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Advancing Fault Diagnosis through Ontology-Based Knowledge Capture and Application

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ABSTRACT This article addresses a critical gap in the field of fault diagnosis for complex systems, focusing on the development and application of an ontology-based approach to capture and utilize expert knowledge. The key objective is to enhance fault diagnosis precision and effectiveness, specifically in challenging No-Fault-Found (NFF) scenarios, by harnessing the extensive, often implicit, understanding of seasoned professionals. The study uses a comprehensive methodology that includes creating a specialized ontology called DIAGONT, which captures the expert reasoning in fault diagnosis. Field experts contribute to the development of this ontology, ensuring its relevance and applicability. Real-world case studies and controlled experiments are used to rigorously validate the ontology. The goal of these experiments is to evaluate how effective the ontology is in enhancing fault diagnosis procedures when compared to traditional methods. Our case studies focused on two complex engineering assets, a loading arm and a helicopter mission system, due to their complexity and the frequency of non-functional failure scenarios. The analysis shows that using the DIAGONT ontology leads to improved accuracy and efficiency in fault diagnosis. A structured format allowed experts to successfully capture and reuse diagnostic knowledge, resulting in a noticeable reduction in NFF scenarios. The application of ontology-based approach exhibited potential in enhancing knowledge transfer between experts and less experienced technicians, potentially resulting in long-lasting improvements in maintenance practices. The results highlight how ontology-based systems can improve fault diagnosis in complex engineering systems.

INDEX TERMS Data integration, knowledge management, fault diagnosis, ontology-based reporting, ontology-based monitoring, semantic web, no-fault-found

I. INTRODUCTION

Industry 4.0 has led to major advancements in domains like Cyber-Physical Systems, Artificial Intelligence, and Augmented Reality [1-4]. These advancements have not only made it easier for different devices to exchange data automatically, but they have also brought about real-time data management and process optimization. Nevertheless, this automation presents its unique difficulties, specifically in data collection and identifying errors. Barriers to its broader implementation include data heterogeneity and unstructured data sources. With the rise of automation comes an increased occurrence of faults, emphasizing the importance of robust fault diagnosis systems. Effective fault diagnostics and addressing these challenges are essential for the uninterrupted operation of assets. Fault investigation usually depends on unorganized diagnostic reports, which require extensive knowledge and aim to trace a failure's root cause from the first symptom. Despite the increasing use of automated diagnostic systems, the knowledge and skills of field professionals are still crucial, particularly in cases where automated solutions are inadequate, like No-Fault-Found (NFF) situations [7]. NFF signifies ineffective efforts in fault analysis where no definitive cause is pinpointed, often because of inadequate failure modes in diagnostic systems.

Accurate reporting is essential for effective diagnostics, which involves identifying failure modes and conditions. The use of structured formats for capturing experts' knowledge can help overcome the challenges of insufficient failure modes. This structured approach to knowledge capture enhances maintenance efficiency and effectiveness, while also facilitating the reuse of expert knowledge by others in activities like repair or monitoring. This approach is crucial for maximizing the benefits of Industry 4.0 advancements, enhancing fault diagnosis processes [5-10].

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The robust expressiveness and logical reasoning support of ontology make it a powerful tool for semantics-based knowledge representation, particularly in intelligent fault diagnosis in maintenance applications [11]. Ontologies have played a key role in organizing and linking information from unstructured sources in maintenance diagnosis research. Two main areas where their application has been extensively studied are diagnosis decision support and data modeling for maintenance planning. Some notable examples involve utilizing natural language processing to analyze diagnosis reports and employing fault propagation modeling for maintenance planning. The literature lacks ontology-based methods for capturing and reusing expert diagnosis knowledge to enhance monitoring systems, leading to lower fault diagnosis efficiency. Failure modes are frequently identified by experts using unstructured data, like inconsistent signals, to determine component conditions. If a systematic structure were applied to these conditions, monitoring systems could see significant improvements by imitating the identification of such conditions. A gearbox failure can be detected by an expert based on auditory cues like a 'cranky' sound or visual indicator like a 'corroded' surface. Quantifying these observations would allow monitoring systems to detect them with devices such as microphones and cameras. To implement this approach, we need AI that can interpret diverse data sources and a framework to organize the expert's diagnostic reasoning.

Although there is growing research in AI for capturing heterogeneous data, there is a lack of academic work on organizing experts' diagnostic reasoning. Thus, improving techniques for acquiring and organizing expert knowledge in diagnosing is a crucial research hurdle in Industry 4.0. Tackling this challenge has the potential to greatly improve fault diagnosis systems. The main goal of this study is to create and apply an ontology-based method for capturing and reusing expert knowledge in fault diagnosis. The purpose of this approach is to address research gaps and improve fault diagnosis in complex systems. Its objective is to enhance diagnostic accuracy and minimize NFF incidents.

The findings of this study are highly relevant for diagnosing and maintaining complex systems. The use of expert knowledge and an ontology-based approach improves fault diagnosis methods, resulting in more accurate, efficient, and reliable maintenance processes that enhance system reliability and longevity.

In summary, the research evaluated three hypotheses:

- Ontology Schema for Representing Experts' Rationale
    - The initial hypothesis suggested that the ontology's schema accurately reflects experts' reasoning on diagnostic tasks.
    - Validation is done through methods like expert interviews and analyzing the structure of the ontology. The goal was to verify that the ontology accurately represents and mirrors the experts' reasoning and decision-making in diagnostic activities.
- The value of reporting methods in capturing expert knowledge:
    - According to the second hypothesis, the suggested reporting method is valuable for capturing experts' knowledge in diagnosis tasks.
    - Validation involves testing the usability of the reporting tool through expert feedback and user surveys. The objective was to assess if the reporting method helps document and capture expert knowledge for fault diagnosis.
- The influence of the monitoring technique on diagnostic efficiency and effectiveness.
    - According to the third hypothesis, the monitoring method improves diagnostic efficiency and effectiveness.
    - Efficiency, effectiveness experiments, and usability surveys are used for evaluation. The objective was to evaluate if the integrated monitoring method, incorporating expert knowledge from diagnostic reports, enhances the efficiency and effectiveness of fault diagnosis compared to traditional methods.

The remainder of the article is organized in the following manner: the introduction establishes the research background, explaining the context and importance of the study. In Section 2, the current literature on ontology in fault diagnosis is thoroughly reviewed, identifying research gaps and establishing the study's objectives. The methodology for the ontology-based approach is described in detail in the following section. Section 4 explains how expert involvement and feedback were incorporated into the approach. Section 5 provides details about the tools and software utilized to implement the ontology, demonstrating its practical application. This is followed by a case study and discussions in Section 6, and concluding remarks.

II. LITERATURE REVIEW

A. Literature Review on Ontology in Fault Diagnosis

Identifying the causes of failures or abnormal behaviors in assets is crucial through failure diagnosis [15]. Maintainers typically follow this process, which includes formulating and testing hypotheses to diagnose the root causes of failures. It covers various areas of knowledge like failure modes and dismantling equipment.

Failure diagnosis applications benefit greatly from the use of ontologies, which define information and its relationships

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within specific domains [16]. They are highly skilled at sorting information from unorganized sources and have been used in different maintenance operations, such as decision support and maintenance planning. For example, ontologies have been used in natural language processing of diagnosis reports to suggest failure modes and assist in maintenance planning.

Over the past decade, studies have consistently shown the effectiveness of ontology-based methods in fault diagnosis across different domains. The role of ontology is highlighted for improving diagnostic accuracy, knowledge sharing, and integrating machine learning for enhanced fault diagnosis. Liu (2019) made a notable contribution to this field by presenting a comprehensive review of ontology-based fault diagnosis over the past decade [39]. Ontology-based methods have gained attention for their support in logical reasoning and knowledge sharing, as highlighted by the authors. The authors highlight the benefits of combining ontology with other methods for better fault diagnosis. The suggestion is to combine machine learning and ontological engineering for comprehensive fault diagnosis knowledge.

An important aspect to consider is data granularity, which pertains to the level of detail in the information description. In the context of ontologies, this is commonly depicted by the count of properties and relationships belonging to a class. The academic literature demonstrates the use of various failure diagnosis ontologies in a wide range of maintenance operations and case studies, including both rockets and factory settings. Many of these methods revolve around recognizing flaws and categorizing them as symptoms, traces, or causes, often utilizing techniques like FMEA. On the contrary, failure modes refer to the physical events that lead to component failures. Zhao et al. exemplified this by utilizing ontology to represent fault diagnosis knowledge in hydraulic systems [18]. The authors systematically analyze faults, including their interconnections, and emphasize the benefits of ontology for knowledge expansion and reuse. Its reliability and practicality are confirmed through a case study.

Sensor data plays a vital role in many reviewed ontologies, helping set fault analysis thresholds and showcasing the value of data integration for knowledge reuse. This research aims to fill the gap of limited research on structuring experts' diagnosis rationale. This research aims to improve fault diagnosis in monitoring systems by using ontology-based reporting and monitoring methods to capture experts' diagnosis knowledge. This involves creating an ontology to capture experts' reasoning, a reporting tool based on ontology for describing diagnosis activities, and a monitoring tool based on ontology for identifying real-time monitoring rules through inferencing.

The use of failure diagnosis ontologies has greatly aided in managing and analyzing diagnosis-related information [19]. The ontologies have multiple purposes, customized for specific case studies and maintenance operations, especially in planning and prognosis areas. In general, failure diagnosis ontologies are classified into two primary groups, as outlined in Table 1.

- Ontologies for data modelling: serve as the foundation for applications that go beyond diagnosis by representing system behavior. Understanding complex systems and foreseeing potential failures heavily rely on these models. They frequently utilize advanced computational techniques such as probabilistic algorithms and neural networks to enhance analysis and prediction accuracy.
- Data capture ontologies: place an emphasis on the organization and capture of sensor data to improve diagnosis. The collection and utilization of real-time data for fault diagnosis heavily rely on these ontologies. To improve maintenance operations, they frequently use SWRL rules and case-based reasoning systems to analyze sensor data and historical records, thus enhancing accuracy and efficiency.

