

Risk Analysis of Solar Photovoltaic Systems

A. Terry Bahill and Andrea Chaves

Systems and Industrial Engineering, University of Arizona

terry@sie.arizona.edu chaves.andrea@gmail.com

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Abstract. This paper presents a common industry approach to risk analysis, points out problems and pitfalls with it, and suggests ways to ameliorate them. Then it summarizes the main risks associated with incorporating solar photovoltaic (PV) systems into an existing commercial electric power grid. Finally, the paper explains the reason for frequency and severity normalization, presents the results of a sensitivity analysis and shows some possible unintended consequences of incorporating solar PV systems.

1. Problem Statement

Economically viable harvesting of renewable energy is one of the most profound challenges of the 21st century. The most promising renewable energy source in the southwest United States is solar photovoltaic (PV). However, incorporating solar PV systems into an existing electric power grid presents a significant challenge, because of the intermittent and diurnal characteristics of the environment. This, and the uncertainty of dealing with the unknown, means that evolving such a big complex system is risky. Therefore, a risk analysis is a crucial part of the system design. This paper presents a risk analysis of a large-scale grid-tied solar PV system for Tucson Electric Power (TEP), the electricity service provider for the Tucson Arizona metropolitan area. TEP needs to increase their renewable-energy electric-generating capacity in order to comply with the Arizona Corporation Commission's Renewable Energy Standard & Tariff [2006] that requires that by the year 2025, 15% of the utility companies' retail sales must be supplied from renewable-energy sources. Presumably, most of this renewable energy will be satisfied with solar PV systems. In this study, we analyzed the risks and complications associated with incorporating solar PV systems from the perspective of the utility company.

The United States National Renewable Energy Laboratory estimates the annual national theoretical maximum electric energy obtainable from renewable sources as follows (units are terawatts): solar PV 155, concentrated solar power 38, wind 15, geothermal 0.04, water 0.07, and biomass 0.06 [Lopez, 2012]. The ratio of solar PV to wind is 10. In the southwestern United States, the advantage of solar energy is even greater: the ratio of solar PV to wind is 22. This is the reason why this paper focuses on solar PV systems.

2. Definition of Risk

The world is full of uncertainty and this makes risk an inherent component in the design of any system. Risk is an expression of the potential harm or loss associated with an activity executed in an uncertain environment. Three hundred and fifty years ago, Arnauld and Nicole wrote that risk had at least two components, "Fear of some harm ought to be proportional not only to the magnitude of the harm, but also to the probability of the event [Arnauld and Nicole, 1996, p. 274]."

We quantify risk as the product of the frequency of occurrence (or the relative likelihood) of a potential failure event and the severity of consequences for each occurrence of that failure event, as in Eq. (1) [Bahill and Smith, 2009].

$$risk = frequency\ of\ occurrence \times severity\ of\ consequences \quad (1)$$

This definition uses the product combining function, although many other combining functions have been used [Daniels, Werner and Bahill, 2001]. This product combining function of frequency and severity makes intuitive sense. People are familiar with multiplying data; for example, multiplication is used in computing a benefit to cost ratio. (A ratio is just multiplication by the reciprocal.) The product combining function is used in many different realms for example, a person buying a lottery ticket should care about the size of the pot divided by the number of people buying tickets; insurance rates on a Corvette are higher than for a typical automobile, because the frequency of accidents is higher and it is an expensive car, so the monetary loss in an accident is higher: it seems intuitive to multiply the frequency times the monetary loss. The product combining function can also have weights of importance, as shown in Eq. (2).

$$R = F^{w_F} \times S^{w_S} \quad (2)$$

There are also many other approaches for risk analyses. The approach of this paper has been compared to that of Haimes [2009] in Chaves and Bahill [2013].

2.1 Frequency of Occurrence

Of course, a risk analyst would never give a decision maker a single number and say, “This is the most important risk.” The risks must be prioritized and discussed with the decision makers. The decision makers must understand the plan for managing risk. Figure 1 presents a risk plot, using the definition of Eq. (1), that can facilitate these discussions. It is similar to the DoD Risk Reporting Matrix [DoD, 2006], common industry approaches [Bahill and Smith, 2009] and the INCOSE Handbook [Haskins, 2011, Fig. 5-10].

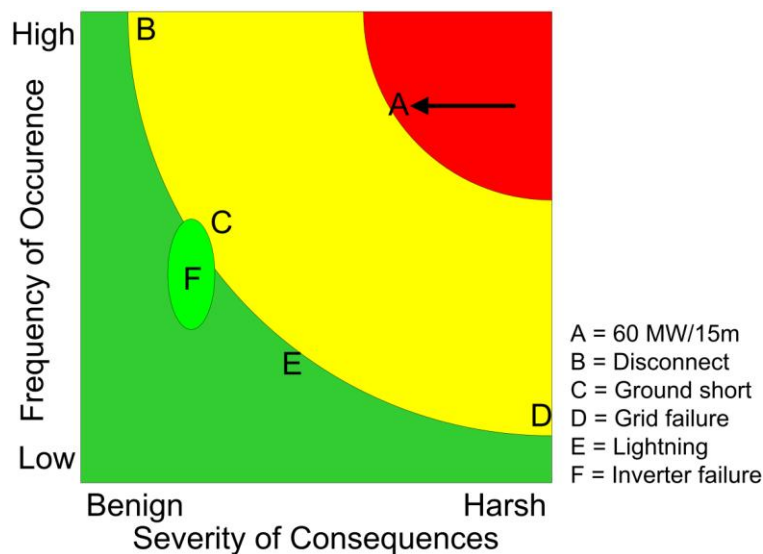


Figure 1. A typical industry risk chart for some potential failure events explained in Table 2. The arrow shows that the biggest risk, risk A, has dropped in severity since the last review, due to risk mitigation action, namely installing backup motor-generator sets. Uncertainty in the frequency and severity numbers can be shown with ellipses,

as is illustrated with risk F. Risk events in the red region are high risk and must be managed. Risks in the yellow region are medium risk and should be managed, if it fits within the budget. Risks in the green region are low risk and need only to be monitored. The curves are iso-risk contours.

