BJ O&PM Brazilian Journal of Operations & Production Management

ISSN 2237-8960 (Online)

ABEPRO ASSOCIAÇÃO BRASILEIRA DE ENGENHARIA DE PRODUÇÃO

RESEARCH PAPER

Method for risk assessment in aeroengine overhaul using a combination of bayesian networks and fuzzy logic in the context of Industry 5.0

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How to cite: Pereira, J. C. and Reis, J. C. G. (2026), "Method for risk assessment in aeroengine overhaul using a combination of bayesian networks and fuzzy logic in the context of Industry 5.0", *Brazilian Journal of Operations and Production Management*, Vol. 23, No. 1, e20262991. https://doi.org/10.14488/BJOPM.2991.2026

ABSTRACT

This study presents a method for identifying and managing risks in the aeronautical engine overhaul process. It emphasizes the integration of this process with the Safety Management System (SMS) to enhance quality and meet regulatory requirements. The study also introduces an optimized risk prioritization process using Bayesian Networks (BBN) and Fuzzy Logic (FL). As technology evolves, it brings both advancements and new risks. In aircraft engine maintenance, effective risk identification and response are vital due to the potential catastrophic consequences of engine failure during flight. The study combines a literature review on probabilistic risk analysis with a case study of the aircraft engine overhaul process, presenting a method for integrating risks from various sources into a unified model. The mathematical method, employing BBN and FL, aids in prioritizing risk mitigation actions. By integrating the overhaul process with SMS using this method, aero engine operations can enhance quality and operational safety while reducing costs. The approach aligns with industry standards and regulations. In conclusion, this method offers significant potential for optimizing risk management, especially in the context of aeronautical engine maintenance. It contributes to the knowledge of process and aero engine maintenance, can aid safety professionals, and its implications can extend to various industries where safety and risk management are paramount.

Keywords: Bayesian Belief Networks, Fuzzy Logic, Risk Management. Operational Safety, Probabilistic Risk Assessment, Aeroengine Overhaul. Quality and Safety.

The following symbols and abbreviations are used in this paper:

BBN - Bayesian Belief Networks
BBN-Fuzzy – Combination of BBN and Fuzzy Logic. BE – Basic Event
FIO - Failure in Operation FL - Fuzzy Logic
FST - Fuzzy Set Theory FTA – Fault Tree Analysis
ICAO – International Civil Aviation Authority IE - Intermediate Events
MOC – Management of Change
MRO - Maintenance, Repair, and Overhaul NPI - New Products Introduction
PFMEA - Process Failure Mode and Effects Analysis.
RPN - Risk Priority Number
SAG – Safety Action Group
SMS – Safety Management System
TE - Top event

Financial support: none.
Conflict of interest: The authors have no conflict of interest to declare.
Corresponding author: joao.reis@ulusofona.pt
Received: 13 November 2025.
Accepted: 18 March 2026.
Editor: Osvaldo Luiz Gonsalves Quelhas.

1 INTRODUCTION

The relentless advancement of aero-engine technology, while pushing the boundaries of performance and sustainability, introduces escalating complexity and novel risks. In this high-stakes domain, engine failure is not an option, as it can have catastrophic human consequences. This makes robust risk management during aero-engine overhaul not just an operational priority but a moral imperative. Furthermore, the financial stakes are significant, with maintenance constituting approximately 9.5% of aviation operational expenses. To manage these risks, the aviation industry relies on SMS and stringent standards like AS9100D. However, a critical gap often exists in quantitatively prioritizing the multitude of interconnected risks identified. The absence of a robust, integrated methodology can lead to inefficient resource allocation, increased quality costs, and potential non-compliance with aviation regulations.

The proposed method surpasses traditional risk assessment techniques such as PFMEA and classical FTA by integrating probabilistic reasoning with FST to handle uncertainty and interdependencies. Unlike PFMEA, which often relies on subjective RPN without capturing causal relationships, the BBN-Fuzzy model dynamically updates risk scores based on evidence, incorporates detectability and functional criticality, and provides a unified risk score that consolidates multiple risk sources.

This enables more nuanced and actionable risk prioritization, reducing reliance on expert judgment alone. It aligns with SMS evolution toward AI-augmented resilience (Adler et al., 2024). Recent research emphasizes strategic integration of safety into operations. This study aligns by explicitly integrating engine overhaul processes with SMS. Prior research has explored probabilistic models for risk assessment. For instance, studies have combined BBN with bow-tie diagrams for systemic risk analysis in related fields, such as aero-engine manufacturing (Pereira, 2017) and oil and gas systems (Di Maio, 2020). While these demonstrate the value of BBN, a specific methodology for integrating quantitative risk prioritization directly into the SMS of an operational aero-engine repair station is lacking. Moreover, the inherent subjectivity and uncertainty in risk data call for a hybrid approach that BBN alone does not fully address. This study bridges this gap by proposing a novel hybrid framework integrating BBN with FL. FL was selected to address the inherent subjectivity and uncertainty in risk data, where traditional binary logic fails to capture partial truths or degrees of failure. By integrating FL with BBNs, the model accommodates qualitative expert judgments, imprecise data, and variably defined risk thresholds, thereby enabling more accurate and flexible risk prioritization within the SMS framework. The selection of FL as a primary analytical tool is justified by its capacity to handle the 'subjectivity and uncertainty' inherent in aeroengine overhaul operations. Unlike traditional binary risk assessments, FL facilitates the transformation of qualitative expert insights into actionable quantitative data. This approach is essential for MRO (Maintenance, Repair, and Overhaul) managers who must navigate complex safety protocols where risk boundaries are often blurred, and data is linguistically derived rather than purely numerical.

This approach is designed to quantify, consolidate, and dynamically prioritize risks from various sources into a single operational risk score. The research is guided by the following objectives: 1 - Develop a method for integrating the aero-engine overhaul process with an operational SMS using BBN and FL to enhance safety and regulatory compliance. 2 - Optimize risk prioritization and resource allocation within the SMS to reduce quality costs. 3 - Explore the synergy between this proposed framework and Industry 5.0 concepts, such as human-machine collaboration and real-time data analytics, for future advancements.

By providing a structured, probabilistic model for risk analysis, this work offers a significant contribution to aviation maintenance safety, promising to enhance decision-making, improve cost-efficiency, and strengthen the overall safety culture within aero-engine overhaul operations.

