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► **To cite this version:**

Ibrahima BARRY, Meriem Hafsi. Towards Hybrid Predictive Maintenance for Aircraft Engine: Embracing an Ontological-Data Approach. 20th ACS/IEEE International Conference on Computer Systems and Applications, Dec 2023, Giza, Egypt. hal-04369673

HAL Id: hal-04369673

<https://hal.science/hal-04369673v1>

Submitted on 2 Jan 2024

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Towards Hybrid Predictive Maintenance for Aircraft Engine: Embracing an Ontological-Data Approach

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Abstract—This article introduces a novel Remaining Useful Life (RUL) estimation method using Machine Learning techniques, guided by domain knowledge, and applied to a dataset of aircraft engines (C-MAPSS). Predictive maintenance, or prognostics, offers the opportunity to predict the lifespan of aircraft engines, thereby reducing costs, minimizing breakdowns, and ensuring their reliability. While existing solutions in the literature primarily rely on either physical modeling or data-driven methods, they have achieved promising results, but they often face limitations, such as the interpretability of models, their reusability, and scalability. Knowledge-based methods have the potential to overcome these limitations, but they introduce their own set of challenges during implementation. In this article, we address a new hybrid method for predictive maintenance of aircraft engines. A case study combining a data-driven approach and knowledge will be presented as a proof of concept to demonstrate the feasibility of this hybrid solution and the possibilities it can offer.

Keywords—Predictive maintenance, Prognostic, Remaining useful life (RUL), Machine Learning, Ontology, C-MAPSS.

I. INTRODUCTION

In the context of Industry 4.0, predictive maintenance (PdM) enables the identification of anomalies and the foresight of potential system or component failures. Through the continuous collection of multi-sensor data and system monitoring, this maintenance strategy relies on machine learning (ML) algorithms capable of building models able to detect early signs of impending failures. Early detection of anomalies allows for prevention, anticipation of corrective actions, and reduced downtime by estimating the remaining useful life (RUL), which corresponds to the operating time before a system failure. Several approaches are used: model-based, data-driven, knowledge-based, or hybrid. Aircraft engines, regarded as a safety-critical asset, demand substantial attention owing to the constant and rigorous monitoring they entail [14]. Undoubtedly, unanticipated issues with an aircraft can lead to logistical disruptions such as delays or cancellations, substantial repair expenses and the potential risk to passengers. To prevent these unforeseen failures and increase the reliability of such systems, it is important to predict the RUL of the essential aircraft components, like reactors or engines, allowing airlines to make appropriate maintenance before the inevitable engine failure or breakdown happens, thereby reducing maintenance costs while ensuring high reliability [2]. Diagnostic and Prognostics

in aeronautics have become a focal point of interest, especially since the release of the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset by NASA in 2010 [8]. Many works have been carried out to test various methods for RUL estimation. While some methods rely on physical principles, the majority are data-driven. These approaches yield promising and increasingly efficient results but they face several limitations such as model explainability, the black-box effect of some algorithms, limitations in solution scalability, adaptability issues, and more. Despite their potential, it is challenging to find knowledge or hybrid techniques integrating domain expertise when estimating the lifespan of engines.

Therefore, the main objective of this work is to investigate a novel hybrid approaches that combine data-driven techniques with domain expertise and present a comprehensive end-to-end prototype proof of concept for aircraft engines PdM, integrating domain knowledge with large datasets. Following a comprehensive review of the current state-of-the-art, our focus will shift to the C-MAPSS dataset, a well-referenced resource in the domain's literature, to construct an initial data-driven model. Afterwards, we propose to develop an ontology describing the concepts of the aeronautics domain considering aircraft engines, their components, and the environment surrounding them. Reasoning rules and axioms will be defined to create new knowledge to guide data-based method steps.

