Relating Measured Component Damage to Assessed Component Reliability in Reliability Integrity Management

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Abstract: There is currently no widely agreed detailed general method for licensing a novel plant incorporating novel materials (or materials being deployed in novel environments); in many such situations, there are no directly applicable engineering code cases for decision-makers (including regulators) to rely on. It may be possible to develop an approach to licensing such a plant that is based on the Reliability and Integrity Management (RIM) approach delineated in ASME BPVC Section XI Division 2. NRC Regulatory Guide 1.246, Rev.0, endorses, with conditions, the subject portion of the ASME Code. But that portion of the ASME code is written at a very high level, and there are fundamental technical challenges associated with applying it literally to licensing a real plant. In the RIM approach, applicants need to do the following (among other things):

- Allocate target reliabilities to structures, systems, and components (SSCs) that collectively support the top-level plant safety and availability objectives;
- Understand failure modes of those SSCs, and the degradation mechanisms that could lead to those failure modes;
- Develop and propose a program of surveillances that will identify degradation prior to failure of SSCs;
- Provide a means of reporting results, taking actions for anomalous or undesirable conditions, and give the regulator assurance of continued safe operations.

Applying RIM in a specific case will call for advances in the state of practice of relating physical observables to functional reliability of certain component types. Except where a given level of damage corresponds to a failed (or nearly failed) state, it is not practical to establish a precise quantitative relationship between physical observables and reliability. This paper focuses on managing risk of passive component failures based on observable damage parameters. A simple approach to cumulative damage modeling will be illustrated with a view to possible use in RIM applications.

Keywords: Reliability and Integrity Management, RIM, cumulative damage modeling.

1. INTRODUCTION

This paper explores the applicability of cumulative damage modeling (CDM) to Reliability Integrity Management (RIM) as described in [1].

The RIM approach manages the risks associated with novel materials/designs/operating conditions through a carefully considered application of Monitoring and Nondestructive Examination (MANDE), including repair or replacement if necessary, to maintain the reliability of in-service components based on the degradation mechanisms that may exist throughout the life of the plant. In the RIM approach, applicants need to:

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- Understand failure modes of those SSCs, and the degradation mechanisms that could lead to those failure modes;
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RIM shares with the Licensing Modernization Project (LMP) [2] the idea that the component-level allocations are to be derived from plant-level targets. But the emphasis of RIM is on formulating and executing the component-level treatments that make sure that the component-level targets - and therefore the plant-level targets - are in fact met.

Refer to Figure 1, which is loosely based on [3]. Per RIM, component-level reliability targets are allocated, as suggested in the "Reliability Space" portion of the figure; and MANDE is formulated and executed with a view to assuring satisfaction of the target, or detection of failure to satisfy the target. MANDE operates in "Observables Space;" this is suggested in Figure 1 by the plot of a hypothetical "damage" variable being monitored under MANDE. It is necessary to establish a relationship between the reliability target and current MANDE observations. This paper will not complete that task, but will offer a tool for addressing it.

