Reliability Growth of Autonomous Underwater Vehicle – Dorado

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Abstract – *Underwater environments are highly unstructured, uncertain, and dynamic. However, over the past three decades many autonomous underwater vehicles (AUVs) have been developed and successfully deployed for various oceanographic applications. There is a growing need for the AUVs to be reliable for collecting useful data and samples for their users. An AUV is a typical one-of-a-kind product for which it is difficult to derive a mathematical/ statistical model for reliability prediction. The failure modes effects and criticality analysis (FMECA) can produce more effective results. However, the assessment of reliability growth of an AUV is very important for predicting its operational success in challenging underwater environments. In this paper, we present the identification of different types of failures that occurred during the past one and a half years of operation of MBARI's Dorado AUV, classification of those failures, and the reliability growth analysis for the vehicle. Reliability issues of various subsystems and operational procedure of the AUV have also been discussed. An extensive analysis of operational data and test results are presented in this paper.*

I. INTRODUCTION

Autonomous Underwater Vehicles (AUVs) are gaining popularity for use as mobile platforms in the ocean. Many sectors such as military, scientific, and commercial are using AUVs to carry out their data acquisition needs. Military users, for example, are concerned with harbor security and anti-submarine warfare issues where autonomous vehicles can help to carry out missions to identify mines and enemy subs. Physical oceanographers, biologists, chemical oceanographers, geologists, and others within the scientific community use AUVs to collect data in the water column where traditional assets like ships and towed devices are costly to operate and often difficult. Commercial vehicles are generally used for seafloor surveys of industrial structures, pipelines, and to locate buried oil and gas fields.

In each case AUVs are depended upon to bring back copious amounts of quality data. The missions are deemed successful when the vehicles surface at the endpoint intact, without any irrecoverable faults during the mission, and most importantly with all data stored onboard. A successful mission concludes with the final step of recovering the vehicle to the deck of the ship where the data is safely downloaded. Occasionally a vehicle will get into a situation that it does not know how to recover from, and it will not be able to continue. This is considered as a fault since the mission could not continue and a mission abort occurs.

Mission aborts can be very costly. For example, consider a vehicle performing a seafloor survey at a depth of 4000m. If its maximum speed is 2.0 m/s, the vehicle would take approximately an hour to surface at an angle of 30 degrees. If there was a fault with the power or propulsion system, the vehicle may ascend to the surface slowly with only its positive buoyancy to propel it. In this case, operators on the surface would have to wait hours for its return before they could recover the vehicle and diagnose the problem. Costs in excess of $1000 per hour are common for research vessels. It is easy to see that a faulted AUV can incur excessive costs very quickly with no useful output.

The Monterey Bay Aquarium Research Institute (MBARI) develops one-of-a-kind AUV systems; i.e. each system is configured for a different application with different instrument and payload requirements. Therefore it is difficult to assess the reliability of MBARI's AUVs as a single entity since there is no standard product, and the resulting dataset used to make the reliability calculations is so limited. An effort was successfully completed transitioning a vehicle from the engineering department to the operations department, where no further core modifications are to be made. The vehicle has been operated for scientists, and every mission has been logged. A very few publications are available on reliability study of AUVs. The most prominent study is on the Autosub AUV from Southampton Oceanography Centre [1]-[2].

This paper describes the reliability issues found with MBARI's AUV while the vehicle was used in an operational state. The paper continues with a reliability growth analysis using several different models. It follows up with the results of the analysis and a conclusion of the reliability of the system over time.

II. RELIABILITY ISSUES

An AUV is an oceanographic platform that consists of many different subsystems that were not designed to necessarily work together. The task of the systems engineer is to design an inherently reliable vehicle from individual parts that are highly reliable. Most manufacturers will give a mean time before failure (MTBF) rating for their products, but the MTBF of an entire vehicle is not simply the lowest common denominator of all of the subsystems. The overall system reliability is a measure of the amount of time the vehicle as a whole has operated properly without faults.

