Photovoltaic Prognostics and Heath Management using Learning Algorithms

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ABSTRACT

A novel model-based prognostics and health management (PHM) system has been designed to monitor the health of a photovoltaic (PV) system, measure degradation, and indicate maintenance schedules. Current state-of-the-art PV monitoring systems require module and array topology details or extensive modeling of the PV system. We present a method using an artificial neural network (ANN) which eliminates the need for *a priori* information by teaching the algorithm "good" performance behavior based on the initial performance of the array. The PHM algorithm was tested on two PV systems under test at the Outdoor Test Facility (OTF) at the National Renewable Energy Laboratory (NREL). The PHM algorithm was trained using two months of AC power production. The model then predicted the output power of the system using irradiance, wind, and temperature data. Based on the deviation in measured AC power from the AC power predicted by the trained ANN model, system outages and other faults causing a reduction in power were detected. Had these been commercial installations, rather than research installations, an alert for maintenance could have been initiated. Further use of the PHM system may be able to indicate degradation, detect module or inverter failures, or detect excessive soiling.

INTRODUCTION

Photovoltaic (PV) monitoring systems have been designed to measure module and array performance, grid stability, islanding, and power factors. Often monitoring systems are built into inverters or converters and designed to connect and disconnect from the grid during low or high voltage events, prevent islanding, and report on PV status (e.g., current, voltage, power). There is growing interest in PV PHM systems for arc-fault and ground-fault mitigation. Series arc-fault protection devices are newly required by the 2011 National Electrical Code [1]; however fault prevention via PHM tools is preferred over reactive arc-fault circuit interrupters: the best fault is one that never occurs.

PV monitoring system concepts are designed to detect, classify or locate faults when system behavior deviates from the expected [2-8, 10]. To predict the expected PV performance at a given time, various PV system models using meteorological conditions inputs have been created. Often these models calculate expected power using temperature and irradiance data gathered from sensors [2-4] or weather and satellite systems [5-6]. Different PV system models have been employed including PV circuit models [2, 7], PV plant-specific fits [6], matter-element models [3], and expert systems with updating warning criteria [8]. The models in conjunction with current, voltage, or power measurements from the physical system are used to detect a number of fault conditions such as shading [2, 5-8] , inverter failure [5-6, 8], snow cover [5-6], module failures or short circuiting [4, 7-8], and string-level malfunctions [2, 5-6]. Learning algorithms [4, 8-9], Bayesian networks [10], and fuzzy logic [11-12] have also been used successfully to estimate PV output or perform fault diagnoses. Unfortunately, most of these systems are designed to detect catastrophic failures and do not monitor system degradation over time. Hamdaoui designed a method of tracing I-V curves to measure degradation of the modules [13], but this is not practical for field installations.

In previous work, artificial neural network (ANN) models of PV systems were shown to closely match performance array models [14]. The current work combines the areas of PV modeling with prognostics and health management. This learning technique can be performed in situ—requiring only basic system monitoring hardware. Advantages of the ANN PV health monitoring system are 1) it requires no a priori information of the system components or topology to accurately model the output power, 2) the system can monitor the degradation of the system over its lifetime, and 3) the system can prognostically indicate catastrophic failures by monitoring the degradation rate.

PV PHM SYSTEM

Two systems, each approximately 1.1 kW_P, were monitored at NREL's Outdoor Test Facility (OTF). System 1 was monitored for 6 years, while System 2 was monitored for 1.5 years. The health of each photovoltaic systems was monitored by the difference in performance of the physical PV system and the artificial neural network model. Plane of array (POA) irradiance, wind speed, ambient air temperature, and AC power output data were used to perform the study; information regarding the PV system components or configuration was not necessary. The performance metric used in this study was AC power; however, other outputs of interest could also be implemented.

In general, the PV PHM system compares the measured metric of interest (in this case AC power) to a prediction of the metric from a model. As emphasized in [14] the benefit of using a neural network based model is that the user does not need to know any specifics about the PV system components. The neural network simply identifies the relationships between the PV system's environment (input) and its power production (output).

