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Designing a semantic based common taxonomy of mechanical component degradation to enable maintenance digitalisation

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Abstract

Digital data management and enterprise systems have become key to support the digitalisation of maintenance activities. With traditional maintenance activities still striving for efficiencies, platforms such as the natural language processing (NLP) are supporting industries to mine textural data, not just extracting degradation terminologies but providing the maintainer with holistic insights on the degradation process. Traditionally, the degradation analysis, the first step in maintenance, is a manual process for defect characterisation, followed by failure investigation and a remaining useful life estimation. To enable digitalisation, transfer of human cognitive decision making from the physical world to the digital world is key. This paper enables this cognitive knowledge transfer through the design of a common degradation taxonomy and extracting terminology relationships to produce degradation causality with an NLP knowledge extraction approach. Further, this paper proposes and demonstrates a framework to present the data in the form of a knowledge graph populated using an application-level ontology. Use cases in the aerospace context have been used to show the power of the NLP and conceptual journey into the digitalisation of maintenance.

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1. Introduction

Maintenance engineering has been the backbone of a majority of complex and heavy engineering industries and continues to play a vital role in the in-service maintenance and upkeep of high value assets (HVAs), especially over the last few decades. Be it the aerospace industry or the oil and natural gas industry, maintaining long-life assets against stringent regulations backed by international standards has been of utmost importance as failure of such assets could be catastrophic. Whilst there have been tremendous improvements in streamlining manufacturing processes to achieve high quality standards achieved with a degree of automation, the processes being repetitive; the maintenance of those complex engineered assets is still a massive undertaking as most of the decisions are expert driven and heavily based on tacit and experience-based knowledge[1].This is purely due to the high levels of uncertainty associated with the occurrence of deterioration (in terms of the certainty of occurrence, its characteristics like exact type, location and geometry and its behaviour over time), the environment where the asset operates and its detrimental impact on the performance of the asset. There is still a large uncertainty associated with the prediction and establishment of exact progression pathway of the deterioration and the timeline when it becomes a failure. Multiple researchers have attempted to reduce this uncertainty by creating run-to-fail (RTF) models and or developing an accurate remaining-useful-life (RUL) model that helps predict the rate of failure and or progression of damage [2,3]. Now this information, combined with the physics-based and experience-based knowledge serves as a

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fundamental building block on making timely decisions thereby preventing failure from occurring in the first place. This is achieved by performing maintenance and repair on a regular basis, thus extending the life of the complex HVA.

1.1. Importance of maintenance

The last decade has seen a huge shift in the maintenance attitude moving away from the erstwhile reactive maintenance behaviour to pro-active predictive maintenance. For instance, a report from the U.S. Department of Energy's Operations & Maintenance Best Practices Guide (2010) suggests that predictive maintenance could yield savings of between 30-40% when compared with reactive maintenance with a further 8-12% savings coming from preventative maintenance strategies [4]. This report is a good example as to why the industries are moving towards the predictive maintenance approaches.

Research initiatives such as the ones led by the Pacific Northwest National Laboratories [5,6] and the one reported by the Prognostics and Health Monitoring Society [6] establish that degradation causation helps identify early deteriorations. This, when combined with health and reliability models, could help predict failures which becomes the fundamental philosophy for predictive maintenance. This is just one of many approaches of how deterioration knowledge combined with reliability data modelling could improve the understanding of the asset behaviour [5]. At the outset, it may look like business value in terms of cost and the asset availability that drives these initiatives. However, in most of the cases, cost might not be the only driver and the requirement to achieve high to optimal performance of the asset functionality in-line with the standards and regulations associated with safety-critical assets, especially those operating in harsh environments that drives these initiatives.

