JOURNAL OF SPACECRAFT AND ROCKETS
Vol. 46, No. 5, September–October 2009

Satellite Reliability: Statistical Data Analysis and Modeling

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DOI: 10.2514/1.42243

The technical literature has long recognized the importance of satellite reliability, but a statistical analysis of expansive on-orbit failure data is still lacking. As a result, inconsistencies persist in the literature due to the absence of an empirical basis for settling the issues, for example, regarding the existence or absence of satellite infant mortality. Weibull distributions with a shape parameter larger than one are commonly used to model satellite reliability. This choice for the shape parameter fails to capture infant mortality and is shown here to be flawed. The present work fills a gap in the technical literature by 1) conducting a thorough nonparametric statistical analysis of recent on-orbit failure data, 2) fitting a parametric model to the actual/observed spacecraft reliability, and 3) quantifying the relative contribution of each subsystem to satellite failure and identifying the subsystems that drive spacecraft unreliability. The sample analyzed in this study consists of 1584 Earth-orbiting satellites successfully launched between January 1990 and October 2008. The results presented here should prove useful for the space industry, for example, in redesigning satellite (and subsystem) test and screening programs and in providing an empirical basis for subsystem redundancy allocation and reliability growth plans.

Nomenclature

$D(t)$	=	dispersion of the 95% confidence interval around $\hat{R}(t)$
m_i	=	multiplicity of ties at time $t_{(i)}$
n_i	=	number of items functioning right before $t_{(i)}$
$\hat{P}_{\text{sat}}$	=	probability of satellite failure
$\hat{P}_{\text{sub},j}$	=	probability of satellite failure due to subsystem j
$\hat{p}_i$	=	conditional probability of surviving $t_{(i)} + \delta t$
$R(t)$	=	reliability function, also known as the survivor function
$R_n(t)$	=	reliability estimate from a complete data set with n units
$\hat{R}(t)$	=	Kaplan–Meier estimator of the reliability function from a censored data set
R^2	=	coefficient of determination in a regression analysis
r_j	=	percent contribution of subsystem j to the probability of satellite failure
T_F	=	random variable time to failure
$t_{(i)}$	=	ith failure time, arranged in ascending order
$\hat{\text{var}}$	=	estimated asymptotic variance of $\hat{R}$
β	=	Weibull shape parameter, dimensionless parameter
δt	=	arbitrary small time interval in which no failure or censoring occurs
θ	=	Weibull scale parameter, years
$\lambda(t)$	=	failure rate, also known as the hazard function
σ	=	estimated asymptotic standard deviation of $\hat{R}$

I. Introduction

RELIABILITY is a critical design attribute for systems operating in remote or inhospitable environments. Consider, for example, satellites or subsea installations: because physical access to these high-value assets is difficult or impossible, maintenance cannot be relied upon to compensate for substandard reliability [1]. As a result, designing high-reliability into these systems is an essential engineering and financial imperative.

For space systems, statistical analysis of flight data, in particular of actual on-orbit reliability and multistate failures, would provide particularly useful feedback to spacecraft designers. In particular, it would help guide satellite test and screening programs and provide an empirical basis for subsystem redundancy and reliability growth plans. Unfortunately, limited empirical data and statistical analysis of satellite reliability exist in the technical literature. In the following, we highlight three limitations with this state of affairs, namely that of 1) data obsolescence, 2) missing prerequisite/absence of realistic inputs, and 3) reliability specification/absence of model validation.

Before discussing these three points, it is worth addressing a common argument, which is that competitive sensitivity is one reason for the lack of published data and statistical analysis of on-orbit reliability. Although this might be true for satellite manufacturers, it is not the case for satellite operators (private or government agencies) whose interests are better served by transparent reliability analysis of different spacecraft buses. Furthermore, satellite manufacturers could also benefit, in the long-term, in having satellite reliability analyzed and published. For example, such studies would constitute a transparent benchmark against which satellite manufacturers can compete and hence improve their products' reliability. They can also constitute a strong motivation for satellite manufacturers to (re-)design their reliability improvement programs.

We start with the data obsolescence problem in satellite reliability studies. Binckes [2] provides one of the early references on satellite reliability. The author analyses communication satellite reliability and identifies mission-critical subsystems. This work, however, presents a mathematical model based on the Intelsat IV series of communications satellites of the 1970s. Given the significant technological changes in spacecraft design since the 1970s, the data on satellite reliability presented in [2] is obsolete and of limited relevance for today's spacecraft. Krasich [3] uses flight data from the Voyager, Magellan, and several of the Mariner probes to demonstrate a decreasing failure rate and infant mortality and concludes that an exponential lifetime distribution cannot match data from flight experience. Krasich [3] adds, "reliability predictions with MIL-HDBK 217 constant failures rates are unrealistic." Krasich's contribution is significant, but it is confined to interplanetary spacecraft "and other orbiters" (which are not identified). As a result, the range of applicability of that analysis is uncertain, and the data used, although more recent than that in [2], is two decades old or more, and thus suffers similar obsolescence and validity (or lack of) concerns.

Received 17 November 2008; revision received 13 March 2009; accepted for publication 13 March 2009.

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Next, we highlight the missing prerequisite/absence of realistic inputs problem in satellite reliability studies. Recent publications continue to recognize the importance of reliability for space system. Satellite reliability is often discussed and emphasized in the technical literature (see, for example, [4]), its impact on satellite revenue generation capability is investigated [5], and its allocation in spacecraft design is optimized [6]. However, although these studies make important analytical contributions, the key input to their models, namely the actual satellite reliability, remains missing. These studies assume a hypothetical satellite (and subsystem) reliability profile. Although the frameworks proposed in these papers remain valid irrespective of the particular inputs used, the applicability of the results to present-day spacecraft is contingent on how representative these inputs are of actual satellite reliability. Unfortunately, this last point remains unaddressed because limited recent empirical data and statistical analysis of satellite reliability exist in the technical literature.

Finally, we discuss the reliability specification/absence of model validation problem in satellite reliability studies. Other studies have proposed reliability budgets for satellites and satellite subsystems. These reliability calculations have been picked up by other works, and the results have probably been misinterpreted, as we briefly discuss in this paragraph. For example, Dezelan [7] calculated the required reliabilities for the sensors and bus of the GOES satellite. The author adopts a Weibull reliability distribution, based on Lawless [8]. Dezelan [7] then clarifies, “next, the [shape] and [scale] parameters values were adjusted to achieve an overall Mean Mission Duration of 7 years.” In other words, the parameters of the reliability function(s) flowed from an overall mean mission duration requirement and resulted in reliability requirements for the bus, payload, and overall spacecraft. Dezelan [7] finds, for example, a scale parameter of 111 months and a shape parameter of 1.6 for the Weibull distribution of the (whole) spacecraft reliability. It is important to keep in mind that these parameters do not constitute actual spacecraft reliability. Instead, they are reliability requirements necessary to satisfy an overall mean mission duration requirement. These values are also not unique, that is, another combination of shape and scale parameters can satisfy the same mean mission duration requirement. These reliability requirements have not been compared with or validated by actual flight data and, as a result, they are not necessarily representative of actual satellite reliability. This nuance may be subtle, but it is important. Brown et al. [9] based their analyses in part on reliability input from Dezelan [7] as well as a related work by the Aerospace Corporation (cited in [9]) and adopted a shape parameter for the Weibull distribution of 1.7, which they state is “a value commonly used for satellite systems.” This shape parameter is a commonly used requirement specification, but, as mentioned previously, it does not correspond to a commonly observed satellite reliability. In fact, in this paper, we show that this shape parameter of 1.7 is incorrect and falls in the wrong range of the shape parameter for actual satellite reliability. Recall that a shape parameter greater than one for a Weibull distribution, as used by Dezelan [7] and Brown et al. [9], corresponds to an increasing failure rate, which models wearout failures and therefore is at odds with the limited flight data analyzed by Krasich [3] showing a decreasing failure rate and infant mortality.

How do we resolve the inconsistencies between the findings of Krasich [3] and the calculations of Dezelan [7] and other work by the Aerospace Corporation [9]? These contradictions (decreasing versus increasing failure rate) arise and persist because of the surprising gap in the technical literature discussed previously, which recognizes the importance of satellite reliability but has not fully analyzed it based on actual expansive flight data. In this paper, we propose to fill this gap and help resolve some of these contradictions in the estimation of spacecraft failure rates. We do this by 1) conducting a thorough statistical analysis of recent flight data, 2) fitting a parametric model to the actual/observed spacecraft reliability, and 3) identifying and quantifying the relative contribution of each subsystem to the overall satellite failure probability.

