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Statistical analysis and modelling of small satellite reliability

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Smaller launching systems and highly reliable components have become dominant demand in the small satellite sector. This notwithstanding small satellites have been the cause of the majority of space debris. It is therefore correct to ask, what is the survivability of small satellites? To address this question a small satellite database was constructed based on 4567 small satellites deployed from 1990 to 2022. All satellites are restricted with a launch mass of no more than 500kg. In this paper, we present the survival distributions for different types of satellites based on satellite mass category, standard compliance and subsystem contribution. Our findings show that after the successful launch, microsatellites and minisatellites are equally reliable within the first 20 years on-orbit, with approximately a 98% reliability rate. Compared to microsatellites and minisatellites, picosatellites and nanosatellites exhibit high infant mortality and short lifetimes, which is no more than 10 years. We have found that the small satellite designed based on ECSS (European Cooperation for Space Standardization) and NASA (National Aeronautics and Space Administration) standards have a relatively higher reliability rate than that of satellites that comply with JAXA and other standards. With respect to subsystem behaviour, the communication system is the major contributor to small satellite failure, thus designers should pay more attention to addressing no signal, and software disconnection-related problems.

Keywords: Reliability, small satellite, statistical analysis, On-orbit failure, Mass, Standard.

1. Introduction

The development of the New Space industry increases attention to the reliability of small satellites. The reliability of small satellites could be affected by various factors. Satellite mass categories have been identified as a major factor. The correlation between satellite mass and satellite reliability has been explored based on the statistical analysis method (Castet and Saleh, 2009; Dubos *et al.*, 2010; Guo *et al.*, 2014). Also, investing failure of specific subsystems is another major trend in reliability analysis (Castet and Saleh, 2009; Kim *et al.*, 2012; Langer and Bouwmeester, 2016; Perumal *et al.*, 2021).

Reliability studies often focus on investing dependence among various micro-characteristics but neglect macro-consideration. Regard as the visible highly commercial value of the New Space market, several countries in European are pursuing a united standard for common progress. To our best knowledge, there is no research investigating the correlation between standard compliance and small satellite reliability. Accordingly, this study aims to fill this gap by answering the following question: does standard compliance matter to small satellite reliability? To gain further insight into the failure behaviour of small satellites, more updated small satellite data are collected in this research.

The paper is organized as follows. Section 2 describes the data and database used in this study. Section 3 introduces nonparametric analysis, followed by parametric analysis introduction in Section 4. The results are represented in Section 5. Section 6 presents the conclusions.

2. Database and data description

The small satellite data is acquired from Union of Concerned Scientists (UCS) Satellite Database (Union of Concerned Scientists, 2022), eoPortial Dictionary (European Space Agency, 2022), Gunter's space page (Gunter, 2022), Nanosat Database (Erik, 2022) and SpaceTrack Database (Ascend worldwide, 2022). The consolidated dataset consists of 4567 satellites weighing from 1-500kg launched from 1990 to 2022 The dataset is restricted to satellites that were successfully launched into Earth-orbits. There were 149 failures within 4567 missions, not including launch failures.

For each satellite, the following data are collected: 1) satellite name; 2) launch date; 3) failure date, if a failure occurred; 4) censor date, if no failure occurred; 5) mass; 6) culprit subsystem, the subsystem identified as having caused the spacecraft failure; 7) country of the owner.

In our study the satellite failures according to their severity. We adopt the failure classification system proposed by Kim *et al.* (2012), which consists of the following four failure categories:

- Class IV: Minor/temporary/repairable failure that does not have a significant permanent impact on the operation of the satellite or its subsystems.
- Class III: Major non-repairable failure that causes the loss of redundancy to the operation of a satellite or its subsystems on a permanent basis.
- Class II: Major non-repairable failure that affects the operation of a satellite or its subsystems on a permanent basis.
- Class I: Subsystem failure causing satellite retirements. This effectively means the total failure of the satellite due to a (dramatic) subsystem failure.

3. Nonparametric analysis of satellite failure data

Censoring in data analysis and the Kaplan-Meier estimator. Nonparametric means that the statistical analysis does not assume any specific parametric distribution. Based on the nonparametric analysis, we compute subsystem relative contribution to small satellite failures.

