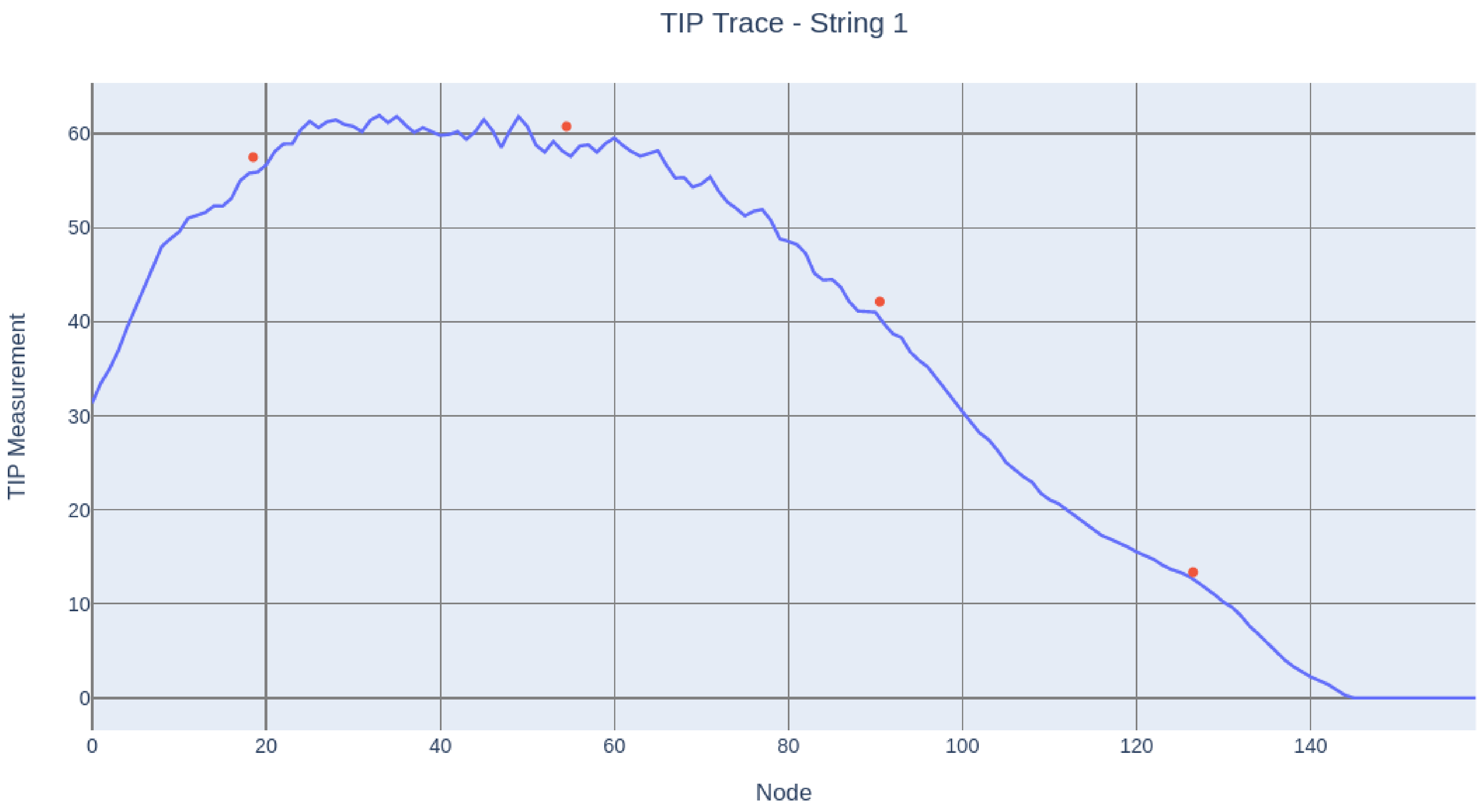




Improved characterization of axial power distribution

→ **LPRM Location**

TIP TRACE



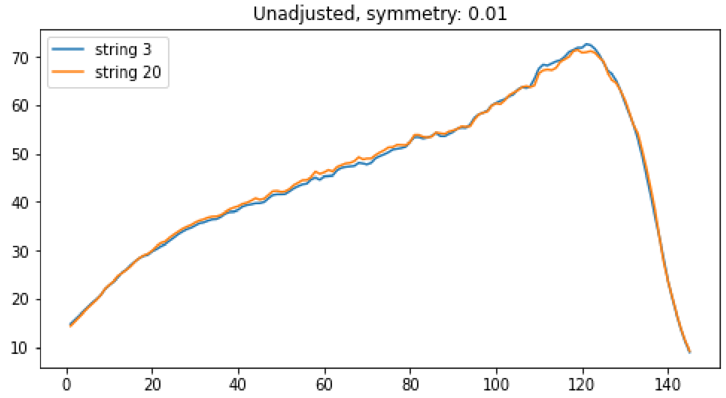
Sources of Error:

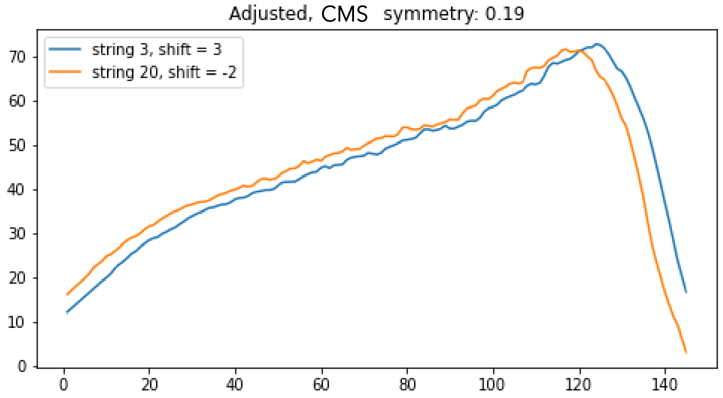
1. Wrong identification of spacer locations
2. “Slope Effect”.Small changes in position result in high changes in count rate.

Current methods require frequent LPRM recalibration via time-consuming TIP Trace process, which is further prone to gross inaccuracies.

