

## Final Technical Report (FTR) Template

**Project Title:** PV Fault Detection Tool

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**Executive Summary:**

The **PV Fault Detection Tool** project plans to demonstrate that the FDT can (a) detect catastrophic and degradation faults and (b) identify the type of fault. This will be accomplished by collecting fault signatures using different instruments and integrating this information to establish a logical controller for detecting, diagnosing and classifying each fault.

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## **Background:**

The current state of the art within the PV industry for automated detection and mitigation of common faults is simplistic and proprietary. There are two common implementations. In the more common of the two, fault detection is integrated into the inverter. The inputs to this type of system typically are the DC input from the array and the AC available from the grid. Some implementations may employ auxiliary inputs but these tend to still be focused on instantaneous electrical measurements. Most commonly, these systems are used to detect grid errors (voltage and frequency deviations) or array faults that might trigger a safety concern, such as an arc or ground faults. The other common implementation is a monitoring system that operates independently of the inverter. The focus of these systems typically is on providing a real time update of energy harvest and conversion efficiency. More advanced monitoring systems may enunciate catastrophic failures. Few, if any of these systems employ sophisticated diagnostics to compare actual system performance to predicted system performance beyond a simplistic performance ratio (Pr).

These simplistic systems typically look for discrete changes in performance from individual sensors rather than cross-correlation between multiple sensors or any analysis of historical information. For example, if DC voltage drops below a certain level, the inverter will shut off and attempt to reconnect after a predetermined time period. No distinction is made as to whether or not the reason for the voltage drop is due to low irradiance conditions associated with sunrise/sunset, sudden thunderstorms or module/wiring failure. Likewise, systematic shading may be detected as a decrease in power (or current) but may be indistinguishable from a solder joint failure within the module without historical analysis of the time-series data. Further, the underlying algorithms employed by these monitoring systems are typically proprietary.

This project will develop prototype fault diagnostic tools to address these known limitations. The algorithms will be open source/freely distributable so that other researchers or industrial partners can adopt them. We will not attempt to develop a full software package including a GUI; this is beyond the intended scope of this project and does not play to the strengths of the assembled team. Ultimately, we believe that providing the underlying fault detection and classification methodology will be of the most benefit, because this will allow industrial partners to integrate them into either embedded code or stand-alone applications as they see fit.

**Project Objectives:** The current state of the art within the PV industry for automated detection and mitigation of common faults is simplistic and proprietary. These simplistic systems typically look for discrete changes in performance from individual sensors rather than cross-correlation between multiple sensors or any analysis of historical information. In this project, we will develop prototype fault diagnostic tools for detecting and classifying multiple fault types that impact the performance and reliability of PV plants.

## Project Results and Discussion:

### Subtask 1: Fielded PV Array

The fielded PV array and associated instrumentation was a key component of this project as it serves as the experimental test bed. First, performance is defined without faults and then different faults scenarios are systematically introduced. Data from the baseline and fault conditions be collected through a data acquisition system. In the proposal phase of this project, we planned to build a 5kW array. However, in defining the array requirements to meet project objectives, it was determined that we should move to an array more than twice this size. Design criteria included;

1. Commercially available residential or commercial sized conventional silicon module
2. Realistic system voltage (i.e. 350-600VDC)
3. Maximize string length
4. Maximize number of strings
5. Inverter availability
6. American module manufacturer
7. Budget

Modules from Suniva, Solarworld and JA Solar (non-US) were considered. For each module under consideration, system voltages and currents were explored as a function of string length and number of strings. These values were iteratively calculated to match the specifications of various commercially available inverters. This process led us to choose Suniva 60-cell modules paired with a Fronius IG Plus Advanced inverter. Nameplate rating of the system will be 10.8 kW. A particular challenge that was encountered in designing the system was inverter selection. There is a trend in these smaller sized inverters toward multiple MPPT inputs. While system voltage for these inverters remains high, current is limited for each input, limiting the number of parallel strings. The 10.8kW system, consisting of 4 strings each with 10 modules, is shown in Figure 5.1.

