Redundancy: How Many Unreliable Spares are Needed for High Reliability and Confidence?

Harry W. Jones, Ph.D., MBA, NASA Ames Research Center

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SUMMARY & CONCLUSIONS

This paper investigates the number of redundant units needed to achieve high reliability with high confidence. The approach is developed for the case when the system failure rate is too high for a single unit to provide the required reliability over the mission duration. To achieve high reliability, N redundant units can be used, one operating unit and N – 1 spares. If the unit failure rate is f, the mission length is L, and f * L is small (not the case assumed here), the unit failure probability over the mission duration is F1 = f * L << 1. In this case, the probability that all N units will fail is Ffail = $F1^N$, and the needed redundancy N = LN(F)/LN(F1). For the case of large f * L assumed here, F1 = f * L > 1, and F1 is the expected number of failures during the mission. (When F1 = f * L << 1, F1 is the probability that a unit will fail during the mission. When F1 = f * L > 1, F1 is the expected number of failures during the mission.) The needed redundancy, N, to achieve the required N redundant unit reliability, FN, can be computed using the cumulative Poisson distribution with mean equal to F1. The number of spares, N - 1, is increased until the probability - that the total number of failures will be less than N -1 - is equal to the required reliability. The confidence that this reliability can be achieved can be computed using the cumulative Poisson distribution or the chi-square distribution. Since the measured unit failure rate, f, has some probabilistic uncertainty, the actual failure rate will be randomly higher or lower. This means that the reliability of the N redundant systems will be overestimated about half the time. Adding more redundant units increases the confidence that the required reliability will be achieved. For a fixed number of redundant units, the expected reliability and confidence can be traded off, since lower reliability goals will be achieved with higher confidence. Both the desired reliability and confidence can be specified as initial requirements and the needed number of redundant units estimated using the measured failure rate.

1 INTRODUCTION

This paper considers how much test time is cost effective for computing the number of redundant units needed to achieve high reliability with high confidence. This requires a two-phase test program, an initial period of testing to provide reliability growth, followed by life testing to more accurately determine the final failure rate achieved by reliability growth. Newly designed systems often have high initial failure rates. These are often reduced by finding the high-rate failure modes and removing them by redesign. This usually continues until the system achieves an acceptable failure rate. This failure rate will be constant if there are no further redesigns or wear out. For high reliability with high confidence using redundancy, longer test time should be used to better measure the failure rate, since this reduces the number of redundant units needed for high reliability with high confidence.

The measured failure rate decreases throughout the reliability growth period as failure modes are removed. After the reliability growth effort is terminated, the first few failures during life testing provide an estimate of the final failure rate. Given the measured failure rate and the desired reliability using redundancy, the number of spares can be determined and the confidence in the reliability computed. If there are only a few failures, the failure rate estimate will have a wide variance. There is a 50% chance that the actual final failure rate is higher, and it could be much higher. If a too low estimated failure rate is used to compute the redundancy needed to achieve the required reliability, the number of spare units provided will be too low. Using the measured failure rate gives only a 50% confidence that the failure rate and number of spares are not too low.

In the suggested approach, both the redundant reliability and the confidence level are initial requirements. The confidence that the actual redundant reliability is not too low can be increased by increasing the number of spares. When there are only a few failures, the variance of the failure rate is high, and the failure rate and number of spares must be increased greatly to reach high expected reliability with high confidence. The higher number of spares increases the cost of redundancy. Longer test time reduces the variance in the failure rate and reduces the number of spares needed to increase confidence.

As the test time is increased, the test cost increases linearly but the number of needed spares drops, at first exponentially. The total cost of reliability is the sum of the cost of the redundant units and of the test time. There is an optimum test time that produces the minimum total cost for the system failure rate, mission length, reliability, and confidence level. If the total cost must be reduced, the reliability, the confidence level, or both must be reduced. The required reliability and confidence identify and justify a minimum total cost for redundant units and the testing. Determining the optimum test time that minimizes the cost to meet reliability requirements can help plan efficient testing.

2 PRELIMINARY ANALYSIS

The process of developing reliable new systems can take three steps, first designing for reliability, then testing for reliability growth, and finally further testing to accurately measure reliability.

