SENSOR HEALTH MONITORING BASED ON ONTOLOGIES. A SYSTEMATIC LITERATURE REVIEW

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Abstract

Flight research relies on precise and reliable measurement data for validation, collected from highly modified research aircraft. These aircraft integrate data from standard onboard systems and experimental sensor networks. Conventionally, the quality of this data has been systematically examined at the user stage when the data is processed for further work. The validation of sensor data is a highly customized and aircraft-specific process, often requiring manual post-processing before the data can be used for aerophysical, structural, or aeroelastic analysis by domain-specific researchers. As this process requires the domain-specific knowledge of flight test engineers, it can take several weeks before the validation is finalized. Often, the flight test engineers also face obstacles in parameter monitoring in-flight. Some of the extensively equipped aircraft of the German Aerospace Center record up to 3000 parameters. Therefore, the manual detection of sensor faults immediately during or after an experiment is hardly possible. In addition, the specific characteristics of the different research aircraft limit the ability to transfer fault detection methods across aircraft.

This paper presents the first systematic literature review of ontology-based sensor health monitoring (OSHM), conducted according to the PRISMA statement (Preferred Reporting Items for Systematic reviews and Meta-Analyses). We synthesize 70 publications across prognostics and health management (PHM), modeling and simulation (M&S), and related domains. Contributions are classified by expressiveness, reasoning mechanisms, and application scope. Results show two dominant research streams: rule-based ontologies in PHM and more expressive ontology-based methods in M&S. Strengths, limitations, and challenges of OSHM are analyzed, highlighting its potential for predictive aircraft maintenance and its integration with digital twin developments.

Keywords

Sensor Health Monitoring; Ontologies; Fault Detection; Prognostics and Health Management; Aircraft

1. INTRODUCTION

In aviation, predictive maintenance is one of the key enablers for sustainable, safe, and efficient aircraft operations [1]. By predicting component failures and estimating the remaining useful life (RUL), components can be exchanged before they fail, preventing incidents during operations. This approach contrasts with current maintenance strategies that are either reactive by waiting until components fail or preventive by replacing parts at a fixed number of operating hours, even if useful life remains [2].

The economic importance of this shift is considerable. maintenance, repair and overhaul (MRO) activities accounted for approximately US $94 billion in 2023 globally, representing about 11% of total airline operating costs [3]. Studies indicate that predictive maintenance can reduce direct maintenance expenditures by 10–20%, with some analyses reporting potential savings of up to 30% under optimal conditions [4]. Translated into general airline operations, this corresponds to a reduction of 1 to 3% in operating costs. Beyond financial impact, predictive maintenance also improves aircraft availability by reducing unplanned downtime and enhancing schedule reliability.

A key enabler of predictive maintenance is sensor data. By monitoring external influences during the lifecycle of a component, decisions can be made about its RUL. Unfortunately however, sensors often exhibit lower reliability than the components they monitor [5]. In the worst case, faulty sensors may therefore lead to unnecessary component replacements. This challenge highlights the need for methods to actively assess and ensure sensor health.

While system health monitoring and fault detection (FD) algorithms are barely novel, a significant need for vast sensor health monitoring (SHM) arises from the field of research data management and digital twin research, as data becomes transparent with data sources becoming centralized. Centralization of data aside, digital twin research also advances structured system modeling using ontology-based representations. This topic that once surfaced in the semantic web boom in the early 2000s [6] is gaining traction again in the digital twin domain [7] as models need high complexity to represent interconnected knowledge. In this work, the combination of these two domains is proposed. This combination may leverage deterministic SHM and sensor FD by using system ontologies.