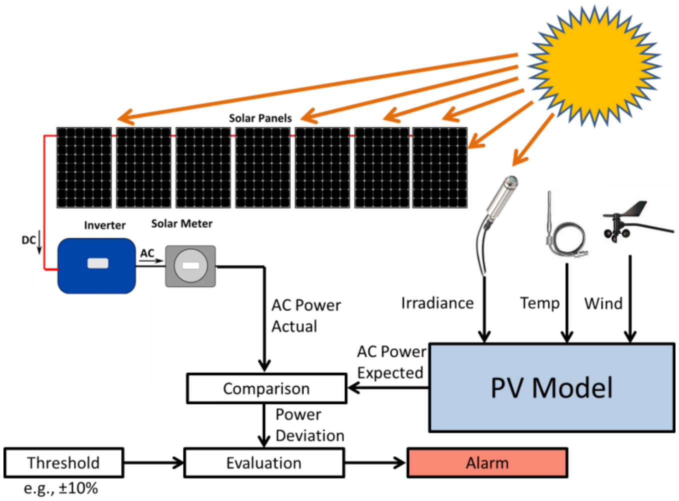

Fig. 1: Schematic of the PV PHM system.

ANN Design

The ANN comprised of a simple 4×20×1 feed-forward multilayer perceptron, trained via particle swarm optimization. The data set used to train the ANN to recognize "optimal" behavior was gathered from the PV monitoring data from the two months following system installation (this may be referred to as the "training" data set). Within two months of installation, the system is assumed to be operating optimally, with little soiling, degradation, or faults. An individual ANN PV model was developed for each system.

DEMONSTRATION

Each ANN PV model was created using two months of monitored irradiance, temperature, wind speed, and AC power. With the neural network model weights locked after the training period (i.e. further learning was disabled) the PV models predicted the AC power produced by each system, given the irradiance, ambient temperature, and wind speed. The PV PHM system then compared the expected power given by the model and the actual power measured from the monitoring system using the equation:

$$\%\ \text{Energy Loss} = 100 * \left(\frac{\sum_n (P_{meas})}{\sum_n (P_{model})} - 1\right) \qquad (1)$$

where

n = number of measurements in the time window
P_{meas} = Measured AC power
P_{model} = AC power modeled by ANN model

Thus, if the sum of measured power is 5% less than the sum of modeled power, equation 1 yields "-5". The testing duration is broken into "windows" of fixed time period (e.g. 2 days), and the comparison calculation is performed for each window.

An alarm threshold of -10% energy loss was set for this demonstration, but could be changed to any value desired by the user. Through the course of the work presented, the authors have noted that larger PV systems may be more amenable to a smaller energy loss alarm threshold.

Figures 2 and 3 show the response of the PV PHM comparison to faults detected in each of the PV systems. In each case, the PV PHM was able to detect a power drop in the PV system which caused energy losses of greater than 10% over the 2 day window period.

