Knowledge-based and Expert Systems in Prognostics and Health Management: a Survey

Kalil Bouhadra[1] and Florent Forest[2]

[1,2] *Intelligent Maintenance and Operations Systems lab, EPFL, Lausanne, 1015, Switzerland*
firstname.lastname@epfl.ch

ABSTRACT

Prognostics and Health Management (PHM) has become increasingly popular in recent years, and data-driven methods and artificial intelligence have emerged as dominant tools within the PHM field. This trend is mainly due to the increasing use of sensors and the ability of machine learning techniques to leverage condition monitoring data. However, despite their utility and effectiveness, these techniques are not without drawbacks. One major issue is that data-driven methods often lack transparency in their reasoning, which is crucial for understanding fault occurrences and diagnostics. Additionally, the availability of data can be a challenge. In some cases, data are scarce or hard to obtain, either due to the cost of installing necessary sensors or the rarity of the required information. Lastly, the insights derived from data can sometimes diverge from those obtained through expert analysis and established norms. This contrasts with knowledge-based approaches such as expert systems, which formally organize the knowledge acquired from norms and experts, and then deduce the desired conclusion. While research is increasingly exploring data-driven techniques, industry tends to still frequently employ knowledge-based methods. To fill this gap, this paper offers a detailed survey of knowledge-based and expert systems in PHM, examining methodologies such as propositional logic, fuzzy logic, Dempster-Shafer theory and Bayesian networks. It assesses the integration and impact of these techniques in PHM for fault detection, diagnosis and prognosis, highlighting their strengths, limitations, and potential future developments. The study provides a thorough evaluation of current developments and contributes significant insights into the current capabilities and future directions of knowledge-based techniques in enhancing decision-making processes in PHM.

1. INTRODUCTION

As the world becomes more complex, issues of sustainability, environmental responsibility, and security of critical services take on critical importance (Sánchez-Silva, Frangopol, Padgett, & Soliman, 2016). Faced with these challenges, the aging of infrastructure raises major concerns (Zio, 2009). Indeed, for large metropolises that heavily rely on transportation systems like subways and trains, the reliability of these systems are absolutely essential (Lidén, 2015). A lack of reliability can shorten the lifespan of these valuable assets, which can result in significant financial costs and compromise people's safety (Zio, 2016; Manzini, Regattieri, Pham, & Ferrari, 2010). Today, technology offers the necessary tools for optimal management of these systems. In particular, by blending data analysis methods, algorithmic techniques, and engineering principles, Prognostics and Health Management (PHM), an interdisciplinary branch of engineering, aims to provide methods and tools in order to design optimal maintenance policies for a specific asset (Fink et al., 2020). In order to do this, PHM enables to control and predict the evolution and the behavior of industrial assets to anticipate failure and avoid accidents (Elattar, Elminir, & Riad, 2016). The process typically begins with the implementation of sensors, which are crucial for monitoring the condition of the asset. Given the complexity of modern systems, these sensors vary in types and capture a diverse range of variables, they are also subject to measurement and transmission noise that can impact the results. Consequently, feature selection, which is a preprocessing step to obtain useful data representations, is commonly employed (Fink et al., 2020). With suitable condition data about the asset in hand, the next three steps are critical for the asset health analysis. The first step involves identifying deviations from the system's normal behavior (fault detection). Upon detecting an anomaly, the goal is to isolate it and determine its origin (fault diagnostics). Subsequently, estimating the remaining useful life (RUL) aims to predict when the asset's performance will decline to an unacceptable level (fault prognostics) (J. Lee et al., 2014). PHM extends beyond prognostics, and is designed to aid in decision-making, taking into account available resources, management strategies, and

https://doi.org/10.36001/IJPHM.2024.v15i2.3986

economic implications.

The effective implementation of PHM strategies relies heavily on leveraging modern technological advancements. Nowadays, the intersection of big data, expansive data storage capabilities, and the evolution of powerful algorithms positioned data-driven approaches and machine learning (ML) as primary tools for condition monitoring and decision-making (I. Lee, 2017). The extensive applications of ML in the PHM paradigm have shown immense promise (Xu & Saleh, 2021). (Biggio & Kastanis, 2020) describe its various applications, including its integration in PHM processes for feature selection using filter-based and wrapper-based approaches, and for health analysis through learning algorithms. (Tsui, Chen, Zhou, Hai, & Wang, 2015) detail applications in diagnostics and prognostics of industrial assets, utilizing classification, Bayesian frameworks, and particle filtering. More recently, deep learning (DL), a subfield of ML, has emerged as a promising approach to address challenges in the PHM process. Its ability to process massive amounts of monitoring data and transfer knowledge across different operating units makes it particularly effective in feature selection. It automates data analysis for feature choice, especially when the feature count is significant, as discussed by (Fink et al., 2020). The advantages of DL in PHM have also been thoroughly explored in (Fink, 2020). While these techniques are really efficient and promising, they come with inherent challenges. A primary concern is their ”black box” nature, where the exact decision-making process remains opaque, leading to misunderstood outcomes or even misguiding results (Rudin, 2019). Indeed, (Barredo Arrieta et al., 2020) points out that explainability is a crucial feature for the practical deployment of artificial intelligence (AI) models. The major obstacle to this deployment lies in the gap between industries and research community. This lead to an hesitancy in adopting some ML models due to perceived risks to assets. Another obstacle is that a too important emphasis is placed on the outcomes which undermines the significance of understanding the underlying mechanisms. Beyond this, other significant challenges include extensive requirements for data collection and labeling and the high computational cost associated with training and deploying complex models. According to (Zio, 2022), while some recent explorations of ML models enhance PHM outcomes with convenient estimation of associated uncertainty, the fact that data could be hard to obtain, developing systematic frameworks to represent and quantify the different sources of uncertainty remains a area for improvement, especially in the prognostics field.

To counterbalance these challenges, expert systems seem to offer convincing advantages. They represent the earliest forms of AI developed in research, and were, in the past, the driving force behind the development of AI problem-solving and knowledge-based processing. More precisely, an expert system is a program designed to simulate the behavior of a specialist in a specific domain with the ambition to capture human insights within algorithmic bounds (Todd, 1992; Kastner, 1984). To function effectively, it should possess the expertise and judgment to produce answers akin to what a human expert would provide. Moreover, to ensure the reliability and trustworthiness of its decisions, it is often designed to explain its reasoning, and has the capability to incorporate new knowledge into its existing database (Lucas, 1991). Once the expert knowledge is appropriately stored, the system performs inferences to provide choices and responses to user requests through an inference engine. The main advantage of this type of intelligent system is its interpretability. The knowledge is explicitly stored, and the inference process is transparent (Weiner, 1980). Despite these qualities, two main flaws need to be mentioned. The first significant flaw concerns the lack of flexibility of the implemented knowledge. Typically, this often represents knowledge linked together and attempting to best qualify a domain that one wishes to study. Due to this, if there is a need to expand the case study or to deviate from it, the system may lack adaptability. A second, related flaw concerns knowledge coverage. Expert systems were initially designed to be competent in specific domains. Representing a complex or interdisciplinary system can become tedious, due to a large number of required rules, or ineffective, due to a lack of knowledge or unsuitable representation frameworks (Buchanan & Smith, 1988).

Following this, one can observe that while ML offers high predictive power, expert systems encapsulate human expertise, providing decisions that are both transparent and well-founded. Recognizing that neither approach is completely satisfying in isolation, there is a growing interest in merging the robust statistical inference of ML with the clarity of expert systems (Barredo Arrieta et al., 2020). This fusion aims to combine the strengths of both approaches, ensuring a comprehensive approach to PHM (Amodei et al., 2016). Having established the current landscape where ML and expert systems intersect, particularly in the field of PHM, we have gained an outline of the importance of expert systems in such applications (which will be expanded later). We now dive into a retrospective review of the various developments concerning the application of these systems and their gradual integration into prognostics and health management. Forty years ago, (Kastner, 1984) has dealt with the development of expert systems at a nascent stage. The paper first details the intrinsic functioning of the expert program before moving on to a variety of applications, from oil exploitation to infectious disease diagnosis. Seven years later, Lucas *et al.* published ”Principles of Expert Systems” (Lucas, 1991), which set the foundation of expert systems theory and offered a comprehensive and detailed view of the subject while also discussing the existing implementation tools. In subsequent years, there has been many publications on various expert systems applications, each generally focusing on a specific domain. We can mention (Kusiak & Chen, 1988) and (Metaxiotis, 2001), who examined the use of expert systems in production, maintenance, and process planning. The first work provides a more exhaustive overview of different knowledge representations in an expert system, and the advantages of various models, each illustrated by examples of applications. The latter paper focuses more on the operational aspects of these systems, covering the different programming tools used in practice and listing applications by domains. Expert systems have also been surveyed from a modeling perspective. Recently, (Zhou, Hu, Hu, Wen, & Chang, 2021) discussed ways to use belief rule-based systems in theory and practice (which we will explore further). Fuzzy set-based systems, predominantly used to handle uncertainty, were reviewed in (Rajabi, Hossani, & Dehghani, 2019), who covered the evolution of these systems over time and discussed the growing popularity of fuzzy set theory through 60 pioneering applications. Given that PHM is currently in rapid development, and expert systems had reached their peak in popularity decades earlier (see Figures 2 and 3), literature discussing the combination of these two domains is limited. Indeed, although there are several reviews on AI techniques such as ML and DL in PHM, the literature focusing on expert systems and knowledge-based techniques in PHM is very scarce. One can mention (R. Liu, Yang, Zio, & Chen, 2018), which discusses the application of artificial intelligence methods in fault diagnosis and prognostics with an emphasis on rotating machinery and the importance of predefined knowledge. Three years ago, the integration of expert knowledge in PHM has been addressed in a short review (Gay et al., 2021). In this paper, the authors provide a classification in question format to identify the type of expert knowledge required for a PHM application. The main goal is to determine which knowledge modeling approach best suits any given PHM application. Additionally, it mainly discusses prognostics (RUL estimation) with little emphasis on fault detection or fault diagnosis, which are crucial components in PHM strategies. Thus, we believe a more comprehensive review of expert systems applied to PHM is still lacking.

While expert systems and PHM have been extensively reviewed independently, little attention was paid to the method development and application of expert systems in PHM. In this paper, we propose a comprehensive review of this type of methods covering the entire PHM process, with an emphasis on fault detection, fault diagnosis and fault prognosis. We present several applications at each of these steps and discuss the strengths and weaknesses of various approaches across a broad timeline, from the early developments of expert systems to the present day. We also delve into different knowledge modeling techniques applicable in an expert system. In short, the primary aim of this survey is to offer a comprehensive review of the current developments and applications of expert or knowledge-based systems (KBSs) in Prognostics and Health Management of engineering systems. Figure 1 presents the different topics discussed in this review. Section 2 discusses the evolution of research interest in knowledge-based systems and specifically their applications in the PHM field. Section 3 introduces the field of PHM, delving into the various maintenance strategies that have evolved over time, leading from corrective maintenance to the emergence of PHM. Section 4 provides an overview of the architecture of expert systems and details their typical components. In addition, we present the various families of expert systems and how they deal with uncertainty. Section 5 reviews the existing research works applying knowledge-based methods in PHM, by examining their findings and applied methodologies. Section 6 provides a discussion on future perspectives and directions for expert and knowledge-based systems in PHM. Finally, we conclude this work in Section 7.

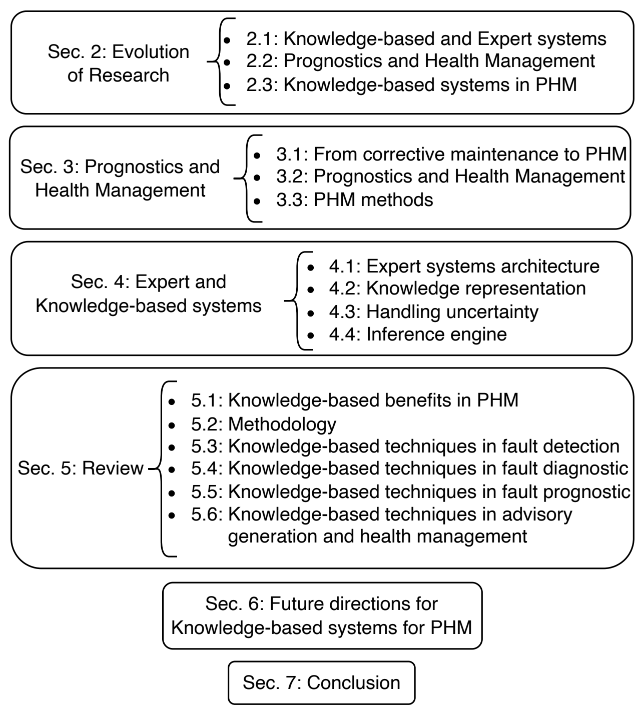

Figure 1. Overview of the structure of this review.

2. EVOLUTION OF RESEARCH

Before delving into the detailed discussion of expert systems and their applications in PHM, it is important to briefly look at the evolution of research interest in these areas over time. For this purpose, we conducted electronic searches on Scopus. This database is multidisciplinary and compiles a wide range of articles from various publishers (ACM Digital Library, Elsevier, IEEE Xplore, Springer, etc).

2.1. Knowledge-based and Expert systems

We begin our study by examining the evolution of research in the field of knowledge-based and expert systems. The methodology employed is detailed in the table below, illustrating our approach using Scopus as the primary search tool. Our investigation involved conducting three independent searches on Scopus, with each search query corresponding to a distinct row in Table 1 and a separate curve in Figure 2. This search was carried out on December 14th, 2023, focusing on papers related to expert systems through three different search queries. We adopted this approach in response to the evolving terminology used to describe expert systems from 1980 to present. Although the terms ”knowledge-based system” and ”expert system” are sometimes used interchangeably, they have subtle differences. Specifically, a KBS is a computer program that employs a knowledge base and artificial intelligence methodologies to solve a specific problem, while an expert system is a kind of KBS designed to emulate the decision-making abilities of a human expert in a particular field (Akerkar & Sajja, 2009). For our discussion, both terms denote a system using a knowledge base and AI to solve a specific problem. The terms ”rule-based system” and ”knowledge-based system” have become increasingly prevalent as reflected in our results: the curves for each term align closely until around the year 2000, after which there is a divergence, indicating a broader range of terms being used to designate expert systems since this period. Setting this aside, the crucial observation from our study is the presence of two peaks in our data curve. The first peak, around 1990, represents the golden era of expert systems. There is also a more recent peak, which signifies a renewed interest in knowledge-based systems today. One can observe a slight decrease around 2013-2014, likely due to the surge in deep learning popularity during that period.

Table 1. Search queries on Scopus and results by query for literature about knowledge-based systems.

Query Expression	Curve in Fig. 2	Results
TITLE-ABS-KEY(”expert system”) AND PUBYEAR(greater than 1979)	ES	68’469
TITLE-ABS-KEY(”expert system” OR ”rule-based” OR ”rule based”) AND PUBYEAR(greater than 1979)	ES_RB	122’325
TITLE-ABS-KEY(”expert system” OR ”knowledge based” OR ”rule-based” OR ”rule based”) AND PUBYEAR(greater than 1979)	ES_RB_KBS	218’512

2.2. Prognostics and Health Management

We now examine the progression of research publications in the field of PHM in Table 2. Figure 3 illustrates a modest increase from 1980 to 2000, transitioning into a period of exponential growth that highlights the rapid advancement of PHM recently. One can notice that half of the publications related to PHM have been produced in the period between 2015 and 2023, underscoring a significant surge in research interest in recent years.

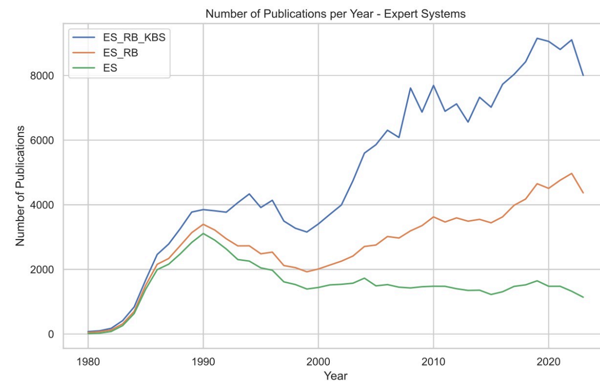

Figure 2. Evolution of the number of research papers published about knowledge-based systems.

Table 2. Search queries on Scopus and results by query for literature about Prognostics and Health Management.

Query Expression	Results
TITLE-ABS-KEY(”PHM” OR ”fault detection” OR ”fault diagnostic” OR ”fault diagnosis” OR ”fault prognosis” OR ”fault prognostic” OR ”prognostics and health management” OR ”RUL prediction”) AND PUBYEAR(greater than 1979)	124’621

2.3. Knowledge-based systems in Prognostics and Health Management

Having traced the development of research in expert systems and PHM independently, it is now interesting to explore the trajectory of publications on the application of expert systems within PHM. The query executed on Scopus, with the resulting data, are detailed in the subsequent Table 3. On Figure 4, one can notice a pronounced initial surge in the 1980s and 90s. This spike can be primarily attributed to the intense development of expert systems during that era, also reflecting a nascent interest in PHM, well before its peak phase. Moving forward, the trend shows a scattered growth from the 1990s to the present, with a notable peak in recent years, aligning with the trends observed in the previously discussed graphs.

3. PROGNOSTICS AND HEALTH MANAGEMENT

This section aims to provide the reader with a comprehensive understanding of maintenance practices up to the present day, and to introduce the PHM paradigm within this established landscape. Then it will offer an in-depth exploration of PHM techniques, covering the underlying processes and the

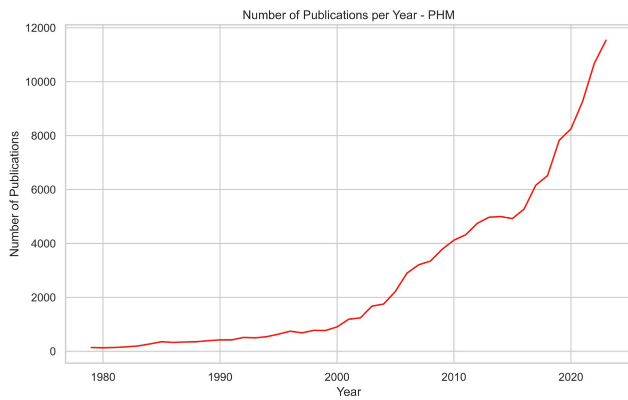

Figure 3. Evolution of the number of research papers published about Prognostics and Health Management.

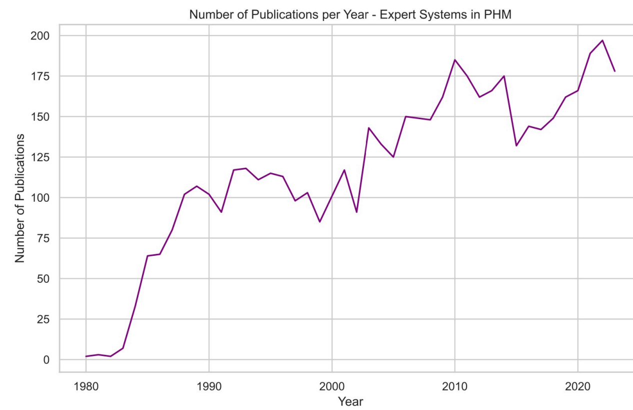

Figure 4. Evolution of the number of research papers published about knowledge-based systems in Prognostics and Health Management.

Table 3. Search queries on Scopus and results by query for literature about knowledge-based systems applied to Prognostics and Health Management.

Query Expression	Results
TITLE-ABS-KEY(((”expert system” OR ”rule-based” OR ”rule based” OR ”knowledge based”) AND (”PHM” OR ”fault detection” OR ”fault diagnostic” OR ”fault diagnosis” OR ”prognosis” OR ”prognostic” OR ”prognostics and health management” OR ”RUL prediction”)) AND PUBYEAR(greater than 1979)	5’159

specific methods employed.

3.1. From Corrective Maintenance to PHM

PHM is intrinsically connected to the optimization of maintenance practices. To fully understand the significance of PHM, it is important to first examine the evolution of maintenance strategies. Maintenance is broadly defined as all the technical and administrative actions necessary to ensure the smooth operation of a system (Swanson, 2001). The most basic form of maintenance, aligning with this definition, is corrective maintenance, which (Sheut & Krajewski, 1994) describes as a ”work-to-failure” approach. Although this strategy may appear rudimentary, it can be the optimal choice for certain assets, especially when system operation is not critical, and failures have minimal impact on safety, reliability, environmental factors, comfort, or economic outcomes. Following corrective maintenance, the next stage in maintenance evolution is preventive maintenance, which involves performing maintenance at predetermined intervals, without considering the system’s current condition. When implemented correctly with the optimal maintenance intervals, preventive maintenance tends to extend the lifespan of equipment. However, optimizing the cost-benefit balance of preventive maintenance is a complex challenge (Malik, 1979). As modern systems have become increasingly complex, the availability of skilled maintenance technicians has been constrained by an aging workforce, declining vocational training, and reduced interest in technical careers among younger generations, necessitating a re-evaluation of traditional maintenance methods. Technological advancements, particularly the widespread deployment of condition monitoring sensors and data capture infrastructure, have enabled continuous monitoring of industrial and infrastructure assets, making condition-based maintenance (CBM) a viable alternative. Unlike preventive maintenance performed at regular intervals, CBM allows for maintenance to be carried out precisely when the system requires it. By monitoring equipment conditions in real time, potential faults can be identified and addressed as they arise (Tsang, 1995). Compared to preventive maintenance, CBM facilitates more efficient operations, but demands significant resources and extensive information (Ahmad & Kamaruddin, 2012). Predictive maintenance advances beyond CBM by not only monitoring the current condition but also forecasting the Remaining Useful Life (RUL) of equipment, allowing maintenance interventions to be strategically scheduled just before the end of the asset’s lifecycle (Fink, 2020). While both condition-based and predictive maintenance rely heavily on the availability of condition monitoring data, CBM primarily focuses on fault detection, with maintenance actions triggered after a fault is identified, without precise knowledge of the system’s RUL. In contrast, predictive maintenance not only detects faults but also estimates the RUL (Mitici, De Pater, Barros, & Zeng, 2023), allowing the system to be operated until the very end of its lifecycle, thus fully utilizing the asset’s lifespan (Figure 6 illustrates this difference). Implementing CBM typically presents significant challenges, including the need for substantial investment in advanced sensor technology and data analytics infrastructure to ensure precise equipment monitoring. Additionally, it requires the development of expertise in data interpretation and the integration of these systems into existing maintenance workflows, which can be complex and resource-intensive. Additionally, successful implementation requires the workforce's acceptance and adaptation, particularly from maintenance engineers, who must be willing to adopt and adapt to new technologies and methodologies (Prajapati, Bechtel, & Ganesan, 2012). While CBM focuses on monitoring the overall condition of machinery to optimize maintenance schedules and prevent failures, Structural Health Monitoring (SHM) specifically targets the structural integrity of infrastructure, such as buildings and bridges, to detect damage and ensure safety. CBM is applied broadly in industrial settings, whereas SHM is used primarily in civil engineering and aerospace (Tinga & Loendersloot, 2014).

