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Ontologies for Prognostics and Health Management of Production Systems: Overview and Research Challenges

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Abstract

Prognostics and Health Management (PHM) approaches aim to intervene in the equipment of production systems before faults occur. To properly implement a PHM system, data-centric steps must be taken, including data acquisition and manipulation, detection of machine states, health assessment, prognosis of future failures, and advisory generation. The data generated by different data sources, such as maintenance management systems, equipment manufacturer manuals, design documentation, and process monitoring and control systems, are fundamental for PHM steps. Discovering and using the knowledge embedded in this data is relevant because, for example, data-driven techniques require knowledge, maintenance data often contain tacit knowledge that can facilitate knowledge transfer and collaboration between maintenance personnel with different levels of experience and expertise, and the knowledge related to the same types of systems could be context-dependent. However, the heterogeneity of data sources, the variety of data types, and the possibility of context-dependent data pose challenges in revealing the real value of data and discovering the useful, yet hidden, patterns embedded in maintenance data that can lead to explicit knowledge. Ontologies can effectively contribute to this issue through the organization of data, semantic annotation, integration, and checking of consistency. Several ontologies contributing to the PHM process have been proposed in the scientific literature. However, to the best of our knowledge, no overview of the available ontologies contributing to the PHM steps of production systems is present in the literature. Therefore, this paper aimed to investigate the ontologies and knowledge graphs proposed in the literature for the PHM of production systems. A systematic analysis and mapping of the literature was performed, and the main information was extracted and discussed according to (i) the type and year of the publication, (ii) the ontological and non-ontological resources adopted for designing the ontology/knowledge graph, (iii) the method adopted for implementing the approach, (iv) the type of application, (v) the step(s) of the PHM process on which the article is focused, and (vi) the type of decisions (strategical, tactical, or operational) to which the ontology/knowledge graph is adopted. Subsequently, the conducted analysis led to the definition of a research agenda in the domain, including the following challenges to address: (1) alignment of the ontologies in the maintenance field with respect to top-level ontologies, (2) connection among the different PHM steps at the operational level, (3) major exploitation of the combination of data-driven AI, ontologies, and reasoning for predictive maintenance, and (4) supporting sustainability-related challenges through the connection between the production system, maintenance system, and product.

Keywords: prognostics and health management, ontology engineering, production systems, predictive maintenance, knowledge modeling

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1. Introduction and motivation for the study

In smart factories, the adoption of emerging technologies, such as the Internet of Things (IoT), digital twins, and big data and analytics, can lead to the concrete adoption of predictive and proactive approaches to equipment maintenance (Canito et al., 2022; Compare et al., 2020). Prognostics and Health Management (PHM) and predictive maintenance approaches aim to intervene in equipment before a fault occurs (Teoh et al., 2023), and condition-based maintenance and predictive maintenance are key solutions in these smart factories to increase competitiveness through the reduction of downtimes and the increase in overall equipment effectiveness (OEE) (Polenghi et al., 2023). Indeed, PHM contributes to a reduction in costs, machine downtime, and system faults and an increase in product quality, productivity, and, consequently, sustainability performance (Dalzochio et al., 2020; Kurappiah et al., 2021; Liu et al., 2019; Vogl et al., 2019; Zonta et al., 2020).

The necessary steps in PHM systems are data acquisition and manipulation, detection of machine states, health assessment, prognosis of future failures, and advisory generation (ISO 13374; OSA-CBM). In this process, data is the key to information generation, diagnosis, prediction of the remaining useful life of industrial assets, and predictive decision making. Data are generated from different data sources, such as maintenance management systems, equipment manufacturer manuals, design documentation, process monitoring and control systems, risk management assessments, and failure investigations (Karray et al., 2019). On the one hand, data requires knowledge to be exploited and provide its full “power,” while on the other hand, data may embed relevant information/knowledge in relation to the usage and health of systems, which needs to be discovered.

Hence, discovering and using the knowledge embedded in this data is relevant for several reasons: (i) data-driven techniques require knowledge, (ii) maintenance data often contain tacit knowledge that can facilitate knowledge transfer and collaboration between maintenance personnel with different levels of experience and expertise, (iii) the knowledge extracted from data can validate and complete human knowledge and make the implicit knowledge of maintenance engineers more explicit, and (iv) the knowledge related to the same types of systems can be context-dependent. However, revealing the real value of data and discovering useful patterns of knowledge embedded in maintenance data have presented a major challenge due to the heterogeneity of data sources and the variety of data types (Karray et al., 2019). Ontologies can effectively contribute to resolving this issue through the organization of data, semantic annotation, integration, and checking of consistency (Karray et al., 2010).

The term “ontology” comes from philosophy and corresponds to the “science of being.” This term has been adopted in computer science to designate a formal definition of objects and their relationships in a specific domain. An ontology aims to structure and formalize an object in a domain as independently as possible of the intended application. In this way, the ontology can be reused with other applications in

the same domain (Lamy, 2021). Gruber (1993) provided a common definition of ontology as “*an explicit, formal specification of a shared conceptualization of a domain of interest.*” More recently, Cho et al. (2020) reported that an ontology is a machine-understandable meta-model that defines concepts and their relations.

With Industry 4.0 and IoT devices, data federation has become one of the biggest challenges, and interoperability is a must; as such, ontology could be a reference model for handling this issue (Cho et al., 2020). Indeed, with the advent of digitalization, several sensors capturing different data on production systems are producing an ever-increasing amount of data, which can be relevant for the PHM domain to better understand failure causes and abnormal behaviors. Ontologies can help address this challenge by providing semantic meaning to the data and making them understandable, in the same way, not only by different stakeholders across company departments but also by machines and algorithms (Cho et al., 2020). Ontologies can play a significant role in connecting IoT devices by providing a structured and standardized way to represent and manage data and knowledge (Mishra & Jain, 2020). They can act as a common layer when several sensors and IoT devices are involved with heterogeneous data sources; facilitate data integration and knowledge representation; capture contextual information about, for example, the location of the sensors and their relationships with other devices in the production environment; and enable knowledge-based reasoning through the data coming from different sensors, which can facilitate the process of decision making.

During maintenance and operation, technicians and engineers must often spend considerable time understanding the missing information and the inconsistency between the actual system and the existing design documents. This involves communicating with data analysts who are not experts in the production and maintenance domain but who must comprehend the system to identify various relationships among the data (Wang et al., 2021). This communication process usually takes place verbally, is time-consuming, and can cause errors. In this context, ontology can serve as an efficient tool to overcome the challenges in communicating, sharing, and reusing knowledge among different company stakeholders while providing knowledge in a structured and standard way (Wang et al., 2021). Moreover, ontologies, with their reasoning and inference capabilities, can augment the information content and empower the processes of PHM (Franciosi et al., 2022; Polenghi et al., 2022a); hence, they have found several applications in the different steps of the PHM process.

For example, the diagnostic process aims to define the reasons for a failure, assess its impacts, and try to apply the correct repair procedures. However, failure details at the process level are typically gathered by hand and in spreadsheets, such as Excel, which are generally adopted in industries. Therefore, this method cannot be fault-proof since every person who compiles the sheet may provide a different amount of information, leading to a probable semantic mismatch (Hossayini et al., 2020). Efficient fault diagnosis is essential in today’s complex systems. Knowledge-based fault diagnosis methods, which utilize ontologies to improve knowledge representation and reasoning mechanisms, are more suitable than model-based and data-driven fault diagnosis methods because they ease fault diagnosis inquiry responses for non-expert users (Chi et al., 2022). Hence, to facilitate the diagnostic step and to avoid semantic mismatch among different industrial actors, several authors have provided ontologies (e.g., Al-Shdifat et al., 2020; Medina-Oliva et al., 2014; Rajpathak, 2013) and knowledge graphs (e.g., Hossayini et al., 2020) for the fault diagnosis of production systems.

In addition, ontologies can be combined with other approaches for prognostic and predictive maintenance purposes (Canito et al., 2022; Cao et al., 2022; Voisin et al., 2013). On the one hand, there is a need to integrate data from various sources and systems within a facility to gather accurate

information for creating prediction models, while on the other hand, the use of machine learning (ML) can allow for the fulfilment of prognostics and the prediction of failures, for example, estimating the lifetime of a machine using a large amount of data to train an algorithm (Dalzochio et al., 2020). A few approaches combining ontologies, reasoning, and ML have recently been proposed, such as that of Cao et al. (2022), who presented a novel knowledge-based system for predictive maintenance that leverages both statistical and symbolic artificial intelligence (AI) technologies.

The background information above motivated the authors to search for scientific literature available in the domain to gain an overview of the current state of the art on ontologies and knowledge graphs for the prognostics and health management of production systems and the related research challenges to be addressed in the short, medium, and long term. However, to the best of our knowledge, no overview of the ontologies in the literature contributing to the PHM domain of production systems is currently available. Three recent literature reviews were identified that targeted ontologies in predictive maintenance (Canito et al., 2022), in fault diagnosis (Chi et al., 2022), and in the combination of reasoning and ML (Dalzochio et al., 2020). However, all are focused on a specific aspect of PHM and address a different objective than the present study. Canito et al. (2022) conducted a systematic literature review to investigate the applications of time-based reasoning in ontology evolution in the field of predictive maintenance; Chi et al. (2022) focused on knowledge-based fault diagnosis with deductive and inductive reasoning methods; and Dalzochio et al. (2020) discussed the main issues related to ML and reasoning for the predictive maintenance of cyber-physical systems.

The authors were thus motivated to conduct a deep analysis in the field to identify, examine, classify, and describe the ontologies developed for knowledge modeling in the PHM domain of production systems, with the intention of providing a wide overview. A systematic literature review was then conducted to organize the information in such a way that a future research agenda emerged, with several gaps and challenges that need to be addressed in the research domain.

The paper is structured as follows. Section 2 provides the methodology adopted in this study, and Section 3 presents the results achieved. Section 4 discusses the conclusions of the work and outlines the identified research challenges and future directions.

2. Methodology

The aim of this paper is, first, to identify and analyze papers that provide ontologies and knowledge graphs for the Prognostics and Health Management (PHM) of production systems. Second, the paper seeks to identify the gaps and challenges in the domain of interest. Providing deep knowledge of such issues will lead to greater awareness among academics and industrialists of the actual potentiality and challenges of ontologies and knowledge graphs in the domain of interest. The research question (*RQ*) addressed in this study is the following:

RQ. What are the existing ontologies and knowledge graphs in the domain of prognostics and health management of production systems?

In response to the *RQ*, a systematic literature review (SLR) was conducted on ontologies and knowledge graphs in the domain of prognostics and health management. Subsequently, some of the ontologies/knowledge graphs were selected based on specific defined criteria. In the second step, the authors requested the specific files of the selected ontologies/knowledge graphs to better understand the

main concepts and the modeling of the relationships among the concepts. Unlike a traditional literature review based on the authors’ knowledge perspective, an SLR comes from a clearly defined research objective, following a structured protocol that minimizes subjectivity and allows for the critical evaluation of relevant studies (Franciosi, Voisin et al., 2020). The methodological steps adopted to conduct this study are summarized in Figure 1 and discussed in subsequent sections.