3.1. *Censored data sample*

Censoring occurs when there is no failure by the end of the observation window or if the small satellite is turned off before it failed. Here, censoring refers to incomplete life datapoint. In contrast to incomplete life datapoint, complete life datapoint refers to a failure occurred within the observation window. In this study, the sample data are right censored and complete with staggered entry. Because as the following reasons: 1) the small satellites are launched at different calendar dates, but their activation times (failure date or censored date) are known in the dataset; 2) Failure dates and censoring are stochastic; 3) censoring occurs at the end of our observation time (6 April 2022). Kaplan-Meier estimator is best suited to handle the dataset containing complete and right-censored data points (Kaplan and Meier, 1958).

3.2. *Kaplan-Meier estimator*

The Kaplan-Meier estimate of the survival function, is also called the reliability function. The reliability function from a complete dataset of n unit $R_n(t)$ is a staircase function with discontinuities at the observed time of failure of each unit and with a downward jump at each discontinuity of $\frac{1}{n}$. Castet and Saleh (2009) derive the estimated reliability function from a complete data set of n_i units, which is given by Eq.(1):

$$\hat{R}(t) = \prod_{t_{(i)} \leq t} \hat{p_i} = \prod_{t_{(i)} \leq t} \frac{n_i - 1}{n_i} \quad (1)$$

where

$$\begin{cases} t_{(i)}\text{: time to ith failure (arranged in ascending order)} \\ \quad n_i = \text{number of operation units right before } t_{(i)} \\ \quad = n - [\text{number of censored units right before } t_{(i)}] \\ \quad\quad -[\text{number of failed units right before } t_{(i)}] \end{cases}$$

If there are ties in the failure times, say m_i units failing at exactly $t_{(i)}$, this situation is referred to as a tie of multiplicity m, then Eq.(1) is replaced by Eq.(2):

$$\hat{p_i} = \prod_{t_{(i)} \leq t} \frac{n_i - m_i}{n_i} \quad (2)$$

Although Eq.(1) provides an estimate of reliability but does not inform the dispersion around $\hat{R}(t)$. The dispersion of the Kaplan-Meier estimate is captured by the variance or standard deviation of estimator, which is make the use of the 95% confidence interval. It shows the 95% likelihood that the actual reliability will fall between the upper and lower bounds. The variance of the Kaplan-Meier estimator is given by Greenwood's formula, as given in Eq.(3):

$$\widehat{var}[R(t_i)] \equiv \sigma^2(t_i) = [\hat{R}(t_i)]^2 \sum \frac{m_i}{n_i(n_i - m_i)} \quad (3)$$

The 95% confidence interval is given by Eq.(4):

$$R_{95\%}(t_i) = \hat{R}(t) \pm 1.96\sigma(t_i) \quad (4)$$

More detail information about Eq.(1)-Eq. (4) can be found in the previous literature (Castet and Saleh, 2009).

3.3. *Relative contribution of each subsystem to small satellite failure*

In our study, we consider six satellite subsystems, including: 1) Electrical Power System; 2) On-Board Computer; 3) Communication System; 4) Attitude Determination and Control System; 5) Payload; 6) Structure and Deployable; 7) Unknown (for failures, where no specific subsystem was identified as a root cause). The description of the failures according to these sub-systems is a generally accepted approach (Langer and Bouwmeester, 2016). For each subsystem j identified in the database, its probability of leading to the failure of a small satellite is computed by Eq.(5):

$$\hat{P}_{subsystem} = 1 - \hat{R}_{subsystem} \quad (5)$$

where $\hat{R}_{subsystem}$ is calculated based on the nonparametric reliability of the subsystem obtained by the Kaplan-Meier estimator Eq.(1). Analogues to the calculation of Eq.(5), the probability of a small satellite is calculated as Eq.(6):

$$\hat{P}_{satellite} = 1 - \hat{R}_{satellite} \quad (6)$$

where $\hat{R}_{satellite}$ is the nonparametric small satellite reliability.

