Assessing the Reliability of Diverse Fault-Tolerant Software-based Systems

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Abstract

We discuss a problem in the safety assessment of automatic control and protection systems. There is an increasing dependence on software for performing safety-critical functions, like the safety shut-down of dangerous plants. Software brings increased risk of design defects and thus systematic failures; redundancy with *diversity* between redundant channels is a possible defence. While diversity techniques can improve the dependability of software-based systems, they do not alleviate the difficulties of *assessing* whether such a system is safe enough for operation. We study this problem for a simple safety protection system consisting of two diverse channels performing the same function. The problem is evaluating its probability of failure in demand. Assuming failure independence between dangerous failures of the channels is unrealistic. One can instead use evidence from the observation of the whole system's behaviour under realistic test conditions. Standard inference procedures can then estimate system reliability, but they take no advantage of a system's fault-tolerant structure. We show how to extend these techniques to take account of fault tolerance by a conceptually straightforward application of *Bayesian* inference. Unfortunately, the method is computationally complex and requires the conceptually difficult step of specifying 'prior' distributions for the parameters of interest. This paper presents the correct inference procedure, exemplifies possible pitfalls in its application and clarifies some non-intuitive issues about reliability assessment for fault-tolerant software.

1. Introduction

Software is increasingly used in safety systems which previously depended on analogue or electromechanical digital technologies. By "safety systems" we mean here those engineered systems that are crucial in avoiding accidents, e.g. railway signalling systems, emergency shut-down mechanisms for dangerous industrial plants, full-authority flight control systems which cannot fail without immediate danger for the controlled aircraft, etc. This increasing dependence on software causes some concerns.

While the use of software may improve performance and/or safety by allowing designers to implement more sophisticated and adaptable rules for controlling dangerous operations, by improving the monitoring of failures of the controlled physical plant, and by reduced use of unreliable electromechanical components, software technology is seen as somewhat risky in itself. Software is known to be subject to design defects that are often subtle and difficult to avoid and to detect. One can in principle build programs that are defect-free, or that will never exhibit unintended dangerous behaviour, but it is unclear in practice which programs can be trusted to do so, or to have a low enough probability of dangerous behaviours. Thus much effort has been spent over the years in creating rules, standards and guidelines for the development of safety-critical software, to specify at least development and verification practices that should be applied as necessary pre-conditions for claiming that a software-based system is fit for a safety-critical role (Herrmann 1999). While such "good practice" standards are certainly useful, the task of deciding whether a piece of software- has low enough probability of causing dangerous failures remains extremely difficult.

One of the practices for reducing the risk of dangerous behaviours by the software is that of redundancy with diversity. Redundancy is used in all areas of engineering. When a component fails, if there is another component waiting to take over its task, the failure can be masked. When, as is the case for software, our concern is with the effects of design defects, which would be automatically replicated in all "backup" components, redundancy must take the form of adding components that are not identical to those whose failure must be tolerated (Lyu 1995). In its simplest form, this "diversity" involves the 'independent' creation of two or more versions of a program, which are all executed on each input reading so that an adjudication mechanism can produce a 'best' single output. The versions have to produce equivalent behaviours, either in detail or just from the viewpoint of their common function in a wider system. For instance, two diverse safety systems for an industrial plant may take as inputs different physical variables - say, pressures and temperatures. Typically, the teams building the versions work 'independently' of one another, without direct communication. They may have free choice of the methods and tools to use, or they may have these imposed upon them in order to 'force' diversity. In the former case, the hope is that identical mistakes will be avoided by the natural, 'random' variation between people and their circumstances; in the latter, the same purpose is pursued by intentionally varying the circumstances and constraints under which the people work to solve the given problem.

Design diversity between the redundant channels of a fault-tolerant architecture appears to be an effective way of improving the dependability of software-based systems (Littlewood, Popov et al. 2001). However, it does not simplify the problem of assessing the reliability or safety of a specific system, e.g. for the purposes of licensing.

Consider for instance a two-channel, 1-out-of-2, software-based diverse system (Fig. 1), as could be for instance a protection (safety shut-down) system for some kind of plant (we will use this example throughout our discussion). Here, the main measure of interest for safety assessment (which we study in this paper) is the probability that the system fails to perform its safety function, i.e., to shut down the plant when required.

