Artificial Intelligence in Predictive Maintenance: A Systematic Literature Review on Review Papers

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Abstract The fourth industrial revolution, colloquially referred to as "industry 4.0", has garnered substantial global attention in recent years. There, Artificial intelligence (AI) driven industrial intelligence has been increasingly deployed in predictive maintenance (PdM), emerging as a vital enabler of smart manufacturing and industry 4.0. Since in recent years the number of articles focusing on Artificial Intelligence (AI) in PdM is high a review on the available literature reviews in this domain would be useful for the future researchers who would like to advance the research in this area and also for the persons who would like to apply PdM in their application domains. Therefore, this study identifies the AI revolution in PdM and focuses on the next stages available in the literature reviews in this area by quality assessment of secondary study. A well-known structured review approach (Systematic Literature Review, or SLR) was employed to perform this tertiary study. In addition, the Scale for the Assessment of Narrative Review Articles (SANRA) approach for evaluating the quality of review papers has been employed to support a few of the research questions. Here, This tertiary study scrutinizes four crucial aspects of secondary articles: (1) their specific research domains, (2) the annual trends in the quantity, variety, and quality (3) a footsteps of top researchers, and (4) the research constraints that review articles face during the time frame of 2015 to 2022. The results show that the majority of the application areas are applied to the manufacturing industry. It also leads to the identification of the revolution of AI in PdM as well. Our final findings indicate that Dr. Cheng et al.'s (2022) review has emerged as the predominant source of information in this field. As newcomers or industrial practitioners, we can benefit greatly from following his insights. The final outcome is that there is a lack of progress in SLR formulation and in adding explainable or interpretive AI methodologies in secondary studies.

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U. Kumar et al. (eds.), *International Congress and Workshop on Industrial AI and eMaintenance 2023*, Lecture Notes in Mechanical Engineering,
https://doi.org/10.1007/978-3-031-39619-9_18

Keywords Predictive maintenance · Artificial Intelligence · Systematic literature review

1 Introduction

The utilization of machinery and other equipment in the industrial sector, such as in construction, transportation, and power generation, mandates routine maintenance and corrective measures. While such maintenance is necessary, it can be costly and may comprise a significant portion of total operating expenses, ranging from 15 to 60% depending on the industry under consideration. Elevated downtime associated with maintenance activities can have a detrimental effect on an industry's operational capacity and financial stability. This, in turn, has a far-reaching impact on the entire manufacturing pipeline and may impinge upon overall corporate performance. To mitigate the risk of unexpected downtime and uphold optimal production facility functionality, the development and implementation of a robust maintenance program are essential. Utilization of data-driven predictive maintenance (PdM) techniques is one of the most potent methods of ensuring sound maintenance scheduling practices. The definition of PdM can be given as:
"Predictive maintenance is a philosophy or attitude that, simply stated, uses the actual operating condition of plant equipment and systems to optimize total plant operation [13]".

However, PdM has a far wider scope. It is the way through which manufacturing and production facilities may increase their overall effectiveness, as well as their productivity and product quality. As a result of the fourth industrial revolution, nearly every production plant is transformed into a smart manufacturing facility. The availability and use of data throughout the whole industrial system is what makes these intelligent production systems knowledgeable and efficient. Applying AI for PdM is one of the hallmarks of smart manufacturing.

AI-driven PdM has emerged as a prominent research area, with a history and evolution that can be traced through secondary literature sources. A thorough understanding of the current state of the field is essential to anticipating the future of PdM, which promises to revolutionize production cost reduction. An effective means of achieving this understanding is to conduct a systematic literature review (SLR) to identify the most influential and informative studies in this field, thereby providing guidance for future research endeavors.

The entire investigation is structured as follows: Sect. 2 the methods are discussed here, Sect. 3 presents the quality assessment criterion of secondary studies, Sect. 4 shows the results, Sect. 5 includes a discussion, and Sect. 6 Conclusions.

2 Method

Systematic literature review, often known as SLRs, are the most organized and standardized approach to determining the current state of any field of study by conducting reviews of previously conducted research in that topic [12]. It's a secondary study and justification is necessary right from the start of a SLR.The aim of SLR is to conduct a survey of previous studies with a similar scope, review their methods critically, and, if possible, combine them into a statistical analysis, which is known as a meta-analysis as well [15]. Although it needs more work than typical reviews, it is more favorable for scholars seeking a broad variety of evidence-based, evolutionary information.In any case, the procedures that required to be carried out in order to acquire an SLR approach are outlined in additional detail for the purpose of our research in the field of AI-driven PdM.

