# Assessment of Economic Impact and Management Techniques of Fault Modes on Photovoltaic Systems

**Carlos C. Bravo[1], Robinson Cavieres[2], Rodrigo Barraza[3], David Godoy[4] and Patricio Valdivia[5]**

1 Universidad Técnica Federico Santa María, Santiago (Chile)

2 Universidad Técnica Federico Santa María, Santiago (Chile)

3 Universidad Técnica Federico Santa María, Santiago (Chile)

4 Universidad Técnica Federico Santa María, Santiago (Chile)

5 Universidad Técnica Federico Santa María, Santiago (Chile)

## Abstract

The knowledge of an adequate risk management is vital at the time of making investments, especially in the photovoltaic (PV) industry, where this issue is currently under development. Therefore, to achieve with the objective of managing the risk, one must have knowledge of the different faults, which can be organized by means of a failure mode and effect analysis (FMEA) and, classified by the same, according to several criteria, such as occurrence, time to detection, time to repair and/or replace and impact on the whole system and energy production. Crossing this information with economic data, fault modes can be ranked with an overall weighted cost. The ranked fault modes are used by a maintenance plan to reduce the overall cost and guide the asset management. This paper proposes a methodology to quantify the economic impact of faults experienced in a photovoltaic power system and how can maintenance plans might mitigate these costs.

*Keywords: Asset Management, FMEA, Maintenance Plan*

## 1. Introduction

Photovoltaic solar power plants have reached a deep spot in the energy market, due to their almost non-existent energy production costs, low environmental impact and government support all over the world (Solar Power Europe, 2016). The market is growing fast, with new technologies being developed and tested in every new installation. Nevertheless, there is still some uncertainty about how a power plant should be operated. Asset management in this area is still in development. Having PV system in different regions with different climates and operating technologies makes reaching a consensus about the maintenance practices and risk evaluation for investors a difficult task. Plant managers create their operating plans on the run, and most of the maintenance and cleaning is done by external contractors. Combined with the confidential information management, there is no practical way to determine if a maintenance technique will be useful in different projects.

To make PV systems attractive for potential investors, it is necessary to have somewhat standardized asset management strategies and risk assessment methods. Being able to identify and classify all the potential failures and quantify their economic impact and how these will be mitigated by maintenance plans in the future can make all the difference when it comes to selling the project. However, asset management techniques rely heavily on historical performance data, and unfortunately, this information is often scarce and confidential.

At present, several studies have been developed with the objective of collecting and requesting maintenance information regarding photovoltaic modules in the field. This is the case of the PhotoVoltaic Energy System of the International Energy Agency, which works on one of its tasks in terms of "performance and reliability". Task "T13 - 01" (Köntges et al., 2014) presents a review of the most common failure modes of photovoltaic modules, which also describes some mechanism for detecting the failure modes observed. In the same way, section nine of task 13 "T13-09" (Köntges et al., 2017) presents how to deal with maintenance data from three different perspectives: scientist, investor (or banker, subscriber) and testing institute (or photovoltaic systems planner).

doi:10.18086/swc.2019.25.01 Available at http://proceedings.ises.org

Other studies suggest adding to the failure mode analysis the degradation effect that the solar module suffers throughout its useful life. This fact is addressed by Jordan et al. in some studies in which they present a compendium of photovoltaic degradation rates (Jordan et al., 2016), as well as a study in which a methodology is proposed on how to determine the rate of degradation (Jordan et al., 2018).

Another important issue to be consider in the maintenance analysis is the information of faults coming from both the inverter element and the substation associated with the PV system. In the inverter system, the temperature at which it works plays a fundamental role in the reliability of the system (Sorensen et al., 2013) and if we want to make predictions of the behavior of this system, it is necessary to have a model that describes the behavior of the inverter in an appropriate way (Rampinelli et al., 2017). In the same way, knowing the factors that affect the reliability of the transformation station of the photovoltaic system, where it allows the solar energy generated to be compatible with the electrical grid, is of utmost importance if you want to determine the reliability of the entire system.

