Information-based reliability weighting for failure mode prioritization in photovoltaic (PV) module design

Royce Francis[*a] and Alessandra Colli [b]
[a] The George Washington University, Washington, DC, USA
[b] Brookhaven National Laboratory, Upton, NY, USA

Abstract: Electric utilities and grid operators face major challenges from an accelerated evolution of grids towards an extensive integration of variable renewable energy sources, such as solar photovoltaic (PV). An opportunity exists to incorporate probabilistic risk analysis into the design and operation of photovoltaic systems to deal with rapidly evolving design and configuration techniques. This could potentially achieve greater design reliability through prediction and remediation of failure modes during design and testing project phases, before project implementation or construction. However, because these systems are novel, detailed component level reliability models are difficult to characterize. In this paper, an approach to the prioritization of PV failure modes extending Colli [1], [2] using a Shannon information-weighted reliability approach is demonstrated. We call this information-weight the "surprise index." The surprise index approach facilitates the prioritization of failure modes by weighting the consequence of their failures by the information in the failure generation model. The surprise index may potentially aid in systematic evaluation of deep uncertainties in PV module design, as failure modes that might be overlooked using traditional PRA may be addressed using the information-based approach.

Keywords: FMEA, photovoltaic module design, reliability, Shannon information, surprise index.

1. INTRODUCTION

Electric utilities and grid operators face major challenges from an accelerated evolution towards an extensive integration of variable renewable energy sources onto the electric power grid, such as solar photovoltaic (PV). The solar radiation is a highly fluctuating variable due size, speed and number of cloud formation. The presence of clouds produces instantaneous variations in the power output of PV installations because of the rapid response of solar cells. This effect is translated into unpredictable variations of node voltage and power in electric networks, leading to instabilities especially in low-voltage distribution grids. Additionally, the integration of such a variable energy source into the existing, sometimes weak or overloaded, electric grid requires an adequate risk-informed decision making approach. The ideal grid integration design for PV systems should optimize the mutual benefits between the grid and the PV system itself. Local weather conditions have a relevant impact on the energy production of PV plants, and they must be taken into account when considering the risks that could affect the PV energy output, along with other relevant risks (for example degradation, technical problems, natural disasters, vandalism) leading to outages and impairments. The use of probabilistic studies is expected to help the power plant and grid operators to prepare energy dispatching plans and size the possible amount of required energy storage for PV arrays, as well as to anticipate actions to address technical risks.

An opportunity exists to incorporate probabilistic risk analysis (PRA) into both the design and the operation and maintenance (O&M) activities of photovoltaic systems [1]. PRA is a technique already applied in the production process of the semiconductor industry and has been already demonstrated as relevant for the PV cell manufacturing industry [3]. It could potentially achieve greater design efficiencies through prediction and remediation of failure modes during design and testing project phases, before project implementation or construction, as well as offer the instrument to evaluate risk

[*] Corresponding Author Email: seed@email.gwu.edu; royce.francis@alumni.cmu.edu

impacts on existing PV plants. However, because PV systems are novel, detailed component level reliability models are difficult to characterize, raising the issue of data availability. In our investigation we considered available open sources reliability data from IEEE standards [4] and from a relevant PV publication [5]. Interaction with the PV industry has been limited to discussion of results as confidentiality concerns exist related to sharing proprietary data.

A preliminary important step used to support the definition of initiating events (IE) for the PRA study is the failure mode and effect analysis (FMEA). To perform the FMEA analysis, the PV system will be represented by a simplified model reporting all the components as by design. Figure 1 shows the simplified model used for the FMEA based on Brookhaven National Laboratory's (BNL) Northeast Solar Energy Research Center (NSERC) research array. Our analysis includes all the plant components up to the grid point of connection: PV modules and their support structures, DC subsystem with string combiner, inverter and AC subsystem. From the perspective of the FMEA development, it is important to know which components are present in the system and how they work. While not included here, functional diagrams are often important when more complex elements are considered, such as the inverter or the transformer. To our knowledge, there are no detailed FMEA analyses for PV systems including risk ranking information published to date.

