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Exploring a Knowledge-Based Approach for Predictive Maintenance of Aircraft Engines: Studying Fault Propagation through Spatial and Topological Component Relationships

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ABSTRACT

Predictive maintenance has become a highly favored application in Industry 4.0, particularly in complex systems with requirements for reliability, robustness, and performance. Aircraft engines are among these systems, and several studies have been conducted to try to estimate their remaining lifespan. The C-MAPSS dataset provided by NASA has greatly served the scientific community, and several works based on physical models and data-driven approaches have been proposed. However, several limitations related to data quality or data availability of failures persist, and integrating domain knowledge can help address these challenges. In this article, we are currently implementing a new approach based on knowledge coupled with qualitative spatial reasoning to study the propagation of faults within system components until complete shutdown. Region Connection Calculus (RCC8) formal model will be used to describe the component relationships, drawing inspiration from the C-MAPSS dataset.

1. INTRODUCTION

In Industry 4.0, predictive maintenance (PdM) allows for the detection of anomalies and the anticipation of upcoming breakdowns in equipment, machines, or components (Nunes, Santos, & Rocha, 2023). Through the continuous collection of multi-sensor data and system performance analysis, this maintenance strategy relies on machine learning (ML) algorithms capable of building models with the ability to detect early signs of impending failures or malfunctions. Early detection of anomalies allows for prevention, anticipation of corrective actions, and reduced downtime. In this context, PdM solutions rely on estimating the remaining useful life (RUL) before failure (Zio, 2022), which represents the remaining operating time before a component or machine failure. Several approaches are cited in the literature: model-based, data-driven, knowledge-based, or hybrid approaches combining the previous three (Cardoso & Ferreira, 2021). In the aeronotic context, Aircraft engines are among these systems, and several studies have been conducted to try to estimate their remaining lifespan (de Pater, Reijns, & Mitici, 2022). The C-MAPSS dataset provided by NASA [1] has greatly served the scientific community. The solutions proposed in the literature mainly address data-driven approaches (Kumar, 2021; Vollert & Theissler, 2021; Barry, Hafsi, & Mian Qaisar, 2023; Asif et al., 2022), but very few hybrid approaches (Dangut, Jennions, King, & Skaf, 2022) are proposed or tested and no approach attempting to integrate domain knowledge or expert knowledge exists (Barry & Hafsi, 2023; Mayadevi, Martis, Sathyan, & Cohen, 2022).

In this study, we aim to focus on the C-MAPSS dataset referenced in the domain literature and attempt to explore a new approach based on knowledge coupled with qualitative spatial reasoning to study the propagation of faults within system components until complete shutdown. RCC8 rules will be used to describe the component relationships, drawing inspiration from the C-MAPSS dataset (Saxena, Goebel, Simon, & Eklund, 2008), which corresponds to a dataset generated by simulating the operational functioning of aircraft engines, with the aim of evaluating the performance of RUL estimation models. The main objective concerns the modeling of a domain ontology or a semantic graph from the domain knowledge integrated into the C-MAPSS dataset. Spatial and topological representation of system components will be addressed by using RCC8 relations.

2. CONTEXT

Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) developed by NASA, is a simulation tool for a realistic large commercial turbofan engine flights, used for the

[1] data.nasa.gov/dataset/C-MAPSS-Aircraft-Engine-Simulator-Data

Table 1. Overview of C-MAPSS Dataset with segmentation into 4 subsets and description of each subset's characteristics.

	FD001	FD002	FD003	FD004
Train Trajectories	100	260	100	249
Test Trajectories	100	259	100	248
Conditions	1	6	1	6
Failure modes	1	1	2	2

PHM'2008 challenge to generate un large dataset called C-MAPSS dataset (Saxena et al., 2008). It consists of a simulated engine model in the $90,000lb$ thrust class. It also includes an atmospheric model that can simulate operations at various altitudes (sea level to $40,000ft$), Mach numbers (0 to 0.90), and sea-level temperatures (-60 to $103F$). The C-MAPSS dataset is commonly utilized in the field of PdM and engine health prognostic (Vollert & Theissler, 2021). These data are often employed for developing and assessing engine health diagnostic algorithms, failure prediction models, and PdM strategies. The dataset is segmented into different simulation units as demonstrated in Table 1, where each representing an individual engine, with varied failure profiles. Due to its complexity and diversity, C-MAPSS serves as a popular testbed for validating PdM techniques in the aerospace engineering field.