While the current literature extensively documents the transition toward Industry 5.0, a significant gap remains in the quantitative integration of human-centric variables within high-stakes MRO environments. Traditional SMS often relies on deterministic models that struggle to capture the inherent vagueness of human error and expert judgment. This study fills this gap by proposing a hybrid structure that synthesizes BBN with FL, allowing for a more resilient and 'quantitatively prioritized' assessment of interconnected risks. This study builds on established probabilistic risk frameworks, such as the bowtie integrated with Bayesian networks proposed for general probabilistic risk analysis (Pereira et al., 2015), by extending it to aero-engine overhaul through a novel BBN-Fuzzy hybrid that explicitly addresses data subjectivity and real-time SMS integration.

The paper is structured as follows: Section 2 presents a literature review on SMS, probabilistic risk analysis, and relevant methodologies. Section 3 details the proposed hybrid methodology. Section 4 showcases the results from the case study, which are discussed in Section 5. Finally, Section 6 concludes the paper.

2 LITERATURE REVIEW

The escalating complexity of modern aviation systems, coupled with the paradigm shift towards proactive safety management, necessitates advanced frameworks for risk assessment. This review synthesizes critical literature across three interconnected domains: the operational context of aero-engine maintenance, advanced probabilistic methodologies for risk quantification, and the enabling frameworks of quality standards and Industry 5.0. It identifies a critical research gap: the absence of an integrated model that effectively links technological advancements in risk assessment with structured change management and tangible economic outcomes in the high-stakes environment of aero-engine overhaul.

2.1. The Operational Context: Aero-Engine Maintenance, Safety, and Change Management

Aviation safety relies on the integration of people, processes, and technology within a structured system (ICAO, 2018). Maintenance ensures systems meet reliability and safety standards (Kinnison, 2013) and accounts for approximately 9.5% of airline operating costs (Lee & Mitici, 2020), forming the specialized MRO sector focused on preserving airworthiness (EFNMS, 2013). Turbofan engines are a key MRO focus due to extreme operational conditions (Sakai, 2022), complexity involving up to 12,000 parts (Pereira, 2017), and long service lives of 25–40 years (Oliveira, 2019). Change is constant in aviation, requiring structured management to prevent hazards (Siong et al., 2017; Lauer, 2021). Digitalization introduces smart sensors and AI diagnostics, demanding robust change management (Zio, 2018; Pang et al., 2020). Recent reviews examine change models for digital transformation in high-reliability organizations (Smith & Papakostas, 2025). Despite proactive safety approaches (Rocha, 2010), the "zero accidents" goal remains unmet, with accident rates from maintenance deficiencies stagnant over 25 years (Boyd & Stolzer, 2015). Accident causation is now viewed systemically, with organizational factors underlying human error and technical failures (Pereira, 2017). Hazard identification remains vulnerable to individual experience and judgment, often resulting in incomplete risk recognition (Goh et al., 2010). This underscores the need for data-driven risk assessment to augment human expertise in critical infrastructure (Qureshi, 2007) and aligns with SMS evolution toward AI-augmented resilience (Adler et al., 2025). Recent scholarship confirms the relevance of these methods in aviation. Studies apply BBN to ground handling and maintenance risk management, validating their use in risk prioritization (Dang et al., 2024). Recent hybrid fuzzy-Bayesian approaches have been developed for aviation systems (Dang et al., 2025), and recent work integrating BBN and deep learning supports real-time dynamic assessment.

2.2. Advanced Probabilistic Methodologies for Risk Quantification

Traditional subjective risk assessment limitations have driven the adoption of probabilistic tools such as Bayesian Belief Networks (BBN) and Fuzzy Logic (FL). BBN enable quantitative analysis through graphical causal modeling and probabilistic inference (Weber & Simon, 2016), making them suitable for complex aviation systems (Zhou et al., 2014; Abebe et al., 2018). Applications include engine failure estimation (Pereira et al., 2015) and decision support (Dang et al., 2020), with recent work integrating BBN and deep learning for real-time dynamic assessment (Liu et al., 2024). FL addresses vagueness and imprecision in risk data (Antunes, 2004) and enhances methods such as FMEA (Gallab et al., 2019) and FTA (Mohammadi, 2021). Recent hybrid fuzzy-Bayesian approaches have been developed for aviation systems (Li & Kang, 2024). Fuzzy Bayesian Networks (FBN) combine FL's qualitative handling with BBN probabilistic reasoning (Ren et al., 2009; Zarei et al., 2019) and have been applied across sectors, including energy and occupational safety (Kraidi et al., 2019; He et al., 2022).

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2.3. Enabling frameworks: quality standards and the Industry 5.0 paradigm

Advanced risk methodologies require structured implementation frameworks. In aviation, AS9100 mandates risk integration into quality systems, requiring change assessment, risk and opportunity identification, and action planning (Gordon, 2009; Oschman, 2017). Non-compliance incurs direct and safety-related costs (Pereira et al., 2015); the standard's role in ensuring safe, consistent product quality and its impact on supplier performance are empirically supported (Kim & Lee, 2024). Industry 5.0 offers a complementary vision emphasizing human–machine collaboration. AI and data analytics enhance decision-making accuracy by up to 20% in high-risk sectors (Cheng et al., 2021; Nahavandi, 2019). Applications include predictive maintenance, dynamic scheduling via reinforcement learning (Zhao et al., 2024; Chang et al., 2024), and automated inspection using few-shot learning (Zajec et al., 2024). The paradigm remains human-centric, augmenting rather than replacing expertise in complex overhaul processes (Horvat et al., 2024; Tortorella et al., 2024). Effective implementation requires deliberate design frameworks (Goujon et al., 2024). Identified Research Gap: Although advanced risk methodologies and enabling frameworks are well documented, their integrated application within aero-engine MRO remains underexplored. No holistic model links technological tools (BBN, FL) and structured change processes (AS9100, digitalization) to measurable economic outcomes such as cost savings or productivity gains during engine overhaul. The AS9110 standard, specifically tailored for aviation maintenance organizations, complements AS9100 by emphasizing risk-based thinking in maintenance processes. Its relevance lies in mandating structured change management and continuous monitoring, which aligns with the proposed integration of BBN-Fuzzy models into SMS. This standard provides a regulatory basis for implementing dynamic risk assessment tools that support compliance while enhancing operational resilience. This study aims to address this gap by proposing a unified, probabilistic risk assessment framework that bridges this divide. Understanding risk in complex, interconnected systems requires sophisticated modelling techniques that can capture dynamic interdependencies. The research by studies using System Dynamics to model critical infrastructure failures at airports exemplifies this systems-thinking approach. Although our method employs a different modelling paradigm (BBN), it shares the fundamental goal of creating a unified model from various risk sources to understand system-wide behaviour. This aligns with the broader industrial need for advancing SMS maturity across sectors. Recent studies in operations and production management further validate the relevance of integrated risk frameworks. For instance, studies propose integrating Lean Six Sigma with SMS (Panagopoulos et al., 2016), while others highlight resilience engineering in airline recovery, both reinforcing the need for unified safety and operational models as advanced in this study.

