Solar Energy Management as an Internet of Things (IoT) Application

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***Abstract*— Photovoltaic (PV) array analytics and control have become necessary for remote solar farms and for intelligent fault detection and power optimization. The management of a PV array requires auxiliary electronics that are attached to each solar panel. A collaborative industry-university-government project was established to create a smart monitoring device (SMD) and establish associated algorithms and software for fault detection and solar array management. First generation smart monitoring devices (SMDs) were built in Japan. At the same time, Arizona State University initiated research in algorithms and software to monitor and control individual solar panels. Second generation SMDs were developed later and included sensors for monitoring voltage, current, temperature, and irradiance at each individual panel. The latest SMDs include a radio and relays which allow modifying solar array connection topologies. With each panel equipped with such a sophisticated SMD, solar panels in a PV array behave essentially as nodes in an Internet of Things (IoT) type of topology. This solar energy IoT system is currently programmable and can: a) provide mobile analytics, b) enable solar farm control, c) detect and remedy faults, d) optimize power under different shading conditions, and e) reduce inverter transients. A series of federal and industry grants sponsored research on statistical signal analysis, communications, and optimization of this system. A Cyber-Physical project, whose aim is to improve solar array efficiency and robustness using new machine learning and imaging methods, was launched recently.**

I. Introduction

The utility of individual solar panel monitoring electronics for fault detection purposes was explored after the Fukushima-Daiichi nuclear accident in Japan, where plans were considered at that time for deployment of solar energy plants in the affected areas [1]. Because of the radiation in the area, the detection of faulty panels became an issue and companies and universities were commissioned to develop hardware and software technologies for remote monitoring of individual panels in large utility-scale solar farms. The need for monitoring was also fueled by elevated standards for solar array efficiencies and the need for analytics. As a result, some Japanese and US companies developed electronics for networked monitoring of solar panels. At that time, a collaboration of these Japanese and US companies with Arizona State University was established to produce hardware, algorithms and software for solar panel monitoring. Industry developed the first-generation monitoring devices that were equipped with sensors for monitoring voltage, current, temperature and irradiance. Ethernet connectivity for these devices was also developed in Japan, and the ASU SenSIP center began developing algorithms for fault detection and control of solar panels. A small 13x1 solar array facility was built at the Arizona Public Service (APS) Star facility near ASU, which allowed the ASU team and industry researchers to begin performing simulations and experiments. The second generation SMDs had enhanced electronics, radios for Wi-Fi connectivity, relays and a new array of sensors. With these hardware technologies and with the algorithms developed by SenSIP, ASU researchers were able to demonstrate efficiencies [2]. SenSIP obtained three consecutive federal grants to develop novel statistical signal processing and machine learning algorithms for fault detection and solar panel topology optimization.

Fig. 1. Smart monitoring devices (SMDs) developed in Japan and used for Solar monitoring and control research. The SMD has a microcontroller, a network radio, relays for reconnecting or bypassing panels, and sensors. With the SMDs, solar panels are seen and managed as IoT nodes.

The latest NSF Cyber-Physical grant [3] has an ambitious plan that will treat solar panels as Internet-of-Things (IoT) nodes and develop a new generation of fault detection and efficiency optimization algorithms, enabled by customized machine learning algorithms, cloud movement detection, and interfaces for inverters that promise to improve efficiencies by as much as 10%.

This paper accompanies the keynote speech of the author at IISA 2017. The paper covers the development of new algorithms, the design of a new experimental facility equipped with IoT-enabled panels, and the integration of vision and fusion algorithms. These promise to achieve efficiencies and create a new generation of solar array farms that continuously optimize their performance, enable mobile analytics, and provide remote control and fault detection capabilities. Outcomes of this research will also enable power prediction and inverter transient control capabilities.

