

TOPICAL REVIEW

A Systematic Mapping Study of Predictive Maintenance in SMEs

MAQBOOL KHAN^{1,3}, (Senior Member, IEEE), ARSHAD AHMAD^{2,3}, FLORIAN SOBIECZKY¹, MARIO PICHLER¹, BERNHARD A. MOSER¹, AND IVO BUKOVSKÝ⁴, (Senior Member, IEEE)

¹Software Competence Center Hagenberg, 4232 Hagenberg, Austria

²Institute of Software Systems Engineering, Johannes Kepler University, 4040 Linz, Austria

³Sino-Pak Center for Artificial Intelligence, Pak-Austria Fachhochschule: Institute of Applied Sciences and Technology (PAF-IAST), Haripur 22620, Pakistan

⁴Department of Computer Science, University of South Bohemia in České Budějovice, 370 05 České Budějovice, Czech Republic

Corresponding author: Maqbool Khan (maqbool.khan@scch.at)

This work was supported in part by the European Interreg Austria-Czech Republic Project “PredMAIn” under Grant ATCZ279, in part by the State of Upper Austria within the Strategic Program Uppervision2030 (SPA), and in part by BMK, BMDW, and the State of Upper Austria in the frame of SCCH, part of the COMET Programme managed by FFG.

ABSTRACT The rapid growth of Industry 4.0 and predictive methods fostered a great potential for state-of-the-art techniques in the industrial sector, especially in smart factories. The equipment failure or system breakdowns during run time of a factory creates a severe problems towards impoverishment of the production system and destitution of the business. Predictive Maintenance (PdM) is a cost-saving and data driven technique to predict the maintenance time of in-service equipment or systems to reduce breakdown time and increase productivity. Although PdM is pragmatically adopted in large-scale industries, there is a lack of studies that map the PdM adoption in small and medium-sized enterprises (SMEs). In this systematic mapping study (SMS), we focus on predictive maintenance from an SME perspective to explore the field for researchers, scientists, and developers to comprehend the potential of PdM systems, their challenges, distinctive characteristics, and best practices in SMEs. Our study is based on four research questions comprised of demographic data, key challenges, distinctive characteristics, and best practices of predictive maintenance in SMEs. We found that the current literature on PdM is deficient in the SME domain, especially the financial side is vague. There is a huge potential for PdM in SMEs to design cost models and focus on data availability impediments. Management and monitoring of PdM and skilled personnel are also inadequate. Thus, we present a study that extracts the knowledge from the existing literature about PdM in SMEs, finds the research gap, and can assist in identifying the barriers and challenges of PdM adoption in SMEs.

INDEX TERMS Condition monitoring, predictive maintenance, PdM, SME, small and medium-sized enterprises, systematic mapping study.

I. INTRODUCTION

Maintenance is a key strategy to ensure continuous production in industries, especially in manufacturing. Maintenance is an expensive process and boosts goods production costs from 15 to 60 percent [1]. Amazon suffered a 4 Million USD loss in its sales in 2013 due to 49 minutes of unplanned downtime [2]. Similarly, the offshore wind turbine cost for operation and maintenance is around 20 to 30 percent of the total income from electricity produced [3]. Different

maintenance strategies are used to avoid breakdown and decrease the cost of production. Maintenance strategies can generally be divided into three categories: reactive maintenance (RM), preventive maintenance (PM) and predictive maintenance (PdM). In reactive or run-to-failure or corrective maintenance, the machine or asset is restored to work again after some failure or breakdown [4]. PM is a planned and scheduled maintenance strategy with specific time intervals to reduce the breakdown.

A. PREDICTIVE MAINTENANCE

Predictive maintenance is a data-driven maintenance strategy that predicts failures and optimizes asset maintenance

The associate editor coordinating the review of this manuscript and approving it for publication was Sunil Karamchandani¹.

plan [5] to avoid sudden breakdowns. It proactively assesses the equipment current condition to maintain the optimal situation and alert when it deviates [6]. Methodologically, PdM is a bag of multiple sets of techniques based on the system, sensors and available data e.g., vibration analysis, thermography, tribology, ultrasonics and visual analysis to name the most important ones. In general, PdM is a holistic approach comprising equipment condition monitoring, fault detection, fault diagnosis, fault prognosis and maintenance plans [7]. In fault detection processes, the faulty components, machines and equipment are detected through data analysis of the system. Possible causes of faults are typically identified in real-time monitoring systems using fault diagnosis algorithms. Data-driven PdM's fault prognosis includes the task to predict the fault and following downtime of a system so that maintenance can be scheduled accordingly. Faults are of diverse types that are based on the equipment. Fault prediction can be done by using degradation models that assist in the remaining useful lifetime of the equipment [8]. Errors or failure history is used for fault analysis. In some cases, internal and external sensor data are used for PdM in combination with environmental data as well as planning data. According to a PwC report [9], PdM increases up-time of assets up to 47%, reduces costs by 17% and leads to a reduction of 11% of safety, health, environmental and quality risks.

B. SMALL AND MEDIUM SIZED ENTERPRISES (SMEs)

Small and medium-sized enterprises are a certain types of industries or businesses with specific threshold values for revenue and number of employees depending on the country-wise definition of SME. For example according to European Union standards, an organization with less than 50 employees is considered as small enterprise, and having less than 250 employees is called a medium-sized enterprise. Thus SME is an enterprise with 250 or fewer employees, or its annual turnover is less than 50 million EUR [10]. SME covers multiple types of business, e.g., manufacturing, banking, workshops, law firms, institutes, trading enterprises etc. However, the current study focuses on the manufacturing domain with machinery and industrial systems, for which maintenance strategies are essential. SMEs are considered the heartbeat of economical development and play a vital role in innovation and advancing emerging technologies in the industrial sector.

C. MOTIVATION

The motivation for the current mapping study is to comprehend the key challenges, salient features and best practices of PdM towards acquisition and application in small and medium-sized enterprises from a literature perspective. The research method is designed in such a way that it will clarify the PdM knowledge from SME perspective and will help:

- Researchers to find out the research gap and future research directions.
- Business owners to select suitable tools to purchase.

- IT developers and architects to use the proper AI methods in PdM solutions for SMEs.
- Management team to plan according to the need of PdM in SME so as to reduce product cost.

D. CONTRIBUTIONS

The primary scope of the current study is to extract knowledge from the existing literature about PdM in SME and find the research gap for further researchers. It also assists the business owners and solution providers in identifying the barriers and challenges of PdM adoption in SMEs. The research questions include demographic data, challenges, distinctive features and best practices of PdM in SMEs. Predictive maintenance is an integrated task of detecting, diagnosing, and predicting anomalies in the industrial data. Predictive maintenance aims to predict failure or the remaining useful life (RUL) of a machine or system. Classification and anomaly detection methods are generally used for failure prediction while regression is used for RUL. Contributions of the current study are summarized as follows:

- A comprehensive time frame is used to cover the overall research trend instead of a decade.
- Snowballing is the first time used in the PdM domain.
- The most needed research questions are mapped.
- Demographic data are covered.
- The two main databases (Web of Science and Scopus) are used.
- Research Questions are validated by an Industrial workshop.

Besides Introduction, the rest of the paper is orchestrated in five sections. Related work is presented in section II and research methodology is enveloped in section III. Section IV is allocated for lessons learned from an industrial event organized by SCCH as part of the PredMAIn¹ project. Results and discussions are enunciated with details in section V, and finally, the paper is concluded in section VI with future works.

II. RELATED WORK

Maintenance is the process of increasing the up time of machines, and reducing the number of failures and downtime to sustain the production system's work. Predictive Maintenance is a prolific field of Artificial Intelligence and smart manufacturing in the research communities. Various survey and review studies are performed to explore the area to practice implementation and adoption by the organization. However, most studies focused on large-scale organizations, and limited papers focused specifically on SMEs. Currently, we found only one systematic literature review (SLR) paper [11] on PdM solutions for SMEs covering literature in the last decade.

