A Reliability Estimation Tool for Reducing Infant Mortality in CubeSat Missions

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Abstract—For many years, traditional satellite design philosophy was dominated by highly reliable components, conservative designs and extensive performance testing at subsystem and integrated system levels to achieve long lifetimes in the harsh space environment. CubeSats attempted to choose a different philosophy, utilizing suitable state-of the art, commercial-off-the shelf products, yielding, if successful, an increased performance per mass figure of merit for those small vessels at potentially higher risk but lower cost. CubeSats seemed to promise universities and companies to be faster, better and cheaper – once more in history. Unfortunately, many CubeSat missions, especially university-built ones, never achieved a detectable functional state or failed shortly after the satellites were ejected from their deployer. Data based on our developed CubeSat Failure Database (CFD) and research carried out by others suggest, that a great percentage of those early failure cases could have been detected and avoided by more careful and adequate system-level functional testing on the ground. However, many university teams still fail to plan with adequate resources for system level functional testing or are confronted with hard deadlines, thus unable to complete appropriate integrated system testing on a sufficient level, and launching a satellite that never was adequately functional. Ongoing work on a novel reliability estimation tool using Bayesian methods is introduced to fill this gap and to provide meaningful data for all developers on the achievable reliability and required functional testing time of their CubeSats. Using test data and reliability goals for their actual mission, merging that data with statistical data from past missions and a database of subjective developer's beliefs, CubeSat developers should now be able to estimate their required functional testing time on subsystem and system level at an early project stage, as a function of the targeted reliability goal for their CubeSat. Alternatively, if the required resources (testing time, money, knowledge) are not available, CubeSat developers and program managers can still use the tool to now quantify a resulting realistic lower boundary for the expected system reliability of the mission, and decide, if their mission goals can be fulfilled or not with a certain probability. To evolve CubeSats into more reliable and accepted platforms for scientific payloads and commercial applications, it is utmost important to avoid or reduce the many infant mortality cases, where no or little useful data is produced by the satellite. To guide developers towards higher success rates without losing the spirit of using novel, state of the art technology in fast mission timelines, the reliability estimation tool should ensure higher reliability of CubeSat

missions without drawing too much resources nor imposing too many burdens on the CubeSat teams.

1. INTRODUCTION

The dawn of the CubeSats in the last decade changed the traditional satellite design philosophy towards state-of the art, commercial-off-the shelf (COTS) products. Data generated in ongoing research [1]-[4] suggests that the success of CubeSats is jeopardized by many dead-on-arrival (DOA) cases and a high ratio of infant mortality (see also Fig. 1-2). Looking closer at the reasons for success and failures, Swartwout suggests that many of the early failures can be traced back to insufficient system level functional testing on the ground [1]. Thereby, those errors detectable by functional testing (called "functional errors" in the paper) can either be of design, manufacturing, workmanship or of operational origin. It is important to note that the proposed research will not replace the environmental tests needed for verifying space hardware (e.g. thermal-vacuum tests, mechanical stress tests, radiation tests).

In this paper we address current reliability prediction methodologies and evaluate their suitability for CubeSat programs with respect to their mostly constrained resources. We report on the ongoing research on a two-fold reliability estimation methodology, aiming to detect functional errors trough subsystem and system level functional testing. The methodology should furthermore help CubeSat developers in

planning their resources (time, money) and in estimating their reliability after launch. All methods were developed based on the lessons learned from the CubeSat First-MOVE [5], launched end of 2013, and are implemented in the currently ongoing CubeSat project MOVE-II [6], which is to be launched end of 2017. Additional refinement work still has to be carried out on the specific reliability prediction methods, but we believe this work to be an essential first step to alleviate the impacts due to the lack of suitable reliability prediction techniques for CubeSat teams.

