Process Reliability Concepts

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"Controversy is common whenever new ideas are introduced into science: people have to invest so much time and effort mastering a narrow field that the thought of having to start anew is repugnant. They therefore take up cudgels, motivated by considerations that are all too human. To survive such a battering, an idea must prove its worth." (Covey 1995)

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Abstract
Weibull analysis, using daily production output data, is used on a production process to find the process reliability. Output from multiple production lines is combined into a Monte Carlo simulation to avoid the typical manufacturing case of "over promise and under deliver" from production operations with process reliability problems. Patterns from several processes are described, and Pareto losses are found to prioritize the problem solving effort. Gross margin losses are quantified in a before/after case to show the value of making improvements.

Initial Comments
The idea using Weibull analysis, in a non-traditional manner, for finding the reliability of a process may be controversial. It is now proving it's worth by finding patterns for losses. The author hopes these ideas will be valuable for reducing costs in your processes.

Process reliability is a method for identifying problems, which have significant cost reduction opportunities for improvements. It started with the question: "Do I have a reliability problem or a production problem?" The author has reviewed hundreds of processes and found only one that did not need significant improvements—thus the chance for finding a process not requiring improvement is very small.

This technique of using Weibull analysis to analyze for process reliability **will not** tell you failure modes, it **will not** plot age-to-failure, it **will not** (usually) contain suspensions, it **will not** use data which motivate failures, and it **will not** usually give a single straight line as it will often have cusps on the data trends showing unusual patterns for failure of the process. The process **will** identify gaps in output for potential cost reduction opportunities.

The technique will present important facts as an engineering graphic, which is useful for people to solve business problems. On one side of one sheet of paper, the Weibull plot tells the story. This is very important for busy people.

The hardest part of reliability analysis is getting the data. However, process reliability techniques use data available at any plant---daily output of prime quantities produced. Production quantities are precursors for money. This Weibull technique aids in solving business problems where cash is king, money is the oil for progress, and the cost of **un**reliability for processes is important—which requires quantification of process reliability. Reliability is about making businesses better. This is particularly true when we summarize problems on one page to initiate corrective action. We Weibull analysts are a pragmatic lot! We're biased for solving problems quickly. Weibull process reliability techniques will help define a strategic course of action to obtain significant improvements.

Definitions

Crash and burn output: A euphemism for seriously deficient production quantities during periods of substantial process upsets or deteriorations.

Cutbacks: A production quantity recorded during a period when output is restricted by partial failures resulting in a slowdown from the intended/scheduled production rate. The zone is often characterized by a cusp at either end of the zone on a Weibull plot.

Demonstrated Weibull production line: A straight-line trend in upper reaches of the Weibull probability plot defining "normal" production when all is well—as quantities deviate from this segment, failures occur (by definition) because the process loses it's predictability.

Demonstrated capacity: A single "talk about" number at 63.2% CDF or 36.2% reliability which best represents a stretch goal for production output.

Efficiency/utilization losses: The difference between the nameplate capacity and the demonstrated Weibull line; generally a result of efficiency losses or under-utilization of the facility.

Nameplate capacity: a) For a single piece of equipment, it is the maximum production capacity of the equipment under ideal operation and control as described by process planners or supplier of the equipment. b) For a process comprised of many different components of equipment it is the maximum production capacity of the factory under ideal operation and control as provided by the site contractor that designs and constructs the factory.

Pareto principle: A few contributors are responsible for the bulk of the effects—the 80/20 rule whereby 10% to 20% of the things are responsible for 60% to 80% of the impact. Named for the Italian economist Vilafredo Pareto (1848-1923) who studied the unequal distribution of wealth in the world and by Dr. Juran who described the Pareto concept as separating the vital few issues from the trivial many issues.

Processes: Processes are collections of systems and actions following prescribed procedures for bringing about a result. Processes are often used for manufacturing saleable items.

Production losses: The difference between the demonstrated Weibull line and the actual production data point associated with the same % CDF.

Process reliability: The point on a Weibull probability plot where the demonstration production line shows a distinct cusp because of cutbacks and/or crash and burn problems.

What Is Weibull Production Process Reliability?

Processes vary from the simpler systems of producing and delivering water to complex systems for producing and delivering complex chemicals and every thing in between. Process reliability is important for manufacturing processes to assess the health of the system and maximize gross profits. Seldom is process reliability quantified and controlled for maintaining the health of the money machine (i.e., the process).

Some processes are discrete, others are continuous—the **Weibull process reliability** technique works for both. For most manufacturing companies, the key process issues are

1. How well are the production systems functioning and being utilized to generate cash, and as
2. Production quantities are precursors for gross profits—more output is better.

Typical reliability issues drive process reliability as follows:

- We can define reliability for components, sub-assemblies, assemblies, and systems.
  Question 1: What is the reliability of your process?
- We know data is required to define reliabilities relating to "things".
  Question 2: What data is required for identifying process reliability?
- We know reliability problems require a definition of failure.
  Question 3: What is a process failure and how is it defined?
- We know some reliability issues are trivial and others of great importance.
  Question 4: Why is it important to measure process reliability?
- We know the average daily production is useful for production planning
  Question 5: What do the Weibull statistics tell about the process?
- We know that every process has problems and we need to prioritize the issues.
  Question 6: How do we use the production gaps to build Pareto distributions?

Specific Situations

Consider a process as viewed from a top down perspective from say 65,000 feet elevation. Think of the process as a black box. Look at the output using Weibull techniques for analyzing the output and reliability from the black box. This top down view produces specific patterns on Weibull plots for understanding process reliability and other features important to manufacturing operations. Most production data will produce a straight line or series of straight-line segments on a Weibull plot. Using the customary pragmatic concepts of Weibull analysis, if the data gives a straight-line plot on Weibull probability paper, it is a satisfactory fit to a Weibull distribution. (Abernethy 1998).

