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Development of a Decision Support System for Maintenance Troubleshooting: A Case Study in Aviation Maintenance, Repair, and Overhaul

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This work presents the development of a Decision Support System (DSS) for prescribing corrective maintenance actions, a process known as troubleshooting, within the context of aviation Maintenance, Repair, and Overhaul (MRO). Framed within the methodological area of "Decision Making under Uncertainty," the primary goal of the DSS is to assist technicians and engineers in identifying the most probable root causes of failures and selecting the most appropriate maintenance actions to correct them, thereby reducing diagnostic time and increasing decision accuracy and consistency. The system integrates a hybrid approach combining rule-based decision logic, derived from the equipment's maintenance manual, with a probabilistic component built from historical maintenance records. The deterministic component maps symptoms and test results to documented root causes, ensuring traceability and compliance with technical guidelines. In parallel, the probabilistic component estimates the likelihood associated with each failure based on frequency observed in past cases, reinforcing the prioritization of recommended actions. Thus, the system does not predict the occurrence of failures; instead, it uses historical evidence to support the interpretation of past diagnostic results. The implementation is entirely developed in Python, utilizing data processing libraries, inference engines, and modular structures that facilitate continuous updates of both rules and historical data. The integration of these deterministic and probabilistic components creates a robust decision-support mechanism for scenarios where uncertainty and failure variability hinder a quick and accurate assessment. This work contributes to the advancement of intelligent tools applied to industrial maintenance, particularly in aviation, demonstrating the relevance of DSSs that combine technical information with probabilistic inference to improve the efficiency and effectiveness of troubleshooting operations.

Keywords: Decision Support System, Maintenance, Aviation, Troubleshooting, Uncertainty Management.

1. Introduction

Aviation has experienced significant growth in recent decades, driven by increased globalization, the continued rise in air traffic, and advances in aeronautical systems technology. This scenario makes Maintenance, Repair, and Overhaul (MRO) activities progressively more complex, imposing heightened requirements for safety, traceability, and technical rigor (Kabashkin and Perekrestov 2025). The heterogeneity of equipment, the critical nature of potential failures, and the need to ensure high levels of operational availability underscore the importance of robust maintenance practices, particularly within troubleshooting operations, where the goal is to identify the root cause of an anomaly swiftly and accurately, in order to correct it.

In the context of aviation maintenance, *troubleshooting* corresponds to a systematic process involving the analysis of observed symptoms, the execution of specific tests, and the definition of the most appropriate corrective action or actions. It is an activity significantly dependent on the accumulated experience of technicians, the use of maintenance manuals, and the interpretation of results obtained under real operating conditions (Lee and Kim 2025; Iyer et al. 2022).

Despite the existence of detailed guidance, the increasing complexity of aeronautical systems and the variability associated with failure modes make the diagnostic process particularly vulnerable to uncertainties, divergent interpretations, and inconsistencies among technicians. These constraints are further exacerbated by phenomena such as *No Fault Found* (NFF), which hinder the precise identification of anomaly root causes and can lead to unnecessary interventions (Khan et al. 2017). This context highlights the relevance of developing a Decision Support System (DSS) capable of integrating tacit expert knowledge, formal technical information, and empirical evidence from data, aiming at reducing diagnostic time and promoting greater uniformity in maintenance actions.

DSSs applied to maintenance have evolved from strictly deterministic approaches, supported solely by the rules established in technical manuals, to hybrid models that incorporate probabilistic components (A. et al. 2022). The literature demonstrates that this combination of technical information and data analysis significantly contributes to improving diagnostic accuracy, reinforcing decision traceability, and reducing costs arising from repeated tests, unnecessary replacements, or prolonged aircraft downtime (Kabashkin and Perekrestov 2025).

Despite the advances made, a gap persists in the application of hybrid systems specifically designed for the aviation MRO context, where safety, regulatory compliance, and operational reliability are of particular importance. Challenges remain associated with integrating multiple information sources, continuously updating rules, the variability of failure modes, and the need for mechanisms that assist technicians in interpreting ambiguous or competing symptoms. Thus, a clear opportunity exists for the development of tools capable of articulating tacit expert knowledge, from human technicians, deterministic logic, derived from maintenance manuals, and probabilistic inference, estimated from historical operational records.