Artificial intelligence (AI) has also emerged as a promising technology for maintenance. machine learning (ML) techniques are particularly effective for anomaly detection and physics-informed modeling; however, their applicability remains largely confined to the component level, limiting their usefulness for system-wide monitoring. More recently, large language models (LLMs) have been explored in this domain, yet they are prone to hallucinations, producing results that may appear plausible but lack factual grounding. These methods also face constraints due to their considerable computational demands. In contrast, ontology-based approaches offer deterministic outcomes, can be validated by human experts, and provide correctness that can be formally assured. [8]

A comprehensive survey on ontology-based sensor health monitoring (OSHM) frameworks is provided in this pa-

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per. Ontology and semantics-based methods are examined in the domains of prognostics and health management (PHM), FD, and modeling and simulation (M&S) methods. The literature is organized into two different domains: PHM and M&S methods. Additionally, limitations and challenges are identified for the emerging field of OSHM.

Previous work prospected literature regarding ontologies in PHM [9], ontologies in fault diagnosis [10–12], and scoping of methods and challenges in constructing ontologies that have been reported on in biology [13] and in engineering [7, 14, 15]. In contrast, this paper aims to survey the role of ontologies to structure input knowledge in SHM or components thereof. Specifically, the use of ontologies as a description between physical quantities and systems in the SHM-intersecting domains of FD and simulation methods. No previous work has provided a survey focused on ontology-based computations.

In summary, the contributions of this paper are:

1) Enactment of the first systematic literature review on OSHM, synthesizing findings across 70 publications from various domains (natural sciences, civil engineering, process engineering, and industrial engineering).
2) Analysis of the historical development and distribution of research, identifying trends, recurring themes, and limitations in current OSHM approaches.
3) Highlight of open challenges and future opportunities for OSHM, offering a foundation for guiding further research and application in this field.

2. PROBLEM STATEMENT

This section defines the research questions and the terms SHM and OSHM. Three research questions shape the work in this paper, as defined in TAB 1.

TAB 1. Research questions in this work

ID	Research Question
R1	What are the limitations of current approaches to SHM, and how can existing contributions be categorized along dimensions such as expressiveness, semantic modeling depth, reasoning mechanisms, and use cases?
R2	To what extent do ontology-based approaches to SHM demonstrate advantages in scaling and cross-domain adaptation compared to conventional SHM methods?
R3	What limitations and challenges hinder the development and adoption of OSHM?

R1 identifies the current state of the art. Contributions are classified and clustered into emerging groups. Along these clusters, attributes such as use cases and reasoning mechanisms are examined.

In R2, the ontology-based contributions towards SHM are compared to conventional SHM methods. The current state of the art on SHM will be compared to OSHM methods in terms of scalability and cross-domain adaptation. Scalability describes the ability of an algorithm to apply quickly to large systems once developed. Cross-domain adaptation describes the ability to take an algorithm developed for a system in process engineering and quickly deploy it on an aircraft use case.

The limitations and challenges that arose in R2 are examined in R3. They are clustered in groups and then examined to determine if there are solutions available to solve these challenges that prevent wider adoption of OSHM methods.

2.1. Ontology-based Sensor Health Monitoring

SHM is defined in this paper's scope, analogous to structural health monitoring. SHM is defined as: *"The process of implementing a fault identification strategy for aerospace, civil, and mechanical engineering infrastructure."* This process involves the observation of a sensor signal over time using periodically spaced measurements, the extraction of appropriate fault-sensitive features from these measurements, and the subsequent analysis of these features to determine the current state of system health. In the following, OSHM is defined as: *"The use of ontology knowledge from digital twins or other domains to detect faults and determine the health of a sensor at a given point in time"*. [16]

3. LITERATURE COLLECTION AND REVIEW SCHEMA

In this section, the scope, methodology, and results of the literature collection are introduced.

3.1. Review Scope

The following exclusion criteria (EC) in TAB 2 are applied in the collection of publications. If a publication fulfills one or more EC, it is excluded. EC1 excludes methods that use non-deterministic methods, such as LLMs, to process vast amounts of natural language data, as used in maintenance documentation. EC2 excludes documents compiled in languages other than English. FD without ontologies are excluded in EC3. EC4 describes any literature that includes a fault diagnosis method. These methods frequently use pre-detected faults by machines and reason over the fault origin. Furthermore, literature introducing new ontologies (EC5), reviews (EC6), and unrelated topics (EC7) are also not included. Also, fault taxonomies (EC8) and developments of databases (EC9) are not defined as relevant in this work.

