Novel strategies for PV system monitoring

System monitoring | Maximising production from a PV system is critical, since nearly all of the investment is made prior to system activation. Monitoring of PV systems allows operators to identify any performance or safety problems early so that they can be repaired quickly, thus minimising energy losses. Joshua Stein of Sandia National Laboratories and Mike Green of M.G. Lightning Electrical Engineering discuss some new monitoring strategies that are necessary for expeditiously identifying and locating system faults

The state of the art in PV system monitoring is relatively simplistic, relying either on comparisons of outputs between various parts of the system (e.g. inverters), or on an evaluation of a performance metric which normalises output to available irradiance and other environmental conditions. However, neither of these methods is very effective in discovering the source of identified problems or in identifying component-level failures, especially if they occur at the module or string level and thus have only a small, proportional effect on system output at the inverter or plant energy meter: hence the need for new system-monitoring methods.

> "PV systems tend to suffer from a lack of monitoring, since, in principle, no danger is involved, no serious safety issues exist, and monitoring is easily overlooked"

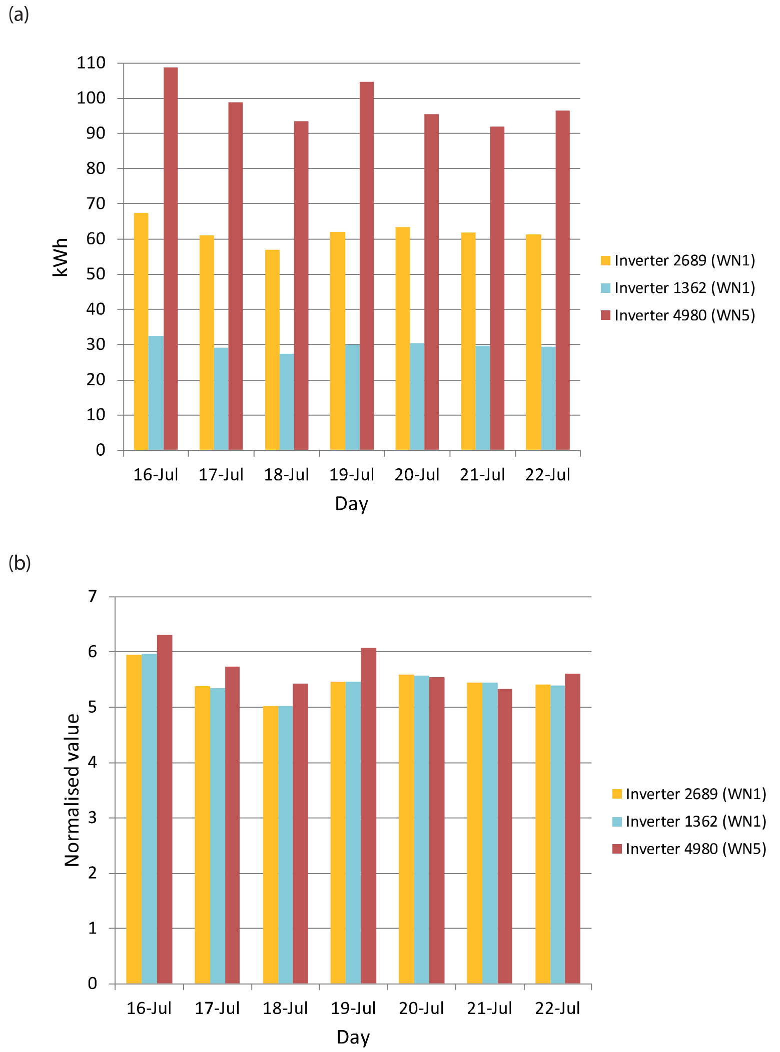


Figure 1. (a) Energy output comparison; (b) normalised energy comparison.

PV solar energy technology is usually static in nature. Aside from fans used to cool inverters, and when tracking systems are used, there are no moving parts, and these systems run cool and quiet compared with conventional energy-producing systems. It is not surprising, then, that PV systems tend to suffer from a lack of monitoring, since, in principle, no danger is involved, no serious safety issues exist, and monitoring is easily overlooked. However, PV systems have high parts counts and are characterised by numerous identical pieces (e.g. modules). Even low failure rates for individual components are more likely to occur when there are many components, and the failure of one component can put more stress on other components and thus lead to cascading failures.

