A Causal Approach to Integrate Component Health Data into System Reliability Models

Diego Mandelli[1] and Congjian Wang[1]

[1]*Idaho National Laboratory (INL), 1955 N Fremont Ave., Idaho Falls, ID, 83415, USA*

Diego.Mandelli@inl.gov
Congjian.Wang@inl.gov

Abstract

Two challenges of current plant reliability approaches are the ability to integrate plant health data and to support decision-making. Condition-based, diagnostic, and prognostic data are in fact not considered in plant reliability models to inform system engineers on the most critical components. Currently, the propagation of quantitative health data from the component to the system level is a challenge given the diverse data nature and structure. On the other hand, plant reliability methods (typically based on fault trees or reliability block diagrams) can effectively propagate data from the component to the system level, but values of failure rates or failure probabilities are an approximated integral representation of the past industrywide operational experience, and they neglects the present component health status (e.g., diagnostic and condition-based data) and health projection (when available from prognostic data). Our first claim is that system reliability models should propagate health information from the component to the system and plant level in order to provide a quantitative snapshot of system and plant health and identify the most critical components. Our second claim is that component health should be informed solely by that specific component current and historical performance data and should not be an approximated integral representation of the past industrywide operational experience. This paper is directly supporting these two claims by proposing a different approach for reliability modeling that relies on available component diagnostic, prognostic, and condition-based data to measure component health, and it propagates this information through fault tree models. The propagation of health data from the component to the system level is performed not in terms of probability but in terms of margins where margin is the "distance" between the present actual status and an undesired event (e.g., failure or unacceptable performance). Through a *cause-effect* lens, while classical reliability models target the *effect* associated with a component performance, a margin-based approach focuses on the *cause* of an undesired component performance (i.e., component health). Hence, thinking of reliability in terms of margins implies decision-making based on causal reasoning. We will show how fault tree models can be solved using a margin language and how this process can effectively assist system engineers to identify the most critical components.

1. Introduction

Typically, risk is defined by three elements: what can go wrong, what are its consequences, and how likely is it to occur. Although this definition makes sense in a regulatory-based framework to estimate the potential public health risk associated with power plants (in terms of core damage frequency and large early release frequency), this approach does not provide a useful snapshot of the health of the plant based on its current condition and performance. Some observations to support this claim include that testing, maintenance, and surveillance operations are not completely integrated into a plant probabilistic risk assessment (PRA) model, at least on a frequency that reflects current condition of significant plant structures, systems, and components (SSCs). Second, a probability value associated with an event is an approximated integral representation of the past operational experience for such an event, and it neglects the present component health status (e.g., diagnostic and condition-based data) and health projection (when available from prognostic data) of anticipated changes in SSC condition and performance in the near future.

2. Risk in a Plant Operation Context

Given these conditions, the decision-making process related to health and asset management is not well suited to being evaluated and managed using classical PRA tools. A possible alternate path can start by redefining the word "risk" to encompass a broader meaning that better reflects the needs of a system health and asset management decision-making process. Rather than asking how likely an event is to occur (in probabilistic terms), we ask how far this event is from occurring.

This new interpretation of risk transforms the concept from one that focuses on the probability of occurrence to one that focuses on assessing how far away (or close) an SSC is to an unacceptable level of performance or failure. This transformation has the advantage that it provides a direct link between the SSC health evaluation process and standard plant processes used to manage plant performance (e.g., the plant maintenance and budgeting processes). The transformation also places the question into a more familiar and readily understandable form for plant system engineers and decision makers.

The concept of margin is well suited to provide information about how close an SSC is to an unacceptable level of performance or failure. More precisely, an SSC margin $\widetilde{M}$ can be defined (Mandelli, 2021) as the "distance" between the present and actual status and an undesired event (e.g., failure) for an SSC (see Figure 1).

At this point, we identify how to measure SSC margins as a distance of occurrence between the SSCs existing condition and the point where its performance or condition becomes unacceptable (i.e., action is required). Note that the concept of "distance" does not necessarily need to be measured in terms of time as we will clearly show in the next sections.

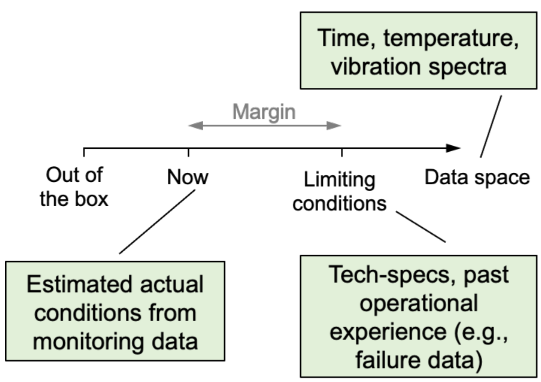

Figure 1. Graphical representation of margin to failure.

