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The application of reasoning to aerospace Integrated Vehicle Health Management (IVHM): Challenges and opportunities

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ABSTRACT

This paper aims to discuss the importance and the necessity of reasoning applications in the field of Aerospace Integrated Vehicle Health Management (IVHM). A fully functional IVHM system is required to optimize Condition Based Maintenance (CBM), avoid unplanned maintenance activities and reduce the costs inflicted thereupon. This IVHM system should be able to utilize the information from multiple subsystems of the vehicle to assess the health of those subsystems, their effect on the other subsystems, and on the vehicle as a whole. Such a system can only be realized when the supporting technologies like sensor technology, control and systems engineering, communications technology and Artificial Intelligence (AI) are equally advanced. This paper focuses on the field of AI, especially reasoning technology and explores how it has helped the growth of IVHM in the past. The paper reviews various reasoning strategies, different reasoning systems, their architectures, components and finally their numerous applications. The paper discusses the shortcomings found in the IVHM field, particularly in the area of vehicle level health monitoring and how reasoning can be applied to address some of them. It also highlights the challenges faced when the reasoning system is developed to monitor the health at the vehicle level and how a few of these challenges can be mitigated.

1. Introduction

A study in 2018 by International Air Transport Association (IATA)'s Maintenance Cost Task Force documents that the aerospace industry spent $76 billion for Maintenance Repair and Overhaul (MRO) of commercial aircraft in the financial year 2017 and this is expected to go up to $118 billion by 2027 [1]. It is a well-known fact that the MRO costs make up to 10% of the overall operation costs of an airline. Owing to the increased autonomy and the resulting complexity in aircraft systems, industries are investing heavily in health management systems to improve their Condition-based Maintenance (CBM) programs. This would help in increasing the availability and dispatch reliability of the aircraft, reduce the MRO cost significantly, and also avoid any unplanned downtime or accidents. Integrated Vehicle Health Management (IVHM) is a technology that offers a paradigm shift in support of CBM. IVHM was initially introduced by the National Aeronautics Space Administration (NASA) in 1992, as a technology to collect data, diagnose, predict, mitigate the faults, and support the operational decisions and post-operational maintenance activities of space vehicles [2]. Ever since, IVHM has been expanded to other vehicles like aircraft, ships, and automobiles. The current version of IVHM encompasses many roles throughout the lifecycle of a vehicle as a product and process, from the beginning idea or business proposition, going through design, development, testing, analysis, until the long last stage of after-sales service [3]. IVHM aims to ensure that the host system functions as it is intended, without failure, thus increasing the availability of the systems, and reducing the cost and time involved due to unplanned maintenance activities. To achieve this, IVHM aids the use of data from the host systems, not only for the purpose of diagnosis and prognosis that help CBM but also for optimizing the troubleshooting activities. For this purpose, IVHM makes use of emerging technologies in the fields of sensor technology, systems and control engineering, communications technology, and Artificial Intelligence [2]. This paper focuses on the growth and the challenges in aerospace IVHM with respect to the field of AI, particularly the technology of reasoning.

1.1. Background

This section presents the growth of aerospace health monitoring which includes both spacecraft and aircraft, with respect to AI technologies. Fig. 1 shows the timeline comparison of widely used technologies in the field of AI since the 1980s versus the AI technologies used in aerospace IVHM in that particular timeframe. In Fig. 1, the technologies in the general AI field are mentioned only for comparison

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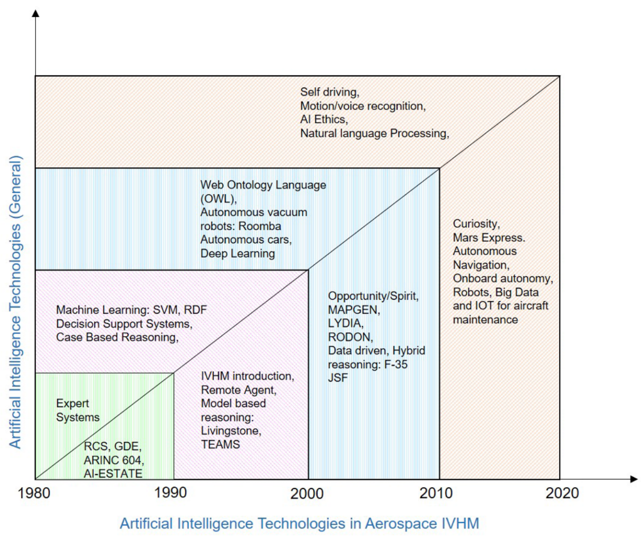

Fig. 1. Trend of AI technologies in Aerospace IVHM versus general AI technologies.

purposes and are not discussed in this paper; further reading can be found in these references [4,5]. This section discusses only the technologies used in the aerospace IVHM field with respect to AI.

1.1.1. Spacecraft health monitoring

While the goal of IVHM with respect to the spacecraft health monitoring is to improve the reliability of space transportation [6], it also aims to play an advisory role for providing reliable contingency management [7]. The spacecraft health monitoring system has to ensure that the mission objectives are met with respect to the constraints and the spacecraft is protected from failures that could lead to the loss of operation [8]. To achieve these objectives, the spacecraft health monitoring system has used a variety of AI technologies. In fact, the trend of technologies used for the Spacecraft health monitoring systems, show a correlation with the trends in the technologies used in the field of AI, wherein, those AI techniques that are introduced and matured over a few years are implemented in the aerospace IVHM field in the next few years. The examples of this correlation can be seen in Fig. 1. It shows that considering a timeline starting from the 1980s, rule-based expert system was the widely used AI technology. During this time period, technologies like the expert system for scheduling, NAVEX [9], and the Procedural Reasoning System (PRS) for health monitoring Reaction Control System (RCS) [10] were developed in aerospace. Moving to the 1990s, after the ‘AI Winter’ when the expert system was reaching its bottom, the focus turned to developing other technologies like Decision Support Systems (DSS) and improving the related fields like machine learning. While AI techniques like neural nets and evolutionary algorithms are in use for a long time, the other machine learning algorithms like Random Decision Forests (RDF) and Support Vector Machines (SVM) were introduced only in the mid-90s [11,12]. Model-based reasoning was being widely used in the ‘90s in aerospace industry, influenced by the General Diagnostic Engine (GDE) that was presented by de Kleer in 1987 [13]. In 1999, Remote Agent, developed by NASA, was the first fully autonomous AI system used in a spacecraft which included a model-based reasoning system (Livingstone) and a DSS [14]. Similarly, TEAMS is a model-based diagnostic tool that was used for ground-based diagnostics of power distribution systems in International Space Station [15]. In the 2000s, when the AI field started focusing on robotics, speech recognition, deep learning, and autonomous vehicles, the aerospace IVHM focused mainly on model-based reasoning engines. As a result, RODON, LYDIA, and several other reasoning engines were developed in the 2000s. The aerospace field also focused on sending rovers to the planet Mars, leading to launch of the Mars Exploration Rovers Spirit and Opportunity in 2003. These rovers had a DSS, namely, MAPGEN (Mixed Initiative Activity Planning Generator) that carried out automated constraint-based planning, scheduling, and temporal reasoning for the rovers [16]. In this decade of 2010s, there is a further increase in the development and applications of space robots, especially the Mars Exploration rovers like Curiosity and Mars Express. The focus in space transportation shifted to autonomous navigation and onboard autonomy via Fault Detection Isolation and Recovery systems [8], whereas the focus in AI field is on motion recognition, natural language processing as well as self-driving vehicles.

1.1.2. Aircraft health monitoring

In the aircraft industry, the main goal of IVHM is to reduce MRO costs and increase the availability of aircraft by enabling integrated health monitoring and supporting CBM. As for the timeline, since the operation of aircraft and its maintenance go hand in hand, the evolution of aircraft design and operations naturally led to the periodically updated maintenance programs. Besides, development in the field of aircraft maintenance is in line with the stabilized AI technologies at that period, similar to spacecrafts (Fig. 1). The earlier form of troubleshooting involved testing the circuit for continuity in the mechanical-analog devices of aircraft systems, and in the 1980's technologies moved towards digital systems leading to electronic testing of the Built-In Test (BIT) circuit to detect faulty Line Replaceable Units (LRU) [17]. The first formal standard for health monitoring, ARINC-604, ‘Guidance for Design and Use of Built-in Test Equipment’, was formulated in 1988 [17] and the guidelines for using matured AI techniques in diagnostics systems was provided in 1995 by IEEE standard 1232 AI-ESTATE (Artificial Intelligence- Exchange and Service Ties to All Test Environments) [18]. Moving to the early 90s, Centralized Maintenance Computers (CMC) were developed for B747 aircraft to diagnose the health of multiple LRUs. These CMCs were initially implementing AI technologies like rule-based expert systems and then evolved to apply model-based failure propagation techniques in B777s in the later 90s, similar to the spacecraft model-based reasoning techniques as shown in Fig. 1. The maintenance systems like Honeywell Prime Epic Aircraft Diagnostic Maintenance Systems (ADMS) developed in the early 2000s, used modular systems, data-driven approaches for diagnosis and loadable database [17]. In this period, the maintenance systems used AI techniques like Case-Based Reasoning (CBR), and Web of Language (OWL) for troubleshooting activities with the help of historical records. Further, hybrid combinations of model-based and data-driven approaches were widely used in health management programs for F-35 Joint Strike Fighter [19]. The maintenance system in B787 uses model-based diagnostic approaches with loadable databases to isolate faults and carry out model corrections. It uses information from various sources like control and design documents as well as FMEA [17]. The maintenance programs like AiRTHM by Airbus enable real-time monitoring by onboard maintenance systems with the help of web-based technologies and wireless communications [20]. Over the years, several standards like ARINC 624, 664, and 666 were published to help design the onboard health monitoring systems [17], whereas the PHM standards like OSA-CBM provided frameworks to implement CBM systems and the IEEE standards like SIMICA provided support for PHM systems to use historical data for diagnostics and prognostics [18]. It is to be noted that the focus in IVHM systems which were earlier at the LRU level is able to move towards the subsystems/systems level owing to the advancement in sensor technology, data analytics, communication protocols, and computing power.

In the present decade, the IVHM field is taking advantage of cloud-based computing and big data analysis for improving real-time health monitoring. Moreover, the aerospace industries like Rolls Royce are attempting to use robotics to inspect the systems and assess the need for maintenance [21], in order to save time that would otherwise be spent for repair and overhaul.

1.2. Need for Vehicle Level Health Monitoring

In the previous section, it was discussed that the focus of IVHM systems is moving from the LRU level to the Systems level due to the advancement in supporting technologies. This is because the main goal of IVHM is to ‘integrate’ information from all the systems of a vehicle and to make a well-informed decision on maintenance considering the health of the systems. According to the FAA report on General Aviation Safety 2018, 2 out of 10 leading causes of fatal accidents between 2001 and 2016 were due to System component failure [22]. In spite of the preventive and periodic maintenance, there are several occasions where a system still fails on its own, or due to its interaction with other systems, leading to extended downtime and added maintenance cost, if not, accident. For example, a Boeing 777-200 ER had an engine rollback in 2008, because of which the aircraft touched down 300 m short of the pavement path in the runway. The root cause, however, was found to be in the fuel oil heat exchanger, where a restriction due to the formation of ice has reduced fuel flow to both the engines resulting in reduced pressure ratio [23]. Incidents like this emphasize the importance of having a holistic view of aircraft systems, instead of performing analysis only at the component and the subsystem levels. While the state-of-the-art IVHM system ADMS in B777 can capture the cascading faults due to the interactions between the components, it uses an expert-derived fault propagation model as a systems reference model [24]. Any unexpected fault propagation could not be captured by this system and a complete IVHM system could not be fully realized. There is still a lack of health monitoring systems that could function at the vehicle level to detect and isolate faults, that cascade between the systems before it is too late. In order to identify the root cause of a fault that has affected another system and predict its cascading effect, the health monitoring system needs to reason through data from multiple systems in a vehicle, consider the causal relationships of the systems, assign priorities, and resolve conflicts. In short, the IVHM system requires an intelligent reasoning system that could analyze and make decisions regarding any system fault, its root cause and the effect at the vehicle level.

With this purpose in mind, the paper explores the AI reasoning technology. This section gave an overview of IVHM over the years and the need for vehicle health monitoring and Section 2 aims to answer the basic questions like what is reasoning, where is it applied, and how does it function. Section 3 summarizes the applications of reasoning in aerospace IVHM and Section 4 discusses the shortcomings in IVHM, the ways to mitigate them with reasoning, along with the challenges and opportunities. Lastly, Section 5 concludes the paper.

2. Reasoning – a literature review

In general, the term ‘reasoning’ is a derivative of human reasoning, where the methodology for problem-solving is governed by applying logic and cognition. The origin of reasoning as a study traces back to Greek Philosophy. Aristotle coined the term ‘Syllogism’ which is the study of logic that defines the rules for reasoning to operate [25]. Reasoning is applied in every existing field, to tackle everyday problems. Reasoning can be as simple as deductions like ‘a = b, b = c and hence a = c’, or as complicated as a combination of multiple strategies, based on the problem to be solved. To align with the scope of this paper, the literature review on reasoning restricts itself to the field of engineering. Even a short survey on the functions of reasoning in engineering results in a wider range of industrial applications.