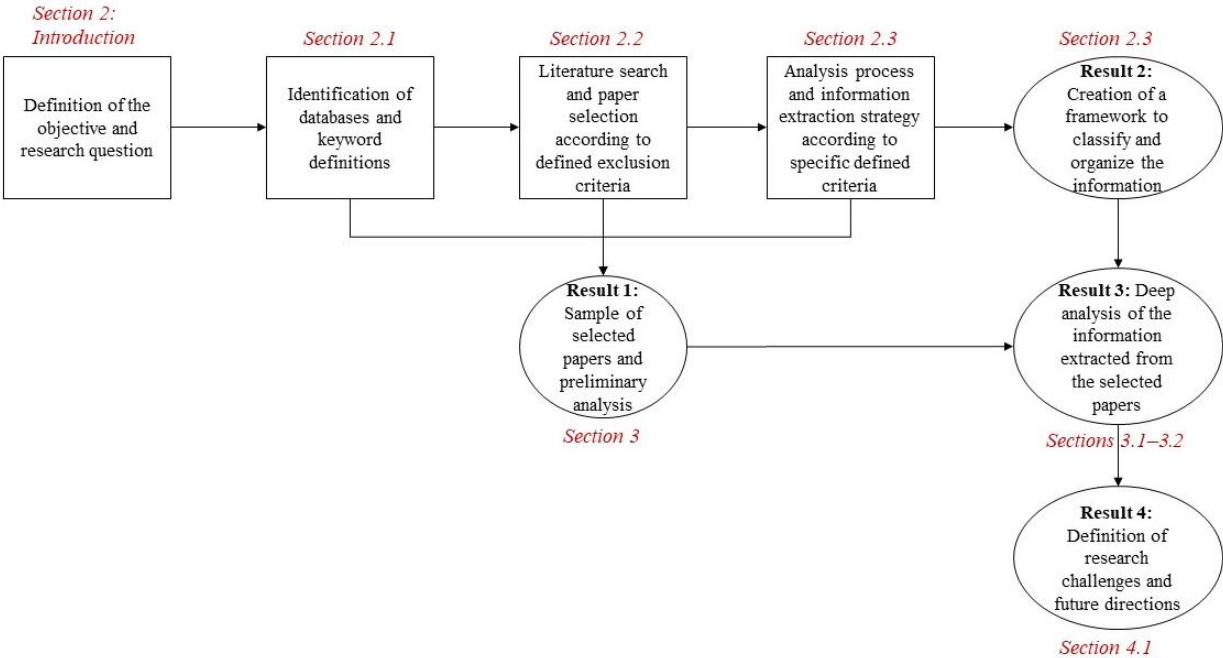


Figure 1 – Overview of the methodology adopted to achieve the results

2.1 Identification of research databases and keyword definitions

Systematic searches were conducted in Scopus and Web of Science, two of the largest scientific multidisciplinary abstract and citation databases of peer-reviewed literature. The two sources cover major journal publishers (e.g., Elsevier, Taylor & Francis, Wiley, Emerald, and IEEE) and conferences in the science and technology fields and allow for fast and customized searches. To conduct the research in these databases, keywords structured in three different sets were prepared, chosen as coherent with the goal of the review and the RQ (Table 1).

Table 1 – Sets of keywords

← AND →			
	Set A	Set B	Set C
← OR →	Predictive maintenance	Manufacturing	Ontolog*
	Prognostics health management	Production	Glossary
	“Fault detection”	Industr*	Taxonomy
	Diagnosti*		“Knowledge formalisation”

			“Knowledge modeling”
			“Knowledge extraction”
			“Knowledge graph”

Set A includes keywords related to the prognostics and health management field; Set B is composed of keywords related to the industrial and production fields to contextualize the search; and Set C introduces the keywords related to knowledge modeling, such as ontology and knowledge graph.

When more than one keyword is included in a set, they are linked with the Boolean operator OR, whereas the sets are connected to each other through the Boolean operator AND.

The defined keyword sets allowed the authors to achieve the string of keywords used for the research as: *((predictive AND maintenance) OR (prognostics AND health AND management) OR (“Fault detection”) OR (diagnosti*)) AND (manufacturing OR production OR industr*) AND (taxonomy OR glossary OR ontolog* OR “knowledge formalisation” OR “knowledge modeling” OR “knowledge extraction” OR “knowledge graph”)).*

2.2 Literature search and paper selection

The literature search covered the period until April 2022. All the papers published in Scopus and Web of Science were screened; therefore, no limits were placed on the publication year range. Papers that included the chosen keywords in the “abstract, title, and keywords” were extracted. Only papers published in peer-reviewed journals, conference proceedings, or books, and those providing an English version, were considered for analysis. To facilitate the analysis process, all the papers extracted during the first search run in the two databases were uploaded to Excel, and duplicates were eliminated.

In the second phase, three screening steps were conducted to select papers relevant to the study’s aim.

1. The first step involved reading the papers restricted to the title and abstract. In this screening phase, articles were classified as “included” or “excluded” based on six exclusion criteria (EC) defined by the authors:

(EC1) Out of topic: (e.g., an ontology or a knowledge graph is not presented in the industrial prognostics and health management domain, and the paper only argues in relation to predictive maintenance/PHM; or an ontology/knowledge graph is provided, but in domains different from PHM; or a methodology is provided for converting maintenance data into a knowledge graph).

(EC2) Literature review on ontologies/knowledge graphs in the industrial maintenance domain: i.e., no specific new ontologies/knowledge graphs were provided in the PHM domain.

(EC3) Conference proceedings or editorials

(EC4) No full text available

(EC5) The ontology/knowledge graph is not the goal of the paper, but it is part of it.

Therefore, the ontology/knowledge graph is only mentioned in the paper, but the details are not provided.

(EC6) The full text is not in the English language.

(EC7) The paper is not in the production domain (e.g., it targets the building sector).

2. The second step consisted of reading the full text of the selected papers during the first screening phase; hence, a definitive assessment was made to include the papers relevant to the aim of the research. During this phase, papers that did not precisely respond to the *RQ* were excluded according to the *ECs*, while papers proving ontologies or knowledge graphs for knowledge modeling in the domain of PHM were considered included.
3. Finally, the third step consisted of the snowball process, i.e., the references screening of the papers selected in the second step. The references were then investigated for relevance to the research to check whether additional papers could be included.

Subsequently, an email was sent to the authors of the papers definitively selected in the second and third steps of the review to ask for the OWL file of their ontology when it was unavailable. The purpose of this step was to allow for a deeper understanding of the knowledge modeled in the PHM domain.

2.3 Analysis process and information extraction strategy

To classify the definitively selected papers and extract the main information, the following criteria were set:

- (i) publication type (e.g., journal article, conference, or chapter of a book) and publication year
- (ii) ontological and non-ontological resources adopted for designing the ontology/knowledge graph
- (iii) method and tool adopted for implementing the ontology/knowledge graph
- (iv) application of the ontology/knowledge graph
- (v) steps of the PHM process on which the article is focused
- (vi) type of decisions (strategical, tactical, or operational) for which the ontology/knowledge graph is adopted

All this information was extracted and reported in a specific worksheet to allow the authors to have a global vision and perform a detailed assessment of the current state of the art in the investigated research field.

The general results according to criterion (i) are reported at the beginning of Section 3, while the information extracted according to criteria (ii), (iii), and (iv) is discussed in subsection 3.1.

Moreover, to enable an organized and clear classification of the information extracted based on criteria (v) and (vi), a general framework reporting all the main elements of the PHM process was built and is provided in Figure 2. The ontologies/knowledge graphs were then classified in subsection 3.2 according to the blocks of this framework to which they contribute and the type of decisions made (strategic, tactical, and operational).

Figure 2 reports the PHM framework designed for classifying the information extracted from the papers with respect to criteria (v) and (vi). Concerning the PHM blocks, the framework is divided into two main parts: one part includes the blocks MPS and PHM-RA representing, respectively, the Maintenance Policy Selection and the PHM Resources Allocation; the other part includes the operational steps of the PHM process, classified according to ISO 13374-2:2007, namely, Data Acquisition (DA), Data Manipulation (DM), State Detection (SD), Health Assessment (HA), Prognostic Assessment (PA), and Advisory Generation (AG). Another preliminary step was also included, adapted from Cattaneo et al. (2021), concerning the Asset and Context Analysis (ACA), which was a pre-step needed for the Maintenance Policy Selection, PHM Resources Allocation, and the operational steps of the PHM. A pyramid reporting the different levels of decisions for which the ontology/knowledge graph is used is shown in Figure 2. Each approach developed in the selected articles could contribute to strategic, tactical, and operational decisions (Marquez and Gupta, 2006).

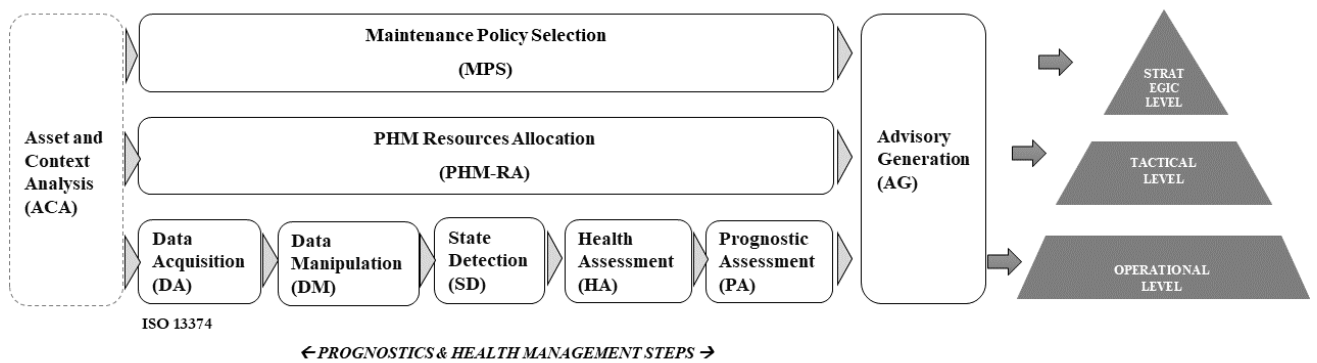


Figure 2 – PHM framework

Furthermore, a brief description of each block of the framework is reported below to clarify its objectives and outputs. This allows the reader to easily understand the classification made in Section 3.2.

The description of ACA is adapted from Cattaneo et al. (2021), while the objectives and main outputs of the DA, DM, SD, HA, PA, and AG are according to the BS ISO 13374-2:2007. For further details, refer to the above-mentioned sources.

- The **Asset and Context Analysis (ACA)** is a preliminary fundamental activity for PHM involving the analysis of the context and the selection of the most critical asset(s) in the portfolio, along with their decomposition and functioning. All the modes in which the components could fail and the corresponding causes and effects should be identified. The assets and their failure modes on which to focus the implementation of PHM should be prioritized.
- The **Data Acquisition (DA)** block has been generalized to represent the software module that provides system access to digitized data entered automatically or manually.

- The **Data Manipulation (DM)** block processes the digital data from the DA block to convert it to a desired form that characterizes descriptors (features) of interest in the machine condition monitoring and diagnostic process.
- The **State Detection (SD)** block has the function of comparing the DM and/or DA outputs against expected baseline values to generate enumerated state indicators with respective boundary exceedances.
- The **Health Assessment (HA)** block is an information block that utilizes expertise from a human or automated agent to determine the current health of the equipment and to diagnose existing fault conditions. This block determines the state of health and potential failures by focusing on the outputs of the DA, DM, SD, and other HA blocks.
- The **Prognostic Assessment (PA)** block has the primary function of projecting the future state of the monitored equipment using a combination of prognostic models and their algorithms. This block determines the future state of health and failure modes by combining the relevant outputs of DA, DM, SD, HA, and other PA blocks and applying a prognostic algorithm or model based on the supplied projected operational utilization. The prognostics layer can report the health grade at a time of failure or may estimate the remaining life of an asset given its projected usage profile.
- The **Advisory Generation (AG)** block has the primary function of integrating information from the DA, DM, SD, HA, PA, and other AG blocks and external constraints (such as safety, environmental, and budgetary) and providing optimized recommended actions and alternatives to personnel or external systems. The recommendations from this block may include prioritized operational and maintenance actions, capability forecast assessments, or modifying operational profiles to allow mission completion. Maintenance advisories from this block should detail the future maintenance work required, while operational advisories can be immediate, such as the current notification of operators of alerts and the resulting action steps. Other production-related advisories can be more strategic, such as sending a notice to a production planning system about the high risk of failure on a production line due to a soon-to-fail critical piece of equipment.

In addition to the definition provided by the ISO, in the proposed framework, we consider that the AG block includes recommendations related to the selection of maintenance policy and the allocation of maintenance resources as an output of the MPS and PHM-RA blocks described in the following.

- The **Maintenance Policy Selection (MPS)** and the **PHM-Resources Allocation (PHM-RA)** blocks have, respectively, the function of choosing among the most suitable maintenance strategies for the assets' components and allocating the right resources for the PHM steps, such as sensors and maintenance personnel.