All the different maintenance strategies are illustrated in Figure 5. Figure 6 illustrates the different ways of handling a fault by the various types of maintenance as discussed in the previous paragraph. Corrective maintenance involves major repairs after a component fails. Preventive maintenance includes regular minor maintenance and major repairs upon failure, regardless of the component's current condition. Condition based maintenance monitors the component's health in real time, preventing failure but struggles to accurately predict the RUL of the component. Predictive maintenance prevents failures and schedules maintenance at the most optimal time for the component by predicting its RUL.

3.2. Prognostics and Health Management

The primary goal of Prognostics and Health Management (PHM) is to develop methods and tools that facilitate the creation of optimal maintenance strategies, specifically tailored to an asset's unique operating and degradation conditions, thereby maximizing availability while minimizing costs. PHM embodies a holistic approach to effective system health management, covering fault detection, fault isolation, diagnosis of fault origins and types, and the prediction of remaining useful life (RUL).

However, PHM goes beyond merely predicting RUL. It encompasses the broader objective of making informed maintenance and logistical decisions that consider available resources, operational context, and the economic implications of different faults. PHM focuses on managing the health and performance of complex systems by minimizing downtime, reducing maintenance costs, and extending the operational life of assets. This approach leverages real-time data, predictive analytics, and resource availability to align maintenance decisions with the system's operational requirements. Ultimately, PHM aims to reduce the operational impact of failures and optimize maintenance strategies, enhancing overall efficiency and cost-effectiveness.

To achieve these objectives, the following PHM process is usually admitted in the literature, illustrated on Figure 7. The PHM process typically comprises several steps. It begins with understanding the mechanisms of degradation and failure modes, using various inputs like raw sensor data or normative knowledge (Hu, Miao, Si, Pan, & Zio, 2022). These inputs are processed to produce usable information. Then, the development phase involves analyzing these inputs to characterize the system, including fault detection, fault diagnosis, and assessing the remaining useful life of degrading components (fault prognosis). The final phase is decision-making, where the output is an actionable information such as maintenance strategies or resource allocation (Elattar et al., 2016; Compare, Bellani, & Zio, 2019).

3.2.1. Integration Phase

As shown in Figure 7, the integration phase plays a vital role in the overall PHM process. During this phase, data is collected and processed, which is essential for evaluating the health and behavior of the system's individual components. Before any raw data is collected from the system, it is important to first identify the available physical sensors or performance metrics (L. Tang, Saxena, Evans, Iyer, & Goldfarb, 2023). These sensors should be strategically placed throughout the system to ensure that comprehensive information is collected. Following this, the process acquires data from these sensors along with information about the system's health. It is crucial for engineers to carefully determine which data is most relevant to capture. In the final step, the collected data is transformed into meaningful information that can quickly indicate whether an asset is operating abnormally. This involves identifying, selecting, and refining the key predictive features from the acquired data. Expert knowledge can be particularly beneficial in this phase, providing valuable insights that complement machine learning efforts by leveraging a deep understanding of indicators related to system's health (Cathignol et al., 2024).

3.2.2. Development Phase

The development phase is the main focus of our study and will be explored in detail through applications in Section 5. It aims to detect and diagnose faults within an asset, and assess its overall health state. This involves identifying the type of fault, determining its severity, and estimating the time remaining until the asset fails. Each task — fault detection, diagnosis, and prognosis — presents unique challenges. These challenges provide key insights for integrating knowledge-based techniques, which we will discuss later.

Fault detection involves identifying deviations from a system's expected behavior, with the primary goal of initiating a maintenance intervention upon detecting a fault to prevent

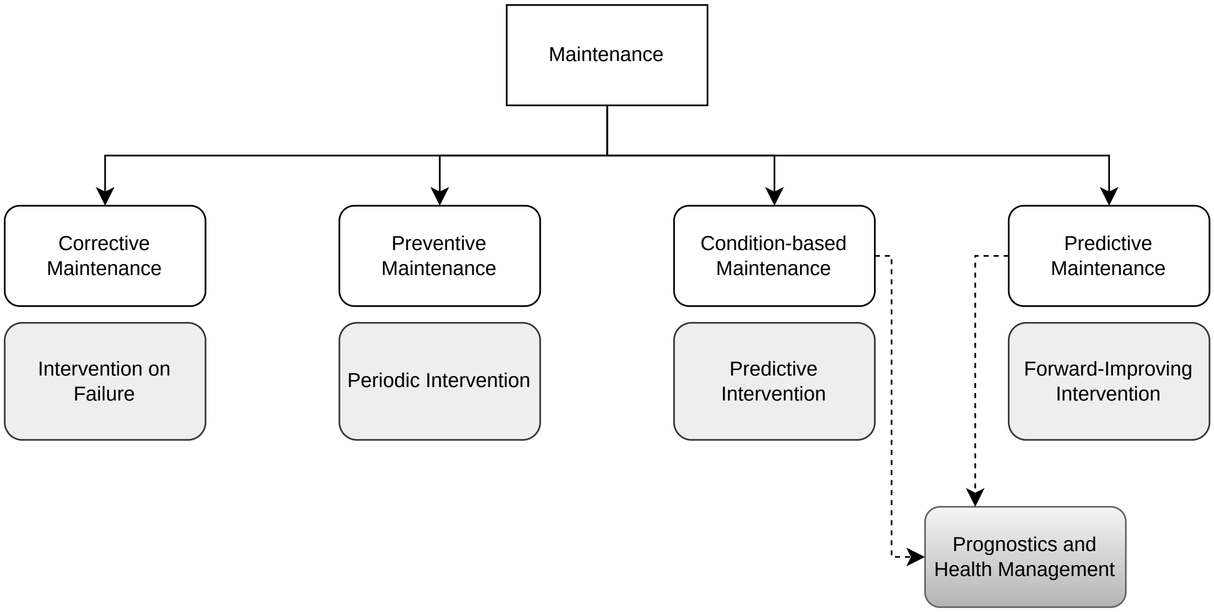

Figure 5. Different types of maintenance strategies and their characteristics, with the place of Prognostics and Health Management in this framework.

its potential consequences and enhance system availability (Miljkovic, 2011; Abid, Khan, & Iqbal, 2021). Depending on the availability and quality of data, various approaches can be employed to achieve effective fault detection. Rule-based approaches, for example, often involve setting predefined thresholds for individual sensor measurements or derived features, triggering alerts when these thresholds are exceeded. These thresholds are typically established based on historical data, expert knowledge, or a combination of both. When a sensor reading crosses its threshold, it signals that the system is deviating from its normal operational state, prompting a maintenance action to prevent further degradation. In more advanced scenarios, data-driven and machine learning techniques may be employed, allowing for more sophisticated analysis that can account for complex interactions between multiple parameters and provide more accurate fault detection in systems with diverse operational conditions (Michau & Fink, 2021; Hsu, Frusque, & Fink, 2023).

Fault diagnostics is the process of systematically identifying and analyzing a detected fault within a system. It involves three key steps:

1. **Fault Isolation:** This step focuses on determining the specific component or subsystem within the larger system where the fault has occurred. By narrowing down the location of the fault, the diagnostic process becomes more targeted and effective.
2. **Identification of the Fault's Origin:** Once the fault is isolated, the next step is to identify the root cause of the fault. This involves understanding what triggered the anomaly, whether it's due to wear and tear, external environmental factors, operational errors, or other underlying issues.
3. **Identification of the Specific Fault Type:** The final step is to classify the fault based on its characteristics, determining the exact nature of the issue. This classification helps in deciding the appropriate corrective actions and ensuring that similar faults can be prevented in the future.

Together, these tasks form the comprehensive process of fault diagnostics, enabling precise and informed decisions for maintenance and system management. After the fault is diagnosed, a critical decision must be made regarding the appropriate corrective action. This decision involves evaluating the severity of the fault, the impact on system performance, and the available maintenance resources. Depending on the diagnosis, the action might range from immediate repairs or component replacements to scheduling maintenance at a later, less disruptive time. The decision-making process also considers the potential risks of continuing operation versus the benefits of addressing the fault promptly, aiming to minimize downtime, reduce costs, and ensure the safety and reliability of the system (Leonhardt & Ayoubi, 1997). In practical applications, this step often involves uncertainty during data processing. This uncertainty can arise from imprecise measurements of from the incomplete information they provide (J. Lee et al., 2014). Such challenges add some complexity to the process of finding the sources of the fault and its type.

Fault prognostics involve assessing the remaining time before a component fails (*i.e.*, looses its function). The goal is to

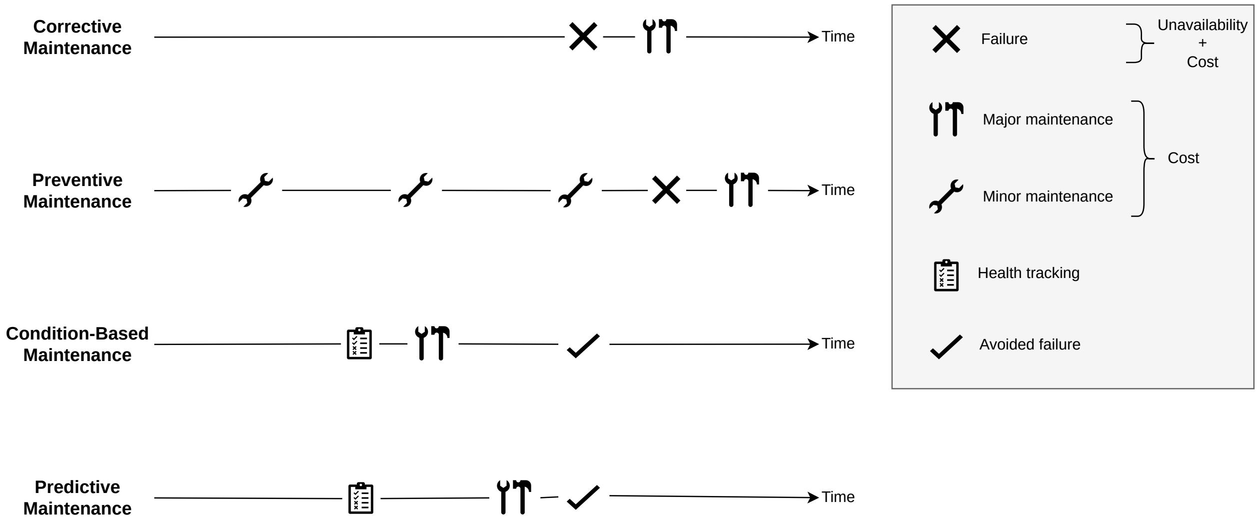

Figure 6. Illustrative comparison of typical timelines using the different types of maintenance strategies. Figure adapted from (Fink et al., 2020).

anticipate and schedule maintenance based on accurate predictions of the component's RUL (Medjaher, Tobon-Mejia, & Zerhouni, 2012). Once detection and diagnosis are established, prognostics introduce its own set of challenges that add complexity to the process. Indeed, factors such as environmental changes, usage patterns, and the inherent nature of the components themselves can influence the trajectory of degradation state evolution (Nejjar, Geissmann, Zhao, Taal, & Fink, 2024). To evaluate the performance of a prognostics approach, (Saxena, Celaya, Saha, Saha, & Goebel, 2021) presents several metrics, including algorithm and cost-benefit performance, which help in selecting the most suitable methods.

Each of these tasks are illustrated in the following Figure 8. In short terms, fault detection is an anomaly detection or binary classification problem, distinguishing between normal and degraded states; fault diagnostics assesses the fault characteristics and severity level, and fault prognosis focuses on estimating the RUL of the asset.

3.2.3. Decision Phase

After obtaining diagnostics and prognostics output from the development phase, the core objective of the PHM decision phase is to support system maintenance. This phase is divided into two main sub-steps: Advisory generation and Health management. Advisory generation involves interpreting the results of diagnostics and prognostics to formulate specific recommendations. These recommendations are developed based on the analysis of the system's current state and predictions about its future evolution. They aim to guide maintenance teams or management systems in making informed decisions. For instance, if a component shows signs of imminent failure, the system might recommend specific preventive maintenance, or if a trend indicates future performance decline, operational adjustments may be suggested. The key to this step is providing advice that is not only accurate but also directly applicable and tailored to the specific conditions of the system in question. In this context, using PHM information to optimize maintenance workflows is crucial, especially as maintenance tasks become increasingly integrated with system operations, demanding comprehensive approaches that optimize both maintenance and operational performance simultaneously (Hu et al., 2022). The second sub-step, health management, turns the recommendations into actions. This involves planning and carrying out the necessary corrective measures to keep the system healthy or bring it back to optimal performance. It requires careful coordination of resources, including spare parts and personnel, and executing the interventions as planned. After these actions are taken, ongoing monitoring is crucial to assess their effectiveness and make adjustments as needed. By using structured approaches like multi-criteria optimization models, decisions can be made more effectively, balancing important factors such as cost, reliability, and resource availability (Ref: Review of Machine Learning Approaches for Diagnostics and Prognostics of Industrial Systems Using Industrial Open Source Data). This continuous loop of action, monitoring, and adjustment helps keep the system running smoothly and constantly improves health management strategies.

3.3. PHM Methods

In literature, PHM methods are primarily categorized into

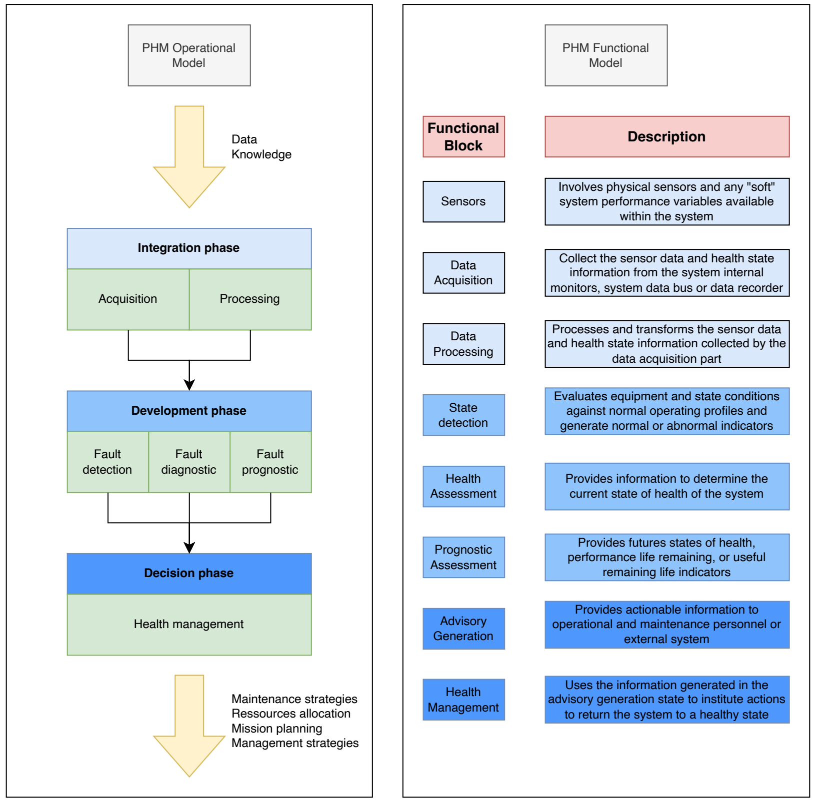

Figure 7. Prognostics and Health Management process from the data/knowledge integration to the decision-making.

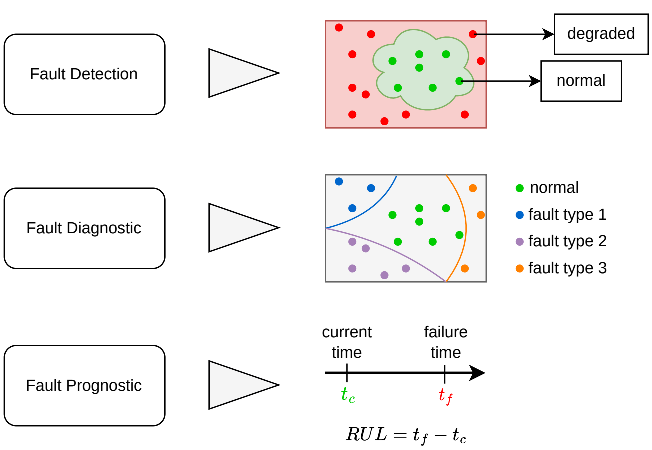

Figure 8. Overview of Prognostics and Health Management tasks: fault detection, fault diagnosis and fault prognosis.

three distinct approaches: physics-based, data-driven, and hybrid approaches mixing data- and model-based approaches (Zio, 2022). Notably, the prominence of data-driven methods has been on the rise (Fink et al., 2020). However, these methods are not without their limitations, especially when data is insufficient. An invaluable alternative in such scenarios is the incorporation of expert knowledge. The following paragraphs explain how each type of method (model-based, data-based and knowledge-based) addresses the three previously discussed tasks of the development phase.

Model-based. To deal with fault detection, these approaches simulate the system's behavior through a detailed understanding of its underlying physical laws. By constructing a mathematical model that represents the system, this method anticipates the expected operation and, when real-time data diverges from this model, a potential fault may be indicated. Since the system and the degradation processes are modeled, when a deviation from the overall behaviors is detected, it is often simpler than for its two counterparts to locate the fault and therefore to identify its cause. Generally, techniques such as sensitivity analysis or failure mode analysis are used to achieve fault diagnosis (Gao, Cecati, & Ding, 2015). For prognosis, we need degradation models to predict the system's future behavior, thereby estimating the RUL of its components. Such models are crucial for determining when a system component reaches its failure threshold.

Data-driven. Currently one of the most widespread approaches in literature, data-driven approaches leverage the data retrieved from sensors to recognize anomalous patterns. The effectiveness of this method relies on the ability to detect irregularities within the data that deviate from established norms. There is also an increasing necessity to detect anomalous conditions when the available data represents normal operation, for which methods capable of reproducing complex data distributions can be beneficial. Then, traditional data-driven fault diagnostic systems generally require measurements where the actual states of degradation are known. Based on this, a data analysis can be performed using ML methods. However, unsupervised learning struggles with long-term dependencies, and supervised learning methods often require a significant number of specific data points that are difficult to obtain for diagnostics. The effectiveness of data-driven approaches in prognostics relies on the availability of extensive data (Khan & Yairi, 2018). It requires comprehensive run-to-failure data and detailed information about the degradation process. A broad variety of machine learning techniques, including Convolutional Neural Networks, Support Vector Machines (SVM), and Denoising Auto Encoders, are employed to estimate the RUL (Si, Wang, Hu, & Zhou, 2011).

Knowledge-based. Considering fault detection, these methods rely on predefined rules that describe when problems are likely to occur based on measurements. Information is collected from sensors and processed using expert knowledge or directly collected from experts or normative knowledge. It is then coupled with an inference engine, to determine the presence of anomalies. The transition from fault detection to fault diagnosis is quite straightforward for purely knowledge-based methods, as the predefined rule set based on knowledge allows for the inference of the cause of the fault (Isermann, 1997). In practice, this type of method is often combined to increase the certainty of the result (Gharib & Kovács, 2023). In the field of prognostics, knowledge-based approaches are generally less widespread in literature but look particularly interesting in industry. These approaches, once successful in extracting degradation laws, often attempt to formulate these laws into rules for estimating RUL. However, this rule-based formulation is not always effective. Although it can provide a structured approach, the complexity and variability of real-world degradation processes can make such rule-based systems less effective than more dynamic methods such as physics-based models or data-driven techniques.

Figure 9 illustrates some of the techniques used by each method to perform PHM tasks. This list is not exhaustive and some of the methods classified in one branch can be used in another depending on the application.

In certain complex systems, the utilization of a single method may not be sufficient. In such scenarios, a combination of methods is often employed to enhance accuracy and reliability. Here, we focus on knowledge-based methods and their integration with other approaches, predominantly data-driven methods. The following section discusses why incorporating knowledge-based techniques has many advantages.

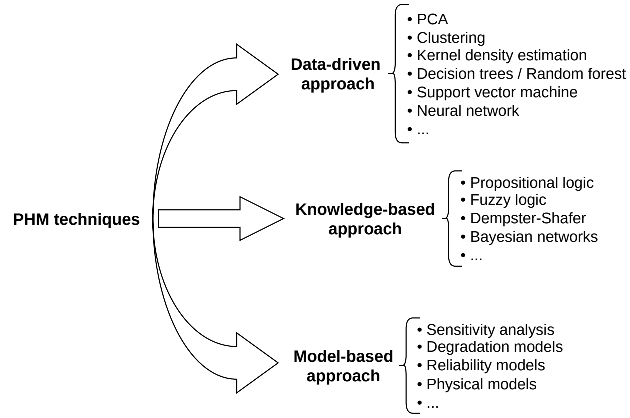

Figure 9. Some of the model-based, data-driven and knowledge-based techniques used in PHM.

4. EXPERT AND KNOWLEDGE-BASED SYSTEMS

This section has for purpose to provide the reader with a clear and comprehensive understanding of expert systems, from their construction to their architecture. We begin by discussing the key actors involved in the project and the design process of the system, providing the reader with a practical understanding of how to implement an expert system. We then delve into the modeling of the system, starting with an exploration of the different types of knowledge representations, each with its unique strengths and limitations. Following this, we examine how these systems handle uncertainty, focusing on the mathematical tools that make expert systems so intriguing. Indeed, the formalization of uncertainty through clear and understandable relationships between facts allows users to comprehend the underlying mechanisms and to tailor them as needed. Lastly, we describe the two main types of inference processes in an expert system, which facilitate the journey from input to output.

4.1. Expert Systems Architecture

There are three crucial actors contributing in the development of an expert system. The *Expert*, who holds domain-specific knowledge; the *User*, the end beneficiary, ensuring the user-friendliness of the system; and the *Knowledge Engineer*, responsible for the design and implementation of the system, ensuring its fidelity and efficacy (GUIDA & TASSO, 1989a). Frequent interactions between the three actors are often important to ensure the quality and efficiency of the system (Davis, 1979). Indeed, the process of creation involves many steps interconnected as represented in the diagram on Figure 10.

1. The first step is defining the problem and its boundary. This involves determining the necessary knowledge to understand the problem. However, it is common to adjust this definition as development progresses, because

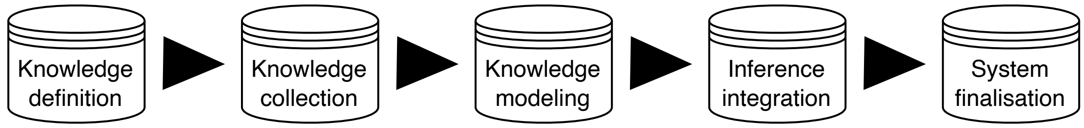

Figure 10. Design process of an expert system: Knowledge definition → Knowledge collection → Knowledge modeling → Inference integration → System finalization.

the problem's scope may be broader or different than initially thought (Steels, 1990).