The present work seeks to address this need through the development of a DSS that integrates an expert knowledge component, extracted from human maintainers, a deterministic component, structured from the rules present in the maintenance manuals, and a probabilistic component, supported by historical data.

The main objective of this work is to investigate and develop a structured approach for decision support in troubleshooting processes, formalizing technical and operational information and integrating it into a system capable of guiding maintenance interventions in a consistent and well-founded manner. Its specific objectives are:

- To formalize the technical knowledge associated with troubleshooting, including symptoms, causes, and actions.
- To define a conceptual decision support model applicable to diagnostic processes.
- To develop a consistent knowledge base to represent decision rules and relationships.
- To implement a decision engine that operationalizes the defined conceptual model.
- To validate the system using real or simulated cases, evaluating its effectiveness in supporting diagnosis.

2. Research Methods

The methodology adopted for this work is based on a qualitative and exploratory-descriptive literature review, integrated with the analysis of a case study applied to aviation maintenance. The process was structured into three main axes: 1) review planning; 2) execution of the bibliographic search; and 3) critical synthesis of the results.

The research protocol focused on thematic axes such as DSS, fault diagnosis, hybrid models (deterministic and probabilistic), and uncertainty management within the MRO context. The research was conducted using the Scopus database, covering the period from 2004 to 2025, focusing on peer-reviewed journal articles and technical reference books.

The inclusion criteria selected studies specifically addressing troubleshooting processes and decision-making in industrial or aviation maintenance. The synthesis of evidence allowed for the identification of theoretical and empirical gaps, detailed in Table 1, which served as the foundation for the conceptual development of the proposed system.

3. Literature Review

3.1. *The Maintenance, Repair, and Overhaul (MRO) Ecosystem in Aviation*

Aviation maintenance has evolved into a strategic pillar for economic sustainability and operational safety (Mobley 2004). However, the stochastic nature of failures introduces uncertainties that conventional planning methods cannot effectively absorb (Dinis et al. 2019). A critical challenge is the NFF phenomenon, in which the lack of an accurate diagnosis leads to unnecessary replacements and increased downtime (Khan et al. 2017; Tao et al. 2024). Historically, DSSs relied on rigid "if-then" logic rules (Yung et al. 2022). While transparent, these models are limited when faced with incomplete or inconsistent data, requiring significant effort to maintain their knowledge bases. Similarly, decision-trees lose efficiency in highly complex systems and dynamic diagnostics.

3.2. *DSS: From Rule-Based Logic to Hybrid Intelligence*

To overcome deterministic limitations, literature highlights the use of probabilistic models, such as Bayesian Networks (BNs) (Pearl 1988) and Fuzzy

Table 1. Characterization of included studies.

Context	Year	Study Objectives	Identified Barriers	Contribution to Decision Support / MRO	Ref.
Railway	2025	Integrates language models (Transformers) with Case-Based Reasoning (CBR).	Over-reliance on specialists and delays in diagnosing complex failures.	Proposal of a hybrid model to suggest maintenance strategies based on historical data.	Lee and Kim 2025
Aerospace	2017	Propose an approach for decision-making in No Fault Found (NFF) scenarios.	Lack of clear accountability and high costs of unnecessary replacements.	Framework for managing uncertainties in value-based MRO services.	Khan et al. 2017
Aviation	2025	Create the "Maintenance Advisor" platform based on Big Data and AI.	Inconsistent records and difficulty in analysing unstructured logs.	Digitization and data structuring for faster and more accurate diagnostics.	Kabashkin and Perekrestov 2025
Aviation	2019	Capacity planning using Big Data and Bayesian Networks (BN).	Uncertainty in scheduled and unscheduled maintenance workload.	Improved decision-making based on incomplete information from real datasets.	Dinis et al. 2019
Industrial	2016	Develop “MyAID”, an interactive technician support application.	Limitations of printed documentation and difficulty in human-machine interaction.	Modular tool connected to the control unit for alarm verification.	Márquez 2022
Aerospace	2016	Apply Causal Bayesian Networks (CBN) for failure isolation.	Complexity of interactions between components in military systems.	Improved flight safety through causality-based diagnostics.	Tao et al. 2024

Logic (Zadeh 1965). In the MRO context, these techniques enable abductive reasoning, inferring probable causes from symptoms, and integrate expert knowledge with operational data (Kim et al. 2014; Korbicz et al. 2004). The current frontier points toward *hybridization*: the fusion of technical information with probabilistic models based on historical cases. This duality allows the system to operate on a deterministic layer, following, for example, maintenance manuals, while utilizing a probabilistic layer to prioritize actions based on successful past resolutions (Lee and Kim 2025; Korbicz et al. 2004; Debeljak et al. 2019).

