Exploring the Nexus between Sensor Reliability and System Performance: A Comprehensive Analysis

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Abstract

In contemporary technological landscapes, sensors play a pivotal role in enabling diverse applications across industries, from healthcare to manufacturing. This paper undertakes a thorough investigation on system performance (reliability and availability of a system), focusing on the critical interplay between baseline performance, performance with integrated sensors and performance considering sensor reliability, recognizing the foundational importance of sensors in data-driven decision-making processes. The research employs a causation-based approach to systematically develop functional relations within the system. The failures identified of each component and functional relationships will then be analyzed using a simulation technique to understand the inherent performance of the engineering system. From here, a genetic algorithm is used to design a sensor set and tailor it for an engineering system, providing a foundation for conducting trade studies in the paper's subsequent sections. Through rigorous quantitative analysis and simulations, we compare the impacts of the performance of the sensor set design compared to the baseline performance. The paper then investigates the complexities of sensor reliability on overall system performance. Through advanced simulations, we elucidate the potential cascading effects that variations in sensor reliability can have on the system's performance. By exploring these ripple effects, we aim to provide a comprehensive understanding of how sensor reliability plays a crucial role in determining the success of complex systems. Beyond the immediate considerations of sensor characteristics, the paper analyses the maintenance aspects of sensors by performing a series of analyses to suggest maintenance aimed at improving the sensor and hence system reliability. Highlighting the relationship between sensor reliability and system performance, this section stresses the critical role of consistent maintenance practices in ensuring sustained data quality and system functionality. In conclusion, this paper aims to highlight the different perspectives that can be analyzed to understand the reality of system performance, considering facets such as sensor maintenance and reliability. It also aims to demonstrate various approaches that can be applied to engineering systems to uncover truths about sensor performance and reliability.

1. Introduction

The increasing demand for diagnostics has made sensors essential in planning and managing systems throughout their lifecycle. Symptoms in a system, which are visible or detectable indicators, provide crucial information about the system's state. Identifying and deploying appropriate sensors to capture these symptoms in real-time can inform maintenance decisions, prevent failures, and ensure continuous operation.

A model-based approach helps define functions, simulate failures, identify critical functions, and diagnose appropriate sensor responses that can detect failures before they occur, enabling effective maintenance planning. This methodology can be applied at any stage—early in development or before specific missions—to gain valuable insights into system performance and enhance the decision-making process. Incorporating sensor analysis into this methodology further enriches overall system effectiveness and efficiency.

This research develops a virtual model of a generic aircraft, focusing on one of its key subsystems to assess baseline system performance. It then evaluates whether all critical functions have sensors capable of detecting failures before they occur. This analysis aids in planning for specific missions, such as those where certain functions are allowed to fail to stay within constraints, if any, for instance, weight. Finally, the study assesses system performance with integrated sensors, highlighting different perspectives in optimizing system reliability and efficiency.

2. DIGITAL RISK TWIN FOR SYSTEM ANALYSIS

A Digital Risk Twin (DRT) is a virtual representation of a physical system, capturing its complexities and nuances. This digital model can encompass the entire system or focus on specific sections, depending on the system's complexity and areas of interest. By simulating the system's configuration and operating context, the DRT enables a detailed analysis of potential risks and hazards, including safety implications, operational impacts, and cost of ownership consequences.

The DRT is integral to performing Reliability, Availability, Maintainability, and Safety (RAMS) analysis by integrating various data points and simulating different scenarios to predict potential failures and their impacts. This capability supports proactive risk mitigation and decision-making processes, contributing to more resilient and cost-effective operations while maintaining safety standards.

It operates as a logical, functional, and physical model where the functional dependencies of all components are defined and interconnected through causal relationships (Stecki, Andrew, & Rudov-Clark, 2008). This detailed modelling approach ensures that each component's function is understood in the context of the entire system, highlighting how changes or failures in one area can impact the others. An essential aspect of the DRT is the definition of the mission profile, which outlines the various phases the system will undergo during its operational lifecycle. This includes regular phases, transition phases, and operating / environmental conditions (Conroy, Stecki, & Thorn, 2016), ensuring that the model accurately reflects real-world usage patterns.

3. OPTIMIZING SENSOR DEPLOYMENT THROUGH DIAGNOSTIC ANALYSIS

Diagnostic Analysis is crucial for determining the optimal combination of sensors to ensure comprehensive system monitoring (Stecki , Stecki, Rudov-Clark, & Ryan , 2009). Utilizing a Genetic Algorithm, this analysis leverages dependencies identified in the DRT to guide sensor selection and placement. Key parameters, including in-built sensors, sensor locations, and the specific failures that must be detected, guide the algorithm. The goal is to achieve thorough coverage and unique identification of system failures while maintaining efficiency and cost-effectiveness.

By integrating these optimized sensor combinations, the system's overall diagnostic capabilities are significantly improved. This integration ensures that potential failures are detected promptly and accurately, allowing for timely interventions and reducing the risk of system downtime.

4. DISCRETE EVENT SIMULATION IN SYSTEM PERFORMANCE ANALYSIS

Discrete Event Simulation (DES) is a modeling technique used to analyze complex systems over time by focusing on events that occur at discrete points, triggering changes in system states. Unlike continuous simulations, DES captures the timing and sequence of events, making it suitable for event-driven systems such as manufacturing and service operations. This approach provides insights into system performance, identifies bottlenecks, and tests various scenarios without physical trials.

DES is particularly useful in systems characterized by randomness, incorporating stochastic elements like random arrival times and failure rates, which are critical for accurate modeling. It enables the simulation of various scenarios to assess impacts and make informed decisions regarding system design and operation.

One key advantage of DES is its ability to model intricate processes with numerous interacting components through discrete events such as arrivals, departures, and maintenance activities. By tracking these events, DES generates performance metrics, including throughput, utilization, and waiting times. Furthermore, DES facilitates scenario analysis and optimization, allowing experimentation with different maintenance schedules and resource allocation plans to determine the most effective strategies for optimizing system performance.

