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Probabilistic detection of high-dimension failures in complex systems: A case study of photovoltaics



PRESENTED BY

Michael Hopwood, Lekha Patel, Thushara
Gunda

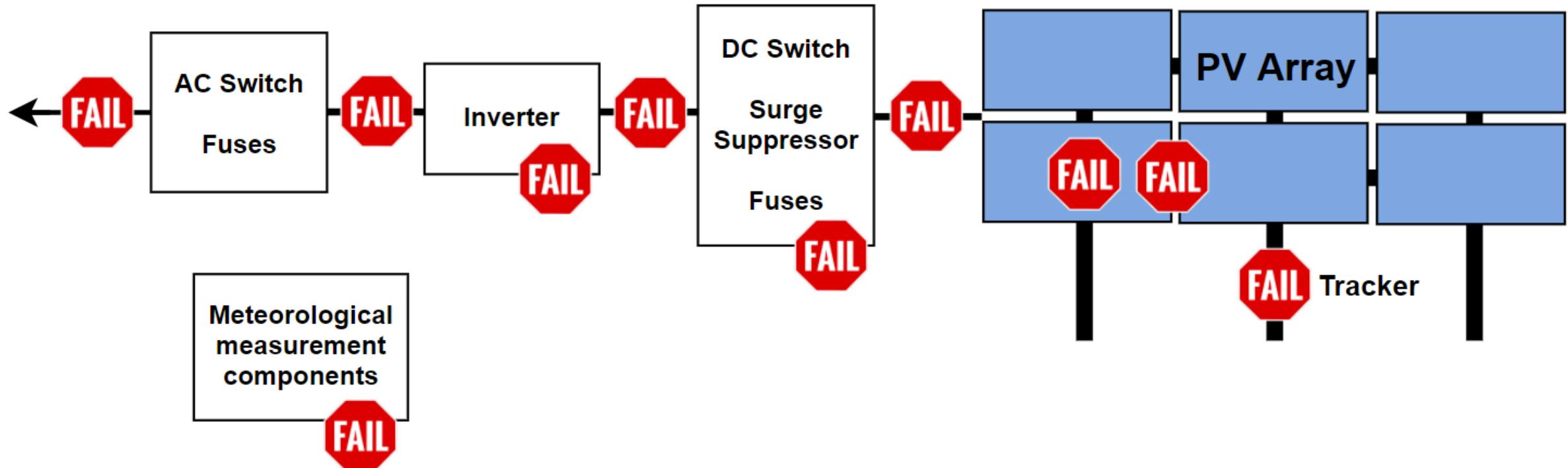


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Motivation



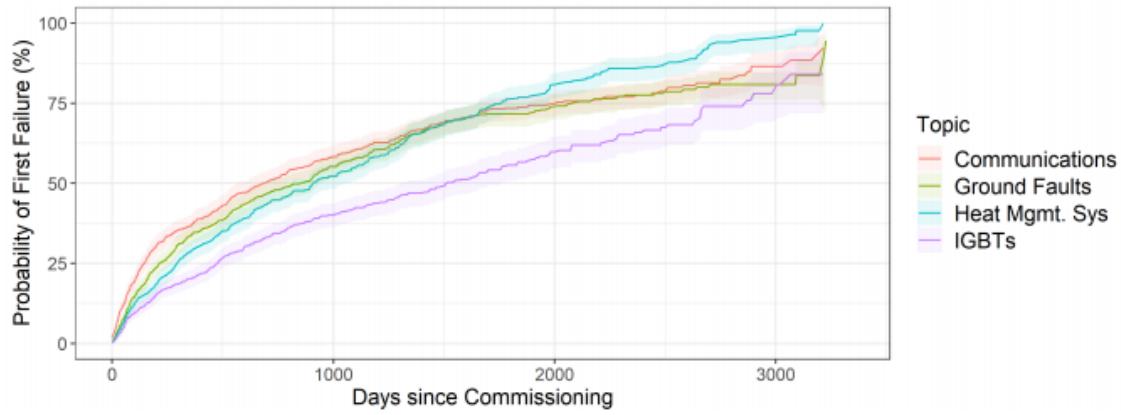
- ❖ Photovoltaic systems are one of the fastest growing renewable energy sectors
- ❖ Similar to other energy systems, PVs are subject to failure with diverse causal mechanisms
- ❖ Numerous components and connections result in multiple locations for potential failures



