Automating Detection and Diagnosis of Faults, Failures, and Underperformance in PV Plants

Applications of AI/ML

Scott Sheppard, Turbine Logic
Lead Engineer – Renewables Monitoring

Daniel Fregosi, Wayne Li, EPRI
Kamran Paynabar, Georgia Tech

Solar Applications of Artificial Intelligence and Machine Learning
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The Problem…Using Available Data to Full Potential

- Large plant may have “10s” of inverters
- Limited sensor data available to detect DC side faults

- Each Inverter contains 10s to 100s of Combiner Boxes
- Each CB may have current and voltage measurements
- <u>Can be used for diagnostics – not typically used today</u>

Can we couple physics-based modeling and AI to better detect and localize string level faults?

Motivation

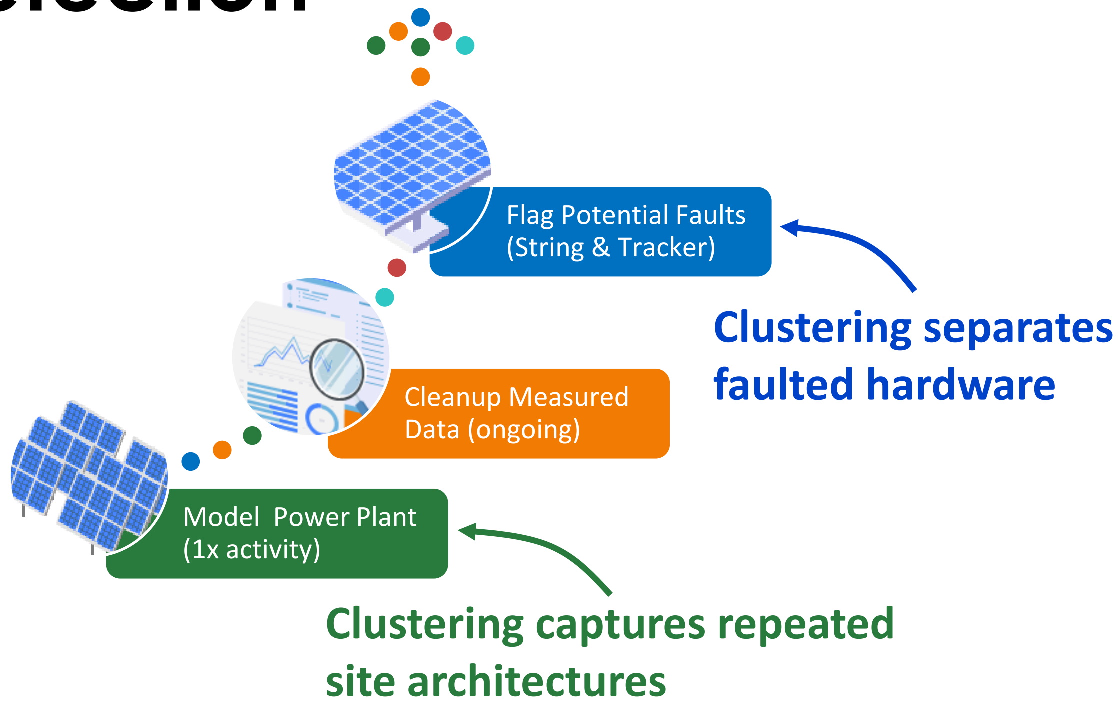
- **Goal:** Provide a better diagnostic solutions with fewer false alarms and actionable M&D insight
- Subtle failures across the DC collector field often go undetected for large amounts of time
  - Determining the source of the failure is time consuming
  - Aerial inspections
    - Performed to detect small-scale faults across the DC collector field
    - Are typically performed infrequently
    - Current gold standard
- Model-driven approach uses big data available at PV sites enables real-time detection
  - Improves ability to detect faults while reducing presence of false alarms
  - Improves ability to locate faults to more specific hardware components
  - Provides further aid in diagnosing cause of underperformance