Then the percentage contribution of subsystem j to the failure of a small satellite within a given time t is defined as Eq.(7):

$$r_j(t) = \frac{\hat{P}_{subsystem,j}\left[1 + \sum_{i=1}^{n-1} \frac{(-1)^i s_i}{i+1}\right]}{\hat{P}_{satellite}(t)} \quad (7)$$

where S_i is the sum of all possible combination of products of i $\hat{P}_{subsystem,k}$, $k \neq j$. Here, k refers to multi-state of subsystem severity, which is determined in terms of classes of failures (Kim *et al.*, 2012). If the subsystem failure $\hat{P}_{subsystem,j}$ are $\ll$, then r_j can be approximated by Eq.(8):

$$r_j \approx \frac{\hat{P}_{subsystem,j}}{\hat{P}_{satellite}(t)} \quad (8)$$

More detail information about Eq.(1)-Eq.(8) can be found in previous literature (Castet and Saleh, 2009; Kim *et al.*, 2012). Although nonparametric analysis provides a powerful analysis of the raw data, its good practice to conduct a parametric analysis of failure as parametric models are better suited for predictive analysis.

4. Parametric analysis of satellite failure data

In contrast with nonparametric analysis, parametric analysis is used to explore, to what extent the sample does fit for a specific distribution. The Weibull distribution is one of the most common distributions in reliability analysis (Castet and Saleh, 2009; Peng *et al.*, 2012; Yang *et al.*, 2018). This subsection provides a brief review of Weibull distribution.

4.1. *Weibull distribution*

The Weibull distribution has two parameters, the dimensionless shape parameter β and the scale parameter θ expressed in units of time. The probability density function of a continuous random variable with a Weibull distribution is given in Eq.(9) where t represents the time in orbit before failure

$$f(t) = \begin{cases} \lambda(t)R(t) & for\ t \geq 0 \\ 0 & for\ t < 0 \end{cases} \tag{9}$$

where $\lambda(t)$ is failure rate and $R(t)$ is the resulting reliability function of Weibull distribution as Eq.(10) and Eq.(11) shown:

$$\lambda(t) = \left(\frac{\beta}{\theta}\right)\left(\frac{t}{\theta}\right)^{\beta-1} \tag{10}$$

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

More detail information about Eq.(9)-Eq.(11) can be found in previous literature (Castet and Saleh, 2009; Guo *et al.*, 2014). The shape of the hazard function depends on the value of shape parameter β: 1) If $0 < \beta < 1$, then the failure rate decreases overtime, thus simulating infant mortality; 2) If $\beta = 1$, then the failure rate is constant, and the Weibull function in this case is equivalent to the exponential distribution; 3) If $\beta > 1$, then the failure rate is increasing over time, thus modelling wear-out behaviour (Castet and Saleh, 2009; O'Connor and Kleyner, 2012).

4.2. *Weibull plot and satellite reliability*

The shape β and scale θ parameter of Weibull distribution from data is generated by either a graphical method (linear regression) or maximum likelihood estimation. Perumal *et al.* (2021) compare graphical method and MLE and found that using MLE can generate more accurate Weibull model than graphical method. This subsection provides a brief review of graphical method and maximum likelihood estimation.

4.1.1. *Graphical method*

One of the ways to estimate Weibull parameter is using linear regression, as Eq.(12):

$$y = \beta x - \beta \ln \theta \tag{12}$$

Eq.(12) is obtained by twice natural logarithm of Eq.(10). Eq.(12) is equal to Eq.(11). A least-square fit is used to approximate the line's equation. If the discrete points are highly aligned with the estimated line, then we can say the underlying distribution of nonparametric analysis follows the Weibull distribution. To measure how well the discrete data is fitted with estimated linear line, coefficient of determination (R^2) is an indicator. R^2 ranges between 0 to 1, where 1 indicates that the regression model (Weibull distribution) perfectly fits the data.

4.1.2. *Maximum likelihood Estimation*

Another way to estimate the Weibull parameter is using maximum likelihood estimation (MLE). The likelihood function is defined as a function that expresses the joint density of all observations in the dataset. The small satellite data are defined as failure status and censored status. If the failure occurs for a small satellite is defined as 1; if censoring, then it is defined as 0, Eq.(9) is developed into Eq.(13):

$$L\left(t_f, t_c|\theta, \beta\right) = \prod f(t) \prod R(t) \tag{13}$$

where t_f refers to failure lifetime, t_c censored lifetime. The shape and scale can be estimated via maximizing Eq.(13). More detail information about Eq.(13) can be found in the book of Collect (2015) . Similar to the R^2 for graphical method and Akaike information criterion (AIC) is the goodness-of-fit indicator for maximum likelihood estimation. Lower AIC indicates better-fit model (Perumal *et al.*, 2021).

