Probabilistic Assessment of Availability from System Performance Data

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Jan B. Smith • Applied Reliability, Inc. • Baton Rouge
W. Bryan Smith • Applied Reliability, Inc. • Baton Rouge

NOTE: This paper was published in 2002 before the reliability analysis application was developed. The terminology "Capacity and Availability Assessment Process" and the CAAP trademark have since been abandoned. "PMF series" for probability mass function series better describes this technology that works not only for availability, but equally well for reliability. The unconditional reliability distributions discussed briefly in this paper are a special case of the PMF series reliability application more recently developed.

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Key Words: Availability assessment, Repairable system, System availability, Probability distribution, Decision making, Data permutations

SUMMARY & CONCLUSIONS

The traditional means of availability assessment as a probability distribution are not widely used on manufacturing plants and facilities producing goods and services, in part because of a lack of accurate data. An alternative method was developed for such plants using permutations of readily available system data. The method may be found to be of value for other repairable systems.

This paper presents a method of calculating system availability and reliability probability distributions using permutations of inseparable system failure and restore data sets. Such data sets usually come from system history, as reflected in a performance measurement such as daily production. A direct relationship is maintained between any failure and its consequence; that is, time-between-failure (TBF) and time-to-restore (TTR) are an inseparable set. Furthermore, TTR need not be single-valued but may take the form of another data set to accommodate system degradation and dependent failures. A time line can be developed (in a computer spreadsheet or as a mathematical concept) on which the data sets are placed. A time window (W) equal to a time interval of interest (mission time) is advanced along the time line returning an availability discrete random variable value at each position. In general, there are {H(N!) – (W-1)} mission times of length W in history of length H containing N independent failures. For example, 12 failures in two years provide about 350 billion mission time values. From these values, or a sample of the values, availability frequency distributions are formed for all mission times of interest. When the mission times of interest are continuous, as is necessary for certain business decisions, the distributions form a 3-dimensional probability surface. From this data, both the probability and expected magnitude of performance below or above any value is calculated for use in making a large range of technical and business decisions.

The avoidance of traditional assumptions, the accuracy of calculation and the abundant supply of accounting quality data provide an opportunity to make risk-based decisions that are not otherwise possible. For example, in manufacturing the issues which can now be optimized with known probability and consequence include production budgeting, product inventory control, profit projections, material requirements planning, production scheduling and measuring the statistical significance of any change in production output. This capacity and availability assessment process (CAAP™) is patented in the United States for systems producing products and services, such as manufacturing, telecommunications, power generation and other utilities.

1. INTRODUCTION

Usually availability and capacity of systems, for which there is some operating history, are measured using mean values. An expectation of future performance is based on mean availability over recent history. It may be factored up or down to reflect expected change in the system, but the basis is measured past performance. Variation in future performance is often not realistically considered. Safety margins are subjectively and perhaps subconsciously built in through conservative goals, lower production budgets, etc., but these are of unknown magnitude. For example, setting production targets is often a negotiation between plant operators that want a conservative target they are sure to reach and the corporate business managers that want a stretch production target for maximum profits for their business sector. Both parties are establishing their positions without knowledge of the stochastic characteristics of their plant availability.

Monte Carlo simulation has been used to assess availability, but is not used on most systems. For whatever reasons, there is a perceived lack of cost effectiveness. We believe a major weakness is the quality of the required data. Failures of complex systems stem from multiple roots such as human reliability, management systems, design, operation, maintenance and physical environment. Root cause failure analysis usually reveals failure to involve system root causes that are specific to that system. Monte Carlo modeling can not simulate this ill-defined environment of system influences and must logically be of questionable accuracy; where as, system performance data captures the impact of these system influences. Additionally, the equipment failure data required for conventional computer simulation is often sparse and of unknown accuracy. The collection of generic data that Monte Carlo methods need in order to become widely useful is likewise hindered by the presence of system failure roots. The system that generates the failure data and the system that uses the failure data have different system failure roots, thus compounding the accuracy problem. The CAAP™ concept evolved from early attempts to check the accuracy of Monte Carlo results against actual experience.

The probabilistic assessment process described here is an inherently precise calculation, arguably a measurement, of the availability variability embedded in a set of system failure data where the failures are either independent or the dependency is described. The family of availability distributions for all mission times from the shortest to longest of interest form an availability probability surface. The same data used to generate a single-valued mean availability is used in this method to calculate the relationship between availability, mission time, and probability. When this availability surface is used for a forecast, only the most fundamental assumption is required; that is, system availability in the immediate future will be like that in the historic period from which the failure data were acquired (except as the failure data are modified to reflect anticipated change). This is the same practical assumption basic to any forecast, including those based upon single-valued numbers. System performance in the recent past is used to predict the immediate future.