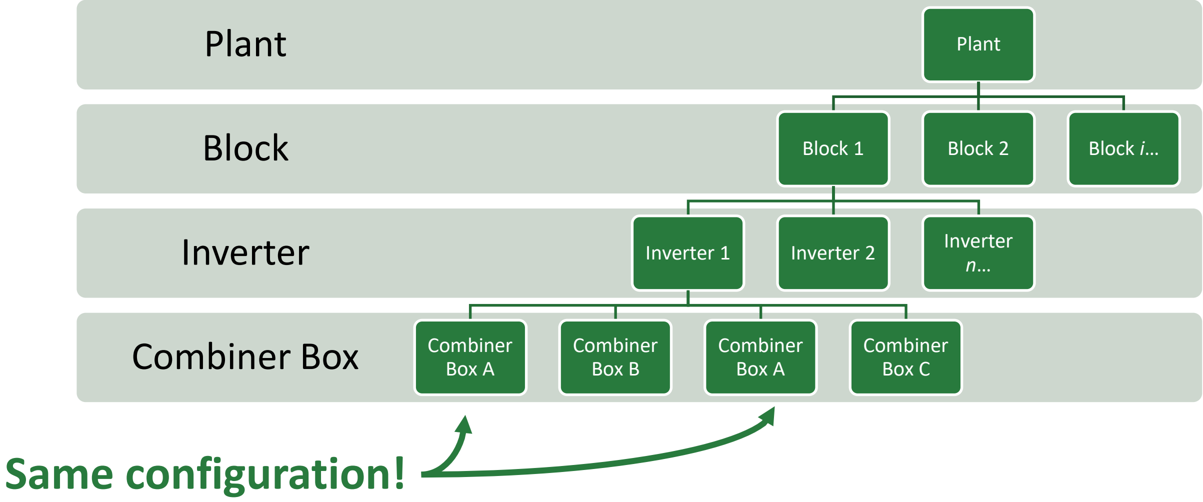
M&D centers have abundant data available, how can it better be used for detection of subtle faults?

Modeling Approach – Fault Detection

Physics-based models coupled with AI to identify failed string and tracker outages

- ML/AI used to determine repeated hardware configurations through plant
  - Enables automatic setup of plant layout, reducing time spent by 90%
- Fault detection driven by feature extraction of measured and modeled signals



