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# Hierarchical Fault Detection and Multimodal Diagnosis in Large-Scale Photovoltaic Systems

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# Outline

## — FDD (Fault Detection and Diagnosis ) in large-scale photovoltaic (PV) systems

**Part 1: Background**

**Part 2: Challenges**

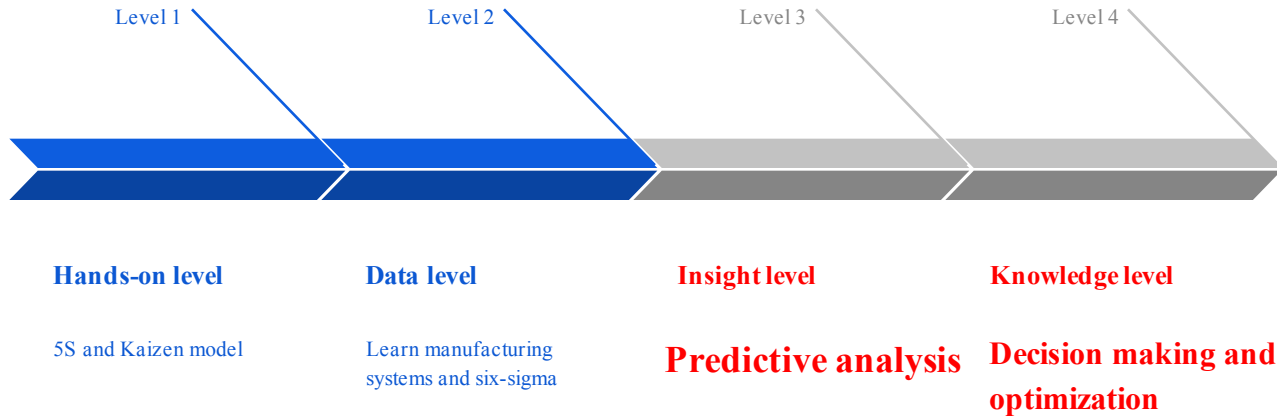
**Part 3: Proposed Solution**

**Part 4: Experiments and Results**

**Part 5: Industrial Application**

**Part 6: Conclusions and Future Work**

# Intelligent Operation and Maintenance (O&M) in large-scale Photovoltaic (PV) Systems



## FDD:

- Effectiveness
- Reliability and robustness against unforeseen circumstances

# 1st Challenges: diverse and complex faults



**Glass (front-cover)  
breakage**

**Grassing shading**

**Building shading**

**Hot spot**

**Surface soiling**

**Fig. 1: Commonly occurred faults in PV system.**

# 2nd Challenge: limited information collected

SCADA systems only provide current and voltage information at individual string level

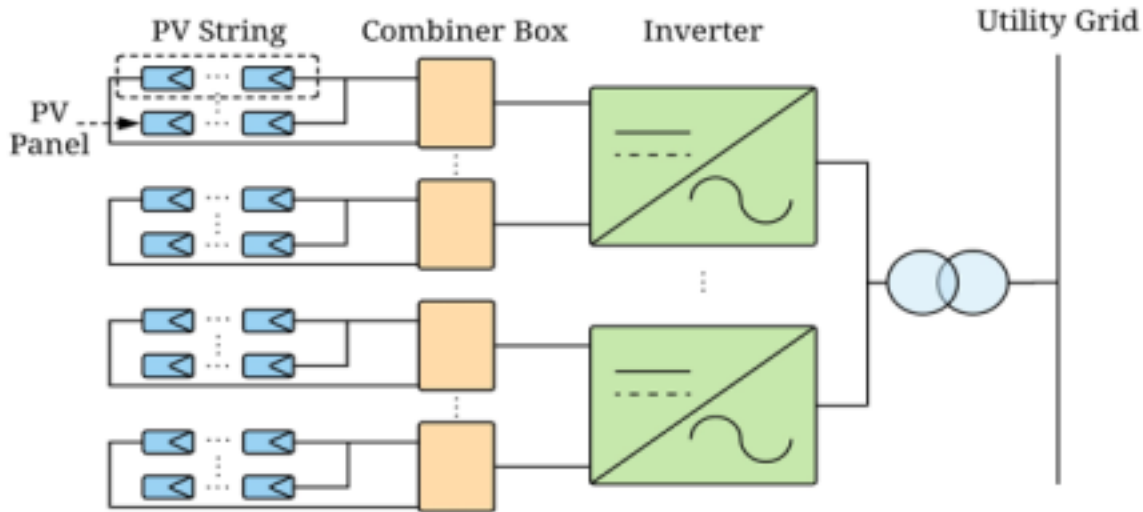


Fig. 2: Diagram of a grid-connected large-scale PV system.

