Where Is My Data For Making Reliability Improvements?

by H. Paul Barringer, P.E.
Barringer & Associates, Inc.
Humble, Texas USA

and

David P. Weber
D. Weber Systems, Inc.
Mainville, Ohio USA

Fourth International Conference on Process Plant Reliability

Marriott Houston Westside
Houston, Texas

November 14-17, 1995

Organized by
Gulf Publishing Company
and
HYDROCARBON PROCESSING

Where Is My Data For
Making Reliability Improvements?

H. Paul Barringer
Barringer & Associates, Inc.
P. O. Box 3985
Humble, TX 77347-3985
Phone: 713-852-6810
FAX: 713-852-3749

David P. Weber
D. Weber Systems, Inc.
1018 Seapine Ct.
Maineville, OH 45039
Phone: 513-677-9314
FAX: 513-697-0860

All failure data for plant equipment and processes contains problems with definition of failure, data accuracy, data recording ambiguities, data accessibility, and lack of currency values. These are not reasons for ignoring data. Data banks of plant maintenance and cost records are a gold mine for starting a chain reaction of improvements. Data analysis puts facts into an action oriented format involving age-to-failures, along with suspended data from successes, to focus on making improvements to reduce the cost of unreliability. Five data sets are analyzed to show how data is used. Understanding data is helpful, but making cost effective improvements by use of the data is the business objective!

Consider these recent quotations about data for making reliability improvements:

- *"A persistent theme is the lack of data bases for reliability engineering. Continual cries for general and specific reliability data fill the literature."* [1]
- *"…the first step is try to get good data. This step is the most difficult…."* [2]
- *"The major need in HRA* [Human Reliability Analysis] *is for quality data."* [3]
- *"…successful application of RCM [Reliability-Centered Maintenance] needs a great deal of information."* [4]

Data appetites for making reliability improvements are high and many engineers do not know what data to acquire or how to analyze the facts. Jones [5] says "*…we're often left with a glut of unused data. Our challenge is to closely examine our systems, and our needs, measure only the essential data, and then put our measurements to productive and profitable use*."

An extension of a familiar adage may be: You can never be too rich, too thin, or have too much useful reliability data.

Definitions-

It's important to have the same definitions for reaching the same conclusions about reliability:

- **Failure-**"*Loss of function when we want the function.*" [6] "*The event, or inoperable state, in which any item or part of an item does not, or would not, perform as previously specified.*" [7]
- **Failure Rate-** "*The total number of failures within an item population, divided by the total number of life units expended by that population, during a particular measurement interval under stated conditions.*" [7] (Failure rate is the reciprocal of MTBF or MTTF for exponential distributions but this is not strictly correct for Weibull distributions when $\beta \neq 1$.)
- **MTBF (Mean Time Between Failure)-** "*A basic measure of reliability for repairable items: The mean number of life units during which all parts of the time perform within their specified limits, during a particular measurement interval under stated conditions.*" [7] (Often refers to the mean life for a population.)
- **MTTF (Mean Time To Failure)-** "*A basic measure of reliability for non-repairable items: The total number of life units of an item divided by the total number of failures within that population, during a particular measurement interval under stated conditions.*" **[7]** (Often refers to the mean life for a single piece of equipment.)
- **Reliability-**"*The probability that an item can perform its intended function for a specified interval under stated conditions.*" [7]
- **Reliability Data**-*A collection of numerical facts based on measuring the motivation of failure by cumulative insults to the component or system where three requirements are precisely defined:*
  — *an unambiguous measurement time origin must be defined,*
  — *a scale for measuring passage of "time" must be set: and*
  — *the meaning of failure must be entirely clear.* [2] [8]

- **Reliability Engineering-**“*Appropriate application of: engineering disciplines, techniques, skills and data to assess problems or improvements, achieve the required reliability, maintainability, serviceability, exchangeability, availability, and yield of products and processes at a cost that satisfies business needs.*” [8]

When catastrophic failure occurs, the time of failure is clear. However, when failure is slow deterioration of a component or system to meet a desired standard of performance, then you must define and quantify failure clearly to avoid confusion such as:

— What we want to achieve versus what we can do. (Arguments over failures occur because usually the “want” is a production viewpoint whereas “can do” is usually a maintenance or engineering viewpoint of equipment capability. When “can do” exceeds “want”, few arguments occur.)

— What we are capable of achieving versus the inherent performance capability. (When “inherent” performance exceeds required capability few arguments exist, but problems occur when requirements exceed built-in “capability”.)

Two common threads frequently occur concerning reliability data:

— How am I doing compared to others?

— How do I make improvements?