5. SUSTAINING SENSOR PERFORMANCE THROUGH MAINTENANCE STRATEGIES

Optimizing sensor deployment involves maintaining sensor performance to ensure system availability throughout its lifecycle. This is achieved by devising adequate maintenance strategies specifically tailored for the sensors. Effective maintenance strategies are crucial for preventing sensor failures, extending sensor lifespan, and ensuring consistent system reliability. By implementing a proactive maintenance schedule, potential issues can be identified and addressed before they lead to significant system disruptions.

Evaluating system reliability with these maintenance strategies involves continuous monitoring and periodic assessments of sensor performance. This helps in refining maintenance plans to adapt to changing conditions and emerging challenges. This methodology enhances the reliability of individual sensors and contributes to the overall robustness and efficiency of the entire system, ensuring sustained operational effectiveness over time.

6. CASE STUDY

In this case study, a generic aircraft is analyzed at the system level, including the complexity and numerous subsystems that constitute it. The platform-level model is the aircraft, which includes various subsystems, one of which is the Landing Gear System. The Landing Gear System includes Wheel Braking Assemblies - Wheel Brake Assembly 1 and Wheel Brake Assembly 2. The focus of this study is on Wheel Brake Assembly 1, which comprises three key components:

the Hydraulic Line, Brake Caliper, and Brake Disc and Wheel Hub. The initial task involved developing a DRT for Wheel Brake Assembly 1 that serves as a virtual representation, facilitating the analysis. Parallel efforts by other teams will create similar models for other sub-systems within the aircraft.

The core of the methodology involves conducting a Diagnostic Analysis to optimize sensor allocation across the entire model. This process incorporates existing legacy sensors, ensuring they are integrated into the new sensor framework where applicable. The result of this analysis is an optimal sensor set designed for maximum efficiency and coverage. Specifically, for Wheel Brake Assembly 1, the analysis suggests the inclusion of a sensor for one of its three components (Brake Disc and Wheel Hub). Before implementing this recommendation, the impact of this sensor on the subsystem's performance metrics such as reliability, availability, and cost, must be thoroughly evaluated. This evaluation is conducted using MADE software (https://www.phmtechnology.com/) for DRT and Diagnostic Analysis, while DES is employed to assess the metrics, using Python. This comprehensive approach ensures that the decision to include the sensor is based on a detailed understanding of its potential benefits and drawbacks.

The following assumptions are considered for DES:

- Maintenance strategies and metrics: The simulation incorporates predefined maintenance strategies, along with their associated metrics, to evaluate system performance.
- The choice of the exponential failure distribution is guided by its simplicity and relevance for components expected to have relatively constant failure rates.
- Independent component failures: The model assumes that the failure of each component occurs independently, meaning that the failure of one component (e.g., Hydraulic Line, Brake Caliper, or Brake Disc and Wheel Hub) does not accelerate the degradation or influence the failure rates of other components. Each component’s failure is treated as a discrete event without direct impact on the operational state or performance of other subsystems. This assumption simplifies the system's complexity by isolating component behaviors.
- No sensor redundancies: The model assumes that there are no redundant sensors, implying that each sensor is unique and has a specific role without backup sensors.
- Sensor intrinsic properties and reliability: The intrinsic properties, such as sensitivity and specificity, and reliability of sensors are factored into the simulation to assess their impact on system performance.

Operational cost and downtime loss metrics: The simulation considers operational costs and downtime losses but does not account for procurement costs. This helps in focusing on the ongoing operational efficiency and the financial impact of system downtime. The interactions and dependencies from DRT and the above assumptions provide a structured framework for the DES simulation, ensuring a realistic yet simplified modelling of the system dynamics and maintenance processes. This approach aids in understanding the potential impact of sensor integration on the subsystem's performance metrics, thereby supporting informed decision-making. From here onwards, Wheel Brake Assembly 1 is referred to as the system, as the evaluation of the sensor impact is focused on this specific assembly. DES investigates system performance across four scenarios:

1. Scenario 1: Baseline with Breakdown maintenance for Hydraulic Line, Brake Caliper, and Brake Disc and Wheel Hub.
2. Scenario 2: Condition-based maintenance (CBM) on Brake Disc and Wheel Hub (using an ideal sensor), with breakdown maintenance for Hydraulic Line and Brake Caliper.
3. Scenario 3: CBM on Brake Disc and Wheel Hub, considering the sensor's intrinsic properties (Specificity and Sensitivity), with breakdown maintenance for Hydraulic Line and Brake Caliper.
4. Scenario 4: CBM on Brake Disc and Wheel Hub, considering the sensor's reliability along with intrinsic properties (Specificity and Sensitivity), with breakdown maintenance for Hydraulic Line and Brake Caliper.

Baseline performance is estimated before Diagnostic Analysis is conducted. To establish baseline system metrics, failure rates are assigned to each component to conduct reliability analysis. Maintenance strategies are then defined to perform availability analysis. These steps are essential for understanding the inherent performance of the system under normal operating conditions. The resulting baseline metrics serve as critical reference points for comparing the system's performance with and without sensor integration.

After identifying the optimal sensor set through Diagnostic Analysis, DES assesses the impact of various sensor parameters (specificity and sensitivity) on system performance. These simulations allow us to evaluate sensors of the same type with different parameters configurations, determining which setup maximizes system efficiency and reliability. By examining how sensor parameters influence the system under various operational scenarios, the best sensor is identified that enhances overall performance.

The failure distribution of the sensor is then incorporated into the simulation for reliability analysis. This step is crucial for understanding the likelihood of sensor failures and their effects on system performance. This comprehensive approach helps to optimize sensor deployment, balancing the need for high performance with the practical considerations of sensor reliability and redundancy.

6.1. Optimization Framework and Methodology

Figure 1 summarizes the optimization process for this case study. Design data is first input into the DRT for RAMS analysis, which generates insights into potential failure paths. This information informs a Diagnostic Analysis to identify an optimal sensor set. The sensor configuration is then evaluated through DES simulations across various scenarios, assessing their impact on the system.