The maintenance industry has built a lot of infrastructure ranging from inspection certifications, through to supporting organisations with reliability and RUL models to maintain and extend the life of long-life HVAs. Due to the high levels of uncertainty associated with defect characterisation, a detailed investigation report prepared by a maintenance expert is usually a firm requirement. Furthermore, in a majority of the organisations, a domain or field expert similar to a level-3 non-destructive testing (NDT) inspector will have the authority to sign-off the investigation report, as the consequences for missing or wrong identification of defects could be severe in terms of both the health and safety (H&S) requirements and the financial liabilities ranging from losses through-to damage of institutional reputation. It must be noted that a level-3 NDT inspector is a technical expert who undergoes extensive training and certification in NDT methods and has in-depth knowledge and experience to not just detect defects but also supports the sentencing (the process of checking part compliance with the design) of the part as per the set maintenance inspection standards. To add to the challenge, the entire process is heavily manual and requires an expert at every stage to interpret and make appropriate decisions.

1.2. Digitalising maintenance

The last decade has seen significant improvement in defect characterisation by the application of pattern recognition algorithms, machine learning techniques, deep learning and other artificial intelligence methods to characterise damage features, location, geometry and behaviour [7]. With the global maintenance engineering industry undergoing digitalisation, the focus is on creating knowledge based intelligent and smart systems that can automate the maintenance cycle of the asset aligning well with both predictive and preventative maintenance approaches [8]. Typical developments include e-Maintenance, maintenance-as-a-service, smart sensors, guided maintenance that employ a combination of augmented reality (AR) and virtual reality (VR) (also extended reality – XR), digital project methodologies (e.g, combination of agile and scrum methods with waterfall or stage gate methods that could improve agility) and decentralised repair teams [9]. To utilise these digital tools and techniques, having a fundamental understanding of degradation causation and utilisation of this knowledge is of utmost importance. While the digital maintenance technologies show great benefits, they are yet to mature where a system is intelligent enough to provide the maintainer with comprehensive information on the maintenance required so as to make a fully informed decision. The potential automation of maintenance decision making could significantly reduce the maintenance downtimes of service-critical assets. Further, it is crucial to build the fundamental blocks with the correct knowledge and identify logical relations which will allow the maintainer to make high confidence based decisions.

2. The fundamentals of causation

The first step in the maintenance activity is inspection, where a component is inspected for defects using a suite of NDT techniques such as visual inspection, dye penetrant inspection, magnetic particle inspection, ultrasonic inspection and x-radiographic inspection [10]. Once the defect is identified, a root cause analysis is conducted to identify both the root cause and the mechanism (or physics) by which the defect was created in the first instance, which is referred to as degradation knowledge. This enables the maintainer to both identify a suitable repair strategy and provide feedback to the designer to improve the design of the part itself. As indicated previously (see Section 1), this process of sentencing a component by the NDT inspector is heavily reliant on human tacit and experience-based knowledge. If we were to automate this process of deciding the next steps from the inspection, it is important to capture all the related terminologies and their relationships using terminology recognition and extraction algorithms. This will not just provide the entire root cause map but will allow the maintainer to make strategic repair decisions and enable automation of those decisions through advanced artificial intelligence methods. Thus, this activity of extracting degradation causation terminologies using text-mining and presenting them in the form of a taxonomy becomes the first step to achieve an intelligent digital system of the future.

Degradation causation digitalisation in this instance can be understood as the process of transferring tacit and physics based expert knowledge on degradation to machine recognisable knowledge [11,12]. The focus of this research is to establish a detailed method through a framework that shows how degradation causation can be digitalised. This paper further exploits how the future of maintenance can be undertaken using digital technologies such as the digital twin and how modelling taxonomy could significantly support this digital platform of the future.

Before proceeding to establish causation in the context of mechanical component degradation, the following fundamental definitions are presented to provide an understanding of the terminologies used in this paper.