Answers to these questions involve:

1. What are the specific numerics for existing age to failure or failure rates?
2. What is the cost of unreliability for funding reliability improvements?
3. How good is good enough?
4. Do I have a system for reporting the data in a useful format?
5. Where is my data?

Some data always exist within any company even when the data are less than perfect for reliability purposes. Reliability Engineering efforts must use data effectively.

Example 1-Pump Seal Life

Two companies lack detailed failure reporting systems—one is a chemical company and the other a refinery. Their raw data comes from two sources:

1. A nose count of pumps from asset records, and
2. A nose count of seals replaced from purchasing/inventory records.

The count of pumps is used for determining the number of operating hours to which seals are exposed. Pumps running full-time are exposed at 8760 hours per year. Spared pumps are exposed 8760 hours per year <u>for the set</u> assuming each pump runs one-half time.

Purchasing/inventory values of seals consumed help find the number of failures experienced during the year. (The number of failures recorded are assumed as correct values since both purchasing and inventory records are usually audited).

Compute mean time between failures (MTBF) by dividing the number of failures into the summation of exposure hours. *MTBF is a yardstick (not a micrometer) for reliability performance.* For example, if operation plans for a 5 year turnaround and the MTBF is 10 years, seals are considered as highly reliable. However, if MTBF is 1 year, seals are considered highly <u>un</u>reliable. Thus MTBF is a rank indicator of reliability using 5 year mission time between turnarounds for Example 1.

MTBF is a simple reliability indicator. It is descriptive for showing substantial differences in MTBF for:

- good grade, good reliability, ANSI pumps,
- better grade, better reliability, ANSI-enhanced pumps, and
- best grade, best reliability API pumps.

Furthermore MBTF data often shows a severe decline in reliability with tight emission controls. This occurs because failure definitions change to a more severe criteria resulting in more failures.

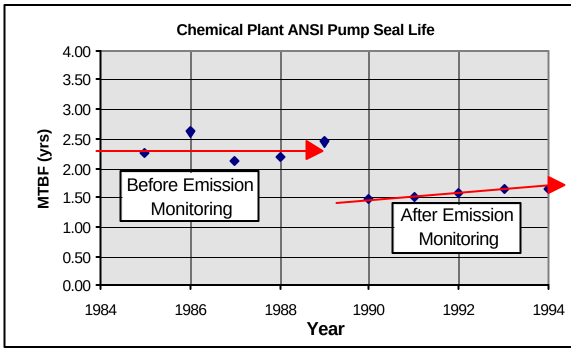
Example 1:

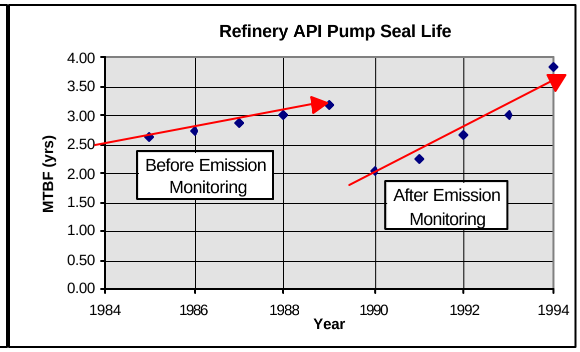
Chemical Plant ANSI Pump Life

Year	Number Of Unspared Pumps	Number Of Spared Pumps	Total Hours Of Pump Operation	Number Of Seal Failures	Seal MTBF (yrs)	Seal Failure Rate (fail/hr)	Conditions
1985	937	2996	21,330,000	1083	2.25	50.8E-6	No
1986	943	2996	21,380,000	937	2.60	43.8E-6	Emission
1987	950	2998	21,450,000	1156	2.12	53.9E-6	Monitoring
1988	950	3008	21,500,000	1127	2.18	52.4E-6	
1989	953	3012	21,540,000	1003	2.45	46.6E-6	
1990	955	3028	21,630,000	1689	1.46	78.1E-6	
1991	957	3036	21,680,000	1628	1.52	75.1E-6	
1992	963	3048	21,790,000	1581	1.57	72.6E-6	
1993	955	3038	21,670,000	1517	1.63	70.0E-6	Emission
1994	951	3026	21,580,000	1487	1.66	68.9E-6	Monitoring