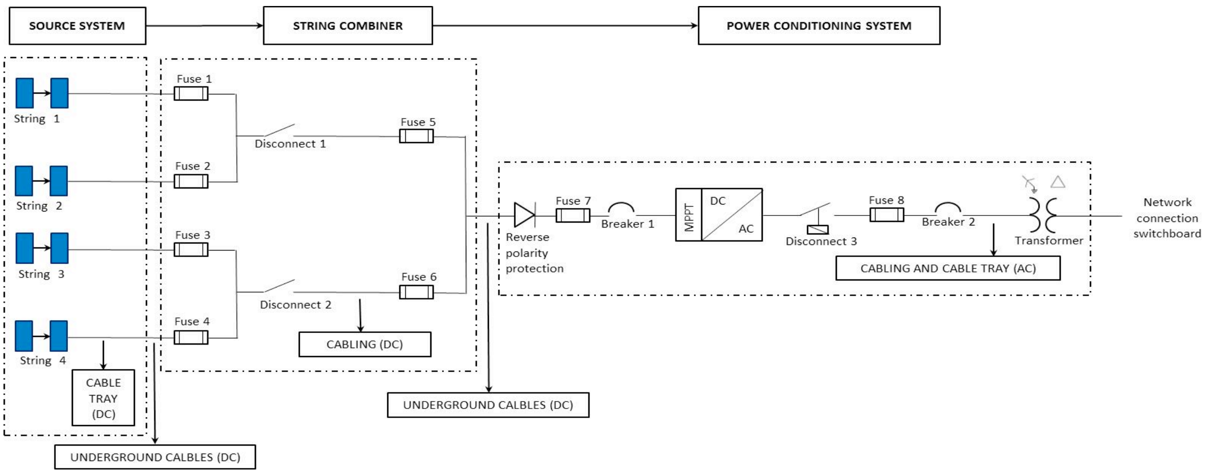

Figure 1. Simplified photovoltaic system model with the principal components of the BNL's NSERC PV array.

Starting from the FMEA analysis developed at BNL, in this paper the approach of using an information-weighted reliability metric is demonstrated. Our entropy inspired approach is distinguished from the current approach to FMEA in that the Shannon information weight gives more importance to extreme events relative to common ones. This is in contrast to traditional subjective expected utility (SEU) based approaches in which events are weighted by their probability, thus giving much higher relative weight to common events. This may be helpful since it is often interesting to understand system performance under very rare, yet highly consequential events. As FMEA is not a simulation-based approach, it provides a useful case study for comparing the information metric with traditional SEU based approaches to systems analysis.

The information-based prioritization of the failure modes is discussed at the level of the FMEA analysis, where it is compared with the ranking normally obtained by the FMEA analysis. Moreover, this paper is distinguished from PRA analysis, presently under development, as our present goal is to discuss the use of the information-weighted metric. The next step in our research is to evaluate the use of the information-weighted approach in PRA by weighting the consequence of cutset failures by the information structured in fault trees and event trees. This may potentially aid in systematic evaluation of deep uncertainties in PV module design and O&M, as failure modes that might be overlooked using traditional PRA may be addressed using the information based approach.

2. FAILURE MODE AND EFFECT ANALYSIS

Failure mode and effects analysis (FMEA) or failure mode and effects criticality analysis (FMECA) is a semi-qualitative approach to systematically evaluating system design, on a component-by-component basis, to identify failure modes and their effects on system function and other system components. The FMEA is a systematic technique for failure analysis and it is performed ahead of the development of fault trees (FT) and event trees (ET) models in the probabilistic risk analysis (PRA).

FMEA is adopted to identify failure modes along with possible causes and effects. The process performed during the FMEA analysis requires to identify the system model, its components, requirements, descriptions, and when useful also functional diagrams. In the selected system, failure modes are investigated at system, component or subcomponent level, according to the desired level of information and data availability.