Researchers often leverage this dataset to benchmark their algorithms and methodologies, comparing the performance of different approaches in predicting engine failures and assessing the health status of engines. Moreover, C-MAPSS provides a valuable resource for studying the behavior of engines under various operating conditions and environmental factors (Vollert & Theissler, 2021).

3. Related work

3.1. Predictive Maintenance & PHM Background

In light of the evolving and knowledge-intensive nature of the manufacturing domain, there has been a growing interest in employing semantic technologies (Xia, Zheng, Li, Gao, & Wang, 2022), particularly ontology-based approaches, for PdM. Recent research has introduced various ontologies and rule-based extensions aimed at enhancing knowledge representation and reuse in PdM with several applications in Industry 4.0 (Dalzochio et al., 2020) like in Machinery: (mechanical machines) (Nuñez & Borsato, 2018), (bearings) (Cao, Giustozzi, Zanni-Merk, de Bertrand de Beuvron, & Reich, 2019), elevator running systems (Hou, Qiu, Xue, Wang, & Jiang, 2020), hydraulic systems (Yan et al., 2023), Cyber-Physical Systems (Cao et al., 2022a; Oladapo, Adedeji, Nzenwata, Quoc, & Dada, 2023) and industrial robots (X. Wang, Mingzhou, Liu, Lin, & Xi, 2023). This section provides a review of the most significant research efforts in this area. In

Table 2. Related work applied semantic approaches in the context of Industry 4.0.

Reference	Application Field	Proposition
(Nuñez & Borsato, 2018)	Mechanical machines	Ontology-based model
(Cao, Giustozzi, et al., 2019)	Bearings / rotating machinery	Ontology-based approach
(Hou et al., 2020)	Elevator running system	Knowledge graph-based approach
(Cao et al., 2022a)	Cyber-Physical Systems	Hybrid approach based on statistical and symbolic AI technologies
(Chhetri, Kurteva, Adigun, & Fensel, 2022)	Hard Drive Failure Prediction	Knowledge Graph Based approach
(Yan et al., 2023)	Hydraulic systems	Knowledge graph-based approach
(X. Wang et al., 2023)	Industrial robots in intelligent manufacturing	PdM method based on data and knowledge
(Oladapo et al., 2023)	Routine maintenance in Industry 4.0	Fuzzified Case-Based Reasoning
(Li, Zhang, Li, Zhou, & Bao, 2023)	steel factory bridge cranes	Knowledge-based approach

(Cao, Samet, Zanni-Merk, De Bertrand de Beuvron, & Reich, 2019), the authors argue that existing PdM approaches have been limited to predicting the timing of machinery failures, while lacking the capability to identify the criticality of the failures. This may lead to inappropriate maintenance plans and strategies. Authors introduce a novel ontology-based approach to facilitate PdM in industry, by combining fuzzy clustering with semantic technologies. Fuzzy clustering techniques are employed to determine the criticality of failures based on historical machine data, while semantic technologies utilize the results of fuzzy clustering to predict the timing and severity of these failures. In (Cao et al., 2022b), the authors address the problem of complexity arising from heterogeneous industrial data, which leads to a semantic gap among manufacturing systems. There is an increasing need for uniform knowledge representation and real-time reasoning in Cyber-Physical Systems (CPS) to automate decision-making processes. In response to this challenge, the authors propose a hybrid approach that combines statistical and symbolic AI. They introduce a system called Knowledge-based System for PdM in Industry 4.0 (KSPMI), which utilizes statistical techniques such as ML and chronicle mining, along with symbolic AI technologies like domain ontologies and logic rules. This hybrid method enables automatic detection of machinery anomalies and prediction of future events. The effectiveness of the approach is demonstrated through evaluation on both real-world and synthetic datasets. In (Chhetri et al., 2022), authors raise the need to improve hard drive failure prediction, given its critical role in computing systems. The authors point out that existing studies mostly rely on either ML or semantic technology, but each approach has its limitations: ML lacks context-awareness, while semantic technology lacks predictive capabilities. To address these limitations, the authors propose a hybrid approach that combines the strengths of both ML and semantic technology to enhance hard drive failure prediction accuracy. In (Yan et al., 2023), authors are interested in the problems due to the knowledge-intensive and heterogeneous nature of the manufacturing domain, the data and information required for PdM are normally collected from ubiquitous sensing networks. This leads to the gap between massive heterogeneous data/information resources in hydraulic system components and the limited cognitive ability of system users. To address this limitation, the authors propose a virtual knowledge graph-based approach for digitally modeling and intelligently predicting maintenance tasks.