Refinery API Pump Life

Year	Number Of Unspared Pumps	Number Of Spared Pumps	Total Hours Of Pump Operation	Number Of Seal Failures	Seal MTBF (yrs)	Seal Failure Rate (fail/hr)	Conditions
1985	313	1542	9,500,000	415	2.61	43.7E-6	No
1986	313	1542	9,500,000	398	2.72	41.9E-6	Emission
1987	313	1548	9,520,000	380	2.86	39.9E-6	Monitoring
1988	310	1560	9,550,000	361	3.02	37.8E-6	
1989	305	1580	9,590,000	343	3.19	35.8E-6	
1990	295	1580	9,500,000	535	2.03	56.3E-6	
1991	290	1590	9,500,000	481	2.25	50.6E-6	
1992	280	1598	9,450,000	403	2.68	42.6E-6	
1993	270	1602	9,380,000	354	3.02	37.7E-6	Emission
1994	265	1610	9,370,000	278	3.85	29.7E-6	Monitoring





Notice the rate of improvements (as shown by the slope of the trend lines) between the two companies in Example 1 plots. These two companies not only have different grades of equipment but they have substantially different operating philosophies. The chemical company has the usual antagonism between operations and maintenance, whereas the small refinery has embraced principles of TPM (Total Productive Maintenance) resulting in production treating their equipment with tender loving care (i.e., reducing the human error failure rate and using human senses to detect impending problems) thereby increasing component life and reducing costs.

Personal involvement in operation of equipment can substantially improve MTBF as 50% to 70% of failures are typically the result of human error in some industries. [3] Note improvements in Example 1 are underway even though the refinery does not have a detailed reporting system. Their improvements stem from working with operators to improve performance, and this sets a sound datum for obtaining additional growth in MTBF through use of modern data collection/analysis systems and the use of reliability engineering principles.

From failure data in Example 1, the cost of unreliability cannot be accurately calculated. Unfortunately where the failures occurred is not known, and the cost of failures is not recorded. Seldom does the failure of a spared pump shut down the production train, however, failure of an unspared pump can have catastrophic effects on production which contributes major losses into the pool of funds comprising the cost of unreliability.

The question can be answered about how good is the MTBF. You don't need the best MTBF of all industries in the world. However, you do need a competitive advantage (i.e., larger MTBF) over your fiercest competitor—other cost being equal.

MTBF provides a clue about how well your facility is operating. The real key about performance lies in the cost of <u>un</u>reliability. Cost of unreliability determines what must be spent (either capital expenditures, upgrade costs, or ongoing costs) to reduce overall costs.

Typically, chemical plants have a cavalier attitude about how pumps operate as expressed by "All pumps cavitate". Light weight ANSI pumps are not so tolerant of misoperation. Thus MTBF for ANSI pumps is often low (and maintenance replacement effort is high). Often chemical plant pumps have MTBF of 1 to 1.5 years. If your plant shows a 3 to 4 year MTBF you will often have a major competitive advantage.

Many refineries have a 2.5 to 3.5 year MTBF using higher grade, lower failure rate API pumps. If your plant shows a 4 to 5 year MTBF you will often have a major competitive advantage.

Plant performance is not always influenced by average MTBF values as shown in Example 1. These indices have the advantage of simplicity and account for all potential operating hours. However, the disadvantage is these arithmetic calculations do not weight extreme values in data which can overwhelm the calculation because of their specific arithmetic influence on results.

Pareto distributions of failures usually show “bad actor” seal failures are concentrated in a handful of troublesome pumps which generate most of the cost of unreliability. Correcting the behavior of these vital few pumps will have major influence over the performance metrics and major influence over the cost of unreliability. However, this requires specific data rather than generalities available from the analysis of Example 1.

Example 2-Pooled Data

Often data is available for a single model of equipment with multiple pieces of equipment in service at the same time under similar operating conditions. The data often includes both successes and failures which cause much confusion in analyzing the data. Thus engineers often conclude they have no useful data. In fact, the sparse information of a few failures and many successes contains a wealth of useful details.

Data shown in Example 2 has a few failures. Most of the information resides in suspended data representing successes. Reliability engineering calculations must include successes in the calculation of the MTBF to arrive at the correct index. The calculated failure data can be distorted by the method used to make the calculations. This is illustrated with several methods shown using techniques mentioned in Denson. [9]

Generally speaking the Weibull method of calculating the MTBF is a better method of obtaining the central tendency of life. In this case the Weibull MTBF is shown as 38,031 hours/failure (round the data to show 38,000 hours/failure). It is more accurately obtained than the arithmetic calculation and properly reveals the aging relationship of the MTBF.

