Investigation of Dominant Failure Mode(s) for Field-Aged Crystalline Silicon PV Modules Under Desert Climatic Conditions

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Abstract—The first step in developing a life prediction model for photovoltaic (PV) modules is the identification of dominant failure modes/mechanisms for given environmental and operating conditions. Although important, the literature is very scarce. The Jet Propulsion Laboratory (JPL) approach consists of identifying the weakest link in module construction and the failure modes or mechanisms susceptible to the link are considered dominant. The failure mode and effects analysis/failure mode and effects criticality analysis approach, proposed and tried by a few authors, provides a more analytical alternative. It uses the risk priority number (RPN) as a ranking metric for failure modes prioritization. The RPN is a product of three parameters: severity of a failure (S), occurrence of the failure (O), and detection of the failure (D). Typically, the values for S, O, and D are assigned based on qualitative analyses. As such, the values assigned for the failure modes to those factors are highly subjective, leading to considerable variations from one analyst or design team to another. The main objective of this study is to move as far away as possible from this traditionally subjective approach to a formal, objective, and data-driven determination of RPN. The approach described in this paper relies on quantitative measures and sizable datasets. For the hot and dry climatic conditions of Phoenix, Arizona USA, solder bond failures and encapsulant discoloration are found to be the dominant failure modes.

Index Terms—Decision trees, failure mode and effects analysis (FMEA), materials reliability, photovoltaic (PV) systems.

I. INTRODUCTION

The warranty period provided by crystalline silicon photovoltaic (PV) module manufacturers typically ranges from 20 to 30 years. Therefore, deployed modules must demonstrate that the required performance criteria can be maintained throughout the warranty period. Unfortunately, it is not currently possible to test for a 20–30 year lifetime, making it difficult, if not impossible, to accurately and precisely predict service lifetimes.

It has been 26 years since systematic studies on solar PV module lifetime prediction were undertaken as part of the 11-year flat-plate solar array (FSA) project [1]. This project resulted in the development of qualification testing [2]. Since then, PV modules have gone through tremendous changes in construction materials and design. Efforts [2], [59], [60] have been made to adapt some of the techniques developed to the current technologies, but they are too often limited in scope and too reliant on empirical generalizations of previous results.

JPL’s methodology for developing prediction model includes four major elements [3]: 1) identification of key degradation mechanisms; 2) establishment of mechanism-specific reliability goals; 3) quantification of mechanism parameter dependences; and 4) development of degradation prediction methods. A few other researchers have since proposed more elaborate methodologies. McMahon et al. [4] discusses a five-step protocol to use accelerated environmental tests (AET) for life-prediction: 1) identify and isolate all failure modes; 2) design and perform AETs; 3) use appropriate statistical distributions to model specific failure rates; 4) choose and apply relevant acceleration models to transform failure rates; and 5) develop a total module failure rate as a composite of individual rates to allow service lifetime prediction for each use condition. Quintana and Kurtz [5] identify four elements as the basis for the predictive model: 1) field testing; 2) failure mechanisms identification; 3) failure analysis and modeling; and 4) accelerated testing.

A common element to these systematic approaches to PV module lifetime prediction is identifying and ranking field failure modes/mechanisms. While a myriad of studies [29]–[33], [52]–[58] have been done and published on identifying field failure modes/mechanisms, determining the dominant mode(s) or mechanism(s) has received very little attention. The JPL approach was to first identify what is perceived as the weakest link in a module construction; the anticipated failure modes for that link are then assumed dominant [6]. The problem with such an approach is its heavy reliance on engineering judgment. Another commonly used technique consists of carefully inspecting individual modules for major defects as defined in the international standards [7], [8] and identifying the highest frequency of these defect(s). As exemplified in [9], this approach does not consider whether or not the observed “major defect” affects the performance output.

In this paper, the failure mode and effects (criticality) analysis (FMEA/FMECA) technique is used in determining the dominant failure mode(s) of c-Si PV modules under the hot and dry climatic conditions in Arizona, USA. Conventionally, the FMEA/FMECA approach is very subjective. It uses the risk priority number (RPN), which is a product of three parameters:
severity of a failure (S), occurrence of the failure (O), and detection of the failure (D). The values for S, O, and D are subjectively assigned, based on qualitative analyses and engineering judgments. The main objective of this study was to move as far away as possible from the traditionally subjective approach to a formal, objective, and data-driven determination of RPN.

Yang [42] and Bowles [43] discuss the deficiencies of the RPN technique in prioritizing failure modes, which is due to the fact that the values of RPN are not continuous and they may contain many duplicates. However, it shall be noted that these deficiencies are inherent to the RPN concept, rather than the methodology presented in this paper. The aim of this study is to devise an approach for objectively determining RPN, assuming it is the technique of choice to the analyst.

There are different types of FMEA/FMECA [system FMEA/FMECA, design FMEA (dFMEA)/FMECA, process FMEA/FMECA] that are used to address quality and reliability aspects; including identifying, prioritizing, and eliminating potential failure causes from system/product design or manufacturing process. This paper focuses on prioritizing known failure modes from c-Si PV modules operating under specified climatic conditions.

In the next section, we review the literature on FMEA/FMECA concepts, reliability of PV modules under hot and dry climate conditions, application of FMEA/FMECA in PV, and decision trees in data mining concepts. The methodology used in this study is described in Section III and the results of our investigation are presented and discussed in Section IV.

