FY'23 – FECM Spring R&D Project Review

Award FE0032035 – Predictive Analytics for Thermal Power Plants

SPS DATA FUSION

April 19, 2023

Agenda

- Who is on the Team?
  - ✓ **Project team**
  - ✓ **Advisors**
- Brief overview
  - ✓ **Project review – background of the project**
  - ✓ **Strategic value**
  - ✓ **Advisor input & feedback**
- What’s been done so far?
  - ✓ **Understanding the Data**
  - ✓ **Machine Learning Models**
  - ✓ **Weibull Model**
  - ✓ **Machine Learning Model Validation**
- SPS Perspective & What’s Next
- Questions???

The Project Team

- ✓ Omer R. Bakshi - Project Manager
- ✓ Andrew Kinsel - Contract Specialist

Project Leadership, Data analytics & Support, IT

- ✓ Sal DellaVilla – CEO & Principal Investigator
- ✓ Bob Steele – Vice President IT
- ✓ Tripp DellaVilla – Sr. Project Manager & Business Analyst

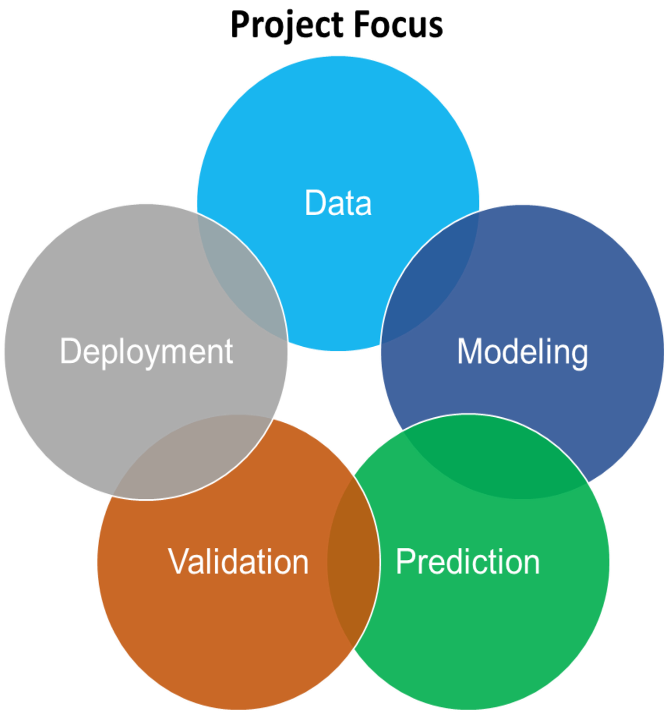
Project Management, Support, and Engineering

- ✓ Chris Perullo – Directing & Supporting technical input & providing SME for modeling & Weibull Analysis
- ✓ Scott Sheppard – Data Analysis
- ✓ Steven Koskey – Data Analysis

Data Analysis and AI/ML Model Building Capability

- ✓ Edgar Lara-Curzio– Leadership
- ✓ Matt (Sangkeun) Lee – RAM Data & Machine Learning
- ✓ Olivera Kotevska – RAM Data & Machine Learning

Roles & Responsibilities



- SPS
  - ✓ Provide project direction & leadership
  - ✓ Provide ORAP data expertise & expectations
  - ✓ Engage Owner/Operators – Participation
  - ✓ Sensitivity analysis, validation and verification
  - ✓ Deployment strategy
- Turbine Logic
  - ✓ Lead ORNL effort
  - ✓ Develop strategy for processing synthetic events
  - ✓ Develop Weibull & simulation model - Python
  - ✓ Prepare for deployment
- ORNL
  - ✓ Refine ML model
  - ✓ Create synthetic events (Unit & technology focused)
  - ✓ Support Weibull modelling
  - ✓ Recommend deployment options – Migrate from HPC

Advisors

- Rick Tomlinson, Chevron Pipeline & Power
- Don Haines, PPOMC
- Steve Worthington, Arizona Public Service
- Ed Fuselier, Kindle Energy – Retiring, No longer active on the Board

A Review – Background of the Project

- Project work initiated under 2 HPC4Mtls Projects: Performed by NETL & ORNL teams

- Extend the research results beyond the proof-of-concept phase
  - Including verification and validation testing
  - With direct support and collaboration from operating power plants

- Rely on the field data that is available for use in the ORAP® (Operational Reliability Analysis Program®) database
  - Historical Time Series Data to a component level
  - Near Real-Time Process Data (sensor quality process data points)

- Data Fusion: **To benefit operating plants**
  - <u>Not remote monitoring</u> & <u>Not the Digital Twin</u>
  - Reduced plant disruptions – impact of changing service demand (operating flexibility)
  - Understand the impact of more challenging duty cycles (cyclic), readiness for green fuels (H2)

