U.S. DEPARTMENT OF ENERGY | Office of NUCLEAR ENERGY

ASI | Advanced Sensors and Instrumentation

Machine Learning Enhancement of BWR Neutron Flux Measurement and Calibration

Advanced Sensors and Instrumentation (ASI)
Annual Program Webinar
October 24 – 27, 2022

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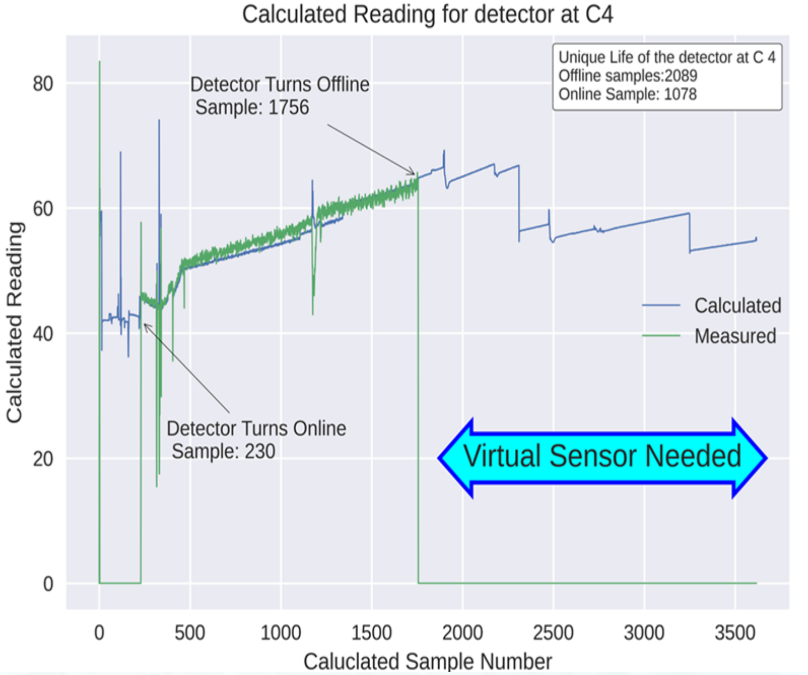
Blue Wave AI Labs

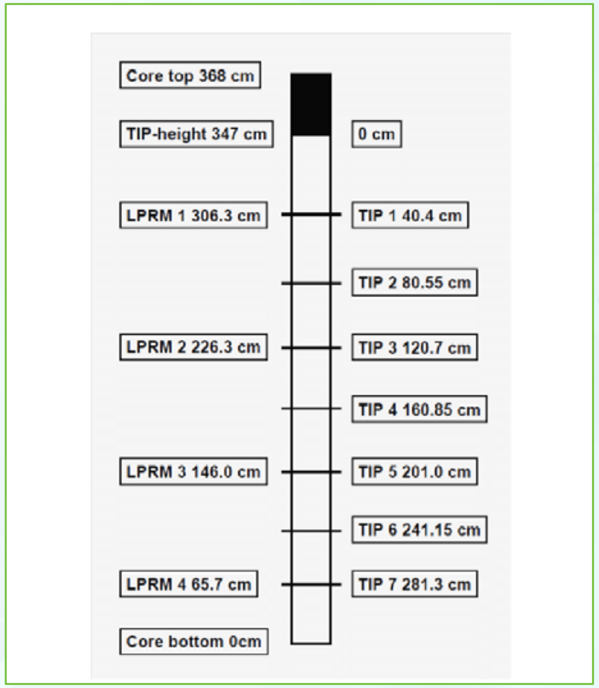
Project Overview

Gaps in our physical understanding of BWRs leads to shortfalls in predicting key parameters in BWR core design and cycle management

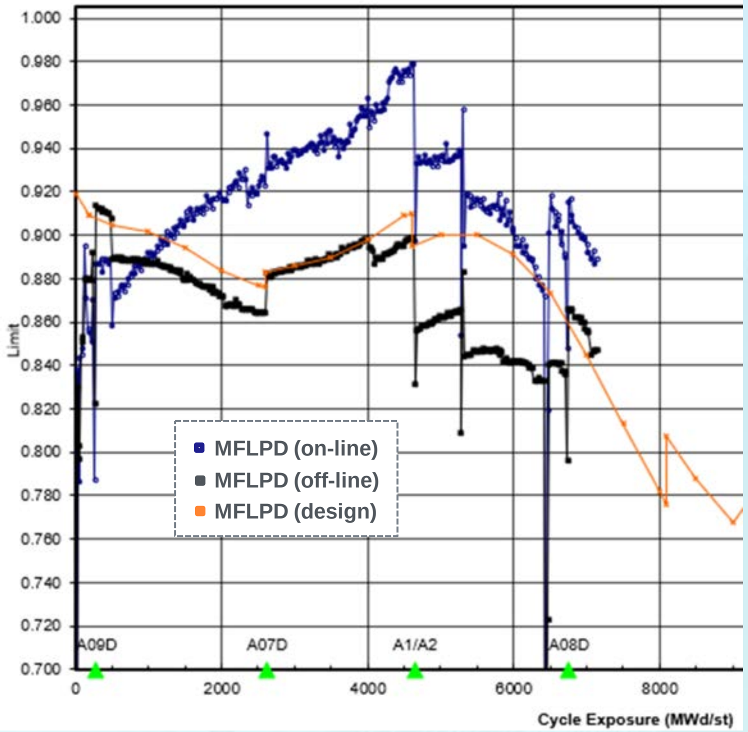
LPRM Virtual Sensor



TIP LPRM Calibration



Thermal Limit Biases



Project Overview

- Project Title:
  - *Application of Machine Learning for Enhanced Diagnostic and Prognostic Capabilities of Nuclear Power Plant Assets*

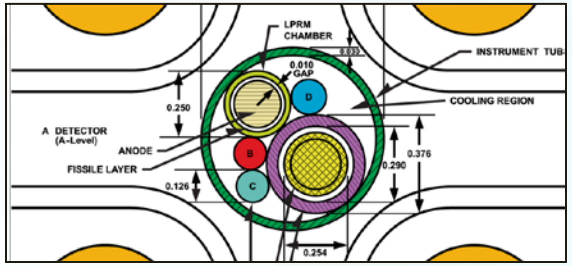
- Project Schedule
  - Currently Under One Year No-cost Extension-7/19/2023 Completion
  - Key Milestones
    - Finalize Remaining Useful Life Models for LPRM's
    - Improve existing LPRM predictive models
    - Document TIP trace algorithm and improvements
    - Complete documentation and final report