The DRT can be tailored to meet different program requirements and adapt it as the system evolves. The initial optimization focuses on design data; however, once the system is operational, conducting trade studies will provide further insights into maintenance strategies and sensor effectiveness.

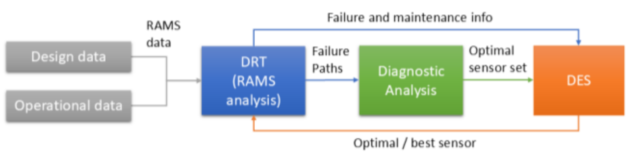

Figure 1: Framework for sensor optimization

6.2. Modelling DRT of Wheel Brake Assembly 1

Figure 2 illustrates the DRT of Wheel Brake Assembly 1 that is modelled with the following functional definition. The Hydraulic System in the aircraft plays a crucial role in operating various components, including the Wheel Brake Assembly 1. Its primary function is to transmit force using a fluid under pressure, which allows for the precise control and application of mechanical force required for braking. In the context of Wheel Brake Assembly 1, the hydraulic system is responsible for delivering the necessary pressure to actuate the brakes, ensuring effective and reliable braking performance. The Hydraulic Line serves as the conduit for the pressurized hydraulic fluid from the aircraft's Hydraulic System to the Brake Caliper. When the pilot applies the brakes, hydraulic fluid is forced through the Hydraulic Line to the Brake Caliper. The Brake Caliper, in turn, uses this hydraulic pressure to push the brake pads against the Brake Disc, which is attached to the Wheel Hub. This action generates the friction needed to slow down or stop the aircraft.

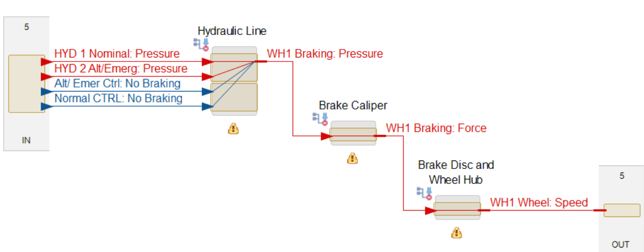

Figure 2 DRT of Wheel Brake Assembly 1

The pressurized hydraulic fluid during normal and alternate/emergency braking scenarios is modelled as separate inputs for failure analysis. A similar approach is used to model braking signals (normal and alternate/emergency braking) as inputs. Figure 18 expands this concept to model the DRT of the entire aircraft, providing a comprehensive view of how the Wheel Brake Assembly 1, within the Landing Gear System, integrates with the broader Hydraulic System.

6.3. Scenario 1: Baseline Performance Metrics

A mission duration of 10,000 hours is considered to estimate the baseline reliability, availability, and cost incurred for the system. All components within the system are in a ‘series’ operational dependency group, where the failure of any single component leads to the failure of the entire system. Each component's failure time is modelled using an exponential distribution with Mean Time to Failure (MTTF) listed in Table 1. For instance, Brake Caliper has an MTTF of 5000 hours indicating the time to failures is exponentially distributed with a mean of 5000 hours. In DES, failure times are sequentially sampled from this known exponential distribution. For example, the first failure time might be 2000 hours, the next could be 10000 hours, and so on. These failure times are not random in a purely arbitrary sense but are instead probabilistically determined based on the exponential distribution characterized by the MTTF. This method ensures that the simulated failure events accurately reflect the statistical properties of the assumed failure distribution, providing realistic failure intervals. Figure 3 shows the reliability of the system considering MTTF in Table 1.

Table 1: MTTF of components in Wheel Brake Assembly 1

Component Name	MTTF (Hours)
Hydraulic Line	700
Brake Caliper	1500
Brake Disc and Wheel Hub	500

Operational Availability (Ao) is the total time of utilization of a machine. Availability is the ratio of the difference between the total available hours and total breakdown hours to the total available hours (Kolte & Dabade, 2017). Table 2 outlines the baseline maintenance strategies, including maintenance cost, defined for each component.

To evaluate the baseline availability, failure events were generated, and the resulting downtime was recorded for each iteration in DES. Availability is then computed using Eq.(1) and displayed as a percentage. This process is repeated for 10,000 iterations to account for variability and provide a robust statistical distribution of availability.

$$A_o = \frac{\text{Mission Duration} - \text{Downtime}}{\text{Mission Duration}} \tag{1}$$

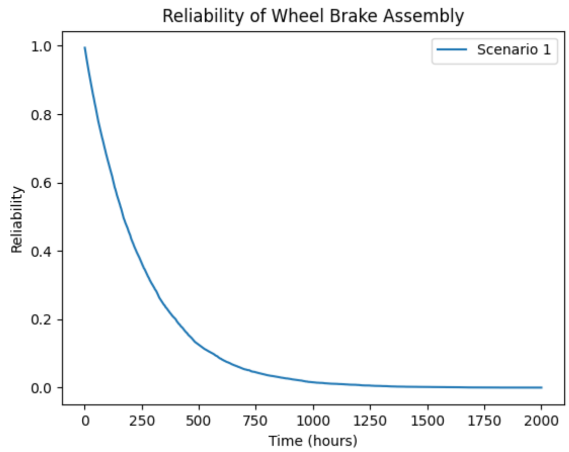

Figure 3: System reliability for baseline scenario

Table 2: Baseline Maintenance Strategy

Component Name	Maintenance Strategy	Downtime (Hours)	Cost ($)
Hydraulic Line	Breakdown	4	500
Brake Caliper	Breakdown	9	300
Brake Disc and Wheel Hub	Breakdown	12	200

Figure 4 presents the Probability Density Function (PDF) plot of the system's availability, fitting a normal distribution. The x-axis represents the percentage availability for each iteration, while the y-axis indicates the density. The distribution shows a mean availability of 96.1996% with a standard deviation of 0.5921, demonstrating the system's high availability and minimal variance in performance. The spread of the PDF indicates that most availability values are close to the mean, suggesting high consistency.