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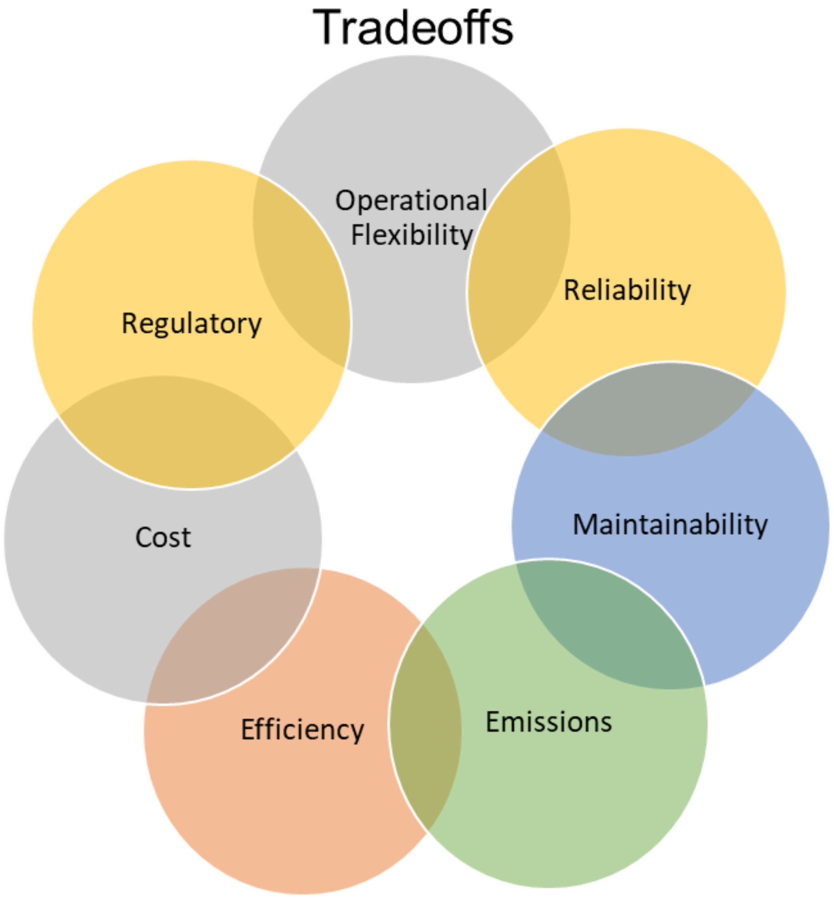
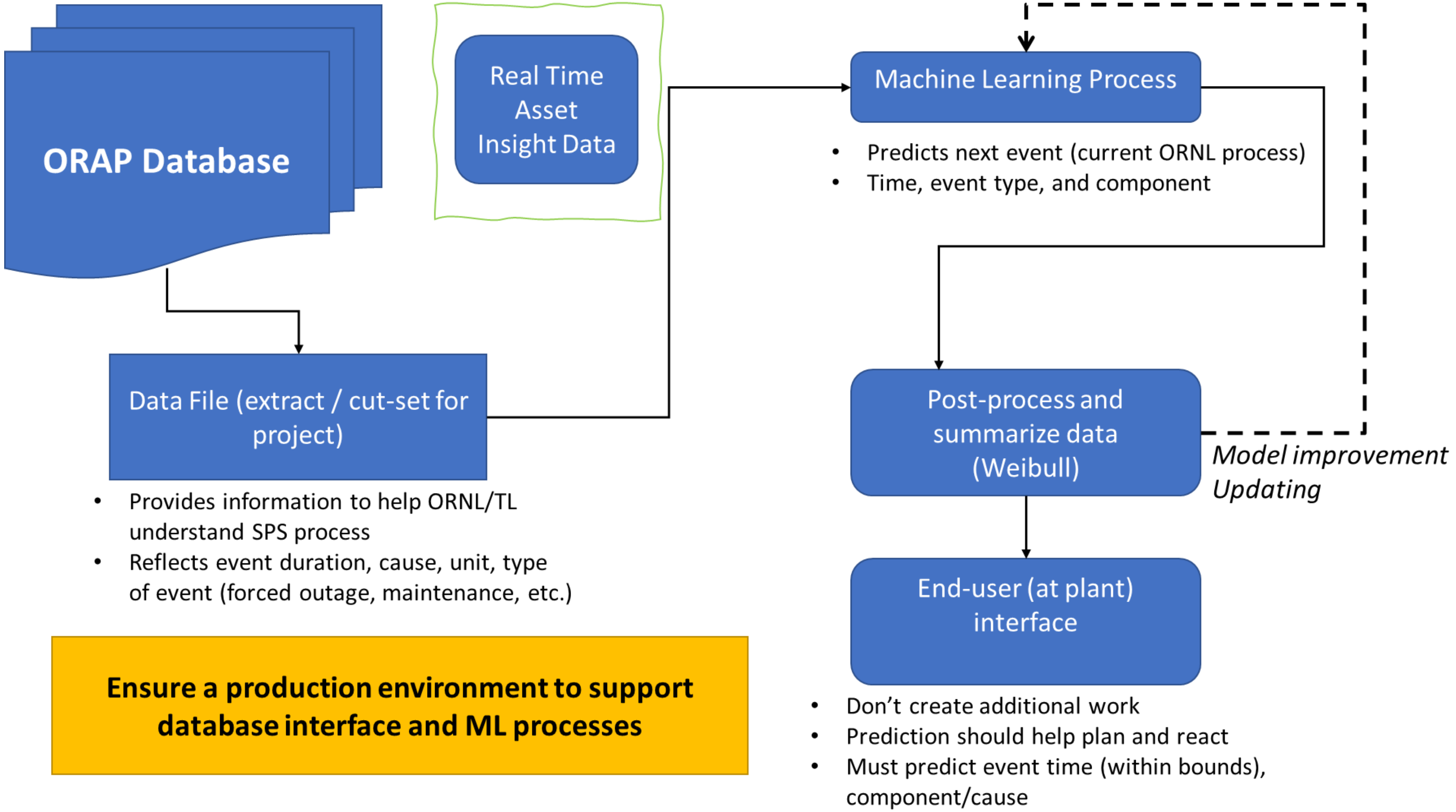
Challenges Facing Plant Operators

- Responding to Faults During Plant Lifecycle
- Anticipating and Reducing the Impact of Impending Failures
  - ✓ Complex technology & total plant
- **Predicting** Plant Events & Outage Durations (Cost)
  - ✓ How quickly can we look back at data for analysis, use and decision-making?
  - ✓ M&D (Monitoring & Diagnostics) Evolved to mitigate OEM (Original Equipment Manufacturer) risks… not to be predictive



What’s the big picture?

Fit into existing workflow and tools



Ensure a production environment to support database interface and ML processes

Strategic Value

- It is important to recognize that the owner/operator (Asset Manager) **already have an abundance of technical and operating knowledge, with lots of data at their fingertips**; experience and expertise that, for many, results in “best in class” performance

- The intent of FE0032035 is not to replicate or replace what already works in the Asset Manager’s best interests, rather, its purpose is **to fill a large gap** providing something that **they don’t currently have and that they absolutely need**

- Asset Managers are concerned with **what is going to prevent their operating plant from fulfilling its operating “mission” now**

- They are concerned about issues/events that **they are not expecting to happen**, and when they do happen, **how long it will take to recover and at what total cost**

- The value is to predict the adverse behavior of physical systems, components, materials, and designs with **sufficient time and guidance for cost effective corrective action at the plant**