Table 1: Tailoring ontologies for various applications

Application	Paper Reference
Ontologies for Data Modelling:	
Fault propagation analysis in ventilation systems	Ferrari et al. [27]
Analysis of system component connections using SWRL rules	Dibowski, Holub, Rojíček [13]
Power transformer behaviour modelling and neural network integration	Akbari et al. [21]
Analysis of interconnected electronic system failures in cars	Behravan, Meckel, Obermaisser [26]
Roller model for continuous monitoring and contextual linking	Mishra and Thaduri [23]
Manufacturing plant model for maintenance planning and alarm classification	Bekkaoui et al. [17]
Probabilistic modelling of system interconnections for fault analysis	Ferrari et al. [27]
Ontologies for Data Capture:	
Historical data analysis for aircraft maintenance	Aircraft case study [24]
Wind turbine maintenance and fault analysis	Wind turbine case study [6]
Pneumatic system failure diagnosis	Pneumatic system case study [20]
Fleet-wide predictive diagnosis using SWRL rules	Medina-Oliva et al. [15]
Decision support for maintenance experts using experience models	Bekkaoui, Karray, Sari [28]
Case-based reasoning for failure prediction in diverse systems	Khadir and Klai [22], Dendani, Khadir, Guessoum [29], Wang et al. [30]
Linking failure diagnosis with equipment operation and repair scenarios	Rajpathak and Chougule [16]
Utilizing ontologies for predictive maintenance in manufacturing	Manufacturing case study [17]
Advanced text mining for unstructured data classification in fault diagnosis	Zhong et al. [12], Xu et al. [18], Zhou et al.

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	[25], Rajpathak and Singh [19]

B. Identifying gaps in the present research

The literature review on ontology in fault diagnosis has identified certain gaps:

- Despite advancements in ontology-based fault diagnosis, there is still potential for improved integration with emerging technologies such as machine learning and artificial intelligence. Liu et al. (2019) propose that the integration of ontology and machine learning can enhance fault diagnosis knowledge, highlighting a potential research gap in their combined application.
- Theoretical models and simulations are abundant, but there is a lack of real-world implementation and testing for these systems. Widespread practical applications are necessary to prove the effectiveness of ontology-based systems in real operational environments.
- The current literature lacks extensive coverage of usability and user interface design for ontology-based diagnostic tools. Further research is required to improve the user-friendliness and accessibility of these systems, with a focus on human-computer interaction.
- The development of fault diagnosis ontologies lacks standardization and interoperability. This creates difficulties in ensuring compatibility across various systems and tools. Standardized frameworks and protocols are required for ontology creation and implementation in fault diagnosis.
- The research on enhancing data granularity in diagnosis activities appears to be limited. This pertains to the reduction of unorganized text in applications like expert assistance and prediction.
- Academic literature lacks ontologies that capture maintainers' diagnosis rationale.
- Despite previous research on ontologies in data modelling, there is a lack of studies on reusing experts' knowledge with these ontologies.

This research will address the last three gaps by proposing methods that improve data granularity in fault diagnosis. It will achieve this by developing an ontology-based approach to capture and utilize expert knowledge and rationale from maintainers. The purpose of the 'diagont' ontology schema is to model how subject-matter experts approach diagnosis. The schema encompasses classes, attributes, relationships, and corresponding axioms. Experts continuously update the schema based on feedback to ensure an accurate representation of their diagnostic rationale. Experts' diagnosis knowledge is effectively captured and reused through ontology-based diagnosis reporting and monitoring methods.

C. Contributions of This Work

This article adds to the following areas, in comparison to the studies mentioned in this review.

- Evaluating data granularity: Numerous studies primarily concentrate on identifying major faults. The focus of this work is on capturing in-depth diagnostic activities, which includes the reasoning behind experts' decisions. The purpose of providing this level of detail is to minimize unorganized text in applications like expert assistance and prognosis, resulting in improved accuracy of diagnostic procedures.
- Current literature lacks emphasis on structuring experts' diagnostic reasoning. Through the creation of 'diagont,' an ontology schema is developed to capture the reasoning behind diagnosis activities performed by experts. The schema contains precise classes, attributes, relationships, and axioms that accurately depict expert diagnostic knowledge, making it easier to reuse for future maintenance tasks.
- Current research often overlooks the integration of ontology-based methods with real-time monitoring systems. This integration enables a flexible and adaptable diagnostic environment that can handle new data and changing conditions, resulting in a stronger solution for fault diagnosis in operational settings.
- Exploring novel approaches to combining ontology and machine learning, inspired by Liu et al.'s (2019) suggestion on data-driven synergy. The study aims to improve fault diagnosis accuracy and completeness by combining ontology and machine learning algorithms.

III. METHODOLOGY

A. Detailed description of the ontology-based approach

This study uses the Design Science Research (DSR) methodology [32], taking inspiration from related studies [9,19,33] and following established practices in ontology literature [34,35]. The DSR methodology consists of multiple steps that contribute to research development and validation.

- To identify objectives, start by defining the specific opportunity and explaining the value of a solution.
- The design solution targets the identified research opportunity. The NeON methodology [36] was used to develop the ontology in this case.

- The solution's effectiveness was demonstrated by developing research contributions into software tools and conducting experiments in two separate case studies.
- The impact of the solution is assessed using different experimental methods in the case studies to validate achievements. The methods used are ontology structure analysis, expert interviews, usability surveys, and efficiency and effectiveness experiments.

To enhance the efficiency and effectiveness of fault diagnosis, expert diagnosis knowledge can be captured and re-used.

- Creating an ontology that connects expert diagnoses with asset conditions using quantitative measures.
- Creating a cloud-based reporting system that uses ontology-inferred forms to capture experts' knowledge in diagnosis reports.
- Developing a cloud-based monitoring approach that uses real-time ontology inferencing to create and oversee control rules using expert reports and fresh sensor data.

The reporting and monitoring methods using an ontology approach are depicted in Figure 1 of the methodology framework. It outlines the necessary steps for retrieving and applying expert diagnosis knowledge in fault diagnosis tasks. Experts can generate new reports as needed for each failure using forms based on the ontology's schema. Once finished, these forms are sent to the ontology's knowledge base. The monitoring method ensures real-time operation, using sensor control rules, expert reports, and sensor data in a continuous loop for up-to-date monitoring and diagnosis. Each proposed method is explained in-depth in the following subsections.

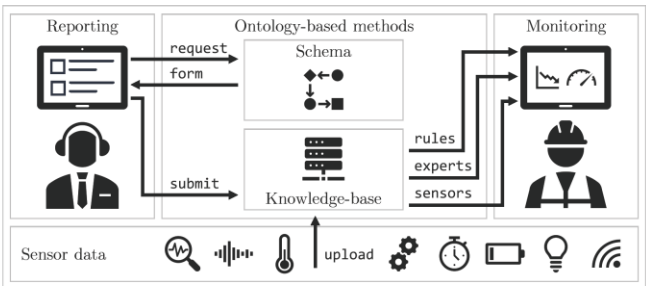

Figure 1. A framework for the proposed ontology-based expert diagnosis reporting and monitoring methods.

1) Experts' diagnosis rationale ontology (Diagont)

This subsection presents the specialized ontology created for expert diagnosis and condition monitoring. The quantification of asset conditions, a crucial aspect of the ontology, is highlighted.

Ontologies can be used as a foundation for organizing expert knowledge and monitoring asset conditions systematically using measurable parameters. To address the gap in integrating expert diagnosis logic into monitoring systems, a diagnosis rationale ontology (diagont) is proposed, designed using the NeOn methodology. The method successfully connects knowledge with quantitative measures using data structures that outline procedural knowledge in basic steps. Several key stages were involved in the development process of diagont.

- The authors completed a thorough literature review to identify pertinent papers and define their areas of expertise. Establishing a foundational understanding of the academic landscape and relevant knowledge domains was essential for expert diagnosis.
- Developing a conceptual ontology model by incorporating insights from the literature review. This model acted as an initial framework for capturing the procedural knowledge and logic employed by experts in diagnostic tasks. Conducting expert interviews refined the conceptual model into a formal ontology. The interviews gathered feedback from experts, ensuring the ontology accurately reflected real-world diagnosis processes.

Competency Questions:

The CQs are based on expert interviews and used to develop the ontology. These questions guarantee that the ontology fulfills the practical requirements of fault diagnosis and encompasses all essential aspects. The following competency questions were used to guide our ontology development process:

Diagnosis Documentation:	
Q1	CQ1: How can the system document the rationale behind each diagnostic step performed by an expert?
Q2	CQ2: How can the ontology capture and represent the detailed sequence of actions taken during fault diagnosis?
Real-Time Data Integration:	
Q3	How can real-time sensor data be integrated into the ontology to update diagnostic information dynamically?
Q4	How can the ontology support real-time monitoring and alert generation based on sensor data?
Knowledge Reuse and Sharing:	

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Q5	How does the ontology enable the sharing of expert knowledge across diverse systems and domains?
Q6	How can the ontology enable seamless knowledge sharing between various maintenance teams and systems?
Error Reduction and Automation:	
Q7	What methods can the ontology use to reduce errors by minimizing manual intervention in data entry and updates?
Q8	How can automated inferencing rules be applied to enhance the accuracy and efficiency of fault diagnosis?
Interoperability:	
Q9	How can the ontology ensure interoperability with existing systems and data sources?
Q10	In what ways does the ontology structure facilitate the integration of diverse data from various sources?

Ontology Structure:

The ontology model is depicted in Figure 2, highlighting its classes and relationships. The ontology aims to clarify how experts justify diagnoses and connect them with monitoring tool logic.

- The ontology comprises classes such as 'Task,' 'Step,' 'Failure,' and 'State' to explain the rationale behind diagnosis.
- The condition monitoring logic is represented by classes such as 'Monitor,' 'Auditor,' 'Failure,' and 'State.' The purpose of a "Monitor" is to identify a "Failure" by utilizing different "Auditors" that observe distinct "States" of "Components." When these assessments match, the 'Monitor' is considered to have experienced a 'Failure.'
- The ontology's attributes, like 'hasComparison,' play a crucial role in inferring knowledge for reporting and monitoring methods. The attributes in Table 2 are created with specific data types to reduce the need for unstructured text in diagnosis reporting, improving the clarity and structure of the captured information. Table 3 lists the datatypes and their corresponding value sets. You can find the full schema of 'diagont' at https://www.doi.org/10.17862/cranfield.rd.12279152.