Current monitoring practice

Because of the overall lack of a monitoring imperative in the PV industry, the state of the art for monitoring is relatively simplistic, compared with the overall capex when related to that of other industries. There are two basic types of monitoring employed today:

1. Comparative monitoring

2. Performance metric monitoring

A good overview of current best practices employed in PV system monitoring is discussed in a recent report from the International Energy Agency’s (IEA) Photovoltaic Power Systems Programme (PVPS) Task 13 [1].

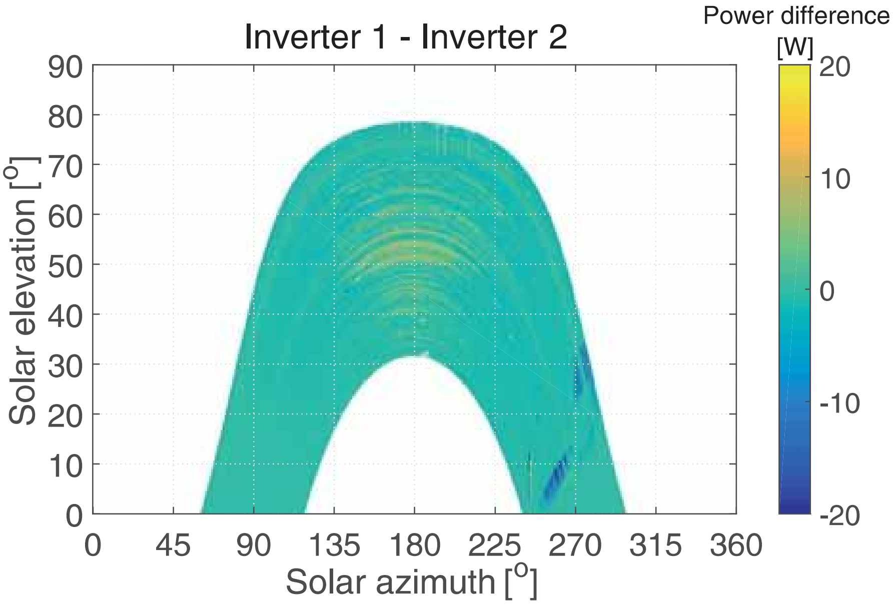
Comparative monitoring

Comparative monitoring is used in smaller systems in which no meteorological sensors are installed. In this method, the power output from various inverters is compared. The preferred method is to normalise the energy with respect to the installed power of the array: this makes the comparison easier when the inverters are of different sizes or the number of modules attached to each inverter differs. Fig. 1 presents the advantage of a normalised energy comparison as opposed to a direct comparison of energy produced by inverters of different sizes. The inverter shown in red appears to experience a problem on the fifth day, as evidenced by a relative reduction in its output when compared with two other nearby inverters. This is readily apparent in the normalised graph (Fig. 1 (b)), but difficult to detect in the raw energy data graph (Fig. 1(a)). This method only works when there is more than one inverter or monitoring point to compare.