Fig. 2 shows a representative sample of various functions of reasoning as an AI technology and their applications in different sectors. The first layer from the centre shows the different problem fields where reasoning is applied; this includes, but not limited to, diagnosis, scheduling, reporting, decision support, troubleshooting, behavioral analysis, strategy planning, optimization and context awareness. The second layer shows their respective applications in the industries and the outer layer shows the corresponding industries. This non-exhaustive

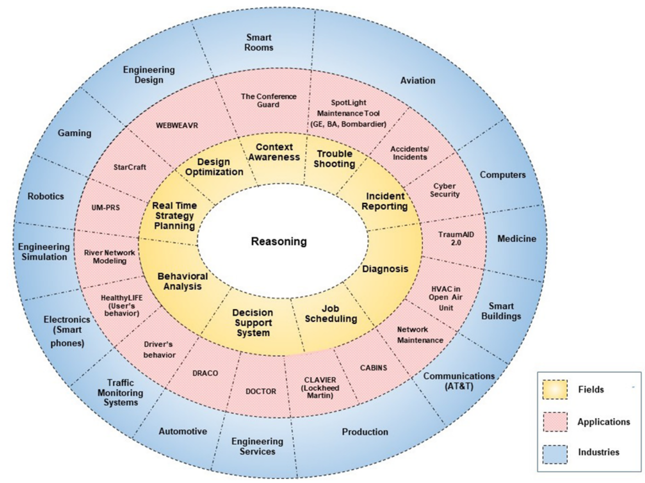

Fig. 2. Applications of reasoning in engineering.

list of industries that employ reasoning encompasses aviation, medicine, gaming, robotics, traffic monitoring, design, simulation, production, services, communication, electronics, automotive, computers, smart rooms, and smart buildings. The applications in the middle layer that are developed to solve the problems shown in Fig. 2, use different types of reasoning methods and reasoning systems to achieve their respective goals. For example, tools like SpotLight Maintenance developed for troubleshooting in aircraft engines [26], the expert system DOCTOR developed for field service of air conditioners [27], the scheduling system CABIN [28], and the decision support system CLAVIER developed by Lockheed Martin [29] use Case-Based Reasoning (CBR) systems. The CBR systems are also used for incident reporting for aircraft accidents [30] and cybersecurity threats [31]. Similarly, Rule-Based Reasoning (RBR) is used in the context-aware application for a smart room, namely, The Conference Guard [32], and in the goal-driven diagnosis application, namely, TraumAID 2.0 [33]. The UM-PRS is a Procedural Reasoning System (PRS) that is designed for robotic reconnaissance task [34].

Apart from CBR, RBR, and PRS, there are other reasoning methods which are used for solving various problems in the industries as shown in Fig. 2. WEBWEAVR developed for design optimization is a Bayesian reasoning engine [35]. DRACO, an Intelligent Decision Support System (DSS) used a fuzzy reasoning, along with neural network models for the quality control process of automotive coating operations [36]. HEALTHYLIFE, used in smartphones for recognizing user behaviors, applies Answer set programming based Stream Reasoning along with Artificial Neural Networks [37]. A Model-Based Reasoning with mathematical modeling is used to represent a river network model for simulation of water quality control [38]. A Real-Time Strategy video game, Starcraft, extensively uses several reasoning methods including CBR, Neural Networks, and Bayesian Models for tactical decision making as well as strategic planning [39]. Furthermore, reasoning methods are used to infer the driver's behaviors during traffic in traffic monitoring systems [40]. A hybrid reasoning system with model-based and Tree Augmented Naïve Bayesian Network has been used to diagnose and find anomalies in the Open-Air Unit installed in a smart building, like a public health centre, in order to increase air quality and reduce Heat and Ventilation and Air Conditioning costs [41]. Dynamic Mental Models (DM2) used analytical model and pattern recognition rules and have been tested by applying hypothetical diagnostic reasoning on expert systems for networks maintenance at AT&T [42].

2.1. Definitions

It is to be noticed from Fig. 2 that, in the applications presented, reasoning is implied both as a problem-solving strategy as a part of another system, and as a system in itself. This difference can be better explained with defining the terminologies 'reasoning strategy', 'reasoning system', 'reasoner' and 'reasoning'. While the term 'reasoning strategy' refers to the approach with which the data is assessed in a certain way, a 'reasoning system' refers to a software system that applies reasoning strategies in an 'input-process-output' manner to achieve the specified goal. The term 'reasoner' is used in literature many times referring to the reasoning system [43] and sometimes to the algorithms that carry out reasoning [44]. To avoid confusion, in this paper, 'reasoner' refers to the reasoning system itself. Finally, the term 'reasoning' itself refers to the process of analyzing the given data using reasoning strategies and other algorithms in order to achieve the goal of the reasoning system or any system that the reasoning is a part of. The next sections further explore the commonly used reasoning strategies as well as the reasoning systems in the field of aerospace IVHM.

2.2. Reasoning strategies

Several reasoning strategies are applied in the general problem-solving systems. In the case of health monitoring systems, reasoning helps in achieving the goals of diagnosis and prognosis, which is to detect and isolate the fault and to estimate the Remaining Useful Life (RUL) respectively. These systems can use one or a combination of the reasoning strategies to reason through and reach their goals. Table 1 presents the different types of reasoning strategies, along with illustrations from health monitoring systems. Each reasoning strategy has a different way of approaching a problem depending upon the type of data available. For example, if the given set of data is definitive but small, inductive reasoning will help in projecting or predicting the generic observations, whereas, in the case of abundant data and a certain hypothesis, deductive reasoning will help in drawing the conclusions. If the given data is insufficient or incomplete, abductive reasoning will form and test hypothesis based on the incomplete dataset, whereas, analogical reasoning will draw conclusions based on similar experiences from other cases. Likewise, depending on the type of data, if the data possess time information, temporal reasoning could be chosen for problems like timestamp comparison, whereas for data with statistical information, statistical reasoning can be used. Causal reasoning draws conclusions based on the cause-effect relationship of the data and approximate reasoning is applied in the cases that require less computational time.

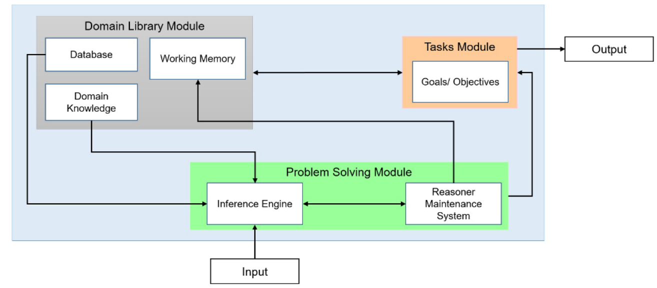

Fig. 3. The architecture of a generalized reasoning system.

2.3. Reasoning system – a generalized architecture

A reasoning system is a piece of software that implements reasoning strategies, alongside other problem-solving techniques to achieve certain objectives with the help of available knowledge. A generalized reasoning system architecture, shown in Fig. 3, has a basic set of components which can be adapted to address particular goals based on the existing resources. The general components of a reasoning system can be grouped under three modules (Fig. 3): i) Domain Library module, ii) Problem-Solving module, and iii) Tasks module. The Domain Library module contains domain knowledge, the database of the application, and the working memory. The database includes the data of the measured inputs and outputs of the system using which, reasoning will be carried out, and the domain knowledge consists of knowledge about the system represented in a certain format. The dynamic knowledge specific to the problem is stored in the working memory. In the Problem-Solving module, the components include i) an inference engine (also referred to as reasoning engine) which performs the action of reasoning based on the methodology chosen and the type of available data, and ii) a reasoner maintenance system which communicates with the inference engine to maintain consistency of the belief or truth of the system. The reasoner maintenance system can be either assumption based or justification based [45].

The Tasks module of the reasoning system contains its objective or goal for a given problem. The reasoning system can deal with problem types like i) Constraint Search Problem (CSP), and ii) Planning and Decision Making [30]. CSP is a data-driven problem, where the problem is solved with an assumed set of variables and a defined set of constraints; variables get updated in every iteration with respect to the constraints to search for the solution in the solution space. Diagnosis

Table 1
Reasoning strategies.

	Strategy	Features	Examples
1	Inductive Reasoning or induction	A bottom-up approach which makes a set of generic projections from observations or data.	Inductive Monitoring System on TACSAT-3 detects anomalies by supervised learning with the help of a model constructed from nominal data [130].
2	Deductive Reasoning or deduction	A top-down approach wherein, a certain solution is found from the given premises by holding the hypothesis true.	Livingstone is a model-based reasoner in Remote Agent and it uses deductive reasoning. It draws conclusions based on the given commands and comparing the corresponding observations with the optimal responses [14].
3	Abductive Reasoning or abduction	A logical reasoning which constructs and tests a hypothesis based on the observations even if they are incomplete	As a part of the reasoning process patented by GE, the Advanced Diagnostic and Prognostic Reasoner uses abductive reasoning to construct a minimum set of fault conditions to associate with ambiguity groups [142].
4	Analogical Reasoning	Uses past experience to provide new conclusions by analogy	An intelligent maintenance support system for aircraft is developed using Genetic Algorithm and Case based reasoning (CBR) which retrieves the similar past cases by analogy [113].
5	Temporal reasoning	Helps to the reason of dynamic systems by considering time as an additional dimension	In the integrated prognostic reasoner developed for bearings, temporal reasoning is used to integrate a priori reliability information and correct the disagreement of the information source, with respect to time [150].
6	Statistical reasoning	Uses statistical information of data sets.	Statistical Reasoning is used with fuzzy inference algorithm to develop a DSS [101].
7	Causal reasoning	Uses the relationship between the causes and their effects to draw conclusions	The data driven model developed to detect pipeline leak uses causal inference to find the pattern between the antecedents like flow difference and pressure difference to the consequent, leak size [70].
8	Approximate reasoning	Speeds up the process of finding a solution by sacrificing its completeness	The approximate reasoning is used with a Belief Rule Based methodology to reduce the complexity of the causal inference model for detecting pipeline leak [70]

and classification problems are of the CSP type, as their constraints are defined as fault symptoms, and classification group characteristics respectively. Planning and Decision Making is a goal driven problem, where the initial conditions and possible final solutions are pre-defined and the problem is driven in a certain path by applying rules to attain the defined goal.

To illustrate the functioning of a reasoning system, consider a scenario of isolating a fault in a fuel system that operates under a constant fuel flow. In this case, the goal/objective of the reasoning system is to isolate the fault. The domain library will consist of a database of the fuel system like sensor data of the parameters that are monitored for the health of the fuel system. It will have the domain knowledge consisting of relationships between the monitored parameters and fault signatures of various faults. In this case, once an anomaly is fed as an input, the inference engine will search the database with the help of fault signatures to match the input anomaly with the fault signature in the database. The working memory will keep track of the transition states of the system when the problem is being solved. The reasoner maintenance system helps in keeping up with the consistency of the truth or the assumptions of the system, in this case, a constant fuel flow. Hence in the case of contradicting truths, the reasoner maintenance system updates the working memory. The inference engine communicates with the reasoner maintenance system to check the assumptions and uses different reasoning strategies and algorithms appropriate for this problem to derive the required solution. The output can either be the 'name of the fault' in case of a fault known to the reasoning system already or 'Not found' in the case of a new fault.

2.4. Types of reasoning systems

There are different types of reasoning systems depending upon the availability of domain knowledge, data, and the chosen problem-solving methodology. The knowledge-based systems use domain knowledge that is derived from the experts, the model-based reasoning systems use domain knowledge that is derived from the governing equations or behavior of the systems and the data-driven reasoning systems are used when there is lack of domain knowledge and reasoning is dependent mainly on the datasets. This section presents different reasoning systems, various types of knowledge representation and problem-solving methodologies they use. Several review papers discuss in depth about the problem-solving methods used for diagnosis and prognosis [15,46–54], only a few methods are discussed in this section.

2.4.1. Knowledge-based systems

The knowledge-based systems carry out reasoning based on the existing knowledge base. This knowledge can be anything like procedural or declarative, structured or unstructured and are represented in such a way that the reasoner understands. In general, the knowledge can be represented in the form of a concept, its intent, and the context. The Concept is the basic unit of knowledge, providing the abstraction of real-world things. Concepts have an association with other concepts which give context of the knowledge. Concepts and its associations can be represented using any of the technologies like Rules, Procedures, Frames, Nets, Models, Ontologies, and Scripts, based on the intent of knowledge, which is the ability or the skill required to achieve the goal [55]. Some of the knowledge-based systems are discussed here and Table 2presents the comparison of advantages and disadvantages of these systems.

2.4.1.1. Expert system. The Expert System architecture consists of a knowledge base and an inference engine (Fig. 4). Its knowledge is generally represented in terms of rules. Rules represent domain knowledge in an 'if-then-else' format and they can be written in different programming languages like C, LISP, and OWL. For example, in the CLIPS expert system used by Siemens, rules are written in OWL 2 language in the format of concept-ontology and instance-ontology [56]. In some cases, frames are also used to represent the knowledge in expert systems. Frames are used to represent the stereotyped knowledge as a collection of attributes and their associated values. An example is the meteorological vehicle system, wherein the expert system for fault diagnosis is built using object-frame structure, with the frame being a collection of state-object, test-object, rule-object, and repair-object [57]. Most Expert systems employ Rule-Based Reasoning (RBR) methodology to solve their problem. The RBR is executed in the following two ways: i) Forward Chaining, and ii) Backward Chaining. Forward Chaining starts with the initial state of facts and applies the rules until the endpoint is reached. Backward Chaining starts from a hypothesis and looks for rules that will allow the hypothesis to be proven. In other words, it starts with an effect and looks for the possible root causes that could lead to that effect. Forward Chaining is data driven whereas Backward Chaining is goal driven [58].