This mapping study scope includes PdM challenges, stakeholder's expectations and concerns in implementation, appropriate solutions, and required resources for PdM in SMEs. Rastogi *et al.* [12] reviewed recent technologies available in

¹www.scch.at/project/predmain

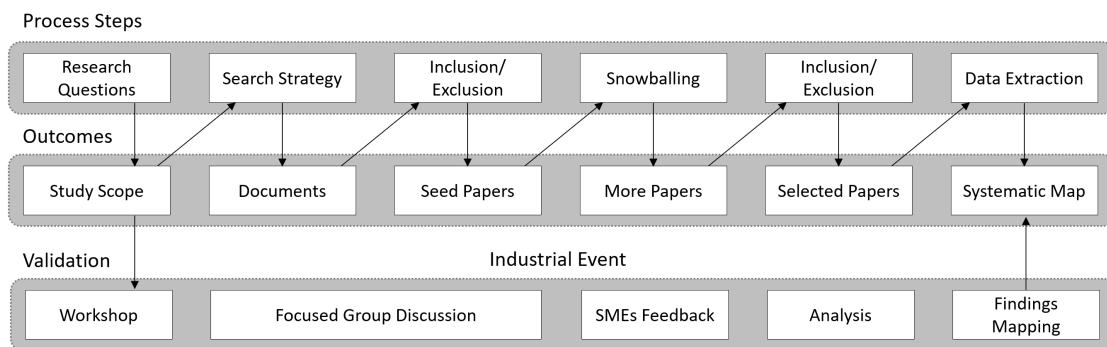


FIGURE 1. Research methodology steps.

PdM with Industry 4.0 for SMEs. They studied 13 targeted parameters of PdM in Industry 4.0, including Remaining Useful Life (RUL), anomaly detection, performance, accuracy, efficiency, failure detection, cost, adaptability, reliability, power consumption, quality, scheduling and robustness. The study also discussed cloud computing, fog computing, cyber-physical system, and edge computing architectures of PdM in SMEs. The systematic mapping [13] studied machine learning techniques for PdM riveting in the manufacturing domain. The nucleus of this study is machine learning methods for PdM and does not cover the SME side. Another systematic mapping [14] concentrated on PdM techniques, especially on RUL. There are also some relevant systematic mapping studies and literature reviews that indirectly assist some specific fields of PdM, e.g. [15] studies machine learning life cycle, [16] is about Knowledge Graphs in manufacturing and production. In [2], the author surveyed a variety of PdM systems architecture, purposes and approaches toward PdM 4.0 with objectives of cost minimization, reliability, growth, and optimization.

A huge number of systematic literature reviews and mapping papers have been published on different aspects of PdM, including fault diagnosis, fault prognosis, condition monitoring, machine health management, and RUL prediction in the last two decades. For instance, work [17] reviewed applications of different deep learning techniques in health management systems, e.g., auto-encoder, convolution, and recurrent neural networks. The study [18] categorized deep learning architectures into four types with applications in machine health monitoring. The limitation of published literature on PdM in SMEs are:

- Most of the surveyed and review articles covered PdM for large-scale enterprises.
- The studies are done for some specific time duration, e.g., one decade, etc.
- The implementations and adoptions of PdM in SMEs have limited review and research articles in general and systematic studies specifically.
- There is no systematic mapping study (SMS) available in current literature so far on the topic of PdM in SMEs.

Except for one specific SLR [11], we did not find any SMS on PdM in SMEs. Here it is important to know that SLRs are differ from SMSs in various aspects; as enunciated in [19], that SLR deals with specific research questions narrowing the literature search for some specific answers, while SMS covers a broader research area. Firstly, the current study is the first SMS to fulfill the review gap to cover abroad literature on the topic of PdM in SMEs in general. Secondly, the current study has open coverage without limiting it to some specific duration to enfold more literature on the topic.

III. RESEARCH METHODOLOGY

The Mapping studies are also reviews but they do not discuss the findings [20]. SMS is an effective technique used in software engineering and other related research subjects. In this study, we followed software engineering guidelines presented in [21] and [22]. Based on the steps in these articles and guidelines, our research methodology consists of research questions, search strategy, inclusion/exclusion criteria, snowballing, and data extraction, as shown in Fig. 1. These terms are briefly described in the following subsections.

A. RESEARCH QUESTIONS

The research questions in a systematic mapping study are more generic to grasp the research trends over time and topics covered in the literature [21]. The current study focused on four main research questions, as given in Fig. 2. The description and motivation for each question are as below.

1) RQ1: WHAT ARE THE BIBLIOMETRIC KEY FACTS OF PdM PUBLICATIONS IN SMEs?

These are the key facts of publication related to PdM in SME and their classification that covers the other research questions of the current study. We used a comprehensive approach to map the aggregate research work in this area, i.e., without giving any specific time frame. The purpose of the question is that we will understand the current trend of PdM in SMEs from different perspectives.

Q. No.	Research Questions
RQ1	What are the bibliometric key facts of PdM publications in SME?
RQ2	What are the key challenges for PdM adoption in SME?
RQ2.1	Knowledge, Management and Skill (KMS) Challenges
RQ2.2	Data Availability, Analysis, Management Challenges
RQ2.3	Financial Challenges
RQ2.4	Monitoring, Implementation or other technical Challenges (Technical)
RQ3	What are the distinctive characteristics for adopting PdM in SME?
RQ3.1	Proposed or discussed available methods/techniques
RQ3.2	Proposed or discussed available tools/technologies/solutions in the market
RQ3.3	Proposed or discussed available Cost models
RQ4	What are the best practices of PdM in SME?
RQ4.1	Benefits of PdM adoption - Easiness, cost-effective
RQ4.2	Recommended and proposed designs, methods and solutions

FIGURE 2. Research questions with sub-questions.

TABLE 1. Search string.

Source	Search String
Scopus and Web of Science	(“Predictive Maintenance” OR “PdM” OR “preventive maintenance” OR “run-to-failure” OR “cognitive maintenance” OR “Remaining Useful Lifetime” OR “RUL” OR “Failure Detection” OR “Prognostics” OR “Prognostics and Health Management” OR “PHM” OR “Anomaly Detection” OR “Outlier Detection” OR “Data-driven” OR “Decision support”) AND (“SMEs” or “SME” or “Small and Medium-sized Enterprises” or “Small Manufacturing Enterprises”)

2) RQ2: WHAT ARE THE KEY CHALLENGES FOR PdM ADOPTION IN SMEs?

The question is about to find out the main barriers for SME to adopt PdM. The motive of the question is to map the challenges for PdM from different angles so that other researchers leverage this study in searching for a research gap.

3) RQ3: WHAT ARE THE DISTINCTIVE CHARACTERISTICS OF ADOPTING PdM IN SMEs?

This question is about the distinctive features and characteristics of PdM for SMEs so that factories’ owners are convinced to use state-of-the-art technologies. This question intends to attract business owners, SME managers, and other investors to adopt PdM.

4) RQ4: WHAT ARE THE BEST PRACTICES OF PdM IN SMEs?

The focus of this question is to find out the best practices of PdM that can be adopted in SMEs. Understanding the best practices before using PdM will assist the end users in selecting maintenance solutions that bring expected value to the SME.

To unfold the PdM with multiple facets, the main questions are divided into sub-questions with their goal, related papers, and support level from the selected research papers, as depicted in Table 2.