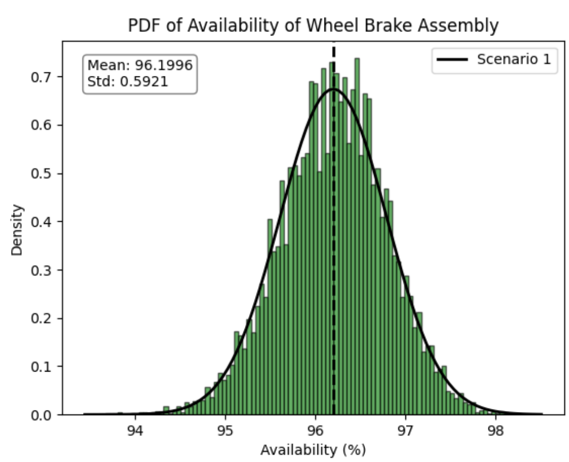

Figure 4: PDF of system availability for baseline scenario

Figure 5 is the Cumulative Distribution Function (CDF) plot of the system's availability. The steepness of the CDF curve around the mean indicates how rapidly the cumulative probability increases, reaffirming that extreme deviations from the mean are rare.

To estimate the system cost over the mission duration, operational cost, downtime loss, and maintenance cost for each of the three components are considered (Table 2 and Table 3). The operational cost accounts for the expenses associated with running the system under normal conditions. The downtime loss reflects the financial impact of system downtime, including lost production and potential revenue loss, which is critical for capturing the economic consequences of system failures. The breakdown maintenance cost for each component encompasses the expenses incurred when repairing or replacing a failed component. By incorporating these costs, the simulation closely mirrors real-world scenarios where both operational efficiency and failure-induced losses significantly influence total costs.

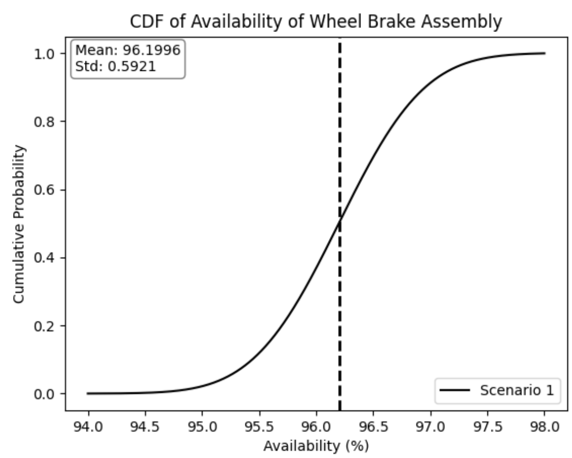

Figure 5: CDF of system availability for baseline scenario

Table 3: Cost considerations

Component	$/Hour
Operational	40
Downtime Loss	50

Figure 6 illustrates the baseline cost distribution, also fitting a normal distribution, with a mean cost of $418,461.8240 and a standard deviation of $2864.1840. This consistent cost estimate highlights the predictability of the financial requirements for maintaining the system’s high availability. Figure 7 is the CDF plot of the system's cost.

Together, the PDF and CDF plots provide a comprehensive view of the system’s availability and cost, highlighting its high consistency and the low likelihood of significant deviations from the expected performance.

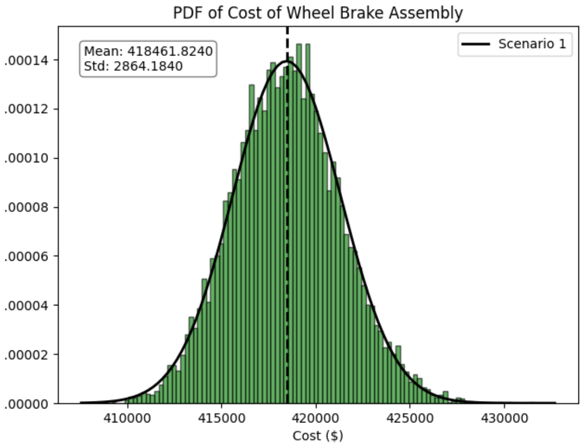

Figure 6: PDF of system cost for baseline scenario

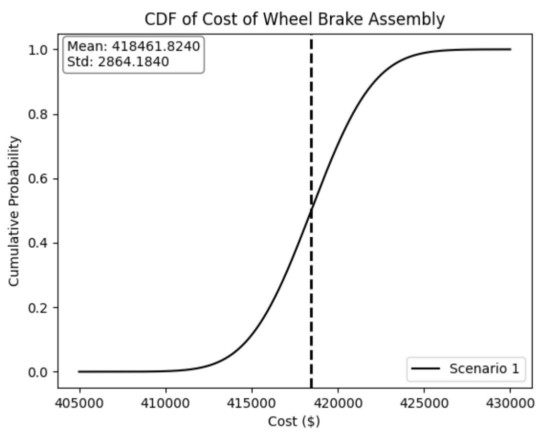

Figure 7: CDF of system cost for baseline scenario

These analyses provide a comprehensive understanding of the system's baseline performance with the expected range and variability. This foundational assessment is crucial for identifying potential improvements and ensuring the long-term efficiency and cost-effectiveness of the system.

6.4. Diagnostic Analysis for Sensor Deployment

Diagnostic Analysis is performed on the Landing Gear System to uniquely identify all potential failures while minimizing the number of required sensors. By strategically deploying sensors, the analysis aims to achieve complete failure coverage with optimized resource utilization.

Figure 8 illustrates the necessary responses within the Landing Gear System that require sensor detection to ensure unique failure identification. One critical location identified is the wheel speed sensor on Brake Disc and Wheel Hub in Wheel Brake Assembly 1 (highlighted in Figure 8). Installing a sensor at this location ensures the identification of all failures within Wheel Brake Assembly 1, as all components in this assembly are modelled in a series configuration (Figure 2). This strategic placement of sensor in Wheel Brake Assembly 1 is then used to assess the impact of sensor integration on its performance.

