EISSN: 2707-0425

East African Journal of Science, Technology and Innovation, Vol. 4 (Special Issue 2): September 2023

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Exploring current and future trends of predictive maintenance 4.0 in Tanzania: A systematic literature review

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Abstract

Manufacturing industry systems necessitates a good engineering strategy, improved maintenance and optimal operations that are necessary to keep the systems in its ideal condition. Industry 4.0 predictive maintenance (PdM 4.0) centers on the planning of maintenance tasks in accordance with the system real condition of health, targeting at providing an exact signal of when to do maintenance and whenever necessary. PdM 4.0 is employed by means of integration of several industry 4.0 pillars that incorporate models to attain diagnostics and prognostics activities. As far as industry 4.0 concern, Tanzania manufacturing industries (TMI) they hardly manage to fulfill all requirements for PdM 4.0. It is uncommon to find research works that have addressed on PdM 4.0 maturity levels, factors that influences its adoption and approaches or tools to overcome complexity of PdM 4.0 adoption by considering the advantages and disadvantages of each approaches and addressing the best of them. Decision support tools for PdM 4.0 adoption have not yet extensively addressed by previous review studies in manufacturing industries. Besides, the abundance of maintenance decision support tools but the ones for PdM 4.0 adoption remains unexplored; this provides opportunities for architecting PdM 4.0 in manufacturing systems. This systematic literature review aims at presenting the current and future trends of PdM 4.0 in TMIs through giving special attention to decision support tools for its adoption and summarizing the current and future trends for TMIs in transition. To attain this aim, social network analysis using VOS viewer 1.6.18 enhanced a systematic literature review. The sources of literature were found from seven academic databases: Scopus, TJET, Emerald, Elsevier, Springer, Ebschohost and Taylor and Francis. The literature searches custom ranges from 2016 to 2022. In 200 publications exploring PdM 4.0 in MIs, only 2 percent is from developing countries and 7 percent of publications from Africa. The study shows that their insufficiency in research publications on PdM 4.0 adoption in Africa MIs; as a result, there is a low adoption rate of PdM 4.0 in developing countries MIs. It is recommended that more studies on the adoption of PdM 4.0 and decision support tools, factors for PdM 4.0 adoption be conducted in TMIs.

Keywords: *predictive maintenance, industry 4.0, Maturity, Manufacturing industries, Adoption, decision support tool*

Received: 27/06/23
Accepted: 06/07/23
Published: 14/09/23

Cite as: *Peter et al., (2023)* Exploring current and future trends of predictive maintenance 4.0 in Tanzania: A systematic literature review. *East African Journal of Science, Technology and Innovation 4(special issue 2).*

Introduction

The emergence of technological advancements in the internet of things (IoT), has caused significant improvement of manufacturing strategies. To this era, new concepts such as "Industry 4.0", "Digital factory" or "Smart manufacturing" have emerged (Bousdekis *et al.,* 2019).

Industry 4.0 is gaining a lot of attention, particularly on its potential impact on humanity and the potential it has in changing how human beings live, work and how the economies work as well as how we are governed (Mhlanga, 2021). Industry 4.0 in particular artificial intelligence has greater influence in attaining sustainable development goals (SDGs) with a greater focus on poverty reduction, agriculture, industries and infrastructure development in upcoming economies.

In Industry 4.0, predictive maintenance is gaining important role in cost minimization and improvement of business performance since abundancies of heterogeneous data assists in anomaly detection (diagnosis) , anticipating future failure (prognosis) and support decision making (proactive actions for rescuing equipment from the unplanned downtime) (Bousdekis *et al*., 2019)

Therefore, Predictive maintenance is regarded as one of industry 4.0 initiative as it overcomes barriers in production concerning maintenance of assets. However, the adoption of predictive maintenance techniques is not a free ride process but there are some barriers and obstacles. Hence, there is a need to establish factors that provide guidance to Tanzania's industrial sustainability through adoption of industry 4.0 predictive maintenance policies for sustainable production of goods.