B. SEARCH STRATEGY

The Search strategy is performed in two ways [23], manual search and automated search. In Manual search, most relevant conferences are considered, and libraries are visited for searching documents. While in automated search, digital libraries are searched online. The automated search strategy consists of two portions: first to choose the right digital search engines, also known as research databases, and second, to make an appropriate search string that covers the research questions of the current study. A search string, as given in table 1, is prepared to find the target research articles in two famous research engines Scopus and Web of Science (WoS). Scopus and WoS are the most comprehensive search engines for research articles covering a variety of fields and research databases including IEEE Xplore, ACM, Springer, and Elsevier, among others. The work presented in [22] took four sources, i.e., ACM DL, IEEE Xplore, Scopus, and WoS. However, IEEE Xplore and ACM research articles are two databases that already included in WoS search. The search strategy of this study is limited to Scopus and WoS, and other sources are not considered to avoid duplication of articles. Secondly, Scopus is the largest multidisciplinary database for peer-reviewed literature, and Google scholar also has some drawbacks and limitations [24]. Thus to avoid repetition of research articles, separate searches in these two databases are excluded from our search strategy.

The first part of our search string is composed of key terms that have been used in previous papers and joined with the logical operator “OR” as they are synonyms or relevant to prediction. Some research articles are indirectly relevant to PdM, e.g., anomaly detection, outlier detection, decision support, etc. The second part of the search string is about the SME containing abbreviation, full text, singular and plural keywords joined with the logical operator “OR”. Both the sections are combined with logical operator “AND” as the current study is comprised of predictive maintenance in SMEs. Besides search strategy, the snowballing technique [21] is also applied to reduce the threat of

TABLE 2. Research questions with support level.

RQs	Sub-RQs	Goal	Related Papers	Support Level
RQ1	RQ1	Bibliography	Demographic Data	34
RQ2	RQ2.1	KMS	[25], [26], [27], [28], [29], [30], [31]	7
	RQ2.2	Data	[32], [33], [34], [35], [36], [37], [38], [39]	8
	RQ2.3	Financial	[40], [41]	2
	RQ2.4	Technical	[42], [43], [44], [45], [46], [12], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57],	17
RQ3	RQ3.1	Methods	[27], [32], [41]–[43], [29], [33]–[35], [44], [12], [45], [46], [48], [49], [36] [37], [50]–[52], [39], [53], [57]	23
	RQ3.2	Tools	[25], [26], [28], [30], [47], [31], [38], [54]–[56]	10
	RQ3.3	Cost	[40]	1
RQ4	RQ4.1	Adoption	[32], [26], [27], [40], [43], [41], [33], [28], [34], [44], [29], [35], [45], [46] [47], [49], [50], [51], [36], [52], [53], [56], [57],	23
	RQ4.2	Recommendation	[25], [42], [12], [30], [31], [48], [37], [38], [54], [55], [57]	11

missing any relevant paper. Snowballing follows the guidelines of [58], [59] as backward and forward snowballing. Using the search strategy, we get a total of 1021 research articles, consisting of 700 articles from Scopus and 321 papers from WoS.

C. INCLUSION-EXCLUSION CRITERIA

In the automatic search strategy, we get an issue of a massive number of documents from the digital research database, where all the documents are not relevant to the current study. To avoid this problem, we apply clearly defined inclusion-exclusion criteria following [22] to get the most relevant articles. The inclusion-exclusion criteria are not like an automatic search, and it needs the author's effort to decide what documents to include or exclude keeping in mind the research questions (stated in section III.A). The selection of the relevant research articles in the systematic mapping study comprised two tasks. Firstly, the inclusion of the most suitable papers that are related to the research questions. The inclusion criterion applied here is to select original research articles according to the search string. Secondly, to exclude the irrelevant documents that do not fall within the scope of the current study topic or are unable to answer the research questions. The current study's exclusion criteria (EC) are based on the following points.

- EC1: Exclude papers that are not written in English.
- EC2: Limited research articles having a length of fewer than 4 pages.
- EC3: Non-peer-reviewed research documents.
- EC4: Secondary or Tertiary studies.
- EC5: Exclude grey literature, i.e., documents like a book, presentation slides, talks or training materials, etc.
- EC6: Student Theses (Master or PhD).
- EC7: Repeated or revised articles of the same study, i.e., only the latest version is considered.

TABLE 3. Snowballing.

Description	Seeds	Citations
1st Iteration (Forward)	26	328
1st Iteration (Backward)	-	4
2nd Iteration (Forward)	8	28
2nd Iteration (Backward)	-	0
Total	34	360

- EC8: Duplicate papers that come from multiple sources.
- EC9: Exclude papers that are out of the scope of the current study.

Applying inclusion-exclusion criteria and refining the article collection is hard for the author. There is also a chance of some biases that the predefined inclusion-exclusion criteria somehow control. Besides, small biases could be ignored as different authors and researchers have different opinions. However, the above inclusion-exclusion relies on the previous software engineering studies, and all the retrieved documents are passed manually through the specified criteria.

D. SNOWBALLING

Snowballing is a literature review technique where the references (backward snowballing) and citations (forward snowballing) of a research article are checked to select further relevant documents. Blending snowballing with database search proliferates the quality, and literature coverage and ameliorates the search strategy [60], [61]. Snowballing technique was applied with an initial seed of 26 articles. The snowballing process was completed in two iterations. In the first iteration, we got 328 articles in forwarding snowballing and 4 ones in backward snowballing, 332 articles in total.

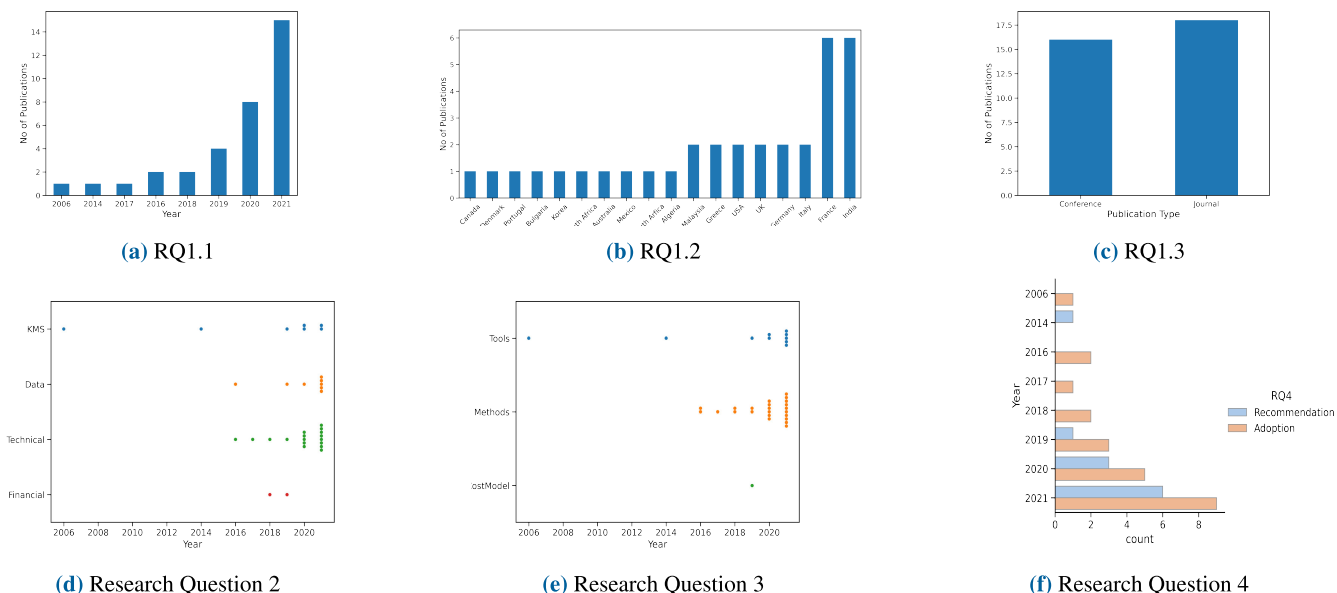


FIGURE 3. Bibliographic information.

Inclusion/Exclusion criteria were applied to these 332 documents, and we got 8 articles as final selected papers for the next iteration. The second iteration started with an initial seed of 8 articles. We got 28 articles in the forward snowballing while we did not get any article in backward snowballing; thus, the snowballing finished. We got 360 articles in total from the snowballing process, as given in table 3.