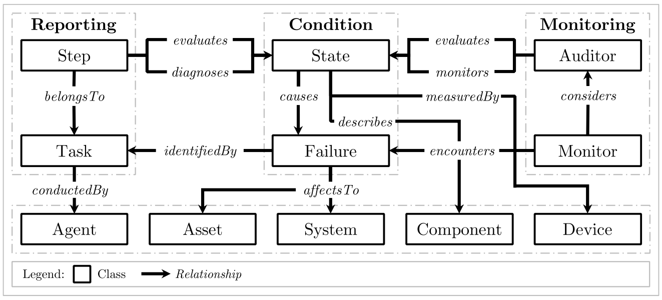

Figure 2. Depiction of class and relationships of diagont's ontology schema.

Table 2. Depiction of classes and attributes of diagont's ontology schema.

Task		**Failure**		**Monitor**	
hasDescription	*string*	hasDescription	*string*	hasDescription	*string*
		hasImpact	*impact*		
		hasDomain	*domain*		
		hasPhenomenon	*phenomenon*		
		hasImage	*anyUri*		
		hasAudio	*anyUri*		
Step		**State**		**Auditor**	
isCritical	*boolean*	hasStatus	*status*	isValidated	*boolean*
isContributory	*boolean*	hasDomain	*domain*	hasComparison	*comparison*
hasObject	*object*	hasPhenomenon	*phenomenon*		
hasMethod	*method*	hasMeasureValue	*double*		
hasComparison	*comparison*	hasMeasureUnit	*unit*		
		hasMeasureDate	*date*		

Legend: **Class** | Attribute | *Datatype*

Table 3. Summary of diagont's proprietary attributes datatypes.

impact	**status**	**domain**	**phenomenon**		
local	*normal*	*mechanics*	*fracture*	*thermal shock*	*signal error*
global	*safely degraded*	*electrics*	*fatigue*	*thermal runaway*	*error*
	unsafely degraded	*electronics*	*corrosion*	*short circuit*	*material*
	faulty	*hydraulics*	*impact*	*open circuit*	*process*
		pneumatics	*blockage*	*electric loss*	
		humanics			
object	**method**	**comparison**	**unit**		
symptom	*inspect*	*equal to*	*metre*	*pascal*	*hertz*
trace cause	*measure*	*not equal to*	*degree*	*joule*	*watt*
	repair	*greater than*	*kilogram*	*mol*	*ampere*
	replace	*less than*	*second*	*kelvin*	*volt*
		less than or equal to	*newton*		*ohm*
		greater than or equal to			

Legend: datatype | *datavalue*

Capturing the Nuanced logic of Experts

The purpose of the DIAGONT ontology is to accurately represent the rationale of experts in fault diagnosis. Multiple key features and processes are involved in achieving this.

- Systematic outline of diagnostic steps:
    - The ontology consists of classes like 'Task', 'Step', 'Failure', and 'State'. The classes are interconnected to show the sequence and logic of diagnostic activities. One example is that a 'Task' consists of several 'Steps', where each step involves assessing the component's state to detect a failure.
    - Detailed attributes for each class capture specific details like the methods used, objects involved, and comparisons made. The detailed granularity guarantees documentation of every aspect of the expert's reasoning.
- Capturing Procedural Knowledge:
    - Types of faults and their interrelationships are described using ontology elements such as 'Symptom', 'Trace', and 'Cause'. It facilitates a comprehensive diagnostic process, covering symptom identification to root cause analysis.
    - The ontology includes quantitative measures, like 'hasMeasureValue' and 'hasMeasureUnit', to record the precise parameters and thresholds utilized by experts in diagnosis. The diagnostic process can be accurately replicated with this method.
- Integration and inference of real-time data.
- Integration of sensor data: Real-time data from sensors is incorporated into the ontology, allowing for live updates and monitoring. By doing this, the diagnostic process is based on the most recent data, accurately reflecting the system's current state.
- SWRL rules automate inferencing, allowing the system to derive new knowledge and update diagnostic rules with incoming data. The expert can adjust and improve their diagnosis as new information emerges.

2) Reporting expert diagnoses based on ontology

The focus of this subsection is on inferencing rules that are essential for creating reporting forms. The forms are based on the ontology's elements, guaranteeing data consistency with the ontology's structure. It clarifies the formulation and application of these rules in order to create accurate forms that reflect the ontology's schema, allowing experts to input their diagnoses in a structured and coherent way.

The intended ontology aims to capture experts' reasoning in diagnosing activities, with a focus on documenting their understanding of failure modes and conditions. Experts need tools to report their diagnostic activities in real-time without disrupting their workflow. Due to the intricate nature of interfaces and the need for specialized knowledge in ontology modelling, conventional ontology editing software like Protégé may not be the most convenient option for this task. We propose a simplified cloud-based reporting method that utilizes web forms based on ontology classes. The main objective of this approach is to mirror the ontology's reasoning in web forms, reducing disruption to diagnostic activities. The reporting method includes the following details:

- The proposed reporting method and its inferencing rules in SWRL notation are depicted in Figure 3. The process starts with a user request, which includes choosing an ontology class from a hierarchical menu in the cloud, as depicted in Figure 4. The SWRL rule "rdfs:subClassOf(?c)" is used to structure this hierarchy.
- The method infers attributes ("owl:DatatypeProperty(?a)") and relationships ("owl:ObjectProperty(?r)") upon a user's request. Users can create new individuals or reference existing ones while filling out the form, as it identifies all individuals linked by the retrieved relationships ("?r(?x,?i)").
    - The inferred data is used by a web template to create a form for the user. The reporting method reviews the form submission for any individuals marked as "new" by the user. When new individuals are found, the method automatically asks for their classes to make new forms in different tabs, making it easier to move between forms in the report.

The intuitive and user-friendly interface of this cloud-based reporting method simplifies the knowledge capture process for experts. It enables efficient and accurate recording of diagnostic activities, capturing expert insights in a structured and accessible way. By improving data quality and respecting expert workflows, this approach is a practical solution for real-time knowledge capture in fault diagnosis.

The diagont ontology's rationale is demonstrated visually in Figure 4, showing the forms for reporting a simple diagnosis task with a focus on 'Task' and 'Step' aspects. Here is the outlined process for an expert to report a diagnosis activity using this method.

- Reporting a 'Task':
    - The expert starts by discussing a diagnosis-related 'Task'. The first step

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establishes the context for the following diagnostic steps and outlines the overall objective of the diagnosis.

- Reporting 'Steps' for Each Fault:
    - The expert provides a distinct 'Step' for each fault found during the diagnosis, which could be a 'symptom', 'trace', or 'cause'. By taking a granular approach, we ensure thorough documentation of every aspect of the fault.
- Declaring 'States' for Each 'Step':
    - The expert identifies and diagnoses the evaluated 'States' within each 'Step' to determine the fault. This involves providing specific conditions or observations that led to identifying each fault aspect.
- Reporting the 'Failure':
    - The expert reports the 'Failure' discovered once the root cause is determined to be a 'Step'. The diagnostic report is finalized by connecting the identified faults to the asset's overall failure.

In diagont, the user can declare all attributes and relationships associated with the specific class, as listed in Table 2 and shown in Figure 2. Users can thoroughly document every aspect of the diagnosis with this feature. To enhance its versatility, it utilizes generic SWRL rules ("owl:" and "rdfs:") instead of ontology-specific ones ("diagont:"). Furthermore, it can detect unasserted attributes or relationships in a submitted form without classifying them as errors, preserving the ontology's open-world assumption.

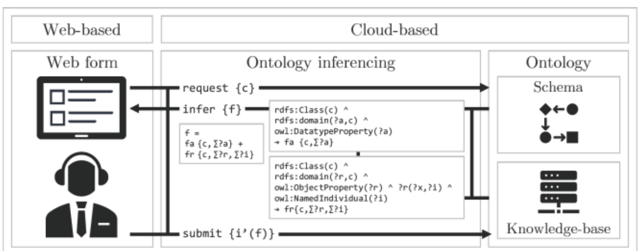

Diagram 3 illustrates the methodology of expert reporting based on ontology and its inferencing rules. SWRL rules are used to present inferencing rules that identify datatype and object properties for a specific class, and individuals created through object properties are used to generate a reporting form when requested by the user.

Figure 4. Demonstration of the ontology-based expert reporting tool. The screenshots in Figure 3 demonstrate different reporting steps.

3) Utilizing ontology for real-time monitoring and expert recommendations

This section explains the inferencing method created to convert expert reports into practical monitoring rules. It explains the effective assessment of asset conditions by combining sensor data with expert reports. The subsection explains how qualitative expert insights are transformed into measurable monitoring parameters, improving the accuracy and dependability of the condition monitoring process.

Identifying abnormal behaviors is a crucial part of condition monitoring, which helps maintain physical assets. Typically, it includes three important steps: acquiring data, processing data, and making decisions. Literature mainly focuses on data-driven or analytical monitoring methods, with fewer knowledge-based approaches. Existing methods are usually customized for specific assets and lack versatility in knowledge re-use.

The monitoring method proposed in this research combines data-driven, analytical, and knowledge-based approaches to overcome these limitations. The goal of this integration is to use expert knowledge from diagnostic reports to improve the monitoring process. The approach uses ontology inferences to transform expert knowledge into monitorable rules, similar to data-driven or analytical methods. In monitoring methods, this conversion happens prior to the usual steps of data acquisition, data processing, and decision-making.

The process illustrated in Figure 5 shows how monitoring rules are inferred from expert diagnosis reports. Figure 6 illustrates the integration of data- and analytical-driven monitoring approaches in these steps. The method displays 'Monitors' and 'Auditors' assigned to a specified 'Asset' and retrieves reported 'Tasks' and 'Steps' for the same 'Asset'. Using a SWRL rule, it effectively applies expert knowledge to infer additional 'Monitors' and 'Auditors' from these reports. The most recent 'States' assessed by each 'Auditor' are implied, and can be added either manually through expert reports or automatically through 'Devices'. The method assesses the control monitoring rule (Auditors) and each 'Monitor' to propose a decision on controlling the 'Failures'.