5. Analysis results

We use Minitab (Pochampally and Gupta, 2016) to conduct nonparametric and parametric analysis of the database. In this section we present the parametric and non-parametric survival analysis of small satellites.

5.1. Estimated Weibull parameters for small satellite reliability based on mass categorized

Data is organized in mass bins, as follows: 1) Picosatellite (0-1kg); 2) Nanosatellite/CubeSat (1-10kg); 3) Microsatellite (10-100kg); 4) Minisatellite (100-500kg). The mass bins are analysed by nonparametric model Eq.(1) and Eq.(2), and the Kaplan-Meier plot of small satellite reliability for each mass category is exhibited in Fig. 1. The results of Weibull parametric, computed by graphical method and maximum likelihood estimation (MLE), are separately summarized in Table 1. The goodness of the Weibull distribution fit is summarized in Table 2.

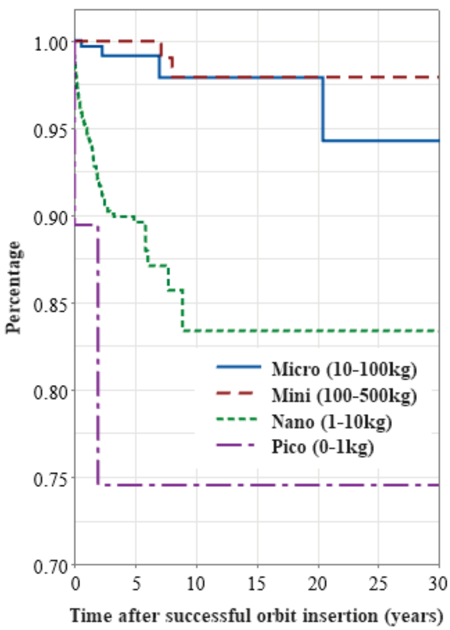


Fig. 1. Survival function of small satellite reliability for each mass category.

Fig. 1 shows that different mass categories do indeed have different reliability profiles and failure behaviours. The reliability trend of the small satellite examined here is consistent with the findings in Guo *et al.* (2014) research. That is, compared to micro- and mini-satellites, pico- and nano-satellites exhibit high infant mortality and short lifetimes, which is no more than 10 years.

Table 1. Estimated Weibull parameters for small satellites categorized based on mass.

Mass category	Graphical method		MLE	
	β	θ Years	β	θ Years
Pico	0.889	535.769	0.998	462.807
Nano	6.531	14.615	2.414	72.922
Micro	0.603	120.960	0.529	268.081
Mini	0.413	52.268	0.387	140.091

Corresponding Fig. 1 with Table 1, some important failure trends and differences between the four satellite mass categories can already be seen:

- **Infant mortality** ($0 < \beta < 1$): micro- (10-100 kg), nano- (1-10 kg) and pico- (0-1 kg) satellites exhibit a significant drop in reliability during first two years after successful launch. Compared with the three mass categories, minisatellites (100-500 kg) has the lowest infant mortality. Two months after the orbit insertion, the reliability of microsatellites is 99%, for nanosatellites is 92%, for picosatellites is 75%.
- **Wear-out** ($\beta > 1$): Nanosatellites (1-10 kg) exhibit a steep decrease during the first 8.9 years on-orbit, which is more severe than after 9 years on-orbit.
- **Similar reliability behaviour**: micro- (10-100 kg) and mini- (100-500 kg) satellites exhibit a steady reliability of 98% from year 9 to year 20. After 20 years on-orbit, the reliability of microsatellites again drops more significantly, at 94%; whereas that one of minisatellites remain relatively high, at 98%.

Table 2. The goodness-of-fit parameter for different mass categories.

Mass category (kg)	R^2	AIC
0-1	1.000	94.750
1-10	1.000	51.043
10-100	0.982	2608.312
100-500	0.878	62.094

Table 2 shows that small satellite reliability organized in terms of different mass categories can all be modelled with reasonable accuracy by a Weibull distribution as R^2 for four mass categories are near to 1.