E. DATA EXTRACTION

Data were extracted from the finalized research articles according to the sub-research questions to support answers to the main research questions. The data were extracted using the manual method, i.e., by reading the 34 research articles to find and extract the relevant data. The first research question was about bibliometric key facts including year, country and author-wise data. To cover the second research question, the papers were read and searched for sub-RQs, i.e., knowledge, management and skills (KMS), data availability, analysis, management, monitoring, implementation, financial, and technical challenges. Similarly, for the third question, the selected papers were analyzed for distinctive characteristics of PdM in SMEs including methods, techniques, tools, technologies, solutions, and cost models discussed somewhere in it. The papers were thoroughly studied to find discussions about PdM adoption, recommended cost-effective solutions, and proposed designs, methods, architectures, and solutions that best fit the SME domain.

F. VALIDATION THROUGH WORKSHOP

An industrial workshop was organized with SMEs as a part of the PredMAIn project. The three research questions were presented in focused groups for deep discussion to get expert

TABLE 4. Retrieved documents.

Source	Documents
Web of Science (WoS)	321
Scopus	700
Total	1021

opinions and feedback from SME personnel. The discussions were analyzed, and summarized findings were mapped with literature output as portrayed in section V with detail.

IV. RESULTS AND DISCUSSIONS

In this section, we present and discuss the current study’s results according to the search strategy outlined in the methodology section III and the research questions. Implementing our search strategy, initially, we retrieved a total of 1021 documents from both the digital databases as in table 4. Following the inclusion/exclusion steps described in the research methodology section, 26 research articles were selected. These 26 articles are considered as an initial seed for the pipeline process of snowballing. Applying the backward and forward snowballing we got 34 research papers as the final selected articles for our mapping study. The results of the research questions in the current study are portrayed in fig 3. The results aligned with RQs are illustrated in detail in the following sub-sections.

A. BIBLIOMETRIC KEY FACTS (RQ1)

The first research question is answered by analyzing the attributes of 34 selected papers. Initially, we explored the year-wise publication frequency so that to get the publication

trend of PdM in SMEs. Starting from the year 2006 up to 2021, we observe an increasing trend in publication which has enormously increased in the last three years, as shown in Figure 3. The interesting finding is that 79% of the papers were published in the last three years, and 21% were published before 2019. It means that the research work on PdM in SMEs has increased almost four times over the previous three years and has a considerable potential for further research.

We explored the publication data country-wise in the second sub-analysis, as plotted in Figure 3b. The selected 34 articles are published by 18 countries. France and India are the two top-most countries that published 6 articles each on this domain. Six countries, including Italy, Germany, UK, USA, Greece and Malaysia published two articles each, while each country published one paper in the remaining ten countries. This result shows that France and India have a great interest in this field compared to the rest of the world. The first reason is that they have most SMEs, and second cause would be the huge population as India has the second largest population in the world and France is the fourth largest EU country population-wise. The result also shows that 44% of publications belong to European Union (EU) countries while 56% to non-EU countries. In the third part of RQ1, it is analyzed that 47% of articles are published in conference proceedings and 53% in journals as shown in Figure 3c. By analyzing the selected papers from author perspectives, we found that Omri [34], [35], [36], [37], [39] is the author who published 5 research articles, i.e., highest among all others.

It is worth mentioning that researchers and business developers target the European countries in general and especially focus on Austria, Germany for Predictive Maintenance implementation barriers in SMEs as their economy has potential in the industrial sector. The focus of this study belongs to an Interreg project of the two countries, i.e., Austria and the Czech Republic. Unfortunately, we did not find any publication in these two countries that implies a vast potential for researchers of these countries to study small and medium-sized enterprises for PdM adoption and implementation.

B. CHALLENGES FOR PdM ADOPTION IN SME (RQ2)

The second question is to find the key challenges in PdM adoption in SMEs using the data of 34 selected papers. The question is further sub-divided into four sub-research questions as shown in fig 3d, so as to unfold the answer from multiple aspects. The data is analyzed for knowledge, management, and skilled people challenges to answer the first sub-question. 21% of the selected literature discussed the problems related to knowledge, management and skilled resources for PdM in SMEs. The second sub-question is supported by 23% of articles that seized the barriers of analysis, management and related data availability. Besides availability, there are various challenges for PdM in big data scenarios of Industry 4.0 as described by [62]. In RQ2.3, 5% of the research articles reported the finance problem to answer the third sub-question. Responding the RQ2.4, the authors

described fences of monitoring, system implementation, and technical fences in 50% of the nominated articles for this study. The analysis demystifies that the existing research has more focused on technical challenges and is destitute of the financial facet. Approximately half of the papers in RQ2.4 published in the 2021 depict that the technical aspect of PdM in SMEs is a hot topic for researchers.

The impetus of these obstacles for PdM is scarcity of awareness, communication and clinging with the technology in use. The SME have limited or no knowledge about the latest solutions, innovations and technologies provided by the researchers and IT industries. There is also a dearth of skilled people to use neoteric data-driven software and solutions. The primary rationale for the non-availability of data is that equipment and systems used in SMEs are nearly obsolete and unable to generate data due to the absence of sensors. The outdated equipment in SMEs also has problem with monitoring as PdM is working in a real-time environment to scan the data and generate alarms for expected failure. Implementation of PdM in SME is a barrier due to the lack of expert technicians. The technical challenges are most despairing after adopting PdM, as the enterprise is sure that our work will not stop due to breakdown; however occurring technical problem in PdM solution would stop the processes that leads to decelerate the production.

The majority of the selected papers enunciated the challenges of technical methods, non-availability of data, and skilled personnel shortage of PdM in the SME domain as shown in systematic map Fig. 4 with the support level accordingly. Further, it is described that the installed equipment in SME lack sensors technologies to collect data for monitoring specific devices conditions leading to the non-availability of data analysis problem. Equipment vendor lock issue is also a challenge for PdM solution providers in SMEs. These cross-cutting barriers to the manufacturing shop floor result in limited AI based methods development. To overcome these obstacles for PdM implementation in SMEs, initially, the researchers need to focus on the cost models e.g., how for an ordinary SME it would cost to upgrade the equipment to sensors technologies towards the smart factory concept.

C. DISTINCTIVE CHARACTERISTICS (RQ3)

The third research question comprised of three sub-research questions covering methods, tools, and cost models of predictive maintenance in small and medium-sized enterprises, as shown in Figure 3e. 68% of papers debated or proposed methods and techniques of PdM in SMEs from multiple aspects. 29% of research articles presented their findings and proposals concerned with tools, techniques, and solutions in the available markets or points of interest for researchers, business developers, and solution providers. Only one paper, i.e., 3% of the focused literature, proposed a cost model for predictive maintenance focusing on SMEs. Interpreting these results, a crucial finding is that the current research lacks cost models, which could be the giant hurdle for small and medium-sized enterprises to adopt PdM. This is because

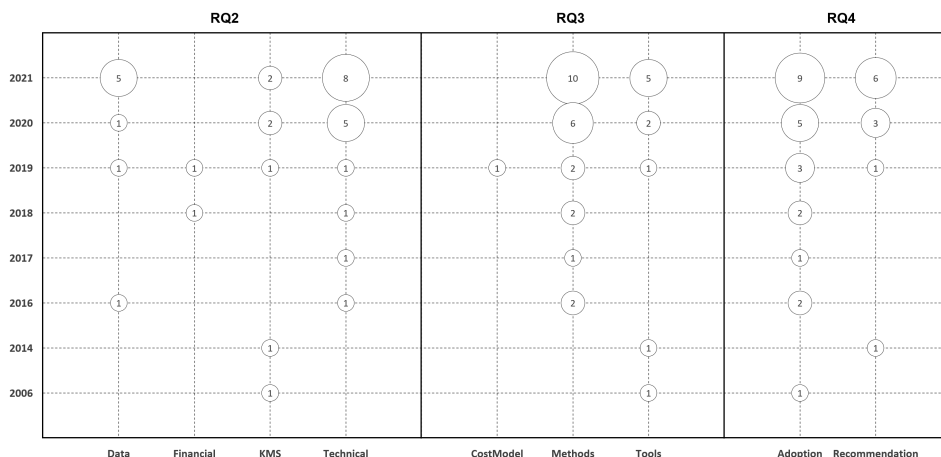


FIGURE 4. Systematic map of RQs.