TAB 2. Definition of EC to provide the review scope.

ID	Criterion
EC1	Literature introduces natural language processing (NLP) using LLMs.
EC2	Literature is written in languages other than English.
EC3	Literature introduces FD but contains no ontology.
EC4	Literature introduces a fault diagnosis method.
EC5	Literature introduces the development of an ontology.
EC6	Literature introduces a review.
EC7	Literature defines an unrelated topic.
EC8	Literature introduces a fault taxonomy.
EC9	Literature develops a sensor database.

3.2. Literature Collection Methology

The databases Scopus and Web of Science are used to query literature, and the review is split by three search terms as defined in TAB 3. First, SHM is researched. Second, a PHM-centric string is queried, searching for any FD solutions that have been developed for aircraft and sensors. Third, a search for ontology-driven computation methods that have rich expressions is conducted. Rich expressions are defined in this work as the ability to express differential equations and any other mathematical equations. For larger research fields, a search by title only instead of title, abstract, and keywords is performed.
These separate queries emerge from limited results in the SHM and PHM-centric search with M&S methods to bolster the depth and expressiveness of the results. In PHM and SHM, some rule-based approaches are found, but actual ontology-based approaches appear to be scarce. Thus, a deeper fundamental search is entertained to find results in other research domains.
For better readability, the following search string substitution is introduced for TAB 3.

$$\Omega = (ontology|taxonomy|semantic|metamodel) \qquad (1)$$

In query 1, all records regarding the exact term *SHM* were retrieved, and in query 2, all records regarding ontology-based PHM followed. FD for sensors or aircraft was also searched in combination with the term Ω. Ω in combination with only FD was limited by title searches only.
To screen abstracts, the ML-based screening tool ASReview was engaged. ASReview is a tool that sorts literature for relevance based on user-labeling using a recommendation algorithm. Following this method, all records that are deemed relevant by the software can be screened first. Efficiency is gained by having an automatic clustering performed based on your automatically determined preferences. In addition, a cutoff value can be defined if, i.e., 30 consecutive abstracts are deemed irrelevant. [17,18]

3.3. Collection Results

In this work, three separate reviews are performed. The numbers according to the PRISMA statement are illustrated in FIG 1 and detailed in the following. 2304 contributions are collected from databases in total. After deduplication and relevance screening, 74% are removed. In the first review, all records are reviewed. In the second review, the review cutoff for 30 consecutive irrelevant labels is reached after 155 contributions as shown in the rightmost column, second row.
FIG 2 portrays the historic trend of publications in general ontologies and SHM ontologies, with publications on ontologies having a peak in 2009, followed by a plateau that starts to recover in 2018. The publications on OSHM roughly follow, but are likely to be affected by noise due to

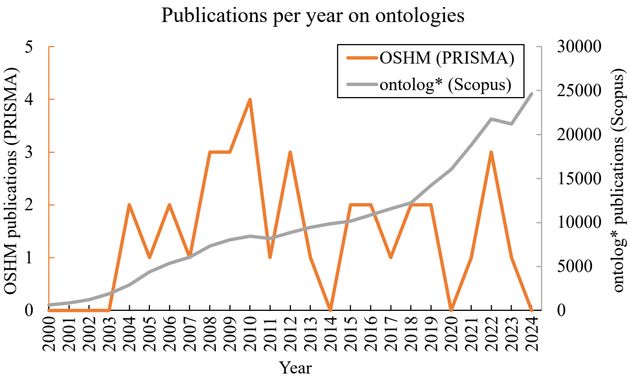

FIG 2. PRISMA-selected studies accumulated per year for OSHM methods (orange). Overall trends on the search term *ontolog on the search platform Scopus are plotted in grey.**