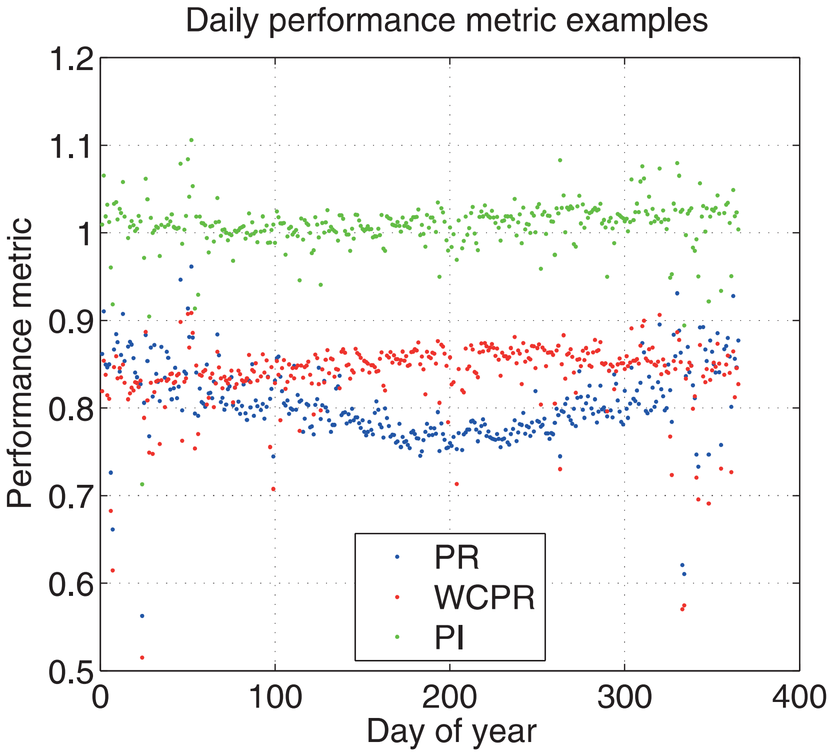
For a single inverter (e.g. residential system), this method is not very useful, unless other systems from the same neighbourhood can be used for comparison. However, since different small systems usually differ in array tilt and orientation, even these comparisons are difficult to perform in practice. In the case where a local monitoring company has access to a number of systems in the same neighbourhood, it is possible to perform comparative monitoring, even with the differences in system orientation, if the comparisons are carried out at particular times of the day and sun positions. This method is used by a number of PV-monitoring and operations-and-maintenance (O&M) companies.

When differences between inverters are observed, plotting these differences as a function of other variables can be informative. For example, Fig. 2 shows the difference in power between two inverters (in this case, microinverters) plotted as a function of sun position. The negative differences that appear in the late afternoon are due to shading of one of the systems by a nearby large power distribution pole. Simply comparing these differences daily, as in Fig. 1, might mislead the operator into thinking that there were equipment problems.

▼Figure 2 (top). Comparative monitoring between two microinverters plotted as a function of sun position illustrates shading effects.



▼Figure 3 (bottom). Comparison of three different performance metrics applied to the same system data.



Performance metric monitoring

Monitoring using a performance metric simply involves comparing the measured performance with a prediction of what the performance should have been, as determined from a model. Performance metrics vary in sophistication and in their required inputs; the more inputs needed, the more barriers there are to implementation, because of the lack of installed sensors.

The performance ratio (PR), currently the most popular metric, is also the least accurate measure of performance. Defined in IEC 61724, the PR is essentially a quantity that normalises the energy output of a PV system with respect to measured insolation and DC system capacity at standard test conditions (STC). This metric requires the measurement of plane-of-array (POA) irradiance in addition to AC power output. The standard version of the PR does not include corrections for changes