Project Overview

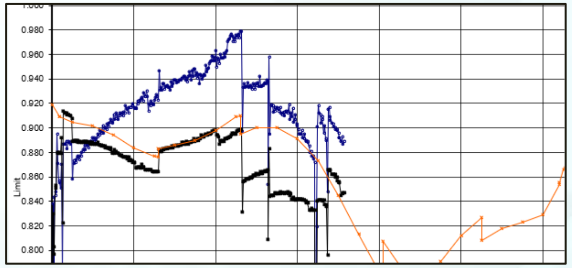
- Participants
  - PI: Tom Gruenwald
  - Key technical leads
    - Jonathan Nistor
    - Jordan Heim
  - Interns
    - Gautham Vinod (ME)
    - Isha Singh (NE)
    - Rizki Oktavian (NE)
    - Alina Nesen (CS)
    - Georgios Georgalos(AE)
- Partners
  - Argonne National Lab
  - Brookhaven National Lab

Project Overview

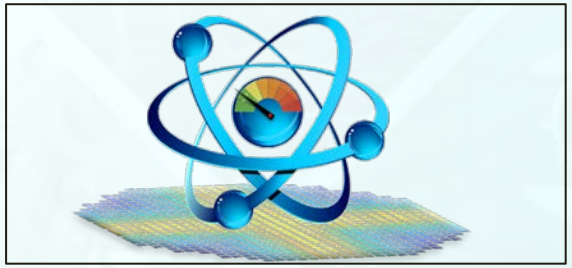
Artificial Intelligence (AI) and Machine Learning (ML) can fill the gaps in conventional methods for reliable predictability of key parameters



Diagnostic & Prognostic Modeling of LPRM / TIP



Application to Thermal Limit Bias Predictability



ThermalLimit.ai

Accurate on-line and off-line neutron flux measurement essential to safe & reliable operation

Results and Accomplishments

Three classes of models have been developed that are based on the nature of available inputs

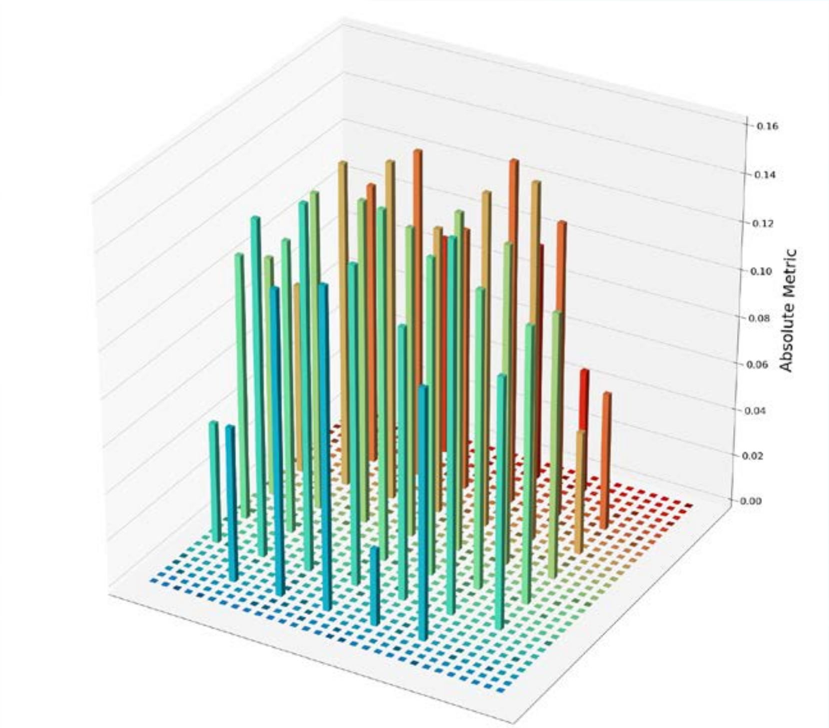
Model	Application
SURROGATE LPRM MODELS ▪ **Input:** LPRM String(s) ▪ **Output:** LPRM String	Real-time virtual readings Virtual calibration Anomaly Detection
CYCLE PARAMETERS MODEL ▪ **Input:** Operation Cycle Parameters ▪ **Output:** Single LPRM Reading	Future LPRM predictions Virtual calibration Anomaly detection
CORE SIMULATOR ERROR CORRECTION MODEL ▪ **Input:** CMS Calculated LPRM Values ▪ **Output:** Set of LPRM Readings	Future LPRM predictions