2.1 Research Questions

The first step in both making an SLR approach and putting it into action is to come up with research questions. The following are the research questions that will be addressed in the article:

- RQ1: What particular areas of PdM have been examined in reviewed articles since 2015?
  In accordance with the RQ1, we have begun our search between January 1, 2015 and September 30, 2022. Industry 4.0's optimal maintenance schedule is now being determined by data-driven industrial AI solutions, which are a top-tier research trend. Solution of this RQ will assist us in determining which industrial segments were or were not included in the secondary study of AI-driven and/or data-driven PdM.
- RQ2: What are the yearly tendencies in the quantity, variety, and quality of secondary research?
  This will provide a clear picture of the study paths pursued in the past, the present, and the future.
- RQ3: Identify the footsteps of top researchers who conducted the most successful secondary research in PdM according to the quality?
  This RQ would lead us to analyze the relevant literature in order to follow in the footsteps of top researchers who have been successful in predictive maintenance research.
- RQ4: What are the existing contributions and industrial research constraints of secondary study is for AI driven PdM? This is the most crucial and significant conclusion, which will direct us to design our future research route for using AI to apply PdM industrial settings. Consequently, answering this RQ will have the most influence in this study.

2.2 Systematic Searches

Identifying search strategies is crucial to acquiring an SLR. The systematic literature search starts with the selection of authoritative research databases (IEEE, Scopus, Science Direct). Due to their applicability sectors, several academic research article databases, such as PubMed, were ignored in this study. Keyword selection was essential for the perfect SLR. The keywords were:

("Predictive Maintenance" AND ("Review" OR "Survey" OR "systematic Literature Review") AND ("Artificial Intelligence" OR "Deep Learning" OR "Machine Learning")

The systematic search for SLR was conducted using the aforementioned keywords, namely in the titles and abstracts of research publications in several academic databases. After the search, we were eager to determine which publications would be included in our SLR and which would be excluded.

2.3 Criteria

Articles published in peer-reviewed journals and conferences between January 2015 and October 2022 that met the following criteria were included: (1) Articles that serve as reviews for the areas of computer science and engineering. (2) Both formally and informally published SLR and international reviews.

Articles based on the following criteria were excluded: (1) Non-relevant review articles about PdM and Artificial Intelligence. (2) Articles that are not in English. (3) Reviewed articles that are shallow analysis.

3 Quality Assessment Criterion of Secondary Studies

SANRA [1] is a mechanism for evaluating the quality of secondary research. In accordance with the SANRA technique, a review's quality could well be determined by responding to the following questions.

- QA1: Was the importance of the article to the readers justified?
- QA2: Were the specific goals or questions put up in an appropriate way?
- QA3: Were the strategies for finding relevant literature provided effectively?
- QA4: Were the essential assertions backed by appropriate citations?
- QA5: Were valid arguments used to support the scientific evidence?
- QA6: Were the data presented in the optimal manner?

Table 1 Literature review studies

Authors and review type	Review period	Databases	No. of reviewed articles	Application's area	Review type
Zhang et al. [21]	2015–2019	Not mentioned	Not mentioned	Manufacturing industry	NR
Carvalho et al. [2]	2009–2018	IEEEXplore, ScienceDirect	18	Manufacturing industry	SLR
Dalzochio et al. [5]	2015–2020	IEEEXplore, Springer, ACM Digital Library, ScienceDirect	38	Manufacturing industry	SLR
Zonta et al. [22]	2008–2020	ACM Digital Library, IEEEXplore, Scopus, Web of Science, ScienceDirect	118	Manufacturing industry	SLR
Xie et al. [20]	1999–2019	ScienceDirect, Scopus, IEEEXplore	218	Railway industry	SLR
Davari et al. [6]	2010–2021	Not mentioned	Not mentioned	Rainway industry	NR
Lima et al. [10]	2011–2020	IEEEXplore, Science Direct, Springer, ACM Digital Library	32	Manufacturing industry	SLR
Mahmoud et al. [11]	2012–2020	Scopus, ScienceDirect, IEEEXplore, Web of Science	65	Power industry	SLR
Schwendemann et al. [17]	Not mentioned	Not mentioned	Not mentioned	Manufacturing industry	NR
Es-sakali et al. [8]	Not mentioned	Not mentioned	Not mentioned	Building engineering	NR
Drakaki et al. [7]	2015–2021	IEEEXplore, Elsevier, Wiley, Springer, Taylor, Francis	109	Manufacturing industry	NR
Jain et al. [9]	2009–2022	IEEEXplore, ScienceDirect	Not mentioned	Automobile industry	SLR
Cheng et al. [4]	Not mentioned	Scopus, Web of Science, IEEEXplore	37	Manufacturing industry	SLR
Nor et al. [14]	2018–2022	Scopus, IEEEXplore, Elsevier,	56	Nuclear energy industry	NR
Toumi et al. [18]	2016–2021	IEEEXplore, Elsevier, Springer, ASME, Autres	91	Manufacturing industry	SLR