The application of this framework to system health as proposed here is centered on the integration and evaluation of available data to assess SSC condition and performance. Thus, this framework requires the definition of:

- *Space*: The "space" definition should be based solely on the type and dimensionality of the available equipment reliability (ER) data that can be directly measured and obtained by the system engineer.
- *Distance metric*: Once the space is defined, it is necessary to provide a measure of the "distance" between two points located in this space.

As indicated by Mandelli (2021), throughout this paper, we follow the convention where the component margin $\widetilde{M}$ is defined in the $[0,1]$ interval where:

- $\widetilde{M} = 1$ indicates component perfectly healthy
- $\widetilde{M} = 0$ indicates component at limiting conditions or failed.

3. INTEGRATION OF ER DATA

While a detailed description on the mathematical determination of component margin can be found in previous research (Mandelli, 2021), this section focuses on few practical examples of how the component margin can be assessed from practical situations.

3.1. Condition-Based Data

As indicated in Section 2, the margin can be calculated as the distance between actual and limiting conditions. In practical settings, limiting conditions can be represented by technical specifications specific to the component. As an example, for induction motors, oil viscosity must be below a specified limiting condition to ensure proper motor function. Oil viscosity can significantly change as a function of motor rotation speed. Hence, the margin can be calculated as the difference between the specified limiting condition and currently measured oil viscosity.

For rotating components (e.g., centrifugal pumps), a typical degradation process affects pump mechanical seals. The pump vibration signal is constantly monitored, and statistical indicators, such as the root mean square (RMS), of the signal are determined (Luo, 2021). In such scenarios, RMS analyses observed when seals are degraded beyond their limit are available from the manufacturer for different pump rotation speeds. In this case, margin could be defined as the difference between the manufacturer-specified acceptance level and observed RMS data.

3.2. Anomaly Detection Data

Anomaly detection methods (Nassif, 2021) are designed to identify unexpected behaviors (i.e., outside the normal operation boundaries). Hence, they provide binary information about the status and health of a particular component (it either works normally or abnormally). In a margin context, an anomaly identifies an unexpected behavior (or an unknown failure model) that requires immediate attention. In this scenario, the quantification of a margin value from an anomaly detection method can be as follows:

$$\widetilde{M} = \begin{cases} 1 & \text{for normal conditions} \\ 0 & \text{for abnormal behavior} \end{cases} \tag{1}$$

Note that such an anomaly can be triggered by either an internal (e.g., degradation or rupture of an internal part) or external (e.g., failure of another component that support a function of the monitored component) event.

3.3. Prognostic Data

For components where a prognostic analysis is available, it is possible to estimate the component's remaining useful life (RUL) when component degradation starts to emerge. Typically, RUL is quantified in probabilistic terms where a probabilistic distribution function (PDF) defined over the time axis t is generated, $RUL \sim PDF_{RUL}(t)$. In such a case, the margin can be estimated using two approaches. The first defines the margin as $\widetilde{M} = 1 - CDF_{RUL}(t)$ where CDF_{RUL} indicates the cumulative distribution function corresponding to PDF_{RUL}. The second approach estimates the margin as the distance between the actual component life and a point estimate of the RUL distribution (e.g., the 5th percentile).

A graphical representation of the margins for both approaches is in Figure 2 for an estimated RUL that is normally distributed shown in red. Note that the proposed approach updates the margin value when component health is measured and when a better RUL estimation (i.e., less uncertainty associated with RUL) is available from the corresponding prognostic model.

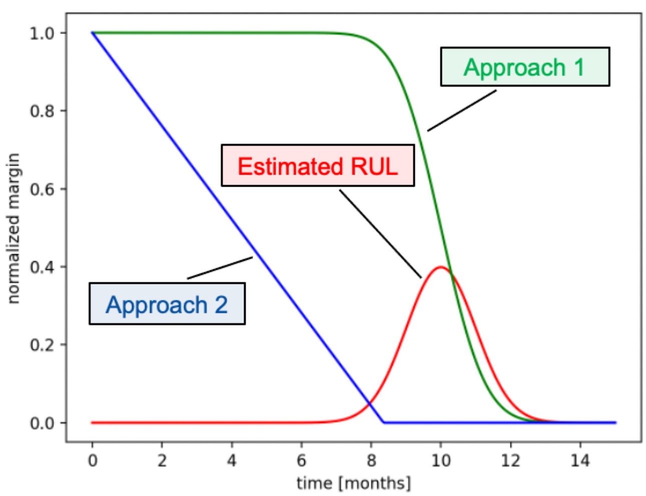

Figure 2. Margin values obtained from the two proposed approaches (green and blue lines) given an RUL estimate (red line).