II. LITERATURE REVIEW

A. Failure Mode and Effects Analysis/Failure Mode And Effects Criticality Analysis General Concept

The IEC 60812 standard [10] defines the FMEA as a systematic procedure for the analysis of a system so as to identify the potential failure modes, their causes, and their effect on system performance. The FMEA is an extension to the FMECA. Letter “C” indicates that the criticality (or severity) of the various failure modes are considered and ranked. There are many types of FMEA/FMECA, each of which may be conducted for many purposes. The concept described here focuses on system FMEA/FMECA, which would lead to a ranked list of potential system failure modes.

The system design FMECA analysis process consists of two main steps: preparation of an FMECA worksheet and identification of the rating guidelines.

1) Failure Mode And Effects Criticality Analysis Worksheet:
The major elements of an FMECA worksheet include:

Potential failure modes: There are many ways a component or system may fail. Identified failure modes depend on system components, environment, and past history of failures in similar systems.

a) Potential cause of the failure: For any given failure mode, there could be more than one cause. The cause or mechanism of a failure mode is the physical or chemical processes that cause an item to fail. The IEC standard points out that the identification and description of failure causes is not always necessary for all failure modes, rather, should be done on the basis of the failure effects and severity. The more severe the effects of failure modes, the more accurately failure causes should be identified and described.

b) Potential effects of the failure mode: This is the consequence of a system failure mode. A failure effect may be caused by one or more failure modes of one or more items. Warranty documents, field service data, and reliability data can be used to identify potential effects.

c) Current controls/fault detection: This identifies the way by which occurrence of failure is detected and the means by which the operator is made aware of the failure. It could be a procedure, test, design review, or an engineering analysis.

2) Rating Guidelines: There is no universal or standard rating guideline. In general, it can be qualitative or quantitative; with the numerical values from 1 to 5 or 1 to 10. The potential system deficiencies are ranked using the RPN, which is defined as

\[ RPN = S \times O \times D \]

where S, O, and D are rating values, respectively, representing the severity of effect, occurrence, and detection.

Severity of effect (S): This rating indicates the seriousness of the effect of the potential system failure mode. It is based on the worst effect of the failure mode. The severity is high for critical effects and very low for noncritical effects. We reproduce in Table I below an example of qualitative severity classification from SEMATECH [11].

<table>
<thead>
<tr>
<th>Rank</th>
<th>Severity Ranking Criteria [11]</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>Failure will cause non-system operation or non-compliance with government regulations</td>
</tr>
<tr>
<td>8 – 9</td>
<td>Failure will cause non-functionality of system</td>
</tr>
<tr>
<td>6 – 7</td>
<td>Failure will result in deterioration of part of system performance</td>
</tr>
<tr>
<td>3 – 5</td>
<td>Failure result in slight deterioration of part of system performance</td>
</tr>
<tr>
<td>1 – 2</td>
<td>No discernible effect</td>
</tr>
</tbody>
</table>

Occurrence (O): This rating value corresponds to the estimated number of failures that could occur for a given cause over the operational life of the system. Failure modes are identified in terms of probability of occurrence, grouped into discrete levels. These levels establish the qualitative failure probability level. An example of frequency classification can be found in [12]. It is reproduced in Table II below.

Detection (D): This rating corresponds to the likelihood that the detection method or control will detect the failure before the system reaches the end-user. The detection ranking presented in Table III is extracted from [11].

3) Concluding Notes on Rating Guidelines: Alternate evaluation criteria provides ranking on a 1–10 scale [10], [13]. As noted in [10], rating numbers 6 and up are usually very straightforward, whereas those below are very subjective. In addition, the MIL-STD-1629A standard [13] indicates that the analysis requires an equal scale (i.e., 1–10 or 1–5) for both the severity and
A crystalline silicon PV module is made by connecting individual cells. The typical construction is superstrate/encapsulant/cells/encapsulant/backsheet. Glass is the common choice for superstrate. Ethylene vinyl acetate (EVA) copolymer has been the dominant encapsulation material for crystalline silicon modules since it was introduced in the 1980s. Encapsulants are used as a means to dissipating heat and protecting PV modules against harsh environmental conditions, including vibration, moisture, stresses, etc. Metal contacts are often attached on the top of solar cells to define a grid pattern called bus-bars. Tinned copper ribbons called tabs or interconnects are soldered to the bus bars at the front to form a series (S) or series-parallel (SP) arrangement of the cells. The cell arrangement is then sandwiched between two layers of encapsulants and laminated.

Failure and degradation mechanisms of PV modules are dictated by their design/construction and the field environment in which they operate. The design/construction of PV modules has gone through a dramatic change since 1975 [15]. The design and component changes include cell type (from mono-Si to poly-Si and mono-Si along with various thin-film technologies), superstrate (from silicone to glass), encapsulant (from silicone to EVA), substrate (from fiberglass board to polymeric backsheet), cell string (from one to multiple), interconnect between cells (from one to multiple), and bypass diode (from none to multiple).

The key field degradation mechanisms identified in the 1970s and 1980s for crystalline silicon PV modules are summarized in [16]. That paper indicates that the module encapsulation system and the circuit integrity are the area most susceptible to reliability issues. The identified issues related to the encapsulated system include soiling, yellowing, delamination, and corrosion; and those related to circuit integrity include interconnect fatigue and solder joint failures. Cell cracking, metallization adherence, series resistance, and durability of antireflective coatings were also identified as major issues.