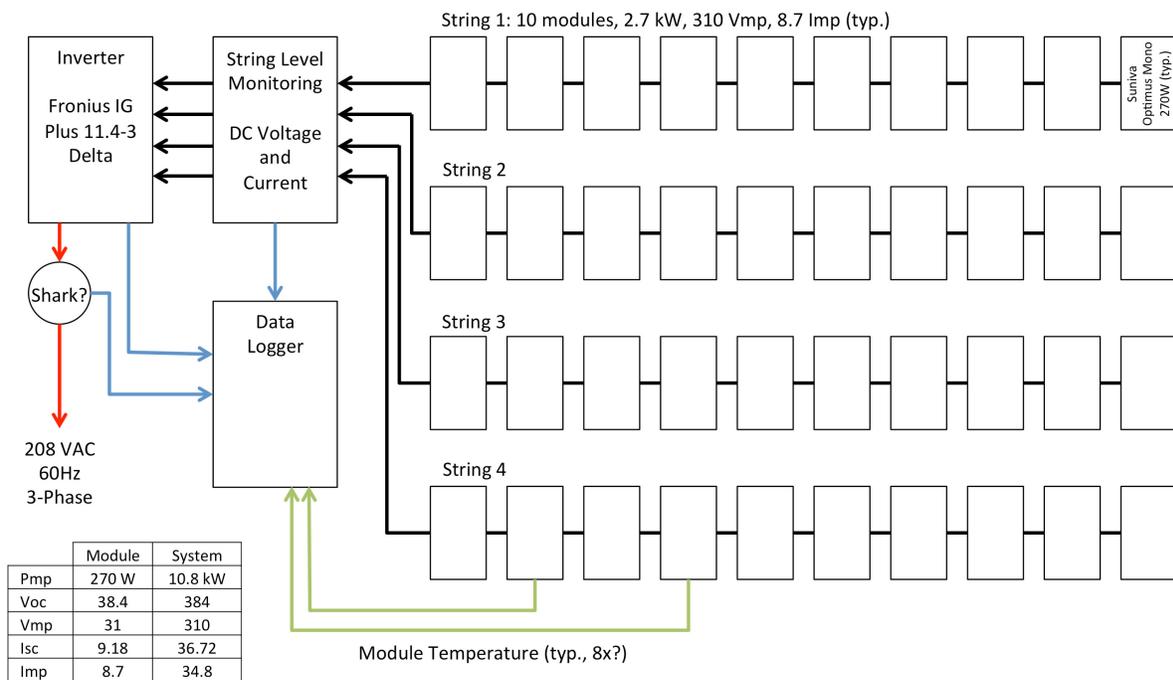
**Table 1.1.** System Design

	Module	System
Module	Suniva Optimus Mono	
Inverter	Fronius IG Plus 11.4	
String length	10 modules	
Number of strings	4	
Pmp	270	10800
Voc	38.4	384
Vmp	31	310
Isc	9.18	36.72
Imp	8.7	34.8



**Figure 1.** 10.8kW PV Array, consisting of 4 strings each with 10 modules.

The installation of the data collection system that includes DC voltage and current, and others is currently in progress. The monitoring system includes low and high frequency data collection through multiple devices as shown in image on the left side of Figure 5.2



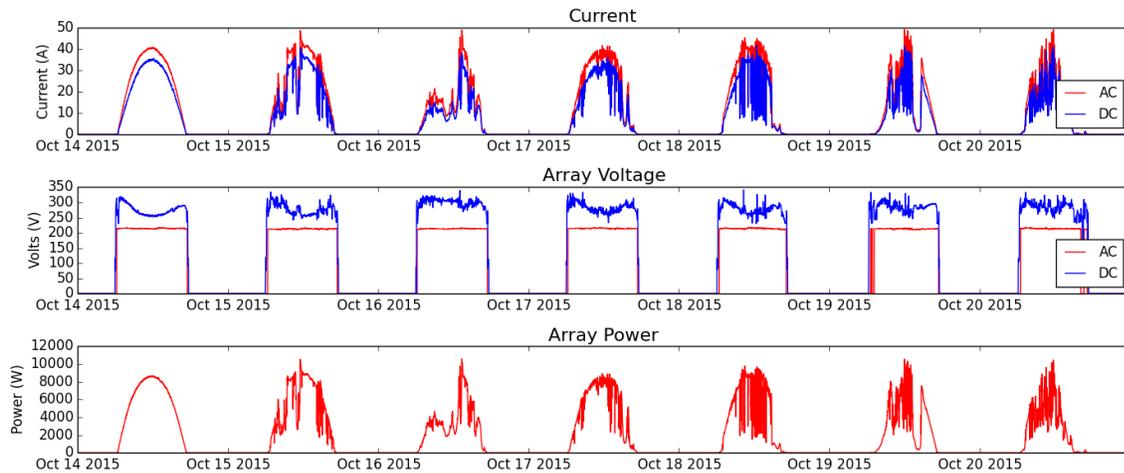
**Figure 2.** Array and instrumentation schematic.