The engineering process of Design for Reliability (DfR) is described in many books and articles. First, the reliability requirement is defined, then a system reliability model is developed, next the reliability requirement is allocated to the subsystems, and finally an estimate of reliability is made. If the expected reliability is considered inadequate, the system can be redesigned for higher reliability. The difficulty of increasing reliability varies greatly, depending on the technology and how much previous effort has been made to improve reliability. A proportional cost increase formula with a variable exponent can be used to model the additional cost incurred to reduce the failure rate. Suppose the current system cost C0 to achieve a failure probability F0. The cost C(F1) to achieve a failure probability of F1 can be estimated as

$$C(F1) = C0\ (F0/F1)^{a} \qquad (1)$$

The exponent "a" can vary from 0.25 to about 2.5. This formula can approximate many of the cost of reliability formulas in the literature [1]. Designing to reduce the failure rate can be expected to have diminishing returns. At some point the Design for Reliability process is completed and then reliability growth testing usually begins.

Newly designed systems often have an unexpectedly high initial failure rate, possibly due to mistaken performance assumptions or design oversights. Testing identifies the failure modes and, if these are removed by redesign, the failure rate will decrease. The process of identifying and removing the failure causes creates reliability growth, but the frequent observation of a continually declining failure rate over time is sometimes a mathematical artifact.

The failure rate is $\lambda(t) = n(t)/t$, where n(t) is the number of failures occurring up to time t. If N failures occur in time T, $\lambda = N/T$. Suppose that these failure causes are corrected, and no further failures occur. Then $\lambda(t) = N/t$ and declines as t^{-1}, ultimately approaching zero. This rapid failure rate decline is due to averaging the initial failure count over longer time periods, unlike true reliability growth created by identifying and removing failure modes.

In a more typical case, rather than no failures occurring during continued testing, there may be continuing random failures with different causes that are too infrequent to require redesign. As the early failure count is averaged down over time, the time varying failure rate often declines to a constant value. The abcd model for reliability growth includes a period of failure rate decline followed by a period with a constant failure rate. The abcd mathematical model for reliability growth is

$$\lambda(t) = n(t)/t = a\ t^{-b} + c, \text{ from } t = 0 \text{ to } t_d. \qquad (2a)$$

$$= c + d \text{ after } t_d, \text{ where } d = a\ t_d^{-b} \qquad (2b)$$

The failure rate is n(t)/t, a is a constant and b is the reliability growth rate, the downward slope of n(t)/t versus t. The parameter c is the constant failure rate due to failure modes that will not be corrected. The time t_d is when reliability is no longer being improved by correcting failure modes and the failure rate becomes constant. The longer t_d, the more failures are found and removed. The parameter d is the constant failure rate due to failure modes that could have been corrected during a longer reliability growth period. It measures the remaining unused reliability growth potential. [2] [3] [4] [5]

The abcd reliability growth model was fit to different failure test data sets. The most surprising result was that b, the exponential decline rate is often exactly 1, reflecting the fastest possible reliability growth. This indicates that the reliability growth process of finding and fixing failures was well implemented. In most cases the final failure rate is significant, typically fifteen percent of the initial failure rate. Usually, the reliability growth period td is relatively long, and d is approximately zero. [2] A normalized general model for reliability growth would be

$$\lambda(t) = n(t)/t = t^{-1} + 0.15 \qquad (3)$$

If the final failure rate, equal to c + d in the abcd model, is relatively high or the mission length, L, is relatively long, redundant units or spares are needed to achieve the required overall system failure rate.

Table 1 shows the data points, $\lambda(t)$, for a 41-failure data set with a continually declining failure rate. [6, p. 121] The last failure is at t = 43.1 and $\lambda(t)$ continues to decline until t = 49.2, due to the division of the total number of failures by the increasing test time. The final failure rate is 0.8 and the required mission operating length is L = 2. The expected number of failures during the mission is 0.8 * 2 = 1.6 and so spares are needed to prevent mission failure.

The data in Table 1 include the failure count, n, the failure times, t, the decreasing failure rate $\lambda(t) = n(t)/t$, the increased failure rate for confidence = 0.9, $\lambda0.9(t)$, the required number of units N for reliability = 0.9 and confidence = 0.9, the increasing test time cost for testing one unit, and the total cost. The cost unit is the cost of developing one system. The test cost is assumed to be 0.015 of the unit cost per unit time.