3.2. Knowledge Representation & Spational Reasoning

In the industrial domain, representing knowledge involves organizing and structuring information about processes, systems, and domains. This helps in better understanding and decision-making. With the advancement of technology in Industry 4.0, effective knowledge representation is crucial for optimizing operations and driving innovation. In (Smith et al., 2019), authors highlight the need for a comprehensive ontology to support digital manufacturing, particularly in terms of standardizing terminology across various branches of the advanced manufacturing industries. They propose to develop an upper ontology for the Industrial Ontologies Foundry (IOF), based on the Basic Formal Ontology (BFO), to serve as a foundation for creating a suite of ontologies tailored for digital manufacturing. In (Confalonieri & Guizzardi, 2023) authors discuss the Multiple Roles of Ontologies in Explainable AI. Knowledge-based approaches for RUL estimation have several advantages over other methods (Barry & Hafsi, 2023), including the ability to incorporate domain-specific knowledge and experience into the model, and the ability to handle complex systems where data-driven methods may not be effective. However, they also have limitations, such as being dependent on the availability of expert knowledge and the potential for subjective judgments to influence the model. From an Operations perspective, knowledge-based methods, including fuzzy systems, provide a direct and cost-effective means for RUL estimation by leveraging expert knowledge. These methods prioritize ease of implementation and inter rater reliability. However, their effectiveness is closely tied to the quality of expert input.

Qualitative spatial reasoning, a branch of artificial intelligence, plays a significant role in enhancing decision-making processes within the industrial domain (Fraske, 2022). This approach focuses on analyzing spatial relationships and configurations without precise numerical measurements, allowing for a more intuitive understanding of industrial environments and processes. In the context of Industry 4.0, where smart manufacturing systems heavily rely on interconnected and sensor-rich environments, qualitative spatial reasoning offers valuable insights for optimizing resource allocation, scheduling tasks, and ensuring efficient workflow management (Ladron-de Guevara-Munoz, Alonso-Garcia, de Cozar-Macias, & Blazquez-Parra, 2023).

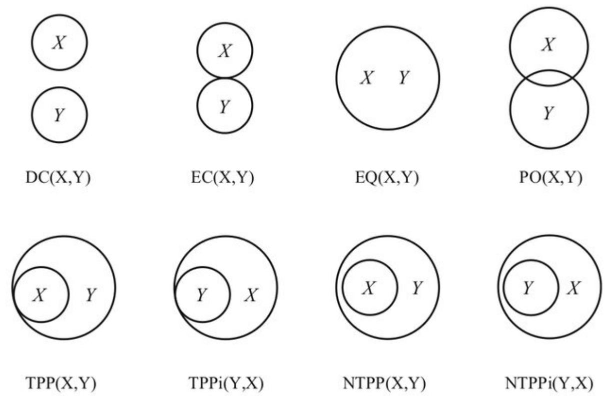

Figure 1. The 8 basic relations of RCC formalism.