SMEs are unaware of the cost of PdM implementation and are uncertain about the return on investment (ROI). Although PdM has ten times ROI for large-scale enterprises, 25 to 30 percent reduction in maintenance cost, reducing breakdown from 70% to 75%, downtime decreased by 35% to 45%, and production is step-up 20% to 25% [63]. The unique characteristics of PdM that attract SMEs are maintenance cost and downtime reduction, product quality and production speed enhancement, boosting OEE [56], and extending equipment operational life and availability. Some recommended and proposed tools and solutions in the literature having distinctive features are listed in table 5.

Machine learning, neural networks and deep learning are the mostly commonly used and trending technology in predictive maintenance. These technologies need a systematic and pragmatic methods to incorporate it in SME use case of predictive maintenance [27]. One of the main characteristics of predictive modeling is that it does not depend on the standard programming practices like object-oriented design principles, but the algorithms learn from data [53] during the training phase. The second feature of predictive maintenance is that once the models are trained then its dependency on history data is limited and system is matured day by day in continuous online learning paradigm. The most important characteristics of predictive maintenance discussed in the selected literature are that it is cost-effective, time-saving, elimination of scheduled maintenance and step-up the production speed in SME.

D. BEST PRACTICES (RQ4)

In the last question, we covered best practices of PdM that are suggested, proposed or recommended for SME as shown in Figure 3f. 68% papers illustrated PdM adoption, while 32% research articles discussed recommendation of PdM in SME. Although all the articles did not clearly mention some specific solution or technique, their discussions are relevant to PdM adoption, recommendation and their pros and cons in some aspect from SME point of view. [30] recommended

that the best practices for existing old systems like Manufacturing Execution System (MES), SCADA and DCS would not be replaced with new systems and it can be integrated with new technologies of control. [31] recommended predictive maintenance and presented case study of self-aware machines for condition monitoring in polymer industry that increased overall equipment effectiveness (OEE). [56] presented PdM implementation approach to ensure adaptability and cost-effectiveness of the legacy data so as SMEs align and adopt smart factory architecture and principles.

Besides these challenges, characteristics, tools, solutions, adoption, and recommendations in these papers as shown in the systematic map in Figure 4, interpretable and Explainable machine learning models are deficient [64], [65], which is remarkable in SME scenarios. For example, [66] proposed Explainable Artificial Intelligence (XAI) in remaining useful life prediction of Turbofan Engines. Various XAI methods are summarized in [67] that could be leveraged for PdM in the SME domain. Similarly Graph based approaches could be leveraged in PdM as described in the survey [68], e.g., Knowledge graph [69] and virtual Graph [70] would be useful from an SME perspective to work with limited computing resources. Another state-of-the-art software architecture for Human-AI teaming [71] for smart factories could also be handy for adopting Human-Center AI-based PdM methods in SMEs.

Big data generation from sensors in industries accelerated several naive techniques as a central point of focus for smart factories, leading to Industry 4.0 and digital twin. PdM is one of such techniques that several large enterprises such as General Electric (GE), Microsoft, IBM, Honeywell and Rockwell Automation etc. took keen interest in it to reduce their product cost by avoiding unplanned breakdowns. The best practices of PdM in the selected literature are to use vibration, thermography, acoustic, pressure and oil analysis.

V. LESSONS LEARNED FROM INDUSTRIAL WORKSHOP

In this section, we report some observations from the discussion during the organized public event in the framework

TABLE 5. Tools and solutions.

S.No	Tool / Solution	Description	Ref.
1	Computer Maintenance Management System (CMMS)	Policy-based Prognostics and health management for shop floor	[25]
2	Performance, Development and Growth (PDG) System	Hybrid diagnostic-advisory system using AI and DSS for SME	[26]
3	Asset Condition Management System	Real-time condition monitoring, diagnostic and asset health system for manufacturing	[28]
4	Product Quality Driven Auto-Prognostics solution	Low-cost digital solution for CNC milling cutters	[47]
5	IoT-enabled Refrigerator and Cold Storage Systems (RCSS)	Platform for remote monitoring and PdM	[38]
6	PdM 4.0	Platform for Management of PdM	[54]
7	User-centric DSS for PdM	User-centric dashboard	[55]

TABLE 6. Questions asked in discussion groups.

RQ	Questions asked
RQ2.1 vs. RQ2.2	"Which represents the bigger challenge: To manage data or to collect sufficiently descriptive data?"
RQ3.1/2/3 vs. RQ4.1	"Are data scientific methods, tools available? If yes, is there an available assessment of the financial risk of putting them into use?"
RQ2.1 vs. RQ3.2	"Is it difficult to obtain data scientific expert knowledge to implement available PdM-solutions? Are these implementations accepted, comprehended, and adopted for use by existing staff?"

of the PredMAIN project concerning the research questions from Section III. Fifty tickets are issued to registered people using online platform of eventbrite.² Thirty-nine people from twenty-four companies took part in the event and participated in the discussion group activity. Out of these companies there were three enterprises falling into the category 'large enterprise' (>300 employees), eighteen SME and further three companies were universities. Twenty-nine of the participants were actually employed by small and medium sized enterprises. Three discussion groups were confronted with questions regarding the relative eminence of the research questions RQ2, RQ3, and RQ4 for twenty minutes to collect experiences and views. The precise questions are listed in Table 6.

The industrial workshop was organized to comprehend the opinion of SME stockholders about PdM and to validate the current study. PdM has lack of studies, industrial workshop and specific conferences in SME and this study tried to find how much research is done in this gap area. We summarized the opinion of participants in the following sub-sections of data, methodological and human resources based on the groups discussion.

A. DATA RESOURCES

The most pressing issue is the non-availability of data, both in terms of necessary volume and qualitative expressiveness (lack of labeled faults). Financial resources to provide adequate sensory equipment and big data management plays some role, and the employment of cloud solu-

²<https://www.eventbrite.at/e/predmain-communication-event-tickets-293787605637>

tions to manage adequate high-capacity data transfer is increasingly accepted for use, primary as found by the 2020 survey [72].

B. METHODOLOGICAL RESOURCES

Curiously, small enterprises seemed to be more aware of PdM's potential gains for the company in terms of the algorithmic possibilities and the state-of-the-art of PdM software packages. On the other hand, they expressed concerns about the methodological complications arising from the data incompleteness issue. On the other hand, medium-sized companies pointed out the risk of investing in a modernization of the maintenance strategy without a quantitative analysis of the induced gain in production time. Knowledge about a systematic comparison of the effectiveness in the sense of production cost and profit of the different maintenance strategies was only reported in a single case [73].

C. HUMAN RESOURCES

While human resources for operation of state of the art machine learning and data monitoring tasks were less mentioned to be an issue of concern, the readiness of existing personnel to adapt to a modernized maintenance procedure was clearly reported to be connected with significant investment into training and redefining the quality assurance protocol. This coincides with an observation of a 2007-report of the EU-DG "Employment, Social Affairs and Equal Opportunities" (see [74], Section on "SME's Training, Main Challenges").

VI. CONCLUSION AND FUTURE WORKS

A. CONCLUSION

The aim of current study is to find out bibliometric facts, PdM challenges, distinctive characteristics and best practices in SME. In this regard, Initially 1021 articles were found in total, using snowballing technique and after thoroughly filtering, finally, 34 papers were selected for this study to fulfill objectives of the study. Although research on predictive maintenance in SME domain is boomed in 2021, however it is worth mentioning that European countries has limited research focus on PdM adoption in SMEs. As only France and India published more than five articles in this area. We found

that new methods for PdM implementation, availability of public dataset and skilled personnel of PdM equipped with SME domain knowledge are the most demanding facets that need attention of researchers and business developers. The pivotal finding of this study is that technical challenges and methods are the central point of research in this domain and the financial side is the more ignored side as only one paper proposed a cost model for PdM in SME. The second most weak area that has fewer articles is data availability. It means that data availability for PdM is a second big challenge for adoption in SMEs as it is also validated by the industrial workshop.