Example 2:

Pump Seal Life (hours) $^{+}$ signifies seals are still running without failure				
Pump #1	Pump #2	Pump #3	Pump #4	Pump #5
22,000	41,000	33,000^{+}	23,000^{+}	17,000^{+}
33,000^{+}	14,000^{+}			

Method #1 (Use RAC method #1, page 1-12, **Nonelectronic Parts Reliability Data -1995**):

Failure rate = λ = 1/MTBF = (sum all failures)/(sum all exposure hours) =

2/(22+33+41+14+33+23+17)*1000 = 2/183,000 = 0.000,010,9 failures/hour, or

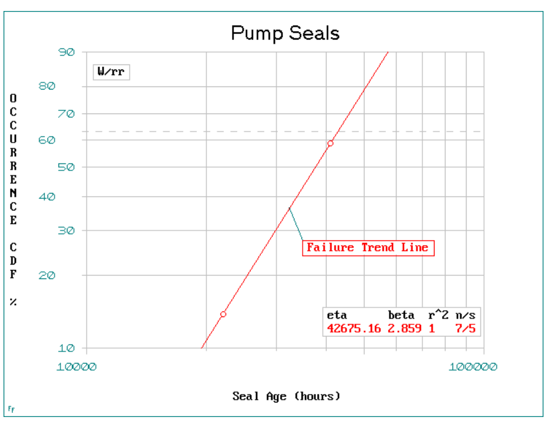
MTBF = 1/0.0000109 = 91,500 hours/failure (This simple method gives distorted values because 70+% of the data does not contain failures thus making it difficult to derive a failure rate.)

Method #2 (Use RAC method #5, page 1-13)

Failure rate = λ = 1/MTBF = (geometric mean of all failure rates associated with failures)*(observed hours with failures)/(total observed hours)=

0.00003329636*((22,000+41,000)/183,000) = 0.000,011,4 failures/hour, or

MTBF = 1/0.0000114= 87,719 hours/failure (Note: Geometric mean was computed by EXCEL® software using the failure rates of 1/22,000= 0.00004545455 and 1/41,000= 0.00002439024 failures/hour which equals a geometric mean of 0.000,033,296,36. This method has the same problems of method 1.)



Method #3 Find Weibull characteristics using WeibullSMITH software: The slope of the line, β = 2.859 indicates wear-out failure modes and characteristic life, η = 42,675 hours.

The MTBF = $\eta * \Gamma(1/\beta + 1)$ = 42,675*0.89117 = 38,031 hours/failure.

The Weibull method produces a more accurate value for MTBF considering the large number of suspended values which are put into the failure distribution to produce a CDF that is correctly calculated for the statistical parameters. Note that $\Gamma(1/\beta + 1)$ is the Gamma function. Since the slope of the Weibull line is greater than 1, failure rate increases with time (and MTBF diminishes) so the values calculated in methods #1 and #2 are only early estimates of a diminishing MTBF which is properly revealed by the Weibull analysis.

Weibull methods, using WeibullSMITH™ software [10] are better because a cumulative distribution function is built including the suspended data at the correct portion of the cumulative distribution function (CDF). Then the data is fit to a flexible curve that more accurately shows small amounts of data in rank regression considering both failures and successes. The result is none of the sparse data is wasted for reaching useful conclusions.

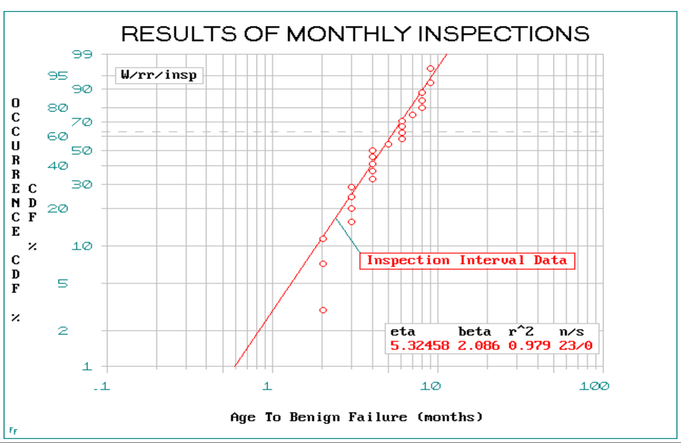
Example 3-Inspection Intervals

Interval inspection data is often confusing to casual observers as shown in Example 3. The actual age to failure is unknown as benign failures are reported in this case. However, the benign failure is known to have occurred prior to the inspection date.

Example 3:

Inspections Occur At The End Of Each Month For Stress Corrosion Cracks
No Catastrophic Failures Occurred. Only Benign Cracks Were Discovered

Month	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Number Cracks Found	0	3	4	5	1	4	1	3	2



Age to benign failure (months)=

2, 2, 2, 3, 3, 3, 3, 4, 4, 4, 4, 4, 5, 6, 6, 6, 6, 7, 8, 8, 8, 9, and 9.

Each crack has its own age to failure.