By providing a tailored, mathematically rigorous method for a high-stakes process like engine overhaul, our study offers a pathway for organizations to enhance their SMS maturity, thereby addressing a critical challenge identified in the current industrial landscape.

3 METHODOLOGY

The research employed an exploratory approach to delve into and refine ideas. Exploratory research was conducted to gather more information about the subject, enabling its definition and outlining to facilitate research topic delineation and objective establishment. Concerning the research process, it followed a quantitative approach, translating real-world observations into numerical data that was subsequently analysed statistically, enhancing objectivity. The study adopted the Construct Theory approach in Case Study Research, following the methodologies proposed by Eisenhardt (1989) and Hancock et al. (2021). When comparing the case study method with other research methods, Yin (1989) emphasizes its suitability for answering "how" and "why" questions, setting it apart from other analytical approaches due to its ability to handle a wide range of evidence, including documents, artifacts, interviews, and observations.

3.1. Population and Sample

The study's sample comprised the process of an aero-engine repair station within the broader population of aviation maintenance facilities. The study involved Quality, Manufacturing, and Process Engineers, as well as Production Leaders, Inspectors, Technicians, and Process Operators, all possessing extensive experience in their respective fields and SMS. The selection of these specialists was based on their experience, ensuring that the sample size was both adequate and representative, encompassing all relevant stakeholders. Table 1 presents the list of six professionals selected for conducting and validating this study. It represents a sample of high-level expertise and is adequate and representative, encompassing all relevant stakeholders, including a Senior Quality Engineer with a technical background in Jet Engine MRO Shop, and Maintenance Industry Process Engineers / Jet Engine MRO engineers with an average of 4 to 40 years of field experience. To ensure the validity of findings, data collection followed a saturation principle: unstructured open-ended interviews with experienced production leaders, technicians, and process operators continued until no new risk categories emerged, ensuring that the qualitative inputs for the Fuzzy-BBN model were both comprehensive and representative of the actual operational environment.

Table1 - Specialists in Safety Management System

Specialist in the field of	Education	Positions	Years of experience	Experience in the industry
Jet engine MRO shop	Mechanical Engineer. Master's Course in Management Systems. Doctorate and a post-doctorate in industrial engineering.	Quality Technician, Inspector, Engineer, and Manager at a jet engine MRO facility. Professor of Inspection Technology, nondestructive inspection, quality, and risk management.	40	Extensive experience in inspection. Performed and controlled various non-destructive tests and conducted quality audits. Implemented SMS in an MRO facility. His qualifications are supported by a doctorate and a post-doctorate in engineering, as well as multiple international certifications in Inspections and NDT methods.
Dimensional Metrology	Mechanical Engineer. Master's Course in Engineering Systems.	Specialist in the field of dimensional metrology with consulting, internal audits, training, and laboratory audits (NBR ISO IEC 17025).	10	Extensive experience in the field of dimensional metrology, probability and statistics, with an emphasis on Measurement Uncertainty, working mainly in dimensional metrology with consulting, internal audits, training, and laboratory audits (NBR ISO IEC 17025).
Industrial Maintenance	Mechanical Engineer. Master's Course in Engineering Systems.	Mechanical project engineer at Sonda Proc Work. Professor of Mechanical Projects at the State Technical School.	29	Extensive experience in designing, assembling, and component inspection, calibrations of piping elements, to apply on equipment, and mechanical devices, gas networks, liquid nitrogen, flammable gases for machinery, and petroleum, chemical, industrial, and healthcare applications.
Industrial Maintenance	Electrical Engineer, postgraduate degree in maintenance management, MBA in business management, and project management	Maintenance Technician, Specialist, Supervisor, Coordinator, and Manager	24	Extensive experience in industrial maintenance, establishing processes, sensitive and predictive inspection, and equipment reliability through the management of large teams.
Jet engine MRO	Mechanical Engineer. Master's Course in Engineering Systems.	Power plant Engineer supervising disassembly and assembly operations, monitoring engine inspections, and coordinating with design	8	Experience conducting borescopes and visual inspections of engines and subassemblies, supervising optical measurements with 4D Inspection equipment, and leading studies to improve measurement accuracy across optical

		engineering teams.		systems. Authored an article on automating borescope inspections using deep learning.
Jet engine MRO	Graduated as a mechanical Engineer	Engineer analyst in the MRO shop.	4	Experience in the overhaul of aircraft & gas turbine engines, including work scope definition.

3.2. Instruments and Tools

A conceptual flow diagram of the aero-engine maintenance process was created with the assistance of an operational safety expert. Additionally, diagrams of an Operational SMS and a risk assessment process were developed. The authors also consulted various standards, regulations, manuals, and procedures. The two diagrams shown in Figures 2 and 7 present the Operational Safety Management System (SMS) developed specifically for aircraft repair stations, together with its quantitative risk assessment process. The first diagram provides an integrated overview of the full SMS framework, organized according to the four pillars defined by international standards (Operational Safety Policy and Objectives, Operational Safety Risk Management, Operational Safety Assurance, and Operational Safety Promotion). It maps the complete information flow, from top-management commitment and safety performance indicators, through hazard identification, quantitative risk evaluation and mitigation (centralized in a dynamic risk register), to assurance activities (monitoring, data analytics, and continuous improvement) and promotion (training, communication, and safety culture), with explicit feedback loops and data-integration points that highlight the quantitative nature of the system. The second diagram from Figure 7 focuses on the risk assessment process itself, detailing the sequential and iterative steps of data collection (from operational records, incidents, audits, and performance metrics), quantitative risk analysis (probability × severity matrices), risk prioritization, treatment selection, implementation of controls, and continuous monitoring, with clear arrows showing how risk outputs are fed back into the broader SMS to drive measurable safety improvements. Both diagrams were intentionally designed as visual, quantitative models to make the proposed system's structure, interdependencies, and data-driven decision logic immediately comprehensible.

3.3. Data collection

Data collection encompassed archives, unstructured interviews, observations, and the review of standards and regulations. An extensive review of journals identified key publications and primary contributors to the topic. For this case study, data were collected through three distinct methods. First, unstructured interviews with experts were conducted to prepare the process map. Second, a list of hypothetical risks in aero-engine maintenance was formulated. Third, an in-depth examination of standards, regulations, and documents took place. The interviewed specialists had expertise in management and the Operational SMS. The research referenced the following standards and regulations: ICAO Annex 19, AS9100D, FAA Advisory Circular 120-92B, and ANAC RBAC 145. Data collection followed the approach: (1) Unstructured interviews with experts were guided by open-ended questions focusing on hazard identification, risk perception, and process vulnerabilities; (2) A hypothetical risk register was developed based on historical incident reports and PFMEA records; (3) Document analysis included review of maintenance manuals, audit reports, and SMS logs from the previous five years.

