Operationalizing Industrial Sensor Data for Scalable Asset Management of PV Inverters

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in collaboration with

Overview of the Cyber Physical Systems Laboratory

CPSL focuses on fundamental problems that revolves around advancing the integration of mathematical programming and data analytics in cyber physical application domains, including energy, mobility and manufacturing.

Sensor Driven Diagnostics and Prognostics ⟷ Large Scale Decision Optimization Models

	Domains	***Partners***	***Data***
Energy *Support: DoE, NSF*	• *Solar* • *Wind* • *Hydro* • *Marine*	*Engie NA, CB Solar, Ideal Energy, Ontario Power Generation, Pacific Gas & Electric Company, Hydropower Research Institute, Resolute Marine, Waves4Power* *Argonne, Sandia, Idaho, NREL*	*Industry Sensor Data & Maintenance Records for the following assets:* • *PV Inverters* • *Hydropower Systems* *Accelerated Life Testing Records*
Mobility *Support: Ford, NSF*	• *Electric Vehicles*	*Ford Motor Company*	*Battery Health Data*
Manufacturing *Support: MTRAC, NSF*	• *Automotive Parts Manufacturing*	*Detroit Manufacturing Center*	*Multi-Robot Mfg. Cell Data*

cpsl cyber-physical-systems-lab

AGENDA:

Part I. PV Inverter Monitoring using Industry Data

Part II. Operationalizing Sensor Data for Improved O&M

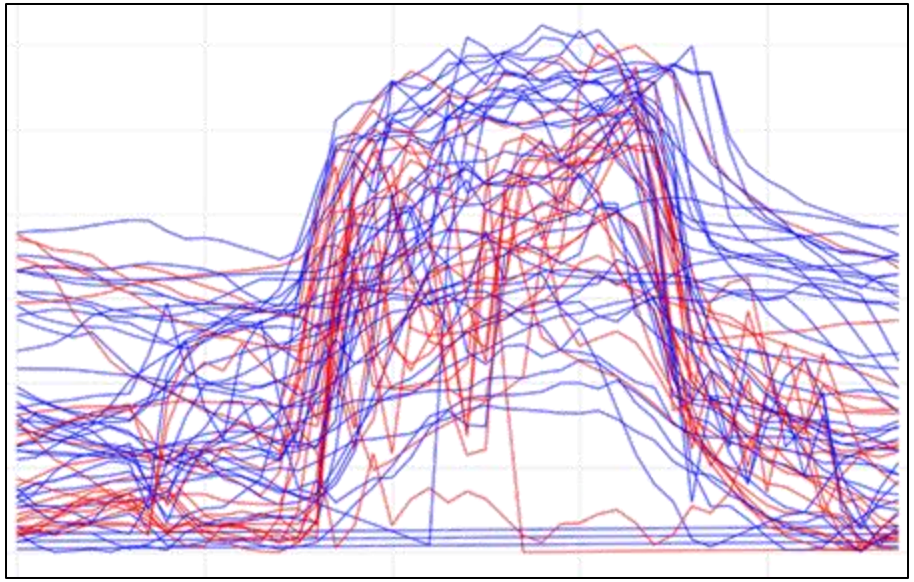
PV Inverter Monitoring using Industry Data

Objective and Challenges

Objective: *Developing an industry-validated monitoring tool to discover meaningful patterns from raw industrial data for degradation*