2. ASSESSMENT CONCEPT

We will use a simple example to illustrate the availability assessment process so that all calculations can be seen. For purposes of our example, during 30 days of system operation, three system failures were extracted from system performance data with time-between-failure (TBF) and time-to-restore (TTR) as seen in Table 1. The system performance data may be daily production for a manufacturing plant, for example. Mean availability for the 30 days is 0.80. The system starts up after repair on Day 1 and completes a repair on Day 30, for simplicity of example.

Table 1
Simple Example – Three failures with Time-Between-Failure (TBF) and Time-To-Restore (TTR) Data

Failure	TBF (days)	TTR (days)
A	5	2
B	12	1
C	7	3
	24	6

$$\text{Availability} = \sum\text{TBF}/(\sum\text{TBF} + \sum\text{TTR}) = 24/30 = 0.80$$

The TBF and TTR for each failure of Table 1 are treated as an inseparable set. A time line can be established on which N failures over a selected history of length H is used to forecast N factorial permutations of future operation of length H(N!). The concept of the time line is seen in Figure 1 for our example of three failures in 30 days. The only requirement on the data is that failures must either be independent or dependency must be defined. Usually only common knowledge of the system failures is necessary to know the failures are independent, otherwise failure analysis is required. Because these are system failures, presumably of economic importance, any failure analysis that may be required for this purpose should already be justified. We only assume that the availability of the plant (equipment, people, management systems, etc.) in the immediate future will be effectively the same as that in a selected history. The data from history can be changed for anticipated availability improvement or deterioration. Often, but not necessarily, the selected history extends backward from current time and is continuous.

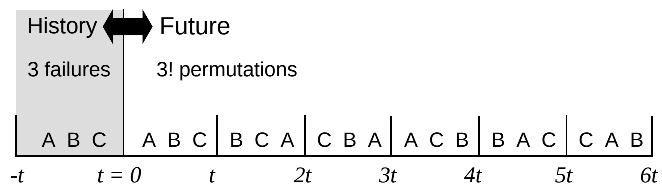


Figure 1
The time line concept showing selected history (actual, modified or simulated) consisting of three failures in time t. All permutations of failures A, B and C are laid down on the time line extending into the future. Actual time line values are seen in Figure 2.

Figure 2 is the actual time line with TBF and TTR data reflected in the availability for each day. In this example, the smallest time increment of interest is one day. A time window equal to a mission time of interest is incrementally advanced along the time line. Availability within the time window is determined at each location, thus returning a discrete random variable value for availability. An availability frequency distribution for that time window (mission time) is now known. The process is repeated with other time windows (mission times) of interest. The cumulative distribution forms for the simple example data are seen in Figure 3.

It is immediately recognized that not all of the data of Figure 2 was evenly weighted. Because of the initiation and termination of the moving window, the data at the beginning and end of the 180 day time line is counted less frequently than that in the middle. This is generally not an issue with real failure data; however, it is corrected as will be explained.

The length of the time line with N number of failures is N factorial times the length H of the historical data record. The historical record is one month in our simple example. In general, the length is then:

$$\text{Time Line} = H(N!)$$

An example of real data may be, say, 12 failures over an historical record length of two year. The length of this time line to record all permutations of the 12 failures is then:

$$\text{Time Line} = (2 \text{ years})(12!) \approx 1 \text{ billion years}$$

The number of random variable values for availability obtainable for a time window of length W in days is, in general:

$$\text{Number of values} = H(N!) - (W-1)$$

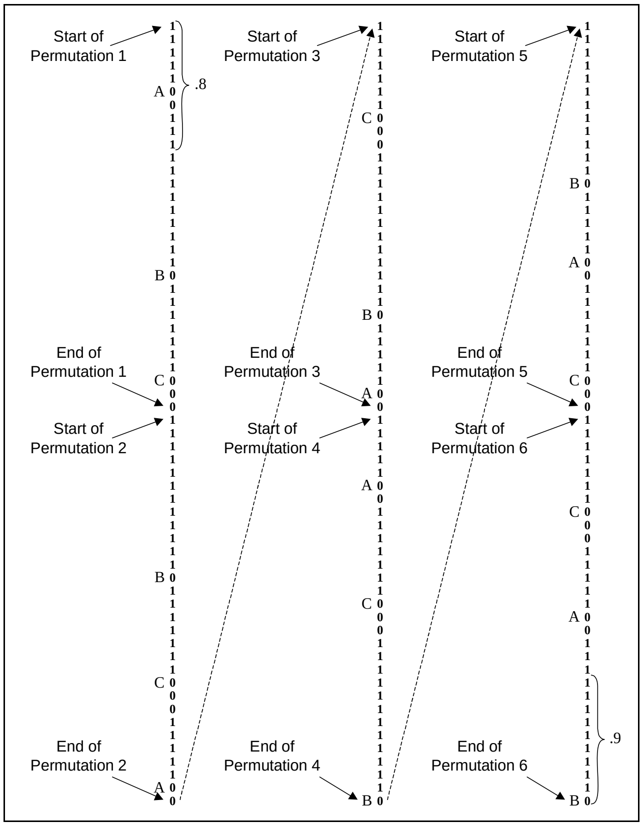


Figure 2

TBF and TTR data for the three failures (A, B and C) in 30 days of history with all six permutations forming a time line extending 180 days into the future, broken at two locations for convenience of display. Availability for each day is displayed as a number from 0 to 1. For this simple data all days have an availability value of either 0 or 1, indicating either down or up operation, respectively. The first 10 contiguous days returns a random variable value of 0.8 for availability (upper left). The window is advanced one time increment at a time returning an availability value at each. The last window returns a value of 0.9 (lower right).

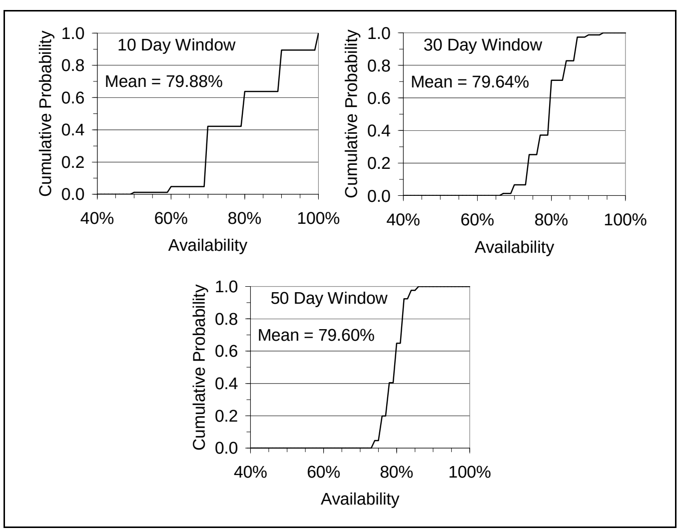


Figure 3

Cumulative availability distributions from the 3 failures of Figure 2. Time windows (mission times) are 10, 30 and 50 days as indicated on each distribution. Note each time window has a different distribution. The means are somewhat less than the actual data mean of 80% because of unequal data weighting in the time window process of Figure 2.
This is corrected by random sampling in Figure 4.

The example of real data with H = 2 years and N = 12 failures provides the following (window length W being insignificant to this calculation):

$$\text{Number of values} = 2(365)(12!) - (W-1)$$
$$\approx 350 \text{ billion values}$$

We see that the time line is so long that the uneven weighting at the beginning and end is not an issue. Also, the number of availability values is so great that a time line containing all of the failure permutations, such as in Figures 1 and 2, is both problematical and unnecessary. The permutations can be randomly sampled until convergence. Convergence is accomplished when cumulative distributions for availability cease to change with increasing number of data permutations and time line length. The example data permutations were randomized repeatedly and laid down on a time line of convenient length. The distributions, seen in Figure 4, are not smooth because we only have three failures in this simplistic example, but they are accurate with only trivial error due to sampling and data manipulation.

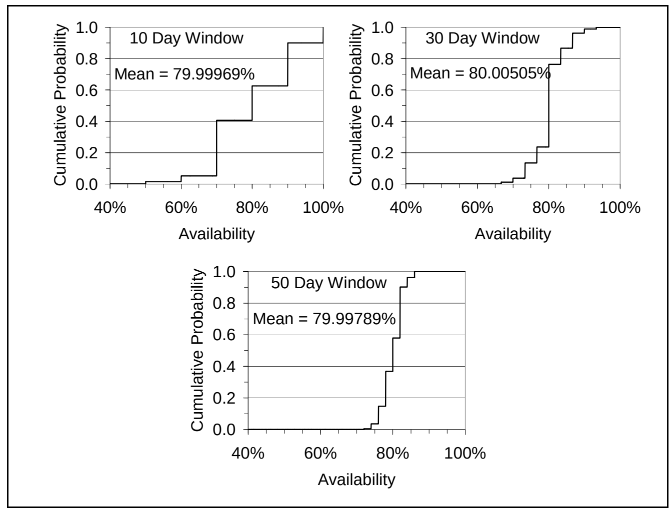


Figure 4

The permutation order for the three failures of Table 1 are randomized 2,184 times and the daily availability values laid down in a time line of 65,520 days. Convergence is achieved sooner, but this time line was used because it is a convenient limit of a computer spreadsheet. Note little change in the distributions from those of Figure 3 because only three failures greatly limit the possible availability outcomes. However, means are very close to the actual with the difference being insignificant process error.