Improved Trace Alignment

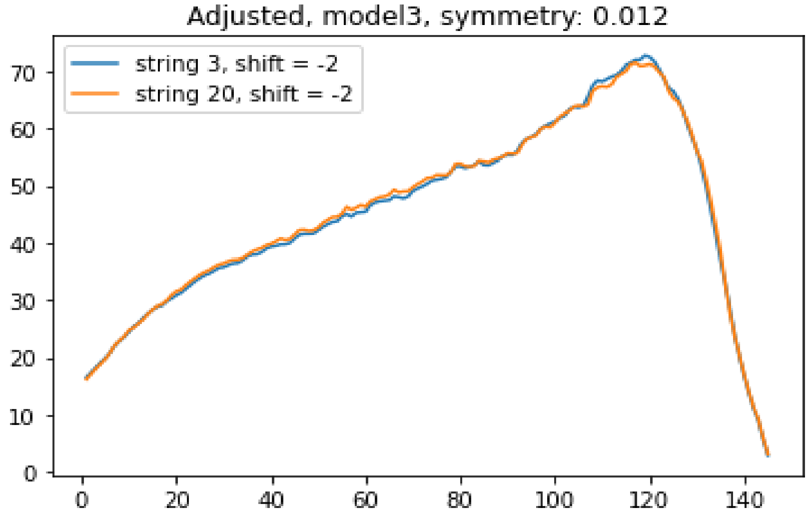
- More accurate LPRM calibrations
  - → Improved power adaption
  - → Improved thermal limits / margin
- Detection of anomalies
  - → Increased visibility for Reactor Engineering





Current methods require physical recalibration every ~2 months due to drift (degradation).

Determined TIP trace shift is sometimes much too large, and adaption is discarded (vendor recommended to turn it off).