This paper is organized as follows. Chapter 2 describes current reliability prediction methodologies for satellites and their suitability for CubeSats. In Chapter 3, the CubeSat Failure Database (CFD) is introduced as one means of prior knowledge for addressing the "one-of-a-kind" problem many CubeSat missions face. In Chapter 4, the ongoing work on the Reliability Estimation Tool is presented. Chapter 5 describes the application of the methodologies on the satellite project MOVE-II. Finally, in Chapter 6, we conclude with the implications of this work and give an outlook.

2. RELIABILITY PREDICTION METHODOLOGIES

The high percentage of DOAs and early failures is not acceptable if CubeSats should evolve into reliable and accepted platforms for scientific payloads and commercial applications. Nevertheless, to stay attractive and affordable, traditional space industry processes and testing cannot be implemented in CubeSat projects.

We performed a literature research on reliability prediction methodologies and evaluated them for their suitability in a CubeSat project. Since these methods are not necessarily developed for CubeSat projects, specific requirements have to be considered, to evaluate the methods:

- The methodology shall focus on detecting functional failures (i.e., out of design and/or manufacturing-related failures), since they are the most critical aspect for infant mortality in CubeSats [1]-[4].

- Lack of time and lack of resources are critical aspects in CubeSat and SmallSat projects, especially when late in the project [7],[8].

- General validity: The method has to be generally valid. It has to be suitable for hardware as well as software and for mechanisms as well as electronic circuits. This ensures a continuous use in the whole project and that leads to comparable results [7].

- The method has to be feasible without any experience in the field of risk management. Even if the involved persons have attended risk management training that does not necessarily mean that they can or will apply their theoretical knowledge in practice [4], [7].

System Level Integrated Modeling Language (SLIM)

The SLIM language was developed within the scope of the COMPASS (Correctness, Modeling and Performance of Aerospace Systems) project in cooperation with the European space industry [9]. In general, SLIM allows the modelling of complex technical systems and the subsequent analysis of their reliability. The SLIM syntax is based on AADL (Architecture Analysis and Design Language). AADL is a standard modeling language, used in automotive applications and the SAE (Society of Automotive Engineers) maintains the standard AS5506B [10].

The SLIM syntax emulates different aspects of the real system in different model parts. The hierarchical structure is emulated by components and interfaces. These components can be hardware, software or composites of both. The description of failures is realized by mathematical equations, which describe the relation between the cause of failure and its impact. It is possible to create templates for risk assessment methods with additional software tools, for example Failure Mode and Effect Analysis (FMEA) tables. The SLIM system has the ability to use an already created model for a similar technical system, reducing expenses in serial production. We came to the conclusion that, due to its complexity, SLIM is too elaborate for a CubeSat-like project.

United States Military Standard Defense Handbook 217f

The standard MIL-HDBK-217f was released in 1991 by the United States Army [11] and is still the state-of-the art for reliability prediction in many application areas. Its initial purpose was to standardize the cooperation between the Army and civil suppliers in the field of electronics. Nowadays the standard is also used in entirely civilian areas of industrial production. Although some other standards are also capable to assess the reliability of electronics (such as PRISM, Telcordia SR-332, Physics of Failure,), MIL-HDBK-217f is still the most commonly used. According to [12], the underlying databases of the other standards can differ a bit from MIL-HDBK-217f, depending on their exact field of interest. The MIL-HDBK-217f handbook is divided in two parts:

- Parts Count Method: This analysis is able to calculate an estimation of the reliability of an electronic system in an early phase of the development, based on the types and numbers of every component used and their usage environment. The Part Count Method does not consider interconnections between the components, making it most suitable for early design phases, where only the circuits are defined but not the layout of the printed circuit board.

- Parts Stress Analysis: The Parts Stress Analysis can only be performed in later design phases. It emulates the connections between the electronic components and considers also details about the components and their usage environment, allowing a precise reliability estimation for many technical systems.

The obsolescence of the database is the biggest concern while using MIL-HDBK-217f, making it unsuitable for state-of-the-art COTS-based systems with novel electronics, such as CubeSats.