# FDD Solution overview

- **Data preprocessing**
- **Hierarchical fault detection**
- **Multimodal fault diagnosis**

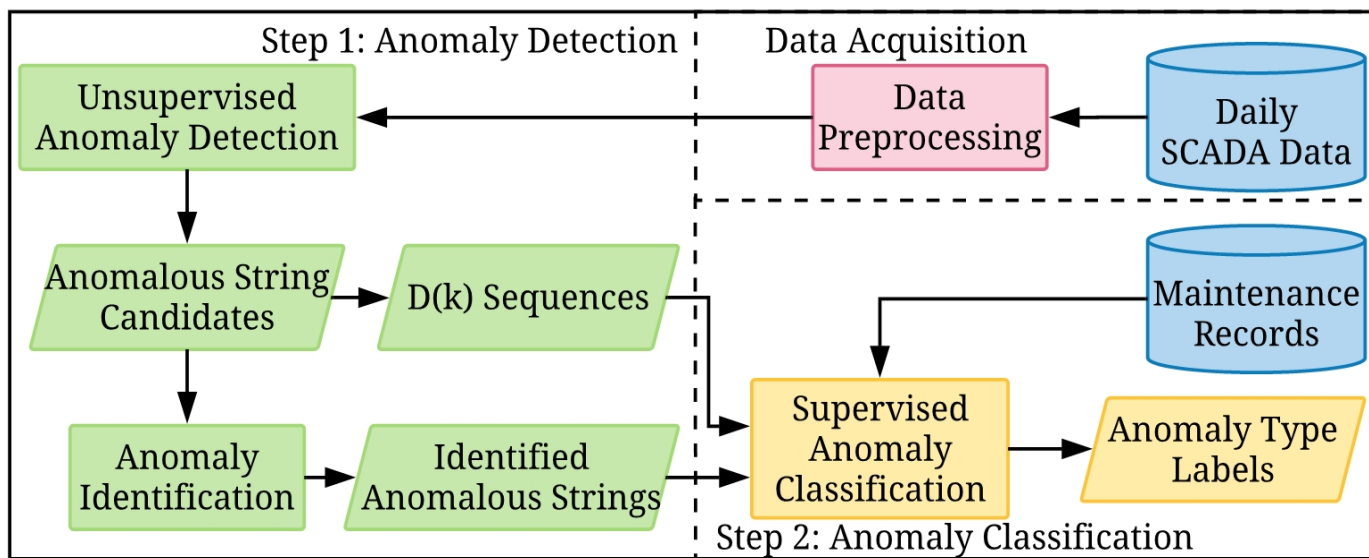
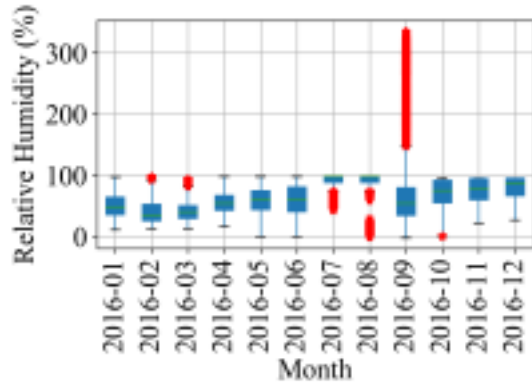


Fig. 3: Overview of the proposed FDD solution for PV systems.

# Data preprocessing

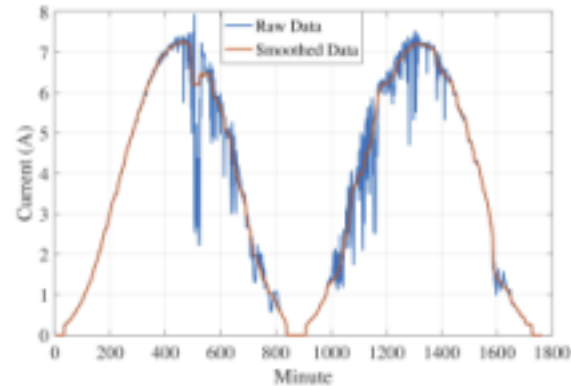
Data cleaning

Remove errors



Data filtering

Smooth noise caused by environmental variations (e.g., drifting clouds) and measure variabilities

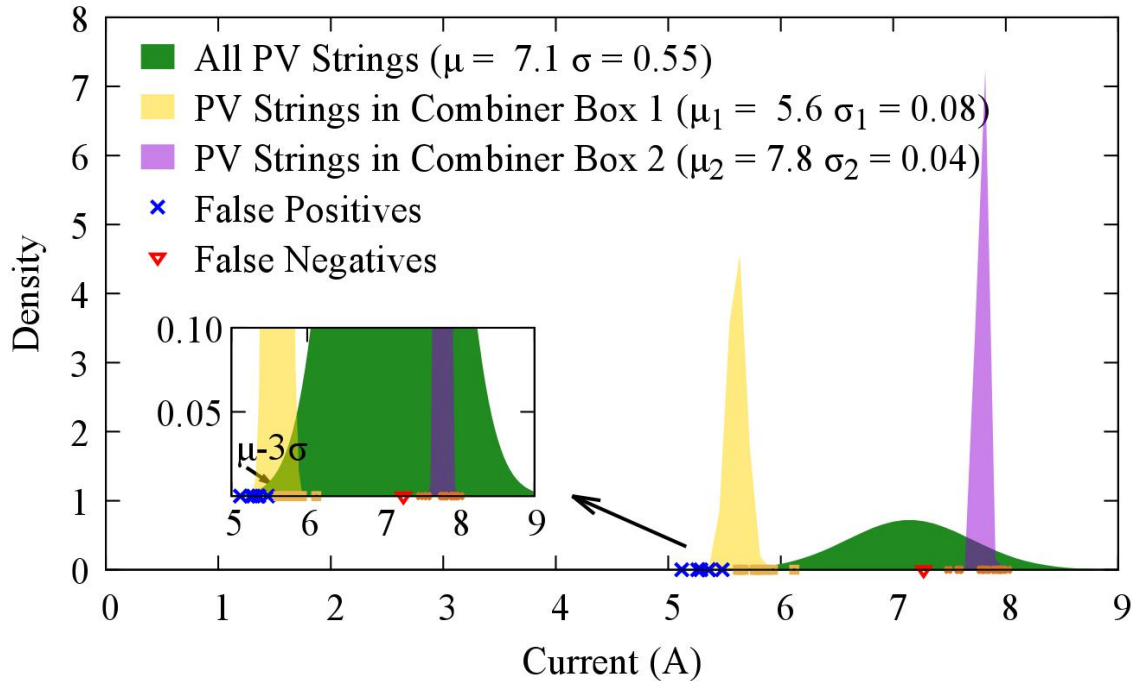


Data downsampling

Reduce computation cost

- 1 min
- 5 min
- 10 min

# Motivations of fault detection



Hierarchical detection:

- **Local:** combiner box level



- **Global:** system level

Fig. 4: Gaussian distributions of PV strings at the same timestamp for a 39.36 MWp PV system



# Fault detection

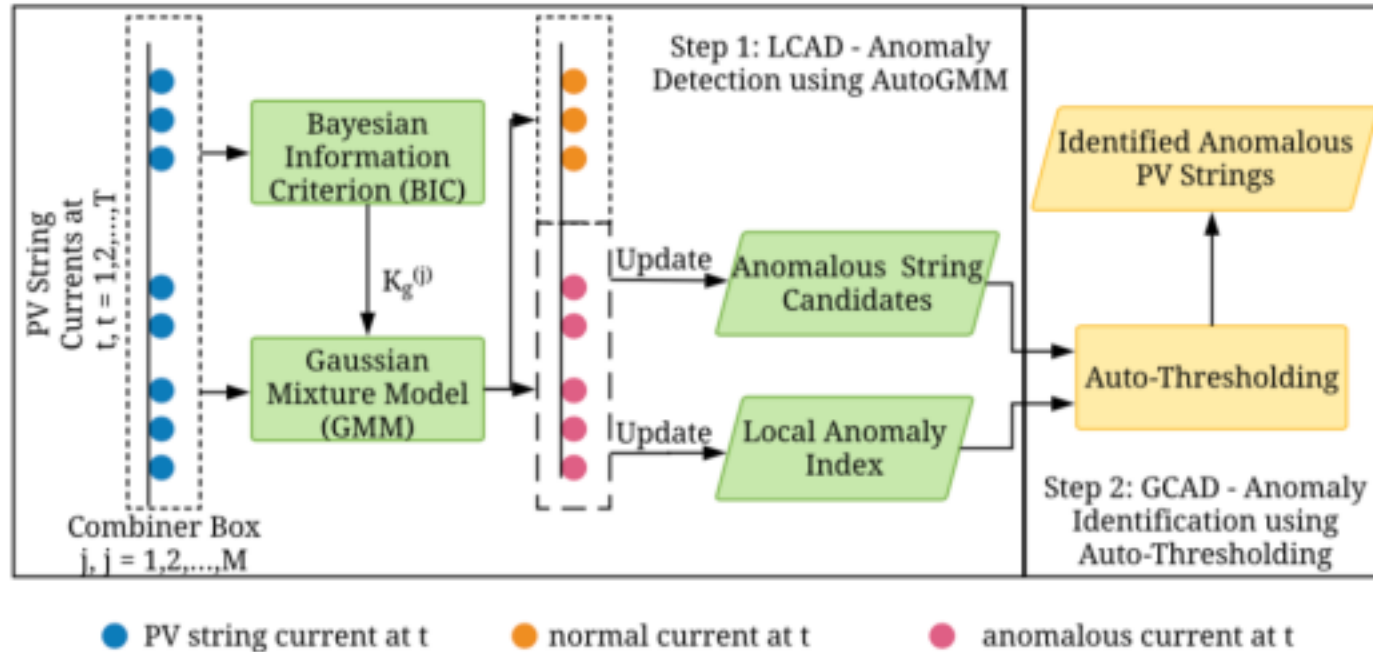


Fig. 5: Diagram of fault detection process.

# A case study of hierarchical fault detection

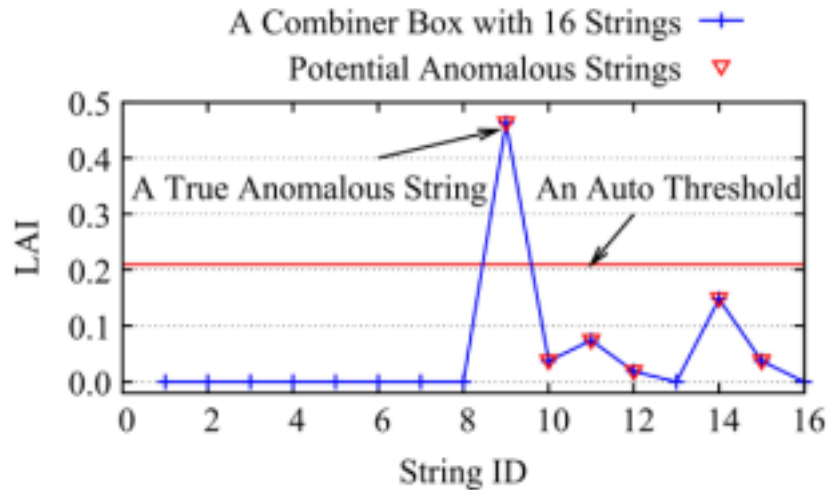


Fig. 6: A case study: local anomaly indices for 16 strings in the same combiner box.