Statistical analysis of reliability data should not be confined to the mere assessment of system reliability. Similarly, our objective in this work is not only to fill the gap in the technical literature by providing an empirically based spacecraft reliability model. We also hope this work provides helpful feedback to the space industry, for example, in redesigning satellite and (subsystem) test and screening programs and providing an empirical basis for subsystem redundancy allocations. Finally, we hope this work will invite academics and analysts to refocus their interest in satellite reliability on more practical and useful studies for the space industry than what has been done to date.

The remainder of this paper is organized as follows. In Sec. II, we describe the data and database used in this study. In Sec. III, we conduct a nonparametric analysis of satellite failure data. Building on the results of Sec. III, we perform in Sec. IV a parametric analysis and Weibull fit to satellite reliability. Next, in Sec. V, we provide a confidence interval analysis of our nonparametric analysis of satellite reliability. Finally, in Sec. VI, we identify and quantify the relative contribution of each subsystem to the failure of the satellites in our sample. Section VII concludes this work. The organization and flow of this work are illustrated in Fig. 1.

II. Database and Data Description

For the purpose of this study, we used the SpaceTrak® database [10]. This database is used by most of the world’s launch providers, satellite insurers, satellite operators, and manufacturers. The database provides a history of on-orbit satellite failures and anomalies, as well as launch histories since 1957. It should be pointed out that this database is not necessarily complete in a statistical sense because some military or intelligence satellites may not have their failures reported. Similarly, the database cannot be considered complete with respect to anomalies or partial failures because satellite operators may not report all partial failures, especially the ones that can be recovered from in a timely manner. This being said, the database is considered to be the most authoritative in the space industry with failure data for over 6400 spacecraft.

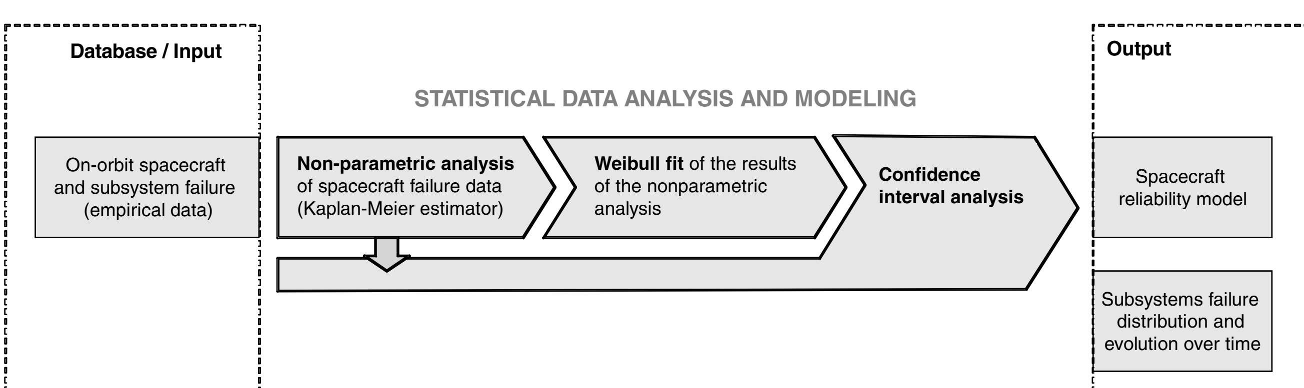

Fig. 1 Input, output, and organization of the present work.

The sample we analyzed consists of 1584 satellites from SpaceTrak®. We restricted the present study to Earth-orbiting satellites successfully launched between January 1990 and October 2008. We used what is referred to in the database as a class I failure, that is, a retirement of a satellite due to failure. In addition, the subsystems recognized in the database, and whose failures are identified as the cause of the spacecraft failures, are later discussed in Sec. VI. When the culprit subsystem (whose failure led to the spacecraft failure) could not be identified, the failure of the spacecraft is ascribed to an unknown category in the database. We used this categorization as well as the 13 specific subsystems identified when we analyzed the subsystems' failure distribution, that is, how much each subsystem contributes to overall spacecraft failure probability (details are in Sec. VI).

For each spacecraft in our sample, we collect 1) its launch date, 2) its failure date, if failure occurred, 3) the subsystem identified as having caused the spacecraft failure, hereafter referred to as the culprit subsystem, and 4) the censored time, if no failure occurred. This last point is further explained in the following section, where we discuss data censoring and the Kaplan–Meier estimator. The data collection template and sample data for our analysis are shown in Table 1.

One note is in order regarding the limitation of the present work. Although we statistically analyze the collective failure behavior of satellites recently launched, it can be argued that no two (or more) satellites are truly alike, and that every satellite operates in a distinct environment (in different orbits or even within the same orbit, where satellites, unless they are colocated, are exposed to different space environment conditions and events). As a result, the situation of the space industry is very different from that, for example, of the semiconductor industry where data on, say, millions of identical transistors operating under identical environmental conditions are available for statistical analysis (or other industries with items for which failure data can be easily obtained from accelerated testing or field operation).

The consequence is that, in the absence of satellite mass production, statistical analysis of satellite failure and reliability data faces the dilemma of choosing between calculating precise average satellite reliability or deriving a possibly uncertain specific satellite reliability. This dilemma is explained in the following two possible approaches.

The first approach is to lump together different satellites and analyze their collective on-orbit failure behavior [assuming that the failure times of the satellites are independent and identically distributed (IID)]. The advantage of doing so is that one can work with a relatively large sample and thus obtain some precision and a narrow confidence interval for the collective reliability analyzed. The disadvantage is that the IID assumption may not be realistic, and the collective reliability calculated (with precision) may not reflect the specific reliability of a particular type of spacecraft.

The second approach is to specialize the data, for example, for specific spacecraft platform or mission type or for satellites in particular orbits. The advantage of doing so is that the reliability analyzed is specific to the type of spacecraft considered (it is no longer a collective on-orbit reliability). The disadvantage is that the sample size is reduced and, as a consequence, the confidence interval expands (i.e., the results become increasingly uncertain). Given the available number of satellites (a few thousand), data specialization, which could reduce the sample size to, say, fewer than a hundred data points, would result in significantly large confidence intervals and thus highly dispersed and uncertain specific satellite reliability calculations.

In this paper, we adopt the first approach. We discuss the second approach in [11–13] and analyze on-orbit reliability of satellites by mission type, orbit, and mass categories (data for specific satellite platforms and by manufacturer are also available). Reliability of satellite subsystems can be found in [14].

III. Nonparametric Analysis of Satellite Failure Data

In this section, we briefly review censoring in statistical data analysis and the Kaplan–Meier estimator of reliability when the underlying data are right censored, as is the case in our sample. Nonparametric means that the statistical analysis does not assume any specific parametric distribution (also sometimes referred to as distribution-free analysis).

A. Censored Data Sample

Censoring occurs when life data for statistical analysis of a set of items are incomplete. This situation occurs frequently in multiple settings (e.g., medical and engineering contexts) and can occur because some items are removed before failure or because the test or observation window ends before all items failing. By contrast to censoring, a life data set is said to be complete if one observes the actual time to failure of all items in the sample under study. Censoring introduces particular difficulties in statistical analysis which, if not addressed and accounted for, can significantly bias the results. There are multiple classifications and types of censoring and different statistical techniques for dealing with them. In the following, we focus on what is relevant for our study and setting. The reader interested in more extensive detail is referred to three excellent books on the subject [8,15,16].

Our sample is right censored with staggered entry (type IV censoring, also referred to as random censoring). This means the following: 1) the units in our sample are activated at different points in time (i.e., the satellites are launched at different calendar dates), but all activation times in our sample are known; 2) failures dates and censoring are stochastic; and 3) censoring occurs either because a unit (satellite) is retired from the sample before a failure occurs or because the satellite is still operational at the end of our observation window (October 2008). This situation is illustrated in Fig. 2.

Staggered entries are easily handled by shifting all the activation times to $t = 0$, which changes the approach, and the x axis in Fig. 2, from a calendar-time to a clock-time analysis of satellite reliability. We therefore investigate satellite reliability as a function of time from successful launch.

Censoring of data requires particular attention. Deriving a reliability function from censored life data is not trivial, and it is important that is it done properly if the results are to be meaningful and unbiased. In this work, we adopt the powerful Kaplan–Meier estimator, which is best suited for handling the type of censoring in our sample. This reliability estimator is discussed in the next subsection.