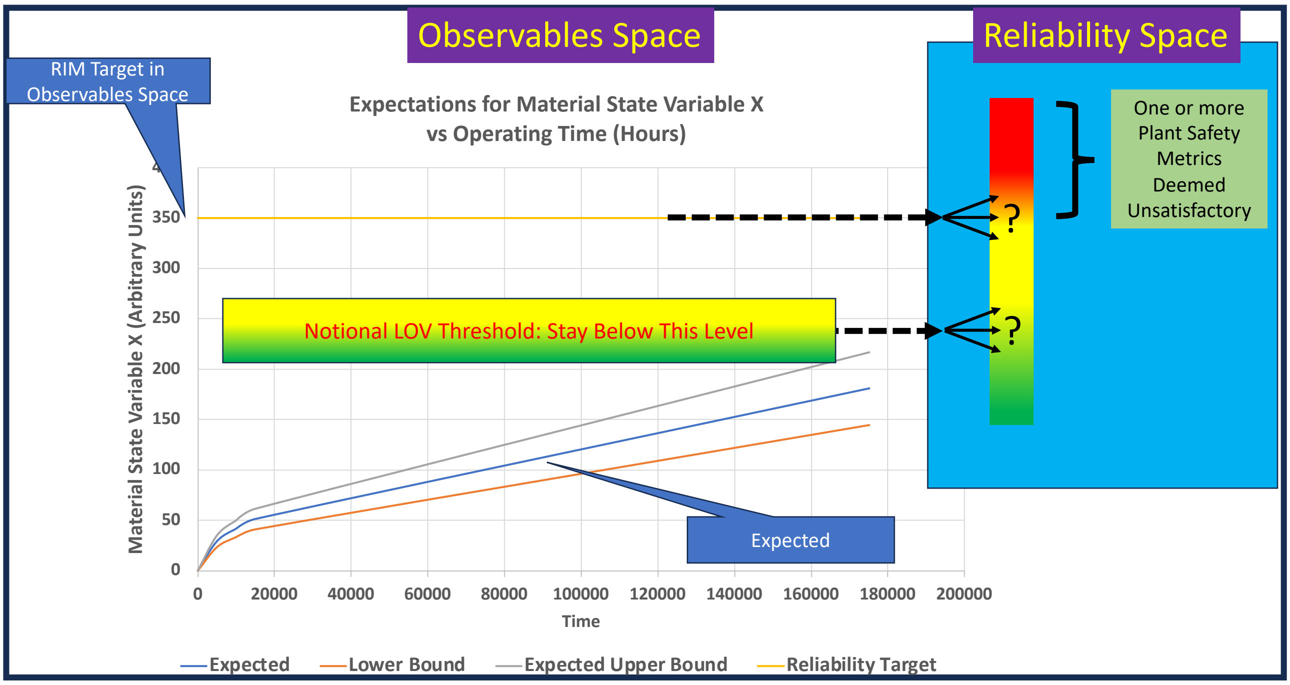


Figure 1. Mapping Between "Reliability Space" and "Observables Space"

At the leadership level, stakeholder expectations concerning the plant risk posture (accident risk, generation risk, …) may be qualitative. However, adherence to such a risk posture is easier if it is formulated at a high level in terms of allocatable quantities. For high-priority objectives, it is expected (in LMP and in RIM) that stakeholders' qualitative risk tolerances will tend to be translated into quantitative risk tolerances as an integral part of the Systems Engineering process, and those risk tolerances are then partitioned down to the level of verifiable requirements and specifications (e.g., as margins, operating limits, quality controls, etc.) [4]. This is what RIM calls for.

Figure 1 notionally illustrates a "LOV Threshold" in observables space. LOV stands for "Loss of Validity," a term borrowed from aviation [5, 6], and applied in regulatory oversight of fatigue damage in aircraft. In that domain, affected parties are required to:

> Establish a limit of validity of the engineering data that supports the structural maintenance program (hereafter referred to as LOV) that corresponds to the period of time, stated as a number of total accumulated flight cycles or flight hours or both, during which it is demonstrated that widespread fatigue damage will not occur in the airplane. This demonstration must include an evaluation of airplane structural configurations and be supported by test evidence and analysis at a minimum and, if available, service experience, or service experience and teardown inspection results, of high-time airplanes of similar structural design, accounting for differences in operating conditions and procedures. [5]

The curves shown in Figure 1 (Expected, Lower Bound, Upper Bound) represent results from a notional prior model of that damage variable's behavior in time. If the damage variable is seen (e.g., through MANDE) to impinge on the "LOV" region, then corrective action of some kind is warranted. The determination of the LOV region in a particular application depends on the uncertainties affecting that application and on the risk posture.

The aviation community has been paying attention to this matter for many years, as illustrated in [6]. Those authors analyzed fatigue damage in aircraft operating under a range of conditions, addressing a range of stressors, some essentially chronic (steady operation) and some episodic (particular maneuvers or events).

Below, we will propose a framework for modeling cumulative damage, and suggest a mode of applying that model in a way that generally resembles the thought process sketched above. Physical observations are made and interpreted through a model of cumulative damage that could, when adequately supported by data and models, be applied within a sort of "digital twin" paradigm: we make component renewal decisions based on a physics-based understanding of component status.

The framework illustrated does not solve the whole problem, but it may help to integrate the insights that seem to be emerging from recent advances in materials science.

2. CUMULATIVE DAMAGE MODELING

This section presents a "cumulative damage model" (CDM) and contrasts it with conventional reliability modeling. The next section will illustrate notional applications of it.

The present CDM is loosely based on a well-known Markovian model of piping reliability due to Fleming [7]. The model is shown in Figure 2 below:

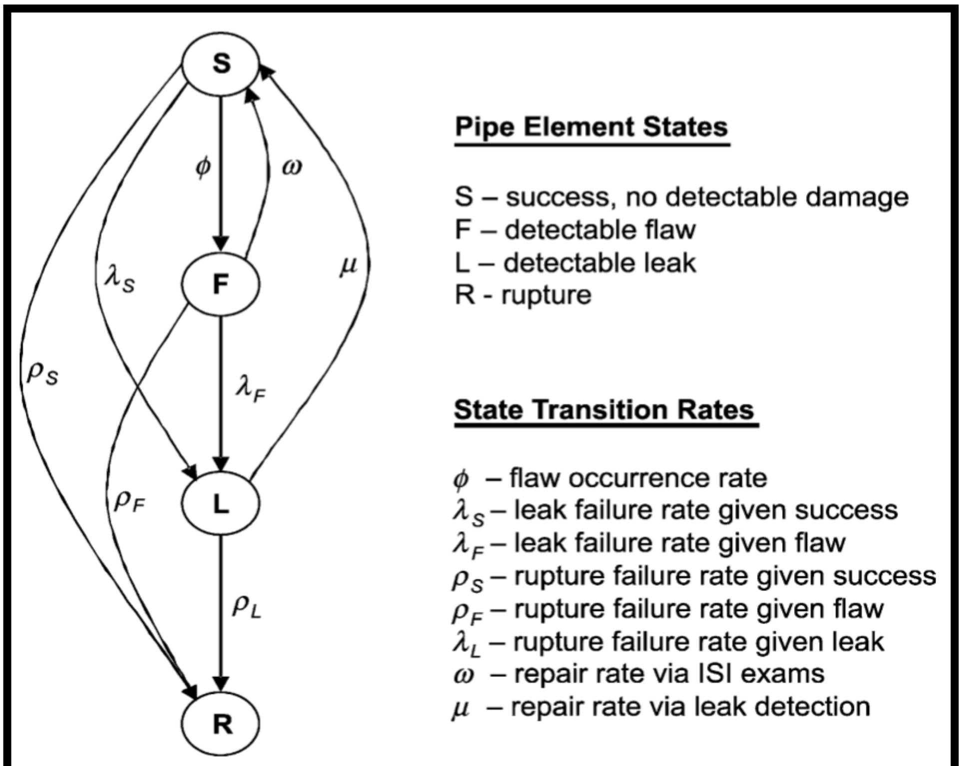


Fig. 1. Four state Markov model for all failure mechanisms.

Figure 2: A Markovian model of piping reliability, appearing as "Figure 1" of Fleming [7].

Figure 2 is essentially a picture of a classical reliability analysis. A space of states is defined; the occupancy of a given state at a given time represents the fraction of systems occupying that state at that time. Transitions between states are modeled in terms of rates such as those illustrated in the lower right of Figure 2. In this kind of model, the transition from (say) "flaw" to "leak" does not depend on dwell time in the flaw state; the rate of those transitions depends only on the current occupancy of the initial state (e.g., "flaw") and on the specified rate parameter. The repair rates can be modeled to reflect certain parameters of the MANDE program, such as frequency of surveillances and probabilities of failure to detect specific component states. Each transition arc in the figure represents a differential equation relating the time rate of change of the initial component state in terms of that state's occupancy and the transition rates to other states. These equations are solved to quantify time-dependent state occupancies and time-dependent rates of transitions to failed states (e.g., rates of rupture).

Meaningful results are obtainable from such a model despite its simplicity. But here, we begin with the above state space, and add certain details with a view to providing more actionable results to MANDE. The structure of the present CDM is shown below in Figure 3.