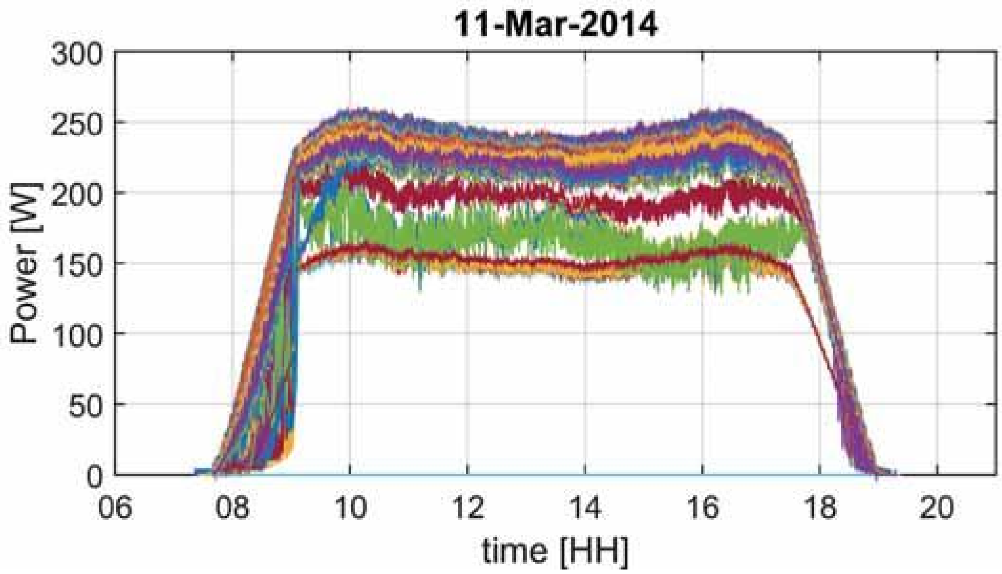


Figure 4. One day of module-scale monitoring data from over 400 PV modules in a 500kW PV array at a PV plant near Santa Fe, New Mexico.

in temperature, spectrum or angle of incidence of the sunlight, which all affect the performance of a PV system: PR values will therefore vary when any of these inputs change (e.g. as a function of weather, season or time of day). Since the purpose of employing a performance metric for monitoring is to use variations in the metric as an indicator of performance problems, the use of the standard PR is not a very sensitive indicator of health, because of its natural variations.

A newer version of the PR, called the *weather-corrected performance ratio* (WCPR) [2], has been proposed and shown to better stabilise annual calculations, but has not yet gained much of a following in the industry. One possible reason for the slow adoption of the WCPR is that it requires the measurement of more quantities, such as back-of-module temperature or air temperature and wind speed, in addition to POA irradiance.

Perhaps the best performance metric, which is referred to as the *performance index* (PI), is the ratio of measured performance and predicted performance using the best performance model available. This metric is typically used for large installations where sufficient meteorological inputs are measured to run a full PV performance model. Such models predict performance by accounting for the effects of irradiance, temperature, spectrum, angle of incidence, soiling, etc. There are many commercial examples of such models (e.g. PVsyst and PVSol). There are also free modelling applications available (e.g. PVWatts, SAM and PV_LIB Toolbox, among others).

Fig. 3 compares the three performance metrics, calculated daily over one year using PV system-monitoring data from a small, fixed tilt (1.1kW) c-Si array deployed in Albuquerque, New Mexico, USA. Noteworthy features include the seasonal dip in PR values (blue) during the summer due to high temperatures, the lack of such dip in the WCPR values (red), and significantly less scatter in the PI values (green) due to the ability of the performance model to account for more-realistic performance processes (spectral effects, angle of incidence, nonlinear low-light efficiency, etc.). The remaining scatter represents either variables that are not controlled (e.g. soiling) or measurement or modelling uncertainties.

New novel approaches to monitoring PV systems

As described above, the current state of the art in PV system monitoring is generally limited to comparisons between systems and the use of performance metrics, neither of which includes information about the nature of any discovered problem or its location. New monitoring approaches are needed that can quickly identify, classify and locate faults, ideally before they result in any system losses. The following sections will introduce a number of different approaches, ranging from laboratory and commercial research projects to early commercial deployments. What must be considered when evaluating any monitoring solution is that the monitoring method cannot cost more than the value of the energy that is recovered. This means that the best solutions for small residential systems will quite likely be different from those for large commercial- and utility-scale systems.

Community-scale monitoring

One of the barriers to employing performance metrics is the need for local irradiance measurements at the POA. One solution that is being employed by M.G. Lightning is to use communal irradiance and weather stations as the input to performance metrics for systems in the same vicinity (e.g. city or town). One challenge of this approach is that it may not work during certain types of weather: for example, under partly cloudy skies, cloud shadows will affect some systems and not others, even over relatively small distances. Fortunately, many regions experience at least some period of time each week when clear conditions prevail, even if only for part of the day. Another source of irradiance data is satellite irradiance vendors. While the errors in these data sources can be large for short time periods, over longer periods beyond a few days, the errors decrease significantly and this data can provide valuable inputs to calculations of performance metrics.

> "New monitoring approaches are needed that can quickly identify, classify and locate faults, ideally before they result in any system losses"

Another issue that is easily solved relates to systems having different orientations. In this application, simple models are available to translate horizontal irradiance to different tilt angles for use in calculating a performance metric. However, these models are most accurate during clear sky conditions.