MBARI's AUV (see Figure 1) is a simple mechanical configuration of free-flooding plastic fairings, coupled with joining rings and band-clamps [3]. Faults have not been expected with the structure and to date none were recorded. The propulsion system is made up of linear actuators and a brushless DC motor connected to a propeller through a gearbox. Many faults were expected with these moving parts, but nothing has occurred since the vehicle went into an operational state. Preventative maintenance is performed periodically to alleviate possible problems with the mechanical systems.

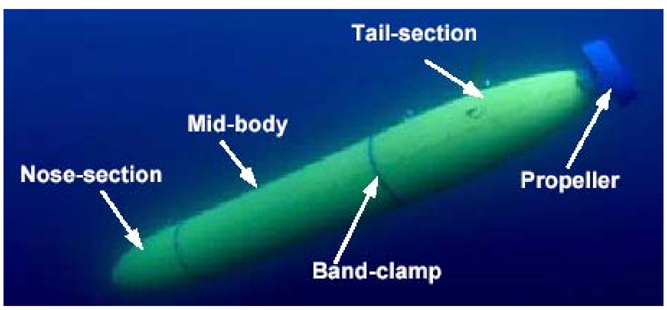


Figure 1: Dorado AUV

Frequently the software systems, particularly for a stable AUV platform, will under go changes. This is a direct result of scientists wanting to add a new instrument, which requires a new software driver to be added to the main vehicle. Since time is never abundant for integrating new instruments during the operational cycle, faults frequently occur during missions just after new software is added.

While designing the electronics and deciding on what consumer off-the-shelf (COTS) parts to use in the vehicle, all parts were put through rigorous testing in the lab before final integration. Since the AUV is free-flooding, some of the electronics are housed in a simple enclosure with pressure compensating oil increases in pressure as the AUV descends (see Figure 2 & 3). The pressure tolerant electronics can experience pressures up to 6,000 dBar for a deep mission. Common engineering practice is that all electronics are first tested in a hyperbaric pressure chamber to pressures greater than are expected for at least ten cycles at a faster rate than is typical for an AUV at sea. Screening electronic parts in the pressure chamber raises the confidence factor greatly, especially since no semiconductor manufacturers offer pressure testing as a standard specification or practice.

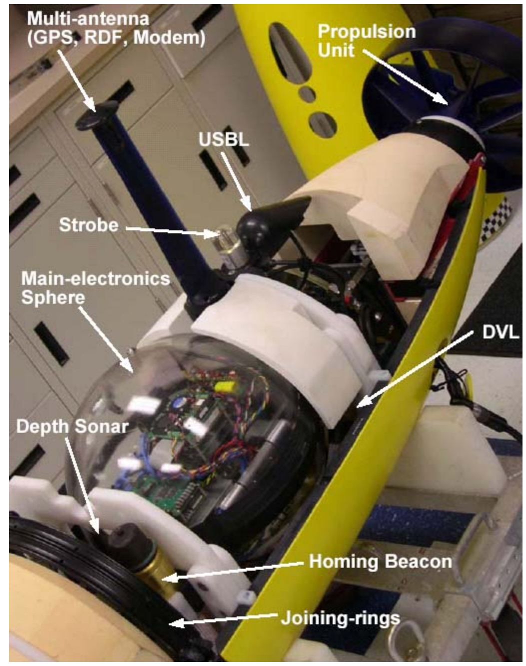


Figure 2: Tail-section of Dorado with navigational instruments.

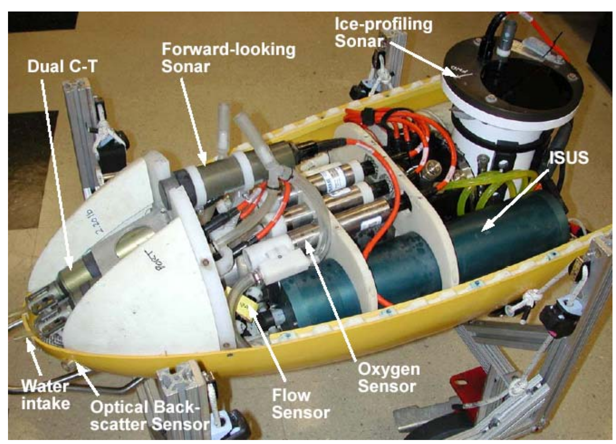


Figure 3: Nose-section of Dorado with science payload for Arctic mission.