Challenges: *Industrial data introduces significant roadblocks:*

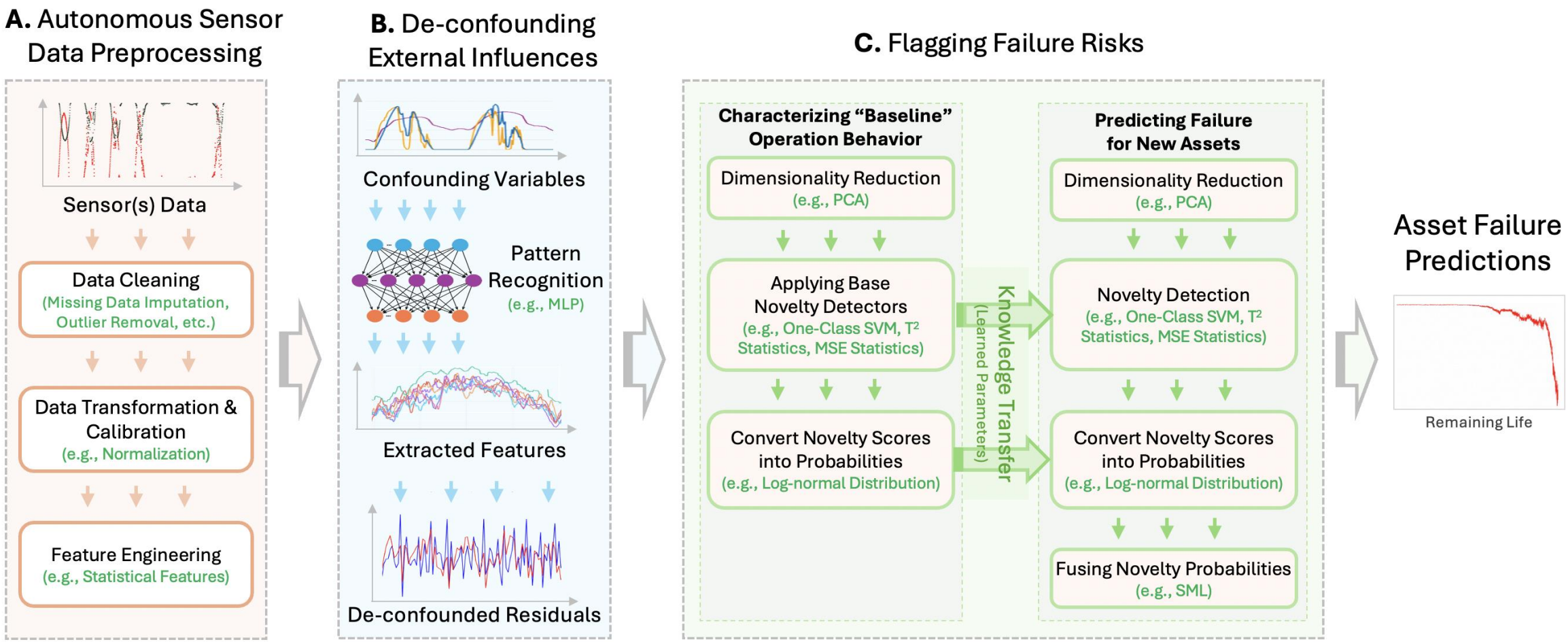
- *Confounding factors complicate the monitoring process* due to sensor behavior driven by environmental and operational conditions
- *Dynamic behavior impact monitoring* as the behavior of the sensor data evolves over time
- *Degradation signatures are only revealed in sequential data, point observations do not provide any meaningful patterns for degradation*
- *Any single data-driven model falls short of offering reliable predictions, as each has its own unique strengths and weaknesses*



How to distinguish anomalous condition states from normal states?

Preemptive Failure Prediction Framework

PV Inverter Monitoring using Industry Data



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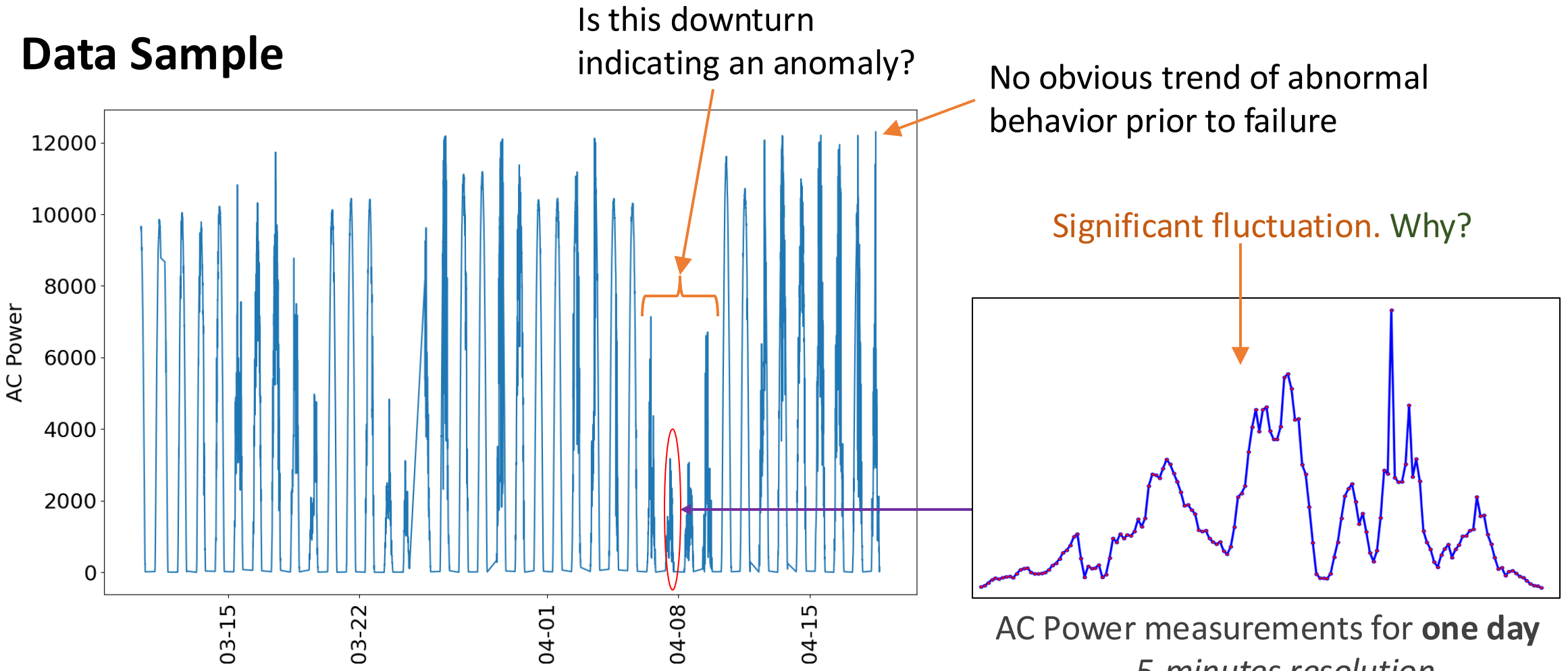
Framework Details: Decounfounding External Effects