2. Knowledge elicitation, also referred to as knowledge collection, is a task extensively explored in academic literature (Leu & Abbass, 2016; Gnanamalar, Janani, & Devi, 2013; Song, Jiang, & Li, 2015; Nakakoji & Fischer, 1995; Boose, 1985; Forsythe & Buchanan, 1989). This process involves extracting expertise from those with significant experience in their field. Either from experts who can offer insights based on their experience, or from established standards that gather a wide range of theoretically and practically acknowledged information. This knowledge is then applied either directly or used to interpret the results from sensor data, depending on the situation. During this phase, some challenges need to be taken into account (Musen, 1993). Firstly, the core of this expertise is often challenging to state in a logical and coherent way, as some knowledge may be part of common sense and obvious to the expert, who won't express it explicitly. Secondly, experts, with their profound understanding, tend to possess a 'know-how' of performing tasks rather than a straightforward 'know-what', which adds complexity to the task of conveying this knowledge to a system. Finally, the mental models held by experts are shaped by various social processes and biases. This influence necessitates careful consideration in deciding whether or how to incorporate these models into a system, as these factors can significantly affect the representation of knowledge. According to (Moore & Miles, 1991), the most effective way to create a comprehensive knowledge base is to involve multiple experts who collectively cover the entire spectrum of the subject area in order to attenuate the bias.

3. The knowledge modeling phase is typically the most technical aspect of the process. Once all the knowledge has been collected from the previous step, it involves organizing it into a knowledge base. This base serves as a central archive for all the information and expertise provided by the experts (Lucas, 1991). What's more important than the knowledge itself for the operability of the expert system is how this knowledge is modeled (Muhammad, Garba, Oye, & Wajiga, 2019). This aspect has been extensively reviewed in literature, and some of the main mathematical tools used for this will be detailed later.

4. The inference engine is the algorithmic heart of the system, its integration to the system is the last step required to have an operational system (Maria Malek, 2008). It uses the data from the knowledge base to produce appropriate responses to user queries (this part will be expanded later).

5. The final step in the expert system development is its industrialization, focusing on making the system user-friendly and comprehensible (GUIDA & TASSO, 1989b). In one hand, the user interface, serving as the interaction platform between the user and the system, is crucial for ease of use. This is where users input queries and receive responses. In the other hand, to ensure understandability, an explanation module is often included. This module justifies or explains the system's deductions, providing traceability and transparency to the reasoning process. This feature helps users grasp the underlying logic, and trust the system's capabilities.

A high-level overview of an expert system with the components discussed previously is illustrated as a diagram in Figure 11.

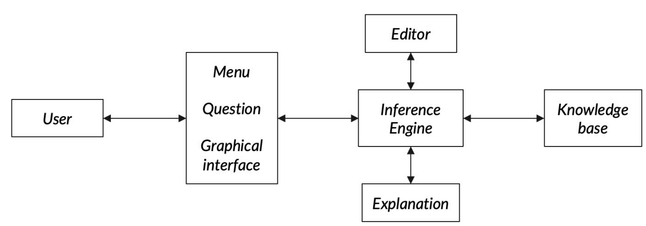

Figure 11. Typical architecture of an expert system. The user is the person who operates the system - The interface is the interactive part where the user submits their queries - The editor allows for editing the knowledge base - The knowledge base is where facts are stored and modeled appropriately - The inference engine is the algorithmic part of the system that transforms the facts from the knowledge base into a response to the user's request - The explanation component is the module that explains the system's reasoning in responding to the user's request.

4.2. Knowledge Representation

KBSs can model their knowledge in various ways, whether through production rules, semantic nets, or frames to obtain rule-based system (RBS), semantic-based system or frame-based system. This section aims to define and describe those three kinds of systems.

4.2.1. Rule-Based Systems

A RBS is the simplest form of artificial intelligence. It is a system that makes decisions or generates outcomes based on a predefined set of rules. It is also, by far, the most commonly used knowledge representation in expert systems (Grosan & Abraham, 2011). These rules are typically formulated following an ”if-then” logic, where the ”if” part defines a condition to be met (called the *premise*), and the ”then” part dictates the action to be taken or the conclusion to be drawn if the condition is satisfied (called the *conclusion*). The reader can look at (Ligêza, 2006) for further literature about the logical foundations behind production rules. Furthermore, in 2019, (Masri et al., 2019) conducted a review of the most popular RBS found in literature.

4.2.2. Semantic-based and Frame-based systems

Semantic nets (or ontologies) have consistently held a significant role in expert systems. They belong to the realm of knowledge representation, offering a visual and descriptive approach to model knowledge through nodes and arrows. Each node stands for an entity, while each arrow represents the relationship between two entities. Beyond their clear visual interpretation, the advantage that semantic networks hold over more rudimentary logical representations, like production rules, is their ability to articulate a multitude of relationships between entities, such as ”is a”, ”has a”, or ”part of” (Fritz Lehmann, 1992; John Sowa, 1992). Figure 12 represents an example of semantic net about a fault detection problem in a railway track illustrating the vast range of relations that can be represented.

By adding a layer of complexity to the semantic net, we can transition to a frame-based system. In this system, what was once a node in the net becomes a frame, with each frame possessing attributes that define its relationships to other elements. While this approach may slightly complexify the conceptual view, it introduces a richer variety of relationships, such as ’Instance-Of’ and ’Superclass’ links. These links enrich the taxonomy, allowing different levels of abstraction. For a more detailed exploration of this concept, readers may consult (Lucas, 1991; Fikes & Kehler, 1985).

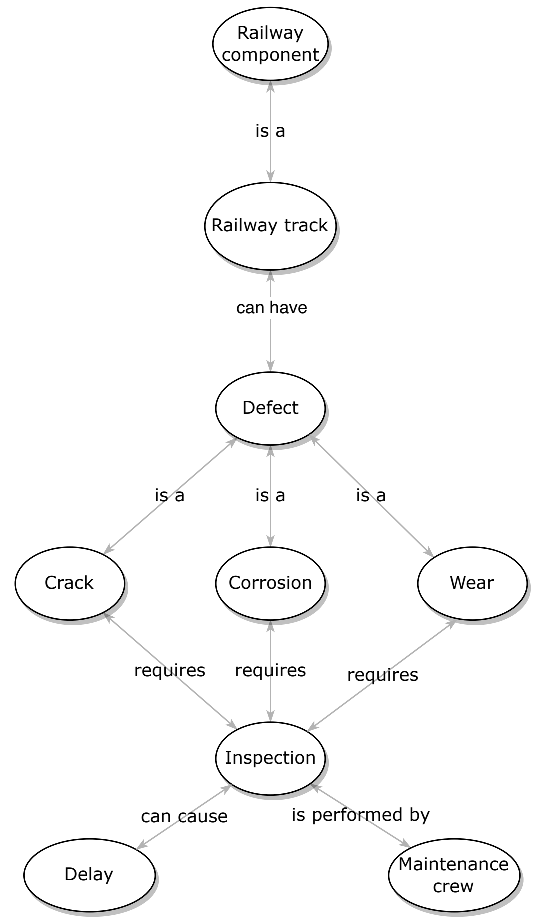

Figure 12. An example of a semantic network about a fault detection problem in railway tracks.

4.3. Handling Uncertainty

After having examined the various types of knowledge representations in expert systems, we must now address an inherent concept of our world: uncertainty. Specifically, how can we incorporate uncertainty into these representations? In this section, we explore various tools designed to handle uncertainty. In expert systems, uncertainty is commonly addressed using the concept of belief. In belief rule-based systems, belief is a broader notion that assigns a degree of belief to any defined element. This theory can then be refined with additional concepts to define more precisely the type of uncertainty being considered (Jian-Bo Yang, Jun Liu, Jin Wang, How-Sing Sii, & Hong-Wei Wang, 2006; Mahesar, Dimitrova, Magee, & Cohn, 2017). The first type of refinement we address here lead to consider uncertainty as imprecision. In expert system, we often encounter terms with vague or inexact definitions and the main tool to tackle this is fuzzy logic which provides a framework to handle such ambiguities. A second aspect of uncertainty treated is probabilistic uncertainty, which is first addressed by using Probability Theory, it enables us to deal with scenarios where terms or events may or may not be. More specifically, it is the application of Bayes’ Rule in Bayesian Networks that is widely used in expert system applications. Then, we explore the Dempster-Shafer theory, which offers a modification to the first axiom of Probability Theory, allowing greater flexibility in handling uncertainty.

4.3.1. Belief Rule-Based Systems

Belief Rule-Based (BRB) systems refers to RBS that assign a belief degree to facts and/or rules. The belief degree can be considered as a degree of truthfulness between 0 and 1 to assert how confident we are in a fact. These systems are as transparent as their deterministic counterparts but have the advantage of handling uncertainty in a general setting.

Let us consider a set of facts $\mathcal{F} = \{F_i\}$ and a set of rules $\mathcal{R} = \{R_j\}$. Each fact F_i and rule R_j is associated with a degree of belief $b_f(F_i)$ and $b_r(R_j)$ respectively. The belief degrees can be defined as

$$b_f : \mathcal{F} \rightarrow [0, 1] \tag{1}$$

$$b_r : \mathcal{R} \rightarrow [0, 1] \tag{2}$$

where $b_f(F_i)$ represents the confidence level (belief degree) regarding the truthfulness of fact F_i. $b_r(R_j)$ symbolizes the trust that if the premises of rule R_j are validated, then the consequence will follow.

The determination of the belief degrees can either come from data analysis or expert experience. Also, to determine the degree of belief necessary to assert that the facts are validated, and to activate inference, weights are assigned to each rule. For a deeper dive into this topic, the reader may refer to the article by (Zhou et al., 2021).

As we can see, this theory is very comprehensive, allowing us to develop theoretical frameworks that clarify certain aspects while fitting within its vast field of application. Fuzzy logic is generally regarded as a method for treating beliefs as degrees of truth in scenarios where information is not clearly defined or is ambiguous. On the other hand, Dempster-Shafer theory is seen as representing belief as a measure of confidence derived from evidence, capable of accommodating uncertainty and partial information (Jian-Bo Yang et al., 2006; Cao, Zhou, Hu, He, & Tang, 2021).

4.3.2. Fuzzy logic

Fuzzy logic is a branch of mathematics that allows reasoning with imprecise terms, in contrast to classical logic where terms are either true or false (Zadeh, 1999). In fuzzy logic, an object can be both true and false simultaneously, but with different degrees of membership (Trillas & Eciolaza, 2015; Dubois & Prade, 1996). Consider the fuzzy descriptors 'high' and 'low' as an example. One might describe a value as being 'very high' or 'somewhat low'. Fuzzy logic provides a means to capture and express numerically these nuances.

Implementing the fuzzy logic technique in real applications, specifically in RBS, involves the following steps (Bai, Zhuang, & Wang, 2006) as pictured in Figure 13:

1. **Fuzzification**: This step involves transforming classical data into fuzzy data. For example, instead of stating unequivocally that something is "high", we quantify its degree of intensity on a scale from 0 to 1 (how high is it in a scale from 0 to 1?). In this stage, we utilize a membership function that maps a value or indication of a particular attribute to a number between 0 and 1 for fuzzy sets of the premises. Consider the scenario where we have a general rule linking temperature (A) to air conditioning settings (B). This global rule can be broken down into two more specific rules based on fuzzy logic: "If the temperature is warm (A1), then set the air conditioning to high (B1)," and "If the temperature is cool (A2), then set the air conditioning to low (B2)." The actual temperature provided by the user determines the extent to which the conditions of A1 and A2 are met, reflected by the values of their respective membership functions.
2. **Fuzzy Inference Process**: This step combines the fuzzy sets and membership functions from the premises to derive the membership functions for the conclusions based on a given fuzzy rule. The degree of membership in the premises facts A1 and A2 determines the degree of activation for each rule. This activation level then dictates the value of the membership functions for the conclusions B1 and B2 . Basically, the more a temperature aligns with either the "warm" or "cool" fuzzy set, the more it activates the corresponding rule, leading to a stronger influence on the respective air conditioning setting.
3. **Defuzzification**: The outputs obtained from the combination of inputs remains fuzzy entities (B1 and B2). Defuzzification is the process of converting these fuzzy values back into one crisp, clear value. Different methods exists to do it (centroïd, bisector, mean of maximum, etc.) (Roychowdhury & Pedrycz, 2001; Leekwijck & Kerre, 1999). The defuzzification process uses the values of the membership functions of B1 and B2 to determine a unified output. This involves finding a balance between B1 and B2, based on their respective membership values.

4.3.3. Bayesian networks

A Bayesian Network (BN) is a mathematical tool that bridges graph and probability theory, offering a valuable framework for representing probabilistic knowledge and conducting inference in intelligent systems. It consists of two components: a qualitative part and a quantitative part (Guinhouya, 2023).

The qualitative component is a directed acyclic graph that represents the dependencies between variables. An arrow from X_i to X_j indicates a probabilistic dependency between these variables; specifically, knowledge of the value of X_i influences the potential value of X_j. Each vertex in the graph is called a node, with each node corresponding to a specific variable. The connections between these nodes are referred to as edges or arcs.

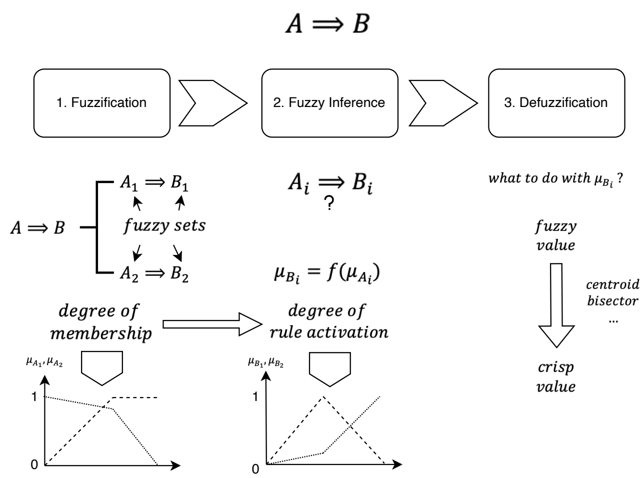

Figure 13. Typical application of fuzzy logic in a knowledge-based system.

The quantitative component of a Bayesian Network comprises the Conditional Probability Table (CPT). Each node X_i has its associated CPT, which details the strength of dependency between X_i and every node connected to X_i. The entries of the CPT are determined using Bayes' rule:

$$P(X_i|X_j) = \frac{P(X_j|X_i) \times P(X_i)}{P(X_j)} \tag{3}$$

- $P(X_i)$ and $P(X_j)$ represent the individual probabilities of observing X_i and X_j, respectively.
- $P(X_i|X_j)$ denotes the conditional probability of observing X_i given X_j.
- $P(X_j|X_i)$ signifies the conditional probability of observing X_j given X_i.

The data required to construct BNs can be derived from datasets, expert knowledge, or a combination of both. Once set up, BNs enable two primary types of inferences: predictive inference (or forward chaining), which determines effects based on their causes; and diagnostic inference (or backward chaining), which infers causes from observed effects (Pearl, 1988). For a deeper understanding of Bayesian networks, readers can refer to (Darwiche, 2008; S. H. Chen & Pollino, 2012; Kitson, Constantinou, Guo, Liu, & Chobtham, 2022).

4.3.4. Dempster-Shafer Theory

According to probability theory, knowing nothing about two distinct sets or being certain that these sets have equal probabilities is mathematically equivalent; both scenarios attribute an equal probability of 0.5 to each set. The Dempster-Shafer Theory (DST), however, provides a richer framework to model uncertainty, allowing for a distinction between genuine ignorance and equal likelihood (Gordon & Shortliffe, 1984). The key elements of DST are the following (Yager, 1987):

1. **Frame of Discernment:** This is a finite set, Θ, consisting of mutually exclusive propositions.
2. **Mass Function:** A function $m : 2^{\Theta} \rightarrow [0, 1]$, assigning a degree of belief (or "mass") to each subset of Θ verifying two conditions :
   - $m(\emptyset) = 0$
   - $\sum_{A \subseteq \Theta} m(A) = 1$

   It is important to note that the mass function allocates belief specifically to the given subset, not to its parts.
3. **Belief and Plausibility:** These two functions provide quantification of uncertainty:
   - **Belief:** It measures the total belief assigned to a set A (a fact of our knowledge base) with the information we have at the moment:
   $$\text{Bel}(A) = \sum_{B \subseteq A} m(B)$$
   - **Plausibility:** It measures the maximum possible belief for a set by considering eventual further information:
   $$\text{Pl}(A) = \sum_{B: B \cap A \neq \emptyset} m(B)$$

   It follows naturally that $\text{Bel}(A) \leq \text{Pl}(A)$.

The DST is an extension of classical probability theory that offers a more nuanced way to represent information. For instance, rather than merely stating a probability, one might express: "I have a 65% belief that it will rain, but it is 100% plausible based on the available evidence". By using this framework in a rule-based system, one can effectively manage uncertainty, fuse information from diverse sources and make suitable decisions when faced with conflicting or incomplete data (Zhou et al., 2021). For example, the Dempster-Shafer combination rule, a key element of DST often applied in practice (as we will discuss in 5), enables us to calculate the combined belief from multiple sources of belief. This is achieved by considering the intersections of evidence sets from the original belief functions (Yager, 1987; Sentz & Ferson, 2002).

4.4. Inference Engine

Let us consider a knowledge base that consists of either production rules, semantic nets, or frames. This knowledge base is filled with well-defined information, uncertain or not. The element that combines this information to provide answers to user queries is called the inference engine. As previously mentioned, the inference engine scans the knowledge base to provide the response queried by the user. There are two main methods to accomplish this, forward chaining and backward chaining. To illustrate these two procedures, let us consider a RBS containing the set of rules {R1, R2, R3, R4} involving the set of facts {A, B, C, D, E, F, G}, defined as follows:

- R1 : IF A AND B, THEN E
- R2 : IF A AND C, THEN F
- R3 : IF C, THEN G
- R4 : IF D, THEN C

Backward chaining is an inference method that starts with the desired goal. The system then searches its knowledge base for rules that conclude with the desired goal. The premises of these rules then become sub-goals for which the system will again look for rules with these sub-goals as conclusions. By continuing in this manner, the system can trace back to the initial premises that indirectly imply the final goal. Suppose we want to determine which set of facts leads to the conclusion F. Upon inspecting the knowledge base, the inference engine finds that conclusion F is derived from rule R2, which has conditions A and C. Thus, A and C become new conclusions to achieve. The engine further observes that A is not the conclusion of any rule, but C is derived from rule R4 with D as the condition. Ultimately, to arrive at conclusion F, the combination of facts A and D or A and C is required (Jose, 2011; Chubb, 1984).

Forward chaining operates in the opposite direction to backward chaining: it starts from the initial premises provided and explores the rules to determine possible conclusions. Let us consider the case where the user wants to know what conclusions can be derived from the fact D. So we start with a virtual set where only the fact D is present, the system then applies rule R4 to infer fact C, followed by rule R3 to infer fact G. Then from C and G alone, no other facts can be deduced using the set of rules. Therefore, the answer is that from the fact D, conclusions C and G can be drawn (Jose, 2011; Chubb, 1984).

It is evident from these two examples that forward chaining and backward chaining serve different purposes. Forward chaining is especially useful in the event of a system fault, and one seeks to determine the appropriate maintenance actions. Conversely, backward chaining is relevant when an anomaly or failure is observed, as it allows tracing back to the root cause of the disruption. Moreover, forward chaining is often more computationally demanding. Designed as a search algorithm, it does not have a predefined optimal method to reach the result and may require exhaustive exploration of the knowledge base. On the other hand, backward chaining, being goal-driven, breaks down the problem starting from the end goal and avoids unnecessary computations (Al-Ajlan, 2015). Although the given example deals with inference in rule-based systems, the process in semantic-based or frame-based systems is similar in its aim to connect facts. However, the main difference lies in the knowledge representation. In these systems, the relationships between facts are not limited to the "IF, THEN" conditionals typical of production rules. They are more complex and varied, and may require the user to explicitly specify the link sought or that the system enriches the information with existing relationships between facts.

5. REVIEW

This section introduces the key differences between data-driven, model-based, and knowledge-based systems, and highlights the growing importance of merging these approaches. We will emphasize how KBSs offer significant advantages for implementing PHM processes, either on their own or more often in combination with data-driven or model-based approaches. Following this, the main objective of this section is to review various research articles that discuss the application of knowledge-based techniques in PHM, providing insights into their effectiveness and practical use in different industrial settings.

5.1. Knowledge-based benefits in PHM

Data-driven approaches are prominent in the literature, mainly because of their ability to exploit historical data for predictive modeling and decision-making, and the advent of new technologies (ML, big data) which enables us to access and analyze huge amounts of data. This method, while advantageous for its ability to identify patterns and insights from vast data sets, is not without its drawbacks. In signal analysis, for example, frequent inaccuracies occur in data processing when signals are long, non-linear or non-stationary. Also, estimation accuracy depends on the quality and quantity of available data. These problems can hamper the effectiveness of the approach, particularly in situations where labeled data (failure data) are scarce and measurements are unevenly distributed between components (Y. Wang et al., 2024; Gay et al., 2021). On the other hand, model-based methods in PHM are known for their reliability and accuracy. They rely on a thorough understanding of the system's physical mechanisms and failure processes. However, these methods come with their own set of difficulties, not least the complexity of model development, which can be time-consuming and require considerable domain expertise. In addition, they often lack flexibility and struggle to adapt to changes in system dynamics that were not initially taken into account in the model (Soualhi, Lamraoui, Elyousfi, & Razik, 2022). Hybrid approaches merging data-driven approach and model-based method, seem ideal in theory. They aim to capitalize on the strengths of both approaches, potentially offering more comprehensive solutions. However, these hybrid systems introduce added complexity, making modeling, debugging and data synchronization more difficult. It can also be complex to balance the contributions of data- and model-based components. In this paradigm, KBSs are emerging as an alternative that addresses some of the limitations of data-driven and model-based methods (Peng, Xia, Li, Song, & Hao, 2022). KBSs make use of domain expertise, which is particularly valuable in scenarios where data is scarce but expert knowledge is abundant (Ruan, Wang, Yan, & Gühmann, 2023). They facilitate decision-making by providing interpretable information, and prove robust in the face of problems such as noisy or incomplete data (Sarazin et al., 2021). For small and medium-sized enterprises, which are often faced with data accessibility problems, incorporating expert knowledge into the PHM process offers solutions that improve the system's ability to explain and adapt (Omri, Masry, Mairot, Giampiccolo, & Zerhouni, 2021). KBSs also simplify interpretation through, for example, the use of linguistic variables in fuzzy rules (Ishibashi & Lucio Nascimento Junior, 2013). It's also worth noting that KBSs are generally much more interactive, favoring user-software interaction and system readability (Biagetti, 2004). However, KBSs alone are not without their drawbacks. They can be limited by the extent and currency of the included expert knowledge, and may struggle with processing large volumes of data or adapting to new, unforeseen scenarios. Consequently, the optimal solution often lies in a combination of these approaches (Radtke & Bock, 2022). It aims to offer a balanced, robust, and flexible PHM system, capable of addressing the diverse challenges faced in various industrial contexts.

The advantages and disadvantages of the main knowledge-based techniques when applied to PHM tasks are informatively presented in Table 4. The following section will highlight and further develop these points through the described applications.