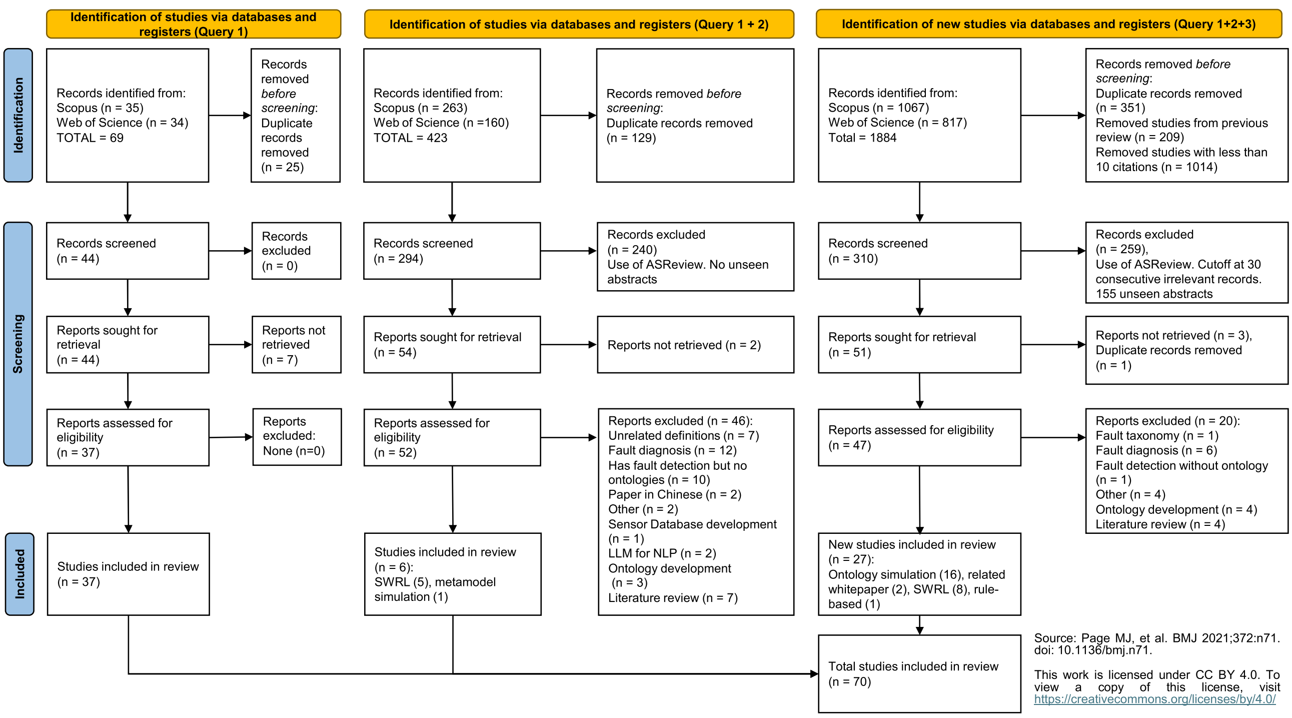

FIG 1. Following the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement, three reviews are performed to study use case specific solutions and find the general state of the art. The queries are defined in TAB 3

TAB 3. Search queries 1-3 including their search scope in title, abstract, and keywords with the previous definition of Ω in EQ.1

Query	Search string	Title	Abstract	Keywords
1	[SHM]	x	x	x
2	$\Omega+$ ([prognostics and health management] | PHM)	x	x	x
2	$\Omega+$ [fault detection] + (aircraft | sensor)	x	x	x
2	$\Omega+$ [fault detection]	x		
3	$\Omega+$ [fault detection]	x	x	x
3	(ontology | ontologies) + ([mathematical expression] | [differential equation] | [mathematical model]) + (simul* | [system simulation])	x	x	x
3	(ontology | [semantic model] | [knowledge representation]) + ([mathematical expression] | formula* | equation* | model*) + (simul* | [system simulation] | [physics-based simulation] | [computational modeling])	x		

the small sample size. Returning to ontologies, the peak and plateau may be explained by the semantic web boom in the early 2000s, followed by the AI hype from 2012 on. Adoption of ontologies followed in some disciplines, such as genetics in the gene and cell ontology, which sustained the growth after with industry 4.0 and digital twins accelerating the growth from 2018 on. [6]

4. ONTOLOGY-BASED SENSOR HEALTH MONITORING FRAMEWORKS

This chapter organizes itself along the queries 1-3 (see TAB 3) in condensing results on SHM and ontology-based PHM and M&S literature.