PV Inverter Monitoring using Industry Data

Data Sample



AC Power measurements for an inverter **until failure**

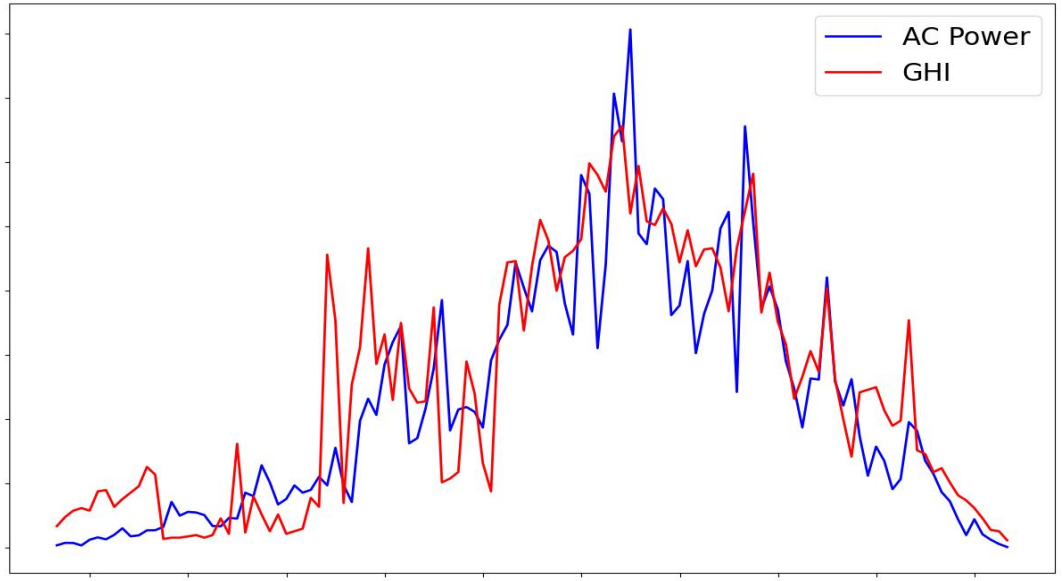
AC Power measurements for **one day**
5-minutes resolution

Framework Details: Decounfounding External Effects

PV Inverter Monitoring using Industry Data

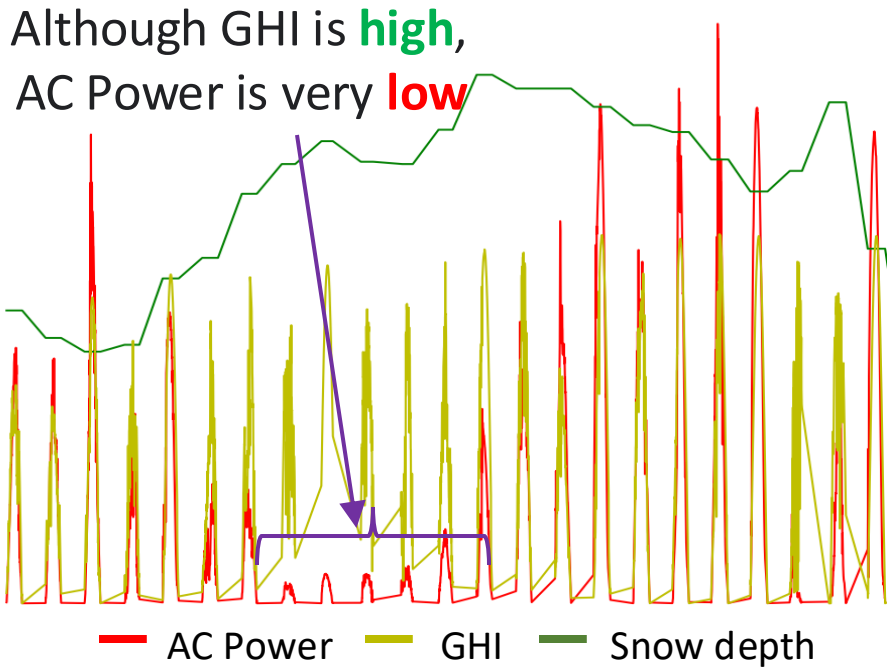
Confounding effects in sensor data due to the environment