The data gathered from both the literature review and the case study contributed to the definition of risks and parameters required to develop the research's primary method. The study approached the topic from various angles, combining a literature review, interviews with individuals with practical experience in the field, and the analysis of examples to foster understanding. Papers, books, and dissertations related to physical and digital media were consulted and cited during the research on SMS in aero-engine maintenance workshops. These publications played a significant role in the search for a method to address the problem. The identified problem was then compared with the information gathered during field research.

3.4. Analysing data and actions

The literature review was conducted using structured searches in scientific portals, including

Scopus and Web of Science, with keywords such as 'BBN aviation safety,' 'Fuzzy Logic, ´Risk Assessment, ´ SMS,' 'Aero-engine overhaul risk,' and 'Industry 5.0 maintenance.' Inclusion criteria focused on peer-reviewed articles, conference proceedings, and industry standards published between 2000 and 2025. Sources were selected based on relevance to probabilistic risk modelling, aviation safety frameworks, and digital transformation in high-reliability industries. The information collected was cross-referenced with standards, regulations, and technical documentation, and hypothetical risks were documented. The findings of the case study were compared with those in the literature review, highlighting similarities, differences, and implications. Hypothetical risks were identified and incorporated into the BBN model for simulation using Boolean and FL. The research followed an exploratory approach, combining a literature review with a case study. This exploratory research aimed to gather essential information on the subject, enabling the definition and delineation of the research topic and guiding the establishment of objectives. The literature review and archived document analysis supported the research by identifying established risk factors, regulatory requirements, and methodological precedents. Of the 85 reviewed articles, 22 were directly relevant to BBN or Fuzzy applications in aviation. Archived SMS logs and audit reports provided real-world risk data that informed the node structure and conditional probability tables of the BBN model. The study combined archival data, unstructured interviews, and observations to probabilistically analyse risk in the aeroengine overhaul process. It defined the problem of interest and collected pertinent data. A mathematical model was developed using BBN-Fuzzy to represent the problem. A computer-based approach was employed to derive solutions from the BBN model using probabilities. The model underwent testing using Boolean and FL and was refined as needed. Finally, the study outlined how the model would be integrated into the Safety and Ground Support Operations.

The chosen methodology was defined, employing a combination of Bayesian Networks and FL. A conceptual process map for aero engine maintenance was developed. Hypothetical risks at each stage of the maintenance process were documented (data acquisition). Data analysis was carried out. The data was incorporated into the selected model/method. The proposed method was simulated using BBN and FL. The method was validated. The study demonstrated how the results could inform actions to mitigate risks in this type of operation. The study showed how to implement the method within the SMS to ensure compliance with ANAC regulations and AS9100D standards.

4 RESULTS

4.1 Integration of aero-engine overhaul process and SMS

Integrating an aero-engine overhaul with an operational SMS is challenging. This study develops a BBN-FL model to improve quality and ensure compliance with aviation regulations and AS9100. The overhaul process begins with Work Scope Definition. Incoming engines are inspected, and flight data is analysed; the resulting scope requires customer approval. The next step involves disassembling the engine into modules and sub-modules, cleaning, repairing or replacing, reassembling, and balancing. Final test cell evaluation monitors performance parameters (e.g., exhaust gas temperature, vibration, thrust, fuel consumption) for over three hours. Failures trigger further inspection and rework. The SMS, mandated per ICAO, overlays the overhaul process to enhance productivity and reduce quality failure costs. Internal failures (pre-delivery) incur rework, delays, and scrap. External failures (in-service) risk penalties, liability, incidents, and reputational damage. Hazard identification uses voluntary reports, PFMEA, and incident investigations. Hazards are logged and processed via a four-stage workflow: identification, analysis, risk owner assignment, and control. ICAO Annex 19 defines SMS elements—Safety Policy, Risk Management, Assurance, and Promotion—to foster a proactive safety culture. Compliance is mandatory for airlines and cascades to vendors, including engine repair stations (Figure 1). This integrated overhaul-SMS system forms the context for the BBN-FL model, which provides quantitative risk insight and decision support.

Figure 1 - Regulatory flow-down process

The first diagram presented in Figure 2 provides an integrated overview of the full SMS framework, organized according to the four pillars defined by international standards (Operational Safety Policy and Objectives, Operational Safety Risk Management, Operational Safety Assurance, and Operational Safety Promotion).