RCC (Region Connection Calculus) is a logical formalism used in qualitative geometry intended for representing and reasoning about qualitative spatial relations among regions (Marc-Zwecker, De Bertrand de Beuvron, Zanni-Merk, & Le Ber, 2013). Based on the primitive connection relation $C(x, y)$, where x and y represent spatial regions consisting of a set of points in a plane, delimited by a continuous boundary. The RCC8 formalism defines eight basic relations between regions in space. These relations are exhaustive and mutually disjoint, allowing the definition of any relation between two spatial regions (Y. Wang, Mengling, Liu, & ye, 2018). The eight basic relations are DC (disconnected), EC (externally connected), PO (partially overlapping), EQ (equal), NTPP (non-tangential proper part), TPP (tangential proper part), NTPPi (the inverse of non-tangential proper part), and TPPi (the inverse of tangential proper part) as illustrated in Figure 1 (Lima, Costa, & Moreno, 2019).

4. PROPOSITION

To develop a PdM method based on relationships between industrial components, we propose an approach with application to C-MAPSS aircraft engines as follows: (1) Domain study and advanced data characteristics analysis of aircraft engine components and sensors. (2) Formalization of knowledge in concepts and relationships with a focus on topological relationships between components. (3) Upgrading and describing topological relationships between components based on basic RCC8 relationships. (4) Configuration of a rule-base (based on assumptions) for error propagation across defined relationships. (5) Determination of alert thresholds for each sensor and component to configure reasoning rules by using data-driven techniques. (6) Test the method and compare it with existing data-driven approaches.

This structured approach describes the steps involved in applying a knowledge-based PdM approach to aircraft engines, integrating domain knowledge with data-driven techniques for effective fault detection and planning main

4.1. Practical Insights into Knowledge Representation for C-MAPSS Scenario

To model and formalize domain knowledge, it is important to understand the functioning of the engine, its components, and the generated data. C-MAPSS consists of four datasets, with each dataset further divided into training and test subsets (Saxena et al., 2008). Each time series originates from a different engine of the same type. Three operational settings, which significantly affect engine performance, are included in the data. Furthermore, the data are contaminated with sensor noise. The engine operates normally at the beginning of each time series but begins to degrade at some point during the series. Multiple aircraft engines undergo varied usage throughout their operational history. A single engine unit may experience different flight conditions from one flight to another. Due to various factors, such as flight duration and environmental conditions, the extent and rate of damage accumulation will vary for each engine. Although the data is simulated, numerous phenomena and challenges have been incorporated to enhance the realism of the dataset. For instance, an initial wear is simulated reflecting typical manufacturing inefficiencies observed in real systems. The initial wear, manifested as minor alterations in pressure, temperature, airflow measurements, etc., is primarily intended to introduce a certain level of manufacturing variability into the data. Indeed, each engine is not identical upon leaving the factory due to manufacturing tolerances and differences in production processes, introducing variability right from the beginning of their use. Additionally, some non-ideal starting conditions or pre-existing degradations are simulated as initial wear due to manufacturing inefficiencies or storage conditions prior to use. Finally, noise is introduced at various stages of the simulation process, ultimately affecting the sensor measurements and mirroring real-world conditions (Saxena et al., 2008).

The engine consists of multiple components, as depicted in Figure 2 (Sánchez-Lasheras, Garcia Nieto, de Cos Juez, Bayón, & González, 2015) :

- **Fan:** The fan component draws in air, providing the initial thrust and airflow into the engine, crucial for combustion.
- **Combustor:** This section mixes fuel with the incoming air and ignites it, generating high-pressure and high-temperature gas for propulsion.

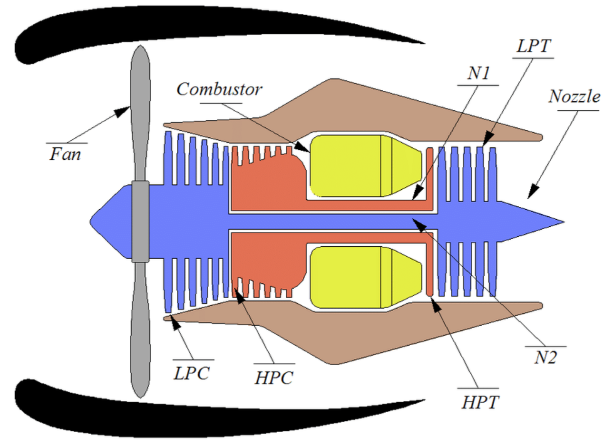

Figure 2. Schematic illustration of an aircraft engine model.