The Expert System is one of the initial implementations of AI software, with DENDRAL and MYCIN being two of the earliest rule-based expert systems developed for analyzing chemical components and for diagnosing infectious diseases respectively [59]. Expert System was popular in the 1980s and it has been implemented for several health monitoring and maintenance systems. However, it could not sustain the growing demands of the field. While expert system required straightforward implementation, its knowledge base is dependent on the experts and hence, brittle and needed frequent maintenance. It could not provide intuitive results and incurred high computational costs [60]. Furthermore, the expert system could not handle the dynamics and uncertainty involved in the aerospace models [46]. Hence, it was integrated along with other frameworks like in Blackboard architecture in BEST (Blackboard-based Expert System Toolkit) [61] to enhance performance of the application. It is used along with model-based methods as well. An example is the expert system patented by GE that applies model-based reasoning for diagnosing faults in rotary machines. In this system, the model is represented by partial differential equations based on their first order; the vibrations measured were used by the rule-based expert system to identify the root cause [62].

2.4.1.2. Procedural Reasoning System (PRS). The PRS is a knowledge-based reasoning system which has its knowledge in the form of procedures called the Knowledge Areas. The PRS implements the Belief-Desire-Intention concept of modeling for real-time reasoning of dynamic systems [10]. It consists of the following modules (Fig. 5): i) a goal or objective set, ii) a database with domain knowledge and beliefs that update themselves with new knowledge, iii) a knowledge area which is a library of procedures for actions and tests to achieve the goals, iv) an intention graph which has partially completed procedures to run real-time, and v) an interpreter which communicates with all these modules and carries out reasoning. The interpreter receives the goal or objective for the system, chooses the correct procedure required from the knowledge area, places it on the intention graph to narrow down the set of actions, chooses the correct action based on the intention, and finally starts the procedure which will update the next goal [10]. Fig. 5 shows the general architecture of the Procedural Reasoning System [10]. The PRS has been applied to monitor the malfunctioning of the RCS of NASA's space shuttle and also to diagnose and control the overloading of telecommunication networks [63]. The PRS architecture is simple for execution and reduces the computational time as the procedures can skip unnecessary steps for a particular problem, and narrow down rules to the relevant set directly [63]. The PRS can implement real-time reasoning and handle dynamic systems, but it can handle only simple plans; any changes to the existing plans and procedures will be time-consuming and tedious.

2.4.1.3. Case-Based Reasoning (CBR) system. The CBR has its knowledge derived from the historical cases. It has a simple framework consisting of four phases: i) retrieve, ii) reuse, iii) revise,

Table 2
Advantages, Disadvantages, and applications of Knowledge-based reasoning systems.

Reasoning Systems	Advantages	Disadvantages	Applications
Expert System	Easy to implement (straight forward) Transparent	Extrapolation not possible The system needs to be updated frequently Depends on expert knowledge – brittle Computationally expensive	DENDRAL [59] MYCIN [59] CLIPS [56]
Procedural Reasoning System	Real Time and meta level Reasoning Simple Semantics Can act upon partial plans	Indexing mechanism makes it difficult to delete or change rules Tasks have to be kept short Needs updating if plans are changed	RCS in NASA Space shuttle [10] Robotic reconnaissance [34]
Case Based Reasoning System	Simple to use Problems that cannot be expressed mathematically can be dealt with Learning capacity – knowledge evolution possible Flexible architecture	Depends only on historical information Time-consuming Retrieval process needs powerful algorithm to get exact match	IDS [124] ISAC [65]

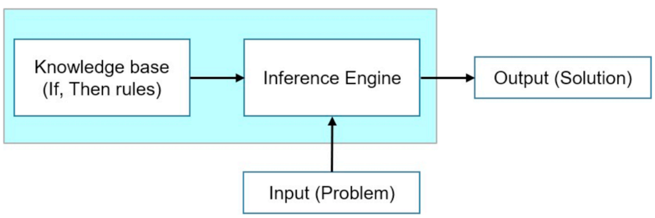

Fig. 4. Expert System Architecture [60].

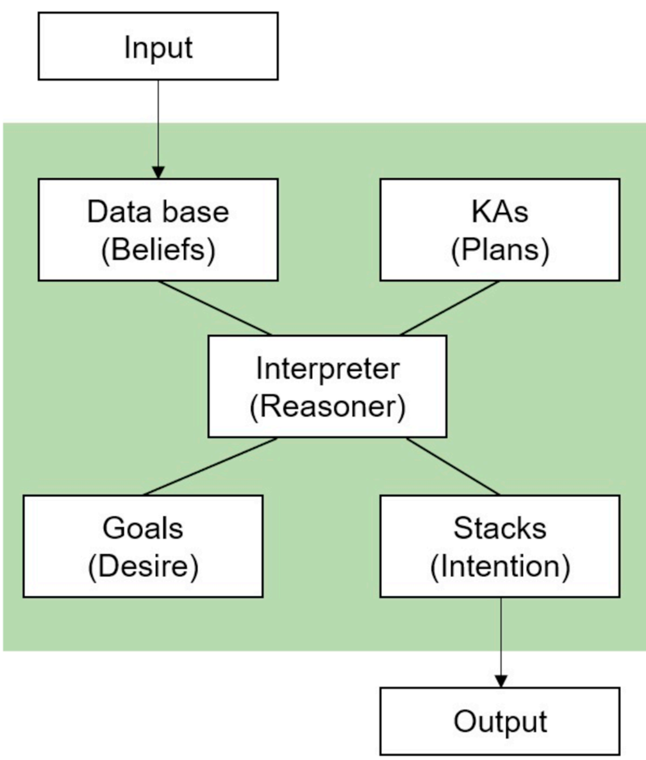

Fig. 5. Procedural reasoning system (PRS) architecture (adapted from Ref. [10]).

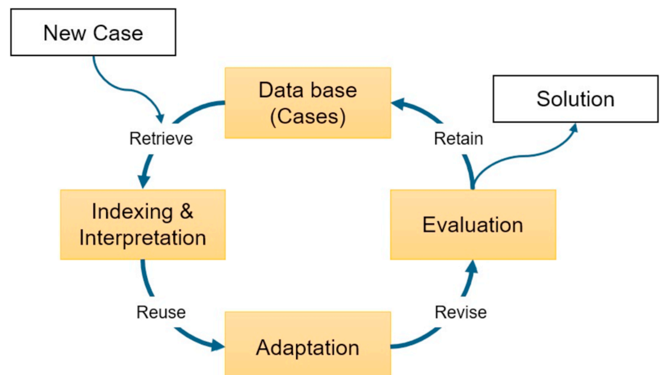

Fig. 6. Case based reasoning architecture (adapted from Ref. [64]).

and iv) retain (Fig. 6). In the retrieval phase, knowledge in the database (case repository) in the form of previous experiences and histories (cases) related to the application are searched for. These old cases are then retrieved based on their index and interpreted for the current problem. In the reuse phase, the old cases are adapted to the present situation in order to find the solution. Evaluation of the new cases is carried out and solutions suggested in the revise phase and the new cases are then added to the case repository for future learning, as a part of the retain phase [64]. One of the examples of CBR application is Intelligent Systems for Aircraft Conflict Resolution (ISAC) [65] which was developed to help the decision-making process of aircraft controllers to resolve the conflicts between aircraft. CBR is one of the most commonly used reasoning systems, as its architecture has the capability of accommodating any advanced algorithms, mainly text processing techniques. Moreover, CBR does not require prior knowledge about the system as it solely depends on past experience. Since the CBR involves learning as a part of its methodology enabling knowledge evolution, the CBR can evolve and become expert in the domain, thus having the potential of becoming the future expert systems [66]. This is an advantage over the other frameworks since the other reasoning systems require maintenance time for updating the knowledge base. Nonetheless, the CBR system is computationally demanding when compared with the PRS and simple rule-based Expert Systems.

The knowledge from historical records or cases can be represented in a variety of graphical representations. One such method, Semantic nets, are used for representing the relationship between the concepts that are usually described with verbal information. Knowledge is extracted by mining text with a defined set of rules and finding relationships between the phrases, and it is represented in accessible formats like tables or matrices. Semantic nets are used in CBR in cases like searching the maintenance repair records to find similar cases [67]. They can also be used for text mining the datasets to find anomalies [68]. Dependency Matrix or D-Matrix [69,70] is a commonly used representation in the field of diagnosis as well. It consists of dependency/causal models represented in the form of a matrix using the logical relationship between the elements. D-matrix is used in CBR to represent the relationship between the tests and diagnosis, where a case is a collection of test results that are mapped to the appropriate diagnosis based on its results. Thus when a new case or test result is given, similar cases are retrieved and the corresponding diagnosis is chosen [69].

Apart from Semantic nets and D-Matrix, there are several other graphical methods that can be used for historical knowledge representation. These methods can as well be used to represent the knowledge of model-based systems and the apriori knowledge of data-driven systems.

2.4.2. Model-based reasoning systems

Model-based reasoning systems are used when there is a rich domain knowledge about the system. Its knowledge i.e., the concepts and their relationships to the other concepts are represented based on their physics-based or functional relations [71]. For example, NASA developed a physics-based model for diagnosis of the Liquid Hydrogen Propellant Loading System, as it requires a detailed model for understanding the system under healthy and faulty conditions, enabling quick detection and recovery, in case of failures [72]. On contrast, a fuel system was represented by a functional model in MADe, in which, the functional flow in terms of energy, material, and signal between the components. This model differentiates nominal cases from faults and helps in isolating the identified faults [73].

The theory of Model-Based Diagnosis was first formulated and applied in a General Diagnostic Engine by de Kleer [13]. This framework used a diagnostic reasoner to identify behavioral discrepancy between the model and the observed value and it made use of the assumption-based truth maintenance system to achieve efficiency. Ever since, a lot of methods have been developed for representing and solving the model-based problems efficiently. Presently, the model-based reasoning uses both qualitative and quantitative methods to solve its problems. The quantitative methods involve comparing the output predicted values generated by analytically redundant models, with the measured sensor values from systems to generate residuals. The error can be reduced by solving the algebraic or differential equations for the best set of parameters. Parity equation is a residual generation method which consists of linear equations that link different variables by their mathematical relationships. The deviation in parameters can be found through the residuals and faults can be flagged if the errors cross the set threshold [74]. These equations can also be grouped in a way that, a set of parity equations could represent a diagnostic model and are solved in order to isolate the faults [75]. Developing this model is time-consuming because of the complexity involved. Kalman Filter is another approach for residual generation, which estimates the state of a system in presence of noise and is used widely in diagnostics for its ability to adaptively estimate the state parameters of the degradation model, as time evolves [76]. One drawback of this method is that, it assumes the equations to be linear and noise to be of Gaussian distribution [77]. These drawbacks are mitigated by using derivatives of this method like Particle filters, Switching Kalman Filters, and Extended Kalman Filters [52,76,78].

Among the qualitative methods, Timed Failure Propagation Graph (TFPG) [79] is used for the abstract representation of a system behavior during failure propagation. It is a directed graph consisting of nodes representing the failure modes as well as the possible deviation in system behavior in the form of discrepancies, and the edges that connect the failure modes to their respective discrepancies. TFPG helps in tracing the root cause of a propagated fault as well as the likelihood of further failure progression and it is used widely for representing the complex dynamic systems. TFPG is applied in an embedded systems environment to isolate the faults [80] and a hybrid version of TFPG is applied in the diagnosis of switching systems [81]. Petri-Net, a bipartite graph, is another qualitative model used in model-based reasoning. It is a mathematical modeling language used to represent the relationship between the conditions and the events in a distributed system. It consists of i) nodes representing events or transitions, ii) places representing conditions and containing tokens, and iii) arcs representing the direction of transition from a place (condition). Petri-Net is used for analyzing the dynamic behavior of the system where the firing of a token from one place to another represents the transition taking place in the system. Petri-Net is used in failure analysis in many systems [82,83] and a hybrid version of the Petri-Net, combined with fuzzy reasoning, called Fuzzy Petri-Nets is used for fault diagnosis while dealing with uncertainty [84]. The other commonly used qualitative methods are Fault Tree Analysis and Multi-flow Models. Fault Tree [85,86] expresses the logical relationship between a failure and its possible causes, but it can be modeled only for the expected failures. Multi-Flow Model [87] represents the system and its subsystems in terms of its goals, functions and the networks connecting these functional flows.

2.4.3. Data-driven reasoning systems

Data-driven reasoning methods extract the underlying patterns in the datasets and use them for understanding the systems' characteristics to reason through them. They are generally used in the cases which have rich datasets and have a very little or no domain knowledge itself. This section briefly discusses the most widely used data-driven methods.