Highly Accelerated Life Testing (HALT)

The HALT method was developed in the early 1990s by Hobbs [12], targeting the overloading of products or components to detect their weakest parts. During the test process, an increasing load is applied to a small number of test objects, until a function of the test object is affected or something is permanently damaged. This procedure is repeated for every kind of load the test object experiences during its lifetime [14]. In contrast to other tests, HALT aims at the destruction of the product (called "testing to failure"). Pitfalls mentioned in [15] lead to possible problems for CubeSat teams for applying HALT. Purchasing several subsystems for destruction is not a feasible option for CubeSat teams.

Reliability Growth in Assembly, Integration and Testing

Cho proposed a method to estimate the reliability growth through assembly, integration and testing (AIT) for a nanosatellite [16], [17]. The method is based on the model by Duane [18], assigning a reliability growth to failure detection in the AIT test activity. As it is more and more time consuming to detect the next potential failure, the purpose of the method is to find the optimal point to stop the test activities (i.e., finding the next failure would statistically be very time consuming). The model supposes, that every detected failure will be completely removed and no new failures are induced by doing that. It is also assumed that the test object has a limited numbers of failures and these failures are homogeneously distributed over the whole test object. The last assumption is that the applied tests are also homogeneously distributed over the whole state space of the test object.

Cho assumes [17], that the distribution of the cumulative failures over time should reach a saturation over time. The distribution of the cumulative failures can be mathematical modeled by a Weibull distribution:

$$\lambda(t) = \frac{\beta}{\alpha^\beta} t^{(\beta-1)} \qquad (1)$$

with:

$\lambda(t)$ = cumulative failures over time
α = scale parameter of the Weibull distribution
β = shape parameter of the Weibull distribution
t = time

To reach the best approximation of this function to the real values, α and β have to be optimized. That can be done by the sum of squared deviations method. By extrapolating the saturation curve into the future, the time needed to find the next failure can be estimated. From a project management point of view, resources (in time and money) can be traded-off against further tests against the reliability growth that is expected by these tests, allowing a data-based decision whether the tests shall be continued or stopped.

Cho also presented Monte Carlo simulations for calculating the reliability in orbit after a certain time in AIT [17]. Being conservative with his assumptions, the calculated results show only little positive impact of testing time on reliability after launch. The presented method has two main disadvantages for CubeSat projects:

- The method is not focused on functional failures. Instead, different AIT activities and phases are merged and the total time in testing used.

- The time needed to correct a failure and the time to repeat previous AIT activities, as required after the failure correction, is not taken into account. That makes the time-estimation for future activities very uncertain.

Although having those two disadvantages, the reliability growth model by Cho has been used by us as one of the two main models of the proposed reliability prediction tool for CubeSats (see Chapter 4).

3. THE CUBESAT FAILURE DATABASE (CFD)

The growing number of CubeSat missions allowed a statistical analysis of the reliability of past missions, both on system as well as on subsystem level. By doing so, non-parametric and parametric analysis can help the CubeSat developers to identify critical subsystems in their systems.

We examined three available databases in detail:

- Castet and Saleh collected data from 1584 satellite missions up to 2006 of all weight classes and published work on satellite and subsystem reliability [19], data analysis and modelling [20], as well as Weibull distribution modelling for parametric analysis [21]. Although the results and analysis methods are interesting for CubeSat teams to understand general correlations, no dedicated analysis is specifically addressing CubeSat failure rates.

- Swartwout collected data from 483 CubeSat missions, building an online available database dedicated on CubeSat success and failure. Data on the type and origin of the mission as well as a mission success criterion is provided. Swartwout analyzed the reasons for success and failure [1]-[3], but their time dependence remains unknown.

- Guo et.al. [22] researched small satellite reliability on spacecraft under 50 kg. Analyzing the data of 222 small satellites, parametric a non-parametric models were built and published. CubeSats were not specifically addressed in this study.

To fill this gap, the CubeSat Failure Database (CFD) was built in late 2014 by the authors. It is comprised of 178 individual CubeSats up to a launch date of 30/06/2014 and was created with the goal to collect time of failure and root cause data of all CubeSats launched so far. More information on the database can be found in [4] and further results can be accessed in [23] and [24].