- **LPC (Low-Pressure Compressor):** It further compresses the air before it enters the combustion chamber, enhancing efficiency and power output.
- **HPC (High-Pressure Compressor):** This component significantly raises the pressure of the air, preparing it for combustion and ensuring optimal engine performance.
- **N2:** Represents the low-pressure shaft, connected to the LPC and fan, responsible for driving the fan and low-pressure compressor.
- **HPT (High-Pressure Turbine):** Extracts energy from the high-pressure gas flow to drive the HPC, maintaining compression efficiency.
- **LPT (Low-Pressure Turbine):** Utilizes remaining energy in the gas flow to drive the fan and LPC, contributing to overall engine power generation.
- **Nozzle:** This component accelerates the exhaust gases to produce thrust, directing the flow and converting thermal energy into kinetic energy.

The C-MAPSS dataset simulates engine operation data without providing a detailed description of the sensors utilized. In real-world engines, a diverse array of sensors is commonly employed to monitor various operational and performance parameters. These sensors may encompass:

- **Pressure sensors:** To measure pressure in different parts of the engine, such as combustion chambers, air inlets and outlets, and fuel lines.
- **Temperature sensors:** To monitor temperature in critical areas of the engine, such as combustion chambers, turbines, and exhaust sections.
- **Flow sensors:** To measure the flow rate of fuel, air, or coolant circulating through the engine.
- **Vibration sensors:** To detect abnormal vibrations or signs of imbalance in rotating components of the engine, such as turbine shafts and bearings.

Table 3. Description of the 21 C-MAPSS Sensors.

Sensor ID	Measurement	Unit
T2	Fan inlet temperature	$^\circ$R
T24	LPC outlet temperature	$^\circ$R
T30	HPC outlet temperature	$^\circ$R
T50	LPT outlet temperature	$^\circ$R
P2	Fan inlet pressure	psia
P15	bypass-duct pressure	psia
P30	HPC outlet pressure	psia
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
epr	Engine pressure ratio	-
Ps30	HPC outlet Static pressure	psia
Phi	Ratio of fuel flow to Ps30	pps/psi
NRf	Corrected fan speed	rpm
NRc	Corrected core speed	rpm
BPR	Bypass Ratio	-
htBleed	Bleed Enthalpy	-
Nf_dmd	Demanded fan speed	rpm
PCNfR_dmd	Demanded fan conversion speed	rpm
W31	HPT Coolant air flow	lbm/s
W32	LPT Coolant air flow	lbm/s

- **Speed sensors:** To monitor the rotational speed of engine components, such as turbines and compressors.
- **Position sensors:** To determine the position of valves, flaps, and other moving components of the engine.
- **Exhaust gas sensors:** To analyze exhaust gases and monitor emissions, including gas composition and pollutant levels.

These sensors play a crucial role in collecting engine operation data, which is then used to assess performance, diagnose issues, and predict potential failures as part of PdM and engine health monitoring. Table 3 provides an overview of the sensors included in C-MAPSS.

4.2. Conceptualization and Formalization of Knowledge Domain Ontology

A specialized methodology is used to conceptualize and develop the domain ontology. The Methontology methodology, developed by (Fernández-López, Gomez-Perez, & Juristo, 1997), provides a framework for constructing ontologies at the knowledge level. It includes the identification of the ontology development process and a lifecycle based on evolving prototypes, along with specific techniques for process description as depicted in Figure 3 (Blázquez, Fernández-López, García-Pinar, & Gomez-Perez, 1998).