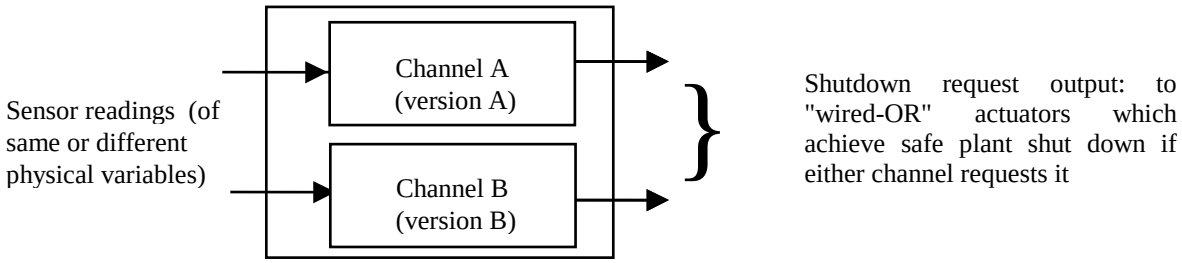


Fig. 1. Our example system

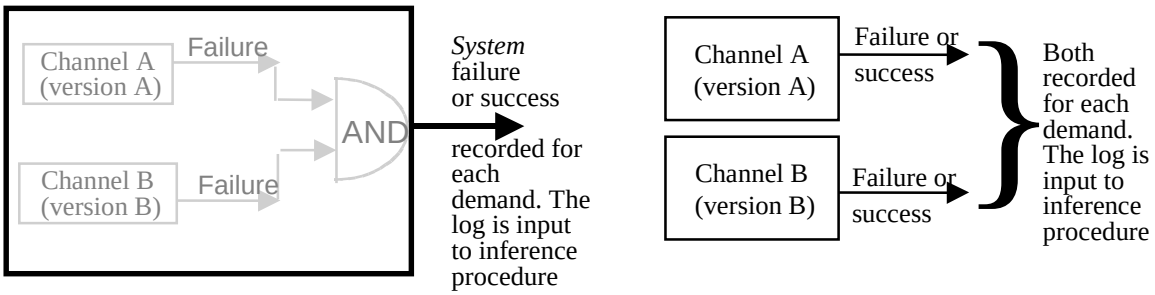
Estimating this probability of failure per demand (*pfd*) would be simplest if we could assume independence between failures of the two channels. Then, we could just assess the *pfd*s of the two channels separately and multiply them together. Evidence of even modest reliability of the channels would suffice to claim much higher reliability for the system. But assuming independent failures has been shown to be completely unrealistic by both experiments (Knight and Leveson 1986) and theoretical modelling (see (Littlewood, Popov et al. 2001) for a detailed discussion). Positive correlation between channel failures should normally be expected, essentially because, for the builders of diverse versions of a program, some demands will be more difficult - more error-prone - than others. So, even if diverse versions of the software are produced ‘independently’, their failures are more likely to happen on certain demands than on others, which leads to positive correlation. What is worse, research has found no simple way of setting an upper bound for the correlation between failures of the two channels. A specific diverse system may well achieve independence or even negative correlation between failures of the two channels, especially if its development was managed so as to "force" diversity, but the problem is how to estimate the level actually achieved in a specific system, before the system is deployed in its safety role. So, it is necessary actually to evaluate the *pfd* of the two-channel system as a whole.

The need to evaluate probabilities of common failures of redundant subsystems is not limited to software-based systems. It arises whenever redundancy is used to improve system reliability and safety. Assuming independence of their failures is a tempting mathematical simplification, and would allow one to believe that arbitrarily reliable systems can be built out of arbitrarily unreliable subsystems, but this is generally over-optimistic. A theoretical explanation of positive correlation among failures from random physical causes is due to Hughes (Hughes 1987). Littlewood (Littlewood 1996) summarises and compares the models concerning design faults and physical faults. To avoid overoptimism, various constraints are often imposed on the reliability gain that one is allowed to claim from redundancy. For instance, lower limits may be imposed on the probability of failure per demand that one is allowed to claim for a redundant system, or on the conditional probability of a second failure given that a first failure occurred. However, the status of these methods is essentially that of "rules of thumb" which are consensually accepted (within an industrial sector) as sufficiently conservative, although they may not have a solid scientific basis. This creates special problems when the redundant system is software-based, where there is comparatively little experience on which to base this consensus.

The simplest way to assess the reliability of a system - fault tolerant or otherwise - is to observe its failure behaviour in (real or simulated) operation. If we treat the fault-tolerant system as a black box (Fig. 2a), i.e., we ignore the fact that it is indeed fault-tolerant, we can apply standard techniques of statistical inference to estimate its *pfd* on the basis of the amount of realistic testing performed and the number of failures observed. However, this ‘black-box’ approach to reliability estimation has severe limitations (Littlewood and Strigini 1993), (Butler and Finelli 1991): if we want to demonstrate very small upper bounds on the *pfd*, the amount of testing required becomes very expensive and then infeasible. It is then natural to ask whether we can use the additional knowledge that we are dealing with a fault-tolerant system to reduce this problem - to achieve better confidence for the same amount of testing. The assumption of independence would fulfil this role: if it held, we would only need to test each channel enough to demonstrate a much less stringent *pfd* bound than required for the two-channel system. Since this assumption cannot be made, we explore what other information we can obtain from the fault-tolerant nature of the system.