Bayesian reasoning uses the estimates based on data from statistics and deals with uncertainty in the system model. The cause-effect relationship between the variables have to be known probabilistically but the entire system model knowledge is not required [88]. The Bayesian Network is a probabilistic graphical model which uses a set of nodes to represent variables of a system and directed edges, the relationships between the variables. It uses Bayes' theorem as its principle to decide the root cause based on a priori probability with respect to the observed value. Conditional probabilities are specified for every node on this network and probability estimates get updated based on every new observed value. The Bayesian Network was first introduced by Pearl in the 1980s [89] and has been widely used for a variety of intents including tacking uncertainties, within the broad field of diagnostics. For example, the Bayesian Network and its derivatives like Dynamic Bayesian Network, and Tree Augmented Naïve Bayesian Network have been applied for fault diagnosis of a fuel system [90], auto-generation of the nets for diagnosis of an Electrical Power System [91], benchmarking of diagnostic systems [92], enhancing existing diagnostic models [93,94], and for change point detection of a valve failure in a fuel system in Unmanned Aerial Vehicle [95].

Fuzzy Reasoning is a data-driven method that deals with uncertainty using Fuzzy Set theory and the theory of fuzzy relations. Fuzzy logic was introduced by Zadeh (1965), in order to describe the systems that are 'too complex or too ill-defined' for mathematical analysis [96]. Fuzzy logic is a three-step process: i) Fuzzification, ii) Evaluation, and iii) Defuzzification. In the first step, the inputs representing a range of variables in overlapping regions are fuzzified by applying membership functions. These functions overlap and hence, there is a possibility of variables belonging to more than one membership. Then, a set of 'IF-THEN' rules (generally known as a deductive form) are applied to evaluate the response to each input. These sets of consequences are then evaluated to give one final output using the aggregation principle. The output is then converted to crisp quantities in the defuzzification stage [97]. Fuzzy Reasoning has been used directly for fault diagnosis in various industries [98,99] or in the derived form combined with Petri-Nets [100], besides developing Decision Support Systems (DSS) [101]. Likewise, Evidential Reasoning is another data-driven method that deals with uncertainty and imprecise information, by handling the evidence to make an assertion. It uses the Dempster-Shafer theory of beliefs which replaces probability distributions with belief functions. This theory is very useful in modeling uncertain conditions where probabilities in subjective judgments can be assigned a base degree of belief. Such degrees of belief can be combined from multiple independent evidence as well. One of the major advantages of Dempster-Shafer is that it enables reasoning with partial or conflicting pieces of evidence [102]. The lack of knowledge on assigning belief to the evidence and the computational complexity has made it a 'difficult to use' reasoning method. Dempster-Shafer reasoning has been used for fault diagnosis [103,104] and for developing the BNs for DSS [105].

Machine learning algorithms are the most commonly used data-driven methods in the current period. Albeit being in existence over several decades, they are used extensively in the recent times, owing to their capability to analyze enormous data sets generated by the industries, and to the aid provided by the increased computing power. One of the most popular machine learning algorithms is Artificial Neural Networks (ANN). ANN is modeled after the biological neuron structure; it is used widely for pattern classification problems of diagnosis and prognosis, because of its ability to infer functions from the observations. A neural network is composed of several layers (mainly the input, hidden and output layers) with interconnected nodes which have activation function and are connected to the network by the weighted edges. Back Propagation Neural Network, a type of ANN, is a multi-layer feed forward network which learns by adjusting the weights and thresholds to reduce the feedback error [106]. Deep learning is a neural network with multiple hidden layers and is helpful in mining the information from big data sets in order to achieve the classification and other goals [107]. The neural networks do not require the background of the data for analysis and use less operational time after training, but their major drawback is their need for big datasets for training the network. K-Nearest Neighbor is another non-parametric pattern recognition algorithm, which clusters a sample to the k nearest subsets from the trained data set based on the majority vote from the k-subsets [108]. Similarly, the Support Vector Machine (SVM) is a classification algorithm which groups the datasets by introducing the boundaries or hyperplanes with a maximum distance of separation [109]. Principal Component Analysis (PCA) is a parametric algorithm which is used to derive the statistical model from historical data. It reduces dimensionality of data by projecting the historical training data onto a lower dimensional space and uses it to study the factors that contribute to the major trends [48]. The Decision tree algorithm uses a divide and conquer approach on the datasets to classify the data space by recursive partition until there is no further splitting possible [109].

The data-driven algorithms include traditional statistical models like Weibull, Normal distributions, Hidden Markov model and Cox Proportional Hazard models. Weibull and normal distributions are used to fit the failure data to predict the time-to-failure [77]. Hidden Markov Model contains the transition and observation probabilities and is used for detection in the stochastic processes where transition is not directly observed [110]. Cox Proportional Hazard model is a powerful regression method that uses hazard function or conditional failure rate function as a baseline, to build predictive models for failure events based on the trigger events. These trigger events can be characterized as anything like a failure or a particular behavior and the model can be used to build a framework that connects the failure mode with its indicator [111].

Fig. 7 shows the Strengths, Weaknesses, Opportunities, and Threats (SWOT analysis) of both model-based and data-driven methods. Though the model-based method can be precise and could be extrapolated, it requires domain knowledge and can be time-consuming. Further, modeling errors and under-modeling are the downsides to this approach. As for the data-driven approach, it does not require detailed domain knowledge and modeling skills, but, it does require immense data and risk misinterpretation of results as well as imprecise outputs. Thus, the choice of problem-solving methods depends on the factors like available knowledge, data, time, and skill.

2.4.4. Hybrid reasoning systems

These systems use a combination of reasoning techniques, applied in order to compensate for the disadvantages the algorithms possess. There are several studies that carried out reasoning by combining different methods. For example, a combination of Artificial Neural network and Fuzzy Inference System (ANFIS) is one of the most used hybrid methods in diagnosis applications [58]. Fuzzy algorithm is used with Bayesian Networks as well, to model the gray-scale health as component degradation for a lithium-ion battery [112]. Another such combination is the Genetic Algorithm that is used with the CBR, to

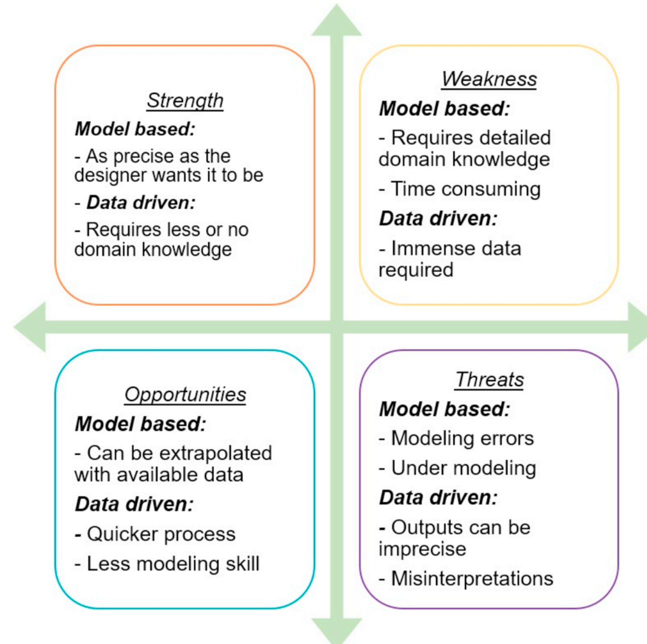

Fig. 7. SWOT analysis on Model-based and Data driven methods.

enhance the retrieval ability of the CBR mechanism for fault diagnosis of electronic ballasts in aircraft [113]. Apart from the combination of multiple data-driven methods, in many cases, data-driven methods are combined with model-based reasoning as well. One example is Abductive Diagnosis through Adaptation of Past Episodes for Reuse (ADAPtER) [114], where a CBR system is integrated with model-based reasoning system in a master-slave architecture, using two knowledge bases, i) solved diagnostics problems in the case memory, and ii) a behavioral model in place of the domain knowledge. Another such combination can be found in the hybrid prognostic model, that was developed using a physics-based model and similarity-based data-driven approach ,in order to carry out short-term predictions as well as RUL estimations in the cases of a clogged filter and fatigue crack propagation [115].

3. Applications of reasoning in aerospace IVHM

As the previous section discussed the different techniques used in the reasoning systems and the various problems that could be solved by reasoning, this section discusses how the reasoning systems are applied practically in aerospace IVHM. It is already known that, the aim of IVHM is to collect and utilize as much useful information as possible to understand the behavior of the systems, to diagnose and predict their health in order to aid CBM. Hence, in aerospace applications, reasoning systems are implemented mainly with the goal of real-time health monitoring, diagnostics, and prognostics as well as the troubleshooting activities. A select few examples of applications of reasoning in these areas are discussed below. Table 3 summarizes the various reasoners developed by different industries for health monitoring in aerospace IVHM.

3.1. By NASA

NASA is a pioneer in the field of aerospace IVHM. Over the years, it has developed several reasoning systems for monitoring the health of its space shuttles, satellites, and aircrafts. Space Health Inference Engine (SHINE) is a reusable expert system used for real-time and non-real-time health monitoring and diagnosis. It consists of a blackboard structure, a knowledge base, and a database; it has high computational

Table 3
Applications of reasoning in aerospace IVHM.

Reasoner	Organization	Used in/Experimented on
NASA		
SHINE	JPL	Deep Space Missions [116]
Livingstone	NASA AMES Research Centre	Deep Space Missions [14]
BEAM	NASA AMES Research Centre	Propulsion IVHM Test Experiment [118]
R2U2 Framework	NASA AMES Research Centre	Electric Unmanned Aerial Vehicle health management program [119]
MAPR	NASA AMES Research Centre, Ridgetop Group, Inc	Anomaly detection and fault classification in the Electro Mechanical Actuator (EMA) [71]
Aerospace OEMs		
AGET	Pratt & Whitney	Aircraft Engines [120]
IOT based ontological reasoning	Siemens	Gas turbines [121]
CONSOLIDATE	Smith Industries Aerospace and Defense, Inc	Aircraft engines [43]
Meta-diagnostic reasoner	Airbus	Centralized Maintenance Systems' knowledge database [122]
Smart TPS	Boeing	Navy/Airforce aircrafts [123]
IDS	For Air Canada	Generic Maintenance Management System [127]
COTS Packages		
RODON	Uptime Solutions AB	Adapt [125]
eXpress	DSI International Inc	Multi-disciplinary applications [127]
TEAMS	Qualtech Systems INC	EMA [128], Naval Shipboard Systems [129], TacSat3 [130]
MADe	PHM Technology	Multi-disciplinary applications [131]
ReasonPro	Impact Technologies	Avionics [132]
Health Management Programs		
Bayesian network top level reasoner	Impact Technologies	Avionics Vehicle Health Management [133].
Ground based reasoner	Boeing	Integrated Diagnostics System [134], Aircraft Electrical Power Systems Prognostics and Health Management (AEPHM) program [135]
Model-based TRANSCEND + Data driven reasoning	NASA	PHM for EMA [136]
Academia		
FACT	Vanderbilt University, and Budapest University of Technology and Economics	Fault diagnosis in aircraft fuel system [137]
LYDIA	Delft University	Implemented in TELEMOS, HMS-RSTS, and Harbour Cranes [138].
PHM reasoner	Cranfield University, IVHM Centre	EPGS Failure prediction [139]
HyDE	University of California, NASA Ames Research centre	Propulsion system in ALDER, EPS in ISS [140]

power and speed that is required for real-time monitoring of deep space missions like Voyager, Galileo, and Cassini [116]. The first fully autonomous AI system in a spacecraft, Remote Agent, has a planning and scheduling AI module, a multi-threaded executive module and its centerpiece is a model-based reasoning software, Livingstone [14]. Livingstone is developed to monitor the overall behavior of a complex system. Livingstone consists of qualitative models for both nominal and off-nominal behaviors and is capable of reasoning through system-wide interactions, thus enabling inference of the effect of any failure over the complex system [6]. Similarly, Beacon-based Exception Analysis for Multi-missions (BEAM) [117], also developed by NASA ,consists of several signal processing modules, which was integrated with Livingstone, where it functioned as a virtual sensor to resolve the ambiguities for multiple fault scenarios in Propulsion IVHM Test Experiment [118]. In this, BEAM was used to detect and isolate a local fault, whereas Livingstone used the BEAM's output as evidence to reason through the entire system, thus complementing each other. NASA developed the Realizable Responsive Unobtrusive Unit (R2U2) framework, in order to improve the diagnostic capability in an electric Unmanned Aerial Vehicle health management program. The R2U2 framework was adapted to use the prognostic information derived from a Bayesian Network to improve diagnostic accuracy [119]. Another reasoner, namely the Model-based Avionic Prognostic Reasoner (MAPR) [71] is capable of real-time monitoring, processing as well as reconfiguring the model, based on the system's health and it was used for anomaly detection and fault classification in the Electro Mechanical Actuator (EMA).