    - **What, and when, is the next significant event?**

Advisor input and feedback

- **Safety** – not putting people in harm’s way is critical to operations.
- Consider the **operating envelope** – can we safely extend outside of the operating envelope
- More automation **less human input** – “Self Sufficient”
- Application needs to be **pragmatic** – it needs to integrate into current practices and be easily useable, not be a totally new workflow
- M&D good at telling you things that are degrading, but **real challenge is one-off events**
- Since we are providing probabilities of failure, will want to **watch out for “false positive-type”** situations for the one-offs
- Need to be sure to **consider downstream components** – especially equipment that may be shared across units at the plant, such as boiler feed pumps that may be shared among two HRSGs

Understanding the Data is Key

- ORAP RAM (Reliability, Availability, and Maintainability) is a **complex** dataset that tracks plant operational, performance, and event data

Pedigree information	*Events*
• Unit characteristics that can influence performance/risk of failure (e.g., fuel types, duty ... includes plant arrangement and applications • Characteristics may change over time (e.g., turbine gas path upgrades, inlet cooling)	• List of outage events • Start and end time • Outage duration • Type of event (forced, maintenance, planned) • Thousands of component codes • Ability to filter to events of interest
Operations	*Age*
• Periodic operational data (nominally monthly) • Useful for identifying impact of short time scale ... • Large dataset	• Cumulative age at the end of each period • Time at temperature (fi... (starts/trips from load) • Used for assessing life consumption • Useful for assessing likelihood of certain events versus long time scales

What They Are

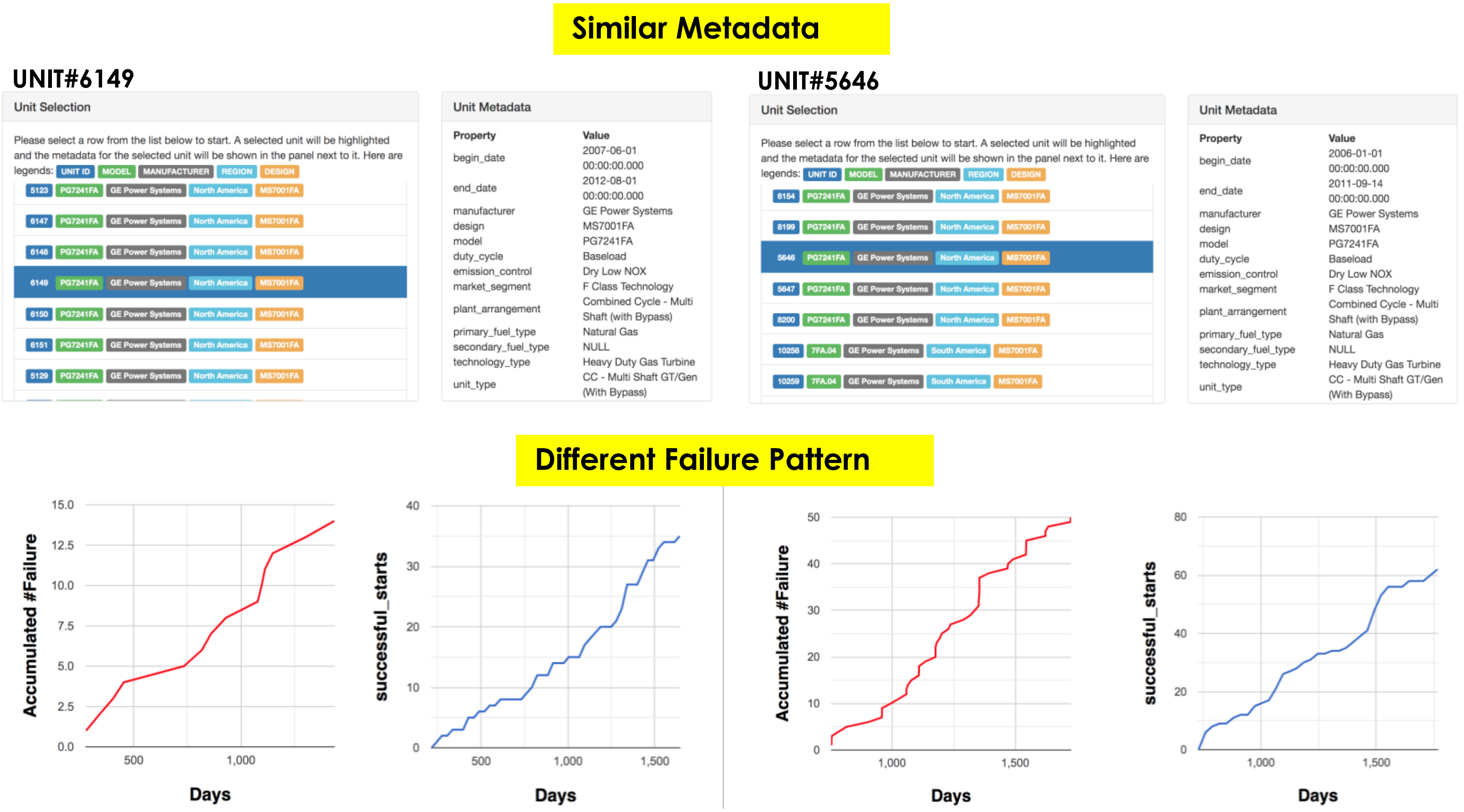
What Happened

How Operated (in the last period)

How Old

Understanding the Data is Key (cont'd)

- Similar units can show different failure pattern
- How can we learn from historical failures of many units?



ML: Independent yet Synergistic Approaches

- **<u>Approach 1:</u>** Failure Trend Forecasting Model (Major System)
  - ML Process – Random Forest
  - Provides pattern of how failures accumulated over time
  - Leads to a set of failure predictions
  - At the Major System Level
- **<u>Approach 2:</u>** The Next Failure - Equipment Code Prediction Model
  - ML Process – Long Short Term Memory (LSTM)
  - LSTM chosen because it captures the temporal dependencies in the dataset
  - Predicts the Equipment Code at the Next Failure
  - At the Component Level

Machine Learning: Data Preprocessing

- Focus on Historical Failures
- Filter out Unnecessary Data

Pedigree (What They Are)

Event (What Happened)

Age (How Old)

Operation (How Operated)