3. Results

A total of 897 papers resulted from the search process in the two databases, based on the keywords reported in Section 2.1. After removing the duplicates, 687 articles were identified for analysis. From

this sample, 94 papers were included, while the other 593 were excluded during the first screening step, according to the exclusion criteria outlined in Section 2.2. Forty-two papers were selected after reading them fully. Seventeen additional articles were found through the screening of references (snowball process), which resulted in a total of 58 papers identified as relevant to the purpose of this study.

Figure 3 shows the systematic process with the defined steps and the associated results.

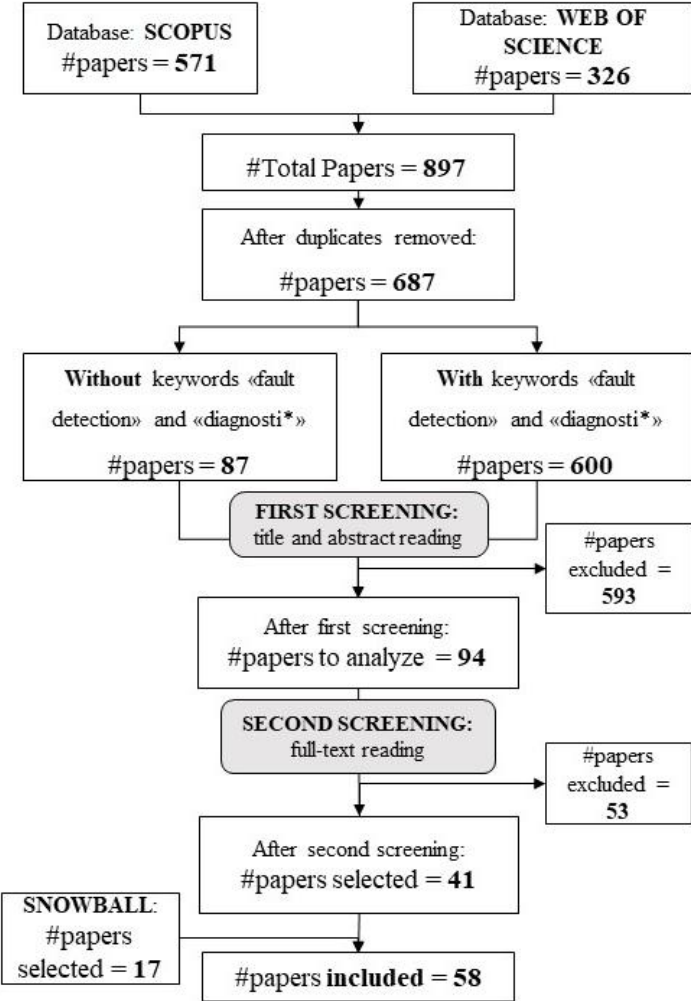


Figure 3 – Systematic literature review process and results

Among the 58 selected papers, 43% were published in journals, 55% in conference proceedings, and 2% in book chapters. Figure 4 shows the number of publications over the years: 86% of the selected papers were published in the last 10 years, with a growing trend, indicating an increasing interest by academics and researchers. It is worth noting that the low number of papers in 2022 could be related to the fact that the search was run in the databases in April 2022.

The selected journal articles were published in different kinds of journals, the most frequent of which were *Advanced Engineering Informatics*, *Journal of Industrial Information Integration*, *International*

Journal of Advanced Manufacturing Technology, Journal of Intelligent Manufacturing, and Computers and Chemical Engineering. Concerning the conference papers, the highest number of articles were published in IFAC proceedings, IEEE proceedings, and Procedia CIRP.

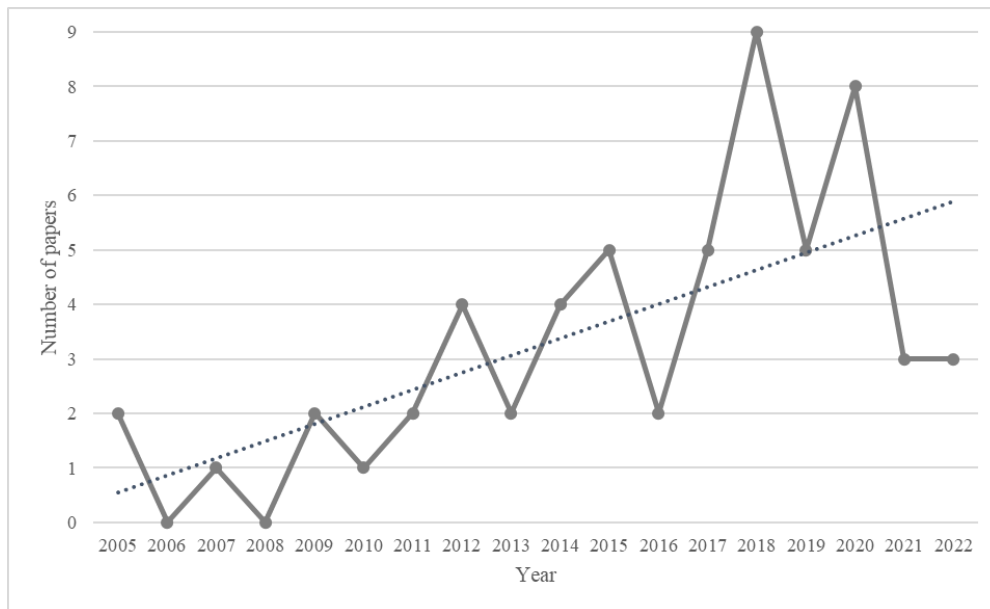


Figure 4 – Trend of selected papers over the years

Each selected paper is discussed in the following subsections, according to the information extraction criteria defined in Section 2.3 of the methodology, describing the content analysis of the papers.

3.1. Results related to extraction criteria (ii), (iii), and (iv)

The general information related to the ontologies and knowledge graphs available in the domain of PHM was extracted with respect to criteria (ii), (iii), and (iv) provided in Section 2.3, and the details are reported in Appendix 1. For each selected document, a set of information is provided: the authors' name and the year of publication of the document, the name of the ontology, the ontological resources (e.g., top-level or domain ontologies) and the non-ontological resources (e.g., international standards) adopted for building the specific ontology, the method used for designing the ontology/knowledge graph, and the eventual application in a case study.

Concerning the tool adopted for implementing the ontology, the most frequently used tool is Protégé, an ontology editor that supports the Web Ontology Language (OWL). The ontology is coded in OWL and is used to represent knowledge and explicit semantics, allow binary relationships between ontology classes, and distinguish the data properties that link objects to data values and object properties that link objects to other objects (Medina-Oliva et al., 2014). Moreover, through plugged reasoners, the tool can provide inference capabilities.

Regarding the implementation of the ontology/knowledge graph, 20 of 58 papers adopted a methodology

for this purpose. The most recurrent method is Ontology Development 101 (Noy & McGuinness, 2001), which was adopted by nine documents, followed by the seven-step method and then by METHONTOLOGY.

Going into the details of the information reported in Appendix 1, 18 of the 58 papers (around 31%) reused already developed ontological resources for the development of their own ontology/knowledge graph. The main ontological resources adopted by these authors are top-level ontology, i.e., domain-independent (such as UFO – Unified Foundational Ontology (Guizzardi et al., 2022), BFO – Basic Formal Ontology (Arp et al., 2015)), mid-level reference ontology, such as CCO – Common Core Ontologies for Data Integration, RO – Relation Ontology, IAO – Information Artifact Ontology (Ceusters, 2012), and application-level ontologies specific to industrial maintenance domains, such as IMAMO (Karray et al., 2012) and ROMAIN (Karray et al., 2019).

Concerning the non-ontological resources adopted by the selected documents, 17 of the 58 papers (around 29%) considered the use of maintenance-related ISO, IEC, and SAE standards. Some of the most repeated ones are ISO 13372 and ISO 13374 for the condition monitoring and diagnostics of machines, ISO 13306 for maintenance terminology, IEC 60812 for the FME(C)A – Failure Mode Effects (and Criticality) Analysis, ISO 55000 for asset management, ISO 2041 for mechanical vibration, shock, and condition monitoring, and ISO 14224:2016 related to petroleum, petrochemical, and natural gas industries – Collection and exchange of reliability and maintenance data for equipment, and SAE J1739 – Potential Failure Mode and Effects Analysis (FMEA).

Around 80% of the selected papers (47 of the 58) provided an application. The most recurrent applications relate to rotating machinery and its elements, such as pumps, bearings, and the oil and gas industry. The details are provided in Appendix I.

3.2 Results related to extraction criteria (v) and (vi): Classification of the ontologies/knowledge graphs with respect to the PHM framework

The ontologies and knowledge graphs were then classified with respect to criteria (v) and (vi) provided in Section 2.3, namely, the steps of the PHM process on which the article is focused and the type of decisions (strategical, tactical, or operational) for which the ontology/knowledge graph is adopted. Therefore, the ontologies/knowledge graphs provided in the 58 selected papers were classified according to the block(s) of the PHM framework (Figure 2) to which they contribute and according to the type of decisions made (strategic, tactical, or operational).

A summary of the classification of the 58 selected papers with respect to the PHM steps is reported in Figure 5, and the detailed information is reported in Appendix 2.

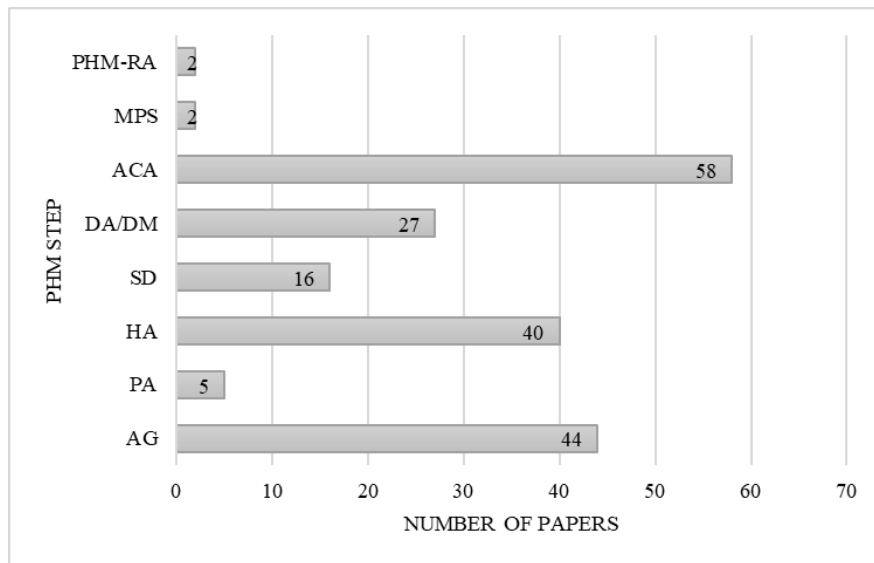


Figure 5 – Classification of papers with respect to PHM steps

It can be derived from Figure 5 that most of the papers contribute to more than one PHM step. All 58 selected papers provided an ontology or a knowledge graph for the **ACA**. In fact, an ontology allows context and asset modeling, thus facilitating the analysis. However, most of the papers combined the **ACA** phase with at least one other block of the PHM framework, except for eight papers that provided only the modeling of the context. Twenty-seven of the 58 papers focused on the **DA/DM** blocks of the PHM. Fifteen papers provided an approach in which the ontology was adopted in the **SD** and **AG** phases; 10 of 15 papers also considered the **HA** block, while 5 of 15 considered the **PA** block. Forty papers focused on some aspects of the **HA** block, generally combined with the **AG**. Only five papers of 58 contributed to the **PA** block, which means that the ontology contributed to the prognostics, whereas four papers concentrated on the **MPS** and **PHM-RA** blocks.

Concerning the type of decisions made by the approach in which the ontology/knowledge graph is integrated, operational is the dominant type, while in only three papers, the chosen approach is or could be implied in strategic or tactical decisions.