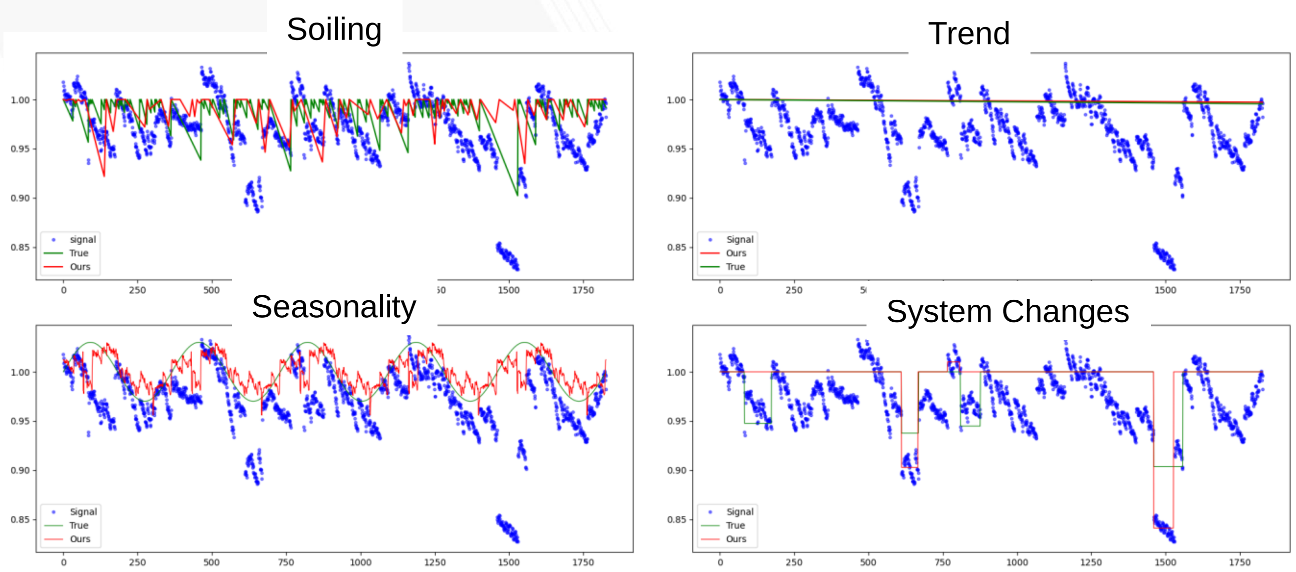


Sensitivity	TPR	FPR	F1
High	65%	19%	0.57
Med	49%	10%	0.54
Low	36%	7%	0.46

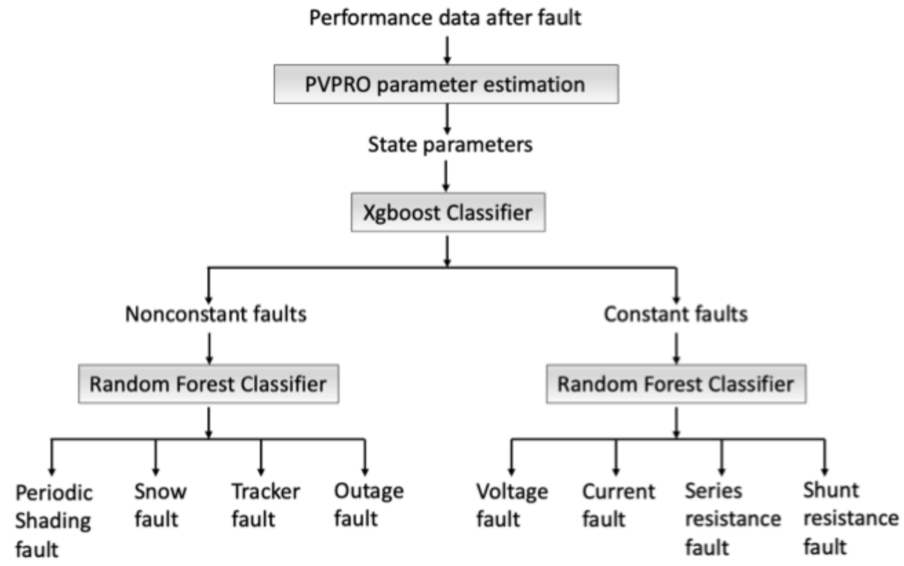
Tunable detection algorithm allows user to tailor results to personal needs.

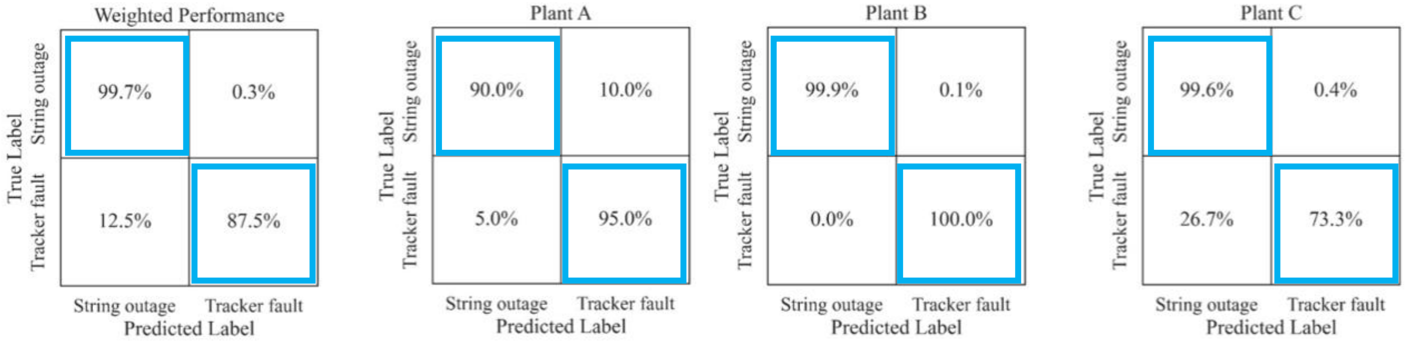
Modeling Approach – Fault Diagnosis

Decomposition-based approach integrates optimization and dictionary learning to decompose signals



Functional PCA, Xgboost, and Random Forest were used to diagnose the fault type.





Methodology enables accurate classification of DC-side faults typically only detected through aerial scans.