4.1. Conventional Sensor Health Monitoring

The literature at hand is classified by use case domain and its definition of sensor health as illustrated in TAB 4. FD methods defined sensor health as either healthy or faulty. This binary representation was used for autonomous vehicles [19, 20], heating, ventilation and air conditioning (HVAC) in building information management (BIM) [21], control systems [22–24], fault detection and diagnosis (FDD) methods [25–27], and in PHM [28]. FD methods were also advanced to expand the binary results to more nuanced fault descriptions and fault classification (FC). Faults such as bias and scale factor are detected. Control system domains [29, 30] and FDD methods [31] used FD in conjunction with classification. Other work in FDD quantifies the probability of a sensor failure to FD and FC [32]. Determining RUL, predicting sensor faults, and FD are only found once in the literature [33]. Other hits on SHM include those relating health to humans instead of sensors [34–41] and literature that mentions SHM without reference or specification [42–55]. Within these 11 results not specifying SHM, there are 6 results from structural health monitoring that reference SHM as using sensors to monitor the health of structures.

4.2. Rule-based fault detection using ontologies

Domain-specific, rule-based approaches in PHM do not use any complex or expressive mathematical expressions. The majority of the literature uses the semantic web rule language (SWRL), which directly deposits the logical rules in ontology web language (OWL) files. In the following, approaches are presented that are closer to FD and system monitoring. These approaches use simpler mathematical models, like rule-based models and black-box models such as machine learning algorithms. They generally rely on less information about the physical system while being closer to application use cases in engineering research. The selected contributions consist of three production system examples, two in the domain of BIM, one in maritime fleet management, followed by the last in aircraft maintenance. The clustering of these methods is shown in TAB 5.

Nagy et al. employ fault tree analysis, root cause, and SWRL in a production facility for an automotive wire harness assembly. They propose a reasoning process using a knowledge graph that contains ontology schema, SWRL, and data extraction from various sources. A control response for the machine is formulated for the system, addressing whether operation shall be stopped, changed, reconfigured, or maintenance shall be performed. This reasoning is based on the previously mentioned knowledge graph, which is built based on data from fault tree analyses, production processes, failure mode and effects analysis (FMEA), Hazard and Operability Study (HAZOP), and industrial standards for their wire harness use case. [56]
Zhou et al. work on a hobbing machine tool for production. They propose an ontology for system and fault modeling that includes a knowledge modeling methodology based on formal semantics (KMM-MTFD) to build an open, shared, and scalable ontology-based knowledge model of fault diagnosis of different machine tools (OKM-MTFD). They then use OWL axioms, SWRL, special fault attributes, and SPARQL protocol and RDF query language (SPARQL). While they do not use advanced mathematical modeling, they present their method in high detail and show hobbing machine tool ontologies written in OWL. [57]
Wang et al. present a demonstrator on a scaled-down car production line. They use qualitative rigid-body mechanical modeling with ontologies and do a plausibility check on the car production line sleds. They generate a model value based on redundant data, inputting discrepancies as a FD basis, thus only using qualitative physical modeling and no rules. [58]
In BIM, Li et al. present a semantic model-based FD approach that mimics the intelligence of human experts in understanding a large amount of data in an ontology. Their FD is implemented by using SWRL in OWL and employing set theory logic expressions such as "greater,

TAB 4. Use of the term *sensor health* across domains, synthesized by associated aspects: FD, FC, fault prediction (FP), and RUL. Source: TAB 3, query 1.