Based on the data, a non-parametric model, a parametric Single Weibull and a parametric 2 Weibull Mixture model was built for the overall reliability of CubeSats after successful launch. Specifically, dead-on-arrival cases are addressed in the parametric Weibull functions using the Percent Non-Zero (PNZ) calculation [25] for out-of-the box failures. In Figure 1, the non-parametric reliability of CubeSats over time after successful orbit insertion is depicted using the Kaplan-Meier estimator [26]. For Parametric Assessment, a Single Weibull function was fitted using the Maximum Likelihood Estimation (MLE) method. The parameters of the Single Weibull function were estimated as $\beta = 0.4797$, PNZ = 0.8146 and $\theta = 4661.7975$. Figure 2 depicts a MLE-fitted parametric 2-Weibull-Mixture function with parameters of: $\beta_1 = 0.9017$, PNZ = 0.8146, $\theta_1 = 57.9715$, $\alpha_1 = 0.2115$, $\beta_2 = 1.0710$ and $\theta_1 = 4837.3947$.

The parametric Weibull functions are the basis for the second model of the Reliability Estimation Tool, proposed in chapter 4. Ongoing work is carried out to further expand the database to satellites launched since the end of 2014 and to enhance the resulting parametric models.
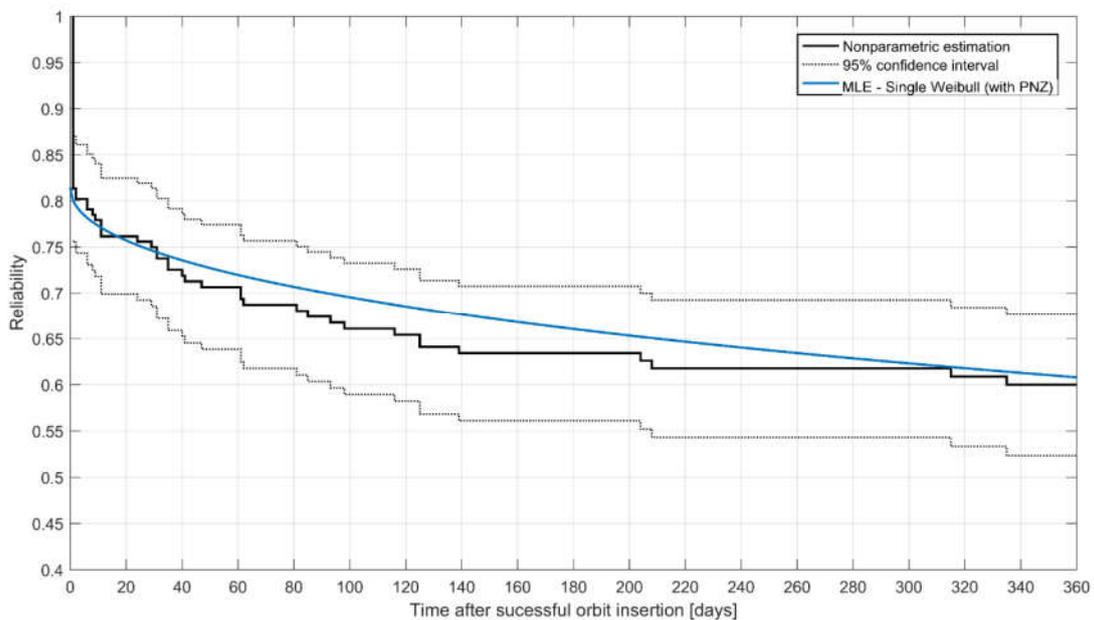