With the information presented, it is possible to build reliability models of the complete photovoltaic system with the aim of reducing maintenance costs as indicated in (Zhang P. et al., 2013), where the state of the art of the year 2013 is presented, that includes system connection diagrams, reliability indices and reliability evaluation methods. A more detailed qualitative analysis is included in (Sayed A. et al., 2019.), where it is presented a mixed analysis between reliability, availability and maintainability (RAM), considering faults and repair rates, available in the current state of the art, for calculate the reliability of the system using a reliability block diagram to describe the behavior of the system. The authors conclude that the best probability density function (PDF) for some parts of the system is an exponential distribution, while for other parts they are the Weibull or lognormal distributions. In a complementary way, (Ahadi A. et al., 2014) presented an analytical approach to evaluate the reliability of the system through fault trees, where it is concluded that the inverter is the most critical component of the photovoltaic system.

For the reliability analysis to be useful, it is necessary to cross that information with the cost associated with the maintenance plan. This is studied in (Zhou P., 2016.) in a general manner, i.e., applied to renewables energies. In that study, the authors given some tools to make an economic evaluation like the cost-benefit function. On the other hand, (Moser D., 2017.) proposed a methodology to evaluate the cost of maintenance but with a large amount of information using a Cost Priority Number (CPN) which is like information retrieved from the Risk Priority Number (RPN). Despite this, in this last study, no reference is made to the maintenance plans used by the company, so that possible improvements in detection, repair or replacement factors that a maintenance plan can provide are left out.

There is a limited number of operating plants with a significant power output that records historical performance data, and an even smaller number that are willing to share this information. The authors of this work encourage plant managers and owners to share their records so that researchers can devise new management strategies based on deep statistical analysis.

This paper presents a methodology to assess maintenance costs with limited information so that plant managers and researchers can have a guide for decision making. In the future this study can be extended to integrate degradation rates cost, based on an improved measurement system. Section two explains failure classifications. Section three shows examples of asset management approaches and section four explain the methodology proposed. Finally, section five end the paper with conclusions.

## 2. Failure Classification

Several studies have described the most common failure modes on every level in a PV power plant, ranging from the module itself (Köntges et al., 2014), to inverters (Flicker J, 2014) to transformer stations (Barbosa et al, 2018). Even when some of the faults are caused by localized phenomena, such as weather or operating condition, most of them are transverse to every system. Furthermore, this paper encourages plant managers to use their own data, so they can focus on their most recurrent failures.

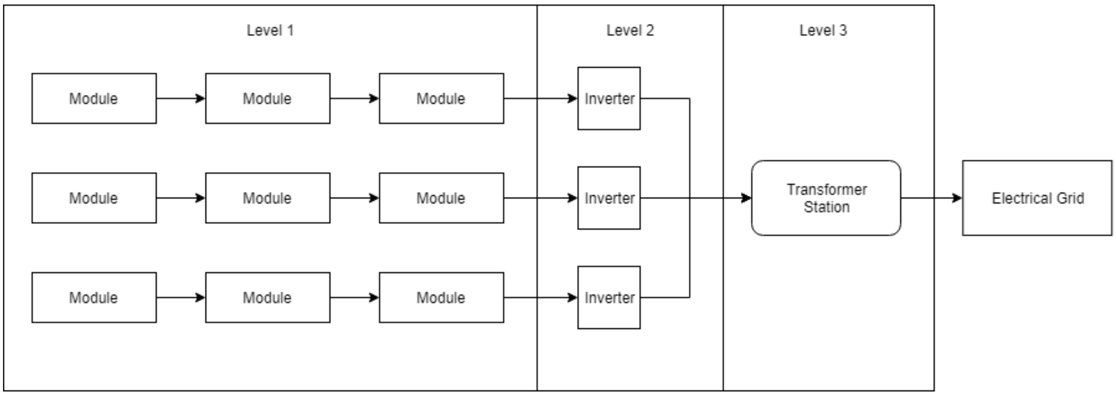

**Fig. 1: General diagram for the proposed methodology.**

To simplify the analysis, the plant is divided in the three sub levels shown in figure 1. Each zone has its own failure modes and different asset management approaches and must be studied accordingly. It is crucial for this analysis to have information about the power losses associated to fault modes. This data can be measured empirically or can be found in the literature.