We reasonably assume that we can observe whether either channel fails, so that testing produces evidence about the reliability of each channel by itself as well as of the whole system. Thus, we treat the system as a ‘clear box’ (Fig. 2b). In addition, we have a priori knowledge about the effect of the channels' failures on

system failure: we know that we are dealing with a 1-out-of-2 system. In short, we have much more information than in the 'black box' scenario. We may hope that this additional information can be used to reduce the uncertainty about system reliability. This is the problem which we address in this paper.



a) **b)**

Events in clear-box view		***Events in black-box view***
Channel A reaction	*Channel B reaction*	*System reaction*
Shutdown request (correct action)	shutdown request (correct action)	Success (shutdown)
	no shutdown request (failure)	
No shutdown request (failure)	shutdown request (correct action)	
	no shutdown request (failure)	Failure (no shutdown)

Fig. 2. Black-box vs. clear box inference. In response to a "demand" (the plant enters a hazardous state and should be shut down) there are four possible outcomes in the clear box view, which are collapsed into two in the black-box view.

We first briefly introduce Bayesian inference: the more widely known approach of "classical" inference, which typically employs different ad hoc methods for different inference problems, does not seem suitable in this case in which we wish to perform inference in a consistent way on various aspects of a system. We then describe the procedure for applying Bayesian inference to our 2-channel system. Bayesian inference presents two kinds of difficulty: conceptually, it depends on the user specifying "prior" probability distributions, which many people find difficult to specify; computationally, it can be very demanding, requiring numerical computation of complex integrals. Various methods are commonly applied to reduce both difficulties. In the rest of the paper we proceed to discuss both some standard method and some apparently promising ad hoc methods. It turns out that none of these will be useful in all cases.

2 Bayesian inference

In our scenario, we count the demands to the system and the failures (of one or both channels) observed, and from this information try to predict the probability of failures on a future demand. This is a problem of

statistical inference. Standard techniques for statistical inference are divided into "classical" and "Bayesian". Their applications to estimating the reliability of a system as a black box (i.e., ignoring how it behaves internally - in our case, ignoring that one channel may fail without the whole system failing) is standard textbook material. The classical methods produce "confidence" statements, like "we have 95% confidence that the *pfd* is less than 10^{-3}". Classical inference is the more widely known approach, but it has drawbacks. The meaning of a "confidence level" is defined in terms of the experiment that produced it: a high confidence level means that the experiment had a high probability of refuting a wrong hypothesis, but is not a direct statement about the likelihood of the hypothesis itself being true. This limits the usefulness of classical confidence statements in various ways. It is difficult or meaningless to compare values of confidence bounds and confidence levels obtained for different systems or under different regimes of observation. For instance, referring to the system in Fig. 1, suppose that we had tested Channel A alone on 100 test demands, and then tested the whole system (Channel A plus Channel B) on 50 test demands (both sets being chosen randomly from the expected statistical distribution of demands under which the system will be used), and in neither test sequence we observed any failure. Deriving from this evidence a classical confidence level for the statement "the tested item's *pfd* is less than 10^{-3}" would give us a *lower* confidence for the whole system than for Channel A alone, despite our knowledge that the whole system can behave no worse than Channel A alone. It is also difficult to translate classical confidence statements into probabilities for events of actual interest, e.g. system failure over a pre-specified duration of operation, and to devise a classical inference procedure for a system described by multiple parameters, as is our case. The Bayesian approach avoids these problems, as we briefly discuss below

In our case, the Bayesian approach considers that the actual *pfd* of the system is unknown, and thus treats it as a random variable. In a sense, the system that one is trying to evaluate was extracted at random from a population of possible systems, with different reliabilities and different probabilities of being actually produced. Any one of these *could* have been delivered, as far as the observer can tell from the available information. Reliability estimation consists, roughly speaking, in deciding whether the actual system is, among this population, one of those with a high *pfd* or with low *pfd*. This population is described by a *prior* probability distribution: for each possible value of the *pfd*, a probability is stated that the system has that value of *pfd* (more precisely, a *probability density function* is specified). This prior distribution must

describe the knowledge available before testing. Then, the frequency with which we observe failures gives us reason to alter this probability distribution. For instance, passing a certain number of tests shows that the system is less likely to be one with very high *pfd*. Bayes's theorem completely specifies the changes in probabilities as a function of the observations. A *posterior* distribution for the *pfd* is thus obtained, which takes account of the knowledge derived from observation.

With Bayesian inference, one can thus answer the question 'How likely is it that this software has *pfd* $\leq 10^{-4}$?' with an actual probability, which we can manipulate using the calculus of probabilities to derive probabilities of other events of interest. For instance, one can, given the probability distribution for the *pfd* of a system, calculate the probability of the system surviving without failures a given number of future demands, i.e., of an observable event of direct interest. By contrast, classical confidence statements about a descriptive parameter like the *pfd* cannot be used this way. Furthermore, Bayesian inference procedures for any situations can be easily derived from the general approach.