A summary of the papers contributing to the PHM framework's blocks, with their respective methodologies used for building the ontologies, the domain-independent and domain-dependent ontologies adopted, and the application domain, is provided in Table 2. The paper IDs reported in Table 2 are associated with the papers in Appendix 1. The **ACA** step is not reported because all 58 selected papers provided a description of the context; therefore, these ontologies will be described in the other steps. For the eight papers that only contributed to the **ACA** step, their content descriptions are reported directly in Section 3.2.1. The **AG** block is not summarized either because the type of generated advisory relates to the previous blocks (**MPS**, **PHM-RA**, **DA**, **DM**, **SD**, **HA**, and **PA**), and the respective papers will be directly described in these blocks.

In subsections 3.2.1–3.2.6, the details of the selected papers are discussed according to their contribution to the blocks of the framework shown in Figure 2.

Table 2 – Summary of the information extracted from the papers described in subsections 3.2.1–3.2.6

PHM framework block	Papers	Domain-independent ontology used	Domain-dependent ontology used	Methodology used for building the ontologies	Application domain
MPS & PHM-RA	<i>4 papers:</i> [2], [26], [30], and [39]	BFO, CCO, RO, and IAO	IMAMO, OntoProg, and ROMAIN	Ontology Development 101, NeOn, and DOGMA	A laser-cutting machine, an air compressor, and a food company.
DA & DM	<i>27 papers:</i> [2], [3], [5], [6], [7], [8], [18], [19], [23], [24], [25], [27], [28], [29], [31], [32], [37], [41], [42], [44], [45], [46], [47], [49], [50], [52], and [56]	SWRL Temporal Ontology, Spatial Ontology, Time Ontology, Geospatial Ontologies, UFO, and Semantic Sensor Network (SSN) Ontology	IMAMO, MSDL, MASON, MRO, MaRCO, ONTO-PDM, OntoProg, System Service (Condition Monitoring MODULE), Siemens Technical System Ontology, OntoCAPE, AuomationML, CAEX, and ReferenceOntology	Ontology Development 101, Middle-out approach, and Top-down modeling approach	A semi-conductor manufacturing process, a SECOM dataset, a self-priming pump, train diagnostics and turbine diagnostics, rail systems at Siemens, Siemens monitoring and diagnostic services, Lathe Machine, Diesel engines (Naval sector), dataset on 50 Siemens gas turbines, offshore oil and gas production process, gearbox of a wind turbine, automotive industry, bearing, diagnostic use-case at Siemens smart factory, assembly station, aluminum production company, industrial transportation system (laboratory), and wheel loader
SD	<i>16 papers:</i> [2], [3], [4], [5], [6], [7], [8], [27], [31], [32], [33], [34], [37], [38], [44], and [49]	SWRL Temporal Ontology, Spatial Ontology, Time Ontology, Geospatial Ontologies, UFO, Semantic Sensor Network (SSN) Ontology, BFO, IAO, and CCO	IMAMO, MSDL, MASON, MRO, MaRCO, ONTO-PDM, OntoProg, System Service (Condition Monitoring MODULE), Manufacturing CM Ontology, Sensor Ontology, Context Ontology, Product Ontology, OntoCAPE, and ROMAIN	Ontology Development 101, Middle-out approach, Top-down modeling approach, and METHONTOLOGY	Bearings in rotting machinery, a SECOM dataset, a semi-conductor manufacturing process, Lathe Machine, offshore oil and gas production process, a centrifugal pump, gearbox of a wind turbine, Flexible Manufacturing Line (at laboratory-scale), a bearing, and an aluminum production company
HA	<i>40 papers:</i> [3], [4], [5], [6],	SWRL Temporal Ontology, Spatial	MSDL, MASON, MRO, MaRCO, ONTO-PDM, OntoProg, System Service (Condition	Ontology Development 101, Middle-out approach, Seven-steps method	Bearings in rotting machinery, a SECOM dataset, a semi-conductor

	[7], [8], [10], [11], [12], [14], [15], [16], [18], [19], [20], [21], [23], [24], [25], [28], [29], [31], [32], [33], [34], [36], [41], [42], [43], [45], [46], [50], [51], [52], [53], [54], [55], [56], [57], and [58]	Ontology, UFO, Semantic Sensor Network (SSN) Ontology, Time Ontology, and Geospatial Ontologies	Monitoring MODULE), PSL Ontology, Sensor Ontology, Context Ontology, Product Ontology, OntoTurb, PSL Ontology, Siemens Technical System Ontology, OntoCAPE, AuomationML, CAEX, and ReferenceOntology		manufacturing process, a petroleum production and separator facilities, a pallet transfer system, a rotor, a hexane surge tank, a self-priming pump, a robot arm, train diagnostics and turbine diagnostics, rail systems at Siemens, Siemens monitoring and diagnostic service, diesel engines (naval sector), an offshore oil and gas production process, a centrifugal pump, an automotive industry, assembly station, an industrial transportation system, a wheel loader, hydraulic automated gauge control system, a wind turbine, a rolling bearing, and a hobbing machine tool
PA	<u>5 papers:</u> [5], [6], [7], [8], and [44]	Time Ontology, Geospatial Ontologies, and UFO	-	Ontology Development 101	A SECOM dataset, a semi-conductor manufacturing process, and a bearing

3.2.1 Asset and Context Analysis (ACA)

In 2009, Jin et al. (2009) highlighted the potentiality of ontologies for knowledge representation in the condition monitoring and maintenance of production systems. Eight of the 58 papers presented an ontology contributing only to the block of asset and context analysis/representation in the PHM domain in different production sectors.

Concerning the manufacturing domain, Cao et al. (2019) developed an ontology representing the core condition monitoring entities, and Al-Shdifat et al. (2020) provided an ontology for modeling the failure analysis of mechanical components that can help answer queries concerning how faults manifest and how they can be addressed in order to inform diagnostics or maintenance actions in a condition-based maintenance setting. Emmanouilidis et al. (2020) proposed an ontology mainly focused on FMECA (Failure Mode, Effects, and Criticality Analysis) concepts to support context management for predictive

maintenance, considering that, as stated by the authors, it allows the processing of data to assess the likelihood and criticality of functional disruptions.

Other developed ontologies are mainly focused on highly specific assets. To name a few, Nuñez and Borsato (2016) provided the first version of OntoProg, which aimed to identify failure modes in a mechanical component, namely, a bearing. Qin and Jin (2020) represented knowledge for the maintenance of a shield tunneling machine, and Shen et al. (2013) presented an ontology for the fault diagnosis knowledge representation of a CNC machine tool.

Most of the ontologies described so far can help make operational decisions. However, the Z-BREAK ontology proposed by Cho et al. (2020), accompanied by the competency questions reported in the paper, could be used in future applications to help make strategic, tactical, and operational decisions. Indeed, the Z-BREAK ontology (i) allows the identification of the domain of interest, covering all relevant products, data sources, information flow resources, design and manufacturing processes, user-interface access points, and dynamics of the entire system; (ii) provides a data integration framework that will extract, export, and harmonize data from various sources; (iii) enables semantic enrichment of data originating from disparate research or existing systems; and (iv) provides an intelligent engine that will allow for the active exploration of the linked datasets and implicit knowledge discovery.

3.2.2 Maintenance Policy Selection (MPS) and PHM Resources Allocation (PHM-RA)

Concerning the MPS and PHM-RA blocks of the framework, four papers were identified.

Bekkaoui et al. (2015) and Maleki et al. (2018) focused on the PHM-RA block. The first study provided an ontology for selecting the most suitable experts in maintenance to make decisions in a fault diagnosis and repair context, while the second study presented an ontology for choosing the sensor type to adopt to measure machine parameters (e.g., vibration) in order to allow the system to monitor the health status of a machine, verify the alert threshold overcoming, and understand when performing predictive maintenance. Therefore, both studies contributed to making operational decisions. No top-level ontology was used in these two papers, but Bekkaoui et al. (2015) considered reusing the IMAMO ontology in the maintenance field to build their ontology.

Regarding the other two papers, Montero et al. (2022) and Polenghi et al. (2021), two new ontologies for MPS were proposed that were oriented more to strategic and tactical decisions in maintenance. The OMSSA ontology (Montero et al., 2022) facilitates the selection and assessment of maintenance strategies based on FMEA analysis. The multi-attribute ontology-based criticality analysis (MOCA) (Polenghi et al., 2021) can infer the maintenance strategy planning for the asset under analysis according to the criticality value provided by the company experts; the maintenance strategies that can be selected are corrective, preventive, condition-based, and predictive maintenance. The applications are related to an air compressor and a food company. The authors of these two articles both developed an ontology compliant with BFO (top-level ontology, domain-independent), and both provided the OWL file of the ontology, which allowed us to understand the positioning of their maintenance and production concepts with respect to the high-level concepts. Notably, several concepts are defined and therefore positioned in different classes of BFO, highlighting the need to have a shared and common vision related to this aspect. Both papers followed a structured methodology for building their ontology: Ontology

Development 101 in the case of Montero et al. (2022) and NeOn and DOGMA in the case of Polenghi et al. (2021).

3.2.3 Data Acquisition (DA) and Data Manipulation (DM)

Twenty-seven of the 58 selected papers contributed to the DA and DM blocks of PHM, generally combined with the SD, HA, or PA blocks.

The potential of semantic technologies to enhance data access is discussed in Kharlamov et al. (2014). The authors also confer the relevance of this task for Siemens to perform remote monitoring and diagnostics of gas and steam turbines, generators, and compressors installed in power plants. They stated that among the many tasks conducted by service engineers, gathering the requested data can take up to 80% of the overall time needed for diagnostics. Therefore, they used the Ontology Based Data Access (OBDA) to mediate between users and data. Other works, namely, Kharlamov et al. (2018), Savković et al. (2018), and Kharlamov et al. (2019), also adapted the OBDA for the knowledge representation of sensors and the Siemens technical system and for the diagnosis of train faults to reduce operator time for diagnostics. Their semantic solution allows diagnostic engineers to simplify the diagnostic process and focus more on analyses of diagnostic output rather than on data understanding and gathering, the tasks they had to perform for authoring data-driven diagnostic rules. They reported that the use of ontologies allowed for a reduction of up to 66% in their time. Kharlamov et al. (2019) showed the practical benefits of ontology-based compared with data-driven solutions in two industrial use cases: trains and turbines, integrated into industrial IoT.

Other benefits of the use of ontologies for DA and DM in the PHM process were pointed out by Rajpathak et al. (2012), who proposed an ontology-driven data collection framework for the automotive domain to facilitate the automatic collection of diagnosis and repair data. In addition, Schmidt et al. (2017) presented an ontology-based approach for data aggregation to support context-aware, cloud-enabled diagnostics and prognostics in application to the maintenance of a manufacturing asset.

The other papers that contributed to the DA and DM blocks are described in detail in the following subsections because they mainly contributed to the SD, HA, and PA services; therefore, they are mainly focused on these steps.

Concerning the ontology engineering methodology used in these 27 papers, Cao, Giustozzi et al. (2019), Cao, Samet et al. (2019), and Medina-Oliva et al. (2014) adopted the Ontology Development 101; Xu et al. (2018) adopted the seven-steps method, Rajpathak et al. (2012) adopted a previous methodology developed by the authors, and Papadopoulos and Cipcigan (2009) adopted a top-down modeling approach.

Regarding the reuse of other ontologies, the most frequently adopted are the Unified Foundational Ontology (UFO), the Time Ontology and the Geospatial Ontologies (Cao, Giustozzi et al., 2019; Cao, Samet et al., 2019); the Semantic Sensor Network (SSN) Ontology and the Siemens Technical System Ontology (TSO) (Kharlamov et al., 2018; Kharlamov et al., 2019; Savković et al., 2018); and the OntoCAPE ontology, specific to the process engineering domain (Natarajan et al., 2012; Natarajan & Srinivasan, 2014).

3.2.4 State Detection (SD)

Sixteen of the 58 papers provided ontologies contributing to the SD block.