Our ontology creation follows a systematic approach. The initial step involves the preparation of a formal document meticulously describing the domain to be represented according to the previous section. Subsequently, the conceptualization phase ensues, entailing the definition of concepts, properties, and relationships. For instance, an illustration of the main concepts related by three types of relations in two levels

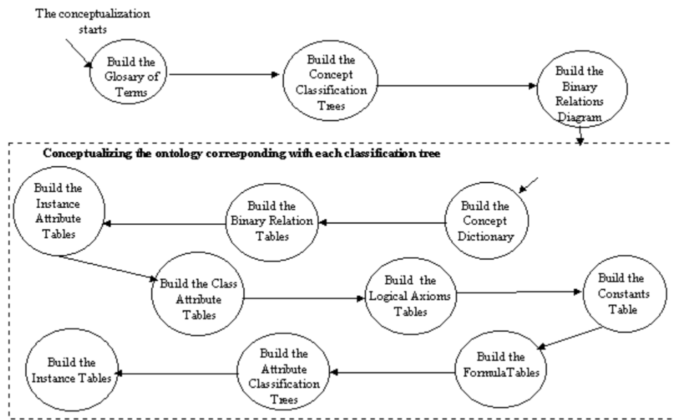

Figure 3. Development process ontology with the Methontology methodology.

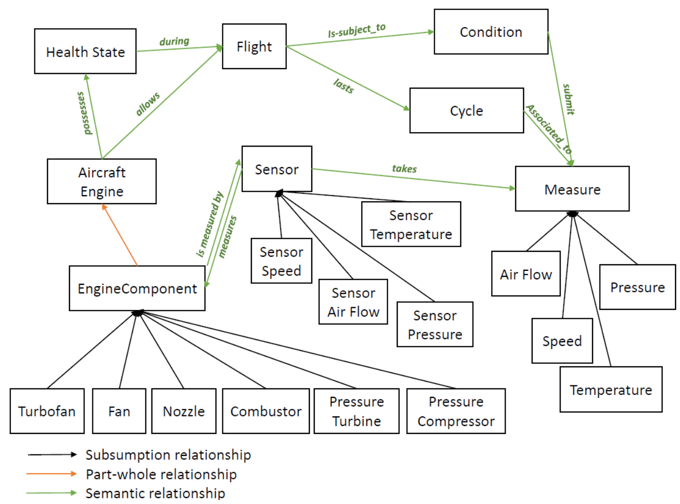

Figure 4. Diagram of ontology classes (concepts) in two main levels.

(subsumption relation/is-a, part-of/part-whole relation, and semantic relations) is provided in Figure 4. Following conceptualization, the third step focuses on formalizing the conceptual knowledge into a language understandable by computers. This modeling can be implemented in an ontology editing tool. In our case, we express the formal ontology in Description Logics (DL) language (Baader, Horrocks, & Sattler, 2005) and implement it using the OWL (Web Ontology Language) format (Taylor, 2009) within the open-source ontology editor Protégé 5.6 [2]. Once the ontology is created, it can be used to annotate and enrich the C-MAPSS dataset with semantic information about the components and their relationships, facilitating advanced analyses and data interoperability. In line with these principles, we establish a conceptual framework to represent pivotal elements and relationships within the C-MAPSS dataset domain. This domain in-

[2] Protégé editor: `https://protege.stanford.edu/`

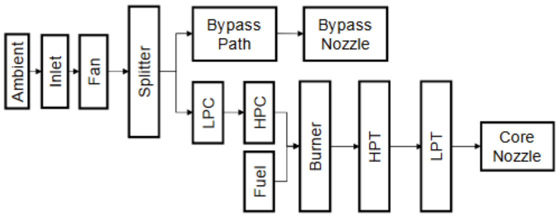

Figure 5. Diagram of modules and their connections in the aircraft engine model.

formation is captured as knowledge within a domain ontology named EngineFailureOntology. Within this ontology, we delineate various concepts, including: Aircraft engine, Engine component, Flight, Condition, Cycle, Measure, Sensor, Heath state, etc. The Definition in DL of Some Design Examples is Provided as Follows:

Engine $\equiv$ ComplexDevice $\wedge$ hasComponent some (Turbine $\sqcap$ Compressor $\sqcap$ Shaft)

Sensor $\equiv$ Device $\wedge$ measures some (Temperature $\sqcap$ Pressure $\sqcap$ Vibration)

TemperatureSensor $\equiv$ Sensor $\wedge$ measures only Temperature

OperationalSetting $\equiv$ Setting $\wedge$ includes some (EngineSpeed $\sqcap$ Load $\sqcap$ AmbientConditions)

4.3. Description of Topological Relationships Between Components

This step involves defining the topological relationships between components using the extension of RCC8 relations and drawing inspiration from diagram in Figure 5, which highlights the interconnections between components.