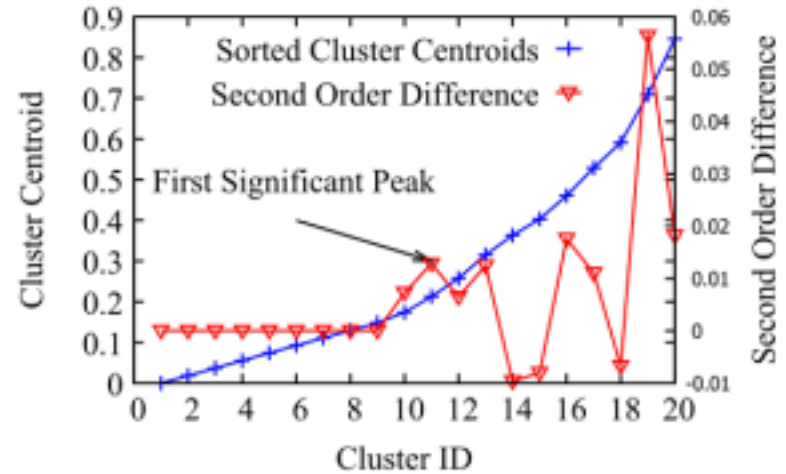
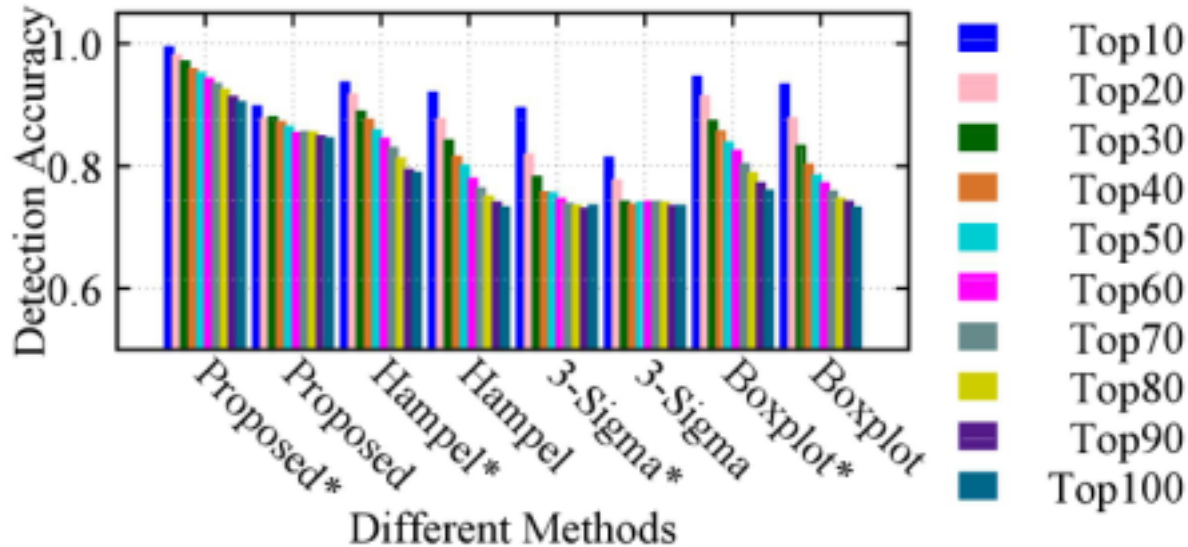


Fig. 7: An illustration of automatically identifying local anomaly index threshold.

# Overall performance of fault detection



**Improved detection accuracy:  
from 78.8% to 90.2%**

Fig. 8: Detection accuracy with top-k faults. (\* indicates the use of filtered data)

# Sensitivity analysis

- The proposed solution achieves **higher detection accuracy**.
- This accuracy exhibits **less variation** under the same conditions.

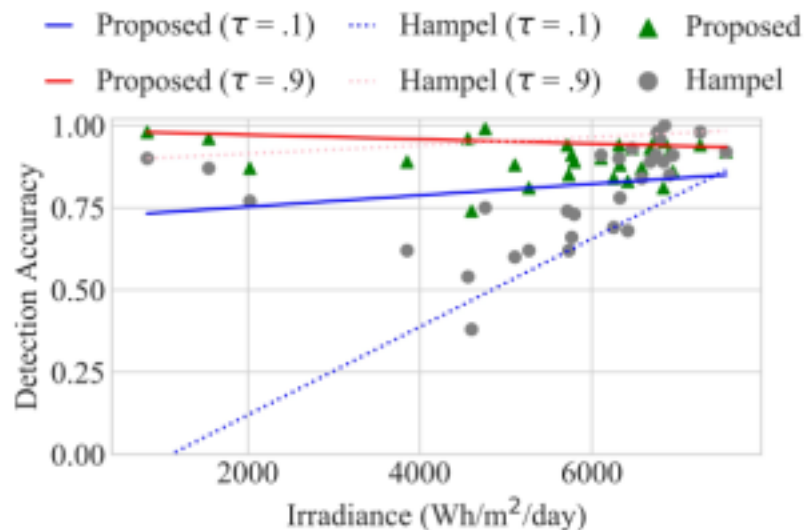


Fig. 9: Fault detection accuracy vs. irradiance.