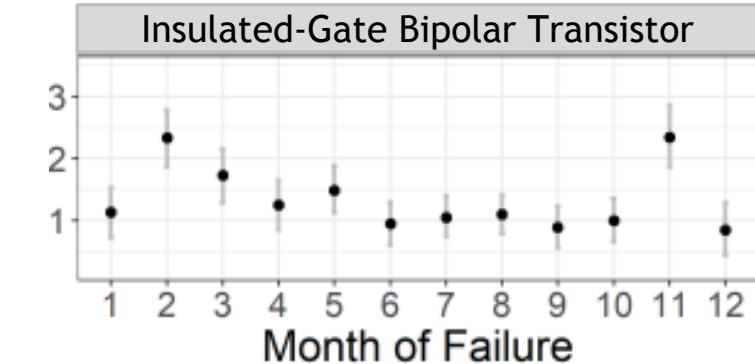
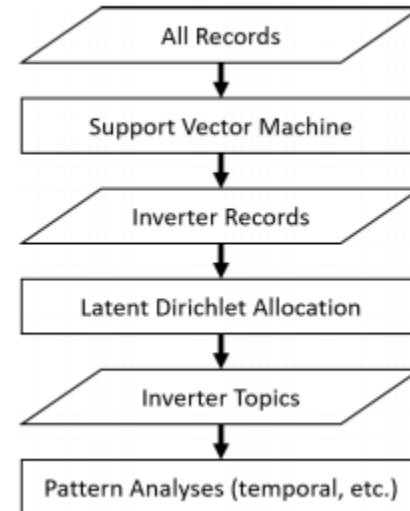
Current Approaches for Characterizing Failure Patterns



Statistical distributions of specific failures



Leverage machine learning to identify common failure modes and patterns



Source: Gunda and Homan, 2020 and Gunda et al 2020

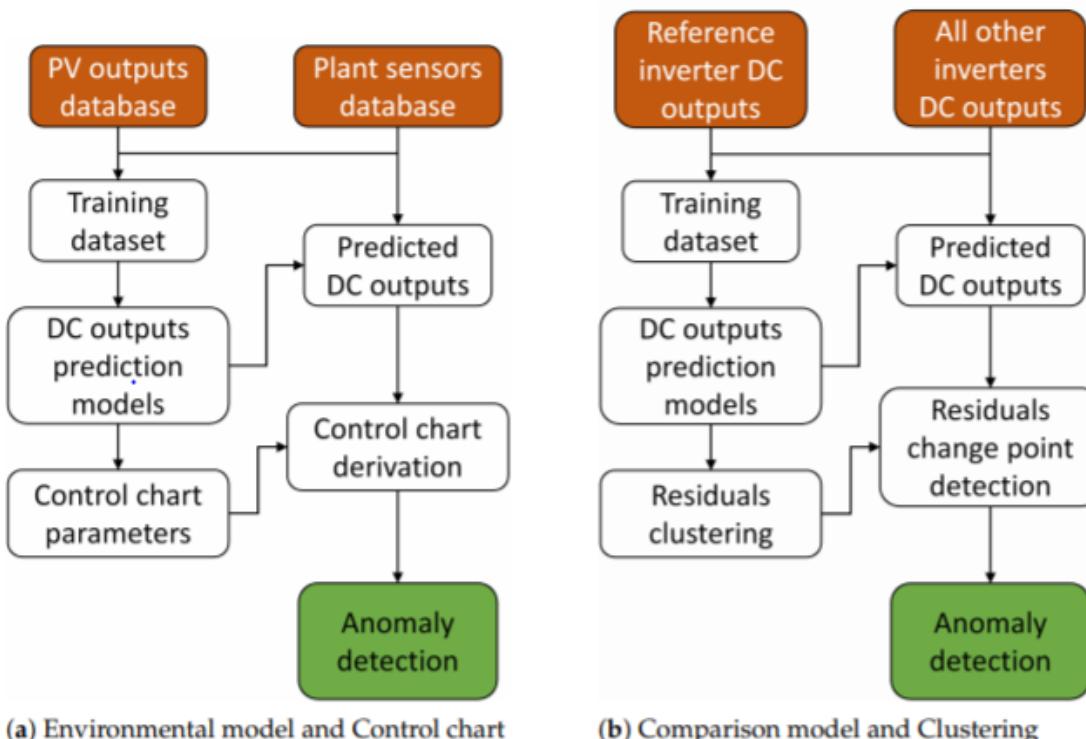
Curve fitting for parametric (Weibull) and non-parametric (Kaplan-Meier estimator)

