

Explaining Reliability Growth

WHITE PAPER

Table of Contents

Introduction	1
Reliability	1
Reliability Growth	2
What is Reliability Growth?	2
Test Phases	2
Reliability Growth as a Process	3
Why Should We Employ Reliability Growth Methods?	4
The Mathematical Modeling Pioneers	4
<i>T. P. Wright</i>	4
<i>J. T. Duane</i>	4
<i>L. H. Crow</i>	7
Benefits of Crow-AMSAA Methodology	7
Technical Details	8
The Poisson Process	8
Rate of Occurrence of Failures	9
The Homogeneous Poisson Process (HPP)	9
The Nonhomogeneous Poisson Process (NHPP)	9
The Weibull NHPP (Crow-AMSAA Model)	9
The Reliability Growth Slope and the Weibull NHPP	11
Reliability Growth Test Structure	12
Exact Failure Times versus Interval-Censored Failure Times	12
Failure and Time Termination of Test Phases	12
JMP® Implementation	12
JMP® Examples	13
Example 1: New Engine - Crow-AMSAA Model	13
Example 2: Turbine Design - Piecewise Weibull NHPP	16
Example 3: Gaskets - Piecewise Weibull NHPP, Date in Timestamp Format	19
The Recurrence Platform	22
Recurrence	23
<i>Available Models</i>	23
<i>Popular Features</i>	23
Reliability Growth	23
<i>Available Models</i>	23
<i>Popular Features</i>	24
Conclusion	24

Co-authors of this white paper are Marie Gaudard, a consultant with the North Haven Group, a consulting firm specializing in statistical training and consulting using JMP; and Leo Wright, product manager of reliability and quality solutions for the JMP division of SAS.

Introduction

Quality of manufactured goods continues to be of critical importance for organizations intent on remaining competitive in today's global marketplace. Reliability of products and processes is a critical component of the quality equation. In the words of Dr. Bill Meeker, "Reliability is quality over time."

This paper focuses on the general area of reliability growth, whose goal is to increase product and process reliability. We engage in a general discussion of the reliability growth methodology and describe some of the technical details behind the methodology. We then provide some illustrations of how JMP supports reliability modeling, tracking, and evaluation through the Reliability Growth platform introduced in JMP 10.

Reliability

When and how do we apply reliability methods? First, we mention that reliability methods can be applied very widely, to processes as well as products, and to transactional processes as well as to manufacturing processes. But to limit our discussion somewhat, let's talk about manufactured products. We can think of manufactured products as having different types of lifetime assumptions: perishable, disposable (by design or due to low cost of replacement), or repairable.

Reliability techniques are useful for all these assumptions, but the nature of the methodology employed may be dictated by the lifetime assumptions. Repeated Measures Degradation can be used for shelf life studies on perishable items. Lifetime analysis can be applied to understand failure performance for durable or disposable goods. For example, you might want to determine the B10 life – namely, the time point at which 10 percent of products can be expected to fail. For repairable systems and durable goods, models of the mean time between failures (MTBF) and the mean time to repair (MTR) are of value.

Perhaps the best known and most documented area of reliability is that referred to variously as lifetime analysis, life distribution analysis, or failure analysis. This methodology is usually applied to products that are not repairable; by definition, these products are subject to only one failure. The objective of life distribution or failure analysis is to assess reliability performance over time, focusing on the time to that first failure.

Though the area of lifetime analysis is well documented and very rich in terms of analytic methodologies, methods for the analysis of repairable systems are of equal importance. Many products, processes and systems are intended to be repaired, rather than replaced, following a breakdown. Examples of these products, processes and systems include automobiles, refrigerators, washers and dryers, computers, high-end electronic equipment, aircraft, radar systems, satellites, computer networks, software systems, manufacturing processes and delivery processes.

With this background, let's talk about reliability growth.

Reliability methods can be applied widely, to processes as well as products, and to transactional processes as well as to manufacturing processes.

Reliability Growth

What is Reliability Growth?

Reliability growth is a methodology used in modeling, designing, and improving repairable systems. It consists of a collection of techniques designed to improve the reliability performance of a new or existing product, component, or system over time.

Reliability growth is often used in the design of complex systems, where once a prototype is designed, it is put on test with the goal of identifying and correcting failure modes. When a failure occurs, the failure mode is identified, and a change is made to the design that, if effective, keeps that failure mode from recurring. The prototype is fixed and testing continues until the next failure occurs. As more and more failure modes are surfaced and addressed, the reliability of the prototype, measured as the mean time between failures, is expected to increase.

The idea is that surfacing failure modes and then addressing them in a methodical fashion by improving the design will lead to a design with higher reliability. Once the test period is completed and all corrective design improvements have been applied to the prototype, it is assumed that the ongoing reliability will remain at the constant level that has been achieved at the end of the test period.

Test Phases

In many cases, a reliability growth program consists of several test phases. Once a prototype is built, there is often a validation phase during which it is determined whether or not the prototype can meet the performance requirements. The validation phase can be followed by a development testing phase, where the prototype is refined to meet or exceed the performance requirements. This development phase can be followed by an operational testing phase, where the system is built as if in production. As part of the operational test, details of the manufacturing process are tested and finalized. At this point, the typical assumption is that the ongoing failure rate will remain constant.

The strategy used in addressing failure modes is another factor that leads to segmentation in terms of test phases. Some failure modes can be easily addressed with corrective actions during the testing period. Other failure modes may be difficult or impractical to address during a test phase. Corrective actions for these failure modes may be delayed so that they are implemented during a corrective action period at the end of the test period.

These strategy decisions often lead to a need to structure reliability growth programs in terms of several phases of active testing, each followed by a period during which formal testing is suspended while major redesign changes are implemented. It is typically the case that, during a given phase, some failure modes are addressed with corrective actions intended to improve reliability over the period of the test phase. It is also typical that some fixes are delayed and implemented during a corrective action period between active test phases. These corrective action periods, if successful, result in a redesign with increased reliability. Once the next test phase is initiated, the redesigned system is tested for additional failure modes – note that new failure modes may have been introduced by the corrective actions – and the process of implementing some corrective actions and delaying others continues. The process ends when the target reliability and other performance objectives have been achieved.