How many benign failures can occur? When will benign failures become catastrophic failures? When will the benign failure cease? These answers are unknown except during the 9 month inspection interval where no catastrophic failures were reported. Each month, more data is added to the accumulated pool of information; and the questions cannot be answered accurately until a longer period of study has been completed.

One of the key points to make is that it is important to separate benign failures from catastrophic failures. Don't treat all benign problems as catastrophic events—they may not grow into catastrophic failures. Don't ignore benign failures—they may grow into critical events. Thus continue a prudent watch by means of periodic inspections which return stacks of data on the Weibull chart at the periodic intervals.

Correct evaluation of inspection interval data shows this problem will continue longer than would be predicted by traditional methods. For this case, the age to 99% occurrence is projected to be 11 months which is ~10% longer than if simple curve fits are used.

Does the projection mean all data will be in-hand at the end of the 11 month interval? Answers for this question depend on the "physics of the failure" driven by the "load-strength interference"--if the physics can't answer the question, then continue the inspection watch to determine if the cracks in Example 3 will grow to catastrophic proportions or if they remain as non-relevant indications.

It is unwise to spend too much money chasing will-of-the-wisp problems. It is clearly not prudent to ignore potential problems that can grow to catastrophic proportions. The key is to keep benign issues in a business perspective and not waste money on non-relevant issues.

Example 4–Terse Vs Rich Data Descriptions

Maintenance problems are often reported by production in very terse statements. These statements, if taken literally, often result in non-sensible conclusions for Example 4 as shown by the terse portion of the example.

Example 4:

Terse statements of problems:

Failure Data With Terse (And Often Misleading) Descriptions Of Symptoms

Note: **s** = Suspended data — Age To Failure (days)

Action	Date	Seal	
Commissioned	10/27/81		
Seal Burned Up	4/13/85	1264	
Seal Burned Up	12/12/88	1339	
Seal Burned Up	1/6/89	25	All failures are reported as aging problems.
Seal Burned Up	12/31/89	359	
Seal Burned Up	6/21/91	537	
Seal Burned Up	1/31/92	224	
Seal Burned Up	7/12/92	163	
Seal Burned Up	3/13/93	244	
Data Analized On This Date-->	4/27/95	775s	

	System Interarrival Time	Seal	
Arithmetic Analysis on 4/27/95			
Simplified MTBF Estimate=	616	616	
Weibull Analysis on 4/27/95			
β =	—	0.871	<--Infant Mortality Suggested (β<1)
η =	—	647.1	
Mean =		693.59	
Median = B_{50} =		424.92	

Rich statement of problems:

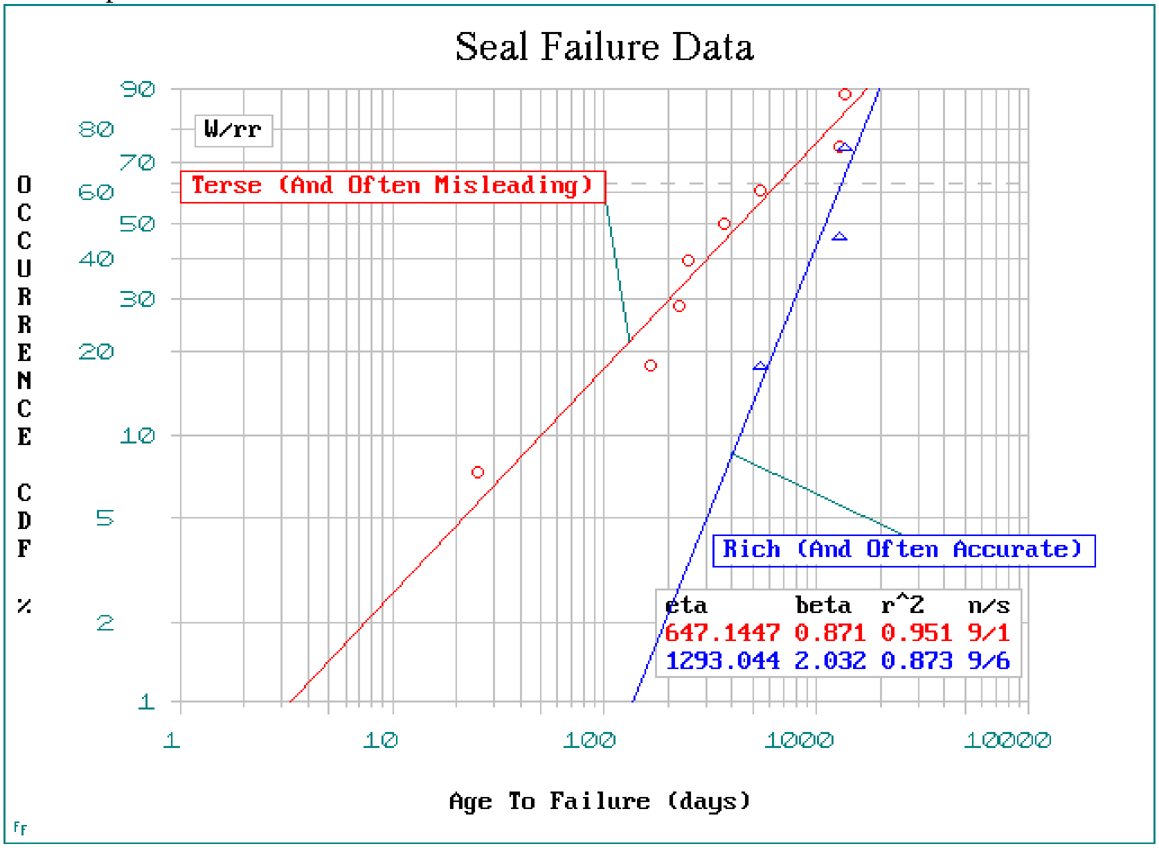
Failure Data With Rich (And Often Accurate) Descriptions Of Symptoms