Understand seasonal temporal patterns in failure frequency

Current Approaches for Characterizing Failure Patterns



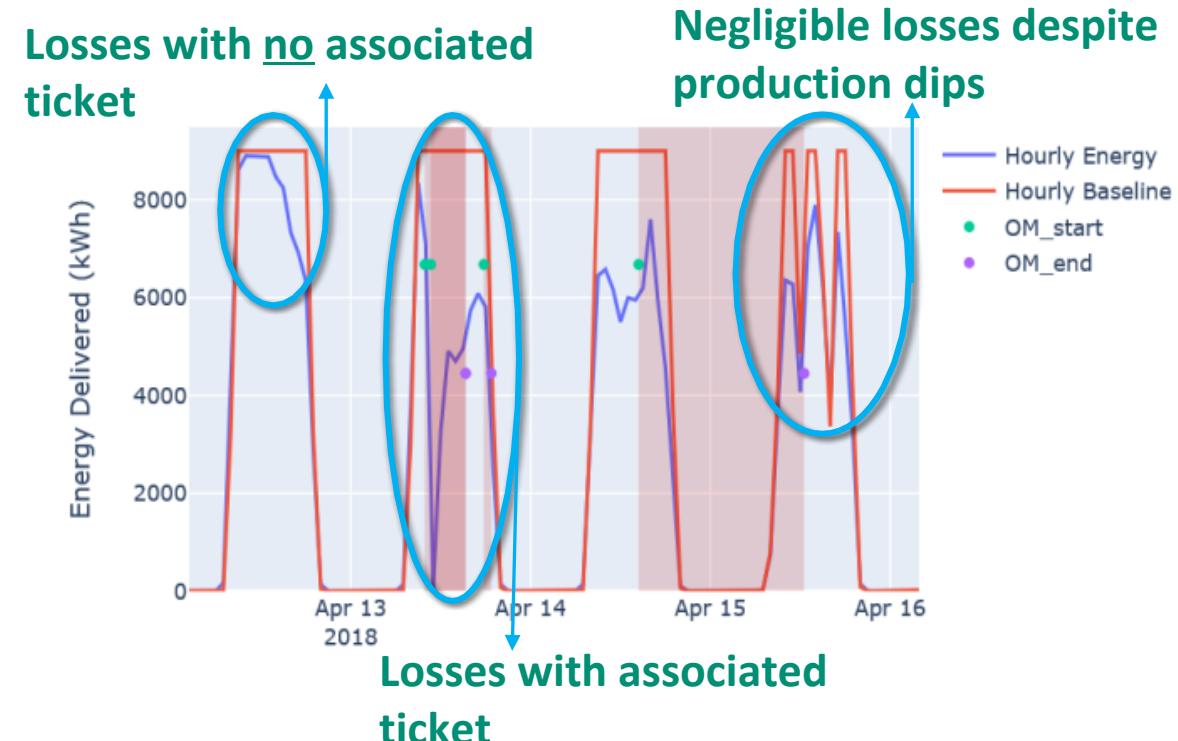
Statistical methods for degradation estimation and anomaly detection



Source: Dimitrievska et al, 2021

Conduct anomaly detection through cluster analysis and change point detection methods to determine degradations