The Bayesian approach thus has the advantage of a consistent and rigorous treatment of all inference problems, but in our case we have additional reasons for preferring it over the "classical" approach: we need to produce an inference procedure for a new, non-textbook scenario - a fault-tolerant system; and we need inference about multiple variables (the *pfd*s of the individual channels and of the system) linked by mutual constraints.

Bayesian methods, however, present two difficulties. First, although the formulae for the inference are straightforward to derive, the calculations which they require may be very complex, often with no closed-form solution. Numerical solutions may be time-consuming and vulnerable to numerical errors. Fast computers help, but one may need to write ad hoc software.

The second difficulty is more basic. Bayesian inference always requires one to start with prior probability distributions for the variables of interest: it (rightly) compels us to state the assumptions that we bring to the problem. But formulating the prior distributions may require somewhat subtle probabilistic reasoning. The prior distribution must be one that the assessor does consider a fair description of the uncertainty about the system before the system is tested. Even experts in a domain may find it very difficult to specify their prior beliefs in a mathematically rigorous format. In some cases, if undecided between alternative prior distributions, the only practical solution may be to adopt the more *pessimistic* one (i.e., the one that causes the more pessimistic conclusions in the results of inference). The difficulty may be alleviated by

checking how sensitive the predictions are to the variation between the different prior distributions that appear plausible. As observations accumulate, they may start to "speak for themselves", making the differences in the priors irrelevant. Statisticians have developed various ways for simplifying both problems (computational complexity and difficulty in specifying priors). In our discussion we will consider the most popular among such general "tricks", as well as some ad hoc ones.

3 Problem statement and Bayesian inference procedure

We consider the system of Fig. 1, subjected to a sequence of *n* independent demands.

If we treat the system as a black box, i.e. we can only observe *system* failure or success (Fig. 2a), the inference proceeds as follows. Denoting the probability of failure on demand for the system as *p*, the posterior distribution of *p* after seeing *r* failures in *n* demands is:

$$f_p(x \mid r,n) \propto L(n,r \mid x)\, f_p(x)\,, \tag{1}$$

where $L(n,r \mid x)$ is the *likelihood* of observing *r* failures in *n* demands *if* the *pfd* were exactly *x*. This is given in this case by the *binomial* distribution, $L(n,r \mid x) = \binom{n}{r} x^r (1-x)^{n-r}$. $f_p(\bullet)$ is the prior distribution of *p*, which represents the assessor's beliefs about *p*, *before* seeing the result of the test on *n* demands.

(1) is the general form of Bayes's formula, applicable to any form of the likelihood and any prior distribution.

In the clear box scenario, instead, we can discriminate among four different possible outcomes for each demand: We use these notations:

Event	Version A	Version B	Number of occurrence in *n* tests	Probability
α	fails	fails	r_1	P_{AB}
β	fails	succeeds	r_2	$P_B - P_{AB}$
γ	succeeds	fails	r_3	$P_A - P_{AB}$
δ	succeeds	succeeds	r_4	$1 - P_A - P_B + P_{AB}$

The probability model now has the four parameters shown in the last column of the table, but since these four probabilities sum to unity, there are only three degrees of freedom: the triplet P_A, P_B and P_{AB}

completely specifies the model. An assessor will need to specify a *joint* prior distribution for these three parameters, $f_{P_{AB},P_A,P_B}(x,y,z)$.

The likelihood of observing r_1 common failures of both channels, r_2 failures of channel A only and r_3 failures of channel B only in n tests is now given by a *multinomial function*:

$$L(r_1,r_2,r_3,n \mid P_{AB},P_A,P_B) = \frac{n!}{r_1!r_2!r_3!(n-r_1-r_2-r_3)!} P_{AB}^{r_1}(P_B-P_{AB})^{r_2}(P_A-P_{AB})^{r_3}(1+P_{AB}-P_A-P_B)^{n-r_1-r_2-r_3} \quad (2)$$

The posterior distribution, similarly to (1), is:

$$f_{P_{AB},P_A,P_B}(x,y,z \mid r_1,r_2,r_3,n) \propto L(r_1,r_2,r_3,n \mid P_{AB},P_A,P_B) f_{P_{AB},P_A,P_B}(x,y,z) \quad (3)$$

Given a joint distribution for P_A, P_B, P_{AB}, we can always deduce the distribution $f_{P_{AB}}$ of the system *pfd*, by integrating out P_A and P_B. So, for a given *prior* joint distribution, there are two options for inferring system reliability from the test results. in the clear box method, we obtain the posterior joint distribution via (3) and then deduce the posterior $f_{P_{AB}}$ from this. We can also apply the black-box method: we first derive the prior probability density function, $f_{P_{AB}}$, and then update it to obtain a posterior density function via (1). Comparing the two results will be for us a way of comparing the two methods.