However, in Tanzania manufacturing industries (TMI) the adoption of PdM 4.0 in operations appears to lag behind its actual use from theoretical point of view. Moreover, experts seem to observe a gap between the significant and attained benefits. This may be due to an inadequate understanding of how manufacturing industries can achieve the benefits of PdM 4.0 and the means that are required to translate those benefits into tangible value propositions (Tanuska *et al.,* 2021)

Material and methods

The Role of Industry 4.0 Predictive Maintenance in Manufacturing Industries

There is an increasing consideration on how new emerging technologies are enabling the rise of the fourth industrial revolution. The digital transformation can be taken as a troublesome phenomenon (Bettiol *et al.,* 2020). Transforming the rules of competitions (Mhlanga, 2021) and the rise of a new paradigm (Bettiol *et al.,* 2020). Firms able to exploit technological advancements to strengthen their competitive advantages can obtain superior performance.

TMIs experience the need for transformation, changing of working practices for the sole intent to sustainability. To guarantee that the basic foundations need to be well established and maintained, since MIs keeps on updating their systems and production lines, therefore pledging for a viable position in their respective market (Kafuku, 2019) ;(Bousdekis *et al.,* 2019).

With the sole purpose of facing the challenges of new industrial revolution, Industry 4.0. With multiple definitions emerging, this concept is characterized by Zonta as "conjunction of many technologies both existing and new - which now work together." (Zonta *et al.,* 2020)

Related Literature Reviews

Since dynamicity and complexity of manufacturing industries environment to arrive into sustainable decision is very challenging, there is an increasing interest into using digital technologies or industry 4.0 aspects to simplify maintenance decisions. To best of our knowledge this is among of the literature review for the adoption of industry 4.0 predictive maintenance, maturity levels and available tools to assist Tanzania manufacturing industries to embark in a new journey of technological revolutions. Related literature reviews published between 2016 to 2022 (Nhelekwa *et al.,* 2022) ,(Ngowi, 2020) ,(Maganga and Taifa, 2022b),(Taifa & Vhora, 2019),(Maganga and Taifa, 2022a), (Bousdekis *et al.*, 2019), (Zonta & da Costa, 2020) have the following limitations (i) they do not show the industry 4.0 predictive maintenance maturity levels among Tanzania MI, (ii) they deal with various industry 4.0 applications and not predictive maintenance 4.0 (iii) they do not discuss factors for industry 4.0 predictive maintenance adoption rather they focus on specific factors adoption factors for industry 4.0 .

Methodology of the literature review

The current literature review follows the methodology proposed by Tranfield et al. (2003). The review protocol is shown in table 1. It should be noted that we selected from 2016 to 2022. To carry out this study, we based on the principles of systematic reviews to achieve producibility and good results (O'Donovan *et al.*, 2015; Petersen *et al.*, 2008; Zaveri *et al.*, 2016). The main scientific challenges to be addressed in this review are:

Table 1

Review protocol

Item	Description
keywords	"predictive maintenance" AND "Industry 4.0" AND "Manufacturing industry"
Inclusion criteria	Papers with industry 4.0 predictive maintenance in manufacturing industries
Exclusion criteria	Papers with conceptual approaches; papers with technological contributions
Scientific databases	Scopus, TJET, Emerald, Elsevier, Springer, Ebschohost and Taylor and Francis
Time period	January 2016 to December 2022

1- What taxonomy in the context of industry 4.0 for predictive maintenance;

2- Organize the main concepts related to the area;

3- Present the main decision support tools applied to PdM 4.0;

4- Identify the main challenges and future issues related to industry 4.0.

Table 1, demonstrates the sequence of the methodology used, with the accomplishment of the research and definition of the articles we started the identification, separation, and discussion of the results. For this, we use the VOS viewer tool to contribute to the visualization of the main terms found and creates a more comprehensive taxonomy than the initially planned.

Results

In this section, we present the results and discussions based on the questions previously elaborated with the objective of responding to the main review question. What are the techniques for disseminating research aligned with PdM 4.0? To answer this question, we present the analysis of:

Articles distribution by publisherFigure 1, which shows the articles distribution by publisher and publication type. The bar graph we can highlight Springer, IEEE and Elsevier as publishers with the most significant number of publications. The distribution of articles analysis using means of publication reinforces the observation that PdM applications present a multidisciplinary characteristic involving several areas of knowledge. In TJTE case, the Computation does not give a volume of publications linked to PdM precisely because computing is one of the tools used and requires knowledge aligned with automation, mechanical, and electrical generating more content in other means of dissemination.