Figure 1 shows daily production output for one year from 1) a highly desirable process and from 2) a less desirable process. Neither process has a reliability problem—both are healthy.

Output from the highly desirable process in Figure 1 varies over a very small range. However, the less desirable process has a wider range of output. The highly desirable process has a $\beta = 100$ and $\eta = 1000$. The less desirable process has a $\beta = 32$ and $\eta = 962$. Both processes appear to have the same installed capacity, as they are both capable of producing the same maximum output. Notice how well the production data fits a straight line without cusps.

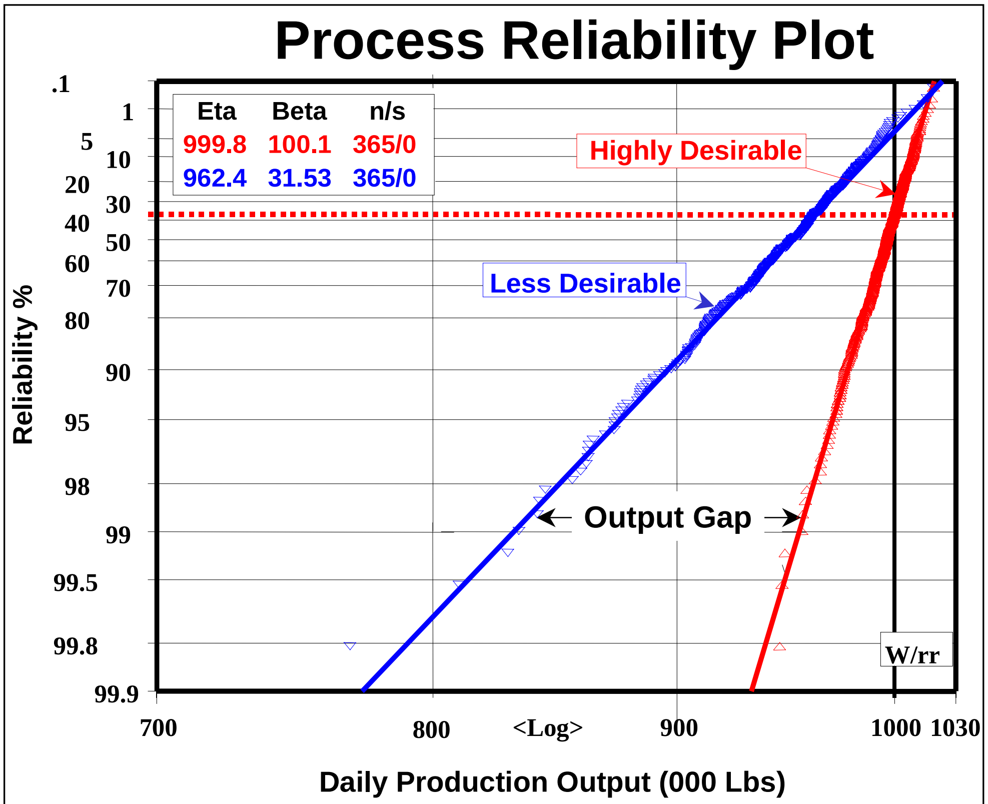

Figure 1: Two Processes Without Reliability Problems

An output gap exists between the two processes in Figure 1. The gap between the trend lines can easily be quantified by using the Weibull equations for the trend lines at specified CDF or (1 - CDF) = R for a specified number of days—in this case use 365 days with an Excel™ spreadsheet as shown in Table 1:

Table 1: Sample Calculation Of Production Output Gap

Row	Column A	Column B	Column C	Column D	Column E
1	**Day**	**Reliability =**	**Output**	**Output**	**Output**
2		**1 - Bernard's**	**Highly Desirable**	**Less Desirable**	**Gap**
3		**Median Rank**	**β = 100.1**	**β = 31.53**	**(Col C -D)**
4		**(1 - BMR)**	**η = 999.8**	**η = 962.4**	
5	1	99.808%	939.22	789.18	150.04
6	2	99.535%	947.60	811.74	135.86
7	3	99.261%	952.00	823.77	128.23
8	4	98.987%	955.01	832.08	122.93
9	5	98.714%	957.31	838.46	118.86
10	6	98.440%	959.17	843.64	115.53
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364	360	1.560%	1014.14	1006.91	7.23
365	361	1.286%	1014.60	1008.36	6.24
366	362	1.013%	1015.14	1010.07	5.07
367	363	0.739%	1015.82	1012.20	3.61
368	364	0.465%	1016.73	1015.10	1.63
369	365	0.192%	1018.28	1020.03	-1.75

The equation for the Weibull trend lines can be found in Abernethy where the Weibull equation has been solved for time (or in this case, output) where $t = \eta*(\ln(1/(1\text{-CDF})))^{(1/\beta)}$ recognizing that (1 - CDF) = reliability.

Of course Table 1 could also be comprised of actual ranked data for calculating the specific gaps rather than using the trend lines. The actual production output gap is 17,660.6 ('000 Lbs). If the variable gross margin between the highly desirable plant and the less desirable plant is $0.10/lb, then the less desirable plant has suffered an unprofitable financial consequence of $1,766,060! Most operations personnel are very concerned about million dollar problems and want the problems fixed!