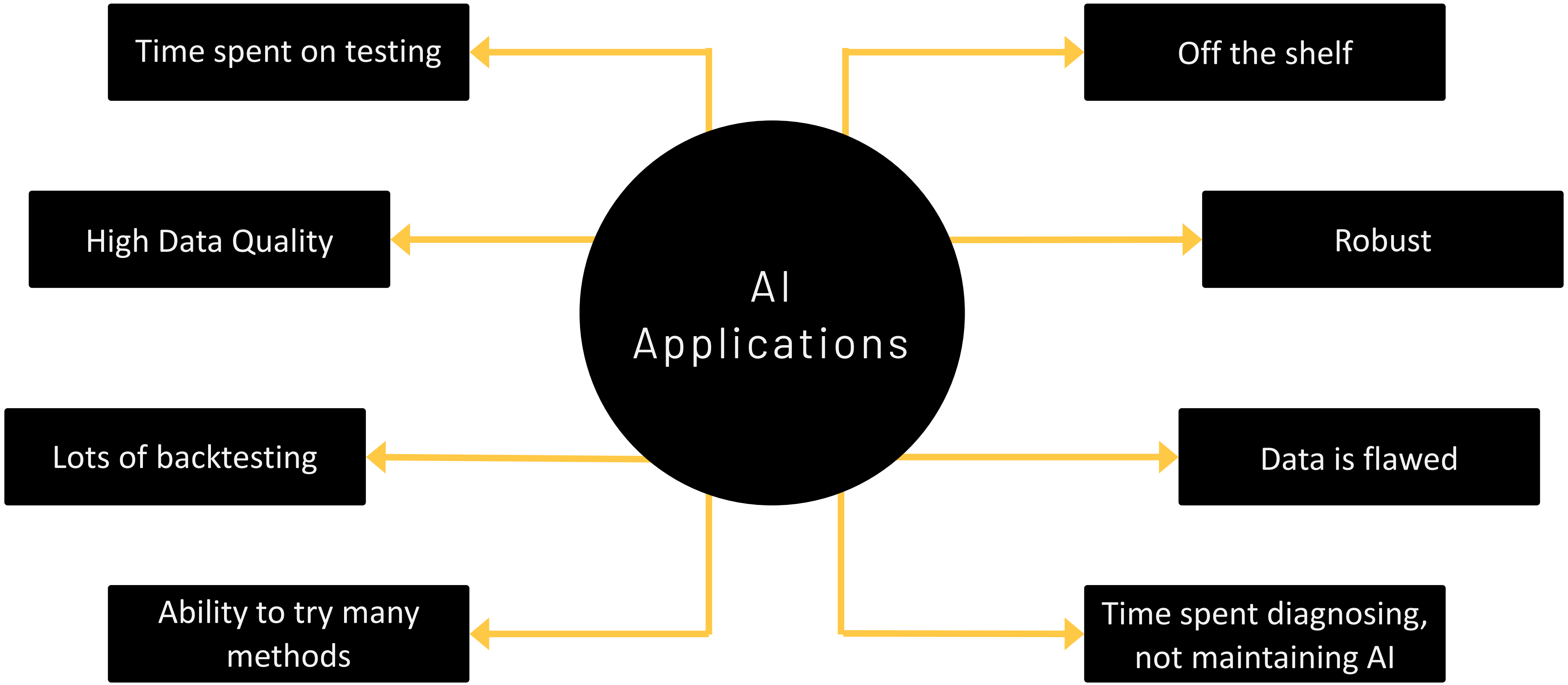
Georgia Tech
CREATING THE NEXT

OTHER APPLICATIONS OF ML/AI IN POWER GENERATION

RESEARCH VS INDUSTRIAL APPLICATIONS

RESEARCH

INDUSTRY



SETO funding and industry partners have allowed us to focus on solutions that work for industry.

Which Tool?

What are the problem features?

Time dependent?

Must run in real-time?

Must update automatically?