Reliability Growth as a Process

Reliability growth is frequently part of a design for reliability effort. It entails an iterative design-develop process that includes: detection of failure modes, identification of root causes, feedback of problems identified, redesign based on failure mode root causes, implementation of redesign, and verification of redesign effectiveness by retesting and iterating the process. (See Figure 1, as depicted in the “AMSAA Design for Reliability Handbook.”¹)

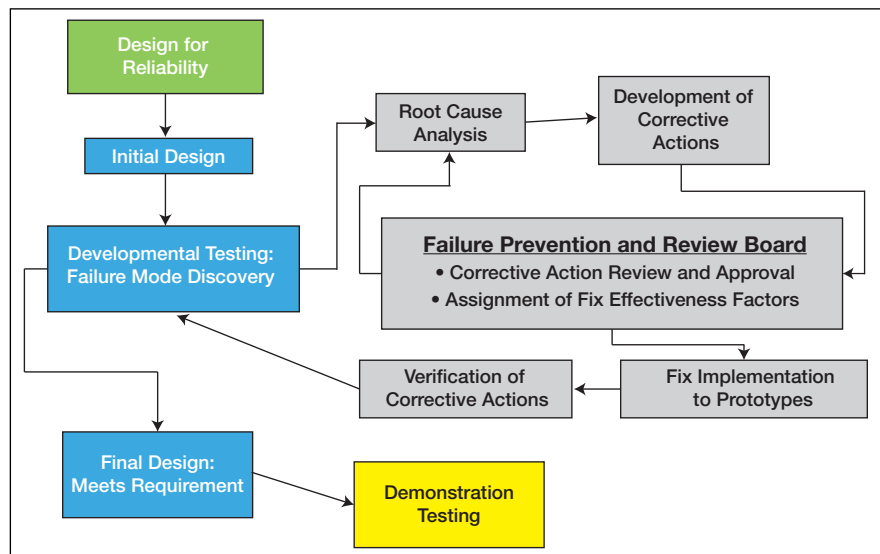


Figure 1: Reliability Growth Testing Process

Benefits of a sound reliability growth approach to product and process design include:

- Consumer safety, satisfaction and loyalty.
- Product and process dependability.
- Warranty and replacement cost minimization.
- Manufacturing and delivery cost reduction.

¹ Page 10, “AMSAA Design for Reliability Handbook,” TECHNICAL REPORT NO. TR-2011-24 AUGUST 2011 US ARMY MATERIEL SYSTEMS ANALYSIS ACTIVITY ABERDEEN PROVING GROUND, MARYLAND 21005-5071 APPROVED.

Why Should We Employ Reliability Growth Methods?

There are numerous reasons to engage in a sound reliability growth approach to product and process design. Some key benefits include: consumer safety, satisfaction and loyalty; product and process dependability; warranty and replacement cost minimization; and manufacturing and delivery cost reduction. More generally, these techniques support organizations in being profitable, healthy and competitive.

The Mathematical Modeling Pioneers

If we were to look back through history, we would find examples of colossal product failures such as manmade wheels that couldn't roll properly, horseshoes that did not last or that needed frequent repair, and planes that wouldn't fly. English craftsmen were producing large numbers of tools in the early 1800s, American military production ramped up in the early 1900s and, of course, everyone is familiar with Henry Ford and his mass production of the Model T. All of these efforts would have benefited from reliability growth methodology.

But let's move a little closer to the current day, starting in 1936. That year marks the start of the development that brings us to the methods that support what the global marketplace needs today.

T. P. Wright

In 1936, T. P. Wright proposed the idea that improvements in the time required to manufacture an airplane could be described mathematically. His findings showed that as the number of airplanes produced in sequence increased, the direct labor input per plane decreased in a mathematical pattern that forms a straight line when plotted on log-log paper (Comerford, N., "Crow/AMSAA Reliability Growth Plots," 2005).

J. T. Duane

In 1964, J. T. Duane of the General Electric Motors Division noted that successive cumulative estimates of mean time between failures (MTBF) plotted versus the cumulative operating time on log-log paper typically follow an approximately straight line. He found this to hold true across many reliability applications over diverse industries.

We will construct an example of what has come to be called a *Duane plot*. Consider a system with failures at various ages, as shown in Figure 2.

Failure Number	Age of System	Cumulative MTBF
1	33	33.00
2	76	38.00
3	145	48.33
4	347	86.75
5	555	111.00
6	811	135.17
7	1212	173.14
8	1499	187.38

Figure 2. Data for Duane Plot Example

A plot of the cumulative mean times between failures (**Cumulative MTBF** in Figure 2) against the operating time of the system (**Age of System**) is given in Figure 3. Note that the estimates of MTBF are increasing, which is a desirable situation.

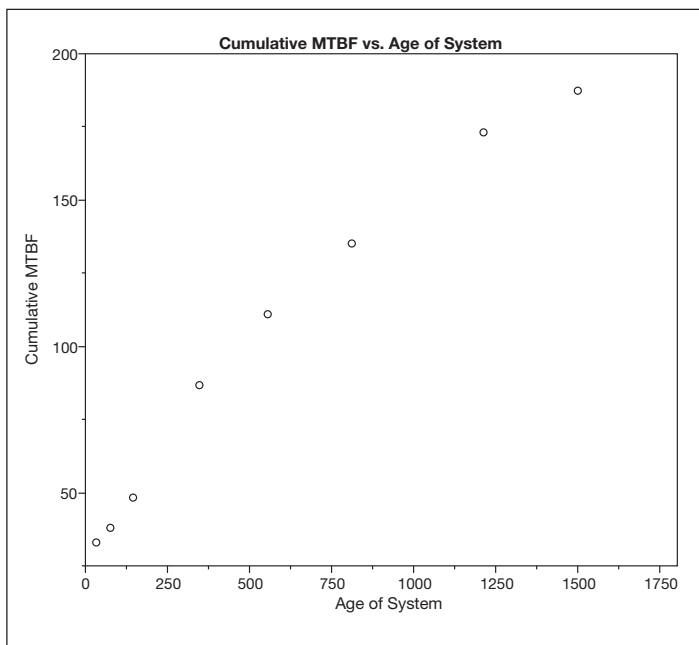


Figure 3. Cumulative Mean Time between Failures versus Age of System

When plotted using logarithmic scaling for both axes, the points follow a linear pattern, as shown in Figure 4.

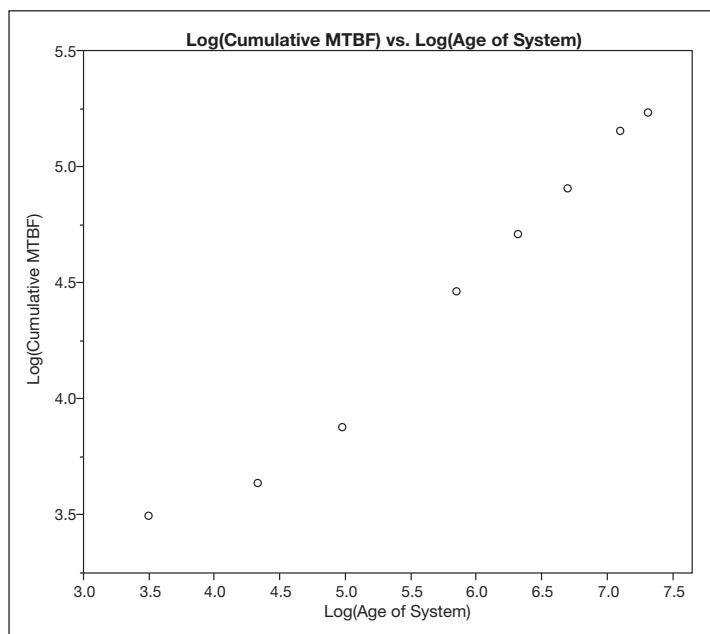


Figure 4. Cumulative Mean Time between Failures versus Age of System on Log-Log Scale

The points on the plot appear fairly linear. Figure 5 shows a fit using a least squares line. The slope of this line is 0.493.