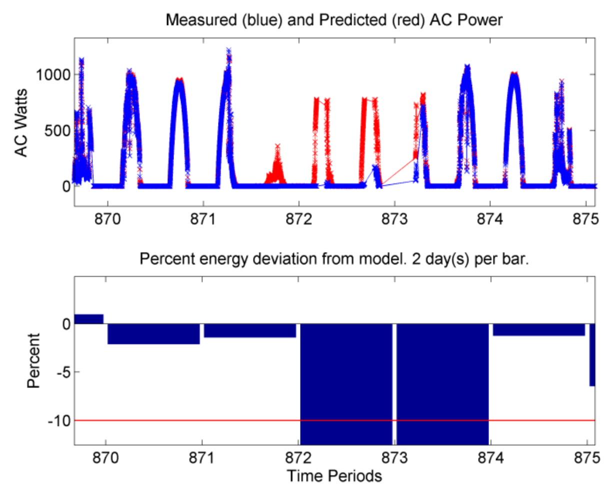

Fig. 2: PV PHM finds problems in system 1

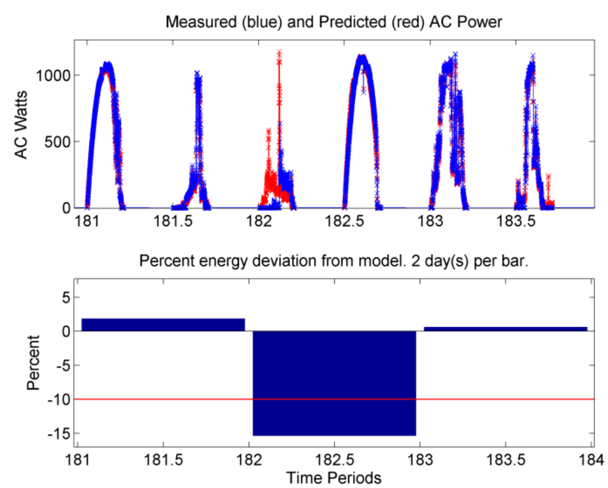

Fig. 3: PV PHM finds problems in system 2

Effect of Training Period Length

Initial implementation of the PHM system utilized a neural network trained on two months of concurrent weather and AC power data. When this neural network was used to predict performance of the PV system, the variance in predicted and measured power was highly correlated to seasons, i.e. the neural net performed best under temperature conditions over which it was trained. Figure 4 shows this seasonal variation in model errors from a neural network trained with only two months of data. Figure 5 shows the same PV system output prediction differences when the neural network was trained with six months of data.

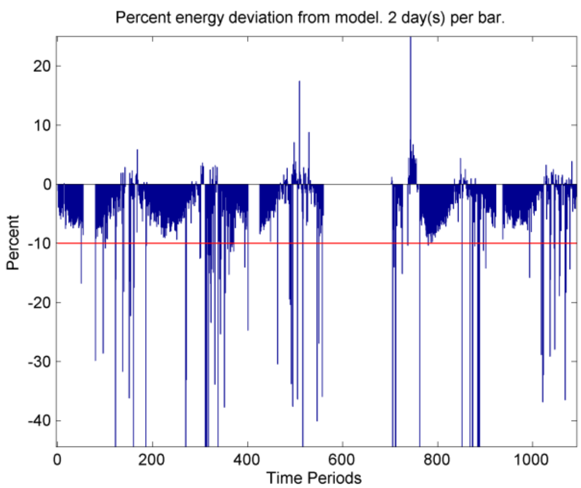

Fig. 4: ANN prediction differences, trained with two months of data. Note seasonal nature of errors.

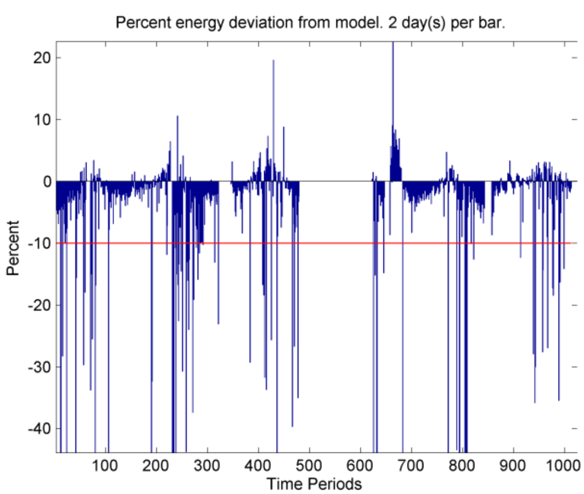

Fig. 5: ANN prediction differences, trained with two months of data. Note reduced seasonal errors.