However, the terms relative likelihood and frequency of occurrence are not quite synonyms. If we are using historical data for an event, then we use the term frequency of occurrence. Otherwise, if we are guessing the future, then we use the term relative likelihood. The word *relative* emphasizes that it is the relationships between risks that are being illustrated. The word *likelihood* is not used in a probabilistic sense, but rather in its dictionary sense to indicate the events that are likely to happen. Frequency is used instead of probability, because humans evaluate probability poorly: the frequency approach helps humans to partition a set of cases into exclusive subsets, which is a mental operation that is performed quite well [Gigerenzer, 2002; Bahill and Smith, 2009].

The events in Table 2 have uncertainty in both the relative likelihood of occurrence and the severity of consequences. However, sometimes we know *when* an event will occur, so the likelihood that the event will occur is 1.0 and we only need to estimate the severity of the consequence. For example, assume that you have bet on tails in a coin flipping game and you are about to flip the coin. The likelihood that the event will occur is 1.0 and the severity of the consequence is that you will lose half the time. Therefore, the risk of losing your bet in the next moment is 0.5. Most gambling games are of this nature.

On the other hand, sometimes there is no uncertainty in the consequence, only uncertainty that the event will occur in the specified time interval. For example, assume that you are performing an experiment with radium and an alpha particle would ruin your day. In radioactive decay of radium-226 into radon-222, we can estimate the likelihood of the event as 3.7×10^{10} decays/sec-gm. When the event occurs, we know with absolute certainty that the consequence will be an alpha particle; therefore, the severity of this consequence is 1.0. Therefore the risk of getting an alpha particle is 3.7×10^{10} /sec-gm. If you have one gram of radium (about 10^{22} atoms) and the experiment lasts one second, then the risk is 3.7×10^{10} .

We can compare these three types of events and consequences {(1) uncertainty in both the event and the consequences, (2) uncertainty in only the consequences and (3) uncertainty in only the occurrence of the event} as long as the time interval is the same. In a fourth case, the likelihood of the event occurring cannot be estimated, for example when dealing with terrorist attacks on population centers.

2.2 Severity of Consequences

The severity of consequences of a risk event is the perceived damage due to its occurrence. Determining severities is an important step, because it allows us to calculate the risks and rank them in order to identify the most critical events. Severity values can be derived using brainstorming, group decision techniques, expert opinion, historical data, modeling and simulation. However, in this study, severity values are subjective and depend on the perception of the analyst. Fortunately, it is possible to reduce analyst-induced bias by sharing the resulting severity values with system experts and other analysts so that they can validate the severity values.

Analyzing risk severities is a common practice. Insurance companies have developed tables to quantify risk so that different risks can be compared. They assess policyholders' risk in order to estimate the total risk of their insured pool and derive the expected payout costs. Understanding risk severities allows them to quantify the risk and act accordingly. By estimating expected payout costs, insurance companies are able to set the price of insurance

premiums so that they almost always generate a profit. (It is only the rare but catastrophic events that bankrupt them.) Utility companies also routinely analyze risk severities. If the utility company understands the severity of consequences, they will be able to prioritize risk mitigation strategies.

2.2.1 The problem with different ranges. Our risk analysis process makes the range of the frequency data the same as the range of the severity data. This guarantees that the risk does not depend *only* on the frequency or the severity. If the event's frequency and severity ranges were different (e.g. frequency had five orders of magnitude, but severity had only one), then it is possible that the severities would have no impact on determining the highest risks; risk would be dependent only on the frequency data. When the frequency and severity ranges are equal, they will have the same weight in the quantification of risk and bias will be eliminated. For example, if the frequency data go from 10^{-6} to 10^{-1} , then the range has five orders of magnitude and thus the severity data should also have a range with five orders of magnitude (e.g., from 1, very low, to 10^5 , very high).

Table 1: The problem with different ranges for frequency of occurrence and severity of consequences.							
Example 1				Example 2			
Frequency	Severity	Risk equals Frequency times Severity	Risk Rank Order	Frequency	Severity	Risk equals Frequency times Severity	Risk Rank Order
10^{-1}	1	1×10^{-1}	1	10^{-1}	6	6×10^{-1}	1
10^{-2}	2	2×10^{-2}	2	10^{-2}	5	5×10^{-2}	2
10^{-3}	3	3×10^{-3}	3	10^{-3}	4	4×10^{-3}	3
10^{-4}	4	4×10^{-4}	4	10^{-4}	3	3×10^{-4}	4
10^{-5}	5	5×10^{-5}	5	10^{-5}	2	2×10^{-5}	5
10^{-6}	6	6×10^{-6}	6	10^{-6}	1	1×10^{-6}	6

The two examples in the left and right halves of Table 1 have the same frequency of occurrence data, but the severity column in the right half has been turned upside down. The resulting risk columns are different, but the risk rank order columns are identical. Severity has no effect!

More generally, let F_i, S_i and R_i and F_j, S_j and R_j be, respectively, the frequency, severity and risk data for any two rows of Table 1. Clearly $R_i > R_j$ if and only if

$F_i \times S_i > F_j \times S_j$, that is, when $\frac{F_i}{F_j} > \frac{S_j}{S_i}$. For the data of Table 1, the smallest possible value of

$\frac{F_i}{F_j} = 10$, when $F_i > F_j$. The largest possible value of $\frac{S_j}{S_i} = 6$. Since $10 > 6$, the ratio $\frac{F_i}{F_j}$ will

always dominate S, regardless of the order of the rows.

In general, if two functions are multiplied together and they have different ranges, the one with the bigger range has more weight, perhaps secretly. To explicitly weight frequency and severity, weights of importance can be used as exponents, as shown in Eq. (2) and the next section.