6.5. Impact of Sensor on System Performance

Following the recommendation from the Diagnostic Analysis to install a wheel speed sensor, this section evaluates the sensor's impact on the system by simulating Scenario 2, Scenario 3 and Scenario 4. In Scenario 2, the maintenance strategy of Brake Disc and Wheel Hub is changed from breakdown to CBM using an ideal sensor that provides perfect measurements without any errors & is 100% reliable. Scenario 3 examines CBM along with the sensor's intrinsic parameters, specifically specificity (the ability to correctly identify true negatives) and sensitivity (the ability to correctly identify true positives) while assuming the sensor is 100% reliable. Scenario 4 explores CBM and the impact of sensor reliability on system performance. By evaluating these different aspects, the simulation provides a comprehensive understanding of how the sensor influences the system's performance.

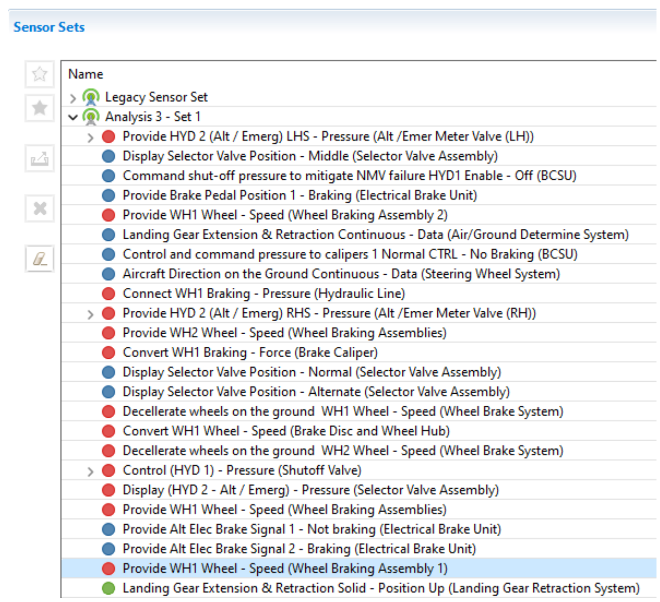

Figure 8: Identification of location for sensor deployment

6.5.1. Scenario 2: System Performance Using an Ideal Sensor

An ideal sensor is one that does not fail and has perfect measurement capabilities. For instance, 100% specificity and 100% sensitivity. In this section, an ideal sensor identifies failure symptoms in the Brake Disc and Wheel Hub, prompting timely CBM. This proactive approach significantly minimizes stoppages and reduces downtime that would otherwise result from breakdown maintenance. Table

4 illustrates the revised maintenance metrics, highlighting the reduced downtime achieved by implementing CBM.

Table 4: Revised maintenance metrics

Component Name	Maintenance Strategy	Downtime (Hours)	Cost ($)
Brake Disc and Wheel Hub	CBM	4	300

An Effectiveness Factor (EF) is introduced to estimate the efficacy of CBM in preventing failure of Brake Disc and Wheel Hub. An EF of 1.0 indicates a "perfect" corrective action, while an EF of 0 signifies a completely ineffective action. In this case study, an EF of 0.411 is considered for reliability analysis. Teal curve in Figure 12 illustrates the resulting improvement in the system's reliability against baseline scenario (blue curve in Figure 12).

PDF of the system using revised maintenance metrics is teal region in Figure 13. The updated PDF, with a mean availability of 97.1347% and a standard deviation of 0.4850, shows a shift to the right compared to the previous mean of 96.1996% (black curve in Figure 13), indicating an overall improvement in system availability. Additionally, the narrower spread of this PDF suggests that the availability values are more tightly clustered around the mean, indicating increased consistency and reliability in the system's performance.

The teal curve in Figure 14 presents CDF for system availability. It shows that reaches higher probabilities more quickly, demonstrating that a higher percentage of the system's availability values are concentrated near the new mean. Furthermore, teal curve in Figure 15 shows reduction in cost against baseline (Scenario 1). Overall, these comparison plots reveal that sensor integration for implementing CBM has not only enhanced the system's performance but also made it more predictable and stable.

6.5.2. Scenario 3: System Performance Considering Sensor Intrinsic Properties

This section simulates how various sensor parameters influence system performance, helping identify the best-fit sensor from a pool of sensors (wheel speed sensor). For this case study, sensor parameters specificity and sensitivity are considered, with the assumption that the sensor is 100% reliable (i.e., it does not fail).

Sensitivity Analysis

To understand the impact of sensor parameters on system availability and cost, sensitivity analysis is performed focusing on two key parameters: specificity and sensitivity of the sensor. Figure 9 shows the availability increases as both specificity and sensitivity increase. The sensitivity parameter has a more pronounced effect on the mean availability compared to the specificity. This indicates that improvements in sensitivity lead to a more significant enhancement in system availability than equivalent improvements in specificity. Figure 10 shows the cost decreases with an increase in both specificity and sensitivity. The sensitivity of cost to both parameters is quite similar, without a clear distinction between the impact of specificity and sensitivity. This suggests that the cost is equally influenced by changes in either parameter.

System Performance Analysis

Table 5 lists the wheel speed sensors evaluated in this case study and Figure 11 presents the CDF of system availability considering these sensors. Among these, Sensor 2 achieved the highest mean availability of 96.8059% with a standard deviation of 0.5164 in line with the sensitivity findings. This sensor is identified as the best possible option and is used for comparing system metrics.