Application

Application to Thermal Limit Bias Predictability

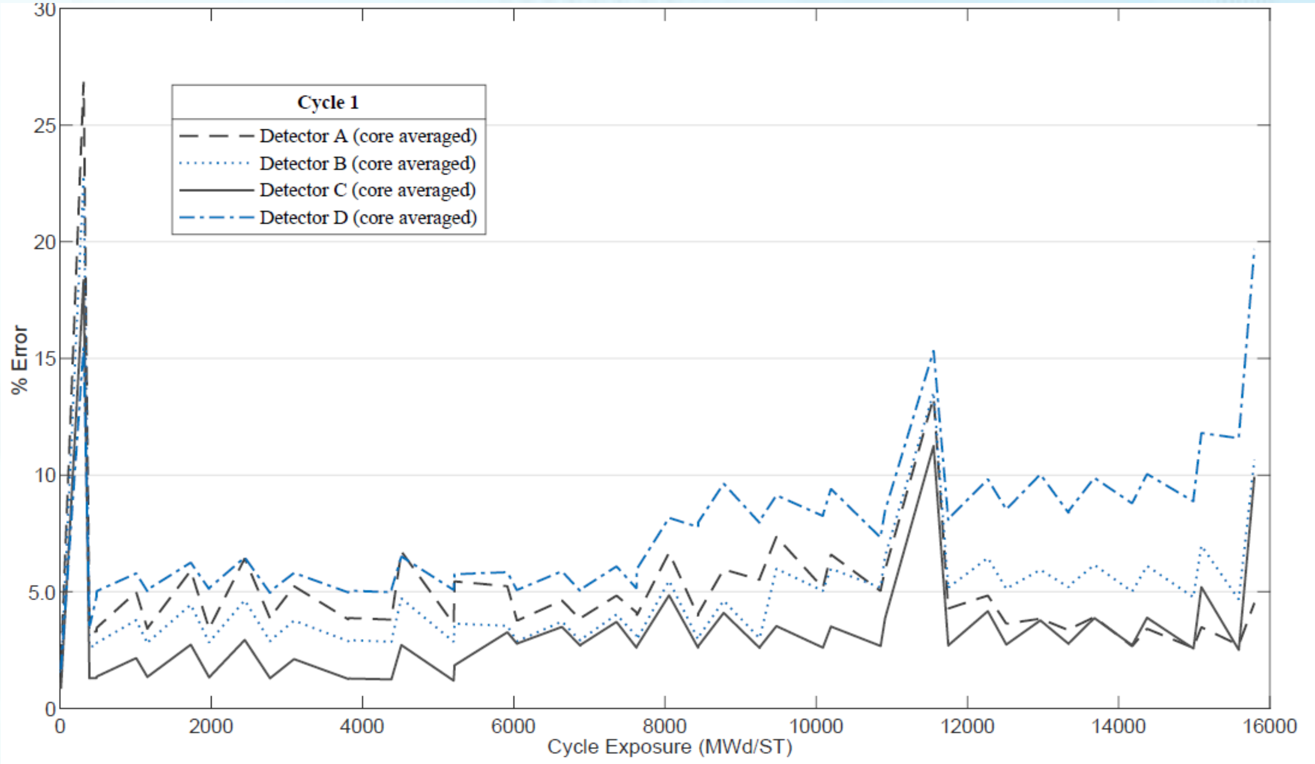
LPRM Uncertainty

1. Accuracy of LPRM measured values depends on TIP Calibrations (more on that later)
2. LPRM values calculated from core simulator have spatial and temporal disagreement from measurements (**up to 15%** in some locations for extended sequences)



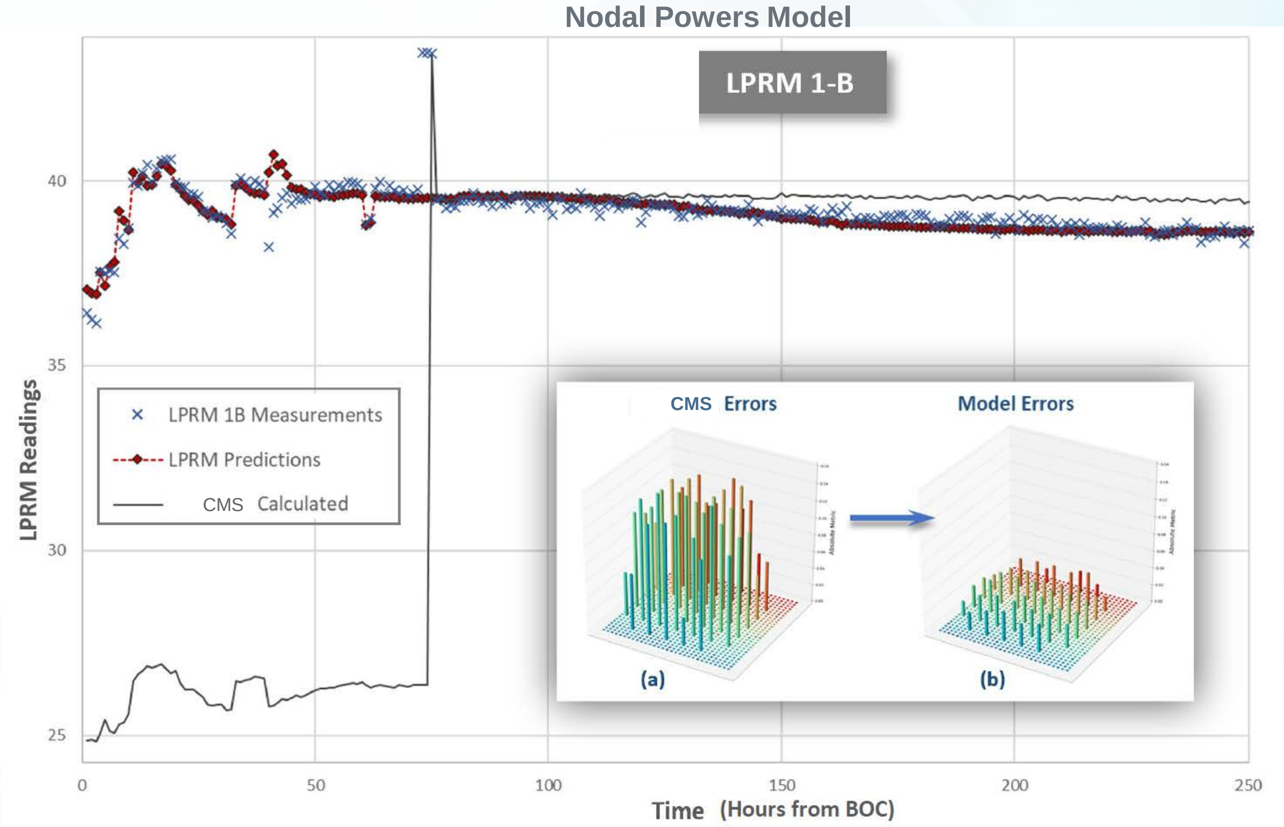
Average over all detectors in string over 8 fuel cycles (2006-2021 for Station A, Unit 3)