For each failure mode a severity, occurrence and detection rating is defined and rated according to subjectively defined scales, based on available information and supported by expert opinion and evaluation. The combination of these three ratings is used to define an overall risk rating, which should indicate the importance of each failure mode in affecting the system. However, the rating system involves expert opinion and a level of subjectivity typical of rating systems based on user-defined scales. In future research we will use the FMEA primarily as an investigation to support the PRA model and identify elements and failures to be represented in the PRA in relation to the rest of the system. A fundamental difference between the FMEA and PRA is actually that the former is focusing on individual components, while the latter is modeling the interactions between components in the entire system, thus providing a holistic overview.

The FMEA/FMECA technique is bottom-up, but the FMECA is concerned primarily with characterizing the fragility of components and rank potential failures by the severity of their potential consequences. This ranking might be thought of as a priority ranking by which mitigation investments might be prioritized. Alternatively, the priority ranking might be used as a guide to identification of potential problems in early system development and design.

The basic concept of FMECA can be described as obtaining the criticality of a component by summing the "criticality numbers" of each failure mode relevant to a given component [6]. For example, the criticality number of a single failure mode, obtained generally from the product of the probability of a failure and the consequence of that failure, is:

$$\begin{aligned} C_{m,sc} &= \beta_{sc}\alpha\lambda_p \\ &= \beta_{sc}\alpha\lambda_b\pi_A\pi_E \end{aligned} \tag{1}$$

Where: $C_{m,sc}$ is the criticality number for failure mode *m* given severity classification *sc* for system failure; β_{sc} is the probability the failure effect will be classified as severity *sc* given that failure occurs; α is the failure mode ratio; λ_p is the component failure rate in failures per hour $\lambda_p = \lambda_b\pi_A\pi_E$; λ_b component basic failure rate; π_A is the application factor adjusting for operating stresses; and, π_E is the environmental factor adjusting for environmental stresses. From this, we can obtain the component criticality number given all its *n* failure modes:

$$C_{sc} = \sum_{m=1}^{m=n} C_{m,sc} \tag{2}$$

In contrast to PRA, which identifies the criticality of minimal cutsets of component failures, the FMECA approach is particularly useful for identifying the most critical initiating component failures or failure modes, supporting the definition of IE in the PRA modeling activity. In this vein, Kumamoto and Henley [6] recommend several uses for FMECA that may be useful for PV system design:

1. Identification of critical components for fail-safe design, failure-rate reduction, or damage containment;
2. Identification of components requiring particularly stringent quality control;
3. Formulation of special requirements to be included in specifications for suppliers;
4. Formulation of special procedures, safeguards, protective equipment, monitoring, or warning systems; and,
5. Distribution of project funds across these areas.

In our case study below, we modify the FMECA approach described above by implementing the FMEA using the risk priority number (RPN) [7]. Villacourt describes this approach in relation to the semiconductor industry, a sector that has always been used as a benchmark for the PV industry. The RPN simplifies the computation of the criticality number by requiring only the probability of failure and the severity classification; however, the RPN extends the criticality number approach by incorporating the detection likelihood rating. This is crucial in evaluating PV systems since system downtime directly leads to power supply interruption and financial losses when energy purchase agreements or feed-in tariffs exist. Thus, quick, efficient detection of failures is critical, and the RPN is implemented such that the detection of failures is a conscious goal of the FMEA application. Suppose we have severity classes S_{sc}, detection likelihood classes D_{dc}, and failure likelihood classes L_{fc} for each failure mode m possible failure modes. The RPN is calculated for each failure mode as:

$$RPN_m = S_{sc,m} \cdot D_{dc,m} \cdot L_{fc,m} \tag{3}$$

3. INFORMATION-BASED WEIGHTING—THE “SURPRISE INDEX”

3.1. Subjective Expected Utility

The FMEA and FMECA approaches are clearly based in decision analytic practice. FMEA is implemented as a semi-quantitative, structured approach to prioritizing failure modes for design attention. Traditionally, such difficult decision problems involving uncertain outcomes and/or consequences of events that are unresolved beforehand have been addressed using the subjective expected utility approach. Generally, the subjective expected utility (SEU) approach to any problem can be characterized by an analyst given a mechanism for the event of concern, the potential outcomes of instantiating that event, a value or preference structure over those outcomes, and probability models for both the event’s instantiation and the consequences of the event’s instantiation. Typically, the consequences are conditional on the adoption of one or more alternatives from a set of pre-specified actions. Mathematically, Equation 4 summarizes the SEU approach:

$$U(X) = \sum_i p_i(x_i) \cdot w_i(x_i) \cdot u_i(x_i) \tag{4}$$

Where X is the consequence vector, x_i is the *i-th* consequence of concern, i is the number of specific consequences of interest, $p_i(x_i)$ is the marginal probability distribution for the *i-th* consequence, $w_i(x_i)$ is the decision-maker’s tradeoff weight indicating their relative emphasis on the *i-th* consequence, $u_i(x_i)$ is the marginal utility function for consequence i (i.e., the preference structure for levels of the *i-th* consequence under uncertainty), and $U(X)$ is the overall utility for the action selected given the consequences and their probability of occurrence.

The SEU approach has had a transformative influence on the way decisions are approached in complex systems under uncertainty by providing a framework for tractable decision analysis. Analysts are empowered by a potent mathematical language for aiding decision makers in rigorously exploring and structuring preferences, assumptions, and actions, and the family of techniques that has emerged from this discipline has been immensely productive in the risk analysis and management sciences especially. The main shortcoming of the SEU-based decision making approach is the stringent resource requirements placed upon the decision maker(s) and analyst(s). Consider the following "axioms" suggested by Ralph Keeney [8]: i.) *Generation of Alternatives and Identification of Consequences*—at least two alternatives, and their possible consequences, can be identified; ii.) *Quantification of Judgment*—the relative probabilities of each possible consequence can be quantified; iii.) *Quantification of Preference*—the relative desirability of all possible consequences can be established; and, iv.) *Comparison of Alternatives, Transitivity of Preferences, and Substitution of Consequences*—the alternatives can be structured such that the alternative with the highest possibility of desirable consequences to be preferred over other alternatives.

At first glance, these axioms seem straightforward, and Equation 4 can be translated to the RPN by replacing the probability and weights with the detection and likelihood ratings, the utility with the severity classification, and the overall utility measure with the RPN. Instead of rating alternatives, we are ranking component failures or failure modes. However, upon further reflection, the SEU axioms require complete specification of all potential consequences, specification of all relative probabilities, and they make the rather strong assumption that the alternative with the highest expected value is preferred over the others. Although there are some important differences between FMEA practice and decision analysis, FMEA faces the same challenges. The key difference is that FMEA is typically undertaken in complex systems where all failure modes are known. Where the main goal in decision analysis is to select the optimal "unified" alternative, the main goal in FMEA is to evaluate failure modes to prioritize design effort or hardening investment. Otherwise, the same information requirements and knowledge is assumed. It is very rare in most applications that complete knowledge of consequences is possible. For this reason, several investigators have begun to debate the challenges associated with the practice of various risk-based management techniques applied to complex engineered or critical infrastructure systems [9]-[13]. We touch on this in the next section, and propose an alternative approach.

3.2. The Information-Based Weighting

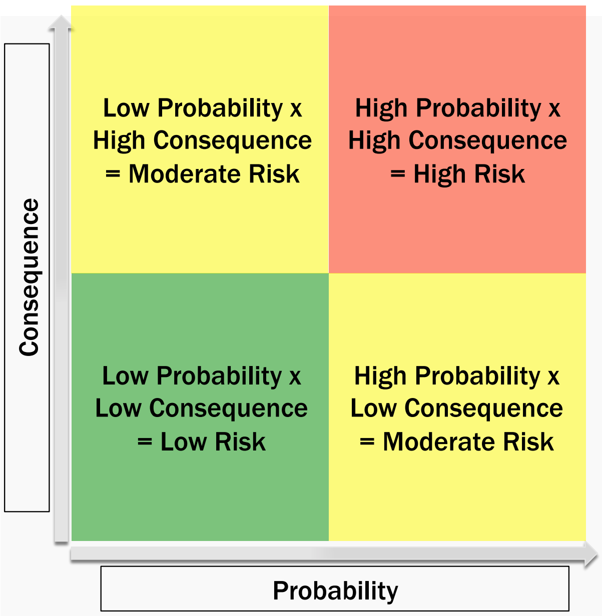

Figure 2. Traditional risk matrix approach based on product of consequence and likelihood.