5.2.*Estimated Weibull parameters for small satellite reliability based on standard compliance*

The dataset is spat into four groups: ECSS (European Cooperation for Space Standardization), NASA (National Aeronautics and Space Administration), JAXA (Japan Aerospace Exploration Agency) and others to investigate small satellite reliability variation among each standard. ECSS membership includes Italy, the United Kingdom, France, Germany, Norway and the Netherlands. Accordingly, the small satellites which are registered by one of that countries are regarded as complying with ECSS standards. The small satellite registered by the United States is regarded as complying with NASA standards. For Japanese small satellites, the JAXA standard is used to conduct an analysis.

Fig. 2 depicts the Kaplan-Meier plot of small satellites for four standard categories. Table 3 shows the results of the nonparametric analysis using the graphical method and MLE. The nonparametric reliability curve for each standard category, as well as the MLE Weibull fit, is exhibited in Fig. 3. The goodness of Weibull distribution fit results is summarized in Table 4.

In Fig. 2, the small satellite complied with ECSS standards and exhibits relatively higher reliability than that of other small satellites that complied with NASA, JAXA and other standards after a successful launch within 6 years. However, from year 6.06 to year 8.92, the reliability of small satellites that complied with ECSS standards (93%) is relatively lower than that of small satellites that complied with NASA standards (94%) on orbit. The reliability of small satellites complied with NASA dropped again in year 8.92 to 91%.

The shape parameter in Table 3 reflects that small satellites that complied with ECSS standards exhibit wear-out failure behaviour, as reflected by a change of convexity of the reliability curve after orbit insertion, whereas small satellites that complied with NASA, JAXA and other standards exhibit infant mortality failure behaviour.

Table 4 shows that the Weibull model estimated a reasonably good fit for different standard compliance due to relatively high values of R^2

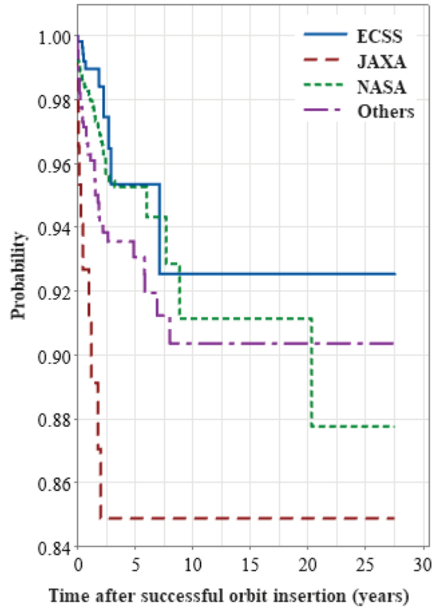


Fig. 2. Survival function of small satellite for each standard category.

Table 3. Estimated Weibull parameters for small satellites categorized based on standard compliance.

Standard category	Graphical method		MLE	
	β	θ Years	β	θ Years
ECSS	1.034	77.509	0.953	132.36
NASA	0.625	40.644	0.435	375.03
JAXA	0.564	878.690	0.511	1160.78
Others	0.756	85.679	0.527	692.45

Table 4. The goodness-of-fit parameter for different mass categories.

Standard category	R^2	AIC
ECSS	1.000	94.750
NASA	1.000	51.043
JAXA	0.982	2608.312
Others	0.878	62.094

5.2.*Subsystem relative contribution to small satellite failure*

The contributions of each subsystem to the satellite failures are depicted in Fig. 3. Electrical power system is the may source of error in the early stages for small satellites. The finding here is consistent with that of previous research conducted by Langer and Bouwmeester (2016). From a long-term perspective, the electrical power system and communication system are the two main contributors that caused small satellite failures, reflected by alternatively transformed contributions from year 1 to year 5 in orbit. Interestingly, the contribution of the unknown category progressively increases from 6.15% at 1 year to 22.22% at 5 years.