How to solve these formulas is clear even though it may be computationally expensive. There remains the problem of specifying prior distributions, which we address in the next section.

4 Prior distributions

Here we study ways of specifying prior distributions. Our main concern is to help assessors to specify priors, by imposing a useful structure for their interrelated beliefs about the *pdf*s of the channels and of the system. A useful side effect is often a simplification of the calculations. We omit the mathematical details and concentrate on the practical conclusions; a more mathematical and more detailed discussion is available in (Littlewood, Popov et al. 2000).

4.1 Dirichlet distribution

It is common in Bayesian statistics to use a *conjugate family* of distributions to represent prior beliefs. This term denotes a parametric family of distributions that has the property for a particular problem (i.e. likelihood function) that if an assessor uses a member of the family to represent his/her prior beliefs, then the posterior will automatically also be a member of the family. If a conjugate family exists for a certain likelihood function (this is not always the case), it is unique. For our clear box scenario, the conjugate family is that of *Dirichlet* distributions (Johnson and Kotz 1972).

It turns out that, with a Dirichlet prior distribution, the posterior distributions for the probability of system failure derived via the 'clear box' and via the 'black-box' methods are identical, no matter what we observed. In other words, whatever the detailed failure behaviour of the two channels, there is no benefit from taking this extra information into account in assessing the reliability of the system. So if an assessor's prior belief is indeed a Dirichlet distribution, there is no advantage in using 'clear box' inference. On the other hand, if the assessor's belief are *not* represented by a Dirichlet distribution, choosing this distribution as a convenient simplification would make it impossible to exploit any potential gain from the clear box inference.

4.2 Prior distributions with known failure probabilities of the versions

Another form of simplification of the prior distribution may be possible if there is a very great deal of data from past operational use for each version (e.g. if they are commercial-off-the-shelf - COTS - items), so that each channel's probability of failure on demand can be estimated with great accuracy. We can then approximate this situation by assuming that the *pfd*s of the versions are known *with certainty* and are P_{Atrue} and P_{Btrue}. In other words, the uncertainty of the assessor concerns only the probability of *system* failure.

We illustrate this set-up with a few numerical examples, shown in Table 1. In each case we assume that $P_{Atrue} = 0.001, P_{Btrue} = 0.0005$. Clearly, a 1-out-of-2 system will be at least as reliable as the more reliable of the two versions, so the prior distribution of the system *pfd* is zero outside the interval [0, 0.0005]. We consider two examples of this distribution: a uniform distribution and a Beta(x, 10, 10) both constrained to lie within this interval.

We make no claims for 'plausibility' for these choices of prior distributions. However, it should be noted that each is quite pessimistic: both prior distributions, for example, have mean 0.00025, suggesting a prior belief that about half channel *B* failures will also result in channel *A* failure.

Table 1

Uniform prior distribution $P_{AB}|P_A,P_B$

		Percentiles					
		10%	50%	75%	90%	95%	99%
	Prior	0.00005	0.00025	0.000375	0.00045	0.000475	0.000495
	Black Box	0.000011	0.00007	0.000137	0.000225	0.000286	0.00041
r_1=0	Clear box (version failures)	0.000008	0.00005	0.000095	0.000148	0.00018	0.000245
	Clear box (no version failures)	0.000268	0.00042	0.000462	0.00048	0.000485	0.00049
r_1 = 1	Black Box	0.000045	0.000155	0.000246	0.000342	0.000396	0.000465
	Clear box (version failures)	0.00004	0.00012	0.000179	0.000238	0.000271	0.00033
r_1 = 3	Black Box	0.00015	0.0003	0.000384	0.000443	0.000465	0.000485
	Clear box (version failures)	0.000165	0.000283	0.000343	0.00039	0.000413	0.000448
r_1 = 5	Black Box	0.000235	0.000375	0.000435	0.00047	0.00048	0.0004878
	Clear box (version failures)	0.000345	0.00044	0.000469	0.000482	0.000485	0.0004892

Non-uniform prior distribution $P_{AB}|P_A,P_B$

		Percentiles					
		10%	50%	75%	90%	95%	99%
	Prior	0.000175	0.000245	0.000283	0.000317	0.000335	0.000368
r_1=0	Black Box	0.000146	0.000215	0.000253	0.000286	0.000306	0.000343
	Clear box (version failures)	0.00013	0.000188	0.00022	0.00025	0.000269	0.0003
	Clear box (no version failures)	0.000205	0.000278	0.000313	0.000345	0.00036	0.00039
r_1 = 1	Black Box	0.000161	0.000228	0.000265	0.0003	0.000318	0.000353
	Clear box (version failures)	0.00015	0.00021	0.000244	0.000275	0.000291	0.000325
r_1 = 3	Black Box	0.000185	0.000251	0.000287	0.00032	0.000336	0.00037
	Clear box (version failures)	0.000195	0.000255	0.00029	0.00032	0.000335	0.000365
r_1 = 5	Black Box	0.000205	0.000271	0.000305	0.000335	0.000353	0.00038
	Clear box (version failures)	0.00024	0.000304	0.000335	0.00036	0.000375	0.000402