Sensor Health Definition /Domain	FD	FD + FC	FD + FC + FP	FD + RUL+ FP	Human Health	Not Specified	Σ
Autonomous vehicle	[19,20]					[42]	3
BIM	[21]						1
Control systems	[22–24]	[29,30]					5
FDD	[25–27]	[31]	[32]			[43–49]	12
PHM	[28]			[33]			2
Medicine					[34–41]		8
Structural Health Monitoring						[50–55]	6
Σ	10	3	1	1	8	14	37

smaller, assert". They validate their approach with an industrial building HVAC use case. Their approach generates an ontology modeling 9 air zones and 51 HVAC systems that contains a detailed methodology for ontology modeling. [59]
Mallak et al. use a diagnostic directed graph to store their rules. They show the first steps of an implementation by allowing logic using limit checking and boolean expressions. However, they mention performance issues that might need to be addressed at a later point by using machine learning to combine data-driven as well as model-based methods. Their use case lies in BIM with HVAC monitoring as their specific use case. The limited complexity in rule-based approaches works in their case due to the limited complexity in fault modeling for HVAC systems. Overheating and unhealthy amounts of carbon monoxide/dioxide are validation examples in their paper. Such cases can be detected using their rule-based logic. Their validation stack contains MATLAB SimScape to simulate their building air data to generate input data. [60]
Voisin et al. work on a maritime fleet management use case. Although their approach comes close to the research questions in this paper in regard to ontology-based condition monitoring, they diverge by applying concepts of fault diagnosis and health degradation monitoring. FD does not concern them since the objects they observe (boats, engines) already output faults. Their labeled faults comprise engine faults, engine temperatures that are too high, and anomalous vibrations. They filter diagnosed data on relevance by using SWRL in conjunction with the PHM-focused software platform KASEM. [61]
Tang et al. use ontologies in combination with machine learning to display and examine fault graphs while not examining FD, situating them in the domain of fault diagnosis. They examine an aircraft maintenance use case and do not provide much info about the ontology model, and use a long short term memory (LSTM). Their specific approach builds an ontology-based fault model and then uses a BI-LSTM (Bidirectional LSTM) to identify faults and SWRL to model some of the aircraft relations manually. [62]

4.3. Ontology-based Simulation Methods

The most relevant results in ontology-based simulations range from the years 2005 to 2012. Contributions appeared in industrial engineering, natural sciences, and financial research.

Industrial use cases comprise industrial plant simulations in which bearings and other industrial components are proposed as simulation objects and validated by creating an ontology-based simulation of an electric circuit [74]. This use case includes in its development the universal simulation library and simulation ontology (SIM).
In the process industry, a software platform for simulation model reuse is proposed by Karhela et al.. Simulation model reuse is facilitated by exchanging the simulation model with ontological connotations. As an example, the combination of a computational fluid dynamics (CFD) simulation and a large-scale process simulation is reported using the computer aided process engineering (CAPE)-OPEN standard. A semantic enrichment of this combined simulation is proposed to automate deterministic parameter tuning of a control system. Semantically-annotated simulations could then be used to tune parameters and test complicated control functions off-site. They propose significant potential in time-saving for cutting down commissioning time of control systems and cutting down the required time on-site for tuning the control systems. [12]
Kukkonen et al. work on the flow system ontology (FSO) to create a lumped simulation of flow in chemical plants. This is achieved by modeling the entire system in ontologies first and then assigning simulation formulas to the ontologies. SPARQL queries are used to efficiently query the system and cluster system attributes. [65]
As the final case in industrial systems, Cheong et al. propose an approach for continuous simulations and validates it with a finite element method (FEM) of heat transfer. Their system consists of the physics-based simulation ontology (PSO) based on the basic formal ontology (BFO) in conjunction with the FEniCS solver library. Compared to previous publications, their work is relatively new and thus uses newer conventions of sharing source code and implementation details. [77]
Research in natural sciences yields three relevant examples, two of which are in cell research and one in soil simulation. Chandran et al. propose the software Tinkercell that connects multiple mathematical models with experimental data in a single system. One limitation addressed is that of various mathematical models that simulate a biological system. These models tend to focus on different strengths (e.g. simulation complexity vs. runtime), and bundling of models presents challenges. Their solution is based on storing various models in a hierarchical format. Ontologies are used to store semantic model information. Their work's proposal is using ontologies to map conceptual models to specific simulation models. [67]

TAB 5. R1: Contributions to ontological SHM, classified by methods, use cases, and reasoning mechanisms.