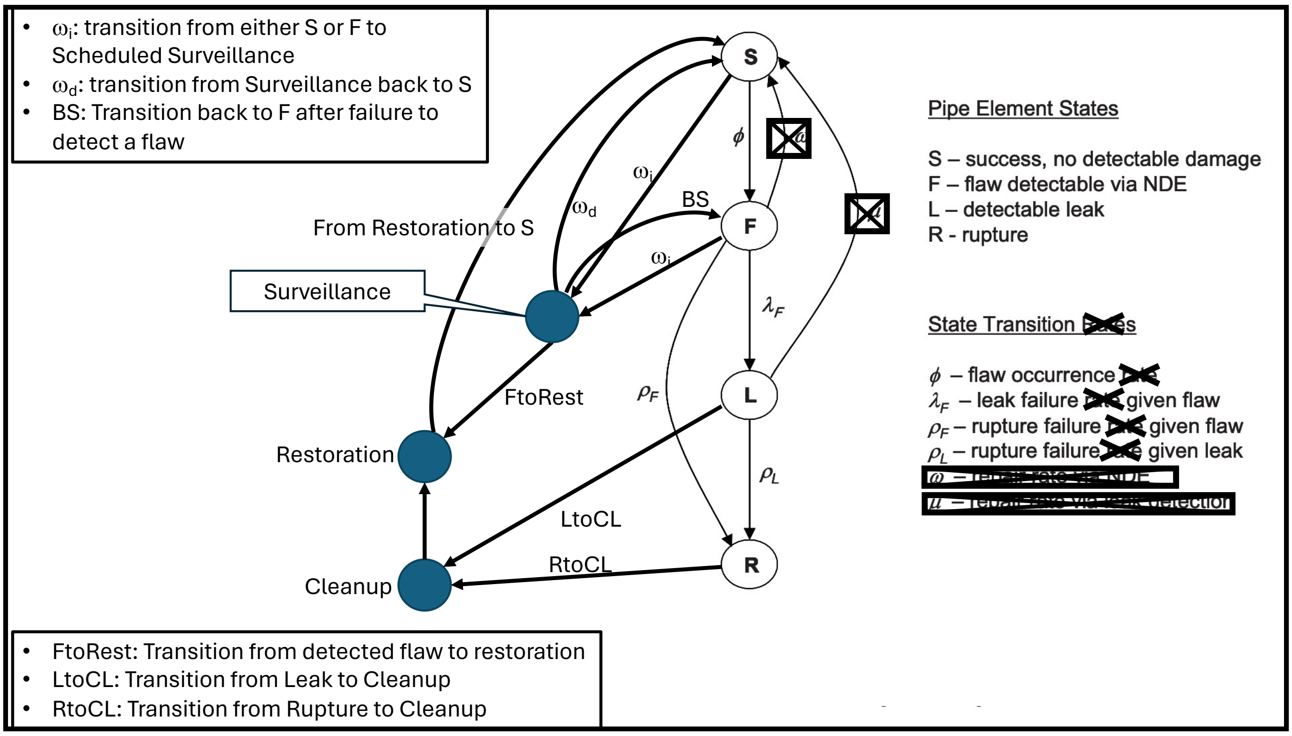


Figure 3. The Cumulative Damage Model

Although Figure 3 is inspired by Fleming's Markov model, the underlying CDM is very different. In the CDM, a specific component is in precisely one of the states shown, rather than the system being described in terms of state occupancies, as in the Markov model. Instead of solving differential equations to describe the time evolution of average state occupancies, one simulates a large number of time histories describing the progression of a given component through the various states (good, flaw, surveillance, leak, etc.), culminating in "Restoration" (repair, replacement, …), followed by progression of the renewed component through the various states, and so on. To that degree, the CDM simulation resembles discrete-event simulation, but in CDM, transitions from one state to another are not modeled by sampling failure times based on failure rates; they occur when specific damage thresholds are crossed. Damage to the component is modeled as resulting from external influences on the component; in the present application, component damage results either from a chronic stressor (normal operation) or the incidence of episodic stressors (such as severe thermal transients). This approach has been formulated in imitation of [6], and in recognition of the point that if episodic stressors are relatively important, but arrive sporadically, then significant variation occurs from one component life history to the next even if nothing else changes, and this needs to be reflected in the formulation of the model, in interpretation of its results for RIM purposes, and in the approach to tracking damage in real time.

It may be asked whether it is necessary for a RIM application to consider states such as Cleanup and Restoration. The above framework was developed for a broader class of applications than RIM; in those other applications, the Cleanup and Restoration states may be more useful. The example results shown below are provided to illustrate the modeling potential of the cumulative-damage framework, not to suggest realistic values for failure times in any particular technology.

3. APPLICATION OF CUMULATIVE DAMAGE MODELING (CDM)

3.1. Base Case

The model parameters and the implied results are provided strictly to illustrate the properties and possible benefits of applying CDM within a RIM program. The results are not meant to suggest specific conclusions for any particular technology.

The key parameters of the model are shown below in Table 1. The "damage" model is:

$$Damage=Factor1*Operating\ Hours + Factor2\ *(\#\ of\ episodic\ stressors) \tag{1}$$

"Episodic stressors" are incidents that cause momentary stress (as opposed to something like normal vibration). In [6], the analysis considered high-stress aircraft maneuvers, and the present concept of "episodic stressor" is analogous to that. For convenience, we measure "damage" in units of the amount of damage caused by one hour of normal operation, and all the runs shown in this paper assume *Factor1 = 1*. Flaws, leaks, and ruptures occur when their time-history-specific thresholds are crossed; if the flaw threshold is 10000, and no episodic stressors occur, then a flaw is created after 10000 hours of operation. If Factor2 is 1000, and two episodic stressors occur early on, then a flaw is created after 8000 hours of operation, and so on.

Table 1. Model Parameters

Parameters	Values
Factor1 (Damage Model)	1
Factor2 (Damage Model)	1000
Parameters (μ,σ) of Gaussian Distributions for Flaw, Leak, Rupture Thresholds:	
Flaw (μ,σ)	(8760,100)
Leak (μ,σ) (additional damage given flaw)	(12000,100)
Rupture (μ,σ) (additional damage given flaw)	(14000,100)
Average rate of episodic stressors (their times are Poisson distributed)	3.42E-4 / hr (about 3 per year)

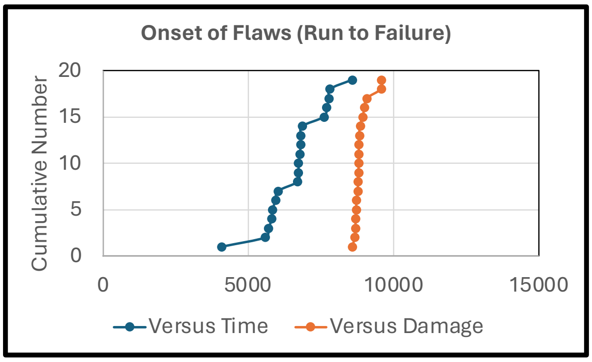
In a given campaign (e.g., 300000 hours, or about 20 component lifetimes), flaw, leak, and rupture thresholds are sampled for each new component from Gaussian distributions. The values shown in Table 1 imply a small variability in threshold values from one component to the next; this is done for ease of interpreting the results. One case will be shown later where the σ for flaw is changed to 2000, and this has a significant effect on the viability of particular monitoring approaches.