A. Problem Overview

C-MAPSS dataset is the result of a simulation model of a specific turbofan engine 1 provided the Nasa's simulation system where run-to-failure measurements are recorded under different conditions. It is widely recognized in the literature as the benchmark dataset and as an excellent example for studying current methodologies for RUL prediction and for addressing associated challenges [3]. It encompasses several turbofan engines commonly used in commercial aircraft (Figure 1) and using gas combustion to generate power for a fan, which in turn, propels air to produce forward thrust [21]. This dataset is derived from simulations and comprises 21 distinct sensor measurements (Figure 2) represented as multivariate time series data, distributed into four labeled subsets labeled FD001 to FD004, along with an additional competition subset. Within each of these subsets, there is a 24-dimensional vector

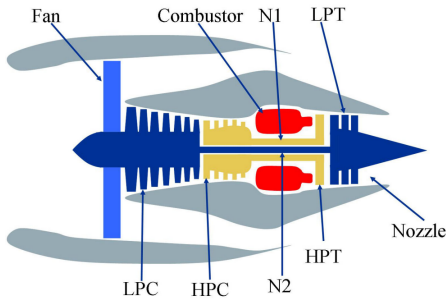


Fig. 1. C-MAPSS aircraft engine architecture in C-MAPSS dataset [20].

encompassing three operational parameters, in addition to the 21 sensor signals. The primary objective is to predict the RUL of the turbofan engines [21]. Each dataset contains multivariate time series data under different kinds of operational conditions and fault modes separated into a training and a testing set. One of the main characteristics of C-MAPSS is the lack of anomaly faults and failure mode which are not covered and note explicitly provided. Further analysis is required to obtain the original cause and the fault detection system. Thus, further research can explore this opportunity to create a more comprehensive approach. Although the literature works can

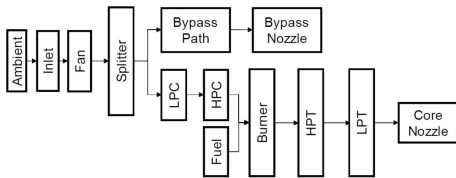


Fig. 2. C-MAPSS aircraft engine components and their interconnections [20].

identify the engine's degradation, the failure mode of the failed component is not considered and literature papers focuses on the engine as the whole system rather than individual sub-system failure [14].

II. RELATED WORKS

A. Predictive Maintenance in Industry 4.0

PdM has emerged as a highly significant and widely discussed topic, especially in the context of Industry 4.0, the rise of the Internet of Things, and advancements in Artificial Intelligence [16]. Indeed, the substantial data collected from sensors and system metadata hold valuable insights that can enhance our understanding of degradation processes, potentially leading to longer component lifespans and reduced downtime. However, hinges on effective data processing and the extraction and utilization of relevant and valuable information, made possible by the continuously improving computing capacities and advancements in Machine Learning (ML) and Deep Learning (DL) techniques. With the increasing focus on research and investigations in this field, various methods are under exploration and development in the literature, resulting in increasingly intriguing and promising outcomes.

B. Predictive maintenance approaches

Research on PdM has highlighted three primary approaches that can be implemented either separately or in combination as a hybrid approach [15] as summarized in Figure 3.

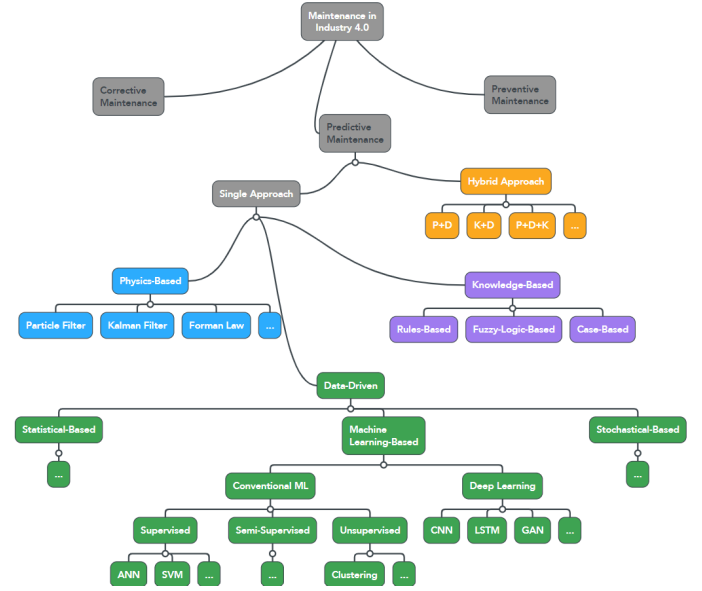


Fig. 3. Categorizing PdM approaches regarding of the literature review.