Module-scale monitoring

Several companies have developed module-scale monitoring solutions. Perhaps the best-known examples of these are microinverters, almost all of which include the ability to monitor the output from each module individually. This feature is one of the main selling points used to market this technology, and can be quite valuable for small residential installations that suffer from partial shading from trees and building features. However, the higher costs and lower inverter efficiencies of microinverters make their use less desirable in large systems.

Other companies offer module-scale monitoring devices that attach to the module in series with the standard connectors and communicate wirelessly to a base station. These devices can be either attached to every module in the field or connected to only one or two modules per series string. In the string configuration they measure the current and voltage in the string, and this information may be sufficient for detecting a single-module failure.

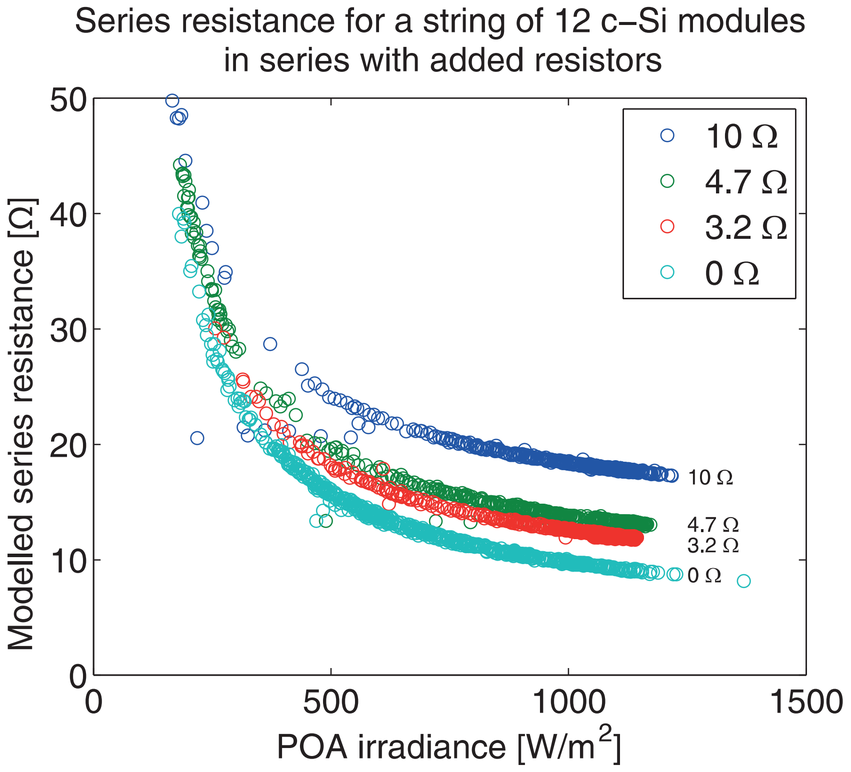
Sandia National Laboratories (Sandia) recently participated in a project to evaluate module-scale monitoring at a 1MW single-axis tracking PV plant near Santa Fe, New Mexico. In half of the plant (500kW), module-scale monitoring was installed on one module per string, for nearly 400 modules in the array. Fig. 4 shows an example of a clear day of data. A few modules (9) were 'dead' and reported no power output, several (~20) performed at approximately two-thirds power, a few had noisy signals, and the majority (~350) operated within around ±20W of one another. The modules running at two-thirds power most likely had a substring of cells that was disconnected, possibly arising from a failed bypass diode.

The fidelity of this level of monitoring is impressive and provides very detailed information about this plant. If the costs associated with such a solution are sufficiently low, this technique provides valuable information to a system owner.