Most of the papers are in the manufacturing domain, such as Cao (2018), Cao, Giustozzi et al. (2019), Cao, Samet et al. (2019), Cao, Samet et al. (2020, February), Cao, Samet et al. (2020), Cao et al. (2022), Matsokis and Kiristis (2012), Polenghi et al. (2022a), along with others in chemical plants, namely, Natarajan et al. (2012) and Natarajan & Srinivasan (2014). Papadopoulos and Cipcigan (2009) presented an ontology model for a wind turbine, and Siaterlis et al. (2022) tested their approach in an aluminum production company. Nuñez and Borsato (2017; 2018) focused on a specific component, i.e., a centrifugal pump, and Roopa et al. (2021) concentrated on a bearing.

Some of the 16 papers provide ontologies that contribute not only to the SD service but also to the HA and/or to the PA services. In the following paragraphs, the ontologies described contribute mainly to the SD block. The remaining ontologies are described in subsections 3.2.5 and 3.2.6 and are related, respectively, to the HA and PA services.

Cao (2018) and Cao, Giustozzi et al. (2019) presented an ontology contributing to the condition monitoring (CM) performed in manufacturing processes. A formal representation of domain knowledge related to CM concepts, the manufacturing processes, and the context is presented in their studies, as well as the SWRL (Semantic Web Rule Language) rules that allow for machinery state identification. Polenghi et al. (2022a) developed an Ontology for Reliability-centred MAintenance (ORMA) that can infer product feasibility based on the current state of the assets and their functional units. Matsokis and Kiristis (2012) proposed a model including an ontology for managing the input data from the sensors and creating events and alarms that might trigger activities when the temperature of the monitored system exceeds certain limits. Natarajan et al. (2012) and Natarajan & Srinivasan (2014) developed an ontology for chemical plants that contributes to process state identification and description, as well as to monitoring. Process supervision is a means of ensuring safe process operation by assisting human operators in the management of abnormal situations and increasing the reliability and availability of the process. Papadopoulos and Cipcigan (2009) presented an ontology contributing to the CM of the gearbox present in the wind turbine, which creates fault alarms in the case of failure of any part under inspection. Siaterlis et al. (2022) developed a knowledge graph that captures the knowledge from maintenance personnel to assess the production status and provide information regarding the conditions of the key equipment parts. Nuñez and Borsato (2017; 2018) developed OntoProg, an ontology that responds to queries related to the state of the system before facing a functional failure.

The remaining papers by Cao et al. (2020, February), Cao et al. (2020), Cao, Samet et al. (2019), and Cao et al. (2022) contributed to all the PHM steps. The paper by Roopa et al. (2021), which contributed to the PA service, will be discussed in subsection 3.2.6.

With respect to ontology engineering methodology, among the 16 papers addressing the SD block, the most frequently used is Ontology Development 101 (Cao, Giustozzi et al., 2019; Cameo, Samet et al., 2019; Nuñez & Borsato, 2017; Nuñez & Borsato, 2018). The top-level ontologies employed are UFO (Cao, 2018; Cao, Samet et al., 2020; Cao et al., 2022) and BFO (Polenghi et al., 2022a). Several different domain-specific ontologies have also been adopted, such as SSN Ontology (Cao, 2018), ROMAIN (Polenghi et al., 2022a), and OntoCAPE (Natarajan et al., 2012; Natarajan & Srinivasan, 2014).

3.2.5 Health Assessment (HA)

The typical aim of the diagnostic reasoning process is to identify the root cause of an observed failure mode(s) to allow remedial action (Sayed & Lohse, 2014). Since a machine is highly complex and has many components, making the diagnosis of machine failure or degradation requires experience and technical skills (Medina-Oliva et al., 2014). This becomes even more complex when large systems are involved, such as aircrafts, power plants, and ships, because they are structured in multiple systems, subsystems, and components, each with their own technologies, ages, and uses (Medina-Oliva et al., 2014). To perform the diagnosis, first, an understanding of the machine's operation through a functional analysis of the normal functioning of the system is needed. Then, abnormal situations can be studied through dysfunctional analysis (such as FMECA and a Hazard and Operability Study (HAZOP)) in which degradation modes at different abstraction levels are identified (Medina-Oliva et al., 2014).

Most of the papers selected in this study contribute to the diagnosis step (40 of the 58 papers (69%)) and mainly support the operational decisions in production systems. Most of these papers provided an ontology for modeling and representing the knowledge in a specific context, supporting human operators and facilitating fault diagnosis in several production systems, such as petroleum production (Chan, 2005); a pallet transfer system (Chebel-Morello et al., 2005; Rasovska et al., 2007); an industrial transportation system on a laboratory scale (Steinegger et al., 2017); power transformers (Wang et al., 2010); a steam turbine (Dendani et al., 2011; Dendani-Hadiby & Khadir, 2012; Ebrahimipour & Yacout, 2015), a wind turbine (Zhou et al., 2015), and an industrial turbine (Mehdi et al., 2017); an aircraft (Yang et al., 2011); naval systems (Medina-Oliva et al., 2014); assembly systems (Sayed & Lohse, 2014); rotating machinery (Chen et al., 2015); hydraulic systems (Zhao et al., 2015); avionics (Palacios et al., 2016); hazardous chemical storage devices (Feng et al., 2018; Feng, Chen and Peng, 2018); a centrifugal pump (Nuñez & Borsato, 2017); loaders (Xu et al., 2018); machine tools (Zhou et al., 2017, 2018); rolling bearings (Zhou et al., 2019); and production line equipment (Geng & Fu, 2020).

Therefore, the adoption of an ontology-based approach for supporting fault diagnosis in enterprises may effectively promote fault knowledge-sharing among stakeholders (Yang et al., 2011). At the operational level, the adoption of knowledge-based fault diagnosis approaches facilitates the discovery of best-practice repair actions for frequently observed symptoms and can be used to handle similar cases in the future to reduce downtime and avoid unnecessary part replacements (Rajpathak, 2013). Also, it may allow the improvement of machine maintenance and the OEE, as well as the reduction of failure diagnostic time (Hossayini et al., 2020). At the same time, at the strategic level, establishing the associations between failure modes and symptoms leads to the improvement of the product design (Rajpathak, 2013).

With respect to the ontology engineering methodology, the most frequently used is Ontology Development 101 (Cao, Giustozzi et al., 2019; Cao, Samet et al., 2019; Medina-Oliva et al., 2014; Nuñez & Borsato, 2017; Nuñez & Borsato, 2018) and the seven-step method (Ebrahimipour & Yacout, 2015; Hossayini et al., 2020; Wang et al., 2020; Xu et al., 2018). With respect to the top-level ontologies used, only Cao (2018), Cao, Samet et al. (2020), and Cao et al. (2022) adopted the UFO ontology, while several domain-specific ontologies were employed, such as OntoTurb (Dendani et al., 2011; Dendani-Hadiby & Khadir, 2012) and OntoCAPE (Natarajan et al., 2012; Natarajan & Srinivasan, 2014).

3.2.6 Prognostic Assessment (PA)

Only five of the 58 selected papers proposed an approach to contribute to the prognostic assessment. Roopa et al. (2021) developed an ontological model to assist the implementation of prognostics and health management to predict the remaining useful life (RUL) of the machine elements, thereby contributing to the ACA, DA/DM, SD, PA, and AG blocks. The remaining four articles were provided by the same group of authors, who developed two different ontologies: MFPO (Manufacturing Failure Prediction Ontology) and MPMO (Manufacturing Predictive Maintenance Ontology). Cao, Samet et al. (2019) and Cao, Samet et al. (2020, February) developed MFPO, whose objective is to formalize knowledge in the predictive maintenance domain and infer new knowledge about the prediction of the time and criticality of future failures. Instead, the MPMO ontology is presented and used in Cao et al. (2020) and Cao et al. (2022) and takes into account the DA/DM, SD, HA, and PA steps. Of particular interest, the authors introduced a hybrid approach to facilitate the predictive maintenance tasks in manufacturing processes. The proposed approach is a combination of data mining and semantics, within which chronicle mining (a special type of sequential-pattern mining approach) is used to predict the future failures of the monitored industrial machinery, and the MPMO, with its rule-based extension, is used to predict the temporal constraints of failures and to represent the predictive results formally. As a result, SWRL rules can be constructed to predict the occurrence time of machinery failures in the future.

Concerning ontology engineering methodology, the only one used is Ontology Development 101 (Cao et al., 2019), while the top-level ontology employed is UFO (Cao et al., 2020; Cao et al., 2022).

4. Conclusions and research agenda

In this study, a systematic literature review was conducted to respond to the *RQ*: “*What are the existing ontologies and knowledge graphs in the domain of prognostics and health management of production systems?*” and to provide an overview of the developed ontologies and knowledge graphs. The analysis of the selected papers shows that, in recent years, several ontology-based approaches have been developed in the PHM domain.

The ontologies and knowledge graphs developed to date in the PHM field of production systems were identified, classified, and analyzed. The main information was extracted and discussed according to (i) the type and year of publication, (ii) the ontological and non-ontological resources adopted for designing the ontology/knowledge graph, (iii) the method adopted for implementing the approach, (iv) the type of application; (v) the step(s) of the PHM process on which the article is focused, and (vi) the type of decisions (strategical, tactical, or operational) for which the ontology/knowledge graphs were adopted.

This allowed the authors to identify the strengths and weaknesses of the use of ontologies in the field of PHM. On the one hand, integration of data and information in all business processes is needed to optimize the decision-making process related to the life cycle management of assets (Polenghi et al., 2022b). Even though data-driven artificial intelligence plays a relevant role in PHM in the Industry 4.0 context, there is a wide heterogeneity of industrial data, which cannot be easily interpreted by humans and machines. To fill this semantic gap and provide context awareness, ontologies can be developed and employed that can facilitate PHM activities through the representation of knowledge by providing context understanding. Ontologies can organize knowledge related to industrial assets, their subsystems, components and processes, their properties, and relationships, enabling better understanding, sharing, and reuse of knowledge among maintenance personnel and maintenance information systems.

In addition, ontologies support automatic reasoning and inference capabilities and, through the definition of relationships among concepts and logical rules, combined with process monitoring data, additional information can be derived (e.g., information related to the potential causes of failures, thus supporting engineers and maintenance technicians in the diagnosis process) to help in the maintenance decision-making process.

However, several ontologies are static by nature; the concepts cannot change once the ontology is deployed, and the knowledge instantiated is difficult to update in real-time (Polenghi et al., 2022b). Moreover, for making failure predictions and estimating the remaining useful life of an asset's components, other typologies of tools are also needed, such as machine learning algorithms. For example, as reported by Cao et al. (2020) and Cao et al. (2022), chronicle mining has been applied to industrial datasets to extract events' temporal information and to predict potential machinery failures. However, even though chronicle mining results are expressive, domain knowledge is needed for users to have a complete understanding. Considering that the predictive maintenance domain is knowledge-intensive, the activities performed in this domain can benefit from incorporating domain and contextual knowledge (Cao et al., 2020).

Therefore, ontologies must be accurately designed to be flexible with respect to the dynamic industrial context and properly combined with the complementary approaches needed for the prediction of failures.

The deep analysis of the content of the selected papers and the ontology files, where available, allowed the authors to identify the main gaps in the domain. A research agenda is therefore proposed in the following section, which contains several research challenges to address and future directions to undertake in the field of ontologies and PHM for production systems.

4.1 Research challenges and future directions

Ontologies are an effective tool that can provide a formal and structured way to represent knowledge in the industrial maintenance domain and to support maintenance decision making. In the PHM domain, these decisions can be related to state detection, health assessment, and prognostic assessment. Ontologies can play a role in PHM systems through knowledge representation in a human and machine-readable format, possible interpretation of sensor data, detection of anomalies, triggering of maintenance alerts, and suggesting maintenance tasks to perform based on predefined rules and ontological knowledge.