Figure 2 shows daily annual output for 365 days from a process with a reliability problem. Notice the cusp in the Weibull plot. The cusp defines a failure of the data to continue on a more favorable steep, straight line demonstrated by the more favorable production data. The cusp occurs at a reliability value of 52%. Financial problems occur in the lower left hand side of this plot below the reliability value at the cusp.

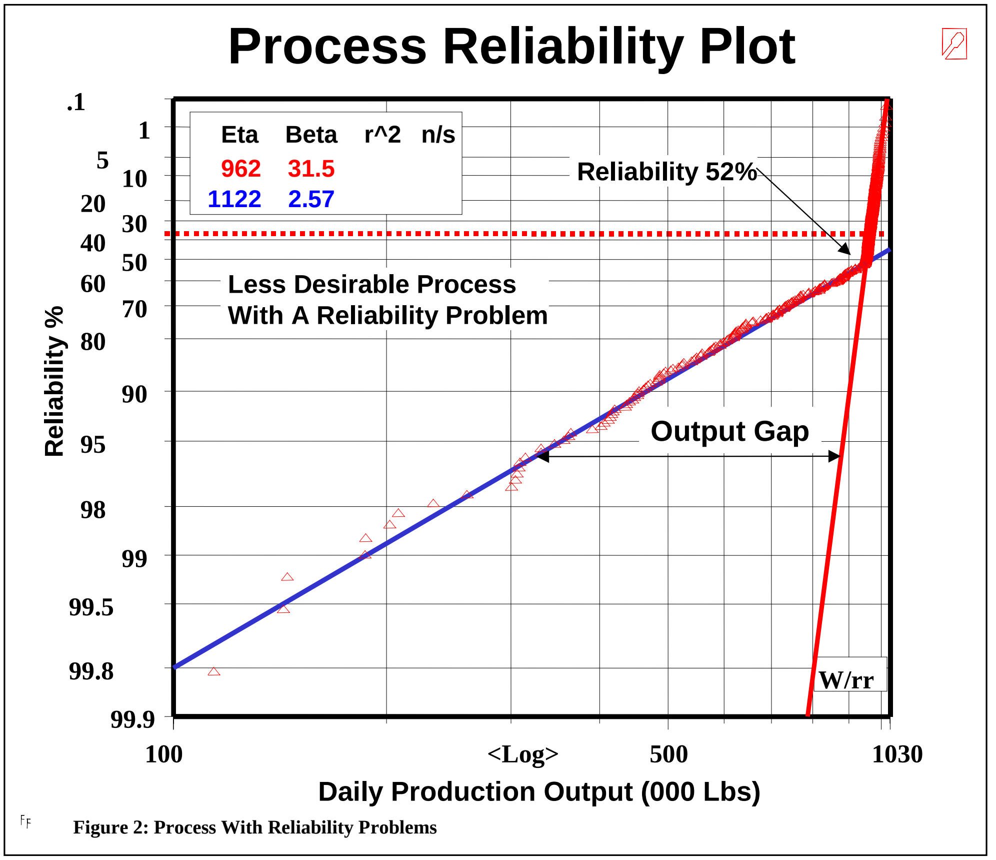

Figure 2: Process With Reliability Problems

The process in Figure 2 has demonstrated a steep beta of 31.5 and to the left of the cusp, the production quantities are deficient which causes a gap in the output. This is an opportunity for making improvements. The lines in figure 2 along with the reliability point can be selected with the click of an icon using WinSMITH™ Weibull software, which will calculate the production output gap between the demonstrated production line and the actual production in the region below the designated reliability point. (Fulton 2000)

The calculation scheme for Figure 2 would be similar to Table 1 where column C would show the demonstrated production line and column D would have the actual output data—the production output gap would then be the difference between columns C and D. The detailed output gap show a 48,851.6 (‘000 Lb) problem in the range from 52% to ~100% reliability. Using the $0.10/lb variable margin from Figure 1, then this plant has a $4.885 million per year financial difficulty!!!!

Notice that Figures 1 and 2 along with the gap analysis do not require the use of the nameplate descriptions. Each figure shows a problem gap based on some sort of datum—Figure 1 used the gap between processes while Figure 2 used the gap between demonstrated control and loss of reliability. The production gaps can be quantified first in terms of production quantities (a precursor for money) and second in terms of lost gross margin money. Also remember the data in Figures 1 and 2 also involves a time frame of one year. Do not lose the point that lost production must be converted into lost money! Money and time are understandable to everyone! Both money and time are actionable items outside of the range of technical talk. Money and time are the language of commerce, and if you want to sell your technical improvements you’ve got to show the problem and solutions in terms of money and time—frankly the individuals with their hands on the money bags are not interested in your intriguing technical explanations because they’re only concerned with money and time.

Figure 3 shows the process data from Figure 1 along with a nameplate rating for the facility. Notice the nameplate line passes through the largest data point (for this case) and it has a steeper slope than the actual output curves. The nameplate line represents a slope of “best in class” or a benchmarked slope for providing a practical and achievable condition.