Another method MBARI engineers use to alleviate reliability problems is by doing extensive testing in a salt-water test tank. Many problems can be discovered in only 10 meters of water including ground faults, leaky pressure vessels, malfunctioning instruments, leaky oil seals, and buoyancy. The faults found in the testing phase are not included in this analysis since they were found prior to the system entering service and corrected at that time. Only faults that occurred after the system was believed to be working correctly were logged and used later in reliability analysis.

III. RELIABILITY GROWTH ANALYSIS

The purpose of reliability growth analysis and testing is to enhance reliability over time through modification and improvement in product design, development, manufacturing and operating procedures. For any one-of-a-kind product, like an MBARI's AUV, this is accomplished through *test-fix-test* cycles of the product. In test-fix-test strategy failure modes are found during the testing and corrective actions for these problems are incorporated during the test. From reliability growth analysis point of view, we consider the whole operational duration, i.e. the past one and a half years of Dorado's operation as testing period. After each significant failure corrective actions were taken and then the AUV deployed for next run. Additionally, for any one-of-a-king product a failure mode, effect and criticality analysis (FMECA) is quite helpful in collection and analysis of the reliability data by identifying and categorizing failure modes. Actions taken during growth testing include the correction of design weaknesses and manufacturing flaws, and the elimination of inferior parts or components. Therefore, the steps important in reliability growth analysis are: (1) Identification and isolation of failures, (2) Classification of failures (or severity analysis), and (3) Trend analysis.

Identification and isolation of failures:

Through the past one and half years, Dorado AUV operations have completed more than 1700km of run distance in the Monterey Bay area. During that time the vehicle encountered different types of failures. Over this period, the vehicle was partially in the engineering development stage and partially performing science operations. Many failures were encountered during the engineering testing phase that generally would not occur in a normal operational stage. Mostly because by the time the vehicle becomes operational it is more stable and reliable. However, it is very important to identify these early failures when they occur, so that appropriate actions can be taken. In practice, we always observe the effects, not the causes immediately. Sometimes it is difficult, if not impossible, to identify and isolate the faults and their causes. A list of Dorado's failures is provided in Table 1.

Classification of failures:

The failures that generally occur during any AUV operation can be categorized in several ways based on: (1) subsystem – which subsystem or component failed, (2) function – which function or workability has been jeopardized because of the failure, and (3) severity – what is the effect/impact of the failure on the assigned mission. Here we classify the failures according to the severity, i.e. effect/impact of the failure on the accomplishment of the mission. The failures and their classification are presented in Table 1.

Table 1: Failure classification.

Cum. Failure No.	Failure Mode	Cum. Time of Occurrence (hr)	Severity of Failure
1	Attempted to double the depth - battery failed at 800m (battery 3, #86 off line – sensor failure.)	2.95	B (BB1)
2	No modem contact, battery down, vehicle recovered	10.73	B (BB2)
3	GPS problem (not communicating), also found battery #84 off	14.23	A/B (BB3)
4	Too close to bottom	16.52	B (BB2)
5	Low voltage (battery discharged quickly), data logs found empty	34.85	B (BB1)
6	Early mission abort (indeterminate/ unknown)	35.02	A/B (BB3)
7	Vehicle failed to dive after 5th resurface	66.85	B (BB2)
8	No ISUS data (hardware problem)	84.90	B (BB1)
9	Indeterminate/Unknown (mission terminated early - getgps behavior active)	137.97	A/B (BB3)
10	Mission script failed to load	147.65	B (BB2)
11	Battery sensor failed; during recovery the vehicle collide with ship and sunk to the ocean bottom	175.95	B (BB1)
12	Software bug (abort voltage setting was wrong)	215.10	B (BB3)
13	No bioluminescence data (software bug)	236.88	B (BB2)
14	Vehicle failed to dive (heavy swells, marine layer – false bottom indication)	298.48	B (BB2)