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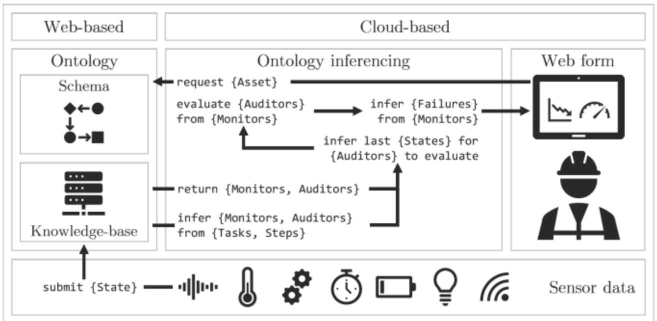

Utilizing ontology, real-time sensor control, and experts' recommendations in monitoring (Figure 5). The data retrieval and inferencing steps are used to infer monitoring rules from expert diagnosis reports and merge them with data- and analytical-driven monitoring approaches. Figure 6 illustrates the inferencing steps referred to as SWRL rules.

```
Infer {Monitors, Auditors} from {Tasks, Steps}:

Failure(?a) ^
Task(?b) ^
Step(?c) ^
State(?d) ^
identifiedBy(?a,?b) ^
belongsTo(?c,?b) ^
isContributory
    (?c,true) ^
diagnoses(?c,?d)
→
Auditor(?c) ^
Monitor(?b) ^
considers(?b,?c) ^
monitors(?c,?d)
```

```
Infer last {States} for {Auditors} to evaluate:

Auditor(?a) ^
State(?b) ^ State(?c) ^
Device(?d) ^
Unit(?e) ^ Unit(?f)
monitors(?a,?b) ^
measuredBy(?b,?d) ^
measuredBy(?c,?d) ^
hasMeasureUnit(?b,?e) ^
hasMeasureUnit(?c,?f) ^
hasMeasureDate(?b,?g) ^
hasMeasureDate(?c,?h) ^
swrlb:equal(?e,?f)
swrlb:greaterThan(?h,?g)
→
sqwrl:select(?c,?h) ^
sqwrl:orderBy(?c,?h) ^
swrlb:first(?c) ^
evaluates(?a,?c)
```

```
Evaluate {Auditors} from {Monitors}:
Auditor(?a) ^
hasComparison
    (?a,?comparison) ^
evaluates(?a,?b) ^
hasMeasureValue(?b,?c) ^
hasMeasureUnit(?b,?d) ^
hasMeasureDate(?b,?e) ^
monitors(?a,?f) ^
causes(?g,?h) ^
hasMeasureValue(?f,?h) ^
hasMeasureUnit(?f,?i) ^
hasImpact(?f,?j) ^
hasDomain(?f,?k) ^
hasPhenomenon(?f,?l) ^
swrlb:?comparison(?c,?h) ^
swrlb:equalTo(?d,?i)
→
Failure(?newfailure) ^
resultIs(?a,?newfailure) ^
hasImpact(?newfailure,?h) ^
hasDomain(?newfailure,?j) ^
hasPhenomenon
    (?newfailure,?k) ^
hasDate(?newfailure,?e)
```

```
Infer {Failures} from {Monitors}:
Single auditors:

Monitor(?a) ^
Auditor(?b) ^
isUnique(?b,true) ^
resultIs(?b,?c)
→
encounters(?a,?c)

Multiple auditors:

Monitor(?a) ^
Auditor(?b) ^
isUnique(?b,false) ^
Auditor(?c) ^
isUnique(?c,false) ^
considers(?a,?b) ^
considers(?a,?c) ^
resultIs(?b,?d) ^
resultIs(?c,?e) ^
swrlb:equalTo(?d,?e)
→
encounters(?a,?d)
```

Figure 6. Extraction of knowledge from expert reports and inference rules for auditor evaluation. The SWRL rules, which refer to the inferencing steps in Figure 5, are presented in this format.

Implementing and cycling in real-time

The method operates in real-time and follows predetermined cycles. The web form and inferencing results for "monitor extraction" from expert reports are depicted in figures 7 and 8. The refresh time of the web form, which triggers the inferencing algorithm, is set based on the periodicity and data rate requirements of the sensors in each case study. To maintain data consistency and avoid duplication, 'Auditors' and 'Monitors' inferred from 'Tasks' and 'Steps' are not asserted to diagont's knowledge base after each cycle. In cases with a short required refresh time, delays may occur.

The utilization of these strategies has ensured that the ontology and SWRL rules developed can be applied to various fault diagnosis scenarios, not just specific case studies. The practicality and versatility of ontology-based methods are enhanced by this methodology, making them valuable tools for maintenance and diagnostic tasks in diverse domains.

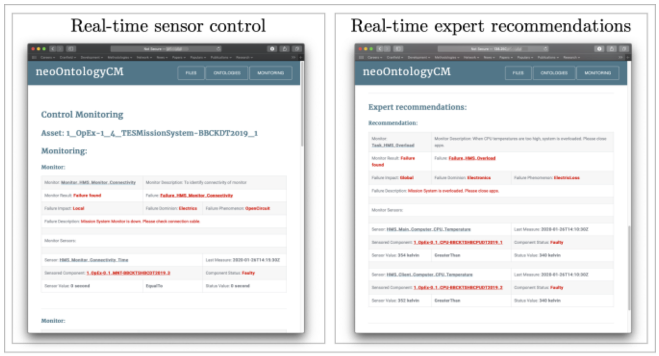

Figure 7. Pictorial demonstration of the ontology-based expert monitoring tool.

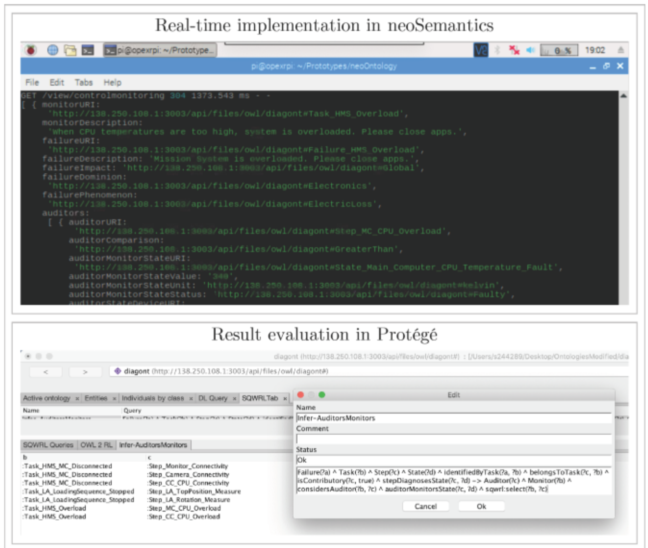

Figure 8. Using neoSemantics and validation in Protegé, we can infer 'Auditors' and 'Monitors' from 'Steps' and 'Tasks' in real-time implementation.

IV. Development of the Ontology

In this section, we cover the ontology's creation, design, and structural analysis, along with expert involvement and feedback during development.

A. Improving through feedback from experts

The diagont ontology's development heavily relied on the insights and feedback of end-users who are experts [53,54]. To guarantee the ontology's alignment with its purpose, nine subject-matter experts from two separate maintenance organizations were interviewed in a series of semi-structured interviews. The experts, aged 30 to 60 and working as engineers, technicians, and managers, had more than 10 years of experience in diagnostic activities.

The interview process was organized in the following manner:

- 10-minute presentation introducing the experts to diagont, its objectives, and how it encompasses diagnosis activities. The purpose of this briefing

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was to familiarize them with the ontology's structure and intended application.

- During a 40-minute interview, a thorough presentation was given on diagont's classes, attributes, and relationships. Experts were then asked to propose changes to better match the ontology with their real-life experience and reporting tasks.

Capturing diverse perspectives was crucial during this process, especially considering the experts' extensive experience with diagnostic reporting tools but unfamiliarity with ontology-based applications. Experts from various organizations, specializing in electro-mechanical and electronic domains, carefully evaluated diagont across different use cases.

B. *Comparative analysis to validate*

A structural analysis was conducted to verify the suitability and effectiveness of the diagont ontology in representing the knowledge domain of fault diagnosis. The task involved evaluating diagont's schema by comparing it to similar ontologies to determine its effectiveness in representing the domain's logic [55,56].
The analysis uses key metrics from OntoQA to assess the ontology schema's richness, width, depth, and inheritance [57,58].

- Relationship Richness (RR) quantifies the extent of non-hierarchical relationships in the ontology, reflecting its capacity to represent individuals through their interconnections.

$$\text{Relationship Richness} = \text{RR} = \frac{|\text{P}|}{|\text{H}| + |\text{P}|} \in [0,1] \qquad (1)$$

- The Attribute Richness (AR) metric measures ontology detail by counting attributes per class, balancing detail with the risk of unstructured text.

$$\text{Attribute Richness} = \text{AR} = \frac{|\text{att}|}{|\text{C}|} \in \mathbb{R} \qquad (2)$$

- The metric Inheritance Richness (IR) evaluates the breadth of the ontology, indicating the general knowledge it contains.

$$\text{Inheritance Richness} = \text{IR} = \frac{\sum_{\text{C}_\text{i} \in \text{C}} |\text{H}^\text{c}(\text{C}_1, \text{C}_\text{i})|}{|\text{C}|} \in \mathbb{R} \qquad (3)$$

A comprehensive assessment compared diagont with various ontologies from 35 papers. Ontologies that did not prioritize failure diagnosis activities or describe failure phenomena and related measures were excluded based on the selection criteria. This comparative approach played a crucial role in ensuring that diagont meets the unique requirements of fault diagnosis and is on par with or surpasses other ontologies in its field.