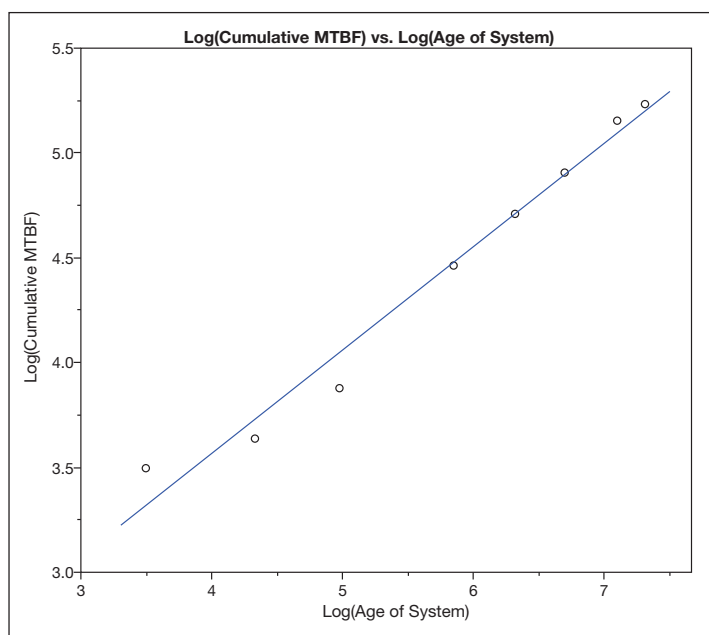


Figure 5. Duane Plot with Least Squares Line

The slope of the line in a Duane plot is known as the *reliability improvement slope*, or beta. A value of beta equal to 0 indicates a constant failure rate. A value of beta between 0 and 1 indicates that the MTBF is increasing and that failures are occurring more rarely. The closer beta is to 1, the lower the failure rate.

L. H. Crow

In a paper published in 1974 (“Reliability Analysis for Complex, Repairable Systems”), Larry H. Crow observed that Duane’s methodology could be formulated in terms of a Weibull process. Crow’s work on this model occurred while he was working at the Army Materiel Systems Analysis Activity (AMSAA). This formulation of the model came to be known as the Crow-AMSAA model.

The Crow-AMSAA model is a non-homogenous Poisson process with a Weibull, or power law, intensity function (see the *Technical Details* section). The Crow-AMSAA model is used to monitor reliability within a test phase.

Benefits of Crow-AMSAA Methodology

The Crow-AMSAA model is considered a “best practice” for reliability growth modeling during the development process (Abernethy, R. B., “The New Weibull Handbook,” 2006, p. 9-1). In addition, the use of the model extends beyond the development process. Here are some examples of its other uses:

- Tracking in-service repairable systems for reliability and maintainability.
- Providing management with significant event information.
- Analyzing “dirty data,” such as systems with changing reliability levels, mixed failure modes and missing data.
- Predicting warranty claims.
- Predicting new failure modes.

Furthermore, the Crow-AMSAA methodology and its extensions allow for the estimation and plotting of auxiliary quantities, such as the MTBF, the failure intensity, cumulative failures, achieved MTBF, as well as analytic results broken down by test phase.

It is important to realize that the use of reliability growth methodology extends beyond the physical system to encompass the entire reliability improvement process. The reliability improvement process must be readily visible to the organization. The Reliability Growth platform in JMP supports this concept by offering numerous graphical options built upon the Crow-AMSAA methodology. These drive efficient and accurate communication across the organization. For example, the JMP Reliability Growth platform provides:

- Graphs that make reliability growth or degradation clearly visible.
- Plots that display progress toward meeting reliability improvement goals, easing interpretation.
- Timely reliability predictions that can be compared with technical requirements or business goals.
- Analytic results that allow adverse trends to be discovered quickly.

Technical Details

The Poisson Process

The reliability of a system refers to its ability to perform as required under given conditions for a specified period of time. Reliability models are built around the occurrence of failures over time. Such models are called *counting* processes.

A very basic set of assumptions for a counting process is the following:

1. The number of failures at time 0 is 0.
2. The numbers of failures occurring in any two distinct time intervals are independent of each other.
3. Only one failure occurs at any given time.
4. There is a function, called the *intensity function*, that gives the instantaneous likelihood of observing a failure at time t .

When these assumptions are satisfied, it can be shown that the number of failures in any given interval has a Poisson distribution. If the intensity function is denoted by $\nu(t)$, then the number of failures in the interval $(a, b]$, say, has a Poisson distribution with parameter:

$$\theta = \int_a^b \nu(x) dx$$

In other words,

$$P(\text{No. failures in } (a, b] = n) = \frac{\theta^n e^{-\theta}}{n!}$$

for θ as above.

A process satisfying conditions (1) – (4) is called a *Poisson process*.

Rate of Occurrence of Failures

The *rate of occurrence of failures* is the instantaneous rate of change in the expected number of failures. For processes, such as the Poisson, that do not allow simultaneous failures, it can be shown that the intensity function equals the rate of occurrence of failures.

The Homogeneous Poisson Process (HPP)

A Poisson process with constant intensity function is called a homogeneous Poisson process. For such a process, suppose that the intensity function is simply $\nu(t) = \lambda$. It can be shown that the times between failures are exponentially distributed with mean $1/\lambda$.

The Nonhomogeneous Poisson Process (NHPP)

A *nonhomogeneous Poisson process* is a Poisson process whose intensity function is a nonconstant function of time.

Recall that a reliability growth program often consists of several test phases. Over the period of each test phase, an NHPP is often assumed as the model for failures. At the end of the final test phase, it is typically assumed that the future failure rate of the system will be constant, and the failure model at this point becomes a homogeneous Poisson process.

The Weibull NHPP (Crow-AMSAA Model)

The *Weibull NHPP*, which is equivalent to the Crow-AMSAA model, is a nonhomogeneous Poisson process with intensity function given by:

$$\nu(t) = \lambda \beta t^{\beta-1}$$

where $\lambda > 0$ and $\beta > 0$. The function $\nu(t)$ is called the *Weibull intensity*. The parameter λ is a scale parameter, because it depends on the measurement scale of the data. The parameter β is a shape parameter. It determines the shape of the graph of the intensity function. By varying β , one can model deteriorating systems ($\beta > 1$), improving systems ($\beta < 1$), and systems with constant failure rate ($\beta = 1$). As the value of β decreases, the rate of improvement increases.

The MTBF at time t is defined as the reciprocal of the intensity function at time t . Figure 6 shows a plot of the intensity function (blue) and of the MTBF function (red) for a Weibull intensity function where $\beta = 0.6$ and $\lambda = 1.0$. Note that the failure intensity function decreases over time, so that the MTBF function increases over time. This is an example of reliability improvement. On the other hand, Figure 7 shows a Weibull intensity with $\beta = 1.5$ and $\lambda = 1.0$. Here, the intensity function increases over time and the MTBF decreases. This illustrates deteriorating reliability.