The physics-based approach entails creating mathematical models to represent the degradation processes of the system, offering greater precision and adaptability to various operational scenarios. Although it is well-suited for contexts with limited data availability, it is an expensive approach requiring expertise in failure mechanisms and lack of scalability [14]. The data-driven approach relies on leveraging monitoring data, which is processed to extract features reflecting the system's evolution or degradation. Statistical models or ML-based models can be employed [14]. This approach is cost-effective and can be flexible and adaptable to large and comprehensive datasets, but it requires a sufficient amount of data with failures [1]. Knowledge-based approach integrates human expertise to anticipate potential issues, it relies on a deep understanding of systems, processes, and operating conditions, as well as the expertise of operators and technicians. Various models such as case-based, rule-based, incorporating knowledge graphs, or ontologies have been proposed. The advantage of this approach lies in the explicative results they offer [15]. However, there are often obstacles encountered, such as the challenge of acquiring precise knowledge for predictability from experience or limited access to experts or knowledge sources to builds system.

C. Estimating Remaining Useful Life for Aircraft Engines

Various studies has been done on turbofan engine prognostics and RUL prediction offering methods based on both physics and data. Several ML methods are commonly applied to C-MAPSS: SVM (Support Vector Machine) in [7], MLP (Multilayer perceptron) in [11], ELM [4], DL methods such as

Convolutional Neural Network (CNN) [12], Long Short-Term Memory Network (LSTM) [2], GRU [13]. Some combinations and variations of physics and data are mentioned: CNN with LSTM in [21], EMD and ESN [18], SVM and ARIMA in [17]. According to [8], when evaluated solely on predictive accuracy measured with root mean square error (RMSE), CNNs and LSTMs outperformed other models. In summary, the state-of-the-art prognostic techniques applied to C-MAPSS dataset are mainly purely data-driven. These techniques mainly deal with a black box process which does not include uncertainty quantification. These two factors are barriers to prognostic applications. To tackle these issues, eXplainable Artificial Intelligence (XAI) is introduced in some works [14], [21]. Moreover, although the work is based on the exploitation of the explicit information contained in the time-series data, the implicit characteristics are not explored with data-driven methods. The correlation between each parameter can display useful information or valuable insights which can enhance anomaly and failure prediction. Additionally, subsystem contribution and failure modes are not considered, whereas further study of each subsystem’s contribution to the motor system could provide a more comprehensive framework [14].

D. Knowledge Representation

Ontology or graph knowledge are a powerful technologies for organizing and structuring extensive heterogeneous knowledge with logical relationships. It achieves this by offering a unified set of formal vocabularies, explicitly representing heterogeneous knowledge. This proactive approach mitigates divergence and misunderstandings among engineers from various domains. Moreover, ontology ensures a robust reasoning ability through in-depth analyses of knowledge relations [6].

III. METHODOLOGY

A. Data-based approach

Within this project, a data-driven method is implemented, which encompasses the training of multiple ML and DL algorithms. Following the preprocessing of the data, these models undergo training and evaluation, and the model demonstrating the most robust RUL prediction performance is ultimately chosen. In parallel, the knowledge-based model undergoes its reasoning process, generating fresh insights that are subsequently employed to retrain all the ML and DL algorithms. These retrained models are then subjected to evaluation in order to determine the best-performing model, as depicted in figure 6. This process is repeated continuously with the goal of achieving increasingly accurate RUL estimations.

B. Ontology-based approach

To integrate expert knowledge, we propose to develop a domain ontology associated with the C-MAPSS dataset according to the methodology suggested by Noy & McGuinness, the development process encompassed the following stages:

- **Ontology domain and Scope:** describing the aircraft engines domain, their components and interactions with the environment and its variations.