Tamizhmani and Kuitche [14] identify the reliability issues associated with each component of the module construction. They are summarized in Table IV below.

There have been numerous recent studies on the reliability of field deployed PV modules operating under dry and hot climatic conditions. Tucker et al. [17] evaluates EVA-based encapsulant modules deployed on a two-axis tracker in Tempe, Arizona, USA, for nine years as part of validation experiments of photothermally-enhanced encapsulant formulations. Visual defects include encapsulant discoloration, corrosion behind junction box, backsheet discoloration, corrosion at the cell interconnects, and encapsulant delamination behind cell. The highest average Isc drop was 2.7%; and a set of two modules exhibiting only encapsulant discoloration showed an average power drop of 3.1%.

Tang et al. [18] evaluated modules removed from a water-pumping array operated in the hot-desert climatic condition of Arizona for 27+ years. The most prominent visual defect found was the graying of the superstrate silicone with hair-thin cracks. No notable delamination of the superstrate and busbar corrosion was observed. A power drop from the initial manufacturer rating was found to be 1.08% per year.
Raghuraman et al. [19] analyze the reliability of 44 PV modules exposed in Mesa, AZ, USA, for 2–7 years. Crystalline silicon modules showed an average performance drop of 0.45% per year; with no visual defect in 2–4 years of exposure.

Singh et al. [20] analyze the degradation of 1900 crystalline silicon modules operating in Tempe, AZ, USA, for 12–18 years. They observed that the degradation ranged from 0.6% to 2.5% per year depending on the manufacturer, with modules exhibiting hot spot defects degrading at a higher rate than others.

Berman et al. [63] evaluated a grid-connected PV system in the Negev Desert, in Israel and observed that the modules had turned yellow-brown after five years of operation.

Cronin et al. [64] studied the degradation rates of 20 grid-tied PV systems installed in Tucson, AZ, USA. Systems with crystalline silicon modules ranged from 2–5 years old. The degradation rates measured with two separate methods are ranged from −4.3 to 0.8 ± 0.5–4.6%/year.

Kopp et al. [66] evaluated grid-tied systems deployed in Tucson, AZ, USA, for 2–12 years. For crystalline silicon modules, they found that 73% of the modules inspected exhibited browning, 77% showed cell discoloration, and 45% suffered delamination. No correlation could, however, be established between visual defects and performance degradation.

C. Failure Mode And Effects Analysis/Failure Mode And Effects Criticality Analysis Application on Photovoltaics

Even although the FMEA/FMECA is the most widely used systematic reliability analysis technique across various industries such as aerospace, electromechanical, computers, semiconductor, medical device, automotive, etc., its application in the PV industry is relatively new. Catelani et al. [21] uses the FMEA/FMECA to analyze and classify the major failure modes of PV modules. However, it follows the traditional qualitative analysis, making it extremely subjective. For instance, the ratings provided for severity, occurrence, and detection are in ranges (1–2, 3–4, 5–6, 7–8, and 9–10). It is not clear how to distinguish between scores of 3 and 4, for example. Moreover, the failures observed on PV modules installed in a dry and hot climatic are different, in terms of modes, occurrence, and effects, to those observed, say, in a humid environment. The paper fails to indicate how the listed failure modes were identified, and for which climatic condition(s) they applied. Sandia National Laboratories use FMEA extensively during the design phase of PV systems [22], [23]. Clearly, their focus is on DFMEA.

D. Data Mining-Decision Trees

Data mining is becoming a matured method for information and knowledge discovery. Large and complex observational datasets, such as field failure data on thousands and thousands of PV modules, contain large amounts of hidden useful knowledge. Data mining techniques enable extraction of such knowledge. Gardner and Bieker [24] show how data mining techniques can increase product yield and quality to the next higher level by quickly finding and solving tougher semiconductor manufacturing problems.

Data mining techniques are classified into four main tasks: 1) classification; 2) association; 3) clustering; and 4) sequence discovery. Classification is one of the most useful techniques. From Kantardzic [25], classification is defined as a process of mapping data items into predefined groups or classes. It is often referred to as supervised learning because the classes are predetermined before examining the data. Classification rules are derived based on the training dataset.

Classification algorithms include decision tree-based algorithms, statistical-based algorithms such as Bayesian classification, distance-based algorithms such as K-nearest neighbors, and neural network-based algorithms [26]. Decision trees are the most popular and useful data mining models. They are generally very efficient and have good accuracy; however, their successful use depends on the quality of the data at hand. Areas of application include financial analysis, manufacturing and production.

A typical decision tree uses the “divide and conquer” technique to construct the tree in a top-down recursive manner (see Fig. 1). The root (topmost node) and each internal node (nonleaf node) denote a test on an attribute. Each branch represents an outcome of the test. Each terminal node (leaf node) holds a class label. Test attributes are selected based on a statistical measure. Attribute selection measures or splitting rules determine how the tuples at a given node are to be split. Three popular splitting rules are Information Gain, Gain Ratio, and Gini Index. The use of information gain is described in Appendix A [62]. A decision tree-based algorithm reproduced from Dunham [27] is presented in Appendix B.