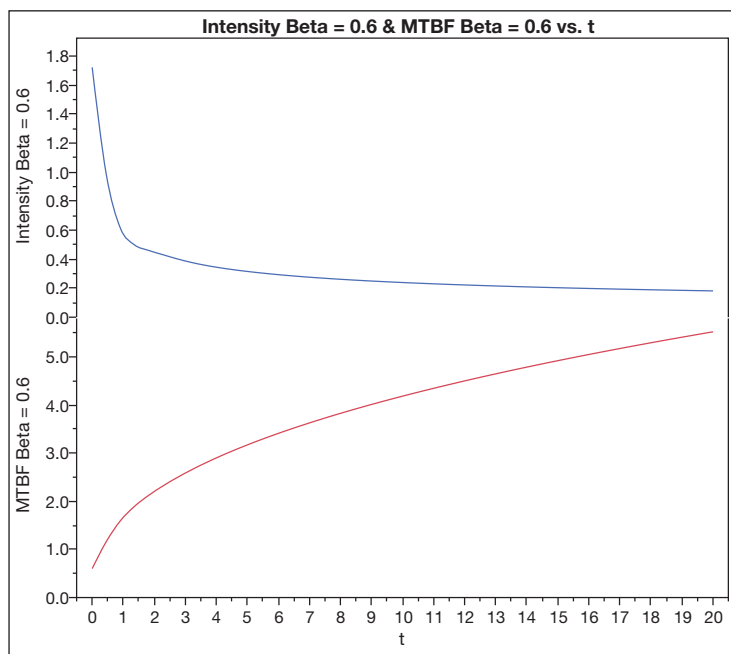


Figure 6. Weibull Intensity and MTBF for $\text{Beta} = 0.6$

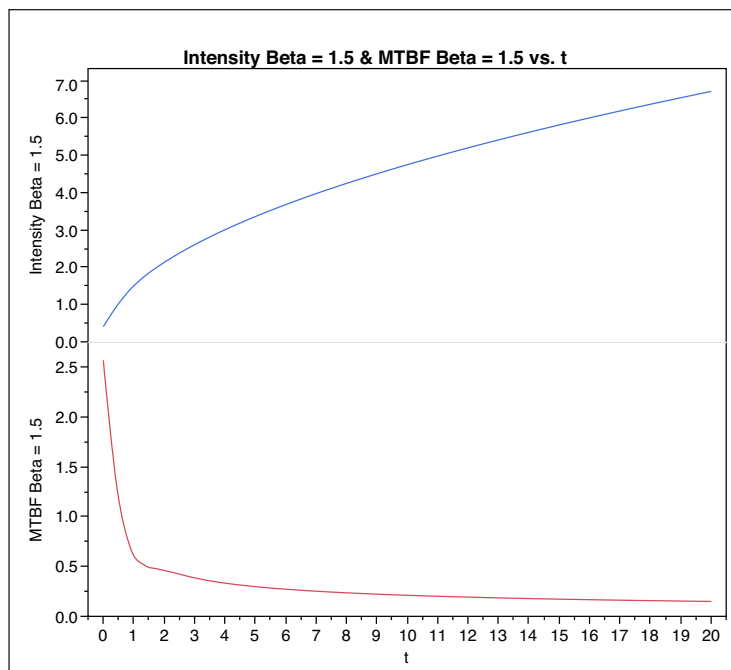


Figure 7. Weibull Intensity and MTBF for $\text{Beta} = 1.5$

JMP derives estimates for the parameters of the intensity function using maximum likelihood. Once estimates are obtained, various plots can be constructed. We will illustrate these in the final section, *JMP Examples*.

The Reliability Growth Slope and the Weibull NHPP

It's an unfortunate accident of terminology that the reliability growth slope in the Duane model is called "beta," and that the Weibull shape parameter is usually represented by the " β " symbol. We will always spell the word "beta" when we reference the reliability growth slope, while we will use the symbol " β " exclusively to represent the Weibull shape parameter.

The definition of the reliability growth slope generalizes to the Weibull NHPP in this way:

$$\text{beta} = 1 - \beta$$

To see this, consider that the Duane plot relates an estimate of the cumulative mean time between failures to the time under test. Given the Weibull intensity function, which gives the rate of failure at any time t , the number of failures occurring before time t is given by:

$$N(t) = \int_0^t \lambda \beta x^{\beta-1} dx = \lambda x^{\beta} \Big|_0^t = \lambda t^{\beta}$$

The cumulative mean time between failures at time t is $t / N(t)$. The reliability growth slope is the slope of a line fitting the points $(\log(t), \log(t / N(t)))$. Now,

$$t / N(t) = t / \lambda t^{\beta} = t^{1-\beta} / \lambda$$

For an NHPP with Weibull intensity, then, we can think of these as the points that are plotted on a Duane plot:

$$(\log(t), \log(t / N(t))) = (\log(t), \log(t^{1-\beta} / \lambda)) = (\log(t), (1 - \beta)\log(t) - \log(\lambda))$$

It follows that the slope of the line that fits these points is $\text{beta} = 1 - \beta$.

(To be precise, the points that are plotted are determined by the random failure times. So t in the above equations is a random variable. It can be shown that the expected values of the points that are plotted on a Duane plot are not exactly linear. See Rigdon, S. E. and Basu, A. P., "Statistical Methods for the Reliability of Repairable Systems," 2000, pp. 90-91.)

Reliability Growth Test Structure

Exact Failure Times versus Interval-Censored Failure Times

There are at least two ways in which failure data can be obtained:

- In some testing situations, a system is monitored or observed in real time and the (exact) time of failure is recorded. In this case, we say that we have *exact failure times*.
- In other testing situations, the system being tested is checked periodically for failures. In this case, failures are recorded as having occurred within time intervals, but the precise time of failure within an interval is unknown. In this case, we say that we have *interval-censored failure times*.

Failure and Time Termination of Test Phases

The plan for a test phase may require test termination once a specific number of failures has been observed or once a certain time span has elapsed. For example, a test plan might specify that testing will terminate once 25 failures occur. Or, it might specify that testing will terminate after 4000 hours of operation.

- If testing terminates based on a specified number of failures, we say that the test is *failure terminated*.
- If testing is terminated based on a specified time interval, we say that the test is *time terminated*.

JMP® Implementation

The Reliability Growth platform accommodates both exact and interval-censored data, as well as failure- and time-terminated test phases. The platform relies on the likelihood function for model-fitting. The likelihood function takes into account the type of failure time data that is obtained as well as the nature of test phase termination.

The user specifies the nature of the failure times and test phase termination by how data is entered into the data table. For details on how to structure the data table, we refer the reader to the JMP documentation.

We will show three examples in the next section:

- Example 1 is based on a single-phase failure-terminated test with exact failure times.
- Example 2 is based on a multiphase time-terminated testing program with interval-censored failure times.
- Example 3 is based on a multiphase time-terminated testing program as well, but the time is given as a timestamp, rather than as the number of time units since test initiation.

The Reliability Growth platform in JMP® provides visual tools that support product and process knowledge and help communicate that knowledge to others.

JMP® Examples

Example 1: New Engine - Crow-AMSAA Model

Open the data table **NewEngineOperation.jmp**, found in the **Reliability** subfolder of the **Sample Data** folder. The data table is shown in Figure 8.

	Hours	Fixes
1	148	1
2	396	1
3	1051	1
4	1858	1
5	2349	1
6	3747	1
7	4456	1
8	4553	1
9	4759	1
10	5192	1
11	7492	1
12	9829	1
13	10057	1

Figure 8. NewEngineOperation.jmp Data Table

The data are for a prototype for a new engine. The prototype was tested until 13 failures were observed. The exact failure times (**Hours**) and number of repairs (**Fixes**) were recorded. This resulted in a test that ran for 10,057 hours. Note that this is a failure-terminated single-phase test for which exact failure times were recorded.