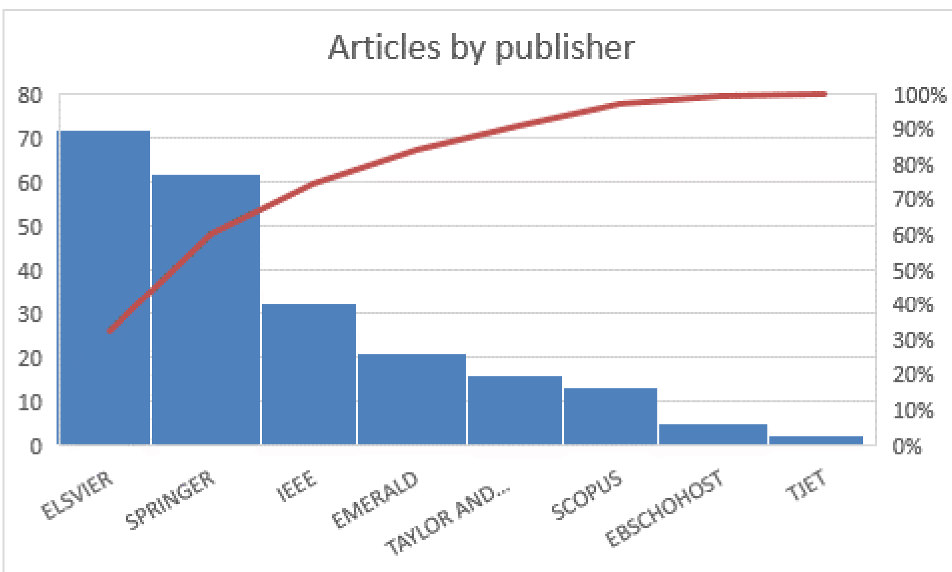

Figure 1. Articles by publisher

Bibliometric analysis by VOS viewer and co- occurrence of terms

In order to establish logical reasons for the process of taxonomic definition, we have adopted three criteria for creating the taxonomy for Industry 4.0 with a focus on PdM: First criterion: Generating the mapping and clustering using VOS viewer, which implements Smart Local Moving (SLM) optimization algorithms and method created by the Center for Science and Technology Studies (CWTS) (Klavans and Boyack, 2017). The first process was the generation of a file with the vital information to create the maps: authors, terms, and citations. For this, we chose Scopus, and an individual search of the selected corpus done. The VOS viewer applies bibliometric data methods for filtering and relating by co-occurrences of keywords. This process analyzes the links between the words using a natural language algorithm. To avoid redundancy, we have applied filters for similar terms, according to Table 2. This technique to prevent that synonymous words, different writing, or even meaning is plotted on the map separately.

Table 2

Co-occurrences of terms

Label	**Replaced by**
Learning algorithm	Machine learning
Learning systems	Machine learning
Internet of things (IOT)	Internet of things
Industrial internet of things	Internet of things
Smart manufacturing	Smart manufacturing
Cyber physical systems (CPS)	Cyber physical systems
Cyber Physical security (CPS)	Cyber physical systems
Cyber physical systems (CPS)	Cyber physical systems

Second criterion: To verify all terms that are related hierarchically with direct relation to Industry 4.0 and PdM, we use the relation map, overlay based on year and heat of the VOS viewer. The maps of Fig. 3a refer to a relationship, 3b overlay based on year of related concepts and 3c the heat map. Therefore, we enable us to see that we contemplate the main terms used in the string proposed in this review. This criterion we highlight the definition of the main terms found for Industry 4.0 with a focus on PdM in Table 2.