In research on resilience of complex engineered systems, the authors have proposed elsewhere the use of entropy based metrics to incorporate surprise and disagreement into resilience preparation decisions [9], [14]. These metrics weight adverse events proportionally to the Shannon information in their event generation mechanism (i.e., probability distribution) alternatively to SEU theory in order that the consequences of surprises are weighted more heavily than the consequences of relatively probable outcomes. [Thus, in our article we use entropy and information-based weighting somewhat interchangeably.] Much of the following discussion adapts these from the authors' prior work to apply them to FMEA analyses.

To illustrate the distinction between information weighting and SEU, consider again the familiar additive form of the expected value function used in multi-attribute decision problems shown in Equation 4 where $S_{sc,m}$ is the severity of the consequences from the failure mode of interest, and $L_{fc,m}$ is the likelihood of observing the failure. The contribution to the RPN from the severity is directly proportional to the likelihood of observing the failure. Essentially, the RPN weights the severity of the most likely failure modes much more heavily than the consequences of the most unlikely failure modes. As a rule of thumb for efficiently allocating resources, this is probably reasonable. But it can have the unintended consequence of diverting attention from those potential failure modes that are quite catastrophic and would require sophisticated contingency plans if those modes were instantiated. To increase the weight of such events at the design or planning phase, we propose to develop an RPN based on the information score and severity of the failure mode. The RPN might be modified as follows:

$$SI_m = S_{sc,m} \cdot D_{dc,m} \cdot I_{fc,m} \tag{5}$$

We call this modified RPN the "surprise index," SI_m, where $I_{fc,m}$ is the Shannon information of the probability a given failure mode is instantiated (i.e., $I_{fc,m} = \ln\left(p_{fc,m}\right)$). We reserve further discussion of the surprise index for the following section.

3.3. The "Surprise Index"

As discussed above, FMEA generally relies on estimates of probability that a failure mode presents, the probability that the failure will be detected, and the severity of the occurrence of that failure mode. As discussed above, this yields a risk priority number. Analysts may operationalize the risk priority number by prioritizing system components for design efforts or risk management decisions.

Recent events call the wisdom of this approach into question. First, the risk priority number weights events based on their likelihood. Consequently, the lowest probability events will be given the least weight in the management process. Perhaps this makes some sense when trying to understand how resources should be allocated among potential risk mitigation investments. It may be the case, however, that some catastrophic failure modes are also very rare in occurrence. These failure modes will receive almost no attention based on the risk priority number, although they may be the most costly from a societal perspective if they are to occur [15].

The surprise index is based on the information score of the failure mode probability. By weighting the risk priority by the failure mode's information score, we are increasing the influence of extremely unlikely, yet extremely catastrophic, events in risk management decision contexts. This also decreases the amount of prominence placed on relatively likely events in the decision context. The reason for this approach is derived from the authors' understanding of work by Epstein [16], [17].

In Figure 2, the traditional risk matrix approach is illustrated. The risk matrix reflects the same underlying assumptions as those encoded by the risk priority number—high likelihood, high consequence failures must be addressed first, whereas low likelihood, low consequence failures should be addressed last. The other diagonal leaves these events in the realm of complicated tradeoffs. Often times, as illustrated by the Fukushima Daichi and Deepwater Horizon disasters, the truly catastrophic events lie on the diagonal of complicated tradeoffs. Specifically, we cannot ignore the low probability, high consequence events, because ignoring them leads to unprimed