To fit a Crow-AMSAA model to this data, do the following:

1. Select **Analyze > Reliability and Survival > Reliability Growth**.
2. Enter **Hours** as **Time to Event**. Enter **Fixes** as **Event Count**.
3. Click **OK**.

The **Reliability Growth** report opens to show a plot of cumulative failures over time (Figure 9). Click the disclosure icon next to **Mean Time Between Failures** to display a plot of observed mean failure times. These are computed over intervals that are chosen by the software, but you can adjust these to reflect time periods that you find meaningful by clicking the red triangle icon next to the plot title.

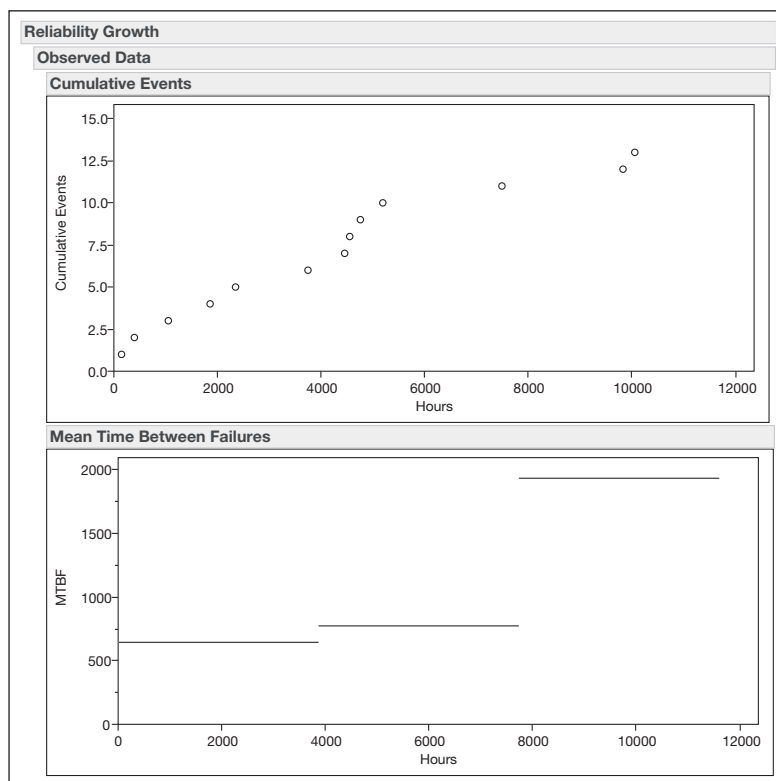


Figure 9. Reliability Growth Report

To fit a Crow-AMSAA model, click the red triangle next to the report title, **Reliability Growth**. From this menu, select **Crow-AMSAA**. The plots update to show the Crow-AMSAA model and confidence bands (Figure 10).

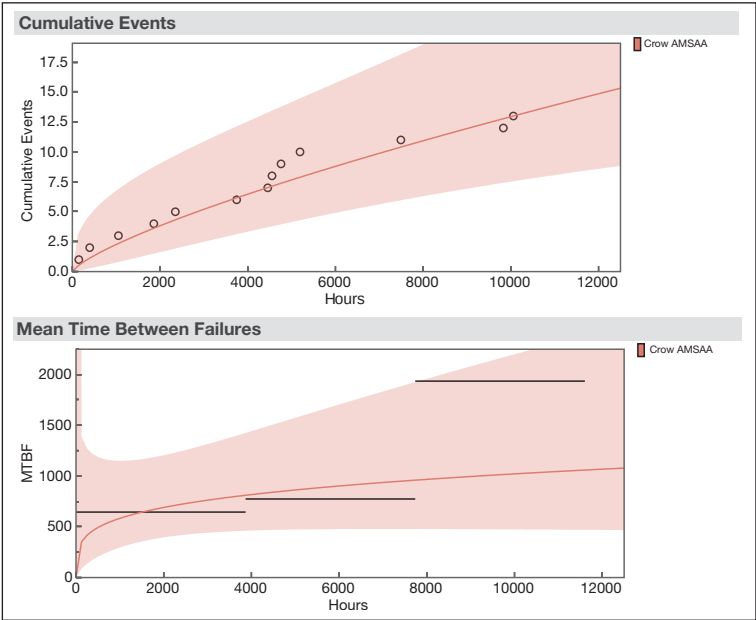


Figure 10. Crow-AMSAA Model Superimposed on Initial Plots

Beneath these plots, you see the Crow-AMSAA report (see Figure 11). This report shows a plot of the MTBF against **Hours**, on logarithmically-scaled axes. Below the plot are the estimated parameters of the Weibull intensity function, along with the Reliability Growth Slope. The reliability growth slope is 0.243, indicating some improvement.

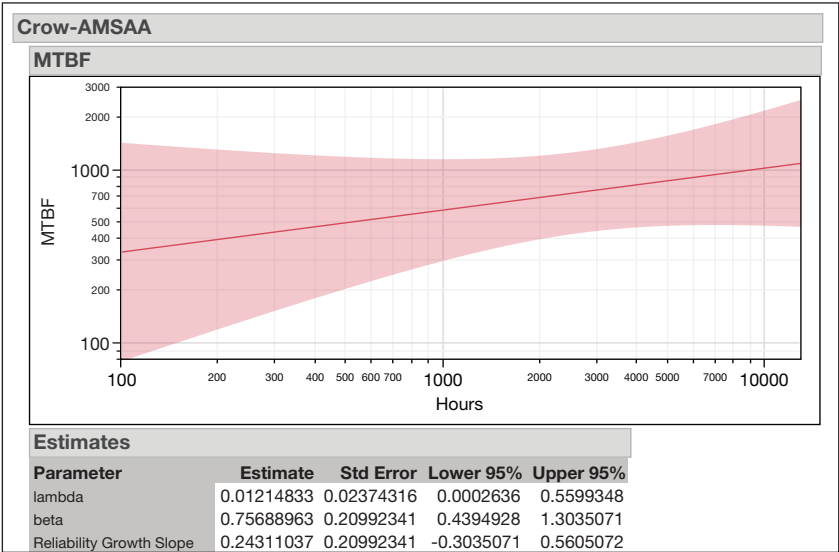


Figure 11. Crow-AMSAA Report

Various options are available from the red triangle menu associated with the Crow-AMSAA report. You can test for goodness of fit, obtain estimates relating to the *achieved MTBF* (the MTBF at the termination of the study), and generate various plots. In particular, you can obtain profilers for the estimated MTBF, the failure intensity function, and the cumulative events (Figure 12). These graphs are not logarithmically scaled, and, by moving the sliders, they allow you to explore behavior at various times during the test.