C. *Criteria for validation and ontological considerations*

Ensuring the effectiveness and applicability of the DIAGONT ontology in real-world fault diagnosis scenarios critically depends on its validation. To ensure its usability and accuracy, this process involves evaluating the ontology against validation criteria and ontological aspects. Various authors have examined diverse validation criteria and ontological aspects for evaluating validation of ontology-based tools [60–63]. According to Table 4, these are the factors most authors agreed on for validating ontology-based tools' usability [64]. The validation process includes expert feedback, usability studies, and comparative analysis with existing ontologies. This comprehensive approach guarantees a thorough assessment of DIAGONT in terms of usability and effectiveness from various perspectives.
This step is crucial for refining DIAGONT and ensuring it meets the high standards needed for practical fault diagnosis. The accuracy and efficiency of diagnostic processes can be improved by using a validated ontology to capture and reuse expert knowledge.

Table 4 provides the definition of relevant ontological aspects and validation criteria for assessing the usability of ontology-based tools, as discussed by Vrandečić [64].

Type	Name	Definition
Ontological aspect	Vocabulary	This refers to the language employed in naming ontology's classes, attributes, and relationships. It assesses the tool's capability to correctly allude to the described concepts.
	Structure	Describes the relationships between elements in an ontology, whether taxonomical or semantical. The tool's capability to navigate through various ontology classes (reporting forms) is taken into consideration.
	Context	Describes the context in which the ontology is applied. The tool's evaluation includes its capacity to generate accurate diagnosis reports by utilizing ontology elements to create individuals.
Validation criterion	Accuracy	This refers to how effectively the ontology can cater to the expert's knowledge domain. It evaluates whether the tool is capable of describing diagnosis reports similarly to an expert.
	Completeness	Refers to the ontology’s ability to fully cover the expert’s knowledge domain. It determines if the tool includes all required elements for creating diagnosis reports.
	Conciseness	This refers to the ontology's capacity to exclusively address the expert's specific knowledge domain. It determines if the tool avoids including any unnecessary aspects in diagnostic reports.

Consistency	The ontology ensures that no contradictions are allowed. It assesses if the tool can generate conflicting information in the reports it generates.

D. *Adding DIAGONT to a Prototype System*

DIAGONT must shift from being theoretical to becoming a practical tool. These measures ensure a seamless integration process and effective real-time data processing. Additionally, the NeOn Methodology and other influential works have influenced the development of DIAGONT [36]. These references offer both a structured approach and a wider view on ontology creation best practices, highlighting the importance of modularization, reuse, and context-specific development.

The necessary elements and steps to make this possible are:

- The Cloud Server acted as the central hub for storing ontology and facilitating interaction between system components.
- The web application served as the main user interface for interacting with DIAGONT, enabling reporting and monitoring.
- DIAGONT's real-time application for fault diagnosis relies on this essential Web API for efficient transfer of sensor data.

The languages and platforms used to code each component are shown in Figure . Protegé, a popular ontology editing software [40], was used to create DIAGONT. Neo4j was selected for its strong graph database capabilities, along with neosemantics for improved schema and knowledge base separation [41,42]. The server was then built using NodeJS [43] and utilized Cypher [44] and neosemantics to generate Semantic Web Rule Language (SWRL) rules for ontology inferencing. Dynamic HTML content generation was facilitated by using Embedded JavaScript Templates (EJS) [45] for constructing the web apps. The API, developed in C++ [46], guarantees efficient sensor data handling due to its performance and reliability.

Figure 9 provides an overview of the system prototype's ontology-based methods. The logos of each tool/language used to develop the prototype are presented, replicating the structure of Figure 1.

V. Implementation Requirements

A. *Conceptualisation*

The system is designed as a private cloud, offering Software-as-a-Service (SaaS) [47]. The primary reason for choosing this is its data security advantages, which are crucial for handling confidential data from the industrial sponsor. To ensure security and privacy compliance, the cloud server is hosted on a Raspberry Pi 3 Model B Plus within the University's private network. The sponsor's requirement is to securely store data within British jurisdiction, which this setup complies with.

The choice to steer clear of popular cloud services such as AWS EC2 or Microsoft Azure PaaS is motivated by the desire for improved data security and the ability to customize the system for future research requirements without sacrificing security. These choices were also influenced by other factors.

- The significance of data security required a system that could ensure the confidentiality and integrity of sensitive information.
- The system's design prioritized reusability for future research, striking a balance between security, accessibility, and adaptability [48,49].
- The system's design takes into account its educational and research value, ensuring researchers can safely use it.

B. *Defining the Hypothesis for Validation*

To validate the effectiveness of the proposed solution (which involves capturing and utilizing expert knowledge for fault diagnosis), our validation hypothesis is:

- Assess the proposed ontology's accuracy in representing experts' rationale in diagnosis tasks.
- Assessing the effectiveness of the reporting method in capturing expert diagnosis knowledge.
- Enhancing fault diagnosis by testing the impact of the monitoring method on efficiency and effectiveness.

Like previous studies [6, 50–52], both quantitative and qualitative measures are considered appropriate for validating these hypotheses. Table 5 classifies the criteria based on their relevance to each proposed contribution and the methods used for data collection and analysis. In order to accurately represent the proposed contributions, multiple assumptions are taken into account.

- If an ontology represents a knowledge domain, its schema should depict the relationships and reasoning within that domain. Thus, it is essential to evaluate the ontology schema through expert validation and comparing it to similar ontologies.
- In addition to expert rationale, the ontology's knowledge base should also capture expert knowledge explicitly. The assessment of its effectiveness relies on its capacity to improve particular tasks, necessitating an individual evaluation of each suggested method (reporting and monitoring).
- How the reporting method affects usability: Its purpose is to gather expert knowledge for the monitoring method. The completeness and quality of the captured knowledge are directly influenced

by its usability. It is crucial to assess the usability of the reporting method with experts.

- The monitoring method's main objective is to detect abnormal asset behavior [37]. It is essential to assess the method's efficiency and effectiveness, specifically in terms of time to complete tasks and error rates.
- The efficiency and effectiveness of fault diagnosis tasks can be greatly affected by the usability of the monitoring method. Because usability is subjective, the most effective evaluation is through qualitative criteria derived from testers' opinions.

The validation process utilizes various experimental methods, each designed to evaluate specific aspects of the proposed solutions. The following subsections outline the methods and criteria for validating the research hypotheses.

Table 5 provides a summary of the validation methods used in this study.

Contribution	Validation method	Quantitative criteria	Qualitative criteria
Ontology	Expert interviews	Schema changes	
	Structural analysis	OntoQA metrics	
Reporting	Usability tests		Cases of study (assets and failures)
	Usability surveys		Accuracy, completeness, etc.
Monitoring	Efficiency experiment	Evaluate how well the proposal reduces time for improving fault diagnosis monitoring efficiency.	
	Effectiveness experiment	Assess the proposal's potential to decrease errors and enhance the effectiveness of diagnostic monitoring operations.	
	Usability surveys		Ease-of-use, visualisation

C. *Reporting validation criteria*

The usability tests for the reporting tool are crucial for two main reasons: first, to obtain expert feedback on its usability in real-life scenarios, and second, to gather data for designing experiments on monitoring efficiency and effectiveness. These tests have a prescribed protocol.

- Testers are familiarized with the reporting tool via a short presentation. The overview covers the tool's functionalities and supported data input formats.
- The testers, who are the identical nine subject-matter experts engaged in the ontology schema validation, must finish two reports. The reports discuss failures recently identified in their professional diagnostic work.

The device provided by the tool simulates real-life usage conditions. The reports provided crucial data that helped identify failures in the case studies used for the monitoring experiments.

Experts are asked to complete a questionnaire evaluating the usability of the reporting tool after the usability tests. Ensuring the quality of captured knowledge is crucial for its applicability in condition monitoring scenarios. Important factors to consider are:

- The tool's usability is assessed to ensure the interface is not too complex and the vocabulary is clear. Insufficient performance in these areas can result in inaccurate or incomplete data gathering, which can negatively impact the monitoring tool's efficacy.
- The usability evaluation of the tool takes into account an ontological perspective, as recommended by different authors [60,61]. This method requires assessing the tool based on validation criteria and ontological aspects essential for ontology-based tools [60–63].

Table 5 outlines the crucial ontological aspects and validation criteria used to assess the usability of ontology-based tools. These factors play a central role in determining the effectiveness of the tools in capturing expert knowledge for diagnosis tasks. However, it's important to mention that the subjective nature of the validation criteria and ontological aspects require a subjective method of gathering data. In order to achieve this, the experts who test the tool are given questionnaires to gather their opinions on usability. Here is the format of the questionnaire:

- The questionnaire includes statements that match validation criteria and ontological aspects. These statements evaluate the tool's vocabulary, structure, context, accuracy, completeness, conciseness, and consistency.
- Experts rate their level of agreement using a Likert Scale from 1 to 7, as recommended by Weijters, Cabooter, and Schillewaert [65].
- The experts' responses are analyzed to assess their perception of the reporting tool's usability. The purpose of this analysis was to evaluate the tool's ability to meet experts' expectations and requirements in capturing and reporting diagnostic information.

The feedback will offer valuable insights to improve the tool's functionality and optimize the fault diagnosis process.

D. *Criteria for validating monitoring processes*

To evaluate the effectiveness of fault diagnosis, we need to prioritize identifying failures accurately and quickly across assets using various monitoring tools. This is the description of the experimental setup and methodology.