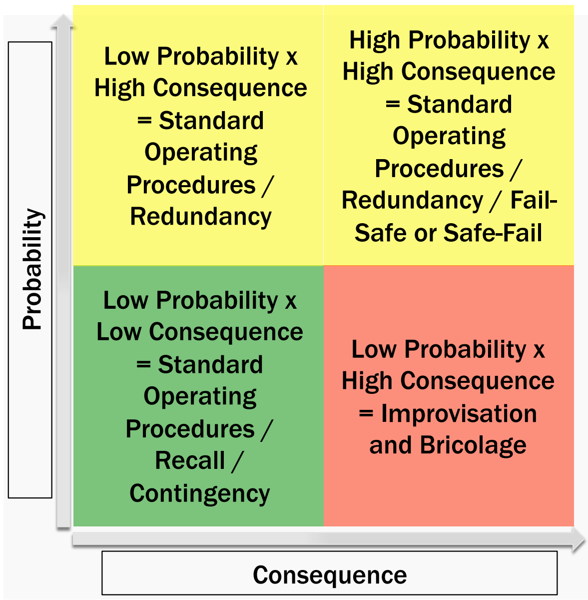

Figure 3. Risk matrix for emergency situations as proposed by Epstein.

bricolage or improvisation if these failures are instantiated. Instead, we should view faults (i.e., failure modes) in the real world according to Figure 3.

Figure 3, adapted from Epstein [17], indicates that the crucial failure modes are those that lie along the diagonal in the lower right hand quadrant. The failure modes in the upper half of Figure 3 should be thought of as “sure things” and should be designed for. The failure modes in the lower left hand corner are also probably not too influential, and subjective expected utility approaches are probably appropriate for making these types of risk management decisions. The failure modes in the lower right hand quadrant are probably not addressable using SEU based approaches since resource allocation is based primarily on the probability of the fault instantiating. This means that consequences of these highly unlikely events are essentially treated as externalities. The costs incurred will, for the most part, be incurred by parties that are external to the system affected. Our hope is that, in developing the surprise index, the FMEA can aid the integrated development of risk response and management plans at the design and development stages of a system.

Table 1. FMEA severity and likelihood classifications used to calculate the RPN. Note that the RPN ranges from 1 to 125 in this application.

	Severity ranking criteria
Rank	**Description**
1	Minor failure/degradation, hardly detected, no influence on the system performance.
2	Failure/degradation will be detected by plant owner/operator and/or will cause slight deterioration of parts or system performance.
3	Failure/degradation will be detected by plant owner/operator, will create dissatisfaction, and/or will cause deterioration of parts or system performance.
4	Failure/degradation will be easily detected by plant owner/operator, will create high dissatisfaction, and/or will cause extended deterioration of parts and system relevant non-functionality/loss of performance.
5	Failure/degradation will result in non-operation of the system or severe loss of performance.
	Occurrence ranking criteria
1	Unlikely - failure rate per unit-hour in the order of E-7
2	Remote probability - failure rate per unit-hour in the order of E-6
3	Occasional probability - failure rate per unit-hour in the order of E-5
4	Moderate probability - failure rate per unit-hour in the order of E-4
5	High probability - failure rate per unit-hour in the order of E-3 and E-2
	Detection ranking criteria
1	Almost certain that the problem will be detected (chance 81-100 %)
2	High probability that the problem will be detected (chance 61-80 %)
3	Moderate probability that the problem will be detected (chance 41-60 %)
4	Low probability that the problem will be detected (chance 21-40 %)
5	None/minimal probability that the problem will be detected (chance 0-20 %)

3.4 Operationalizing the Surprise Index: Redundancy vs. Contingency

So far, we have simply presented the two alternative metrics. The proposed SI requires no additional information from the analyst, and requires little additional effort. How should the SI be operationalized? We suggest using the redundancy vs. contingency dichotomy when comparing the use of the SI against the use of the RPN. The RPN should be used to prioritize redundancy investments. The SI should be used to direct contingency planning.