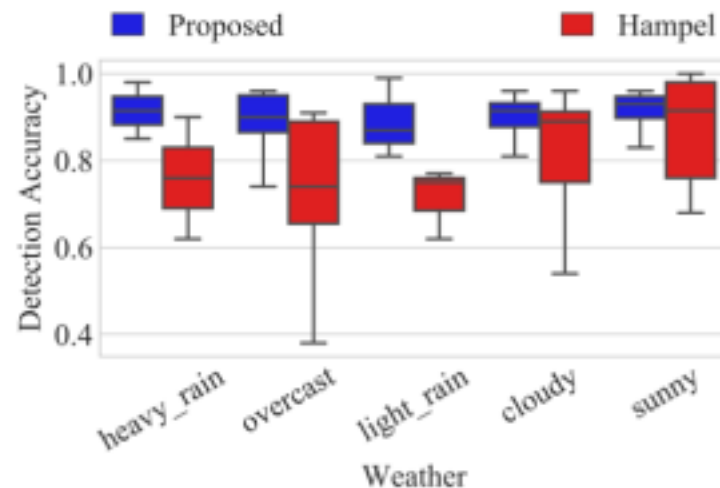


Fig. 10: Fault detection accuracy vs. weather.

# Motivations of fault diagnosis

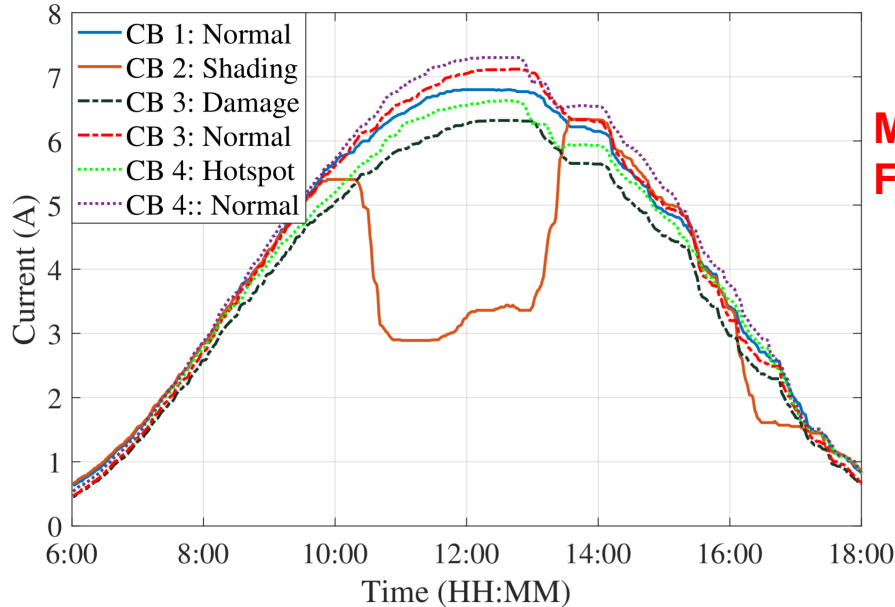


Fig. 11: Commonly occurred faults.

Multimodal  
Features

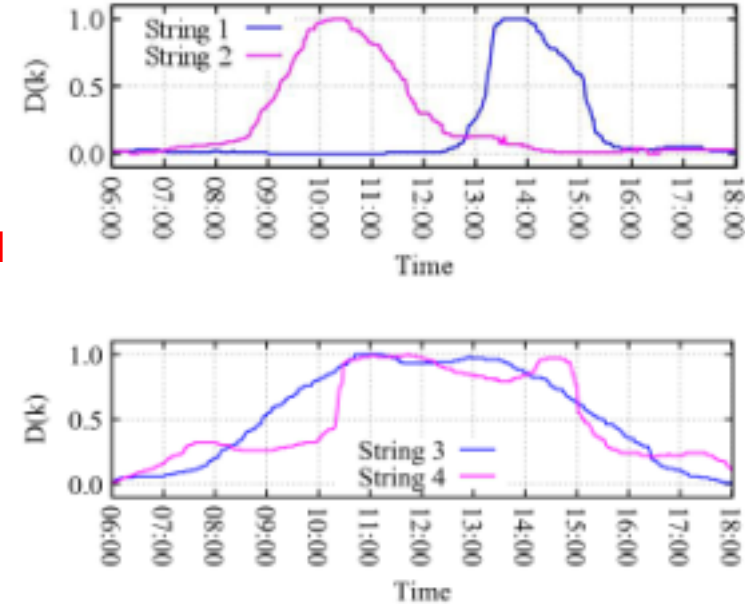


Fig. 12: Scaled  $D(k)$  sequence examples for two building shading faults (string No.1 and No.2), a hot spot fault (string No. 3), and a grassing shading faults (string No. 4).

