Fault Classification in PV Arrays using Machine Learning

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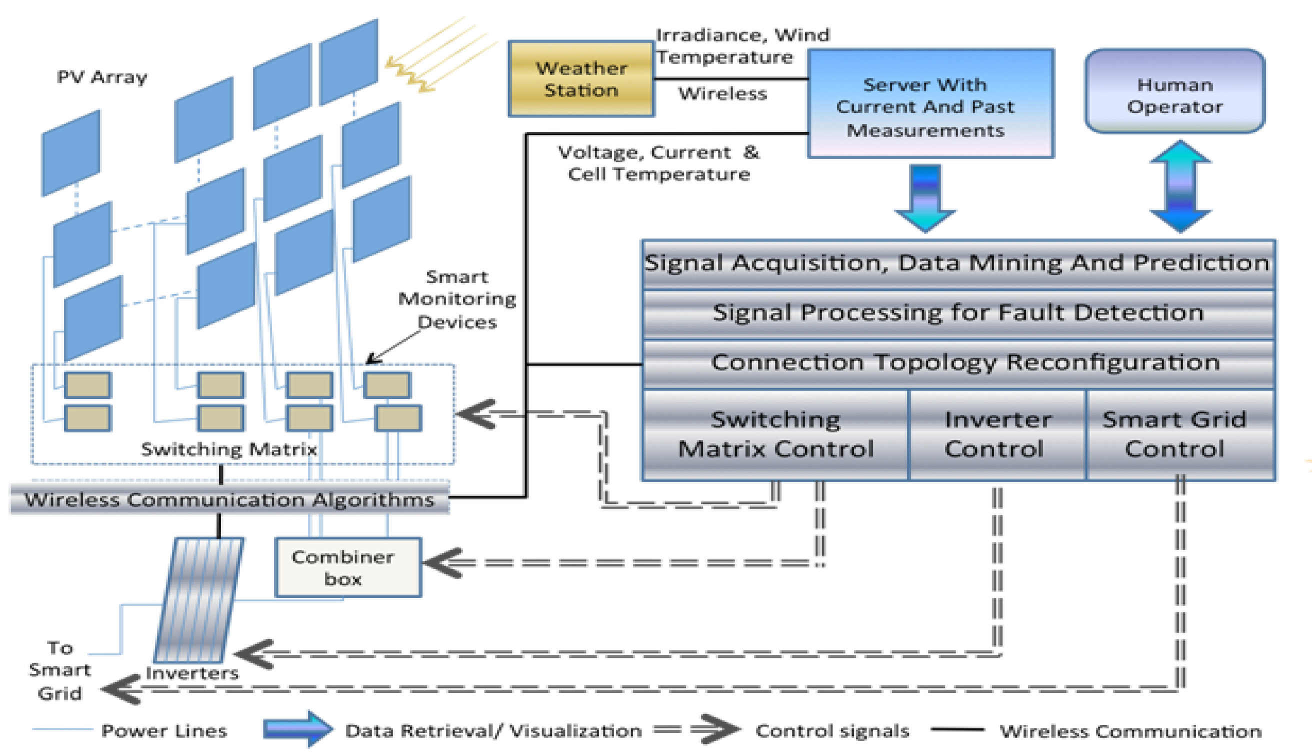
OVERVIEW



Overview of our research vision in Solar Panel Monitoring.

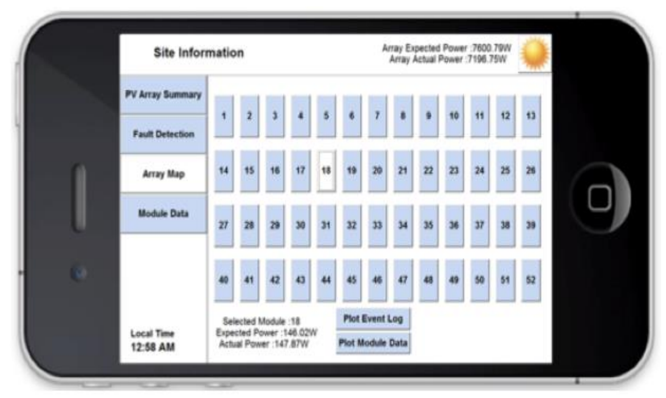
FACILITY AT ASU

Solar Monitoring Facility at the ASU Research Park.

- Structure consists of 104 PV panels.
- Each with a smart monitoring device, installed atop an elevated steel frame.
- Each SMD can measure current, voltage, irradiance, and temperature of the associated panel.