Performance Benchmarking

- Recurrent Neural Networks
- Autoencoders
- Bayesian Regression
- Probabilistic Forecasting

Anomaly Detection

- Dynamic Linear Models
- Auto-associative Neural Networks
- Bayesian Hypothesis Testing

Fault Detection and Diagnosis

- Bayesian Networks
- Xgboost
- Random Forest

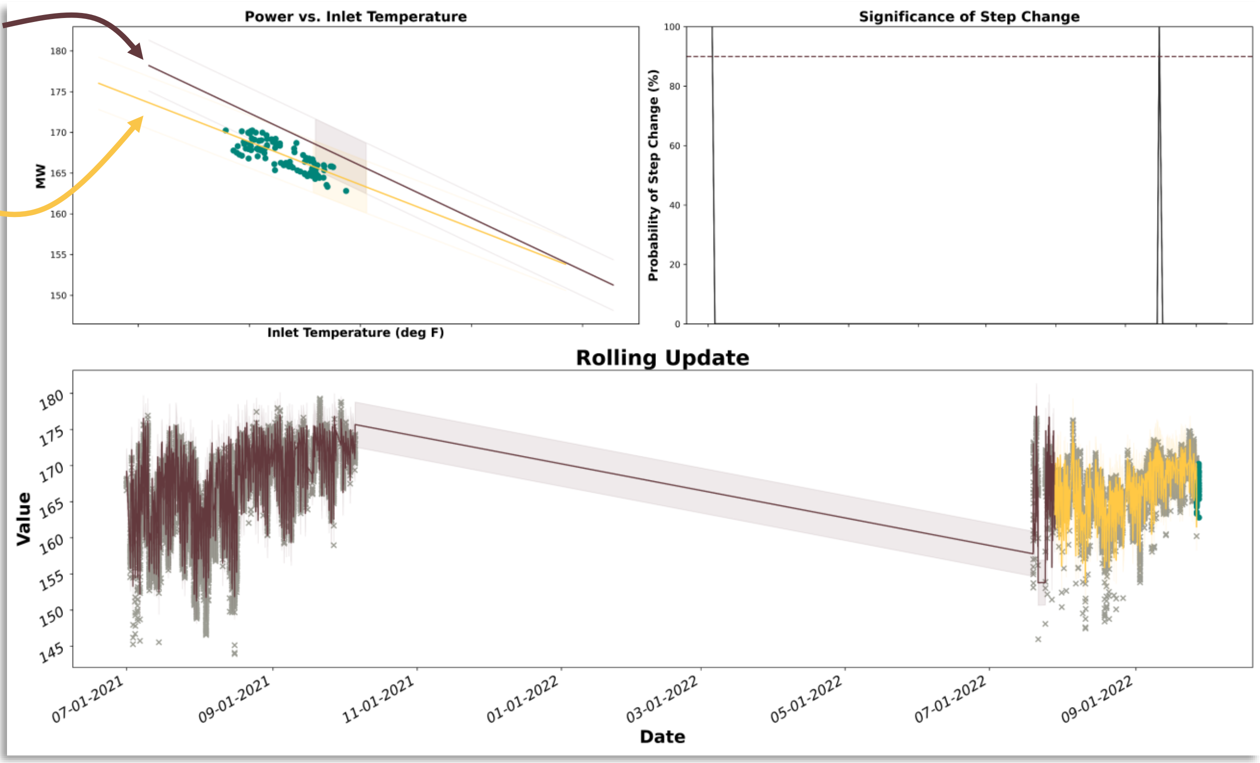
Forecasting

- Artificial Neural Networks
- Uncertainty Quantification
- Uncertainty Propagation

ANOMALY DETECTION

Original model

New model

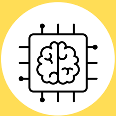


Model is constantly evaluating new data, checking for significant changes

After an outage, the model quickly recognizes that new data belongs to a new trend and automatically retrains itself