The first permutation on the future time line of Figures 1 and 2 is a replication of the history. If the history, and therefore the first permutation, is sufficiently large, then we would expect the cumulative distributions from that one permutation (history) to converge with those developed from all permutations. This was tested with data from a petrochemical plant that spanned a nine-year history with 76 failures. Figure 5 distributions are 30, 90, 180 and 365-day time windows for this plant. Advancing the time windows along a time line containing only the permutation identically equal to history forms the ragged distributions. These distributions simply replicate history. Because the history is quite large, these distributions approach the smoother distributions that include samples of the 76 factorial permutations. Availability distributions formed directly from recorded history converge with those formed from all data permutations, as history is enlarged. This is empirical validation of the process.

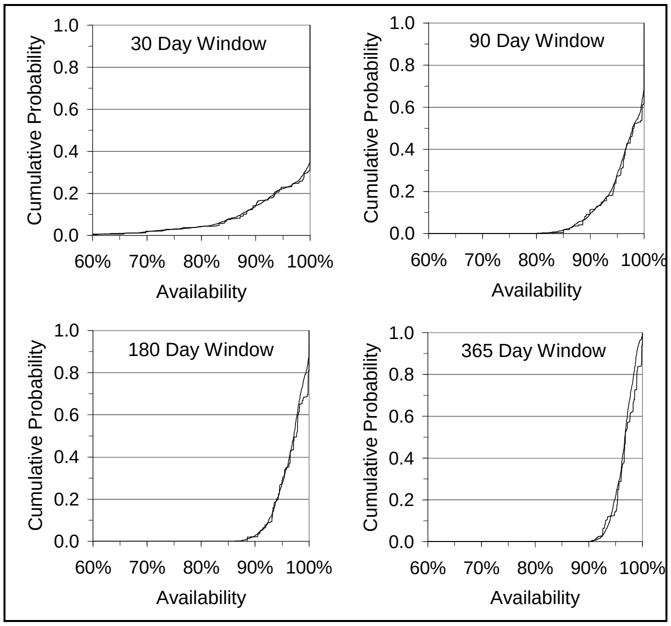


Figure 5
A petrochemical plant with 76 failures over nine years of history. Limiting the window concept to the first permutation that is identically equal to actual history forms the rougher availability distributions. They converge with the smoother distributions formed by random samples of the 76 factorial permutations.

The question may be asked, then, why do we need to examine the failure permutations? Why not obtain a large amount of historical data and use the advancing window technique along the actual history time line? Often system availability changes over time so that only selected segments of the history, and its contained failure data, should be used to forecast future availability. The distributions in Figure 5 are obtained from a long history that includes early years of low availability that is expected to be uncharacteristic of the future. The future can only be forecast with historical data that is expected to represent the future, or that can be modified to represent the future.

To select the appropriate history on which to base a forecast, a variation of a cumulative sum plot is generated. Cycle availability is defined as TBF / (TBF + TTR) for each failure and the cycle time is (TBF + TTR). Upon each failure a target TBF value is calculated by multiplying cumulative cycle time by the mean availability from all data. The difference between this target TBF and the cumulative actual TBF is the ordinate plot location for the particular failure. The corresponding abscissa location is cumulative cycle time upon that failure. Figure 6 is the availability trend plot for the Figure 5 TBF and TTR data. The slope between any two plot points is the availability in the time interval between them. This plot can be used to select the appropriate history for the forecast. The history need not be contiguous. As the historic record becomes shortened in this selection process and there are fewer failures in the analysis, extending the time line by adding failure permutations becomes increasingly important.

When subsystem performance data is available, a parallel time line for each is used and combined with appropriate logic to obtain the system time line. Also, sometimes a system may have a particular failure mode repeated in the history. This is not a significant issue with complex systems like plants, because usually each system failure is unique within any history record of a few years. When repeat system failure modes do occur within the history to be used, consideration should be given to treating them as a subsystem. When the TBF and TTR data for these repeats are significantly different from all other data, then they must be on a separate time line to prevent the availability distributions from being too wide. The availability trend in the form of Figure 6 is useful in identifying and evaluating this situation. A complete discussion of subsystems is beyond the scope of this paper.

The fundamental time increment for which TBF and TTR data are acquired and the time line scale are the smallest of interest. This is usually one day for process plants. The time increment of interest for power generation plants is much shorter, such as ½ hour. The time increment of interest for telecommunications is measured in seconds.

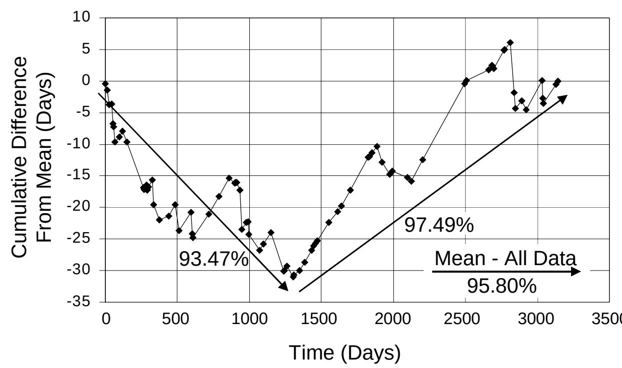


Figure 6
A variation of a cumulative sum plot provides a sensitive availability trend. Each of the 76 failures experienced over nine years produces a data point. The ordinate location is the difference between a target value and cumulative TBF. The target value is a calculated cumulative TBF obtained by multiplying cumulative cycle time by the mean availability for all data. The abscissa location is cumulative cycle time. The slope between any two points determines availability for that interval. Availability for three slopes is recorded.