Joined Data

Filtered & Joined Data

Join Key = Unit Key

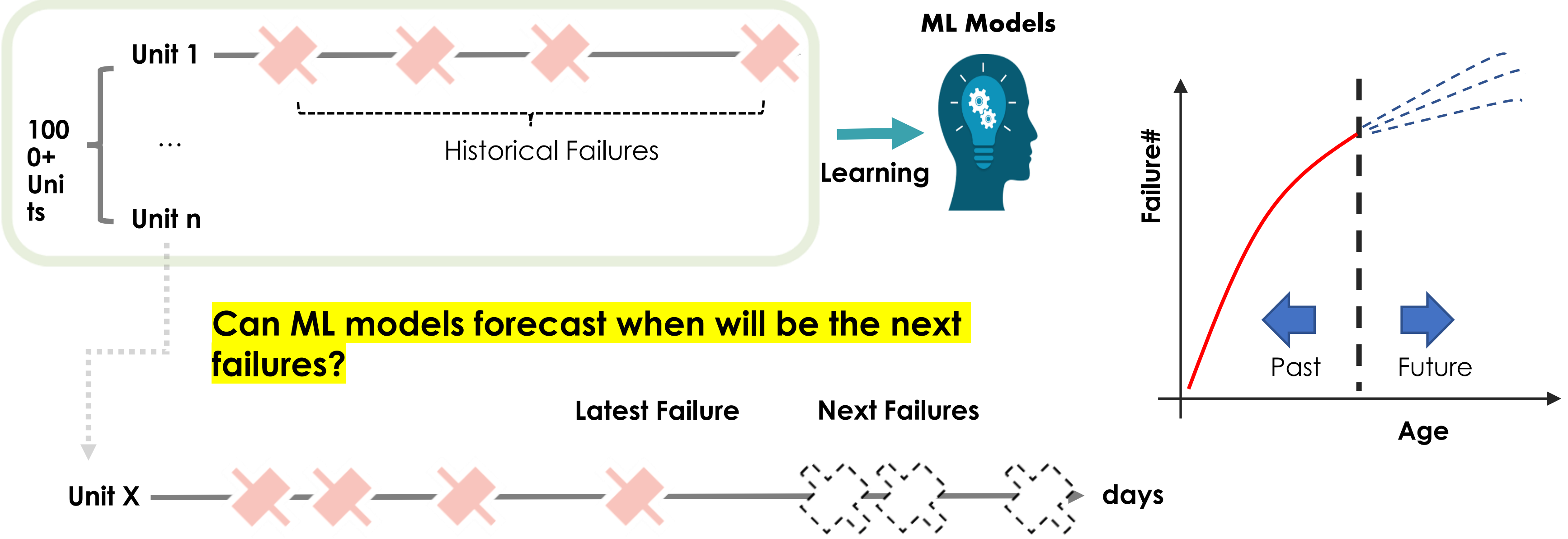
Approach 1: Failure Trend Forecasting Model (Major System)

Approach 2: The Next Failure - Equipment Code Prediction Model

```
dataset_event = dataset_event[dataset_event.event_type_description != 'Non-Curtailing']
dataset_event = dataset_event[dataset_event.equipment_code != 'SENEEC']
```

ML Approach 1: Failure Trend Forecasting

- **Failure (**unplanned disruption of unit operation) can lead to reduced service hours and revenue loss

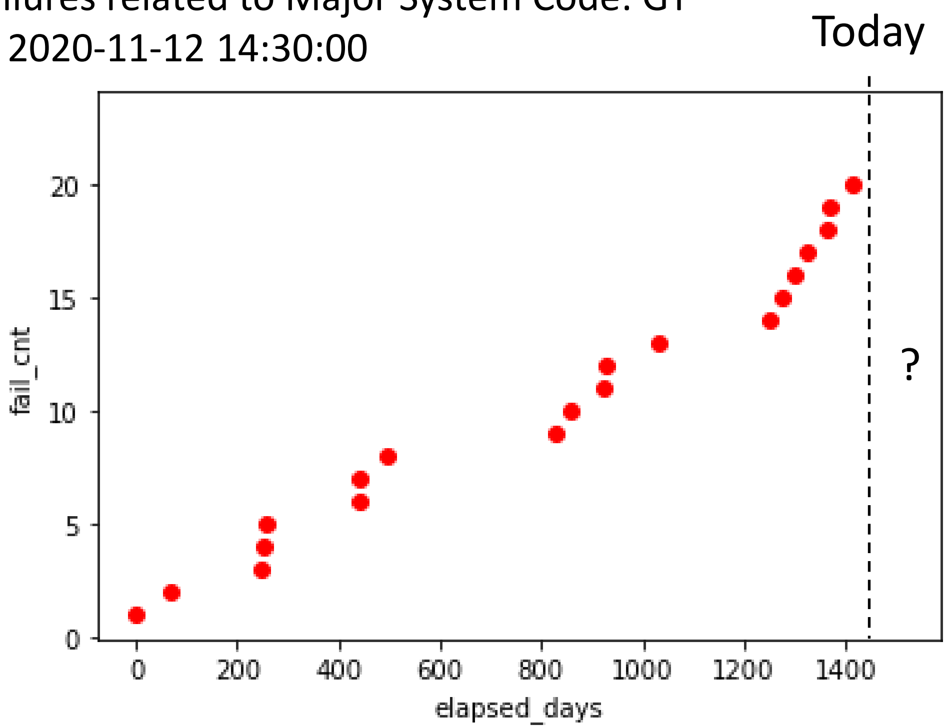


- **Objective:** predicting the trend of the cumulative # of failures for the next n days (e.g., 120 days)

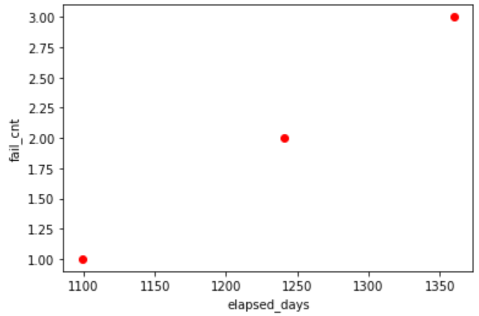
ML Approach 1: Failure Trend Forecasting (cont'd)

- A Closer Look

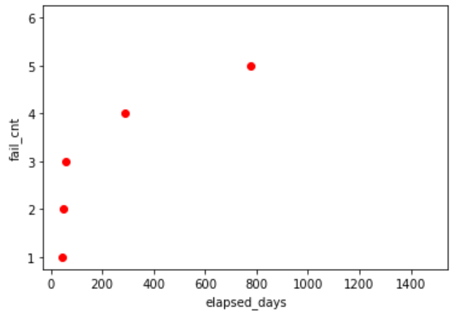
Unit KEY: 430401541200133934917
Failures related to Major System Code: GT
at 2020-11-12 14:30:00