Health of the DC circuit

In addition to monitoring the power output from various parts of the PV array, it is also possible to collect other types of data that can be used to assess the health of the PV system more directly. For example, the series resistance (R_s) of a PV system (i.e. cell, module or array) represents the sum of the resistances contributed by all of the series-connected cell layers, contacts, and wiring between both ends of the system's circuit. Because the series resistance value is affected by changes in resistance in any of these component and subcomponent parts, the monitoring of series resistance over time provides valuable information about the system's electrical health and material properties. Increases in series resistance have been linked to corrosion inside modules and connectors, UV degradation of silicon, and other processes that contribute to overall degradation of PV system performance. Typical methods used to measure R_s involve measuring current–voltage (*I–V*) curves of modules on a flash tester or of strings in the field, and fitting equivalent circuit models (e.g. single-diode model) to the data; R_s is one of the model parameters that results. A problem with this approach is that it is largely manual, requiring labour and specialised equipment. In addition, R_s varies as a function of irradiance and its determination is therefore usually referenced to STC conditions.

Figure 5. Validation results demonstrating a new method for monitoring series resistance without the need to collect and analyse *I–V* curves.



Sandia and Draker Energy have collaborated on a demonstration of a new methodology to monitor R_s without the need for *I–V* curves [3]. Instead, measurements commonly available from an inverter (maximum power DC current and voltage) and the open-circuit voltage, which the authors believe should be relatively easy to obtain, are used to estimate values of R_s. This approach was tested on a string of 12 PV modules in the field, and fixed resistors were added in series to mimic increases in R_s. Fig. 5 shows the results of the predicted R_s values as a function of irradiance for various amounts of added resistance. The fact that each dataset is distinct means that changes in R_s are readily detectable.

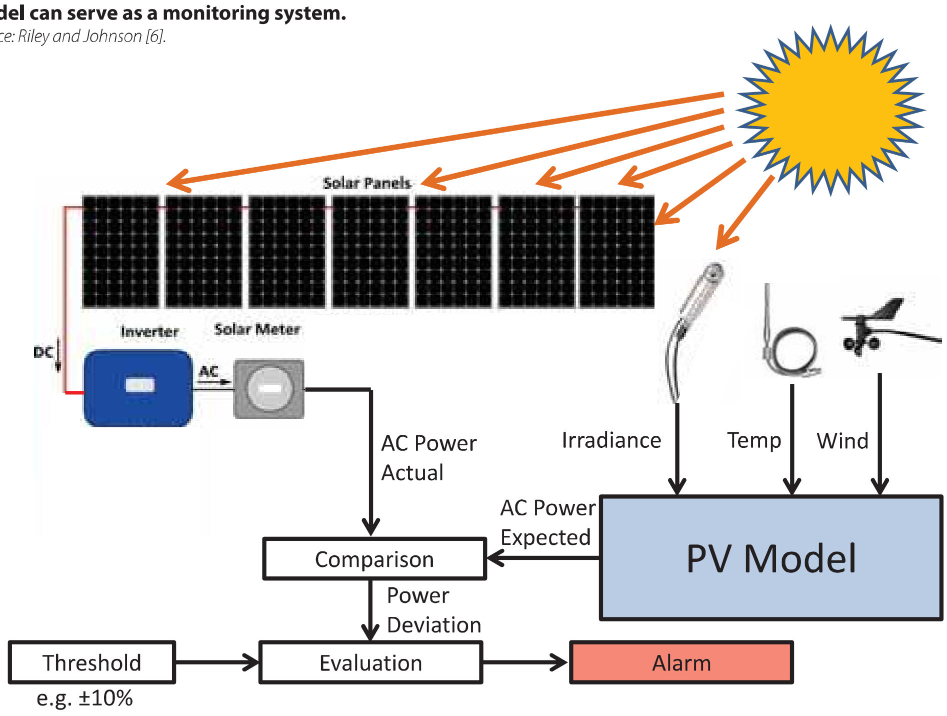
Sandia is also working with several companies to develop new monitoring hardware that would be able to automatically bypass either a single module or a single string, sweep its *I–V* curve and then reconnect it to the system without disrupting the inverter from delivering power to the grid from the rest of the array. Single-module units from Stratasense [4] are currently in the process of being tested, and work with Pordis, LLC [5] is under way to develop a multi-string automated *I–V* tracer, designed for larger commercial PV systems. The capability to automatically measure *I–V* curves from the PV system creates numerous opportunities for more-detailed monitoring in the future.