3. System Performance Degradation and Dependent Failures

Complex systems, exemplified by manufacturing plants, often have availability that is neither 0 nor 1. This may be from operating during only some fraction of the smallest time increment of interest or by operating with a forced reduction in rate. This assessment methodology accommodates partial system operation quite readily. TTR is traditionally a single number, but it can be a data set. For example, a system failure that involves partial availability during the smallest time increment of interest may have a time-to-restore in the form of the following:

TTR = {.1, .3, .6, 1, 1, .5}

Where each value within the set is the unavailability of the system for the smallest time interval of interest. If this were a manufacturing plant, the smallest interval of interest may be one day and the example would read as a reduction from maximum availability of 10%, 30%, 60%, 100%, 100%, and 50%, respectively, for the six days over which the 3.5 days of equivalent downtime is spread. The following data set describes the availability for the six days. It is the complement of the TTR data set:

Availability = {.9, .7, .4, 0, 0, .5}

This data set is inserted at the appropriate locations on the time line prior to advancing the time window.

A system failure may be dependent upon another failure. For example, after a particular plant failure a six-hour shutdown may be required three days later for a follow-up action. The TTR data set above will then be extended with two days of zero TTR followed by one day with six hours (0.25 days) of TTR. This full TTR data set then reads as follows:

TTR = {.1, .3, .6, 1, 1, .5, 0, 0, .25}

The availability data set at the locations of this example failure along the time line will then be the complement of the TTR data set, or:

Availability = {.9, .7, .4, 0, 0, .5, 1, 1, .75}

The unavailability due to the subsequent outage may also be a random variable, but we do not pursue that here.

4. AVAILABILITY AND CAPACITY FORECASTING

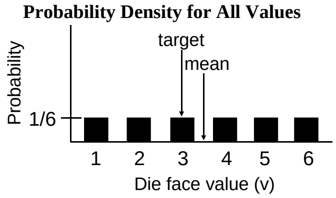
It should be clear that the probability distributions produced by this process are derived by calculation, as opposed to simulation. When we use the distributions for forecasting, we must only assume that the future mean availability and its variability will be like that indicated by the failure data, the data often coming from operating history. The historic data may be modified to reflect anticipated improvement or deterioration in reliability and/or maintainability, but that is not addressed in this paper. If history is not available, estimation or simulation may form substitute failure data. Also, surrogate data from a similar system, with modification if appropriate, can be used until a history is established.

The simple, logical forecast assumption and the inherent accuracy of the system failure data and calculation produces credible availability data. The data are comprehensive even to the point of a dense family of distributions or probability surface. This credible and comprehensive data, when converted to decision information, opens a new domain of engineering and business decisions to quantitative risk analysis. This is particularly so when the availability distributions are accessed by computer with decision-making interfaces tailored to the needs of the particular system managers. For efficient quantitative decisions, segments of the distributions are reduced to expected values in ways that are useful to the particular decision. Before proceeding with a discussion of quantitative analysis using the forecasted availability distributions, we present a simple example that illustrates the basic concept used to extract decision information from the probability distributions.

A die is known to return values of 1, 2, 3, 4, 5, and 6, each with a probability of occurrence of 1/6. The distribution, seen in Figure 7, returns a mean value of 3.5. Say a value of at least 3 is needed. This may be analogous to the availability required to meet a sales forecast over a particular period of time (mission time). A value less than 3 will result in a shortfall. We explore both the probability of a shortfall and the expected magnitude of any shortfall. We recognize that many decisions must be made with only one roll of the die dictating the actual results. For example, there is only one chance to make production during any one future time interval – one chance to make next month's production. The probability of a value less than 3 is 1/3 for any one roll, or $P(v<3) = 1/3$. Thus, there is a one in three chance of obtaining a value below target. To obtain the expected value of below target performance, we convert that portion of the original probability density to a new probability density. This process reduces a selected portion of the original probability density to a single value needed for efficient quantitative decisions. The expected value of all values less than 3 is 1.5, or $EV(v<3) = 1.5$. The mean shortfall, given there is a shortfall, is the difference between this expected value and the target, or $\{EV(v<3) – 3\} = -1.5$. Both the probability of a shortfall and the expected magnitude of the shortfall have now been calculated; namely, there is a 33.3% probability of a shortfall and the size of the shortfall, when there is one, is 1.5 units on average. The likelihood of a shortage and a meaningful measure of the consequence of a shortage are now known. Engineering and business decisions can now be made to reduce the exposure to loss or compensate in some manner as economics dictate. The calculations for shortfall are seen in Figure 7 (left side). The complementary or overage (surplus) situation is seen in Figure 7 (right side). Note the bottom line of Figure 7 calculates a simultaneous mean shortfall and mean overage expectation. This data is appropriate for those situations requiring multiple rolls of the die, such as capital investment decisions.