4. MARGIN-BASED RELIABILITY MODELING

Current reliability models are based on Boolean logic structures (e.g., fault trees), which describe the deterministic functional relationship between SSCs and human interventions. Each basic event in a reliability model represents a specific elemental occurrence (e.g., failure of a component, failure to perform an action by the plant operators, recovery of a safety system), and a probability value is associated with each basic event, which represents the probability that the basic event can occur. However, maintenance and surveillance operations are typically not completely integrated into a PRA structure.

The goal now is to solve the AND and OR gates in a fault tree by feeding margin values. The rationale is to propagate margin values from the component to the system level, where the system reliability model is still represented by classical reliability models (e.g., fault trees). We want to assess the margin at a level where the degraded SSC performance or failures would result in actual consequences to system performance or economics (i.e., at the system or train level). Even though the definition of margin results in a value between 0 and 1, note that it is not appropriate to interpret margin values as a probability.

Consider now two components (A and B). The margin $\widetilde{M}$ for both components can be visualized in a 2-dimensional space, as shown in Figure 3. Starting with brand-new components (i.e., $\widetilde{M}_A, \widetilde{M}_B = 1$), aging degradation that affects both can be represented by the blue line of Figure 3, which parametrically represents the combination of the normalized margins $(\widetilde{M}_A(t), \widetilde{M}_B(t))$ at a point in time t. Note that, if no maintenance (whether preventive or corrective) was ever performed on either component, this path would move from the coordinates (1,1), components A and B at the beginning of life to the coordinates (0,0) where both components had failed. We can identify these regions in Figure 3: the occurrence of both events where $\widetilde{M}_A = 0$ and $\widetilde{M}_B = 0$ and the occurrence of either event where $\widetilde{M}_A = 0$ or $\widetilde{M}_B = 0$. Now we can calculate the $\widetilde{M}$ for the events listed above by following the margin definition by measuring the distance between the actual condition of Components A and B and $\widetilde{M}$ conditions identified by the event under consideration (e.g., the occurrence of both or either events):

$$\begin{aligned} \widetilde{M}(A\ AND\ B) &= dist[(\widetilde{M}_A, \widetilde{M}_B), (0,0)] \\ \widetilde{M}(A\ OR\ B) &= min(\widetilde{M}_A, \widetilde{M}_B) \end{aligned} \qquad (2)$$

The function $dist[X, Y]$ is designed to calculate the Euclidean distance between points X and Y.

Hence, exact solutions can be obtained extremely fast. More precisely, reliability calculations using $\widetilde{M}$-based data can be performed by completing these four steps:

1. Construct the fault tree; at this point, a fault tree only contains deterministic information about the system architecture under consideration (i.e., it simply models how the basic events are related to each other from a functional perspective).
2. Generate the minimal cut-sets (MCSs) from the fault tree; as also indicated in Step 1, an MCS still represents the minimal combinations of basic events that lead to the top event of the fault tree (e.g., system failure).
3. Assign a margin value $\widetilde{M}$ to each basic event.
4. Calculate system margin $\widetilde{M}$ from each MCSs.

As part of system reliability modeling, it is always important to determine the importance of each basic event. In a PRA setting, this is performed by relying on risk-importance measures (Lee, 2011), such as Birnbaum or Fussell-Vesely. Given the different nature of $\widetilde{M}$, it is possible to perform a risk-importance ranking by relying on a classical sensitivity measure (derivative based) for each basic event BE defined as:

$$RIM_{BE} = \frac{\partial \widetilde{M}_{sys}}{\partial \widetilde{M}_{BE}} \tag{3}$$

where RIM_{BE} indicates the risk importance measure for basic event BE. Simply stated, RIM_{BE} indicates how a small variation of $\widetilde{M}_{BE}$ (e.g., improving the health of Component BE) directly affects system margin $\widetilde{M}_{sys}$.

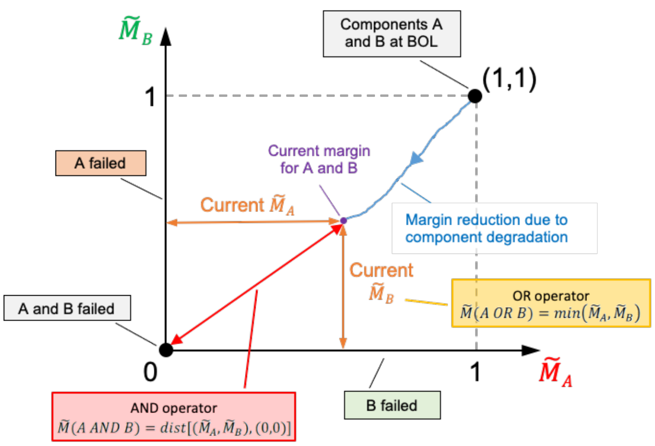

Figure 3. Graphical representation of event occurrences based on a margin framework.

Common reliability analysis methods are designed to work in the "failure space" where the goal is to identify the combination of events that yield adverse consequences. These combinations of events are typically represented as the MCSs as the logic product of basic events (e.g., failure of components or failure to perform recovery actions).