## 3.1 Modules

A fault in a module is defined as a state that degrades the asset energy output and is not reversed through normal operations (IEA 2014). Aesthetic defects that have no impact on energy production will not be considered for this analysis:

**Tab. 1: Failures at the modules level.**

| Fault Mode | Description | Relative Power Loss |
|---|---|---|
| Delamination | Adhesion loss between the different layers in the module due to external factors such as temperature of humidity | 1% |
| Hotspots | Overheating in cells due to reverse bias current | 2% |
| Shading | Mismatching incident radiation over a module | 10% |
| Cracked cells | Microcracks formed in the silicon substrate caused by thermal or mechanical stress | 1% |
| Broken Glass | Fractures in the glass cover of the module resulting from impacts or extreme temperatures | 10% |
| Stolen modules | Missing modules stolen from the plant in operation | 100% |
| Faulty Bypass Diode | Reverse currents circulating through defective module cells | 33% |
| Soiling | Accumulated particles on the surface of a module obstructing incident radiation | 25% |
| Potential Induced Degradation | Degradation in crystalline silicon modules due to potential differences in operating conditions. | 10% |

## 3.2 Inverters

Several studies conclude that the inverter is the critical asset on a PV system due to the higher failure rates (Ahadi, A. et al 2014). Unlike modules, this is a complicated piece of hardware built on numerous electrical subsystems with individual failure modes and reparation costs. (PV System reliability, 2012) and (Moser D., 2017.) gathers information submitted by operators working on different installations on the fault modes experienced:

**Tab. 2: Failures at the inverter level.**

| Fault Mode | Description | Relative Power Loss |
|---|---|---|
| Control Software | Communication issues with the asset and the control station | 15% |
| Circuit/Board | Misconnection of components in different circumstances | 22% |
| Overheating | Faulty cooling system | 20% |
| Power Source | Inverter disconnection due to power supply issues | 100% |
| AC Fuses | Substring disconnection due to spikes in current | 12% |
| Air Filter<br>Capacitors | Particles getting inside the system and causing damage to electrical circuitry | 7% |
| Relay/Switches | Faulty switches causing equipment disconnection | 100% |

### 3.3 Transformer Station

Like inverters, transformer stations are complex systems composed by several pieces of hardware, each one with their own fault modes and costs. (Sihite J., 2013) ranks the most common failures in a transformer station, but a difference of the inverters and photovoltaic modules, it is necessary more detailed studies to estimate the relative power loss. Plant managers are encouraged to use their own data and focus on the most recurrent issues:

**Tab. 3: Failures at the transformer station level.**

| Fault Mode | Description |
|---|---|
| Ferrous Core | Loss of magnetism or flux core fails |
| Overheating | Faulty cooling system. |
| Winding | Augment of resistive and other losses. |
| Bushing | Conductive or insulation part fails. |
| On Load Tap Charger | Drive mechanism, tap selection or control device fails. |

## 3. Asset Management

Several methods are being researched in asset management to optimize power output and lifespan for every component in the PV system. Some of these methods involucres machine learning models that use electrical parameter as inputs and classify t as indicated in (Rodrigues et al., 2017).

Image analysis is being used as a novel tool to diagnose faults at modules. The use of unmanned aerial vehicles can dramatically reduce the time needed to sweep the whole installation. Different fault modes are visible on certain spectrums. Thermography based imagery is useful to detect hotspots and fire hazards (Tsanakas J. et al, 2013), photos on the visible spectrum can be used to quantify the level of soiling and glass impacts (Mehta S. et al, 2017) and electroluminescence is used to identify electrically inactive zones inside a PV module (Burhenne R. et al, 2012)

On the other hand, the prevention soiling motivates to programming a correct clean maintenance plan which affects the overall failure cost, maintenance cost and performance of the solar panels. These facts involve carrying out elaborate studies related to the influence of the cleaning method over the photovoltaic modules (Morraham et al., 2013). In this line of investigation, other methods include new technologies as self-cleaning for solar cells array, e.g., natural means, mechanical means, self-cleaning nano-films and electrostatics means (Gaofa et al., 2011). These methods of self-cleaning are especially important in space applications, like Martian or lunar exploration.