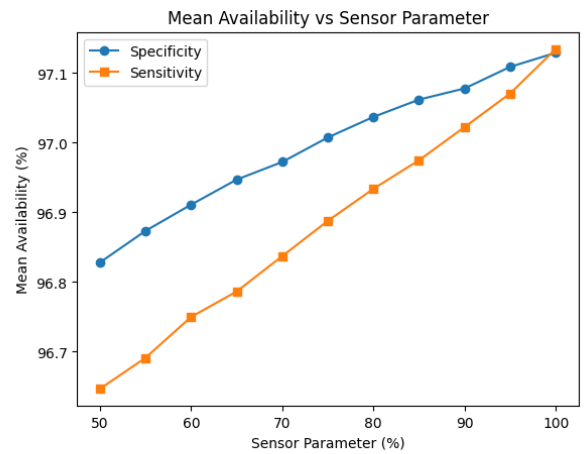

Figure 9: Sensitivity analysis on availability

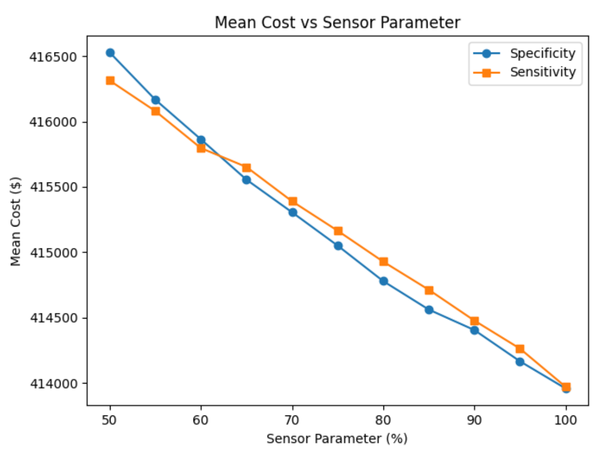

Figure 10: Sensitivity analysis on cost

For reliability analysis, an EF of 0.375 is considered, which is lower than the value used for Scenario 2. This adjustment accounts for the practical performance of a real-world sensor and CBM. The orange curve in Figure 12 illustrates the system's reliability when incorporating a sensor 2, which is lower than using an ideal sensor (teal curve in Figure 12). This comparison reflects a more realistic scenario, highlighting the impact of using a practical, real-world sensor on the system's overall reliability.

Table 5: Sensor Parameters

#	Wheel Speed Sensor	Specificity	Sensitivity
1	Sensor 1	75	75
2	Sensor 2	70	80
3	Sensor 3	80	70
4	Sensor 4	58	64
5	Sensor 5	48	50

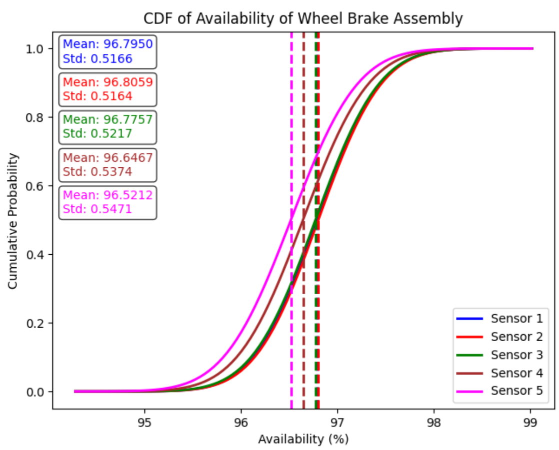

Figure 11: CDF of system availability considering sensors in Table 5

The PDF plot comparison (Figure 13) shows that when considering sensor parameters, the peak (orange region) is slightly lower and broader than with the ideal sensor (teal region), but still higher and narrower than the breakdown maintenance (black region), suggesting an overall improved but slightly less consistent performance.

The CDF plots (Figure 14 and Figure 15) reflect performance changes in a cumulative context. In both figures, the orange curve represents the scenario considering sensor parameters. In Figure 14, this curve is notably steeper than the baseline scenario (black curve), indicating that even with imperfect sensor properties, CBM significantly enhances system availability. Additionally, this scenario proves to be more cost-effective compared to the baseline (black curve in Figure 15), demonstrating the dual benefits of improved performance and reduced costs.

6.5.3. Scenario 4: System Performance Considering Sensor Reliability

This section assesses the system performance by incorporating the reliability of the single best-fit sensor (Sensor 2). Sensor reliability is estimated using an exponential failure distribution with an MTTF of 150 hours.

An EF of 0.333 is considered to estimate system reliability. This value, lower than the one discussed in Scenario 2, accounts for the sensor reliability and CBM. The purple curve in Figure 12 illustrates the system's reliability for this scenario, demonstrating a reduction in reliability that aligns more closely with real-world applications.

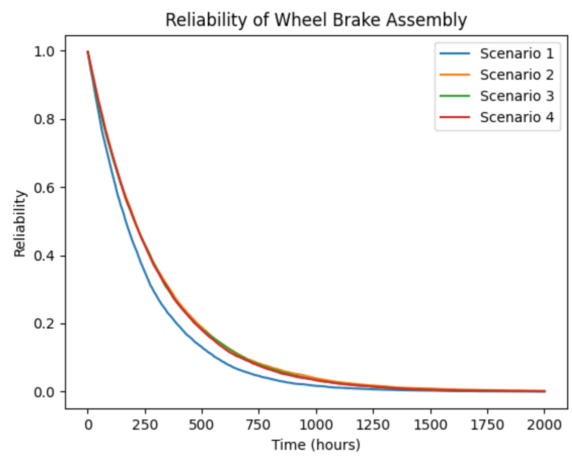

Figure 12: System reliability in all four scenarios

The purple region in Figure 13 presents the PDF of system availability considering sensor reliability. Incorporating sensor reliability resulted in a mean availability of 96.7329% and a standard deviation of 0.5362. This scenario shows a slight reduction in mean availability and an increase in variability compared to the scenario with only intrinsic sensor properties (orange region in Figure 13), reflecting the impact of sensor failures on overall system availability.

The purple curve in Figure 14 and Figure 15 shows the CDF of the system availability and cost considering sensor reliability suggesting enhanced availability and cost effectiveness against baseline case (Scenario 1).

Overall, these comparisons help optimize sensor deployment considering the practical aspects of the sensor. While introducing sensor reliability slightly reduces availability and increases variability, CBM with realistic sensor properties and reliability still offers substantial improvements over traditional breakdown maintenance, providing a more practical yet effective approach to maintaining high system performance.