However, from a system engineer perspective, we are interested to work in the "success space" where the objective is to identify combination of events that guarantee system operation. These new combinations of events are represented by the minimal path sets (MPSs) (Youngblood, 2001) of the system under consideration. In formulating a safety case for a facility, it is beneficial to do a "prevention analysis" to identify combinations of success paths that (together) provide the required levels of functional reliability, redundancy, and diversity. In addition, if something goes wrong and we need to compensate for it lest we lose the function, it is useful to understand what success paths remain available and which of them are more reliable than the others (see the example in Section 5).

5. EXAMPLE OF MARGIN RELIABILITY ANALYSIS

This is an example of margin-based reliability calculation is for the system shown in Figure 4 (Youngblood, 2001) composed of seven components, A–G. An estimation of each component's RUL is available and it is shown at the top plot of Figure 5. RUL estimation is represented here probabilistically, that is RUL is represented by a PDF designed to represent uncertainty associated with RUL estimate (in terms of RUL mean and variance). In this scenario, we represent system reliability in terms of MPSs rather than MCSs. System margin is calculated considering the MPSs of the system in Figure 4 and by applying the margin rules indicated in Section 4 using the following setting:

- The margin of each component is calculated form its RUL using the model of Approach 1 described in Section 3.3 and shown in Figure 2
- Distance metrics for $M(A\ AND\ B)$: Euclidean.

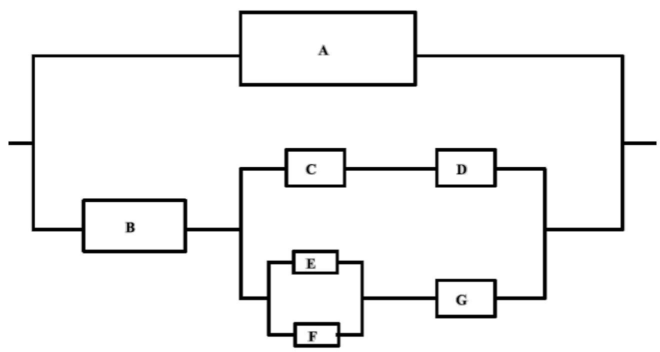

Figure 4. Example of system architecture represented in terms of block diagrams (Youngblood, 2001).

The obtained temporal profile of system margin is shown in the bottom plot of Figure 5. From this plot, note that:

- Even though the component margin is defined in the [0,1] interval, system margin can be higher than one (but still cannot be negative). A system margin greater than one implies that there are redundancies that can compensate for component failures. In other terms, when there are more than one MPS, the system margin is greater than one. At time $t = 0$, there are four MPSs and the margin for each component is set to 1 since the margin model employed for each component is calculated using the model of Approach 1 described in Section 3.3. Hence the system margin can be calculated as $\sqrt{1+1+1+1} = 2.0$.
- When components are approaching their own RUL, their margin decreases to zero until they are considered failed. Hence the number of available MPSs decreases and system margins decrease as well to a value equal to square root of the number of available MPSs.

- At time $t = 8\,months$, Component E fails and, even though Components B and G are working properly, there are no available MPSs, and consequently, the system margin value drops to 0.

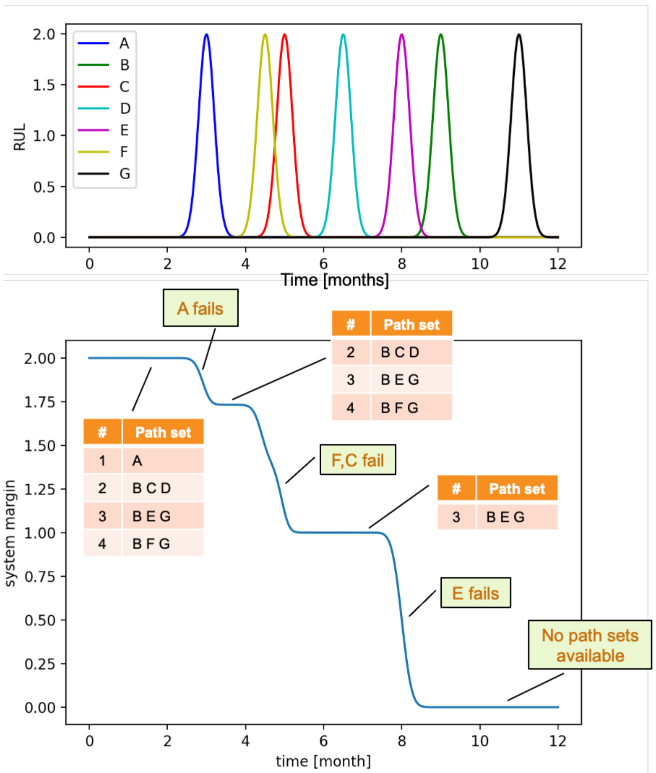

Figure 5. Example of margin-based calculations using prognostic data for the system indicated in Figure 4, with the top plot showing a RUL for each of the seven components, A–G. Corresponding quantification of system margin is indicated in the bottom plot.