PROBLEM

Identify faulted equipment



TECHNIQUE

Dynamic Linear Model
Digital Twin

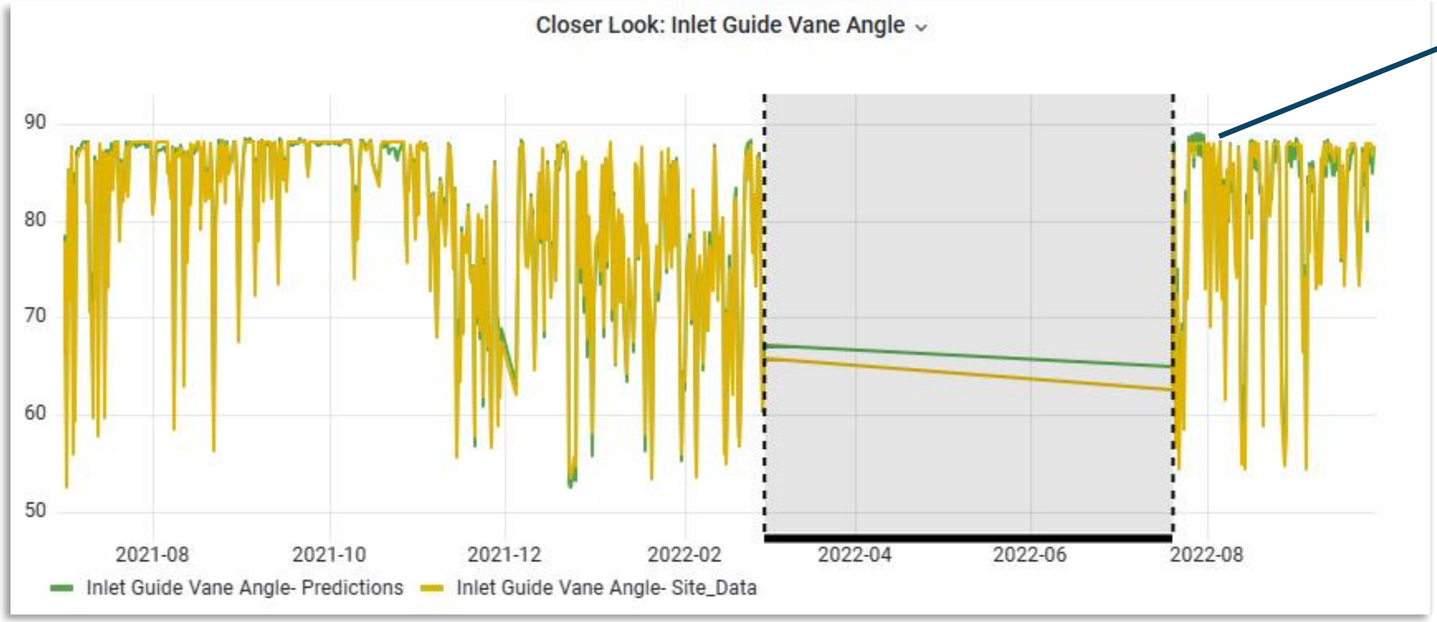
CHALLENGES

Noisy data
Incomplete data
Every site has different data

LESSONS

Automatic trending
Automatic thresholding
Flag items to look at

OUTAGE PERFORMANCE BENCHMARKING



