System-level Prognostics and Health Management for Complex Industrial Systems: An Application to Pressurized Water Reactors

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ABSTRACT

Prognostics and health management (PHM) has become essential to guarantee aware and safe system operation and to inform economic decision-making. However, due to the nature of detection, diagnostics, and prognostic methods, applications have mainly been limited to the component level. In practice, most industrial systems consist of multiple interacting components whose partial degradation could lead to system's failure (or subsystems). This research addresses the limitations of traditional component-level PHM techniques by proposing a novel system-level framework. By implementing a hierarchical structure of components and subsystems, we will select an optimal method for each subsystem to aggregate its component health assessments. The overall system health can then be estimated by further combining the obtained estimates. The research considers simplified and holistic modeling techniques, margin-based methods, and hybrid graphical models. This approach aims to provide reliable system health predictions and online components' sensitivity measures to enhance maintenance decision-making. We consider an application in the context of the nuclear industry, characterized by strict safety and economic requirements. Using a SIMULINK model to approximate a Pressurized Water Reactor (PWR) with real industrial inputs, we plan to add component degradation modules and use simulated sensor data and reliability information to test the proposed framework. Initial results on artificial case studies show the feasibility of integrating component-level health predictions.

1. PROBLEM STATEMENT

Modern industrial systems have gained a high level of complexity. One of the main interests within the current systems is the assessment of their health conditions and the mitigation of possible failure consequences. This can be accomplished by PHM techniques (Hu, Miao, Si, Pan, & Zio, 2022) that have become essential in maintaining the reliability and safety of such systems. The traditional PHM approach focuses primarily on individual components, assessing their health, identifying potential fault modes (diagnostics), and predicting future degradation behaviors (prognostics). While this component-level approach is beneficial, it has significant limitations when applied to complex systems composed of numerous interacting components whose partial degradation could lead to the system's failure. Estimating or predicting the health of a system as a structure of components can give maintenance operators more insight than a simple collection of components' assessments. However, it is particularly challenging to aggregate the health assessments of individual components to form an accurate and reliable system-level health estimate.

The interest in estimating the current and (forecasted) future health of a whole system has led to the emergence of an innovative subfield of PHM, often identified as system-level prognostics (SLP). This methodology considers the interactions, dependencies, and cumulative effects of all components within the system, aiming to provide a comprehensive assessment of system performance at the current time and in the future. By integrating data from various components and accounting for environmental conditions, operational profiles, and non-linear degradation mechanisms, SLP enables more accurate and reliable predictions of system failures. Several literature reviews clearly describe the intentions of SLP, systematically categorize the proposed approaches, and address challenges and research gaps (Tamssaouet, Nguyen, Medjaher, & Orchard, 2023), (Kim, Choi, & Kim, 2021).

Another critical aspect that PHM approaches must consider and tackle is the prioritization of maintenance actions. In a component-level framework, maintenance decisions are made based on the individual health status of components without considering the system-wide implications. This can lead to suboptimal maintenance strategies where critical components that significantly affect the system's performance might be overlooked. Therefore, there is a need for an approach that processes system-level results to efficiently inform maintenance decision-making, optimizing system reliability and performance.

In the context of nuclear power plants, little work has addressed system-level approaches, and much less research has designed maintenance strategies that use the results derived from these approaches (Zhao et al., 2021). Therefore, there is an urgent need for a comprehensive system-level framework that can integrate the health information of all components, consider their interactions, provide a reliable prediction of the system's overall health, and schedule optimal maintenance considering these results.

2. EXPECTED NOVEL CONTRIBUTIONS TO THE FIELD

Although we aim to propose a method adaptable to any industrial system, we will build our framework upon an application involving nuclear power plants, which exemplify complex systems with high safety and economical requirements. This setting will serve as a testbed to evaluate, improve, and validate our theorized approach. Specifically, we aim to apply different system-level techniques within a Pressurized Water Reactor (PWR). Initially, a SIMULINK model, Asherah, that approximates the Vogtle NPP will be used to generate the process data. The description of the considered plant and its model can be found in (Busquim e Silva, Piqueira, Cruz, & Marques, 2021), which also provides interpretable pictures. The model originally takes two distinct inputs that are modeled as time series, namely, the power setpoint and river temperature. We will use real data collected from two years of operation of Vogtle Unit 1. The model will be then modified to simulate degradation processes within its components.

The first contribution of this research is to develop detection, diagnostics, and, when possible, prognostics models to estimate and predict the health of the degrading components. Then, subsystems will be identified and for each of them, an optimal aggregation technique will be identified and applied. The forage of the best model for each subsystem will be a critical task. We will rely on the categorizations provided in (Tamssaouet et al., 2023) and (Kim et al., 2021) to first select the proper category between simplified modeling and holistic modeling.