Figure 4 shows results of a simulation run comprising about 300000 hours in total, which turned out to be around 20 component lifetimes, given these parameters. For reasons explained in [3], the code runs very fast, and is capable of generating an enormous amount of output, but the present amount of output is convenient to work with, and supports some of the necessary discussions. (If we were trying to quantify very small unreliabilities, a different strategy for data handling would be undertaken, as in [8].) In Figure 4, the first component is run to failure (onset of leak) and then renewed, and the next component is run to failure, and renewed, and so on. For ease of viewing, the plotted points are sorted to yield cumulative distributions for onset of flaw and onset of leak.

Figure 4 contrasts plotting onset of flaws or leaks versus *time* at which flaws or leaks occurred with plotting versus level of *damage* at which the subject transitions occurred. For both flaws and leaks, the distribution of onsets versus time is much broader than the distribution of onsets versus damage. This relates to one of the key points about damage modeling. The "damage" plots are narrow because the distributions of damage thresholds are narrow, so everything fails at essentially the same damage level; but the time plots are broad because some of the component histories have more episodic stressors than others. The "damage" symbols at the upper right of the damage curves are displaced because of an artifact in how the code scores damage; if a component is within a few hundred units of a damage threshold, and an episodic stressor occurs, then with Factor2 = 1000, the damage exceeds the threshold by several hundred units. Apart from that artifact, the plot of onset versus damage level will generally look the same, regardless of episodic stressor history, while the "time" plots will be relatively messy.

3.2. Onset of Flaws, Bails, and Leaks given Annual Surveillance

Figure 5 shows a campaign history in which surveillance is conducted annually, regardless of whatever has happened with the component. In this history, flaws occur when components are around a year old, but at that point, there is not much to see, and even if flaws are identified, they are not modeled as warranting component renewal at that point.



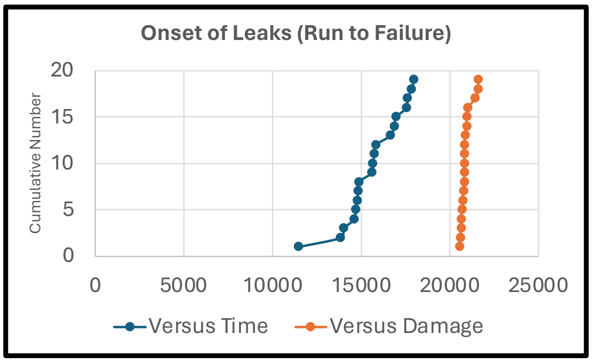


Figure 4. Base case: Results for a series of component lifetimes culminating in failure (in this case, onset of leak). Onset of flaws versus time and versus damage (measured in time units), and onset of leaks versus time and versus damage (measured in time units). No surveillance occurs in this run.

Flaws are expected to occur at a *damage* level around 8760 (mean flaw threshold) +12000 (mean threshold for additional damage beyond flaw), but the *times* at which flaws appear will be earlier than t=20760 as a result of episodic stressors, as explained above, and as suggested in Figure 5.

Given the above parameters, annual surveillance is generally ineffective, but as shown in Figure 5, surveillance did manage to identify 3 cases of incipient failure. The figure refers to these as "Bails," as in "the plant bailed on that particular component because it was near the leak threshold: the plant renewed (repaired or replaced) the component before the leak occurred."