5.2. Methodology

The review focuses on the incorporation of knowledge-based techniques into the PHM development process, structured around three key stages: fault detection, fault diagnosis and fault prognosis. For each of these stages, we explore up to four distinct methodologies: deterministic systems, where behavior is predicted without uncertainty usually through propositional logic; fuzzy logic, which handles imprecision in data and knowledge; the Dempster-Shafer theory, focusing on evidence-based reasoning and belief functions; and Bayesian networks, used for probabilistic inference and decision-making under uncertainty. For each relevant article under each subsection, we start with data collection, followed by data processing. Then, we discuss how knowledge is modeled in the study and conclude by examining the inference methods leading to the necessary results. The taxonomy in Figure 14 outlines the structure of the review and compiles the articles discussed therein.

5.3. Knowledge-based techniques in Fault detection

Table 5 categorizes articles related to fault detection.

5.3.1. Deterministic

A fault detection tool using a variety of subsets of deterministic expert rules was utilized in (Schein et al., 2006) to predict faults in air handling units. These rules are derived from the physical principles of mass and energy conservation. The initial step involves determining the mode of operation using control signals. Subsequently, this information is applied to identify the appropriate subset of rules which ultimately ascertains the presence of a fault. While the rules themselves are fixed, the values within them can be modified, thereby rendering the system adaptable. The study emphasizes the importance of properly setting rule thresholds to balance effective fault detection and minimizing false alarms. This method has been tested in both an emulation environment and in real-world conditions.

(Heidari, 2017) presents an advanced approach for bearing fault detection, combining a rule-based classifier ensemble with a genetic algorithm for feature reduction. The method starts with the collection of vibratory data, followed by feature reduction using genetic algorithms, leveraging expert knowledge to identify the most relevant features. The generated rules, based on expert understanding of bearing failure modes, form the base classifiers. These classifiers are then combined into an ensemble to optimize diversity for increased accuracy. Their effectiveness is tested on a fault decision table (a dataset containing observations on vibration and bearing conditions), significantly improving the accuracy of fault detection.

Semantic networks or ontologies have also been applied to fault detection. In the field of building energy systems, (T. Li et al., 2022) first developed a comprehensive ontology on the basis of existing prior knowledge. It involves developing an ontology to represent this knowledge in a readable format and enriching it with expert knowledge to establish semantic rules for detecting various types of faults (operation problems, control issues, equipment malfunctions, and sensor failures). Finally, building data is collected and aligned with the ontology, creating a knowledge and data graph used to verify the presence of a malfunction. The approach was successfully applied to an air conditioning system comprising 51 units, each with unique characteristics, using 21,844 data series.

Another application is presented in (Azad & Gabbar, 2012), the authors develop a semantic fault detection network for the diagnosis and control of micro-grids. Azad and Gabbar utilize a combination of data from intelligent electronic devices and physical knowledge to assess risk and identify faults in micro-grids. To achieve this, the failure modes of each variable are studied, and the causes and risks are calculated using a fault localization algorithm. In this context, the semantic network acts as a tool for processing deviations, linking the grid's structure, behavior, operation, and associated equipment variables. This methodology has enhanced the reliability of micro-grids by providing automated fault detection.

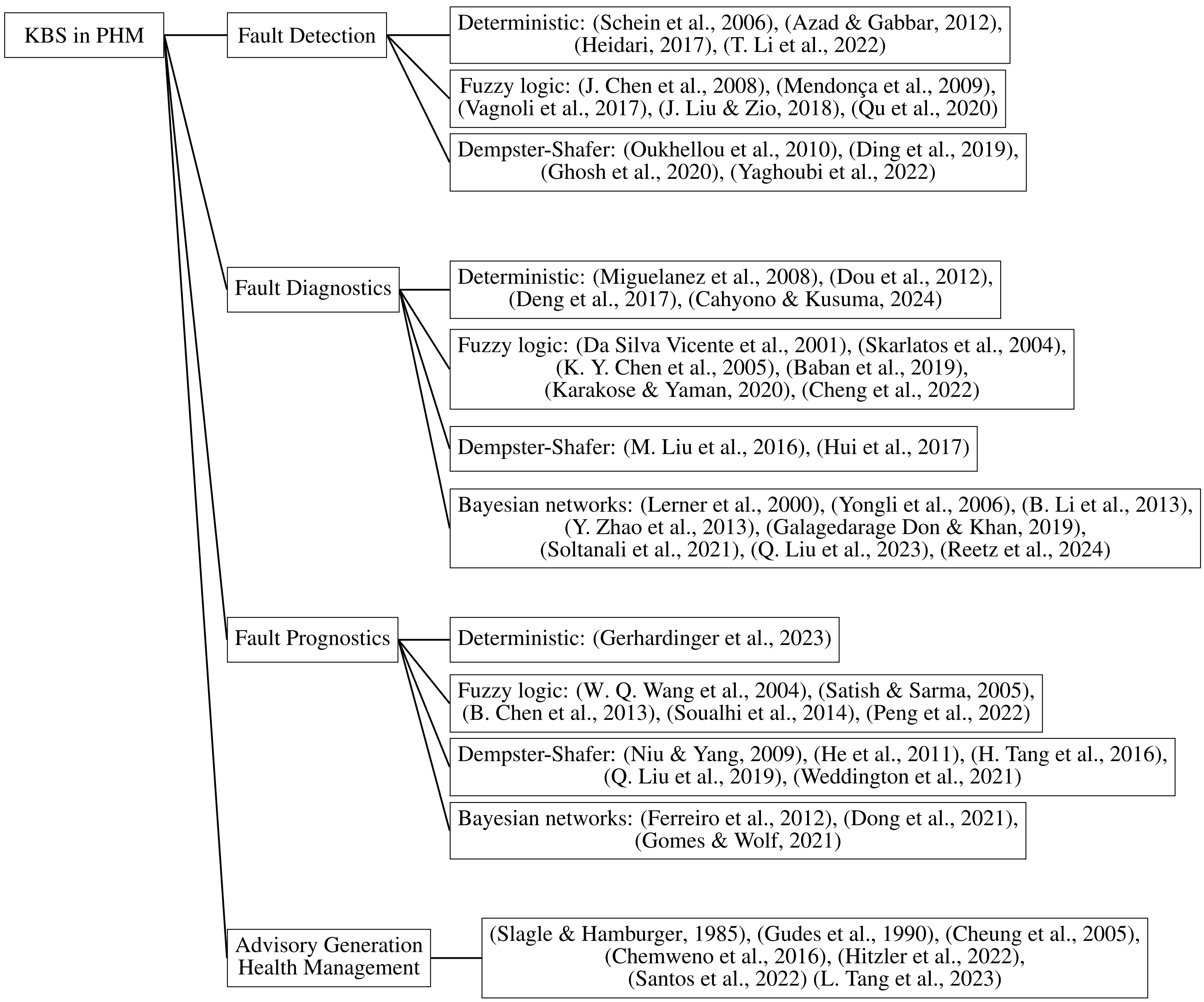

Figure 14. Taxonomy of the reviewed literature on Knowledge-based Systems (KBS) in Prognostics and Health Management (PHM).

Method	Advantages	Disadvantages
Deterministic	• Simple • Reliable • Interpretable	• Rigid • No uncertainty handling • Threshold-sensitive • Data-dependent
Fuzzy Logic	• Handles uncertainty • Adaptable • Interpretable • Integrates well	• Complexity • Needs tuning • Imprecise rules • Computational cost
Bayesian Networks	• Handles uncertainty • Causal modeling • Integrates diverse data • Temporal tracking	• Not suited for fault detection • Complex structure • Data-intensive • Expert-dependent • Computationally demanding
Dempster-Shafer	• Effective information fusion • Handles uncertainty • Conflict resolution	• Complex • Computationally intensive • Needs accurate evidence

Table 4. Advantages and disadvantages of different expert systems methods.

5.3.2. Fuzzy Logic

In (Qu et al., 2020), a novel method for wind turbine fault detection is proposed, using expanded linguistic terms in non-singleton fuzzy logic. The process begins with gathering operational data from wind turbines and transforming it into fuzzy inputs to capture nuances in the data. The fuzzy inference system then employs linguistic terms and rules, which are derived from prior knowledge and expert experience. These terms are qualitative descriptors that represent the value of a variables (”high”, ”medium”, ”low”. . .). The system allows for generating new terms from existing ones by using two adjacent existing terms, allowing the system to define a more granular spectrum of fault conditions. This approach allows for the generation of new rules that incorporate both original and expanded terms, leading to a more detailed and accurate fault detection process. The system can differentiate between multiple levels of fault severity, providing a more comprehensive understanding of the wind turbine's condition. Finally, the fuzzy output sets are de-fuzzified into a crisp output, which quantifies the severity of detected faults. This method not only enhances the detection of various types of faults but also provides a quantifiable measure of their severity, showcasing the effectiveness of integrating expanded linguistic terms and non-singleton fuzzy logic in fault detection systems.

(Mendonça et al., 2009) proposes a model-based architecture for fault detection and isolation that combines fuzzy modeling and fuzzy decision-making. Firstly, data is collected from an industrial valve simulator, then simulated in fuzzy models to understand both normal and faulty operations. Fuzzy logic is used here to manage the imprecision of the data, making the model more realistic and uncertain, but more difficult to estimate. A tree search algorithm is used to optimize the structure of the fuzzy model. Finally, the approach was applied to a pneumatic servo-motor actuated industrial valve, successfully detecting and isolating 10 abrupt and incipient faults. The presence of noise in the data increases the difficulty of detecting and isolating faults, suggesting future research to extend the FDI scheme to a larger number of faults.

Fuzzy systems have been introduced to address imprecision and are known to sometimes lack accuracy in input-output

Table 5. Summary of surveyed literature for fault detection.

Technique	**Article Title**	**Author, Year**	**Method**	**Domain**
Deterministic	A rule-based fault detection method for air handling units	(Schein et al., 2006)	Knowledge	Industrial monitoring
	Fault semantic network for micro grid diagnosis and control	(Azad & Gabbar, 2012)	Knowledge - Data - Model	Energy systems
	Fault Detection of Bearings Using a Rule-based Classifier Ensemble and Genetic Algorithm	(Heidari, 2017)	Knowledge - Data	Mechanical components
	A semantic model-based fault detection approach for building energy systems	(T. Li et al., 2022)	Knowledge - Model	Industrial monitoring
Fuzzy Logic	Fault detection and diagnosis for railway track circuits using neuro-fuzzy systems	(J. Chen et al., 2008)	Knowledge - Data	Industrial monitoring
	An architecture for fault detection and isolation based on fuzzy methods	(Mendonça et al., 2009)	Knowledge - Model	Industrial monitoring
	A fuzzy-based Bayesian belief network approach for railway bridge condition monitoring and fault detection	(Vagnoli et al., 2017)	Knowledge - Model	Infrastructure / Construction
	A scalable fuzzy support vector machine for fault detection in transportation systems	(J. Liu & Zio, 2018)	Knowledge - Data	Industrial monitoring
	Wind turbine fault detection based on expanded linguistic terms and rules using non-singleton fuzzy logic	(Qu et al., 2020)	Knowledge - Data	Energy systems
Dempster-Shafer	Fault diagnosis in railway track circuits using Dempster–Shafer classifier fusion	(Oukhellou et al., 2010)	Knowledge - Data	Industrial Monitoring
	Structural damage assessment using improved Dempster-Shafer data fusion algorithm	(Ding et al., 2019)	Knowledge - Model	Infrastructure / Construction
	Fault Matters: Sensor data fusion for detection of faults using Dempster–Shafer theory of evidence in IoT-based applications	(Ghosh et al., 2020)	Knowledge - Data - Model	Industrial monitoring
	A novel multi-classifier information fusion based on Dempster–Shafer theory: application to vibration-based fault detection	(Yaghoubi et al., 2022)	Knowledge - Data	Industrial Monitoring

mapping due to if-then rules that may have an incomplete description. Consequently, it is common to augment fuzzy systems by combining them with other methods.

(J. Chen et al., 2008) introduced an increasingly popular method known as the Neuro-fuzzy (NF) system. This method is one of the main methods combining data-driven and knowledge based approach. NF systems learn from data, adaptively adjusting their fuzzy rules and functions. Fuzzy inference allows for the management of imprecision, while neural learning optimizes performance (Jain & Martin, 1998). Chen et al. (2008) employed this system for fault detection in a railway track circuit. The first step is collecting data from track circuit components, such as current and voltage measurements, to monitor conditions. Then, these measurements undergo fuzzification and rule-based processing in the NF system. The model, combining fuzzy logic and a neural network, is trained with these data, addressing uncertainty and improving fault detection. The system's performance, compared to traditional methods, shows enhanced accuracy and efficiency in a laboratory test rig of audio frequency jointless track circuit.

In (J. Liu & Zio, 2018), a fuzzy SVM integrated with K-Nearest Neighbors (KNN) is utilized for fault detection in transportation systems. The process begins with data collection, followed by processing using KNN to pinpoint key borderline data points. Fault detection is often mathematically treated as a classification problem; in this context, KNN enhances the SVM's classification capability. Fuzzy logic is then incorporated, managing uncertainties and imprecision by assigning fuzzy membership values specifically to the borderline data points, which are crucial for the SVM's dependency. The combined approach effectively detects faults, as demonstrated in a case study on a high-speed train's braking system, showing improved accuracy and efficiency in fault detection compared to traditional methods.

In (Vagnoli et al., 2017), a novel approach is developed for condition monitoring of railway bridges, integrating fuzzy logic with a BN. The process starts with data collection from a Finite Element (FE) model simulating the bridge's behavior under various conditions. Based on this FE model, the necessary information to establish prior CPT of the BN are extracted. Then, expert knowledge is captured through fuzzy logic and used to refine the BN. This fuzzy process incorporates fuzzy membership functions to capture vagueness and subjectivity in expert judgment through relationships between linguistic variables. These variables are used to investigate potential relationships between different bridge elements and numerically quantify the opinions of experts. This integrated approach demonstrates the ability to monitor the health state of the bridge and its elements effectively, allowing for a more nuanced and comprehensive understanding of the bridge's condition. It is noteworthy that the Bayesian network primarily facilitates fault diagnosis in this approach.

5.3.3. Dempster-Shafer theory

In fault detection, DST is mainly explored in the literature within the context of classifier fusion. As previously mentioned, fault detection can often be viewed as a classification problem, a scenario where DST offers significant advantages. This theory enhances decision-making by combining information from diverse sources, calculating an overall belief degree while considering the individual contributions of classifiers (see Section 4). Conflicts between classifiers are effectively managed through Dempster-Shafer's combination rule, which redistributes beliefs by excluding conflicting parts (Quost, Masson, & Denœux, 2011). This conflict resolution leads to often more effective fusion than traditional classifier fusion methods.

Indeed, (Yaghoubi et al., 2022) has for purpose to show that DST can be used to improve the accuracy of the classification. The paper compare four methods of classifications (k-nearest neighbours, subspace vector data description with Gaussian kernel, support vector machine with Gaussian kernel and neural network) applied to 15 benchmarks datasets with a classifier fusion based on DST and then compared the performance.

In (Oukhellou et al., 2010), the outputs of a local neural network are interpreted through DST classifier fusion to assist in making a definitive decision on the detection and localization of faults in a railway track circuit system. This technique initially employs a statistical pattern recognition approach on the inspection recordings, which facilitates the derivation of uncertain if-then rules utilizing DST.

In (Ghosh et al., 2020), DST is used for data fusion, not after machine learning classifications, but following data collection from various sensors. The article demonstrates the use of DST prior to fault classification, showing effective results similar to traditional classifier fusion, which usually focuses on combining outputs from different classification algorithms.

Similarly, in (Ding et al., 2019), an integrated fusion algorithm is proposed that considers mass loss in the combination process. Structural health data is collected and then fused using this algorithm. This approach allows for a more accurate assessment of structural damage by effectively managing the inherent uncertainties and complexities in the data.

5.4. Knowledge-based techniques in Fault diagnostics

Table 6 categorizes articles related to fault diagnostics.

5.4.1. Deterministic

With the increasing installed capacity in wind turbines, the need for intelligent systems has become crucial. The expert system developed in (Deng et al., 2017) uses propositional logic to transform expert knowledge and historical data into

Table 6. Summary of surveyed literature for fault diagnostics.

Technique	Article Title	Author, Year	Method	Domain
Deterministic	Fault diagnosis of a train door system based on semantic knowledge representation	(Miguelanez et al., 2008)	Knowledge	Automotive / Transport
	A rule-based intelligent method for fault diagnosis of rotating machinery	(Dou et al., 2012)	Knowledge - Data	Mechanical components
	Rule-based Fault Diagnosis Expert System for Wind Turbine	(Deng et al., 2017)	Knowledge - Data	Energy systems
	Development of an expert system for fault diagnosing of washing machines using Delphi 7	(Cahyono & Kusuma, 2024)	Knowledge	Mechanical components
Fuzzy Logic	Rolling bearing fault diagnostic system using fuzzy logic	(Da Silva Vicente et al., 2001)	Knowledge	Mechanical components
	Railway wheel fault diagnosis using a fuzzy-logic method	(Skarlatos et al., 2004)	Knowledge - Data	Mechanical components
	Application of a Neural Fuzzy System with Rule Extraction to Fault Detection and Diagnosis	(K. Y. Chen et al., 2005)	Knowledge - Data	Industrial monitoring
	Maintenance Decision-Making Support for Textile Machines: A Knowledge-Based Approach Using Fuzzy Logic and Vibration Monitoring	(Baban et al., 2019)	Knowledge	Industrial monitoring
	Complex Fuzzy System Based Predictive Maintenance Approach in Railways	(Karakose & Yaman, 2020)	Knowledge - Data	Industrial monitoring
	A Model for Flywheel Fault Diagnosis Based on Fuzzy Fault Tree Analysis and Belief Rule Base	(Cheng et al., 2022)	Knowledge - Model	Mechanical components
Dempster-Shafer	Fault diagnosis method for railway turnout control circuit based on information fusion	(M. Liu et al., 2016)	Knowledge - Data	Industrial monitoring
	Dempster-Shafer evidence theory for multi-bearing faults diagnosis	(Hui et al., 2017)	Knowledge - Data	Industrial monitoring
Bayesian Networks	Bayesian Fault Detection and Diagnosis in Dynamic Systems	(Lerner et al., 2000)	Knowledge - Model	Energy systems
	Bayesian Networks-Based Approach for Power Systems Fault Diagnosis	(Yongli et al., 2006)	Knowledge - Model	Energy systems
	Fault diagnosis expert system of semiconductor manufacturing equipment using a Bayesian network	(B. Li et al., 2013)	Knowledge - Data	Industrial monitoring
	An intelligent chiller fault detection and diagnosis methodology using Bayesian belief network	(Y. Zhao et al., 2013)	Knowledge - Model	Industrial monitoring
	Dynamic process fault detection and diagnosis based on a combined approach of hidden Markov and Bayesian network model	(Galagedarage Don & Khan, 2019)	Knowledge - Data	Energy systems
	An Integrated Fuzzy Fault Tree Model with Bayesian Network-Based Maintenance Optimization of Complex Equipment in Automotive Manufacturing	(Soltanali et al., 2021)	Knowledge - Model	Automotive / Transport
	Bayesian Uncertainty Inferencing for Fault Diagnosis of Intelligent Instruments in IoT Systems	(Q. Liu et al., 2023)	Knowledge - Data	Industrial monitoring
	Expert system based fault diagnosis for railway point machines	(Reetz et al., 2024)	Knowledge - Data	Transportation

"IF... THEN..." rules. Moreover, the system continuously improves through a self-learning process integrated into the knowledge base. This demonstrates the effectiveness of a simple and powerful expert system that relies solely on expert knowledge to diagnose faults in wind turbines based on symptoms.

(Cahyono & Kusuma, 2024) presents the development of an expert system designed to diagnose washing machine faults using forward chaining. This system is built on a knowledge base created from data gathered through literature review and expert interviews in the field of washing machine repairs. The collected knowledge is transformed into a set of if-then rules. Users input the symptoms they observe (such as noise, motor stoppage, abnormal vibrations), and the system analyzes this information to identify potential faults, such as a broken belt, defective motor, or electrical issue. By applying forward chaining, the system works through the rules to generate a diagnosis and recommend the appropriate repair solution. The expert system effectively diagnoses 13 common washing machine faults, helping to reduce the time required for troubleshooting and repairs.

In a more complex manner, (Dou et al., 2012) utilizes statistical methods and machine learning to generate deterministic rules for diagnosing faults in rotating machinery. The primary advantage of this method lies in its ability to effectively integrate statistical techniques for feature extraction and the use of a machine learning algorithm (MLEM2) for rule induction. This results in precise and reliable rules for fault diagnosis, capitalizing on both the thorough analysis of data (statistical) and the systematic application of rules (deterministic).

Semantic networks is a powerful tool for knowledge modeling, it is illustrated by (Miguelanez et al., 2008) for diagnosing faults in train door systems. This network builds an ontology representing knowledge about the functioning and failures of door systems. This ontology includes several components, such as domain expertise, historical data of failures, and real-time information from sensors. Diagnosis is then made by comparison: sensor data are analyzed and compared with the information contained in the ontology. The relationships and rules defined in the ontology enable the system to accurately deduce the nature and cause of the failures. Additionally, the system has a preventive maintenance function, alerting to components that are likely to fail. This system was tested on pneumatic train doors and showed a significant improvement in diagnosis and a better understanding of the failures.

5.4.2. Fuzzy Logic

Fuzzy logic has been employed in various ways across different domains for fault diagnosis.

(Da Silva Vicente et al., 2001) employs fuzzy logic to diagnose faults in ball bearings. The initial phase involves vibrational signal analysis using spectral and statistical techniques. Subsequently, fuzzy logic is used to interpret the results, with each input from the preliminary analysis being translated into a fuzzy set for a more refined and adaptable classification of bearing faults.

In regards to textile machine maintenance, (Baban et al., 2019) demonstrates an equivalent use of fuzzy logic. Vibration monitoring is used to detect the development of faults, and then fuzzy logic manages the complexity and uncertainty of the machine degradation process.

In the railway industry, To address issues of irregularities in train wheels, (Skarlatos et al., 2004) implemented an intelligent system based on fuzzy logic. This system uses three input variables (vibration level, frequency, and train speed) and one output variable (wheel condition). The inputs were subjected to statistical analysis, which established confidence intervals for healthy and defective wheels. Subsequently, 333 fuzzy rules were defined to establish the relationships between these variables, allowing for an accurate characterization of the wheel condition while managing the uncertainties of the input data.

Similarly, (Karakose & Yaman, 2020) uses a fuzzy system to enhance predictive maintenance. Here, fuzzy logic aids in interpreting thermographic images in electric railway maintenance. The process is as follows: Thermal images are captured along train lines. These images undergo image processing to detect faults, and the type of fault determined by this analysis is then subjected to fuzzy logic interpretation

Each of the four previous examples demonstrates a similar use of fuzzy logic. Initially, a data-driven approach and/or signal analysis is employed. Then, fuzzy logic is introduced to add a degree of flexibility in the fault diagnostic process. It does this by transforming the previously processed inputs into fuzzy sets, thereby enhancing the interpretability and adaptability of the diagnostic process. The following two examples skillfully combine fuzzy logic with two other methods to address two common challenges in fault diagnostics.