Next is the quantification of the reliability measures indicated in Section 4 (see Eq. 3). Given component margin values at each time instant and the obtained system margin (see Figure 5), these measures were calculated and plotted in Figure 6 for all seven components. In order to show the type of information generated by these plots, let's consider the two regions of these plots highlighted in red:

- The first region is located at the beginning of the plot where all components have a margin value of 1 (i.e., all components are healthy). However, note that the RIM_{BE} values are not equal among the seven components. This is due to the fact that each component directly supports a different number of MPSs. As an example, Component B supports three MPSs (i.e., BCD, BEG, BFG) while Component A supports one single MPS (i.e., A). Hence, improving the margin of Component B is more beneficial at the system margin.
- The second region is located toward the end on the time axis where only one MPS is available (i.e., BEG). In this case, Components B and G are still healthy (i.e., their margin is still one) while Component E is approaching its RUL. Thus, the importance of Component E is greater than the importance of Components B and G.

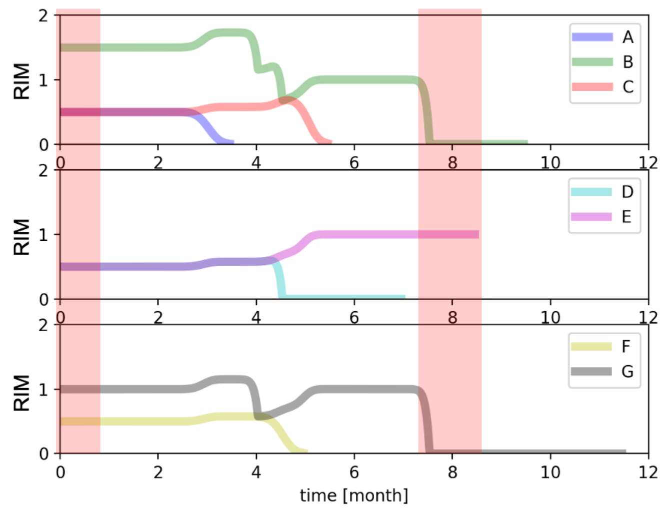

Figure 6. Plot of RIM_{BE} measures for the seven components of the system of Figure 4 given the provided prognostic data (in terms of RUL) indicated in the top plot of Figure 5.

6. LINKS BETWEEN MARGIN AND CLASSICAL RELIABILITY APPROACHES

At this point, it is relevant to present the structural differences between classical reliability models (i.e., based on probability of failure) and a margin-based approach. These differences can be described though a cause-effect lens, as in Figure 7. Classical reliability models focus on the effect node (i.e., to model component failure) where component reliability data are used to assess the system failure probability. Such models monitor plant risk (as currently done by plant risk monitors) and set "offline" decisions, such as setting periodic surveillance and maintenance activities, or set the duration of planned system maintenance outages (either as part of a plant configuration risk-management program or a plant risk-managed technical specification program).

Over the past several decades, plants have been moving from a reliance on periodic to more comprehensive predictive maintenance strategies where the goal is to only perform intrusive maintenance operations when needed. Advanced monitoring and data analysis technologies are essential to support predictive strategies. This is where margin-based reliability approaches can support this type of "online" decision-making where, based on current condition-based data, component health data are employed to assess component and system health (i.e., the focus is now shifted to the cause node of Figure 7).

7. NUMERICAL COMPARISON BETWEEN MARGIN AND CLASSICAL RELIABILITY APPROACHES

The goal of this section is to provide a more concrete bridge between margin and classical reliability approaches in support of the statements provided in Section 5. A common ground for these two kinds of reliability approaches can be established if ER data is composed solely by component failure time values. In this scenario, we are considering the failure time value for each component, and the objective is to determine system failure time for the most common system configurations: series, parallel, stand-by, and KooN.

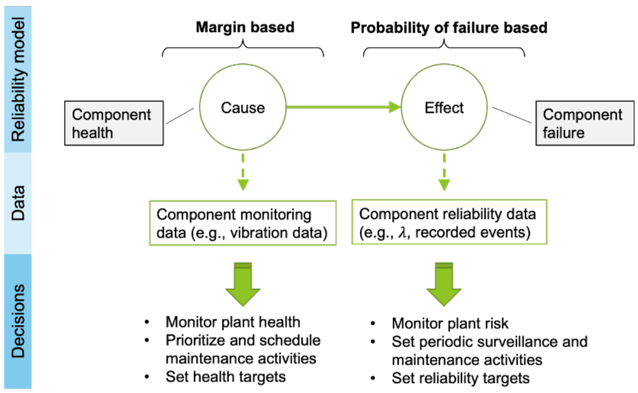

Figure 7. Comparison between margin-based and probability of failure-based reliability modeling approaches.