THERMAL LIMIT BIAS

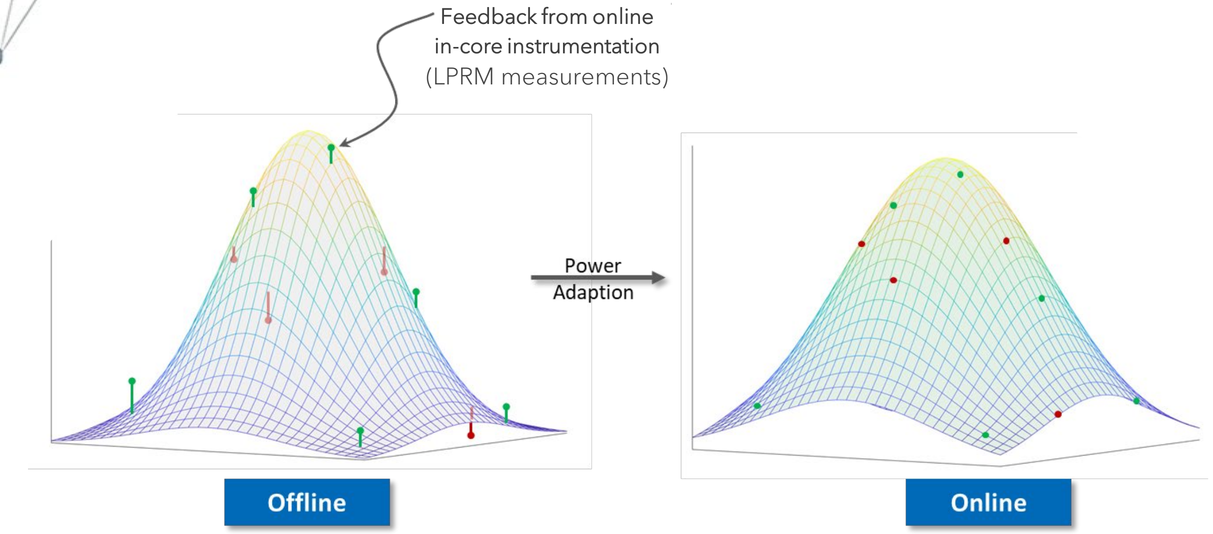
Methodology for Thermal Limit Bias Predictability

MANAGING THERMAL LIMIT BIAS

- Bias between off-line and on-line thermal limits stems from the on-line feedback (adaption) applied to the offline power distributions.
- Uncertainty in calculating nodal power distribution is comparable to in-core instrumentation uncertainty.