3.2. By aerospace OEMs

Several Original Equipment Manufacturers (OEMs) of aircraft industry have developed their own reasoning systems and a combination of strategies to aid their maintenance programs. For example, Automated Ground Engines Test Set (AGETS) Model-Based Reasoner developed by Pratt & Whitney uses an AI tool called Qualitative Reasoning System, to run diagnostics tests and isolate failures using a troubleshooting approach involving F100-P100/200 gas turbine engines [120]. Siemens uses the Internet of Things (IoT) architecture and ontological reasoning to carry out diagnosis and prognosis of turbines [121]. Smith Industries Aerospace and Defense, Inc. developed a diagnostic reasoning system called CONSOLIDATE, which uses an Object Oriented Database and hypothetical reasoning to diagnose the faults in aircraft systems like engines [43]. Airbus developed a meta-diagnosis methodology to reason through and isolate faults in their Centralized Maintenance System's knowledge database [122]. Boeing developed a Smart Test Program Set (TPS) software suite with AI Estate architecture, that was utilized to communicate with multiple system reasoners and to provide suggestions for aircraft in the Navy and the Airforce. In this, the diagnostic reasoners used were developed in MATLAB and were capable of using the BIT data, historical diagnostic, and maintenance records and other related information, to provide suggestions on entry points and call outs in the test programs to the engineers via the Smart TPS suite [123]. The Integrated Diagnostic System (IDS) developed as a generic maintenance management system for Air Canada, uses CBR to retrieve and classify the warning and failure messages from aircraft with case bases, as the original messages cannot be tracked with simple string matches. Furthermore, a case-base for diagnostics is developed which serves as a corporate memory that stores historical information of an aircraft fleet, thus helping the repair and the maintenance processes across the fleet [124].

3.3. COTS packages

Numerous commercial reasoning packages are used by the industries for both health monitoring as well as maintenance. RODON is a commercial model-based diagnostic reasoning system from Uptime Solutions AB. It generates hypotheses based on contradictions between the simulated and observed systems. A declarative equation-based language called Rodelica is used to capture the model's knowledge. RODON has been tested on the ADAPT system [125] and is capable of generating decision trees which can be used for troubleshooting of the system [126]. DSI International Inc. developed the eXpress Embedded Reasoner, which is capable of being embedded into the HM system, in order to receive systems data and provide a diagnosis of the system including root cause of failures, instructions for repair, as well as suggestions on further tests to be carried out [127]. Another commercial package, Testability Maintenance and Engineering Systems (TEAMS) is developed by Qualtech Systems Inc. (QSI). It is a domain-neutral Decision Support Software Suite that has been applied for integrated diagnosis and prognosis of various systems like EMA [128], Naval Shipboard Systems [129], and Tactical Satellite 3 (TacSat 3) spacecraft [130]. Similarly, PHM Technology developed the Maintenance awareness Design Environment (MADe), which is an integrated model-based design, analysis and DSS software suite [131]. MADe is capable of functional modeling, failure reporting as well as health-related analysis. ReasonPro, another COTS package developed by Impact Technologies, has automated many reasoning processes, including the Built-In-Test (BIT) reasoning that uses system level knowledge and LRU level data. ReasonPro provides interactive diagnostics solutions to the maintainers, based on the information and codes collected from the aircraft, and it further helps fault isolation through ambiguity reduction and evidence-driven diagnostics [132].

3.4. Health management programs

Several health management programs have implemented reasoning as a part of the monitoring process as well. Impact Technologies developed a Bayesian Network top level reasoner for Avionics Vehicle Health Management [133]. The Integrated Diagnostics System [134] and the Aircraft Electrical Power Systems Prognostics and Health Management (AEPHM) program [135], both developed by Boeing, use a Ground-Based Reasoner component, to optimize maintenance of hydraulic subsystem in legacy aircraft, and to improve the mission readiness of Electrical Power Systems in military aircraft, respectively. A Prognostics Health Management (PHM) program for EMA uses model-based TRANSCEND approach as well as a data-driven reasoning for diagnosis of the faults in the EMA [136].

3.5. Academic work

Some of the reasoners developed by the academia are presented here. Fault-Adaptive Control Technology (FACT) was developed by Vanderbilt University, and Budapest University of Technology and Economics, with support from NASA and Boeing. It uses Temporal Causal Graph at a lower level and TFPG at system high level to describe the effect of the faults. FACT was tested on an aircraft fuel system; it was able to identify the fault injected, as well as reconfigure the control system to maintain continued operation [137]. Similarly, a modeling language, Language for sYstem DIAgnosis (LYDIA), developed by Delft University was implemented in TELE-operations and Model-based Supervision of instruments for planetary exploration (TELEMOS), a model-based diagnostic reasoning system. It has been demonstrated on several other projects like Health Management System for Reusable Space Transportation System (HMS-RSTS), and Harbour Cranes [138]. Another model-based prognostic reasoner was developed in Cranfield University for an Electrical Power Generation System, based on power management design. In this work, a hybrid mathematical model was developed to study structural and parametric faults; a framework with PHM reasoner was developed to predict the failures accurately, along with the warning of secondary damages that might affect aircraft operations [139]. Furthermore, the Hybrid Diagnostic Engine (HyDE) reasoning system was developed by the University of California along with NASA Ames Research Centre. It is used for diagnosis of faults in several components of the propulsion system in the Autonomous Lander Demonstration Project (ALDER), the Electrical Power System of the International Space Station (ISS), and the landing gear of an aircraft [140].

4. Reasoning for IVHM at the vehicle level

4.1. Opportunities

The previous section discussed how reasoning is used for health monitoring by different sectors within the aerospace industry. However, among the health monitoring systems cited, the major focus was on the component or the systems level, but not at the vehicle level. This is an important shortcoming, considering that one of the main objectives of IVHM is to assess and predict the health of the system and its effect at the vehicle level and avoid unexpected downtime, thereby supporting CBM.

There are only a handful of studies that consider the notion of 'vehicle level' as the primary driver. For example, Vehicle Integrated Prognostic Reasoner developed by a team from Honeywell, Vanderbilt University, and NASA Langley Research Centre, integrates information from various aircraft subsystems, namely APU, Avionics, Flaps, and LRUs, to generate multiple evidence and simulate evidence and false alarms for other subsystems [141]. Dinkar et al. [142] patented a Vehicle Level Reasoner Engine that consists of an Advanced Diagnostic and Prognostic Reasoner, and a System Fault Model which has fault models from components level, group area level, and subsystems level, and a set of diagnostic and prognostic algorithms, in order to provide diagnostic and prognostic conclusions, based on the observed failure modes. An evolvable tri-reasoner conceptual framework [143] was developed by Boeing, along with Impact Technologies, NASA and Vanderbilt University which consisted of reasoners for anomaly, diagnosis, and prognosis, that provided health information of the vehicle. This was used by the Reasoner Integration Manager as evidence to prioritize the faults based on their interaction with the integrated model. Khan et al. [144] developed a Vehicle Level Reasoning System framework, that takes the health status of several subsystems like the engine, the fuel system and the electrical system into account, and weighted health indices were calculated based on behavioral evidence and diagnosed faults. Schoeller et al., [54] proposed a reasoning structure that had hierarchical layers of reasoning where, health monitoring techniques are focused on the component or the LRU level, the sub-system level, and the system level. Failure mechanisms of multiple sub-systems of the main system like the engine, actuators and drive trains of an aircraft are monitored and overall functionality of the vehicle (aircraft) during simultaneous degradation of all the monitored failure mechanisms is calculated. Thanigaivelu et al. [145] developed a methodology for the BIT Effectivity analysis, which is based on the Failure Mode and Effect Summary, to calculate the probability of BIT fault detection and isolation in a control system, considering its effect at the LRU, the system and at the aircraft level.

Most work presented in the previous paragraph, show only the effect of a single component's or a sub-system's failure at the vehicle level. The effects of these failures on other subsystems, i.e. the effect due to their interactions and their root causes, at the vehicle level are not widely explored. Only a very few works have so far considered the effect of subsystem interactions. For example, Lopez et al. [146] demonstrated the effect of a fault in a fuel-cooled oil cooler on the independent systems using a modular framework. However, the finding did not describe the effect at the vehicle level and focused mainly on the cross-system diagnostics. Similarly, Nwadiogbu et al. [147] from Honeywell International Inc. patented a vehicle health monitoring system architecture, in which the DSS would choose to ignore the fault issues reported by the Environmental Control system when there is a fault in the engine. The drawback of this decision is that, it runs the risk of ignoring the faults that originate in the Environmental Control System that is independent of the faults in the engine. Another such example is the Vehicle Health Monitoring algorithms developed for diagnosis of the flight control system in a space shuttle [148]. The multivariate algorithm is used with parametric models to detect the fault onset by combining the prediction models of three subsystems: Guidance, Navigation and Control System, Propulsion system, and Gimbal actuation, and study the effect of four faults on these three systems. This study suggests that a vehicle level reasoner is required to find the root cause of faults by combining the symptoms from other systems as well as BIT data.

The number of examples in this section and their findings are evidence to the point that, the area of diagnosis and prognosis of interacting faults requires considerable exploration. On another note, it is worth noticing that, even among these few numbers of works on vehicle level frameworks, reasoning seems to play a key role in assessing the effect of the system's fault in most of them. Hence, it is safe to assume that reasoning, both as a system as well as a strategy, is an inevitable requirement for any work related to vehicle level health monitoring. Any research in the detection and prediction of interacting faults is, thus, a great opportunity to harness the full potential of reasoning. At the vehicle level, reasoning could be used to make inferences with the information available from multiple systems, ranking priorities, and solving conflicts. It could make use of the connectivity between the components and the systems, consider the health information from all the levels, i.e. at the component/subsystem/system levels (as shown in Fig. 8), process the data at each stage, and give decisions on the root cause of the faults and their cascading effects [88].

4.2. Challenges

The implementation of reasoning at the vehicle level is a challenging task and would face a lot of hurdles. One of the major reservations faced by IVHM is access to data. In general, the systems are manufactured by different suppliers, and the OEMs assemble these individual systems onto a common platform. Hence, there is a problem of intellectual property which prevents the suppliers from sharing data to the OEMs or the airliners. The other challenge is that, these systems have their own methods of data processing and monitoring, which may not be compatible with other systems' methods [149]. Hence, the integration of information from these systems at the vehicle level requires a framework, that could accommodate the processing of different types of data sources.

A reasoning system for vehicle level health monitoring would require a robust framework that could clearly distinguish between the different layers of the vehicle and accommodate different data from multiple systems. Since the database is mainly dependent on sensor data, suitable algorithms have to be chosen for data processing, feature selection, and extraction [44]. Correspondingly, methods to enable sensor data fusion and methods to mitigate the risk of sensor failure should be chosen as well [44]. A database management system is required, which could maintain all the different types of data, link their functionalities, and make them accessible [44]. In order to mitigate the challenge of knowledge acquisition, the systems could use modular architecture to protect the IP protected and the private data. For this reason, suitable communication protocol has to be established between the database modules that possess the system health information and the reasoning system developed at the vehicle level. Apart from this, suitable knowledge representation and problem-solving methods have to be chosen, depending upon the type of interaction between the systems and the data sources. For example, if the reasoning system is being built for a vehicle that has rich data sources, the CBR methodology can be chosen to make use of the existing data as historical information. This would be an advantage to the reasoning system, in terms of developing the knowledge as well, since the CBR methodology allows learning through its revise and retain phases. Apart from these requirements, performance metrics like efficiency, false negatives, and false positives need benchmarking [44]. Lastly, developing a reasoning system for vehicle level health monitoring will require rigorous verification and validation for qualifying the system.

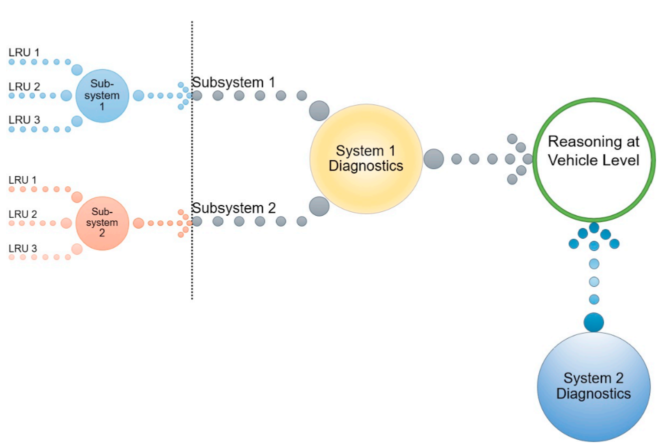

Fig. 8. Information flow in a Reasoning System at Vehicle Level.

5. Summary and conclusions

Following contributions are made in this literature review on reasoning in aerospace IVHM and its potential.

i) A timeline comparison of the AI technologies used in the aerospace IVHM versus the AI technologies in general (Fig. 1).
ii) Applications of reasoning as an AI technology in the engineering field (Fig. 2)
iii) Different reasoning strategies with examples (Table 1).
iv) A generalized architecture for reasoning system (Fig. 3)
v) Pros, cons, and applications of different knowledge-based reasoning systems (Table 2).
vi) A SWOT analysis for model-based and data-driven methods (Fig. 7).
vii) Applications of reasoning in aerospace IVHM (Table 3).
viii) Shortcomings in the existing health monitoring systems in aerospace IVHM and the opportunities for reasoning in vehicle level health monitoring along with the potential challenges.