Table 1. Two groups of results are summarised: with uniform prior and with a non-uniform prior distributions, *Pab|Pa,Pb=Beta(x,10,10)* on the interval [0, 0.0005]. The percentiles illustrate the cumulative distribution $P(\theta \leq X) = Y$, where X are the values shown in the table and Y are the chosen percentiles, 10%, 50%, 75%, 90%, 95% and 99%. Rows labelled 'Black box' represent the percentiles, calculated via "black-box" inference; those labelled 'Clear box' show the percentiles calculated for a posterior derived with 3 and then integrating out P_A and P_B. The labels '(no version failures)' and '(version failures)' refer to two different observations, in which no individual failures of channels and individual channel failures were observed, respectively.

We assume that n=10,000 demands are executed in an operational test environment and we consider which conclusions an assessor should draw, depending on the observed behaviour of the two versions. The rows in Table 1, for each of the two prior distributions studied, differ in the numbers of failures (of each channel and of both together) assumed to have been observed over the 10,000 demands. The rows

marked “version failures” describe cases in which the observed numbers of channel *A* and of channel *B* failures take their (marginal) expected values, i.e. 10 and 5 respectively. The other case is the extreme one where there are no failures of either channel.

In each case our main interest is in how our assessment of the system reliability based upon the full information, r_1, r_2, r_3, (“clear box”) differs from the assessment based upon the black-box evidence, r_1, alone.

In Table 1, the first row with $r_1=0$ shows the increased confidence that comes when extensive testing reveals *no system failures*. The black-box posterior belief about the system *pfd* is more optimistic (all percentile values are lower) than the prior belief. More importantly, the posterior belief in the *'$r_1=0$,* Clear box (version failures)' rows, based on observing version failures but no system failures, is more optimistic than the black-box posterior. Here the extra information of *version* failure behaviour allows greater confidence to be placed in the system reliability, compared with what could be claimed from the *system* behaviour alone.

The result is in accord with intuition. Seeing no system failures in 10,000 demands, when there have been 10 channel *A* failures and 5 channel *B* failures suggests that there is some *negative correlation* between failures of the channels: even if the channels were failing *independently* we would expect to see some common failures (the expected number of common failures, conditional on 10 *A*s and 5 *B*s, is 2.5).

The rows where ($r_1\neq0$) show what happens when there are system failures (common failures of the versions), with the same numbers of version failures (10 *A*s, 5 *B*s). As would be expected, the more system failures there are on test, the more pessimistic are the posterior beliefs about system reliability. More interesting, however, is the relationship between the black-box and clear box results. Consider the rows with ($r_1=5$). These rows of Table 1 represent the most extreme case, in which all demands that are channel *B* failures are also channel *A* failures. This would suggest strongly that there is *positive correlation* between the failures of the two versions. Here the black-box method gives results that are too optimistic compared with those based on the complete (clear box) failure data.

These results show that ‘clear box’ inference can produce advantages (albeit small ones in this example).

However, this table also shows a consequence of our simplifying assumption (perfectly known channel *pfd*s) that is clearly wrong. When $r_1=0$, that is there have been no failures of either version (and hence no

system failures), the posterior distribution of the *pfd* is worse than it was *a priori*. How can the observation of such 'good news' make us lose confidence in the system?

The reason for this paradox lies in the constraints on the parameters of the model that are imposed by assuming the versions reliabilities are known with certainty. Consider Table2:

Table 2

		A fails	A succeeds	*total*
B fails		θ	$P_B-\theta$	P_B
B succeeds		$P_A-\theta$	$1-P_A-P_B+\theta$	$1-P_B$
	total	P_A	$1-P_A$	1

There is only one unknown parameter, θ, the system *pfd*, which appears in all the cells above representing the four possible outcomes of a test. If we observe no failures in the test, this makes us believe that the entry in the (*A* succeeds, *B* succeeds) cell, $1-P_A-P_B+\theta$, is large. Since P_A, P_B are known, this makes us believe that θ is large.

Of course, it could be argued that observing no version failures in 10,000 demands, with the known version *pfd*s 0.001, 0.0005, is extremely improbable - i.e. observing this result in practice is essentially impossible. This does not remove the difficulty, however: it can be shown that *whatever the value of n*, the 'no failures' posterior will be more pessimistic than the prior.

The practical conclusion seems to be that this particular simplified prior distribution is only useful (provided, of course, it approximates the assessor's understanding of the prior evidence about the system) if the number of demands in test is great enough to ensure that at least some version failures are observed.