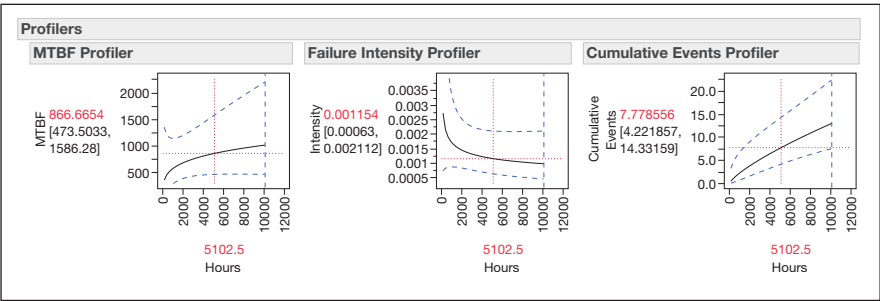


Figure 12. Profilers for Crow-AMSAA Fit

Example 2: Turbine Design - Piecewise Weibull NHPP

For our second example, open the data table **TurbineEngineDesign2.jmp**, found in the **Reliability** subfolder of the **Sample Data** folder. The data table is shown in Figure 13.

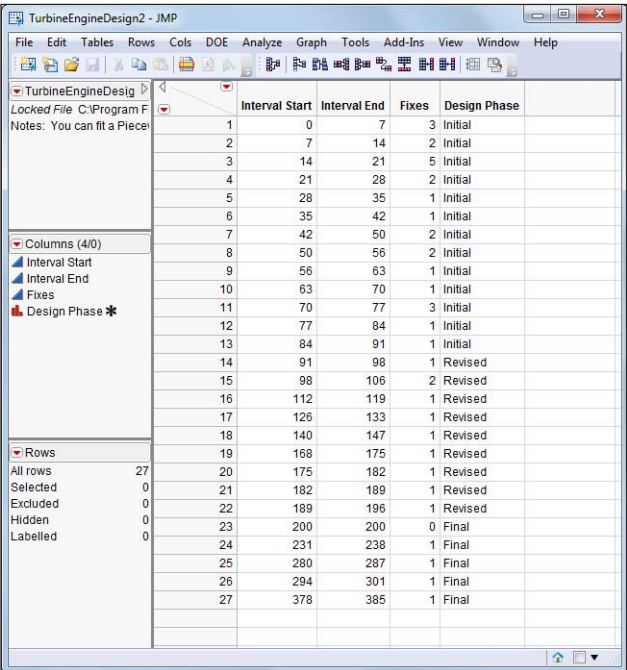


Figure 13. TurbineEngineDesign2.jmp

These data are for a turbine engine. The design and validation of the engine was conducted in three phases (**Design Phase**). Each phase has a specified time duration: the Initial phase begins on day 0 and runs for 91 days, the Revised phase begins on day 91 and runs for 109 days, and the Final phase begins on day 200 and runs for 185 days. The numbers of failures and repairs (**Fixes**) were recorded essentially weekly, and so start and end days are given in the first two columns (**Interval Start** and **Interval End**). Delayed fixes were made to the design during two corrective action periods, between the Initial and Revised, and between the Revised and Final, design phases.

Consider row 23, which gives the first entry for the Final phase. Here, both the **Interval Start** time and the **Interval End** time are recorded as 200, with 0 **Fixes**. This is to indicate the start of the Final phase. This was necessary, since there were no failures in the Final phase for approximately a month, until the week reflected in row 24. In contrast, the start of the Revised phase in row 14 was marked by a failure in the first week, and so no special indication was required. (The details of how to structure the data table to properly reflect phase termination are given in the JMP documentation.)

In summary, this data table reflects a three-phase test with time-terminated phases and interval-censored failure times.

We will fit a model that accommodates all three phases, the *Piecewise Weibull NHPP* model. To fit this model, do the following:

1. Select **Analyze > Reliability and Survival > Reliability Growth**.
2. Select **Interval Start** and **Interval End** under **Select Columns**.
3. Click **Time to Event**.
4. Select **Fixes** and click **Event Count**.
5. Select **Design Phase** and click **Phase**.
6. Click **OK**.
7. Click on the report's red triangle menu and select **Fit Model > Piecewise Weibull NHPP**.

The Cumulative Events plot updates to show the Piecewise Weibull fit (Figure 14). This model fits a Weibull NHPP model to the data from each test phase. These models track cumulative reliability growth over all phases. They are fit under the constraint that the cumulative number of events at the start of a given phase matches the number at the end of the preceding phase. The Cumulative Events plot shows vertical dashed blue lines at the phase transitions.

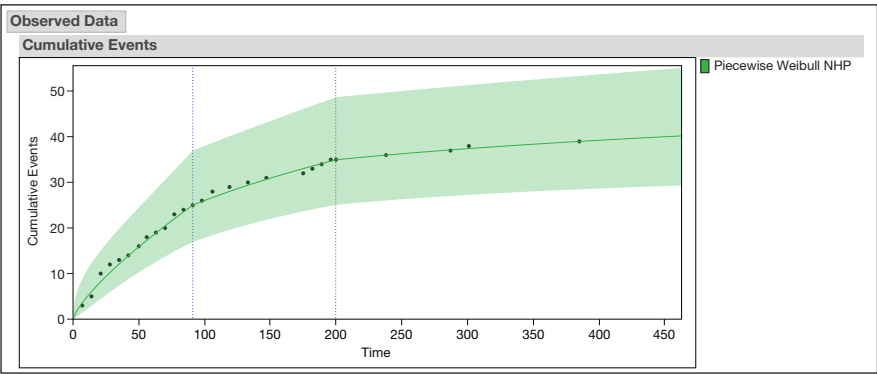


Figure 14. Cumulative Events Plot

The Piecewise Weibull NHPP report shows a logarithmically scaled plot of the MTBF against time (Figure 15). Note that the phases are color-coded for easy visualization. The slope of the line within each phase is an indicator of the amount of reliability growth that occurs within that phase. Here, we see that the Final phase has the largest slope.

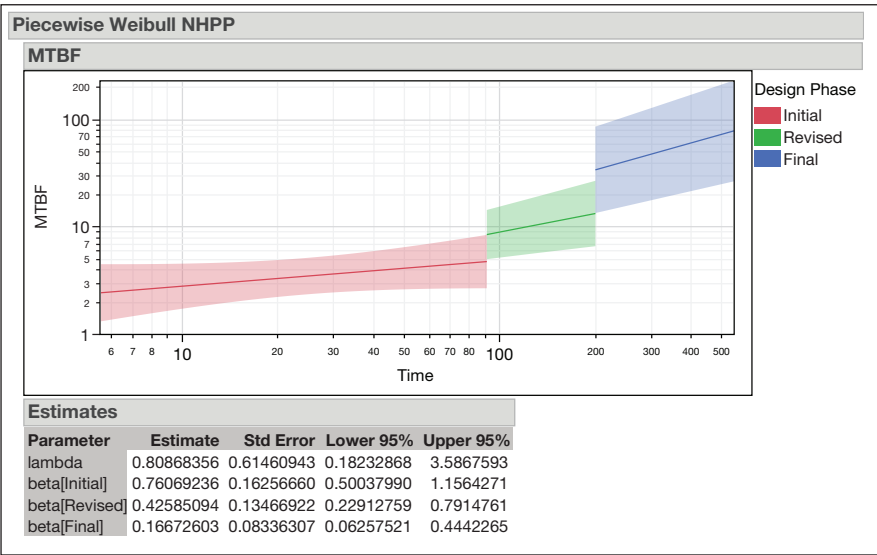


Figure 15. Piecewise Weibull NHPP Report

From the red triangle menu in the Piecewise Weibull NHPP report, choose **Profilers**. This displays three profilers; these plots are not logarithmically scaled.