- Defect – This is a generic term used to describe an anomaly / feature / imperfection / non-conformity / damage that occurs on a component and is deemed to be detrimental to the structure's structural integrity of the component. (E.g., corrosion, fatigue cracks, pitting, dents, etc.)
- Root cause – this is the process of determining why a particular damage feature was caused in the first instance.
- Degradation mechanism – this is the physical process or mechanism driven by the service environmental interaction on the asset by which the damage was created. Researchers also refer this as failure modes.
- Causation – This is the process of establishing the relationship between the defect, degradation mechanism and the root cause. Some of the recent literature report that causal claims or in other words causal relationships between terminologies could be either generic or specific depending upon their occurrence and their primary context [13]. Unfortunately, the ability to distinguish and differentiate them becomes a huge challenge and deploying artificial intelligence methods without this understanding would mean the quality of the output is extremely poor. To provide strong evidence based outcomes, only the degradation terms occurring in mechanical components have been used. Further, to demonstrate the value of this taxonomy creation, two specific use cases were chosen;
  (i) Use case 1: Rolling bearings was used as the context to manually establish the relationship between the root causes, the defects and their failure modes. This was based on the availability of a structured and established causation data in the form of the international standard ISO 15243:2017 [14].
  (ii) Use case 2: Nozzle guide vanes or NGVs are aero-engine components that are susceptible to harsh operational environments and have a measurable uncertainty of failure [15]. This use case represents a safety-critical component that does not have a well-established causation knowledge and represents an unstructured dataset with degradation knowledge restricted to the expert in the field.

Use Case 1: To demonstrate how causation can be built, a manual mapping activity was conducted by choosing the use case 1 on rolling bearings to demonstrate if causation mapping can be taken up in the first instance. The ISO 15243:2017 describes the various defects, the failure modes and the root causes (also referred to as the '*triples*') that occur in rolling bearings. As part of the mapping activity, the authors manually extracted the terms (the '*triples*') and performed a manual mapping taking the defect as the datum or reference. Fig. 1 represents an extract from the mapping activity where the appropriate defect and the associated degradation mechanism has been mapped against the root causes. For example, the defect score mark occurs due to plastic deformation (mechanism) (see table row4) and is caused by improper mounting (root-cause) (see column) during maintenance. To decipher detailed information from rich documents such as a standard and presenting this information in a useful form requires expert interpretation and is extremely laborious. The example of score marks may look easy, however, if we take spalls, the root causes are in excess of 10 different parameters suggesting high levels of uncertainty. The only way to characterise this defect would be to look into the associated and secondary data captured as part of the inspection process, and this comes with the need for expert human intervention. It is this fundamental problem this paper aims to address so that digitalisation of this knowledge can become a reality.

3. Methodology to design and model degradation taxonomy

Use case 1 demonstrated that establishing degradation knowledge makes the metaphysics of causation [13] a possibility allowing the knowledge to be captured in a

			Root Causes																																		
			Lubricant, Lubrication							Operating Conditions & Maintenance										Handling & Mounting								Design & Adjacent Parts						Bearing Marking			
Part	Damage (ISO)	ISO Failure Modes	Lubricant not enough	Excess Lubricant	Inappropriate Viscosity	Wrong Lubricant	Oxidized Lubricant	Liquid Contamination		High Static or Dynamic Load	Insufficient Load	High Speed	Rapid Acceleration / Deceleration	Variable load / rotation	Vibration excitations	External Heating / Insufficient Cooling	Poor Maintenance	Oil Filter Clogged		Inappropriate Storing Conditions	Transportation Vibrations	Wrong Clearance / Preload Setting	Inappropriate Radial / Axial Preload	Misalignment	Improper Mounting		Shaft/Housing Spahe/Size	Rigidity - Non-Uniform Ring Support	Inappropriate Fits/Tolerances	Inappropriate/Failed Sealing	Insufficient Heat Removal		Material / Heat Treatment	Machining & Assembly	Handling, Package & Transport	
Rolling Surfaces	Spalls, subsurface fatigue	5.1 Rolling Contact Fatigue	■			■	■			■							■	■				■	■	■										■	■		
	Microspalls, surface initiated fatigue	5.1 Rolling Contact Fatigue	■		■	■	■	■		■							■	■						■										■	■		
	Surface removal by wear, abrasive wear	5.2 Wear	■			■	■	■									■	■																			
	Score marks	5.5 Plastic Deformation															■	■							■												
	Smearing, seizing mark	5.2 Wear	■		■	■	■			■	■	■	■	■		■																■					
	Nicks	5.5 Plastic Deformation															■	■																			
	Rust, corrosion	5.3 Corrosion						■									■	■		■										■							

Fig. 1. Causal factors mapping damage, failure modes and root causes for bearings - extracted from ISO 15243:2017 [14]

meaningful format in-line with the DIKW pyramid framework [16]. Knowledge only transcends to wisdom when the relationship is fully established and validated, in this case it is achieved through a combination of a-priori of knowledge, the extracted interconnected relationship between the terms achieved through the metaphysics of causation philosophies so that early detection of damage in safety-critical components can be detected and appropriate corrective actions be made in a timely manner preventing not just failure but also conserving valuable resources. This is still by large dependent on expert interpretation and validation of the knowledge through fact and evidence based claims.