4.3 Prior distributions allowing conservative claims for system reliability

Here we show that even if P_A and P_B are not known with certainty, assuming that they are can be used to obtain conservative estimates in many cases, and is therefore useful despite the problems described in section 4.2.

Clearly for every joint prior distribution, $f_{P_{AB},P_A,P_B}(\bullet,\bullet,\bullet)$, (with its corresponding marginal distribution of the probability of system failure, $f_{P_{AB}}(\bullet)$), if we have upper bounds on the probabilities of channel failures, P_{Amax} and P_{Bmax}, we could define a new joint prior distribution, $f^*_{P_{AB},P_A,P_B}(\bullet,\bullet,\bullet)$, such that

$P_A = P_{A\max}$, with certainty, $P_B = P_{B\max}$ with certainty, and the probability of system failure is as in the true prior distribution, $f_{P_{AB}}(\bullet)$.

Now we compare the posterior marginal distributions, $f_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$ and $f^*_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$, derived from the same observation (n : r_1, r_2, r_3), respectively with the true and the approximated prior distributions, $f_{P_{AB},P_A,P_B}(\bullet,\bullet,\bullet)$ and $f^*_{P_{AB},P_A,P_B}(\bullet,\bullet,\bullet)$. We illustrate the relationship between the two posterior distributions in Table 3.

The prior distribution $f_{P_{AB},P_A,P_B}(\bullet,\bullet,\bullet)$ used in Table 3 is defined as follows:

- $f_{P_A,P_B}(\bullet,\bullet) = f_{P_A}(\bullet) f_{P_B}(\bullet)$, i.e. the prior distributions of P_A and P_B are independent.[1]
- The marginal distributions $f_{P_A}(\bullet)$ and $f_{P_B}(\bullet)$ are Beta distributions, $f_{P_A}(\bullet)$ = Beta(x,20,10) and $f_{P_B}(\bullet)$ = Beta(x, 20, 20) within the interval [0, 0.01]: $P_{Amax} = P_{Bmax} = 0.01$.
- The assessor is "indifferent" among the possible values of P_{AB}, i.e.:

$$f_{P_{AB}}(\bullet \mid P_A, P_B) = \frac{1}{\min(P_A, P_B)} \text{ within } [0, \min(P_A, P_B)] \text{ and 0 elsewhere.}$$

The system was subjected to n = 4000 tests, and the assumed number of observed failures of the system, of channel A and of channel B, represented by r_1, r_2 and r_3, respectively, are shown in the table. The selected examples cover a range of interesting testing results: no failure, no system failure but some single-channel failures, system failure only, a combination of system and single-channel failures.

The percentiles reveal that the simplified prior distribution always gives more pessimistic predictions than the true prior: the probability that the system reliability will be better than any reliability target will be greater with the true prior, $f_{P_{AB}}(\bullet \mid data)$, than with the simplified one, $f^*_{P_{AB}}(\bullet \mid data)$.

[1] The assumption we make can be spelled out as: "Even if I were told the value of P_A, this knowledge would not change my uncertainty about P_B (and vice versa)". Notice that this assumption is not equivalent to assuming independence between the failures of the two channels, which is well known to be unreasonable. In fact, our assumption says *nothing* about the probability of common failure, P_{AB}.

This observation, if universally true, suggests a relatively easy way of avoiding the difficulty in defining the full $f_{P_{AB},P_A,P_B}(\bullet,\bullet,\bullet)$. If assessors can specify their beliefs about upper bounds on the channels *pfd*s, P_{Amax} and P_{Bmax}, and system *pfd*, $f_{P_{AB}}(\bullet)$, these can be combined into the simplified prior, $f^*_{P_{AB},P_A,P_B}(\bullet,\bullet,\bullet)$, to obtain conservative prediction.

Table 3 illustrates a small part of the numerical experiments we carried out with different prior distributions and assumed testing results. It presents the *typical* cases in which the observations are consistent with the prior distributions: the number of channel failures are within the variation due to the random failures. In all cases the simplified prior distribution produced more conservative predictions than the true prior distribution. It must be noted, however, that for some extreme case of observations which are not consistent with the prior distributions (their occurrence is virtually impossible with the assumed prior distributions) the conservatism of the simplified prior distribution is not guaranteed. General conditions under which the simplified prior distribution is guaranteed to generate conservatism are yet to be identified.