Note: **s** = Suspended data — Age To Failure (days)

Action	Date	Seal	Dry Seal	LoFlo Seal	
Commissioned	10/27/81				Age To Failure Data
Seal Burned Up-Heavy Wear Track	4/13/85	**1264**			Operator Event Data
Seal Burned Up-Heavy Wear Track	12/12/88	**1339**			*(Not an aging process)*
Seal Burned Up-No Fluid In System	1/6/89	25s	**25**		
Seal Burned Up-Low System Flow	12/31/89	359s		**359**	**Note!!!**: 5 of 8 failures (or **62.5%** of the problem) is caused by <u>events</u> and <u>not by aging conditions!</u>
Seal Burned Up-Heavy Wear Track	6/21/91	**537**			
Seal Burned Up-Low System Flow	1/31/92	224s		**224**	
Seal Burned Up-No Fluid In System	7/12/92	163s	**163**		
Seal Burned Up-No Fluid In System	3/13/93	244s	**244**		
Data Analized On This Date-->	4/27/95	775s			

	System Interarrival Time	Seal	
Arithmetic Analysis on 4/27/95			
Simplified MTBF Estimate=	616		
(Incorrect method) MTBF =		1305	<--(1264+1339+537+775)/3 w/o suspensions
(Incorrect method) MTBF =		1643	<--(Sum of all failure and suspended data)/3
(Correct method) MTBF =		1208	<--Fit curve to suspension adjusted median ranks and estimate life at the median (50%) position.
Weibull Analysis on 4/27/95			
β=	—	2.032	<--Wear-out Suggested (β > 1)
η=	—	1293	
Mean =		1145.64	
Median = B_{50} =		1079.67	

Example 4 continued-
Weibull plot of terse and rich information:



Routine data analysis would conclude that the seals have an infant mortality failure mode. Infant mortality is not the expected failure mode for a well designed, proven pump seal, which is correctly installed and correctly operated. The Weibull results of Example 4 show substantial differences in both slope and location. Notice how the terse data (comprised of mixed failure modes) produces a pessimistic appraisal of the mean life compared to the more accurate (and longer) mean life from a single failure mode. The mean life is reflected in the value of eta for the Weibull characteristic life.

If descriptions in the maintenance/repair records are enriched to include only a few more words, the results of the terse data are very enlightening as shown in Example 4. Only a few more words show the problem cannot likely be solved by hardware. The root cause of the problem is most likely corrected through people/procedure solutions.

Problems of poor reporting of vague symptoms are wide spread in many industries. History records must be updated and corrected with proper information for solving the correct problem. If the root problem is not solved, then efforts are not cost effective and money is thrown at wrong problems!

Substantial progress is underway in developing and adding cutting-edge technology for data extraction from field maintenance report data analysis efforts. [11] This new effort can enrich data for analysis.

New systems can "read" field maintenance reports using special dictionaries, grammar, and syntax data bases to "understand" the context of reported problems and solutions. The expert systems perform both a top-down and bottom-up language analysis. Then the computer systems use a built-in linguistic knowledge base and a conceptual knowledge base which interact with each other and with a conceptual data base derived from expert systems. Benefits from this high technology computer analysis of problem and solutions are productivity improvement, error reduction, and early detection of failure patterns.