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- Objective: The main aim is to assess the efficiency and effectiveness of the proposed monitoring tool for fault diagnosis tasks.
- The experimental setup (Figure 10) requires testers to use a tablet device to interact with the monitoring tool to identify asset failures.
- Quantitative variables:
  - Time is measured as the duration from the experiment's start to correctly identifying the failure.
  - Errors are calculated by tallying the testers' incorrect failure hypotheses in the experiment.
- Factors considered (Table 6):
  - The expertise level of testers (IT or NOIT) was crucial in recognizing that the monitoring tool doesn't offer task guidance, as it could impact their diagnostic efficiency and effectiveness.
  - The nature of failure had a significant impact, as it influenced the case studies and testers' familiarity with similar failures.
  - Tool for monitoring used: Three scenarios were examined:
    - There is no monitoring tool, which serves as a control group.
    - KRD (Knowledge Recommendations Disabled) is a conventional monitoring tool with typical condition monitoring rules.
    - KRE (Knowledge Recommendations Enabled): The suggested monitoring approach combines conventional rules and expert diagnostic knowledge.
- The experiment consisted of 12 different groups based on the combination of factors (2x2x3) in a between-subjects design. Testers were assigned to groups randomly, guaranteeing an equal distribution of expertise levels in each group. The sample size calculation for a three-way ANOVA showed that we need 50 participants. In the end, the study included 48 participants as testers.
- Profile of participants: Testers, aged 22 to 30 years, were all enrolled in different MSc programs related to engineering. They were categorized as 'IT' or 'NOIT' based on their previous encounters with electric and electronic malfunctions.
- The next section discusses the asset used for the case study and its failures. The chosen experiment failures were based on the most frequently reported issues in NFF scenarios during the reporting tests.
- Results analysis: The experiments' outcomes, including the efficiency and effectiveness of various monitoring tools, are examined.

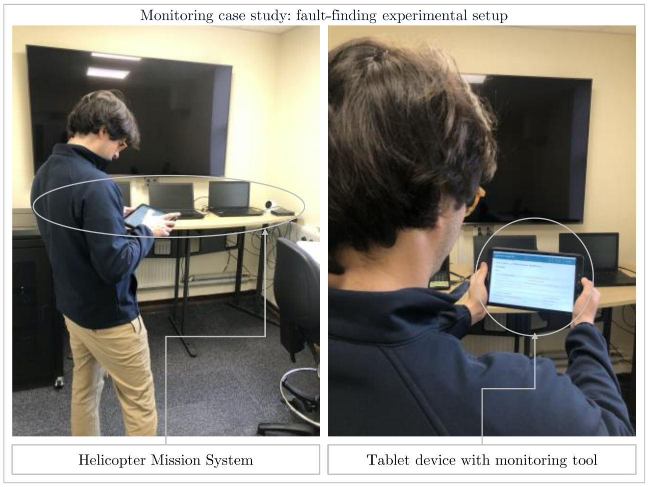

Figure 10. Explanation of the experimental setup for monitoring efficiency and effectiveness. In the pictures, a tester is using a tablet device to examine the monitoring tool for detecting experimental failures.

Table 6. Definition of experimental effects, factors and their definitions from monitoring efficiency and effectiveness experiments.

Effect	Factor	Definition
Expertise level	IT	Tester has previous experience on electric and electronic failures
	NOIT	Tester has no previous experience on electric or electronic failures
Failure's nature	CNN	The nature of the failure is electric
	TEM	The nature of the failure is electronic
Monitoring tool	None	Tester has no support to diagnose the experimental failure
	KRD	Tester has support of a monitoring tool without expert knowledge
	KRE	Tester has support of the monitoring tool with expert knowledge

KRD = Knowledge Recommendations Disabled | KRE = Knowledge Recommendations Enabled

E. *Post-usability Surveys for Monitoring Tools*

The post-monitoring experiments usability surveys were crucial in evaluating the practicality and user-friendliness of the monitoring tools (KRE and KRD). The surveys offer valuable insights into user experiences with monitoring tools, enhancing the quantitative data from efficiency and effectiveness experiments. The collected feedback will play a key role in pinpointing areas for improvement in the tools, especially in terms of user interface design and information presentation.

Here is the description and importance of the usability surveys.

- Usability assessment criteria:

- Simplicity and user-friendliness were the key factors evaluated in the Ease-of-Use criterion. The assessment tests if users can effectively navigate and use the tool to analyze asset condition and detect failures.
- Visualization: This feature assesses how well the tool helps users diagnose faults by presenting information effectively. The tool incorporates visual elements to enhance clarity and usefulness.

- In the survey, participants rate a series of statements using a Likert scale from 1 to 5. Weijters, Cabooter, and Schillewaert [65] conducted research that supports the use of a 5-point Likert scale in surveys, particularly with non-expert populations, as it maximizes information transmission.
- The details of experimental steps to validate this study are listed in Table 7 for the participants. The testers with experience used either the KRE or KRD tools during the experiments. The testers are students, not experts like those in the usability surveys, and they represent a non-expert sample for fault diagnosis.
- Testers must finish the usability surveys right after the monitoring efficiency and effectiveness experiments. By timing it this way, their feedback becomes more accurate and relevant due to the fresh experience with the tools. Testers without a monitoring tool (None) will not be included in the analysis.

Table 7 provides a summary of the experimental steps, methods, purposes, and participants involved in each stage of the research validation process.

Step	Method	Description	Participants	Purpose of Data Collection	Purpose of Data Analysis
1	Ontology Expert Interviews	Capture qualitative data on diagont schema	9 Experts	To gather expert opinions on the ontology schema	To evaluate changes proposed for ontology validation
2	Ontology Structural Analysis	Analyse OntoQA metrics of similar ontologies	10 Literature Ontologies	To capture quantitative data for comparison	To validate the ontology's structure and fit for purpose
3	Reporting Usability Tests	Capture real-life data from physical assets and failures	9 Experts	To collect data on failures in NFF scenarios for case studies	To evaluate reports for designing experimental cases
4	Reporting Usability Surveys	Gather opinions on the tool's usability for diagnosis reporting	9 Experts	To capture expert opinions on the tool's usability	To analyse the tool's usability and its impact on knowledge validity
5	Monitoring Efficiency and Effectiveness Experiments	Capture data on the efficiency and effectiveness of KRE	48 Testers	To assess the impact of KRE compared to other methods	To study the effect on task time and errors, considering factors like expertise and failure nature
6	Monitoring Usability Surveys	Gather opinions on the usability of KRE compared to KRD	32 Testers	To capture tester opinions on the usability of monitoring tools	To analyse ease-of-use and effectiveness in task accuracy

VI. Case Study

The system prototype and experimental protocol developed in this research were rigorously tested using two distinct case studies, specifically chosen for their frequent mention in the diagnosis reports from the reporting tests. These case studies represent complex engineering assets, each with its unique characteristics and challenges:

- Complexity and relevance: Both systems, with their designs and critical roles, provide a realistic and challenging environment for testing the proposed methods. Their complexity ensures that the ontology-based methods are tested under conditions that closely mimic real-world scenarios.
- Data richness: The presence of various sensors and actuators in these systems offers a wealth of data, essential for validating the ontology's ability to capture and process detailed diagnostic information.
- Practical application: The selection of these case studies aligns with the research's objective to improve fault diagnosis in complex engineering systems. The real-life application of these systems ensures that the research outcomes are grounded in practical utility.
- NFF scenarios: The propensity of these systems to encounter NFF scenarios provides a robust test bed for evaluating the effectiveness of the ontology in diagnosing and monitoring faults that are not immediately apparent.

Figure 11 provides a visual representation of these two case studies.

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A. The Systems

Loading Arm: The electromechanical system depicted in Figure 11(a), is a crucial part of a naval ship. It enables the swift transportation of heavy loads. The complexity stems from the precise arrangement of mechanical parts, actuators, and sensors, controlled by a central monitoring panel. The design of the system enables precise control of load movement, making it vital for naval operations. The Loading Arm's complexity and criticality, along with its mechanical and electronic components, make it perfect for testing ontology-based diagnosis and monitoring methods. Regular maintenance checks are necessary due to its frequent use in high-stakes naval operations, making it a valuable data source for research. The Loading Arm experiences occasional movement failures as reported during routine inspections. Traditional diagnostics used to lead to a non-fault-found situation due to inconsistent fault manifestation.

The Helicopter Mission System, depicted in Figure 11(b), is a case study that focuses on a replicated electronic system for navigating helicopter missions. This replica allows for controlled laboratory experiments and was built to match the original system's specifications. The system consists of computers, a camera, and an ethernet switch that collaborate to control and monitor the helicopter's navigation. The 'main mission' computer serves as the central controller, while the 'client mission' computer and the 'monitor' aid pilot interactions. The camera enhances the piloting experience by providing visual feedback of the terrain. The unique challenges in diagnosing and monitoring arise from this system's critical role in helicopter navigation and its sophisticated electronic configuration. The control monitoring system's limitations complicate the management of specific electronic parameters, resulting in NFF scenarios. Sporadic communication failures occur between the mission computer and navigation unit. The intermittent nature of the fault resulted in multiple NFF scenarios despite traditional diagnostics.

B. Use Cases

Use case 1: Documenting Diagnostic Steps for the Loading Arm

- Scenario: An engineer identifies a malfunction in the Loading Arm of a naval vessel. Each step taken during the diagnosis process is documented.
- Ontology Requirement: The ontology must capture detailed information about each diagnostic step, including the rationale, actions taken, and observations made.
- Implementation: Classes such as 'Task', 'Step', 'Failure', and 'State' were created to represent the diagnostic steps and their relationships.

Use Case 2: Real-Time Monitoring of the Helicopter Mission System

- Scenario: The Helicopter Mission System's real-time sensor data is continuously monitored to detect and diagnose faults.
- Ontology Requirement: The ontology must integrate real-time sensor data and update diagnostic information dynamically.
- Implementation: Classes like 'Monitor', 'Auditor', 'State', and 'Device' were developed to represent real-time monitoring components and their interactions.

Use Case 3: Knowledge Reuse for Fault Diagnosis Across Systems

- Scenario: Maintenance teams from different systems (Loading Arm and Helicopter Mission System) need to share diagnostic knowledge and strategies.
- Ontology Requirement: The ontology must enable the reuse and sharing of expert knowledge across different systems.
- Implementation: Ontology mappings and shared classes such as 'Symptom', 'Cause', and 'Phenomenon' were designed to facilitate knowledge sharing.

Use Case 4: Automated Inferencing and Alert Generation

- Scenario: The system needs to automatically infer potential faults based on sensor data and predefined rules, generating alerts for maintenance teams.
- Ontology Requirement: The ontology must support automated inferencing and rule-based alert generation.
- Implementation: SWRL rules and properties like 'hasComparison', 'hasMeasureValue', and 'hasMeasureDate' were created to enable automated reasoning and alert generation.