Category /Domain	PHM SWRL	PHM Other	M&S Domain-specific	M&S Domain-independent	Σ
Aerospace Actuator		[5]			1
BIM	[59, 60, 63, 64]	[65]			5
Cell Research			[66, 67]		2
Critical Infrastructure	[68]				1
Finance			[69]		1
Manufacturing	[56, 70–72]	[73]	[74]		6
Simulation Modeling				[75–81]	7
Pharmaceutical Production			[82, 83]		2
Process Engineering	[84, 85]	[86]	[12, 87]		5
Rail	[88]				1
Soil Simulation			[89]		1
Wind Turbines	[90]				1
Σ	13	4	9	7	33

Asai et al. present a more ontology-based approach by storing formulas and ontological relations between entities. Validated on a cardial cell membrane, this model presents its results as insilicoML, which in turn is a subproject of CellML in bioinformatics, both XML-based formats. This model generally provides a sensible and complete starting point for further development. However, its domain-specific development may necessitate significant tooling adaptation effort to be converted to an aerospace use case. [66]

Finally, Beck et al. present the Lyra ontology management system, which is an advanced development of the citrus and water management system (CWMS) and OntoSim-Sugarcane. The goal of this model is to simulate soil development regarding moisture and nutrient levels under a modular software architecture by integrating ontologies into the various simulation components. The system structure is generally modeled using ontologies, and extended by a custom equation representation that exports equations to MathML and OpenMath for data exchange with other systems. Their simulation editor seems to be proprietary code developed for their use case only. [89]

Financial research yields the last simulation ontology with the framework JontoRisk developed by Cuske et al. that build a financial risk modeling simulation. By using the ANTLR formula parser and the OWL API, complex mathematical equations are developed in a framework containing two distinct components of a simulation kernel, which receives OWL files, reasons, and parses the formulas and returns the simulation results to a result analyzer, which seems to be a plotting tool that is not described in detail. [69]

5. COMPARISON TO CONVENTIONAL METHODS

In chapter 4, SHM methods were reviewed by focusing on conventional methods and ontology-based approaches in PHM and M&S. Conventional SHM methods largely focused on FD, while some contributions advanced to FC, FP, and RUL estimation. Ontology-based approaches in PHM and M&S were reviewed, which generally focused on rule-based FD and ontology-based simulation models. The following examination will focus on the relationship between conventional SHM and OSHM, scaling, and cross-domain adaptation.

Scalability is defined in the following as the reduction of effort in building a large-scale SHM from a prototype. Cross-domain adaptation is defined as the effort to transform an FD model to another domain.

Data-driven methods are excluded since they did not appear in the ontology-based methods and thus have no equivalent to compare to. To summarize their behavior in scalability, they possess excellent scaling once enough data is present to learn from. Insufficient training data, however, makes their use difficult. Similar to scalability, cross-domain adaptation requires sufficient training data for adapting to new use cases. Their accuracy diminishes quickly if not sufficiently trained. An additional current challenge in data-driven methods remains their likelihood of hallucinations, including false positives and false negatives.

Ontology-driven model-based SHM has limited scalability as evidenced from the literature. There are many developments, but few examples that reached wider adoption, except for CAPE use cases that have static systems. Studies of cross-domain applications of ontologies in established use cases have not been found in the literature of this review. However, M&S ontologies are fundamentally cross-domain since their modeling is sufficiently abstract.