B. FUTURE WORKS

The financial side needs more attention, and we plan to work further on a cost model of PdM in SMEs in the future. It will assist SME's business and developer communities in comprehending the PdM cost and clearly understanding of return on investment. The solution providers of PdM also need cost models to offer PdM services. The second most interesting research area is to collect relevant data and make it available for further research so that PdM is more optimized for SMEs. We learned from the industrial event that data availability is a massive barrier from various facets. Thirdly, we are interested in incorporating state-of-the-art AI methods like Explainable AI, Interpretable machine learning models, knowledge graph, transfer learning, domain adaptation, and Human-AI teaming in the predictive maintenance portfolio of SME as mentioned in the last paragraph of discussion section.

ACKNOWLEDGMENT

The research reported in this paper has been funded by the Interreg project PredMAin (ATCZ279), the State of Upper Austria within the strategic program upperVision2030 (SPA) and by BMK, BMDW, and the State of Upper Austria in the frame of SCCH, part of the COMET Programme managed by FFG.

REFERENCES

- [1] R. K. Mobley, *An Introduction to Predictive Maintenance*. Amsterdam, The Netherlands: Elsevier, 2002.
- [2] Y. Ran, X. Zhou, P. Lin, Y. Wen, and R. Deng, "A survey of predictive maintenance: Systems, purposes and approaches," 2019, *arXiv:1912.07383*.
- [3] X. Gong and W. Qiao, "Current-based mechanical fault detection for direct-drive wind turbines via synchronous sampling and impulse detection," *IEEE Trans. Ind. Electron.*, vol. 62, no. 3, pp. 1693–1702, Mar. 2014.
- [4] M. Hodkiewicz, S. Lukens, M. P. Brundage, and T. Sexton, "Rethinking maintenance terminology for an industry 4.0 future," *Int. J. Prognostics Health Manage.*, vol. 12, no. 1, pp. 1–14, Mar. 2021.
- [5] V. F. M. zu Wickern, "Challenges and reliability of predictive maintenance," *Rhein-Waal Univ. Appl. Sci., Fac. Commun. Environ.*, pp. 1–24, Mar. 2019, doi: [10.13140/RG.2.2.35379.89129](https://doi.org/10.13140/RG.2.2.35379.89129).
- [6] T. Cerquitelli, N. Nikolakis, N. O'Mahony, E. Macii, M. Ippolito, and S. Makris, *Predictive Maintenance Smart Factories*. Springer, 2021, doi: [10.13140/RG.2.2.35379.89129](https://doi.org/10.13140/RG.2.2.35379.89129).
- [7] J. Wang, L. Zhang, L. Duan, and R. X. Gao, "A new paradigm of cloud-based predictive maintenance for intelligent manufacturing," *J. Intell. Manuf.*, vol. 28, no. 5, pp. 1125–1137, Jun. 2017.
- [8] D. Divya, B. Marath, and M. B. Santosh Kumar, "Review of fault detection techniques for predictive maintenance," *J. Quality Maintenance Eng.*, early access, Apr. 2022, doi: [10.1108/JQME-10-2020-0107](https://doi.org/10.1108/JQME-10-2020-0107).
- [9] M. Haarman, M. Mulders, and C. Vassiliadis, "Predictive maintenance 4.0: Predict the unpredictable," *PwC Mainnovation*, vol. 4, no. 20171016, pp. 1–32, 2017.
- [10] *E. Directorate-General for Internal Market, Industry, and SMEs, User Guide to the SME Definition*, Publications Office Eur. Union, Luxembourg, 2017, doi: [10.2873/782201](https://doi.org/10.2873/782201).
- [11] S. H. Dolatabadi and I. Budinska, "Systematic literature review predictive maintenance solutions for SMEs from the last decade," *Machines*, vol. 9, no. 9, p. 191, Sep. 2021. [Online]. Available: <https://www.mdpi.com/2075-1702/9/9/191>
- [12] V. Rastogi, S. Srivastava, M. Mishra, and R. Thukral, "Predictive maintenance for SME in industry 4.0," in *Proc. Global Smart Ind. Conf. (GloSIC)*, Nov. 2020, pp. 382–390.
- [13] M. Nacchia, F. Fruggiero, A. Lambiase, and K. Bruton, "A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector," *Appl. Sci.*, vol. 11, no. 6, p. 2546, Mar. 2021.
- [14] A. Begüm, A. Akbulut, and A. H. Zaim, "Techniques for apply predictive maintenance and remaining useful life: A systematic mapping study," *Bilecik Şeyh Edebali Üniversitesi Fen Bilimleri Dergisi*, vol. 8, no. 1, pp. 497–511, 2021. [Online]. Available: <https://www.mdpi.com/2075-1702/9/9/191>
- [15] Y. Xie, L. Cruz, P. Heck, and J. S. Rellermeier, "Systematic mapping study on the machine learning lifecycle," in *Proc. IEEE/ACM 1st Workshop AI Eng.-Softw. Eng. AI (WAIN)*, May 2021, pp. 70–73.
- [16] G. Buchgeher, D. Gabauer, J. Martinez-Gil, and L. Ehrlinger, "Knowledge graphs in manufacturing and production: A systematic literature review," *IEEE Access*, vol. 9, pp. 55537–55554, 2021.
- [17] S. Khan and T. Yairi, "A review on the application of deep learning in system health management," *Mech. Syst. Signal Process.*, vol. 107, pp. 241–265, Jul. 2018.
- [18] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep learning and its applications to machine health monitoring," *Mech. Syst. Signal Process.*, vol. 115, pp. 213–237, Jan. 2019.
- [19] B. Napoleao, K. R. Felizardo, E. F. de Souza, and N. L. Vijaykumar, "Practical similarities and differences between systematic literature reviews and systematic mappings: A tertiary study," in *SEKE*, vol. 2017, pp. 85–90.
- [20] I. D. Cooper, "What is a 'mapping study?'" *J. Med. Library Assoc.*, vol. 104, no. 1, p. 76, 2016.
- [21] K. Petersen, S. Vakkalanka, and L. Kuzniarz, "Guidelines for conducting systematic mapping studies in software engineering: An update," *Inf. Softw. Technol.*, vol. 64, pp. 1–18, Aug. 2015.
- [22] A. Ahmad, J. L. B. Justo, C. Feng, and A. A. Khan, "The impact of controlled vocabularies on requirements engineering activities: A systematic mapping study," *Appl. Sci.*, vol. 10, no. 21, p. 7749, Nov. 2020.
- [23] F. Pinciroli, J. L. B. Justo, L. Zeligueta, and M. Pma, "Systematic mapping protocol—coverage of aspect-oriented methodologies for the early phases of the software development life cycle," 2017, *arXiv:1702.02653*.
- [24] S. Bonato, "Google scholar and scopus," *J. Med. Library Assoc.*, vol. 104, no. 3, pp. 252–254, 2016.
- [25] A. K. Pagare, N. Kumar, M. S. Ilahi, R. Khandelwal, and M. Israr, "A case study on manufacturing industry used prognostic tools to remove the problems in shop floor challenges faced in maintenance engineering," *Int. J. Sci. Technol. Res.*, vol. 8, pp. 1–4, Oct. 2019.
- [26] S. Delisle, J. St-Pierre, and T. Copeck, "A hybrid diagnostic-advisory system for small and medium-sized enterprises: A successful AI application," *Int. J. Speech Technol.*, vol. 24, no. 2, pp. 127–141, Apr. 2006.
- [27] R. Welte, M. Estler, and D. Lucke, "A method for implementation of machine learning solutions for predictive maintenance in small and medium sized enterprises," *Proc. CIRP*, vol. 93, pp. 909–914, Jan. 2020.
- [28] N. Diaz-Elsayed, L. Hernandez, R. Rajamani, and B. A. Weiss, "Asset condition management: A framework for smart, health-ready manufacturing systems," in *Int. Manuf. Sci. Eng. Conf.*, vol. 84256, 2020, pp. 1–7.
- [29] H. E. D. Kang, D. Kim, S. Kim, D. D. Kim, J. H. Cheon, and B. W. Anthony, "Homomorphic encryption as a secure PHM outsourcing solution for small and medium manufacturing enterprise," *J. Manuf. Syst.*, vol. 61, pp. 856–865, Oct. 2021.
- [30] L. A. Doukowska, V. G. Nikov, V. V. Monov, S. L. Kojnov, and M. Hadjiski, "Significance of the predictive maintenance strategies for SMEs," in *Proc. 4th Int. Symp. Bus. Modeling Softw. Design*, 2014, pp. 24–26.