**Figure 3.** Monitoring system, weather station and inverter for the PV array.

### Subtask 2: Baseline Data

A detailed model of the system was created using the PV\_LIB Python package and was used to simulate normal operating behavior. The simulated normal behavior was used for training and testing of machine learning and artificial neural network algorithms to perform advanced and automatic fault detection. Following this demonstration, actual weather and system data was used to train the Gaussian Process Neural Network over six days of operation (Figure 4). The resulting model was then validated against several days of operation (Figure 5).



**Figure 4.** Baseline training data for the GPNN

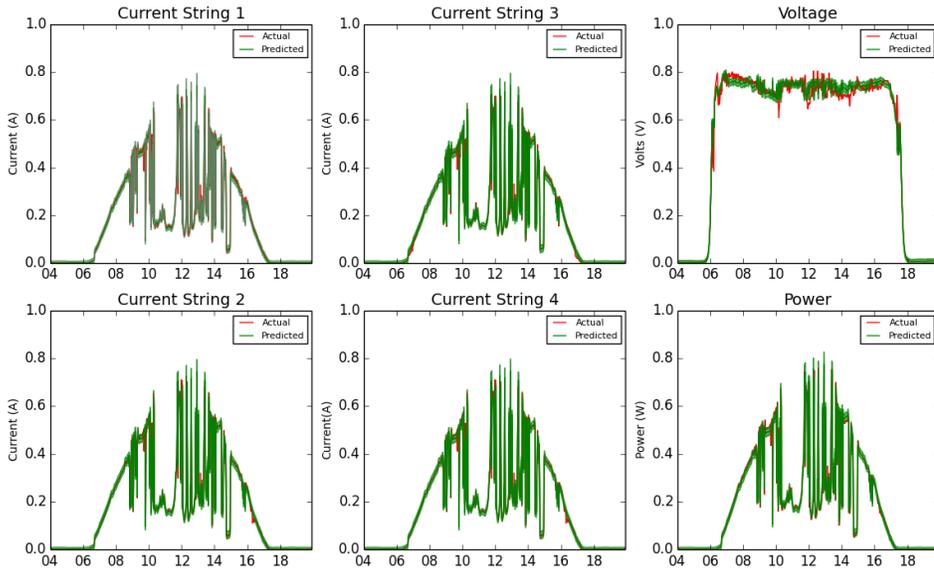


Figure 5. GPNN validation data

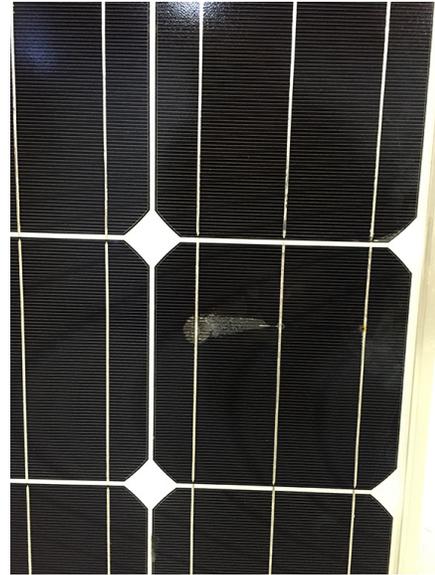
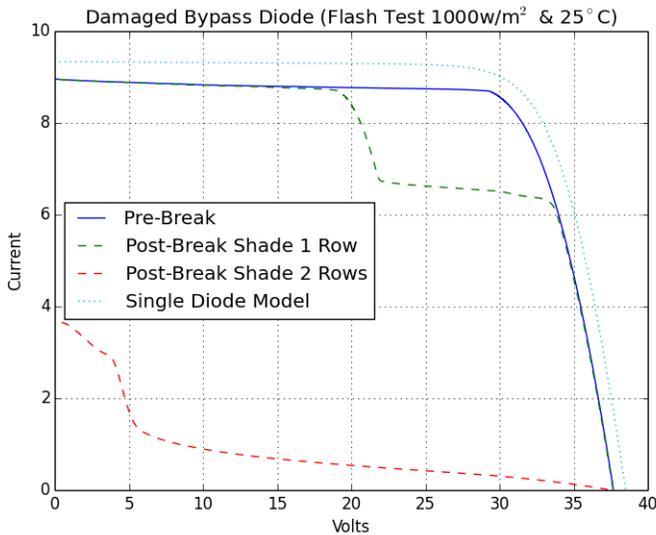
### Subtask 3: Fault Introduction

As of this report, four faults have been introduced; inverter failure, shading, bypass diode failure and cracked cells. Inverter failure was simulated by simply initiating inverter