II. The IoT-enabled 18kW Solar Facility

A solar facility was developed at the MacroTechnology

Works (MTW) facility (Fig. 2) located at the Arizona State University park. This facility consists of 104 panels with an estimated output of 18kW. The 8x13 array was fitted by smart monitoring devices which enable users to obtain analytics for each panel, detect faults, bypass faulty panels, monitor cloud movement, and change connectivity to maximize power output. The details on all the elements, sensors, communications and relays of this experimental facility have been reported in [4]. In addition to management and control of all IoT nodes on this facility, the experimental platforms will enable researchers to validate machine learning and imaging algorithms used for fault detection and cloud movement prediction.

The facility will be soon capable of obtaining visual information through a sky camera and a set of three irradiance sensors. This information will be used to predict cloud movement and provide lookahead data for control.

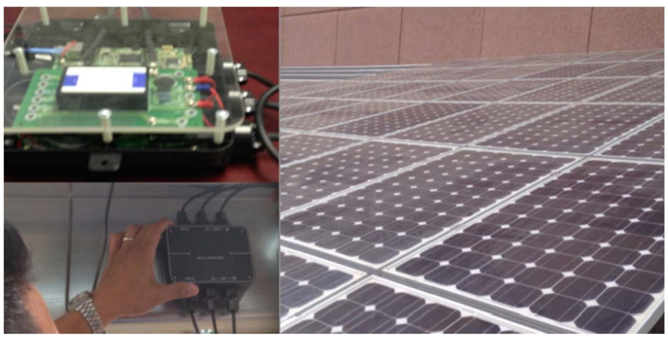

Figure 2. The solar energy monitoring facility at ASU showing the sensor fusion center, the smart monitoring device, and the solar panels. One SMD is dedicated for each solar panel rendering it as an IoT programmable node.

IoT node control will enable the user of the system to change the connections from say serial to parallel and form new connection topologies to respond to different shading conditions. The SMD matrix is shown in Fig. 3 together with the relays and the facility at MTW.

The ability to change the connections of these IoT enabled panels poses several interesting optimization problems. In addition, the detection and repair of faulty panels becomes less expensive for remote solar farms. Prior work from the group [2-7,34] demonstrated potential for significant gain in efficiency. A simulation is described below with shading.

III. Solar Array Simulation With Shading

Even one under-performing module in a string affects the output of the array. It is hence beneficial to rearrange the array configuration to either remove the under-performing module entirely or position it in a way that its effects are reduced.

Figure 3 illustrates a scenario where reconnection benefits the array output. The example has 52 modules in a 13-series, 4-parallel strings configuration. Two of the 52 modules are shaded and this is simulated by reducing the irradiance values for these two modules to 25% of the actual irradiance. It is seen that by removing the two shaded modules and configuring the remaining 50 modules in 10 series, 5 parallel configurations, we observe an increase in power output.

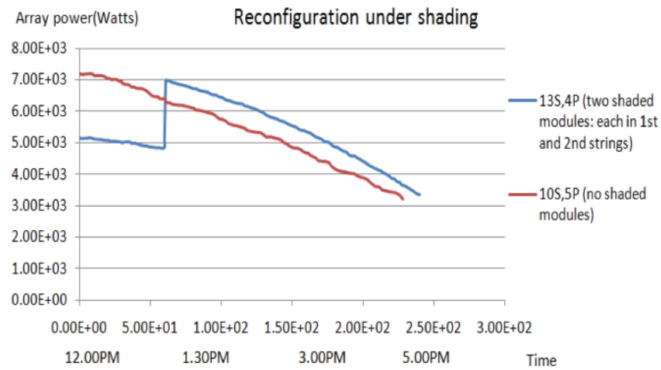

Figure 3. Improvement of array output under shading by changing the array topology. Example taken from [2].

IV. IoT Solar Array Analytics

The overall concept for IoT analytics for solar farms is shown in the block diagram of Figure 4., where the various components of the systems and their role is shown. The modules form a matrix whose connections are controlled by relays embedded in the SMD (switching block in Figure 5). The connection topology of the array can be changed by issuing a local or a remote (IoT) instruction. If the fault detection algorithm indicates a faulty panel that disrupts the efficiency of the PV array, the panel can be bypassed by issuing a programming command to the appropriate SMD. Connections can also be changed to optimize output under different shading conditions. This was previously simulated [2, 32] and shown to produce increased efficiencies.