Figure 1. CubeSat reliability with 95% confidence interval and MLE Single Weibull parametric fit – 360 days in orbit
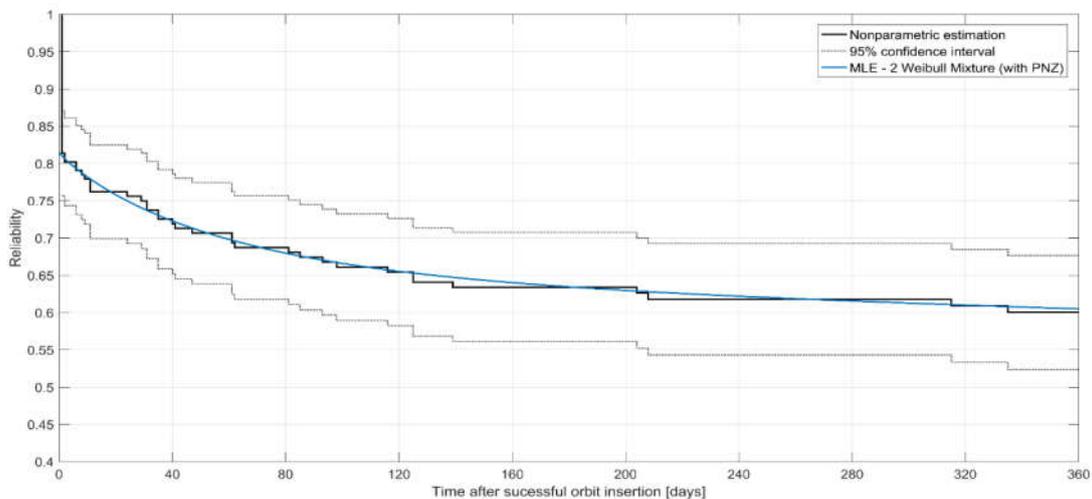

Figure 2. CubeSat reliability with MLE 2-Weibull mixture parametric fit. – 360 days in orbit

4. THE SEARCH FOR A RELIABILITY ESTIMATION TOOL FOR CUBESATS

The Reliability Estimation Tool was foreseen to help planning appropriate tests for reducing the high ratio of DOA- and infant-mortality cases [1]-[4] in the CubeSat-class of satellites. Currently, lack of conception or lack of schedule margin often lead to inadequate subsystem and integrated system-level testing for many CubeSats [1]. A survey [24] end of 2014 showed more than 34% of CubeSat builders (n=114) were not using any failure or risk analysis on their system [4].

The two-fold tool shall help CubeSat developers in allocating their resources adequately for subsystem and integrated system tests. Combined with carefully selected environmental tests (i.e., thermal-vacuum test, vibration, acceleration), infant mortality cases should be reduced or eliminated. First, the research on the tool will be introduced in chapter 4. Within chapter 5 it will be explained how the tool influenced decisions in the MOVE-II development process.

The Adapted Reliability Growth Model

The complexity of CubeSats (as well as many other systems) makes it impossible to test every input configuration. The Reliability Growth Model was built with the intention to help decide on "how much functional testing is enough?". To refine the method of Reliability Growth in AIT, we adapted the methodology from Cho [16], [17] for the CubeSat-specific requirements mentioned in chapter 2 [27]:

While time is the input parameter leading to saturation of detectable failures in the model by Cho, varying input configurations are the underlying parameter to be explored in our model. Focusing on infant mortality, certain input configurations are tested and functional failures detected. We have chosen Anti-Random Testing [28] as the best method to get a homogenous state space coverage of our system [29]. Despite this change, the saturation of cumulative failures, now plotted over the number of tested input configurations, remains a valid output value for quantifying remaining functional failures. Ideally, while combinatorial testing all possible input configurations of the CubeSat and its subsystems, the whole state space is explored and all functional errors can be found. In reality, time and resources might restrict teams to certain input configurations for testing. With the Reliability Growth Tool, the failures remaining in the subsystem or system can be predicted if no further testing is possible.