2.2.2 Data range is proportional to the weighting exponent. Assume that the frequency (F) data extend from 1 to 100, but the severity (S) data only extend from 1 to 10. We then need a function that will transform the S data so that they have the same range as the F data. First, let's try an exponential function like $f(S) = S^{w_s}$, where the weight of importance for severity $w_s \geq 1$.

If $w_s = 1$ then the S data will extend from 1 to 10.

If $w_s = 2$ then the S data will extend from 1 to 100.

If we want the S data to extend from 1 to α , then we want $f(S) = S^{w_s} = \alpha$. The original maximum value of S was 10 and now we want it to be α . So we want

$$f(10) = 10^{w_s} = \alpha$$

$$w_s \ln 10 = \ln \alpha$$

$$w_s = \frac{\ln \alpha}{\ln 10}$$

$$w_s \approx 0.43 \ln \alpha$$

In contrast, for a different set of F and S data, we might need to compress the data range of S. We could compress data range of S by using a logarithmic transform, $f(S) = \ln S$. This is how the data of column D of Table 3 were transformed into column H. Note that all of these transforms are nonlinear. In summary, for an equation in the form of two exponential functions being multiplied together, the exponents are proportional to the data ranges.

2.2.3 An algorithm for computing severity values. The following algorithm is used for computing values for the severity of consequences [Bahill and Smith, 2009].

1. Assign a relative likelihood of occurrence to each potential failure event.
2. Find the failure event that might have the most severe consequences, call its value S_{worst} .
3. For each other failure event, ask, "How many of these failures would be equally painful to the Worst?" Call this N_i . This can be rephrased as, "Cumulatively, how many of these failures would have an equal impact to the Worst?" This step implies that the severity values are cardinal numbers on a linear scale. However, experience has shown that this technique is also useful with nonlinear scales. Because this step is subjective, numerical values for severity and estimated risk cannot be directly compared from one study to the next.
4. Compute the severity of consequences for each failure event as $S_i = S_{\text{worst}} / N_i$
5. Remove the low-frequency and high-severity failure events and the high-frequency low-severity failure events.
6. Normalize the severity values so that their range equals the range of the likelihood values.
7. Compute the estimated risk using a combining function [Bahill and Smith, 2009].
8. Prioritize the risks to show which are the most important [Botta and Bahill, 2007].

Another technique for step 6 is to restrict the likelihood to values in the range 0 to 1, and then for each row, assign a scoring function [Daniels, Werner and Bahill, 2001] for the severity of consequences. Scoring functions also produce outputs in the range of 0 to 1. Therefore, the range for both likelihood and severity will be between zero and one. On the other hand, if you use the probability of occurrence and the dollar value of the loss in a risk analysis, you are certain to create confusion.

2.2.4 Extreme events. Decision makers should be interested in rare but potentially catastrophic events. Over the last decade, we have witnessed a few such events. In April 2010, a British Petroleum oil well in the Gulf of Mexico exploded and leaked five million barrels of oil. The terrorist attacks on the World Trade Towers September 11, 2001 caused severe physical and emotional damage. Hurricane Katrina of August 2005 was the costliest natural disaster in the history of the United States, probably because so many properties were built below sea level: total property damage was \$81 billion. These three events are mentioned because they indicate that the probability density function for the severity of consequences is not Gaussian. The right tail has far more occurrences than a Gaussian distribution would allow. Insurance companies and politicians have a hard time dealing with such rare events. The left tail of the probability density function for the severity of consequences is also not Gaussian. Microsoft, the Internet, Google and Social Networking are much too successful to fit in a Gaussian distribution

To avoid skewing the statistics with extreme events (as explained in section 3.2), events with low-frequency but high-severity (such as category 5 hurricanes, volcanic eruptions, terrorist attacks and acts of wars) were removed from our numerical computations and have been marked in the risk tables with a “ $0 \times \infty$ ” symbol. These rare but potentially catastrophic events would have been in the lower-right corners of Figures 1 and 2. The upper-left corners of these figures would have contained high-frequency but low-severity events (such as solar PV customers connecting to and disconnecting from the electric power grid, birds and airplanes casting shadows on the solar panels, and solar corona mass ejections).

3. Risk Analysis for Solar Photovoltaic Systems

There are two categories of risk for incorporating solar photovoltaic (PV) systems into a commercial electric power grid: risks related to uncontrollable factors such as weather and risks related to software, hardware and human error. Although many papers on risk do not consider uncontrollable factors or acts of God, because they cannot be predicted, we deem them important given that weather risk is one of the greatest sources of uncertainty for solar power production.

Our project started with a search for risks of using renewable energy resources in an electric power grid [Bahill, 2010 and 2012]. Then to help expand and solidify the risk descriptions, we interviewed TEP managers and directors, academics and project managers of renewable energy projects. The information provided by them was summarized and analyzed to determine the possible risks. After identifying the risks, risk frequencies were calculated or estimated based on the available information. Finally, the risks were prioritized and discussed with the decision makers.

3.1 Description of Identified Risks

We will now describe the risks that are associated with the operating performance of the system. These data come from TEP managers, databases and documents. Our preliminary risk analysis indicated that the greatest risk for an electric power grid with solar PV systems was weather causing the solar panels to receive less sunlight than expected. This is a crucial factor for a self-sustaining PV system, but it is less important for a large-scale system comprised of both renewable (solar) and non-renewable resources. This risk can be mitigated by using energy storage systems or increasing backup generating capacity. In consequent iterations, this risk was modified in order to encompass output energy variability: large changes in solar energy output (± 60 MW) that would correspond to a solar energy output variation of ± 3 sigma

in a 15-minute period. This change in energy output could introduce transients onto the electric power grid and could produce load shedding.

Grid related risks are another risk category. These risks include the grid frequency going out of the ± 0.5 Hz limit, feeder circuits disconnecting and shorts to ground. The first two risks are expected to increase as the penetration of solar PV generation increases, because the solar systems may introduce transients or voltages that are out of phase with the grid. The frequency of occurrence of these failures was obtained from TEP.