A fully realized IVHM system is required to face the high demand for CBM and reduce the MRO costs. Nevertheless, it is a challenging task, considering that the development of such an IVHM system depends on equally advanced supporting fields. This paper attempts to learn the importance of the AI technology reasoning and its capability to contribute to the shortcomings in the aerospace IVHM field. To that effect, the paper reviews the reasoning system's architecture, its types, and functions along with its applications in various fields, and explores the spaces where reasoning can further contribute to IVHM. It is identified from the paper that the vehicle level health monitoring system requires reasoning in any format: a strategy or a system. Likewise, the challenges involved in developing a reasoning system for vehicle level health monitoring is presented too and a few suggestions provided to mitigate some of them. The full potential of reasoning, as both a strategy and a system, can be harvested by combining a suitable technology that has the capability of negating the challenges faced by reasoning. In identifying such potential technologies and making them function alongside reasoning, lies the key to the future of a fully functional IVHM system.

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References

[1] O.C. Management, Preliminary analysis of MCTF FY2017 data preliminary analysis of FY2017 data, 14th Maintenance Cost Conference, 2018 Available at: https://www.iata.org/whatwedo/workgroups/Documents/MCC-2018-ATL/Day1/1000-1030-prelim-analysis-of-mctf-data-iata.pdf.

[2] L. Redding, An introduction to integrated vehicle health management - a perspective from literature, in: I.K. Jennions (Ed.), Integrated Vehicle Health Management: Perspectives on an Emerging Field, SAE International, 2011, pp. 17–26, https://doi.org/10.4271/R-05.

[3] I.K. Jennions, Introduction, in: I.K. Jennions (Ed.), Integrated Vehicle Health Management: Perspectives on an Emerging Field, SAE International, 2011, pp. 1–8, https://doi.org/10.4271/R-05.

[4] Wikipedia. Timeline of artificial intelligence. Available at: https://en.wikipedia.org/wiki/Timeline_of_artificial_intelligence (Accessed: 3 August 2018).

[5] Wikipedia. Timeline of machine learning. Available at: https://en.wikipedia.org/wiki/Timeline_of_machine_learning (Accessed: 3 August 2018).

[6] Schwabacher M., Samuels J., Brownston L. The NASA integrated vehicle health management technology experiment for X-37. Proc. SPIE 4733, Component and Systems Diagnostics, Prognostics, and Health Management II. Available at: https://doi.org/10.1117/12.475494.

[7] A. Krichene, M. Roemer, Design tool and toolkits, in: I.K. Jennions (Ed.), Integrated Vehicle Health Management: Perspectives on an Emerging Field, SAE International, 2011, pp. 77–88, https://doi.org/10.4271/R-05.

[8] M. Tipaldi, B. Bruenjes, Spacecraft Health Monitoring and Management Systems, IEEE Metrology for Aerospace (MetroAeroSpace). IEEE, 2014, pp. 68–72 https://doi.org/10.1109/MetroAeroSpace.2014.6865896.

[9] T.J. Laffey, P.A. Cox, L. James, S.M. Kao, J.Y. Read, Real-time knowledge-based systems, AI Mag. 9 (1) (1988) 27–45.

[10] M.P. Georgeff, A.L. Lansky, Reactive reasoning and planning, Proceedings of the Sixth National Conference on Artificial Intelligence (AAAI), 1987, pp. 677–682. Available at: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Reactive+reasoning+and+planning#0.

[11] Tin Kam Ho. Random decision forests. Proceedings of 3rd International Conference on Document Analysis and Recognition. IEEE Comput. Soc. Press; pp. 278–282. Available at: https://doi.org/10.1109/ICDAR.1995.598994 (Accessed: 27 November 2018).

[12] Brief History of Machine Learning - A Blog From Human-engineer-being. Available at: http://www.erogol.com/brief-history-machine-learning/(Accessed: 27 November 2018).

[13] J. de Kleer, B.C. Williams, Diagnosing multiple faults, Artif. Intell. 32 (1) (1987) 97–130 https://doi.org/10.1016/0004-3702(87)90063-4.

[14] M. Fudge, T. Stagliano, S. Tsiao, Non-traditional Flight Safety Systems & Integrated Vehicle Health Management Systems, (2003) Available at: https://www.faa.gov/about/office_org/headquarters_offices/ast/licenses_permits/media/DO3_Report_final.pdf.

[15] M. Schwabacher, A Survey of Data-driven Prognostics, Infotech at Aerospace. AIAA, 2005, https://doi.org/10.2514/6.2005-7002.

[16] J.L. Bresina, A.K. Jonsson, P.H. Morris, K. Rajan, Mixed-initiative planning in MAPGEN: capabilities and shortcomings, Proceedings of the ICAPS-05 Workshop on Mixed-initiative Planning and Scheduling, 2005, p. 8. Available at: https://ti.arc.nasa.gov/m/pub-archive/960h/0960 (Bresina).pdf.

[17] P.A. Scandura, M. Christensen, D. Lutz, G. Bird, Commercial Aviation Health Management. Systems Health Management: with Aerospace Applications, John Wiley & Sons, 2011, pp. 589–603.

[18] J.W. Sheppard, M.A. Kaufman, T.J. Wilmering, IEEE Standards for Prognostics and Health Management, IEEE A&E Systems Magazine, 2009, pp. 34–41 https://doi.org/10.1109/AUTEST.2008.4662592 (September).

[19] E.R. Brown, F. Worth, F. Worth, F. Worth, Prognostics and health management a data-driven approach to supporting the F-35 lightning II, 2007 IEEE Aerospace Conference, IEEE, 2007, pp. 1–12, https://doi.org/10.1109/AERO.2007.352833.

[20] Airbus Customer Service, AiRTHM Airbus Real Time Health Monitoring, (2014), pp. 1–16. Available at: https://www.iata.org/whatwedo/workgroups/Documents/MCC-2014-ATH/D2/1210-1250-realtime-health-monitoring-Airbus.pdf , Accessed date: 16 January 2018.

[21] David Reid (CNBC), Rolls-royce Is Developing Tiny 'cockroach' Robots to Crawl in and Fix Airplane Engines, CNBC, 2018 Available at: https://www.cnbc.com/2018/07/17/rolls-royce-is-developing-tiny-cockroach-robots-to-fix-airplane-engines.html , Accessed date: 26 November 2018.

[22] Federal Aviation Administration), Fact Sheet – General Aviation Safety, (2018) Available at: https://www.faa.gov/news/fact_sheets/news_story.cfm?newsId=21274 , Accessed date: 26 November 2018.

[23] P.A. Sleight, R.D.G. Carter, Aircraft Accident Report 1/2010, (2014) Available at: https://doi.org/EW/C2008/01/01.

[24] D.L.C. Mack, G. Biswas, X.D. Koutsoukos, D. Mylaraswamy, Using tree augmented Naïve bayes classifiers to improve engine fault models, CEUR Workshop Proceedings 818 (December) (2011) 91–98.

[25] R. Smith, Aristotle's Logic, Stanford Encyclopedia of Philosophy, 2017 Available at: https://en.wikipedia.org/wiki/Reason , Accessed date: 21 August 2018.

[26] K.M. Gupta, Case-based Troubleshooting Knowledge Management. AAAI Technical Report SS-99-04, (1999) Available at:: DOI:10.1.1.582.2503.

[27] H. Sugimatsu, S. Hori, A. Sawada, K. Azuma, A CBR application: service productivity improvement by sharing experience, IEEE Symposium on Emerging Technologies & Factory Automation, 1994, pp. 132–141, https://doi.org/10.1109/ETFA.1994.402012.

[28] K. Sycara, Learning from failure experiences in case-based schedule repair, Proceedings of the Twenty-seventh Hawaii International Conference on System Sciences HICSS, 1994, pp. 122–131, https://doi.org/10.1109/HICSS.1994.323359.

[29] D. Hinkle, C.N. Toomey, CLAVIER: applying case-based reasoning to composite part fabrication, IAAI-94 Proceedings, 1994, pp. 55–62. Available at: https://www.aaai.org/Papers/IAAI/1994/IAAI94-007.pdf.

[30] C. Johnson, Software tools to support incident reporting in safety-critical systems, Saf. Sci. 40 (9) (2002) 765–780 https://doi.org/10.1016/S0925-7535(01)00085-6.

[31] S.M. Woskov, M.R. Grimaila, R.F. Mills, M.W. Haas, Design considerations for a case-based reasoning engine for scenario-based cyber incident notification, Symposium on Computational Intelligence in Cyber Security (CICS), 2011,https://doi.org/10.1109/CICYBS.2011.5949397.

[32] D. Nicklas, M. Grossmann, J. Mínguez, M. Wieland, Adding high-level reasoning to efficient low-level context management: a hybrid approach, 6th Annual International Conference on Pervasive Computing and Communications, PerCom. IEEE, 2008, pp. 447–452, https://doi.org/10.1109/PERCOM.2008.64 Available at:.

[33] R. Rymon, Goal-directed Diagnosis - Diagnostic Reasoning in Exploratory-corrective Domains. IRCS Technical Reports Series vol. 187, (1993) Available at: https://repository.upenn.edu/ircs_reports/187/.

[34] J. Lee, M.J. Huber, E.H. Durfee, P.G. Kenny, UM-PRS: an implementation of the procedural reasoning system for multirobot applications, AIAA/NASA Conference on Intelligent Robots in Field, Factory, Service, and Space (CIRFFSS '94), AIAA, 1994Available at: DOI:10.1.1.51.6247.

[35] J. Jones, Y. Xiang, S. Joseph, Bayesian probabilistic reasoning in design, Conference on Communications, Computers and Signal Processing. Pacific Rim, IEEE, 1993, pp. 501–504, https://doi.org/10.1109/PACRIM.1993.407312.

[36] H.H. Lou, Y.L. Huang, Hierarchical decision making for proactive quality control: system development for defect reduction in automotive coating operations, Eng. Appl. Artif. Intell. 16 (3) (2003) 237–250 https://doi.org/10.1016/S0952-1976(03)00060-5.

[37] M. Thang, S.W.L. Do, F. Liu, Mobile and ubiquitous Systems : computing, networking, and services, in: K. Zheng, M. Li, H. Jiang (Eds.), 9th International Conference, MobiQuitous, Springer, 2012, pp. 188–199, https://doi.org/10.1007/978-3-642-40238-8.

[38] S. Ma, Automatically Modeling , Simulating and Explaining Physical Systems. 17th International Conference on Computers and Industrial Engineering, Elseiver Science Ltd, 1995, pp. 187–191.

[39] G. Robertson, I. Watson, A review of real-time strategy game AI, AI Mag. 35 (4) (2014) 75–104 https://doi.org/10.1609/aimag.v35i4.2478.

[40] M. Rigolli, M. Brady, Towards a behavioural traffic monitoring system, AAMAS '05 Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems, ACM, 2005, pp. 449–454, https://doi.org/10.1145/1082473.1082542.

[41] H. Khorasgani, G. Biswas, A combined model-based and data-driven approach for monitoring smart buildings, in: M. Zanella, I. Pill, A. Cimatti (Eds.), 28th International Workshop on Principles of Diagnosis (DX'17), Kalpa Publications in Computing, 2018, pp. 21–36.

[42] N.S. Lee, DM2: an algorithm for diagnostic reasoning that combines analytical models and experiential knowledge, Int. J. Man Mach. Stud. 28 (6) (1988) 643–670 https://doi.org/10.1016/S0020-7373(88)80066-X.

[43] L. a. Reibling, W. Lafayette, Diagnostic reasoning technology for the on-board maintenance system, Proceedings of the National Aerospace and Electronics Conference, NAECON. IEEE, 1993, pp. 930–936, https://doi.org/10.1109/NAECON.1993.290818.

[44] G. Vachtsevanos, K. Goebel, Basic principles, in: I.K. Jennions (Ed.), Integrated Vehicle Health Management: Perspectives on an Emerging Field, SAE International, 2011, pp. 55–65, https://doi.org/10.4271/R-05.

[45] M. Stanjevk, S. Vranos, Using truth maintenance systems - a tutorial, IEEE Expert 9 (6) (1994) 46–56 https://doi.org/10.1109/64.363270.

[46] J. Marzat, H. Piet-Lahanier, F. Damongeot, E. Walter, Model-based fault diagnosis for aerospace systems: a survey, Proc. IME G J. Aero. Eng. 226 (10) (2012) 1329–1360 https://doi.org/10.1177/0954410011421717.

[47] V. Venkatasubramanian, R. Rengaswamy, S.N. Ka, A review of process fault detection and diagnosis Part II : qualitative models and search strategies, Comput. Chem. Eng. 27 (3) (2003) 313–326. Available at: https://doi.org/10.1016/S0098-1354(02)00161-8.

[48] V. Venkatasubramanian, R. Rengaswamy, S.N. Ka, A review of process fault detection and diagnosis Part III : process history based methods, Comput. Chem. Eng. 27 (3) (2003) 327–346. Available at: https://doi.org/10.1016/S0098-1354(02)00162-X.

[49] K.D. Forbus, Qualitative Reasoning, CRC Handbook of Computer Science, 1996 Available at: http://www.qrg.cs.northwestern.edu/papers/Files/crc7.pdf.

[50] A. Patterson-Hine, G. Biswas, G. Aaseng, N. Sriam, K. Pattipati, A Review of Diagnostic Techniques for ISHM Applications, (2005) Available at: https://ti.arc.nasa.gov/m/pub-archive/1094h/1094 (APH).pdf.