Bayesian Reliability Estimation on System Level

Current CubeSats often face the problem of "small sample" and "no-failure" situations while performing their system level functional test. To answer the question of "how much functional testing is enough", even when no failure has been detected, while operating the system in a "day in the life mode", Bayesian Methods can be used to estimate the probability of fulfilling certain reliability goals. Especially

for CubeSats, this approach could lead to realistic reliability estimations and optimized test durations with respect to the high infant mortality.

In general, by using the Bayes Theorem [30], prior knowledge can be combined with test results to a posterior knowledge:

$$P(\theta|D) = \frac{P(\theta)P(D|\theta)}{\int P(\theta)P(D|\theta)d\theta} \qquad (2)$$

By using Bayesian inference, uncertainty in the underlying models, assumptions and test data can be quantified. Depending on the choice of prior (P(θ)) model and the observed test result (P(D|θ)), the posteriori knowledge can either be calculated using a closed-form expression (if a conjugate prior can be chosen) or Markov Chain Monte Carlo (MCMC) methods. So far, work has been published on the analysis of deployment systems [31] and on the analysis of design risk for small satellites [32] using Bayesian Methods.

So far, 3 possible ways of utilizing Bayesian inference within system level testing of CubeSats have been identified as suitable candidates for the Reliability Estimation Tool. In every case, heritage information from past CubeSat missions in the system level (e.g., the Weibull functions of chapter 4) or on subsystem level ([4]) shall be used as an input for prior knowledge. Furthermore, for upcoming mega-constellations or series of satellites, in-field data could be used as an alternative source of prior knowledge. Prior knowledge in our Bayesian Reliability model means to have a certain probability density function (PDF) or a certain cumulative density function (CDF) for the reliability of the system or the subsystem over time.

Weibayes Analysis—A classical approach to deal with small test data and no-failure situations in reliability prediction is the Weibayes Analysis [33]. Using historical failure data, prior knowledge or engineering knowledge, a reasonable shape parameter β has to be assumed in the beginning. In our case, historical data for β can be obtained through the CFD. It still has to be evaluated if Weibayes is not too conservative for Reliability Estimation purposes on system level.

Bayesian Updating using Gamma Prior and Poisson Likelihood Models— Another way of dealing with the prior information would be to assume a Gamma Function (1-CDF) of past CubeSats (3) as our prior knowledge. The Gamma function in Figure 3 was built using a shape parameter k = 0.442028 and a scale parameter θ = 8000. As described in [34], a Poisson likelihood model could subsequently be used to update the gamma function with test data obtained through continuous testing.

Bayesian Updating using alternative Prior & Likelihood Models—As a third option, other prior models and likelihood models could be used to describe the test data obtained. Other statistical distributions could be more suitable to correctly describe the prior and likelihood data obtained. Although, from a mathematical point of view, it will be easier to search
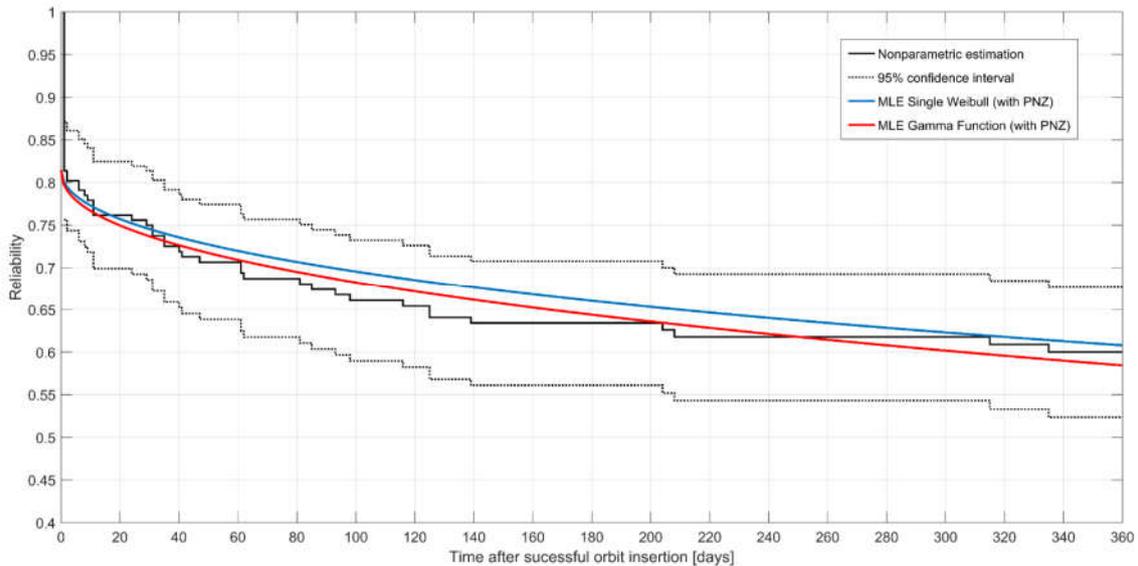
Figure 3. CubeSat reliability with MLE Gamma parametric fit. – 360 days in orbit