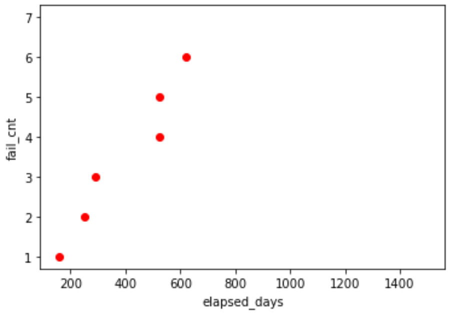
Major System Code: HR



Major System Code: GN



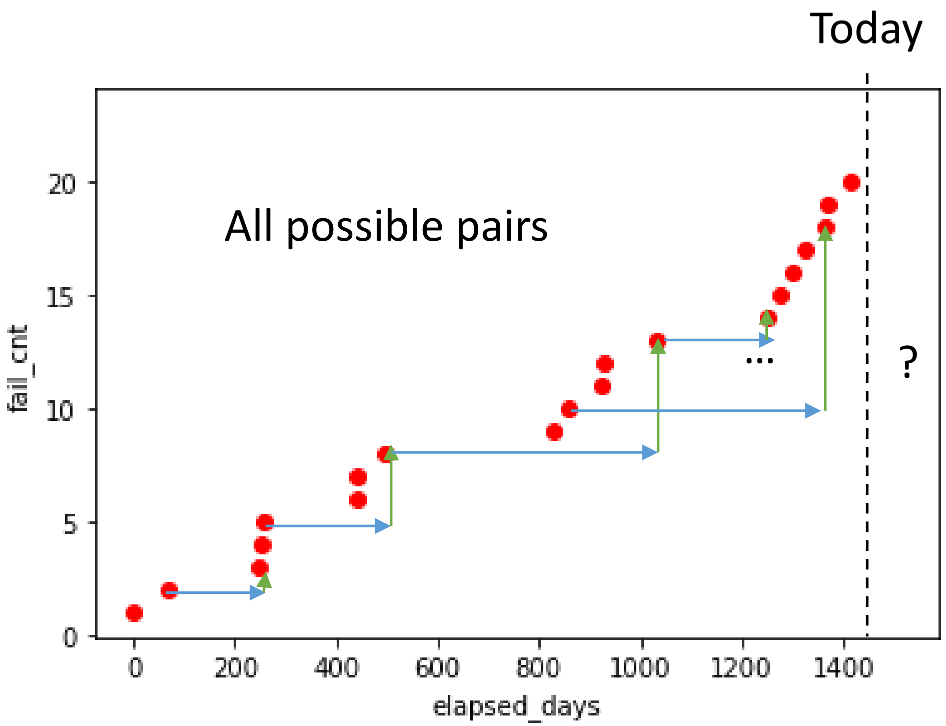
Major System Code: SE



- Continuing work from the previous HPC4Materials project
  - In the last project, we predicted trend of total cumulative failure count, but we need to look at failures in more detail (i.e., which major system is related)

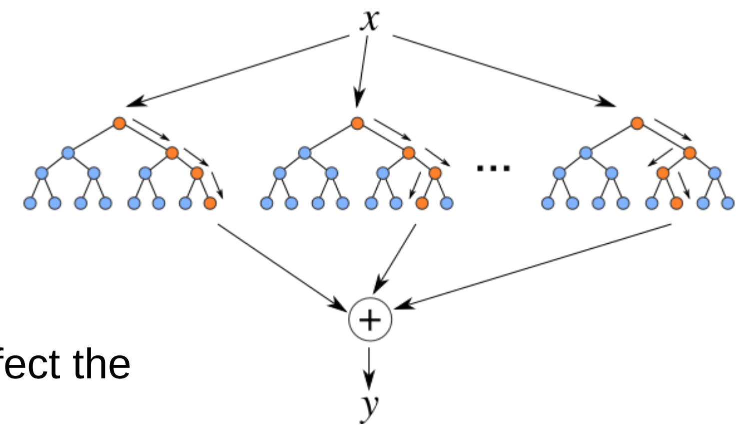
ML Approach 1: Failure Trend Forecasting (cont'd)

- **Getting the data ready:** Generating many datapoints (X, y) from historical data to train ML models



X:
Unit Metadata (plant unit count, maximum capacity, etc.)
ΔAge (# of starts, hours, etc.)

y:
ΔFailure (# of failure increased)



- We train ML models to learn how Age/Ops/Unit data affect the increases of failure counts

- We used Random Forest regressor model with empirically selected set of age, ops, unit data variables

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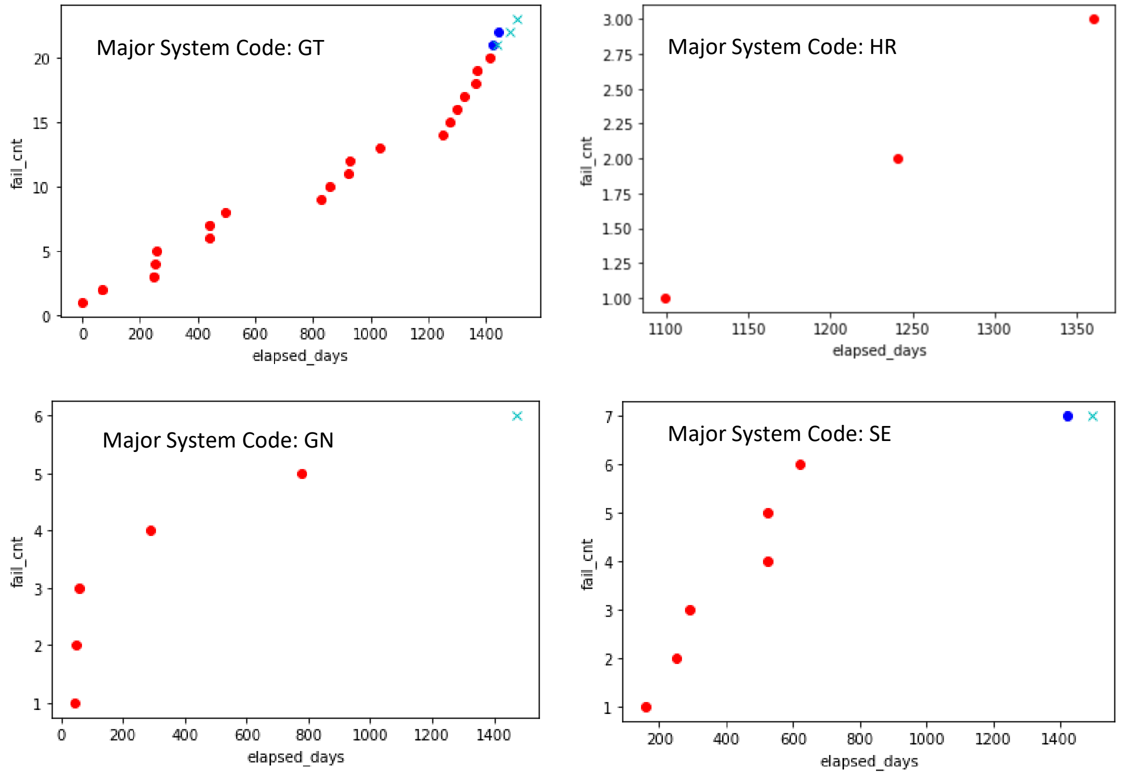
ML Approach 1: Failure Trend Forecasting (cont'd)