Table 1. Data, units, and cost for the 41-failure data set.

n	Time t	λ(t)	λ0.9(t)	Units N	Test cost	Total cost
7	1.9	3.7	6.2			
8	3.1	2.6	4.2	13.0	1.0	14.0
9	4.3	2.1	3.3	11.0	1.1	12.1
10	5.5	1.8	2.8	10.0	1.1	11.1
11	6.8	1.6	2.5	9.0	1.1	10.1
12	8.0	1.5	2.2	8.0	1.1	9.1
13	9.2	1.4	2.1	8.0	1.1	9.1
14	10.4	1.3	1.9	7.0	1.2	8.2
18	15.3	1.2	1.6	7.0	1.2	8.2
19	16.5	1.2	1.6	6.0	1.2	7.2
20	17.7	1.1	1.5	6.0	1.3	7.3
23	21.4	1.1	1.4	6.0	1.3	7.3
24	22.6	1.1	1.4	6.0	1.3	7.3
27	26.2	1.0	1.3	6.0	1.4	7.4
28	27.4	1.0	1.3	5.0	1.4	6.4
29	28.7	1.0	1.3	5.0	1.4	6.4
30	29.9	1.0	1.3	5.0	1.4	6.4
31	31.1	1.0	1.3	5.0	1.5	6.5
35	35.9	1.0	1.2	5.0	1.5	6.5
36	37.2	1.0	1.2	5.0	1.6	6.6
37	38.4	1.0	1.2	5.0	1.6	6.6
40	42.0	1.0	1.2	5.0	1.6	6.6
41	43.1	1.0	1.2	5.0	1.6	6.6
41	44.3	0.9	1.1	5.0	1.7	6.7
41	49.2	0.8	1.0	5.0	1.7	6.7

3 UPPER CONFIDENCE BOUNDS

The failure rate data for the 41-failure data set in Table 1 show the typical pattern of a rapid initial decline during a reliability growth period followed by a long period when the cumulative average failure rate declines due to averaging the initial failure count over time. The actual failure rate for the 21 failures over time 17.7 to 49.2 is 0.67. An important reason to continue testing beyond the reliability growth period is determine the final failure rate to more accurately, which is used to determine the required number of spares.

The measured failure rate λ(t) = n(t)/t is a data-based average subject to random variation. The fewer the failures, the wider the computed λ(t) may vary. If testing stops after only a few failures, it is possible that the true system failure rate would have produced many more failures than occurred. This would make the measured λ(t) much lower than the true λ(t), and so the calculated number of redundant units N would be too few to provide the required reliability.

If the measured failure rate is used to determine the number of spares, there is only a 50% confidence that the number of spares is not too low. If a higher, say a 90%, confidence is needed that there are sufficient spares, this can be achieved by using an increased failure rate λ(t) that would produce fewer than the measured number of failures only 10% of the time. Instead of using the measured failure rate to determine the number of spares, the 90% upper confidence bound on λ(t), λ0.9(t), would be used. If this is done, there is a 90% confidence that λ0.9(t) is not lower than the actual failure rate and the number of spares is not too low for 90% confidence in the predicted reliability. λ0.9(t) is the 90% upper confidence bound on λ(t) and is shown in Table 1.

The upper confidence bounds on λ(t) can be determined using either the Poisson distribution or the chi-square distribution, which are included in available spreadsheets. [7] [8] The chi-square distribution approach is most direct.

$$\sum m^x e^{-m}/x!,\ x = 0, 1, 2, \ldots M = \text{Probability } \chi 2\ (x, f) > 2m \quad (4)$$

The "m" is the mean number of failures, m = λ(t) L, where L is mission length. The summation is over the number x = n of failures included, 0 to M. The x in χ2 (x, f) is not the counting index x = n. The x in χ2 (x, f) is the fraction of the distribution summed, equal to the cumulative probability of being below the upper bound when the mean of the Poisson distribution is mu = λx(t) L. And f is the number of degrees of freedom. Here f = 2 (n(t)+1) where n(t) is the number of failures. [7] [8]

The available spreadsheets have a function that iteratively computes the inverse of the chi-square distribution. The confidence bound λx(t) is the inverse of the left-tailed probability of the chi-square distribution for probability P and f degrees of freedom.

$$\lambda x(t) = \text{Inverse chi-square } (x, 2*(n(t)+1)/(2\ t) \quad (5)$$

The 90% confidence bounds equal to λ0.9(t) are shown in Table 1. As expected, the distance between the upper 0.9 probability confidence bound and the measured failure rate decreases as the test time t increases.