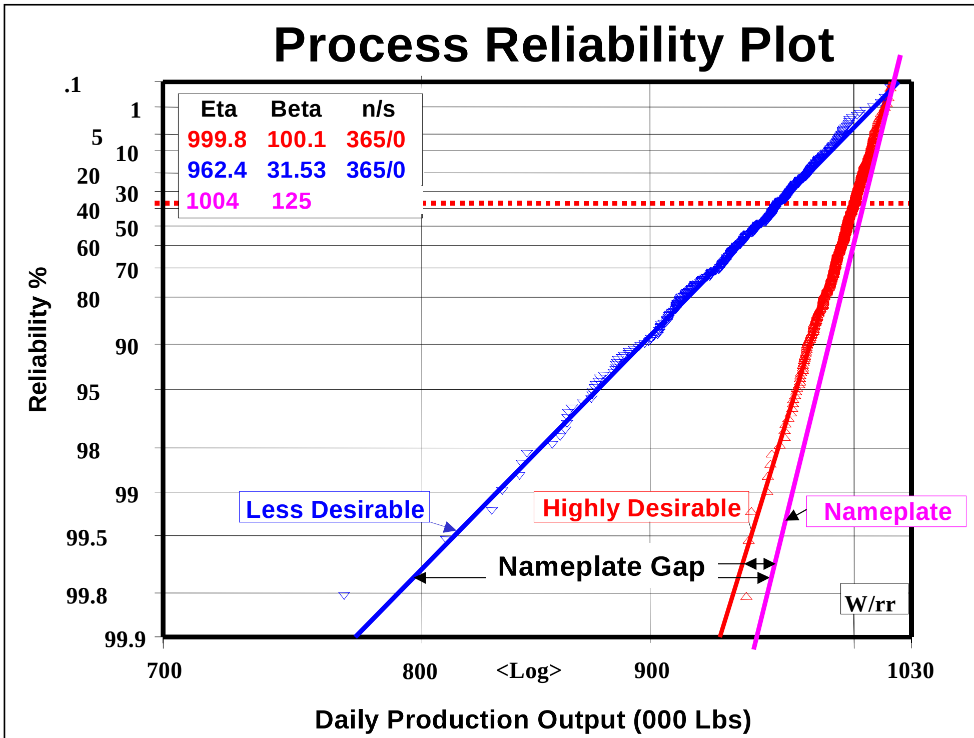

Figure 3: Nameplate Line With Gaps In Production For Two Processes Without Reliability Problems

In an idealized case, the nameplate line would be vertical with β = ∞; however, since Weibull analysis is a practical tool, the beta values should be established on a reasonable situation rather than using idealistic and impossible conditions—practicality is very important when dealing with production personnel for achieving credibility.

The nameplate line for Figure 3 has β = 125. The line passes through the highest data point of 1019 at 99.80843% as determined by Bernard's median rank = (i - 0.3)/(N + 0.4) for i = 365 and N=365. The nameplate line has β = 125 and η = 1004. Notice the small gap between the nameplate line and the desirable process trend line. However, for the less desirable process, the gap between the nameplate line and the less desirable trend line is large. Gaps between nameplate lines and demonstrated production lines are usually associated with utilization and efficiency losses.

Figure 4 increases the complexity of the problem. Figure 4 uses the data from Figure 2 and adds a nameplate line based on the demonstrated production line or by an actual recorded data point.

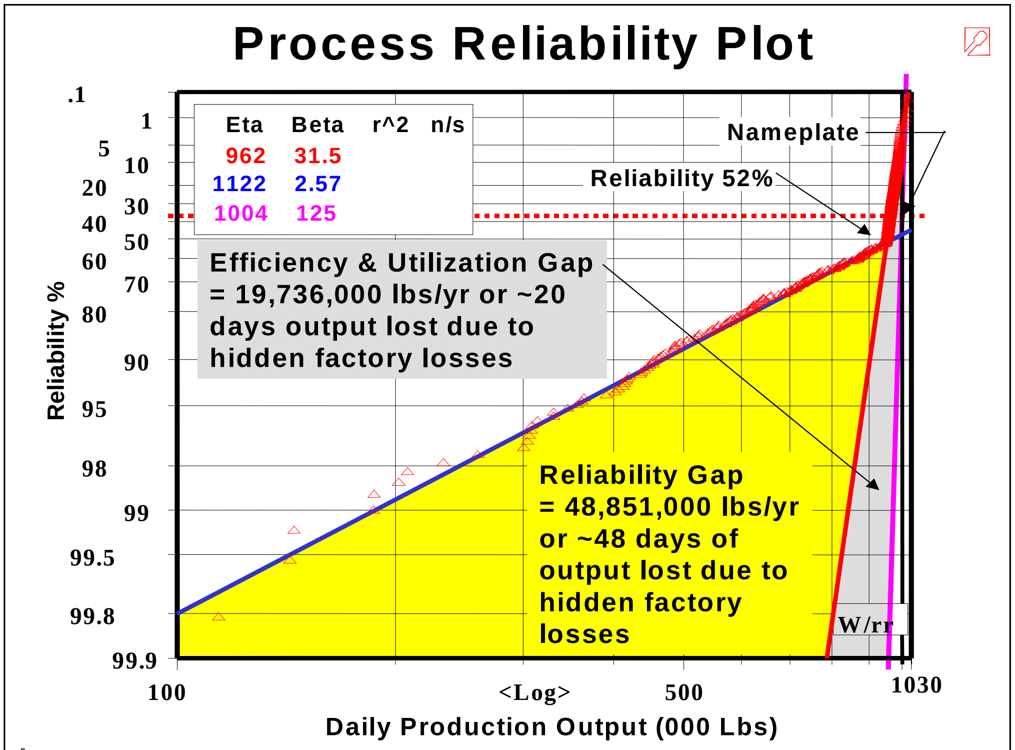

Figure 4: Production Gaps Quantified To Find Size Of Hidden Plants

From Figure 4, losses can now be categorized as problems associated with 1) reliability problems and 2) efficiency and utilization problems. Based on the losses, a Pareto distribution can be established:

A. Gap from reliability losses = 48,851,000 lbs/year ←#1 problem
B. Gap from efficiency & utilization losses = 19,736,000 lbs/year ←#2 problem
C. Gap from total losses identified = 68,587,000 lbs/year = ~71 days of lost production