New technologies are investigated in (Pandey et al., 2016), where integrated photovoltaics systems are investigated. This is the case of desalination and concentrated photovoltaics applications. Another new approach indicates that using mathematical models of the photovoltaic system, it can be monitored mixing Artificial Intelligence (AI) and Big data analysis. This method usually is called PV digital twin and can be used to estimate different operating conditions of the PV system (R.M. Asimov et al., 2018). It is important to know how this new knowledge will affect power output and energy revenue in the long term and add to as input for a maintenance model.

Asset management techniques must be classified according to the following criteria, which fault modes do the attend and how. It is up to the managers and researchers to classify their strategies accordingly.

## 4. Methodology

The proposed methodology attempts to make a general cost estimation when it is known several previous information, i.e., cost data, maintenance data and cost model, with the objective to make the best decision that reduce the overall failure cost. If the user knows the cost data, it could analyze different maintenance plans strategies like corrective, preventive, predictive or proactive. In this way, for make better decisions it must be considered the cost of implement a more elaborated maintenance plan in the overall failure cost, however, in this paper this cost does not be considered. The figure 2 resume the proposed methodology.

In the case of it has historical maintenance data, the maintenance plan could be improved by determining better inspections times. On the other hand, if the historical data is not available or it does not exist, maintenance data can be generated along the way. Finally, with the information coming from the cost model, the user can make the decision that reduce the cost over a set of maintenance plan and techniques.

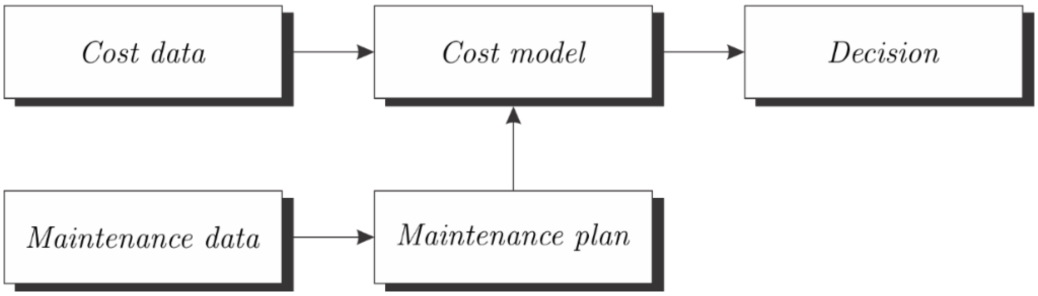

**Fig. 2: General diagram for the proposed methodology.**

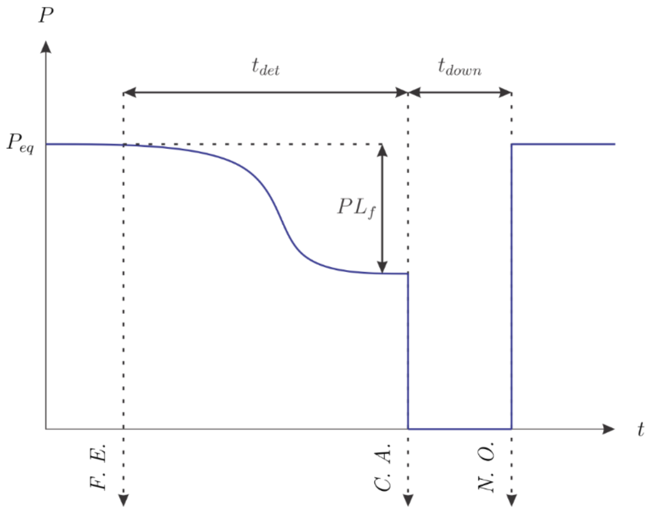

**Fig. 3: Fault mode evolution over time (F.E. = Failure Event, C.A. = Corrective Action, N.O. = Normal Operation)**

Figure 3 shows a typical failure behavior in an operating PV system. It is important to note this image represents a general behavior and does not include an asset management strategy. The shape of this curve changes with a different approach (be corrective or preventive).