3.3. *Evolution and Architecture of Hybrid DSS*

The effectiveness of modern DSSs relies on the integration of four core components: 1) the Data Management Subsystem, for quality-controlled information gathering; 2) the Model Management Subsystem, for scenario evaluation; 3) the Knowledge Management Subsystem, for solving unstructured problems; and 4) the Interface Subsystem, for real-time analysis (Villani et al. 2016; Scheffer et al. 2023).

While traditional DSSs relied on static rules, contemporary literature identifies a shift towards interactive, adaptive platforms to address the complexities of interdependent system failures (Villani et al. 2016; Scheffer et al. 2023). This has led to a *hybridization* paradigm, fusing deterministic case-based reasoning with learning-oriented probabilistic models. This dual-layered approach ensures that systems maintain strict normative compliance with maintenance manuals while simultaneously prioritizing actions based on successful historical resolutions (Lee and Kim 2025; Sala et al. 2024; Debeljak et al. 2019).

In the context of Industry 4.0, and, more recently, Industry 5.0, these systems enable complex data analysis across three levels: strategic (long-term/risk), tactical (planning/ supply chain), and operational (real-time control) (Wallace 2020; García-Díaz 2021; Rashidi et al. 2018). It is at this last level that hybridization finds the greatest applicability, using advanced algorithms, such as Fuzzy Logic, for fault diagnosis and waste reduction (Wallace 2020; Rashidi et al. 2018).

3.4. *Natural Language Processing (NLP) and Records Mining*

A persistent barrier in the digitalization of MRO is the unstructured nature of maintenance reports. Free-text records contain critical knowledge that remains inaccessible to conventional algorithms (Yung et al. 2022). The use of Natural Language Processing (NLP) techniques, such as transformer-based classification models, allows for the transformation of narrative descriptions into structured data (A et al. 2022; Wagner 2010). The extraction of technical semantics from failure logs enables the automatic mapping of symptoms to root causes (Iyer et al. 2022). Furthermore, mixed-initiative approaches allow the artificial intelligent system to collaborate with human experts to validate and label ambiguous information, thereby increasing the reliability of the model's predictions (Márquez 2022).

3.5. *Technological Implementation and Industrial Software Architectures*

The practical feasibility of these systems relies on the choice of modular and scalable frameworks. There is a notable convergence toward the Python ecosystem due to its maturity in data science libraries and inference engines (Iyer et al. 2022; A et al. 2022). Proposed architectures tend to follow cloud computing models, structured to facilitate the continuous updating of knowledge bases (Kabashkin and Perekrestov 2025; Kabashkin et al. 2023). The integration of Large Language Models (LLMs) with industrial knowledge graphs represents the current frontier, enabling more natural human-machine interaction and superior traceability in resolving long failure chains in complex industrial equipment (Korbicz et al. 2004; Sala et al. 2024).

4. Proposed Case Study and DSS Framework

This section presents the case study with the objective of contextualizing the application of the proposed DSS within the aircraft maintenance troubleshooting process. The main purpose of this case study is to demonstrate how the DSS can be integrated into the existing operational workflow, supporting the diagnostic of failure root causes and the prescription of maintenance actions.

4.1. *Troubleshooting Process*

The case study is framed within an aviation MRO environment, characterized by strict procedural requirements, high technical complexity, and the need for consistent, traceable, and justifiable decisions. The troubleshooting process under consideration begins with the removal of the unit from the aircraft, following a reported anomaly. Subsequently, the unit is received at the maintenance facility, where it undergoes preliminary inspection and a set of diagnostic tests, in accordance with the applicable maintenance documentation and standard operating procedures, as illustrated in Figure 1.

Once the reported anomaly has been validated through inspection and testing, the process enters a critical decision-making phase. At this stage, it becomes necessary to identify the root cause of the failure and to determine the most appropriate corrective maintenance action. It is precisely at this point in the operational workflow that the integration of the proposed DSS is foreseen.

The DSS is intended to be used as a tool, assisting maintenance technicians and engineers in the interpretation of test results and observed symptoms, and in the selection of corrective actions to be applied. The system does not replace human judgment; rather, it provides structured and probabilistic support to enhance the accuracy, consistency, and transparency of maintenance decisions.