SMART MONITORING DEVICE

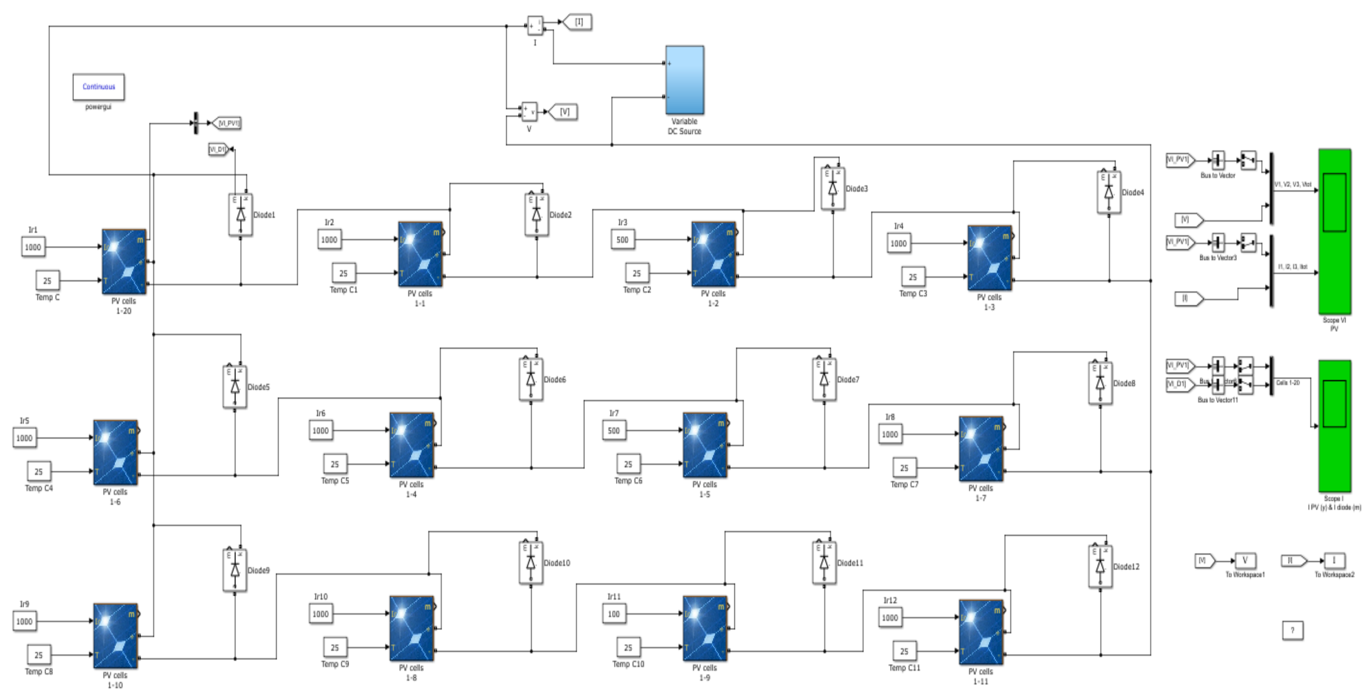
Smart Monitoring Device (SMD).



An app to visualize data.

- Each SMD communicates wirelessly and provides analytics to an access point located at one of the PV panels.
- This access point in turn communicates with a central gateway which connects to the ASU Network.
- The app has a graphical user interface.

SIMULINK MODEL

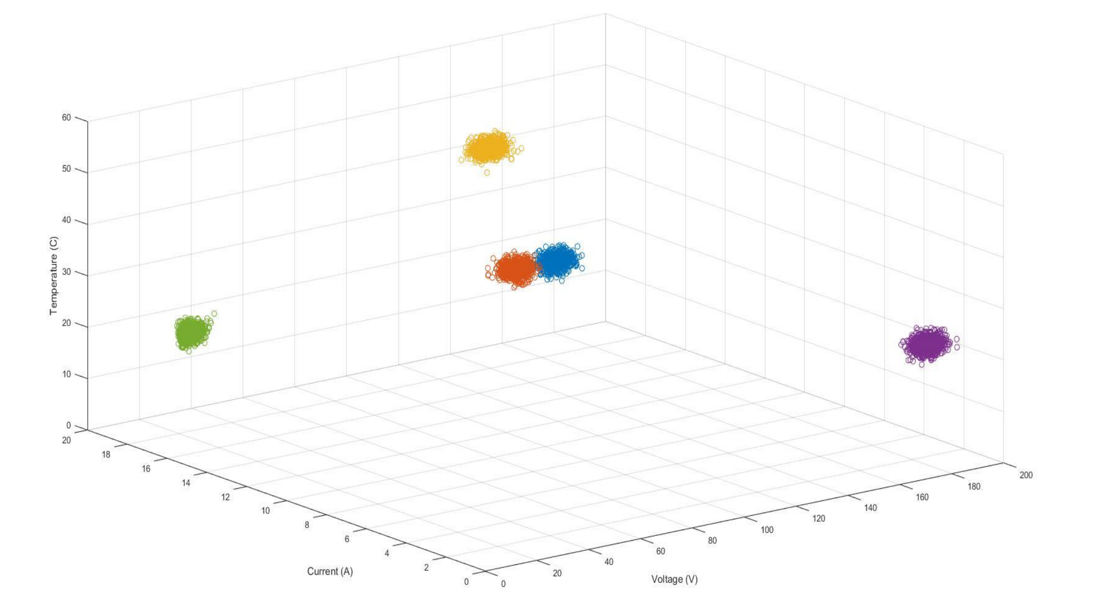


Simulation model used for Data generation.