SMD sensors connected to each PV panel collect the individual panel measurements (current, voltage, and temperature) periodically (about every 8 seconds). The collected information can be transmitted to an IoT central server. The weather data consists of irradiance, wind and atmospheric temperature, and is obtained from a locally installed weather station.

V. Third Generation SMD For Solar IoT Control

Research towards developing a third generation SMD is continuing. The envisioned SMD will be equipped with state of the art machine learning algorithms that identify and track time-varying events such as: underperforming panels, shading, and faults. The SMD will interface with IoT networked imaging sensors to predict shading (Figs. 4 and 5). The development of customized prediction algorithms for cloud movement and panel shading, represents a significant advancement over previous efforts and will enable new strategies for power grid control, array topology reconfiguration, and control of inverter transients.

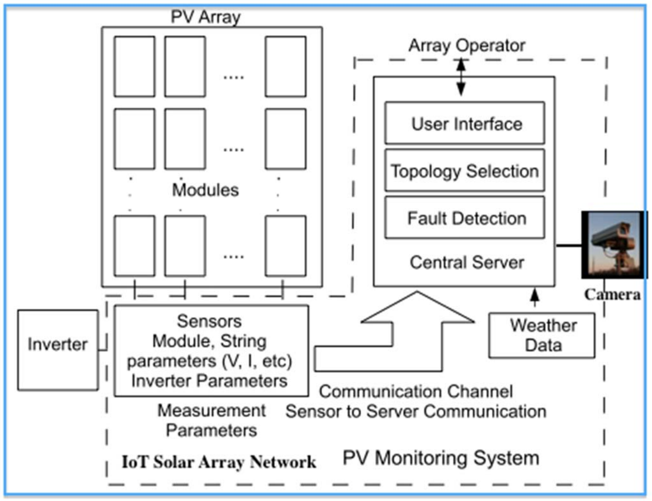

Figure 4. The IoT Networked PV Array Concept enabling: shading prediction, fault detection, mobile analytics, power optimization under shading conditions, inverter transient control, and interface to smart grid.

The study of solar power analytics, where the solar array is viewed as an IoT network enabled by remotely programmable SMDs that communicate with one another, promises to elevate efficiency particularly in cases involving cloud shading and faults. The new SMDs will enable us to develop and embed machine learning methods that employ recently developed divergence measures [31] which will reduce uncertainty in fault detection. Moreover, new imaging techniques [22,32,34] will allow improved shading prediction.

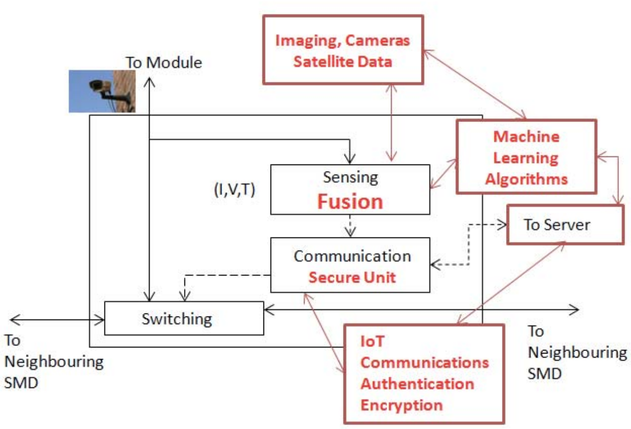

Figure 5. Envisioned third generation SMD enabling IoT Solar Panel Interfaces for PV Array Management

VI. Using Computer Vision To Predict Shading

Weather and cloud motion prediction is very useful for forecasting the power output [8-12] of the solar array. Several methods have been used for shading prediction [15] including Kalman methods [16,17], machine learning and neural networks [18-20], and Autoregressive (AR) models [13, 21]. The research described here will use sky imaging features for predicting cloud movement. Image-based sky-clarity measures are described in [12] where a linear dynamical model was shown to represent the variations of texture patterns. The work here focuses on developing computationally efficient algorithms to describe skyline features from the imagery. The planned research involves statistical correlation analyses with the estimated skyline dynamical models [22]. Previous work [14, 22-25] has studied the use of Riemannian and other geometric concepts that can be applied in cloud motion prediction (see [12] for algorithm details and for all the associated mathematical equations).