If the unit fails to meet the acceptance criteria during functional testing after the execution of the corrective action, the troubleshooting process iterates back to previous diagnostic stages. In such cases, the DSS can be reused to support subsequent decision-making cycles by incorporating new evidence as it becomes available. Once all functional requirements are satisfied, the unit proceeds to certification and release for installation or storage, at which point the intervention of the DSS is no longer required.

Thus, the proposed DSS is selectively integrated into the troubleshooting workflow, focusing specifically on phases characterized by high diagnostic complexity and significant decision impact. This selective integration ensures that the system enhances, rather than replaces, the expertise of maintenance professionals. Overall, this framework highlights the potential contribution of the DSS to improving accuracy, decision consistency, and traceability within aircraft maintenance operations.

4.2. *DSS Architecture*

From a functional perspective, the DSS follows the architecture illustrated in Figure 2. The diagnostic process is initiated by the user through the selection of the specific equipment or unit under analysis. Each equipment type is associated

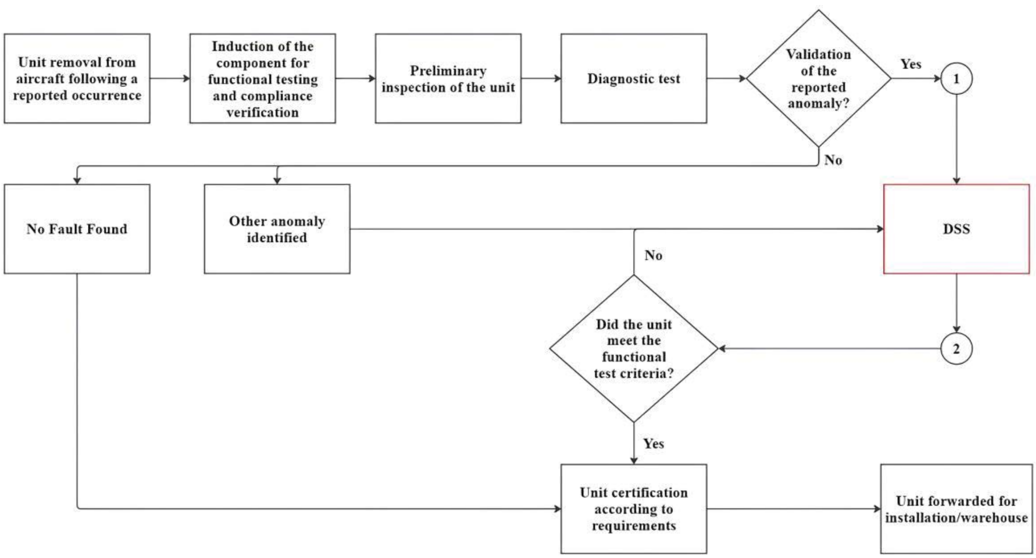

Fig. 1. Troubleshooting process workflow and proposed DSS integration.

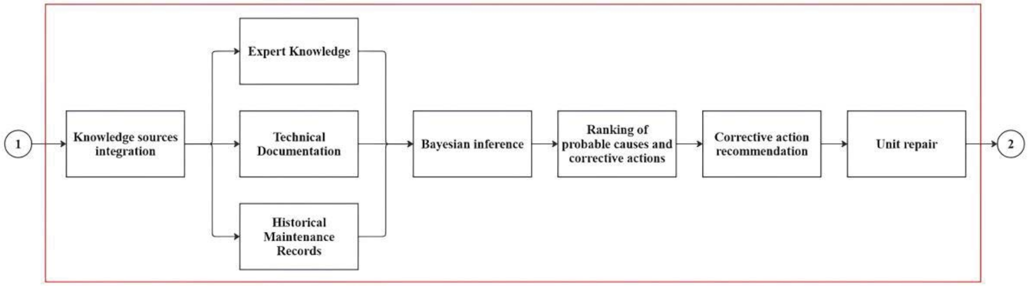

Fig. 2. Proposed DSS architecture.

with a dedicated knowledge base, stored in the form of structured CSV files, which contain fault isolation data, probable causes, and recommended maintenance actions.