Fuses O&M tickets with timeseries of production data



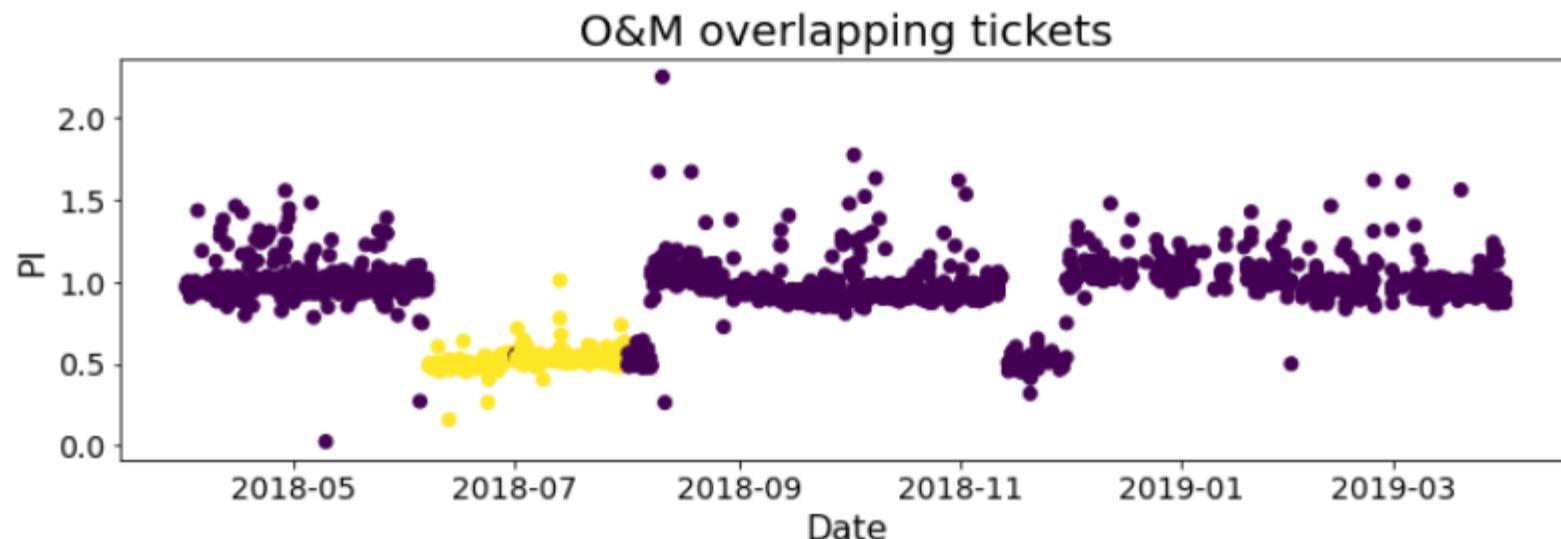
Source: Mendoza et al, 2021

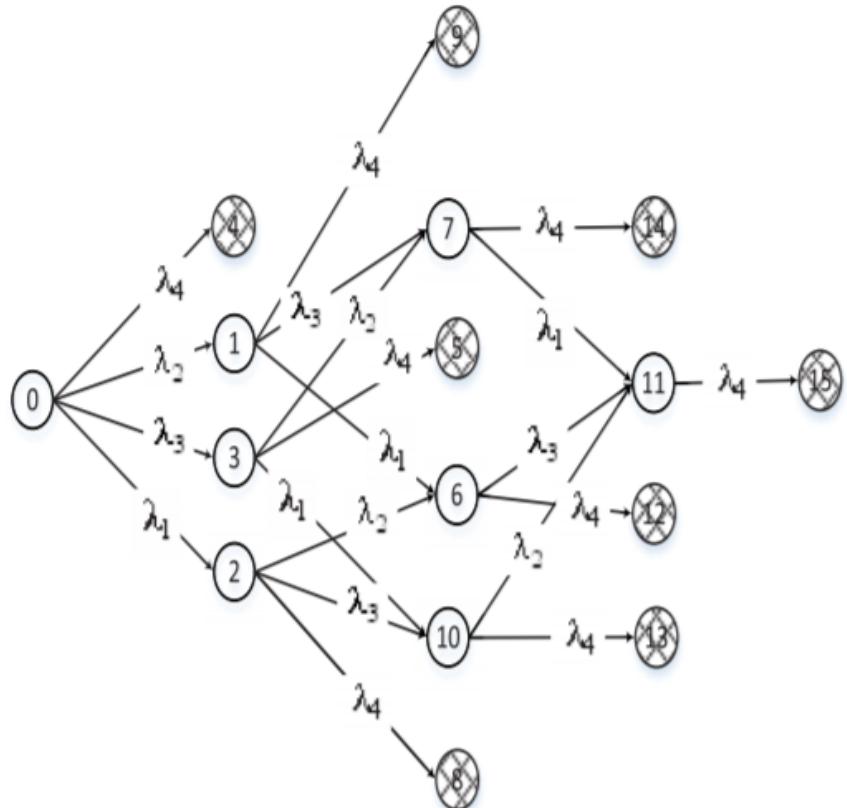
O&M tickets do not consistently capture all performance deviations

Study Objectives



- ❖ Unsupervised method is required due to constraints with labels (O&M tickets)
- ❖ Build probabilistic framework to characterize PV failures, with some quantification of **failure states**
- ❖ These new fault diagnostic methods...
 - ❖ can be leveraged for developing predictive capabilities for failures within PV
 - ❖ can be expanded to other (renewable) energy sectors.





Source: Cristaldi et al, 2015

Our Strategy:

1. Estimate the underlying state at each time using a **Gaussian emission density**
2. Utilize a **discrete time Gaussian Hidden Markov Model (GHMM)** which moves between 2 states that is observed via gaussian emission density (assumed: failed and not failed)

Benefits:

1. Don't require predefined thresholds to determine what resembles a failure
2. Don't require pre-labeled entries (e.g. O&M tickets)