The RPN conforms to existing decision-analytic practice, based on SEU. An increasing RPN indicates a higher priority for redundancy investments. Because the RPN weights more likely events more highly, it should be used to ensure that relatively likely events are guarded against. The most effective way to reduce the likelihood of relatively likely events is to reduce their probability by altering the basic design or implementing redundancy in the system. The SI is a bit more difficult to operationalize. It is opposite the intuition reflected by the RPN. In the SI’s case, the goal is to proactively identify events to guard against based on the product of their consequence and surprise. Thus, the SI should be used to prioritize the development of contingency plans. The goal here is to counteract overconfidence in the design team concerning the ability to identify important failure modes and design appropriate actions to be taken in the event of a failure.

4. CASE STUDY

In our case study, we modify FMEA data as discussed in Colli [2] to compute the SI for a research solar PV array. The FMEA severity, occurrence and detection classifications are given in Table 1. The scales have been subjectively determined based on the information obtained and the available data. It must be stated that literature shows scales ranking 1-10 for each category (Villacourt, 1992), where more sensitivity is offered. Given the limitations in the data and sometime in the information available, we decided to act on a less sensitive scale, thus limiting the range to 1-5.

The system under consideration, presented in Figure 1, consists of PV modules, racks, cables, string combiners, and power conditioning units. The DC and AC systems on both sides of the inverter unit are considered. Table 2 shows a portion of the FMEA worksheet for the PV modules, in particular considering crystalline silicon PV technologies.

Table 2. FMEA Worksheet excerpt for case study PV modules.

Sub-component	Function or Process	Potential Failure Mode	Potential Effects	Potential Causes	Severity Rating	Occurrence Rating	Detection Rating
Module (active components - cells and contacts)	Electric connections	Loss of electric function	No energy output, safety, fire	Shorts, arcs, open contacts.	5	2	3
		Impairment of electric function	Reduced energy output, hot spot damage	High series resistance, low shunt resistance, aging, shading, soiling.	4	2	4
Junction box/bypass diode	Electric connections	Open contacts	No energy output	Disconnections, improper installation, corrosion	5	1	3
		Short, arc in contacts	No energy output, safety, thermal damages, fire	Damaged insulation, aging, animals, lightning	5	1	2
		Poor contact/ intermittent	Reduced energy output, no energy output, thermal damage	Material defects, oxidation, aging	4	1	4
		Shorted diode (end-to-end)	Reduced energy output, loss of module power	Material defects, aging, thermal stress, mechanical stress, electrical stress, contamination, processing anomaly	4	1	4
		Open diode	Reduced energy output, thermal damages in module, fire, safety	Very high resistance, material defects	3	1	5

Sub-component	Function or Process	Potential Failure Mode	Potential Effects	Potential Causes	Severity Rating	Occurrence Rating	Detection Rating
		Parameter change in diode	Reduced energy output, improper intervention	Material defects, aging, continuous thermal stress	3	1	5
Connectors	Electric connections	Open	No energy output	Damage, disconnection, animals, vandalism, strong wind, pulled cables	5	1	2
		Poor contact/ intermittent	Reduced energy output, no energy output, thermal damage	Corrosion, improper installation, lightning damage	5	1	4
		Short	No energy output, safety, thermal damages, fire	Damages, improper installation, disconnections, animals, vandalism	4	1	5
Encapsulation	Encapsulation	Loss of air tightness	Humidity/ water/ contaminant entrance, increased degradation, reduced energy output, no energy output	Bad lamination, high voltage stress, hot spots, high cell/module temperature, corrosive effects in the module structure, aging, damage from frame distortion, cleaning actions, extreme wind, snow load, vandalism, animals, lightning, earthquake, accidental impacts	2	2	5

Our analysis considers 12 failure modes for the PV modules. However, the entire FMEA analysis for the PV system reports a total of 37 failure modes. This table gives the severity, likelihood, and detection ratings for each failure mode considered, while Table 3 indicates the probabilities considered and the information scores for use in computing the SI. Table 4 finally indicates the comparison between the SIs and RPNs. Notice that while some rankings are similar for both the SI and the RPN, some of the rankings are quite different.