4 THE INCREASED NUMBER OF REDUNDANT UNITS N BASED ON CONFIDENCE BOUNDS

The Poisson distribution gives the number of failures that occur during a given time interval, for the expected number of failures. It is used to calculate the probability of any given number of failures. For high reliability, the number of spares provided must be greater than the expected number of failures.

The Poisson distribution gives the probability (Pr) that the number n events will occur in an interval, given that the expected or mean number of events is m.

$$\text{Poisson } (x, m) = \Pr(n = x) = m^x e^{-m}/x! \quad (6)$$

The number of redundant units, N, must be sufficient that the probability of N-1 failures is less than the required reliability y. N-1 is determined by the cumulative Poisson distribution, which is the sum of the probabilities of n =0, 1, 2, …N-1 failures occurring.

$$\text{Cumulative Poisson} = \sum m^x e^{-m}/x!,\ x = 0, 1, 2, \ldots M \quad (7)$$

The number of redundant units, N, can be determined from tables of the cumulative Poisson distribution.

The upper 0.9 probability confidence bound, λ0.9(t), is set as the expected failure rate. The increased number of failures for a single unit over the mission length L is λx(t) L. The increased number of failures is set equal to the expected number of failures for the required confidence bound. The values for λ0.9(t) are listed in Table 1. The required number of redundant units can be computed for confidence = 0.9 and any reliability. Here a reliability of 0.9 is chosen. The mission duration is L = 2. As shown in Table 2, the cumulative Poisson distribution is scanned down for an increasing number of failures and an increasing probability that the # of failures will be less than indicated.

Table 2. Using the cumulative Poisson table to determine N for reliability y = 0 9 and confidence x = 0.9.

	Time, t	3.11	4.32	9.18	17.7	27.44
	F0.9(t)	8.36	6.58	4.13	3.06	2.30
N = 1 + # failures	# failures	Cumulative Poisson				
1	0	0.00	0.00	0.02	0.05	0.10
2	1	0.00	0.01	0.08	0.19	0.33
3	2	0.01	0.04	0.22	0.41	0.60
4	3	0.03	0.11	0.41	0.63	0.80
5	4	0.08	0.21	0.60	0.81	**0.92**
6	5	0.16	0.36	0.76	**0.91**	0.97
7	6	0.27	0.51	0.88	0.96	0.99
8	7	0.40	0.66	**0.94**	0.99	1.00
9	8	0.54	0.78	0.97	1.00	1.00
10	9	0.67	0.87	0.99	1.00	1.00
11	10	0.78	**0.93**	1.00	1.00	1.00
12	11	0.86	0.96	1.00	1.00	1.00
13	12	**0.92**	0.98	1.00	1.00	1.00
14	13	0.95	0.99	1.00	1.00	1.00
15	14	0.98	1.00	1.00	1.00	1.00

Table 1 shows that as the test time t increases, the increased failure rate for confidence = 0.9, λ0.9(t), decreases from 6.2 to 1.0. F0.9(t) = λ0.9(t) L is the increased single unit failure probability over the mission length L = 2 that is required to achieve confidence x. Table 2 describes a segment of time horizontally, from 3.11 to 27.44, and F0.9(t) decreases from 8.36 to 2.30. The single unit failure probability for confidence 0.9, F0.9(t), is used as the mean of the Poisson distribution. The cumulative Poisson is tabulated for 0 to 14 failures. Scanning down the table shows the # failures that must be replaced using spares for the redundancy reliability of 0.9 or more to be achieved. To always have an operating system, the number of redundant units N ≥ 1 + # failures. The numbers in bold are the smallest reliability that exceeds the required reliability of 0.9. The number of required units drops from 13 to 5 as test time increases. The failure rate decrease that occurs during reliability growth reduces the number of redundant units needed to achieve a particular mission reliability with a particular confidence. Longer testing produces a slower reduction in the number of redundant units because it reduces the width of the confidence interval.