III. METHODOLOGY

In order to determine the dominant failure mode(s) under the targeted environment, the RPN is used as the quantitative metric. As previously mentioned, the RPN is defined as the product of severity S, which ranks the seriousness of the failure mode; the occurrence O, which ranks the frequency of the failure mode; and the detection D, ranking the likelihood the failure will be detected before it reaches the end-user. To minimize subjectivity, we will use a scale from 1–5 for all ranks. The classification found in the literature and presented in Section II previously is adapted as summarized in Table V below. The last column, “Score,” indicates our ranking scales.
TABLE V
SEVERITY, OCCURRENCE, AND DETECTION RATINGS USED IN THIS STUDY

<table>
<thead>
<tr>
<th>Defect Description</th>
<th>Severity (S)</th>
<th>Occurrence (O)</th>
<th>Detection (D)</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Defect will cause module not to work and become a safety hazard</td>
<td>5</td>
<td>Defect frequent: $fp &gt; 0.20$</td>
<td>Controls will not or cannot detect the existence of a deficiency or defect: $0%$ chance</td>
<td>5</td>
</tr>
<tr>
<td>Module might be safe, but non-functional: Pmax drop &gt; 20%</td>
<td>4</td>
<td>Defect probable: $0.10 &lt; fp \leq 0.20$</td>
<td>Controls not likely to detect the existence of a deficiency or defect: $50%$ chance</td>
<td>4</td>
</tr>
<tr>
<td>Module not meeting warranty requirement: Rd &gt; 0.8% AND Pmax drop &lt; 20%</td>
<td>3</td>
<td>Occasional probability of occurrence: $0.01 &lt; fp \leq 0.10$</td>
<td>Controls are likely to detect the existence of a deficiency or defect: $50%$ chance</td>
<td>3</td>
</tr>
<tr>
<td>Slight deterioration of part or system (long term concern): Rd &lt; 0.8% AND Pmax drop &lt; 20%</td>
<td>2</td>
<td>Remote probability of occurrence: $0.001 &lt; fp \leq 0.01$</td>
<td>Controls have a good chance of detecting the existence of a deficiency or defect: $50%$ chance</td>
<td>2</td>
</tr>
<tr>
<td>No effect on performance: Pmax drop ≤ 8%</td>
<td>1</td>
<td>A very unlikely probability of occurrence: $fp \leq 0.001$</td>
<td>Controls will almost certainly detect the existence of a deficiency or defect: $100%$ chance</td>
<td>1</td>
</tr>
</tbody>
</table>

$P_{\text{max}}$ = Maximum power output. $R_d$ = degradation rate. $f_p$ = Failure mode probability per operating time.

![Annual degradation of PV modules based on 2074 reported data [28.]](image)

It is necessary to explain the use of some of the classifying variables in the table above, such as $R_d$ and $P_{\text{max}}$ drop.

Jordan and Kurtz [28] conducted an extensive literature search on PV module degradation rates and found that for crystalline silicon modules, the average published degradation rate was 0.8% per year (see Fig. 2). Since the warranty period provided by manufacturers typically ranges from 20–30 years, if we assume an average of 25 years for the warranty, and an average of 0.8% drop from the initial power output each year, then we have $0.8 \times 25 = 20\%$ drop in performance throughout the warranty period. Thus, a PV module is generally considered nonfunctional when its maximum power output drops by more than 20% of the initial power while still under warranty.

We describe later in this section our decision tree approach for determining the effect of each defect on the performance drop, the failure mode probability ($f_p$), and the chances for each existing control to detect individual defects.

TABLE VI
DESCRIPTION OF TEST SAMPLES

<table>
<thead>
<tr>
<th>Model Code</th>
<th>Technology</th>
<th>Fixed Tilt/Tracking</th>
<th>Construction*</th>
<th>Number of Modules in the System</th>
<th>Exposed Years at the Time of Evaluation</th>
<th>Evaluation Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-18</td>
<td>mono-Si</td>
<td>Fixed latitude</td>
<td>G/P/FR</td>
<td>216</td>
<td>18</td>
<td>2009-2011</td>
</tr>
<tr>
<td>A-13</td>
<td>mono-Si</td>
<td>2-axis</td>
<td>G/P/FR</td>
<td>168</td>
<td>13</td>
<td>2009-2011</td>
</tr>
<tr>
<td>B</td>
<td>mono-Si</td>
<td>2-axis</td>
<td>G/P/P</td>
<td>1153</td>
<td>13</td>
<td>2009-2011</td>
</tr>
<tr>
<td>C-12</td>
<td>poly-Si</td>
<td>2-axis</td>
<td>G/P/FR</td>
<td>177</td>
<td>12</td>
<td>2009-2011</td>
</tr>
<tr>
<td>C-4</td>
<td>poly-Si</td>
<td>3-axis</td>
<td>G/P/FR</td>
<td>39</td>
<td>4</td>
<td>2009-2011</td>
</tr>
<tr>
<td>D</td>
<td>poly-Si</td>
<td>1-axis</td>
<td>G/P/FR</td>
<td>48</td>
<td>12</td>
<td>2009-2011</td>
</tr>
<tr>
<td>E</td>
<td>mono-Si</td>
<td>1-axis</td>
<td>G/P/FR</td>
<td>50</td>
<td>12</td>
<td>2009-2011</td>
</tr>
<tr>
<td>F</td>
<td>mono-Si</td>
<td>1-axis</td>
<td>G/P/FR</td>
<td>120</td>
<td>12</td>
<td>2009-2011</td>
</tr>
<tr>
<td>G</td>
<td>mono-Si</td>
<td>3-axis</td>
<td>G/P/FR</td>
<td>2352</td>
<td>12</td>
<td>2012-2013</td>
</tr>
<tr>
<td>BR01</td>
<td>mono-Si</td>
<td>Fixed horizontal</td>
<td>G/P/FR</td>
<td>756</td>
<td>16</td>
<td>2012-2013</td>
</tr>
<tr>
<td>BR02</td>
<td>mono-Si</td>
<td>Fixed horizontal</td>
<td>G/P/FR</td>
<td>756</td>
<td>16</td>
<td>2012-2013</td>
</tr>
</tbody>
</table>