Among the analyzed studies, some provided a real case application of their ontology-based approach, showing their potentiality in real industrial context. For example, Kharlamov et al. (2019) proposed the use of ontologies to mediate the sensor signals and the rules and showed practical benefits of their approach in two industrial use-cases: Siemens trains and turbines, integrated in industrial IoT. These benefits are related to the ease of formulation and the execution time of diagnostic programs on industrial IoT with hundreds of pieces of complex industrial equipment in trains and turbines. Natarajan et al. (2012) and Natarajan and Srinivasan (2014) proposed and used an ontology, called OntoSafe, in the process industry. Indeed, considering that the chemical plants are complex systems, they stated that the information necessary for process supervision is increasingly becoming distributed across several and dynamic systems. Therefore, the proposed ontology provided the means to clearly represent the dependencies between the process descriptors such as flowsheet, instrumentation, control system and the elements of the supervision system. Another example is the study conducted by Medina-Oliva et al. (2014), in which, to ease diagnosis activities, they proposed to use a fleet-wide approach based on

ontologies to capitalize knowledge and data and hence help decision makers to identify the causes of abnormal operations in the naval domain. In complex domains such as the naval one, it can be challenging, particularly for junior maintainers and even for experts, to generate the hypotheses about the failure causes or abnormal behavior. Indeed, the use of the developed ontology allowed to retrieve data from a set of heterogeneous units through the identification of common and pertinent points of similarity. Consequently, it allows to reuse previous feedback experiences to build fleet-wide statistics and to search the causes generating an operation drift.

From the literature analysis performed in this study, several challenges and gaps related to ontologies in the PHM domain emerged. These challenges and gaps, discussed below in detail, pointed out the need for more structured, knowledge-based integrated solutions for PHM systems to be potentially combined with data-driven AI techniques in order to contribute to the sustainability-related challenges of production systems.

In subsections 4.1.1–4.1.4, the challenges, gaps, and possible future directions are detailed. This research agenda will serve to (1) raise stakeholders' awareness of the potentiality of knowledge modeling and formalization in the prognostics and health management domain and (2) guide interested researchers in specific domains in the next directions that could be undertaken.

4.1.1 – Challenge 1: Alignment of the ontologies with respect to top-level ontologies

Top-level ontologies are domain-independent and describe general concepts, such as a class, event, and process, which are independent of a particular problem or domain (Chan, 2005). These ontologies can be adopted for building other ontologies and allow interoperability among domain-ontologies that incorporate the same top-level ontology (Karray et al., 2019). An important issue to consider when developing domain-dependent ontologies is how to facilitate knowledge reuse and data integration. When multiple ontologies are created in isolation by different persons, disconnected information silos can form. Therefore, to guarantee that different application ontologies use mutually understandable definitions and knowledge constructs, they must share a common top-level formal ontology (Karray et al., 2019).

In the production domain, communication among several systems becomes increasingly important, highlighting the need for interoperability among domain-specific ontologies. The first effort in this direction is ongoing, thanks to the Industrial Ontology Foundry (IOF), an initiative with the objective of creating a set of open and principle-based reference ontologies that span the entire domain of digital manufacturing (<https://www.industrialontologies.org/>). The idea of IOF is that, from these created ontologies, other domain- or application-dependent ontologies can be derived in a modular way, while remaining generic in the sense that they can be reused in other industry domains. Several working groups (WG) are defined in the IOF, such as maintenance WG, production planning and scheduling WG, supply chain WG, systems engineering WG, and product-service WG. To ensure that the ontologies are developed in a structured and coherent manner, the IOF is committed to adopting a layered architecture for ontology building based on Basic Formal Ontology (BFO), a top-level ontology (Drobnjakovic et al., 2022).

Several top-level ontologies are available in the literature, for example, the Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE), the Basic Formal Ontology (BFO; ISO 21838-2), and the Unified Foundational Ontology (UFO). Among these, the BFO has recently become an ISO standard

and has been adopted in several ontologies developed in the industrial maintenance domain, such as Cho et al. (2020), Montero et al. (2022), Polenghi et al. (2022a), and the IOF initiative mentioned above.

As discussed in Section 3.1, only about 31% of the papers examined in this study reused previously developed ontological resources for the development of their approaches, and only some of these utilized top-level ontologies. Therefore, this is not in line with methodologies encouraging knowledge reuse in the development of new ontologies (Polenghi et al., 2022b). Moreover, the analysis of those ontologies whose OWL file was available (e.g., Montero et al., 2022; Polenghi et al., 2021; Polenghi et al., 2022a) showed that there is no coherence in the positioning of the maintenance and production concepts in the BFO top-level ontology. Also, there is no block of the PHM framework where the top-level ontologies are adopted more than other blocks.

According to this gap, a future direction could be the exploration of all the industrial maintenance ontologies available in the literature (not limiting the search to the PHM domain) in order to understand the provided definitions of the main concepts in the domain. This exploration would allow an understanding of the BFO-compliant ontologies in the industrial maintenance field and the positioning of the concepts with respect to the BFO macro classes. Hence, a first step toward the formalization of a PHM domain-specific ontology is a taxonomy of maintenance and production concepts, with shared definitions and common positioning in the high-level classes. Filling this gap, therefore, means formalizing a domain-dependent taxonomy and ontology to improve semantic interoperability for industrial maintenance applications.

However, the maintenance system does not work in isolation but is strictly interconnected with production IT systems (such as ERP, MES, and SCADA). Therefore, it is recommended to enlarge the vision by analyzing the ontologies in the production domain, particularly the ontologies compliant with the BFO top-level ontology.

Addressing this gap will allow for the comprehension of the definitions and the positioning of the concepts in the BFO classes. Most importantly, a future common view of the ontologies related to different systems in the production domain with respect to the BFO will enhance communication among ontologies and systems. Finally, if different ontologies contributing to the PHM blocks are aligned to one top-level ontology, this will ease the communication between the blocks of the PHM framework presented in Figure 2.

4.1.2 – Challenge 2: Connection among the different PHM steps at the operational level

The PHM engineering discipline aims to provide users with an integrated view of the health state of an overall system or machine (Lee et al., 2014). An effective PHM system should allow the early detection and isolation of faults related to specific components; the monitoring and prediction of the progression of the fault; and the advisory generation, thus triggering, in an autonomous way, the maintenance schedule and asset management decisions (Lee et al., 2014). Therefore, the PHM process should be considered an integrated pipeline in which all the steps are interconnected rather than separate processes.

In this frame, as discussed in Section 3, semantic technologies can effectively contribute (alone or combined with other approaches and technologies) to: (1) all the steps of the PHM process and (2) facilitate the integration and communication among the PHM steps.

First, with respect to (1), we showed that semantic technologies can lead to several benefits and improve performance at each step of the PHM process. For example, they can facilitate the gathering and understanding of the needed data (contributing to the DA/DM steps), leading to savings in the time operators and diagnostics engineers need to perform diagnostics activities (Kharlamov et al., 2018; Savković et al., 2018; Kharlamov et al., 2019) by simplifying the diagnostic process and allowing them to be more focused on the analysis rather than on the comprehension and gathering of data (contributing to the HA step). In addition, semantic technologies can effectively contribute to the monitoring and the SD step, assisting operators in the management of abnormal situations, thus leading to increased reliability and availability of the process (Natarajan et al., 2012; Natarajan & Srinivasan, 2014), and providing context awareness. Also, at the HA step, the semantic technologies can facilitate the discovery of the best-practice repair actions for the frequently observed symptoms and can be adopted to handle similar cases in the future to diminish downtime, improve the OEE, reduce the failure diagnostic time, and avoid unnecessary part replacements (Hossayini et al., 2020; Rajpathak, 2013). Moreover, the ontology can store HA or PA algorithms and deduce, through reasoning, the most suitable to use in the specific context in addition to the range of parameters to be used. Finally, ontologies combined with rules and data-driven AI can contribute to the PA step through ontology reasoning, thus enabling the automatic detection of machinery anomalies and the prediction of future events (Cao et al., 2022).

With respect to (2), as emerged from the conducted analysis (Appendix 2), only four papers provided an ontology adopted in all the PHM steps at the operational level (DA/DM, SD, HA, PA, and AG) in an integrated way. As discussed in Section 3.2.6, these four papers belong to the same group of authors, and two ontologies (MFPO and MPMO) are provided. Concerning the other analyzed papers, as summarized in Figure 5, most of the papers contribute to two or three PHM steps at the operational level.

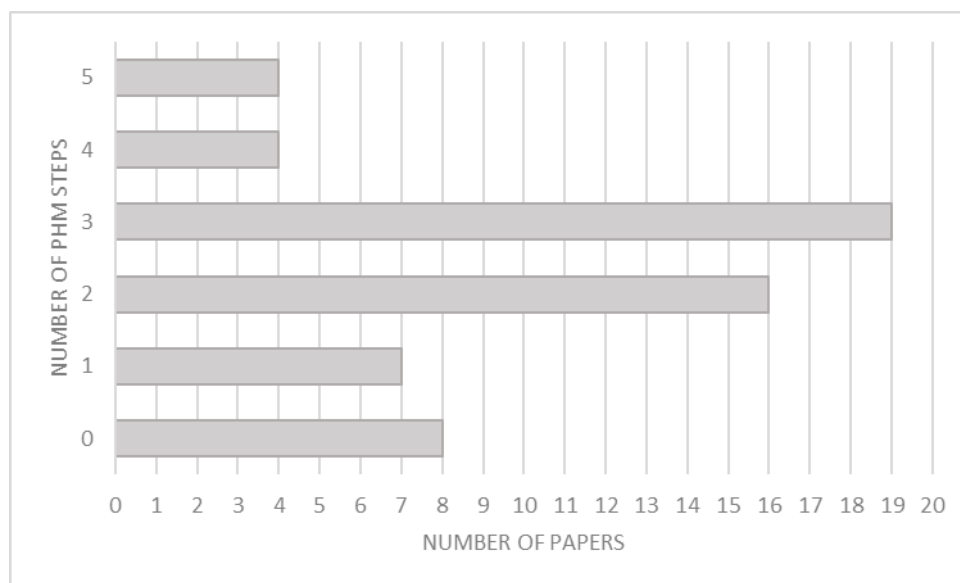


Figure 5 – Number of PHM steps considered in the selected papers

Considering the gap that emerged in the study, a possible future direction could relate to the development of a PHM-integrated system through the employment of ontologies that could serve as the backbone for the integration of the PHM steps. As such, the ontologies would work with other approaches and

algorithms developed at different PHM steps, and due to ontology's capability to provide context awareness and perform reasoning, it will deduce the proper information for the algorithms along the PHM pipeline. Also, when heterogeneous databases of production systems' units are available, the ontology can provide a common semantic level, allowing for queries on heterogeneous databases (Medina-Oliva et al., 2014). In this respect, the heterogeneity and lack of datasets negatively affect machine learning models for predictive maintenance (Dalzochio et al., 2020).

In summary, considering the PHM process as a pipeline in which all the steps are strictly interconnected toward predictive maintenance decision making, the adoption of the ontologies in the process can enhance the communication between the DA, DM, SD, HA, PA, and AG steps. Indeed, this is also straightforward in the framework proposed in Figure 2, where all its modules and steps at operational level are sequential towards the advisory generation. In fact, as reported in the ISO13374-2:2007 and explained in the framework description, each following step along the PHM process is strictly dependent and interconnected with the previous one(s). The SD needs the DA and DM outputs to generate state indicators and boundary exceedances; the HA determines the state of health and potential failures based on the DA, DM, SD outputs; the PA block determines the future state of health and failure modes through the combination of the output of DA, DM, SD, and HA output. Finally, the AG should consider and integrate the information coming from the previous steps to provide optimized recommendation actions to maintenance personnel and external systems.

Ontologies can bring a clearer view of the modeling of concepts, relationships, and properties of the elements of several systems. Indeed, if we think about one single component of a piece of equipment with which to make predictive maintenance decisions, the adoption of specific algorithms and software for the PHM steps could be enough; however, when the predictive maintenance decisions should be taken and coordinated at the production line level on several components, a common ontology could help to optimize maintenance and the AG at the line level, and potentially connect the several PHM modules of the framework.