In fault diagnostic with uncertain input information, BRB system are good to deal with uncertainty, however the initialisation need to relies on a fiable source and it is quite difficult to obtain accurate knowledge. (Cheng et al., 2022) integrated fuzzy logic into a fault tree and uses BN as a bridge to obtain knowledge. This tree represents various events that could lead to a failure and, through fuzzy logic, it is possible to manage the uncertainty and imprecision of information about the failures. The BN acts as a translator from fuzzy fault tree to BRB. This method facilitates effective mapping of the knowledge base for a diagnostic system based on belief rules.

In (K. Y. Chen et al., 2005), the inherent 'black box' issue associated with the use of neural networks in fault diagnostics is overcome through the use of fuzzy logic. The fuzzy system is employed on real-world sensor data for diagnosing heat transfer and tube blockages in a power plant The method enhances interpretability of neural network predictions, aligning with expert opinions and domain knowledge. The integration of fuzzy logic with neural networks, as seen in this example, follows a trend similar to other examples in previous sections.

5.4.3. Dempster-Shafer theory

As seen in fault detection, DST is mainly used for classifier fusion, a trend that also applies to fault diagnostics. In diagnostics, DST is primarily used to amalgamate different fault analysis results to classify faults optimally, thereby improving the precision and dependability of the classification.

(M. Liu et al., 2016) explores various fault diagnosis models applied to the maintenance of railway turnouts and then uses the DST to combine the results of two distinct methods. The first method is a model based on fuzzy logic, which takes as input the symptoms detected on the turnouts and as output, identifies the corresponding faults. However, this system may show difficulties in accurate diagnosis after defuzzification. In parallel, a neural network is also employed, despite its dependence on a large volume of data that is not always available. The DST intervenes here by providing a framework for managing uncertain information. It merges the diagnostic results obtained by the two methods, thus compensating for their respective weaknesses and significantly improving diagnostic intelligence and accuracy.

In a similar fashion, (Hui et al., 2017) utilizes DST as a tool for classifier fusion. In this context, DST is employed to amalgamate the outcomes of various SVM models.

5.4.4. Bayesian Networks

Bayesian Networks are prevalent in the literature concerning fault diagnosis but are less common or even nonexistent in the literature on fault detection. Due to their structure as presented in Section 4, they excel at handling uncertainty and making inferences based on causal relationships, which is crucial in diagnosing specific faults because they can integrate diverse data types and prior knowledge to model complex systems, making them highly effective in diagnosing where a fault originates and how it propagates. In contrast, fault detection typically focuses on identifying the presence of a fault, often requiring different approaches like threshold-based or pattern recognition methods (Langseth, 2008).

In (Verbert, Babuška, & De Schutter, 2017), BN and DST are compared in the context of condition-based maintenance. Where DST seems particularly suited for non-causal reasoning tasks, such as information fusion, BN appear more suited for reasoning about conditional relationships, like the connections between faults and features (Cobb & Shenoy, 2003). The process of developing a BN for fault detection and diagnostic involves several key steps. Initially, the structure of the BN must be modeled, taking into account the specific characteristics and relationships within the system. Following this, the parameters of the BN are defined, which involves setting the probabilities and relationships between different nodes in the network. The next step is BN inference, where the network is used to draw conclusions based on the input data. After inference, the focus shifts to fault identification, where the network helps to pinpoint specific faults within the system. The final step is validation and verification of the BN, ensuring its accuracy and reliability in real-world applications (Cai, Huang, & Xie, 2017)

(B. Li et al., 2013) describes the development of an expert system using BN for diagnosing root failures in semiconductor manufacturing equipment. The system's knowledge are derived exclusively from expert insights. It employs two development approaches: a direct mode, where experts contribute their knowledge verbally or in writing for formalization into the knowledge base to feed the BN, and an indirect mode, where expert knowledge is collected and converted into a machine-learned knowledge representation. Experts also estimate probabilities in the BN's CPT using linguistic terms akin to fuzzy logic. However, this approach's reliance on expert subjectivity can significantly impact the diagnosis accuracy due to the conditional probabilities being expert-determined. Leveraging historical data and machine learning algorithms could significantly enhance the accuracy of Bayesian Networks.

(Y. Zhao et al., 2013) conduct a study on a three-layer BN, designed to emulate the diagnostic process of chiller system experts. Beyond the expertise of these specialists for estimating a priori probabilities in the CPT, historical data and prior surveys also contribute key insights. The first layer of the network focuses on factors or information relevant to fault diagnosis, which are not directly linked to the faults themselves, such as maintenance records or contextual data. The second layer lists various types of faults, while the third layer depicts the associated symptoms. Although the system does not collect real-time data, in-depth knowledge and historical data enable an accurate estimation of parameters, yielding reliable results. However, acquiring these parameters remains a significant challenge.

In a similar way, (Reetz et al., 2024) discussed an expert system designed for diagnosing faults in railway point machines using Bayesian networks. The system integrates both expert knowledge and measurement data to provide probabilistic fault diagnostics. The focus is on detecting the root causes of faults, particularly using motor current curve features as key evidence, along with additional inputs like past maintenance actions, environmental factors, and railway metadata.

The system processes data to output a ranked list of the most likely faults, providing maintenance engineers with actionable insights. The use of fuzzy multi-label classification allows the model to handle multiple potential faults simultaneously.

(Q. Liu et al., 2023) present another application of BNs combine with fuzzy logic. The developed procedure is as follows: Initially, define the scope of the model and construct a fault tree. Then, convert the fault tree into a BN, followed by the acquisition of prior probabilities through expert knowledge. This expertise is translated using fuzzy logic to optimally preserve linguistic uncertainty. Finally, determine the conditional probability tables using the leaky noisy-OR model. One drawback, which is common to nearly all systems reliant on expert knowledge, is the lack of standardized criteria for expert selection. Consequently, the results inherently carry a degree of uncertainty.

In (Yongli et al., 2006), a knowledge-based system is presented for estimating faulty sections in transmission power systems. The system utilizes sensor data and expert knowledge to structure a BN and estimate the probabilities among variables. To enhance accuracy, two significant modifications are introduced: the use of noisy OR and AND models for probabilistic expansion of traditional logic connectors in order to allow for different contributions to the overall outcome, and the application of an error back propagation algorithm for continuous refinement of the BN's parameters. These improvements aim for more precise fault identification in the power system.

In the research presented in (Soltanali et al., 2021), the integration of fuzzy logic and BN is employed for the diagnosis and optimization of maintenance processes in the automotive manufacturing sector. The process begins with the collection of subjective expert opinions and operational data, which are depicted as fuzzy numbers. By constructing a fuzzy fault tree, these fuzzy entries are eventually converted into probabilities of failures following a defuzzification process, and these probabilities become the inputs for the BN. The BN utilizes the dynamic interactions among components to effectively diagnose failures. Finally, the BN in this study also encompasses recommendations for optimizing maintenance strategies.

When facing fault diagnostic problems in temporal or complex systems, traditional BN often encounter inevitable difficulties. To overcome these, Dynamic Bayesian Networks (DBN) are utilized (Ghahramani, 1998; Murphy, 2002). These networks effectively represent temporal processes using a Temporal Causal Graph as their structure, addressing measurement errors and parameter drifts. DBN can also handle hybrid systems comprising both discrete and continuous variables, aiding in the prediction of discrete failure modes. An additional advantage of DBN is their capability to track the current system state, maintaining a probability distribution over possible states based on all available measurements, as detailed by (P. Liu et al., 2020).

(Lerner et al., 2000) demonstrate DBN' effectiveness in a complex system of five interconnected water tanks. This system posed a challenge with its limited measurements and various potential failure modes, including drifts, bursts, and measurement errors. The experiment showcased the DBN algorithm's ability to accurately track and diagnose faults in dynamic systems.

A common theme in the literature on DBN is the use of Hidden Markov Models (HMM) for fault detection, which are then combined with a BN for fault diagnosis. As previously discussed, the strengths of BN are particularly highlighted in fault diagnosis. (Galagedarage Don & Khan, 2019) exemplifies this perfectly by employing an HMM that relies on a continuous data stream to detect a fault. Subsequently, the HMM outputs, which are log-likelihood values, are utilized to estimate the probabilities for the CPT required for fault diagnosis. The dynamic nature of the system is illustrated by the HMM continuously providing information to the BN.

5.5. Knowledge-based techniques in Fault prognostics

Table 7 categorizes articles related to fault prognostics.

The literature on fault prognostics is less extensive compared to fault diagnostics, and this gap widens further when focusing on knowledge-based methods. Utilizing these methods seems challenging when seeking high accuracy for three main reasons:

1. Prognostics often deal with complex and diverse fault patterns, especially in dynamic systems. Rule-based methods, relying on predefined rules, might not effectively capture this complexity (Brotherton, Jahns, Jacobs, & Wroblewski, 2000).
2. Knowledge-based systems depend heavily on expert knowledge, which can be limiting in rapidly evolving fields or in situations where exhaustive expert knowledge is challenging to obtain or update (Tung & Yang, 2009).
3. The growing emphasis on data-driven techniques, such as machine learning and pattern recognition, offers more flexibility and adaptability in handling the vast and varied data associated with machine faults and prognostics (Tsui et al., 2015; Schwabacher, 2007).

While knowledge-based systems may appear less prevalent in contemporary scientific literature on prognostics, their practical utility in industry should not be underestimated. For those aiming to develop techniques with the highest possible accuracy, relying solely on knowledge-based systems might seem counterproductive. However, in business contexts where financial constraints are a primary consideration, these methods can indeed be quite fruitful. All that aside, the literature

Table 7. Summary of surveyed literature for fault prognostics.

Technique	Article Title	Author, Year	Method	Domain
Deterministic	Predicting the Remaining Useful Life of Light Aircraft Structural Parts: An Expert System Approach	(Gerhardinger et al., 2023)	Knowledge	Transportation
Fuzzy Logic	Prognosis of machine health condition using neuro-fuzzy systems	(W. Q. Wang et al., 2004)	Knowledge - Data	Mechanical components
	A fuzzy bp approach for diagnosis and prognosis of bearing faults in induction motors	(Satish & Sarma, 2005)	Knowledge - Data	Mechanical components
	Wind turbine pitch faults prognosis using a-priori knowledge- based ANFIS	(B. Chen et al., 2013)	Knowledge - Data	Energy systems
	Prognosis of Bearing Failures Using Hidden Markov Models and the Adaptive Neuro-Fuzzy Inference System	(Soualhi et al., 2014)	Knowledge - Data	Industrial monitoring
	Knowledge-based prognostics and health management of a pumping system under the linguistic decision-making context	(Peng et al., 2022)	Knowledge	Industrial Monitoring
Dempster-Shafer	Dempster–Shafer regression for multi-step-ahead time-series prediction towards data-driven machinery prognosis	(Niu & Yang, 2009)	Data	Industrial monitoring
	Prognostics of lithium-ion batteries based on Dempster-Shafer theory and the Bayesian Monte Carlo method	(He et al., 2011)	Knowledge - Model	Energy systems
	Uncertainty quantification using evidence theory in concrete fatigue damage prognosis	(H. Tang et al., 2016)	Knowledge - Model	Infrastructure / Construction
	A Novel Method Using DS-MCM for Equipment Health Prognosis with Partially Observed Information	(Q. Liu et al., 2019)	Knowledge - Model - Data	Industrial monitoring
	Lithium-ion battery diagnostics and prognostics enhanced with Dempster-Shafer decision fusion	(Weddington et al., 2021)	Knowledge - Model	Energy systems
Bayesian Networks	Application of Bayesian networks in prognostics for a new Integrated Vehicle Health Management concept	(Ferreiro et al., 2012)	Knowledge - Model - Data	Automotive / Transportation
	Health Monitoring System for Autonomous Vehicles using Dynamic Bayesian Networks for Diagnosis and Prognosis	(Gomes & Wolf, 2021)	Knowledge - Model	Automotive / Transportation
	Dynamic Bayesian Network-Based Lithium-Ion Battery Health Prognosis for Electric Vehicles	(Dong et al., 2021)	Knowledge - Model - Data	Energy systems

does include instances of effective combinations of methodologies, incorporating knowledge-based components. This suggests a balanced approach, blending knowledge-based approach with advanced data-driven techniques, can be both feasible and beneficial in some academic works and real-world applications.

5.5.1. Deterministic

(Gerhardinger et al., 2023) presents an expert system that predicts the remaining useful life of light aircraft structural parts operating through four modules: knowledge acquisition, knowledge base, inference, and explanation. It collects operational data from sources like aircraft logbooks, stores specific RUL values based on load profiles in the knowledge base, and the inference module estimates accumulated fatigue damage. The system uses an "if-then" framework to calculate the remaining life of a part by summing damage increments from different flight phases. The explanation module then suggests appropriate maintenance actions based on the calculated RUL, helping optimize maintenance schedules and prevent part failure.

5.5.2. Fuzzy Logic

(Peng et al., 2022) introduces a model that integrates fuzzy logic to synthesize knowledge from both data and expert input for prognostics and maintenance decision. This approach has been effectively applied to predict the consequences of specific faults in the pipeline of a pumping system and the best maintenance strategy to apply. The initial stage involves data collection from observations by field engineers or from expert knowledge and data processing, during which fuzzy linguistic terms are selected in order to develop operational information about the health of components. These terms are then interpreted using trapezoidal fuzzy functions in fuzzy logic. Once the function is established, its output (the RUL) is evaluated based on the input information. The final step involves the inference process, leading to a conclusion that aids in selecting the optimal maintenance decision.

In the field of prognostics, applications of fuzzy logic usually involve its integration with neural networks, forming a NF system. (DePold & Gass, 1998) introduces at first the combination of neural networks and expert system. The synergy allows for more accurate data analysis and informed decision-making.

In (B. Chen et al., 2013), data is retrieved from Supervisory Control and Data Acquisition systems, which encompass alarms and signals that could provide early indications of component faults. Critical features, which are parameters associated with the failure of components, are utilized to train neural networks. Simultaneously, the system facilitates the integration of a-priori knowledge into the training process, enhancing reliability and interpretability. Fuzzy logic then assists in classifying the severity of each fault, offering an initial assessment of when maintenance might be necessary. An algorithm, leveraging this system, is implemented to determine the earliest date for potential faults within predetermined prognostic horizons (7, 14, 21 days) to minimize the risk of false identifications.

In (Satish & Sarma, 2005), parameters such as stator current and rotor speed are continuously measured and inputted into the system. The output of the neural network represents the bearing condition expressed by linguistic fuzzy terms, which discretize into an estimation of RUL. For accuracy purpose, the weights of the connections between neurons in the network are constantly adapted by an error back propagation algorithm to enhance the model's accuracy in diagnosing and prognosticating bearing faults

(W. Q. Wang et al., 2004) compare two well-known techniques based on neural networks for prognostic estimation, recurrent neural networks and NF systems. The article emphasizes that NF systems outperform their counterparts because of their ability to handle non-linearities and stochastic behavior in time-series data effectively. Additionally, the synergy of neural networks' adaptability with the interpretability and uncertainty management of fuzzy systems results in higher forecast accuracy and more efficient training.

In (Soualhi et al., 2014), the NF system is integrated with HMM for the effective prognosis and health management of roller bearings. Time-domain features from vibration signals are employed as health indicators, with expert knowledge applied to interpret these signals. HMM ascertain the immediacy of upcoming degradation states based on these indicators. Subsequently, the NF system uses this information to accurately estimate the remaining time before the bearing reaches its next degradation state in a similar way to above.

5.5.3. Dempster-Shafer theory

In contrast to fault detection or diagnostics, DST is not unilaterally used as a classifier fusion tool for prognostics.

In the study (H. Tang et al., 2016), DST is utilized as a method to represent uncertainty in predicting the fatigue life of concrete. Due to the lack of sufficient or accurate information, traditional probability theory appears to be less suitable for representing this uncertainty (see Section 4). The estimation of the RUL is subsequently conducted using a differential evolution algorithm, which propagates the uncertainty through the fatigue life prediction model. The article compares the results obtained from both DST and probability theory with experimental data and observes a higher precision in the results derived from DST.

Lithium-Ion batteries are widely used in various applications due to their high energy density. (He et al., 2011) study the degradation of such batteries through a decrease in capacity over time. The degradation process is complex due to inherent system uncertainties, measurement uncertainties, operation environment uncertainties, and modeling uncertainties. To manage this complexity, He et al. (2011) proceed as follows: The first step concerns the utilization of DST by combining evidence from various datasets to initialize model parameters. Then, the Bayesian Monte Carlo (BMC) method is employed to update model parameters with new capacity data. At each cycle, BMC is used to approximate the posterior probability density function, thereby enabling the estimation of RUL. This new method outperformed traditional ones with more accurate estimations and a higher level of confidence.

In (Q. Liu et al., 2019), the study combines DST with a Markov Chain Model (MCM) to develop a comprehensive state recognition framework for equipment. This approach employs DST's frame of discernment to encapsulate all conceivable states of the equipment. Then, Basic Probability Assignments (BPA) are utilized to measure the confidence in the accuracy of each potential state. These BPAs are then transformed into a probability distribution to facilitates the accurate identification of the equipment's health state. The study successfully demonstrates the application of this framework, highlighting its precision in health state recognition.

In (Niu & Yang, 2009), a novel approach is adopted for machinery prognosis using the DST. The study introduces a novel Dempster-Shafer regression model (DSR) for multi-step-ahead time-series prediction, to handle effectively uncertainties and imprecision in time-series data. The DSR method treats each training sample as a piece of evidence, assigning weights based on their proximity to the input vector and aggregating these evidences using Dempster's rule of combination. Then, the study employs an iterated multi-step-ahead prediction strategy, which is crucial for predicting the degradation trend of machinery performance and estimating the RUL of the system. This approach is validated using condition monitoring data from a methane compressor by reducing error and enhancing reliability in prognostic assessments.

Prognostication of equipment health utilizing DS evidence fusion theory can diminish the uncertainty associated with information sources concerning the health status of equipment (K. Zhao et al., 2022). In (Weddington et al., 2021), results from extended Kalman filter (EKF) and particle filter (PF) are fused using an application of DST. Initially, both EKF and PF are individually tasked with estimating the RUL of lithium-ion batteries. Following this, DST is employed, using Basic Belief Assignments to evaluate the confidence levels in the RUL estimates from both EKF and PF sources. Subsequently, the Dempster-Shafer combination rule is applied, producing a final RUL probability distribution. On comparing the performance of this combined RUL distribution against the individual outputs of EKF and PF, a notable enhancement in terms of accuracy and reliability is observed

5.5.4. Bayesian Networks

BN are particularly effective in managing uncertainty and variability in data, which is crucial for the estimation of RUL. Moreover, the ability to integrate a temporal component and dynamically adapt data through DBN makes them especially useful for fault prognostics (Verduijn, Peek, Rosseel, De Jonge, & De Mol, 2007; Medjaher, Moya, & Zerhouni, 2009; Bartram & Mahadevan, 2020; Bektas, Marshall, & Jones, 2020).

In (Dong et al., 2021), the process of constructing a DBN for battery health prognosis begins with the utilization of expert opinions. These opinions are used in the initial stages for defining the problem's scope, identifying the relevant variables and faults, and establishing the DBN's structure. Following this foundational step, heterogeneous data sources, including reliability data, operational data, and experimental data, are employed to estimate the CPT of the DBN. these probabilities are then employed to simulate the system's behavior over time, ultimately aiding in the prognosis by estimating battery's state of health and predicting the RUL. The paper illustrates this approach with experimental tests on different battery cells, showing accurate state of health estimation and reliable RUL prediction.

(Gomes & Wolf, 2021) presents a DBN-based health monitoring system for autonomous vehicles, designed for both diagnosis and prognosis. The DBN structure comprises three layers: Evidence, Symptom, and Fault. The Evidence Layer inputs new information at specific times for fault detection and diagnosis. The Symptom Layer interprets this evidence as potential indicators of faults, while the Fault Layer denotes the abnormal states of system components. This DBN model also includes time-related layers, allowing it to utilize past and current information to predict future states of the system over a predefined time horizon, thus facilitating prognosis. The efficacy of this approach is validated through experimental tests on various battery cells, demonstrating the model's high accuracy and effectiveness in fault detection and diagnosis for autonomous vehicles.

The aeronautics industry have approved the application of knowledge-based systems, as shown in (Ferreiro et al., 2012), where a Bayesian Network model is used for predictive maintenance to reduce maintenance costs and enhance aircraft operability. The paper emphasizes future maintenance scenarios, particularly focusing on avoiding unscheduled maintenance. The paper highlights three key components to learn with BNs: Constructing the network's structure through data and experts insights, learning probabilities based on existing network structures and using BN for prognostic purposes. The latter is particularly important for estimating RUL, because BN enable the discovery of links between different variables, and effectively integrate various attributes from datasets.

5.6. Knowledge-based Techniques in Advisory Generation & Health Management

Although this review focuses on the application of KBS in the development phase of the PHM process—i.e., fault detection, diagnostics, and prognostics tasks—we briefly review the subsequent stages, consisting of advisory generation and health management. To recap, advisory generation involves providing actionable information to operational and maintenance personnel or external systems, while health management uses this information to implement actions that restore the system to a "healthy state." These two stages are typically supported by what is known as a Decision Support System (DSS). A DSS is a computerized system that assists maintenance and operational personnel in making well-informed decisions regarding the maintenance and management of physical assets (Bumblauskas, Gemmill, Igou, & Anzengruber, 2017). A typical process for employing a DSS in the decision phase might involve the following steps. The DSS begins by collecting and analyzing real-time data to assess asset health and identify components likely to require maintenance. Based on this analysis, the system generates maintenance recommendations, providing actionable service proposals—this step aligns with advisory generation. The DSS then prioritizes these tasks, considering factors such as equipment criticality and cost, to support health management tasks like mission planning and resource allocation, ensuring efficient and effective maintenance execution. In literature, expert systems alone have been mainly used for resource allocations tasks. For instance, in the aviation industry, an expert system allocates resources, specifically labor, by utilizing a fuzzy Analytical Hierarchy Process. The system constructs a hierarchical model to prioritize criteria such as licenses, experience, and regulations, assigns fuzzy values to handle uncertainties, and ranks candidates for maintenance tasks, optimizing resource management in aircraft maintenance operations (Cheung et al., 2005). Similarly, in a military context, an expert system optimizes resource allocation through a two-phase process. It evaluates weapon effectiveness using a computation network with expert-defined rules and Bayesian logic, and then determines optimal allocations via an allocation tree, refining decisions through user interactions and adapting to real-time changes on the battlefield, ensuring dynamic and effective resource management (Slagle & Hamburger, 1985). (Gudes et al., 1990) also utilized a general control strategy through expert systems to efficiently allocate resources across these diverse domains. More recently, in the field of infrastructure management, (Santos et al., 2022) employed a fuzzy logic expert system to select optimal and sustainable maintenance and rehabilitation (M&R) strategies for road pavements. This system considers both economic and environmental objectives, converting these criteria into fuzzy linguistic terms. By applying expert-defined fuzzy rules, the system evaluates and ranks M&R strategies based on a global performance score, enabling decision-makers to choose the most appropriate strategy from a set of Pareto-optimal solutions. This approach ensures that the selected strategy aligns with sustainability goals while effectively managing costs and environmental impact. Nowadays, due to the emergence of highly efficient machine learning-based techniques, advisory generation and health management are mainly performed by hybrid systems combining knowledge-based and data-driven techniques. One can mention the development of neuro-symbolic approaches to leverage the strengths of deep learning for pattern recognition, while incorporating expert knowledge through symbolic methods for explainability and structured decision-making (Hitzler et al., 2022). This integration allows for solving complex problems that require both data-driven insights and formal reasoning, enabling more accurate, interpretable, and reliable AI solutions that can effectively handle tasks such as logical deduction, planning, and knowledge representation. In the same vein, (L. Tang et al., 2023) describes the OSPtk toolkit, which optimizes sensor placement in critical industrial systems. This system integrates performance and cost considerations using a Dependency Matrix (D-Matrix) to model the relationship between sensors and fault detection capabilities. It incorporates data-driven insights from simulation data and historical maintenance data to refine the D-Matrix, alongside expert knowledge in its construction. Genetic Algorithms are employed to find the optimal sensor configurations, allowing designers to select sensors that meet PHM requirements while balancing cost constraints, ultimately enhancing the reliability and cost-effectiveness of the system. As a self-optimizing system, (Chemweno et al., 2016) presented an i-RCAM expert system which enhances health management and advisory generation by enabling proactive maintenance through continuous improvement and early detection of potential failures. By analyzing maintenance data with association rule mining, i-RCAM uncovers patterns and detects early warning signs, which are then validated by experts. This system continuously updates its rule base, allowing it to generate timely and accurate maintenance recommendations, thus ensuring that potential issues are addressed before they escalate, leading to more effective and reliable health management.