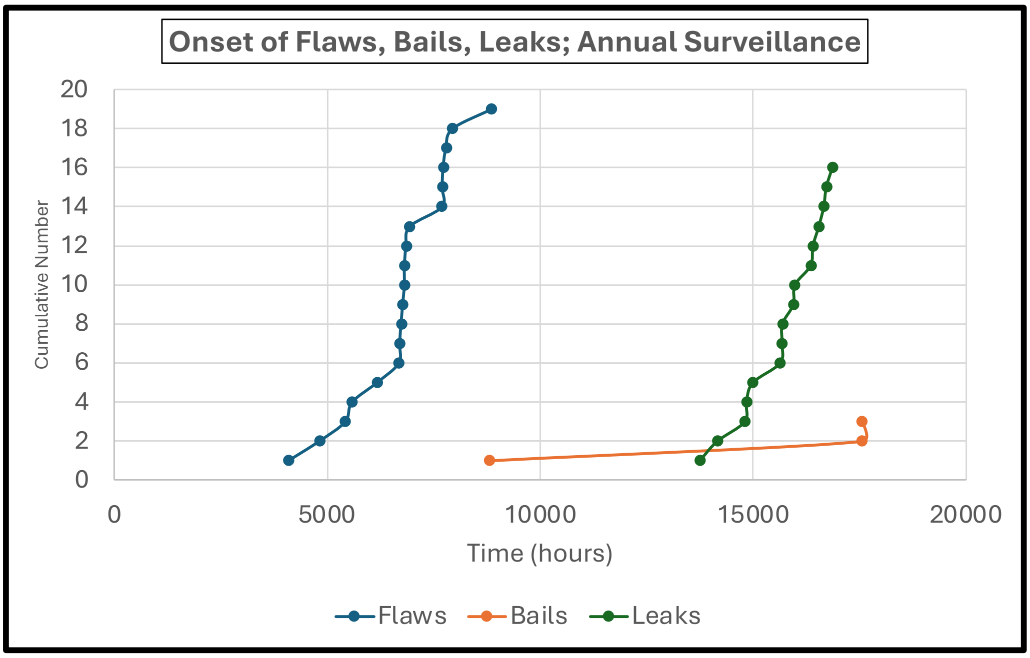


Figure 5. Onset of Flaws, Bails, and Leaks, plotted against time. In this run, surveillance occurs annually, and if observed damage exceeds a specified damage threshold, the component is renewed ("Bail").

3.3. Onset of Flaws, Bails, and Leaks Given Adaptive Surveillance

Figure 6 presents the results for a case in which surveillance is "adaptive." By "adaptive," we mean that after the first surveillance, an attempt is made to plan the next surveillance, based on an estimate of when the component would be near (but not quite at) the leak threshold. In this run, it was assumed that

- current damage would be measured, and, together with component age, used to estimate the average rate of damage accumulation;
- this average rate would be used to estimate the time at which the component would be near the leak threshold;
- the surveillance was planned and executed accordingly.

We see that in this campaign, quite a few Bails occurred (representing successful avoidance of a leak), even though the estimation of failure time was simplistic. But several leaks also occurred. This adaptive scheme is not perfect: if that first damage measurement included a number of episodic stressors, then the extrapolation will assume a greater than average number of episodic stressors, and the next surveillance will occur needlessly soon; but if that first damage measurement included a less-than-average number of episodic stressors, then the extrapolation will be off in the opposite direction, and the surveillance may occur too late to prevent a leak.

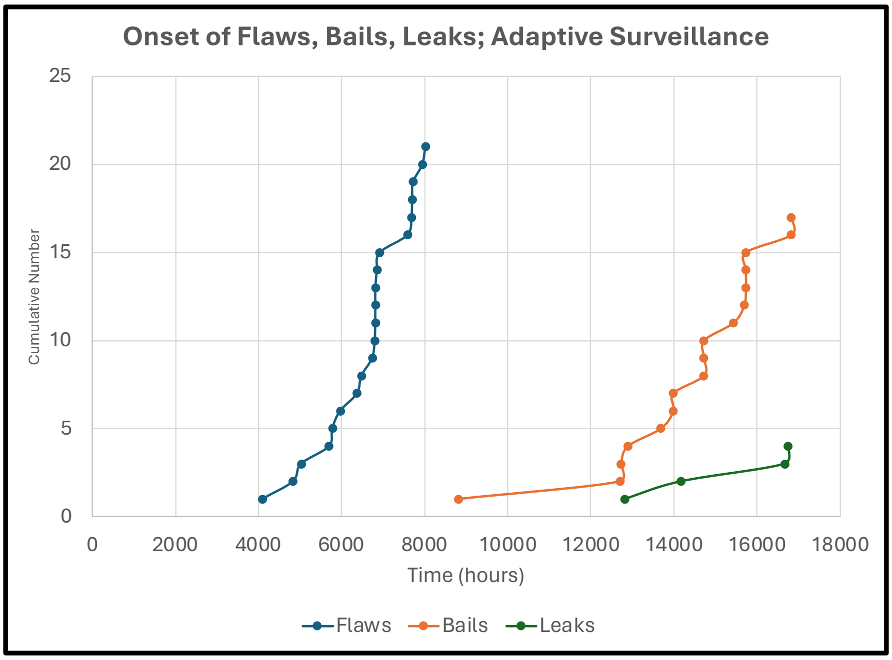


Figure 6. Onset of Flaws, Bails, and Leaks versus time. In this run, surveillance is adaptive; in the first surveillance, damage is observed, and "damage per unit time" is determined. Then a linear extrapolation is used to determine when component renewal should occur.

3.4. Onset of Flaws, Bails, and Leaks Assuming a Perfect Digital Twin

Figure 7 shows the case where the form of the Damage Model (eq. 1) is correct, its parameters are known, and the plant continuously tracks operating hours and episodic-stressor incidence.

On these assumptions, the plant staff know the current level of damage at all times, and can renew the component at the right time. This concept resembles the "LOV" idea illustrated in Figure 1, and is a case of the widely-discussed "digital twin" idea, which was formulated for this sort of application.