*G=Glass; P=Painted; FR=Frameless; FL=Frameless.

A. Degradation Rate

Assuming a linear degradation, the degradation rate ($R_d$) was determined as follows:

$$R_d = \frac{\text{percentage of power drop} \ (P_{\text{mdrop}})}{\text{years of operation} \ (age)}$$

The percentage of power drop is calculated as follows:

$$P_{\text{mdrop}} = \frac{(\text{Manufacturer rated Power} - \text{Present Day Power})}{\text{Manufacturer rated Power}} \times 100.$$  

As noted by Jordan and Kurtz [28], calculating the degradation rate using the manufacturer’s rated power as opposed to the baseline measurements can add significant error to the final value. This must be taken into consideration when reporting degradation rate. The approach above is deemed sufficient for the purpose of this study. Other studies related to the measurement of degradation rates include Cronin et al. [64] and Davis et al. [65].

B. Data Description

Our approach is a data-driven approach. Table VI provides the descriptions of the PV systems evaluated. A total of 5835 modules from 11 different PV systems installed in the Phoenix, AZ, USA area were inspected. Performance measurements were collected on a lesser number of samples (2538). Module ages ranged from 4–18 years.

In the next subsections, we discuss failure mode identification and our methodology for assigning $S$, $O$, and $D$ values to individual failure modes.

C. Failure Mode Identification

Procedures for capturing failure modes/mechanisms as fully as possible on module designs have been evolving since the FSA project [1]. Techniques used for failure identification include careful monitoring/inspections of field application with statistically significant number of modules, observed failure data from qualification testing, and failure data from 0.5–2 years intermediate length tests with relevant stresses [3]. Wohlgemuth
TABLE VII
CHECKLIST OF DESIGN FAILURE MODES AND RELEVANT QUALIFICATION/SAFETY TESTS [30]–[33]

<table>
<thead>
<tr>
<th>Field failures</th>
<th>Causes/Mechanisms</th>
<th>Characterization Test</th>
<th>Accelerated stress test per IEC61215 standard</th>
</tr>
</thead>
<tbody>
<tr>
<td>Broken Interconnects</td>
<td>Thermal expansion and contraction, repeated mechanical stress</td>
<td>Visual inspection</td>
<td>200 Thermal Cycles (TC200) Mechanical load (ML)</td>
</tr>
<tr>
<td>Broken cells</td>
<td>Mechanical stresses</td>
<td>Electroluminescence (EL)</td>
<td>TC200 ML Hail</td>
</tr>
<tr>
<td>Corrosion</td>
<td>Moisture induced corrosion of cell metalization</td>
<td>Visual inspection</td>
<td>1000h Damp heat (DH1000)</td>
</tr>
<tr>
<td>Delamination</td>
<td>Adhesive bond sensitive to UV or contamination from the material</td>
<td>Visual inspection</td>
<td>DH1000 Humidity freeze 10 cycles (HF10) Ultra-violet (UV)</td>
</tr>
<tr>
<td>Encapsulant discoloration</td>
<td>Heat and UV</td>
<td>Visual inspection</td>
<td>UV</td>
</tr>
<tr>
<td>Solder bond failures</td>
<td>Stresses induced by thermal cycling or vibration</td>
<td>Visual inspection</td>
<td>TC 200 ML</td>
</tr>
<tr>
<td>Hot spots</td>
<td>Operating current &gt; Isc</td>
<td>Infra-red scan (IR)</td>
<td>Hot spot test (HS)</td>
</tr>
<tr>
<td>Bypass diode failures</td>
<td>OC diode inspections with handheld device</td>
<td>HS Diode test</td>
<td></td>
</tr>
<tr>
<td>Backsheet</td>
<td>Visual inspection</td>
<td>UV</td>
<td></td>
</tr>
</tbody>
</table>

**Fig. 3.** Examples of IR scan (left) and EL image (right).

**D. Determining the Occurrence of Failure**

There are three steps involved in determining the occurrence of defects:

1) Each module is carefully inspected against a checklist of potential defects, similar to that in [33]. Inspections are carried out visually, with an infrared (IR) camera, and in some cases with electroluminescence (EL). The IR scanning enables identification of hot spots. A Fluke infrared camera was used to scan the modules. The EL was used to identify microcracks in the cells and inactive portions of the cells. Our EL setup uses CoolSamBa Camera from Sensovation. Examples of an IR scan and an EL imaging are shown in Fig. 3.