6. FUTURE DIRECTIONS FOR KNOWLEDGE-BASED SYSTEMS FOR PHM

The evolution of Knowledge-Based Systems in PHM is driven by the need to enhance decision-making capabilities, increase scalability, and foster greater adaptability in various operational environments. As these systems continue to develop, several key research areas are emerging, reflecting the ongoing integration of traditional knowledge-based methods with cutting-edge technologies.

Hybrid Systems. One of the most significant future directions is the development of *hybrid systems* that combine traditional knowledge-based approaches with artificial intelligence (AI) and machine learning techniques. By integrating rule-based systems with neural networks, reinforcement learning, and deep learning models, these hybrid systems aim to enhance the decision-making process in PHM. A particularly promising area within this evolution is neuro-symbolic AI, which merges the symbolic reasoning of traditional AI with the learning capabilities of neural networks (Lu, Afridi, Kang, Ruchkin, & Zheng, 2024; Barbiero et al., 2023; Konstantinov & Utkin, 2024). This approach allows for more sophisticated analysis and prediction capabilities, where AI models can interpret and reason with vast datasets while traditional knowledge-based systems provide a structured framework for logical decision-making. The synergy between these approaches is expected to lead to more accurate, interpretable, and reliable PHM systems.

Big Data Integration. As PHM systems are required to process and analyze the increasing amounts of sensor data in real-time, the ability to *scale knowledge-based systems to handle big data* has become critical. Future research will likely focus on leveraging distributed computing and cloud-based architectures to efficiently handle and process the growing volume of data (Forest, Lacaille, Lebbah, & Azzag, 2018; Forest et al., 2020). This includes the development of KBS that can operate efficiently in big data environments, providing timely insights and prognostics across various industries. The integration of big data analytics with KBS will enable more informed decision-making, allowing for more precise maintenance and operational strategies.

Adaptive Systems. Another promising direction is the advancement of KBS into adaptive systems that can continuously learn and evolve from new expert inputs, newly captured data, and emerging scenarios. These systems will dynamically refine their knowledge bases, allowing for the development of personalized maintenance strategies that are tailored not only to specific operational conditions and the unique histories of individual machines but also to the specialized insights of domain experts. This adaptability is crucial for PHM applications, where conditions can vary significantly and standardized approaches often are not applicable. The evolution of such systems will ensure that PHM solutions remain effective and relevant as new challenges and data emerge, sustaining their value in continually changing environments.

Transfer Learning The application of transfer learning within KBS for PHM is an area of growing interest. In this context, transfer learning allows a KBS trained on a specific set of machines or operating conditions to apply its learned rules, diagnostic patterns, and predictive models to a different but related domain, such as a different type of machinery or a new operational environment (Q. Wang, Taal, & Fink, 2022). In this context, rules can be transferred by generalizing existing knowledge, mapping rules to equivalent components, or adapting them to account for domain-specific factors. This approach leverages the similarities between systems, allowing for quicker deployment in new applications with reduced retraining needs. As the KBS collects more data in the new domain, these rules can be refined to improve accuracy and relevance. Ultimately, transfer learning can significantly reduce the time and data required to develop effective PHM systems, making it a valuable tool for expanding the applicability of KBS across various sectors.

Cyber-Physical Systems (CPS) and Digital Twins. The integration of KBS with Cyber-Physical Systems (CPS) and digital twin technologies represents a significant advancement in PHM. Digital twins, which are virtual models of physical assets continuously updated with real-time data, enable more accurate prognostics and health management by simulating various scenarios and predicting future states (Thelen et al., 2022a, 2022b). When combined with KBS, digital twins can offer real-time diagnostics, predictive maintenance, and decision support. CPS and KBS complement each other in PHM by providing the data acquisition, real-time monitoring, and interaction capabilities (CPS) that support the decision-making, rule-based reasoning, and predictive analysis functions of KBS. This synergy enables more effective and dynamic maintenance strategies, ultimately enhancing system reliability and efficiency.

Advancing Knowledge-Based Systems with Large Language Models. Large Language Models (LLMs) are revolutionizing the capabilities of KBS by enhancing their ability to process, understand, and generate natural language. LLMs can significantly improve the way KBS handle unstructured data, such as technical documents, maintenance logs, and real-time sensor reports, by extracting relevant information and transforming it into actionable insights. They enable KBS to better interpret complex queries, provide more accurate and context-aware responses, and even generate predictive insights based on historical data patterns. Moreover, LLMs can assist in the automatic updating and expansion of knowledge bases by learning from vast datasets, continuously integrating new information without the need for manual rule coding. Additionally, LLMs can automatically learn and refine knowledge graphs, which represent the relationships between different entities, further enhancing the system's ability to model complex systems and make informed decisions. This allows KBS to stay up to date with the latest knowledge and practices, enhancing their adaptability and relevance across different domains. By combining the structured reasoning of traditional KBS with the linguistic and analytical prowess of LLMs, these systems become more robust, intuitive, and capable of supporting sophisticated decision-making processes in complex environments.

User-Centric Design and Human-Machine Collaboration. As KBS become more sophisticated, the interaction between human operators and these systems will become increasingly important. Future research will focus on user-centric design principles, creating intuitive interfaces and decision-support tools that enhance human-machine collaboration. The goal is to develop KBS that not only provide accurate predictions and diagnostics but also do so in a way that is accessible and understandable to human operators, ensuring effective collaboration and decision-making.

Augmented Reality (AR) and Virtual Reality (VR). The use of augmented reality (AR) and virtual reality (VR) alongside Knowledge-Based Systems (KBS) represents another exciting future direction. These technologies create immersive environments for training, diagnostics, and maintenance tasks, offering real-time guidance derived from the knowledge base. Visual and interactive tools provided by AR and VR bridge the gap between complex data and human understanding, enabling operators to more easily perform maintenance tasks and assess the health status of their systems. This integration enhances decision-making and improves overall system reliability, ensuring more effective and intuitive maintenance processes.

Open Knowledge Bases. Finally, the creation of open, shared knowledge bases will be a significant area of focus in the future. These open knowledge bases can be used across multiple systems and industries, facilitating broader adoption and fostering innovation. By enabling different organizations to contribute to and benefit from shared knowledge resources, the development of open knowledge bases can accelerate the advancement of KBS for PHM and ensure that the latest insights and best practices are widely accessible.

7. CONCLUSION

Knowledge-based and Expert Systems, techniques developed in the early age of artificial intelligence, can provide effective solutions for Prognostics and Health Management (PHM) applications, due to their ability to leverage expert knowledge and their inherent interpretability. In particular, they are complementary to data-driven methods which research has overwhelmingly focused on in recent years. In this paper, we surveyed the literature and covered various techniques, evaluating their effectiveness in fault detection, diagnosrics and prognostics. We highlighted the strengths and limitations of each technique and discussed their applications in complex scenarios. We discussed the evolution of PHM and the potential of KBS in this field to improve the decision-making processes. Indeed, with the rise of big data and deep learning, there is a growing trend towards more mathematically sophisticated and black-box technologies. As we have noted, a core advantage of knowledge-based techniques is providing a high level of interpretability. This aspect is crucial, ensuring that as complexity increases, the ability to understand the underlying decision-making processes remains a priority.

Each method reviewed here has its own advantages and limitations. Propositional Logic is the most usual and simple way to express knowledge. It is valuable in scenarios with well-defined parameters or at the end of a process when uncertainty has been removed. This application alone is limited in complex environments where variables are not strictly controlled or in dynamic systems. This is the primary reason for its limited application for prognostics tasks within the PHM process. Fuzzy Logic is currently a popular and effective approach to manage imprecision without transforming the information. Indeed, it provides a framework that allows for more flexible handling of ambiguous information, in scenarios where conditions are not black and white but more or less grey. The primary challenge in this approach is in accurately and realistically modeling imprecision through fuzzy sets from their initial definition to the eventual defuzzification process needed for clear conclusion. To address this, the inclusion of deep learning to develop Neuro-Fuzzy systems is a promising way to explore further. Dempster-Shafer Theory (DST) provides a rich framework to deal with different problems. In fault detection, it primarily serves as a classification tool thanks to Dempster-Shafer combination rule. For fault prognosis, it is usually used as a way to combine evidence from diverse methods or datasets. In fault diagnosis, it integrates both these approaches. Additionally, DST is useful in representing complex uncertainties where a two-level modeling approach is required. While DST is brilliant in its ability to deal with many methods and express various knowledge, one inherent problem resides in accurately posing the mathematical foundations in practical applications, especially when rapid decision-making is required. Also, one might question whether this method truly offers interpretability. Does it provide a clear and comprehensible picture of the problem? Finally, Bayesian Networks (BNs) are renowned for their probabilistic modeling capabilities, especially when we need to think about conditional relationship, common in PHM problems. Their ability to infer under uncertainty using CPT is a key strength. When the relationships between variables are well-defined, BNs and their dynamic counterparts can be among the most effective methods for addressing the complexity of dynamic systems. Their need for significant computational resources and aim for representing multiple variables and relationships make them ideal for fault diagnosis and prognosis. However, they are less effective for fault detection.

In summary, one can expect the future of expert and knowledge-based systems for PHM to be marked by the integration of advanced emerging technologies, a focus on scalability and adaptability, and an emphasis on human-machine collaboration. These developments promise to make KBS more effective, accessible, and widely applicable across various industries, ultimately leading to more efficient and reliable PHM solutions.

NOMENCLATURE

BN	Bayesian Network
BRB	Belief Rule-Based
CBM	Condition-Based Maintenance
CPT	Conditional Probability Table
DBN	Dynamic Bayesian Networks
DL	Deep Learning
DST	Dempster-Shafer Theory
EKF	Extended Kalman Filter
HMM	Hidden Markov Model
KBS	Knowledge-Based System
KNN	K-Nearest Neighbors
ML	Machine Learning
NF	Neuro-Fuzzy
PF	Particle Filter
PHM	Prognostics and Health Management
RBS	Rule-Based System
RUL	Remaining Useful Life
SVM	Support Vector Machine

REFERENCES

Abid, A., Khan, M. T., & Iqbal, J. (2021, June). A review on fault detection and diagnosis techniques: basics and beyond. *Artificial Intelligence Review*, *54*(5), 3639–3664. Retrieved 2024-08-29, from `https://doi.org/10.1007/s10462-020-09934-2` doi: 10.1007/s10462-020-09934-2

Ahmad, R., & Kamaruddin, S. (2012, August). An overview of time-based and condition-based maintenance in industrial application. *Computers & Industrial Engineering*, *63*(1), 135–149. Retrieved 2023-12-14, from `https://linkinghub.elsevier.com/retrieve/pii/S0360835212000484` doi: 10.1016/j.cie.2012.02.002

Akerkar, R., & Sajja, P. (2009). *Knowledge-based systems*. Jones & Bartlett Publishers.

Al-Ajlan, A. (2015, April). The Comparison between Forward and Backward Chaining. *International Journal of Machine Learning and Computing*, *5*(2), 106–113. Retrieved 2023-12-19, from `http://www.ijmlc.org/index.php?m=content&c=index&a=show&catid=56&id=554` doi: 10.7763/IJMLC.2015.V5.492

Amodei, D., Olah, C., Steinhardt, J., Christiano, P., Schulman, J., & Mané, D. (2016, July). *Concrete Problems in AI Safety.* arXiv. Retrieved 2023-10-09, from `http://arxiv.org/abs/1606.06565` (arXiv:1606.06565 [cs])

Azad, T., & Gabbar, H. A. (2012, August). Fault semantic network for micro grid diagnosis and control. In *2012 International Conference on Smart Grid (SGE)* (pp. 1–8). Oshawa, ON, Canada: IEEE. Retrieved 2023-10-16, from `http://ieeexplore.ieee.org/document/6463963/` doi: 10.1109/SGE.2012.6463963

Baban, M., Baban, C. F., & Suteu, M. D. (2019). Maintenance Decision-Making Support for Textile Machines: A Knowledge-Based Approach Using Fuzzy Logic and Vibration Monitoring. *IEEE Access*, *7*, 83504–83514. Retrieved 2023-12-29, from `https://ieeexplore.ieee.org/document/8740857/` doi: 10.1109/ACCESS.2019.2923791

Bai, Y., Zhuang, H., & Wang, D. (Eds.). (2006). *Advanced fuzzy logic technologies in industrial applications*. London: Springer.

Barbiero, P., Ciravegna, G., Giannini, F., Zarlenga, M. E., Magister, L. C., Tonda, A., … Marra, G. (2023, July). Interpretable Neural-Symbolic Concept Reasoning. In *Proceedings of the 40th International Conference on Machine Learning* (pp. 1801–1825). PMLR. Retrieved 2024-05-06, from `https://proceedings.mlr.press/v202/barbiero23a.html` (ISSN: 2640-3498)

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., … Herrera, F. (2020, June). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82–115. Retrieved 2023-10-12, from `https://linkinghub.elsevier.com/retrieve/pii/S1566253519308103` doi: 10.1016/j.inffus.2019.12.012

Bartram, G., & Mahadevan, S. (2020, November). Probabilistic Prognosis with Dynamic Bayesian Networks. *International Journal of Prognostics and Health Management*, *6*(4). Retrieved 2024-01-04, from `https://papers.phmsociety.org/index.php/ijphm/article/view/2290` doi: 10.36001/ijphm.2015.v6i4.2290

Bektas, O., Marshall, J., & Jones, J. A. (2020, September). Comparison of Computational Prognostic Methods for Complex Systems Under Dynamic Regimes: A Review of Perspectives. *Archives of Computational Methods in Engineering*, *27*(4), 999–1011. Retrieved 2023-12-28, from `http://link.springer.com/10.1007/s11831-019-09339-7` doi: 10.1007/s11831-019-09339-7

Biagetti, T. (2004, December). Automatic diagnostics and prognostics of energy conversion processes via knowledge-based systems. *Energy*, *29*(12-15), 2553–2572. Retrieved 2023-10-18, from `https://linkinghub.elsevier.com/retrieve/pii/S0360544204001082` doi: 10.1016/j.energy.2004.03.031

Biggio, L., & Kastanis, I. (2020, November). Prognostics and Health Management of Industrial Assets: Current Progress and Road Ahead. *Frontiers in Artificial Intelligence*, *3*, 578613. Retrieved 2023-12-22, from https://www.frontiersin.org/articles/10.3389/frai.2020.578613/full doi: 10.3389/frai.2020.578613

Boose, J. H. (1985, November). A knowledge acquisition program for expert systems based on personal construct psychology. *International Journal of Man-Machine Studies*, *23*(5), 495–525. Retrieved 2023-12-17, from https://linkinghub.elsevier.com/retrieve/pii/S0020737385800559 doi: 10.1016/S0020-7373(85)80055-9

Brotherton, T., Jahns, G., Jacobs, J., & Wroblewski, D. (2000). Prognosis of faults in gas turbine engines. In *2000 IEEE Aerospace Conference. Proceedings (Cat. No.00TH8484)* (Vol. 6, pp. 163–171). Big Sky, MT, USA: IEEE. Retrieved 2024-01-04, from http://ieeexplore.ieee.org/document/877892/ doi: 10.1109/AERO.2000.877892

Buchanan, B. G., & Smith, R. G. (1988, June). Fundamentals of Expert Systems. *Annual Review of Computer Science*, *3*(1), 23–58. Retrieved 2023-10-06, from http://www.annualreviews.org/doi/10.1146/annurev.cs.03.060188.000323 doi: 10.1146/annurev.cs.03.060188.000323

Bumblauskas, D., Gemmill, D., Igou, A., & Anzengruber, J. (2017, December). Smart Maintenance Decision Support Systems (SMDSS) based on corporate big data analytics. *Expert Systems with Applications*, *90*, 303–317. Retrieved 2024-08-29, from https://www.sciencedirect.com/science/article/pii/S095741741730564X doi: 10.1016/j.eswa.2017.08.025

Cahyono, B. D., & Kusuma, D. E. (2024). Development of an expert system for fault diagnosing of washing machines using Delphi 7. (4).

Cai, B., Huang, L., & Xie, M. (2017, October). Bayesian Networks in Fault Diagnosis. *IEEE Transactions on Industrial Informatics*, *13*(5), 2227–2240. Retrieved 2023-12-28, from http://ieeexplore.ieee.org/document/7904628/ doi: 10.1109/TII.2017.2695583

Cao, Y., Zhou, Z., Hu, C., He, W., & Tang, S. (2021, November). On the Interpretability of Belief Rule-Based Expert Systems. *IEEE Transactions on Fuzzy Systems*, *29*(11), 3489–3503. Retrieved 2023-12-18, from https://ieeexplore.ieee.org/document/9199531/ doi: 10.1109/TFUZZ.2020.3024024

Cathignol, A., Thuillie-Demont, V., Baldi, L., Micheau, L., Petitpretre, J.-P., & Ouberehil, A. (2024, June). Hybrid AI-Subject Matter Expert Solution for Evaluating the Health Index of Oil Distribution Transformers. *PHM Society European Conference*, *8*(1), 8. Retrieved 2024-08-23, from https://papers.phmsociety.org/index.php/phme/article/view/4102 doi: 10.36001/phme.2024.v8i1.4102

Chemweno, P., Pintelon, L., Jongers, L., & Muchiri, P. (2016, June). i-RCAM: Intelligent expert system for root cause analysis in maintenance decision making. In *2016 IEEE International Conference on Prognostics and Health Management (ICPHM)* (pp. 1–7). Retrieved 2024-08-29, from https://ieeexplore.ieee.org/abstract/document/7542830 doi: 10.1109/ICPHM.2016.7542830

Chen, B., Matthews, P. C., & Tavner, P. J. (2013, December). Wind turbine pitch faults prognosis using a-priori knowledge-based ANFIS. *Expert Systems with Applications*, *40*(17), 6863–6876. Retrieved 2024-01-04, from https://linkinghub.elsevier.com/retrieve/pii/S0957417413003989 doi: 10.1016/j.eswa.2013.06.018

Chen, J., Roberts, C., & Weston, P. (2008, May). Fault detection and diagnosis for railway track circuits using neuro-fuzzy systems. *Control Engineering Practice*, *16*(5), 585–596. Retrieved 2023-10-16, from https://linkinghub.elsevier.com/retrieve/pii/S0967066107001244 doi: 10.1016/j.conengprac.2007.06.007

Chen, K. Y., Lim, C. P., & Lai, W. K. (2005, December). Application of a Neural Fuzzy System with Rule Extraction to Fault Detection and Diagnosis. *Journal of Intelligent Manufacturing*, *16*(6), 679–691. Retrieved 2023-12-29, from http://link.springer.com/10.1007/s10845-005-4371-1 doi: 10.1007/s10845-005-4371-1

Chen, S. H., & Pollino, C. A. (2012, November). Good practice in Bayesian network modelling. *Environmental Modelling & Software*, *37*, 134–145. Retrieved 2023-10-24, from https://linkinghub.elsevier.com/retrieve/pii/S1364815212001041 doi: 10.1016/j.envsoft.2012.03.012

Cheng, X., Liu, S., He, W., Zhang, P., Xu, B., Xie, Y., & Song, J. (2022, January). A Model for Flywheel Fault Diagnosis Based on Fuzzy Fault Tree Analysis and Belief Rule Base. *Machines*, *10*(2), 73. Retrieved 2023-11-15, from https://www.mdpi.com/2075-1702/10/2/73 doi: 10.3390/machines10020073

Cheung, A., Ip, W., & Lu, D. (2005, January). Expert system for aircraft maintenance services industry. *Journal of Quality in Maintenance Engineering*, *11*(4), 348–

358. Retrieved 2024-08-29, from https://doi.org/10.1108/13552510510626972 (Publisher: Emerald Group Publishing Limited) doi: 10.1108/13552510510626972

Chubb, D. W. J. (1984, April). Knowledge Engineering Problems during Expert System Development. *SIGSIM Simul. Dig.*, *15*(3), 5–9. Retrieved from https://doi.org/10.1145/1102872.1102873 (Place: New York, NY, USA Publisher: Association for Computing Machinery) doi: 10.1145/1102872.1102873

Cobb, B. R., & Shenoy, P. P. (2003, December). A Comparison of Bayesian and Belief Function Reasoning. *Information Systems Frontiers*, *5*(4), 345–358. Retrieved 2024-01-03, from http://link.springer.com/10.1023/B:ISFI.0000005650.63806.03 doi: 10.1023/B:ISFI.0000005650.63806.03

Compare, M., Bellani, L., & Zio, E. (2019, April). Optimal allocation of prognostics and health management capabilities to improve the reliability of a power transmission network. *Reliability Engineering & System Safety*, *184*, 164–180. Retrieved 2024-08-29, from https://www.sciencedirect.com/science/article/pii/S0951832017306816 doi: 10.1016/j.ress.2018.04.025

Darwiche, A. (2008). Chapter 11 Bayesian Networks. In *Foundations of Artificial Intelligence* (Vol. 3, pp. 467–509). Elsevier. Retrieved 2023-10-24, from https://linkinghub.elsevier.com/retrieve/pii/S1574652607030118 doi: 10.1016/S1574-6526(07)03011-8

Da Silva Vicente, S., Fujimoto, R., & Padovese, L. (2001). Rolling bearing fault diagnostic system using fuzzy logic. In *10th IEEE International Conference on Fuzzy Systems. (Cat. No.01CH37297)* (Vol. 3, pp. 816–819). Melbourne, Vic., Australia: IEEE. Retrieved 2023-12-29, from http://ieeexplore.ieee.org/document/1009080/ doi: 10.1109/FUZZ.2001.1009080

Davis, R. (1979). Interactive Transfer of Expertise: Acqlfisifion of New Inference Rules.