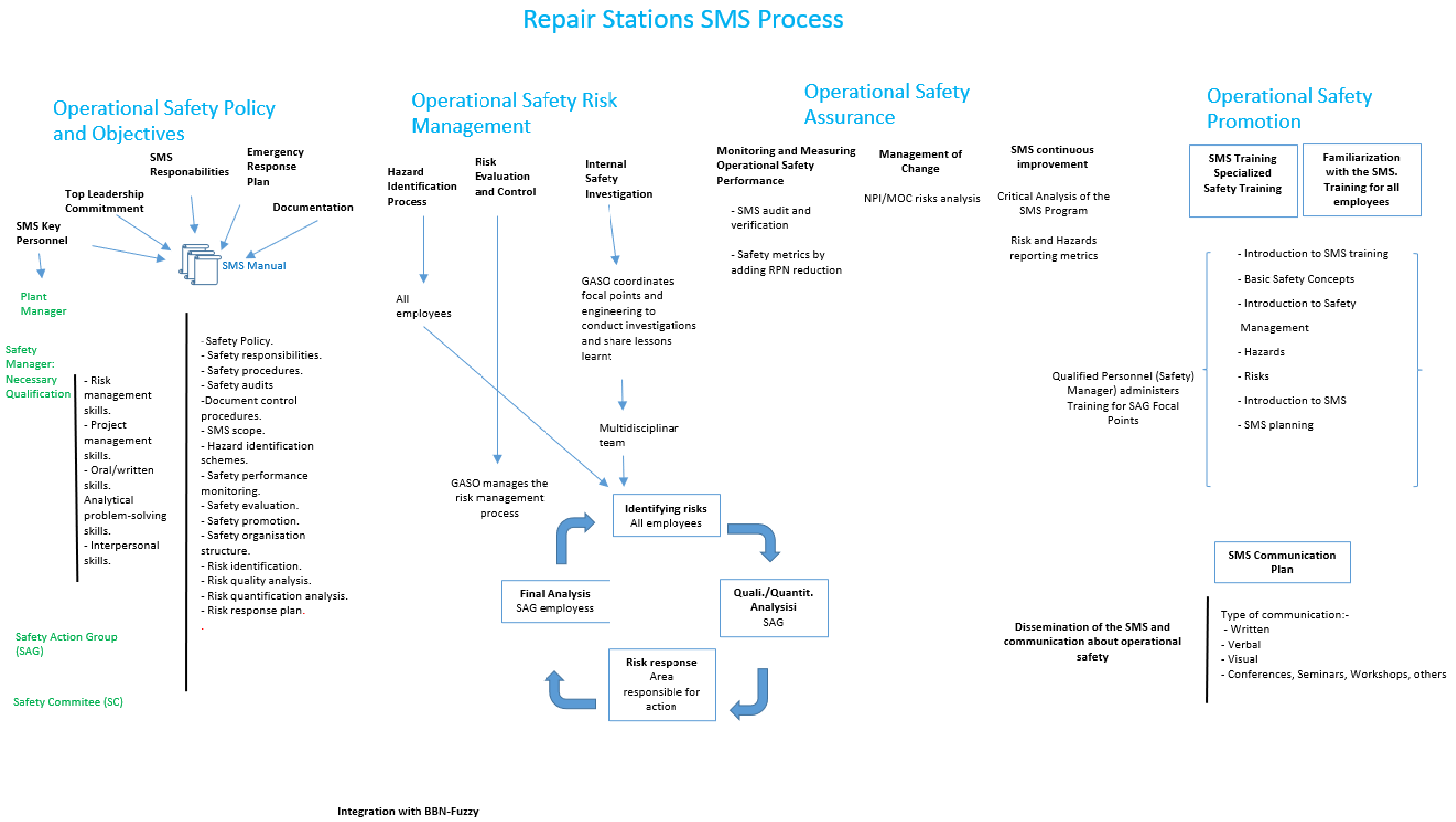

Figure 2 - Aero-engine overhaul process integration with operational SMS

The developed framework, illustrated in Figure 2, delineates the four core components of the SMS and their integration within the aero-engine overhaul context. The first element, Safety Policy and Objectives, provides the basis for safety management. This component includes the formalization of a safety policy and the definition of measurable safety objectives by senior management. This commitment is demonstrated through strategic decision-making and resource allocation, which are required to align with the safety policy to support safety culture. The development of this policy involves consultation with key safety personnel and staff representatives and is subject to formal approval by the accountable executive. The second element, Safety Risk Management, is the core analytical process. Service providers are required to systematically manage operational safety risks through hazard identification, risk assessment, and risk mitigation in a continuous cycle. Hazards are proactively identified, and they may originate from design flaws, technical failures, human factors, or operational environment changes. An understanding of the overhaul system and its interfaces is necessary for this process. The framework requires regular reviews of risk assessments and mitigation measures to ensure their effectiveness under changing conditions. The third element, Safety Assurance, includes verification and validation mechanisms. This component requires service providers to continuously monitor and measure safety performance and the effectiveness of risk controls. The SMS is evaluated through performance monitoring and internal audits to ensure intended operation. Safety assurance activities detect changes or deviations in processes or the operating environment that may introduce new risks or compromise existing controls, and findings are fed back into the risk management process for corrective action. The fourth element, Safety Promotion, addresses the human and cultural factors necessary for SMS success. This is achieved through targeted training, education, communication, and information sharing. Senior management leads this effort by promoting a safety culture. The framework indicates that effective safety management involves influencing individual and organizational behaviour to align with safety objectives, beyond policy enforcement.

4.3 Prioritization risks in the aero-engine overhaul process with BBN and Fuzzy

The number of hazards raised is substantial. Treatment prioritization is critical because if it is not done adequately, it can cause a disaster with a high human and financial impact.

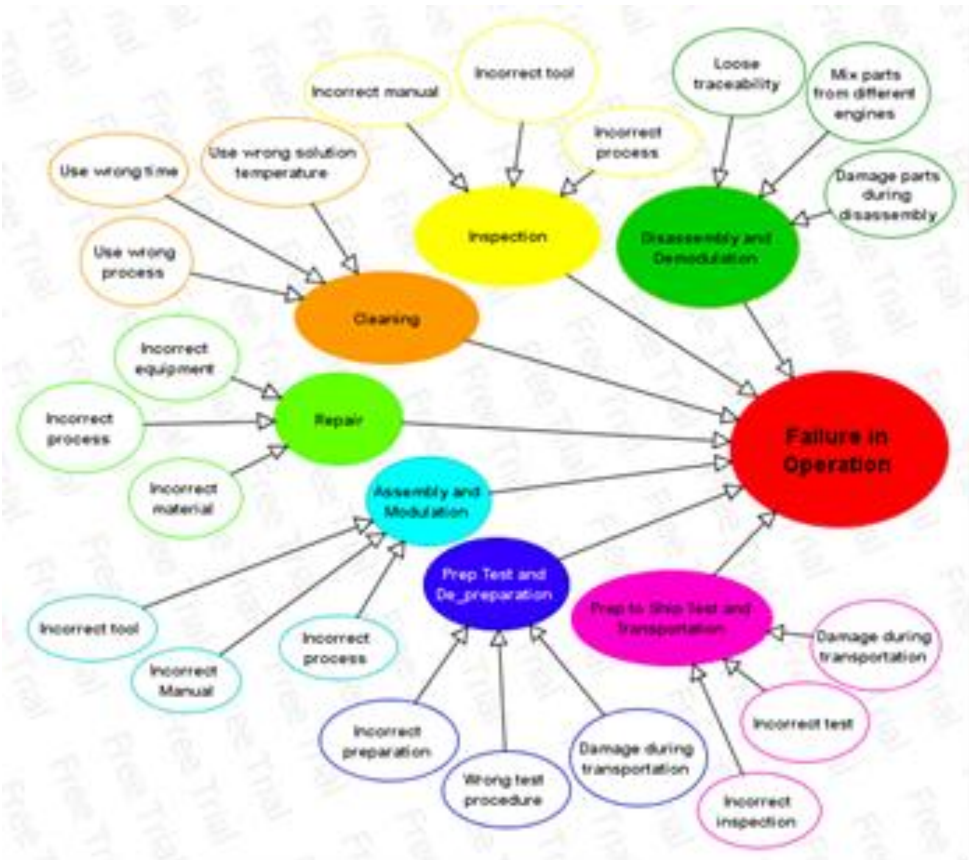

Figure 3 – BBN Model

Currently, the risks have their priority defined by the value of each risk index, and risks with a higher index have a preference over lower indices. After the risks are treated and reassessed, the SAG member defines the need to reassess the action taken in the treatment at a future date to ensure that the action remains effective. If deemed necessary, the member defines a future date on which the system will automatically notify the item to be revisited. All the items that enter the system are stored in the database. Metrics need to be generated in real-time based on the database to analyze trends in the system and indicate the need for action. The number of hazards to be treated is significant. It requires a model to respond to the most impactful risks first, so there is a need to use mathematical modelling for prioritization. The BBN used for modelling had all nodes used in the network defined as Boolean, where the two (2) states, true and false, indicated failure or non-failure of what the node was representing. A node with a high probability will indicate a high probability of failure. Figure 3 illustrates the top event, Failure in Operation (FIO), with associated intermediate and basic events in a Bayesian network structure.