PROBLEM

Quantify outage impact
Benchmark future outages

TECHNIQUE

Recurrent Neural Network
Autoencoder
Digital Twin

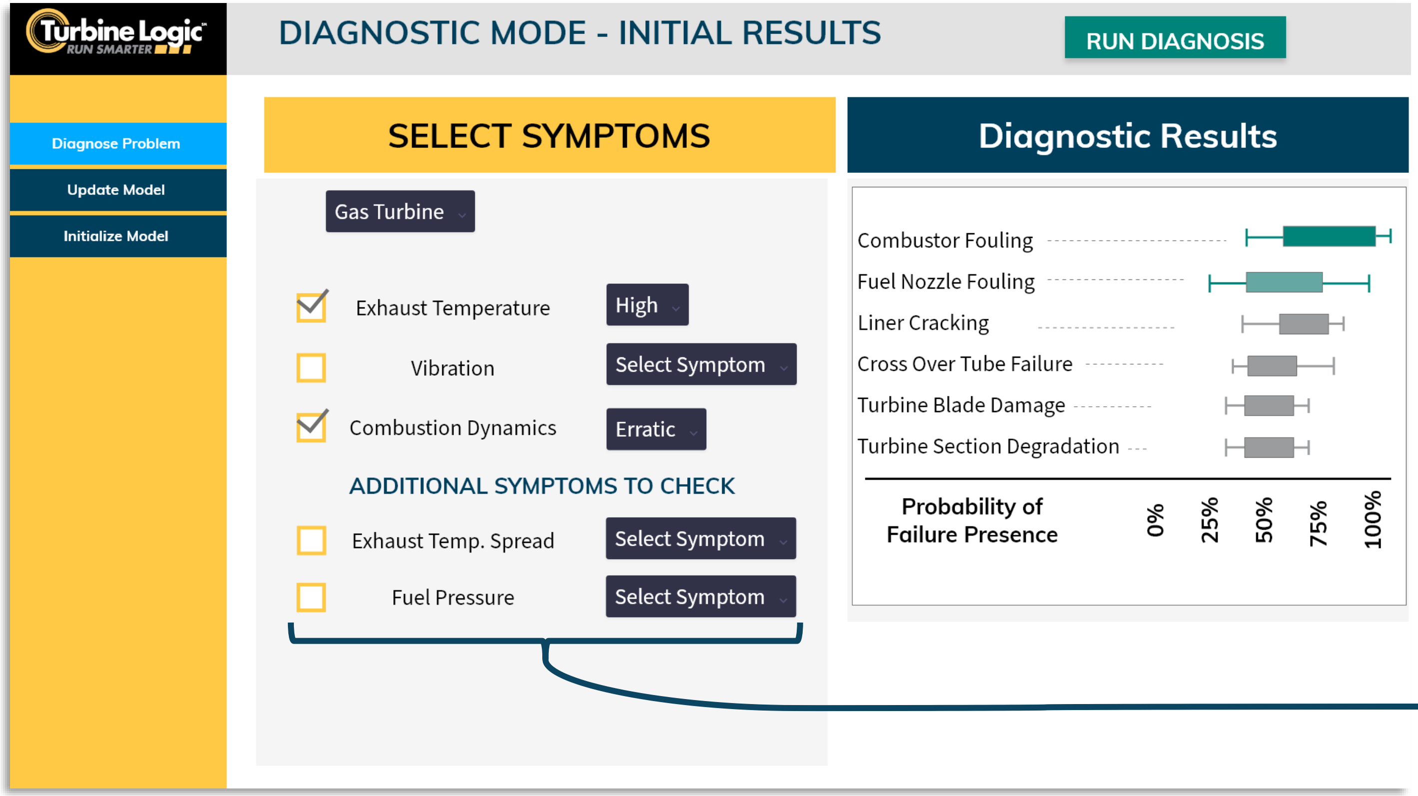
CHALLENGES

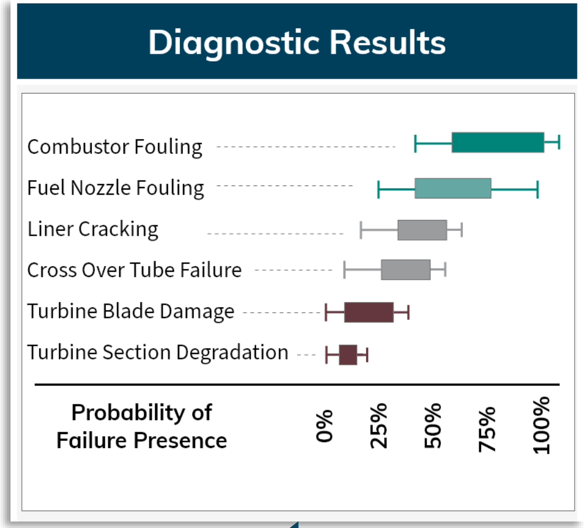
Ambient conditions are cyclic
Some changes are expected