Each fault described in the previous section has its own cost and can be expressed as function of multiple variables:

- Detection Cost: The economic losses incurred from the fault´s beginning up to its detection

$$C_{det} = t_{det} \cdot PL_f \cdot S \cdot EC \qquad \text{(eq. 1)}$$

- Repair Cost: The economic losses incurred from fixing a fault mode

$$C_{rep} = t_{down} \cdot \left(P_{eq} \cdot S \cdot EC + C_{work}\right) \qquad \text{(eq. 2)}$$

With every cost calculated, it is possible to assign an overall failure cost:

$$C_f = C_{det} + C_{rep} + \delta \cdot C_{eq} \qquad \text{(eq. 3)}$$

With each variable defined as:

- $t_{det}$ = The time incurred between the beginning of the failure and the moment where corrective actions are taken. It is important to note that in many cases plant managers know about the existence of faults within the plants, but they do not act immediately because the impact and the scope of the fault are not relevant.
- $PL_f$ = The power loss caused by the fault mode. In operating system, untreated faults evolve over time and the power losses incurred change accordingly. For the sake of simplicity, this analysis will consider this variable as a constant over time.
- $S$ = Scaling factor. This parameter is used to quantify the effect of a faulty unit on the associated subsystem.
- $t_{down}$ = The total time an equipment is disconnected due to maintenance reasons
- $P_{eq}$ = Power generated by a healthy operational unit

- $C_{work}$ = Workforce cost
- $C_{eq}$ = Total cost of a healthy operational unit
- $EC$ = Energy spot price
- $\delta =$ Replacement Factor. This parameter indicates whether a faulty unit needs replacement or not

It is important to notice that the proposed cost does not consider the cost of implement the maintenance plan, so the results of this methodology are only valid as indicatives and not mandatory. Finally, maintenance plans are reviewed and classified on how they can affect variables shown in Table 2, and thus reduce the economic impact from the failures associated. Within the maintenance focuses are corrective, preventive or proactive plans, however, the publication will focus on the preventive and corrective maintenance plans.

The maintenance approaches discussed in section 3 can be summed up and classified according on how they do affect the variables that make up each cost for every fault mode analyzed:

**Tab. 4: Asset management scope and impact**

| Description | Subsystem Covered | Fault modes covered | Impact |
|---|---|---|---|
| Surveillance rounds around the plant | Modules | Broken Glass<br>Delamination<br>Shading<br>Stolen Modules | $-t_{det}$ |
| Infrared inspection of equipment with manual cameras | Modules | Broken Glass<br>Delamination<br>Hotspot<br>Faulty Bypass Diode | $-t_{det}$ |
| Infrared inspection with aerial vehicles | Modules | Broken Glass<br>Delamination<br>Hotspot<br>Faulty Bypass Diode | $-t_{det}$ |
| I-V Curve | Modules | Soiling<br>PID<br>Hotspot | $-t_{det}$<br>$+t_{down}$ |
| Online Monitoring and control | Inverter<br>Transformer Station | Control Software<br>Overheating | $-t_{det}$ |
| Machine learning and data mining | Modules<br>Inverts | * | $-t_{det}$ |
| Electroluminescence | Modules | PID<br>Broken Cells<br>Delamination | $-t_{det}$<br>$+t_{down}$ |

*Depending on the technique, machine learning algorithms can detect different fault modes

## 5. Case study

The case study consists in two strings of three solar modules each, connected to one inverter station (inverter and transformer station, for the sake of simplicity). Then, the system is connected to the electrical grid, as indicated in figure 4. In this case, the system has one failed solar module on a string, so it is necessary to find the scale factor $S$ with the aim to extend the failure over all the system. In addition, it is supposed a failure detection event as indicated in figure 3 and the energy spot price is assumed equal for the different divisions of the case. In this explanatory case, it is studied two different techniques of maintenance: *Surveillance round around the plant and Drone inspections.* For each technique it is defined the same set of fault modes, i.e., soiling and broken glass. The generic photovoltaic module has 310 $Wp$ and the energy per Wp used for the calculation of $P_{eq}$ and $PL_f$ was obtained from www.calculadorasolar.cl, with a value of 191.7 $kWh/kWp$. On the other hand, the energy spot price is assumed as 60 $\$/kWh$.

The explained case is resumed in the table 5, and the results of this are in the last column of this. It can be noticed that the total cost of the S.R. is about double for the case of D.I. for this simplified case study, which implies that the D.I. are a better maintenance strategy than S.R., however as mentioned before, in the future the overall failure cost function should include the maintenance cost.