Figure 16 shows the MTBF Profiler. The solid line segments show how MTBF is increasing over the three phases in terms of days. At the end of the third phase, the expected MTBF, conditioned on the observed failures, is 59.2 days, with a fairly wide confidence interval ranging from 21.2 to 165.7 days. The width of the interval is due, in part, to the fact that there are only five failures in the final phase. (Note that the MTBF, as seen in Figure 15, is actually discontinuous at the phase transition points. This is shown by a near-vertical line in the profiler.)

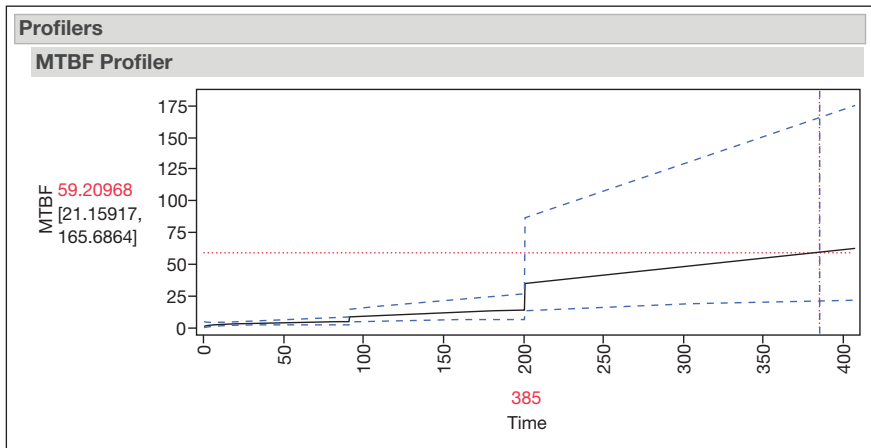


Figure 16. Mean Time between Failures Profiler

Example 3: Gaskets - Piecewise Weibull NHPP, Date in Timestamp Format

The oil and gas industry is heavily dependent on equipment performance. Pumping equipment, in particular, has a critical impact on uptime performance objectives. Reliability improvements that address gasket seal leakage, a common failure, can significantly affect the uptime metric.

This example illustrates the effects of one company's implementation of a reliability growth program to improve gasket seal performance. The goal was to reduce the MTBF to an average of no less than 10 days.

The data, shown in Figure 17, cover five phases of testing. Note that the dates of failures are given in a timestamp format (**Date**). During each **Phase**, failure modes were identified and some design improvement changes were applied as failures surfaced. Major design changes were made during corrective action periods between phases. The phases were time terminated, with rows 1, 12, 24, 29, and 39 each marking the start of a new phase. The program was continued until the desired MTBF average of 10 days was achieved. (This data table, **Gaskets.jmp**, is available on the [JMP File Exchange](#).)

Gaskets - JMP

File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help

Source: Oil and gas refinery indus
Reliability Growth

	Date	Failures	Phase
1	09/01/2011	1	1
2	09/01/2011	2	1
3	09/02/2011	1	1
4	09/03/2011	1	1
5	09/05/2011	2	1
6	09/06/2011	2	1
7	09/08/2011	2	1
8	09/14/2011	3	1
9	09/17/2011	1	1
10	09/26/2011	3	1
11	09/28/2011	1	1
12	09/29/2011	0	2
13	10/01/2011	3	2
14	10/04/2011	1	2
15	10/07/2011	2	2
16	10/10/2011	1	2
17	10/15/2011	1	2
18	10/19/2011	1	2
19	10/19/2011	1	2
20	10/23/2011	1	2
21	10/24/2011	1	2
22	10/28/2011	1	2
23	10/28/2011	1	2
24	10/31/2011	0	3
25	11/04/2011	1	3
26	11/05/2011	1	3
27	11/09/2011	1	3
28	11/13/2011	3	3
29	11/25/2011	0	4
30	11/30/2011	2	4
31	12/03/2011	1	4
32	12/06/2011	2	4
33	12/15/2011	2	4
34	12/18/2011	1	4
35	12/28/2011	3	4
36	12/30/2011	1	4
37	01/13/2012	3	4
38	01/21/2012	1	4
39	01/25/2012	0	5
40	01/29/2012	1	5
41	02/03/2012	1	5
42	03/02/2012	1	5

Columns (3/0)
Date
Failures
Phase

Rows
All rows 42
Selected 0
Excluded 0
Hidden 0
Labelled 0

Figure 17. Gasket Data

To track the company's improvements over the test phases, we will fit a Piecewise Weibull NHPP model to this data. To fit this model, do the following:

1. Select **Analyze > Reliability and Survival > Reliability Growth**.
2. Select the **Dates Format** tab.
3. Select **Date** under **Select Columns** and click **Timestamp**.
4. Select **Failures** and click **Event Count**.
5. Select **Phase** and click **Phase**.
6. Click **OK**.
7. Click on the report's red triangle menu and select **Fit Model > Piecewise Weibull NHPP**.

The Cumulative Events plot updates to show the Piecewise Weibull fit (Figure 18). Recall that the vertical dashed blue lines show the phase transitions. We see evidence of improvement in all phases, with a slight decrease in the improvement trend during the fourth phase.

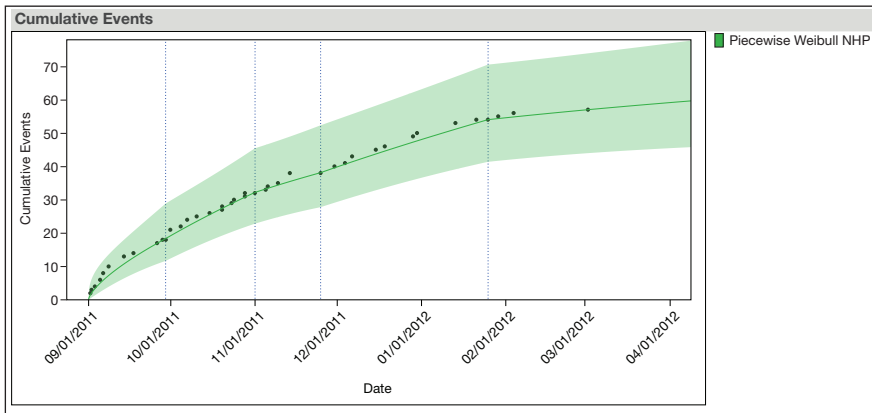


Figure 18. Cumulative Events Plot

The MTBF across all five phases, along with the associated parameter estimates, is shown in the Piecewise Weibull NHPP report (Figure 19). Note the values of the Weibull shape parameter, β , across the phases. The smaller this value is, the greater the improvement in failure rate. By the final phase, the value of β equals 0.241, corresponding to a reliability growth slope of 0.759.

Note that the MTBF average of 10 days is actually achieved prior to the start of the final phase. The company continued with a final phase because of speculation that a few failure modes might surface as a result of phase 4 design changes.