Based on the learnings from the Use Case 1, Use Case 2 was designed by conducting extended discussions (3 academic and industry workshops over a period of 6 months) with subject matter experts (SME) to understand the purpose and use of causation and its digitalisation. Both literature and industry practices indicate that automating knowledge capture and relationship extraction was attractive as a digital platform such as the digital twin can present the information to the maintainer in real-time enabling faster decision making. And to achieve this, it was identified that a semantic based knowledge model would be an ideal candidate and can become one of the fundamental blocks that will enable automation of knowledge extraction helping realise the true vision of eMaintenance.

3.1. Degradation causation for NGV (Use Case 2)

The NGV represents a safety-critical component of the aircraft engine, and the causation knowledge primarily exists within the manufacturing and maintenance practitioners and a select group of academics working in the aerospace and materials sectors. This research extended the work completed as part of Use Case 1 by using a manual rule-based relationship modelling that established causation. The initial taxonomy was kept generic to deploy natural language processing (NLP) based linguistic methods enabling machine based extraction of the terms of interest identified in the initial taxonomy. Then novel machine learning algorithms under semi-supervised approach were used to extract and established relationships between the terminologies enabling conversion of tacit expert knowledge into machine recognisable data. The sections below describe in detail how this has been achieved using a modelling framework.

3.2. Causation extraction using NLP

The last decade has seen a significant increase in the application of data-mining approaches where industries are now trying to extract knowledge that has been collected and stored in their databases for decades. More specifically, text-mining is now a gold standard that processes thousands of investigation reports and other contextual documents to support the maintenance of HVAs [17,18]. NLP techniques such as clustering and semantic-based pattern recognition methods combined with deep neural network based learning techniques such as LSTM, ELMO, Skip-gram, CBOW, CoVe, GloVe, Fast-text, BERT [19]and OpenAI's GPT models have transformed the industry's ability to extract knowledge. A majority of these are efficient in terminology extraction and not prevalent in the relationship mapping aspect. So, we use the bidirectional encoder representations from transformers architecture or BERT [19] to not just automatically extract the terminology but also build causal relationship between the extracted terms through our approach which becomes the novelty of this paper.

3.3. The Framework

Based on multiple discussions with the SMEs in the industry, academic experts and publicly available research in the area of degradation assessment, an approach to model a generic taxonomy is proposed through this paper. To illustrate the modelling framework, Use Case 2 was used to build a taxonomy, the results of which can be seen in Section 4 of this manuscript. The common degradation taxonomy modelling framework (Fig. 2) consists of five building blocks with specific processes that can be used to achieve the combined taxonomy. The following is the detailed explanation of the various blocks and the elements of the framework. For the purpose of this paper, it has been demonstrated with the NGV use case.

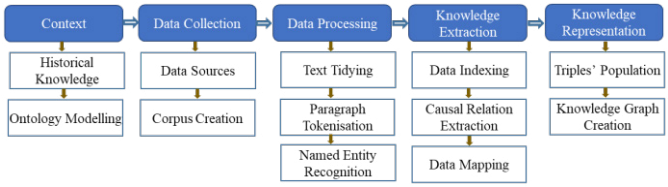


Fig. 2. Taxonomy modelling framework

3.3.1. The Context

As mentioned in the sections above, the context that has been used for this activity is 'in-service' degradation of NGV. This step typically includes the contextual data and represented disparate data including design data, manufacturing data, in-service data and so on to create the historical knowledge specific to the context which became the requirements specification for the ontology.