**Tab. 5: Findings of the case study (S.R. = Surveillance Rounds, D.I. = Drone Inspections).**

| **Element** | **Fault Mode** | $t_{det}$ **days** | $t_{down}$ **days** | $P_{eq}$ **kWh** | $PL_f$ **kWh** | $S$ | $EC$ **\$/kWh** | $\delta$ | $C_{work}$ **\$** | $C_{det}$ **\$** | $C_{rep}$ **\$** | $C_{eq}$ **\$** | $C_f$ **\$** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Solar Module S.R. | Soiling | 60 | 5 | 356.56 | 14.9 | 1.3 | 60 | 0 | 30 | 69530 | 2344 | 300 | 71874 |
| | Broken Glass | 15 | 5 | 356.56 | 5.94 | 1.2 | 60 | 1 | 20 | 6418 | 2156 | | 8874.1 |
| Solar Module D. I. | Soiling | 30 | 3 | 356.56 | 14.9 | 1.3 | 60 | 0 | 30 | 34866 | 1418.4 | 300 | 36284 |
| | Broken Glass | 5 | 4 | 356.56 | 5.94 | 1.2 | 60 | 1 | 20 | 2138 | 1728.8 | | 4167.2 |

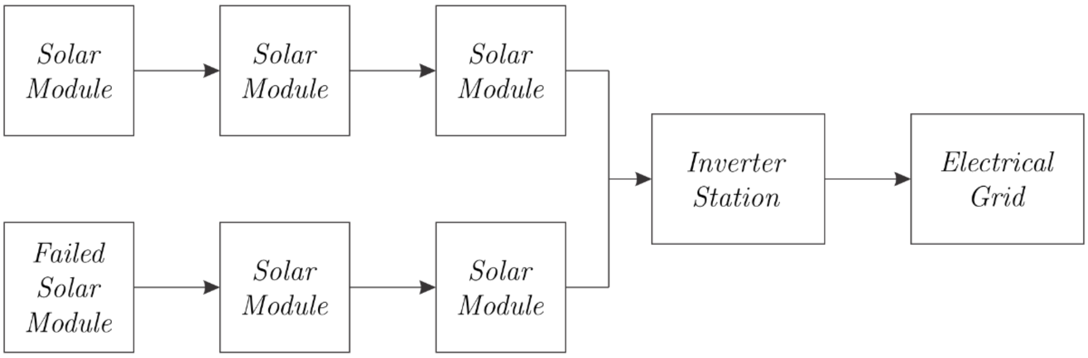

**Fig. 4: Case study scheme.**

## 6. Conclusions

It is important to note that an asset management strategy cannot take in account every single fault mode presented. The proposed methodology can evaluate different maintenance strategies according to the level they work at (be module, inverter or transformer station), the faults they can analyze and how do they change the multiple variables that compose each failure cost. Having this information can help plant managers or researcher to assess the economic impact of a certain strategy. Further work should include the cost of implementing said plans to further evaluate if an approach is financially viable.

## 7. Acknowledgments

The authors gratefully acknowledge the financial support provided by the Solar Energy Research Center, SERC Chile (CONICYT/15110019).

## 8. References

Ahadi A., Ghadimi N. & Mirabbasi D., 2014. Reliability assessment for components of large scale photovoltaic systems. Journal of Power Sources, 264, 211–219.

Barbosa, J.D., Santos, R.C. dos, Romero, J.F.A., Asano, P.T.L., Neto, A.V. da S., Junior, J.B.C., Junior, J.R. de A., Cugnasca, P.S. 2018. Methodology for Determining Reliability Indices of Electric Power Substations. IEEE.

Burhenne, R., Stern, O., Bucher, M., Lynass, M., Mayer, O., Zettl, M., & Mansouri, A. (2012). Defect Detection in Photovoltaic Modules Using Electroluminescence Imaging. 27th European Photovoltaic Solar Energy Conference and Exhibition, 3374-3378.

Flicker J., 2014. PV inverter performance and component- level reliability, Photovoltaic Module Reliability Workshop.

Gaofa He, Chuande Zhou, Zelun Li, 2011. Review of Self-Cleaning Method for Solar Cell Array, Procedia Engineering, Volume 16, Pages 640-645.