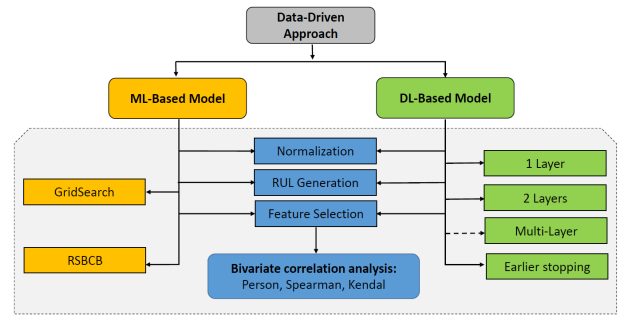


Fig. 4. Proposed Data-Driven Architecture System.

- **Reutilizing existing ontologies:** ontologies describing Air Traffic Management concepts [19] and failure modes with effects of the aircraft lubrication system [9] were released but the covered scope does not concern the concepts of the studied domain, therefore we have not reused them. It would be interesting to connect the concepts to a high-level ontology in future work.
- **Key Terms:** Conceptualize the system and its components, their interactions and behaviors depending on operational conditions. Supporting C-MAPSS and defining expertise rules allows to extract insights from data (table I) and generate new knowledge to better understand the causes of malfunctions and their propagation within the engine, leading to engine failure.
- **Ontology Classes:** define the main domain concepts and their classification with assumption relationship.
- **Object properties:** formalize various types of relationships, such "part-of," "has-property," or custom/semantic relations specific to C-MAPSS.
- **Creating, Asserting, and Inferring Instances:** to populate the ontology with instances or individuals that represent specific real-world objects or entities extracted from C-MAPSS. These instances should adhere to the defined concepts and relationships. Additionally, axioms and rules are defined for reasoning and create new knowledge.
- **Integration and application:** implementing the collaboration with the data-driven method for RUL estimation.

IV. CASE-STUDY & RESULTS

A. Development of a Knowledge-Based System for Case Study Response

Structuring domain concepts (engines, sensors, failure types and operating conditions) in an ontology provides a holistic view of the environment. It allows sensor data to be interpreted in the context of the structure and operation of the engine. For example, if a sensor value exceeds a certain threshold, the data-driven method could detect this as an anomaly. However, by using the ontology, we can understand why this value is abnormal, which engine component could be affected and identify the potential failure. Below is an excerpt of the main

TABLE I
COMPONENTS, SENSORS AND BEHAVIOUS ANALYSIS FOR RULES EXTRACTION AND GUIDING DATA PROCESSING.

Sensor ID	Symbol	Measurement and component concerned	Unit	trend and behaviour extracted	Component	Potential failure
SensorMes1	T2	Fan inlet temperature	°R	-	Fan	Overheating
SensorMes2	T24	LPC outlet temperature	°R	up	LPC	Overheating
SensorMes3	T30	HPC outlet temperature	°R	up	HPC	Overheating
SensorMes4	T50	LPT outlet temperature	°R	up	LPT	Overheating
SensorMes5	P2	Fan inlet Pressure	psia	-	Fan	Blockage
SensorMes6	P15	bypass-duct pressure	psia	-	Bypass	Leakage
SensorMes7	P30	HPC outlet pressure	psia	down	HPC	Blockage
SensorMes8	Nf	Physical fan speed	rpm	up	Fan	Imbalance
SensorMes9	Ne	Physical core speed	rpm	up	Core	Misalignment
SensorMes10	epr	Engine pressure ratio	-	-	Engine	Corrosion
SensorMes11	P30	HPC outlet Static pressure	psia	up	HPC	Blockage
SensorMes12	Phi	Ratio of fuel flow to P30	pps/psi	down	HPC	Incomplete_Combustion
SensorMes13	NRf	Corrected fan speed	rpm	up	Fan	Imbalance
SensorMes14	NRc	Corrected core speed	rpm	down	Core	Misalignment
SensorMes15	BPR	Bypass Ratio	-	up	Bypass	Leakage
SensorMes17	htBleed	Bleed Enthalpy	-	up	Burner	Overheating
SensorMes18	Nf_dmd	Demanded fan speed	rpm	-	Fan	Misfire
SensorMes19	PCNfR_dmd	Demanded fan conversion speed	rpm	-	Fan	Oil_Leak
SensorMes20	W31	HPT Coolant air flow	lbm/s	down	HPT	Overheating
SensorMes21	W32	LPT Coolant air flow	lbm/s	down	LPT	Corrosion

entities and concepts described in our ontology, components (Fig. 1) and interconnection (Fig. 2).