Hardware risks include failures due to component malfunction or external events such as lightning or dust. The frequency of failures of PV system hardware such as data acquisition systems, junction boxes, PV modules, and general failures due to lightning strikes was based on a report of TEP's experience with the Springerville Generating Station [Moore et al., 2010]. Severity for hardware failures went from simple system restarts to complex maintenance procedures [Moore et al., 2010]. The severity values and frequencies were estimated based on hardware-specific reliability rates (assuming an expected lifetime of 30 years).

Accidents and human mistakes are the risks with the highest severities given that they can harm people; however, based on TEP's historical record, the occurrence of such events is extremely low and thus their frequencies are almost negligible. Other extreme events such as terrorist attacks on the Western Power Grid and volcanic eruptions were also considered; however, as can be seen in Table 2, the estimated risks for these extreme events were filled with our null symbol, $0 \times \infty$, which means that they were excluded from our numerical calculations. This is expected to reduce the skewing of numerical calculations that would result by including these rare but potentially catastrophic events [Haines, 2009].

This paper contains risk analyses with both PV system-specific risks as well as risks associated with Tucson Electric Power's AC electric power distribution grid. The data for the distribution grid risks were given to us by Tom Hansen, vice president of TEP in 2008. They were then normalized with the frequency of occurrence and the severity having ranges of about six orders of magnitude. Since the range for frequency and severity should be about the same [Bahill and Smith, 2009] numerical values were assigned to the severities as follows

Severity Description	Numerical Value
Extreme	1,000,000
Very High	100,000
High	10,000
Medium	1,000
Low	100
Very Low	10
Minuscule	1

Must frequency and severity have the same range? Like most systems engineering questions, the best answer is, "It depends." If your customer does not want you to normalize frequency and severity, then don't do it.

It is important to note that neither frequency of occurrence nor severity of consequences should have units of measure. If they had units, then the rank order of the risks would depend on those units. In other words, risk is a unit less measure.

Table 2 summarizes the operating performance risks for solar PV systems and TEP's distribution grid. These risks are related to the functionality of the system. Failure events in the performance category typically result in system downtime and will affect the quality and reliability of system operations.

Table 2 has six columns describing a *Potential Failure Event*, the *Consequences* of that failure event, the *Frequency of Occurrence* (or *relative likelihood*) of the event in the relevant environment, the *Severity of Consequences* for each failure event, the *Estimated Risk* and perhaps a short *Identification Tag*. The *Frequency of Occurrence* was based on historical data and expert opinion. *Estimated Risk* was defined as the product of the *Frequency of Occurrence* and *Severity of Consequences*.

Table 2: Operating performance risks for incorporating solar PV systems into an existing commercial electric power grid. These data are also plotted in figure 2.

Potential failure event	Consequences	Frequency of Occurrence in the TEP control area (events per year)	Severity of Consequences	Estimated Risk, defined as frequency times severity	Identification Tag
Physical or cyber terrorist attack on the Western Power Grid	Load shedding, brownouts, blackouts, transportation gridlocks, hardware damage, chaos and cessation of commerce	0	10^6	$0 \times \infty$	
Nearby volcanic eruption	Clouds of ash and smoke cover the sky blocking sunlight to solar panels and reducing solar PV power output	0	10^5	$0 \times \infty$	
Solar panel output drops 60 MW in 15 minutes due to clouds, thunderstorms, etc.	Power production plummets tripping breakers and leaving customers without electric power. Voltage on the grid drops and frequency of coal-fired generators might change: transients are harmful to big electric generators.	94.6 based on $\pm 3\sigma$ points for data collected at 15-minute intervals for a year	200	18,920	A
Feeder circuit disconnects from the substation	Feeder circuit voltage becomes out of phase with the electric power grid.	330	1*	330	B
Short to ground on the distribution grid	Equipment is damaged, particularly transformers and capacitor banks.	24	10	240	C
Western Power Grid fails (due to other than terrorist activities)	The western United States would be without electric power	0.03	10^4	300	D
Lightning strikes the system	Components are damaged and electric generating capacity is reduced	0.39	100	39	E
Grid voltage exceeds $\pm 5\%$ limits	Customer service deteriorates. Solar PV systems trip off-line.	24*	1*	24	G
Transient local outages	Outages on transmission or distribution lines trigger shutdown of PV systems.	24	1	24	H
Solar panels accumulate dust or other particles	Efficiency of solar panels decreases and power output drops	2	10	20	I
Junction box fails	Loss of generated power output	0.27	50	13	J
Data acquisition system fails	Research and monitoring data cannot be read from the solar farm	0.14	50	7	K

PV modules fail	Loss of power production capacity	0.38	10	3.8	L
Grid frequency goes out of its ± 0.5 Hz limits	Small PV systems and big generators trip off-line, perhaps overloading transmission lines. TEP might be fined.	0.2	50*	10	M
Software fails	Software failures are ubiquitous and insidious. They can cause a myriad of problems.	2	50	100	N
Electric storage system fails	Stored energy is lost. Infrastructure might be damaged.	0.7	20*	1.4	O

*Values marked with an asterisk will increase as the number of solar PV systems increases. *Estimates* are represented with integers or decimals with only one significant figure: *calculated values* are represented with decimal numbers with two or more significant figures.

The range of magnitudes for Frequency of Occurrence and Severity of Consequences must be the same. In Table 2, the frequency of occurrence covers four orders of magnitude (from $10^{-1.5}$ to $10^{2.5}$) and the severity of consequences also covers four orders of magnitude (from 10^0 to 10^4). Low-frequency high-severity risks (such as terrorist attacks and volcanic eruptions) and high-frequency low-severity risks (such as customers connecting to and disconnecting from the grid) are not included in these calculations.