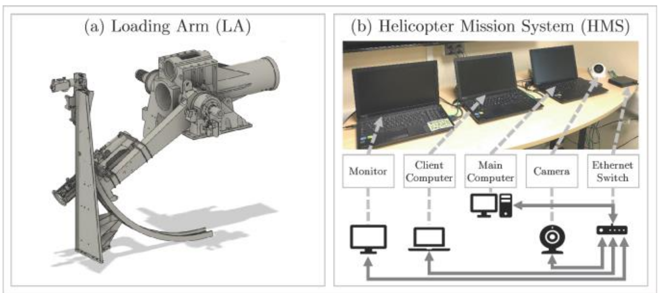

Figure 11. Depiction of complex assets utilised as case studies: (a) Loading Arm, (b) Helicopter Mission System.

The competency questions and use cases directly informed the design of the ontology. Each requirement derived from the CQs and use cases was mapped to specific classes, attributes, and relationships in the ontology. For example:

- CQ1 and Use Case 1 led to the development of classes such as 'Task', 'Step', and 'Failure', ensuring that the ontology could document detailed diagnostic steps.
- CQ3 and Use Case 2 required the integration of real-time data, resulting in the creation of classes like 'Monitor' and 'Device' to represent and manage sensor data.
- CQ5 and Use Case 3 emphasized knowledge reuse and sharing, which influenced the design of shared classes and ontology mappings to support interoperability.
- CQ7 and Use Case 4 focused on reducing manual errors through automation, guiding the development of SWRL rules and inferencing mechanisms.

The ontology was customized to meet fault diagnosis needs by addressing competency questions and use cases, creating a versatile framework for managing diagnostic information in complex systems.

C. *Steps in the Ontology Development*

The NeOn methodology offered a comprehensive framework for developing ontologies, focusing on a modular and iterative approach. It offers a systematic approach that facilitates the development, reusability, and growth of ontologies. The development of the diagont ontology involved the following steps, including scenario-based explanations and justifications.

- We scoped the scenario by identifying key diagnostic tasks, common faults, and user groups involved in diagnosis and maintenance.
- We interviewed nine subject-matter experts from two maintenance organizations to acquire knowledge. This assisted us in collecting comprehensive data on diagnostic procedures, typical issues, and the reasoning behind expert choices.
- Our ontology incorporates elements from 35 relevant ontologies, including classes, properties, and patterns. In spite of reusing, we chose to create new components when current ontologies didn't meet our specific needs.
- We developed a conceptual model that includes classes like 'task', 'step', 'failure', 'state', 'monitor', and 'device', with their respective relationships and attributes. this model was iteratively refined based on feedback from domain experts.
- Ontology design: using the neon methodology, we structured the ontology into modular components, each representing a specific aspect of fault diagnosis. this modularity supports easier updates and maintenance.
- Ontology implementation: we used protégé for ontology development and neo4j for storage, leveraging neosemantics for effective schema and knowledge base management. this setup supports complex queries and real-time data integration.
- Ontology population: we automated data extraction from existing databases and sensor logs to populate the ontology, ensuring that it contains relevant and up-to-date information for fault diagnosis.
- Ontology validation: we conducted expert reviews and usability tests with the same subject-matter experts to validate the ontology's accuracy and usability. structural analysis using ontoqa metrics helped ensure the ontology's robustness and coherence.
- Ontology maintenance: we established a maintenance plan that includes regular reviews and updates based on user feedback and advancements in the field. This plan ensures the ontology remains a valuable resource over time.

D. *Reduction of NFF Scenarios*

The DIAGONT ontology played a critical role in reducing No Fault Found (NFF) scenarios in the case studies.

The movement of the Loading Arm has been reported to be intermittently faulty. The fault did not consistently appear, leading to a non-fault found scenario in previous traditional diagnostics. DIAGONT discovered a correlation between intermittent faults and real-time sensor data. The problem was determined to be a temperature-dependent malfunction in the hydraulic system, specifically occurring under specific load conditions. DIAGONT enabled precise identification, resolving the previously elusive fault and reducing the NFF rate. This is realized by having:

- Structured documentation improved the diagnostic process by providing a complete view, reducing the chance of missing important steps or misinterpreting symptoms.
- By enabling engineers to receive real-time updates, anomalies can be detected as they happen, rather than relying on potentially outdated information. This instant understanding aided in detecting overlooked errors, thus decreasing NFF situations.

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- Automation for inferencing with reduced redundancies.
  Manual data entries for the loading arm result in redundancies and errors, impacting diagnostic accuracy. By utilizing SWRL rules, the system was able to automatically infer relationships and attributes for each class, reducing the need for manual intervention and minimizing errors and redundancies.

The Helicopter Mission System encountered intermittent communication issues between the mission computer and the navigation unit. The intermittent fault led to multiple scenarios of NFF due to traditional diagnostics. DIAGONT's use of real-time data and comprehensive diagnostic documentation showed that the communication issues were caused by electromagnetic interference from a recently installed radio system. By documenting and reusing this knowledge, subsequent similar problems were quickly identified and solved, leading to a significant decrease in NFF occurrences. This is realized by having:

- A detailed framework for documenting diagnostic actions, including dependencies and specific fault characteristics. This allowed for a better comprehension of how the system behaves, minimizing misdiagnoses and NFF situations.
- DIAGONT enabled the reuse of diagnostic knowledge by capturing expert reasoning and past fault resolutions. To illustrate, a previously reported fault linked to GPS signal interference was employed to identify a similar problem in another helicopter mission. Engineers can use historical data and expert insights to swiftly identify and resolve recurring issues, reducing NFF instances.

The improvements successfully identified and addressed faults, preventing NFF scenarios and proving the ontology's value in system maintenance and fault diagnosis.

E. Empirical Results

Additionally, the use case assesses the effectiveness of conventional problem-solving methods. This included:

<u>Error reduction rates:</u> the number of diagnostic errors made by testers using traditional data-driven methods versus those using the ontology-based approach. Errors were defined as incorrect fault diagnoses or misidentifications during the diagnostic process.

Methodology:

- Sample Size: We conducted experiments with 48 participants divided into two groups: one using traditional data-driven methods and the other using the ontology-based approach.
- Tasks: Each participant was given a set of diagnostic tasks involving the Loading Arm and Helicopter Mission System, designed to simulate real-world fault scenarios.
- Measurement: The number of errors made by each participant during these tasks was recorded and compared across the two groups.

Results:

Method	Errors per 100 Tasks	Reduction
Traditional Data-Driven	12	-
Ontology-Based	4	67%

<u>Time Efficiency Calculation:</u> Time efficiency was measured by comparing the average time taken to complete diagnostic tasks using traditional methods versus the ontology-based approach.

Methodology:

- Sample Size: The same 48 participants were used for this measurement.
- Tasks: Participants were timed while performing the same set of diagnostic tasks for both the Loading Arm and Helicopter Mission System.
- Measurement: The average time taken to complete each task was recorded for both groups.

Results:

Method	Average Time per Task (minutes)	Reduction
Traditional Data-Driven	45	-
Ontology-Based	20	55%

<u>False Positive and False Negative Rates</u>

Methodology:

- False Positives: Instances where a fault was incorrectly identified as present.
- False Negatives: Instances where an actual fault was not detected.
- Measurement: Both false positive and false negative rates were calculated by comparing the diagnostic outcomes with a ground truth established by experts.

Results:

Method	False Positive Rate	False Negative Rate Traditional Data-Driven

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Traditional Data-Driven	18%	22%
Ontology-Based	8%	10%

F. Discussion

1) Benefits of using an ontology-based approach instead of traditional models

Previous research has shown limitations in ontology-based methods used in engineering applications, but our work aims to address them.

- Manual processes are needed for axioms, rule designs, ontology mappings, and instantiations in many existing ontology-based systems. The manual process is slow, susceptible to mistakes, and demands a high level of expertise. However, the diagont ontology combines automated data extraction from databases with real-time sensor data. The ontology schema is used by the cloud-based reporting tool to create web forms, streamlining data entry and minimizing manual work. Additionally, SWRL rules automate inference, reducing the need for manual updates and minimizing errors.
- Large ontologies can encounter problems with reasoning efficiency because of the time complexities involved in reasoning mechanisms. On the other hand, the advanced framework applies a modular strategy with the NeON methodology, enhancing reasoning efficiency by dividing the ontology into manageable parts. The system is created to effectively carry out real-time data integration and dynamic rule updates, guaranteeing rapid responses to changing conditions.
- Ontologies assume an open world, leading to uncertainty in complex systems. Although the open world assumption remains, our framework reduces its impact through real-time data and expert feedback integration. By integrating this, we can reason more accurately and contextually, reducing uncertainty from open world assumptions.
- Ontology-based reasoning frequently produces redundant knowledge, necessitating manual extraction of useful information and requiring time and expertise. Our framework reduces redundant knowledge by incorporating automated inferencing and real-time data integration. The design of the system ensures that only useful knowledge is kept, reducing the need for manual extraction and enhancing fault diagnosis efficiency.
- Traditional models would have difficulty capturing the detailed rationale for each diagnostic step in the Loading arm case study, leading to incomplete data in structured knowledge capture and reuse. By utilizing an ontology-based approach, this knowledge was organized into clearly defined classes and relationships, allowing for the accurate capture and reuse of expert diagnostic reasoning. This framework enables thorough documentation of every diagnostic step, enhancing fault diagnosis accuracy and knowledge transfer efficiency.
  By offering a structured framework, ontologies capture expert knowledge comprehensively, facilitating detailed analysis and reuse of diagnostic data.
- The traditional models for the helicopter mission system case study needed manual updates to include new sensor data, leading to delays and errors in diagnostics. The monitoring tool used ontology to integrate real-time sensor data and update diagnostic rules as new data came in. This made sure that the system could promptly adapt to changing conditions, ensuring real-time monitoring and diagnosis.
  Maintenance operations benefit from ontologies by enhancing responsiveness and accuracy through real-time data integration and dynamic rule updates.
- The Loading arm and helicopter mission system case studies both involved integrating data from different sources and systems for interoperability and knowledge sharing. The ontology-based approach enabled smooth knowledge sharing and interoperability among various systems and domains by providing a common data representation and reasoning framework.
  By utilizing ontologies, interoperability and knowledge sharing are improved, allowing for seamless integration of diagnostic data across different systems and domains.