3.1 Documentation of Scoring Criteria

QA1: The significance of rescheduling of secondary articles must be understood within the perspective of reconstruction. The secondary manuscript considers how well the industry outlines the problem of PdM and highlights unanswered questions or gaps in the evidence—fully (2), partially (1), not at all (0).
QA2: A high-quality article will ask relevant questions about one or more specific goals or issues that need to be looked into. The grade should reflect whether the task was completed entirely and clearly (2), partially or ambiguously (1), or not at all (0).
QA3: A competent narrative review will identify the sources of the information in the literature. It is not required that the highest ranking (2) be based on the number of databases used for a literature search rather than a detailed explanation of the search strategy employed throughout the whole investigation. It is more crucial to select the search keyword and establish the inclusion and exclusion criteria in order to attain a high ranking.When it is only descriptive, we will place them in the second position (1), however failing to mention any of them would result in a score of zero (0).
QA4: In any secondary study, all "important claims" must be backed by the appropriate citations. If all "important assertions" in a single research are well supported, the study will earn a flawless grade (2). If just some of the "important claims" are adequately justified, the research will obtain a score of one (1); otherwise, it will receive a score of zero (0).
QA5: The scientific viewpoint had to be validated by sufficient evidence, and the evidence had to be of adequate strength to warrant it. If the proof is sufficient, it will earn two points; if it is just superficial, it will receive one point; and if it is insufficient, it will receive no points (0).
QA6: This question focuses on the information provided by the secondary article, which exhibits a statistical presentation intended to bolster an argument. To be considered, the insight must be relevant and have the proper direction. If the research results are presented in a logical and relevant way, the study will get the best possible grade (2). The second state will be partially (1) followed by the presentation of systematic data, and the final score (0) will be attained through the presentation of irrelevant data in secondary research (Tables 1 and 2).

4 Results

This section provides a concise summary of the findings from the whole research.

4.1 Search Results

The poll was conducted throughout the month of January 2015 to October in 2022. According to our search criteria we have found 42 secondary articles among them 18 paper were focused on application of AI in manufacturing Industry's PdM, rest were

Table 2 Contributions of secondary studies

Contributions	Authors
ML and DL approaches along with potential future research directions	Davari et al. [6], Drakaki et al. [7], Lima et al. [10], Mahmoud et al. [11], Xie et al. [20], Zhang et al. [21], Zonta et al. [22]
ML and DL approaches that lack performance analysis	Carvalho et al. [3], Lima et al. [10], Schwendemann et al. [16]
Only ML approaches	Carvalho et al. [2], Dalzochio et al.[5], Jain et al. [9]
ML, DL and Explainable AI (XAI) approaches	Cheng et al. [4]
ML, Augmented Reality (AR) approaches	Nor et al. [14]
ML, DL approaches including knowledge-based, model-based approaches	Es-sakali et al. [8]
PdM related equipment, Data set, Data description	Davari et al. [6], Nor et al. [14]

Table 3 Quality assessment

Authors	QA1	QA2	QA3	QA4	QA5	QA6
Zhang et al. [21]	2	1	0	1	2	2
Carvalho et al. [2]	2	1	2	1	1	1
Dalzochio et al. [5]	2	1	2	1	1	1
Zonta et al. [22]	2	2	1	1	1	2
Xie et al. [20]	2	1	1	1	2	1
Davari et al. [6]	2	1	1	1	1	0
Lima et al. [10]	2	2	1	2	1	1
Mahmoud et al. [11]	1	0	1	2	1	1
Schwendemann et al. [17]	2	0	0	2	2	2
Es-sakali et al. [8]	2	0	0	1	1	1
Drakaki et al. [7]	2	0	1	2	2	1
Jain et al. [9]	2	2	1	1	1	1
Cheng et al. [4]	2	2	2	1	1	2
Nor et al. [14]	2	0	0	1	2	1
Toumi et al. [19]	2	0	1	1	1	1

in Railway, Power, Automobile, Building, Nuclear Energy Industry, 67% studies were published in peer reviewed journals and rest were in conferences. According to the inclusion and exclusion criteria that were identified before, only 15 of the 42 articles that were discovered throughout the search fulfill the standards to be included in this SLR. Among them 9 articles were SLR and 6 were narrative review (NR).