Given the failure rate for the considered components, the corresponding meant time to failure (MTTF) values can be calculated. Using the set of equations provided by Rausand (2020) (which are summarized in Table 1), it is possible to determine system failure time of the considered system configurations using classical reliability theory basis. From Table 1, we moved forward on calculating the system failure time provided the failure time of two components (i.e., T_1, T_2) for the considered configurations (see central column of Table 2).

Table 1. Summary of reliability and MTTF equations for several configurations (Rausand, 2020).

Config.	Reliability	MTTF
Series	$\prod_{i=1}^{N} R_i(t)$	$\frac{1}{\sum_{i=1}^{N}\lambda}$
Parallel	$1-\prod_{i=1}^{N}(1-R_i(t))$	$\frac{1}{\lambda}\sum_{i=1}^{N}\binom{N}{i}\frac{(-1)^{i+1}}{i}$
Stand-by	$R_1(t)+\lambda\, t\, R_2(t)$	$\frac{1}{\lambda}+\frac{1}{\lambda}=\frac{2}{\lambda}$
KooN	$\sum_{i=k}^{N}\binom{N}{i}R(t)^i(1-R(t))^{N-i}$	$M\sum_{i=k}^{N}\binom{N}{i}\int_{0}^{\infty}R(t)^i(1-R(t))^{N-i}$

Similarly, component MTTF values can be translated in terms of margins with the goal of determining system margin for considered system configurations using the equations provided in Section 4. In this situation, a margin is basically the distance between actual component life and its predicted failure time (i.e., the component MTTF). The system margin M_{sys} for considered system configurations are presented in the right column of Table 2.

The goal now is to translate M_{sys} values back into time values to compare with T_{sys}. We expect that this comparison process will provide identical outcomes from classical and margin reliability methods. At a first look at Table 2, the mathematical expressions for T_{sys} and M_{sys} for the series, stand-by, and KooN configurations are very similar.

Recall that components margin values are defined over the time axis and quantified based on component MTTF value; hence, the translation from M_{sys} to system failure time in a margin-based reliability context gives these outcomes:

- *Series*: given that M_{sys} is defined over a minimum of two component margins, the system failure time derived from margin calculation corresponds to $min(T_1, T_2)$ (see Figure 8).
- *Parallel*: in this configuration, M_{sys} follows the path shown in Figure 9 where components fail at two different time instances while system fails when the latter failure occurs (i.e., $max(T_1, T_2)$).
- *Stand-by*: in this configuration, the sum of two margin values (i.e., $M_1 + M_2$) is translated into the sum of failure time of both components (i.e., $T_1 + T_2$). Note that, in this configuration, $M_{sys} = M(A\ AND\ B)$; if the Manhattan distance is used, $M_{sys} = M_1 + M_2$ (see Figure 10).
- *KooN*: similar to the series configurations, only K components with highest margin values are considered (and consequently the highest failure times). The minimum out of these K values gives the same outcome as min(first K highest T_i).

Table 2. Comparison between system failure time and system margin for four system configurations.

Config.	System Failure Time, T_{sys}	System Margin, M_{sys}
Series	$min(T_1, T_2)$	$min(M_1, M_2)$
Parallel	$max(T_1, T_2)$	$dist[(0,0), (M_1, M_2)]$
Stand-by	$T_1 + T_2$	$M_1 + M_2$
KooN	min(first K highest T_i)	min(first K highest M_i)

8. DECISION-MAKING

As indicated in Sections 4 and 5, a margin-based reliability modeling is able to quantify component health given available ER data and provide insights about the most critical components that might negatively affect system operation (through the reliability measures described in Section 4, Eq. 3). The next step is to decide which operations should be performed to guarantee future system operation. This step requires an additional piece information regarding the timing aspect associated to a component failure. Such an aspect is captured by the concept of *urgency*, which is here defined as the amount of time available between now and when restoration operations need to be started to avoid component failure (see Figure 11).

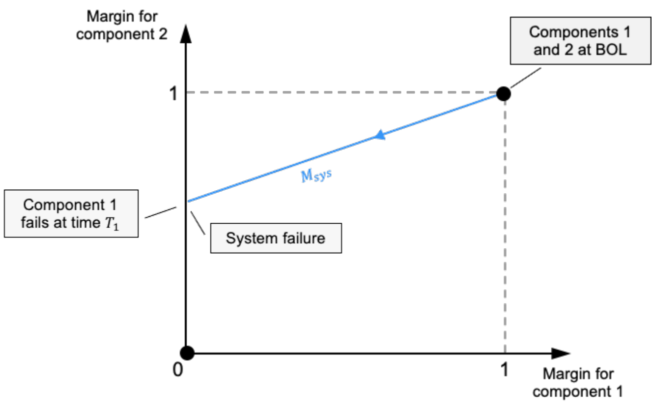

Figure 8. Evolution of M_{sys} for two components in a series configuration.