2) Limitations of the Developed Framework:

Future research should address the limitations of the developed ontology-based framework, despite its advantages.

- Although the framework automates most tasks, manual intervention and expertise are still needed for the initial setup, such as defining axioms and creating initial mappings. Additional automation is needed to lessen the initial workload and reduce possible errors.

- As the ontology grows in size and complexity, the efficiency of reasoning mechanisms may face challenges, despite improvements in modular design. The emphasis for future work should be on improving reasoning algorithms for more efficient processing of larger ontologies.
- While the system decreases the generation of redundant knowledge, eliminating it is still difficult. Development of advanced filtering and validation mechanisms is necessary to retain only relevant knowledge.
- Dealing with the open-world assumption can lead to uncertainties, particularly in complex and dynamic systems. To address these uncertainties, we can enhance inferencing algorithms by incorporating more contextual data.

The use of ontology-based approach improves fault diagnosis by overcoming the limitations of traditional models. Despite this, the framework still encounters issues with manual setup, scalability, redundant knowledge management, and addressing the open-world assumption. Future research should prioritize automating setup processes, optimizing reasoning mechanisms, developing knowledge filtering techniques, and enhancing context-aware inferencing for effective ontology-based fault diagnosis systems.

3) FAIR Guidelines

Effectively managing and utilizing scientific data and resources requires adherence to the FAIR principles. Our efforts in developing the diagont ontology were focused on aligning with these principles, making it a valuable and reusable resource for the scientific community. Here, we analyze how our ontology aligns with these principles and identify possible areas for improvement.

Findable	
Alignment	The diagont ontology comes with extensive metadata and documentation, simplifying the process of discovery. The ontology includes well-defined metadata elements like title, authors, version, date of creation, and description.
	Persistent Identifiers guarantee reliable referencing and locating of each element in the ontology.
Improvements	To improve discoverability, we will ensure that the metadata of the ontology follows recognized standards like Dublin Core or schema.org. Integration with metadata repositories will be simplified, enhancing discoverability on search engines.
	Search Engine Optimization: Improving the ontology's visibility in academic search engines and repositories by using appropriate keywords and tags will further enhance its findability.
Accessible	
Alignment	Open Access: The diagont ontology is hosted on an open-access platform, ensuring that it is freely available to the scientific community.
	Downloadable Formats: The ontology is provided in multiple formats (e.g., OWL, RDF/XML, Turtle) to accommodate different user needs and preferences.
Improvements	Access Protocols: Implementing standardized access protocols such as RESTful APIs can further facilitate access to the ontology. This will enable users to query and retrieve ontology data programmatically.
	User Interface: Developing a user-friendly web interface where users can browse and interact with the ontology without needing specialized tools like Protégé can make the ontology more accessible to a broader audience.
Interoperable	
Alignment	Standard Ontology Languages: The diagont ontology is developed using standard ontology languages such as OWL (Web Ontology Language) and RDF (Resource Description Framework), ensuring compatibility with a wide range of tools and platforms.
	Ontology Reuse: Where applicable, the ontology reuses classes and properties from well-established ontologies (e.g., FOAF, SSN/SOSA) to enhance interoperability.
Improvements	Mapping to Other Ontologies: Creating explicit mappings to related ontologies in the domain of fault diagnosis and maintenance (e.g., using OWL sameAs or equivalentClass properties) will improve interoperability and facilitate data integration.
	Semantic Annotations: Enhancing the ontology with rich semantic annotations and links to external vocabularies and datasets can further improve interoperability.
Reusable	
Alignment	Detailed Documentation: The ontology includes detailed documentation describing its structure, intended use cases, and examples of application. This documentation helps users understand how to apply the ontology in their own contexts.
	Licensing: The ontology is released under a permissive open-source license (e.g., Creative Commons Attribution), allowing others to reuse and adapt it with proper attribution.

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Improvements	Competency Questions: Providing a set of competency questions that the ontology is designed to answer can help users understand its scope and applicability. This will also aid in evaluating the ontology's effectiveness for specific tasks.
	Community Engagement: Encouraging feedback and contributions from the user community through platforms like GitHub can enhance the ontology's utility and ensure it evolves to meet emerging needs.

By aligning with the FAIR principles, the diagont ontology becomes a valuable resource for the scientific community. We can improve its findability, accessibility, interoperability, and reusability by addressing the suggested improvements. By adhering to FAIR principles, the ontology will remain a reliable and adaptable tool for fault diagnosis and maintenance in complex systems, promoting collaboration and innovation in the field.

4) Knowledge Transfer

The DIAGONT ontology improves knowledge exchange between experts and less experienced technicians by organizing and standardizing diagnostic process documentation and enabling easy access to expert knowledge for reuse. By utilizing a collaborative development process and continuous feedback, the ontology remains valuable and useful for experts and novices alike. Multiple strategies and mechanisms were used to make this process easier.

- The DIAGONT ontology has a carefully crafted schema that captures detailed diagnostic steps, decision points, and their rationale. The classes 'Task', 'Step', 'Failure', and 'State' guarantee structured documentation of every aspect of the diagnostic process. This thorough documentation offers a straightforward, detailed guide for novice technicians, minimizing confusion and improving comprehension.
- Real-time data integration is another key feature of the DIAGONT ontology. The ontology uses real-time sensor data to constantly update information on system states and operational conditions. Technicians can use this integration to access both current data and historical fault patterns with expert annotations, enhancing their ability to understand and contextualize encountered issues. The process is further improved by using Semantic Web Rule Language (SWRL) rules for automated inferencing. Less experienced technicians can improve their decision-making process by following these rules, which are based on current data and historical fault patterns.
- The ontology also acts as a centralized repository of diagnostic knowledge, capturing expert insights, historical fault data, and previously successful diagnostic strategies. This repository facilitates the reuse of knowledge, enabling technicians to find similar past cases and leverage this information in their current tasks. The development of user-friendly, cloud-based tools alongside the DIAGONT ontology also plays a significant role. Technicians can easily document diagnostics and access real-time data using these tools, thanks to their intuitive interfaces.
- Knowledge transfer process relies on training and onboarding support. New technicians can learn how to navigate the ontology, use the tools, and follow the diagnostic process through interactive training modules and tutorials. The structured training speeds up onboarding, enabling new technicians to become skilled faster. The ontology's development process includes regular feedback sessions and workshops with experts and technicians, promoting continuous improvement based on user input. By working together, we create a culture of shared knowledge and constantly improve the ontology's relevance and user-friendliness.
- These strategies are proven effective through specific case studies. The Loading Arm case study showed that a less experienced technician successfully identified a recurring issue by using the structured guidance from the ontology. By analyzing real-time sensor data and historical patterns, the technician detected and fixed a temperature-related hydraulic malfunction. In the Helicopter Mission System case study, a new technician utilized the cloud-based reporting tool to identify a sporadic communication issue. The ontology proposed examining electromagnetic interference, which was confirmed by integrating real-time data, resulting in the discovery of a new radio system causing the interference.

VII. Conclusion

The main goal was to show that expert knowledge, when used in an ontology-based system, can greatly improve fault diagnosis efficiency. The versatility of these methods was demonstrated in effectively handling both electromechanical and electronic systems' complexities. The case studies emphasized the significance of context in fault diagnosis. Understanding the operational context of the system, such as the LA on a naval ship or the HMS in a helicopter, is vital for precise diagnosis. The success of these diverse case studies implies that the ontology-based approach can be applied to other complex systems, expanding its potential applications in different industries. The NFF scenarios, especially in the HMS, highlighted the requirement for advanced diagnostic tools to handle ambiguous faults in electronic systems.

The hypotheses were validated using both quantitative and qualitative criteria, such as ontology structure analysis, expert interviews, usability surveys, and efficiency and effectiveness experiments. The research shows that using ontology-based approach can enhance diagnostic processes by reusing diagnosis knowledge. In the context of Industry 4.0, the approach is especially important for effective data management and fault diagnosis.

These discoveries will encourage conversations about establishing standardized maintenance protocols for comparable systems in other sectors. Integrating diverse data sources (mechanical, electronic, operational) is crucial for a holistic approach to fault diagnosis and understanding challenges in interconnected systems.

Although the experimental results show promise, they should be evaluated in relation to the specific case studies and maintenance organizations. To enhance reporting efficiency and quality, it's beneficial to explore alternative information visualization tools and methods. Additionally, adjusting the monitoring approach to cater to different user expertise levels is crucial.

Future Works

Ontology-based methods have the potential to improve operations by ensuring accuracy, efficiency, and reliability. Future studies should focus on quantifying these enhancements using empirical research, offering specific metrics to validate these qualitative results.

Error Rate Reduction	By organizing diagnostic knowledge and documenting each step, the ontology-based approach can greatly decrease error rates in fault diagnosis.
Precision and Recall:	By incorporating real-time sensor data and allowing dynamic rule updates, ontology-based approaches can enhance the accuracy and completeness of fault detection.
Time to Diagnosis:	By offering a structured framework, the ontology-based approach can decrease fault diagnosis time.
Mean Time to Repair (MTTR):	The ontology-based approach can reduce MTTR by enabling faster fault detection and resolution.
Knowledge Reuse Rate:	Ontologies enhance the efficiency and consistency of fault diagnosis by enabling the reuse of expert knowledge across systems and domains.
Interoperability Index:	The organized structure of ontologies simplifies the integration and sharing of knowledge among different systems.
Redundancy Reduction:	The ontology-based approach can minimize redundant data entries through automated data entry and inferencing.
Data Accuracy:	The structured and automated nature of ontologies enhances the accuracy of diagnostic information.

Additional works may include:

- Incorporating real-life conditions in the experiments to further validate the proposed methods under various operational scenarios.
- Exploring additional factors such as ergonomics or environmental conditions that may influence the effectiveness of the ontology-based approach.
- Investigating other information visualization tools and methods, such as Augmented Reality or recommendation algorithms, to enhance the efficiency and quality of diagnosis reporting.
- Adapting the knowledge reuse approach to cater to users with different levels of expertise, potentially through the development of recommender algorithms.

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