- **Engine**
- **Sub-Entities of EngineComponent:** Fan, LPC, HPC, LPT, HPT, Burner, Exhaust, Bypass, Core
- **Sub-Entities of Sensor:** SensorMes1-21.
- **Sub-Entities of Sub-Entities of Failure:** Overheating, Blockage, Leakage, Imbalance, Misalignment, Corrosion, Incomplete_Combustion, Misfire, Oil_Leak.
- **Sub-Entities of OperatingConditionParameter :** Altitude, MachNumber, SeaLevelTemperature
- **Object Properties(Relations):** isCloseTo, hasMultiple, monitoredBy, canHave, flowGoesFrom.

These informations and knowledge are captured from the C-MAPSS engine metadata, his components (Fig. 1) and their interconnections (Fig. 2).

1) *Data integration:* involves converting each row into a unique instance in facts base. Each column is mapped to its corresponding element in the ontology, whether it's an entity, sub-entity, or attribute. This approach ensures that all data points from C-MAPSS have a representation in the ontology, allowing for a combination of knowledge-based reasoning and data insights. The process effectively bridges theoretical knowledge representation with actual data, enhancing the ontology's real-world applicability.

2) *Rules definition (Critical threshold computing):* In the realm of advanced health monitoring, real-time insights into engine health are obtained by determining critical sensor thresholds based on recent sensor data. We introduce the following formula for calculating the threshold for each sensor associated with each engine (1). By computing the average of specific recent readings, typically the most recent 5%, this metric supports PdM and anomaly detection, ultimately enhancing the performance and reliability of aircraft engines

$$\theta_{s,u} = \frac{1}{n} \sum_{i=(1-f) \times m}^m x_{s,u,i} \quad (1)$$

Where:

- $\theta_{s,u}$: critical threshold for each sensor s of unit u .
- $x_{s,u,i}$: value of each sensor s for each unit u at cycle i .
- m : total number of cycles for unit u .

- f : fraction of the last cycles computing the threshold.
- n : number of cycles in fraction, given by $n = f \times m$.

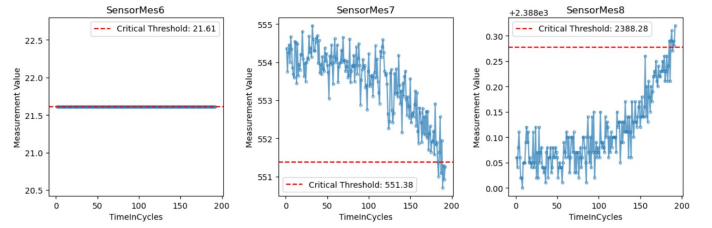


Fig. 5. Sensor thresholds and trends extraction using knowledge-based approach.

Our focus lies in examining the fluctuations in sensor data to establish reasoning rules derived from the patterns observed in different sensors, as documented in Table I. Each sensor's trend can be categorized as either "up", "down", or "" (stable). These trends serve as the basis for determining the health status of engine components linked to the respective sensors.

- **Sensors with an upward trend ("up"):** when the sensor value remains below or equal to its critical threshold, the corresponding engine component is deemed to be in a good condition. If the sensor value exceeds this threshold, it indicates a potential issue, triggering an alert about a specific type of failure in the associated component.
- **Sensors with a downward trend ("down"):** the engine component remains in good health as long as the sensor value is greater than or equal to its critical threshold. However, when the sensor reading drops below this threshold, it signifies a potential problem, prompting an alert about a failure in the associated component.
- **Sensors with a stable value (""):** the sensor values are expected to remain relatively stable. Any deviation from the norm, especially if it crosses the critical threshold, is a sign of a possible anomaly.