LESSONS

Flag items to look at
Automatic training

VIRTUAL EXPERT





Intelligent prompts for additional observations refines diagnoses

PROBLEM

Identify faulted hardware
Knowledge retention

TECHNIQUE

Bayesian Belief Network

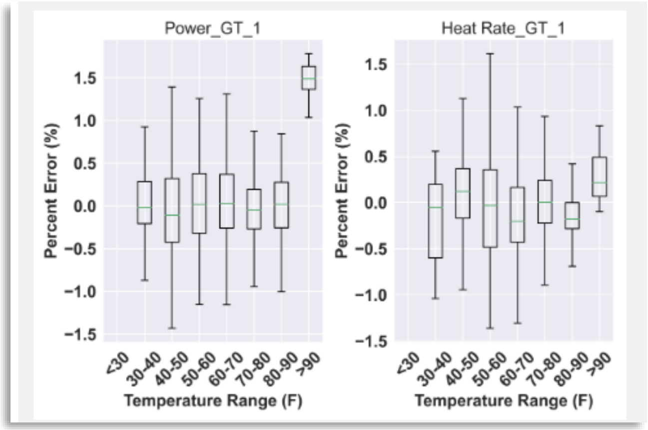
CHALLENGES

Non-centralized failure logs
Sparse data

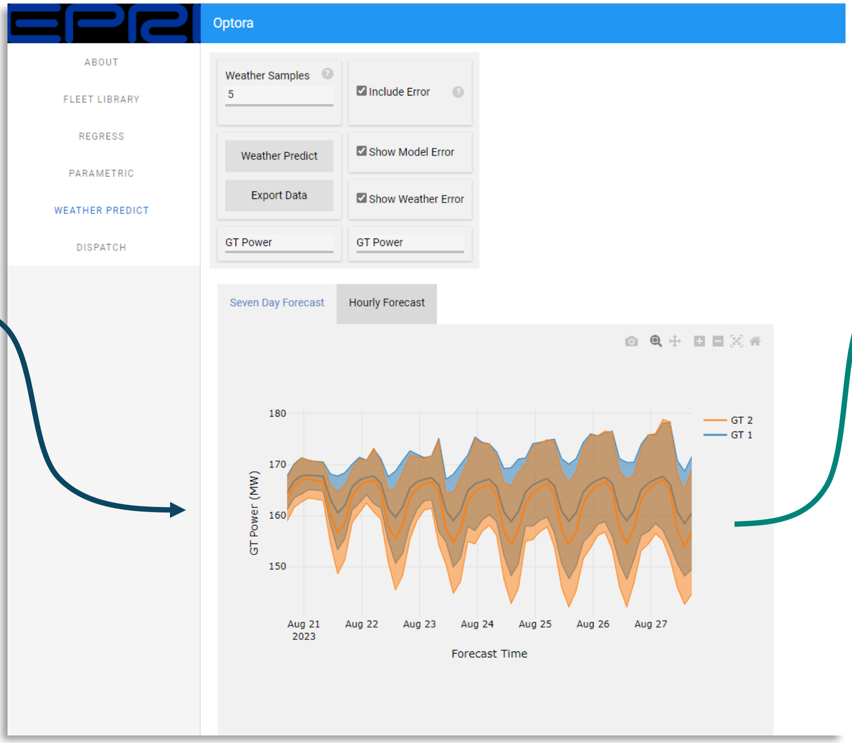
LESSONS

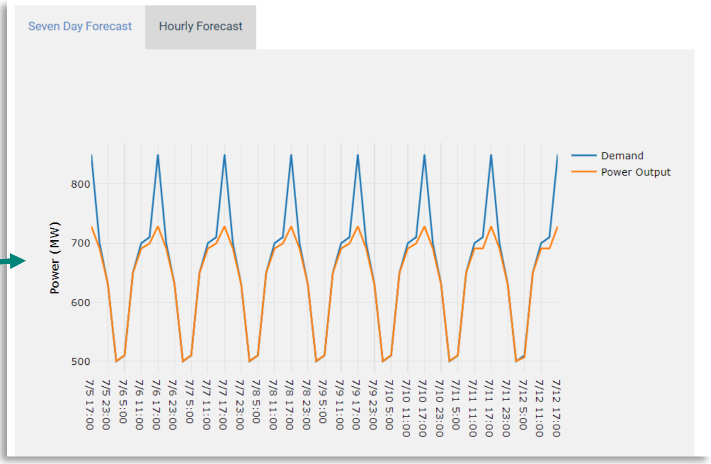
Observations can be overlooked
SME’s implicitly know relationships
Engineers hate data entry

PERFORMANCE FORECASTING (OPTORA)



Prediction uncertainty considers model error and weather forecast uncertainty





Coupling with demand forecast allows optimization of unit dispatch

PROBLEM

Accurately Forecasting Production
Optimizing Unit Dispatch

TECHNIQUE

Artificial Neural Network
Digital Twin

CHALLENGES

Inconstant weather forecasts
Varying operational costs
Varying unit performance

LESSONS

Need “Invisible” AI
Need to correct input data

CLOSING THOUGHTS

- **Ignoring physics in AI/ML?**
  - You're missing its true potential
- **Complex models and architectures designs in solutions?**
  - You're setting up for failure
- **If your AI can't handle messy data, is it even AI?**
- **Static models are just trending**
  - Without automated trend analysis and retraining there’s no learning
- **Without domain expertise, AI/ML is just a novice playing expert**