Discrepancy between LPRM measurements and core simulator

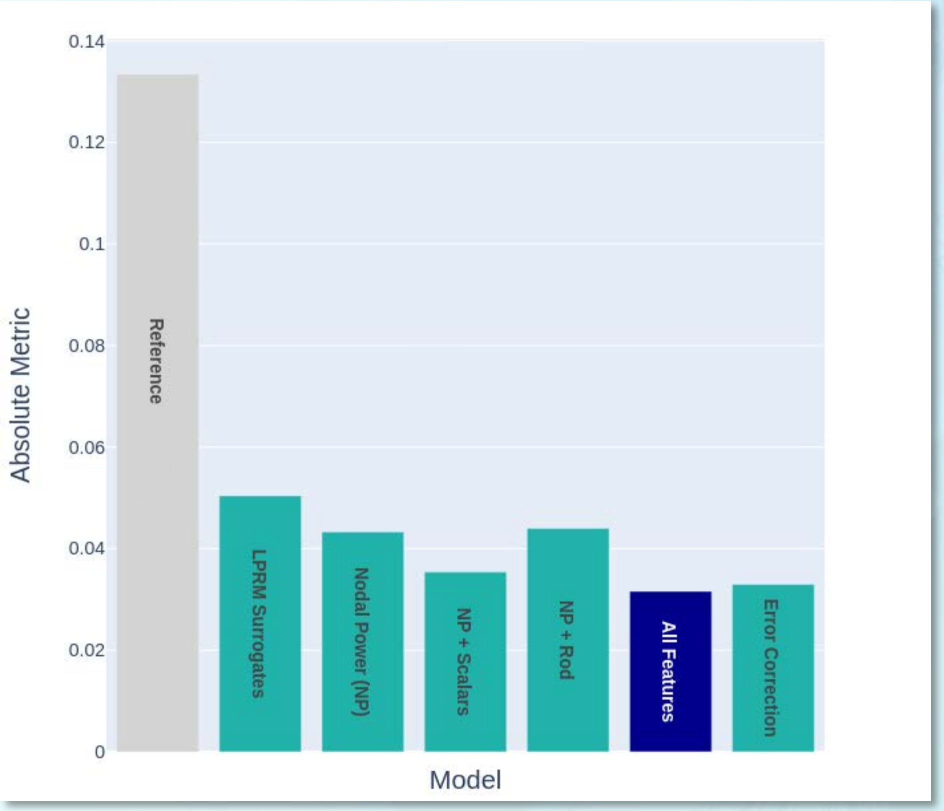


LPRM modeling accuracy

All modeling approaches show a 3x to 4x reduction in prediction uncertainty over the array of LPRMs



Substantial improvement near BOC and for new LPRMs
45% Bias for new LPRMs reduced to <1.5%



Error (in RMSE) averaged over all detectors over entire 2-year test period

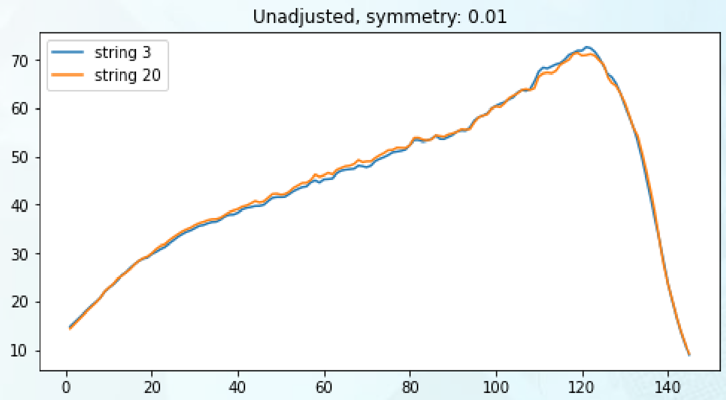
TIP Trace

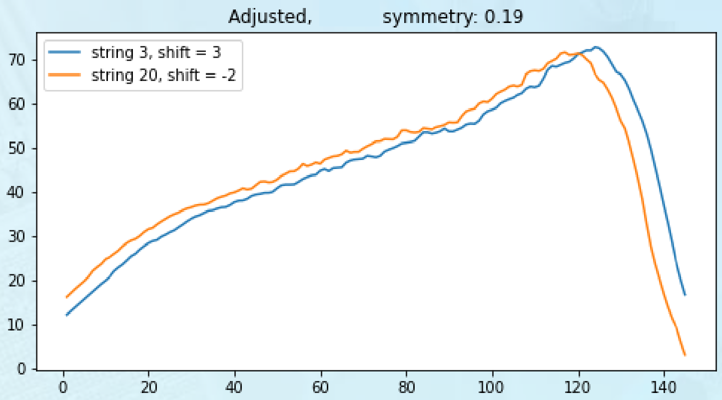
- Current methods require frequent LPRM recalibration via resource-intense TIP Trace process. Method is prone to inaccuracies in trace alignment.

Improved Trace Alignment

- More accurate LPRM calibrations
  → Improved power adaption
  → Improved thermal limits / margin

- Detection of anomalies
  → Increased visibility for Reactor Engineering

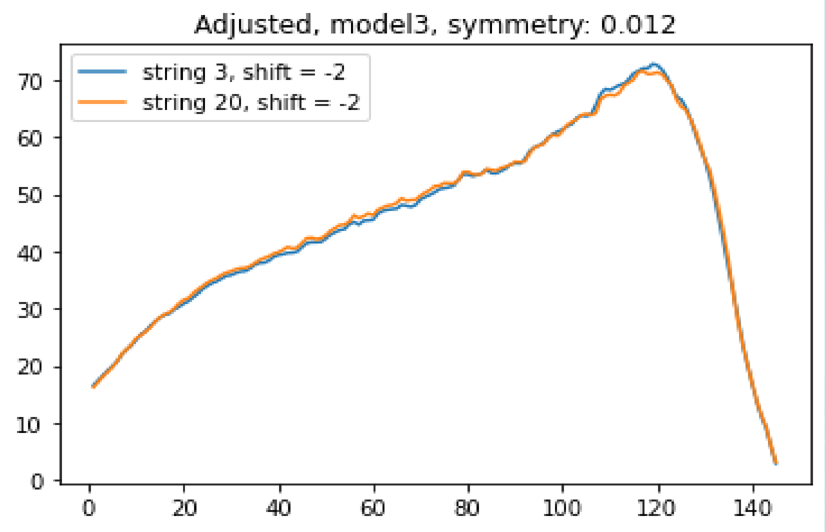




Current methods require physical recalibration every ~2 months due to drift (degradation).

Determined TIP trace shift is sometimes much too large, and alignment may be incorrectly applied or possibly discarded.