The assessment for a chemical plant for a 30-day time window is seen in Figure 8 and Table 2. The data that comprise the availability distribution is analyzed in the same way as the die example. As the probability of each die value is known, so is the probability of each small increment of availability for every time window. Capacity is a useful parameter for many systems and is related to availability by a multiplier. The multiplier is labeled maximum daily capacity in Table 2 and is the expected capacity capability in a failure-free day.

A change in availability or capacity performance is easily evaluated for statisical significance. For the 30-day window of Figure 8 and Table 2, the probability of availability below 68.92% is 5%, as seen in the upper portion of Table 2. In this example, should our measured availability be 68.92% in a



target or goal = 3

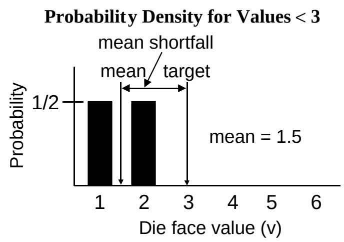
$$\text{mean} = \text{expected value}\,(\text{EV}) = \sum v P(v) = 1\left(\frac{1}{6}\right) + 2\left(\frac{1}{6}\right) + 3\left(\frac{1}{6}\right) + 4\left(\frac{1}{6}\right) + 5\left(\frac{1}{6}\right) + 6\left(\frac{1}{6}\right) = 3.5$$

<u>Below Target Assessment</u>

Probability v < 3: $P(v<3) = \frac{1}{6} + \frac{1}{6} = \frac{1}{3}$

<u>At or Above Target Assessment</u>

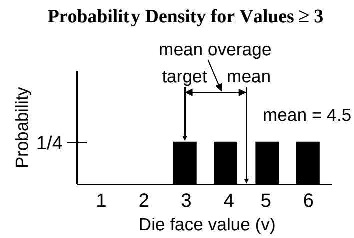
Probability v ≥ 3: $P(v \ge 3) = \frac{1}{6} + \frac{1}{6} + \frac{1}{6} + \frac{1}{6} = \frac{2}{3}$



Mean < 3: $EV(v<3) = 1\left(\frac{1}{2}\right) + 2\left(\frac{1}{2}\right) = 1.5$

Mean shortfall, given < 3: $EV(v<3) - \text{target} = 1.5 - 3 = -1.5$

Mean shortfall: $[EV(v<3) - \text{target}]P(v<3) = (-1.5)\frac{1}{3} = -0.5$



Mean ≥ 3: $EV(v \ge 3) = 3\left(\frac{1}{4}\right) + 4\left(\frac{1}{4}\right) + 5\left(\frac{1}{4}\right) + 6\left(\frac{1}{4}\right) = 4.5$

Mean overage, given ≥ 3: $EV(v \ge 3) - \text{target} = 4.5 - 3 = 1.5$

Mean overage: $[EV(v \ge 3) - \text{target}]P(v \ge 3) = (1.5)\frac{2}{3} = 1.0$

Figure 7
The known probability of each possible outcome of the die roll allows analysis for quantitative decisions. In this case the decisions surround the target or goal of rolling at least a value of three. A roll with its outcome variability is analogous to the availability variability of a system over a particular time window.

Table 2
Capacity and availability risk analysis for Figure 8 distribution. The analysis parallels that of Figure 7. Maximum daily capacity is a multiplier relating capacity to availability. Percentages are availability, fractions are probability, "lbs." is production volume.

30 Day Time Window

Maximum Daily Capacity: 100,000 lbs.

Enter Probability to Get Capacity
Capacity at probability x or (C_x) $C_{0.0500}$ = 68.9219% or 2,067,656 lbs.

Enter Capacity to Get Probability
Capacity to be assessed C_a C_a = 80.0000% or 2,400,000 lbs.

Probability of capacity below C_a $P(C < C_a)$ = 0.1903	Probability of capacity above C_a $P(C >= C_a)$ = 0.8097
Mean capacity below C_a $EV(C < C_a)$ = 72.6269% 2,178,808 lbs.	Mean capacity above C_a $EV(C >= C_a)$ = 93.8589% 2,815,768 lbs.
Mean shortfall, given $C < C_a$ $[EV(C < C_a) - C_a]$ = -7.3731% -221,192 lbs.	Mean overage, given $C >= C_a$ $[EV(C >= C_a) - C_a]$ = 13.8589% 415,768 lbs.
Mean shortfall $[EV(C < C_a) - C_a]$ -1.4033% x $P(C < C_a)$ = -42,098 lbs.	Mean overage $[EV(C >= C_a) - C_a]$ 11.2213% x $P(C >= C_a)$ = 336,638 lbs.