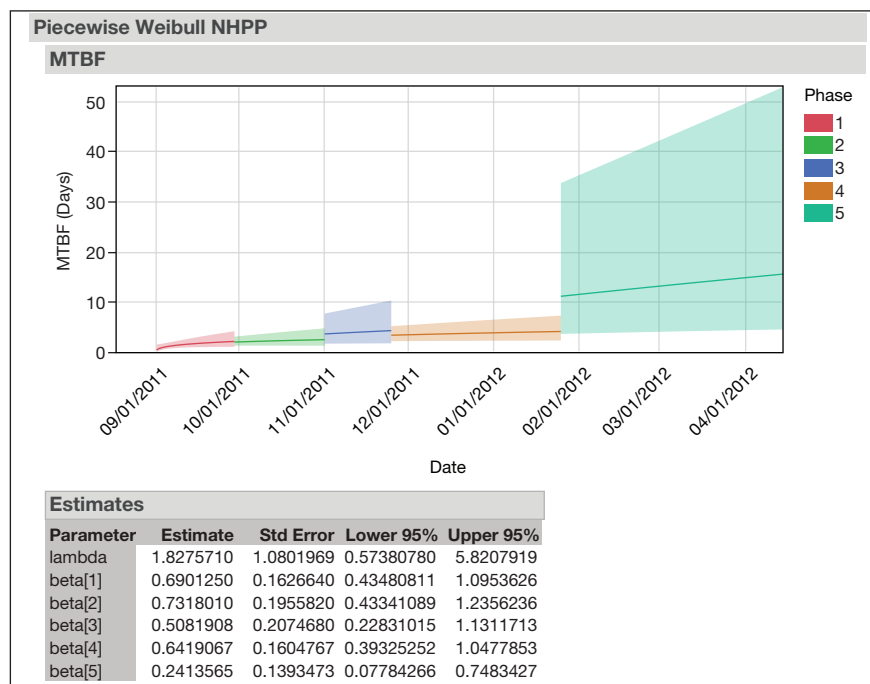


Figure 19. MTBF Plot and Estimates

JMP® provides an extensive array of tools to support reliability analysis for a variety of applications.

The MTBF profiler, shown in Figure 20, shows that, at the end of the final phase, the MTBF predicted by the model is 13.3 days. The confidence interval is wide, ranging from 4.2 to 42.5 days. This reflects, in part, the sparsity of data in the final phase, where only four failures are observed. If no further design changes are contemplated, this system can now be treated as though the failure rate will remain constant, and modeled as a homogeneous Poisson process.

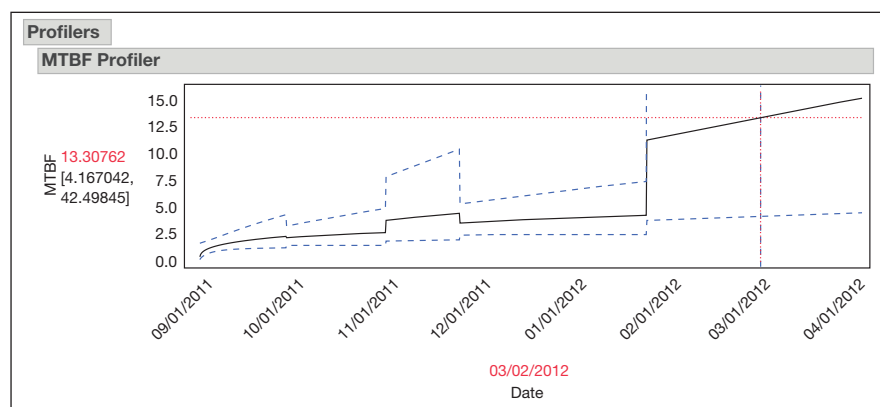


Figure 20. MTBF Profiler Set at 03/02/2012

The Recurrence Platform

JMP provides an extensive array of tools to support reliability analysis for a variety of applications. These include various methods for lifetime modeling, accelerated failure modeling, degradation modeling, product reliability forecasting, and recurrence analysis.

The Reliability Growth platform is one of three platforms dedicated to repairable systems analysis. The Recurrence Analysis platform and the Reliability Forecast platform are also valuable tools.

The Reliability Forecast platform estimates life distribution using production dates, failure dates, and production volume. Using this platform, you can:

- Visualize return data.
- Fit a life distribution.
- Forecast future returns based on current performance and planned future product shipments.

The Recurrence and Reliability Growth platforms have some overlap in terms of models for the analysis of repairable systems. However, they have specific objectives making them unique. Each platform offers visualization and analysis features that are specific to its objective.

To help guide the user in selecting the platform best meeting his or her needs, we offer a summary of key model and feature differences in the next two sections.

Recurrence

The recurrence platform analyzes repairable systems or, more generally, studies with recurrent events. The analysis integrates cost per unit. It models the total number of failures, or total cost of repairs, over time.

Available Models

- Mean Cumulative Function (MCF)
- Power NHPP
- Proportional Intensity Poisson Process
- Loglinear NHPP
- HPP

Popular Features

- Provides nonparametric estimation using the MCF.
- Conducts analysis by group.
- Fits parametric models by group.
- Allows parameters of intensity functions to be linear functions of effects.
- Provides profilers for parametric fits.
- Facilitates comparison of group differences.
- Includes analysis by specific failure modes.
- Tests for homogeneity.
- Tests for each effect in the model.
- Provides cost or repair analysis.
- Provides HPP model if renewal process is appropriate.
- Supports multiple data formats.

Reliability Growth

The Reliability Growth platform focuses on modeling the improvement of repairable systems. It provides plots and analyses relating to MTBF, failure rate and cumulative events over test duration.

Available Models

- Crow-AMSAA
- Fixed Parameter Crow-AMSAA
- Piecewise Weibull NHPP
- Reinitialized Weibull NHPP
- Piecewise Weibull NHPP Change Point Detection

Popular Features

- Provides basic growth analysis.
- Fits growth by phase.
- Automatically detects when a change in growth occurred.
- Provides intensity plots and analysis.
- Provides MTBF estimates and plots.
- Estimates achieved MTBF and confidence interval.
- Calculates the Reliability Growth Slope parameter (Duane).

Conclusion

Numerous tools have been developed and popularized to support continuous improvement professionals, engineers, manufacturers, and others as they improve the quality of their products and processes, thereby improving safety and satisfaction, while also increasing profitability. Those professionals who take advantage of modern software that promotes discovery through data visualization and analysis reap the benefits of rapid learning and deep insight into process performance.

The Reliability Growth platform in JMP provides visual tools that support product and process knowledge and help communicate that knowledge to others. It provides exploratory tools that support the understanding of products and processes. It has the potential to significantly amplify the benefits of reliability growth and design for reliability efforts.

About SAS and JMP

JMP is a software solution from SAS that was first launched in 1989. John Sall, SAS co-founder and Executive Vice President, is the chief architect of JMP. SAS is the leader in business analytics software and services, and the largest independent vendor in the business intelligence market. Through innovative solutions, SAS helps customers at more than 55,000 sites improve performance and deliver value by making better decisions faster. Since 1976 SAS has been giving customers around the world THE POWER TO KNOW®.



SAS Institute Inc. World Headquarters

+1 919 677 8000

JMP is a software solution from SAS. To learn more about SAS, visit sas.com

For JMP sales in the US and Canada, call 877 594 6567 or go to jmp.com

SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. ® indicates USA registration. Other brand and product names are trademarks of their respective companies. 106026_S98412.1012