Table 4 Limitations of secondary studies

Limitations	Authors
The standard SLR methodology is not included	Es-sakali et al. [8], Jain et al. [9], Mahmoud et al. [11], Xie et al. [20]
Systematic literature searches did not meet aims properly	Drakaki et al. [7], Es-sakali et al. [8], Mahmoud et al. [11], Nor et al. [14]
No comparison of the validation or performance measures of ML or DL approaches	Carvalho et al. [2], Davari et al. [6], Jain et al. [9], Lima et al. [10], Schwendemann et al. [17], Zonta et al. [22]
Restricted exclusively to PdM of cyber-physical systems	Dalzochio et al. [5]
XAI, Digital twin in terms of PdM are not included	All except Cheng et al. [4]

4.2 Quality Evaluation of Reviews

It is essential to conduct a quality assessment of the selected review articles using SANRA, as outlined in Sect. 3. In addition, the score for each article is presented in Table 3 in order to determine which article provides the most insightful viewpoint on predictive maintenance in the field of applied AI in best structured way. This was done in order to find the best article and for answering research question that was formulated in our SLR study.

5 Discussions

In the following section, we are going to discuss the findings that pertain to the questions that we posed in our SLR study.

RQ1: What particular applications areas of Predictive maintenance have been examined in reviewed articles since 2015?
In terms of the application areas of PdM addressed by secondary studies since 2015 are: Manufacturing Industry, Automotive or Automobile Industry, Power Engineering, Building Engineering, Healthcare Industry, Nuclear Energy Industry, Telecommunication Industry, Railway Industry.
Initially, we discovered that the Manufacturing Industry had the highest trend, which was 18. In addition, the Automobile Industry ranked second with 6 articles. Further trends were observed in power engineering, building engineering, healthcare, nuclear energy, telecommunications, and railway engineering, in that order.

RQ2: What are the yearly tendencies in the quantity of secondary research?
We came across a total of 42 secondary research that were related to the study that we executed. Up to the year 2022, 14 secondary papers have been published, indicating that this is a relatively young field of research. Prior to the year 2019, it was almost at

zero, even in the primary study as well. The vast majority of secondary research has been published in industry-specific journals that are also concerned with computer-human interactions. The Computer In Industry Journal is one example of such a journal. ACM Computer Survey is the finest publication in computer science for review papers. Surprisingly, we have not discovered any secondary papers linked to data-driven PdM that motivate us to broaden our research towards our future aim of conducting a comprehensive systematic literature review. Prior to that, this study provides a glimpse into future objectives.

RQ3: Who conducted the most successful secondary research in predictive maintenance according to the quality?
Applying the SANRA technique of quality assessment of review articles we found that the SLR of team [4] score the highest value (10) out of 12. They followed the better SLR methodologies for their study. The research question was well formulated and justified accurately. They used preferred reporting items for systematic reviews and meta-analyses (PRISMA), and well structured meta analysis of research articles.

RQ4: What are the existing contributions and industrial research constraints of secondary studies is for AI driven PdM?
SLR is a revolutionary technique for secondary articles, and it is governed by clear and precise rules. In order to assess the state of the art in a given field of study, certain guidelines must be followed. We discovered shortcomings, which are rectified in Table 4, as a result of a quality evaluation. Tables 1 and 2 summarises the overall contributions and constraints for determining the state of the art in PdM secondary research employing AI. Finally, we find that typical SLR methodology and search tactics, as well as the XAI and digital twin concepts, are significantly underutilised.

6 Conclusions

This tertiary study had two main objectives: the first was to classify the secondary research in the field of PdM using AI methodologies according to quality and application area; the second was to find the research constraints for determining the future research scope of survey work for a new Ph.D. student or industrial practitioner in this area. Both of these objectives were accomplished by answering all the research questions. 15 articles were selected according to the search, inclusion and exclusion criteria. The assessment were taken place on those selected articles and the findings are: By providing responses to all of the research questions, both of these goals were successfully completed. Following the search, the inclusion, and the exclusion criteria, 15 articles were chosen for further consideration. The results show that the majority of application areas are applied to the manufacturing industry, which validates the reasons that were presented in support of them. In the year 2022, the Scopus database, and journals have established themselves as the leaders in terms of the number of papers published. In addition to this, it leads to the discovery of the AI revolution in Pdm. The team led by X.Cheng at Universiti Kebangsaan Malaysia (UKM) is at the forefront of this discipline, making it wise for newcomers and indus-

try professionals to emulate their success. This, in turn, indicates that not a great deal of progress has been made in the creation of SLRs and the addition of AI approaches that can be explained or understood in secondary studies. Therefore, the following terms will serve as our chosen keywords for the next secondary research:
"Predictive Maintenance", "Condition Based Maintenance", "Explainable Predictive Maintence", "Prognostic Heath Management", "Prognostic Maintenance", "Explainable Artificial Intelligence", "Explainable AI", "Intepretable Artificial Intelligence", Following the completion of this tertiary study, our next research will focus on developing a standard SLR equipped with Explainable AI in PdM.

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