30-day period, we would know there was only a 5% probability of it being that low by chance. We would conclude that the poor performance is statistically significant.

The lower portion of Table 2 assesses the probability of achieving any value of availability or capacity. This is done in the same manner that the value of 3 was assessed in the die example. A target availability of 80% or 2.4 million lbs. (maximum daily rate is 100,000 lbs.) has a 19% chance of not being reached, just as there was a 33.3% chance of rolling less than 3. Likewise, as in the die example, the expected value of availability (capacity) below the target is 72.63% (2,179,000 lbs.) and the expected value of the shortfall, given there is a shortfall, is -7.37 percentage points (-221,200 lbs.). Therefore, concerning the goal of 2.4 million lbs. for the 30-day period, here is a 19% chance the goal will be missed, and if it is missed, the size of the shortfall will average 221,200 lbs. The acceptability of this risk and consequence can now be considered and ways to manage either the risk or consequence can be evaluated. Similarly, for the complementary condition

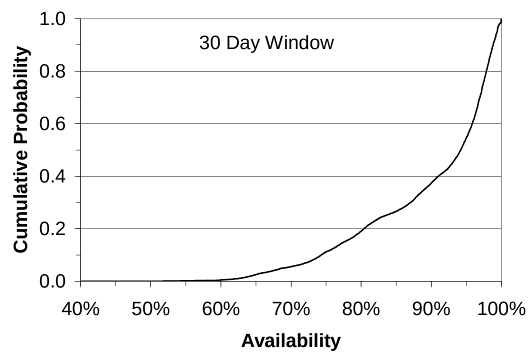


Figure 8
Chemical plant cumulative distribution for availability for a 30-day window (30-day mission time)

there is an 81% chance of exceeding the goal by an average of 415,800 lbs. Here management attention may be directed at whether this potential surplus should be sold, how the overage would impact product inventories, when and how much to reduce production rates, etc.

The class of decisions just discussed are those for which there is only one opportunity to achieve a goal. Some decisions require averaging results. For example, return on investment is determined over a number of years involving multiple proverbial rolls of the die. To illustrate, in the chemical plant example, a new project to increase the production rate may appear to have no value. The needed quantity is below the mean capability. We see in Table 2 (bottom left), however, that there is a mean shortfall of 42,100 lbs. In Table 3 with conditions identical to Table 2 except for a 10% increase in maximum daily capacity, the mean shortfall is 15,000 lbs. Therefore, the new project reduces the average monthly shortfall by 27,100 lbs. This reduction in expected production shortfall can be used for project justification; where as, conventional economic analysis would show no capacity related benefit. (For simplicity, in this example availability is unchanged by the new project and the production requirement does not change over the life of the project.)

Table 3

Availability identical to Table 2, but with an increase in maximum daily capacity. For the identical target used in Table 2, all probabilities and quantities change.

30 Day Time Window	
Maximum Daily Capacity: 110,000 lbs.	
Enter Probability to Get Capacity	
Capacity at probability x or (C_x) $C_{0.0500}$ = 68.9219% or 2,274,422 lbs.	
Enter Capacity to Get Probability	
Capacity to be assessed C_a C_a = 72.7273% or 2,400,000 lbs.	
Probability of capacity below C_a $P(C < C_a)$ = 0.0758	Probability of capacity above C_a $P(C >= C_a)$ = 0.9242
Mean capacity below C_a $EV(C < C_a)$ = 66.7474% 2,202,666 lbs.	Mean capacity above C_a $EV(C >= C_a)$ = 91.7110% 3,026,464 lbs.
Mean shortfall, given $C < C_a$ $[EV(C < C_a) - C_a]$ = -5.9798% -197,334 lbs.	Mean overage, given $C >= C_a$ $[EV(C >= C_a) - C_a]$ = 18.9838% 626,464 lbs.
Mean shortfall $[EV(C < C_a) - C_a]$ -0.4534% x $P(C < C_a)$ = -14,961 lbs.	Mean overage $[EV(C >= C_a) - C_a]$ 17.5445% x $P(C >= C_a)$ = 578,967 lbs.

5. BUSINESS DECISIONS

Producing and then reducing any segment of any availability distribution, in the manner described in the die and chemical plant examples, allows decision information for a number of new applications. Once availability is fully characterized as a probability surface with axes of mission time, availability and probability, then capacity is characterized by simply multiplying by maximum rate. Introducing other simple information such as sales forecast and yields, and performing simple arithmetic quantifies probabilities and consequences for issues like production budgeting, product inventory control, profit projection, material requirements planning, and production scheduling. Risks from availability variation are fully quantified because not only are probabilities known, as importantly, consequences are measured. Production budgets can be established with known risks. Product inventory can be managed to: 1) set limits of risk, 2) set allowable shortage magnitudes, and 3) optimum economic level. Material requirements, production schedules and profit projections are probabilistically established.