shutdown while the data acquisition system continued to function. Partial shading of the array was conducted by temporarily placing a small tree branch on a module on the west end of the array. The impact to power production for each of these is shown below in Figure 6.

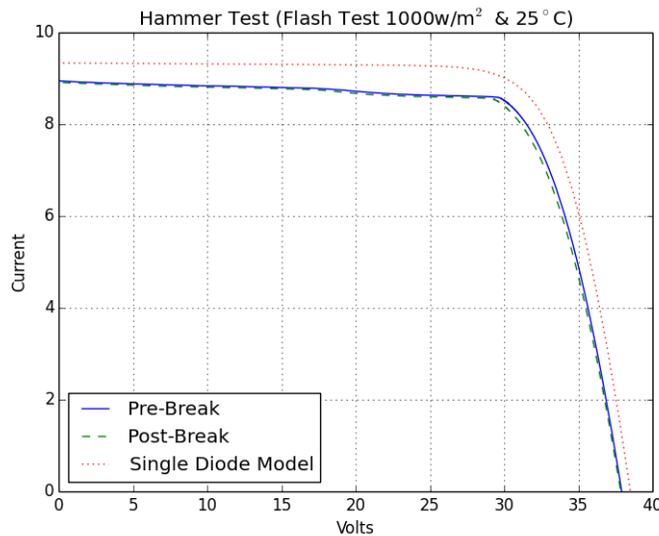


Figure 6. Fault introduction - Inverter shutdown and partial shading

Bypass diode failure was simulated by opening the junction box of one module and desoldering the bypass diode associated with one substring. This module was then placed into the array. Hotspots were induced into the module substring with the “failed” bypass diode by casting a shadow across the module. This was done systematically by placing a single wooden fence slat approximately 5 feet tall to one side of the array. During morning hours, the array was unshaded. As the sun moved past solar noon, the shadow from the fence slat progressively moved across the panel. This led to rapid hotspot formation and module failure. The effect on the module IV curve is shown below in Figure 7.