3.3.2. The data

Due to restrictions associated with using industry supplied data, only information from *publicly available textual data* was used for the demonstration of the framework. The team conducted a web-scrapping activity with the keywords "NGV" and "degradation" and extracted over 6,000 journal and conference papers from databases using search engines such as scopus, IEEE, ACM and arXiv. Once the data was captured, the information was stored in a local database and an initial data pre-processing was conducted on the metadata (title-abstract-keywords) associated with the papers to create the *Corpus*. The data filtering included terms such as 'NGV' or 'degradation' or 'defect' or 'damage' or 'deterioration' or 'failure'.

There were multiple iterations on how to build causation. Initial approaches included the building of causal trees for specific damage purely to understand both what the root causes were and what could potentially happen. Based on three industry-academia workshops facilitated by the industry

consortium, the '*Triples*' method was adopted. In this instance, the *Triple* refers to damage-mechanism-root cause. To model this triple, Protégé software was used to create the information in the form of an ontology web language file '**.owl*'. Common degradation terms, which were populated manually in the form of a taxonomy from the Use case 1 was then converted to an *owl* file. The NLP process (linguistics) used this information to filter the data (*data filtering*) from the created *Corpus* and removed any papers that did not meet the taxonomy specifications (terms associated with degradation and context). This high-level *Corpus* was now stored as a new *database*, to remove any errors and duplications and to reduce the data computing time.

3.3.3. Data processing

Once the data pre-processing was completed and the architecture established, text-mining using NLP was conducted. Where the previous run was purely a search activity to filter data using only the information from the file metadata, this detailed data processing activity was then used to identify and index data using Named Entity Recognition or NER tagging process. The NER tagging was based on the open-source BERT model and considered seven major terms (deform, thermal, wear, corrosion, fracture, fatigue and magnitude). The tagging process yielded high quality outputs reflected by the algorithm accuracy score of 90% and above on initial application. However, this did make the process a little complicated as only terms were identified and their relationship between them was not clear. Now the terms, whilst represented the ones from the taxonomy, the relationship extraction process was not complete. To overcome this issue, a rule was added to the process where by two of the terms should appear in the same sentence and include causal connectives such as 'causes', 'is caused by', 'is due to', 'because of' etc. This then identified all the relevant data that could be used for automating relationship extraction. To expedite this process, the following concepts were used;

- Sentence array – The words in a sentence were represented as an array and provided with tokens and sub-tokens to identify both terms and phrases of interest. To keep this simple, for this operation the sentence was only considered when two of the cause-and-effect terms together with the connective were present in the sentence.
- The connective – The causal connectives presented above were also tokenised and were represented as sub-arrays that exist between the cause-and-effect tokens.

3.3.4. Knowledge extraction

The outputs from the data processing step were then indexed using identified NER tags from the previous step and the dataset was amended accordingly. Based on the data architecture presented in section 3.3.2, BERT was now applied to the dataset to perform both terminology recognition and relationship extraction. In order perform the relationship extraction, a binary model was constructed and was based on the following mathematical expressions [20];

$$S = w_1, w_2, .., e_1, ..., w_j, .. e_2, .. w_n \quad (1)$$

$$F_R(T(S)) = +1, \text{ If } e_1 \text{ and } e_2 \text{ are related} \quad (2)$$

$$F_R(T(S)) = -1, \text{ Otherwise} \quad (3)$$

where S is the sentence, $w_1, w_2, ..w_n$ the words, e_1, e_2 the entities, and $F_R(T(S))$ the mapping function. This mathematical rule identified only those sentences that have the information of the degradation and the connective terms. In addition to BERT a contiguous causal relationship recognition (CCRR) was also used to verify the outputs from BERT and to make sure a high level of accuracy was achieved. CCRR allows neighbouring terms, in this case the degradation terms together with the causal connectives are extracted and verified against the NER tags thereby improving the model's relationship extraction.