Solder bond failures were derived from series resistance (Rs) estimations. Key contributors to Rs include solder bonds, emitter and based regions, cell metallization, and busbars [34]–[36]. Meier et al. [36] shows that more than 70% of Rs is dominated by the solder bonds component. This allows us to assume that an increase in series resistance mostly reflects solder bond defects. An Rs increase of more than 1.5 times the initial value was assumed to indicate a solder bond defect. The Rs of each module was estimated from the performance data using the empirical expression from Dobos [37]

\[
R_s = C_S \frac{V_{OC} - V_{mp}}{I_{mp}}
\]

where \(C_S = 0.32\) for monocrystalline silicon and 0.34 for polycrystalline silicon modules.

2) The cumulative number of component failures per 1000 (CNF/1000) over the operating time of each failure mode is then computed as follows:

\[
\text{CNF/1000} = \frac{\text{(cumulative % defects)} / 10}{\text{cumulative operating time}} = \frac{\sum_{\text{systems}} \text{(% defects)} / 10}{\sum_{\text{systems}} \text{operating time)}
\]

where operating time is in years.

3) Occurrence or frequency ratings are assigned to each failure mode based on Table V, generated using the guidelines presented in Section II.

and the BP Solar reliability team published many studies on reliability issues with c-Si modules between 1994 and 2002 based on long term field installed systems. Failure data were collected by analyzing commercial warranty returns, deploying and monitoring individual modules over long time periods, and monitoring the performance of PV systems over time [29], [30]. In an analysis of nearly two million field returns of crystalline silicon modules, corrosion, cell or interconnect breakage, junction box issues, output lead, and delamination were identified as the primary field failures. In Wohlgemuth and Kurtz [31] and Wohlgemuth [32], the list of major failure modes associated with crystalline silicon modules includes broken interconnects, broken cells, corrosion, delamination, discoloration of encapsulant, solder bond failures, broken glass, hot spots, ground fault, junction box and module connection failures, structural failures, bypass diode failures, and arcing. These reported failures, combined with the checklist recently published by NREL [33], constitute our potential failure modes.

Table VII below provides a summary of the field failure modes used as a checklist in this study, the potential causes/mechanisms, the relevant qualification/safety tests to detect the defects, and the relevant accelerated stress tests used as control before the product is shipped to the consumers.
E. Potential Causes/Mechanisms of the Defects and Existing Control Mechanisms

Descriptions of destructive and nondestructive techniques for evaluating the degradation/failure mechanisms of long-term field-exposed modules can be found in [16]–[21]. The failure or degradation modes (effect) in PV modules indicate symptoms, whereas failure or degradation mechanisms (cause) represent the course to arrive at these symptoms. A failure mechanism is responsible for one or more failure modes. A failure mechanism could be triggered by one or more failure causes and a failure mode could trigger one or more failure effects. A good summary of failure/degradation modes, causes, effects, and mechanisms can be found in [14].

Design qualification and safety standards [7], [8] represent the main controls for uncovering defects before new designs reach the customers. They help identify design, materials, and process flaws that are likely to lead to premature failure (infant mortality) [38]. Qualification and safety testing involves a set of well-defined accelerated stress tests (irradiation, environmental, mechanical and electrical) with strict pass/fail criteria based on extended functionality/performance, minimum safety/insulation, and detailed visual requirements. Wohlgemuth and Kurtz [38], [39] and Wohlgemuth [32] discuss the accelerated stress tests designed to induce known field failure modes (see Table VII).

F. Determining the Likelihood of Detecting Failure Modes

Detection ratings are assigned based on the guidelines presented in Section II and summarized in Table VIII. The question is how do we quantify the likelihood of detection?

In his tutorial, Wohlgemuth [32] discusses the ability of each stress test to effectively induce relevant field failure modes. His verdict is summarized in Table IX. TamizhMani et al. [40], [41] has been conducting failure analyses on the design qualification testing of PV modules since 1997. Data for crystalline silicon modules is shown in Fig. 4. We look at the data as a way to validate Wohlgemuth’s conclusions.

It should be pointed out that most PV systems evaluated under this study are at least ten years old, meaning the PV modules were produced before 2005. In addition, the relevant stresses for the applicable climatic condition of this study are thermal cycling (heat) and ultraviolet radiation (UV). From Fig. 5, less than 5% of the modules were failing in TC200, and no failure was observed in UV test. However, field observations show a high number of encapsulant discoloration defects, which are results of heat and UV (see Table VII). This agrees with Wohlgemuth’s verdict.

The last column of Table IX shows the chances, in percentage, for the given stress test to duplicate the relevant failure mode, based on the verdict. We will assume a 5% risk level. Thus, when the stress is certain to induce the relevant failures/defects, a 95% chance is assigned; when it might, we assign a 50% chance; and when it would absolutely not, a 5% chance is assigned.