B. Kaplan–Meier Estimator

The Kaplan and Meier publication [17], in which the estimator of the same name was proposed, is one of the most cited works in science. The reason for its major influence is that it provides an elegant and simple solution to a problem often encountered in many

Table 1 Data collection template and sample data for our statistical analysis of satellite reliability (satellites are not arranged/shown in chronological order)

Sample unit number	Launch date	Failure date (if failure occurred)	Culprit subsystem	Censored time (if no failure occurred)
Satellite 1	06 Nov. 1998	15 Nov. 1998	TTC	——
Satellite 2	01 March 2002	——	——	02 Oct. 2008
. . .	. . .	. . .	. . .	. . .
Satellite 1584	26 April 2004	28 March 2006	Mechanisms	——

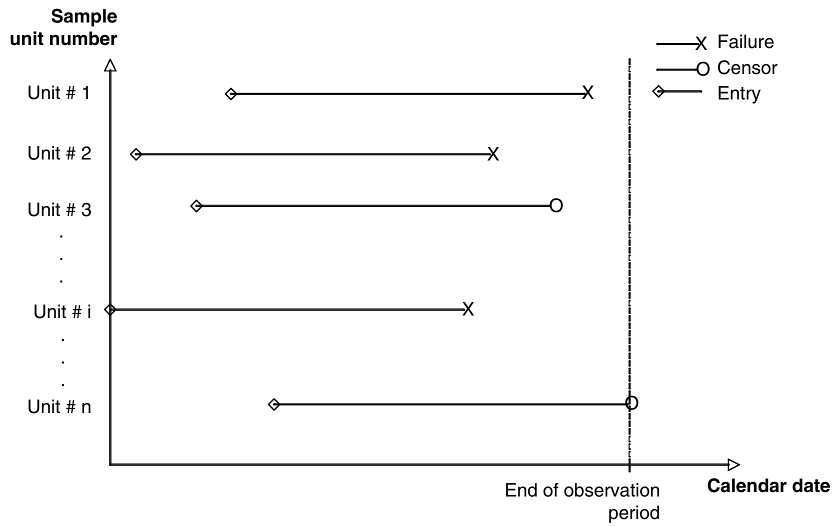

Fig. 2 Censored data with staggered entry.

disciplines (engineering, medical research, economics, etc.). In the following discussion, we first describe the empirical reliability function from a complete data set (i.e., all the failure times of the units in the set are observed). We then introduce the Kaplan–Meier estimator of the reliability function when the data set is incomplete and right censored.

Prerequisite: empirical reliability function from a complete data set. Consider n units activated at the beginning of an experiment, and let the experiment run until all units have failed. Let

$$t_{(1)} < t_{(2)} < t_{(3)} < \cdots < t_{(n-1)} < t_{(n)} \tag{1}$$

be the time to failure of all the units arranged in ascending order. We assume the lifetimes of the units are independent and identically distributed. We also assume that there are no ties in the data set, that is, no two units have exactly the same time of failure (the case with ties is discussed later). The empirical reliability function from this complete data set $R_n(t)$ corresponds to the number of units still operational at time t given the initial n operating units:

$$R_n(t) = \frac{\text{number of units still operational at time } t}{n} \tag{2}$$

We obtain the following results for $R_n(t)$:

1) For $t < t_{(1)}$, no failure has yet occurred, therefore $R_n(t) = 1$.

2) For $t_{(1)} \leq t < t_{(2)}$, only one unit has failed, and $n - 1$ units remain operation within this time frame. Therefore, $R_n(t) = (n-1)/n = 1 - (1/n)$.

3) For $t_{(2)} \leq t < t_{(3)}$, two units have failed, and $n - 2$ units remain operation within this time frame. Therefore, $R_n(t) = (n-2)/n = 1 - (2/n)$.

It is thus easy to see the pattern and generalize the result:

4) For $t_{(i)} \leq t < t_{(i+1)}$, i units have failed, and $n - i$ units remain operation within this time frame. Therefore, $R_n(t) = 1 - (i/n)$.

Finally, for $t \geq t_{(n)}$, all units will have failed and, in this time frame, $R_n(t) = 0$.

To summarize, the empirical reliability function from a complete data set of n units is given by Eq. (3):

$$R_n(t) = \begin{cases} 1 & \text{for } t < t_{(1)} \\ 1 - \frac{i}{n} & \text{for } t_{(i)} \leq t < t_{(i+1)} \\ 0 & \text{for } t \geq t_{(n)} \end{cases} \quad \text{for all } i \text{ such that } 1 \leq i < n \tag{3}$$

The empirical reliability function from a complete data set of n units $R_n(t)$ is therefore a staircase function with discontinuities at the observed time of failure of each unit and with a downward jump at each discontinuity of $1/n$. An example of such a function is illustrated in Fig. 3.

When ties are present in the data set, say m_j units failing at the same time $t_{(j)}$, a simple adjustment to Eq. (3) is required [1]. Equation (2) remains the basis for calculating the resulting empirical reliability, and the discontinuity in $R_n(t)$ at $t_{(j)}$ is now m_j/n, instead of $1/n$ as in the case with no ties.

The Kaplan–Meier estimator. Different presentations of the Kaplan–Meier estimator exist in the literature, some of which have rather involved (and occasionally convoluted) notation, for example, Ansell and Phillips [15] adopt different meanings for the set of data t_i, $t_{(i)}$, and $t_{[i]}$. In the following, we provide a simple presentation of this tool with an easy notation that is consistent with the previous discussion in this section.

We start with n operational units and, because of censoring, we collect m time to failure ($m < n$). For the time being, we assume no ties between failure times and censoring. As done previously, we organize the failure times in ascending order:

$$t_{(1)} < t_{(2)} < \cdots < t_{(m)}$$

The difference between the current situation and that of a complete data set is that some units may have been removed from the experiment (censored) between two consecutive failure times and, as a result, the index of time t in the present case $t_{(i)}$ is no longer indicative of the number of failures before $t_{(i)}$, as was the case in Eqs. (1) and (3). To capture this information, we introduce the following parameter:

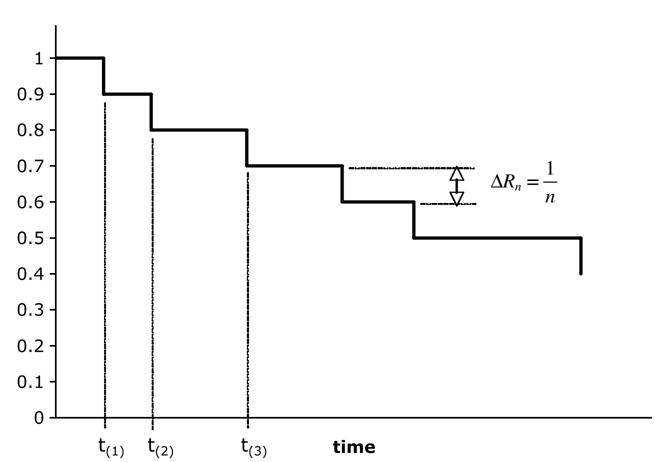

Fig. 3 Illustrative empirical reliability function from a complete data set of *n* units (with no ties).

n_i = number of operational units right before $t_{(i)} = n$

− [number of censored units right before $t_{(i)}$]

− [number of failed units right before $t_{(i)}$] (4)

We then define

$$\hat{p}_i = \frac{n_i - 1}{n_i} \tag{5a}$$

One major contribution of the Kaplan and Meier publication [17] was to note that Eq. (5a) is an estimate of the conditional probability of surviving just past $t_{(i)}$, or, more precisely,

$$\hat{p}_i \text{ estimate of } P(T_F > t_{(i)} + \delta t | T_F > t_{(i)}) \tag{6}$$

δt is an arbitrary small time interval in which no censoring or failure occurs. The other major contribution of Kaplan and Meier was to note that

$$P(T_F > t_{(i)}) = P(T_F > \delta t) \times P(T_F > t_{(1)} + \delta t | T_F > t_{(1)}) \times P(T_F > t_{(2)} + \delta t | T_F > t_{(2)}) \times \cdots P(T_F > t_{(i)} + \delta t | T_F > t_{(i)}) \tag{7}$$

and to replace each factor on the right-hand side of Eq. (7) by its estimate as provided in Eq. (5a). Note that, by the definition of δt, $P(T_F > \delta t) = 1$. Finally, recall that the reliability function is defined as

$$R(t) \equiv P(T_F > t) \tag{8}$$

We thus derive the Kaplan–Meier estimator of the reliability function with censored data by substituting Eqs. (5a) and (8) into Eq. (7):

$$\hat{R}(t) = \prod_{\text{all } i \text{ such that } t_{(i)} \le t} \hat{p}_i = \prod_{\text{all } i \text{ such that } t_{(i)} \le t} \frac{n_i - 1}{n_i} \tag{9}$$

As a result, the estimated reliability function from censored data, as given by Eq. (9), is a staircase function with discontinuities at the observed failure times. The estimated reliability function does not change at the censored times. However, unlike the previous case with complete data [Eq. (3) and Fig. 3], the jumps at the discontinuities are not equal $(1/n)$ but vary with the number of censored units between two consecutive failures [this is the result of Eq. (4) and its propagation through Eqs. (5a) and (9)].