for a conjugate prior to the likelihood of the test result, also numerical solutions using Markov Chain Monte Carlo (MCMC) methods, for example with Weibull distributions, could be implemented. One possible solution with a conjugate prior will be discussed in chapter 6.

Overall, if prior knowledge about past missions (on system as well on subsystem level) are used via Bayesian Inference, a posterior solution of the CubeSats reliability can be assessed not only taking the often limited information on system level testing, but also the reliability from past missions into account. Still, more work has to be done in order to resolve the question which Bayesian inference method is the most suitable to be used for CubeSat reliability prediction.

5. APPLICATION TO MOVE-II

The applicability of the refined Reliability Growth Tool has been proven by its utilization in the CubeSat project MOVE-II. To optimize the resources within our team, we estimate the time needed for any functional test activity. This estimation is based on historical data and expert opinions. The estimated time can be assessed against the predicted time (out of equation (1)) to find the next failure. If we see a saturation before the end of the estimated testing, resources can be reallocated for other test. On the other hand, if there is no saturation foreseeable when the estimated time for the functional test is reached, the remaining risk and the additional time needed can be quantified.

One illustrated example is the functional test of one critical aspect of the command and data handling subsystem (CDH) during the preparation for a high altitude balloon flight of the MOVE-II hardware. The test object was the Serial Peripheral Interface (SPI) bus that connected the command and data handling subsystem with the RF-communications boards. The system is chosen as an example, since the state space of

this interface is actually very small for a technical system. Only ten commands can be transmitted. The used state space included four alternatives for every command [29]:

- a random valid content
- a random invalid content
- the upper limit of the valid contents
- the lower limit of the valid contents

Eighteen of these forty possible input configurations were tested in two steps. Figure 4 depicts the first (red) and second (blue) series of tests. While the first series of tests lead to a quick rise in cumulative failures, signs of saturation can be seen during the second series after corrective actions to the series 1 hardware configuration. For the first series of tests, 5 hours were needed in total for preparation and execution of all tests. With 10 input configurations, a total sum of 10 failures were detected. For the second series of tests, a total sum of 9 hours was needed for preparation and testing. Nevertheless, only 2 failures were detected with 8 input configurations. After the two tests, the state space was covered to 45%. Extrapolating the second series, a total sum of 19 functional failures could be expected in the system with 40 different possible functional test configurations (not including environmental tests, only functional tests considered).