4.1.3 – Challenge 3: Major exploitation of the combination of data-driven AI, ontologies, and reasoning for predictive maintenance

The potentiality of the combination of data-driven and knowledge-based methods has recently been explored in the literature in several fields. For example, Li et al. (2022) combined deep learning and ontology reasoning for remote sensing image semantic segmentation. In the same context, Moran et al. (2017) highlighted the benefits of the coupling of knowledge-guided ontology reasoning and data-driven machine learning as a promising way to achieve intelligent interpretation of remote sensing imagery. Indeed, several advantages can be achieved through the coupling of the methods because data-driven methods (1) and knowledge-based methods (2) are complementary: the first (1) show advantages in terms of accessibility and accuracy, while the reliability could be poor; however, the second (2) have insufficient performance but good interpretability and context awareness (Li et al., 2022). In the production context, Ji et al. (2019) proposed an approach for predicting defect rates using ontology-supported case-based reasoning and machine learning. They reported that the combination allows for an improvement in the accuracy of the prediction.

Also, in the PHM domain, data-driven AI technologies, such as machine learning and data mining, have been used to detect and predict potential anomalies and, hence, improve production efficiency within

manufacturing processes (Cao et al., 2022). However, both the lack and the excess of heterogeneity of data can impact the predictability of the algorithms (Dalzochio et al., 2020) and therefore their performance. Indeed, industrial data are heterogeneous and often context-dependent, and a uniform knowledge representation is increasingly needed in today's knowledge-intensive industrial context. This highlights the opportunity to combine symbolic AI (as ontologies), reasoning (as SWRL rule-based reasoning), and data-driven AI for predictive maintenance. Predictive maintenance can rely on ontologies because they provide context awareness and allow for the storage of semantic information (Dalzochio et al., 2020). Nevertheless, from the literature conducted, it is interesting to note that only five papers focus on the prognostic assessment step (see Section 3.2.6), and only two of them (Cao, Samet et al., 2020; Cao et al., 2022) combined ontologies, reasoning, and data mining for detecting and predicting potential anomalies within the manufacturing process.

Taking this gap into consideration, a future research direction could be to explore the combination of machine learning, ontologies, and reasoning for the predictive maintenance of today's and future complex systems through the development of combined knowledge-based and data-driven approaches. In this respect, symbolic AI and data-driven AI can support each other and be combined toward the development of predictive maintenance approaches. On the one hand, machine learning algorithms can enable the extraction of concepts and patterns (as machine degradation models) from data or the calculation of information (as specific indices) that can then be enriched due to the querying performed by maintenance domain ontologies and rule-based reasoning on this input data. On the other hand, data from various sources and systems within a facility could be integrated to gather accurate information in order to create accurate prediction models. Finally, a further contribution to this challenge could be related to the exploration of the combination of ontologies, reasoning and data-driven AI in each block or combination of blocks of the PHM framework presented in Figure 2, in particular for PHM-RA, HA, PA and AG blocks, which can benefit from this combination.

4.1.4 – Challenge 4: Supporting sustainability-related challenges through the connections among the production system, maintenance system, and product

Most of the ontologies analyzed in this study contribute to a specific step of the PHM process, and the decisions made by the ontology-based approaches are generally related to the state detection, fault diagnosis, or prediction of anomalies of specific assets in production systems. The maintenance concepts are mainly connected with the machines and equipment, often missing the relations with the process- or product- (for the manufacturing domain) related concepts. Explicitly, the analyzed ontologies are mainly focused on specific PHM phases, thus missing a more holistic view oriented to joint production-maintenance decision making. A first effort in this direction was undertaken by Polenghi et al. (2022a), who connected the product, production assets, and maintenance concepts through the development of the ORMA ontology capable of inferring the product feasibility according to the current health state of the assets. However, a major effort should also be made to exploit PHM potentialities in identifying asset health states to support reactive actions in production scheduling (Polenghi et al., 2022a) and to formalize the relationships among process-product-maintenance.

Such an effort would also enable more sustainable-oriented decisions. Undoubtedly, nowadays, attention to sustainability-related performance is increasing, and production and maintenance processes are no exception (Franciosi et al., 2018; 2021). Maintenance has several direct and indirect impacts on the three dimensions of sustainability that should be considered and formalized in making sustainable-

oriented decisions (Franciosi et al., 2020). Ontologies can help in this direction by modeling and formalizing the existing relationships between the maintenance processes, the physical entities of the production systems, the products, the concepts related to failures, and the deviation of sustainability performance indicators of the production systems, maintenance systems, and products. These relationships between the different concepts, populated with different instances, can create a knowledge base for the design of PHM approaches oriented toward sustainable production processes.

Considering the above gap, a future research direction could be the modeling and formalization of the aforementioned relationships and the development of ontology-based approaches aimed to (1) perform advanced diagnoses of unmonitored failure modes based on the monitoring of the performance at the process level and the deviation of sustainable performance, (2) understand the causes affecting the deviation of monitored sustainability indicators, and comprehend on which failure mode acts in order to reduce the impact on sustainable performance (for example, energy consumption). This systemic vision would help contribute to the sustainability goals of production systems and propose PHM approaches aiming to make sustainable-oriented decisions.

Moreover, ontologies could help improve the sustainability of production systems through the standardization of information, thus reducing waiting times in maintenance processes, thanks to better communication between the different actors involved in industrial maintenance activities (e.g., technicians, engineers, and operators), improving coordination and understanding between the different departments, and increasing the effectiveness of maintenance interventions. This could all contribute to the reduction of production costs and the optimization of resource consumption. In sum, the use of ontologies in PHM can favor greater sustainability of production systems, reducing environmental impact, optimizing energy consumption, reducing costs, and favoring major communication among stakeholders.

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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Author Contribution

All the authors have equally contributed to the conceptualisation of the article, the literature search and data analysis, the writing, the review and the editing of the paper.

Data Availability Statement

All data generated or analysed during this study are properly cited in this article and in its Appendix.

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Appendix

Appendix 1 - Classification of selected papers with respect to the extraction criteria (ii), (iii) and (iv)

ID	Authors (year)	Name	Ontological resources	Non-ontological resources	Methodology	Application
[1]	Al-Shdifat, A, Emmanouilidis, C, Khan, M, Starr, A (2020)	-	-	ISO 13372:2012; ISO 13306, ISO 2041:2009; ISO 55000:2014; and MIMOSA standards	Ontology development 101 (Noy and McGuinness, 2001)	A physical gearbox test rig available at Cranfield University laboratories
[2]	Bekkaoui M., Karray M.-H., Sari Z. (2015)	CMDO (Collaborative Maintenance Diagnosis Ontology)	IMAMO	-	Not specified	-
[3]	Cao, Q., Giustozzi, F., Zanni-Merk, C., de Bertrand de Beuvron, F., Reich, C. (2019)	SCMO (Smart Condition Monitoring Ontology)	MSDL, MASON, MRO, MaRCO, ONTO-PDM (Manufacturing process MODULE); Onto Prog, System Service (Condition Monitoring MODULE); SWRL Temporal Ontology, Spatial ontology (Context MODULE)	-	Ontology Development 101 (Noy and McGuinness 2001, adapted)	Bearings in rotting machinery
[4]	Cao Q. (2018)	Manufacturing CM Ontology	UFO (Unified Foundational Ontology), Semantic Sensor Network (SSN) Ontology, PSL Ontology, SWRL Temporal Ontology, MSDL Ontology, MASON Ontology, Sensor Ontology,	-	Middle-out approach (El Ghosh et al., 2016)	-

			Context Ontology, Product Ontology			
[5]	Cao Q., Samet A., Zanni-Merk C., de Bertrand de Beuvron F., Reich C. (2020, February)	MFPO (Manufacturing Failure Prediction Ontology)- Extended with respect to Cao, Giustozzi, et al. (2019)	-	-	Not specified	Real-world data set called SECOM (Dua and Graff, 2017), which contains measurements of features of semi-conductor productions
[6]	Cao Q., Samet A., Zanni-Merk C., De Bertrand De Beuvron F., Reich C. (2020)	MPMO (Manufacturing Predictive Maintenance Ontology)- Extended with respect to Cao, Giustozzi, et al. (2019)	Time Ontology, Geospatial Ontologies, UFO (Unified Foundational Ontology)	-	Not specified	Semi-conductor manufacturing process
[7]	Cao Q., Samet A., Zanni-Merk C., De Beuvron F.D.B., Reich C. (2019)	MFPO (Manufacturing Failure Prediction Ontology) - Extended with respect to Cao, Giustozzi et al., (2019)	-	-	Ontology development 101 (Noy and McGuinness, 2001) and the Middle-Out approach	“Real-world data set”
[8]	Cao Q., Zanni-Merk C., Samet A., Reich C., Beuvron F.D.B.D., Beckmann A., Giannetti C. (2022)	MPMO (Manufacturing Predictive Maintenance Ontology)	Time Ontology, Geospatial Ontologies, UFO (Unified Foundational Ontology)	-	Not specified	The UCI SECOM data set, which contains measurements of features of semi-conductor production within a semi-conductor manufacturing process.
[9]	Cao, Q., Zanni-Merk, C., Reich, C. (2019)	CM-core ontology	UFO (Unified Foundational Ontology), OntoProg, Domain Ontology for Wind Turbine, Ontology for Intelligent Maintenance Systems and Spare Parts	ISO 13372; ISO 9000; ISO 9001	Ontology development 101 (Noy and McGuinness, 2001)	-

			Supply Chain Integration, Ontology system for the condition assessment of power substation apparatus, Railway Ontology.			
[10]	Chan C.W. (2005)	-	-	-	Not specified	A petroleum production and separator facilities
[11]	Chebel-Morello, B., Rasovska, I., Zerhouni, N. (2005).	-	-	-	Not specified	The pallet transfer system SORMEL
[12]	Chen, R., Zhou, Z., Liu, Q., Pham, D. T., Zhao, Y., Yan, J., Wei, Q. (2015)	-	-	-	Not specified	A rotor
[13]	Cho S., Hildebrand-Ehrhardt M., May G., Kiritsis D. (2020)	Z-BRE4K	IOF (Industry Ontology Foundry), BFO (Basic Formal Ontology), PLC, PSS	-	Not specified	-
[14]	Dendani N., Khadir M., Guessoum S. (2011)	-	OntoTurb	-	Not specified	-
[15]	Dendani-Hadiby, Khadir (2012)	-	OntoTurb	-	Not specified	-
[16]	Ebrahimipour, Yacout (2015)	-	-	ISO 15926; ISO 14224; ISO 14424	Seven steps method (Wang et al., 2010)	Hexane surge tank: the hexane supply pipeline is always under pressure
[17]	Emmanouilidis C., Gregori M., Al-Shdifat A. (2020)	-	-	IEC 60812:2018; ISO 13372:2012; ISO 13306:2017; ISO 2041:2018	METHONTOLOGY, adapted (Lopez et al., 1999)	A distributed fleet of connected industrial printers
[18]	Feng L., Chen G., Chen C., Chen L., Peng J. (2018)	-	-	-	Not specified	A self-priming pump
[19]	Feng L., Chen G., Peng J. (2018)	-	-	-	Not specified	A self-priming pump

[20]	Geng D., Fu X. (2020)	-	-	-	Not specified	A robot arm
[21]	Hossayni H., Khan I., Aazam M., Taleghani-Isfahani A., Crespi N. (2020)	SemKore	-	-	Seven steps method	No application (only a proof of concept)
[22]	Jin G., Xiang Z., Lv F. (2009)	-	-	-	Not specified	No application
[23]	Kharlamov E., Mehdi G., Savković O., Xiao G., Kalaycı E.G., Roshchin M. (2019)	Siemens ontology	Siemens technical System Ontology (TSO), Semantic Sensor Network (SSN) Ontology	IEC 81346; ISO/TS 16952-10	Not specified	2 case studies: train diagnostics and turbine diagnostics
[24]	Kharlamov E., Savković O., Ringsquandl M., Xiao G., Mehdi G., Kalaycı E.G., Nutt W., Roshchin M., Horrocks I., Runkler T. (2018)	-	Siemens technical System Ontology (TSO), Semantic Sensor Network (SSN) Ontology	IEC 81346; ISO/TS 16952-10	Not specified	Rail systems at Siemens
[25]	Kharlamov, E., Solomakhina, N., Özçep, Ö. L., Zheleznyakov, D., Hubauer, T., Lamparter, S., ... & Watson, S. (2014)	-	-	-	Not specified	Siemens monitoring and diagnostic service
[26]	Maleki, E; Belkadi, F; Boli, N; van der Zwaag, BJ; Alexopoulos, K; Koukas, S; Marin-Perianu, M; Bernard, A; Mourtzis, D (2018)	-	-	-	Not specified	A laser-cutting machine
[27]	Matsokis, Kiristis (2012)	-	-	-	Not specified	Lathe Machine
[28]	Medina-Oliva, G, Voisin, A, Monnin, M, Leger, JB (2014)	-	-	IEC 60812	Ontology Development 101 (Noy and McGuinness, 2004 and Rector et al., 2004)	Diesel engines (Naval sector)
[29]	Mehdi G., Roshchin M., Runkler T. (2017)	-	-	-	Not specified	A dataset describing 50 Siemens gas turbines
[30]	Montero	OMSSA	BFO (Basic	ISO 13306;	Ontology	Air compressor