By adhering to these rules, real-time monitoring systems can promptly detect potential issues in engine components. This allows for timely interventions, maintenance, or replacements, playing a crucial role in preventing unexpected breakdowns, ensuring safe flights, and prolonging the life of the aircraft engine components [5].

3) *Reasoning*: The reasoning process is a systematic way of deducing new information from existing knowledge. It allows for the extraction of implicit knowledge and the verification of consistency within the ontology [5]. By applying reasoning to the C-MAPSS ontology, we can achieve several objectives: detect failures using the established rules and the data into the ontology, enhance Data-Driven approaches, provide clear and contextual explanations, iterative enhancement as more data is integrated into the ontology and as the rules evolve the reasoning process can continually refine its deductions. In essence, reasoning is a crucial component of a knowledge-based system, acting as the bridge between raw data and actionable insights, and enhancing the capabilities of purely data-driven.

B. Proposed Framework for PdM Hybrid approach

The fusion of knowledge and data methods can enhance the accuracy of RUL prediction and the ontology can offer insights into the relationships between various failures, their propagation, and impact of engine lifespan. To create a PdM hybrid model, three combination methods are needed: sequential method allows for data preprocessing with knowledge approach and then RUL prediction using the data approach; the parallel method employs both approaches simultaneously and then merges the predictions made by these approaches; the integrated method involves directly incorporating the knowledge-based into the data-driven system. In this context, both the sequential and parallel methods were combined (Fig. 6) to yield even better predictions.

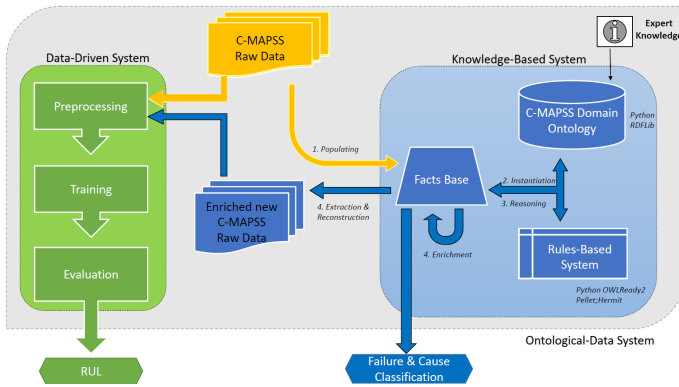


Fig. 6. Architectural Design of the Hybrid System for the Case Study.

Initially, the C-MAPSS dataset is provided to both systems, the data-driven system handles data preprocessing, trains various ML and DL algorithms, and evaluates these algorithms to select the one that best estimates the RUL. Simultaneously, the knowledge-based approach, through reasoning, offers clear explanations related to the detected upcoming failure. Moreover, new connections between variables, which might not be discernible at first glance or by the data-driven method, are provided by the knowledge-based approach. This subsequently enables further data preprocessing, enriching the data, or adding new columns to the dataset. The process then repeats,

aiming for increasingly accurate RUL predictions. In summary, the integration of an ontology not only enhances prediction accuracy but also offers contextual explanations for each detection or prediction. This ensures better decision-making and more efficient maintenance of aircraft engines.

C. Results

After going through all the steps of creating the ontology, we obtained the model in the Fig. 7, which displays all the elements found within the ontology and how these different elements are interconnected.

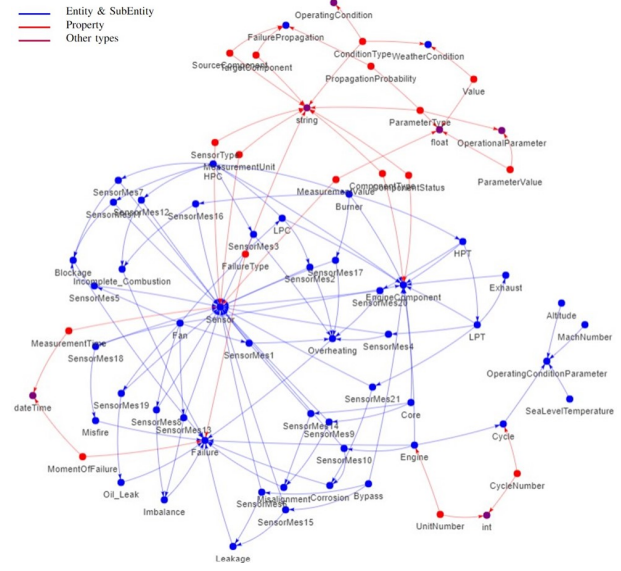


Fig. 7. The C-MAPSS Ontology knowledge graph.