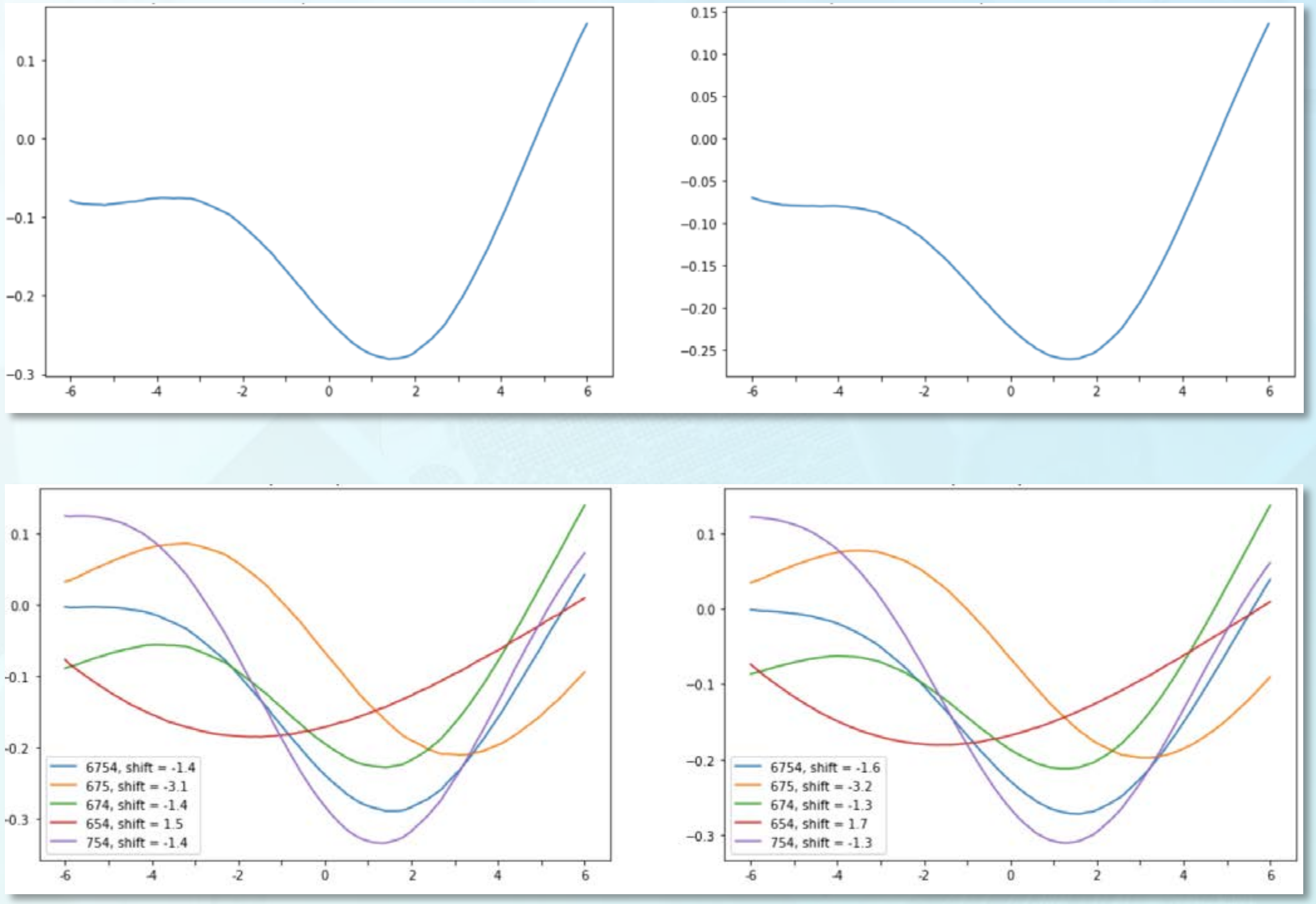
TIP adaption used for online power adaption



TIP Trace

Adaptable / Consensus

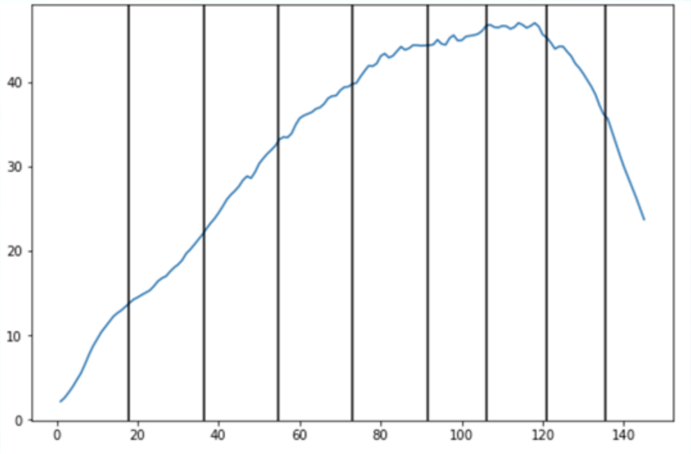
Subsets of trace convolutions produced and evaluated by BW Model



Improved Trace Alignment

- Polynomial fit within moving window
- Genetic algorithm optimization of convoluted ‘pulse’ shape (with spacing constraints)
- Consensus vote / weighting
  - → Prioritize spacer locations exhibiting the strongest signals

TIP Trace



TIP Trace Analysis

Station A

Historical Dataset contains 645 individual traces spread over 15 runs

Both methodologies agree on mean shift of -2.5 inches, with BW methodology having tighter spread

- 31 traces with ≥ |2σ| shift for CMS (~5% of traces)
- 12 traces with ≥ |2σ| shift for BW (<2% of traces)