Simplified modeling treats a system as a single entity, ignoring interactions between components. It uses input-output relations to predict the system's health through data-driven or physics-based methods, often trained on run-to-failure datasets. However, this method struggles with non-linear and non-stationary health indicators, lacks detailed insights into component degradation and interdependencies, and is limited in its ability to diagnose internal faults.

On the other hand, holistic modeling considers the system as a combination of interconnected components, focusing on their interactions and degradation mechanisms. This approach can incorporate environmental effects, mission profiles, and non-linear degradation mechanisms. Holistic modeling can be further divided into model-based and data-driven approaches. Model-based approaches use mathematical, logical, or physical equations to model the structure of the system and aggregate the components' health indicators (e.g., physical quantities, RUL, probability of failure). Data-driven approaches use historical or simulated data to estimate the relationships between components' health and system health.

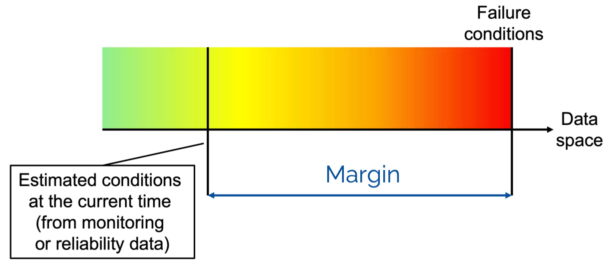

Figure 1. The margin is interpreted as the distance between the current estimated conditions and the failure or limiting conditions. The data space dimension depends on the nature of the failure and estimated conditions (e.g., time, pressure, vibration spectra)

Since different system-level techniques are likely to provide heterogeneous results (e.g., RUL, probability of failure, estimates of physical indicators), it is essential to identify a method that can aggregate these results to provide an indication of the system's health. The selected technique is a margin approach developed by the Reliability Risk and Resilience Sciences group at Idaho National Lab (Mandelli, Wang, Manjunatha, Agarwal, & Lin, 2023). The authors reinterpret reliability by focusing on how close an asset is to failure or unacceptable performance rather than the probability of failure. This method quantifies an asset's health through a "margin" value derived from current and historical monitoring data. The margin is defined as the distance between the asset's current state and its failure threshold, as shown in Figure 1. Using this approach, every health estimate, such as a sensor reading, a RUL, a mean time to failure, or a probability of failure, can be transformed into a margin by normalizing it between 0 and 1. Then, once the margins of the components are computed, they can be aggregated according to the system's structure, which, according to the current implementation of the margin approach, must be modeled with a reliability block diagram using logic operators.

At this point, a question arises: why don't we use the margin approach to aggregate all the component estimates instead? Firstly, because the current implementation of the margin approach requires strong assumptions and simplifications for the aggregation. Specifically, the system must be modeled as a reliability block diagram or another reliability-based structure involving logic operations. Furthermore, when prognostic results are available for all the components we want to aggregate, using the margin approach causes us to lose valuable information about the future, as we only analyze the current health in terms of margins.

In summary, we want a model that allows the use of optimal system-level models for the analysis of the subsystems and leverages the adaptability of the margin approach when heterogeneous results must be aggregated. Therefore, we plan to develop a hybrid graphical model that effectively aggregates the current and future health states (e.g., RUL, physical indicators, virtual indicators) of individual components to predict the overall system's health. For instance, consider a system with 10 components that can be divided into three subsystems. Let's suppose the first 4 components (C_1, C_2, C_3, C_4) are equipped with 4 PHM modules that detect any failure and predict each item's RUL. Let's also suppose that these items form a structure such that the failure of one item is enough to cause the failure of the subsystem. It is then coherent to aggregate the predictions using an OR logic operator, according to the methods explained in (Kim et al., 2021). Suppose that components C_5, C_6, C_7 are equipped with physics of failure PHM models that predict the health in terms of physical quantities. We can then aggregate the current and future health using a physical model, as in (Tamssaouet et al., 2023). Ultimately, let's suppose the components of the last subsystem are equipped with modules that provide heterogeneous results. C_8 is monitored by a single sensor that measures a physical quantity, a PHM module predicts the RUL of C_9, and C_{10} is not monitored, but an estimate of its Mean Time To Failure is available. We decide to aggregate these quantities using the margin approach. Lastly, since the outputs of the subsystems are heterogeneous as well, the margin approach is again selected to aggregate into the system's estimates. Figure 2 shows the graphical representation of the approach.

The structure presented in the example can be modified and extended to model any kind of system with several interacting components. It can potentially include additional graphical elements such as arrows for component interdependencies, equations for subsystems, health indexes, RUL forecasts, and visualizations of uncertainty propagation, enhancing the interpretability of the analysis.