Using Figure 2 and companion Figure 4, we can answers the six questions posed above,

1. **What is the reliability of the process in Figure 2?—**52%
2. **What data is required for identifying process reliability?—**production output data
3. **What is a process failure and how is it defined?—**lack of continuation of a steep, straight trend line on a Weibull plot which usually occurs at a cusp
4. **Why is it important to measure process reliability?—**cusps define regions of undesirable production quantities—more production is usually better and higher reliability is usually better than low reliability—Figures 2 and 4 show problems.
5. **What do the Weibull statistics tell about the process?—**1) beta values tells about predictability built into the process--steep betas are preferred to shallow betas; and 2) eta values are single point estimate of a stretch goal for output (63.2% of the daily production will be less than the eta value) and large eta values are more desirable than small values with eta's magnitude set by physical plant size.
6. **How do we use production gaps from Figure 4 for Pareto distributions?—** The answer is: rank the losses, and start work on the largest losses to reduce them.

    The #1 problem is poor process reliability with a resulting production gap of 48.8 million lbs valued at $4.88 million dollars per year in losses.

    The #2 problem is the efficiency and utilization gap of 19.7 million lbs per year valued at $1.97 million dollars/year in losses.

    On a Pareto basis, 71.3% of the problem is due to reliability (the vital problem) and 28.7% of the problem is due to efficiency and utilization (the trivial portion of the problem).

    Total lost money is ($4.88 + $1.97)E+06 = $6.85 million/year which is equivalent to 71 days of lost production at the demonstrated rate---this is a very large hidden factory for which we are paying the cost but not getting the benefit of money spent.

Paraphrasing Mark Twain (Samuel Clemens) it is amazing what great returns you get from such small amounts of data!

Of course the Weibull process reliability technique has identified the problem from a high altitude. Next is a requirement for a lower altitude search in asset utilization databanks to find where the localized problems are centered—do not focus on the nose count problems but focus on the financial results. (Ellis 1998) Finally a good root cause analysis program helps in permanently removing the problem by a study of cause/effects using a structured program with the understanding that each effect has at least two causes in the form of actions and conditions. (Gano 1999) Weibull process reliability analysis helps to define the problem, which is the first step in performing an effective root cause analysis. Likewise the Weibull process reliability analysis provides the evidence needed for root cause analysis.

As a different view, suppose the production facilities in Figure 5 and Figure 6 have the same technology, same physical size, are owned by the same company, and each year produce about the same amount of product. From a high altitude viewpoint, how would you characterize the plants and what are their reliability problems?

Some days the plants in Figure 5 and 6 did not or could not operate and thus zero output was recorded. Zero values will not plot on a logarithmic scale. The "zeros" are represented by outputs of say two decades smaller than the lowest real output. In the following examples, the "small" value is shown as 100 for ease in presentation. This ploy of handling zero values on a Weibull plot will create small, and usually non-meaningful errors.

Figure 5 shows Plant A with a high reliability of 95%. Reliability losses are 6,790,000 lbs/year in a transition to severe problems for the 6 days of outages. Furthermore, the beta for the demonstrated production line is an uninspiring 12.12, which generates an efficiency and utilization loss of 48,767,000 lbs/year. Clearly this plant's #1 problem is efficiency and utilization when compared to a nameplate line with a beta = 75. Efficiency and utilization losses account for 48,767/55,557 = 87.8% of the total losses. Converting the annual losses into money at $0.1/lb multiplied by total losses of 55,557E+03 lbs/ yr this is a $5.56 million/yr problem.