However, the favorable result shown in Figure 7 results partly from the low variability in leak threshold (the small value of leak σ in Table 1). We can credit the digital twin with a lot, but it may not be realistic to expect it to know specific values of specific properties in a brand-new component subject to variability in manufacturing. In the next subsection, we show what happens when we assume significant variability in leak threshold.

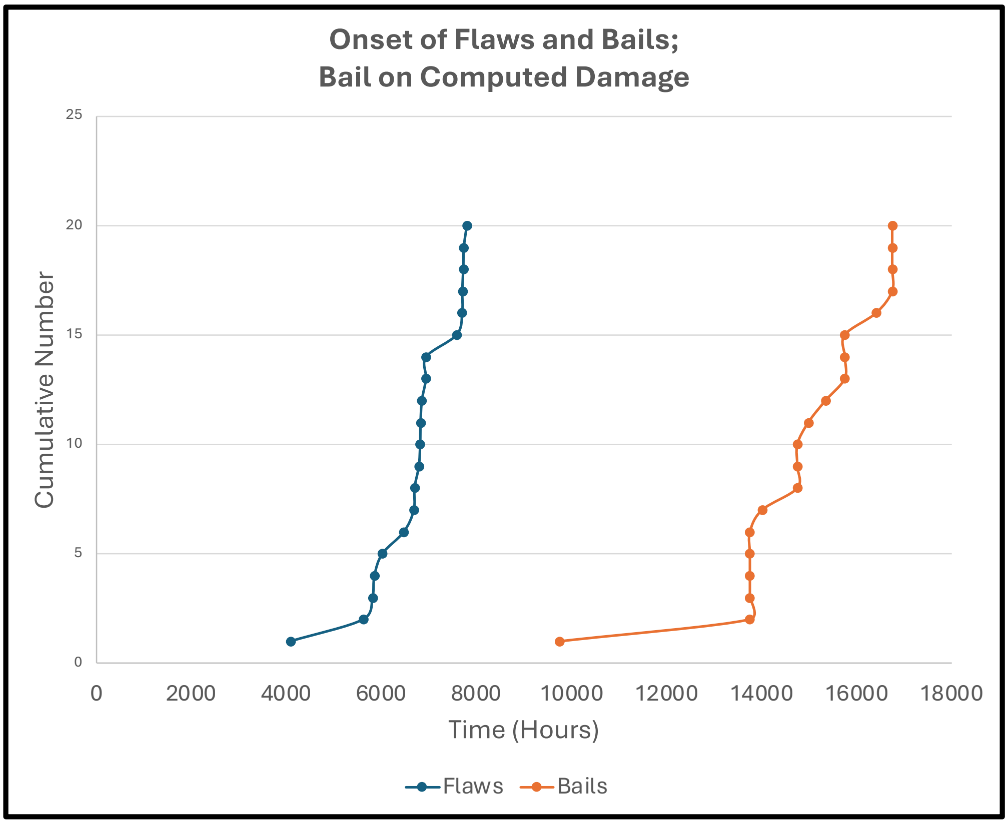


Figure 7. Flaws and Bails versus time. In this run, no surveillance occurs at all; rather, it is assumed that the damage formula (eq. mm) accurately reflects damage to the component, and when operating history implies that the time for component renewal has arrived, the component is renewed. In this campaign, no leaks occur.

3.5. Onset of Flaws, Bails, and Leaks Assuming Large Variance in Flaw Threshold

In Figure 8, we show the effect of assuming much greater variability in the flaw threshold than was used to generate Figure 7. In this model, if flaw occurs earlier, then so, on average, does leak.