Impact of Solar Radiation



AC Power measurements for **one day**
5-minutes resolution

Impact of Snow Cover



AC Power measurements for **multiple days**
5-minutes resolution

**GHI: Global Horizontal Irradiance is an index for solar radiation*

Framework Details: Decounfounding External Effects

PV Inverter Monitoring using Industry Data

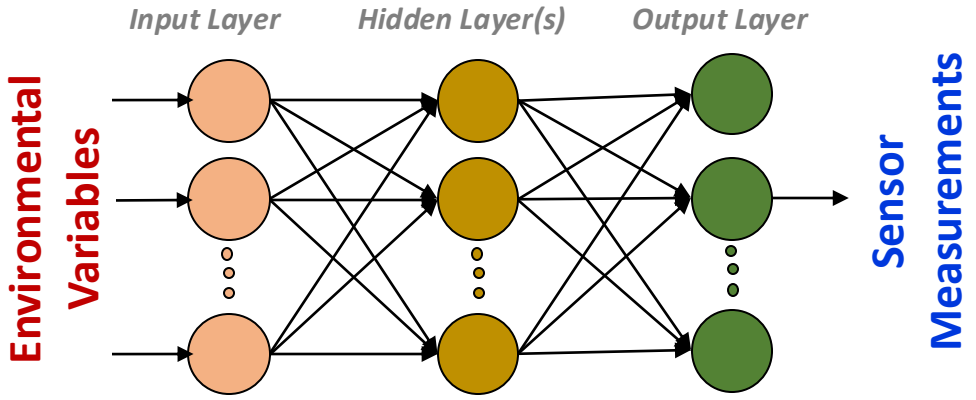
Influence of Environmental Variables

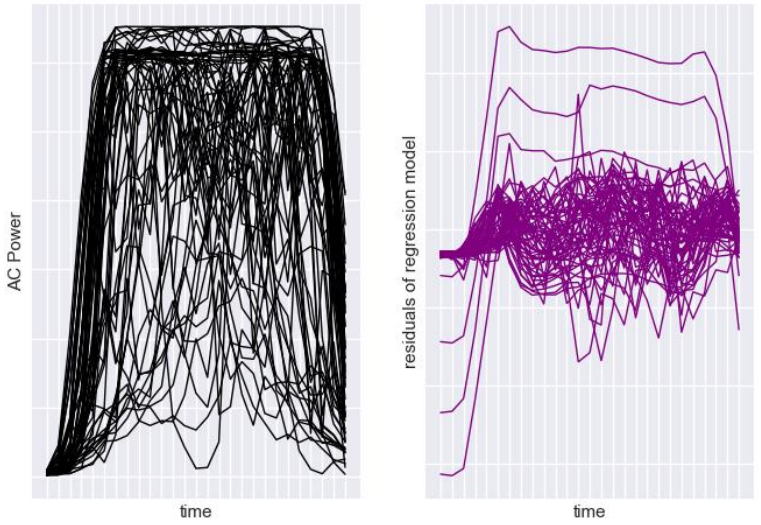
- Environmental variables (e.g., temperature) can affect asset performance and signals
- Deconfounding through regression and other methods critical for improved novelty detection
  - Neural networks and other universal approximators are good candidates
  - Model residuals are employed for novelty detection

$$Residuals = Y - \hat{Y}$$

Actual sensor value (Y)

MLP model estimate ($\hat{Y}$)