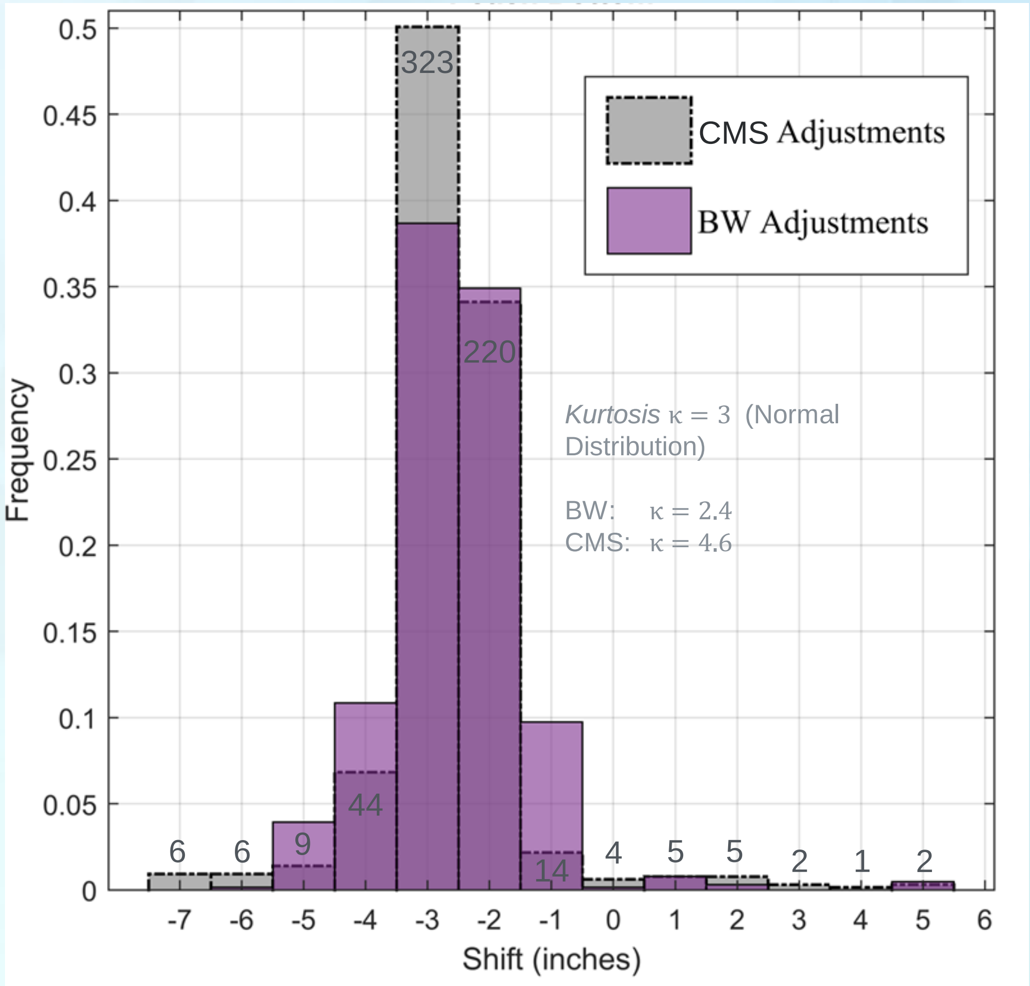
Most Problematic TIP Traces

Date	String	CMS	BW	delta
2020-10-13T11:43:33	40	5	-6	**11**
2021-03-15T10:21:07	40	7	-2	**9**
2021-09-02T11:42:50	32	3	-1	**4**
2021-08-09T10:28:59	24	4	1	**3**
2020-10-13T11:43:33	12	0	-2	**2**
2021-03-16T10:29:26	43	7	-4	**11**
2021-03-16T10:29:26	22	7	-3	**10**
2021-09-17T12:06:39	24	3	-4	**7**
2021-09-17T12:06:39	36	1	-4	**5**
2021-09-17T12:06:39	38	-7	-2	**5**
2021-03-16T10:29:26	40	-3	2	**5**
2021-09-17T12:06:39	6	2	-2	**4**
2021-09-17T12:06:39	17	2	-2	**4**
2020-10-16T12:03:36	8	-7	-3	**4**

Traces with the largest discrepancy between methodologies

	CMS	BW
Mean Shift	-2.57	-2.56
Std. dev	1.41	1.17
Shift		
-7	0.9%	0.0%
-6	0.9%	0.2%
-5	1.4%	3.9%
-4	6.8%	10.9%
-3	50.1%	38.7%
-2	34.1%	34.9%
-1	2.2%	9.8%
0	0.6%	0.2%
1	0.8%	0.8%
2	0.8%	0.3%
3	0.3%	0.0%
4	0.2%	0.0%
5	0.3%	0.5%

Statistics over all 645 traces at both Station A units



TIP Trace

Generating Station A

Most Problematic Tip Runs (as a set):

- **09/17/21 Unit 1**
- **08/03/20 Unit 2**

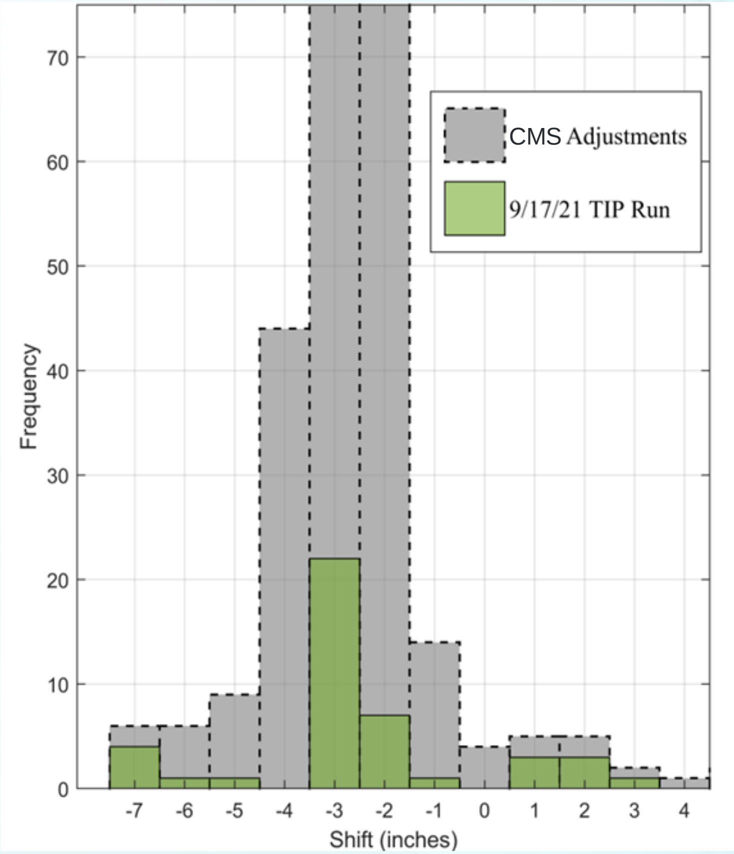
Unit 1

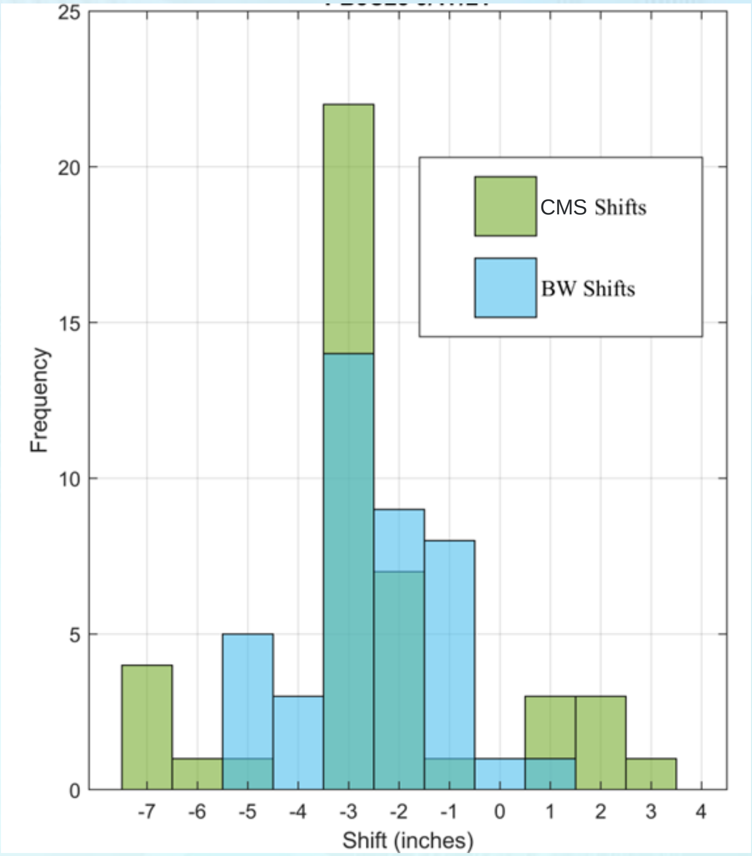
Date	Δ ≥ 2
2021-09-17T12:06:39	**42%**
2022-01-24T10:28:50	25%
2022-01-24T11:14:23	25%
2021-03-16T10:29:26	21%
2020-12-29T10:17:54	16%
2021-11-12T11:23:43	14%
2021-11-12T10:35:01	14%
2021-08-12T10:13:03	14%
2021-06-04T09:54:27	14%
2021-11-07T14:48:45	7%
2020-10-16T12:03:36	4%