Some examples to illustrate how RCC8 relations can be used to describe spatial interactions among components of the C-MAPSS engine as follow:

Disjointness DC(Fan,Nozzle) : Fan and Nozzle components are mutually disjoint, as they occupy distinct spatial areas within the engine. This relationship can be expressed by:

$Fan \sqcap Nozzle \equiv \emptyset$

Others disjoitness relationships can be expressed as follows:
$Combustor \sqcap Nozzle \equiv \emptyset$

$Combustor \sqcap Fan \equiv \emptyset$

$LPC \sqcap LPT \equiv \emptyset$

External-Connected EC(HPC, Combustor): The Compressor (HPC) touches the Combustor because the compressed air from the compressor is then directed to the combustor for the combustion process. This relationship can be expressed as follows:

$HPC \sqcap Combustor \neq \emptyset$

Other components are externally connected to each other; these relations can be expressed as follows:

$HPC \sqcap LPC \neq \emptyset$

$LPC \sqcap N2 \neq \emptyset$

$N1 \sqcap Combustor \neq \emptyset$

$HPT \sqcap LPT \neq \emptyset$

$LPT \sqcap N2 \neq \emptyset$

$LPT \sqcap Nozzle \neq \emptyset$

The shaft or rotor (corresponding to the N2 component) is a tangential proper part of the turbine because it is physically attached to the turbine and rotates together with it. Additionally, some of its parts are covered by two other components: N1 and HPT. These relations can be expressed as follows:

$N2 \sqcap HPT \neq \emptyset$

$N2 \sqcap HPC \neq \emptyset$

Partially Overlapping PO(Fan , LPC): The fan overlap some part of the low pressure chamber and it overlap partially, as they share a common space within the engine. This relation can be expressed by:

$Fan \sqcap LPC \neq \emptyset$

The definition of topological relations based on the 2D diagram allows for connecting various components to facilitate the propagation of alerts if a malfunction is observed on a component. This enables the system to identify spatial interactions and dependencies between components, enhancing its capability to detect and propagate alerts effectively throughout the system.

4.4. Reasoning with SWRL rules

Several reasoning rules can be defined in collaboration with domain experts in aeronautics. In this study, we rely on extracting rules from our understanding of the data.

The first rule that can be defined pertains to subjecting a component to significant variations, which may cause fluctuations in sensor values, potentially leading to component fragility and resulting in localized and then generalized malfunction. The risk of impacting neighboring components directly may consequently increase. This rule will be formulated in the form of a SWRL (Semantic Web Rule Language) rule. After defining this rule, the next steps involve loading the time series data from the dataset, initiating the reasoning process, generating a new dataset, and studying the correlation of the new variables obtained through reasoning, in the form of new links or instance values in the knowledge base, with the RUL value. Although it is a logical rule, it is necessary to define