Methodology



1. Calculate a performance index by finding the ratio of the measured energy E and the expected energy, \hat{E}

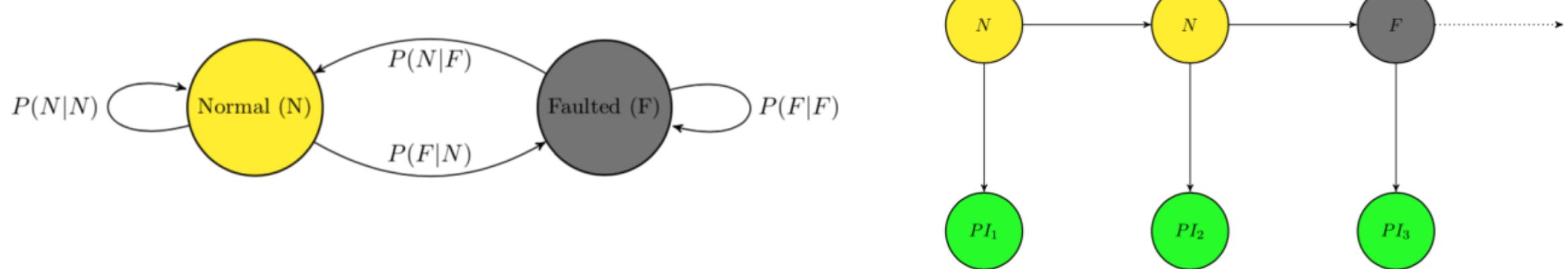
$$PI = \frac{E}{\hat{E}} \quad \text{where } \hat{E} = f(\text{Irradiance, System Capacity})$$

2. Use a Gaussian emission density to conduct univariate clustering on the PI signal

$$PI \in R^N \rightarrow PI_{cat} \in [0,1]$$

- We assume that these signals designate Faulted ($PI_{cat} = 1$) and Normal ($PI_{cat} = 0$) conditions
- Use a Hidden Markov Model (HMM) to learn state transitions in PI_{cat} depending on trends in PI

$$P(PI_{cat} \in [0,1] | PI = x)$$



3. Conduct qualitative assessment of estimates using overlapping O&M tickets

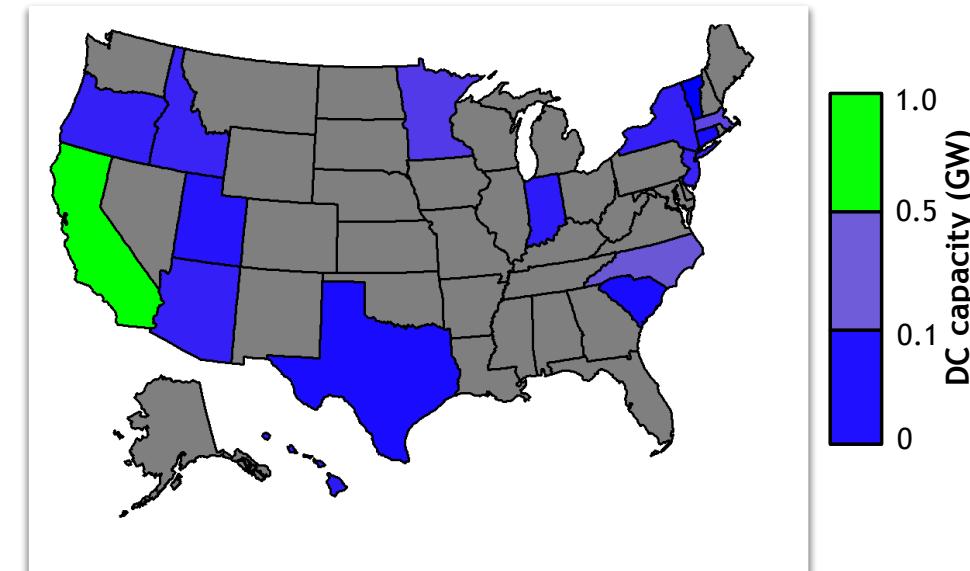
Sandia's PV Reliability, Operations, & Maintenance Database