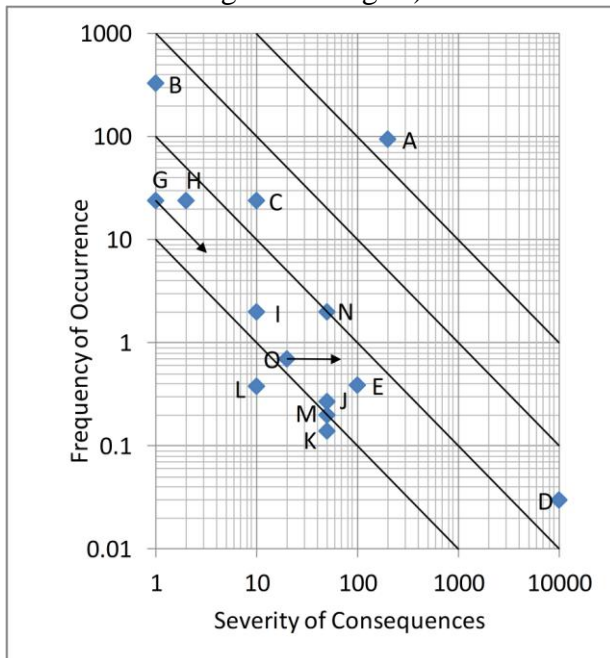


Figure 2. A log-log risk chart for the data of Table 2. The arrows show that in the next few years risk G is expected to move down and to the right and risk O is expected to move to the right. The straight lines are iso-risk contours.

The most interesting points plotted in Figure 2 are (1) risk A, that the “solar panel output fluctuates by more than 60 MW in a 15-minute interval,” is the riskiest, (2) risk D, that the “Western Power Grid fails,” is in the rare but severe corner and (3) risk B, that a “feeder circuit disconnects from its substation,” is in the common but trifling corner. Therefore, our overall advice is to (1) apply risk mitigation to risk A, (2) keep an eye on risk D and (3) ameliorate risk B.

Although Risk B is not high risk, inexpensive mitigation would improve the overall reliability of the system. Now, please compare Figures 1 and 2. They agree except that risk F, “failure of DC to AC inverters,” has been transferred from Table 2 to a table for risks from the consumers’ point of view.

The most common risk graphic used in industry looks like Figure 1: but the qualitative descriptions seem logarithmic. For example in response to the question, “How often will this failure occur?” the recommended answers are Almost Never = 2 points, Occasionally = 4 points, Sometimes = 6 points, Frequently = 8 points and Almost Always = 10 points.

3.2 Normalizing Frequency and Severity

Let us now go back to the principle of normalizing frequency and severity so that they have the same range. In Table 3, columns A to G and rows 7 to 16 are the biggest risks from Table 2. Now we introduce a new technique for computing severity. The severities in column H were assigned using a linear scale of 1 to 10 [DoD, 2006; Bahill and Smith, 2009; Haskins, 2011, Fig. 5-10]. This will be called the linear technique. The severities of column H were then multiplied by the frequencies of column C to estimate the risk given in column I. These estimated risks were used to compute the risk rank orders of column J.

Table 3: The biggest operating performance risks from Table 2, with the addition of columns H, I and J.

Row	A	B	C	D	E	F	G	H	I	J
	Potential failure event	Consequences	Frequency of Occurrence, (events per year)	Severity of Consequences, range 1 to 10 ⁶	Estimated Risk	Risk rank order	Identification Tag	Severity, range of 1 to 10	Estimated Risk	Risk rank order
4				Log-log technique				Linear technique		
5	Terrorist attack	Blackouts, chaos	0.01	10 ⁶	10 ⁴	2		10	0.10	11
6	Volcanic eruption	Ash blocks sunlight	0.01	10 ⁵	10 ³	3		9	0.09	12
7	Solar energy drops 60 MW in 15 minutes	Power production plummets	94.6	200	18,920	1	A	6	568	2
8	Feeder circuit disconnects from substation	Voltage gets out of phase with grid	330	1	330	4	B	3	990	1
9	Short to ground	Equipment is damaged	24	10	240	6	C	5	120	3
10	Western Power Grid fails	Western United States is without electric power	0.03	10 ⁴	300	5	D	8	0.2	10
11	Lightning strikes system	Equipment is damaged	0.39	100	39	7	E	5	2.0	7
12	Grid voltage exceeds limits	Service deteriorates. PV systems trip off-line.	24	1	24	8	G	3	72	4
13	Transient local outages	PV systems shutdown	24	1	24	9	H	3	72	5
14	Dust accumulation	Generated power drops	2	10	20	10	I	5	10	6
15	Junction box fails	Generated power drops	0.27	50	14	11	J	4	1.1	8
16	Data acquisition system fails	Data cannot be read from the solar farm	0.14	50	7	12	K	4	0.6	9

Next, we used Excel to calculate the correlation coefficients (r) between frequency, severity and estimated risk using our old log-log technique and this new linear technique. The results are shown in Table 4.

The fourth row of Table 4 shows that for the linear technique the correlation coefficient, r , of estimated risk (column I of Table 3) and frequency (column C of Table 3) is 0.964: this is a large value, meaning that frequency is dominating the estimated risk calculations. In contrast, estimated risk (column I of Table 3) versus severity (column H of Table 3) has an r of only -0.21, which means that severity is having little effect on the estimated risk. This difference in influence is caused by the mismatch between the range of the frequency data (four orders of magnitude) and the range of the severity data (one order of magnitude).

Table 4: Correlation coefficients between frequency, severity and risk.

