Cyber Physical System based Proactive Collaborative Maintenance

D1.2 Consolidated State-of-the-Art of Sensor-based Proactive Maintenance Appendix 13: Fault detection and identification in PV systems

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Abstract

Vast amount of data is recorded at photovoltaic (PV) plants through the real-time monitoring system. Current use is mainly restricted to basic failure detection and the reporting of system performance. Proactive maintenance of PV plants is highly desirable but requires a more advanced utilization of the monitored data.

Current state-of-the-art of FDI techniques of PV systems rely mostly on limit checking of directly measured or derived variables. Several other approaches for FDI of PV systems, often using more advanced machine learning techniques, have been proposed in literature, but their practical applicability in the field is limited. Only recently, some advanced machine learning techniques have been attempted in the field in order to predict faults.

The residuals used in FDI can be generated using various methods. In the analytical redundancy-based or model-based approach, the residuals are generated based on an explicit mathematical model of the system. The explicit mathematical model of a PV system is derived using data from type tests, from off-line field tests or from operational data.

The PV health scan methodology has recently been explored at 3E for the systematic analysis of operational data in an efficient way, identifying how design choices and O&M practices lead to inferior or superior performance in the field.

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1 PV Monitoring practices

The vast majority of (non-residential) photovoltaic (PV) plants are monitored. Electrical parameters, such as PV array currents and voltages, are measured by the inverter at least every 15 minutes. At many plants also environmental parameters, such as irradiation and temperatures, are recorded. In contrast with measurements obtained during momentary on-site investigations, these data contain longer term information on the evolution since installation and the dependency on constantly changing environmental conditions.

Currently, PV monitoring data is used only in a very limited way to calculate performance ratios and availabilities. This common practice facilitates the detection of sudden and large events such as inverter or string failures. On the other hand, degradation type of issues most often remain undetected as they result in relatively low losses, e.g. below 5 to 10 % of total energy yield. However, over the lifetime, these small losses accumulate to an amount which is often much larger than the losses associated with, for example, the more noticeable inverter downtimes. Examples are potential-induced degradation, bypass diode failures, MPP tracker malfunctioning, moss growth, snail trails due to micro-cracks, etc. Only in case of rare and very severe disturbances when there is noticeable impact on production, an alarm is raised; by this time these issues have gradually impacted production for years and have most likely lead to irreversible damage to the panels (e.g. hotspots), while compromising the safety aspect of the plant and the people.

Some degradation issues can be detected by performing on-site investigations involving visual inspection of the PV arrays, infrared imaging and in-depth analysis of monitoring data by experts in the field. There are some other advanced analysis methods which are gradually becoming more commonly adapted, for example IV curve measurements and Electro-Luminescence (EL) imaging. However, these are rarely applied in the field since they are intrusive, cost- and time-extensive. Finally, there is no established standard yet the PV industry could apply in analysing the outcome of the measurements and as such the results are subject to wide interpretation.

Large amounts of PV data are recorded but currently used in a very limited way. For example, most degradation issues, though important, are not detected let alone identified or mitigated by state-of-the-art operation and maintenance (O&M) practices. Nevertheless, in hindsight the emergence as well as the type of degradation can often be traced back in monitoring data through in-depth analysis of historical monitoring data by experts in the field. This shows that there is potential for automated detection and identification of various degradation types through machine learning techniques.

Irradiation sensors in PV plants are an important tool for assessing the performance of the plant. Often though, the data from these sensors is unreliable as a result of installation, configuration or maintenance issues. Automated validation would enable the detection of such issues. For example, the orientation, inclination, time synchronisation and calibration of irradiance sensors could be validated by use of nonlinear regression techniques.

2 Fault detection and diagnosis methods

A fault is defined by the International Federation of Automatic Control (IFAC) Technical Committee SAFEPROCESS as an “unpermitted deviation of at least one characteristic property of the system from the acceptable, usual, standard condition” [1], [2]. Translated to PV systems, this means that apart from inverter faults and component failures also increased degradation of PV production, leading to unexpected additional losses, are considered as faults.