- [31] S. Krishnaraj, M. Gomathi Prabha, and M. Yuvaraja, "Smart maintenance and analytics for Indian SMEs," in *Materials, Design, and Manufacturing for Sustainable Environment*. Singapore: Springer, 2021, pp. 695–706, doi: [10.1007/978-981-15-9809-8_50](https://doi.org/10.1007/978-981-15-9809-8_50).
- [32] D. Mourtzis, E. Vlachou, N. Milas, and N. Xanthopoulos, "A cloud-based approach for maintenance of machine tools and equipment based on shop-floor monitoring," *Proc. CIRP*, vol. 41, pp. 655–660, Jan. 2016.
- [33] J. Chen, C. P. Lim, K. H. Tan, K. Govindan, and A. Kumar, "Artificial intelligence-based human-centric decision support framework: An application to predictive maintenance in asset management under pandemic environments," *Ann. Oper. Res.*, vol. 3, pp. 1–24, Nov. 2021.
- [34] N. O. Omri, Z. A. Masry, S. Giampiccolo, N. Mairrot, and N. Zerhouni, "Data management requirements for PHM implementation in SMEs," in *Proc. Prognostics Syst. Health Manage. Conf. (PHM-Paris)*, May 2019, pp. 232–238.
- [35] N. Omri, Z. Al Masry, N. Mairrot, S. Giampiccolo, and N. Zerhouni, "Industrial data management strategy towards an SME-oriented PHM," *J. Manuf. Syst.*, vol. 56, pp. 23–36, Jul. 2020.
- [36] Z. Omri, N. Masry, N. Mairrot, S. Giampiccolo, and N. Zerhouni, "Towards an adapted phm approach: Data quality requirements methodology for fault detection applications," *Comput. Ind.*, vol. 127, pp. 103–414, May 2021.
- [37] N. Omri, Z. A. Masry, N. Mairrot, S. Giampiccolo, and N. Zerhouni, "X-PHM: Prognostics and health management knowledge-based framework for SME," *Proc. CIRP*, vol. 104, pp. 1595–1600, Jan. 2021.
- [38] D. Mourtzis, J. Angelopoulos, and N. Panopoulos, "Design and development of an IoT enabled platform for remote monitoring and predictive maintenance of industrial equipment," *Proc. Manuf.*, vol. 54, pp. 166–171, Jan. 2021.
- [39] N. Omri, Z. Al Masry, N. Mairrot, S. Giampiccolo, and N. Zerhouni, "Data quality requirements methodology for an adapted phm implementation," in *Communication and Intelligent Systems*. Singapore: Springer, 2021, pp. 911–919, doi: [10.1007/978-981-16-1089-9_70](https://doi.org/10.1007/978-981-16-1089-9_70).
- [40] K. Adu-Amankwa, A. K. A. Attia, M. N. Janardhanan, and I. Patel, "A predictive maintenance cost model for CNC SMEs in the era of industry 4.0," *Int. J. Adv. Manuf. Technol.*, vol. 104, nos. 9–12, pp. 3567–3587, Oct. 2019.
- [41] E. Sezer, D. Romero, F. Guedea, M. Macchi, and C. Emmanouilidis, "An industry 4.0-enabled low cost predictive maintenance approach for SMEs," in *Proc. IEEE Int. Conf. Eng., Technol. Innov. (ICE/ITMC)*, Jun. 2018, pp. 1–8.
- [42] A. Gaspari and G. D'Emilia, "A maintenance assessment measurement-based method for SMEs: Case study of an Italian mechanical reality," in *A Maintenance Assessment Measurement-Based Method for SMEs: Case Study of an Italian Mechanical Reality*. Budapest, Hungary: IMEKO, 2020, pp. 117–122.
- [43] S. S. Sidhu, K. Singh, and I. S. Ahuja, "An empirical investigation of maintenance practices for enhancing manufacturing performance in small and medium enterprises of northern India," *J. Sci. Technol. Policy Manage.*, vol. 13, no. 1, pp. 132–153, Feb. 2022.
- [44] S. S. Sidhu, K. Singh, and I. S. Ahuja, "Design of an intelligent decision-making system for maintenance practices using fuzzy inference system in northern Indian SMEs," *J. Quality Maintenance Eng.*, vol. 28, no. 1, pp. 154–179, Feb. 2022.
- [45] K. S. Kiangala and Z. Wang, "Initiating predictive maintenance for a conveyor motor in a bottling plant using industry 4.0 concepts," *Int. J. Adv. Manuf. Technol.*, vol. 97, nos. 9–12, pp. 3251–3271, Aug. 2018.
- [46] B. Ji, S. Bang, H. Park, H. Cho, and K. Jung, "Multi-criteria decision-making-based critical component identification and prioritization for predictive maintenance," *Ind. Eng. Manage. Syst.*, vol. 18, no. 3, pp. 305–314, Sep. 2019.
- [47] A. K. Jain, M. Dhada, A. K. Parlikad, and B. K. Lad, "Product quality driven auto-prognostics: Low-cost digital solution for SMEs," *IFAC-PapersOnLine*, vol. 53, no. 3, pp. 78–83, 2020.
- [48] G. Carabin, E. Wehrle, and R. Vidoni, "Smart mechanical systems for manufacturing in the era of industry 4.0: Condition-based predictive maintenance and dynamic system modification for small and medium-sized enterprises. CMUJ," *Natural Sci.*, vol. 20, no. 2, Oct. 2021, Art. no. e2021028.
- [49] K. Velmurugan, P. Venkumar, and P. R. Sudhakara, "SME 4.0: Machine learning framework for real-time machine health monitoring system," *J. Phys., Conf.*, vol. 1911, no. 1, May 2021, Art. no. 012026.
- [50] H. M. Lazim, C. A. Taib, H. Lamsali, M. N. Saleh, and C. Subramaniam, "The impact of preventive maintenance practices on manufacturing performance: A proposed model for SMEs in Malaysia," in *Proc. AIP Conf.*, Aug. 2016, Art. no. 020059.
- [51] C. A. Taib, H. M. Lazim, H. Lamsali, M. N. Salleh, and C. Subramaniam, "The influence of organization capability on preventive maintenance practices and SMEs performance in Malaysia," *Int. J. Supply Chain Manage.*, vol. 6, no. 4, pp. 332–340, 2017.
- [52] G. D. Putnik, V. K. Manupati, S. K. Pabba, L. Varela, and F. Ferreira, "Semi-double-loop machine learning based CPS approach for predictive maintenance in manufacturing system based on machine status indications," *CIRP Ann.*, vol. 70, no. 1, pp. 365–368, 2021, doi: [10.1016/j.cirp.2021.04.046](https://doi.org/10.1016/j.cirp.2021.04.046).
- [53] N. Iftikhar and F. E. Nordbjerg, "Implementing machine learning in small and medium-sized manufacturing enterprises," in *Towards Sustainable Customization: Bridging Smart Products and Manufacturing Systems*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 448–456.
- [54] K. Aksa, S. Aitouche, H. Bentoumi, and I. Sersa, "Developing a web platform for the management of the predictive maintenance in smart factories," *Wireless Pers. Commun.*, vol. 119, no. 2, pp. 1469–1497, Feb. 2021.
- [55] D. Kellner, M. Lowin, M. von Zahn, and J. Chen, "Towards designing a user-centric decision support system for predictive maintenance in SMEs," *INFORMATIK*, pp. 1255–1260, Sep. 2021, doi: [10.18420/informatik2021-104](https://doi.org/10.18420/informatik2021-104).
- [56] B. Tanane, M. L. Bentaha, B. Dafflon, V. Ferreira, and N. Moalla, "Toward an adaptive approach to implement predictive maintenance in metallurgical industry SMEs through IoT and AI," in *Proc. IFIP Int. Conf. Product Lifecycle Manage.* Singapore: Springer, 2021, pp. 537–547, doi: [10.1007/978-3-030-94335-6_38](https://doi.org/10.1007/978-3-030-94335-6_38).
- [57] K. S. Kiangala and Z. Wang, "An effective predictive maintenance framework for conveyor motors using dual time-series imaging and convolutional neural network in an industry 4.0 environment," *IEEE Access*, vol. 8, pp. 121033–121049, 2020.
- [58] C. Wohlin, "Guidelines for snowballing in systematic literature studies and a replication in software engineering," in *Proc. 18th Int. Conf. Eval. Assessment Softw. Eng. (EASE)*, 2014, pp. 1–10.
- [59] D. Badampudi, C. Wohlin, and K. Petersen, "Experiences from using snowballing and database searches in systematic literature studies," in *Proc. 19th Int. Conf. Eval. Assessment Softw. Eng.*, Apr. 2015, pp. 1–10.
- [60] C. Wohlin, M. Kalinowski, K. R. Felizardo, and E. Mendes, "Successful combination of database search and snowballing for identification of primary studies in systematic literature studies," *Inf. Softw. Technol.*, vol. 147, Jul. 2022, Art. no. 106908.
- [61] M. van Haastrecht, I. Sarhan, B. Y. Ozkan, M. Brinkhuis, and M. Spruit, "SYMBALS: A systematic review methodology blending active learning and snowballing," *Frontiers Res. Metrics Anal.*, vol. 6, p. 33, May 2021.
- [62] M. Khan, X. Wu, X. Xu, and W. Dou, "Big data challenges and opportunities in the hype of industry 4.0," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2017, pp. 1–6.
- [63] G. Sullivan, R. Pugh, A. Melendez, and W. Hunt, "Chapter 5: Types of maintenance programs," in *Operations & Maintenance Best Practices—A Guide to Achieving Operational Efficiency*. Piscataway, NJ, USA: IEEE, 2010, pp. 1–9.
- [64] S. Vollert, M. Atzmueller, and A. Theissler, "Interpretable machine learning: A brief survey from the predictive maintenance perspective," in *Proc. 26th IEEE Int. Conf. Emerg. Technol. Factory Autom. (ETFA)*, Sep. 2021, pp. 01–08.
- [65] W. J. Murdoch, C. Singh, K. Kumbier, R. Abbasi-Asl, and B. Yu, "Definitions, methods, and applications in interpretable machine learning," *Proc. Nat. Acad. Sci. USA*, vol. 116, no. 44, pp. 22071–22080, Oct. 2019.
- [66] C. W. Hong, C. Lee, K. Lee, M.-S. Ko, and K. Hur, "Explainable artificial intelligence for the remaining useful life prognosis of the turbofan engines," in *Proc. 23rd IEEE Int. Conf. Knowl. Innov. Invention (ICKII)*, Aug. 2020, pp. 144–147.
- [67] I. Ahmed, G. Jeon, and F. Piccialli, "From artificial intelligence to explainable artificial intelligence in industry 4.0: A survey on what, how, and where," *IEEE Trans. Ind. Informat.*, vol. 18, no. 8, pp. 5031–5042, Aug. 2022.
- [68] L. Xia, P. Zheng, X. Li, R. X. Gao, and L. Wang, "Toward cognitive predictive maintenance: A survey of graph-based approaches," *J. Manuf. Syst.*, vol. 64, pp. 107–120, Jul. 2022.
- [69] T. R. Chhetri, A. Kurteva, J. G. Adigun, and A. Fensel, "Knowledge graph based hard drive failure prediction," *Sensors*, vol. 22, no. 3, p. 985, Jan. 2022.
- [70] M. Khan, M. Liu, W. Dou, and S. Yu, "VGraph: Graph virtualization towards big data," in *Proc. 3rd Int. Conf. Adv. Cloud Big Data*, Oct. 2015, pp. 153–158.