Table 3

	Percentiles	10%	50%	75%	90%	95%
	Prior distribution	0.00025	0.00225	0.0035	0.00435	0.00485
$r_1 = 0, r_2 = 0$	$f_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$	0.00278	0.003525	0.00406	0.00445	0.00473
$r_3 = 0$	$f^*_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$	0.0055	0.00635	0.0067	0.00705	0.00725
	Black-box posterior	0	0	0.000125	0.00035	0.0005
$r_1 = 1, r_2 = 0$	$f_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$	0.0029	0.00372	0.0042	0.00455	0.0048
$r_3 = 0$	$f^*_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$	0.0055	0.00638	0.0067	0.00685	0.00735
	Black-box posterior	0	0.00033	0.00058	0.00092	0.00115
$r_1 = 1, r_2 = 24$	$f_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$	0	0.0001	0.00035	0.00062	0.00076
$r_3 = 20$	$f^*_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$	0.00035	0.00123	0.00178	0.00235	0.00275
$r_1 = 0, r_2 = 20$	$f_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$	0	0	0.00022	0.00049	0.00067
$r_3 = 15$	$f^*_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$	0.00015	0.00135	0.00224	0.0029	0.00331

Table 3: The percentiles of the marginal prior distribution $f_{P_{AB}}(\bullet)$ and the following three posterior distributions: $f_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$, $f^*_{P_{AB}}(\bullet \mid n, r_1, r_2, r_3)$ and black-box posterior.

The usefulness of the conservative prior distribution $f^*_{P_{AB},P_A,P_B}(\bullet,\bullet,\bullet)$ seems *limited*. Indeed, for the important special case of testing which does not reveal any failure ($r_1 = 0$, $r_2 = 0$, $r_3 = 0$), the conservative result is *too conservative* and hence not very useful: the posterior will be more pessimistic than the prior

distribution, due to the phenomenon explained in section 4.2. This fact reiterates the main point of this paper: elicitation of prior distributions is difficult and there does not seem to exist easy ways out of this difficulty.

The last two cases presented in Table 3 with testing results ($r_1 = 1$, $r_2 = 24$, $r_3 = 20$) and ($r_1 = 0$, $r_2 = 20$, $r_3 = 15$), respectively, illustrate the interplay between the black-box and the clear box inferences. In the case with a single system failure the black-box posterior is more pessimistic than the full clear box posterior, while in the case with no system failure the black-box posterior gives more optimistic prediction about system reliability. In the case ($r_1 = 1$, $r_2 = 24$, $r_3 = 20$) we have evidence of negative correlation between failures of channels. The expected number of system failures under the assumption of independence is 1.4 in 4000 tests, while we only observed 1. In the case ($r_1 = 0$, $r_2 = 20$, $r_3 = 15$) even though no system failure is observed the evidence of negative correlation is weaker (lower number of individual failures is observed). As a result, the clear box prediction is worse than the black-box one.

In summary, using the black-box inference for predicting system reliability may lead either to overestimating or to underestimating system reliability.

5. Conclusions

We have studied how to use the knowledge that a system is internally a fault-tolerant system, of which we can observe the individual channels, to improve the confidence in the reliability assessments that we can derive from observing its behaviour under realistic testing. I.e., we have studied what we call 'clear box' inference, in which failures of the channels, masked by fault tolerance, are taken into account, as opposed to 'black box' inference in which they are ignored.

Bayesian inference is the correct method for 'clear box' inference about a fault-tolerant systems: we do not see a better way for consistently performing inference about multiple parameters (the *pfd*s of the channels and of the whole systems) linked by reciprocal constraints.

We have described the proper application of this approach to infer the *pfd* of a 1-out-of-2, on-demand system.

Recognising that this method, albeit correct, is practically very cumbersome to apply, we have then looked for ways of simplifying its practical use. The most standard method - using prior distributions from a conjugate family of distributions, which is often a somewhat arbitrary but useful approximation - turns out

to be useless for this particular problem as it is equivalent to ignoring the fault-tolerant structure of the system. We have then explored more ad hoc methods for simplifying the correct inference method. In one simplification, the reliabilities of the channels are taken as known with certainty. It turns out that this approximation, plausible in some situations, produces the artefact of counterintuitive (and useless) conclusions in the important case of no observed failures. Last, we showed that even if this assumption is not justified it may be used in some cases (see 4.3) as it seems to allow a conservative approximation that dispenses with the need to specify complete prior distributions: this may be useful in practice, but not universally so.

In conclusion, it is for the time being unavoidable to adapt the application of the inference procedure to the specific case at hand, selecting those specific approximations that work best for the conditions observed. The practical difficulties could be alleviated by better, specialised software tools, relieving the burden of the multiple sensitivity analyses and 'what if' analyses that may be necessary. The main requirement is that such tools must guarantee the necessary numerical precision, to avoid the risk of decisions being driven from mere artefacts of numerical error.

The immediate conclusion is that it is important to be aware of how 'clear box' inference should be performed, but in many cases its difficulties will make it unattractive. We expect that in some cases its outcome will appear immediately useful (e.g. as a way of trusting that a certain claimed pfd is conservative), and hope that these will lead to improving mathematical techniques and tools and thus reduce the mechanical difficulties of applying the approach. The more basic difficulty - the dependence on prior distributions - is actually at the same time the basic advantage of Bayesian inference: it requires one to make explicit the assumptions underlying the inference activity and it clearly measures how much *added* confidence can really be derived from observing the system's behaviour.

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