Transformation

Framework Details: Flagging Reliability Issues

PV Inverter Monitoring using Industry Data

Proposed Ensemble Algorithm

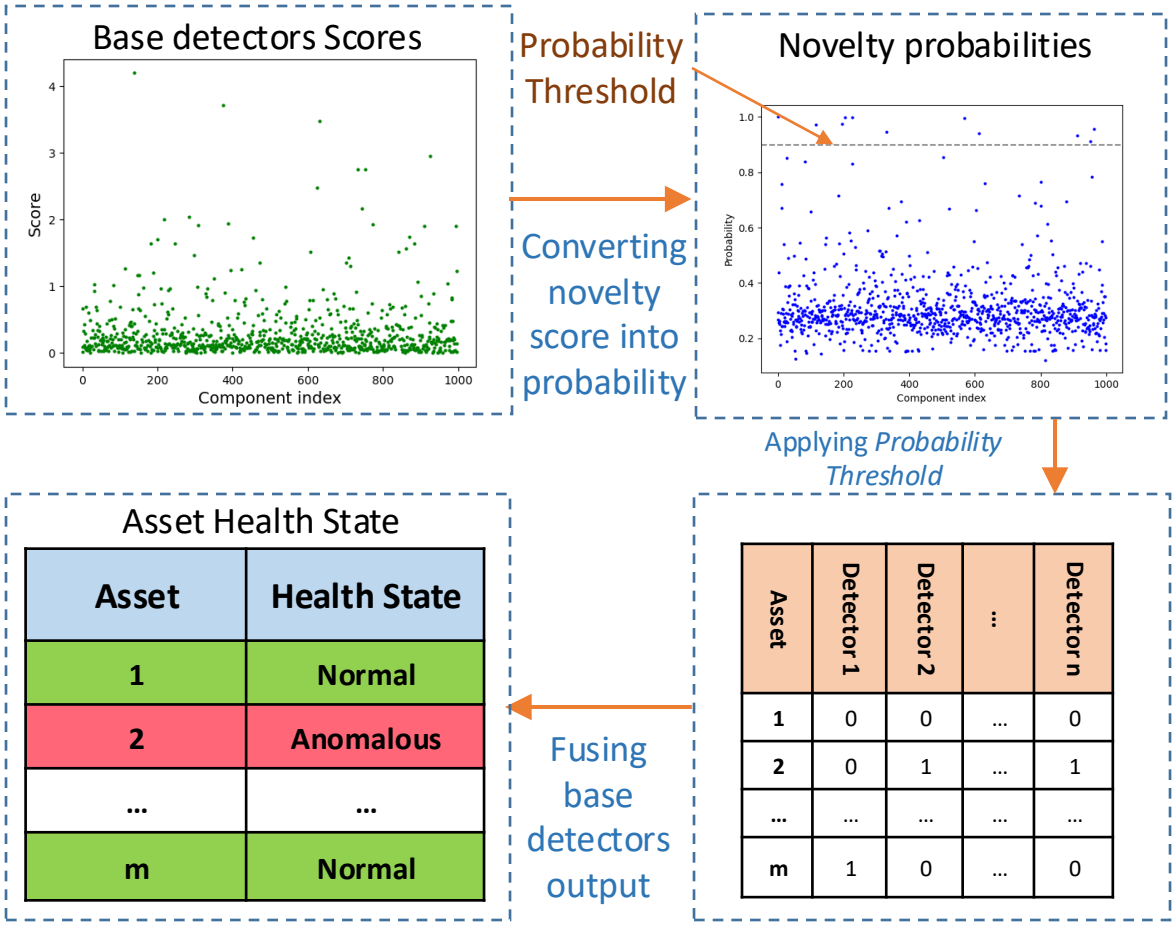
- Execute a series of novelty detectors in parallel
- Convert novelty scores to probabilities
  - Employed Lognormal distribution for effectiveness
  - Employed a probability threshold to produce a binary output for each detector
- Fuse binary outputs
  - Spectral Meta Learner (SML) used for fusion
  - *Robust SML* to enhance robustness