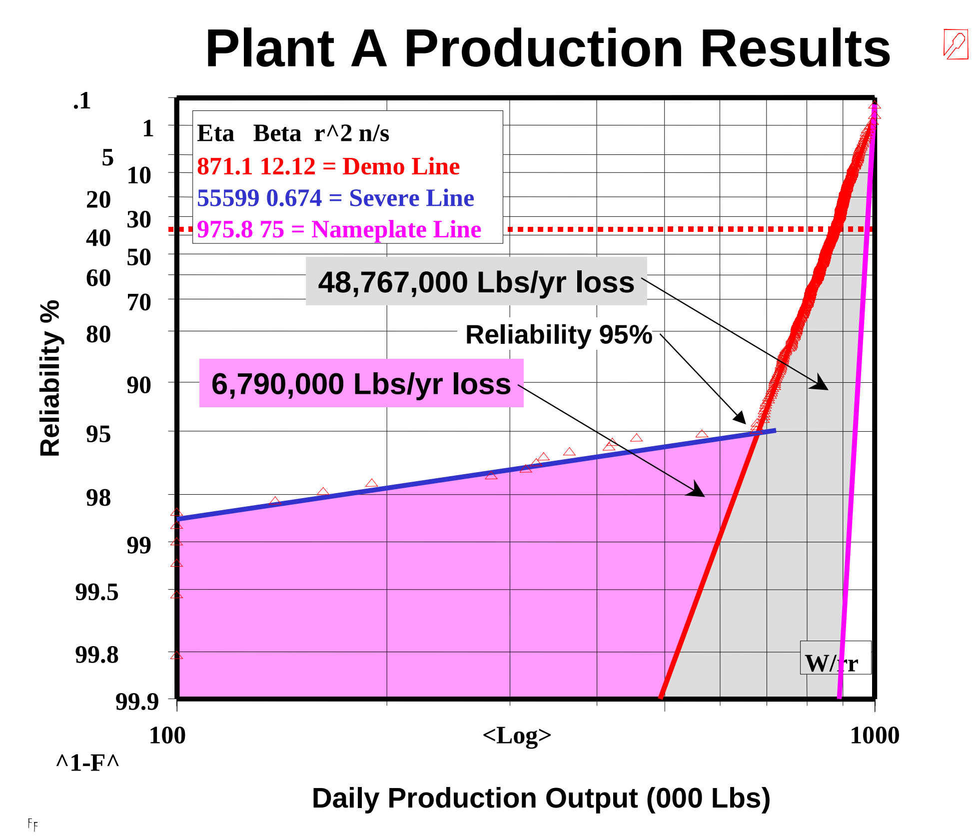

Figure 5: Plant A Production Gaps With Total Losses = 55,557,000 Lbs

Figure 6 shows Plant B with a low reliability of 17%. Reliability losses are 55,163,000 lbs/year compared to the efficiency and utilization losses of 150,000 lbs/year. Thus 99.7% of the problem is associated with reliability. Notice that 17,546,000 lbs/year is from a cutback in output with a trend line for this segment which is nearly parallel to the higher production rates. The loss of 37,617,000 lbs/year is associated with days of downtime and the transition to and from total outages. Converting the annual losses into money at $0.1/lb multiplied by total losses of (55,163 + 150)E+03 lbs/ yr is a $5.53 million/yr problem.

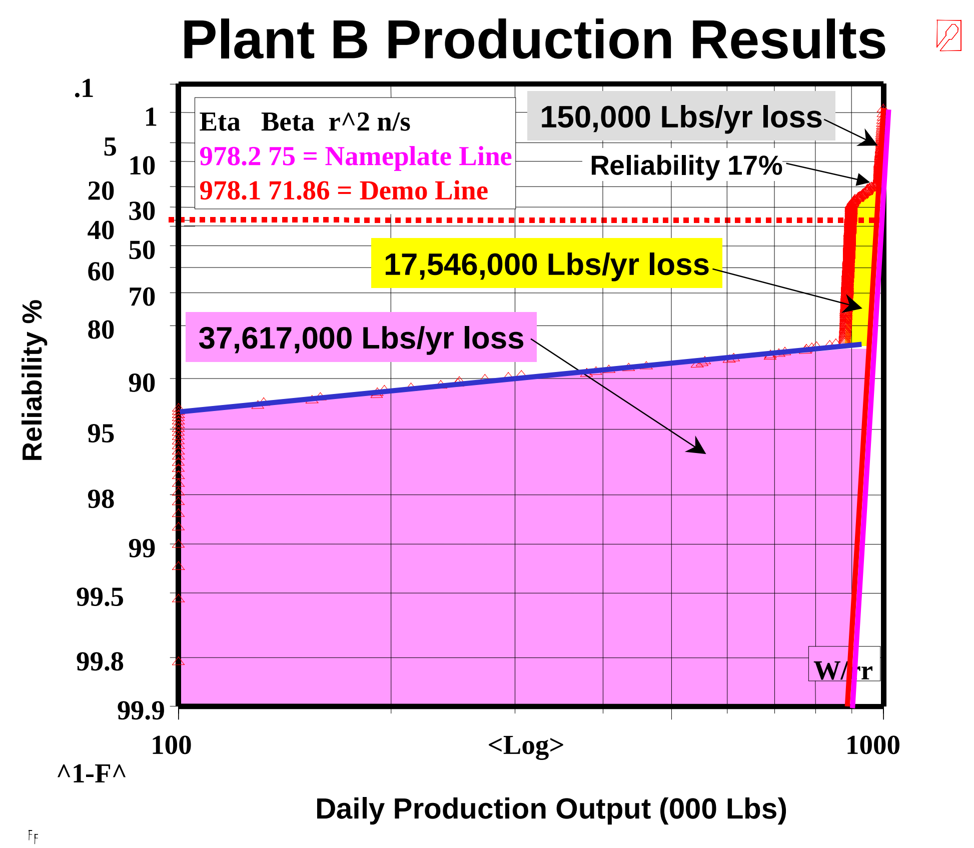

Figure 6: Plant B Production Gaps With Total Losses = 55,313,000 Lbs

The total production output from Plant A is 298,065,000 lbs/year. Plant A has losses of 55,557,000 lbs/year (55,557/(298,065+55,557) = 15.7% loss production attributed to the hidden factory. Output from Plant B is 299,054,000 lbs/year with losses of 55,313,000 lbs/year. For practical purposes, the output from both plants is the same and the losses are the same. The **type of loss** is different between Plant A and Plant B. Because the types of losses are different, expect solutions for reducing losses will also be considerably different between the two plants.

In Figure 5 and 6, which problem will be easier to solve?—most likely Plant B because the cutback in output will be easier to observe and correct, and likewise, the number of outage days stands out like a sore thumb. These types of losses are usually easier to solve than the systemic (efficiency and utilization) problems associated with Plant A.

Plant A and Plant B in Figure 5 and Figure 6 can be expected to have similar looking Weibull plots of the production data from year-to-year as they operate under some degree of self-organizing control. Self-organization is one of the principles of the modern theory of complexity which also argues that we need to look at results from the top down and set the few rules using non-linear (i.e., Weibull) mathematics to govern the system. (Waldrop 1992)

Shewhart defined control as "…a phenomenon will be said to be controlled when, through the use of past experience, we can predict, at least within limits, how the phenomenon may be expected to vary in the future." (Shewhart 1931) Shewhart went on further to describe, "…unknown cause of a phenomenon will be termed a chance cause.", and "…assignable causes of variation may be found and eliminated.". Both conditions of chance variation and assignable cause variation are seen in the figures previously described. The steepness of the data trend shows evidence of chance events at work (even though most production people will swear their production processes are strictly cause and effect at work).