Severity of Failures:

A => no/ minimum action taken
B => action taken
BB1 => extremely critical
BB2 => moderately critical
BB3 => not critical

Here we have attempted to capture all the failures that caused the mission abort and vehicle recovery along with very critical failures like temporary vehicle lost (or severely damaged) and loss of mission data. Minor faults, which were detected and rectified on the ship's deck or in the laboratory, have not been included in Table 1. One of the critical issues in identification and isolation as well as classification of failures is the documentation of the failure modes and its effects. In many instances, the reliability personnel find it very difficult, if not impossible, to interpret the failure history because of poor or misleading information; sometimes people are preoccupied (or negligent) to document the failure immediately. All of these issues make the analysis of reliability more difficult.

Trend analysis:

For any one-of-a-kind product like an AUV, it is important to find out the failure trend, i.e. whether the failure rate is increasing or decreasing with time of operation. Failures occurring in AUV operations can be considered as *stochastic point processes*. In this type of non-homogenous Poisson process (NHPP) the point process is non-stationary, such that the distribution of the number of events in an interval of fixed length changes as the number of events increases. Therefore, the trend can be analyzed using the statistics of *event series* like Centroid test or Laplace test, which states the test statistic for trend as [4]

$$\xi = \frac{\sum t_i / N - T/2}{T\sqrt{1/(12N)}}, \tag{1}$$

where t_i is the arrival values of each event (e.g. time from $t = 0$), T is the period of observation, and N is the number of events. If $\xi = 0$ there is no trend, i.e. the process is stationary. If $\xi < 0$ the trend is decreasing, i.e. the interval values tend to become larger. Conversely, when $\xi > 0$ the trend is increasing, i.e. interval values tend to become progressively smaller. Putting data from Table 1 along with T = 309hr (total operation/ observation time) into Eq. (1), we get $\xi = -2.05 < 1$. This indicates two important points: (1) there is a significant trend in the AUV failure data, and (2) the interval values are gradually becoming larger. Since the failure occurrence interval is increasing, i.e. the less number of failures in a particular time interval, the system reliability exhibits an increasing trend.

The most commonly used and widely accepted models for analyzing and predicting reliability growth of a system are: (1) Duane's model, and (2) Crow's model, or AMSAA model (Army Material Systems Analysis Activity model). They are as follows:

Duane's model-

Duane's model states that a plot of the cumulative number of failures per test time versus the test time during growth testing is approximately linear when both are plotted on a logarithmic scale [5]. This observation can be expressed mathematically and then extrapolated to predict the growth in MTBF (Mean Time Before Failure).

Crow's model, i.e. AMSAA model-

Although there are differences in underlying assumptions of the Duane's model and Crow's model, this model also leads to a linear relationship between cumulative failure rate and observation time when plotted on a log-log scale [6].

In case of Type-I data, i.e. for a given N successive failure times $t_1 < t_2 < .... < t_N$ that occur prior to the accumulated test time or observed system time, T, the shape parameter for AMSAA model (for NHPP Power Law distribution) is written as follows [7]-[8]:

$$\beta = \frac{N}{N \ln T - \sum_{i=1}^{N} \ln t_i}. \tag{2}$$

The scale parameter (also known as Weibull failure rate function) for AMSAA model is

$$\lambda(T) = \alpha\beta T^{\beta-1}, \tag{3}$$

where, $$\alpha = \frac{N}{T^{\beta}}. \tag{4}$$

The mean time before failure (MTBF) is

$$MTBF = \frac{1}{\lambda(T)}. \tag{5}$$

Two-sided confidence intervals for MTBF can be obtained from the following expression,

$$\frac{L}{\lambda(T)} \le MTBF \le \frac{U}{\lambda(T)}, \tag{6}$$

where *L* and *U* are the lower and upper confidence interval factors. This model is applicable for test-fix-test strategies, like AUV operations, where the problem modes are found during testing and corrective actions for these problems are incorporated during the test.