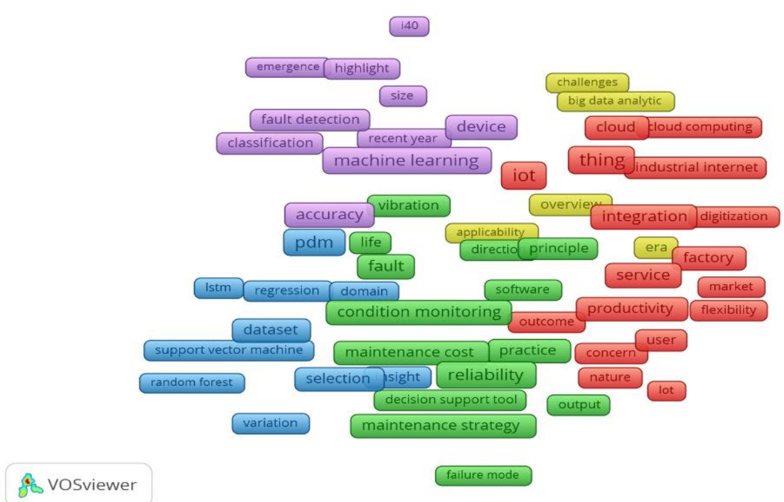

Figure 2. Map of related concepts

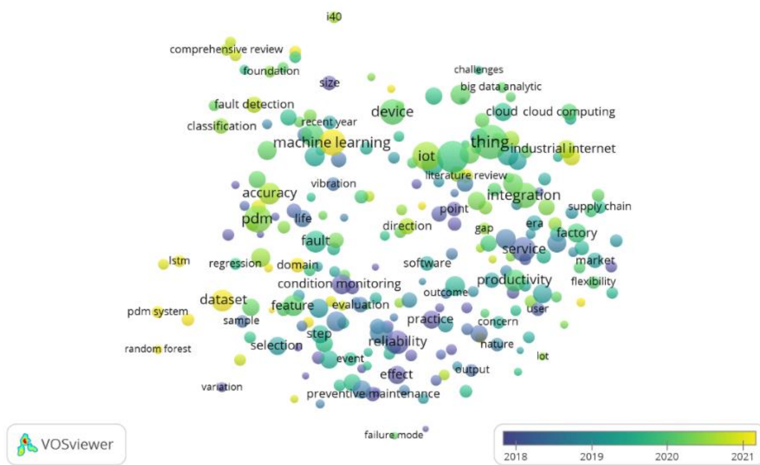

Figure 3. Overlay based on year of related concepts

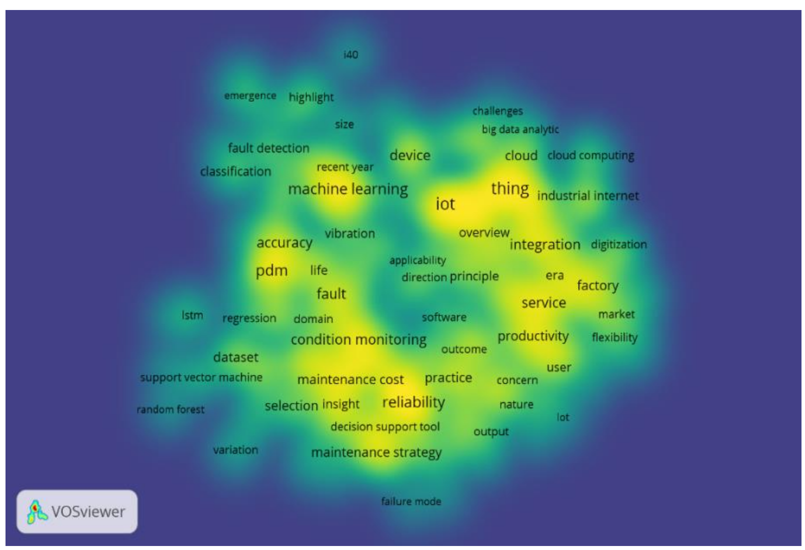

Figure 4. Heat map of the related concepts

The increasing complexity and uncertainty of the manufacturing environment has leveraged the emergence of several methods and algorithms aiming to better support decision making (Ruschel *et al.,* 2017). Smart decision making is a core aspect of Industry 4.0 that is enabled by processing sensor data (Amruthnath and Gupta, 2018). However, the uncertainty existing in predictive analytics but also in the degradation process itself and the time constraints under which a decision should be taken pose challenges in the applicability of the decision-making algorithms. During the last years, with the emergence of predictive maintenance as a novel lever of maintenance management, there is an increasing interest in algorithms aiming to better support maintenance decisions that improve equipment operating life.