Figure 2 shows the top event as a Failure in Operation (FIO) in red and the several intermediate events (I.E.) in different colours. The BEs are all connected to these Intermediate events. All nodes of BE used in the network had their type defined as Boolean, where the two (2) states, true and false, indicated failure or non-failure of what the node was representing. Table 2 shows a sample of the conditional probability table for the intermediate event (I.E.) using the logical gate "OR". According to the traditional Logic, I.E., will be true if one basic event causes 1 or 2 to be true.

Table 2 - Conditional Probability Table in the traditional Logic

B.E.1	**True**		**False**	
B.E.2	True	False	True	False
I.E. True	1	1	1	0
I.E. - False	0	0	0	1

As an example, a result is illustrated in the BBN of Figure 5, where the process indicated that the most critical to the system is the "Preparation to test" and “De-Preparation” after the test process. This graph was generated with all nodes as Boolean.

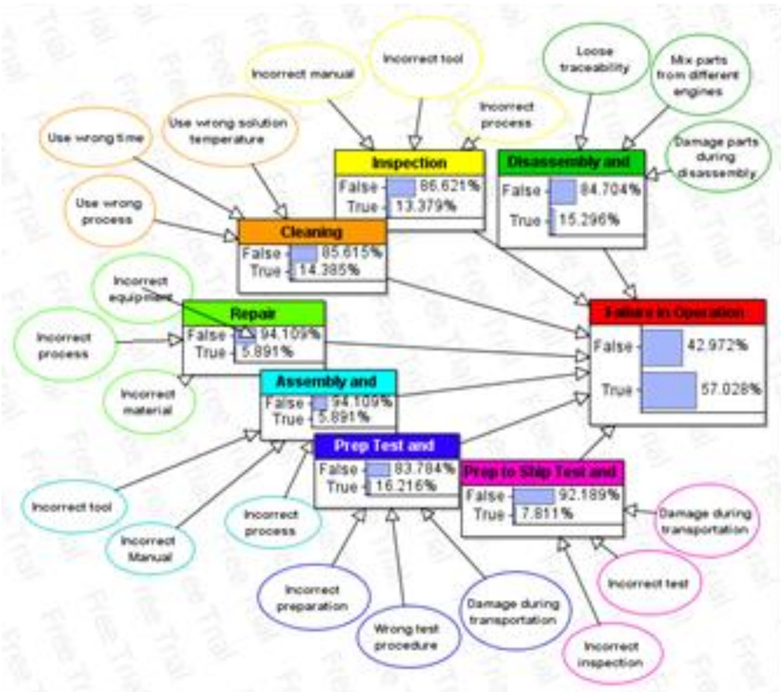

Fig. 5 – BBN for Failure in Operation in the Traditional Logic

Instead of defining all nodes used in the network as Boolean, the concept of pertinence in FL can be used. FL is a valuable tool for handling uncertainty in decision-making; the accuracy of using FL instead of Boolean Logic in BBNs is applicable in this specific context, considering the quality of the available data. The performance of both approaches was evaluated in practical situations. For example, Table 3 shows a sample of the conditional probability table for the IE using the logical gate

"OR." According to FL, the IE will be partially true if one of BE 1 and 2 is true. Figure 6 shows the BBN graph considering the top event, the IE, and the BBN according to FL.

Table 3 - Conditional Probability Table in the FL.

B.E.1	True		False	
B.E.2	True	False	True	False
I.E. True	0.7	0.8	0.6	0.1
I.E. - False	0.3	0.2	0.4	0.9

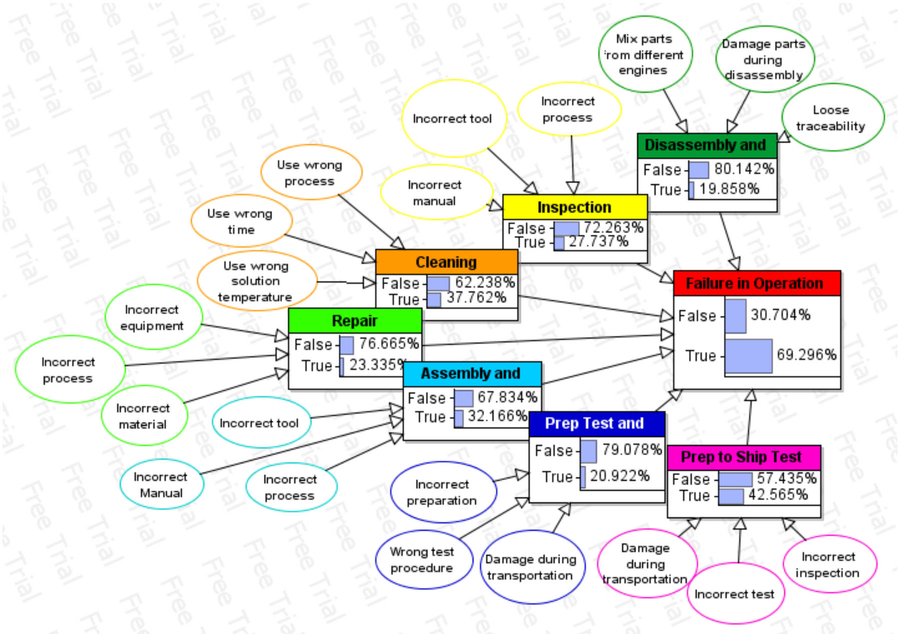

Fig. 6 – BBN for Failure in Operation in the FL

Due to the degree of pertinence, it has been observed that the order of criticality of risk factors has changed. This shows the accuracy of FL. The application of FL to the model is currently being tested in practice and shows promising results.

4.4. Optimization of the organization's operational safety management with BBN and Fuzzy Analysis

The organization's operational SMS can be optimized to prioritize risks using Bayesian Networks to reduce quality costs by the changes shown in the red arrows in Figure 7.