$$\hat{Y}_j^{SML} = sign\left(\sum_i f_i(x_j)\hat{V}_i\right)$$

Health state of asset j

Binary label of base detector i for component j

Dominant eigenvector of population covariance matrix of base detectors



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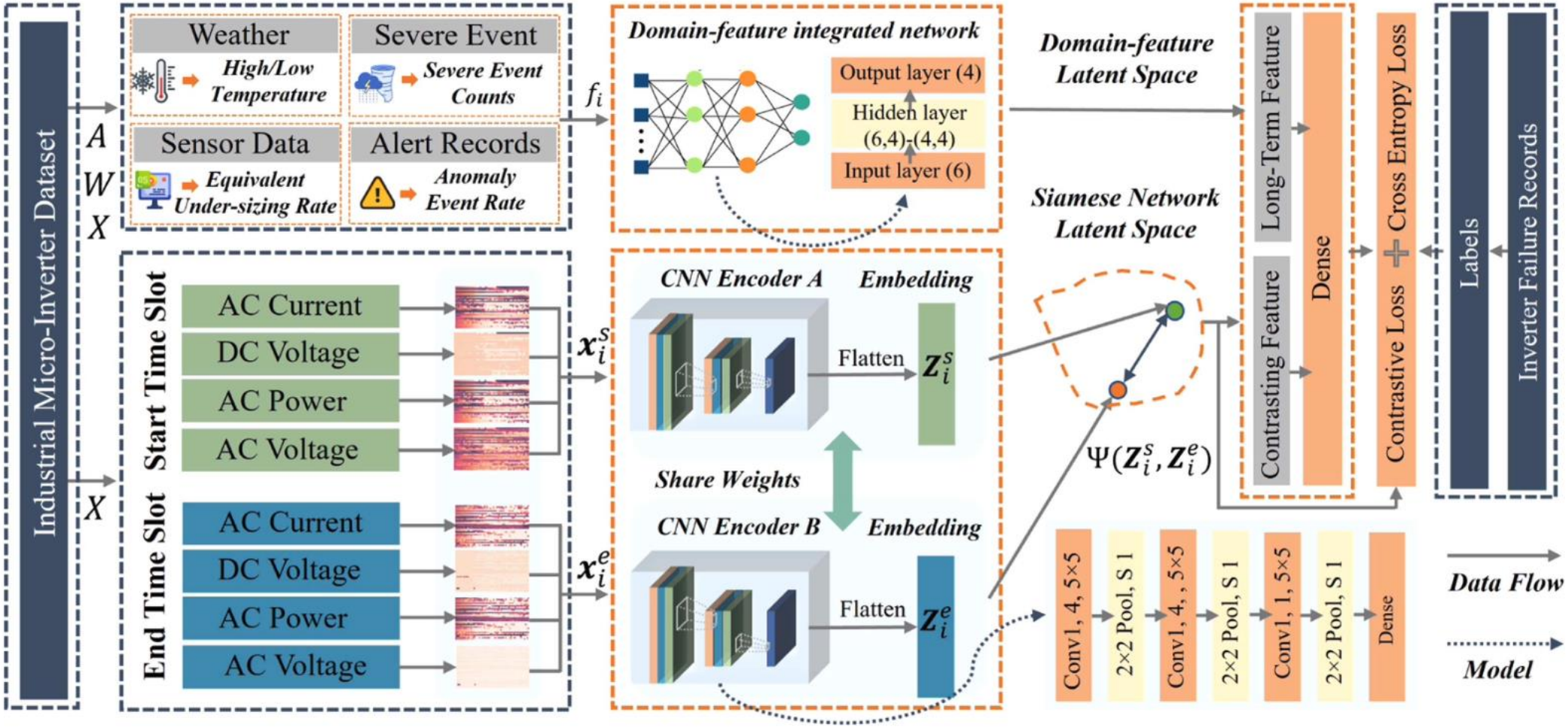
Deep Learning Framework for PV Inverter Monitoring

PV Inverter Monitoring using Industry Data



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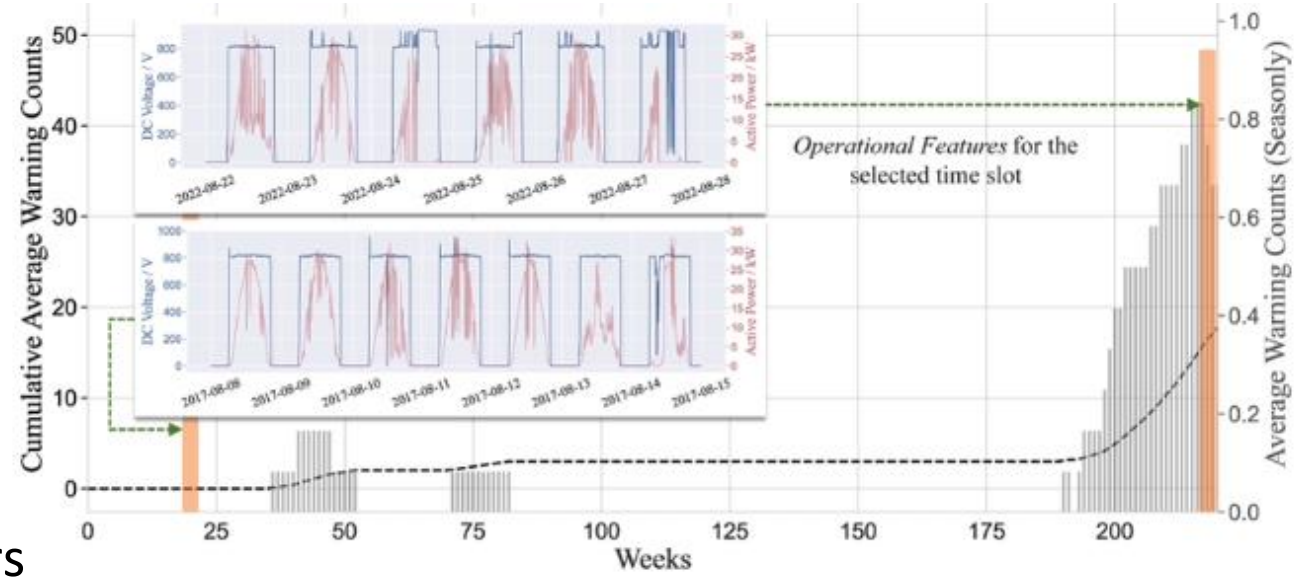
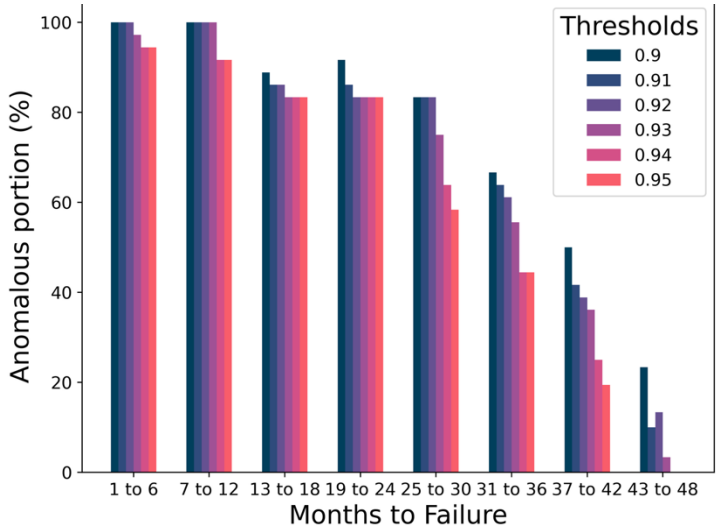
Case Study