Reliability Bounds:

If $$0 < \lambda_L \le \lambda(t) \le \lambda_U. \tag{7}$$

Then $$\int_0^t \lambda_L \, dt' \le \int_0^t \lambda(t') dt' \le \int_0^t \lambda_U \, dt', \tag{8}$$

and $\exp\left[-\int_0^t \lambda_L dt'\right] \geq \exp\left[-\int_0^t \lambda(t')dt'\right] \geq$

$$\exp\left[-\int_0^t \lambda_U dt'\right], \qquad (9)$$

or $$e^{-\lambda_L t} \geq R(t) \geq e^{-\lambda_U t}. \qquad (10)$$

Therefore, if the hazard rate function, $\lambda(t)$, is bounded, the reliability function, *R(t)*, can also be bounded. According to Barlow and Porschan [9] for a DFR (decreasing failure rate) process, reliability is

$$R(t) = \begin{cases} e^{-t/MTBF} & for \quad t \leq MTBF \\ \dfrac{MTBF}{t} e^{-1} & for \quad t > MTBF \end{cases} \qquad (11)$$

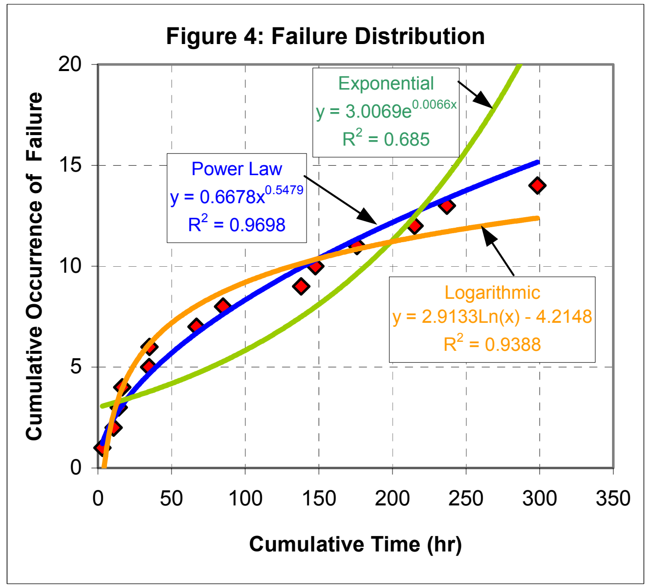
IV. RESULTS AND DISCUSSION

MTBF is an important measure for assessing reliability of a product in operation. We have computed MTBF and other parameters using Eq. (2) through Eq. (6) of AMSAA model. Taking values from Table 1 and considering 309 hours of operations (about 1700km of run) we obtained β = 0.584, λ = 0.0265 and MTBF = 37.8hr. As we know, if β = 1, no reliability growth; β < 1, positive reliability growth; β > 1, negative reliability growth. Here, β = 0.584 < 1, which indicates a positive reliability growth for the AUV. Since the intensity function is not constant, i.e. $\beta \neq 0$, the NHPP should be considered for the analysis. From the Chi-square (χ^2) statistics for the trend test we found χ^2 = 2*N*/ β = 48.0 > $\chi^2_{crit,0.05}$ = 38.9. Therefore the hypothesis of significant trend is accepted. Since β is less than 1, the AUV's reliability is improving.

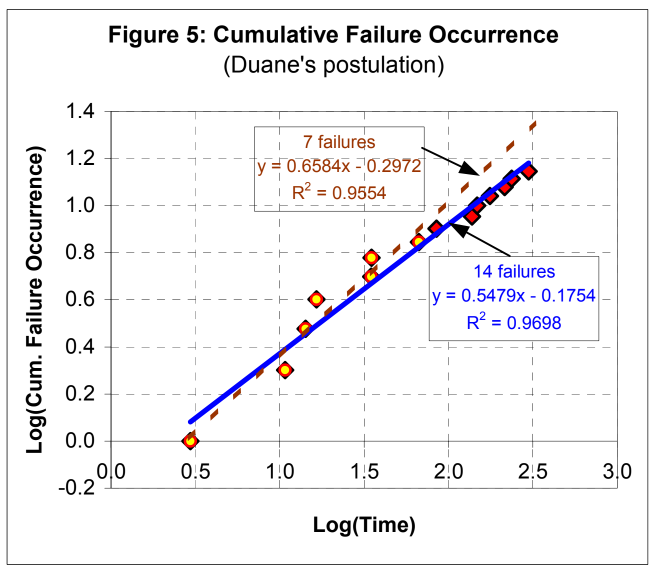
Table 2: MTBFs for different types of failures.