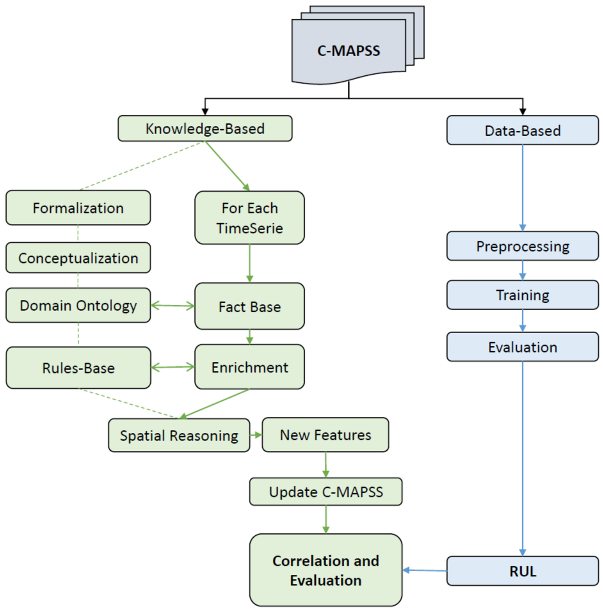

Figure 6. Main steps of the proposed approach involve treating each time series separately and creating features based on the proposed spatial reasoning.

alert thresholds for each sensor to weigh the estimated risk on each component. The definition of these thresholds can be initially done through advanced analysis of the C-MAPSS dataset using ML techniques. Subsequently, collaboration with aeronautical experts can further refine these thresholds.

Finally, we propose this validation technique because the dataset does not provide information on the types of failures and faulty components. Therefore, we will evaluate the validity and performance of our approach by assessing whether the learned knowledge has a positive or negative impact on the estimation of RUL through ML techniques.The process of the proposed approach is illustrated in Figure 6.

5. Discussion

The present study aimed to investigate a novel approach grounded in knowledge representation and spatial reasoning to predict failures by examining fault propagation and its repercussions across components, ultimately impacting the entire system. While similar methodologies have been explored in scientific literature for analogous yet distinct problems, the application of this approach remains novel within the context of our investigation. Despite the inherent complexity associated with its implementation, the potential contribution of this approach towards enhancing the explainability of machine learning (ML) models and elucidating degradation mechanisms holds substantial promise.

5.1. Consensus on the representation of domain and expert knowledge

The conceptualization, formalization, and formulation of rules within this study are predicated upon assumptions crafted within the confines of our research framework. However, it is imperative to acknowledge that such methodologies necessitate close collaboration with domain experts to ascertain the validity and relevance of the defined rules for effective reasoning. To further validate the efficacy of the approach delineated in this article, future endeavors will entail concerted efforts to engage domain experts in refining the formalization of knowledge and iteratively updating the associated reasoning rules. This iterative process of validation and refinement holds the potential to fortify the robustness and applicability of the proposed approach in real-world industrial settings.

5.2. Transition to RCC8 3D Formalism

Furthermore, it is essential to note that the rules of RCC8 pertain to regions in a 2D plane. In this study, we took into account the 2D diagram of components; however, transitioning to 3D objects could offer intriguing avenues for exploration in future research. By extending our analysis to encompass 3D objects, we can potentially enhance the fidelity and accuracy of our predictive models, thereby augmenting the applicability of our approach in diverse industrial scenarios.

5.3. Lack of data on failure types and their origins

Our study is based on the analysis of failure propagation among components, which assumes that a malfunction in one component can be detected or identified. However, the C-MAPSS dataset does not provide the necessary data to obtain this information. Preliminary work is required to estimate the health status of each component and define a threshold indicating failure at its level, as well as to study the propagation to other components. For this purpose, several SWRL reasoning rules can be specified to transition a component to a failure state when its condition is deemed critical. This also involves a detailed analysis of sensor data. For instance, sensors that detect abnormal fluctuations in the data of a component may indicate an impending failure.

6. Conclusion & Future Work

In the context of Industry 4.0 overall, and specifically in the estimation of aircraft engine lifespan, our objective in this article was to investigate the possibility and feasibility of a knowledge-based approach focusing on component degradation as a separate entity before overall system failure, by exploring the potential of qualitative spatial reasoning. The proposed method is currently under implementation, and its results have not yet been evaluated. However, the approach appears to offer tangible benefits, particularly in enhancing our understanding of internal functioning and incident propagation among components. The next steps in this work involve finalizing the proof of concept and obtaining preliminary results. Subsequently, we plan to engage with domain experts to refine the established conceptualization and define reasoning rules that accurately reflect real-world scenarios. Depending on the outcomes, there is potential for applying the method to a cyber-physical system to enhance the explainability of machine learning models in place.

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