**Figure 7.** Fault introduction – Bypass diode failure

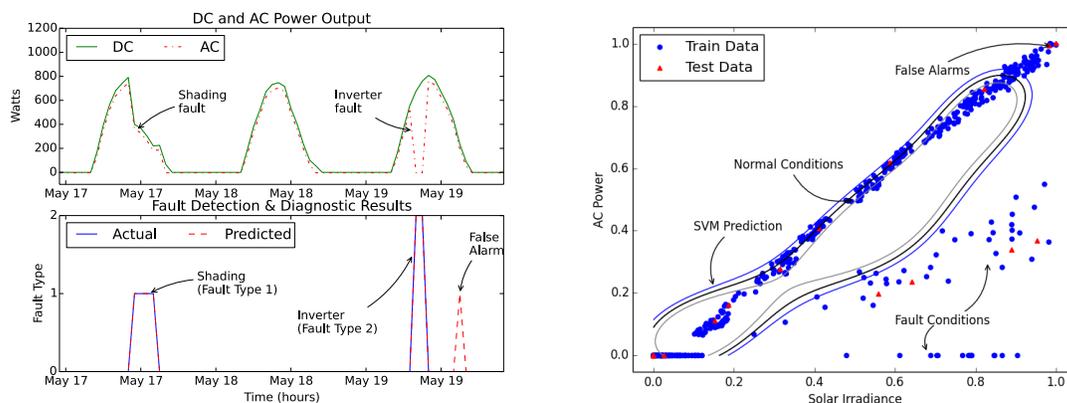


**Figure 8.** Fault introduction – Hammer test

The last fault introduced so far was cell cracking induced by hammer blows to the back of the module. This fault introduction proved to be much more difficult than originally imagined. Modern module construction in many respects resembles automotive safety glass. The presence of EVA encapsulant on the front and rear of the module limit crack propagation through the cell. Cracks seem to be confined to the spot directly underneath the hammer blow. The impact to the IV curve and measured power was minimal. Regardless, this module will be placed in the array to determine if failure can be induced.

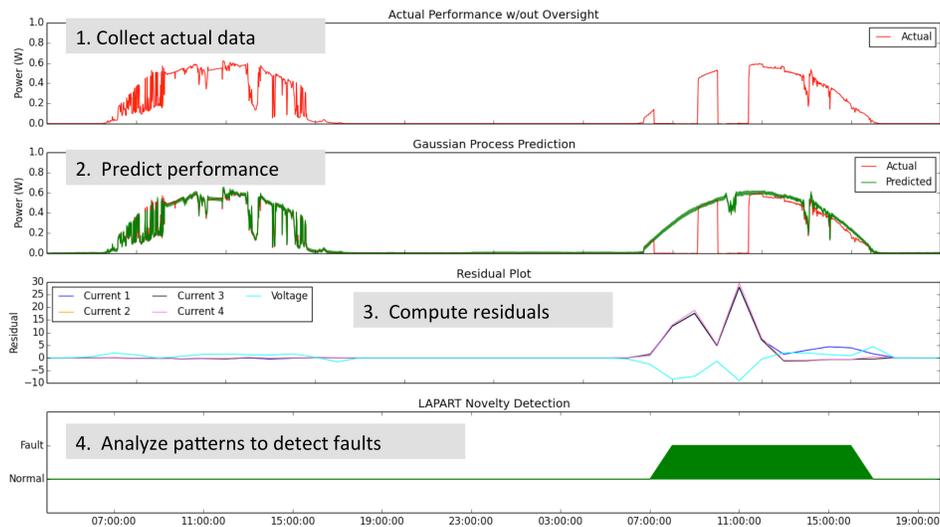
#### Subtask 4: Analyze FDT Signals to Identify Fault Characteristics

In advance of completion of the test array, we began work on analysis and classification techniques. This work included the development and implementation of fault detection and diagnostic algorithms. A Laterally Primed Adaptive Resonance Theory (LAPART) artificial neural network algorithm was developed and presented with synthetic normal and fault condition data produced by a PV array model. The model, developed in MATLAB using the PV\_LIB package, produced data outputs such as DC voltage, DC current, and AC power. Based on the presentation of the model outputs, the LAPART algorithm was able to accurately detect and diagnose system faults that included inverter failures and partial shading as shown in Figure 9. The results from this preliminary investigation were accepted as a Late Abstract submission to the 42<sup>nd</sup> IEEE Photovoltaic Specialists Conference and presented as a poster.



**Figure 9.** Right: Synthetic DC and AC power output that includes normal behavior, shading fault, and an inverter fault. The Laterally Primed Adaptive Resonance Theory (LAPART) algorithm was able to detect and diagnose the shading and inverter faults. Left: Preliminary training and test data obtained from a functioning PV array.

These algorithms have been tested using the data generated from actual fault introduction. An example of their application is shown below in Figure 10. Thus far, the algorithms have successfully been able to identify and classify the faults that have been presented. Training and analysis is still in process for bypass diode failure and cracked cells. Following successful training on these additional faults, each fault is planned to be reintroduced to test the algorithm's ability to correctly classify multiple fault types.