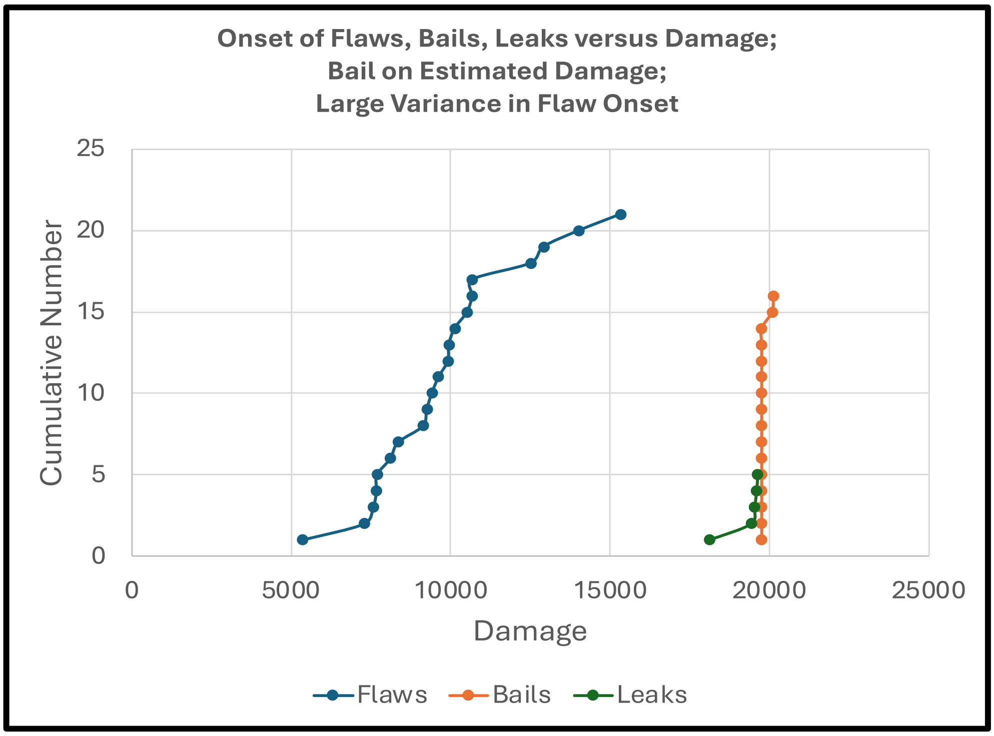


Figure 8. Onset of Flaws, Bails, Leaks versus Damage.

Figure 8 resembles Figure 7 in all but two respects: (1) it is plotted against damage rather than time; (2) a relatively large variance (σ=2000) has been added to the specification of the flaw threshold (which translates into a similarly large variation in leak threshold). This does not change the *average* thresholds for onset of flaws or leaks, but bailing based on an *average* leak threshold is much less reliable in Figure 8 than in Figure 7, and in Figure 8, in 5 out of 21 cases, leaks occurred at a level of damage below the level at which renewal would have been carried out. In fact, there is a resemblance between the lower tail of the flaw distribution and the lower tail of the leak distribution, and this is not an accident.

4. DISCUSSION

Unfortunately, satisfaction of quantitative risk indices is not practically observable. This is one of the factors driving the need for "assurance cases:" [9]

> The need for assurance case arises when one realizes the properties of the systems in the real world can never be completely formalized in a logical theory, but there is always something which is not covered by any logical formalization.
>
> NOTE 1 When the top-level claim is about safety, security, dependability or RAM (reliability, availability and maintainability), assurance cases associated with these claims are called safety cases, security cases, dependability cases or RAM cases, respectively.

This suggests that we need to use observables to manage risk without necessarily quantifying a reliability metric. This is the reason for the question marks on Figure 1. If we can establish values of physical state variables that correspond to low risk of failure, and we can successfully monitor those variables, we can show that risk is being adequately managed, even if we do not explicitly quantify a reliability metric. A program of MANDE – and interpretation of MANDE results based on a convincing model of the system – is therefore essential to risk management. Applying RIM to management of reliability of a passive component calls for a deep understanding of the degradation mechanisms to which the passive component is susceptible, and a program of monitoring and nondestructive evaluation that is sufficiently thorough to provide the necessary assurance (not proof) regarding satisfaction of component-level reliability targets.

The present paper illustrates the potential benefits of cumulative damage modeling in such an application, and the usefulness (technical and economic) of certain types of uncertainty reduction. But those illustrations are predicated on very specific knowledge of current component conditions. Some of the illustrations took credit for surveillance determining "damage" with high accuracy; the dominant uncertainty in those illustrations was the timing of episodic stressors. But when we introduced a significant uncertainty in flaw threshold, the difficulty of determining a good renewal strategy without excessive surveillance increased dramatically.

These examples indirectly illustrate the "value of information" concept introduced by Howard. [10] The level of accuracy in damage assessment implied in some of the illustrations may not be available currently, but understanding of materials behavior (including the ability to image materials at small length scales) is advancing rapidly. With recognition of the costs of leaks and ruptures and the costs and benefits of surveillance (well-timed or ill-timed), and with understanding of the uncertainties in damage causation and in damage characterization, a "value of information" framework may soon be able to support improved planning of surveillance.

5. CONCLUSION

This paper has argued the potential benefit of a "cumulative damage modeling" (CDM) framework. Such a framework superficially resembles discrete-event simulation based on classical reliability modeling, and in some respects resembles probabilistic fracture mechanics (e.g., [8]), but yields results of a different sort, and calls for different inputs. Given those inputs, the modeling is no more difficult than discrete-event simulation, but bears more directly on planning surveillance and tracking details of component history. This comes about because the models of component behavior are based on physical observables, rather than on statistical abstractions such as "failure rates."

The approach illustrated is presently limited by limits on the level of detail of our understanding, especially of novel materials. The potential value of the approach seems clear. Whether it can be realized in practice arguably depends on developments in our understanding of the issues affecting MANDE.

Acknowledgements

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