- Simulink Model used for data generation.
- 4 configurations simulated using Simulink.
- Data obtained used for training and testing.

MACHINE LEARNING RESULTS

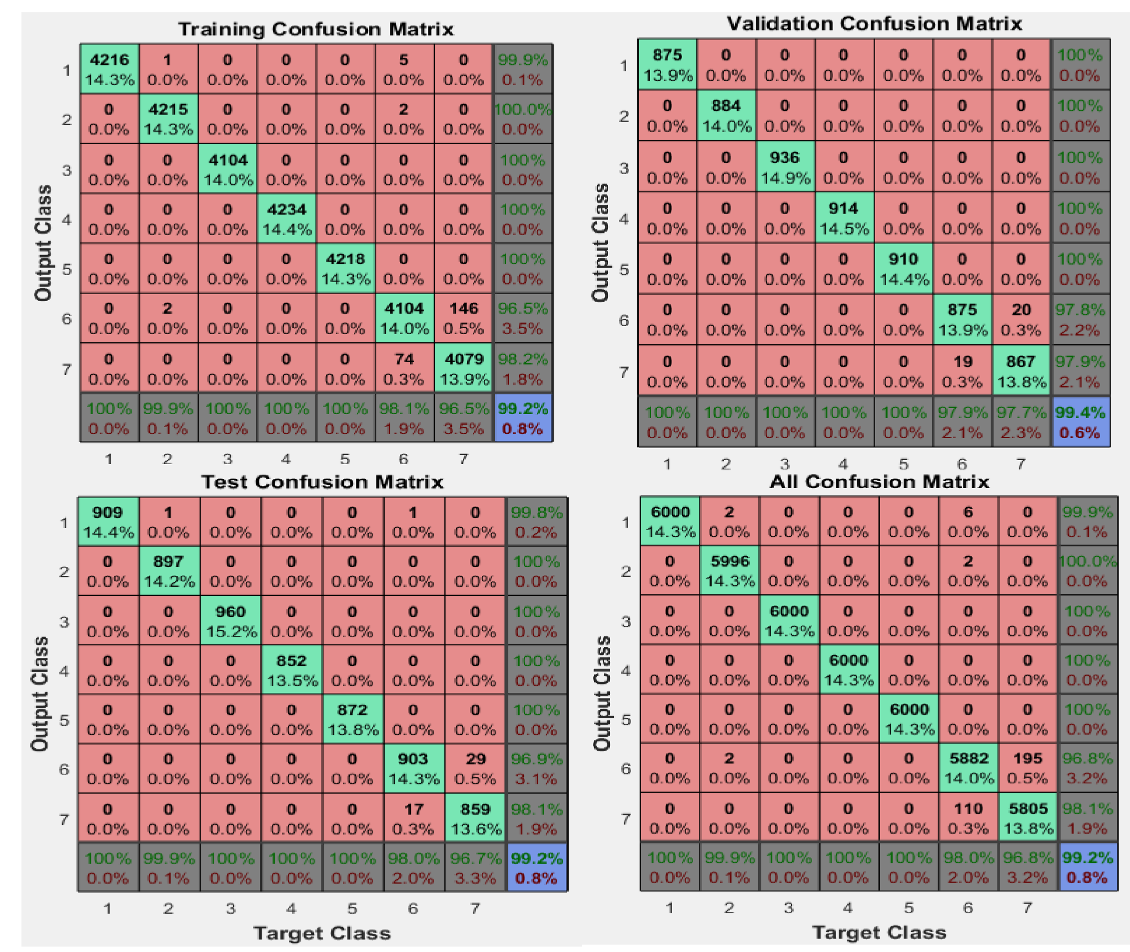
- Use of Clustering algorithms to identify faults in PV arrays.
- K-means and GMM used for clustering.



K-means algorithm identifies temperature conditions.

NEURAL NETWORK RESULTS

- Use neural nets to identify faults.
- Fully connected neural network used.



Confusion matrix identifying seven cases in PV arrays.

DROPOUT NEURAL NETWORKS

- Real dataset from PV Watts.
- Dropout Neural Networks with different probabilities used.
- Concrete Dropout architecture used to prevent overfitting.
- Monte Carlo simulation and K-fold cross validation performed.

Architecture	Train Accuracy(%)	Test Accuracy(%)	Test Accuracy Change
Fully connected	91.62	89.34	Baseline
Concrete Dropout	91.45	89.87	+0.5%
Dropout with p=0.1	89.71	89.34	0%
Dropout with p=0.2	89.29	89.13	-0.21%
Dropout with p=0.3	88.92	88.77	-0.57%
Dropout with p=0.4	87.38	88.77	-2.14%
Dropout with p=0.5	85.51	85.42	-3.92%
Random Forest Classifier	100	86.32	-3.02%
KNN Classifier	87.15	85.76	-3.58%
SVM Classifier	83.51	83.29	-6.05%

TABLE I: Comparison of various classifiers used for fault classification in PV Arrays.

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