Evaluation of Comparison Criteria

Early work on the PV PHM system utilized a 10% energy loss alarm as calculated from equation 1. However, the sensitivity of the alarm is greatly affected by the windowing period over which the sum occurs (i.e. the value of n in equation 1). For example, summing over two days, as shown in Figures 2-5, produces a good indication of problems only after a fault in the PV system has persisted long enough to cause a significant energy loss. The size of the windowing period may be reduced to increase the time sensitivity of the comparison, but may cause more false alarms, particularly during periods of low irradiance. Figure 6 shows a day and a half of performance data with a possible false alarm condition due to low irradiance and a short (twelve hour) window period. Conversely, the size of the windowing period may be increased to reduce the time sensitivity of the comparison. Increasing the window period to several days or weeks may also allow for a lower alarm threshold value of perhaps 4-6% instead of 10%.

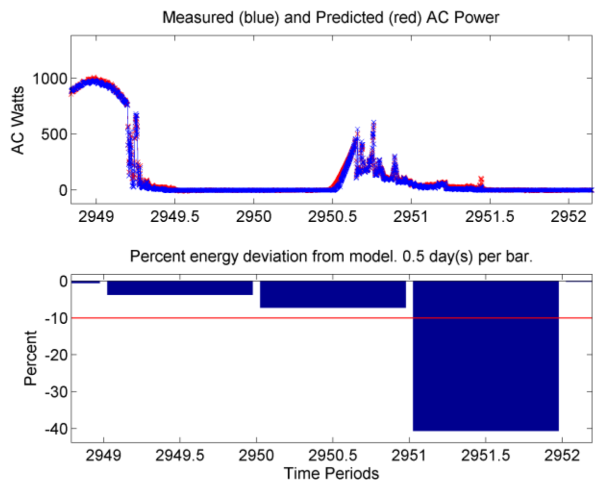

Fig. 6: Possible false alarm due to short 12-hour summation window.

Thus, using the energy loss metric, there is a tradeoff between the length of time which must pass to trigger an alarm and the possibility of false alarms. A different comparison metric than the energy loss given by equation 1 may be able to more quickly determine an acute failure in a PV system.

For example, if the statistics of the training data set are examined for PV system 1, the neural network's model residuals (i.e. $P_{AC,model}$ - $P_{AC,measured}$) may be used to identify the likelihood of a PV system performing below the modeled performance. Figure 7 shows a portion of the model residual cumulative distribution function (CDF) obtained from the neural network training data. Assuming that the training data set is representative of the PV system's operation, there is a 1% chance that the model will overestimate the PV system's AC power by more than 71 watts, and a 0.18% chance of the model overestimating by more than 200 watts.

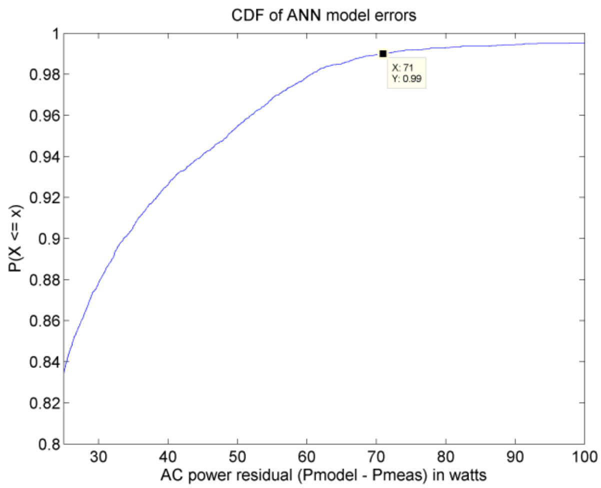

Fig. 7: CDF of model errors

A method of detecting acute PV system faults can utilize the improbability of differences in the model prediction and the PV system output to detect a fault condition. This PV system fault detection method is shown in Figure 8. With an energy summation window of 20 days, the PV system would not register a 10% loss in energy in the one and a half days of time where the system was malfunctioning. However, the abnormally large drop in power triggers the acute fault detection many times in a short period of time.