Areas for industry 4.0 PdM in Manufacturing industries

In order to facilitate the comprehension and the investigation of the existing decision-making algorithms, we structured the literature in 4 areas of industry 4.0 PdM transition among TMI, as shown in Table 3. Most of the papers belong to more than one area. However, the categorization to these 4 areas was formulated based on the focus as well as the main contribution and novelty of each work to the specific area. These areas are:

Industry 4.0 technologies for Predictive maintenance

Figure 4 shows industry 4.0 is the joint effect of Cyber physical system (CPS) ,Internet of Things (IoT) and Artificial intelligence, therefore, creating a decentralized control and advanced connectivity (Ferreira, 2019). Taking into consideration the relevance of these three pillars, an analysis of pillars is conducted in the following.

Table 3

Areas of industry 4.0 PdM adoption

Area of contribution	Number of references	References
Industry 4.0 technologies for Predictive maintenance	16	(Achouch *et al.,* 2022; Caldana *et al.,* 2021; Chiu *et al.,* 2017; Einabadi *et al.,* 2019; Kamat & Sugandhi, 2020; Kiangala & Wang, 2018; Maintenance, 2017; Mulders & Haarman, 2017; Zonta & da Costa, 2020)(Ardito *et al.,* 2018; Calabrese, 2022; Lass & Gronau, 2020;Morenas & ..., 2022; Okeagu & Mgbemena, 2022; Orošnjak *et al.,* 2021; Rai *et al.,* 2021; Rehman *et al.,* 2018; Rodríguez *et al.,* 2022; Sahba *et al.,* 2021; Terrissa *et al.,* 2016; Vijayaraghavan & Leevinson, 2019)
PdM maturity levels	9	(Achouch *et al.,* 2022;Kans, 2010; Rosenius, 2020)(Achouch *et al.,* 2022; Errandonea *et al.,* 2022; Mesarosova & Martinovicova, 2022;Schuh *et al.,* n.d.; Taifa & Maganga, 2022a)
Adoption factors for industry 4.0 PdM	10	(Achouch *et al.,* 2022; Bettiol *et al.,* 2020; Burger, 2022; Haarman *et al.,* 2018; Maintenance, 2017; X. T. Nguyen & Luu, 2020; Oliveira *et al.,* 2013; Parhi *et al.,* 2022; Robatto Simard *et al.,* 2023; Taifa & Maganga, 2022a; Zonta & da Costa, 2020)
Decision support tools for PdM 4.0 Adoption	7	(Carnero,2006; Faiz and Edirisinghe, 2009; Van Horenbeek and Pintelon, 2013; Nguyen, Do and Grall, 2015; Bousdekis *et al.,* 2017, 2019; De

	Benedetti *et al.,* 2018; Thesis and Sequeira, 2020; Tiddens, Braaksma and Tinga, 2020; Zonta *et al.,* 2020; Compare, Baraldi and Zio, 2020; Kaparthi and Bumblauskas, 2020; Burger, 2022; Taifa and Maganga, 2022a)