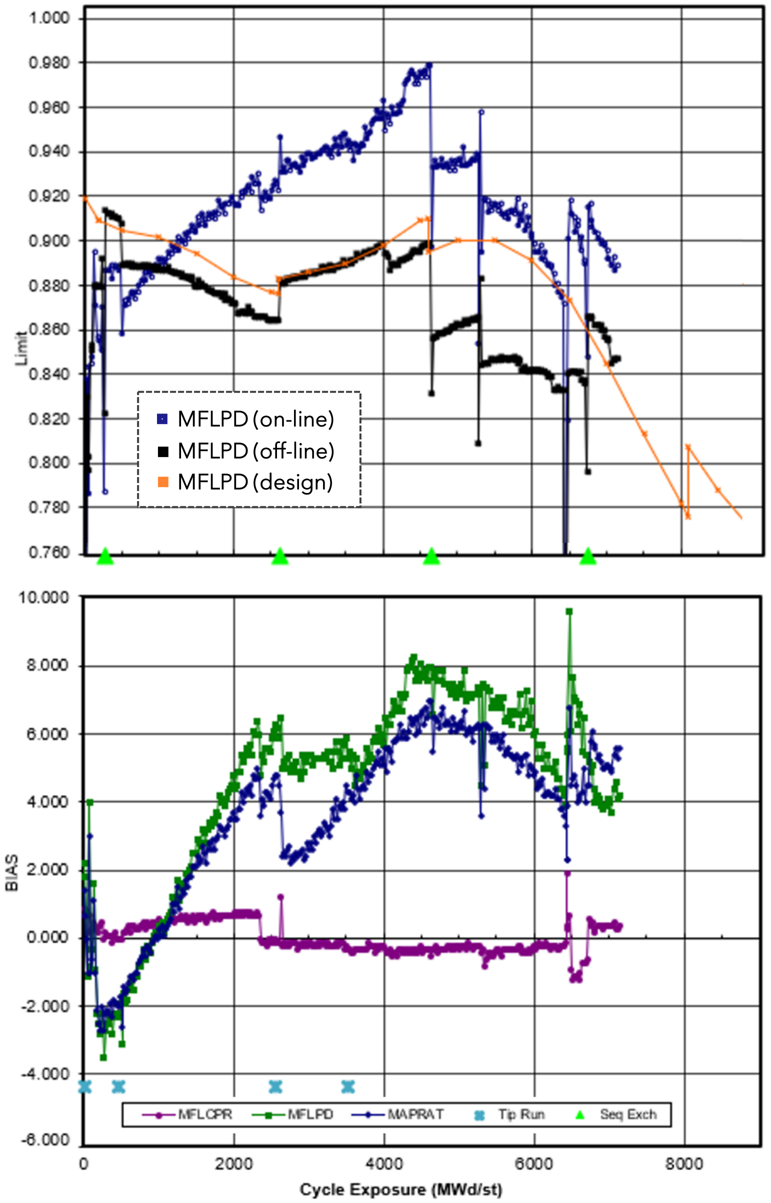
EXCESSIVE MARGIN IS OVERSPENDING

Core simulator inaccuracies lead to TL bias which can lead to overly conservative operation.



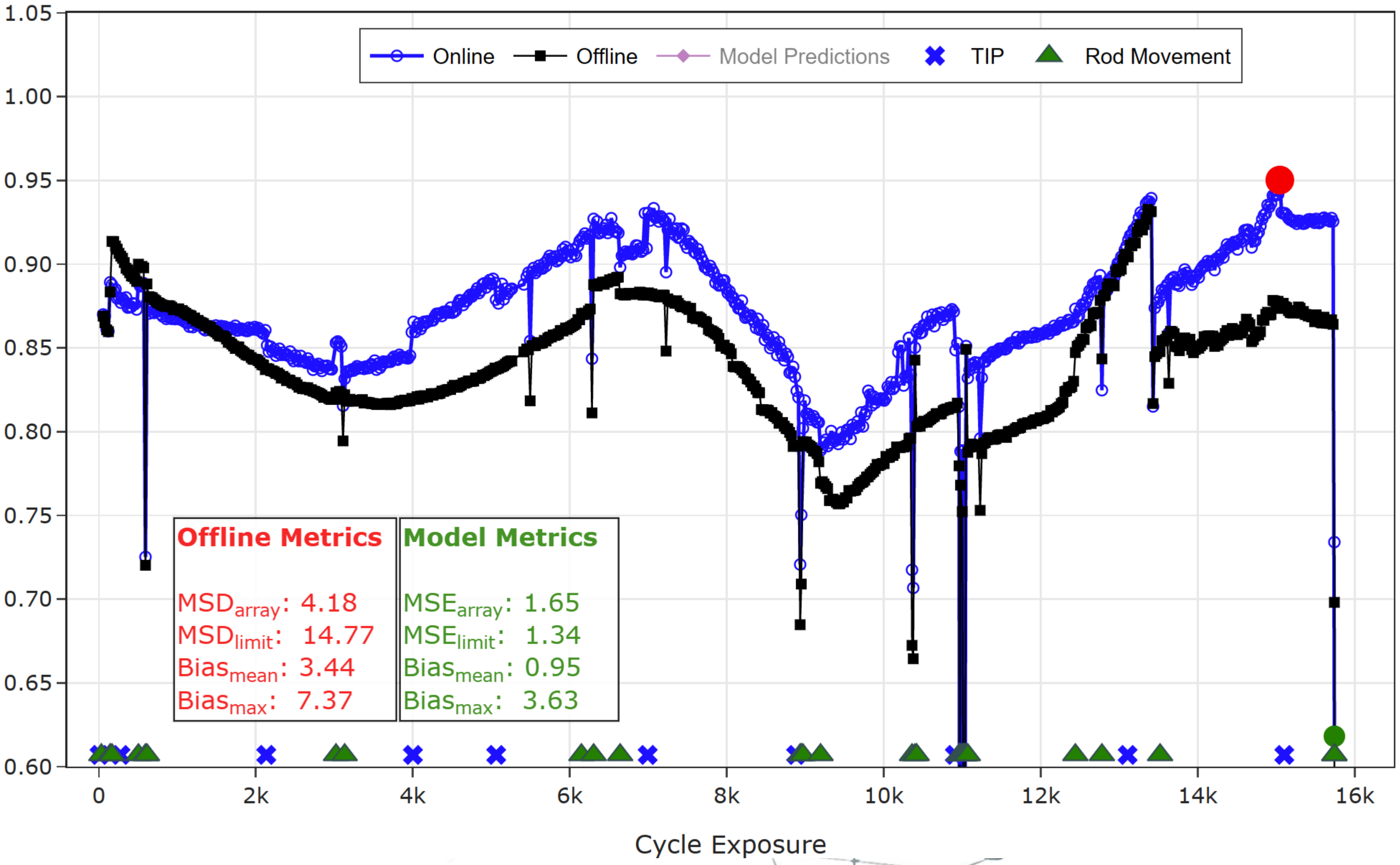
Nodal Power Distribution
(SIMULATOR)