Row	Technique	Data set	Range, orders of magnitude	Correlation coefficient, r , for estimated risk (col I or E) versus frequency (col C)	Correlation coefficient, r , for estimated risk (col I or E) versus severity (col H or D)
3					
4	linear	10 failure events; columns C, H, I and J; rows 7 to 16	frequency= 4 severity = 1	(C, I) 0.964	(H, I) -0.21
5		11 failure events; columns C, H, I and J; rows 6 to 16	frequency= 4.5 severity = 1	(C, I) 0.965	(H, I) -0.27
6		12 failure events; columns C, H, I and J; rows 5 to 16	frequency = 4.5 severity = 1	(C, I) 0.965	(H, I) -0.30
7					
8	log-log	10 failure events; columns C to F; rows 7 to 16	frequency = 4 severity = 4	(C, E) 0.17	(D, E) -0.08
9		11 failure events; columns C to F; rows 6 to 16	frequency = 4.5 severity = 5	(C, E) 0.17	(D, E) -0.06
10		12 failure events; columns C to F; rows 5 to 16	frequency = 4.5 severity = 6	(C, E) 0.10	(D, E) 0.39

Next, frequency of occurrence for Terrorist Attacks and Volcanic Eruptions were assigned non-zero values and put into rows 5 and 6 of Table 3 in order to change the frequency and severity ranges. Column C now has a range of 4.5 orders of magnitude and column H still has a range of one. Row 6 shows that the correlation coefficient of the linear technique estimated risk (column I) versus frequency (column C) is now 0.965. An r of 0.965 is a large value indicating that frequency is totally dominating the calculation of risk.

Data from the log-log technique in row 8 show that the correlation coefficient of estimated risk (column E) versus frequency (column C) is 0.17: this is a small value, meaning that frequency is not dominating the estimated risk calculations. Furthermore, estimated risk (column E) versus severity (column D) has an r of only -0.08, which means that severity is having little effect on the estimated risk. These low correlation values, indicate that the estimated risk is a combination of frequency and severity and neither one dominates. We note that both frequency and severity have a range of four.

When frequencies for Terrorist Attacks and Volcanic Eruptions were added in rows 5 and 6 of Table 3, the range of the frequency data (column C) became 4.5 orders of magnitude and the range of the severity data (column D) became six. The correlation coefficient of estimated risk

(column E) and frequency (column C) decreased from 0.17 to 0.10. The correlation coefficient of estimated risk (column E) and severity (column D) increased from -0.08 to 0.39. The range for the severity data has become larger than the range for the frequency data and severity is now becoming more important than frequency.

Excel's CORREL and PEARSON functions are the same. They return a value for r that indicates the goodness of a linear fit between two data sets. But what does r mean if the data sets are not *linearly* related? To answer this question, we fit exponential, linear, logarithmic, second-order polynomial and power law trend lines to the data sets. Different functions fit different data sets better or worse. For example, Table 4, row 4, column 5 shows $r = 0.964$. The functions CORREL, PEARSON, RSQ and the linear trend line from the scatter chart all have the exact same number (to fourteen decimal places). However, the power function trend line gave $r = 0.995$. Differences like these were common. We used all five of the Excel functions to fit every combination of data sets that we were considering. Functions other than the linear function were not useful: using them did not change the conclusions of this paper. Investigating these other functions merely ensured that we were not trying to fit (for example) a sinusoid with a linear regression line.

Finally, the most important risks are different for the two severity techniques. The log-log technique (columns A to G) indicates that the most serious risks are (in order of importance): (1) Solar energy drops 60 MW in 15 minutes, (2) Terrorist attack, (3) Volcanic eruption and (4) Feeder circuit disconnecting from the substation. Whereas, the linear technique (columns A to C and H to J) indicates that the most serious risks are (in order of importance): (1) Feeder circuit disconnecting from the substation, (2) Solar energy output drops 60 MW in 15 minutes, (3) Short to ground and (4) Grid voltage exceeds its $\pm 5\%$ limits. To quantify this mismatch we note that the correlation coefficient between the log-log estimated risk (column E) and the linear estimated risk (column I) is only 0.3. It seems that it is time to discuss these results with the customer.

3.3. The Biggest Risk

Weather is the most uncontrollable factor for a solar PV system. When clouds appear between the solar panels and the sun, there is an immediate and significant drop in power output. What would happen if there were a total blockage of the sun (due to total cloud coverage) when the system load peaked? There are two important factors to consider: first, in the summer, the maximum electric demand typically occurs in the late afternoon and second, during these late afternoon hours, electric generating capacity of the solar PV panels has fallen.

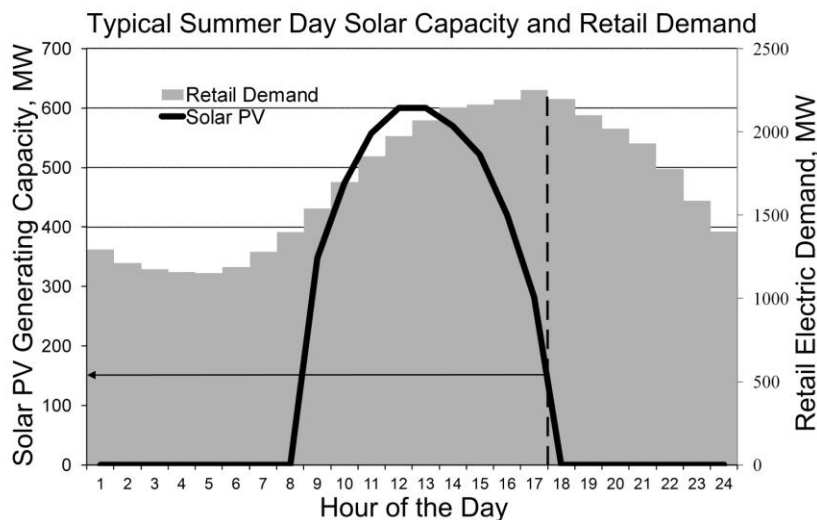


Figure 3. Solar PV generating capacity and retail electric power demand projected for a typical summer day in Tucson in 2025. The solar PV generating capacity peaks at 600 MW around noon and drops to 25% of its peak capacity by 5:30 PM (the dashed vertical line).

In order to meet the Arizona Corporation Commission, *Renewable Energy Standard & Tariff* [2006], TEP predicts that by 2025 its system will have about 600 MW of utility-scale renewable-generating capacity. Assuming that this is all fixed solar PV systems, this would produce 600 MW at noon and 150 MW at 5 PM.

