CPS: Synergy: Image Modeling and Machine Learning Algorithms for Utility-Scale Solar Panel Monitoring A Cyber Physical System for Solar Array Fault Classification and Topology Optimization

CYBER-PHYSICAL SYSTEMS PRINCIPAL INVESTIGATORS' MEETII

Schools of Engineering

ARIZONA STATE UNIVERSITY

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OVERVIEW OF PV MONITORING SYSTEM SOLAR ARRAY SIMULINK MODEL Human Server With Continuous Current And Past Operator Measurements /oltage, Current & Cell Temperature ignal Acquisition, Data Mining And Prediction Monitori Signal Processing for Fault Detection Connection Topology Reconfiguration Smart Grid Matrix Control Control Control Combiner box 🔷 Data Retrieval/ Visualization = 奏 Control signals 🛛 — Wireless Communication Simulation model used for Data generation. FAULT DETECTION USING NEURAL NETS SOLAR ARRAY FACILITY AT ASU **Fault Detection**: 4 configurations (12S-1P, 6S-2P, 4S-3P, 3S-4P) to analyze 8 different faults. **Topology Optimization**: Performance with partial shading. SP, TCT, BL, HC structures. **PV data** is used for training and testing. ---- Ground Fault ---- Arc Fault Temperature PV array consists of 104 PV panels. Irradiance Shading Fill Factor 🔶 Soiling Each panel has a smart monitoring device. 🛶 Short Circuit SMDs sense current, voltage, irradiance, temp. Decision Layer Output Input Layer They have sensors, actuators, RF, Wi-Fi. Real dataset from PV Watts. Fully Connected and Dropout Neural Nets with different probabilities used. Concrete Dropout reduces overfitting. Monte Carlo simulation and K-fold cross validation performed. Ira A. Fulton





Train Accuracy (%) **Test Accuracy** Architecture (%) Fully Connected 91.62 89.34 91.45 89.87 **Concrete Dropout** 89.34 Dropout with p=0.1 89.71 Dropout with p=0.2 89.29 89.13

Dropout with p=0.3	88.92	88.77
Dropout with p=0.4	87.38	88.77
Dropout with p=0.5	85.51	85.42
Random Forrest Classifier	100	86.32
KNN Classifier	87.15	85.76
SVM Classifier	83.51	83.29

and Uniform Concrete overfitting reduces and classification accuracy.

PV TOPOLOGY OPTIMIZATION

Need Topology for Depending upon partial shading, array topologies such as series parallel (SP), Bridge Link (BL) or HoneyComb (HC) and total cross tied (TCT) produce different maximum power points



Comparison of maximum power points for different topologies under a partial shading condition.

Sensor Signal and Information Processing Center https://sensip.asu.edu

INDUSTRY CONSORTIUM



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BL SP TCT

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[5] Provisional Patents: Topology: US 62/808,677 / Fault Detection: US 62/843,821

ACKNOWLEDGEMENTS

This work is supported in part by the NSF CPS Award 1646542, Poundra, and NSF I/UCRC.