The graphic representation of Eq. (9) is referred to as a Kaplan–Meier plot. When the data set is complete, the Kaplan–Meier estimator is equivalent to the empirical reliability function, that is, Eqs. (3) and (9) provide identical results.

Ties in the data set are handled in the following manner. The following two situations arise:

1) If one faces ties in the failure times, say m_i units failing at exactly $t_{(i)}$, this is referred to as a tie of multiplicity m. Equation (5a) is then replaced by

$$\hat{p}_i = \frac{n_i - m_i}{n_i} \tag{5b}$$

2) If a censoring time is exactly equal to a failure time $t_{(i)}$, a convention is adopted that assumes censoring occurs immediately after the failure, because a unit that is censored at a given time can survive an infinitely small period past $t_{(i)}$ [15,16].

C. Kaplan–Meier Plot of Satellite Reliability

We can now analyze the on-orbit satellite reliability from our censored data set. For the 1584 satellites in our sample (Sec. II), we have 98 failures times and 1486 censored times. The (ordered) failure times are provided in Table 2.

The censored times occupy a four-page list; for reading convenience and space, they are not included in this work. They can be made available from the authors upon request.

The data is then treated with the Kaplan–Meier estimator [Eq. (9)], and we obtain the Kaplan–Meier plot of satellite reliability shown in Fig. 4. Figure 4 reads as follows: For example, after a successful launch, satellite reliability drops to approximately 96% after two years on orbit. More precisely, we have

$$\hat{R} = 0.964 \quad \text{for } 1.982 \text{ years} \le t < 2.155 \text{ years}$$

Satellite reliability drops to approximately 94% after 6 years on orbit. Past 12 years, satellite reliability lies roughly between 90 and 91%. The precise data are provided in the Appendix. Recall that these are actual/observed satellite reliability values (not reliability specifications, as discussed in the Introduction). In addition, several trends can be seen in Fig. 4, the most noticeable one being the steep drop in reliability during the first year of operation. These trends are better captured in a parametric analysis of reliability, as discussed in the next section.

IV. Parametric Analysis and Weibull Fit of Satellite Reliability

Nonparametric analysis provides powerful results because the reliability calculation (e.g., Fig. 4) is not constrained to fit any particular predefined lifetime distribution. However, this flexibility makes nonparametric results neither easy nor convenient to use for different purposes, as often encountered in engineering design (e.g., optimization, value analysis). In addition, some trends and patterns are more clearly identified and recognizable with parametric analysis. In the following, we provide a brief review of the Weibull distribution and then demonstrate that the nonparametric results of satellite reliability in Sec. III fit the Weibull distribution considerably well. We then calculate the shape and scale parameter of the corresponding Weibull distribution.

A. Weibull Distribution and the Weibull Plot

The Weibull distribution is one of the most commonly used distributions in reliability analysis. The reason for its wide adoption is that it is quite flexible and, with an appropriate choice of one of its two parameters (the shape parameter, as discussed next), it can model different kinds of failure behaviors. More specifically, the Weibull distribution can model an increasing the failure rate (wearout), a decreasing failure rate (infant mortality), or a constant failure rate (i.e., an exponential distribution). The Weibull distribution has two parameters: the shape parameter β and the scale parameter θ. Its failure rate can be written as follows:

Table 2 Failure times (in days) of satellites launched between January 1990 and October 2008

1	1	1	1	2	3	3	4	4	5	5
7	9	12	15	15	16	16	23	36	51	53
64	68	73	79	89	102	107	123	128	131	167
190	197	221	229	237	252	271	309	314	317	334
364	465	515	696	701	713	722	724	787	1053	1073
1122	1146	1167	1184	1233	1256	1347	1458	1551	1637	1778
1797	1836	1967	2009	2091	2097	2098	2181	2191	2237	2429
2434	2472	2577	2580	2624	2702	2917	2947	2963	3038	3077
3159	3268	3455	3684	3759	4192	4324	4909	5043	5207	

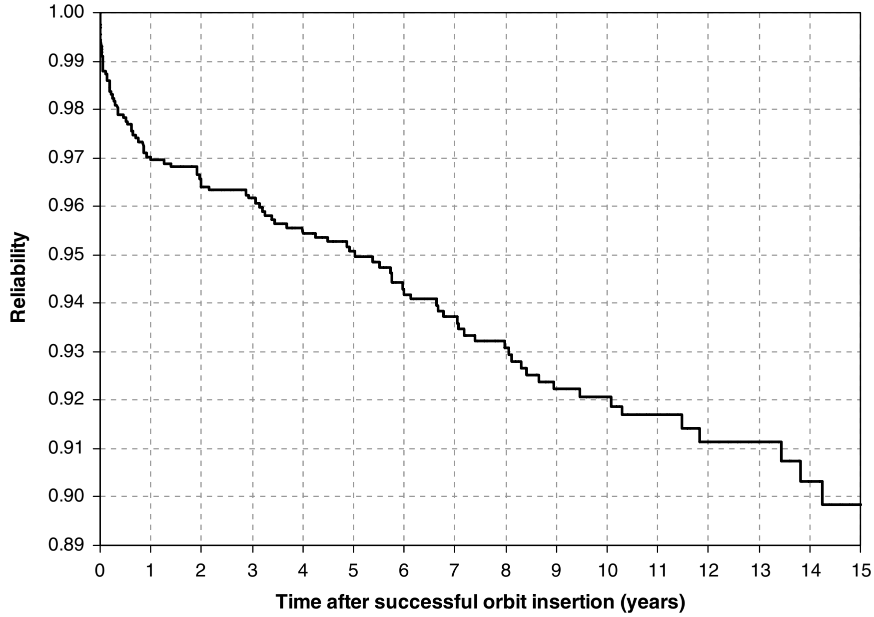

Fig. 4 Kaplan–Meier plot of satellite reliability.

$$\lambda(t) = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1} \quad \text{with } \theta > 0, \quad \beta > 0, \quad t \geq 0 \tag{10}$$

The shape parameter β is dimensionless, and the scale parameter θ is expressed in units of time. The resulting reliability function is

$$R(t) = e^{-(t/\theta)^{\beta}} \tag{11}$$

The effect of the Weibull shape parameter β on the failure rate is summarized next (this illustrates the flexibility of the Weibull distribution):

1) For $0 < \beta < 1$, the failure rate is decreasing, thus a choice of β within this range allows us to model infant mortality.

2) For $\beta = 1$, the failure rate is constant, and the Weibull distribution in this case is equivalent to the exponential distribution.

3) For $\beta > 1$, the failure rate is increasing, thus a choice of β greater than one allows us to model wearout. More specifically,

a) For $1 < \beta < 2$, we have an increasing concave failure rate.

b) For $\beta = 2$, we have a linear failure rate, and the Weibull distribution in this case is equivalent to the Rayleigh distribution.

c) For $\beta > 2$, we have an increasing convex failure rate.

d) For $3 \leq \beta \leq 4$, the Weibull distribution approaches the normal distribution.

The Weibull plot. Consider Eq. (11). By taking the natural logarithm of both sides of the equality, we obtain

$$\ln[R(t)] = -\left(\frac{t}{\theta}\right)^{\beta} \tag{12}$$

Taking again the natural logarithm of the (negative) two sides of the equality in Eq. (12), we obtain

$$\ln[-\ln R(t)] = \beta \ln t - \beta \ln \theta \tag{13}$$

By considering the following change of variables in Eq. (13)

$$\begin{cases} y = \ln[-\ln R(t)] \\ x = \ln t \end{cases} \tag{14}$$

we obtain a linear function with a slope equal to the shape parameter of the underlying Weibull distribution:

$$y = \beta x - \beta \ln \theta \tag{15}$$

Equations (11) and (15) are equivalent. To understand how this is helpful for nonparametric reliability analysis when we do not know what the underlying distribution is, consider the reverse of the flow of the discussion in this subsection. A nonparametric analysis provides us with reliability estimates at each of the failure times in the sample $\hat{R}(t_{(i)})$. We therefore plot $\ln[-\ln \hat{R}(t_{(i)})]$ as a function of $\ln t_{(i)}$. If these discrete points are aligned, then the underlying distribution of the nonparametric analysis is a Weibull distribution. A least-square fit is then used to provide an approximation of the line's equation. The estimated Weibull scale and shape parameters are obtained as follows from Eq. (15): the scale parameter β is given directly by the slope of the line, and the shape parameter θ can be evaluated from the value of the intersection of the line with the y axis. The plot of $\ln[-\ln \hat{R}(t_{(i)})]$ as a function of $\ln t_{(i)}$ is referred to as a Weibull plot. In the following discussion, we provide the Weibull plot of the satellite reliability from our analysis in Sec. III.