Finally, OSHM suffers from the same challenges as model-based systems. In addition, OSHM methods do not need just physical modeling for the simulation but also ontological modeling that needs to be validated as well, leading to twice the modeling. Regarding cross-domain applicability, OSHM may be the more efficient choice, given that ontological system descriptions are already present, as evident in some current digital twin developments.

6. DISCUSSION

In this section, the answers to the research questions as defined in TAB 1 are discussed.

R1: What are the limitations of current approaches to SHM, and how can existing contributions be categorized along dimensions such as expressiveness, semantic modeling depth, reasoning mechanisms, and use cases?

SHM contained no mention and use of ontologies and expressive metadata embedding in the examined literature. RUL and health index (HI) calculation was only present once. Fields contributing towards OSHM include PHM and M&S. Literature in M&S showed the most expressiveness and modeling depth while having the least use cases towards SHM. PHM approaches use less expressive ontologies and are set closer to real-world problems. R1 was therefore answered in the identified literature.

R2: To what extent do ontology-based approaches to SHM demonstrate advantages in scaling and cross-domain adaptation compared to conventional SHM methods?

Regarding scaling, data-driven solutions will be conventionally superior due to their low-knowledge approaches. There is no current available ontology-knowledge base to validate claims towards significant scaling of ontology-based methods. Towards cross-domain adaptation the advantages of ontologies remain theoretical and rely on well-designed and standardized ontologies that are not currently in widespread use. No arguments for scaling and cross-domain adaptation were identified. To answer R2, an ontology-based knowledge base needs to be constructed first.

R3: What limitations and challenges hinder the development and adoption of OSHM?

The topic of ontologies is currently adopted by mechanical engineering. Knowledge graphs are increasingly employed to represent realistic relationships between physical entities such as is happening in industry 4.0 and digital twins for knowledge representation. However, key challenges remain unsolved. Lack of efficient tooling, standards as well as viable use-cases remain scarce. In R3, challenges and limitations could be identified.

The focus of this work was SHM combined with ontologies to leverage system information. The literature review shows the developmental status of ontology-based computations to increase towards fundamental research in M&S. The applicaton-centric PHM field produces ontology-based methods that tend to lack expressiveness. This lack of expressiveness illuminates the research gap for OSHM.
This study has some limitations. Search terms constrained the scope, omitting major ontologies like ONTOCAPE [91]. Scopus and Web of Science were used because of their known high-quality publications. However, some relevant publications might not have made it through the chosen filters. Source code was rarely available in older studies, limiting reproducibility and deeper evaluation. These restrictions mean the review provides an overview rather than an exhaustive mapping. Still, peer-reviewed sources ensured quality and the results are sufficient to answer the research questions on ontology use in SHM.
Novel technologies could be integrated to reduce previous deficits. LLMs can assist by extending existing ontologies by transforming available information into ontologies while the definition of complex relationships in ontologies remains a manual task. Digital twin technologies and digitalisation in industry 4.0 increase structured knowledge in engineering, embedding ontologies as an exchange format. Shared version control could be employed to ease complexity management in large ontologies.

7. CONCLUSION

This paper provides the first systematic review of OSHM in the context of predictive aircraft maintenance. Three main contributions were achieved: (1) a comprehensive overview of ontology-based approaches, (2) a comparison with conventional SHM methods, and (3) an analysis of strengths and challenges that shape adoption. The review revealed that OSHM remains an emerging and fragmented field, with limited direct applications but substantial related work in ontology-based FD and simulation. Current approaches split into rule-based PHM methods and more expressive but less mature M&S methods. Key barriers include limited expressiveness, weak standardization, lack of reproducible implementations, and immature tooling requiring ontology expertise.

Despite these gaps, developments in digital twins and structured metadata frameworks create opportunities for OSHM. Ontologies provide deterministic, cross-domain adaptability and can enhance FD, especially when combined with advances in AI and industrial digitalization. Future research should focus on consistent definitions of sensor health, scalable ontology frameworks, improved tooling, and integration with digital twin ecosystems. With these advances, OSHM can play a central role in reliable, efficient, and predictive maintenance of next-generation aircraft.

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