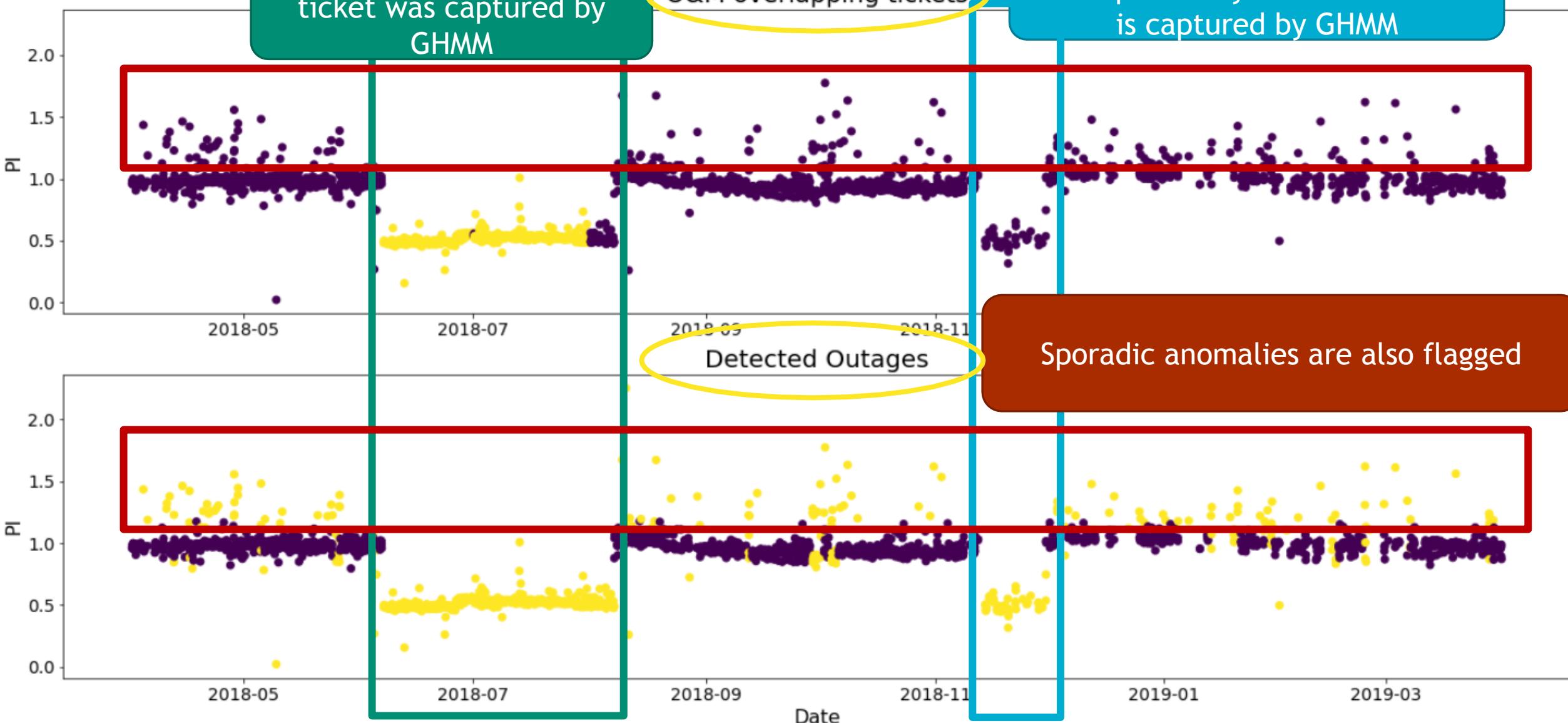
Available Data	Strengths	Limitations
Temporal sensors (i.e. energy, meteorological, etc.)	350 thousand hours across 100 sites	Discrete (hourly) data
Operations & Maintenance tickets	Provides labels for operations on systems	Not comprehensive

- Site level evaluations of performance were done to assess the capabilities of proposed methods
- The resulting state transition probabilities is summarized for 100 sites