And finally, to evaluate the overall model efficiency, the accuracy in the form of F1 scores was used. The F1 scores are calculated based on Precision and Recall metrics which are based on true positives (*tp*), false positives (*fp*) and false negatives (*fn*) together with a Jaccard Index (*J(a,b)*) to achieve high-levels of matching. Mathematically, F1 can be calculated using;

$$F1 = (2 \times precision \times recall)/(precision + recall) \quad (4)$$

$$precision = |tp| / (|tp| + |fp|) \quad (5)$$

$$recall = |tp| / (|tp| + |fn|) \quad (6)$$

$$J(a,b) = |a \cap b| / |a \cup b| \quad (7)$$

The next step is to populate the extracted knowledge in a representative form. Based on the emergence and wider acceptance of knowledge graphs, the '*Triples*' data was populated automatically and presented in the form of an ontology. Tools such as *Protégé* and *Neo4j* can be used to create the ontology represented as an **.owl* file. For the purpose of demonstrating the framework, we have used Protégé to model the degradations ontology.

4. Results from the NGV use case

The outputs from the use case show the functionality of the framework and the following are the high-level outputs attained from the framework.

Original corpus: 6000 papers
Final corpus: 1237 papers

Table 1. Typical output from the BERT model.

Sentence: "Thermal fatigue was the dominant mechanism for premature damage of the nozzle"		
Root Cause	**Mechanism**	**Damage**
heat	thermal fatigue	premature damage

Table 2. BERT performance evaluation for relationship extraction.

	Precision	Recall	F1
Connective	0.68	0.90	0.77
Cause	0.62	0.72	0.67
Damage	0.70	0.76	0.73
Sentence	0.59	0.70	0.64

Table 1 was an extraction from one of the papers from the corpus. It must also be noted that, most of the fundamental root causes for degradation were a combination of pressure, temperature, chemical properties, contaminants etc. To reduce uncertainty, high level terminologies were also proposed through this research. The list included, mechanical action,

chemical reagent, thermal / heat radiation, a combination of the above and so on (as extracted from literature [21]) and was duly included in the taxonomy.

The performance scores reported in Table 2 above were obtained by using the equations (4)-(7). It can be inferred from Table 2 that the overall scores are low due to inaccuracies in the identified terminologies. However, the recall score (90%) is much higher for the connective method against other extraction metrics and resulted in a higher degree of matching, which justifies the approach taken to include causal connectives in the as reported in sub-section 3.3.3. However, there is still work to be completed to improve the errors and uncertainties associated with the data itself. The primary reason is the lack of a set standard such as the one presented in use case 1 combined with textual errors including terminologies wrongly represented in the data. We envisage that, further filtering and performing linguistic extraction would improve the precision and recall scores. As indicated in sub-section 3.3.2, the taxonomy was modelled using Protégé and the following is the excerpt from the *owl* file (Fig. 3). All of the ontology information was verified manually.

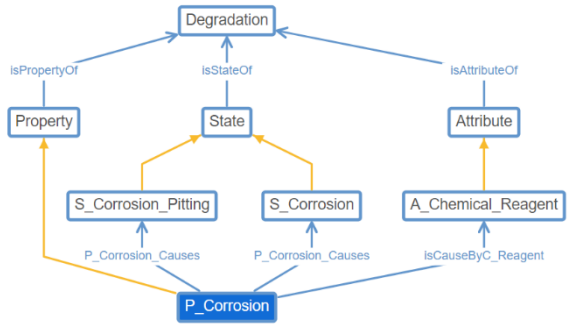


Fig. 3. The taxonomy represented in the form of an ontology

5. Discussions and conclusions

There has been tremendous development in the area of digital data-mining with the trend of representing the data in the form of a knowledge graph. Whilst, a lot of the research reports the knowledge extraction and representation as separate activities, this paper proposes a novel methodology that enables AI based relationship extraction improving our ability to consume the knowledge. Where we have achieved higher levels of accuracy (over 90%) for the terminology extraction activity, the combination of both the terminology extraction and automated relationship mapping has not been attempted in the maintenance domain. It should be noted that further work is needed to improve the overall efficiency and performance of the relationship extraction. Further, the application of such automated knowledge extraction methods to degradation assessment becomes the overall novelty of the work presented in this paper. A typical scenario would be where an inspector inspects the part using an inspection system. The digital asset such as the digital twin, recognises the part automatically, then extracts the relational data by accessing the knowledge graph, presents the inspector with complete knowledge of the part, including statistical reliability of success that could be achieved through an array of available decisions thus improving the overall inspection activity. This could evolve into a digital data management system, that recognises, classifies and presents data in real-time to the end user. Building a semantic approach will not just make this modular, where other related knowledge could be attached, but will improve aspects of improved reliability and interoperability.