Condition	Peak retail load obligation, MW	Planning reserve, MW	Necessary condition	Conventional generating capacity, MW	Solar generating capacity, MW	Equation satisfied?
5 PM, normal	2250	300	\leq	2400	150	Yes
5 PM, total cloud coverage	2250	0	\leq	2400	0	Yes
Noon, normal	2000	300	\leq	2400	600	Yes
Noon, total cloud coverage	2000	0	\leq	2400	0	Yes

Table 5 shows that TEP can meet its load obligations under the worst weather conditions (total cloud coverage) during peak summer loads (5 PM). It shows that the peak load in the summer at 5 PM plus the planning reserve must be less than or equal to the conventional generating capacity plus the solar generating capacity. The other rows show that the load obligations can be met at other significant conditions.

3.4. Quality and Uncertainty of the Data

Data collection for this paper started with electric distribution grid risks given to us by Tom Hansen, vice president of TEP in 2008. These data were supplemented with data from the Springerville plant that TEP has been operating since 2000 [Moore, Post, Hansen and Mysak, 2010]. These databases were further expanded by Excel files given to us by Mike Sheenan [2009]. Many of these were annual databases with datapoints every 15 minutes. This was the basis of the frequency of occurrence data for the operating performance risks of Table 2. These data are reliable, with the exception of terrorist attacks on the Western Power Grid and volcanic eruptions, which are of low quality and high uncertainty.

Another facet of our data collection concerned renewable-energy electric-generating systems in general. The professor, three dozen students and eight senior systems engineering advisors scoured the Internet in the fall of 2009 searching for risks that might be associated with renewable-energy electric-generating methodologies [Bahill, 2010 and 2012]. This gave us another risk database. This one was less concerned with the electric distribution grid and more concerned with individual hardware and software methodologies. This database was less reliable than the other.

Once we created a risk database, the resulting risks were discussed with managers, domain experts, systems experts, academics, and other people that could help verify, quantify, add or eliminate risks from the database. Next, we used sensitivity analyses and scenarios of potential future failure events to facilitate the completeness of the database. Finally, the risks were prioritized and discussed with the decision makers. The risk databases summarized in this paper required multiple iterations often in monthly meetings. As time went by and as risk management strategies were implemented, risk severities and frequencies were revised so that the database would remain a true representation of the existing system.

In summary, the frequencies of occurrence that were derived from TEP databases are of high quality and low uncertainty. Frequencies derived by Internet searches were only included

if two or more independent sources were in agreement. Even then it only yielded frequencies of moderate quality and uncertainty. Finally, the severities of occurrence were based on human judgment. Each person has his own values and biases, so these data must be considered of lower quality and higher uncertainty.

3.5. Sensitivity Analyses

You should perform a sensitivity analysis anytime you create a model, write a set of requirements, design a system, make a decision, do a tradeoff study, originate a risk analysis, or want to discover the cost drivers [Hsu, Bahill and Stark, 1976; Karnavas, Sanchez and Bahill, 1993; Smith et al. 2008]. A sensitivity analysis of risk analyses is simple and it can be done in general terms. In this risk analysis case study, our problem statement is: In a risk analysis, what parameters can change the rank order of the most important risks?

To be general, we will use the definition of Eq. (2) where the frequency and severity have weights of importance as exponents. Risk (R) equals Frequency of occurrence (F) raised to the power of weight of importance of frequency (w_F) times Severity of consequences (S) raised to the power of weight of importance of severity (w_S), like this, $R = F^{w_F} \times S^{w_S}$. In economics, this functional form is called the Cobb-Douglas [1928] production function. Our first step is to derive the partial derivatives.

$$\frac{\partial R}{\partial F} = S^{w_S} w_F F^{w_F-1} = S^{w_S} F^{w_F} \frac{w_F}{F} = R \frac{w_F}{F}$$

$$\frac{\partial R}{\partial S} = w_S S^{w_S-1} F^{w_F} = F^{w_F} S^{w_S} \frac{w_S}{S} = R \frac{w_S}{S}$$

$$\frac{\partial R}{\partial w_F} = S^{w_S} F^{w_F} \ln F = R \ln F$$

$$\frac{\partial R}{\partial w_S} = F^{w_F} S^{w_S} \ln S = R \ln S$$

Now the partial derivatives will be multiplied by the normal values of the parameters to get the semirelative sensitivity functions [Smith et al. 2008]. In the following equations, the $|_{NOP}$ symbol means evaluated at the Normal Operating Point.

$$\tilde{S}_F^R = \frac{\partial R}{\partial F} F_0 \Big|_{NOP} = R_0 w_{F_0}$$

$$\tilde{S}_S^R = \frac{\partial R}{\partial S} S_0 \Big|_{NOP} = R_0 w_{S_0}$$

$$\tilde{S}_{w_F}^R = \frac{\partial R}{\partial w_F} w_{F_0} \Big|_{NOP} = R_0 w_{F_0} \ln F$$

$$\tilde{S}_{w_S}^R = \frac{\partial R}{\partial w_S} w_{S_0} \Big|_{NOP} = R_0 w_{S_0} \ln S$$

Note that $\tilde{S}_{w_S}^R$ is the semirelative sensitivity function of R with respect to w_S , whereas S (without the tilde) is the severity of the consequences. Let F, S, R, w_F and $w_S \geq 1$. Which

data set (F or S) is most important? If $w_{F_0} > w_{S_0}$ then $\tilde{S}_F^R > \tilde{S}_S^R$. This is simply a statement that the data set with the bigger weight (bigger data range) is more important.

Next, which individual failure events are the most important? If the weights of importance are the same, then the failure events with the largest sensitivity values are the greatest risks, because the sensitivities are determined by the values for R_0 , as shown in the above equations. This means that we should spend extra time and effort estimating the frequency and severity of the highest ranked risks, which seems eminently sensible [Smith et al., 2008]. Of the failure events in Table 2 for which data could be collected, the most important are “Solar energy output drops 60 MW in 15 minutes” and “Feeder circuit disconnects from substation.” TEP already has good data for the former (a database with a data set every 15 minutes for a year). Therefore, they should spend more time and resources getting better data for the Feeder circuit failure event.