Geographical extent of PVROM data



Results: Site A

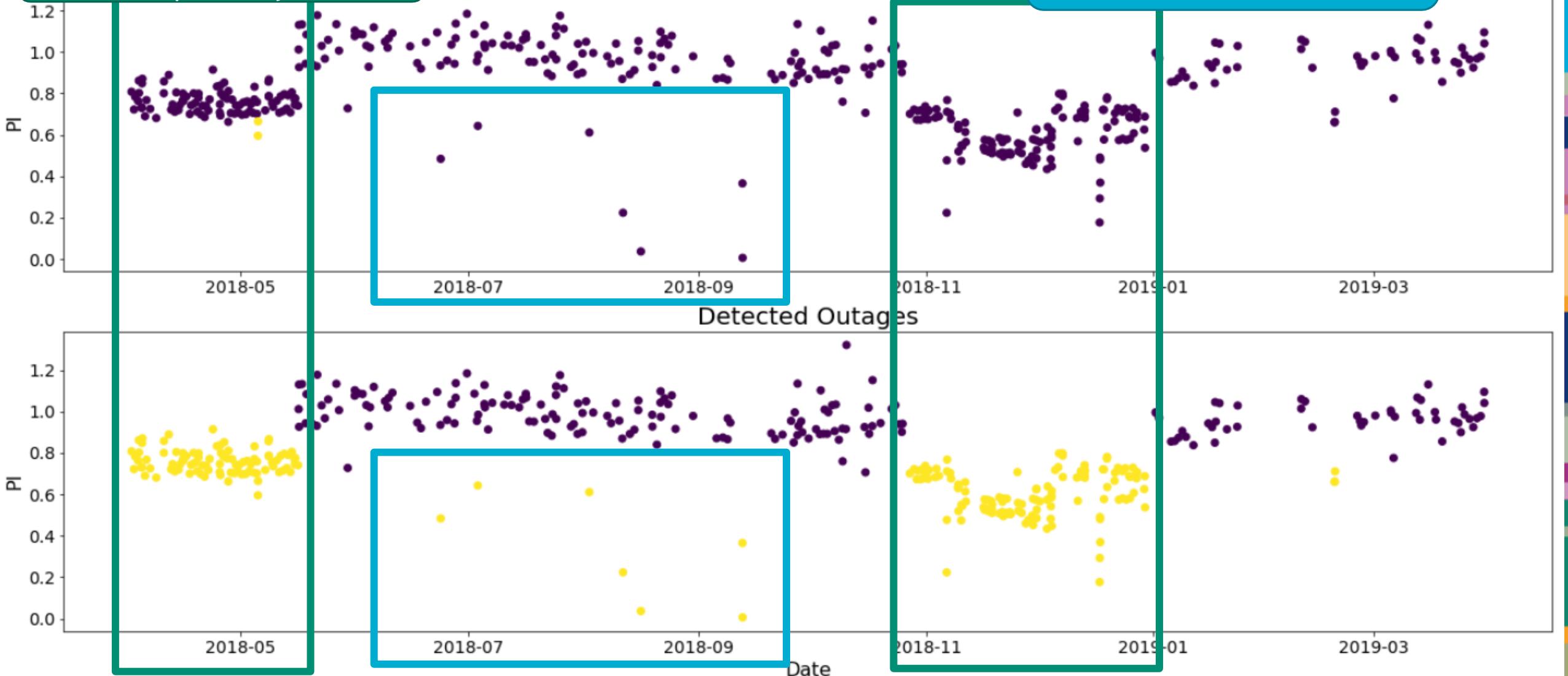


Results: Site B

Performance drop is not accompanied by a O&M ticket but is captured by GHMM

O&M overlapping tickets

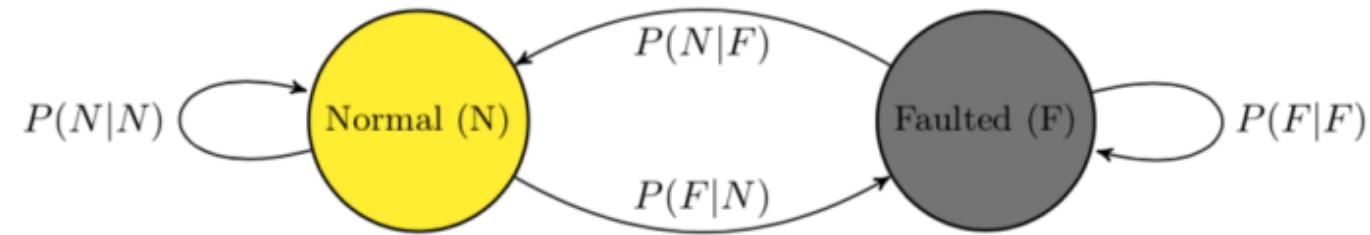
Sporadic anomalies are also flagged



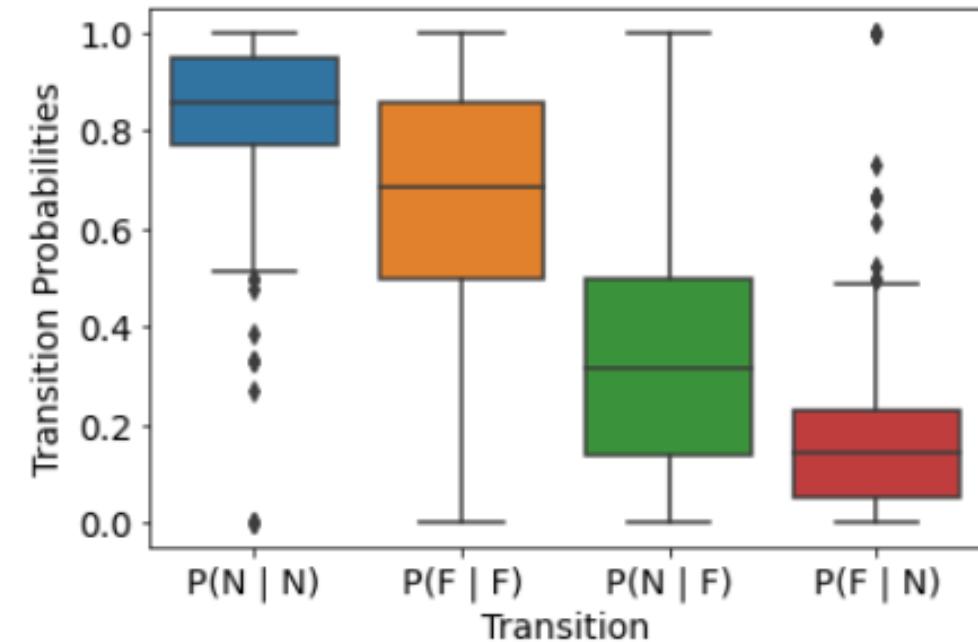
Results



- ❖ Probability of current state being normal, given prior state is also normal is 78.9% (on average)
- ❖ 21.1% probability of failure in next state given current state is normal