Deming points out that without statistical control, the chaos of the system mask effects to make improvements and "With statistical control achieved, engineers and chemists became innovative, [and] creative. They now had an identifiable process." In the war against waste and hidden factories, Deming also says "We in America have worried about specifications: meet the specifications. In contrast, the Japanese have worried about uniformity, working for less and less variations about the nominal value…". (Deming 1986).

Deming's tightness of control is illustrated in Figure 7 by looking at the output from two plants with nameplate trend lines with betas of 75 and eta = 978.2 and eta 975.8. The combined results will give a cumulative condition for Plant A + B output nameplate with beta = 125.4 and eta 1949. This clearly emphasizes and reinforces the adage—the rich get richer and the poor get poorer! Multiple good and consistent plants show very predictable aggregated production, but inferior plants produce much misery as shown by the demonstrated line from aggregating the outputs from the two plants where the combined line slope is very flat and roughly 30% of the production will cause many heartaches.

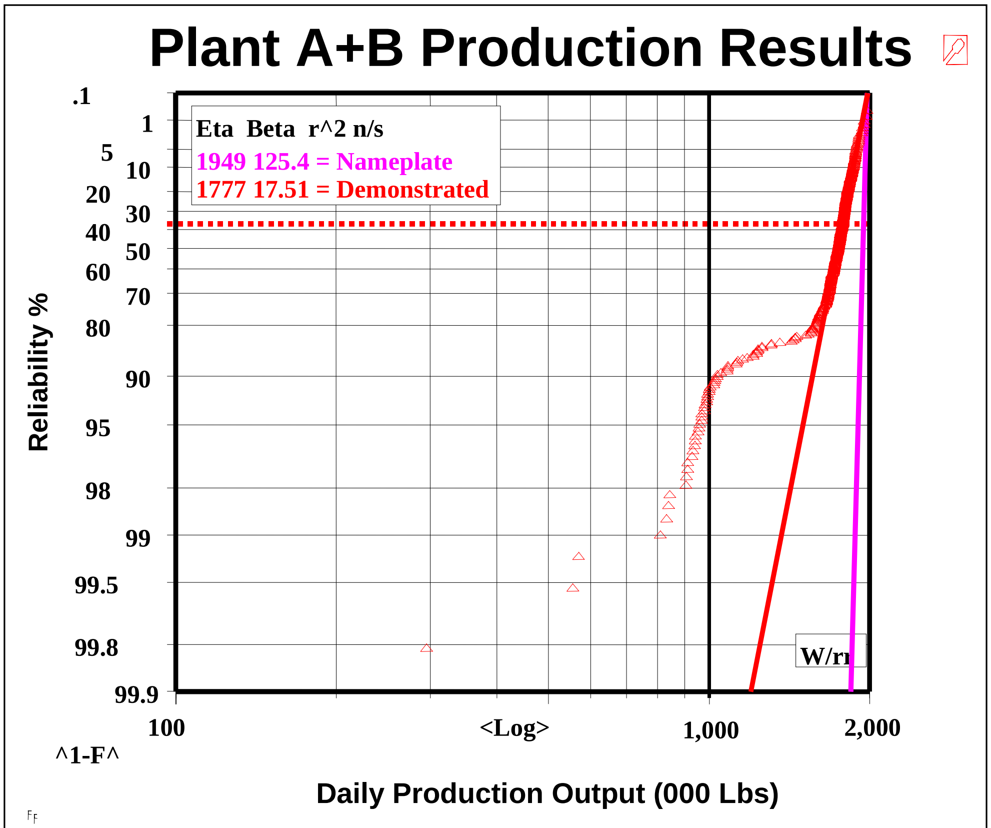

Figure 7: Combined Output Of Plants A & B

Monte Carlo Simulations

How were the actual combined results of Plants A+B and the steep beta of the nameplate line obtained? A simple Monte Carlo simulation using an Excel™ spreadsheet with 365 rows of data with column A simulating Plant A line segments in Figure 5, and column B simulating Plant B line segments in Figure 6. The combined output in column C summed the results from Plant A and B. The Monte Carlo simulation method is explained in Abernethy's book. Table 2 shows an illustration of the technique for several rows in the spreadsheet.

Table 2: Sample Calculation Of Nameplate Output For Plant A + Plant B

Row	Column A	Column B	Column C	Column D	Column E	Column F
1	**Day**	**Plant A**	**Plant A Output**	**Plant B**	**Plant B Output**	**Output**
2			**From Random #**		**From Random #**	**A + B**
3		**Reliability =**	**β = 75**	**Reliability =**	**β = 75**	**(Col C + E)**
4		**(1 - Rand #)**	**η = 975.8**	**(1 - Rand #)**	**η = 978.1**	
5	1	93.692%	940.91	1.711%	996.57	1937.48
6	2	3.373%	991.81	92.238%	945.84	1937.65
7	3	4.696%	990.45	44.892%	975.21	1965.66
8	4	2.580%	992.82	59.292%	969.68	1962.49
9	5	20.015%	982.01	82.901%	956.51	1938.52
10	6	49.579%	971.20	50.720%	973.06	1944.26
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364	360	53.500%	969.71	19.261%	984.63	1954.34
365	361	63.798%	965.45	41.441%	976.45	1941.90
366	362	35.617%	976.21	66.684%	966.39	1942.60
367	363	75.354%	959.51	85.309%	954.40	1913.91
368	364	32.719%	977.24	96.319%	936.20	1913.45
369	365	14.945%	984.19	38.700%	977.42	1961.61

The demonstrated production curve for Monte Carlo simulation is more complicated but similar to the nameplate simulation. Each segment of the actual production line must be described in Weibull terms so that when a random number is drawn, it is related to the particular portion of the demonstrated trend line segments. Most actual demonstrated production lines can be represented in 5 or 6 segments in an Excel spreadsheet using IF statements. Patterns on the Weibull plot will be repeated unless effective solutions are implemented to eliminate the root cause of the deficiencies.