B. Weibull Plot of Satellite Reliability

We start with the data calculated in Sec. III.C, $t_{(i)}$ and $\hat{R}(t_{(i)})$, which were used to generated Fig. 4 (the data are provided in the Appendix). We then calculate $\ln[-\ln \hat{R}(t_{(i)})]$ and $\ln(t_{(i)})$ and plot these doublets in Fig. 5.

The results are well aligned, and a regression analysis provides the following result:

$$y = 0.3875x - 3.4972 \quad \text{with } R^2 = 0.9835$$

This provides a strong indication that the Weibull fit is indeed a good one, and that satellite reliability, to a first-order approximation, is indeed Weibull distributed. Although satellite reliability has previously been assumed to be Weibull distributed (see the Introduction of this paper), this analysis constitutes a confirmation that a Weibull distribution is indeed representative of on-orbit satellite reliability. We next discuss the goodness of fit of this distribution.

As a result of the regression analysis and the linear fit shown in Fig. 5, we obtain the following parameters of the Weibull distribution for satellite reliability:

$$\beta = 0.3875 \qquad \theta = 8316 \text{ years} \tag{16}$$

Recall that the slope of the line provides the scale parameter β, and the shape parameter θ can be evaluated from the value of the intersection of the line with the y axis.

The most important result in Eq. (16) is that the shape parameter is less than one. Although the following could have been noticed from Fig. 4, Eq. (16) and the corresponding fit shown in Fig. 5 indicate a

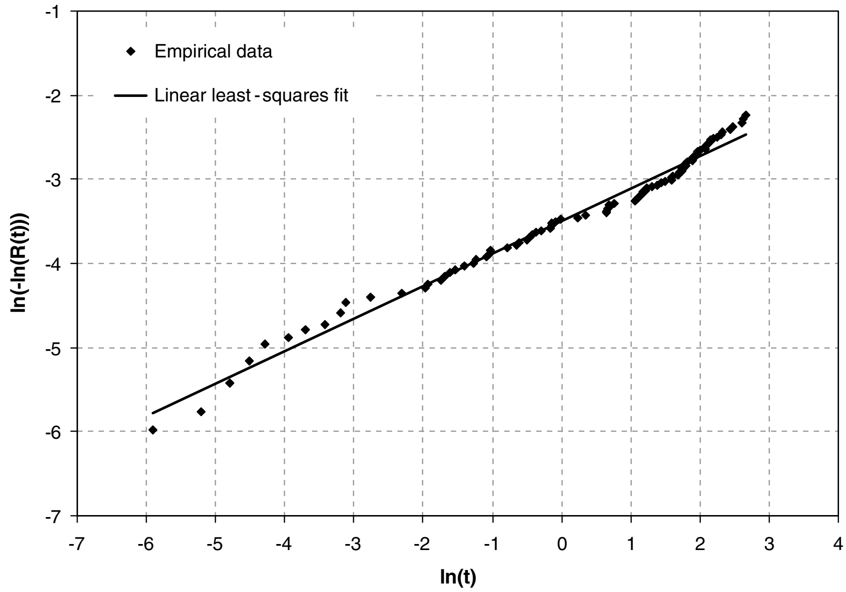

Fig. 5 Weibull plot of the Kaplan–Meier estimated satellite reliability.

clear propensity for infant mortality in satellite reliability and failure behavior (see Sec. IV.A). One implication of this result is that the "commonly used [shape parameter value] for satellite systems" of 1.7 adopted in [7,9] is neither correct nor representative of actual satellite behavior, because a shape parameter greater than one fails to capture infant mortality, which is clearly seen in on-orbit failure data.

Figure 6 shows both the nonparametric satellite reliability derived in Sec. III, and the parametric (Weibull fit) result from the current section in Eqs. (11) and (16). The superposition of these two reliability curves allows us to qualitatively gauge and discuss the appropriateness of the parametric fit.

Statistical analysis is prone to visual misinterpretation. For example, if we represent Fig. 6 with a scale on the *y* axis ranging from 0 to 1 (as done in the Appendix in Fig. A1) instead of from 0.89 to 1 as in Fig. 6, the differences between the nonparametric analysis and the Weibull fit become less visible and appear smaller. It is important that the reader's judgment regarding the appropriateness of the parametric fit not be biased by such visual manipulation, because the goodness of fit remains the same for Figs. 6 and A1. The following observations can be made regarding the appropriateness of the Weibull parametric fit for satellite reliability:

1) A coefficient of determination $R^2 = 0.9835$ suggests that satellite reliability can be modeled with reasonable accuracy by a Weibull distribution.

2) The Weibull model remains within one percentage point of the observed satellite reliability until 13 years of operation. The parametric model's accuracy degrades a little bit after 13 years but remains within 2 percentage points of the observed reliability. We address this loss of accuracy when discussing the confidence intervals for the current analysis in Sec. V.

3) The Weibull model is significantly accurate during the first year of operation and properly captures the observed infant mortality trend.

4) The model then slightly underestimates satellite reliability between years 2 and 6 but remains within half a percentage point of the observed reliability.

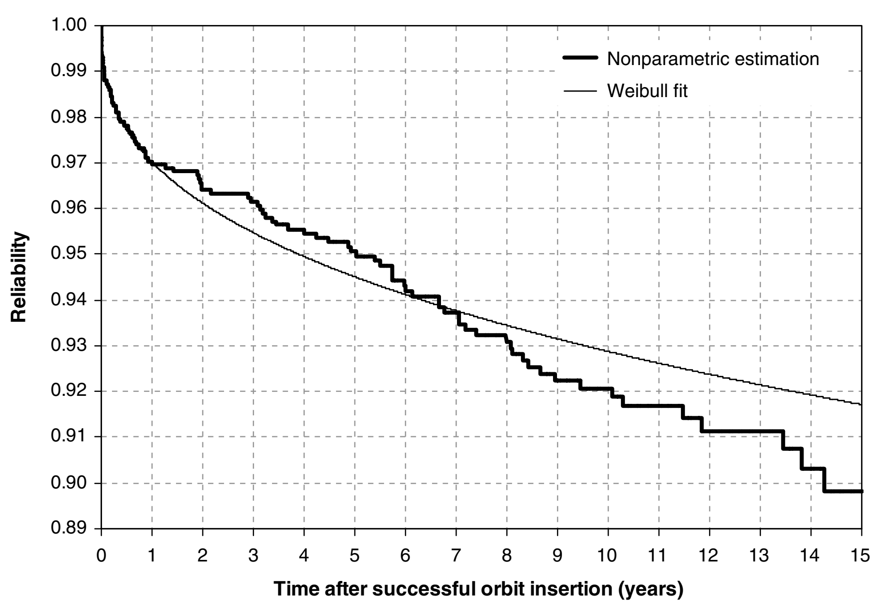

Fig. 6 Kaplan–Meier estimated satellite reliability and Weibull fit.

5) Past 7 years of operation, the model overestimates satellite reliability by 1 (up to 13 years) or 2 percentage points (after 13 years).

The model's accuracy is addressed quantitatively in the following section on confidence intervals.

It should be pointed out that a more accurate model of the nonparametric satellite reliability can be developed, if more accuracy is needed, by adopting either spline functions or a mixed model distribution with more parameters (hence more degrees of freedom) than the two-parameter Weibull distribution or other traditional parametric distributions. Consider Fig. 5: we can see different local slopes on the Weibull plot, and, for example, for $\ln(t) > 1$, we notice a slightly larger slope for those local points than the overall best-fit slope. This indicates a higher failure rate for later periods of operation than the one overall shape parameter we were confined with. Thus, a mixture of several exponential distributions, for example, with different failure rates can provide us with more accuracy in modeling the nonparametric satellite reliability than the Weibull model discussed in this section. More complex models for satellite reliability will be further investigated in future work.

V. Confidence Interval Analysis

In the previous section, we discussed the accuracy of the Weibull fit with respect to the nonparametric satellite reliability results provided in Sec. III and displayed in Fig. 4 and Table A1. In this section, we analyze the confidence interval and dispersion of satellite reliability around the latter's Kaplan–Meier estimate. The Kaplan–Meier estimator [Eq. (9)] provides a maximum likelihood estimate of reliability but does not inform us about the dispersion around $\hat{R}(t_i)$. This dispersion is captured by the variance or standard deviation of the estimator, which is then used to derive upper and lower bounds for, say, a 95% confidence interval (that is, a 95% likelihood that the actual reliability will fall between these two bounds, with the Kaplan–Meier analysis providing us with the most likely estimate). Calculating and displaying confidence intervals is an important part of any statistical analysis.

The variance of the Kaplan–Meier estimator is provided by Greenwood's formula [Eq. (17)]:

$$\hat{\text{var}}[R(t_i)] \equiv \sigma^2(t_i) = [\hat{R}(t_i)]^2 \sum_{j \le i} \frac{m_j}{n_j(n_j - m_j)} \tag{17}$$

And the 95% confidence interval is determined by Eq. (18):

$$R_{95\%}(t_i) = \hat{R}(t_i) \pm 1.96\sigma(t_i) \tag{18}$$

The reader is referred to [8,15,16] for more details about these equations.