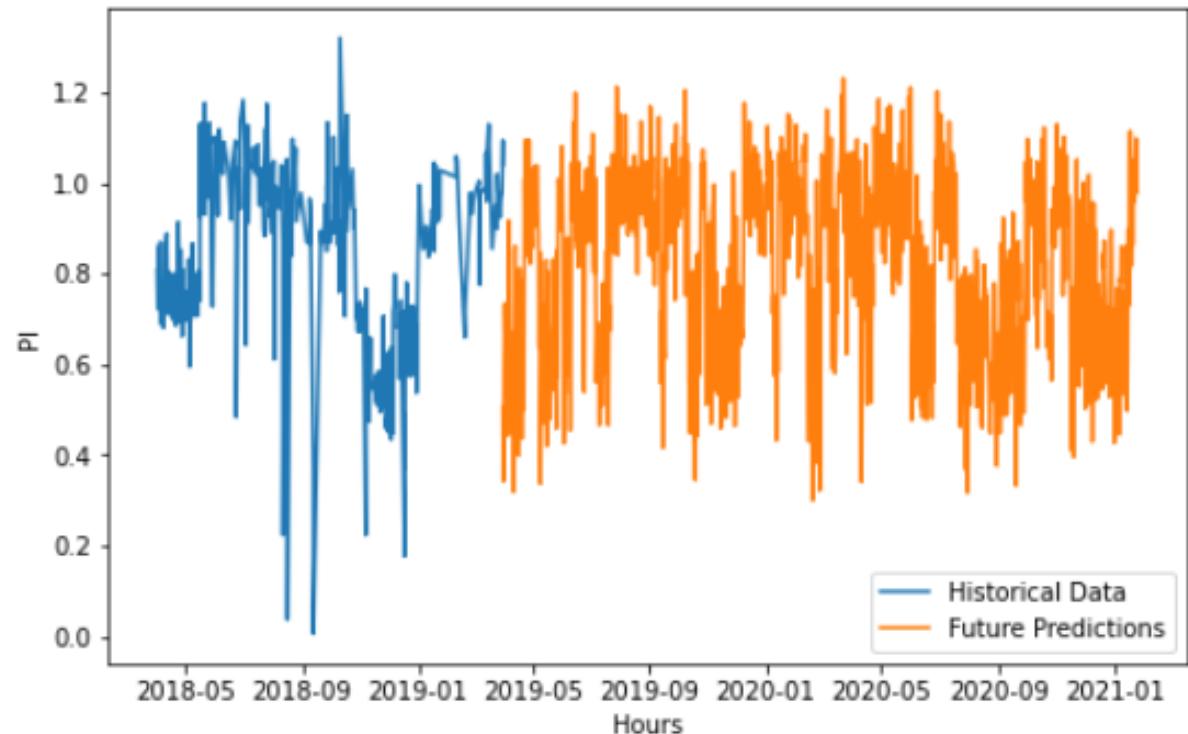
- ❖ Probability of current state being faulted, given prior state is also faulted is 62.7% (on average)
- ❖ 37.3% probability return to normal in next state (i.e., mechanic fixed or self-resolved) given current state is faulted
- ❖ Outlier results are found in systems where the performance index (PI) did not match gaussian assumptions



Conclusions



- ❖ Transition probabilities indicate that the system is more likely to stay in its current state
- ❖ Preliminary prediction results show a realistic time series profile
- ❖ Limitation: Current validation of GHMM is limited to qualitative assessments
- ❖ Future work:
 1. Investigate a non-stationary Markov model to capture time-varying relationships in failure state transitions
 2. Studying the transition states between specific failures (or specific assets) to inform continuous failure diagnostics



Acknowledgements

Gunda, Thushara, and Rachel Homan. *Evaluation of Component Reliability in Photovoltaic Systems using Field Failure Statistics*. No. SAND2020-9231. Sandia National Lab.(SNL-NM), Albuquerque, NM (United States), 2020.

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Dimitrievska, Vesna, et al. "Statistical Methods for Degradation Estimation and Anomaly Detection in Photovoltaic Plants." *Sensors* 21.11 (2021): 3733.

Cristaldi, Loredana, et al. "Markov process reliability model for photovoltaic module encapsulation failures." *2015 International Conference on Renewable Energy Research and Applications (ICRERA)*. IEEE, 2015.

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Questions?

Michael Hopwood
mwhopwo@sandia.gov

Lekha Patel
lpatel@sandia.gov

Thushara Gunda
tgunda@sandia.gov