By zooming in on the Fan component in the C-MAPSS Ontology, we can see how it is connected to other components. For instance: *Fan subClassOf EngineComponet. Fan isMonitoredBy SensorMes1, SensorMes5, SensorMes8, SensorMes13, SensorMes18, and SensorMes19. SensorMes1 canHave OverHeating. Fan flowGoesFrom LCP. Fan isCloseTo LCP.* Finally, the bellow SPARQL query allow to determine which sensors monitor the Fan component.

```
SELECT ?sensor ?failure
WHERE {
  aero:Fan aero:isMonitoredBy ?sensor.
  ?sensor aero:canHave ?failure.
}
```

SPARQL query response:

```
http://www.aero.org/ontologies/CMAPSS#SensorMes1
http://www.aero.org/ontologies/CMAPSS#SensorMes5
http://www.aero.org/ontologies/CMAPSS#SensorMes8
http://www.aero.org/ontologies/CMAPSS#SensorMes13
http://www.aero.org/ontologies/CMAPSS#SensorMes18
http://www.aero.org/ontologies/CMAPSS#SensorMes19
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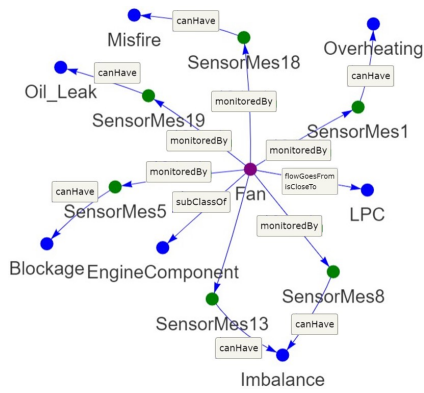


Fig. 8. Detailed Exploration of the Fan in the C-MAPSS Ontology.

V. DISCUSSION

The main objective of this work was to explore the potential of the knowledge to improve the PdM of aircraft engines with a C-MAPSS application. unexplored until now, our goal was to set up a hybrid process combining knowledge and data, and to demonstrate the feasibility of this method. The implementation of our solution was carried out with the Python language and the RDFLib and OWLReady2 libraries [10], this made it possible to overcome the limits often encountered in the Java language and the lack of performance in the face of the needs for population and reasoning. In addition, this makes it possible to implement the data and ontology approaches in a single homogeneous system, thus avoiding having two decompartamentalized systems whose interoperability is difficult. Our solution proved that it was possible to populate an ontology with a massive dataset provided that the knowledge was well conceptualized, and that it was possible to generate new knowledge with rules, which would be impossible to achieve with a data-driven approach. We have demonstrated that it is possible to recover this new knowledge and reintegrate it into the initial dataset to complete and enrich it. The feasibility of such a system opens the field to several possibilities in the explainability of ML and in the structuring of massive data.

VI. CONCLUSION

The aerospace industry, characterized by its complexity and strict safety standards, is consistently on the lookout for cutting-edge methodologies for PdM of aircraft engines. In this context, our work stands out not only for adopting a hybrid approach that combines knowledge-based and data-driven approaches but also by introducing the very first ontology on the C-MAPSS dataset. This innovation isn't merely a theoretical advancement but also demonstrates significant practical relevance in addressing the contemporary challenges of the industry. The efficiency of our implementation, made possible through the use of Python and specialized libraries like RDFLib and OWLReady2, transcends traditional limitations, offering an optimized and swift solution. In essence, our study doesn't just propose a new PdM method, it lays the groundwork for a transformation in how the aerospace industry might approach diagnostics and maintenance in the

future, with potential major implications in terms of safety, operational efficiency, and cost reduction.

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