Results using 80% of Data for training/20% of Data for validation
Prediction for the next 120 days



Red : Failure Data Included for Training
Blue : Failure Data not included for Training for validation
Cyan: Prediction from the model

Hyperparameter tuning of ML model is required

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ML Approach 2: Equipment Code Prediction

- **Approach 2 focuses on a different problem**
  - This approach only focuses on **predicting what EQUIPMENT CODE** will be related to the next failure event?
  - ***Classification* problem**
- vs. Approach 1
  - The models learn from the whole data not filtered data
  - The models learn from the sequences of events (Train with LSTM)
- Reorganizing the data for Approach 2

EQUIPMENT CODE at the next failure (not available at the time, so we predict this)

Long short-term memory (**LSTM**) is an artificial recurrent neural network (RNN) architecture[1] used in the field of deep learning **(DL)**. LSTM can process not only single data points, but also entire sequences of data

ML Approach 2: Equipment Code Prediction (cont'd)

Example Predictions: Generate ranking of equipment codes with likelihood at each level of Equipment Hierarchy

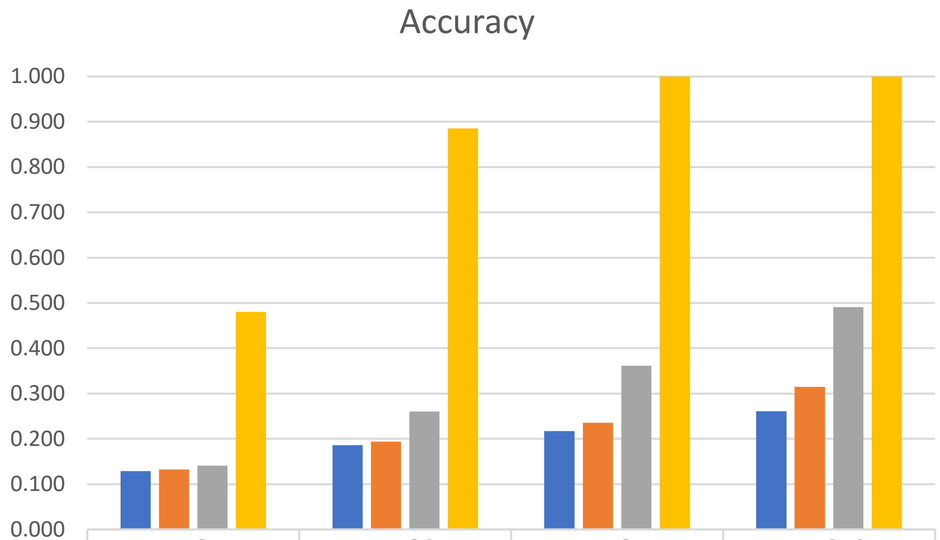
Major System Answer: HR		
1	GT	0.45914
2	HR	0.31367
3	SE	0.12327
4	GN	0.1038

System Answer: HRFH		
1	HRFH	0.20429
2	GTCT	0.074
3	GTLO	0.04898
4	SEPD	0.04437
5	GTFP	0.04152
6	SEG1	0.03705
7	GTGF	0.03592
8	GTCP	0.03398
9	HRRH	0.02863
10	GNGL	0.02535

Component Group Answer: HRFHEV		
1	HRFHEV	0.20087
2	GTCTSF	0.03393
3	GTCPIC	0.03236
4	SEG1IC	0.02696
5	GTLOFL	0.02528
6	GTFPPI	0.02474
7	GNGLFL	0.02248
8	GTGFIC	0.02016
9	GTLOPC	0.01914
10	GTIAFS	0.01905

Component Answer: HRFHEV312		
1	HRFHEV312	0.20087
2	GTCTSF001	0.02975
3	GTLOFL231	0.02528
4	GTFPPI	0.02474
5	SEG1IC166	0.02469
6	GNGLFL231	0.02248
7	GTIAFS441	0.01905
8	GNGHIC	0.01616
9	GNGNSR	0.01565
10	GTCPIC001	0.01410

Machine Learning Approach 2: Equipment Code Prediction Model (cont’d)



	HR@1	HR@3	HR@5	HR@10
C:	0.129	0.186	0.217	0.261
CG:	0.132	0.194	0.235	0.315
S:	0.141	0.260	0.361	0.491
MS:	0.481	0.885	1.000	1.000