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References

[1] Refaiy M, Labib A. The effect of applying tacit knowledge on maintenance performance: an empirical study of the energy sector in the UK and Arab countries. Knowledge Mgmt. Res. & Practice. 2009 Sep 1;7(3):277–88.
[2] Ferreira C, Gonçalves G. Remaining Useful Life prediction and challenges: A literature review on the use of Machine Learning Methods. J Manuf Syst. 2022; 63:550–62.
[3] Xu Z, Guo Y, Saleh JH. Accurate Remaining Useful Life Prediction with Uncertainty Quantification: a Deep Learning and Nonstationary Gaussian Process Approach. 2021 Sep 23.
[4] Sullivan GP, Pugh R, Melendez AP, Hunt WD. Operations & Maint. Best Practices A Guide to Achieving Operational Efficiency. 2010 Jul.
[5] McCloy J, Li Y, Montgomery R, Henager Jr C, Ramuhalli P, Johnson B, et al. Materials Degradation and Detection (MD2): Deep Dive Final Report. 2013
[6] Mandelli D, Wang C. A Causal Approach to Integrate Component Health Data into System Reliability Models. In: Annual Conference of the Prognostics and Health Management Society. 2022. p. 1–9.
[7] Steenwinckel B. Adaptive anomaly detection and root cause analysis by fusing semantics and machine learning. In: The Semantic Web: ESWC 2018, vol 11155, p. 272–82.
[8] McLeman A, Smith J, Parker K. The maintenance function, like manufacturing itself, is a rapidly changing environment [Internet]. Plant Engineering. 2021
[9] Infraspeak. Maintenance Statistics [UPDATED]: Trends, Challenges and Metrics. Maintenance. 2022
[10] Dwivedi SK, Vishwakarma M, Soni ProfA. Adv. and Res. on Non Dest. Test: A Review. Mater Today Proc. 2018;5(2, Part 1):3690–8.
[11] Martinez-Gil J et al. Root Cause Analysis in the Industrial Domain using Knowledge Graphs: A Case Study on Power Transformers. In: Procedia Computer Science. 2022. p. 944–53.
[12] Liu A, Zhang D, Wang Y, Xu X. Knowledge graph with machine learning for product design. CIRP Annals. 2022;71(1):117–20.
[13] Gallow JD. The Metaphysics of Causation. The Stanford Encyclopedia of Philosophy (Fall 2022 Edition). 2022.
[14] ISO/TC 4. ISO 15243:2017, Rolling bearings — Damage and failures — Terms, characteristics and causes. Standards 2017.
[15] Chaharlang R, Hajjari E, Baghal SML, Siahpoosh M. Premature damage of the second stage nozzle guide vanes of a gas turbine made of Inconel 738LC. Eng Fail Anal. 2019 Nov 1;105:803–16.
[16] Frické M. The knowledge pyramid: a critique of the DIKW hierarchy. J Inf Sci. 2008 Nov 21;35(2):131–42.
[17] Steenwinckel B, et al. Towards Adaptive Anomaly Detection and Root Cause Analysis by Automated Extraction of Knowledge from Risk Analyses. In: (ISWC 2018). 2018. p. 17–31.
[18] Zhou B, Li J, Li X, Hua B, Bao J. Leveraging on causal knowledge for enhancing the root cause analysis of equipment spot inspection failures. Advanced Engineering Informatics. 2022 Oct 1;54.
[19] Devlin J, Chang MW, Lee K, Toutanova K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. 2018 Oct 10;
[20] Bach N, Badaskar S. A Review of Relation Extraction. Literature review for Language and Statistics II. 2007;2:1–15.
[21] Batchelor AW, Lam LN, Chandrasekaran M. Mechanisms of materials degradation. In: Matls. Deg. & Its Cntrl by Surf Engg. 2011. p. 11–66.



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