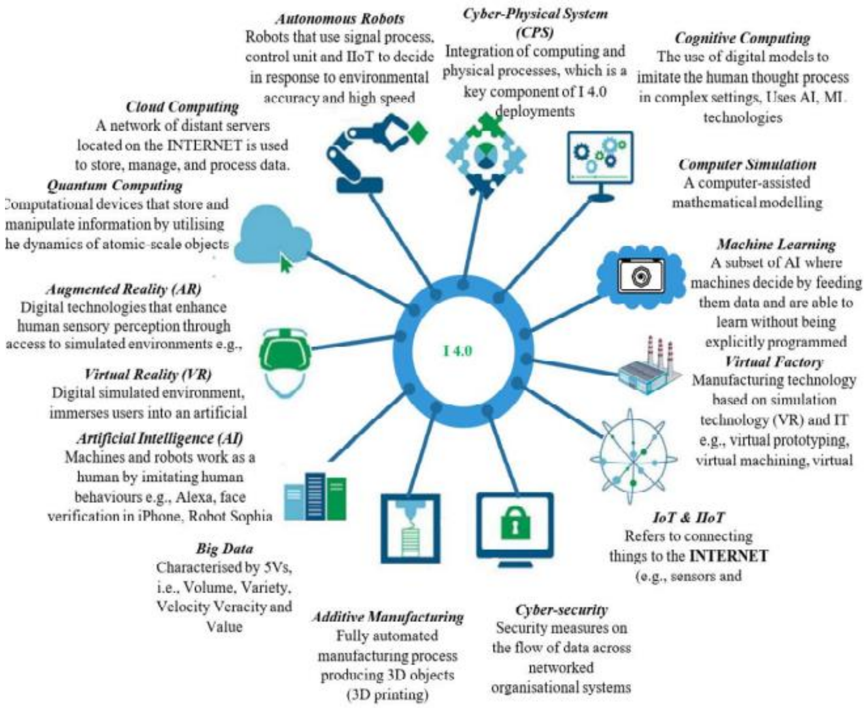

Figure 4. Industry 4.0 pillars

Source: (Taifa and Maganga, 2022a)

Predictive maintenance maturity in manufacturing industries

To cover the main issues of PdM the three main disciplines that have contributed to the (technical) development of PdM in recent years. From Figure 5, traditionally many maintenance programmers rely on previous experiences and expert knowledge (Motaghare *et al.,* 2018). However, the fields of condition-based maintenance (CBM), prognostics and health management (PHM), and structural health monitoring (SHM) have contributed to the development of PdM concepts in which the exact moment to conduct maintenance is based on the actual condition of the assets (Hashemian and Bean, 2011). As pointed out earlier, PdM starts with 'sensing' the situation of the system, and various types of techniques have been developed specifically for PdM purposes. These techniques can be broadly categorized into five: process parameter measurements, vibration analysis, oil analysis, thermography analysis, acoustic analysis (Selcuk, 2017)

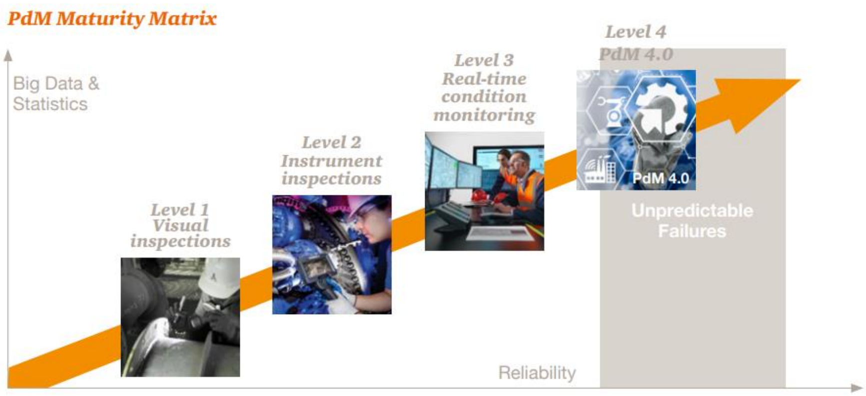

Figure 5. Maintenance Evolution (Mulders & Haarman, 2017)

Predictive Maintenance in Manufacturing Industries

With the amount of data generated, MIs must be able to extract viable knowledge. Maintenance consists of restoring a machine or system into their Original Equipment Effectiveness (OEE) or the desired status (Tiddens *et al.,* 2020). Nevertheless, times changed, and maintenance strategies became more complex and increasingly relevant (Ferreira, 2019). According to Jimenez *et al.,* (2020) "manufacturing systems predictive maintenance is becoming increasingly important, since in many industrial plants, the maintenance costs often exceed 30% of the operating costs and in the context of manufacturing systems lifecycle, maintenance and support, account for as much as 60 to 75% of total lifecycle costs" (Jimenez *et al.*, 2020)

Equipment and production process by utilizing prescriptive analytics, artificial intelligence and machine learning algorithms on the basis of the large availability of real-time (sensor-generated) and historical (logs) maintenance-related data. They will be able to recommend perfect and imperfect maintenance actions, considering other operations in order to improve the overall business performance.