Nodal Power Distribution
(SIMULATOR + TIP/LPRM adaptive factors)



S1C17

MFLPD (Test performance)



Performance Improvement:

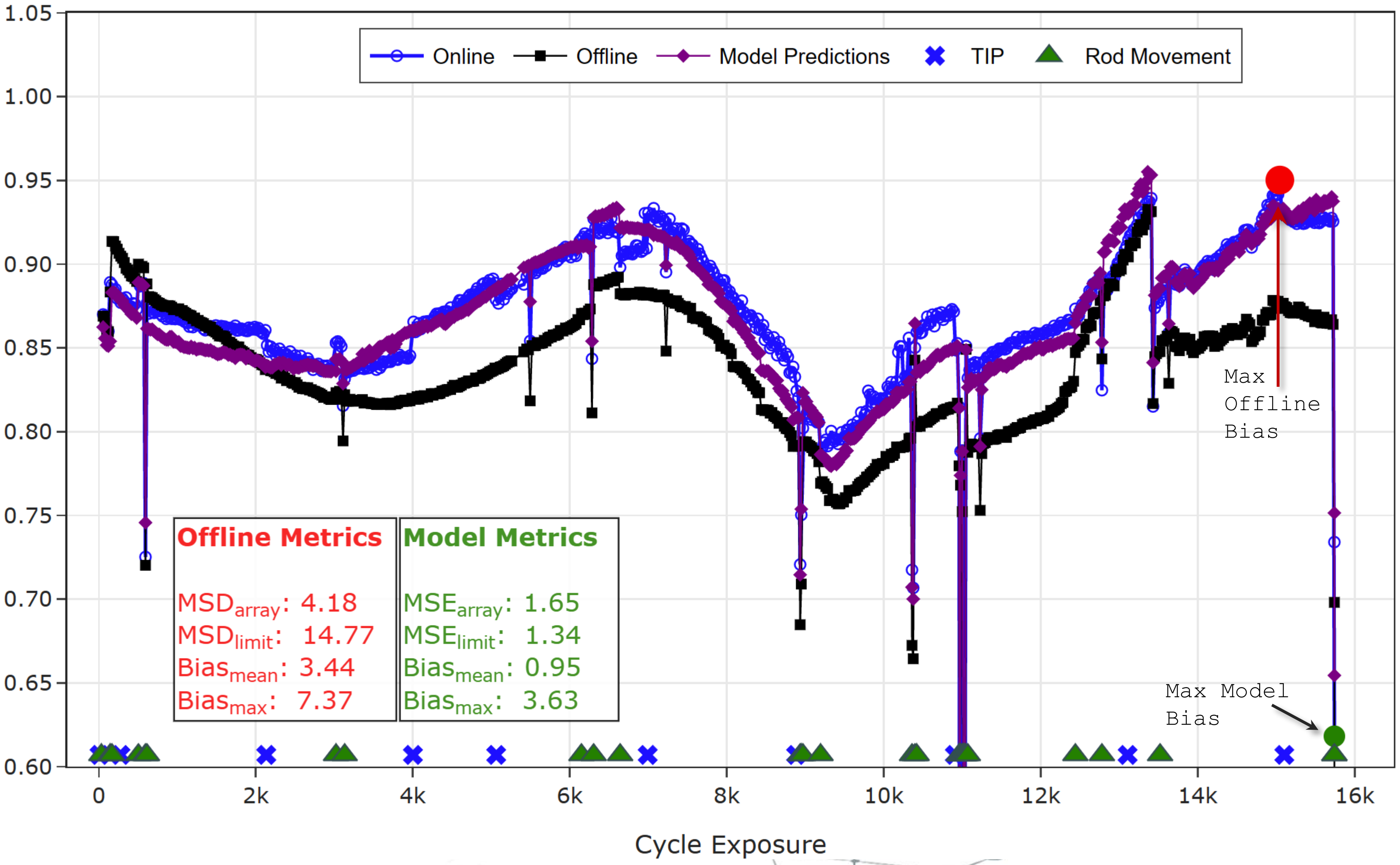
- 72.4% reduction in mean bias throughout cycle
- Mean nodal difference reduced from 2.04% to 1.16%
- Max Bias reduced from 7.4% to 3.6%