# Visualization of features and confusion matrix

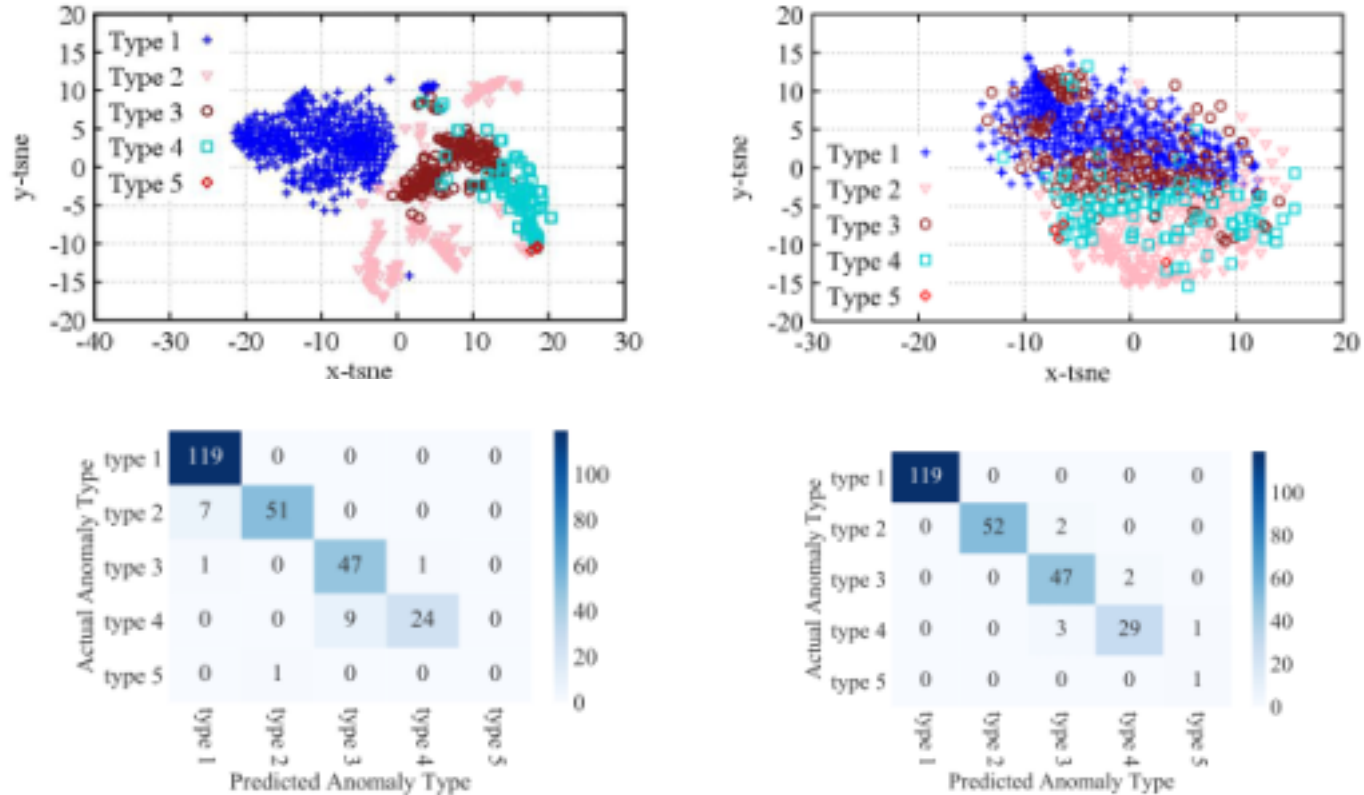
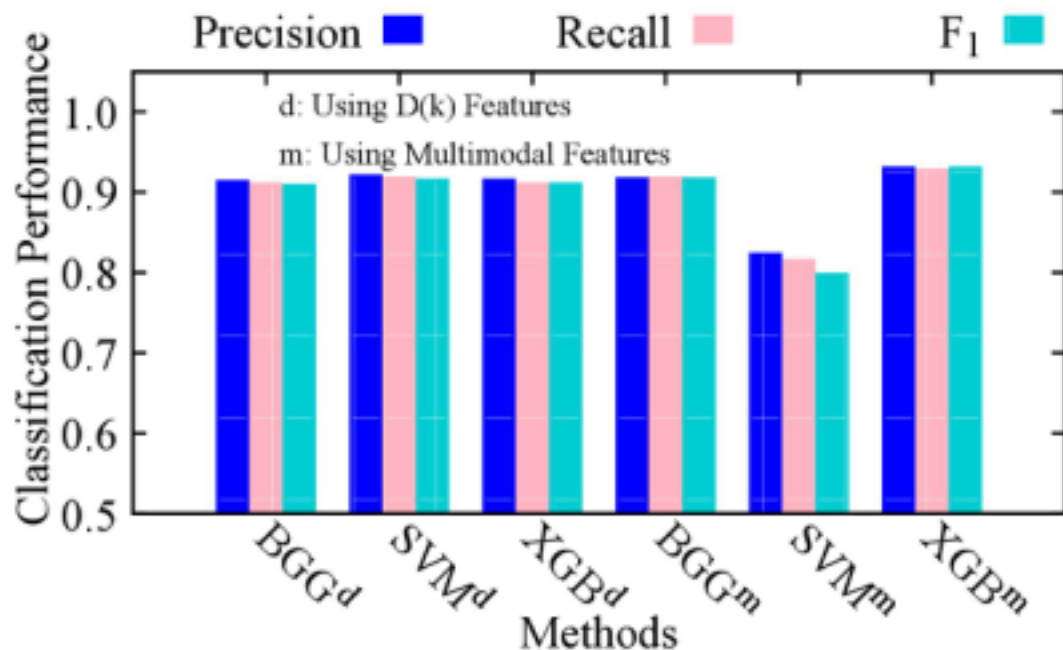


Fig. 13: Visualization of features (upper), confusion matrix (bottom), based on D(k) features (left), and based on multimodal features (right).

# Fault diagnosis



To the best of our knowledge, this is the **first work** that uses SCADA data to classify commonly occurring anomalies at the PV string level in large-scale PV systems.

- Precision: **93.0%**
- Recall: **92.8%**

Fig. 14: Classification performance of different methods.