Denote by \( P(X_i) \) the chance that a stress test \( i \) can induce a relevant failure mode. Let \( i = 1, 2, \ldots, s \) the possible stress tests that can be used to duplicate a given failure mode.
### TABLE X

<table>
<thead>
<tr>
<th>Degradation Rate (Rd)</th>
<th>% of Pnax drop</th>
<th>Age of Module</th>
<th>Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rd ≤ 0.8%</td>
<td>Pmdrop≤ 8%</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Rd ≤ 0.8%</td>
<td>8% &lt; Pmdrop ≤ 20%</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td>Rd &gt; 0.8%</td>
<td>Pmdrop &gt; 20%</td>
<td>10 &lt; age ≤ 20 years</td>
<td>4</td>
</tr>
<tr>
<td>Rd &gt; 0.8%</td>
<td>Pmdrop &gt; 20%</td>
<td>Age ≤ 10 years</td>
<td>5</td>
</tr>
</tbody>
</table>

The likelihood that a failure mode can be duplicated is given by

\[
P \left( \bigcup_{i=1}^{s} X_i \right) = 1 - \prod_{i=1}^{s} \left[ 1 - P \{X_i \} \right].
\]

### G. Determining Severity: Effects of Defects on Module Performance

Table X depicts our approach to quantifying the severity. It is based on the description provided in Table V.

The modules evaluated were all 20 years old or less. Therefore, we consider two categories: those in the infant stage (less than ten years of field operation) and those that have been in the field for over 10 years.

Data mining techniques were used to identify defects corresponding to each severity. Specifically, a decision tree-based algorithm [27] was used on a dataset containing 2538 tuples. Each tuple represents inspection and performance data on an individual field-aged PV module. The data consists of:

1. Percentage of power drop (Pmdrop): This is the module’s output power loss, in percentage, relative to the initial power output. This attribute is grouped into three categories: category C1 consisting of modules with output power loss less or equal to 8%; category C2 consisting of modules with output power loss greater than 8% but less or equal to 20%; and category C3 consisting of modules with output power loss greater than 20%.
2. Degradation rate (Rd): Ratio of power drop (in percentage) by the age of the powerplant or PV system. This quantity is necessary to determine whether or not the module is meeting warranty requirements. Rd = 0.8% represents the warranty limit. Thus, those failing to meet warranty requirements will have Rd > 0.8.
3. Failure modes or defects: Each failure mode has a “Y” (Yes) or “N” (No) outcome. A “Y” indicates that the associated failure mode or defect was observed on the module during the inspection. The potential failure modes are: encapsulant discoloration, Broken or chipped cells; solder bond failure; delamination; metallization discoloration; hot spots; backsheet warping or detaching; cell discoloration; broken interconnect; and burn through backsheet.

Recall from Table X that the severity assignment is based on Rd, Pmdrop, and age. Thus, these attributes were replaced by the severity attribute. The decision tree classifies the degradation severity of a PV module based on its observed defects.

A dataset is full of randomness or uncertainties due to interactions among attributes (some failure modes may lead to others), outliers, etc. The amount of information related to each attribute (failure mode) is associated with the probability of occurrence. The entropy concept, which measures the amount of uncertainty or randomness in a set of data, is used to quantify such information. The dataset is then iteratively partitioned into subsets where all elements in each final subset belong to the same class. The basic strategy is to choose splitting attributes with the highest info gain first; a gain being defined as the difference between how much info is needed to make a correct classification before the split versus how much info is needed after the split.

The inspection data from the 2538 tested modules listed in Table VI are used as the training data to build the decision tree. Using the decision tree, the effect of each defect (failure mode) on the power degradation of PV modules can be computed.

In summary, the characteristics of the algorithm are as followed:

1. Inputs:
   a) Data partition D: Field inspection data on 2560 PV modules;
   b) Attribute_list: Checklist of possible defects (an outcome of “Y” indicates that the defect was observed); and Severity assignment I, II, III, IV, or V (see Table X);
   c) Attribute_selection_method: “Info Gain” splitting rule. This is the rule used to decide, at each node, which attribute to select.
2. Outputs: Decision Tree
3. Outcome: Severity values determination for a set of failure modes.

The decision tree helps partition failure modes into classes. For example, the tree in Appendix C shows that the subset (solder bond, encapsulant discoloration, delamination) belongs to severity class 4 and the subset (backsheet warping, hot spot) belongs to severity class 3. Severities of individual failure modes are assigned by computing the marginal effect of each failure mode.

Let Mi be a failure mode node at a particular position i in the decision tree. Denote Mi (Y) the branch with “Y” outcome and Mj(N) the branch with “N” outcome. Let ni(Y) and nj(N) be the number of associated terminal nodes, and Si(Y) and Sj(N) be the sum of associated severity values. The marginal effect of failure mode M, denoted by ΔM, is obtained as

\[
\Delta M = \frac{\sum_i S_i (Y)}{\sum_i n_i (Y)} - \frac{\sum_j S_j (N)}{\sum_j n_j (N)}.
\]
Then, the severity of individual failure mode is determined from their marginal effect as follows:

If Marginal effect, $\Delta M$ assign severity value of

- $\Delta M > 1$ assign severity value of 5
- $0.75 < \Delta M \leq 1$ assign severity value of 4
- $0.50 < \Delta M \leq 0.75$ assign severity value of 3
- $0.25 < \Delta M \leq 0.50$ assign severity value of 2
- $\Delta M \leq 0.25$ assign severity value of 1

IV. RESULTS AND DISCUSSIONS

The results for occurrence, detection, and severity ratings are shown in Tables XI, XII, and XIII, respectively. Weka 3.6.8 software [61] was used to build the decision tree. The decision tree output for ID3 is shown in Appendix C. The ID3 technique is the basic divide-and-conquer decision tree algorithm that uses information gain as splitting criteria. It was chosen because it does not apply a pruning procedure. While pruning might improve the performance of the tree, it might result in a loss of needed information. For example, a subtree classifying the failure mode “hot spot” could end up being removed to achieve better performance for the overall tree.
Table XIV summarizes the SOD values and computes the RPN. Fig. 5 provides a graphical representation of the defects ranked by their RPN values. It can be observed that solder bond failures and encapsulant discoloration are dominant modes under hot and dry desert climate conditions. Backsheet warping or detaching seems to be significant as well. However, this was mostly observed on one site where the modules were all frameless.