5 ESTIMATING THE NEEDED NUMBER OF REDUNDANT UNITS, N

An equation to estimate N, the needed number of redundant units, was developed by fitting formulas to the data. [7] [10]

$$N = - (0.305\ LN((1.285\ \lambda(t) +(- 1.24\ LN(x) + 0.19)/t)\ L) + 0.86)\ LN(y) + (1.285\ \lambda(t) +(- 1.24\ LN(x) + 0.19)/t)\ L \quad (8)$$

N is the increased number of redundant units required to increase the probability of having sufficient spares to 1 - y. LN is the natural logarithm. The measured system failure rate is λ(t). The failure rate estimation confidence is 1 - x, the probability that the failure rate is not underestimated. The mission length is L.

N depends on the measured system failure rate, λ(t), the mission length, L, the required redundancy reliability 1 -y, and the required confidence in the failure rate estimation upper bound, 1 – x. The value y is the probability that all redundant units fail. The value x is the probability that the upper bound failure rate is too low. The confidence is (1 – x) 100 percent that the probability that the upper bound is not too low. The approximation for N is close for λ(t) L > 0.3, where λ(t) L is the failure probability of a single system over the mission length. The exact N for any case can be calculated as shown above.

6 MINIMIZING THE TOTAL SYSTEM DEVELOPMENT COST

The cost is equal to the cost of developing N redundant operational units and M test units plus the estimated cost of testing the M test units. Suppose as before that the cost of testing is the fraction 0.015 of the unit development cost per hour. The test cost is

$$\text{Test cost} = M + 0.015\ M\ t \quad (9)$$

The total cost is the cost of developing the N redundant units plus the test cost.

$$\text{Total cost} = N + M + 0.015\ M\ t \quad (10)$$

The increasing test time reduces the upper confidence bound on the system failure probability so that the number of redundant units N decreases with test time. Table 1 shows the number of redundant units N, the test cost for M = 1 test unit, and the total cost for the 41-failure data set. The selected cost metric is the cost of producing a single unit, so the cost of N units is N.

The minimum total cost is 6.4 units first reached at t = 27.4 hours. However, a cost of 7.2 is reached at 16.5 hours, so the test time can be cut 40% with only a 13% increase in cost.

The final failure rate is 0.67, so the final Mean Time Before Failure (MTBF) = 1/0.67 = 1.5 hours. The test time for minimum total cost is nearly twenty times the final MTBF. Testing for only about twice the MTBF, t = 3.1, would give N = 13 and total cost =14.0, more than double the minimum cost.

Extended testing reduces the number of units needed for high confidence in high reliability. The extended test time has diminishing returns and it may not be practical to test until the minimum total cost is reached.

7 THE TRADE-OFF BETWEEN CONFIDENCE, 1 -X, AND RELIABILITY, 1 - Y

For any given failure time data set, we can compute the minimum cost and corresponding optimum test time for any required confidence and reliability. There is a defined trade-off between confidence and reliability. For the finally chosen redundancy, N, a higher estimated reliability will be met with lower confidence and a higher confidence can be achieved only at a lower reliability estimate.

For the 41-failure data set of Table 1, we consider the result for N at time t = 10.4 with failure rate λ(t) = 1.3 and mission length L =2. For reliability and confidence both equal to 0.90, the computed integer N is 7, and the N estimated from the equation (8) is 7.01. The trade-off between reliability and confidence is investigated by picking either reliability or confidence and then finding the other so that the estimated N is again 7.01. The trade-off is shown in Table 3 and Figure 1.

Table 3. Reliability and confidence.

Reliability, 1 - y	Confidence, 1 – x
0.94	0.0800
0.93	0.5100
0.92	0.7300
0.91	0.8400
0.90	**0.9000**
0.85	0.9855
0.80	0.9966
0.70	0.9996
0.60	0.9999

Confidence and reliability are varied around the design point where both reliability and confidence are equal to 0.90. Increasing the reliability requirement from 0.90 to 0.91, 0.92, … 0.94 causes the confidence that the requirement will be met to drop rapidly toward zero. Reducing the reliability requirement in steps from 0.90 to 0.60 increases confidence it will be met from one 9 to two, three, and even four 9's.