3.6. Unintended Consequences

New systems, strategies, laws or controls often have negative or positive unintended consequences. Therefore, it is important that, early in the system lifecycle, the designers try to predict what these unintended consequences might be. The systems engineer is responsible for the big picture of system development. Hence, the system engineer must search for unintended consequences of the system under design [Bahill, 2012].

Connecting a solar PV system to an electric power grid could cause problems for the grid. For example, presume that an illumination-controlled building is in the state of Selling AC Electricity [Bahill, 2010], when clouds suddenly cover the sun. The voltage generated by the solar panels will drop as will the illumination in the building. Sensors will sense this drop in illumination and will command the lights to produce more illuminance. The lights will draw more power from the source. This will produce a bigger voltage drop across the source internal impedance, which will further drop the operating voltage. This is a *positive* feedback loop that could cause the electric power grid to become unstable.

A second problem with clouds blocking the sun is that the PV system would soon deplete its small local energy store and would switch to the Buying AC Electricity state [Bahill, 2010]. This would increase the operating voltage. This is a negative feedback loop, but it contains a significant *time delay*. Time delays in feedback loops make systems susceptible to instabilities.

A third problem with clouds blocking the sun is that if the electric power grid voltage drops below its $\pm 5\%$ limits, then most of the local solar PV systems will isolate themselves from the grid. This will further decrease the grid voltage. This is a *positive* feedback loop. Positive feedback loops can cause system instability.

Therefore, to prevent possible system instability, utility companies should create one-second resolution simulations of the interactions between clouds, the electric power grid and customer solar PV systems [Bahill, 2010]. TEP already has ten-second resolution solar generation data and one-minute resolution customer load data. So it seems that they have the technology to collect one-second resolution data for these stability simulations.

Deploying solar PV systems has another interesting possible unintended consequence. Solar panels do two things: they absorb solar energy and transform it into electricity, and they also reflect solar energy back into the atmosphere. Both of these actions reduce the solar energy that hits the ground and is absorbed by the Earth. Therefore, solar panels have the unintended consequence of reducing the amount of solar energy absorbed by the Earth and therefore contribute to *global cooling*.

Solar PV systems are in positive feedback control loops and negative feedback control loops with large time delays. Both of these could cause instability on the electric power grid.

Bahill [2012] has listed other unintended consequences of installing solar panels into a commercial electric power grid.

Summary

This paper suggests two important points. First, the frequency and severity data ranges must be equal in order to give equal weight to frequency and severity data sets [Bahill and Smith, 2009]. Second, beware of problems produced by extreme events. To avoid skewing the statistics, low-frequency but high-severity events (such as volcanic eruptions and terrorist attacks) and high-frequency but low-severity events (such as solar PV customers connecting to the electric power grid) should be removed from the numerical computations.

The risk of clouds blocking the sun and introducing power production output variability is the biggest risk in this analysis. Additionally, as solar PV becomes a larger component of an electric company's energy portfolio, it is important to revise the back-up capacity policies and consider alternative storage methods in order to reduce the risk of reduced power production output during periods with high demand.

After conducting a what-if analysis, even under the worst-case scenario of total sunlight blockage and demand peaking, with appropriate planning, it is possible to develop strategies that will prevent brownouts and power shortages. Based on how much solar PV energy TEP has, it may be important to develop and implement state-of-the-art, one-minute-resolution weather forecasting, which combined with their current demand forecasting methods, will help them identify risky scenarios and act appropriately. Utility companies should also create one-second-resolution simulations of the interactions between customer PV systems and the electric power grid in order to investigate potential instabilities.

In a risk assessment, the risk analyst could spend more time and money getting more and better data, but that would not make the risk recommendations more precise. Haimés and Chittester [2005] drew an analogy to the Heisenberg Uncertainty Principle, which states that a person cannot simultaneously measure the position and the velocity of a particle with high precision. Then they expanded this analogy with, "recall Einstein's statement: 'So far as the theorems of mathematics are about reality, they are not certain; so far as they are certain, they are not about reality.' Adapting Einstein's metaphor to risk assessment and management translates into: 'To the extent risk assessment is precise, it is not real; to the extent risk assessment is real, it is not precise.'"

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Biographies



Andrea Chaves earned a B. S. in Industrial Engineering in 2008, an M. S. in Management with emphasis in Finance in 2009, and an M. S. in Industrial Engineering in 2010, all from the University of Arizona in Tucson. In 2008, she received the Wayne Wymore award for excellence in Systems and Industrial Engineering and was named outstanding senior for her graduating class. During her graduate studies at the University of Arizona, she worked as a teaching and research assistant in areas such as production planning, forecasting and optimization; probability and statistics; and systems engineering. In her spare time, she enjoys triathlon, engaging in races that include swimming, biking and

running. She currently works as a Technology Consultant at Deloitte Consulting LLP in Denver, CO. She may be reached at chaves.andrea@gmail.com



Terry Bahill is an Emeritus Professor of Systems Engineering and of Biomedical Engineering at the University of Arizona in Tucson. He received his Ph.D. in electrical engineering and computer science from the University of California, Berkeley. Bahill has worked with dozens of high-tech companies presenting seminars on Systems Engineering, working on system development teams and helping them to describe their Systems Engineering processes. He holds a U.S. patent for the Bat Chooser, a system that computes the Ideal Bat Weight for individual baseball and softball batters. He received the Sandia National Laboratories Gold President's Quality Award. He is a Fellow of the Institute of Electrical and Electronics Engineers (IEEE), of Raytheon Missile Systems, of the International Council on Systems Engineering (INCOSE) and of the American Association

for the Advancement of Science (AAAS). He is the Founding Chair Emeritus of the INCOSE Fellows Selection Committee. His picture is in the Baseball Hall of Fame's exhibition "Baseball as America." You can view this picture at <http://www.sie.arizona.edu/syseng/>.