Training Set:

- S1C16
- ~~S1C17~~
- S1C18
- S1C19
- S1C20 (first GNF3 reload)
- S2C12
- S2C13
- S2C16
- S2C17 (first GNF3 reload)

S1C17

MFLPD (Test performance)



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- S2C12
- S2C13
- S2C16
- S2C17 (first GNF3 reload)

ThermalLimits.ai AVOIDED COSTLY DERATE

Actual Event: Approaching thermal limits max within two weeks

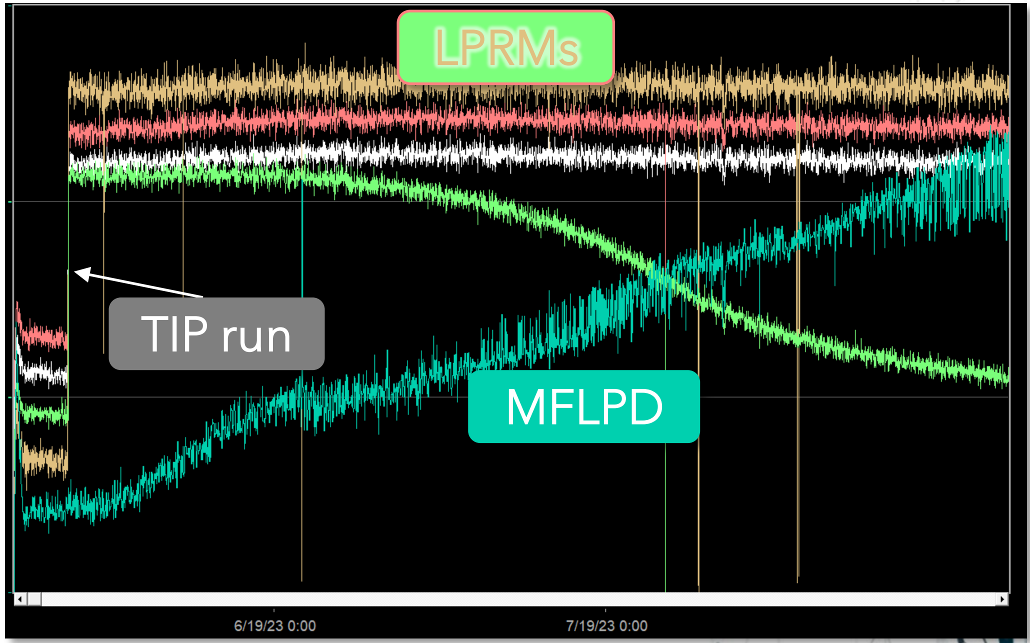
- Runaway MFLPD at .975, Blue Wave model predicted .918
- Operators thought some LPRM's may be out of service or mis-calibrated, but couldn't quickly verify
- Blue Wave analyzed TIP traces and found some potential problematic incl. an LPRM out of service