The new technology uses service reports based on fixed-field failure reporting methods supplemented with narrative fields of information. The fixed-fields contain the statistics, failure symptoms, failure modes, failure descriptions, failure times, etc. Fixed-fields are completed by executing preconceived codes. Often fixed-fields are left incomplete in favor of descriptions in the narrative fields. Automatic processing of on-line text reporting can quickly build statistical data based of the fixed-field data, but human analysts are required (at great cost and time delay) to abstract missing data from the narrative fields into the fixed-fields.

Human analysis effort is now being automated by extensive use of computers. These leading edge computer systems can identify errors in fixed field information, merge free-form and fixed-field information, create new fixed-fields, and support expanded queries. Interfaces to the systems use English to communicate with the computer, and the system can understand and process language.

This emerging technology is very computer intensive and requires reliability experts and computer experts to build the analysis systems so that “thinking” occurs during processing of the reports. Of course these new systems require human input of facts to get the analysis moving in the right direction.

Another cutting edge technology for enriching data descriptions is statistical-pattern recognition. [12] Statistical pattern recognition development is active today in academic and industrial worlds. Document processing, engineering, and medical fields are creating and applying new, more powerful techniques. Solutions to the recognition problems in these areas rest with the accurate classification of data. Statistic-pattern recognition is based on Bayesian statistics for data mining and this has also been applied to design review decision making. [13]

For years, most data put into existing maintenance systems has not been used for solving problems. Thus no one has worked to improve the data—it is the age old chicken or egg problem. Once you understand how failure data is used and nagging problems are solved, the data records get improved.

Example 5--Cost Of Unreliability

Previous history of failures helps predict the cost of unreliability. Assuming no significant improvements have corrected the basic problems with the process or equipment.

A one page spreadsheet often shows the cost of unreliability. A spreadsheet is helpful for understanding and communicating budgets for correcting problems. Of course, if costs for correcting problems exceeds outage costs, then it is unwise to spend correction money. In short, the process may have a built-in unreliability burden not shared by competitors.

Example 5:

Annual Cost Of Unreliability For One Continuous Process

Given: When running, the process produces $10,000/hr of gross margin profit.

When outages occur, scrap is produced at a cost of $15,000 per incident.

Breakdown maintenance costs are $25,000 per incident and 12 hours are lost.

Past failure records will prevail until major changes are made to correct problems.

Find: What is the annual cost of unreliability?

How many failures can we expect during a one year production run?

How much can we afford to spend for corrections (using simple one year payback)?

Management's argument for correcting the cost of unreliability?

	Cell A	Cell B	Cell C	Plant A	
Study period (hrs)	52560	60000	16000		
Number of failures	5	7	1		
MTBF (hrs/failure)	10512	8571.429	16000		
Expected failures/yr.	0.833333	1.022	0.5475	1.855333	Management Priority
Lost gross margin/yr	$100,000	$122,640	$65,700	**$288,340**	**1**
Scrap Cost/yr	$12,500	$15,330	$8,213	$27,830	3
Breakdown Cost/yr	$20,833	$25,550	$13,688	$46,383	2
Total Loss/yr	$133,333	**$163,520**	$87,600	**$362,553**	**<--Cost of unreliability**
Engineering Priority-->	2	**1**	3		

Cost of unavailability ($/hr)= $16,284 Availability = 99.7458%

Answers:

The annual cost of unreliability is $362,553 for this process.

Expect ~2 failures per year (1.8553 failures/year).

Engineering should fix problems in Cell B. They can spend up to $163,520.

Management should argue for correcting problems to increase gross margin $'s

(not arguing against the maintenance cost of breakdown repairs).

Note this example shows both management and engineering priorities for fixing problems. Of course this plant generates high gross margin from operations, but unreliability money is being wasted.

The operation in Example 5 looses $362,500 per year from the cost of unreliability. Correcting this loss requires good, economical ideas which often do not require large expenditures when the true root causes of failures are known, understood, and corrected.

Management's priority is clearly to keep the plant running to generate gross margin. *Engineering, Maintenance, and Production priority* is to fix Cell B for less than $163,500 and thus reduce the cost of unreliability by 45%! Reducing the cost of unreliability requires teamwork.

Summary-

Where's your reliability data? It's all around your plants in various forms. You must extract the important details. Understanding failures and failure data increases the probability for making successful improvements.

Several examples show how to quantify reliability indicators which describe plant problems. Some examples use general failure data, and other cases need specific failure data. All cases should use both failures and costs to describe business problems. Use your data to solve problems, and prevent future costly problems (even though it means you lose the adrenaline flow from chasing the ambulance to the scene of the wreck).