# Automatic soiling loss quantification

Under soiling conditions, the lowest mean relative error (MRE) of the estimated power production:

1. Drops from **0.315** (using the soiling-station-based method) and **0.075** (using the CPR-based method) to **0.007** at one PV site.
2. At another PV site, the MRE drops from **0.452** (using the soiling-station-based method) and **0.061** (using the CPR-based method) to **0.046**.

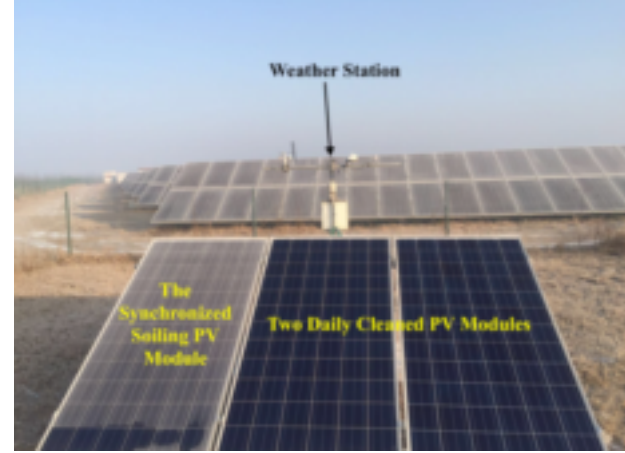


Fig. 15: Picture of the weather station.

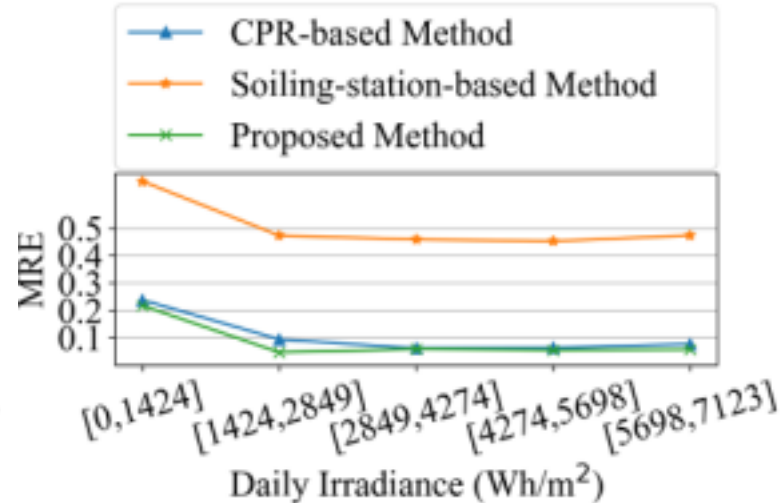
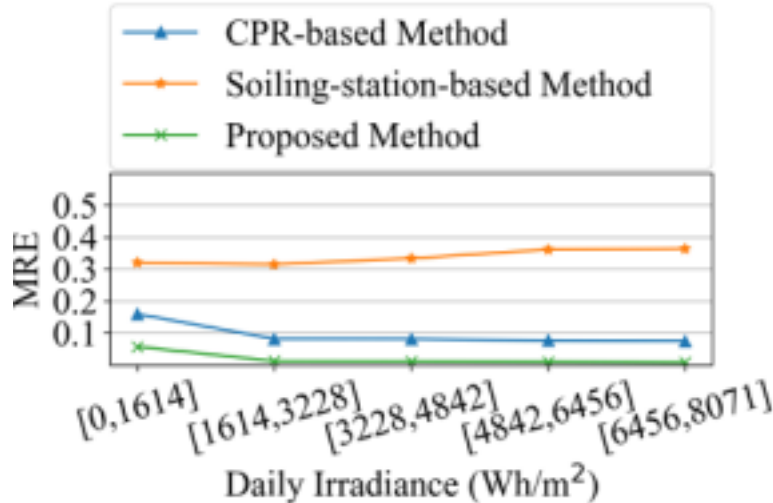


Fig. 16: Performance comparison of different methods.



# Industrial Application



**Concord New Energy Group Limited**  
**协合新能源集团有限公司**  
(0182.hk)

## Sustainable Energy

## Intelligent Sustainable Energy



### Wind Power

- 52 wind power farms
- Installed Capacity 2,483 MW
- 28 GW wind Power stored



### PV Power

- 18 PV power farms
- DC Nominal capacity of 313 MW
- 8 GW PV power stored

### POWER

- Consulting , design
- EPC
- Intelligent O&M
- Electricity Allocation and Sale
- Finance Leasing
- Energy Storage

# Building Intelligent O&M by Energy Internet

Energy internet cloud platform  
"POWER+" has undergone continuous optimization and has been applied total installed capacity of **5GW+**

Through the diagnostic analysis by "POWER+" platform, the average power generation of wind power plants and PV power plants increased more than **1%** and **5%**, respectively.