It shall be noted that the diode failure was not considered in the severity rating for two reasons: 1) modules with open-circuited diodes were removed from the severity analysis as the power output could not be obtained; and 2) OC diode failures were not seen as a cause for intrinsic PV degradation.

The solder bond failures discussed in this paper reflect the relative increases of series resistance. According to King et al. [52], [53], gradual increase in the series resistance may result in system power drop on the order of 0.5%/year. Solder bond failure or series resistance increase is typically caused by mechanical influences of daily thermal cycling. Thermal expansion and contraction cause the solder bond to become more brittle and dissociate into large grains of tin and lead [52], [53]. Thus, the mechanism related to this mode is a thermo-mechanical fatigue.

The exposed surface (superstrate) of modules with encapsulant discoloration show light yellow, yellow brown, or dark brown color. The EVA copolymer is the most widely used encapsulant material in crystalline silicon PV modules since the mid-1980s. All the modules evaluated under this study were EVA-based modules. The primary purpose of the encapsulant is to provide structural support, electrical and physical isolation, and high optical transmittance for the solar cell circuits.

There is rich literature on discoloration of EVA, its causes, and mechanisms. One school of thought, led by Pern and Czanderna [44]–[46], advocates that the main cause for discoloration of EVA of field-weathered modules is the reduction of ultraviolet absorber concentration, the increase of gel content, and the formation of acetic acid. Holley et al. [47], Agro et al. [48], Holley and Agro [49], and Klemchuk et al. [50] countered that the fundamental mechanisms leading to yellowing of earlier EVA encapsulants was due to interaction between the additives in the encapsulant formulation, rather than degradation of the polymeric EVA molecules.

Whatever the cause of EVA discoloration, the mechanism involves two primary factors: photothermal degradation reactions (UV exposure) and thermal degradation reactions (heating). This indicates that encapsulant discoloration is expected to prevail in hot dry climates like Phoenix, AZ, USA, with high solar insolation and elevated temperature.

The discoloration of EVA (and other concomitant reactions from the degradation products) reduces the optical transmission, power output, and service life of PV modules. As reported in [18]–[20], the degradation rate of PV modules installed in Phoenix, AZ, USA, varies from 0.6%/year to 2.5%/year; however, it is unknown how much can be attributed to EVA discoloration. Peike et al. [51] points out that the aging process of EVA degradation under the influence of heat, humidity, and UV is still not fully understood.

V. CONCLUSION

We have developed a procedure for prioritizing failure modes using FMEA/FMECA and data mining (decision trees) techniques. Conventionally, the FMEA/FMECA approach would heavily rely on engineering judgment, making values assigned to parameters very subjective. The approach presented in this paper relies on quantitative measures and sizable datasets. It is determined that solder bond failures and encapsulant discoloration are dominant modes under the hot and dry desert climatic condition of Phoenix, Arizona, USA.

APPENDIX A

Using Information Gain as Splitting Rule [62]

1) Let $D$ be the training set containing tuples of class $C_i$, $i = \{1, 2, \ldots, m\}$. The expected info required to classify any arbitrary tuple in $D$ is

$$\text{Info}(D) = - \sum_{i=1}^{m} p_i \log_2 (p_i)$$

a) $p_i$ = probability that the tuple belong to class $C_i$

$$p_i = \frac{|C_i, D|}{|D|} = \frac{\# \text{ of tuples of class } C_i \text{ in } D}{\# \text{ of tuples in } D}$$

b) Info(D) is also known as the Entropy of D.

2) Entropy of attribute $A$ with values $\{a_1, a_2, \ldots, a_v\}$ is

$$\text{Info}_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \text{Info}(D_j)$$

a) $D_j$ is the # of tuples in $D$ with outcome $a_j$ of $A$.

3) Info gained by branching on attribute $A$ is

$$\text{Gain}(A) = \text{Info}(D) - \text{Info}_A(D)$$

4) Splitting attribute = Attribute with highest Gain(A).
APPENDIX B

DECISION TREE ALGORITHM [27]

Input: Training data—D
Output: Decision tree—T

DTBuild algorithm:
1) \( T = \emptyset \).
2) Apply Attribute selection method.
3) \( T = \) Create root node and label with splitting attribute.
4) \( T = \) Add arc to root node for each split predicate and label.
5) For each arc do
   \( D = \) Database created by applying splitting predicate to \( D \).
   If stopping point reached for this path, then
   \( T = \) Create leaf node and label with appropriate class.
   Else
   \( T = \) DTBuild(\( D \)).
   \( T = \) Add \( T \) to arc.

APPENDIX C

VISUALIZATION OF THE DECISION TREE

REFERENCES


[16] Failure mode and effects analysis (FMEA): A guide for continuous improvement for the semiconductor equipment industry, SEMATECH, Austin, TX, USA, Sep. 1992, pp. 14–16.


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