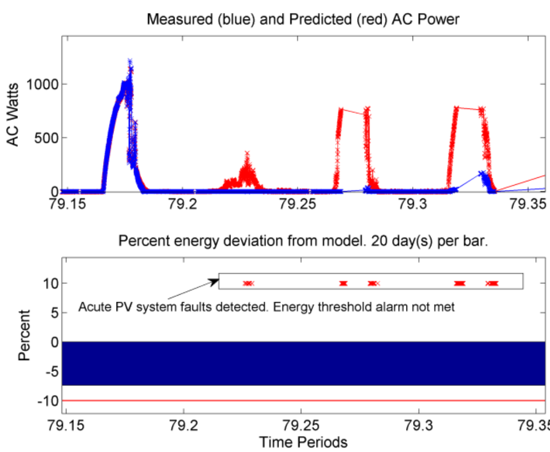

Fig. 8: PV PHM system energy alarm not triggered, but many acute alarms are triggered due to high power loss.

It should be noted that this method of fault detection may be susceptible to generation of false positives under certain situations; any instance where the inverter is shut off (e.g. temporary shading or grid abnormalities) may register a fault due to abnormally high power loss. Thus it may be desirable to only trigger alarms after a series of consecutive fault detections over a time period long enough to allow for the inverter to reconnect to the grid or regain maximum power point tracking.

These two fault detection criteria may be used simultaneously to monitor PV system performance and detect various types of PV system faults. The energy loss fault detection method is useful for detecting long-term faults which may reduce PV system output such as material degradation, shade from growing trees, or excessive soiling. The acute fault detection method is better at quickly detecting PV system faults which greatly reduce power output.

Prognostics

The advantage of a PV PHM system over a monitoring system is that a PHM system is capable of predicting PV faults based on failure precursors. Determining precursors is difficult and often requires extensive historical analysis of system behaviors prior to different failure types. In some fault cases, failure precursors may be linked to failure modes. For instance, an instant drop of power could be attributed to the removal of one of the strings in the array. Ideally, precursors would indicate specific failures, but some fault types may be indistinguishable by short term power comparisons—e.g. power reduction from shading appears the same as module failure. Further, over long time-periods, a slight degradation may be due to soiling or long term degradation of the photovoltaic material. Arguably, the degradation curves due to browning would be different from soiling, but it is difficult to know without historical data. In the case of arc-faults, one precursor could be acceleration in the degradation rate due to module corrosion. These precursors can be incorporated into the PV PHM to identify or predict failures in the PV system.

CONCLUSIONS

The PV PHM could eliminate some of the long-standing problems associated with detecting performance reduction in PV systems. The PV PHM system utilizes a system-specific ANN model with meteorological and power input data to alert system owners of significant performance reductions without the need for information about system components and design. Comparisons between system data and the PHM model can provide scheduling of maintenance on an as-needed basis. The PHM may also provide the means of monitoring system degradation over the lifetime of the PV system.

We show that the PHM neural network model benefits from a longer training data set which includes larger ranges of incident weather conditions. As expected, a more representative training data set reduces seasonal errors in the neural network model.

Two fault detection criteria have been established to better monitor PV system health. The energy loss fault detection method measures the sum of power loss compared against the neural network model over a relatively lengthy time period (several days to weeks). An alarm threshold of perhaps 5%, may be implemented to detect long-term effects such as soiling or material degradation and alert the user to the need for maintenance.

The acute fault detection method evaluates the likelihood of the PV system performing well below the model predictions and should alert the user to a significant system failure such as loss of a string of modules or failure of an inverter.

When used together, these two fault detection schemes may be used to detect both short term PV system faults and long term PV system output reduction. Further analysis of the combination of these two measurement metrics may allow the PV system operator to determine PV system failure precursors linked to failure modes. Upon recognition of a failure precursor, preventative inspections and maintenance may be performed.

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