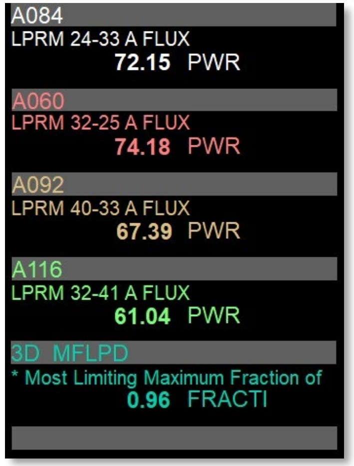
Without Intervention, a derate would be eventual course of action

- MLFPD getting worse, up to .975 (model predicted .92)
- Operator wanted Blue Wave to analyze ALL LPRMs…we did, rank ordering them from most-least problematic
- We showed 7 LPRMs with issues, bypass took it from .975 to .955

Blue Wave predictions proven true and accurate

- Blue Wave suggested performing recalibration with TIP, based on model predictions (still .92) … After TIP the MFLPD went to .92!
- Blue Wave tools also helped address three related IRs
- This event is being submitted for a Top Innovative Practice award





LPRM	Metric	Notes
24-41 A - 40-25 A	241.3	Bypassed, large offset prior to bypass
32-41 A - 40-33 A	220.2	Significant Drift, smaller drift in Delta level
24-49 A - 48-25 A	218.1	Noisy
16-25 A - 24-17 A	182.6	Fixed offset, not particularly drifting apart
08-33 A - 32-09 A	181.4	Large Drift
16-49 A - 48-17 A	173.1	Large Drift, Present in B and C levels to lessor extent
16-41 A - 40-17 A	142.8	Modest Drift
32-49 A - 48-33 A	132.5	Fixed offset, not particularly drifting apart
08-41 A - 40-09 A	130.0	Large Drift
24-33 A - 32-25 A	118.2	Fixed offset, not particularly drifting apart
40-49 A - 48-41 A	110.2	Fixed offset, not particularly drifting apart
16-41 B - 40-17 B	107.2	
24-33 B - 32-25 B	93.0	Significant Drift
40-49 B - 48-41 B	86.5	Fixed offset, not particularly drifting apart