The issue of product inventory control illustrates the requirement for both total characterization of availability as a probability surface and efficient data reduction for these business decisions. To illustrate, first the desired inventory level for the beginning of a future peak sales period is established. The difference in the sales forecast and, for example, the C_{05} (capacity at 5% level of risk) for a mission time of sales season length is the product inventory that is adequate 95% of the time. Thereafter, inventory is managed by using the probability distribution for the remaining time to the peak sales season. Not only are the distributions to be used different from day to day, but current inventory fluctuates with actual production and actual sales. Hence, for that application and many others, all distributions from the shortest to the longest mission time of interest may be required. Therefore, for this new domain of business decisions, availability should be totally characterized with a probability surface. Many applications require frequent and efficient use. Computer interface with the probability surface allows easy and fast access to the decision information.

6. UNCONDITIONAL RELIABILITY DISTRIBUTIONS

Traditionally, reliability is defined as the probability of surviving for a specified period of time, where time begins upon startup. This definition may not be appropriate for repairable systems. Often the reliability (probability of failure-free operation) for a system is desired for a time interval beginning at a future time and the state of the system at the beginning of this future interval is unknown. When reliability is desired for a period of time that starts in the future, the beginning of the period may be located anywhere along the time line of Figures 1 and 2. To obtain the unconditional reliability (not conditional upon the system being just repaired) we use the window technique of Figure 2 on all or a random sample of the failure permutations. For each time window, the ratio of the number of failure-free windows to total windows is the unconditional reliability for that window interval. By examining all windows, a probability distribution for reliability is formed. The unconditional reliability distribution for the chemical plant of Figure 8 and Tables 2 and 3 is seen in Figure 9.

The performance of some systems may be adequate if the system outage is limited in amount or duration. This can be incorporated in the definition of reliability. The window

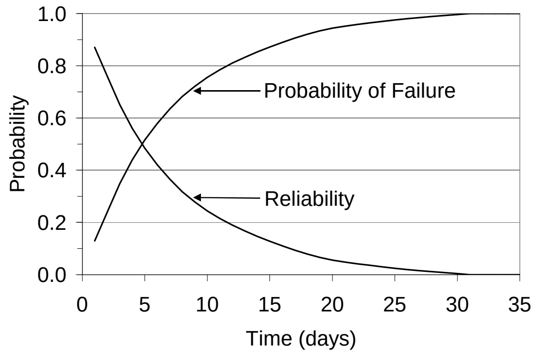


Figure 9

Unconditional reliability distribution for the chemical plant of Figure 8 and Tables 2 and 3. The start of time measurement is not conditional upon a newly repaired system. Also shown is the complement probability of failure.

technique allows the definition of failure to include the degree and duration of system performance reduction. Reductions of a small degree and/or a short duration could be included in the failure-free window count discussed above.

BIOGRAPHIES

Jan B. Smith, P.E.
Applied Reliability, Inc.
11944 Justice Avenue, Suite E
Baton Rouge, Louisiana 70816 USA

Internet (e-mail): jsmith@appliedreliability.com

Jan B. Smith, P.E., BSME, is a Registered Professional Engineer and Certified Reliability Engineer (ASQ) and serves as President and Reliability Engineering Consultant to Applied Reliability, Inc. He has worked continually in Reliability Engineering for over 35 years and in 1986 established Applied Reliability, Inc., an engineering firm working with reliability issues involving root cause failure analysis; finite element analysis; statistical and probabilistic analysis; vibration analysis; and capacity and availability forecasting. Mr. Smith has chaired conferences on plant reliability, authored several technical papers on the subject, and organizes and lectures at seminars on reliability issues.

W. Bryan Smith
Applied Reliability, Inc.
11944 Justice Avenue, Suite E
Baton Rouge, Louisiana 70816 USA

Internet (e-mail): bsmith@appliedreliability.com

Bryan Smith has a Bachelor of Science degree in Informational Systems and Decision Sciences. His work as a Reliability Systems Analyst at Applied Reliability, Inc. includes analyzing various reliability issues and integrating economic and other business considerations to provide business decision information. Much of his work has been spent in the research and development of a new process for probabilistically forecasting availability and capacity of repairable systems such as manufacturing plants. Mr. Smith aided in the development of a methodology for converting system performance data into an availability surface map. He also developed means for interacting with availability surface maps in a dynamic manner to extract business decision information in the areas of product inventory control; capacity/availability risk analysis; production scheduling; profit risk analysis; and analysis of reliability, maintainability, and availability trends for statistical significance.