Preemptive Failure Detection of PV inverters

- ***59** Inverters of different models*
- ***Industrial** data from **2014** to **2022***
- *Inverters located in **different sites***
- ***Sensors:** AC Power/Voltage/Current/Freq, DC Voltage*
- ***Data Resolution: 5 minutes***



- ✓ Framework successfully identified PV inverters approaching failure, flagging anomalies in the months leading up to failure with high accuracy.
- ✓ Results demonstrated robustness in handling noisy and confounded sensor data.
- ✓ Ensemble novelty detection method outperformed individual detectors, reducing false positives and improving the accuracy.



% of PV inverters detected as anomalous over their remaining life

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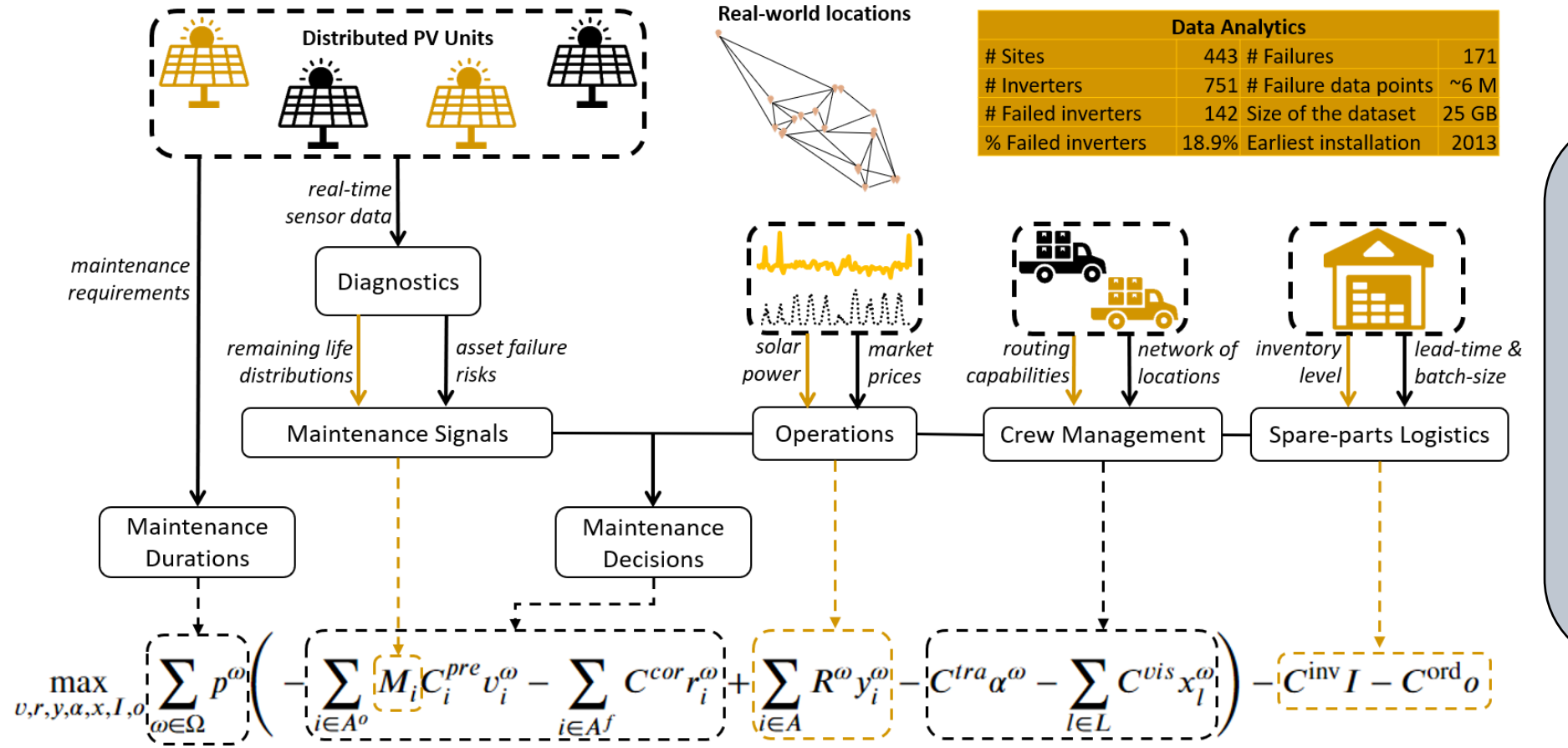
Operationalizing Sensor Data for Improved O&M