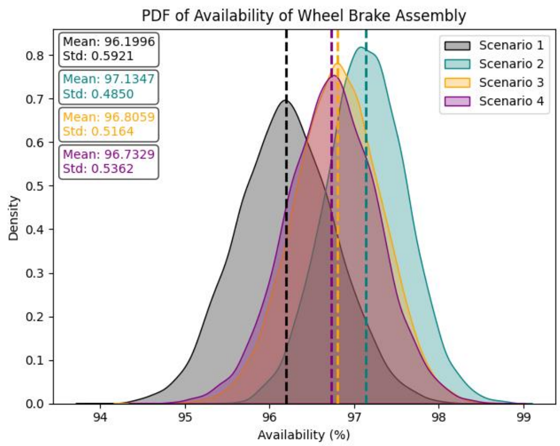

Figure 13: PDF of system availability in all four scenarios

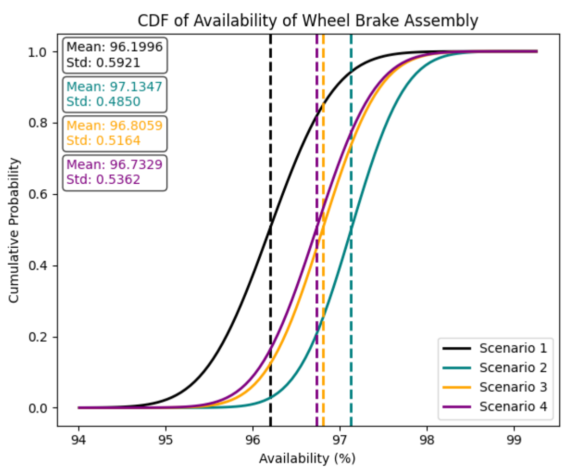

Figure 14: CDF of system availability in all four scenarios

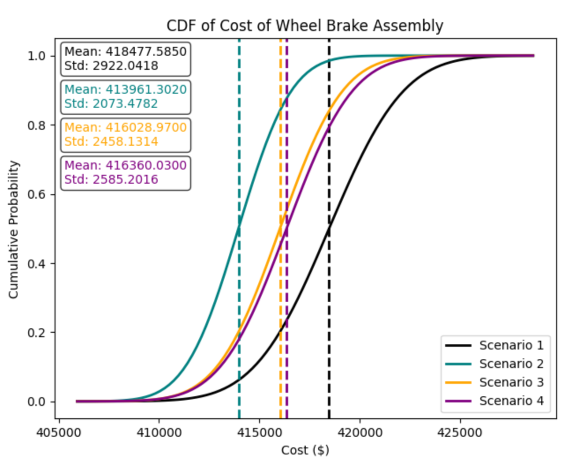

Figure 15: CDF of system cost in all four scenarios

6.6. Implementing Maintenance Strategies for Sensor

Earlier sections discussed the significant impact of sensor integration on system performance. This emphasizes the necessity of devising appropriate maintenance strategies to ensure the sensor functions as intended. To address this, the RCM II (Reliability-Centered Maintenance) methodology (Moubray, 1997) was employed to identify suitable maintenance strategies, although the specific details of this process are beyond the scope of this paper. Figure 16 illustrates the comparison of various maintenance strategies, highlighting that CBM results in the least downtime.

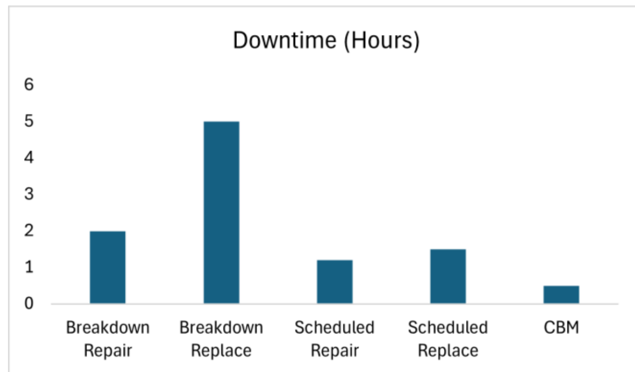

Figure 16: Comparison of Various Maintenance Strategies

This case study adopts the CBM strategy with an EF of 0.367 for wheel speed sensor to assess system reliability. The results, shown by the orange line in Figure 17, indicate an improvement in system reliability with the implementation of CBM. This strategy ensures timely maintenance actions based on the actual condition of the sensor, thereby enhancing overall system performance and reducing the likelihood of unexpected failures.

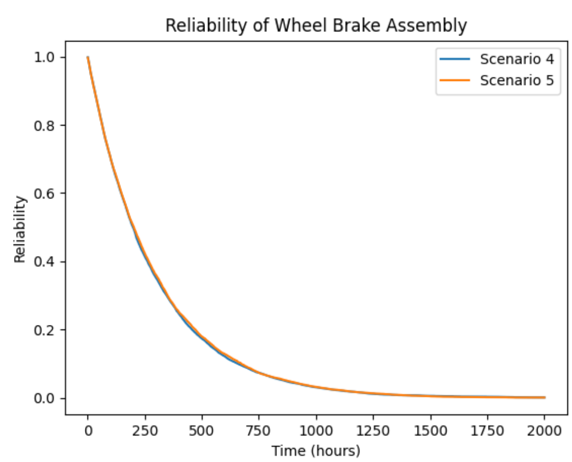

Figure 17: Change in system reliability by incorporating maintenance on sensor

7. DISCUSSION

The investigation into the Wheel Brake Assembly 1 reveals significant insights into the impact of sensor integration on system performance across four scenarios. Firstly, the baseline performance metrics depict the system's operational state under traditional breakdown maintenance. The system achieves a high mean availability, indicative of its reliability under standard operating conditions. However, operational costs associated with this approach are significant, reflecting the expenses incurred due to the maintenance strategy.

Secondly, the implementation of an ideal sensor for CBM on the Brake Disc and Wheel Hub demonstrates improvements in system availability. The adoption of this proactive maintenance strategy results in enhanced availability metrics and a reduction in operational costs compared to the baseline scenario.