Curiously enough, production people accept outputs from Weibull Monte Carlo simulations as being good representations of what they see in their plant outputs. The magic of building plant output in a spreadsheet fits their sense of propriety and what they experience in real life—particularly when the simulation uses patterns previously experience by the process and described in a Weibull probability plot. The expectations of production personnel fits the concept of John Goodman (Dyrck 1999): "There are comparatively few engineering problems in which the data are known to within, say, 5%, hence it is a sheer waste of time for the engineer in practice to use the long complex methods when simple, close approximations, can be used in a fraction of the time".

When you hypothesize changes/improvements in the process, the Monte Carlo simulation can quickly tell you the bottom line for expected output and expected losses. Simulations do not save money—finding the problem and fixing the problem is what saves money.

This Method Extends and Complements Six-Sigma

Six-sigma techniques are concerned about time sequences of data. Weibull analysis looks at the output in a random manner where time sequence of data is not so important. The methods are different—but complementary.

The thrust of 6-sigma is to reduce variations and so is the thrust of Weibull process reliability analysis. The Weibull process reliability issue is to identify problems (and patterns of problems) and solve the problems to reduce losses. Older descriptions of 6-sigma covered a range of $\pm 3*\sigma$ or 99.73% of the output—notice this is close to the percentage covered by the y-axis on Figures 1-7 (99.9% - 0.1% = 99.8%). In a well-controlled process, with small variation in output, the coefficient of variation (sigma/x-bar) for the process is very small—this is similar to having a large beta in Weibull parlance for a given eta value and short cuts for COV are described (Dyrck 1999). Evans in the summary and purpose of a RAMS tutorial says: "Reliability is not a matter of applying the latest statistical techniques. It is blood, sweat, and tears engineering to find out what could go wrong with a product or process, to organize that knowledge so it is useful to engineers and managers, and then to act on that knowledge." (Evans 1999)

Weibull probability distribution curves, PDF, for process with steep betas show a relative distribution of production output, which is believable by production personnel. Weibull PDF curves show limits to higher levels of production but emphasizes greater chances for lower production—this is the case in most production facilities. Look at Figure 8. Compare the believable Weibull curve with its limits on high production to the symmetrical Gaussian curves allowing unbelievable extremes for high production data.

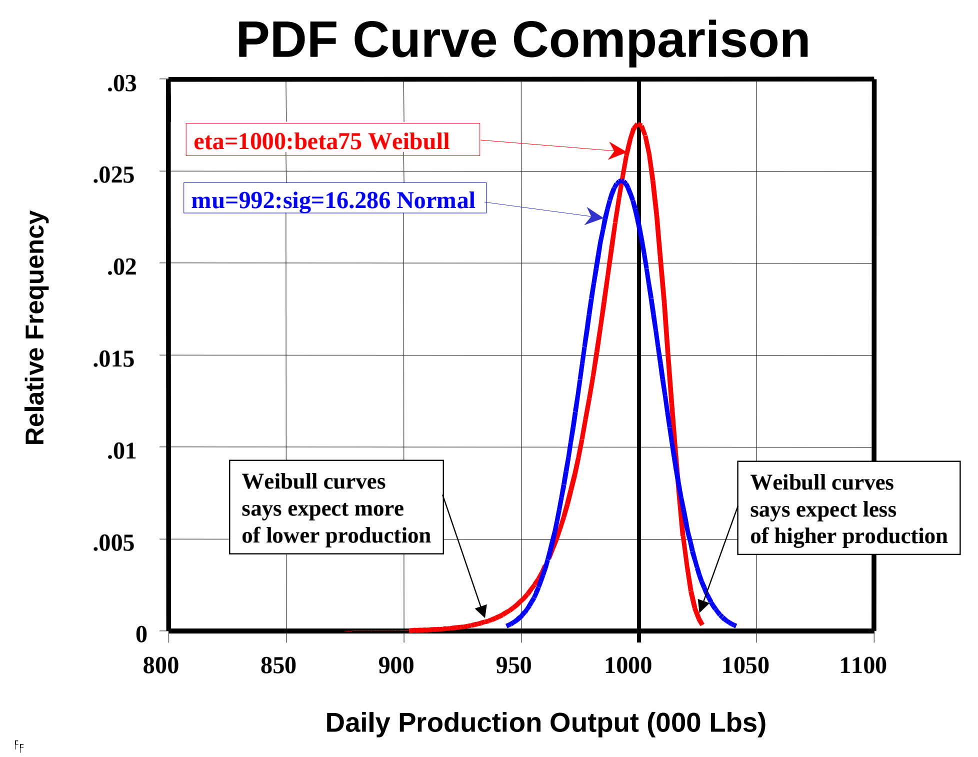

Figure 8: Probability Density Function Curve Comparison

The Weibull distribution is recognized as a universal law linking many scientific situations. The concept appears useful in areas as diverse as turbulence, magnetic characteristics, mineral deposits, floods, land slides, species in ecosystems, self-similarity of vegetation, insurance losses, avalanches, earthquakes, and other issues associated with the edge of chaos which revolves around identifying patterns in apparently unpredictable sequences of events as described by Peel. (Peel 1999) These concepts also fit the emerging science of complexity, mentioned earlier, for explaining many events.

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