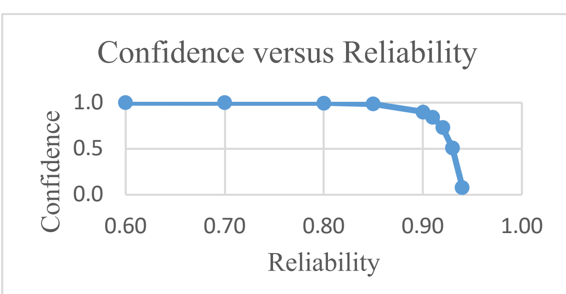

Figure 1. Confidence versus reliability.

8 THE INCREASE IN N AS RELIABILITY AND CONFIDENCE REQUIREMENTS INCREASE

We again consider the result for N at time t = 10.4 with failure rate λ(t) = 1.3 and mission length L =2, in the case where reliability and confidence both have equal requirements, but requirements other than 0.90. The increase of the estimated N for increasing reliability and confidence is shown in Table 4 and Figure 2.

Table 4. Increasing N for higher reliability and confidence

Reliability = confidence	N
0.995	11.84
0.99	10.7
0.98	9.57
0.95	8.10
0.93	7.57
0.91	7.36
0.90	**7.01**
0.85	6.37
0.80	5.93
0.70	5.31
0.60	4.87
0.50	4.53

Although the estimated N is decimal, the actual number of needed units is the next higher integer. As the requirements for the reliability and equal confidence increase from 0.50 to 0.995, the required number of redundant integer units N increases from 5 to 12.

9 CONCLUSION

A statistical process was developed to compute N, the number of redundant units needed to achieve any required redundant reliability at any confidence level. N depends on the measured system failure rate, λ(t), the mission length, L, the required redundancy reliability, and the required confidence in that reliability. The first step is to determine the upper confidence bound on the measured failure rate needed to achieve the required confidence using the Poisson or inverse chi-square distribution. This

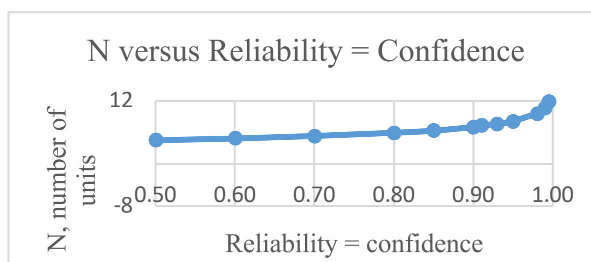

Figure 2. N versus increasing reliability and confidence.

produces λx(t), the increased single unit failure rate over the mission that is used to achieve the required confidence. The second step is to determine N, the increased number of redundant units N required to achieve the required reliability and confidence. This is determined by scanning tables of the cumulative Poisson distribution. Fortunately, the results of this statistical process can be closely approximated by an equation.

It is possible to set the requirements for both the redundant reliability and the confidence level and then test until the time needed to minimize the total cost required to achieve these requirements. The total mission cost is the sum of the redundant units cost and the test time cost. The optimum test time produces the minimum total cost given the unit failure rate, the mission length, and the required reliability and confidence level. Initial testing produces reliability growth, which often has a major impact in reducing the unit failure rate. Testing to better determine the long-term failure rate reduces the confidence interval of the failure rate, which seems to have a smaller effect in reducing cost. Longer testing is justified if total cost is decreasing. If the testing is terminated too soon, a greater number of redundant units must be provided to achieve the required reliability and confidence.

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BIOGRAPHY

Harry W. Jones, Ph.D., MBA
N239-8
NASA Ames Research Center
Moffett Field, CA 94035, USA

e-mail: harry.jones@nasa.gov

Harry Jones is a NASA systems engineer working in life support. He previously worked on missiles, satellites, Apollo, digital video communications, the Search for Extra Terrestrial Intelligence (SETI), and the International Space Station (ISS).