	Jiménez J.J., Vingerhoeds R., Grabot B., Schwartz S. (2022)		Formal Ontology); CCO (Common core ontologies), RO (relation ontology), IMAMO, OntoProg, ROMAIN	ISO/IEC 2382- 14:1997; ISO 13374- 1:2003; IEC 60812:2018; ISO 13379- 1:2012 MIMOSA, 2001	Development 101 (Noy and McGuinness, 2001)	
[31]	Natarajan S., Ghosh K., Srinivasan R. (2012)	OntoSafe	OntoCAPE	-	Not specified	An offshore oil and gas production process: the Kongsberg generic oil and gas production simulator
[32]	Natarajan, S, Srinivasan, R. (2014)	OntoSafe	OntoCAPE	-	Not specified	The Kongsberg ASSETT Generic Oil and Gas Production Simulator, referred to as the offshore oil and gas production process, was used as the test bed for the evaluation of ENCORE
[33]	Nuñez D.L., Borsato M. (2018)	OntoProg (v2)	-	IEC 60812; IEC 60050- 192; SAE J1739; ISO 2041; ISO 13372; ISO 55000	Ontology Development 101 (Noy and McGuinness, 2001)	Centrifugal pump
[34]	Nuñez D.L., Borsato M. (2017)	OntoProg (v1)	-	IEC 60050- 192:2015; ISO 13372: 2012; J1739:2009; ISO 10816- 3: 2006	Ontology Development 101 (Natalya and Deborah, 2001)	Centrifugal pump
[35]	Nuñez D.L., Borsato M. (2016)	OntoProg (v0)	-	SAE J1739, IEC 60050- 192	Ontology development 101 (Natalya and Deborah, 2001)	A bearing component
[36]	Palacios L., Lortal G., Laudy C., Sannino C., Simon L., Fusco G., Ma Y., Reynaud C.	-	-	ISO/TS 15926- 8:2011, 2011; NF EN 13306, 2001	Not specified	-

	(2016)					
[37]	Papadopoulos, P., Cipcigan, L. (2009)	-	-	ISO4406	Top-down modelling approach (M. Schumacher, 2001)	A gearbox of a wind turbine
[38]	Polenghi A., Roda I., Macchi M., Pozzetti A. (2022a)	ORMA	ROMAIN, BFO, IAO, CCO (Common Core Ontologies)	ISO 13374; ISO 14224; IEC 60812	METHONTOLOGY (Fernandez-Lopez et al., 1997)	Flexible Manufacturing Line (at Laboratory-scale)
[39]	Polenghi, A., Roda, I., Macchi, M., Pozzetti, A. (2021)	MOCA	ORMA (based on CCO, IAO, BFO, ROMAIN)	ISO 13306	NeOn, DOGMA	A food company
[40]	Qin H., Jin J. (2020)	-	-	-	Not specified	A tunnel-boring machine
[41]	Rajpathak, DG. (2013)	-	-	-	The ontology development methodology described in Huang and Murphey, (2006).	Automotive Industry (General Motors)
[42]	Rajpathak, D., Siva Subramania, H., Bandyopadhyay, P. (2012)	IVHM ontology	-	-	From Rjpathak et al. (2011)	Real-life data from the automotive domain
[43]	Rasovska I., Chebel-Morello B., Zerhouni N. (2007)	-	-	-	Not specified	The pallet transfer system SORMEL
[44]	Roopa M.S., Pallavi B., Buyya R., Venugopal K.R., Iyengar S.S., Patnaik L.M. (2021)	-	-	-	Not specified	A bearing
[45]	Savković O., Kharlamov E., Ringsquandl M., Xiao G., Mehdi G., Kalayc E.G., Nutt W., Horrocks I. (2018)		Siemens technical System Ontology (TSO), Semantic Sensor Network (SSN) Ontology	IEC 81346; ISO/TS 16952-10	Not specified	Diagnostic use-case at Siemens smart factory
[46]	Sayed M.S., Lohse N. (2014)	-	-	-	Not specified	An assembly station used as an industrial demonstrator in the EU FP7 project FRAME
[47]	Schmidt, B., Wang, L., Galar, D. (2017)	-	-	-	Not specified	-
[48]	Shen, B., Zhao,	-	-	-	Not specified	A CNC lathe

	S. Y., Wang, J. H. (2013)					
[49]	Siaterlis, G., Franke, M., Klein, K., (...), Nikolakis, N., Alexopoulos, K. (2022)	-	-	-	Not specified	An aluminium production company
[50]	Steinegger M., Melik-Merkumians M., Zajc J., Schitter G. (2017)	-	Reference Ontology; CAEX ontology; AutomationML ontology	IEC 61499, IEC 61175, IEC 61131-3	Not specified	Industrial transportation system (laboratory)
[51]	Wang D, Tang WH, Wu QH (2010)	-	-	-	Seven steps method	-
[52]	Xu, F., Liu, X., Chen, W., Zhou, C., Cao, B. (2018)	-	-	-	Seven steps method	A wheel loader
[53]	Yang Z., Qing L., Lu P. (2011)	F-Ont	-	-	Not specified	-
[54]	Zhao X., Ke W., Hu Z., Zhou C., Zhao L. (2015)	AGC (automatic gauge control) fault diagnosis ontology	-	-	Not specified	A hydraulic automated gauge control (AGC) system
[55]	Zhou, A., Yu, D., Zhang, W. (2015)	OKM-MTFD	-	-	Not specified	A wind turbine
[56]	Zhou, Q., Yan, P., Liu, H., Xin, Y. (2019)	OKM-MTFD	-	-	Not specified	A rolling bearing
[57]	Zhou Q., Yan P., Liu H., Xin Y., Chen Y. (2018)	OKM-MTFD	-	-	Not specified	YS3120CNC5 hobbing machine tool: (1) fault diagnosis of rolling bearings; (2) fault diagnosis of gear
[58]	Zhou Q., Yan P., Xin Y. (2017)	OKM-MTFD	-	-	Not specified	YS3120CNC5 hobbing machine tool

Appendix 2 – Classification of selected papers with respect to prognostics and health management process in which the ontology is adopted and with respect to operational/tactical/strategic decisions made.

Authors (year)	ACA	DA/DM	SD	HA	PA	AG	MPS	PH M- RA	Strategical/tactical / operational decisions
Al-Shdifat, A., Emmanouilidis, C., Khan, M., Starr, A. (2020)	•								Operational
Bekkaoui M., Karray M.-H., Sari Z. (2015)	•	•	•			•		•	Operational
Cao, Q., Giustozzi, F., Zanni-Merk, C., de Bertrand de Beuvron, F., & Reich, C. (2019)	•	•	•	•		•			Operational
Cao Q. (2018)	•		•	•		•			Operational
Cao Q., Samet A., Zanni-Merk C., de Bertrand de Beuvron F., Reich C. (2020, February)	•	•	•	•	•	•			Operational
Cao Q., Samet A., Zanni-Merk C., De Bertrand De Beuvron F., Reich C. (2020)	•	•	•	•	•	•			Operational
Cao Q., Samet A., Zanni-Merk C., De Beuvron F.D.B., Reich C. (2019)	•	•	•	•	•	•			Operational
Cao Q., Zanni-Merk C., Samet A., Reich C., Beuvron F.D.B.D., Beckmann A., Giannetti C. (2022)	•	•	•	•	•	•			Operational
Cao, Q., Zanni-Merk, C., Reich, C. (2019)	•								Operational
Chan C.W. (2005)	•			•		•			Operational
Chebel-Morello, B., Rasovska, I., Zerhouni, N. (2005).	•			•		•			Operational
Chen, R., Zhou, Z., Liu, Q., Pham, D. T., Zhao, Y., Yan, J., Wei, Q. (2015)	•			•		•			Operational

Cho S., Hildebrand-Ehrhardt M., May G., Kiritsis D. (2020)	•								Strategic/Tactical/Operational
Dendani N., Khadir M., Guessoum S. (2011)	•			•					Operational
Dendani-Hadiby, Khadir (2012)	•			•					Operational
Ebrahimipour, Yacout (2015)	•			•		•			Operational
Emmanouilidis C., Gregori M., Al-Shdifat A. (2020)	•								Not Specified
Feng L., Chen G., Chen C., Chen L., Peng J. (2018)	•	•		•		•			Operational
Feng L., Chen G., Peng J. (2018)	•	•		•		•			Operational
Geng D., Fu X. (2020)	•			•		•			Operational
Hossayni H., Khan I., Aazam M., Taleghani-Isfahani A., Crespi N. (2020)	•			•		•			Operational
Jin G., Xiang Z., Lv F. (2009)	•								Operational
Kharlamov E., Mehdi G., Savković O., Xiao G., Kalaycı E.G., Roshchin M. (2019)	•	•		•		•			Operational
Kharlamov E., Savković O., Ringsquandl M., Xiao G., Mehdi G., Kalaycı E.G., Nutt W., Roshchin M., Horrocks I., Runkler T. (2018)	•	•		•		•			Operational
Kharlamov, E., Solomakhina, N., Özçep, Ö. L., Zheleznyakov, D., Hubauer, T., Lamparter, S., ... & Watson, S. (2014)	•	•		•		•			Operational
Maleki., Belkadi, F., Boli, N., van der Zwaag, BJ., Alexopoulos, K., Koukas, S., Marin-Perianu, M., Bernard, A., Mourtzis, D. (2018)	•					•		•	Operational
Matsokis, Kiristis (2012)	•	•	•			•			Operational
Medina-Oliva, G., Voisin, A., Monnin, M., Leger, JB. (2014)	•	•		•		•			Operational

Mehdi G., Roshchin M., Runkler T. (2017)	•	•		•		•			Operational
Montero Jiménez J.J., Vingerhoeds R., Grabot B., Schwartz S. (2022)	•					•	•		Strategic/Tactical
Natarajan S., Ghosh K., Srinivasan R. (2012)	•	•	•	•		•			Operational
Natarajan, S; Srinivasan, R (2014)	•	•	•	•		•			Operational
Núñez D.L., Borsato M. (2018)	•		•	•		•			Operational
Núñez D.L., Borsato M. (2017)	•		•	•		•			Operational
Núñez D.L., Borsato M. (2016)	•								Operational
Palacios L., Lortal G., Laudy C., Sannino C., Simon L., Fusco G., Ma Y., Reynaud C. (2016)	•								Operational
Papadopoulos, P., Cipcigan, L. (2009)	•	•	•			•			Operational
Polenghi A., Roda I., Macchi M., Pozzetti A. (2022a)	•		•			•			Operational
Polenghi, A., Roda, I., Macchi, M., Pozzetti, A. (2021)	•					•	•		Strategic
Qin H., Jin J. (2020)	•								Operational
Rajpathak, DG. (2013)	•	•		•		•			Strategic/Operational
Rajpathak, D., Siva Subramania, H., & Bandyopadhyay, P. (2012)	•	•		•					Operational
Rasovska I., Chebel-Morello B., Zerhouni N. (2007)	•			•		•			Operational
Roopa M.S., Pallavi B., Buyya R., Venugopal K.R., Iyengar S.S., Patnaik L.M. (2021)	•	•	•		•	•			Operational
Savković O., Kharlamov E., Ringsquandl M., Xiao G., Mehdi G., Kalayc E.G., Nutt W., Horrocks I. (2018)	•	•		•		•			Operational
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