[51] V. Chandola, A. Banerjee, V. Kumar, Anomaly detection: a survey, ACM Comput. Surv. 41 (September) (2009) 1–58 https://doi.org/10.1145/1541880.1541882.

[52] D. An, N.H. Kim, J.H. Choi, Practical Options for Selecting Data-driven or Physics-based Prognostics Algorithms with Reviews. Reliability Engineering and System Safety vol. 133, Elsevier, 2015, pp. 223–236 https://doi.org/10.1016/j.ress.2014.09.014.

[53] K. Tidriri, N. Chatti, S. Verron, T. Tiplica, Bridging data-driven and model-based approaches for process fault diagnosis and health monitoring: a review of

researches and future challenges, Annu. Rev. Contr. (2016) 63–81 https://doi.org/10.1016/j.arcontrol.2016.09.008.

[54] M. Schoeller, M. Roemer, M. Leonard, M. Derriso, Embedded reasoning supporting aerospace IVHM, AIAA Infotech at Aerospace Conference and Exhibit, 2007, pp. 1–19, https://doi.org/10.2514/6.2007-2820.

[55] C. Ramirez, B. Valdes, A General Knowledge Representation Model of Concepts. Advances in Knowledge Representation, INTECH, 2012.

[56] C. Seitz, R. Schönfelder, Rule-based OWL reasoning for specific embedded devices, in: Aroyo Lora, WeltyHarith Chris, Taylor AlaniJamie, Bernstein Abraham, KagalNatasha Lalana, B. NoyEva (Eds.), The Semantic Web – ISWC 2011. ISWC 2011. Lecture Notes in Computer Science, Springer, Berlin, Heidelberg, 2011, pp. 237–252, https://doi.org/10.1007/978-3-642-25093-4_16.

[57] B. Liu, M. Duan, G. Zhao, An object frame knowledge representation approach for fault diagnosis expert system, International Conference on Future Computer Sciences and Application, IEEE, 2011, pp. 74–77, https://doi.org/10.1109/ICFCSA.2011.24.

[58] C. Grosan, A. Abraham, Intelligent systems, a modern approach, first ed., in: J. Kacprzyk, L.C. Jain (Eds.), Intelligent Systems Reference Library, vol. 17, Springer-Verlag Berlin Heidelberg, 2011, ,https://doi.org/10.1007/978-3-642-21004-4.

[59] B.G. Buchanan, E.H. Shortliffe, The context of the MYCIN experiments, in: B.G. Buchanan, E.H. Shortliffe (Eds.), Rule-based Expert Systems the MYCIN Experiments of the Stanford Heuristic Programming Project MYCIN Experiments of the Stanford Heuristic Programming Project, Addison Wesley, Reading, WA, 1984, pp. 3–19 http://www.aaai.org/Papers/Buchanan/Buchanan03.pdf.

[60] B.G. Buchanan, R.Q. Smith, Fundamentals of expert system, Annu. Rev. Comput. Sci. (1988) 23–58.

[61] Mihailo Pupin Institute). BEST: Blackboard-based Expert System Toolkit. pp. 1–653. Available at: http://static.pupin.rs/2010/07/BEST.pdf.

[62] R.J. Bankert, I. Imam, H. Rajiyah, 5,633,800: Integrated Model-based Reasoning/Expert System Diagnosis for Rotating Machinery, (1997) United States Patent.

[63] F.F. Ingrand, A.S. Rao, M.P. Georgeff, An architecture for real-time reasoning and system control, IEEE Expert 7 (6) (1992) 33–44 https://doi.org/10.1109/64.180407.

[64] J.L. Kolodner, An introduction to case-based reasoning, Artif. Intell. Rev. 6 (1) (1992) 3–34 https://doi.org/10.1007/BF00155578.

[65] A. Bonzano, ISAC: a Case-based Reasoning System for Aircraft Conflict Resolution, PhD Thesis University of Dublin, Trinity College, 1998 Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.159.2126&rep=rep1&type=pdf.

[66] K.-D. Althoff, Case-based reasoning and expert system, in: B.D. Agudo, Ian Watson (Eds.), 20th International Conference on Case Based Reasoning ICCBR, Springer-Verlag Berlin Heidelberg, 2012, ,https://doi.org/10.1007/978-3-642-32986-9.

[67] A. Saxena, B. Wu, G. Vachtsevanos, A hybrid reasoning architecture for fleet vehicle maintenance - artificial intelligence-based diagnostic approach with particular reference to dynamic case-based reasoning, IEEE Instrum. Meas. Mag. 9 (4) (2006) 29–36 https://doi.org/10.1109/MIM.2006.1664039.

[68] A.N. Srivastava, Enabling the discovery of recurring anomalies in aerospace problem reports using high-dimensional clustering techniques, Aerospace Conference, IEEE, 2006, ,https://doi.org/10.1109/AERO.2006.1656136.

[69] J.W. Sheppard, S.G.W. Butcher, A formal analysis of fault diagnosis with D -matrices, J. Electron. Test. Theory Appl. (2007), https://doi.org/10.1007/s10836-006-0628-7.

[70] Y. Chen, Y.W. Chen, X Bin Xu, C.C. Pan, J.B. Yang, G.K. Yang, A Data-driven Approximate Causal Inference Model Using the Evidential Reasoning Rule. Knowledge-based Systems vol. 88, Elsevier B.V., 2015, pp. 264–272 https://doi.org/10.1016/j.knosys.2015.07.026.

[71] S. Vohnout, B.U. Kim, N. Kunst, B. Gleeson, R. Wagoner, E. Balaban, et al., A model-based avionic prognostic reasoner (MAPR), AIAA Infotech at Aerospace Conference and Exhibit, 2012, pp. 1–17, https://doi.org/10.2514/6.2012-2421.

[72] M. Daigle, M. Foygel, Model-based diagnostics for propellant loading systems, Aerospace Conference, IEEE, 2011, ,https://doi.org/10.1109/AERO.2011.5747596.

[73] O. Niculita, P. Irving, I.K. Jennions, Use of COTS functional analysis software as an IVHM design tool for detection and isolation of UAV fuel system faults, Annual Conference of Prognostics and Health Management Society, 2012, pp. 1–18.

[74] T. Höfling, R. Isermann, Fault detection based on adaptive parity equations and single-parameter tracking, Contr. Eng. Pract. 4 (10) (1996) 1361–1369 https://doi.org/10.1016/0967-0661(96)00146-3.

[75] J.J. Gertler, K.C. Anderson, An evidential reasoning extension to quantitative model-based failure diagnosis, IEEE Trans. Syst. Man Cybern. 22 (2) (1992) 275–289 https://doi.org/10.1109/21.148430.

[76] L. Chi, K. Reuben, D. Mba, Diagnostics and prognostics using switching Kalman filters, Struct. Health Monit. 13 (3) (2014) 296–306 https://doi.org/10.1177/1475921714522844.

[77] M.R.J. Alves, C. de O. Bizarria, R.K.H. Galvão, Trend Analysis for Prognostics and Health Monitoring, Brazilian Symposium on Aerospace Eng. & Applications, 2009.

[78] W. Yan, B. Zhang, Extended Kalman Filter Development in Lebesgue Sampling Framework with an Application to Li-ion Battery Diagnosis and Prognosis, European Conference of the Prognostics and Health Management Society, 2016, pp. 1–7. Available at: https://www.phmsociety.org/sites/phmsociety.org/files/phm_submission/2016/phmec_16_001.pdf.

[79] B. Bittner, M. Bozzano, A. Cimatti, Automated synthesis of timed failure propagation graphs, Proceedings of the Twenty-fifth International Joint Conference on Artificial Intelligence, IJCAI, 2016, pp. 972–978.

[80] L. Howard, An algorithm for diagnostic reasoning using TFPG models in embedded real-time applications, Systems Readiness Technology Conference AUTOTESTCON, IEEE, 2001, pp. 978–987, https://doi.org/10.1109/AUTEST.2001.949477.

[81] S. Abdelwahed, G. Karsai, G. Biswas, System diagnosis using hybrid failure propagation graphs, The 15th International Workshop on Principles of Diagnosis, ISIS PUBLICATIONS, 2004Available at:: DOI:10.1.1.2.4683.

[82] T.S. Liu, S.B. Chiou, The application of Petri nets to failure analysis, Reliab. Eng. Syst. Saf. 57 (2) (1997) 129–142. Available at: https://doi.org/10.1016/S0951-8320(97)00030-6.

[83] A. Guia, State estimation and fault detection using Petri nets, in: L.M. Kristensen, L. Petrucci (Eds.), Applications and Theory of Petri Nets. Lecture Notes in Computer Science, vol. 6709, Springer, Berlin, Heidelberg, 2011Available at: https://doi.org/10.1007/978-3-642-21834-7_3.

[84] J. Sun, S. Qin, Y. Song, Member S. Fault diagnosis of electric power systems based on fuzzy Petri nets, IEEE Trans. Power Syst. 19 (4) (2004) 2053–2059 https://doi.org/10.1109/TPWRS.2004.836256.

[85] Q. Yang, K.A. Loparo, Model-based and Data Driven Fault Diagnosis Methods with Applications to Process Monitoring, Phd Thesis Case Western Reserve University, 2004.

[86] Z. Yilin, L. Hongning, Aircraft fault diagnosis based on case — based reasoning and fault tree analysis integrated, International Conference on Electronics, Communications and Control (ICECC), IEEE, 2011, pp. 703–706, https://doi.org/10.1109/ICECC.2011.6067560.

[87] J.E. Larsson, diagnostic reasoning based on means-end models: experiences and future prospects, Knowledge-based Systems (2002) 103–110 https://doi.org/10.1016/S0950-7051(01)00126-5 Elsevier.

[88] A.N. Srivatsava, R.W. Mah, R. Bharadwaj, D. Mylaraswamy, Vehicle-level reasoning systems, in: I.K. Jennions (Ed.), Integrated Vehicle Health Management: the Technology, SAE Publications, 2013, pp. 139–155. Available at: http://books.sae.org/r-429/.

[89] J. Pearl, Bayesian Networks, University of California, Los Angeles, 2000 Available at: http://ftp.cs.ucla.edu/pub/stat_ser/R246.pdf.

[90] Y. Lin, S. Zakwan, I. Jennions, A bayesian approach to fault identification in the presence of multi-component degradation, Int. J. Prognostics Health Manag. 8 (2017) Available at: https://dspace.lib.cranfield.ac.uk/bitstream/handle/1826/11645/A_bayesian_approach_to_fault_identification-2017.pdf?sequence=1.

[91] O.J. Mengshoel, A. Darwiche, K. Cascio, M. Chavira, L. Angeles, S. Poll, et al., Diagnosing faults in electrical power systems of spacecraft and aircraft, Artif. Intell. (650) (2008) 1699–1705. Available at:: DOI:10.1.1.149.7338.

[92] T. Kurtoglu, O.J. Mengshoel, S. Poll, A Framework for systematic benchmarking of monitoring and diagnostic systems, International Conference on Prognostics and Health Management, PHM, 2008, ,https://doi.org/10.1109/PHM.2008.4711454.

[93] D.L.C. M, G. B, X.D. K, D. M, G. H, Deriving bayesian classifiers from flight data to enhance aircraft diagnosis models, Annual Conference of the Prognostics and Health Management Society, 2011, pp. 175–189. Available at: http://www.scopus.com/inward/record.url?eid=2-s2.0-84920517370&partnerID=40&md5=ad0fac69dbdf8abdf471e2e41e9d4883.

[94] D.L.C. Mack, G. Biswas, X.D. Koutsoukos, D. Mylaraswamy, Learning bayesian network structures to augment aircraft diagnostic reference models, IEEE Trans. Autom. Sci. Eng. 14 (1) (2017) 358–369 https://doi.org/10.1109/TASE.2016.2542186.

[95] O. Niculita, Z. Skaf, I.K. Jennions, The application of Bayesian change point detection in UAV fuel systems, Procedia CIRP 22 (1) (2014) 115–121 https://doi.org/10.1016/j.procir.2014.07.119 Elsevier B.V.

[96] S. Vranes, M. Stanojevic, P. Subasic, S. Vraneš, M. Stanojević, P. Subašic, A framework for engineering intelligent control systems, Eng. Appl. Artif. Intell. 7 (4) (1994) 367–380. Available at: DOI:0952-1976(94)00027-1.

[97] T.J. Ross, Fuzzy Logic with Engineering Applications, second ed., John Wiley & Sons, 2005.

[98] Y. Lu, T.Q. Chen, B. Hamilton, A fuzzy diagnostic model and its application in automotive engineering diagnosis, Appl. Intell. 9 (3) (1998) 231–243. Available at: http://www.scopus.com/inward/record.url?eid=2-s2.0-0032206446&partnerID=tZOtx3y1.

[99] S. Dash, R. Rengaswamy, V. Venkatasubramanian, Fuzzy-logic based trend classification for fault diagnosis of chemical processes, Chem. Eng. 27 (2003) 347–362 https://doi.org/10.1016/S0098-1354(02)00214-4.

[100] D.S. Annis, D.F. Mosher, D.D. Roberts, A fuzzy reasoning design for fault detection and diagnosis of a computer-controlled system, Eng. Appl. Artif. Intell. 157–170 (2) (2008) 339–351 https://doi.org/10.1016/j.engappai.2007.04.007.