By taking advantage of its "POWER+" products, the Group actively builds a cloud-based O&M model, which provides the centralized management, personalized and precise operation as well as maintenance services manned by no one or only a few people

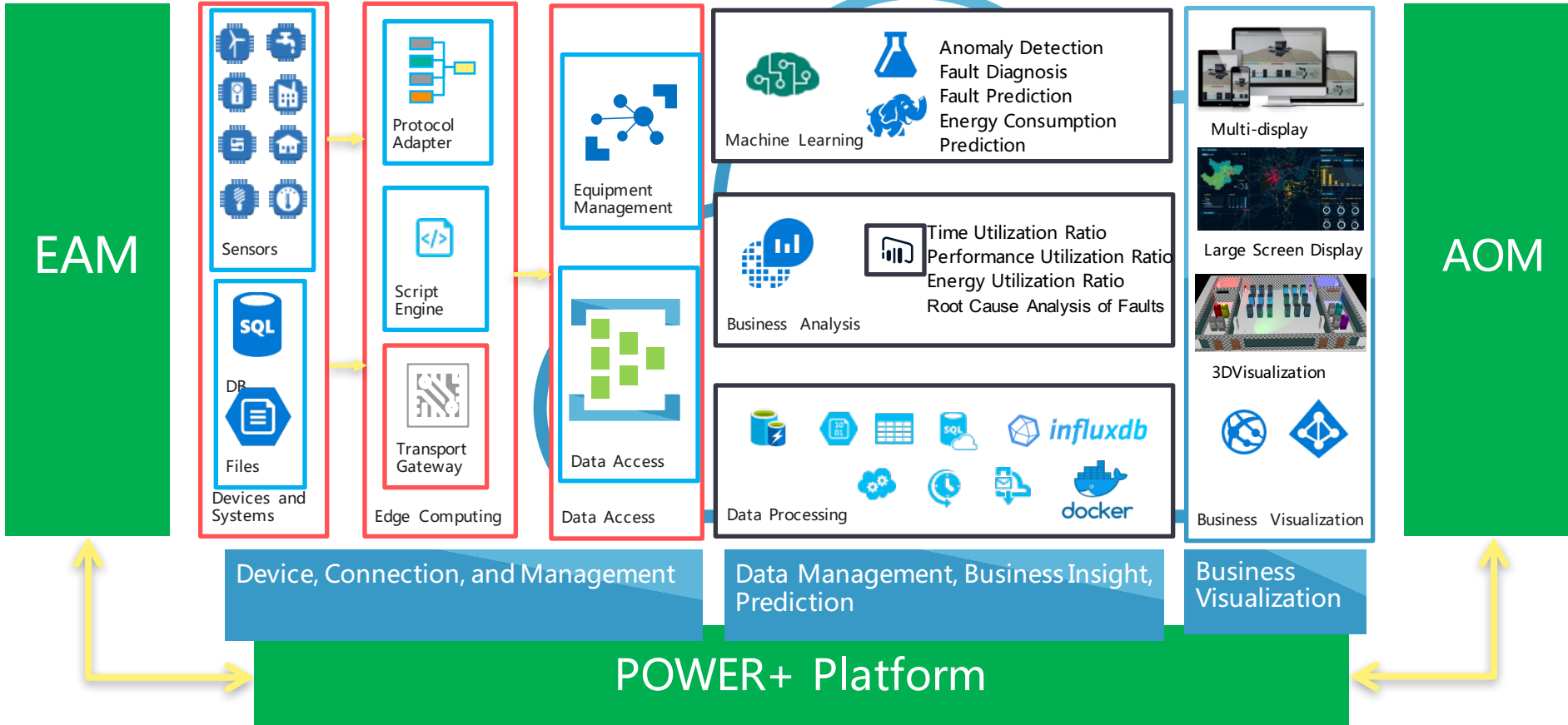
76 wind power and PV power plants' overall O&M in total, with DC nominal capacity 4600 MW

Internet O&M  
Management  
POWER+

On-Site  
O&M

Successfully passed the new standard certification of the "Three-standard System". Obtained the TÜV wind turbine O&M capability certification from Germany as the first third-party independent O&M company that has passed TÜV International certification

# Framework of Intelligent O&M



# Conclusions and Future Work

## Conclusion

1. An **effective and robust FDD solution** for PV systems.
2. The proposed solution has been deployed in sustainable energy systems with the installed capacity larger than **5 GW**, and averaged power generation have increased more than **5%**.
3. Research papers

## Future work

1. Combining **thermal-related** method with **data driven** method, so as to perform **more exact fault localization**.
2. Quantifying soiling loss in **mountainous areas**, as well as in lower irradiance conditions.

- **Yingying Zhao**, Qi Liu, Dongsheng Li, Dahai Kang, Qin Lv, Li Shang. Hierarchical Anomaly Detection and Multimodal Anomaly Classification in Large-Scale Photovoltaic Systems. IEEE Trans. On Sustainable Energy.
- **Yingying Zhao**, Dongsheng Li, Qi Liu, Qin Lv, Li Shang. Deriving Customer Privacy from Randomly Perturbed Smart Metering Data. In IEEE 16th International Conference on Industrial Informatics (INDIN 2018) .
- Dongsheng Li, **Yingying Zhao**, Yawen Zhang, Qin Lv, Li Shang. An Algorithmic Method for Tampering-Proof and Privacy-Preserving Smart Metering. In IEEE 16th International Conference on Industrial Informatics (INDIN 2018) .
- Qi Liu, **Yingying Zhao**, Yawen Zhang, Dahai Kang, Qin Lv, Li Shang. Hierarchical context-aware anomaly diagnosis in large-scale PV systems using SCADA data. In IEEE 15th International Conference on Industrial Informatics (INDIN 2017) .
- Ao Dong ; **Yingying Zhao**; Xiwei Liu; Li Shang; Qi Liu; Dahai Kang, Fault diagnosis and classification in photovoltaic systems using SCADA data, 2017 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC'17)
- Qi Liu, Yawen Zhang, **Yingying Zhao**, Duanfeng Gao, David W Gallaher, Qin Lv, Li Shang. Automatic multi-sensor data quality checking and event detection for environmental sensing, 2017 AGU Fall meeting, 2017.



# Thank you!

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