Unit 2

Date	Δ ≥ 2
2020-08-03T12:09:34	**19%**
2022-01-04T11:37:30	14%
2022-01-04T10:41:49	14%
2021-09-02T11:42:50	9%
2021-03-15T10:21:07	9%
2021-08-09T10:28:59	7%
2020-10-13T11:43:33	7%
2021-06-03T10:00:16	5%
2020-12-28T10:59:54	5%
2020-11-17T04:47:15	2%
2021-10-20T10:34:12	0%

42% (13 out of 31) of the tails are from the 9/17/21 TIP run alone!





TIP Trace Impact on Thermal Limits

Most Problematic Tip Runs (as a set):

- **09/17/21 Station Unit 3**
- **08/03/20 Station Unit 2**

Unit 2

Date	Δ ≥ 2
2021-09-17T12:06:39	**42%**
2022-01-24T10:28:50	25%
2022-01-24T11:14:23	25%
2021-03-16T10:29:26	21%
2020-12-29T10:17:54	16%
2021-11-12T11:23:43	14%
2021-11-12T10:35:01	14%
2021-08-12T10:13:03	14%
2021-06-04T09:54:27	14%
2021-11-07T14:48:45	7%
2020-10-16T12:03:36	4%

Unit 3

Date	Δ ≥ 2
2020-08-03T12:09:34	**19%**
2022-01-04T11:37:30	14%
2022-01-04T10:41:49	14%
2021-09-02T11:42:50	9%
2021-03-15T10:21:07	9%
2021-08-09T10:28:59	7%
2020-10-13T11:43:33	7%
2021-06-03T10:00:16	5%
2020-12-28T10:59:54	5%
2020-11-17T04:47:15	2%
2021-10-20T10:34:12	0%

AR 04457675 Report Status: COMPLETE

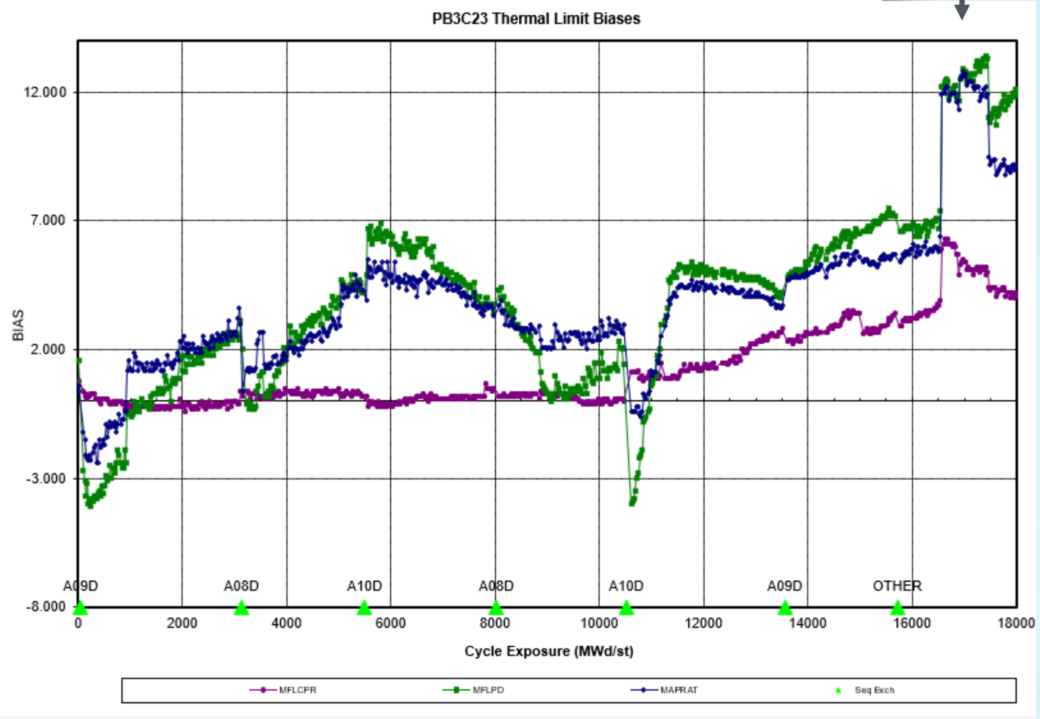
Due Date:	12/01/2021	Event Date:	11/01/2021	Origination Date:	11/01/2021
Affected Facility:	NUCLEAR CORPORATE SUPPORT	Affected Unit:	NOT APPLICABLE	Affected System:	NO SYSTEM IMPACT
AR Type:	NCAP	Owed To:	NUCLEAR FUEL EVAL	CR Level/Class:	4 / D
How Discovered:	TRENDING	WR:	---		

ACTION REQUEST DETAILS

Subject: High Thermal Limit Bias at Peach Bottom 3

Description: Originator:

Condition Description:
The MFLPD, MAPRAT, and MFLCPR bias was trending high at the end of PB3C23. Thermal limit bias is a ratio between the on-line core monitoring system thermal limits and the off-line exposure accounting model thermal limits. The MFLPD bias at the end of cycle reached the highest value of about 12%, the MAPRAT bias reached about 9%, and the MFLCPR bias reached about 5%. The MFLPD Bias has been higher than normal for recent cycles at Peach Bottom and it's largest near end of cycle (within 12-13%). The normal maximum MFLPD bias for other Exelon plants with GNF fuel has been approximately 6-8%. A high bias means that the thermal limits are higher than projected, however, since the bias is a known issue at Peach Bottom, it is accounted for during core design. This issue is being documented per NF-AA-100-1500.