Throughout the development of this hybrid approach, we will try to address most of the requirements that system-level diagnostics and prognostics involve:

- **Component Interdependence**: Focus on how degradation in one component influences others.
- **Modeling Degradation Impact**: Understand the cumulative effect of multiple components' degradation on system health.
- **Uncertainty Propagation**: Address uncertainties in component health indicators and their propagation to system-level assessments.
- **Complex Hierarchical Structures**: Manage and define subsystems, systems, and system interactions.
- **Health Thresholds**: Establish component-level thresholds in the context of a system and system-level health thresholds based on system performance requirements.
- **Multiple Degradation Modes**: Consider and predict different degradation modes within components and understand their combined effects on system health.

Concurrently, we will develop risk-informed measures to assess the attention that each component deserves at each time step given its state and the states of all the other interacting components. Ultimately, we will attempt to integrate these measures within existing maintenance scheduling methodologies.

3. PROPOSED RESEARCH PLAN

The proposed research plan involves several key phases, including:

1. modification of the Asherah model to insert degradation modules for data generation and processing.
2. selection and implementation of component-level detection and prognostics modules.
3. selection and implementation of subsystem and system-level aggregation methods
4. implementation and validation of sensitivity and risk reduction measures.
5. integration of the system-level results and importance measures with LOGOS (Diego Mandelli, 2020), a software developed by Idaho National Lab. LOGOS uses optimization methods for job scheduling and it has been used for constrained maintenance activity scheduling.

3.1. Work Already Performed and Preliminary Results

Initial work has focused on inserting degradation modules within the plant. So far, fouling effects have been inserted within the condenser and the steam generators. Diagnostics and prognostic models were implemented for the analysis of the condenser. A detection module for the steam generation is currently being tested.

Concurrently, the margin approach has been tested using generic reliability block diagrams. Data for computing margins were artificially generated to mimic heterogeneous components and indexes (e.g., RUL, probability of failure, and monitored physical quantities. Risk-informed measures have been implemented to identify the most critical components affecting the system's health. Moreover, methods for propagating the margin uncertainties were implemented and validated.

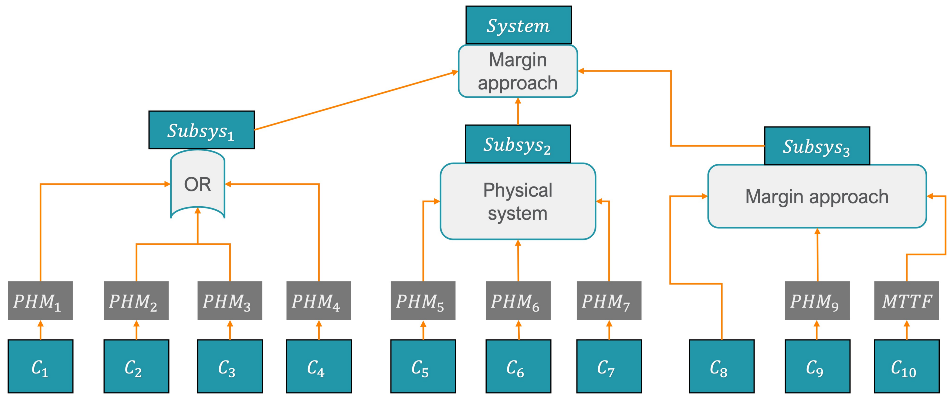

Figure 2. Graphical method to combine different system-level approaches for complex systems.

Another method for aggregating components' health was implemented and improved. Specifically, the method (Ferri et al., 2013) leverages system architecture information combined with component-level time of failure estimations (with uncertainty) to compute system-level failure probabilities using Fault Trees (FTs). A case study on a simplified aircraft electrical system illustrates the application of this approach, demonstrating its potential to improve maintenance planning by identifying optimal repair times and prioritizing interventions. An online Risk Reduction Worth (RRW) measure was used to identify what components should be repaired to keep the system failure probability always below a threshold. The equation for the RRW is given by:

$$\mathrm{RRW}_i = \frac{P(\text{sys failure})}{P(\text{sys failure} \mid P(\text{failure of comp } i) = 0)} \tag{1}$$

The two preliminary applications show that sensitivity measures can effectively identify critical components, and risk reduction strategies have the potential to optimize maintenance schedules and reduce downtime.

3.2. Next steps

The research will proceed by completing the work already performed, adding degradation modules to the Asherah model and accomplishing the other plans listed in the bullet list of section 3. Moreover, we also plan to:

- inspect if the degradation of a component or subsystem affects the health estimate and prediction modules installed on separate components or subsystems.
- test model-based methods to aggregate physical health estimates.
- model and inspect how to propagate multiple degradation modes within single components.

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