Further, a comprehensive examination of the intrinsic properties of the sensors reveals significant impacts on system performance, as illustrated through the sensitivity analysis. The identification and selection of the highest-performing sensor results in marked improvements in availability metrics. These findings emphasize the potential for optimized sensor deployment strategies to enhance overall system reliability.

Moreover, the incorporation of sensor reliability into the analysis highlights the practical implications of sensor failures on overall system availability. While this scenario shows a slight reduction in availability and increased variability compared to ideal conditions, it emphasizes the importance of realistic sensor considerations in maintenance planning.

Throughout the analysis, CBM consistently emerges as the preferred strategy, resulting in the least downtime and offering significant enhancements in system performance. These findings indicate the critical role of sensor integration and maintenance strategies in ensuring the reliability and efficiency of engineering systems.

8. FUTURE WORK

The future improvements to enhance the accuracy and flexibility of the simulation include:

- Expanding Failure Distribution Options: The exponential distribution may not fully capture failure behaviors subject to wear-out or degradation over time. In such cases, alternative distributions like the Weibull or log-normal distributions provide more flexibility, allowing for varying failure rates, such as early-life failures or increased likelihood of failure due to aging. Incorporating additional failure distribution options better captures varying failure rates over time.
- Introducing failure dependencies between components: In reality, a failure in one component could accelerate the degradation of another. For example, if the Brake Disc and Wheel Hub experience a critical failure due to a sensor issue, this could place additional strain on the Brake Caliper, accelerating its wear and potentially leading to premature failure. This capability would enable better predictive maintenance strategies by accounting for the cascading effects of component failures, thus enhancing the overall robustness of the model.

9. CONCLUSION

This case study illustrates the significant impact of sensor integration and maintenance strategies on the performance of systems. Through a combination of Diagnostic Analysis and DES, the study demonstrates that CBM, particularly when implemented with even imperfect sensors, can improve system availability and reduce costs compared to traditional breakdown maintenance. The findings showcase the value of a model-based approach in optimizing system performance across various scenarios.

By incorporating real-world sensor parameters and reliability, the study provides practical insights into enhancing system reliability and cost-effectiveness. This methodology can be extended to other significant performance metrics within the system. Furthermore, sensor parameters can be subjected to sensitivity analysis, as illustrated in the case study where the analysis was conducted for specificity and sensitivity. This approach can also be applied to other parameters of interest such as MTTF, downtime, and maintenance costs. The methodology offers a robust framework for informed decision-making and continuous performance improvement, applicable to diverse engineering systems.

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APPENDIX

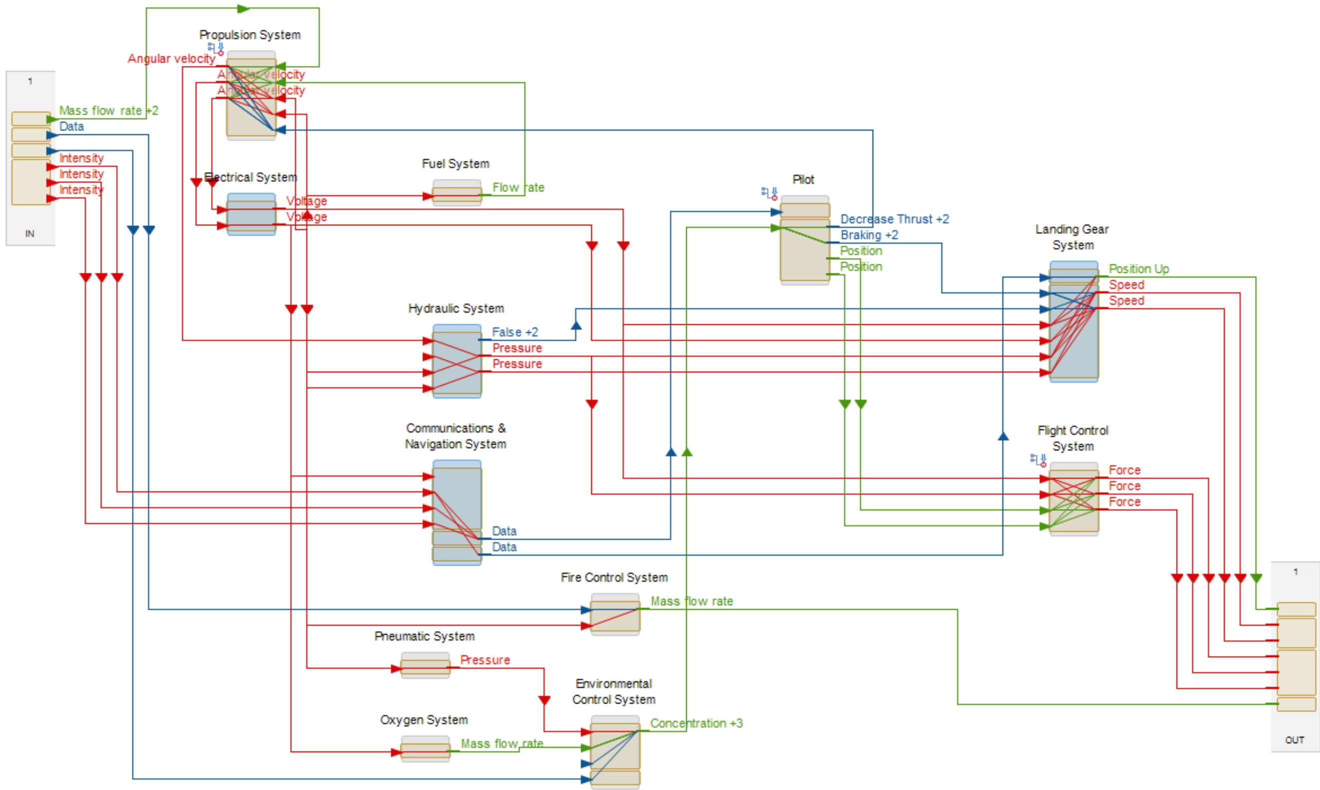

Figure 18: DRT of Aircraft at platform-level