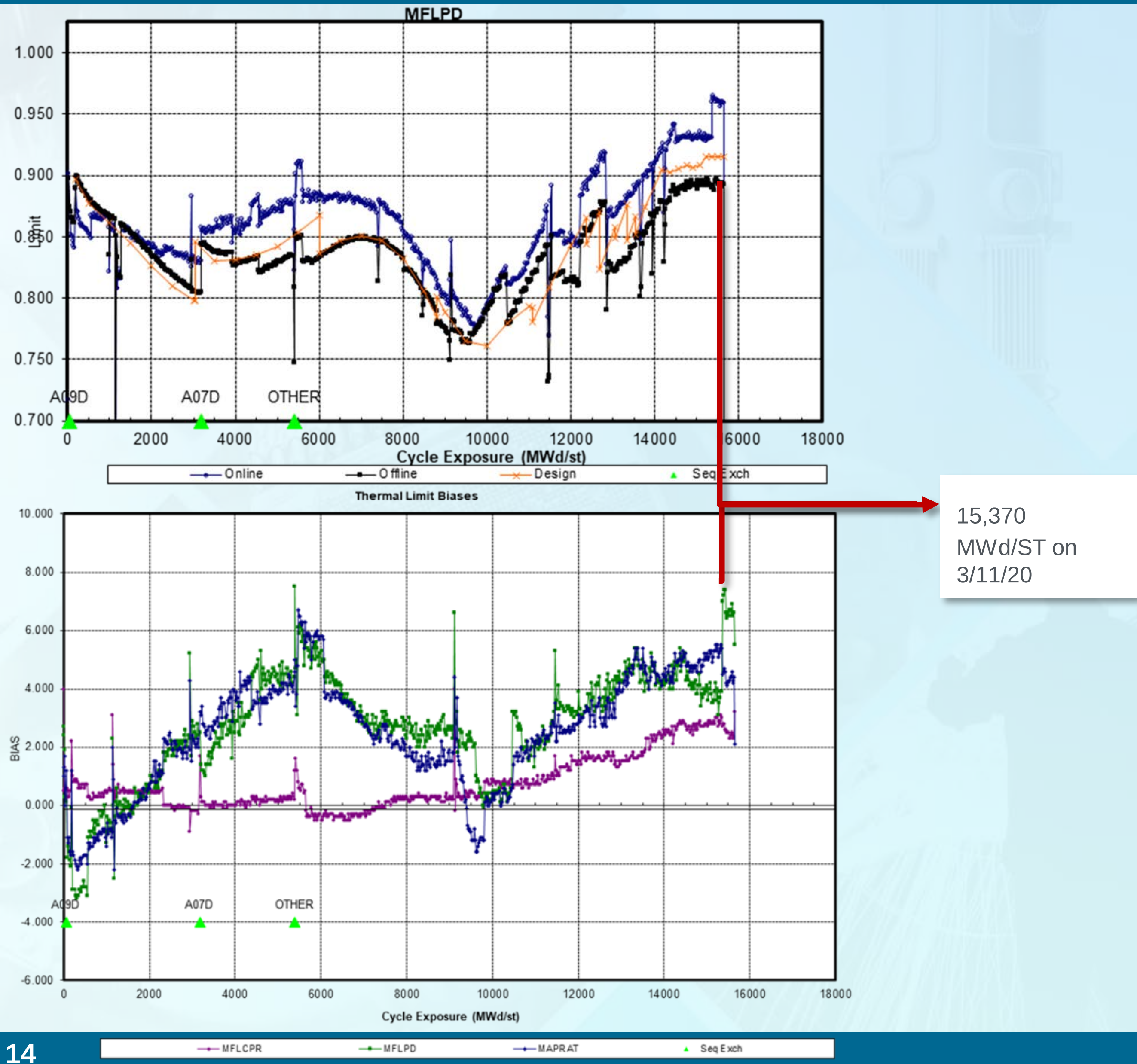
TIP Trace Impact on Thermal limits

Most Problematic Tip Runs (as a set):

- **3/11/20 1C18**
- **2/10/21 2C16**

Date	Δ ≥ 2
2020-03-11T09:41:02	**12%**
2021-06-01T16:20:46	9%
2021-10-21T11:38:20	7%
2021-10-21T08:39:49	7%
2019-07-02T08:57:19	7%
2018-08-01T09:24:03	7%
2022-01-27T12:50:30	5%

Date	Δ ≥ 2
2021-02-10T13:58:47	**13%**
2019-01-09T08:24:50	12%
2022-03-15T11:46:35	9%
2022-03-15T07:24:17	9%
2018-07-18T08:52:33	9%
2020-11-11T09:25:49	7%
2020-08-19T10:55:17	7%
2020-06-03T11:06:50	7%
2020-03-18T08:41:50	7%
2020-01-02T08:59:03	7%
2018-10-10T15:07:47	7%



Summary Remarks

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 (on-line)

- When individual LPRMs begin to exhibit erratic behavior
- When local behavior of core in vicinity of LPRM exhibits unexpected behavior (not predicted from all other LPRMs or symmetric partners)

Use Cases (off-line)

- During the Design Stage
- Improved predictability of on-line thermal limit

Concluding Remarks- Future Work

- Complete analysis of Remaining Useful Life data for LPRMs
- Reconcile exposure calculations
- Develop models of future exposure from LPRM models
- Nuclear News Article on LPRM and TIP results

- Technical Journal Article –Nuclear Technology on LPRM model details

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Thank You

Shift Delta Statistics

Unit C1 (990 Samples)						
Model	$\|\Delta\| = \mathbf{0}$	$\|\Delta\| = \mathbf{1}$	$\|\Delta\| = \mathbf{2}$	$\|\Delta\| = \mathbf{3}$	$\|\Delta\| \geq \mathbf{4}$	Total
BW	0.65	0.27	0.07	0.01	0.0	1.0

Unit A1 (387 Samples)						
Model	$\|\Delta\| = \mathbf{0}$	$\|\Delta\| = \mathbf{1}$	$\|\Delta\| = \mathbf{2}$	$\|\Delta\| = \mathbf{3}$	$\|\Delta\| \geq \mathbf{4}$	Total
BW	0.49	0.43	0.06	0.0	0.01	0.99

Unit A2 (258 Samples)						
Model	$\|\Delta\| = \mathbf{0}$	$\|\Delta\| = \mathbf{1}$	$\|\Delta\| = \mathbf{2}$	$\|\Delta\| = \mathbf{3}$	$\|\Delta\| \geq \mathbf{4}$	Total
BW	0.36	0.43	0.12	0.02	0.05	0.98

$\Delta \equiv$ difference between BW and CMS shift values.