Fault detection and isolation (FDI), also known as fault detection and diagnosis, consists of detecting that a fault has occurred and of isolating the location and nature of the fault. The FDI problem thus consists of two major steps [1]. The first step is to generate one or more residual variables. The second step involves the decisions, based on the residuals, on whether a fault has occurred (fault detection) and on the nature and/or location of the faults that have occurred (fault isolation or diagnosis).

Residuals are assumed to be zero (or zero mean) under no-fault conditions, but whenever a fault occurs, one or more of the residuals will deviate from zero, thus representing the “unpermitted deviation”. These residuals can be generated using various methods. The model-based (also called analytical redundancy-based) FDI methods use explicit mathematical models to generate the residuals [1].

Typical variables that are monitored in a PV park comprise, amongst others, AC power and energy, AC voltage, current and frequency, DC voltage, current and/or power, solar irradiation, ambient and module temperature, wind speed, ground-insulation resistance and various inverter status signals and events. Current state-of-the-art of FDI techniques of PV systems rely mostly on limit checking of directly measured or derived variables (e.g. various performance indicators [3]–[10] and comparison of identical subsystems [11]). Several other approaches for FDI of PV systems, often using more advanced machine learning techniques, have been proposed in literature (e.g. [12], [13]). However, their practical applicability in the field is limited. Only very recently, advanced machine learning techniques have been attempted in the field in order to predict faults (see e.g. [10]).

3 Assessment of expected PV behaviour

The residuals used in FDI can be generated using various methods. In the analytical redundancy-based or model-based approach, the residuals are generated based on an explicit mathematical model of the system [1]. Several approaches exist to develop such a mathematical model for PV systems as described in the following subsections.

The PV system characteristics are traditionally modelled by use of the equivalent single-diode parameters, temperature coefficients, etc., which are derived from measurements of the PV modules during manufacturing. However, due to tolerances, mismatching, spectral dependencies, degradation, soiling or operational issues the real behaviour of the PV system often deviates significantly from this model and evolves over time.

The characterization of the PV array in the field normally requires the offline measurement of its current-voltage (IV) curve. However, as measuring an IV curve in the field is costly and time consuming, it is typically done only at commissioning or when an issue is suspected and for a limited number of arrays or modules. Most often, IV curves of PV arrays are not at all assessed.

In most PV plants, electrical parameters, such as PV array currents and voltages, as well as environmental parameters, such as irradiation and temperatures, are recorded at least every 15 minutes. In contrast with measurements obtained during momentary on-site investigations, these data contain longer-term information on the evolution since installation and the dependency on constantly changing environmental conditions.

Three fundamentally different approaches for the assessment of expected system behaviour of a PV system have been described. Table 1 presents an overview of the qualities for each approach.

Table 1: Comparison of different options for expected PV system behaviour assessment

	Type tests	Off-line IV curve tracer	Operational data
Effort	Low	Very high	Low
Characterisation	Lab up-front	In-Field once	In-field continuously
Accuracy	Low	Moderate	High (potentially)
Methodology	Well defined	Various	Various

3.1 Assessment of expected PV system behaviour from type tests

Traditionally, the expected performance of a PV system is modelled based on datasheet parameters, laboratory tests and system configuration details [14]□[17], most of them based on (a variation of) the well-known five-parameter single-diode PV model. However, as shown e.g. in [18], the predicted performance values from these models can differ significantly amongst each other and from the real observed performance in the field. Recently, for some PV module types, the accuracy (and in particular the dependency on irradiance) of these models has improved considerably thanks to a much improved methodology for the assessment of the model parameters based on laboratory measurements [19]. Still, this methodology represents just the behaviour of one (hopefully) typical PV module in the laboratory. The actual behaviour of even a well-performing PV system is different as a result of: (1) the behaviour of the PV modules deployed in the field may differ from this type model due to tolerances and process variations; (2) the series connection of non-identical PV modules into PV strings and the parallel connection of PV strings into the PV array introduce mismatching losses; (3) varying environmental conditions differ from laboratory conditions, e.g., due to differences in irradiance spectrum, incidence angle, soiling, non-uniformity of module temperature and/or irradiance.