VII. Panel Fault Detection

Reliability in solar arrays is crucial for power generation efficiency. Soiling, partial shading, ground faults have to be detected. Circuit models of solar panels have been used in the past for fault detection purposes [2]. The I-V data at the panel-level is quite useful and can be monitored in an inexpensive manner. An optimal operating point for a panel is the one that yields maximum power. Statistical analysis can be used to detect outliers in I-V data (see [2] and [12] for mathematical details). Fault detection has been described in several papers [26-31,33]. Faults are typically identified by human operators using inverter data. There are several papers on fault detection in solar arrays and in general PV array performance model is used to derive the expected array I-V curve. The expected I-V curve is usually compared with the measured one. Another approach involves taking measurements and detecting outliers. In [2] the Euclidean and Mahalanobis distance were used for detect outliers. These are given below for data vectors $\mathbf{x}_1$ and $\mathbf{x}_2$:

$$d_{EU}(\mathbf{x}_1, \mathbf{x}_2) = \|\mathbf{x}_2 - \mathbf{x}_1\|_2 = \sqrt{(\mathbf{x}_2 - \mathbf{x}_1)^T(\mathbf{x}_2 - \mathbf{x}_1)}$$

$$d_{\mathrm{MA}}(\mathbf{x}_1, \mathbf{x}_2) = \sqrt{(\mathbf{x}_2 - \mathbf{x}_1)^T \mathbf{C}^{-1}(\mathbf{x}_2 - \mathbf{x}_1)}.$$

The simulation from [2] in Figure 6 shows the I-V curve and the tolerance ellipses for a ground fault simulation. It is shown that a minimum covariance determinant (MCD) estimator [2,35] forms a useful cluster to detect outliers while the Mahalanobis distance has an unacceptable tolerance.

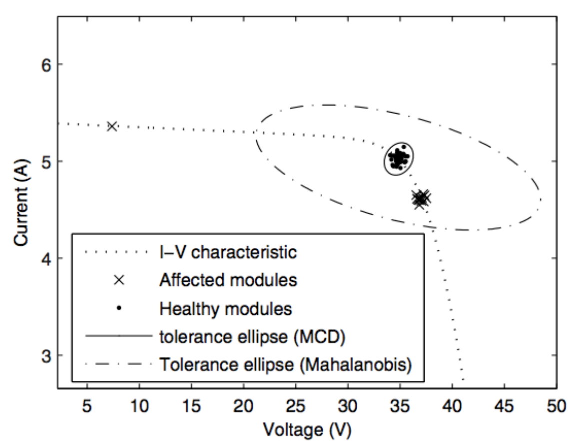

Figure 6. I-V Curves and fault detection (from [2]).

Machine learning approaches for fault detection have been used in some of the studies involving Gaussian Mixture Models trained with Expectation Maximization (algorithm details in [12]).

VIII. CONCLUSION

This paper is associated with the keynote talk of the author at the IISA 2017 which argues that communication aspects of an array of solar panels can be viewed in the context of Internet of Things. We described several new technologies, electronics, and algorithms for solar array monitoring and control. The electronics and algorithms developed by collaborative activities involving industry, university and government organizations demonstrate that an Internet-of-Things framework can be indeed used for utility-scale solar farms. We have discussed several approaches involving statistical signal processing, machine learning and computer vision that can be used in conjunction with this IoT solar energy framework to elevate efficiencies.

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