**Figure 10.** Fault introduction and unsupervised identification and classification.

### Subtask 5: Develop Prototype Software

Prototype software work has focused on the development and implementation of a Laterally Primed Adaptive Resonance Theory (LAPART) artificial neural network algorithm to detect faults within synthetic and actual data sets. The algorithm has the unique ability to learn system behavior quickly and accurately. The initial algorithm was developed in MATLAB using the PV\_LIB package. We have begun investigating the use of embedded software, coded in Python, running on Raspberry Pi hardware. Currently, the Raspberry Pi has been set up to collect and store data through a Modbus connection. However, it can also perform local analysis of array performance and faults. Gantner Instruments, who provided the high speed data acquisition systems for the project, have expressed their interest in incorporating the fault detection algorithms into their data acquisition products.



**Figure 11.** Data logging and fault detection. Currently, fault detection is done on a desktop computer after data has been collected and transferred. The likely future of this capability is as an embedded algorithm running locally on the array for real-time fault detection and annunciation.

### **Subtask 6: Document Methodology for Public Release**

Since this project is not planned for completion until March 2016, final public documentation has not been completed. The results of our preliminary work have been presented at the 42<sup>nd</sup> IEEE-PVSC and published as part of the conference proceedings. We plan at least one journal publication to come from the remaining work, for publication in 2016. Further, subject to restrictions associated with a potential patent application, we plan to release the algorithms publicly through the PV\_LIB Toolbox.

**Accomplishments:**

**Peer-Reviewed Journal Articles:**

C. B. Jones, J. S. Stein, B. H. King, "No data, no time, no problem: accurate fault detection and diagnostics of PV arrays using LAPART neural network and two-class support vector machine," *in preparation*, 2016

**Conference Publications:**

C. B. Jones, J. S. Stein, S. Gonzalez and B. H. King, "Photovoltaic System Fault Detection and Diagnostics using Laterally Primed Adaptive Resonance Theory Neural Network." 42<sup>nd</sup> IEEE Photovoltaic Specialists Conference, New Orleans, LA, 2015

**Patent Applications:**

"Plug and play devices for advanced performance monitoring of PV systems," Technical Advance filed with Sandia Legal for consideration for a Patent Application.

## **Path Forward:**

We plan to continue working on this project using approved FY15 carryover funds until March 2016. Work will focus on additional fault introduction, supervised training and refinements to fault classification algorithms. As time allows, we will continue to develop embedded fault detection algorithms running on Raspberry Pi hardware.

We plan at least one journal publication: "*No data, no time, no problem: accurate fault detection and diagnostics of PV array using LAPART neural network and two-class support vector machine.*" Common perception is that neural networks and other machine learning algorithms cannot provide accurate results with minimal upfront data. However, significant advancements have been made since the original back-propagation neural network. The present work describes the unprecedented abilities of the LAPART neural network and the two-class support vector machine. The two algorithms can accurately and precisely detect PV faults with minimal training data within an on-line learning application. This paper describes false alarm, false normal, true normal, and true positive results from an experiment where the learning algorithms were applied to an actual 10.8kW PV system.

If approved, we plan one patent application: "*Plug and play device for advanced performance monitoring of PV systems.*" This patent describes advanced learning algorithms for fault detection that review the incoming data, identify sensor types, learn system behaviors, and detect fault conditions that impact system operation. The algorithm is broadly applicable to real-time monitoring of complex systems incorporating time series sensor data. It is applied here in the context of photovoltaic power plants. A specific example is given of the concept, design, installation, and operations of an advanced, yet affordable monitoring device that can be integrated easily with sensor networks that transfer data via the Modbus communication protocol. The sensor data extracted from the sensor network are stored internally or on the cloud.

As of this report, the PV monitoring industry is experiencing a shakeup with numerous significant players exiting the business (for example, Draker Labs). While this reduces the number of potential adopters of this technology, Gantner Instruments has expressed interest in obtaining the algorithms. We further believe that inverter manufacturers, particularly those with embedded monitoring solutions, will be interested in adopting the algorithms.