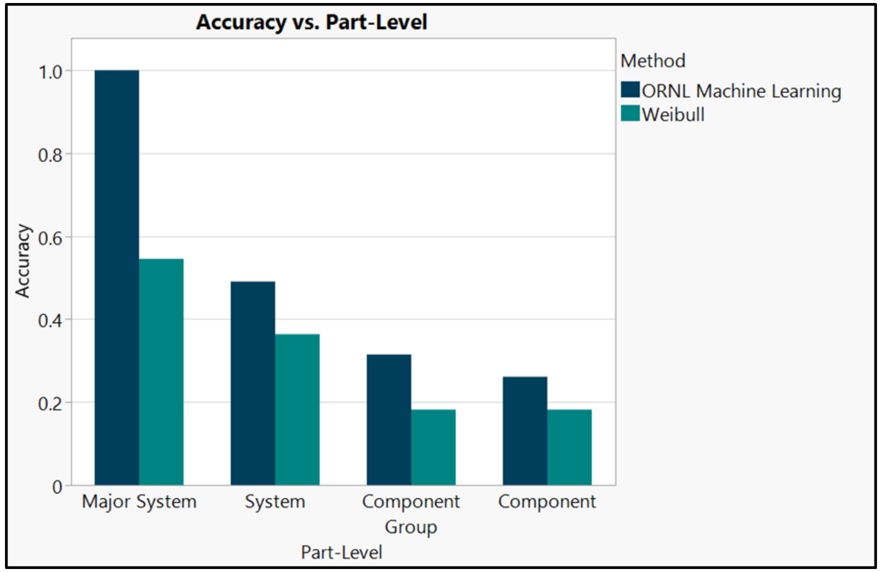
C: CG: S: MS:

- What does ***accuracy*** mean?
  - When the model says the next failure will be related to a C/CG/S/MS, how likely that to be correct
  - Measured by Hit Ratio @k
- Hit Ratio (HR) @ k means the ratio of getting the right answer within the Top k ranking list
  - The chance of Top 10 list will contain the correct system code is 49% *(It’s a challenging problem)*

Hyperparameter tuning of ML model is required

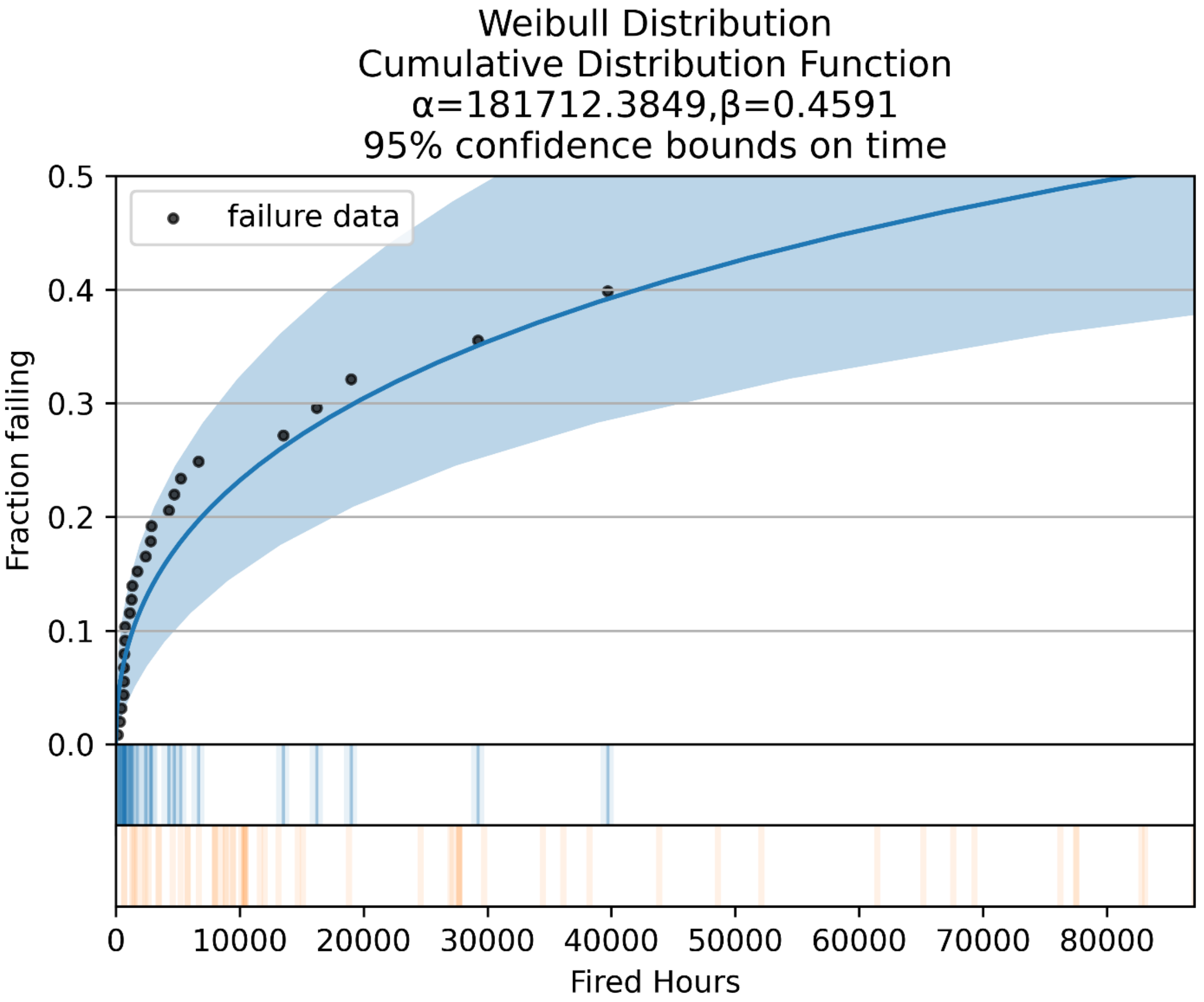
Weibull Sensitivity Analysis (Validation)

- A Weibull model was made for each equipment code in the ORAP database
- For each plant, the machine learning model developed by ORNL and the conventional, Weibull model were used to predict the next 10 highest risk events based on each model.
- There is an improvement in predictive accuracy using the machine learning approach developed.