Health of the whole system

A promising approach to monitoring the whole system has been demonstrated on a small scale using neural network algorithms and is soon to be offered commercially to all sizes of PV system using machine-learning algorithms (Fig. 6). After the system has been commis-

Figure 6. Conceptual diagram of how a learning algorithm PV model can serve as a monitoring system.

Source: Riley and Johnson [6].



sioned, a learning algorithm is trained to estimate AC power production from available meteorological data (irradiance, temperature, wind speed, time of day, etc.). Research has shown that this methodology can be as accurate as the best PV performance models; the advantage of the learning algorithm is that it does not require design specifications for the system components, which can be hard to collect [6,7]. Current research is focused on whether learning algorithms are able to distinguish signatures from specific types of fault (open circuit, short circuit, bypass diode failure, excessive soiling, etc.). If these efforts are successful, it is conceivable that monitoring systems of the future will send out an alarm indicating the type of fault that is suspected.

Prognostic monitoring

Prognostic monitoring is intended to detect and interpret signals which can indicate that a problem or fault is likely to happen in the near future. Machine-learning algorithms are designed to learn the normal behaviour of monitored inverter parameters in conjunction with onsite weather conditions taken from a weather server. When a parameter strays from what is expected, an alarm is issued. Work led by M.G. Lightning in association with the IEA PVPS Task 13 has begun to catalogue these precursors to faults. The goal is to develop a predictive system that will alert system operators of an impending problem. This system with a prognostic capability would monitor system performance and be able to predict imminent faults before they occur, just as an engine check light helps avoid catastrophic failures in a motor car.

Next-generation monitoring systems

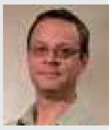
The future is ripe for innovative PV monitoring. The authors believe that monitoring systems of the future will be able to collect data from inexpensive sensors and use it in conjunction with data collected from other systems in the region, including weather and irradiance stations and/or satellite data, to determine the health status of a PV system. In addition, if *I–V* curves can be automatically collected at a low cost without disrupting PV generation, such information would be invaluable for detecting module degradation, locating system faults, and providing diagnostic information for O&M activities, including commissioning. In other words, be on the lookout for new monitoring products and services in the near future.

> "Monitoring systems of the future will be able to collect data from inexpensive sensors and use it in conjunction with data collected from other systems to determine the health status of a PV system"

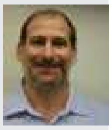
Acknowledgement

Sandia is a multi-programme laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

Authors



Joshua Stein is a distinguished member of the technical staff at Sandia National Laboratories, and works in the area of PV and grid integration. He currently develops and validates models of solar irradiance, PV system performance, reliability, and PV interactions with the grid. Joshua leads the PV Performance Modeling Collaborative at Sandia and is a member of the IEA PVPS Task 13 Working Group on PV performance and reliability.



Mike Green owns and manages the electrical engineering firm M.G. Lightning Ltd, which specialises in the design, consulting and maintenance management of PV systems in the Middle East, Africa and Eastern Europe. The firm has recently initiated iPVsolar, marketing a fault-recognition software as a service (SaaS) using machine-learning software based on predicting next-day hourly yield. Mike has been involved with IEA PVPS Task 13 for over four years, working on PV system reliability.

References

[1] Woyte, A. et al. 2014, "Analytical monitoring of grid-connected photovoltaic systems good practices for monitoring and performance analysis", Report IEA-PVPS T13-03.

[2] Dierauf, T. et al. 2013, "Weather-corrected performance ratio", Report NREL/TP-5200-57991, National Renewable Energy Laboratory, Golden, Colorado, USA.

[3] Stein, J.S. et al. 2014, "Measuring PV system series resistance without full IV curves", *Proc. 40th IEEE PVSC*, Denver, Colorado, USA.

[4] Stratasense [http://pvtracer.com].

[5] Pordis, LLC [http://pordis.com].

[6] Riley, D. & Johnson, J. 2012, "Photovoltaic prognostics and heath management using learning algorithms", *Proc. 38th IEEE PVSC*, Austin, Texas, USA.

[7] Johnson, J. & Riley, D. 2013, "Prognostics and health management of photovoltaic systems", US Patent Application 14/023,296, Filed 16 Aug.