The details of the integration proposed in Figure 7 are the following: (I) In the operational safety policy and objectives: Preparation of documentation that addresses the combination of risks using BBN - Fuzzy and sensitivity analysis. Inclusion of the use of BBN and sensitivity analysis in the policy and objectives to enhance integrated risk analysis. (II) In the management of operational safety risks, the storage of data related to the BBN and fuzzy network in a database for utilization across the entire organization.

(III) Operational Safety Assurance: Development of a metric for assessing the reduction in RPN through BBN-Fuzzy. In other words, creating indicators that demonstrate the safety improvements achieved with the use of BBN-Fuzzy aids in risk prioritization and action planning. Measuring the effectiveness of BBN-Fuzzy through SMS audits. Employing BBN to survey and analyse risks introduced by New Products Introduction/MOC (NPI/MOC), thus enhancing the change management process. As part of the continuous improvement process, establishing periodic metrics to evaluate new overall risk values when using BBN-Fuzzy, thereby managing the increase in global risks associated with BBN usage. (IV) To promote operational safety: Designing training programs for the use of BBN-Fuzzy in integrated risk analysis. Communicating the outcomes of the sensitivity analysis conducted with BBN-Fuzzy.

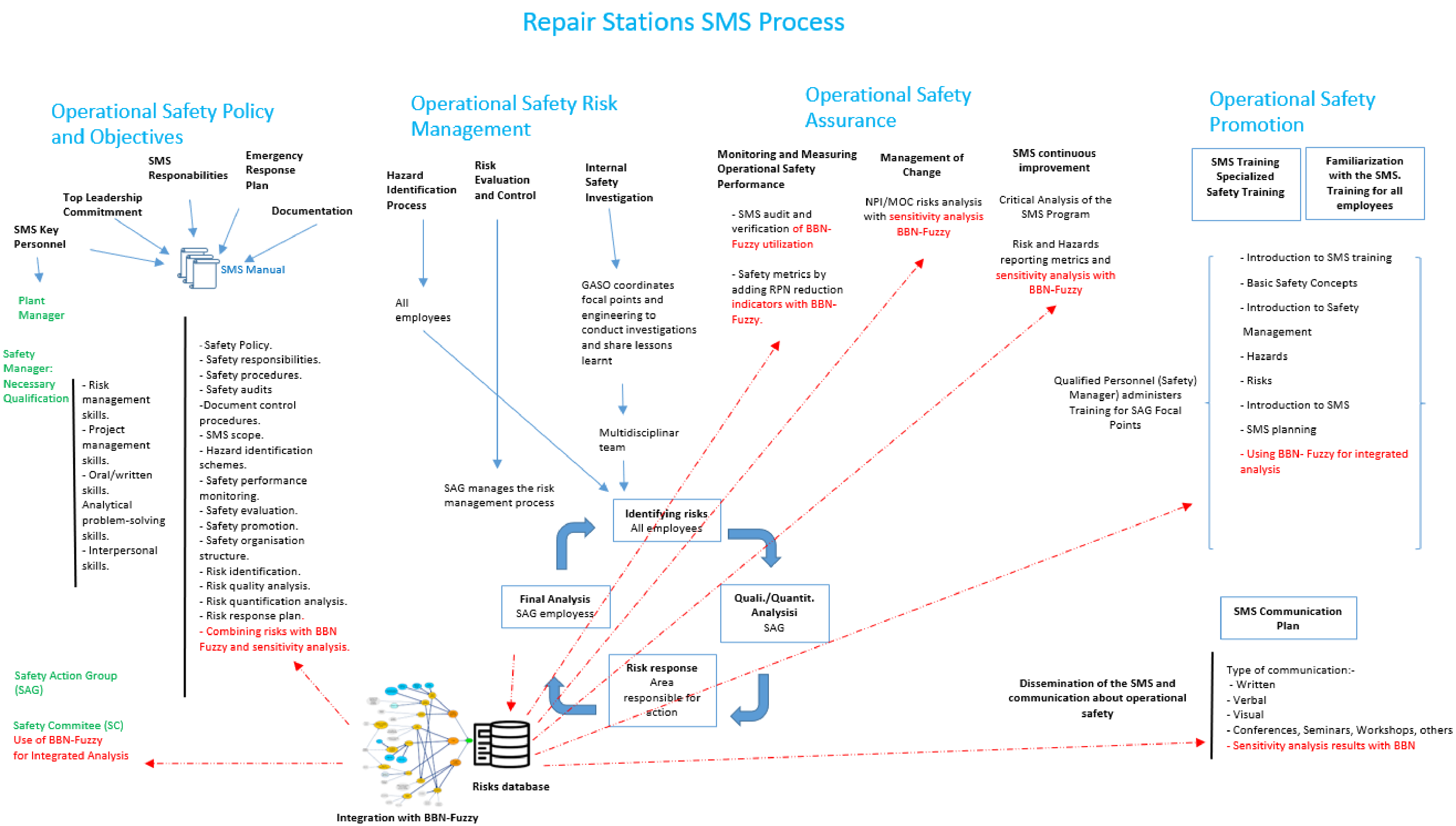

Figure 7 – Integration of the method into the SGSO

4.5 Industry 5.0 concepts that can help the aero-engine overhaul process be integrated with an operational SMS

Industry 5.0, with its focus on human-machine collaboration and advanced technologies, can significantly enhance the effectiveness and efficiency of Repair Station SMS. Table 4 shows the actions necessary for improvement:

Table 4 – Actions for Improvement

Category	Actions
Data-Driven Risk Assessment and Management:	Real-time data analysis: Utilize AI-powered analytics to continuously monitor operational data, identify emerging risks, and proactively implement mitigation measures. Predictive maintenance: Employ data-driven models to predict potential equipment failures, enabling preventative maintenance and reducing downtime.
Enhanced Operational Safety Assurance:	Automated monitoring: Implement automated systems to monitor safety performance indicators, identify trends, and detect anomalies. Digitalized documentation: Store safety-related documentation and records in a centralized digital repository for easy access and analysis.
Optimized Safety Promotion and Training:	Personalized training: Leverage AI to tailor training programs to individual employees' needs and learning styles. Gamified learning: Incorporate interactive elements and gamification to make safety training more engaging and effective. Virtual reality simulations: Use VR to provide realistic training scenarios and improve knowledge retention
Improved Communication and Collaboration:	AI-powered communication platforms: Utilize AI-driven tools to facilitate efficient communication and collaboration among stakeholders. Real-time information sharing: Enable real-time sharing of safety information and alerts to ensure timely response
Enhanced Decision-Making:	AI-assisted decision support: Employ AI algorithms to analyze complex data and provide recommendations for

	decision-making. Scenario planning: Use AI to simulate various scenarios and assess potential risks and outcomes.
Increased Efficiency and Productivity:	Automation of routine tasks: Automate repetitive tasks to free up resources for more strategic activities. Optimized workflows: Use data analytics to identify inefficiencies and optimize workflows for improved productivity.