Weibull Distribution: ***Thermocouple Exhaust Temperature***

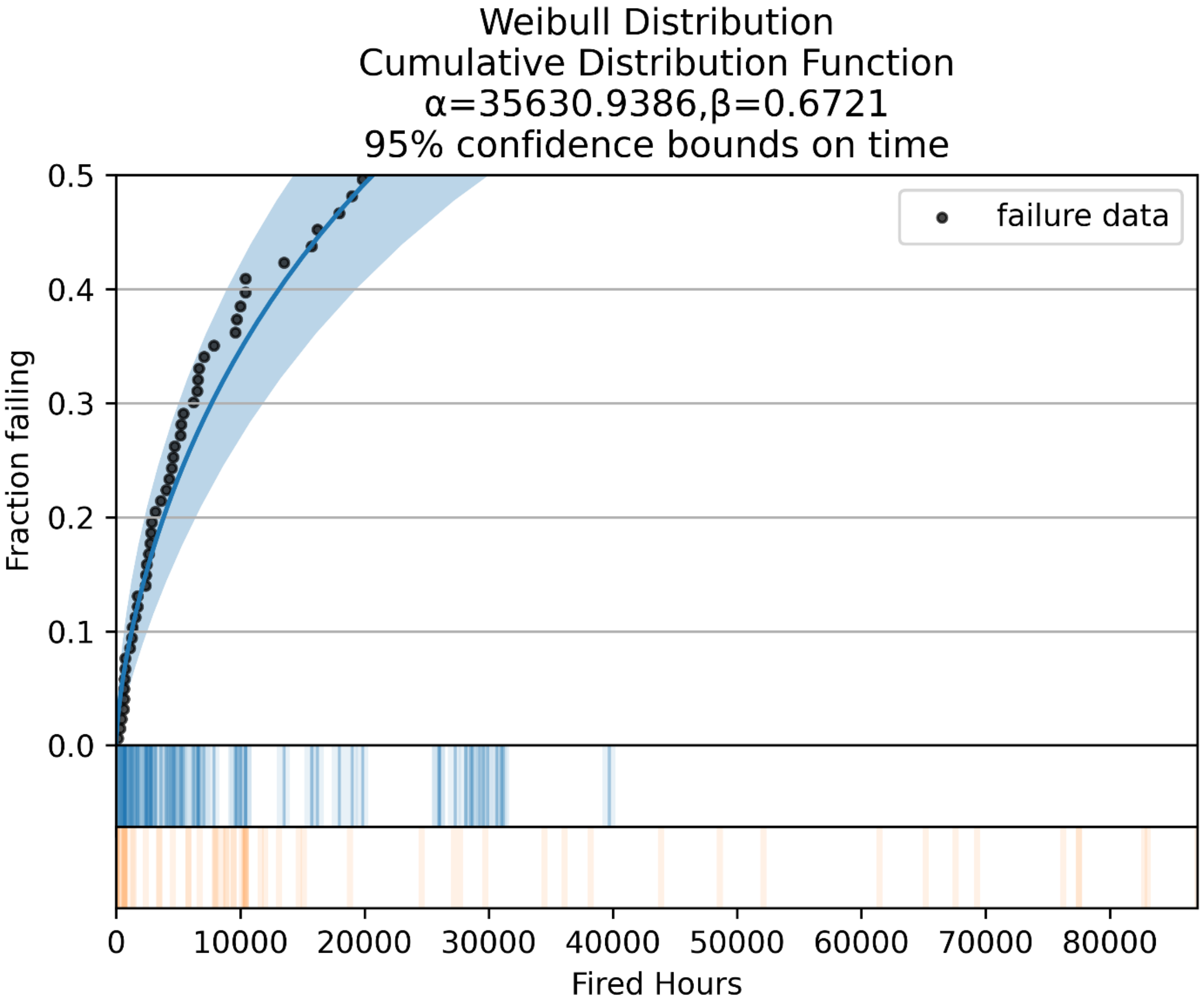
- Includes all forced outages for this equipment code
- Weibull reflects the forced outage history
- Why does the Weibull apparently under-predict at low fired hours?
- *ML can help inform the model*



(*since last forced outage for this equipment code*)

ML-Informed Weibull: Thermocouple Exhaust Temperature

- Supplemented the forced event dataset with ORNL's ML predictions
- ML predictions look reasonable
  - *ML captures the trend we saw*
- This Weibull better fits the forced outage data
  - *outliers are better accounted for*



(since last forced outage for this equipment code)

ML Model Validation

- ML Model was run with 3 time periods for a fleet of units
  - The time periods represent addition of new data to the previous sample:
    - Period from 1/1/2010 to 8/2/2022
    - Period from 1/1/2010 to 10/11/2022
    - Period From 1/1/2010 to 2/1/2023
  - Each time period was also run for different groups of downtime event types:
    - All Downtime Events
    - All Scheduled Maintenance Events
    - All Unscheduled Maintenance Events
    - All Forced Events
    - All Trips from a state of operation
  - Each sample was run 10 times on different PC Hardware

ML Model Validation (Cont'd)

- Validated the models are consistent and repeatable:
  - Models return the same results with a statics sample regardless of when the model run and on what hardware.
- Reviewing clearly shows value is in prediction of Unplanned Events: Forced Events and Trips from Operation.
  - Planned Events are scheduled and are deterministic & Forced Events are probabilistic and 'random'.
  - How maintenance is performed influences forced outages, value is to identify next likely failure so it can be mitigated.
- How model predicts based on the fleet experience vs individual unit operations is weighted too much to the fleet

ML Model Improvements

- Validation has identified specific items necessary for operating in a production environment, including:
  - Current version of the model has data set ‘filters’ hardcoded – this needs to be driven by the model input
    - Equipment being included in model (e.g. Heavy Duty Frame Units v Aero-derivative Units)
    - Exclusion of specific causes of outages that are not equipment related (e.g. lighting strikes)
  - Need to update the starting point for predicting trends based on ‘current data’ for unit, currently model utilizes one date for all units in sample.
  - Need to tune models to weight individual unit operations more

SPS Perspective

- ML process (Macro modeling) –
  - Maximizes use of times series & curated data available in ORAP
  - Uses ‘fleet and unit” specific data to derive patterns, trends, and predictions
  - ORNL two approaches (Random Forest & LSTM) provide independent but correlative evaluation of results
  - Does not require re-initialization as equipment changes are made (Major Benefit)

- APR process (Micro modeling) –
  - Focused on a unit not a fleet (not even a group of units)
  - Need robust analog sensors across systems and components
  - Sensor data is independent – Requires strong SME
  - Does not predict – it infers

- ML forewarns ahead of APR

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What’s Next?

- ORNL to complete work on the ML models including:
  - Hyperparameter tuning
  - Incorporating updates/improvements that have been identified during review and validation
- Incorporate Event Duration Distributions with ML Results
- Field test ML Models at ORAP Participants when the ML Model updates are incorporated
- Production & Plant – Development of User Dashboards

Questions?

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