3.2 Off-line assessment of expected PV system behaviour in the field

Various offline module and array characterization procedures [20]–[23] provide a possible alternative. These characterisation methods usually involve the measurement of PV array IV curves in the field and the calculation of the single-diode PV model parameters from these measurements. With these methods the first two causes of differences are inherently accounted for and only varying environmental conditions remain as a potential cause of error. Therefore, they may, in theory, improve the accuracy significantly. However, in practice, these methods are severely hampered by (1) the need for time-intensive measurements in the field; (2) the requirement of ideal irradiance conditions and (3) dependable measurement practices in the field.

3.3 Assessment of expected PV system behaviour from operational data

Fitting empirical equations to operational data (i.e., at Maximum Power Point, MPP) has proven to be a simple and efficient approach to accurately model the performance of PV systems in the field [24]–[26] (black-box or grey-box models). In contrast to the single-diode model, these equations model the system behaviour for the MPP only. These empirical models currently do not allow making a clear link between performance and underlying physical parameters or design choices as most of these empirical coefficients don't have a physical meaning. Due to their empirical nature, many models do not accurately reflect physical dependencies (e.g. irradiance), which results in systematic errors, e.g., at low irradiance. An example is the photo-diode, which in first approximation behaves in a logarithmic fashion as taken into account, e.g., in the single-diode IV model. Nevertheless, most MPP regression models actually do not even contain a logarithmic term in dependence of irradiance (see e.g. [27]), resulting in large errors at low irradiance. This shortcoming of many regression models has then been circumvented by requiring that only operational data at high irradiance conditions is taken into account for training and applying the regression models. E.g. in the PVUSA method, data where the in-plane irradiance is below 500 W/mfl or even 750 W/mfl are eliminated when training the regression coefficients [24]. Whereas this may be realisable in desert locations, this requirement is impractical in most other regions.

There is significant potential for improvement to future models to assess the system behaviour from operational data (see Table 1):

- Monitoring systems in practice record both DC power and voltage. Modelling of MPP voltage and MPP current independently, instead of just MPP power, provides more information on dependencies and anomalies, thus supporting the creation of more accurate models;
- Use of equations which reflect physical behaviour of the PV array, e.g., by deriving an MPP model from the single-diode model for MPP voltage and MPP current, allowing for the estimation of, amongst others, series resistance, diode ideality factor, temperature coefficient and current and voltage quality factors at standard test conditions (STC);
- Assessment of shading conditions as a function of sun position from operational data;
- Assessment of thermal characteristics (irradiance heating coefficient, wind speed cooling coefficient and time constant) of the PV module from fitting of dynamic regression models of DC voltage and/or measured PV module temperature;
- Continuous estimation of regression parameters (e.g. using a Kalman estimator) in order to evaluate the evolution over time of certain parameters due to soiling, growth of moss, weed or shrubbery, seasonal annealing and various types of degradation.

4 PV Health Scan methodology

A new methodology for characterising the physical parameters of a PV array has been explored at 3E. The PV Health Scan methodology is illustrated in Figure 1, where the modelled system parameters originate from grey-box regression models of DC maximum power point (MPP) voltage and current. These models are derived from physical equations, such as the analytical solution of the single-diode model. The method departs from closed-form relationships between all regression parameters and underlying physical parameters. They allow the identification of the individual contribution of each physical coefficient to the performance in the field. The methodology allows the systematic analysis of operational data in an efficient way, identifying how design choices and O&M practices lead to inferior or on the contrary superior performance in the field. Conceptually, it relies on the following steps:

- Define physical models of MPP voltage and current as a function of the environment;
- Train coefficients of physical models with operational data. Remark that coefficients are correct only when physics are reflected in the model. Sometimes, the lack of certain physical dependencies in the model can be circumvented by training on high irradiation hours only;
- Analyse differences between theoretical and trained model parameters;
- Analyse differences between measured, modelled and theoretical performance.