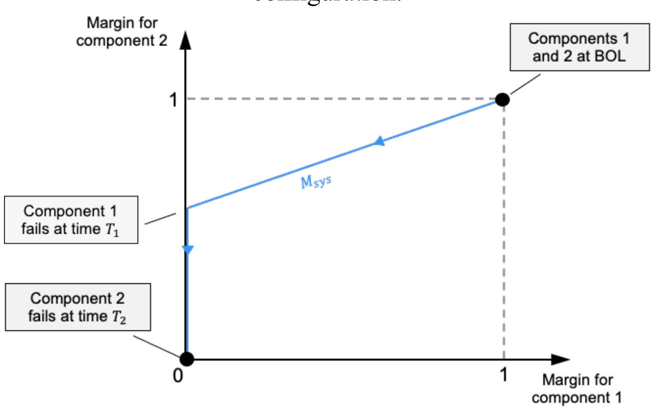

Figure 9. Evolution of M_{sys} for two components in a parallel configuration.

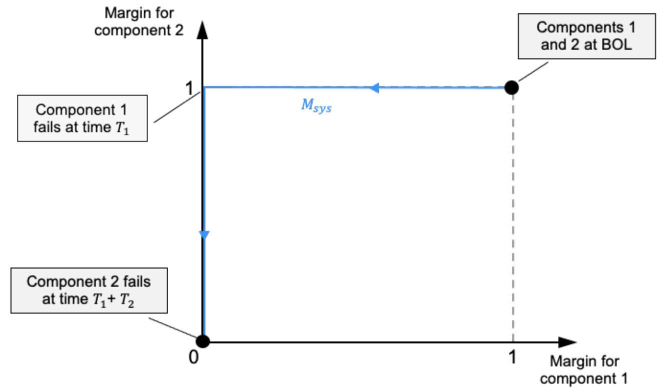

Figure 10. Evolution of M_{sys} for two components in a stand-by configuration.

From a practical standpoint, the estimation of component urgency requires two variables:

- Estimated failure time estimated from prognostic data (i.e., through RUL) or from margin calculations (see Section 4)
- Time required to restore component health. If the restoration process requires the substitution of the component, this time value can include time values to obtain the new component (procurement time), replace the old component, and install the new one. If the restoration process requires activities that can be performed onsite (e.g., chemical treatment of corroded portions of the component), restoration time can include the time values to take the component offline, time to perform restoration activity, and time to take the component back online.

At this point, we can select the most critical maintenance operations based on their urgency and the reliability importance of the components by plotting all operations in an urgency vs. RIM importance (see Eq. 3) plot as indicated in Figure 12. Depending on the industrial and decision-making context, this 2-dimensional plot can be partitioned in multiple regions where the range of each dimension is divided into two or three intervals. The selection of the operations that should be performed to guarantee future system operation can be performed by choosing the ones landing in selected partitions of the urgency vs. importance plot. As an example, for the case shown in Figure 12, the operations landing in the red, dark orange, and light orange sectors should be chosen.

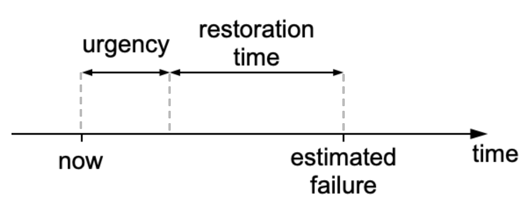

Figure 11. Graphical representation of urgency given estimated component failure and required restoration time.

9. CONCLUSION

This paper complements previous work (Mandelli, 2021) that presents a new way to perform reliability modeling. This margin-based method allows for a complete integration of several types of ER data (from condition to prognostic data), and it directly supports decisions that plant system engineers make regularly through plant lifecycle. As indicated throughout the paper, this approach is not intended to contrast classical reliability models. On the other hand, it is designed to support a different kind of reliability questions and support dynamic decisions rather than static ones (i.e., design related) (see Figure 7). A margin-based interpretation of reliability transforms the concept from one that focuses on the probability of occurrence to one that focuses on assessing how far away (or close) an SSC is to an unacceptable level of performance or failure (Zio, 2013). This transformation has the advantage that it provides a direct link between the SSC health evaluation process and standard plant processes used to manage plant performance (e.g., the plant maintenance and budgeting processes). The transformation also places the question into a more familiar and readily understandable form for plant system engineers and decision makers (Xingang, 2021). When dealing with condition-based data (actual and archived data), margin $\widetilde{M}$ is defined here as the distance between actual SSC observed conditions (e.g., oil temperature, vibration spectrum) that lead to failure.