Deng, X.-W., Gao, Q.-S., Zhang, C., Hu, D., & Yang, T. (2017). Rule - based Fault Diagnosis Expert System for Wind Turbine. *ITM Web of Conferences*, *11*, 07005. Retrieved 2023-10-17, from http://www.itm-conferences.org/10.1051/itmconf/20171107005 doi: 10.1051/itmconf/20171107005

DePold, H. R., & Gass, F. D. (1998). The Application of Expert Systems and Neural Networks to Gas Turbine Prognostics and Diagnostics.

Ding, Y., Yao, X., Wang, S., & Zhao, X. (2019, April). Structural damage assessment using improved Dempster-Shafer data fusion algorithm. *Earthquake Engineering and Engineering Vibration*, *18*(2), 395–408. Retrieved 2023-12-30, from http://link.springer.com/10.1007/s11803-019-0511-z doi: 10.1007/s11803-019-0511-z

Dong, G., Han, W., & Wang, Y. (2021, November). Dynamic Bayesian Network-Based Lithium-Ion Battery Health Prognosis for Electric Vehicles. *IEEE Transactions on Industrial Electronics*, *68*(11), 10949–10958. Retrieved 2024-01-04, from https://ieeexplore.ieee.org/document/9248645/ doi: 10.1109/TIE.2020.3034855

Dou, D., Yang, J., Liu, J., & Zhao, Y. (2012, December). A rule-based intelligent method for fault diagnosis of rotating machinery. *Knowledge-Based Systems*, *36*, 1–8. Retrieved 2023-12-29, from https://linkinghub.elsevier.com/retrieve/pii/S0950705112001578 doi: 10.1016/j.knosys.2012.05.013

Dubois, D., & Prade, H. (1996, December). What are fuzzy rules and how to use them. *Fuzzy Sets and Systems*, *84*(2), 169–185. Retrieved 2023-12-18, from https://linkinghub.elsevier.com/retrieve/pii/0165011496000668 doi: 10.1016/0165-0114(96)00066-8

Elattar, H. M., Elminir, H. K., & Riad, A. M. (2016, June). Prognostics: a literature review. *Complex & Intelligent Systems*, *2*(2), 125–154. Retrieved 2023-12-13, from http://link.springer.com/10.1007/s40747-016-0019-3 doi: 10.1007/s40747-016-0019-3

Ferreiro, S., Arnaiz, A., Sierra, B., & Irigoien, I. (2012, June). Application of Bayesian networks in prognostics for a new Integrated Vehicle Health Management concept. *Expert Systems with Applications*, *39*(7), 6402–6418. Retrieved 2023-10-18, from https://linkinghub.elsevier.com/retrieve/pii/S0957417411016988 doi: 10.1016/j.eswa.2011.12.027

Fikes, R., & Kehler, T. (1985, September). The role of frame-based representation in reasoning. *Communications of the ACM*, *28*(9), 904–920. Retrieved 2023-12-19, from https://dl.acm.org/doi/10.1145/4284.4285 doi: 10.1145/4284.4285

Fink, O. (2020). Data-Driven Intelligent Predictive Maintenance of Industrial Assets. In A. E. Smith (Ed.), *Women in Industrial and Systems Engineering: Key Advances and Perspectives on Emerging Topics* (pp. 589–605). Cham: Springer International Publishing. Retrieved 2024-05-08, from https://doi.org/10.1007/978-3-030-11866-2_25 doi: 10.1007/978-3-030-11866-2_25

Fink, O., Wang, Q., Svensén, M., Dersin, P., Lee, W.-J., & Ducoffe, M. (2020, June). Potential, challenges and future directions for deep learning in prognostics and health management applications. *Engineering Applications of Artificial Intelligence*, *92*, 103678. Retrieved 2023-10-09, from https://linkinghub.elsevier.com/retrieve/pii/S0952197620301184 doi: 10.1016/j.engappai.2020.103678

Forest, F., Cochard, Q., Noyer, C., Joncour, M., Lacaille, J., Lebbah, M., & Azzag, H. (2020, November). Large-scale Vibration Monitoring of Aircraft Engines from Operational Data using Self-organized Models. In *Annual Conference of the PHM Society* (Vol. 12, p. 11). Retrieved 2022-09-08, from https://papers.phmsociety.org/index.php/phmconf/article/view/1131 doi: 10.36001/phmconf.2020.v12i1.1131

Forest, F., Lacaille, J., Lebbah, M., & Azzag, H. (2018, December). A Generic and Scalable Pipeline for Large-Scale Analytics of Continuous Aircraft Engine Data. In *2018 IEEE International Conference on Big Data (Big Data)* (pp. 1918–1924). Seattle, WA, USA: IEEE. Retrieved 2022-09-08, from https://ieeexplore.ieee.org/document/8622297/ doi: 10.1109/BigData.2018.8622297

Forsythe, D., & Buchanan, B. (1989, June). Knowledge acquisition for expert systems: some pitfalls and suggestions. *IEEE Transactions on Systems, Man, and Cybernetics*, *19*(3), 435–442. Retrieved 2023-10-16, from http://ieeexplore.ieee.org/document/31050/ doi: 10.1109/21.31050

Fritz Lehmann. (1992). *1-s2.0-0898122192901355-main.pdf.*

Galagedarage Don, M., & Khan, F. (2019, June). Dynamic process fault detection and diagnosis based on a combined approach of hidden Markov and Bayesian network model. *Chemical Engineering Science*, *201*, 82–96. Retrieved 2023-12-30, from https://linkinghub.elsevier.com/retrieve/pii/S000925091930154X doi: 10.1016/j.ces.2019.01.060

Gao, Z., Cecati, C., & Ding, S. X. (2015, June). A Survey of Fault Diagnosis and Fault-Tolerant Techniques—Part I: Fault Diagnosis With Model-Based and Signal-Based Approaches. *IEEE Transactions on Industrial Electronics*, *62*(6), 3757–3767. Retrieved 2023-12-28, from http://ieeexplore.ieee.org/document/7069265/ doi: 10.1109/TIE.2015.2417501

Gay, A., Iung, B., Voisin, A., Do, P., Bonidal, R., & Khelassi, A. (2021, November). A Short Review on the Integration of Expert Knowledge in Prognostics for PHM in Industrial Applications. In *2021 5th International Conference on System Reliability and Safety (ICSRS)* (pp. 286–292). Palermo, Italy: IEEE. Retrieved 2023-10-18, from https://ieeexplore.ieee.org/document/9660645/ doi: 10.1109/ICSRS53853.2021.9660645

Gerhardinger, D., Domitrović, A., Krajček Nikolić, K., & Ivančević, D. (2023, November). Predicting the Remaining Useful Life of Light Aircraft Structural Parts: An Expert System Approach. *Aerospace*, *10*(11), 967. Retrieved 2024-09-04, from https://www.mdpi.com/2226-4310/10/11/967 doi: 10.3390/aerospace10110967

Ghahramani, Z. (1998). Learning dynamic Bayesian networks. In J. G. Carbonell et al. (Eds.), *Adaptive Processing of Sequences and Data Structures* (Vol. 1387, pp. 168–197). Berlin, Heidelberg: Springer Berlin Heidelberg. Retrieved 2024-01-04, from https://link.springer.com/10.1007/BFb0053999 (Series Title: Lecture Notes in Computer Science) doi: 10.1007/BFb0053999

Gharib, H., & Kovács, G. (2023, July). A Review of Prognostic and Health Management (PHM) Methods and Limitations for Marine Diesel Engines: New Research Directions. *Machines*, *11*(7), 695. Retrieved 2024-08-23, from https://www.mdpi.com/2075-1702/11/7/695 doi: 10.3390/machines11070695

Ghosh, N., Paul, R., Maity, S., Maity, K., & Saha, S. (2020, December). Fault Matters: Sensor data fusion for detection of faults using Dempster–Shafer theory of evidence in IoT-based applications. *Expert Systems with Applications*, *162*, 113887. Retrieved 2023-12-29, from https://linkinghub.elsevier.com/retrieve/pii/S0957417420306898 doi: 10.1016/j.eswa.2020.113887

Gnanamalar, R. H., Janani, C., & Devi, T. (2013). International Journal of Emerging Technologies in Computational and Applied Sciences (IJETCAS) www.iasir.net.

Gomes, I. P., & Wolf, D. F. (2021, January). Health Monitoring System for Autonomous Vehicles using Dynamic Bayesian Networks for Diagnosis and Prognosis. *Journal of Intelligent & Robotic Systems*, *101*(1), 19. Retrieved 2024-01-04, from http://link.springer.com/10.1007/s10846-020-01293-y doi: 10.1007/s10846-020-01293-y

Gordon, J., & Shortliffe, E. H. (1984). The Dempster-Shafer Theory of Evidence.

Grosan, C., & Abraham, A. (2011). *Intelligent Systems: A Modern Approach* (Vol. 17; J. Kacprzyk & L. C. Jain, Eds.). Berlin, Heidelberg: Springer Berlin Heidelberg. Retrieved 2023-12-18, from https://link.springer.com/10.1007/978-3-642-21004-4 doi: 10.1007/978-3-642-21004-4

Gudes, E., Kuflik, T., & Meisels, A. (1990, June). On resource allocation by an expert system. *Engineering Applications of Artificial Intelligence*, *3*(2), 101–109. Retrieved 2024-08-29, from https://www.sciencedirect.com/science/article/pii/095219769090003 5 doi: 10.1016/0952-1976(90)90003-5

GUIDA, G., & TASSO, C. (1989a). *Building Expert Systems: A Structured Bibliography* (Vol. 5). Amsterdam [etc.]: North-Holland. (ISSN: 09243542 Publication Title: Topics in expert system design methodologies and tools)

GUIDA, G., & TASSO, C. (1989b). *Building Expert Systems: From Life Cycle to Development Methodology* (Vol. 5). Amsterdam [etc.]: North-Holland. (ISSN: 09243542 Publication Title: Topics in expert system design methodologies and tools)

Guinhouya, K. A. (2023, March). Bayesian networks in project management: A scoping review. *Expert Systems with Applications*, *214*, 119214. Retrieved 2023-10-13, from https://linkinghub.elsevier.com/retrieve/pii/S0957417422022321 doi: 10.1016/j.eswa.2022.119214

He, W., Williard, N., Osterman, M., & Pecht, M. (2011, December). Prognostics of lithium-ion batteries based on Dempster–Shafer theory and the Bayesian Monte Carlo method. *Journal of Power Sources*, *196*(23), 10314–10321. Retrieved 2023-10-18, from https://linkinghub.elsevier.com/retrieve/pii/S0378775311015400 doi: 10.1016/j.jpowsour.2011.08.040

Heidari. (2017, April). Fault Detection of Bearings Using a Rule-based Classifier Ensemble and Genetic Algorithm. *International Journal of Engineering*, *30*(4). Retrieved 2023-12-29, from http://www.ije.ir/Vol30/No4/A/20.pdf doi: 10.5829/idosi.ije.2017.30.04a.20

Hitzler, P., Eberhart, A., Ebrahimi, M., Sarker, M. K., & Zhou, L. (2022, June). Neuro-symbolic approaches in artificial intelligence. *National Science Review*, *9*(6), nwac035. Retrieved 2024-08-29, from https://doi.org/10.1093/nsr/nwac035 doi: 10.1093/nsr/nwac035

Hsu, C.-C., Frusque, G., & Fink, O. (2023, October). A Comparison of Residual-based Methods on Fault Detection. *Annual Conference of the PHM Society*, *15*(1). Retrieved 2024-01-19, from http://www.papers.phmsociety.org/index.php/phmconf/article/view/3444 (Number: 1) doi: 10.36001/phmconf.2023.v15i1.3444

Hu, Y., Miao, X., Si, Y., Pan, E., & Zio, E. (2022, January). Prognostics and health management: A review from the perspectives of design, development and decision. *Reliability Engineering & System Safety*, *217*, 108063. Retrieved 2024-08-26, from https://linkinghub.elsevier.com/retrieve/pii/S0951832021005652 doi: 10.1016/j.ress.2021.108063

Hui, K. H., Lim, M. H., Leong, M. S., & Al-Obaidi, S. M. (2017, January). Dempster-Shafer evidence theory for multi-bearing faults diagnosis. *Engineering Applications of Artificial Intelligence*, *57*, 160–170. Retrieved 2024-01-03, from https://linkinghub.elsevier.com/retrieve/pii/S0952197616302019 doi: 10.1016/j.engappai.2016.10.017

Isermann, R. (1997, May). Supervision, fault-detection and fault-diagnosis methods — An introduction. *Control Engineering Practice*, *5*(5), 639–652. Retrieved 2023-12-28, from https://linkinghub.elsevier.com/retrieve/pii/S0967066197000464 doi: 10.1016/S0967-0661(97)00046-4

Ishibashi, R., & Lucio Nascimento Junior, C. (2013, June). GFRBS-PHM: A Genetic Fuzzy Rule-Based System for PHM with improved interpretability. In *2013 IEEE Conference on Prognostics and Health Management (PHM)* (pp. 1–7). Gaithersburg, MD, USA: IEEE. Retrieved 2023-12-28, from http://ieeexplore.ieee.org/document/6621419/ doi: 10.1109/ICPHM.2013.6621419

Jain, L. C., & Martin, N. M. (1998). *Fusion of neural networks, fuzzy systems and genetic algorithms: industrial applications* (Vol. 4). CRC press.

Jian-Bo Yang, Jun Liu, Jin Wang, How-Sing Sii, & Hong-Wei Wang. (2006, March). Belief rule-base inference methodology using the evidential reasoning Approach-RIMER. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *36*(2), 266–285. Retrieved 2023-11-13, from http://ieeexplore.ieee.org/document/1597400/ doi: 10.1109/TSMCA.2005.851270

John Sowa. (1992). *semantic-net-sowa.pdf.*

Jose, A. (2011). *Design and development of a rule based expert system for AACR: A study of the application of Artificial Intelligence techniques in Library and Information field.*

Karakose, M., & Yaman, O. (2020, September). Complex Fuzzy System Based Predictive Maintenance Approach in Railways. *IEEE Transactions on Industrial Informatics*, *16*(9), 6023–6032. Retrieved 2023-12-29, from https://ieeexplore.ieee.org/document/8993841/ doi: 10.1109/TII.2020.2973231

Kastner. (1984). *A review of expert systems.*

Khan, S., & Yairi, T. (2018, July). A review on the application of deep learning in system health management. *Mechanical Systems and Signal Processing*, *107*, 241–265. Retrieved 2023-12-28, from `https://linkinghub.elsevier.com/retrieve/pii/S0888327017306064` doi: 10.1016/j.ymssp.2017.11.024

Kitson, N. K., Constantinou, A. C., Guo, Z., Liu, Y., & Chobtham, K. (2022, October). *A survey of Bayesian Network structure learning.* arXiv. Retrieved 2023-10-13, from `http://arxiv.org/abs/2109.11415` (arXiv:2109.11415 [cs])

Konstantinov, A. V., & Utkin, L. V. (2024, February). *Incorporating Expert Rules into Neural Networks in the Framework of Concept-Based Learning.* arXiv. Retrieved 2024-05-28, from `http://arxiv.org/abs/2402.14726` (arXiv:2402.14726 [cs, stat]) doi: 10.48550/arXiv.2402.14726

Kusiak, A., & Chen, M. (1988, March). Expert systems for planning and scheduling manufacturing systems. *European Journal of Operational Research*, *34*(2), 113–130. Retrieved 2023-10-04, from `https://linkinghub.elsevier.com/retrieve/pii/0377221788903463` doi: 10.1016/0377-2217(88)90346-3

Langseth, H. (2008). Bayesian Networks in Reliability: The Good, the Bad, and the Ugly.

Lee, I. (2017, May). Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons*, *60*(3), 293–303. Retrieved 2023-12-14, from `https://linkinghub.elsevier.com/retrieve/pii/S0007681317300046` doi: 10.1016/j.bushor.2017.01.004

Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014, January). Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, *42*(1-2), 314–334. Retrieved 2023-12-28, from `https://linkinghub.elsevier.com/retrieve/pii/S0888327013002860` doi: 10.1016/j.ymssp.2013.06.004

Leekwijck, W. V., & Kerre, E. E. (1999). Defuzziÿcation: criteria and classiÿcation. *Fuzzy Sets and Systems*.

Leonhardt, S., & Ayoubi, M. (1997, May). Methods of fault diagnosis. *Control Engineering Practice*, *5*(5), 683–692. Retrieved 2023-12-28, from `https://linkinghub.elsevier.com/retrieve/pii/S0967066197000506` doi: 10.1016/S0967-0661(97)00050-6

Lerner, U., Parr, R., Koller, D., & Biswas, G. (2000). Bayesian Fault Detection and Diagnosis in Dynamic Systems.

Leu, G., & Abbass, H. (2016, August). A multi-disciplinary review of knowledge acquisition methods: From human to autonomous eliciting agents. *Knowledge-Based Systems*, *105*, 1–22. Retrieved 2023-12-17, from `https://linkinghub.elsevier.com/retrieve/pii/S0950705116000988` doi: 10.1016/j.knosys.2016.02.012

Li, B., Han, T., & Kang, F. (2013, December). Fault diagnosis expert system of semiconductor manufacturing equipment using a Bayesian network. *International Journal of Computer Integrated Manufacturing*, *26*(12), 1161–1171. Retrieved 2024-01-03, from `http://www.tandfonline.com/doi/abs/10.1080/0951192X.2013.812803` doi: 10.1080/0951192X.2013.812803

Li, T., Zhao, Y., Zhang, C., Zhou, K., & Zhang, X. (2022, January). A semantic model-based fault detection approach for building energy systems. *Building and Environment*, *207*, 108548. Retrieved 2023-10-17, from `https://linkinghub.elsevier.com/retrieve/pii/S0360132321009410` doi: 10.1016/j.buildenv.2021.108548

Lidén, T. (2015). Railway Infrastructure Maintenance - A Survey of Planning Problems and Conducted Research. *Transportation Research Procedia*, *10*, 574–583. Retrieved 2023-12-14, from `https://linkinghub.elsevier.com/retrieve/pii/S2352146515001982` doi: 10.1016/j.trpro.2015.09.011

Ligêza, A. (2006). Logical Foundations for Rule-Based Systems.

Liu, J., & Zio, E. (2018, July). A scalable fuzzy support vector machine for fault detection in transportation systems. *Expert Systems with Applications*, *102*, 36–43. Retrieved 2023-12-29, from `https://linkinghub.elsevier.com/retrieve/pii/S0957417418300952` doi: 10.1016/j.eswa.2018.02.017

Liu, M., Yan, X., Sun, X., Dong, W., & Ji, Y. (2016, May). Fault diagnosis method for railway turnout control circuit based on information fusion. In *2016 IEEE Information Technology, Networking, Electronic and Automation Control Conference* (pp. 315–320). Chongqing, China: IEEE. Retrieved 2023-11-15, from `http://ieeexplore.ieee.org/document/7560373/` doi: 10.1109/ITNEC.2016.7560373

Liu, P., Liu, Y., Cai, B., Wu, X., Wang, K., Wei, X., & Xin, C. (2020, January). A dynamic Bayesian network based methodology for fault diagnosis of subsea Christmas tree. *Applied Ocean Research*, *94*, 101990. Retrieved 2024-01-04, from `https://linkinghub.elsevier.com/retrieve/pii/S0141118719304936` doi: 10.1016/j.apor.2019.101990

Liu, Q., Dong, M., Chen, F. F., Li, Y., & Wang,

H. (2019). A Novel Method Using DS-MCM for Equipment Health Prognosis with Partially Observed Information. *Procedia Manufacturing*, *38*, 1159–1166. Retrieved 2024-01-04, from https://linkinghub.elsevier.com/retrieve/pii/S2351978920302067 doi: 10.1016/j.promfg.2020.01.205

Liu, Q., Wang, C., & Wang, Q. (2023, April). Bayesian Uncertainty Inferencing for Fault Diagnosis of Intelligent Instruments in IoT Systems. *Applied Sciences*, *13*(9), 5380. Retrieved 2023-10-16, from https://www.mdpi.com/2076-3417/13/9/5380 doi: 10.3390/app13095380

Liu, R., Yang, B., Zio, E., & Chen, X. (2018, August). Artificial intelligence for fault diagnosis of rotating machinery: A review. *Mechanical Systems and Signal Processing*, *108*, 33–47. Retrieved 2024-01-14, from https://linkinghub.elsevier.com/retrieve/pii/S0888327018300748 doi: 10.1016/j.ymssp.2018.02.016

Lu, Z., Afridi, I., Kang, H. J., Ruchkin, I., & Zheng, X. (2024, July). Surveying neuro-symbolic approaches for reliable artificial intelligence of things. *Journal of Reliable Intelligent Environments*. Retrieved 2024-08-29, from https://doi.org/10.1007/s40860-024-00231-1 doi: 10.1007/s40860-024-00231-1

Lucas, P. J. F. (1991, December). Principles of Expert Systems.

Mahesar, Q.-a., Dimitrova, V., Magee, D., & Cohn, A. (2017, November). Uncertainty Management for Rule-Based Decision Support Systems. In *2017 IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI)* (pp. 884–891). Boston, MA: IEEE. Retrieved 2023-10-16, from https://ieeexplore.ieee.org/document/8372040/ doi: 10.1109/ICTAI.2017.00137

Malik, M. A. K. (1979, September). Reliable Preventive Maintenance Scheduling. *A I I E Transactions*, *11*(3), 221–228. Retrieved 2023-12-21, from http://www.tandfonline.com/doi/abs/10.1080/05695557908974463 doi: 10.1080/05695557908974463

Manzini, R., Regattieri, A., Pham, H., & Ferrari, E. (2010). *Maintenance for Industrial Systems* (H. Pham, Ed.). London: Springer London. Retrieved 2023-12-14, from http://link.springer.com/10.1007/978-1-84882-575-8 doi: 10.1007/978-1-84882-575-8

Maria Malek. (2008). *Systèmes Experts - Cours.pdf.*

Masri, N., Sultan, Y. A., Akkila, A. N., Almasri, A., Ahmed, A., Mahmoud, A. Y., ... Abu-Naser, S. S. (2019). Survey of Rule-Based Systems. , *3*(7).

Medjaher, K., Moya, J.-Y., & Zerhouni, N. (2009, June). Failure prognostic by using Dynamic Bayesian Networks. *IFAC Proceedings Volumes*, *42*(5), 257–262. Retrieved 2024-01-04, from https://linkinghub.elsevier.com/retrieve/pii/S1474667015356305 doi: 10.3182/20090610-3-IT-4004.00049

Medjaher, K., Tobon-Mejia, D. A., & Zerhouni, N. (2012, June). Remaining Useful Life Estimation of Critical Components With Application to Bearings. *IEEE Transactions on Reliability*, *61*(2), 292–302. Retrieved 2023-12-28, from http://ieeexplore.ieee.org/document/6190764/ doi: 10.1109/TR.2012.2194175

Mendonça, L., Sousa, J., & Sá Da Costa, J. (2009, March). An architecture for fault detection and isolation based on fuzzy methods. *Expert Systems with Applications*, *36*(2), 1092–1104. Retrieved 2023-12-29, from https://linkinghub.elsevier.com/retrieve/pii/S0957417407005246 doi: 10.1016/j.eswa.2007.11.009

Metaxiotis. (2001). Expert systems in production planning and scheduling: A state-of-the-art survey.