This evaluation highlights a couple of aspects. First, by using fairly broad likelihood categories, differences in failure mode probabilities over several orders of magnitude may be obscured. Because the principal goal is prioritizing, say, redundancy investments or identifying problem areas, this may be acceptable in development stages. But the failure modes that may require special attention for contingency planning may have been overlooked if relying only on the RPN. Note the difference between the two rankings is the information score. Note also that the information scores for the 12 failure modes considered range only over 3 units difference. This means that under the RPN approach, fairly large differences in severity may be masked simply because the severity rating varies only from 1 to 5, whereas the information score amplifies the differences in severity more prominently despite the fact that there is a smaller range of variation over the information score.

Table 3. Information score for PV module failure modes

Sub-component	Funtion/Process	Potential Failure Mode	Considered probability	Information Score
Module (active components - cells and contacts)	Electric connections	Loss of electric function	1.35E-06	14
		Impairment of electric function	1.35E-06	14
Junction box/bypass diode	Electric connections	Open contacts	4.51E-07	15
		Short, arc in contacts	4.51E-07	15
		Poor contact/intermittent	4.51E-07	15
		Shorted diode (end-to-end)	2.26E-07	15
		Open diode	2.26E-07	15
		Parameter change in dioded	2.26E-07	15
Connectors	Electric connections	Open	4.51E-07	15
		Poor contact/intermittent	4.51E-07	15
		Short	4.51E-07	15
Encapsulation	Encapsulation	Loss of air tightness	4.06E-06	12

Table 4. Comparison of surprise index and risk priority number for PV module sub components.

Sub-component	Funtion/Process	Potential Failure Mode	Surprise Index	Risk Priority Number	SI Ranking	RPN Ranking
Module (active components - cells and contacts)	Electric connections	Loss of electric function	203	30	9	2
		Impairment of electric function	216	32	8	1
Junction box/bypass diode	Electric connections	Open contacts	219	15	7	8
		Short, arc in contacts	146	10	10	11
		Poor contact/intermittent	234	16	4	6
		Shorted diode (end-to-end)	245	16	3	6
		Open diode	230	15	5	8
		Parameter change in dioded	230	15	5	8
Connectors	Electric connections	Open	146	10	10	11
		Poor contact/intermittent	292	20	1	3
		Short	292	20	1	3
Encapsulation	Encapsulation	Loss of air tightness	124	20	12	3

The selected units may lead to reduced deliberation over contingency planning for highly unlikely, yet quite severe failures simply because of the qualitative scale selected. One might argue that this could be remedied by simply increasing the sensitivity of the scale used to assess the likelihood scores. We argue, however, that it might be interesting to look at the information score implied by the failure probabilities assessed. This is due to a close similarity between proper scoring in probability elicitation during decision analysis [18]. The objective of proper scoring is to improve the sensitivity and specificity of expert judgments by “rewarding” expert predictions that are both “risky” and “correct.” For us, this is important because the surprise index allows us to adapt the proper scoring approach to FMECA and avoid overconfidence in the resulting rankings.

5. CONCLUSION

In conclusion, we have demonstrated the use of information scoring to construct a surprise index for use within FMEA worksheets. The surprise index is different from the RPN in that it weights the consequences of more surprising events more heavily than those of less surprising events. This is important because ongoing discussion among the risk assessment community has identified the challenges associated with a “risk matrix” based approach to risk management. The challenge is mainly in that the events emphasized by the risk matrix approach are events that should be adequately addressed by standard operating procedures or other routine design considerations, whereas the consequences of the most surprising events are amplified by our lack of preparedness and subsequent improvisation or bricolage when adverse events highlight the inadequacies in contingency or response plans. It is our hope that the information-based surprise index approach will lead to careful consideration of the ways design and development activities address the most catastrophic, yet rare, failure modes in complex systems.

Acknowledgements

RF acknowledges the George Washington University School of Engineering and Applied Science for financial support of the work reported in this paper. The FMEA work has been developed under the BNL’s LDRD project 13-025. Thanks are due to Tassos Golnas (SunEdison) for the useful suggestions while developing the FMEA analysis.

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