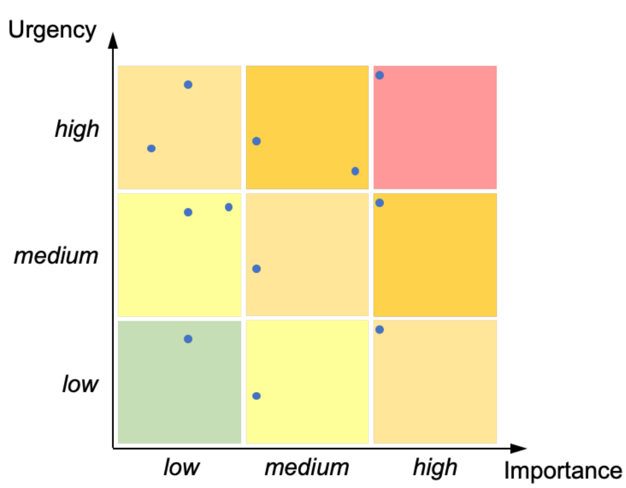

Figure 12. Selection of the most critical components in an urgency-importance diagram.

Note that margin values change with time. As an example, when new component condition data that indicate component degradation are observed, the component margin decreases. Similarly, when maintenance operations are performed to such component, its health is restored, and margin increased.

Lastly, note that this margin-based method relies on a failure mode and effects analysis (FMEA) method to identify component failure modes and their impact on the system level (which is then translated into a fault tree). Note that an additional step is required here: the identification of the ER data that monitor component degradation that might lead to such failure modes.

ACKNOWLEDGEMENT

This manuscript has been authored by Battelle Energy Alliance, LLC under Contract No. DE-AC07-05ID14517 with the U.S. Department of Energy. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for U.S. Government purposes.

REFERENCES

Lee, J. C., & McCormick, N. J. (2011). *Risk and safety analysis of nuclear systems*. Wiley ed.

Luo Y., Zhang W., Fan Y., Han, Y., Li, W. & Acheaw E. (2021). Analysis of Vibration Characteristics of Centrifugal Pump Mechanical Seal under Wear and Damage Degree. *Shock and Vibration*, 2021. https://doi.org/10.1155/2021/6670741.

Mandelli, D., Wang, C., & Hess, S. (2021). On the language of reliability: A system engineer perspective. 2021 Probabilistic Safety Assessment (PSA) Conference, November 7–12, virtual.

Nassif, A. B., Talib, M. A., Nasir, Q. & Dakalbab, F. M. (2021). Machine Learning for Anomaly Detection: A Systematic Review. *IEEE Access*, 9, 78658–78700. https://doi.org/10.1109/ACCESS.2021.3083060.

Rausand, M., Barros, A., & Hoyland A. (2020). *System reliability theory: Models, statistical methods, and applications*. Wiley ed.

Xingang, Z., Kim, J., Warns, K., Wang, X., Ramuhalli, P., Cetiner, S., Kang, H. G., & Golay, M. (2021). Prognostics and Health Management in Nuclear Power Plants: An Updated Method-Centric Review with Special Focus on Data-Driven Methods. *Frontiers in Energy Research*, 9, 696785. https://doi.org/10.3389/fenrg.2021.696785

Youngblood, R.W. (2001). Risk Significance and Safety Significance. *Reliability Engineering & System Safety*, 73(2), 121–136. https://doi.org/10.1016/S0951-8320(01)00056-4.

Zio, E. & Compare, M. (2013). A Snapshot on Maintenance Modeling and Applications. *Marine Technology and Engineering*, 2, 1413–1425.

BIOGRAPHIES

Diego Mandelli is a research and development scientist in the Reliability, Risk, and Resilience Sciences Department at Idaho National Laboratory. His areas of expertise include risk, reliability, and system health management. His research focuses on developing probabilistic methods based on machine learning, data mining, and optimization algorithms. He is currently employing these methods to perform state-of-the-art simulation-based safety assessments (also known as dynamic PRA), system health management, and stochastic resource optimization. His developed methods range from data preprocessing, system modeling, system analysis, data mining and visualization, and decision-making. He holds a Ph.D. in nuclear engineering from The Ohio State University (2011) and is a member of the American Nuclear Society.

Congjian Wang is a computational nuclear scientist at Idaho National Laboratory. He has a B.E. in engineering physics and Ph.D. in nuclear engineering and carried out postdoctoral research focused on machine learning, advanced sensitivity and uncertainty quantification, verification, validation, and data assimilation. He has more than 10 years of experience in developing and implementing artificial intelligence algorithms, including physics-based reduced-order modeling, surrogate modeling, data mining techniques, and deep neuron networks. He is the main developer of the Risk Analysis Virtual ENvironment framework and is mainly responsible for developing and implementing supervised and unsupervised learning algorithms, cross validations, and verification and validation metrics within that framework.