When Eqs. (17) and (18) are applied to the data from our sample of 1584 satellites, along with the Kaplan–Meier estimated satellite reliability $\hat{R}(t_i)$ shown in Fig. 4 and provided in Table A1, we obtain the 95% confidence interval curves shown in Fig. 7. The tabular data for Fig. 7 is provided in the Appendix, Table A2. Vertical cuts across Fig. 7 read as follows, for example:

1) Satellite reliability at $t = 1$ year will be between 96.1 and 97.8% with a 95% likelihood: these values constitute the lower and upper bounds of the 95% confidence interval at $t = 1$ year. In addition, the most likely estimate of satellite reliability at this point in time is $\hat{R} = 96.9\%$.

2) Satellite reliability at $t = 7$ years on orbit will be between 92.2 and 94.9% with a 95% likelihood. In addition, the most likely estimate of satellite reliability at this point in time is $\hat{R} = 93.6\%$.

Notice that the dispersion of $R(t_i)$ around $\hat{R}(t_i)$ increases with time. This increase in dispersion can be seen in Fig. 7 by the growing gap between the Kaplan–Meier estimated reliability and the confidence interval curves. The dispersion is given by Eq. (19), and its growth over time is clearly seen in Fig. 8:

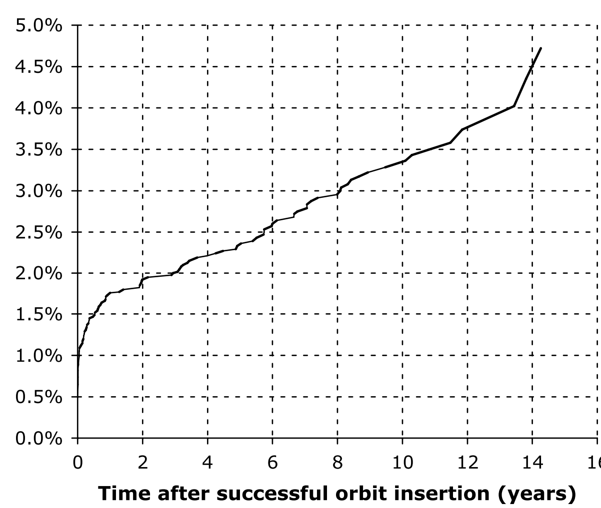

Fig. 8 Dispersion of the 95% confidence interval of satellite reliability.

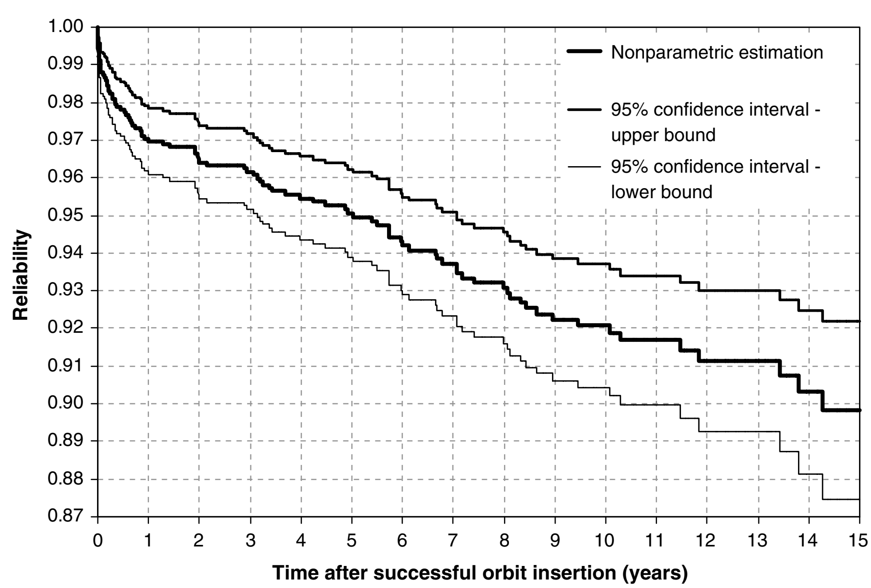

Fig. 7 Satellite reliability with 95% confidence intervals.

Table 3 Spacecraft subsystems and abbreviations for Fig. 9a, 9b, and 10

Subsystem designation	Abbreviation
1) Gyro/sensor/reaction wheel	Gyro
2) Thruster/fuel	Thruster/fuel
3) Control processor	CP
4) Mechanisms/structures/thermal	Mechanisms
5) Payload instrument	Payload
6) Battery/cell	Battery/cell
7) Electrical distribution	Electrical distribution
8) Solar array deployment	SAD
9) Solar array operating	SAO
10) Telemetry tracking and command	TTC
11) Unknown	Unknown

$$D(t_i) = [\text{upper bound } R_{95\%}(t_i)] - [\text{lower bound } R_{95\%}(t_i)]$$
$$= 3.92\sigma(t_i) = 3.92[\hat{R}(t_i)]\sqrt{\sum_{j\leq i}\frac{m_j}{n_j(n_j-m_j)}} \qquad (19)$$

Figure 8 illustrates the increasing uncertainty or loss of accuracy of the nonparametric analysis of satellite reliability with time. For example, after two years on-orbit, satellite reliability is dispersed over a 2% point interval (with 95% confidence), whereas, after 12 years on orbit, satellite reliability is dispersed over a 4% point interval. Our Weibull fit of satellite reliability in Sec. III remains within the 95% confidence interval shown in Fig. 7.

VI. Preliminary Analysis of Subsystems Failures

Our *purely statistical* analysis of satellite reliability ends with Sec. V. In this section, we provide a starting point for the "physics of failure" approach to satellite reliability by identifying the culprit subsystems driving satellite failures and tracking their relative contributions to satellite unreliability. The reader not familiar with this terminology is referred to [18] for a discussion of the statistical or actuarial approach to reliability engineering and the physics-of-failure approach, or what is known as "reliability physics."

In this section, we quantify the relative contribution of each subsystem to the failure of the satellites in our sample, that is, we identify which subsystem leads to the failure of satellites and by how much. In addition, we add a time dimension to this analysis by analyzing the evolution over time of the relative contribution of each subsystem to satellite loss.

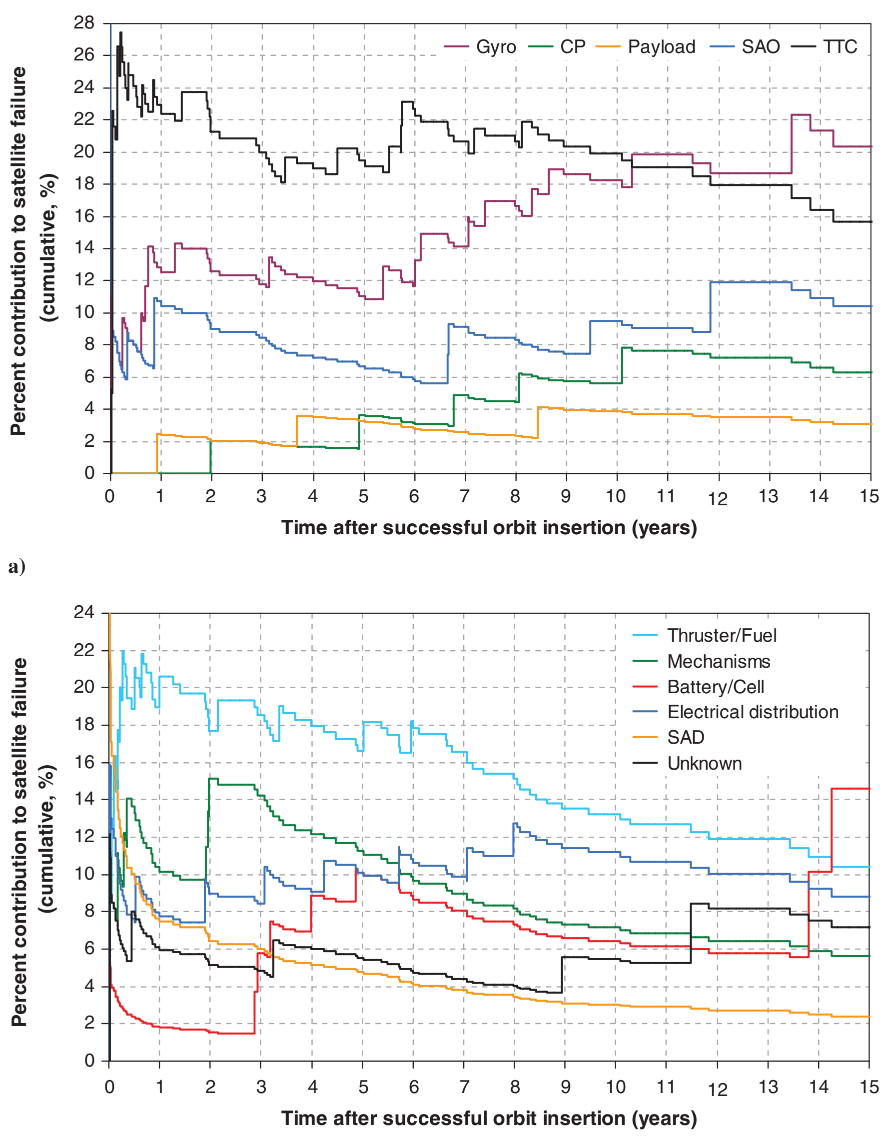

Fig. 9 Relative contributions of various subsystems to satellite failure.