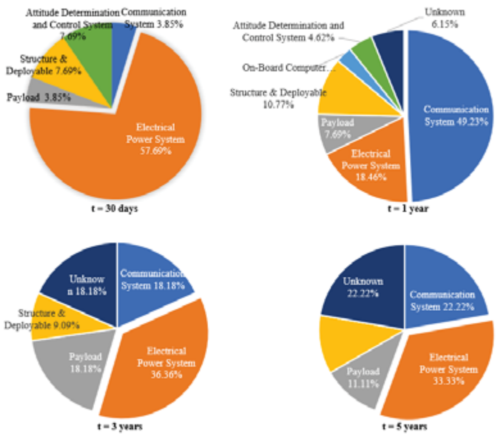
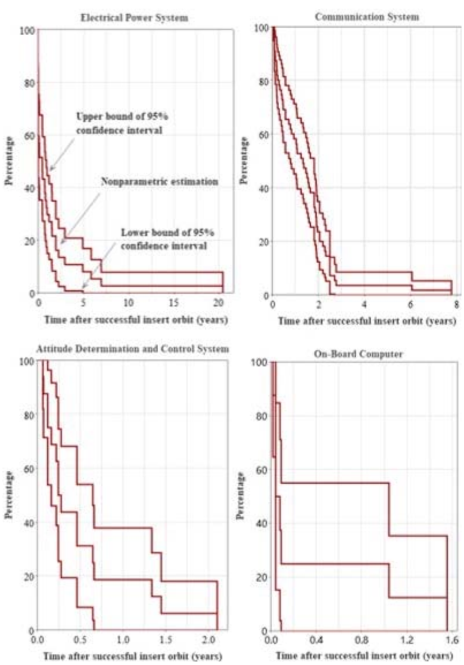


Fig. 3. Subsystem contributions to satellite failures



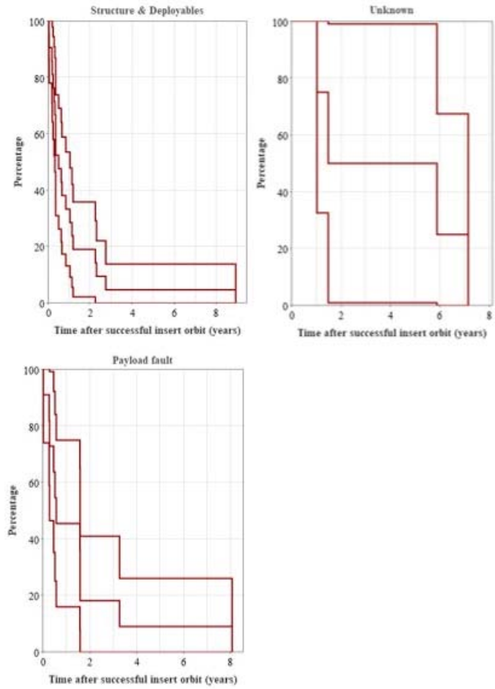


Fig. 4. Survival function of satellite reliability for each subsystem category with 95% confidence intervals.

Fig. 4 depicts a Kaplan-Meier plot of small satellite reliability for each subsystem with the lower and upper bounds of a 95% confidence interval. After successful orbit insertion, the reliability of the electrical power system drops to 44% after 1 year in orbit. The actual reliability of this subsystem will fall between 29% and 15% with a 95% confidence level at this point in this time.

6. Conclusions

A statistical analysis of small satellite reliability has been conducted using empirical data of 4567 satellites, weighing under 500 kg, launched from 1990 to 2022. The data is analysed by nonparametric analysis (the Kaplan-Meier) and parametric analysis (graphical method and maximum likelihood estimation). The reliability of small satellites could be affected by various parametric and characteristics. Satellite mass categories and different standard compliance to satellite failures are identified and investigated in this study. The relative contribution of each subsystem to satellite failure is identified and quantified.

The fundamental results of this study are as follows: 1) after the successful launch, microsatellites and minisatellites are equally reliable within the first 20 years on-orbit, with approximately 98% reliability rate; 2) compared to microsatellites and minisatellites, picosatellites and nanosatellites exhibit high infant mortality and short lifetimes, which is no more than 10 years; 3) the comparison of failure behaviour of different standard compliance show short lifetime for complied ECSS standard compared to complied NASA, JAXA and other standards; 4) the lead subsystem contributors to satellite failures are electrical power system and communication system.

Thus, to reduce the infant mortality rate of picosatellites and nanosatellites, it is suggested that standard developers should consider enhancing design standards by involving more qualified tests. Designers should pay more attention to no signal, and software disconnection-related problems.

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