However, to find the theoretically predicted 7 failures remaining in the system (see equation (1)), a disproportionate expense in resources allocation would have been needed. Out of this considerations, the test was stopped at this stage, accepting the risk posed by the potentially remaining 7 undetected failures. By using the Reliability Growth Model within the Reliability Estimation Tool for CubeSats, tradeoffs can be made whether to continue a certain functional test to detect possible functional deviances in the system or not.
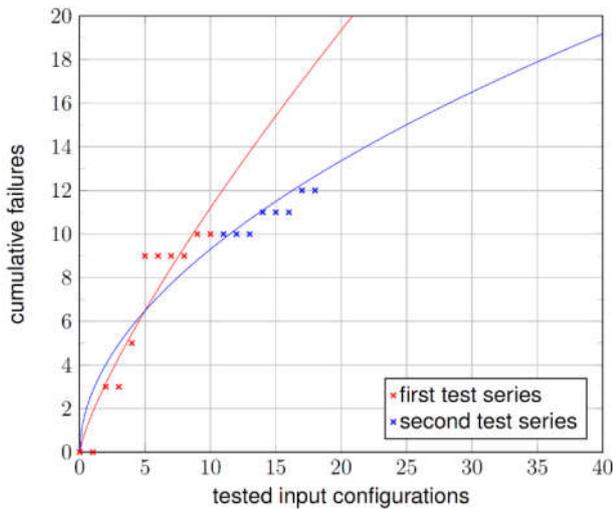
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Figure 4. First and second series of tests on the SPI module of the CDH-subsystem of MOVE-II

6. CONCLUSIONS AND DISCUSSION

We presented ongoing research on a novel Reliability Estimation Tool for CubeSats based on reliability growth models over tested input configurations and based on Bayesian Inference of failure free test data with historical reliability data. Both methods were developed within the CubeSat project MOVE-II, but further work has to been done to fine-tune the underlying models. For the Bayesian Reliability Estimation Model, the right choice of prior and likelihood models for our test data has to be evaluated.

In the case of failure-free testing time, while doing the system level functional test, the test data (i.e. the likelihood) could be interpreted as a Pareto function, with the time of failure-free testing being the known minimum of x_m. Hence, assuming a hypothetical failure-free test time of 100 days, a Pareto function with $x_m=100$ days could be chosen as underlying model for the likelihood function. This resembles, from a functional point of view, all the information we have about the system: while continuously in operation, there are no problems to be expected from a functional point of view until the time x_m. On the other hand, after the 100 days we don't have any information about the system. In the worst case, this could be resembled as a shape parameter of $\alpha = \infty$, resulting in reliability of zero (1-CDF). This rather optimistic ($x_m=100$ days) interpretation of the first 100 days and rather pessimistic ($\alpha = \infty$) interpretation of the time afterwards of the test results could be merged with prior knowledge (precursor mission, other CubeSats, expert knowledge). In our case, the Gamma distribution of the CFD (Fig. 3) could be our prior knowledge. It is a conjugate prior distribution to the Pareto distribution, thus, a closed form of the posterior expression is possible. Hence, no numerical solutions are needed while generating the posterior solution using Bayes' theorem. The resulting posterior knowledge is an interpretation of all the reliability information we have on the system.

Depending on the setting of the mission, other prior information than past CubeSat mission could also be taken into account. Expert elicitation (n=113) on the likelihood of failure for a university-built CubeSat mission within the first six months would be another source of prior information [4], specifically tailored to university teams. Other proprietary knowledge on past missions as well as in-house expert estimations can be included, if desired.

Thus, by using the estimation model, a certain test time for the likelihood of the survival of the system for a pre-defined time could be assessed by the CubeSat developers with respect to their specific heritage, using all information obtainable. Furthermore, simulations can be made on certain reliability goals over time and the necessary failure-free test time needed for that. One must keep in mind that the functional tests mentioned only cover functional errors and not failures due to environmental issues in space, other than those tested in analog environmental tests on ground.

Finally, developers of future constellations and series of SmallSats could use the method while mass producing their vessels. On-orbit data as well as test data on the ground can be incorporated and used for improving the reliability prediction models while reducing the infant mortality due to functional errors. Hence, the testing time and the design-lifetime could be fine-tuned using a methodology like the proposed one.

It is planned to use the Model within the system level tests of MOVE-II starting in May 2017. However, to estimate the necessary failure-free testing time needed for the reliability goals of the mission, an assessment beforehand will be necessary. In the future, it might be possible to use on-orbit reliability data of MOVE-II as prior information on subsequent missions.

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BIOGRAPHY

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