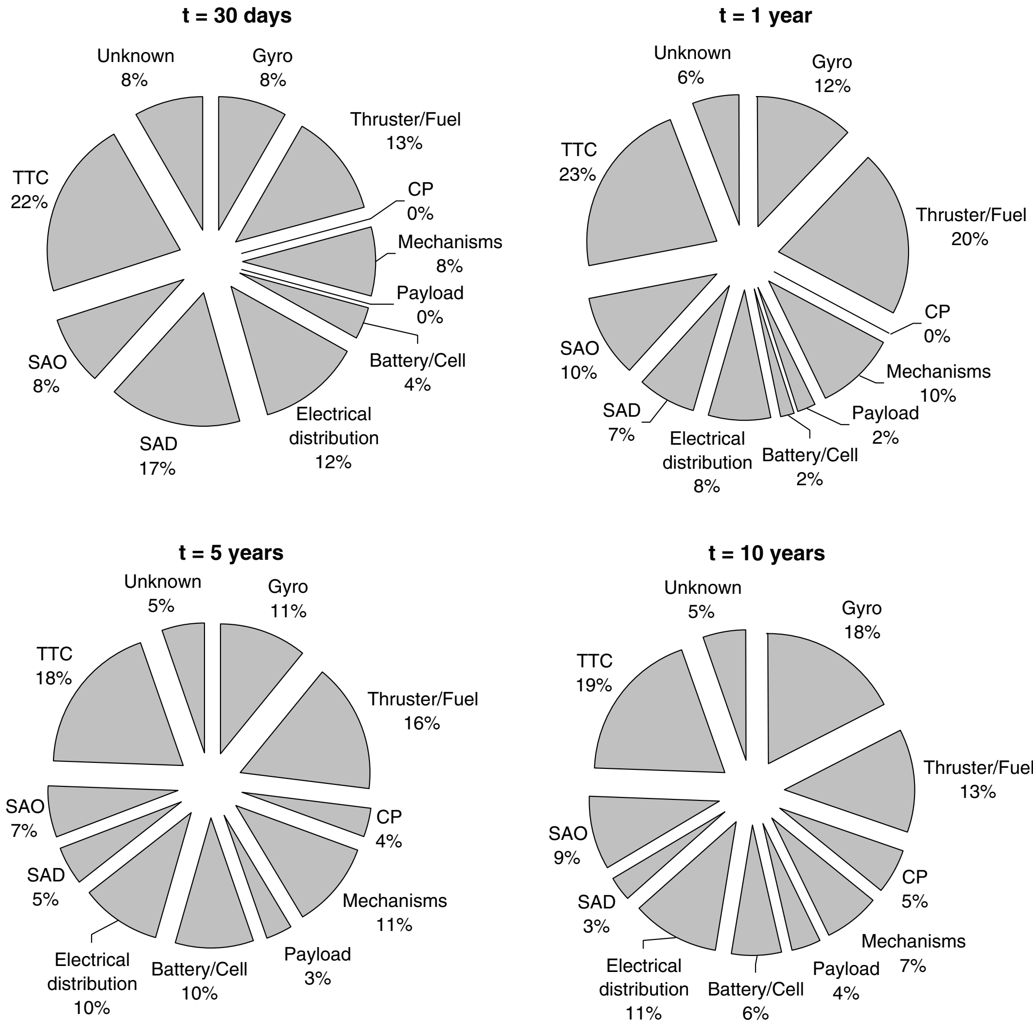

Fig. 10 Subsystem contributions to satellite failures after 30 days, 1 year, 5 years, and 10 years on orbit.

The analysis in this section is a first step toward the identification of various failure modes leading to the loss of satellites. It should prove useful to the space industry in general and satellite designers and program managers in particular [in helping them, for example, to focus attention and resources on subsystems with high(er) propensities for failure and guiding test and screening programs accordingly]. For each subsystem j identified in our database, we calculate its probability of leading to the failure of a satellite $\hat{P}_{\text{subsystem},j}$ [14]. We then compute the probability of failure of a satellite as follows:

$$\hat{P}_{\text{satellite}} = 1 - \hat{R}_{\text{satellite}} \tag{20}$$

The percentage contribution of subsystem j to the failure of a satellite is then given by

$$r_j = \frac{\hat{P}_{\text{subsystem},j}}{\hat{P}_{\text{satellite}}} \tag{21}$$

The subsystems considered and their corresponding abbreviations are shown in Table 3.

Note that the solar array deployment is a one-shot subsystem or, more precisely, a one-shot phase of the solar array subsystem. The results of our analysis can be represented in one figure showing all the r_j for $j = 1$–11 as a function of time. However, for readability purposes, we have split the results into three figures.

Figures 9a and 9b show the evolution over time of the distribution of subsystems failures leading to the loss of the satellite. For example, on Fig. 9a, we see that the control processor (CP) contributes approximately 6% to the total satellite failures over 15 years. Similarly, we observe that the gyro and TTC subsystems are the major contributors to satellite failures with, respectively, 20% and 16% of satellite failures due to these subsystems over a period of 15 years.

It is interesting to note the switch in "failure leadership" between the gyro and TTC subsystems around year 10 on Fig. 9a. TTC is the lead contributor to satellite failure over the first 10 years on orbit, with a relative contribution hovering around 20%. The failures due to gyro subsystem remain around 12% between year 1 and year 6 on orbit, and then they clearly ramp up starting around year 6 and overtake the relative contributions of the TTC subsystem to satellite failure. We term this occurrence the switch in failure leadership between the gyro and TTC subsystems.

Figure 9b shows, for example, that unknown causes account for 5–8% of satellite failures. One particularly interesting trend in Fig. 9b is the evolution of the battery contribution to satellite failure. We observe two clear increases in r_{battery}: the first one around year 3 on-orbit when satellite failures due to batteries ramp up from 2 to 10% by year 5, and the second one around year 14 when satellite failures due to batteries ramp up from 6 to 14% by year 15. These observations may be indicative of two different failure modes and, as such, they should be useful to electrical engineers working on spacecraft power storage and the corresponding reliability testing program.

Figure 10 provides a more readable version of Figs. 9a and 9b. Instead of the evolution over time of r_j, Fig. 10 provides a snapshot or static picture of the subsystems' contribution to satellite failures at four discrete points in time: after 30 days, 1 year, 5 years, and 10 years on orbit. Figure 10 in effect represents vertical cuts across Figs. 9a and 9b, and, although we lose the temporal information portrayed in these figures, we gain in readability and accuracy (or finer resolution) at the discrete points in time selected.

Notice in the upper-left quadrant of Fig. 10 that solar array deployment and TTC account, respectively, for 17 and 22% of the failures of the first 30 days on-orbit. Thus, satellite infant mortality, as discussed in Sec. IV, is driven to a large extent by these two subsystems.

VII. Conclusions

The technical literature has long recognized the importance of satellite reliability but little analysis based on actual extensive flight data has been published. The present work helps to fill this gap by 1) conducting a thorough statistical analysis of recent on-orbit satellite reliability data, 2) fitting a parametric model to the actual/observed spacecraft reliability, and 3) quantifying the relative contribution of each subsystem to satellite failure and identifying the subsystems that drive spacecraft unreliability. The sample analyzed here consisted of 1584 Earth-orbiting satellites successfully launched between January 1990 and October 2008.

The fundamental results of this study are as follows: 1) the satellite failures examined here exhibit a clear infant mortality trend; 2) a Weibull fit is appropriate for modeling the (actual) failure behavior of these satellites; 3) the corresponding Weibull shape parameter is roughly 0.4. One implication of this result is that the “commonly used [shape parameter value] for satellites systems” of 1.7 adopted by the industry is neither correct nor representative of actual satellite behavior, because a shape parameter greater than one fails to capture infant mortality, which is clearly seen in on-orbit failure data; and 4) the lead subsystem contributors to satellite failures are the gyro/sensor/reaction wheel and TTC subsystems, and the time-dependence contribution of each subsystem to the satellite failures examined here is clearly identified.