When you understand how to handle reliability data you are on the road to correcting problems. Make the data talk in terms you can understand. Understanding the data is helpful but the real payoff comes from solving problems that reduce the cost of unreliability—this requires a mutual bias for action by Production, Maintenance, Engineering, and Reliability departments to solve problems rather than talking about solving problems.

Don't wait for magic solutions and tomorrow's computer systems. Put your data to work for business solutions. You'll never have a perfect reporting system for your failure data. You'll never have a perfect analysis system.

Some facts are better than no facts. As you gain experience in extracting reliability data from your system, better data will also direct better improvements.

References:

[1] **RAC Journal**. 1995. *"The Status of the Reliability Technology-Jan 1, 1995"*, Volume 3, No. 1, Rome, NY: Published by Reliability Analysis Center, Rome, NY 13440-6916, 1st Quarter 1995, page 5.

[2] Abernethy, Dr. Robert B. 1993. **The New Weibull Analysis Handbook**, Houston, TX: Gulf Publishing Co., phone 713-520-4467, Page 2-1

[3] Gertman, David I. And Harold S. Blackman. 1994. **Human Reliability and Safety Analysis Data Handbook**, New York: John Wiley & Sons, page 21.

[4] Moubray, John. 1992. **Reliability-centered Maintenance**, New York: Industrial Press Inc., page 223.

[5] Jones, Richard B. 1995. **Risk-Based Management, A Reliability-Centered Approach**, Houston, TX: Gulf Publishing Company, phone 713-520-4467, page 15.

[6] Rees, Roderick. 1993. *"Re-Defining Failure"*, **Reliability Review**, (Published quarterly by the Reliability Division of the American Society of Quality Control), Volume 13, December 1993, page 11.

[7] MIL-STD-721. 1991 *Military Standard Definitions of Terms For Reliability and Maintainability*, Springfield, VA: National Technical Information Service of the U.S. Department of Commerce.

[8] Barringer, H. Paul. 1995. **Reliability Engineering Principles**, Humble, TX: Self published, phone 713-852-6810, page 2-13.

[9] Denson, William, Greg Chandler, William Crowell, Amy Clark, and Paul Jaworski. 1995. **Nonelectronic Parts Reliability Data**, Rome, NY: Reliability Analysis Center, page 1-12 and 1-13.

[10] Fulton, Wes. 1995. **WeibullSMITH™**, software version 5.43, Houston, TX: Gulf Publishing Co., phone 713-520-4467.

[11] Weber, David P., Norman Sondheimer, Paul Jacobs, and George Krupka, 1990, *"Field Service Message Understanding"*, **Workshop Notes from the American Defense Preparedness Association's Meeting on Artificial Intelligence Applications for Military Logistics**, Williamsburg, Virginia.

[12] Cuadrado, John L., 1995, *"Mining Statistics"*, **BYTE** Magazine, February 1995.

[13] Weber, David P., 1992, *Reliability Design Review Expert (RDRx)*, 92-WA/DE-13 in the **Proceedings of the ASME 113th Winter Annual Meeting, Anaheim, CA**, New York: American Society Of Mechanical Engineers.

Biographic Information-

H. Paul Barringer

Manufacturing, engineering, and reliability consultant and author of the basic reliability training course **Reliability Engineering Principles**. More than thirty-five years of engineering and manufacturing experience in design, production, quality, maintenance, and reliability of technical products. Contributor to **The New Weibull Handbook**, a reliability engineering text published by Dr. Robert B. Abernethy. Named as inventor in six U.S.A. Patents. Registered Professional Engineer in Texas. Education includes a MS and BS in Mechanical Engineering from North Carolina State University, and participated in Harvard University's three week Manufacturing Strategy conference.

David P. Weber

Principal of D. Weber Systems Inc., an assurance science consulting firm, with 35 years experience in engineering and management. Formerly Staff Engineer for GE Aircraft Engines (28 years) in Reliability Engineering plus experience as Section Chief of Assembly Engineering for the Saturn Moon Rocket. Recognized as an expert in Weibull probability analysis, life-cycle costing, and modeling of systems for analysis, simulation, and risk assessment. Served on the USAF System Safety Groups for the C5-A and B1-B aircraft. Performed FAA safety certification analysis on commercial engine programs for GE Aircraft Engines. Senior Member of AIAA, 30 year member of ASME, AAAI, ASQC, and MAA. Served on SAE Committee G-11, Reliability, Maintainability and Supportability (RMS) and on the Institute of Environmental Sciences' (IES) Reliability Growth Committee. Holds patents on "Cold Welding" encapsulation of transistors and was named in the first edition of "Who's Who in Aviation and Aerospace". His BS in Mechanical Engineering is from the University of Evansville in 1959.