Development of data-driven techniques for building the decision models. There is the capability of automated data- driven model building and finding appropriate patterns, instead of building manually the decision model by the expert according to their knowledge, the physical model or the industry. There is a clear trend in literature, currently mainly at a conceptual level, towards less human intervention (e.g. information based on the expert judgment) in decision making by conducting advanced big data analytics. Development of feedback mechanisms for improving the decision-making algorithms. In the dynamic, sensor-driven manufacturing environment of Industry 4.0, a problem setting often changes rapidly, e.g. new constraints have to be added and the model may need to be rebuilt or there is an unobservable change, and the model is not valid anymore. Although feedback mechanisms for diagnostic and prognostic algorithms have been well perceived, mechanisms for tracking the recommended actions are an underexplored area. An additional aspect that has not been examined is the feedback given by humans (e.g. engineers, operators) about the suitability of the recommendations.

The implementation of PdM allows to reach a common ground between the Reactive and Planned Maintenance, obtaining the advantages of both while not compromising the integrity of the assets with possible down-time due to malfunction. Regarding its advantages, from various literatures, it is possible to state several factors to which companies may take advantage, upon the correct implementation of this methodology, as follows (Civerchia *et al.,* 2017).Increased useful life (33-60%); The decrease in maintenance expenditures (10-15%); Increase in sustainable capacity (15-40%); Reduce the time required to plan maintenance (20-50%);Increase equipment uptime (10-20%) and Reduce overall maintenance costs by (5-10%).

Discussion

Numerous researches worked on decision making processes for predictive maintenance but they are limited to specific cases, areas and industries requiring maintenance schedules and are workable under specific assumptions. Subsequently, their applications in real industrial settings is too limited, and they cannot be moved to a different setting with similar challenges in straightforwardly.

Other scholars deal with optimization of scrutiny intervals according to the actual condition of the equipment. For this, the aim is to conduct data analytics decision Making for the definition of the inspection intervals. However, this is useful information, since it exploits the availability of historical and real-time data in order to recommend specific actions that should be applied by the engineers and the operators in order to significantly facilitate predictive maintenance.

In addition, it is rarely to find the Reliability and degradation-based decision-making algorithms that considers real time condition of an asset information for generating a real time recommendation for action prior to prevent failure. The underlying practice involves utilization of the current situation of asset degradation that is assumed from the analysis of the measured indicators by sensors along with expert knowledge to arrive into maintenance decision.

Future research directions

In the dynamic manufacturing environment of Industry 4.0, a problem setting often changes rapidly, feedback process for diagnostic and prognostics need to be perceived very well, although mechanisms for administering recommended actions is underexplored area. Moreover, aspects that involving feedbacks provided by experts (e.g. engineers, operators) about recommendations are not well considered.

Conclusion

This systematic literature review unveils that no clear trends of automated in notifications from asset conditions in making predictive maintenance under Industry 4.0 well utilized. The availability of industry 4.0 technologies provides responsive asset information systems that can supporting maintenance decisions before breakdown. Until now in TMIs for alignment with industry 4.0 agenda, predictive maintenance can significantly be benefited through exploitation of asset information from sensors.

For further work, the aim is to extend the literature review in: (i) further identification of PdM 4.0 maturity levels of the reviewed papers; (ii) determining the contribution of operational research, in modelling factors influencing adoption of PdM 4.0 among MIs for decision making in maintenance for the smart factory; (iii) investigating variables for the asset information systems for utilizing PdM 4.0 (e.g. architectures, software, etc.); and, (iv) reviewing the decision making tools embedded for predictive maintenance in industry platforms.

Acknowledgement

We would like to extend our sincere appreciation to the Commission of science and technology in Tanzania (COSTEC-STICE) and the Collage of Engineering Technology (COET-UDSM) for the

administrative support for the work to be completed.

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