Jordan, D. C., Kurtz, S. R., VanSant, K., & Newmiller, J. , 2016. Compendium of photovoltaic Degradation rates. Progress in Photovoltaics, 24(7), 978–989.

Jordan, D. C., Deline, C., Kurtz, S. R., Kimball, G. M., & Anderson, M., 2018. Robust PV Degradation Methodology and Application. IEEE Journal of Photovoltaics, 8(2), 525–531.

K.A. Moharram, M.S. Abd-Elhady, H.A. Kandil, H. El-Sherif, 2013. Influence of cleaning using water and surfactants on the performance of photovoltaic panels, Energy Conversion and Management, Volume 68, Pages 266-272

Köntges M, Kurtz S, Packard C, Jahn U, Berger KA, Kato K, Friesen T, Liu H, Van Iseghem M, 2014. Review on failures of photovoltaic modules. IEA PVPS, IEA-PVPS T13-01:2014.

Köntges M, Oreski G., Jahn U., Herz M., Hacke P., Weiss K., Razongles G., Paggi M., Parlevliet D., Tanahashi T., French R., 2017. Assessment of Photovoltaic Module Failures in the Field. IEA PVPS, IEA-PVPS T13-09:2017.

Mehta, S., Azad, A. P., Chemmengath, S., Raykar, V., & Kalyanraman, S., 2017. DeepSolarEye: Power Loss Prediction and Weakly Supervised Soiling Localization via Fully Convolutional Networks for Solar Panels.

Moser, D., Del Buono, M., Jahn, U., Herz, M., Richter, M., & De Brabandere, K., 2017. Identification of technical risks in the photovoltaic value chain and quantification of the economic impact. Progress in Photovoltaics, 25(7), 592–604.

Pandey A.K., Tyagi V.V., Jeyraj A/L Selvaraj, Rahim N.A., Tyagi S.K., 2016. Recent advances in solar photovoltaic systems for emerging trends and advanced applications, Renewable and Sustainable Energy Reviews, Volume 53, Pages 859-884

PV System Reliability: An Operator's Perspective. IEEE Journals & Magazine. (n.d.). Retrieved July 28, 2019, from https://ieeexplore.ieee.org/document/6305521

Rampinelli, G. A., A. Krenzinger, y A. J. Buhler. 2017. "Methodology for Analysis of Thermal Behavior of Inverters for Photovoltaic Systems". Journal of Solar Energy Engineering-Transactions of the Asme.

Rodrigues, Sandy & Ramos, Helena & Morgado-Dias, F, 2017. Machine Learning in PV Fault Detection, Diagnostics and Prognostics: A Review.

R.M. Asimov, S.V. Chernoshey, I. Kruse, V.S. Osipovich, 2018. Digital Twin in the Analysis of a Big Data.

Sayed, A., El-Shimy, M., El-Metwally, M., & Elshahed, M., 2019. Reliability, Availability and Maintainability Analysis for Grid-Connected Solar Photovoltaic Systems. Energies, 12(7), 1213.

Sihite, J. F., 2013. Failure Analysis of Power Transformer Based on Fault Tree Analysis.

Solar Power Europe, 2016. Global Market Outlook for Solar Power 2016–2020.

Sorensen, N. R., Thomas, E. V., Quintana, M. A., Barkaszi, S., Rosenthal, A., Zhang, Z., & Kurtz, S. , 2013. Thermal Study of Inverter Components. IEEE Journal of Photovoltaic*s*, *3*(2), 807–813.

Tsanakas, J. A., Ha, L., & Buerhop, C. (2016). Faults and infrared thermographic diagnosis in operating c-Si photovoltaic modules: A review of research and future challenges. Renewable and Sustainable Energy Reviews, 62, 695-709.

Zhang, P., Li, W., Li, S., Wang, Y., & Xiao, W., 2013. Reliability assessment of photovoltaic power systems: Review of current status and future perspectives. Applied Energy, 104, 822–833.

Zhou, P., Jin, R. Y., & Fan, L. W., 2016. Reliability and economic evaluation of power system with renewables: A review. Renewable & Sustainable Energy Reviews, 58, 537–547.