Failure Type	MTBF (hr) [lower]	MTBF (hr) [upper]	MTBF (hr)
BB1	52.4	997.9	167.8
BB2	38.7	377.8	100.4
BB3	27.6	526.4	88.5
ALL	20.2	81.4	37.8

We have also calculated MTBFs for different types of failures and presented in Table 2 above. Out of total fourteen failures, there are four BB1 type failures, five BB2 type failures and another five BB3 type failures (see Table 1). The second and third columns in Table 2 show the lower limit and upper limit of MTBF, respectively. These limits are computed using Eq. (6) at 0.9 confidence level. It is observed that the bounds of MTBF are quite large. This range of MTBF narrows down with increase number of data set and it also depends on distribution of failures. The MTBF of most severe type failure, BB1 type, is quite high (167.8hr) as compared to other two types of failures (BB2 and BB3 types). This implies relatively less frequent occurrence of most severe type of failures. However, the overall MTBF, considering all the 14 failures, is 37.8hr.

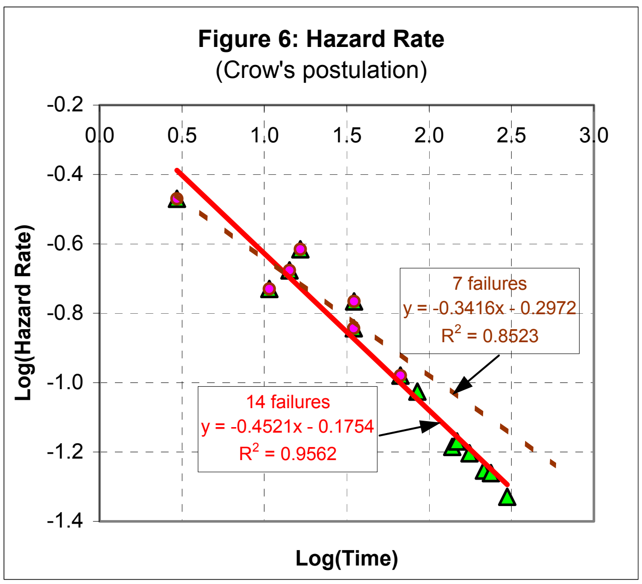


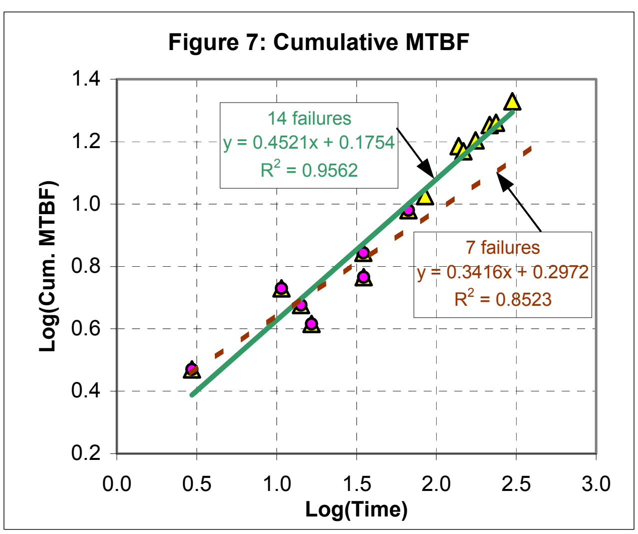
Reliability analysis results are plotted in Figure 4 through Figure 8. As we mentioned at the beginning of this section, the plots of Figure 4 also reveal that the best-fitting curve follows the Power Law, and the next best one is the Logarithmic fitting. The distribution of failure is non-homogeneous, however, we observe a decrease in failure occurrence as time goes on.