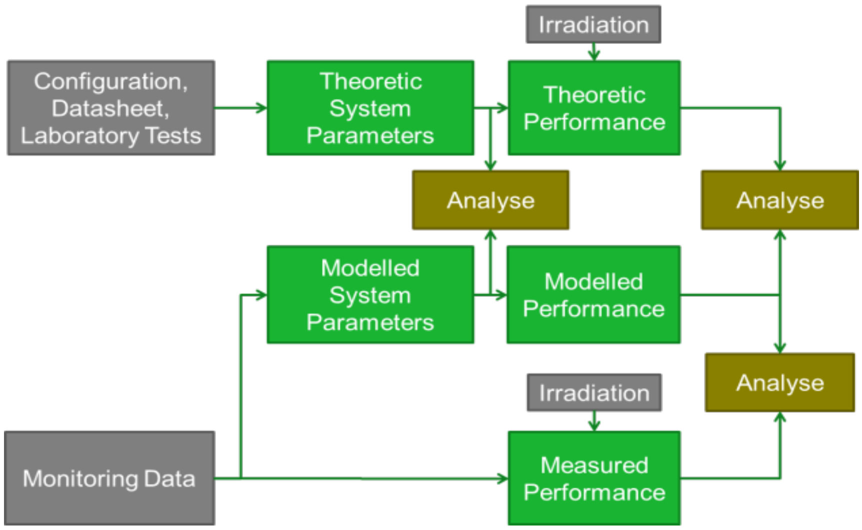

Figure 1: PV Health Scan methodology

Engineering models representing physical behaviour of the PV array have been defined in [28]. By introducing a few smart approximations with non-significant accuracy losses, explicit expressions were derived for the operating voltage and current as a function of theoretic system parameters and environmental conditions.

Here, the very same models have been used with one important difference: instead of using the theoretic system parameters derived from datasheets, the parameters are now considered to be the unknowns. Through regression of the models using operational data, modelled system parameters are obtained. The advantage of this approach is that the in-the-field system behaviour is translated into in-the-field fitted system parameters, which we can compare with the theoretic expected system parameters. The deviations between the fitted and theoretically expected system parameters allow us to isolate the origin of the fault.

A good example is the series resistance of the PV array, being an indicator for a certain type of faults in PV systems, such as corrosion inside modules and connectors [29], [30]. To the best knowledge of the authors, no method has been described in the literature to obtain the series resistance from operational (MPP) data only [30]–[32]. However, with the approach presented here, the series resistance has been obtained from operational data and compared with its expected value. This allows the detection of faults linked with the series resistance in operating PV systems from commonly measured monitoring data.

This approach has been demonstrated at 3E with regression functions for the irradiation sensors, PV module temperature, MPP voltage, MPP current and the inter-array shade profile angle. It is expected that the approach could be extended for other monitored data such as, e.g., the AC output values of the inverter.

Thus, system parameters that can be estimated and compared with their expected values using this approach are amongst others:

- PV array MPP voltage, current and power at STC conditions
- Temperature coefficients of MPP voltage, current and power
- PV array series resistance
- Diode ideality factor
- Offset and slope of irradiation and temperature sensors
- Inter-array shading profile angle
- Equivalent thermal resistance
- Thermal convection coefficient
- Time constants (thermal, MPP tracking)
- Inverter derating limits

3E has tested the health scan methodology as summarized above on some selected PV plants. These tests allowed to prove the concept and it has facilitated the detection of anomalies. However, further research is needed before this methodology could be launched into further product development or be applied effectively for pro-active maintenance of PV plants.

5 Conclusion

Vast amount of data is recorded at photovoltaic (PV) plants through the real-time monitoring system. Current use is mainly restricted to basic failure detection and the reporting of system performance. Proactive maintenance of PV plants is highly desirable but requires a more advanced utilization of the monitored data.

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