Proposed Framework

Integrated Framework for Condition-Based O&M, Crew Management, and Spare-Parts Logistics in PV Systems



Data Analytics			
# Sites	443	# Failures	171
# Inverters	751	# Failure data points	~6 M
# Failed inverters	142	Size of the dataset	25 GB
% Failed inverters	18.9%	Earliest installation	2013

$$\max_{v,r,y,\alpha,x,I,o} \sum_{\omega\in\Omega} p^{\omega}\left(-\sum_{i\in A^{o}} M_i C_i^{pre} v_i^{\omega} - \sum_{i\in A^{f}} C^{cor} r_i^{\omega} + \sum_{i\in A} R^{\omega} y_i^{\omega} - C^{tra}\alpha^{\omega} - \sum_{l\in L} C^{vis} x_l^{\omega} \right) - C^{inv} I - C^{ord} o$$

Comprehensive O&M Model

Planning for next 24 hours, in hourly scale

Hourly Subproblem

Daily Subproblem

Planning for next months, in daily scale

Our Solution: COMPASS (Condition-based O&M Planning Approach for Solar Systems), a stochastic optimization framework that integrates real-world data—PV failure risks, solar power, market prices, and fleet locations—to enhance maintenance, crew, and spare-parts logistics decisions.

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Case Study

Operationalizing Sensor Data for Improved O&M

- Geographical locations of **25 PV inverter sites**.
- Daily market prices and hourly inverter generations (kWh) for each site.
- 289 weeks long monitoring results for 25 PV inverter sites for failure prognostics.
- Stochastic preventive and corrective maintenance durations.

✓ Proposed COMPASS framework significant improved maintenance and reliability outcomes compared to the periodic maintenance (PM) benchmark.

✓ Results demonstrated robustness in handling uncertain maintenance durations.

✓ Economic impact of better predictions can be quantified in operational returns.

	COMPASS	PM	
Expenditures	\$1.64 M	\$2.15 M	24%
Maintenance Cost	\$1.01 M	\$1.16 M	13%
Lost Revenue	\$175 K	\$381 K	54%
Logistics Cost	\$46 K	\$50 K	8%
Deviation Cost	\$38 K	\$48 K	21%
Ordering Cost	\$339 K	\$467 K	27%
Inventory Holding Cost	\$27 K	\$44 K	39%
# Preventive Maintenance	18.1	33.8	
# Failures	11.3	9.6	
# Unscheduled Maintenance	0.1	5.4	
# Orders	5.3	7.3	27%
Average Inventory Level	1.8	2.9	38%
Hours of Unavailability	1,589	2,812	43%
Hours of Deviation	19	24	21%
Hours of Maintenance	291	395	26%

Acknowledgement

Key Takeaway Messages:

- ✓ Existing industrial data can reveal significant insights into state of health and failure risks of energy assets
- ✓ Quantifying the impact of these insights require a path from prediction to fleet-level decision making
- ✓ Sensor adequacy for monitoring is a significant issue
- ✓ Deviating priorities of end-users, operators, and OEMs can pose challenges in data ownership, ease of implementation

Current CPSL members that contributed to the presentation results

Mohammad Badfar
PhD Student

Ceyhan Sahin
PhD Student

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References:

Part I. PV Inverter Monitoring using Industry Data

- [1] Badfar, Mohammad, et al. "A novel sensor-driven framework for preemptive failure detection in energy systems: Application to photovoltaic inverters." *Solar Energy* (2025).
- [2] Liu, Liming, et al. "Deep Learning-Based Failure Prognostic Model for PV Inverter Using Field Measurements." *IEEE Transactions on Sustainable Energy* (2024).

Part II. Operationalizing Sensor Data for Improved O&M

- [3] Sahin, Ceyhan, et al. "A Stochastic Optimization Framework for Condition-Based Maintenance, Crew Management, and Spare Parts Logistics in Solar Energy Systems" under review in *Renewable Energy.*

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