After loading the corresponding knowledge base, the system defines or loads a BN model specifically tailored for the selected equipment (Jensen and Nielsen 2007). This BN model formally represents the causal relationships between observed faults, diagnostic test outcomes, and underlying causes of failure. The structure of the BN is derived from technical documentation and expert knowledge, while its probabilistic parameters can be estimated from historical maintenance data, when available.

Subsequently, the user introduces the available evidence into the system, such as observed fault indications and test results obtained during the diagnostic phase. The diagnostic reasoning within the proposed DSS provides a probabilistic framework capable of handling the uncertainty inherent in maintenance diagnosis processes. Unlike traditional MRO approaches, which often rely on simple descriptive statistics or depend heavily on the individual experience of technicians, BNs () allow reasoning under uncertainty to be formally structured through the graphical representation of dependency relationships between observable symptoms, test results, and possible root causes. This capability is particularly relevant in the aviation context, where the high complexity of systems and the diversity of failure modes may lead to different interpretations among maintenance professionals.

Following the work of Dinis et al. (2019), the development of BN models may be performed through a structured methodology. In an initial phase, the diagnostic objectives are defined, and the relevant variables of the model are identified. These include information variables, such as observable failure codes, and hypothesis variables representing potential failure causes that are not directly observable. Based on these variables, the qualitative structure of the network is defined as a Directed Acyclic Graph (DAG), representing the causal relationships between system conditions, symptoms, and failures. This structure is constructed manually using knowledge extracted from technical manuals and the expertise of domain specialists, ensuring that the model reflects the functional and physical logic of the system components.

In addition to the qualitative structure, the model includes a quantitative component represented by Conditional Probability Tables (CPTs). These tables are populated through parameter learning using historical maintenance data. For this purpose, the Expectation–Maximization (EM) algorithm is often used, as it allows the estimation of probabilities even when the available data is incomplete or only partially observed (Lauritzen 1995). Thus, the probabilities associated with the relationships in the network reflect patterns observed in real maintenance occurrences.

The resulting model allows inference to be performed in both directions. On the one hand, it is possible to predict the effects resulting from known causes. On the other hand, and particularly relevant for the troubleshooting process, the system can perform abductive diagnosis by estimating the probability of possible root causes based on partial evidence entered by the technician. These observations are treated as evidence within the BN. Through Bayesian inference, the system computes the posterior probabilities of the possible failure causes given the observed evidence.

The outcome of the inference process is a ranked list of probable causes, each associated with a quantitative confidence level. These causes are then linked to the corresponding corrective maintenance actions defined in the knowledge base. By prioritizing causes and actions based on probabilistic reasoning, the DSS supports maintenance personnel in selecting the most appropriate and effective intervention.

Finally, the performance of the network is validated iteratively by comparing the model's predictions with real maintenance scenarios. This validation process ensures that the ranking of probable causes and the actions recommended by the DSS are statistically supported and technically consistent with domain knowledge (Pitchforth and Mengersen 2013).

5. Conclusions

This article proposes a theoretical and methodological framework for the development of a DSS applied to failure diagnosis and maintenance actions prescription within the context of aviation maintenance troubleshooting. Based on a literature review focused on DSS, failure diagnosis, and decision-making under uncertainty, the growing relevance of structured and integrated approaches to support decision processes in complex and highly regulated technical environments was highlighted.

The literature review identified a gap in the explicit integration between tacit expert knowledge, formal deterministic information found in maintenance manuals, and probabilistic information derived from historical maintenance data. In this context, a hybrid DSS is proposed, designed to integrate these three information sources to assist technicians in identifying the most likely root causes and selecting the most appropriate maintenance actions. The system is positioned at a critical stage of the troubleshooting process, acting as a decision-support tool during moments of high uncertainty and operational impact.

The proposed case study allows for the conceptual and operational framing of the system within the real flow of aviation maintenance operations, highlighting its potential contribution to improving diagnostic accuracy, increasing decision consistency, and strengthening the traceability of maintenance actions. It is important to emphasize that the system is not intended to replace the technical judgment of professionals, but rather to serve as a complementary decision-making support instrument.

As future work, the effective development and implementation of the envisioned DSS is planned, followed by validation on a real aviation MRO environment. Additionally, integration with existing maintenance management systems, the expansion of the historical database, and the incorporation of more advanced probabilistic models constitute promising lines of research. These developments may contribute to the ever more required digital transformation of MRO processes and the continuous improvement of reliability and safety in aviation maintenance.

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