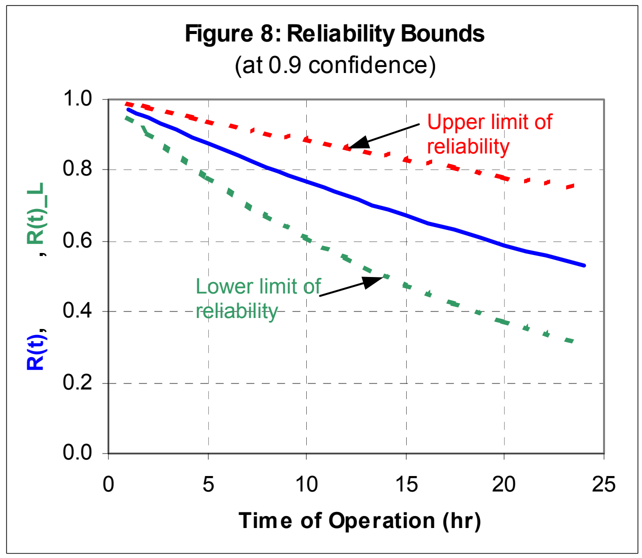
The log-log plot of cumulative failure versus cumulative time in Figure 5 conforms Duane's postulation of linear relationship with a correlation coefficient of 0.97. The slope of this line is about 0.55 (28.7degrees), which is also an indication of change in failure occurrence. In this plot, we have also projected first 7 failures forward (shown in dotted line). The slope of this line is 0.67, which indicates a significant change in failure occurrence with time; the rate of number of failures decreases as time increases.

In Figure 6, we have plotted cumulative failure rate versus cumulative time on log-log scale. These plots clearly agree with Crow's postulation of liner relationship. The 14 failures plot and projected 7 failures plot indicate a significant trend in decreasing failure rates with an increase in observation time.





Cumulative MTBFs for 14 failures and projected 7 failures are presented in Figure 7. They also exhibit linear relationship on log-log plot. It is noticed that the MTBF has improved with increased operational/ testing time. The reliability of AUV for 24 hours of operation has been presented in Figure 8. The upper bound and the lower bound of reliability are indicated by dotted lines. It is observed that 5hr operation can be performed with about 88% reliability. But the predicted reliability for 24hr operation drops down to about 53%. Although the current MTBF is about 37.8hr, the reliability has to be improved especially for longer missions. From the growing trend of MTBF, we can envisage a significant improvement in the reliability in future.



V. CONCLUSION

In this paper, we have analyzed the reliability growth of MBARI's Dorado AUV. Reliability analysis and prediction for this one-of-a-kind type of product is more challenging as compared to mass-production items like TV, automobile, refrigerator, cell phone, etc. The strategy that is commonly followed for testing this type of system, like an AUV, is test-fix-test. During the development and initial operation phases of Dorado we have collected all the failure data to analyze the reliability trend of the system. It has been observed that the MTBF is increasing, i.e. the system is going to be more reliable as time goes on. This makes sense, because when the system failure is analyzed at the subsystem or component level; then the required component/subsystem is modified, or replaced with a new/improved one.

The failure distribution closely follows Duane's postulation as well as Crow's postulation. We observed a gradual improvement in system reliability. Both the Laplace test and the Chi-square test revealed a significant trend in reliability growth. However, for better consistency in MTBF and reliability prediction, more data needs to be collected. The Dorado AUV is currently in regular operation and undergoing occasional upgrades of both hardware and software. Generally, the majority of the failures encountered during the engineering development phase no longer occur. In the science operation phase the vehicle has become more stable. Therefore, we believe that in the future, the vehicle will become yet more reliable. We have a plan to operate the AUV unattended (no presence of mother-ship) for 24 hours. We expect to gather a lot of important data during these runs. We are also working on another project to make use of a Dorado AUV as a docking vehicle for long-term science missions. The work on reliability outlined here is intended to make Dorado reliable enough to be deployed for sustainable science missions with docking capability.

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