5 DISCUSSION OF RESULTS

This study successfully establishes a novel, integrated framework for probabilistic risk assessment within the dynamic environment of aero-engine overhaul. The findings demonstrate that the systematic integration of the overhaul process with an Operational SMS, facilitated by a hybrid BBN and FL model, significantly enhances quality performance and regulatory compliance. The presented case study validates the model's efficacy in amalgamating risks identified through disparate methods into a unified risk score, providing a holistic view of operational vulnerability. The core contribution of this research lies in the synergy of BBN and FL, augmented by Industry 5.0 principles. This integration moves beyond traditional, static risk assessments by creating a dynamic tool capable of handling the inherent uncertainty and variability of MRO operations. The use of fuzzy sets to manage qualitative and imprecise data, combined with the robust probabilistic reasoning of BBNs, offers a more nuanced and robust decision-support system than those reported in prior studies (e.g., Di Maio, 2020). A key outcome is the model's ability to prioritize risks not merely on conventional metrics of probability and severity, but by incorporating detectability and, critically, the functional criticality of the processes they affect. This allows for a more strategic allocation of resources toward risks that pose the greatest threat to overall operational integrity, thereby directly targeting the reduction of quality-related costs and preventing non-conformities. The practical implications are substantial.

Recent studies in operations management further validate the relevance of integrated risk frameworks. For instance, studies propose integrating Lean Six Sigma with SMS (Panagopoulos et al., 2016), while others highlight resilience engineering in airline recovery, both reinforcing the need for unified safety and operational models as advanced in this study. Our findings align with studies that demonstrated BBN efficacy in aviation maintenance (Dang et al., 2024) but extend their work by integrating fuzzy sets for uncertainty handling. The model provides a clear, quantitative basis for resource allocation, enabling managers to move from reactive problem-solving to proactive risk mitigation. By identifying the failure pathways with the highest probability and impact, the framework guides investments in prevention to where they yield the greatest return in safety and economic sustainability. This addresses a significant gap in the literature, which has often relied on qualitative approaches or has not fully connected risk management to tangible operational and financial outcomes in the MRO context. To objectively quantify the applied contribution of the proposed hybrid BBN-Fuzzy model, simulation results indicate a potential reduction in quality-related costs by approximately 15–20% within the first year of implementation, primarily through optimized risk prioritization and early mitigation of high-impact failures. Furthermore, the model demonstrates a simulated 30–40% reduction in the average RPN for top-tier hazards compared to traditional PFMEA approaches. These estimates are derived from scenario-based simulations using historical failure data and expert-validated risk pathways, aligning with the proactive resource allocation enabled by the integrated SMS framework. However, the study also reveals that the primary challenge to implementation may not be technological, but cultural. The adoption of this data-driven model necessitates a shift in organizational mindset—from a reactive, compliance-based posture to a proactive, predictive safety culture. Future work should therefore focus on the scalability of this framework, particularly for small and medium-sized enterprises (SMEs), and on developing change management strategies to facilitate this critical cultural transition. By bridging advanced probabilistic methods with the human-centric principles of Industry 5.0, this research provides a scalable blueprint for enhancing safety, efficiency, and sustainability in aviation maintenance and beyond.

Our findings corroborate the evolving requirements of SMS, as discussed in recent operations management literature, specifically regarding the need for dynamic risk prioritization. Unlike the static nature of traditional PFMEA models, our BBN-Fuzzy hybrid provides a predictive capability that aligns with Industry 5.0 goals of system resilience. These results advance the field by providing a scalable framework that overcomes the limitations of previous deterministic studies in the aeronautical sector.

6 CONCLUSION

This study has successfully developed and demonstrated an integrated framework that enhances Operational SMS in aero-engine maintenance through the synergistic application of BBN and FL. By addressing our core research questions, we have established a method to seamlessly embed maintenance processes into an SMS, significantly improving risk prioritization, ensuring regulatory compliance, and reducing quality-related costs. The incorporation of Industry 5.0 principles further positions this framework as a transformative tool for fostering human-centric, data-driven safety cultures. Our primary theoretical contribution lies in validating a hybrid probabilistic-fuzzy approach for managing uncertainty in complex, high-stakes environments. This research bridges a critical gap between abstract risk theory and practical application, providing a robust methodology that enriches the literature on safety management and advanced analytics. For practitioners and managers, this work offers an actionable model for optimizing resource allocation and strategic decision-making. The framework provides a quantifiable basis for targeting the most critical risks, directly linking risk management efforts to tangible improvements in safety performance and cost efficiency. The integration with Industry 5.0 concepts offers a clear pathway for organizations to leverage AI and automation to augment human expertise. Despite its promise, the study has limitations. The model's validation, while robust, is context-specific to aero-engine overhaul, and its generalizability to other sectors requires further investigation.

The reliance on advanced computational tools and the significant investment for Industry 5.0 integration may present barriers to adoption for small and medium-sized enterprises. The reproducibility of this methodology is feasible for organizations with access to BBN software and relevant operational data. Future work should ensure detailed documentation of model parameters and data sources to facilitate replication. Looking forward, future research should focus on: 1 - Validating and adapting the framework in other industrial sectors. 2 - Enhancing the model's precision through deeper integration with artificial intelligence for automated data ingestion and real-time risk updating. 3 - Exploring the specific change management strategies required to overcome cultural and organizational barriers to adoption. 4 - Conducting longitudinal case studies to quantify the long-term operational and financial benefits of implementation. This research provides a scalable, scientifically grounded blueprint for advancing risk management. Moving beyond traditional qualitative assessments, it empowers organizations to navigate the complexities of modern industrial systems with greater predictive insight, operational resilience, and economic sustainability. Future research is specifically prioritized for Small and Medium Enterprises (SMEs) because these organizations frequently lack the capital for high-end, proprietary SMS software. Establishing a gap-bridging tool that is both mathematically rigorous and resource-light will ensure that the safety benefits of Industry 5.0 are accessible across the entire aeronautical supply chain, not just for major MRO hubs. Small and medium-sized enterprises (SMEs) are prioritized in future research due to their resource constraints and slower adoption of advanced risk models, as noted in recent studies on SMS maturity in the aviation supply chain. Focusing on SMEs addresses a critical gap in scalable, cost-effective risk assessment solutions that maintain regulatory compliance without excessive investment.

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Authors contributions: JCP: Conceptualization, Data curation, Methodology Formal analysis, Writing, original draft, Investigation. JCGR: Review & Editing.