Michau, G., & Fink, O. (2021, March). Unsupervised transfer learning for anomaly detection: Application to complementary operating condition transfer. *Knowledge-Based Systems*, *216*, 106816. Retrieved 2023-11-06, from https://www.sciencedirect.com/science/article/pii/S0950705121000794 doi: 10.1016/j.knosys.2021.106816

Miguelanez, E., Brown, K., Lewis, R., Roberts, C., & Lane, D. (2008). Fault diagnosis of a train door system based on semantic knowledge representation. In *4th IET International Conference on Railway Condition Monitoring (RCM 2008)* (pp. 27–27). Derby, UK: IEE. Retrieved 2023-11-15, from https://digital-library.theiet.org/content/conferences/10.1049/ic_20080333 doi: 10.1049/ic:20080333

Miljkovic. (2011). Fault detection methods: A literature survey.

Mitici, M., De Pater, I., Barros, A., & Zeng, Z. (2023, June). Dynamic predictive maintenance for multiple components using data-driven probabilistic RUL prognostics: The case of turbofan engines. *Reliability Engineering & System Safety*, *234*, 109199. Retrieved 2024-08-29, from https://linkinghub.elsevier.com/retrieve/pii/S095183202300114X doi: 10.1016/j.ress.2023.109199

Moore, C., & Miles, J. (1991). Knowledge elicitation using more than one expert to cover the same domain. *Artificial Intelligence Review*, *5*(4). Retrieved 2023-12-17, from http://link.springer.com/10.1007/BF00141757 doi: 10.1007/BF00141757

Muhammad, L., Garba, E., Oye, N., & Wajiga, G. (2019).

Modeling Techniques for Knowledge Representation of Expert System: A Survey. *Journal of Applied Computer Science & Mathematics*, *13*(2), 39–44. Retrieved 2023-12-18, from https://www.jacsm.ro/view/?pid=28_6 doi: 10.4316/JACSM.201902006

Murphy, K. P. (2002). Dynamic Bayesian Networks.

Musen, M. A. (1993). An Overview of Knowledge Acquisition. In J.-M. David, J.-P. Krivine, & R. Simmons (Eds.), *Second Generation Expert Systems* (pp. 405–427). Berlin, Heidelberg: Springer Berlin Heidelberg.

Nakakoji, K., & Fischer, G. (1995, April). Intertwining knowledge delivery and elicitation: a process model for human-computer collaboration in design. *Knowledge-Based Systems*, *8*(2-3), 94–104. Retrieved 2023-12-17, from https://linkinghub.elsevier.com/retrieve/pii/095070519598371C doi: 10.1016/0950-7051(95)98371-C

Nejjar, I., Geissmann, F., Zhao, M., Taal, C., & Fink, O. (2024, February). Domain adaptation via alignment of operation profile for Remaining Useful Lifetime prediction. *Reliability Engineering & System Safety*, *242*, 109718. Retrieved 2023-11-29, from https://www.sciencedirect.com/science/article/pii/S0951832023006324 doi: 10.1016/j.ress.2023.109718

Niu, G., & Yang, B.-S. (2009, April). Dempster–Shafer regression for multi-step-ahead time-series prediction towards data-driven machinery prognosis. *Mechanical Systems and Signal Processing*, *23*(3), 740–751. Retrieved 2024-01-04, from https://linkinghub.elsevier.com/retrieve/pii/S0888327008002094 doi: 10.1016/j.ymssp.2008.08.004

Omri, N., Masry, Z. A., Mairot, N., Giampiccolo, S., & Zerhouni, N. (2021). X-PHM: Prognostics and health management knowledge-based framework for SME. *Procedia CIRP*, *104*, 1595–1600. Retrieved 2023-12-28, from https://linkinghub.elsevier.com/retrieve/pii/S2212827121011677 doi: 10.1016/j.procir.2021.11.269

Oukhellou, L., Debiolles, A., Denœux, T., & Aknin, P. (2010, February). Fault diagnosis in railway track circuits using Dempster–Shafer classifier fusion. *Engineering Applications of Artificial Intelligence*, *23*(1), 117–128. Retrieved 2023-10-17, from https://linkinghub.elsevier.com/retrieve/pii/S0952197609001109 doi: 10.1016/j.engappai.2009.06.005

Pearl, J. .-. (1988). *BAYESIAN INFERENCE* (Revised 2nd printing ed.). San Francisco: M. Kaufmann. (Publication Title: Probabilistic reasoning in intelligent systems networks of plausible inference)

Peng, J., Xia, G., Li, Y., Song, Y., & Hao, M. (2022, December). Knowledge-based prognostics and health management of a pumping system under the linguistic decision-making context. *Expert Systems with Applications*, *209*, 118379. Retrieved 2023-10-18, from https://linkinghub.elsevier.com/retrieve/pii/S0957417422014920 doi: 10.1016/j.eswa.2022.118379

Prajapati, A., Bechtel, J., & Ganesan, S. (2012, October). Condition based maintenance: a survey. *Journal of Quality in Maintenance Engineering*, *18*(4), 384–400. Retrieved 2023-12-21, from https://www.emerald.com/insight/content/doi/10.1108/13552511211281552/full/html doi: 10.1108/13552511211281552

Qu, F., Liu, J., Zhu, H., & Zhou, B. (2020, March). Wind turbine fault detection based on expanded linguistic terms and rules using non-singleton fuzzy logic. *Applied Energy*, *262*, 114469. Retrieved 2023-12-29, from https://linkinghub.elsevier.com/retrieve/pii/S0306261919321579 doi: 10.1016/j.apenergy.2019.114469

Quost, B., Masson, M.-H., & Denœux, T. (2011, March). Classifier fusion in the Dempster–Shafer framework using optimized t-norm based combination rules. *International Journal of Approximate Reasoning*, *52*(3), 353–374. Retrieved 2024-01-03, from https://linkinghub.elsevier.com/retrieve/pii/S0888613X10001568 doi: 10.1016/j.ijar.2010.11.008

Radtke, M.-P., & Bock, J. (2022, June). Combining Knowledge and Deep Learning for Prognostics and Health Management. *PHM Society European Conference*, *7*(1), 594–597. Retrieved 2024-08-23, from https://papers.phmsociety.org/index.php/phme/article/view/3302 doi: 10.36001/phme.2022.v7i1.3302

Rajabi, M., Hossani, S., & Dehghani, F. (2019, September). *A literature review on current approaches and applications of fuzzy expert systems.* arXiv. Retrieved 2023-12-05, from http://arxiv.org/abs/1909.08794 (arXiv:1909.08794 [cs])

Reetz, S., Neumann, T., Schrijver, G., Van Den Berg, A., & Buursma, D. (2024, February). Expert system based fault diagnosis for railway point machines. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *238*(2), 214–224. Retrieved 2024-09-04, from http://journals.sagepub.com/doi/10.1177/09544097231195656 doi: 10.1177/09544097231195656

Roychowdhury, S., & Pedrycz, W. (2001, June). A survey of defuzzification strategies. *International Journal of Intelligent Systems*, *16*(6), 679–695. Retrieved 2023-

12-18, from https://onlinelibrary.wiley.com/doi/10.1002/int.1030 doi: 10.1002/int.1030

Ruan, D., Wang, J., Yan, J., & Gühmann, C. (2023, January). CNN parameter design based on fault signal analysis and its application in bearing fault diagnosis. *Advanced Engineering Informatics*, *55*, 101877. Retrieved 2024-08-22, from https://linkinghub.elsevier.com/retrieve/pii/S1474034623000058 doi: 10.1016/j.aei.2023.101877

Rudin, C. (2019, September). *Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead.* arXiv. Retrieved 2023-12-14, from http://arxiv.org/abs/1811.10154 (arXiv:1811.10154 [cs, stat])

Santos, J., Torres-Machi, C., Morillas, S., & Cerezo, V. (2022, January). A fuzzy logic expert system for selecting optimal and sustainable life cycle maintenance and rehabilitation strategies for road pavements. *International Journal of Pavement Engineering*, *23*(2), 425–437. Retrieved 2024-08-29, from https://doi.org/10.1080/10298436.2020.1751161 (Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/10298436.2020.1751161) doi: 10.1080/10298436.2020.1751161

Sarazin, A., Bascans, J., Sciau, J.-B., Song, J., Supiot, B., Montarnal, A., … Truptil, S. (2021, December). Expert system dedicated to condition-based maintenance based on a knowledge graph approach: Application to an aeronautic system. *Expert Systems with Applications*, *186*, 115767. Retrieved 2024-08-29, from https://linkinghub.elsevier.com/retrieve/pii/S0957417421011398 doi: 10.1016/j.eswa.2021.115767

Satish, B., & Sarma, N. (2005). A fuzzy bp approach for diagnosis and prognosis of bearing faults in induction motors. In *IEEE Power Engineering Society General Meeting, 2005* (pp. 958–961). San Francisco, CA, USA: IEEE. Retrieved 2024-01-04, from http://ieeexplore.ieee.org/document/1489277/ doi: 10.1109/PES.2005.1489277

Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2021, March). Metrics for Offline Evaluation of Prognostic Performance. *International Journal of Prognostics and Health Management*, *1*(1). Retrieved 2023-12-28, from https://papers.phmsociety.org/index.php/ijphm/article/view/1336 doi: 10.36001/ijphm.2010.v1i1.1336

Schein, J., Bushby, S. T., Castro, N. S., & House, J. M. (2006, December). A rule-based fault detection method for air handling units. *Energy and Buildings*, *38*(12), 1485–1492. Retrieved 2023-10-17, from https://linkinghub.elsevier.com/retrieve/pii/S0378778806001034 doi: 10.1016/j.enbuild.2006.04.014

Schwabacher, M. (2007). A Survey of Artificial Intelligence for Prognostics.

Sentz, K., & Ferson, S. (2002, April). *Combination of Evidence in Dempster-Shafer Theory* (Tech. Rep. Nos. SAND2002-0835, 800792). Retrieved 2024-01-11, from https://www.osti.gov/servlets/purl/800792/ doi: 10.2172/800792

Sheut, C., & Krajewski, L. J. (1994, June). A decision model for corrective maintenance management. *International Journal of Production Research*, *32*(6), 1365–1382. Retrieved 2023-12-21, from http://www.tandfonline.com/doi/abs/10.1080/00207549408957005 doi: 10.1080/00207549408957005

Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011, August). Remaining useful life estimation – A review on the statistical data driven approaches. *European Journal of Operational Research*, *213*(1), 1–14. Retrieved 2023-12-28, from https://linkinghub.elsevier.com/retrieve/pii/S0377221710007903 doi: 10.1016/j.ejor.2010.11.018

Skarlatos, D., Karakasis, K., & Trochidis, A. (2004, October). Railway wheel fault diagnosis using a fuzzy-logic method. *Applied Acoustics*, *65*(10), 951–966. Retrieved 2023-11-15, from https://linkinghub.elsevier.com/retrieve/pii/S0003682X04000672 doi: 10.1016/j.apacoust.2004.04.003

Slagle, J. R., & Hamburger, H. (1985, September). An expert system for a resource allocation problem. *Commun. ACM*, *28*(9), 994–1004. Retrieved 2024-08-29, from https://dl.acm.org/doi/10.1145/4284.4291 doi: 10.1145/4284.4291

Soltanali, H., Khojastehpour, M., Farinha, J. T., & Pais, J. E. D. A. E. (2021, November). An Integrated Fuzzy Fault Tree Model with Bayesian Network-Based Maintenance Optimization of Complex Equipment in Automotive Manufacturing. *Energies*, *14*(22), 7758. Retrieved 2023-12-29, from https://www.mdpi.com/1996-1073/14/22/7758 doi: 10.3390/en14227758

Song, B., Jiang, Z., & Li, X. (2015, February). Modeling knowledge need awareness using the problematic situations elicited from questions and answers. *Knowledge-Based Systems*, *75*, 173–183. Retrieved 2023-12-17, from https://linkinghub.elsevier.com/retrieve/pii/S0950705114004341 doi: 10.1016/j.knosys.2014.12.004

Soualhi, A., Lamraoui, M., Elyousfi, B., & Razik, H. (2022, September). PHM SURVEY: Implementation of Prognostic Methods for Monitoring Industrial Systems. *Energies*, *15*(19), 6909. Retrieved 2023-12-28, from https://www.mdpi.com/1996-1073/15/19/6909 doi: 10.3390/en15196909

Soualhi, A., Razik, H., Clerc, G., & Doan, D. D. (2014, June). Prognosis of Bearing Failures Using Hidden Markov Models and the Adaptive Neuro-Fuzzy Inference System. *IEEE Transactions on Industrial Electronics*, *61*(6), 2864–2874. Retrieved 2024-01-04, from http://ieeexplore.ieee.org/document/6566058/ doi: 10.1109/TIE.2013.2274415

Steels, L. (1990, June). Components of Expertise. *AI Magazine*, *11*(2), 28–28. Retrieved 2023-09-18, from https://ojs.aaai.org/aimagazine/index.php/aimagazine/article/view/831 (Number: 2) doi: 10.1609/aimag.v11i2.831

Swanson, L. (2001). Linking maintenance strategies to performance. *International Journal of Production Economics*, *70*(3), 237–244. Retrieved from https://www.sciencedirect.com/science/article/pii/S0925527300000670 doi: https://doi.org/10.1016/S0925-5273(00)00067-0

Sánchez-Silva, M., Frangopol, D. M., Padgett, J., & Soliman, M. (2016, September). Maintenance and Operation of Infrastructure Systems: Review. *Journal of Structural Engineering*, *142*(9), F4016004. Retrieved 2023-12-14, from https://ascelibrary.org/doi/10.1061/%28ASCE%29ST.1943-541X.0001543 doi: 10.1061/(ASCE)ST.1943-541X.0001543

Tang, H., Li, D., Chen, W., & Xue, S. (2016, June). Uncertainty quantification using evidence theory in concrete fatigue damage prognosis. In *2016 IEEE International Conference on Prognostics and Health Management (ICPHM)* (pp. 1–7). Ottawa, ON, Canada: IEEE. Retrieved 2024-01-04, from http://ieeexplore.ieee.org/document/7542857/ doi: 10.1109/ICPHM.2016.7542857

Tang, L., Saxena, A., Evans, S., Iyer, N., & Goldfarb, H. (2023, October). OSPtk: Cost-aware Optimal Sensor Placement Toolkit Enabling Design-for-PHM in Critical Industrial Systems. *Annual Conference of the PHM Society*, *15*(1). Retrieved 2024-08-29, from http://www.papers.phmsociety.org/index.php/phmconf/article/view/3557 (Number: 1) doi: 10.36001/phmconf.2023.v15i1.3557

Thelen, A., Zhang, X., Fink, O., Lu, Y., Ghosh, S., Youn, B. D., ... Hu, Z. (2022a, September). *A Comprehensive Review of Digital Twin – Part 1: Modeling and Twinning Enabling Technologies.* arXiv. Retrieved 2022-10-07, from http://arxiv.org/abs/2208.14197 (arXiv:2208.14197 [cs])

Thelen, A., Zhang, X., Fink, O., Lu, Y., Ghosh, S., Youn, B. D., ... Hu, Z. (2022b, August). *A Comprehensive Review of Digital Twin – Part 2: Roles of Uncertainty Quantification and Optimization, a Battery Digital Twin, and Perspectives.* arXiv. Retrieved 2022-10-07, from http://arxiv.org/abs/2208.12904 (arXiv:2208.12904 [cs, math])

Tinga, T., & Loendersloot, R. (2014). Aligning PHM, SHM and CBM by understanding the physical system failure behaviour.

Todd, B. S. (1992). AN INTRODUCTION TO EXPERT SYSTEMS.

Trillas, E., & Eciolaza, L. (2015). *Fuzzy Logic: An Introductory Course for Engineering Students* (Vol. 320). Cham: Springer International Publishing. Retrieved 2023-12-18, from https://link.springer.com/10.1007/978-3-319-14203-6 doi: 10.1007/978-3-319-14203-6

Tsang, A. H. (1995, September). Condition-based maintenance: tools and decision making. *Journal of Quality in Maintenance Engineering*, *1*(3), 3–17. Retrieved 2023-12-21, from https://www.emerald.com/insight/content/doi/10.1108/13552519510096350/full/html doi: 10.1108/13552519510096350

Tsui, K. L., Chen, N., Zhou, Q., Hai, Y., & Wang, W. (2015). Prognostics and Health Management: A Review on Data Driven Approaches. *Mathematical Problems in Engineering*, *2015*, 1–17. Retrieved 2023-12-13, from http://www.hindawi.com/journals/mpe/2015/793161/ doi: 10.1155/2015/793161

Tung, T. V., & Yang, B.-S. (2009). Machine Fault Diagnosis and Prognosis: The State of The Art. *International Journal of Fluid Machinery and Systems*, *2*(1), 61–71. doi: 10.5293/IJFMS.2009.2.1.061

Vagnoli, M., Remenyte-Prescott, R., & Andrews, J. (2017). *A fuzzy-based Bayesian belief network approach for railway bridge condition monitoring and fault detection.* (Pages: 390) doi: 10.1201/9781315210469-341

Verbert, K., Babuška, R., & De Schutter, B. (2017, April). Bayesian and Dempster–Shafer reasoning for knowledge-based fault diagnosis–A comparative study. *Engineering Applications of Artificial Intelligence*, *60*, 136–150. Retrieved 2024-01-03, from https://linkinghub.elsevier.com/retrieve/pii/S0952197617300118 doi: 10.1016/j.engappai.2017.01.011

Verduijn, M., Peek, N., Rosseel, P. M., De Jonge, E., & De Mol, B. A. (2007, December). Prognostic Bayesian networks. *Journal of Biomedical Informatics*, *40*(6), 609–618. Retrieved 2024-01-04, from https://linkinghub.elsevier.com/retrieve/pii/S1532046407000615 doi: 10

.1016/j.jbi.2007.07.003

Wang, Q., Taal, C., & Fink, O. (2022). Integrating Expert Knowledge With Domain Adaptation for Unsupervised Fault Diagnosis. *IEEE Transactions on Instrumentation and Measurement*, *71*, 1–12. (Conference Name: IEEE Transactions on Instrumentation and Measurement) doi: 10.1109/TIM.2021.3127654

Wang, W. Q., Golnaraghi, M., & Ismail, F. (2004, July). Prognosis of machine health condition using neuro-fuzzy systems. *Mechanical Systems and Signal Processing*, *18*(4), 813–831. Retrieved 2024-01-04, from `https://linkinghub.elsevier.com/retrieve/pii/S0888327003000797` doi: 10.1016/S0888-3270(03)00079-7

Wang, Y., Li, Y., Zhang, Y., Lei, J., Yu, Y., Zhang, T., … Zhao, H. (2024, January). Incorporating prior knowledge into self-supervised representation learning for long PHM signal. *Reliability Engineering & System Safety*, *241*, 109602. Retrieved 2023-12-28, from `https://linkinghub.elsevier.com/retrieve/pii/S0951832023005161` doi: 10.1016/j.ress.2023.109602

Weddington, J., Niu, G., Chen, R., Yan, W., & Zhang, B. (2021, October). Lithium-ion battery diagnostics and prognostics enhanced with Dempster-Shafer decision fusion. *Neurocomputing*, *458*, 440–453. Retrieved 2024-01-04, from `https://linkinghub.elsevier.com/retrieve/pii/S0925231221009814` doi: 10.1016/j.neucom.2021.06.057

Weiner, J. (1980, November). BLAH, a system which explains its reasoning. *Artificial Intelligence*, *15*(1-2), 19–48. Retrieved 2023-12-14, from `https://linkinghub.elsevier.com/retrieve/pii/0004370280900211` doi: 10.1016/0004-3702(80)90021-1

Xu, Z., & Saleh, J. H. (2021, July). Machine learning for reliability engineering and safety applications: Review of current status and future opportunities. *Reliability Engineering & System Safety*, *211*, 107530. Retrieved 2023-10-09, from `https://linkinghub.elsevier.com/retrieve/pii/S0951832021000892` doi: 10.1016/j.ress.2021.107530

Yager, R. R. (1987, March). On the dempster-shafer framework and new combination rules. *Information Sciences*, *41*(2), 93–137. Retrieved 2024-01-11, from `https://linkinghub.elsevier.com/retrieve/pii/0020025587900077` doi: 10.1016/0020-0255(87)90007-7

Yaghoubi, V., Cheng, L., Van Paepegem, W., & Kersemans, M. (2022, March). A novel multi-classifier information fusion based on Dempster–Shafer theory: application to vibration-based fault detection. *Structural Health Monitoring*, *21*(2), 596–612. Retrieved 2023-12-29, from `http://journals.sagepub.com/doi/10.1177/14759217211007130` doi: 10.1177/14759217211007130

Yongli, Z., Limin, H., & Jinling, L. (2006, April). Bayesian Networks-Based Approach for Power Systems Fault Diagnosis. *IEEE Transactions on Power Delivery*, *21*(2), 634–639. Retrieved 2024-01-03, from `http://ieeexplore.ieee.org/document/1610672/` doi: 10.1109/TPWRD.2005.858774

Zadeh, L. A. (1999). FUZZY SETS AS A BASIS FOR A THEORY OF POSSIBILITY.

Zhao, K., Li, L., Chen, Z., Sun, R., Yuan, G., & Li, J. (2022, July). A survey: Optimization and applications of evidence fusion algorithm based on Dempster–Shafer theory. *Applied Soft Computing*, *124*, 109075. Retrieved 2024-01-04, from `https://linkinghub.elsevier.com/retrieve/pii/S1568494622003696` doi: 10.1016/j.asoc.2022.109075

Zhao, Y., Xiao, F., & Wang, S. (2013, February). An intelligent chiller fault detection and diagnosis methodology using Bayesian belief network. *Energy and Buildings*, *57*, 278–288. Retrieved 2024-01-03, from `https://linkinghub.elsevier.com/retrieve/pii/S0378778812005968` doi: 10.1016/j.enbuild.2012.11.007

Zhou, Z.-J., Hu, G.-Y., Hu, C.-H., Wen, C.-L., & Chang, L.-L. (2021, August). A Survey of Belief Rule-Base Expert System. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *51*(8), 4944–4958. Retrieved 2023-10-23, from `https://ieeexplore.ieee.org/document/8894055/` doi: 10.1109/TSMC.2019.2944893

Zio, E. (2009, February). Reliability engineering: Old problems and new challenges. *Reliability Engineering & System Safety*, *94*(2), 125–141. Retrieved 2023-10-09, from `https://linkinghub.elsevier.com/retrieve/pii/S0951832008001749` doi: 10.1016/j.ress.2008.06.002

Zio, E. (2016, December). Some Challenges and Opportunities in Reliability Engineering. *IEEE Transactions on Reliability*, *65*(4), 1769–1782. Retrieved 2023-12-13, from `http://ieeexplore.ieee.org/document/7530921/` doi: 10.1109/TR.2016.2591504

Zio, E. (2022, February). Prognostics and Health Management (PHM): Where are we and where do we (need to) go in theory and practice. *Reliability Engineering & System Safety*, *218*, 108119. Retrieved 2023-10-18, from `https://linkinghub.elsevier.com/retrieve/pii/S0951832021006153` doi: 10.1016/j.ress.2021.108119