[101] A. Hamilton-wright, S. Member, D.W. Stashuk, Transparent decision support using statistical reasoning and fuzzy inference, IEEE Trans. Knowl. Data Eng. 18 (8) (2006) 1125–1137 https://doi.org/10.1109/TKDE.2006.132.

[102] E.H. Ruspini, J.D. Lowrance, T.M. Strat, Understanding evidential reasoning, Int. J. Approx. Reason. 6 (3) (1992) 401–424 https://doi.org/10.1016/0888-613X(92)90033-V.

[103] K.H. Hui, M.H. Lim, M.S. Leong, S.M. Al-Obaidi, Dempster-shafer evidence theory for multi-bearing faults diagnosis, Eng. Appl. Artif. Intell. vol. 57, (2017) 160–170 https://doi.org/10.1016/j.engappai.2016.10.017 Elsevier Ltd.

[104] K. Verbert, R. Babuška, B. De Schutter, Bayesian and dempster–shafer reasoning for knowledge-based fault diagnosis–A comparative study, Eng. Appl. Artif. Intell. vol. 60, (2017) 136–150 https://doi.org/10.1016/j.engappai.2017.01.011 Elsevier Ltd.

[105] R.P. Srivastava, An introduction to evidential reasoning for decision making under uncertainty: bayesian and belief function perspectives, Int. J. Account. Inf. Syst. 12 (2) (2011) 126–135 https://doi.org/10.1016/j.accinf.2010.12.003 Elsevier Inc.

[106] Z. Zhang, Y. Wang, K. Wang, Fault diagnosis and prognosis using wavelet packet

decomposition , Fourier transform and artificial neural network, J. Intell. Manuf. 24 (2013) 1213–1227 https://doi.org/10.1007/s10845-012-0657-2 Springer.
[107] M. He, D. He, E. Bechhoefer, Using deep learning based approaches for bearing fault diagnosis with AE sensors, Annual Conference of the Prognostics and Health Management Society, 2016, pp. 1–10.
[108] Q.P. He, J. Wang, Fault detection using the k-nearest neighbor rule for semiconductor manufacturing processes, IEEE Trans. Semicond. Manuf. 20 (4) (2007) 345–354 https://doi.org/10.1109/TSM.2007.907607.
[109] M. Jung, O. Niculita, Z. Skaf, Comparison of different classification algorithms for fault detection and fault isolation in complex systems, Procedia Manufacturing 19 (2018) 111–118 https://doi.org/10.1016/j.promfg.2018.01.016 Elsevier B.V..
[110] D. Tobon-mejia, K. Medjaher, N. Zerhouni, G. Tripot, Hidden Markov models for failure diagnostic and prognostic, Prognostics and System Health Management Conference, IEEE, 2011, pp. 1–8, https://doi.org/10.1109/PHM.2011.5939488.
[111] Z. Li, S. Zhou, S. Choubey, C. Sievenpiper, Failure event prediction using the Cox proportional hazard model driven by frequent failure signatures, IIE Trans. (Institute of Industrial Engineers) 39 (3) (2007) 303–315 https://doi.org/10.1080/07408170600847168.
[112] N. Ryhajlo, L. Sturlaugson, J.W. Sheppard, Diagnostic Bayesian networks with fuzzy evidence, Autotestcon (Proceedings), 2013, pp. 242–249, https://doi.org/10.1109/AUTEST.2013.6645075.
[113] C. C, N.-H. C, C.-I. H, Intelligent aircraft maintenance support system using genetic algorithms and case-based reasoning, Int. J. Adv. Manuf. Technol. 24 (2004) 440–446 https://doi.org/10.1007/s00170-003-1707-x.
[114] L. Portinale, D. Magro, P. Torasso, Multi-modal diagnosis combining case-based and model-based reasoning: a formal and experimental analysis, Artif. Intell. 158 (2) (2004) 109–153 https://doi.org/10.1016/j.artint.2004.05.005.
[115] Ö.F. Eker, A Hybrid Prognostic Methodology and its Application to Well-Controlled Engineering Systems, PhD Thesis Cranfield University, 2013, https://doi.org/10.1017/CBO9781107415324.004.
[116] M.L. James, L.P. Dubon, An autonomous diagnostic and prognostic monitoring system for NASA's Deep Space Network, Aerospace Conference Proceedings, IEEE, 2000, pp. 403–414, https://doi.org/10.1109/AERO.2000.878248.
[117] R. Mackey, M. James, H. Park, M. Zak, BEAM: technology for autonomous self-analysis, Aerospace Conference Proceedings (Cat. No.01TH8542), IEEE, 2001, ,https://doi.org/10.1109/AERO.2001.931319.
[118] H.G. Park, H. Cannon, A. Bajwa, R. Mackey, M. James, W. Maul, et al., Hybrid diagnostic system: beacon-based exception analysis for multimissions-livingstone integration, 58th Meeting of the Society for Machinery Failure Prevention Technology, JPL, NASA, Pasadena, CA, 2004Available at: http://hdl.handle.net/2014/38232.
[119] J. Schumann, I. Roychoudhury, C. Kulkarni, Diagnostic reasoning using prognostic information for unmanned aerial systems, Annual Conference of the Prognostics and Health Management Society, 2015, pp. 1–11.
[120] H.A. Winston, R.T. Clark, G. Buchina, AGETS MBR an Application of Model-based Reasoning to Gas Turbine Diagnostics, AI Magazine, 1995, pp. 67–77. Available at: https://pdfs.semanticscholar.org/c1a1/70c154c66fb57ee43a3963fa9d847e994e89.pdf.
[121] G. Mehdi, M. Roshchin, T. Runkler, Internet of Turbines : an outlook on smart diagnostics, Annual Conference of Prognostics and Health Management Society, 2017, pp. 1–7. Available at: https://www.phmsociety.org/sites/phmsociety.org/files/phm_submission/2017/phmc_17_043.pdf.
[122] N. Belard, Y. Pencolé, M. Combacau, A theory of meta-diagnosis: reasoning about diagnostic systems, Proceedings of the Twenty-second International Joint Conference on Artificial Intelligence, 2011, pp. 731–737.
[123] T. Gaudette, A.L. Alwardt, The Boeing smart TPS application executive with MATLAB as a diagnostic reasoner, AUTOTESTCON (Proceedings), IEEE, 2006, pp. 714–719, https://doi.org/10.1109/AUTEST.2006.283754.
[124] M. Lehane, M. Halasz, R. Orchard, R. Wylie, M. Zaluski, Integrated diagnostic system (IDS) for aircraft fleet maintenance, Proceedings of the Fifteenth National Conference on Artificial Intelligence (AAAI), 1998, pp. 26–30.
[125] P. Bunus, O. Isaksson, B. Frey, B. Münker, RODON - a model-based diagnosis approach for the DX diagnostic competition, Available at: http://photon.isy.liu.se/dx09/papers/dx09_submission_dxc7.pdf.
[126] P. Bunus, O. Isaksson, B. Frey, B. Münker, Model-based diagnostics techniques for avionics applications with RODON, 2nd Workshop on Aviation System Technology, 2009 Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.159.3003&rep=rep1&type=pdf.
[127] DSI international inc. . eXpress Embedded Reasoner. Available at: https://www.dsiintl.com/products/diagnostic-reasoners/express-embedded-reasoner/ (Accessed: 10 June 2018).
[128] M. Azam, S. Ghoshal, S. Deb, K. Pattipati, D. Haste, S. Mandal, et al., Integrated diagnostics and time to maintenance estimation for complex engineering systems, Aerospace Conference, Big SKy. IEEE, 2014, ,https://doi.org/10.1109/AERO.2014.6836478 Available at:.
[129] Mathur A., Cavanaugh KF., Pattipati KR., Willett PK., Galie TR. Reasoning and modeling systems in diagnosis and prognosis. Proceedings SPIE 4389, Component and Systems Diagnostics, Prognosis, and Health Management; Available at: https://doi.org/10.1117/12.434239.
[130] R. Mackey, L. Brownston, J.P. Castle, A. Sweet, Getting diagnostic reasoning off the ground: maturing technology with TacSat-3, IEEE Intell. Syst. (2010) 27–35 https://doi.org/10.1109/MIS.2010.124.
[131] PHM Technology, Made, (2017) Available at: https://www.phmtechnology.com/assets/downloads/default/MADe-Overview.pdf , Accessed date: 24 June 2018.
[132] P.W. Kalgren, C.S. Byington, B.P. Donovan, Automated Data Translation for Avionics Health Management through Intelligent Evidence Streams and Databases, The American Helicopter Society 60th Annual Forum., Baltimore, MD, 2004.
[133] C.S. Byington, P.W. Kalgren, R. Johns, R.J. Beers, Embedded diagnostic/prognostic reasoning and information continuity for improved avionics maintenance, IEEE Systems Readiness Technology Conference. Proceedings AUTOTESTCON, 2003, pp. 518–524, https://doi.org/10.1109/AUTEST.2003.1243595.
[134] B. Chidambaram, P.L. Horn, D.D. Gilbertson, P. Pigg, M.A. Talbot, K.C. Cerise, Recorders, reasoners and artificial intelligence – integrated diagnostics on military Transport aircraft, Aerospace Conference, IEEE, 2006, pp. 1–9, https://doi.org/10.1109/AERO.2006.1656074.
[135] K. Keller, Amo, A. Del, Jordan B. Aircraft, Electrical Power Systems Prognostics and Health Management (AEPHM), SAE Technical Papers Series, 2004 Available at: DOI:2004-01-3162.
[136] E. Balaban, A. Saxena, S. Narasimhan, I. Roychoudhury, M. Koopmans, C. Ott, et al., Prognostic health-management system development for electromechanical actuators, J. Aero. Inf. Syst. 12 (3) (2015) 329–344 https://doi.org/10.2514/1.I010171.
[137] G. Simon, G. Karsai, G. Biswas, S. Abdelwahed, N. Mahadevan, T. Szemethy, et al., Model-based Fault-Adaptive control of complex dynamic systems, IMTC-2003 - Instrumentation and Measurement Technology Conference, IEEE, 2003, pp. 20–22.
[138] E.A. Kuijpers, P van Gelder, Y. Pietersma, Automated On-board Model-based Diagnosis during Planetary Mission and Teleoperation, (2008) Available at: https://core.ac.uk/download/pdf/53034129.pdf.
[139] R.K. Sebastian, S. Peripinayagam, I.K. Jennions, A. Alghassi, Prognostic reasoner based adaptive power management system for a more electric aircraft, Proceedings of the Annual Conference of the Prognostics and Health Management Society, 2016, pp. 1–11.
[140] Narasimhan S. Automated diagnosis of physical systems. Proceedings of ICALEPCS07. pp. 701–705. Available at: https://accelconf.web.cern.ch/accelconf/ica07/PAPERS/FOAA01.PDF.
[141] Raj Bharadwaj, Dinkar Mylaraswamy, Dennis Cornhill, G. Biswas, Xenofon Koutsoukos, D. Mack, Vehicle Integrated Prognostic Reasoner (VIPR) Final Report, NASA Langley Research Centre, 2013 Available at: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20130011181.pdf.
[142] D. Mylaraswamy, G.D. Hadden, US 8,285.438 B2: Methods Systems and Apparatus for Analyzing Complex Systems via Prognostic Reasoning, (2012), https://doi.org/10.1021/n10602701.
[143] L. Atlas, G. Bloor, T. Brotherton, L. Howard, L. Jaw, G. Kacprzynski, et al., An evolvable tri-reasoner IVHM system, IEEE Aerospace Conference Proceedings, 2001, pp. 63023–63037, https://doi.org/10.1109/AERO.2001.931322.
[144] F. Khan, O.F. Eker, T. Sreenuch, A. Tsourdos, Health index and behaviour based vehicle level reasoning system, Conference on Prognostics and Health Management (PHM), IEEE, 2015, ,https://doi.org/10.1109/ICPHM.2015.7245042.
[145] V. Thanigaivelu, S. Choksi, On the Use of Built in Test Effectivity Analysis. SAE Technical Paper 2017-01-2051, (2017), https://doi.org/10.4271/2017-01-2051.
[146] B.S. López, A.M. Siddiolo, P.P. Adhikari, M. Buderath, A Bayesian paradigm for aircraft operational capability assessment and improved fault diagnostics, European Conference of the Prognostics and Health Management Society, 2016, pp. 1–14.
[147] Nwadiogbu EO., Mylaraswamy D., Menon S., Voges HC., Hadden G. US008346429B2: Vehicle Health Monitoring System Architecture for Diagnostics and Prognostics Disclosure. United States Patent; 2013. Available at: https://doi.org/10.1016/j.(73).
[148] D. Gorinevsky, S. Samar, J. Bain, Integrated diagnostics of rocket flight control, IEEE Aerospace Conference Proceedings, IEEE, 2005.
[149] F. Khan, I. Jennions, T. Sreenuch, Integration issues for vehicle level distributed diagnostic reasoners, SAE Technical Papers, 2013,https://doi.org/10.4271/2013-01-2294.
[150] K. Goebel, P. Bonanni, N. Eklund, Towards an integrated reasoner for bearings prognostics, IEEE Aerospace Conference Proceedings, 2005, pp. 1–11, https://doi.org/10.1109/AERO.2005.1559670.

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