We hope this work provides helpful feedback to the space industry in redesigning satellite (and subsystem) test and screening programs and in providing an empirical basis for subsystem redundancy allocation and reliability growth plans.

Table A1 Tabular data for the Kaplan–Meier plot of satellite reliability in Fig. 4

Failure time t_i, yr	$\hat{R}(t_i)$	Failure time t_i, yr	$\hat{R}(t_i)$	Failure time t_i, yr	$\hat{R}(t_i)$
0.0027	0.9975	0.6899	0.9740	5.3854	0.9486
0.0055	0.9968	0.7420	0.9732	5.5003	0.9475
0.0082	0.9956	0.8460	0.9725	5.7248	0.9464
0.0110	0.9943	0.8597	0.9718	5.7413	0.9453
0.0137	0.9930	0.8679	0.9711	5.7440	0.9442
0.0192	0.9924	0.9144	0.9703	5.9713	0.9430
0.0246	0.9918	0.9966	0.9696	5.9986	0.9419
0.0329	0.9911	1.2731	0.9688	6.1246	0.9408
0.0411	0.9898	1.4100	0.9681	6.6502	0.9396
0.0438	0.9885	1.9055	0.9673	6.6639	0.9384
0.0630	0.9879	1.9192	0.9665	6.7680	0.9372
0.0986	0.9872	1.9521	0.9657	7.0554	0.9359
0.1396	0.9865	1.9767	0.9649	7.0637	0.9347
0.1451	0.9859	1.9822	0.9641	7.1841	0.9334
0.1752	0.9852	2.1547	0.9633	7.3977	0.9322
0.1862	0.9845	2.8830	0.9624	7.9863	0.9308
0.1999	0.9838	2.9377	0.9616	8.0684	0.9295
0.2163	0.9831	3.0719	0.9607	8.1123	0.9281
0.2437	0.9824	3.1376	0.9598	8.3176	0.9267
0.2793	0.9817	3.1951	0.9590	8.4244	0.9253
0.2930	0.9810	3.2416	0.9581	8.6489	0.9238
0.3368	0.9803	3.3758	0.9572	8.9473	0.9223
0.3504	0.9796	3.4387	0.9564	9.4593	0.9207
0.3587	0.9789	3.6879	0.9555	10.0862	0.9188
0.4572	0.9782	3.9918	0.9545	10.2916	0.9169
0.5202	0.9775	4.2464	0.9536	11.4771	0.9142
0.5394	0.9768	4.4819	0.9527	11.8385	0.9113
0.6051	0.9761	4.8679	0.9517	13.4401	0.9074
0.6270	0.9754	4.9199	0.9507	13.8070	0.9031
0.6489	0.9747	5.0267	0.9496	14.2560	0.8983

Appendix: Parametric Fit and Tabular Data

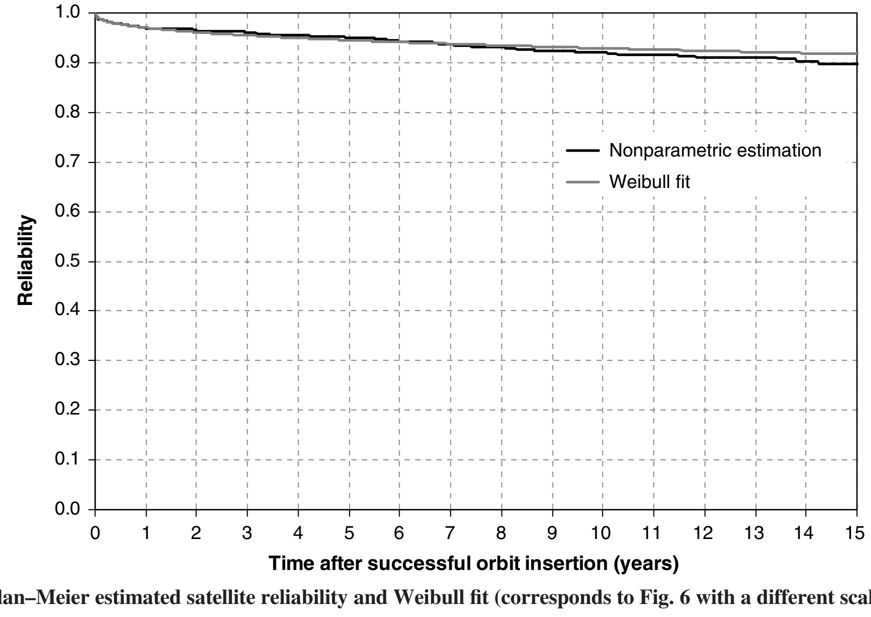

Fig. A1 Kaplan–Meier estimated satellite reliability and Weibull fit (corresponds to Fig. 6 with a different scale on the *y* axis).

Table A2 Tabular data for the confidence intervals of satellite reliability in Fig. 7

Failure time, yr	95% confidence interval		Failure time, yr	95% confidence interval		Failure time, yr	95% confidence interval	
	Lower bound	Upper bound		Lower bound	Upper bound		Lower bound	Upper bound
0.0027	0.995	0.9999	0.6899	0.9659	0.982	5.3854	0.9366	0.9605
0.0055	0.9941	0.9996	0.742	0.965	0.9814	5.5003	0.9353	0.9596
0.0082	0.9923	0.9988	0.846	0.9642	0.9808	5.7248	0.934	0.9587
0.011	0.9906	0.998	0.8597	0.9634	0.9802	5.7413	0.9328	0.9578
0.0137	0.9889	0.9971	0.8679	0.9625	0.9796	5.744	0.9315	0.9568
0.0192	0.9881	0.9967	0.9144	0.9617	0.979	5.9713	0.9302	0.9559
0.0246	0.9873	0.9962	0.9966	0.9608	0.9784	5.9986	0.9289	0.9549
0.0329	0.9865	0.9958	1.2731	0.96	0.9777	6.1246	0.9276	0.954
0.0411	0.9849	0.9948	1.4100	0.9591	0.9771	6.6502	0.9262	0.953
0.0438	0.9833	0.9938	1.9055	0.9582	0.9764	6.6639	0.9248	0.952
0.063	0.9824	0.9933	1.9192	0.9572	0.9757	6.768	0.9234	0.9509
0.0986	0.9816	0.9928	1.9521	0.9563	0.9751	7.0554	0.922	0.9499
0.1396	0.9808	0.9923	1.9767	0.9554	0.9744	7.0637	0.9205	0.9488
0.1451	0.98	0.9917	1.9822	0.9545	0.9737	7.1841	0.9191	0.9478
0.1752	0.9792	0.9912	2.1547	0.9535	0.973	7.3977	0.9176	0.9467
0.1862	0.9783	0.9907	2.883	0.9525	0.9723	7.9863	0.9161	0.9456
0.1999	0.9775	0.9901	2.9377	0.9516	0.9716	8.0684	0.9145	0.9444
0.2163	0.9767	0.9896	3.0719	0.9506	0.9708	8.1123	0.9129	0.9433
0.2437	0.9759	0.989	3.1376	0.9496	0.9701	8.3176	0.9113	0.9421
0.2793	0.975	0.9884	3.1951	0.9486	0.9694	8.4244	0.9096	0.9409
0.293	0.9742	0.9879	3.2416	0.9476	0.9686	8.6489	0.908	0.9397
0.3368	0.9734	0.9873	3.3758	0.9466	0.9679	8.9473	0.9062	0.9384
0.3504	0.9725	0.9867	3.4387	0.9456	0.9671	9.4593	0.9043	0.9371
0.3587	0.9717	0.9862	3.6879	0.9445	0.9664	10.0862	0.902	0.9356
0.4572	0.9709	0.9856	3.9918	0.9435	0.9656	10.2916	0.8997	0.934
0.5202	0.9701	0.985	4.2464	0.9424	0.9648	11.4771	0.8963	0.9321
0.5394	0.9692	0.9844	4.4819	0.9413	0.964	11.8385	0.8926	0.93
0.6051	0.9684	0.9838	4.8679	0.9402	0.9631	13.4401	0.8873	0.9275
0.627	0.9676	0.9832	4.9199	0.939	0.9623	13.807	0.8813	0.9248
0.6489	0.9667	0.9826	5.0267	0.9378	0.9614	14.256	0.8747	0.9219

Acknowledgments

This work was funded in part by a grant from Orbital Sciences Corporation/Defense Advanced Research Projects Agency from the F6 Fractionated Spacecraft Program. The support is gratefully acknowledged. We also wish to thank the Editor, Associate Editor, and two anonymous reviewers for their detailed comments and suggestions for improving the quality and clarity of this work.

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