IN-CYCLE MANAGEMENT

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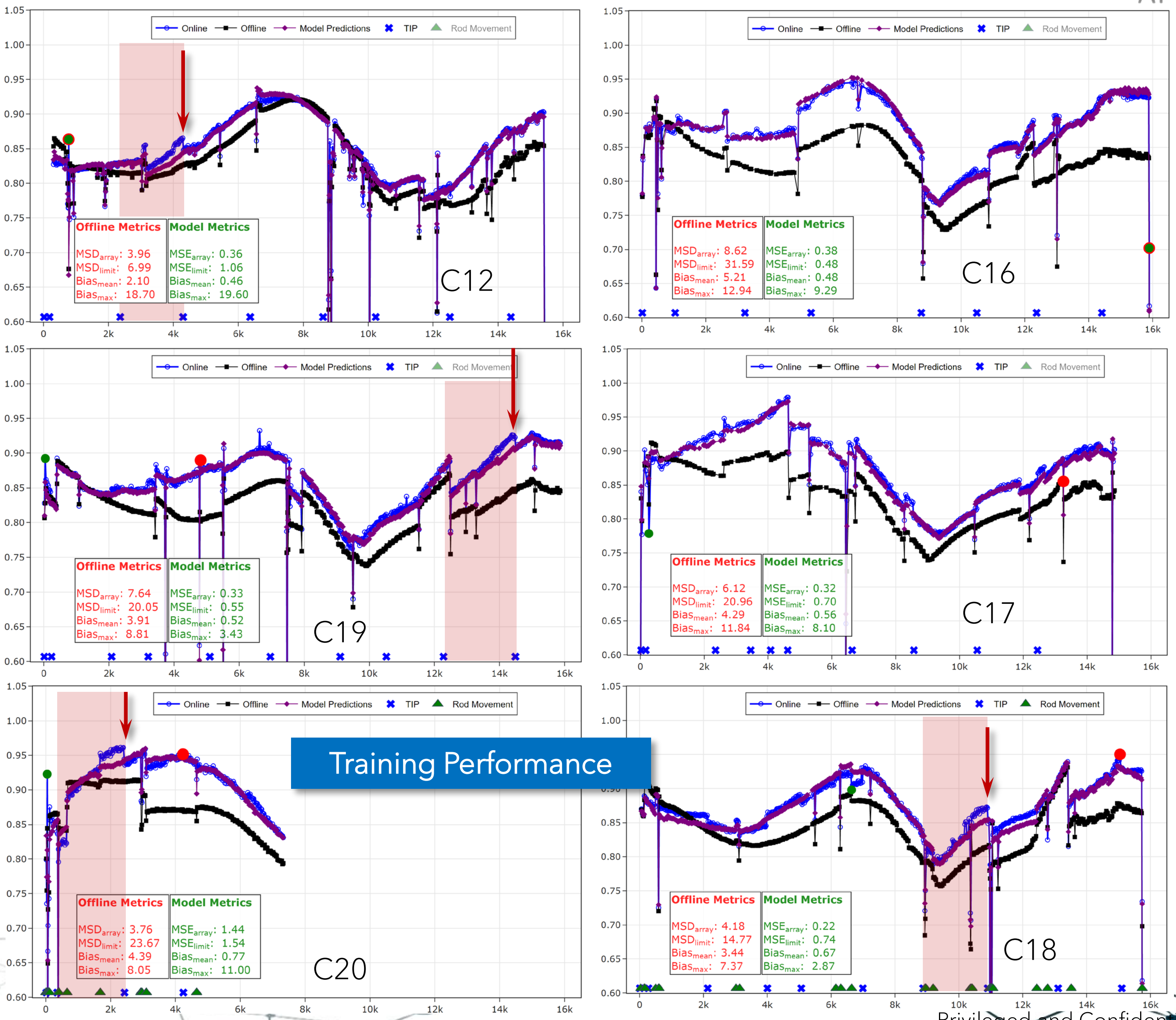
- Universally, all models <u>train</u> very well
  - However, certain features persist that are not effectively captured during model training → This suggests some level of noise in the training targets
  - **Observation:** Discrepancies between online MFLPD and model <u>begin</u> with a rod adjustment, but <u>disappear with a subsequent TIP run</u>
  - This suggests a possible errant TIP trace (or subsequent LPRM mis-calibration) in the vicinity of where max MFLPD moves as a result of the rod adjustment

- BW Analysis
  - Currently evaluating the TIP traces through BW alignment algorithm
  - With supporting evidence, will make a determination whether to exclude ROIs from training population



WRAP UP

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Anomaly Detection

- Anomalies can be detected by tracking the deviation Δ between virtual and actual measurements
  - → Train a classifier to recognize normal v. abnormal trending of Δ
  - → Establish dynamic threshold for flagging an anomaly
  - → This will lead to **advanced warning of when an LPRM will alarm** upscale or downscale

LPRM Forecasting

- Reliable, accurate projections of LPRM readings from cycle depletions
  - → Advanced warning when LPRMs will alarm downscale due to planned axial/radial power distributions
- Establish similar models for forecasting LPRM exposures (SNVT) from cycle depletions
  - → Accurate forecast for RUL based on expected operation through upcoming cycles (vs. average exposure attained from prior cycles)

Use Cases (off-line)

- Thermal Limit bias closely connected with LPRM and TIP accuracy
- Thermal Limit models in conjunction with LPRM and TIP analysis prevent costly derates and unanticipated rod adjustments

Four Year Savings					**Total**
	Adoption Rate	**TIP.ai**	**LPRM.ai**	**ThermalLimits.ai**	
2023	5%	$ 15,000.00	$ -	$ 1,075,000.00	$ 1,090,000.00
2024	30%	$2,640,000.00	$ 3,240,000.00	$ 10,320,000.00	$16,200,000.00
2025	50%	$4,400,000.00	$ 5,400,000.00	$ 17,200,000.00	$27,000,000.00
2026	65%	$5,720,000.00	$ 7,020,000.00	$ 22,360,000.00	$35,100,000.00
				Total	**$79,390,000.00**