- [71] P. Haindl, G. Buchgeher, M. Khan, and B. Moser, "Towards a reference software architecture for human-AI teaming in smart manufacturing," in *Proc. IEEE/ACM 44th Int. Conf. Softw. Eng., New Ideas Emerg. Results (ICSE-NIER)*, May 2022, pp. 96–100.
- [72] A.-I. Neicu, A.-C. Radu, G. Zaman, I. Stoica, and F. Răpan, "Cloud computing usage in SMEs. An empirical study based on SMEs employees perceptions," *Sustainability*, vol. 12, no. 12, p. 4960, Jun. 2020, doi: 10.3390/su12124960.
- [73] A. Kinz, T. Passath, W. Schröder, B. Freudenthaler, and P. Praher, "Dynamisierung und wertschöpfungsorientierte optimierung der instandhaltungsstrategie: Smart maintenance in einem komplexen fertigungssystem," in *Der Instandhaltungs-Berater*. Switzerland: MDPI, 2017, pp. 1–51.
- [74] N. Farvaque, E. Voss, M. Lefebvre, and K. Schutze, "Guide for training in SMEs," Publications Office Eur. Union, Luxembourg, Tech. Rep., Jun. 2009. [Online]. Available: <https://data.europa.eu/doi/10.2767/33612>



MAQBOOL KHAN (Senior Member, IEEE) received the M.S. degree from HUST, in 2011, and the Ph.D. degree from Nanjing University, in 2013. He is currently a Postdoctoral Researcher at Software Competence Center Hagenberg (SCCH), Austria. He is also working as an Assistant Professor at Pak-Austria Fachhochschule: Institute of Applied Sciences and Technology. His M.S. and Ph.D. studies were funded by the China Scholarship Council (CSC) of China. He has multidisciplinary expertise and working experience on very diverse topics of big data analytics, cloud computing, predictive maintenance, data science, and machine learning. He has more than ten years of professional experience while working both in industry and academia. He has worked in multinational companies such as Siemens and Atos. He is a certified Google Cloud Professional Architect. He is an active researcher working on various funded projects with different collaborators. He is currently a member of the European Union Project titled "Human–AI Teaming."



ARSHAD AHMAD received the M.S. degree in software engineering from Blekinge Tekniska Högskola (BTH), Sweden, in 2008 and the Ph.D. degree in computer science and technology from the Beijing Institute of Technology, China, in 2018. He is currently working as a Postdoctoral Researcher with the Institute of Software Systems Engineering, Johannes Kepler University, Linz, Austria. He has worked at Fraunhofer Germany and the Vienna University of Technology, Austria, from 2010 to 2014. He is also working as an Assistant Professor at the Department of IT and Computer Science, Pak Austria Fachhochschule: Institute of Applied Sciences and Technology, Haripur, Pakistan. Previously, he has served as an Assistant Professor at the University of Swabi, and the City University of Science and IT, Peshawar, Pakistan. He has published several research papers in well reputed peer-reviewed international journals and conferences. His current research interests include requirements engineering, text mining, opinion mining, sentiment analysis, and machine learning.



FLORIAN SOBIECZKY received the Diploma degree in physics from Florian Sobieczky, and the Doctorate degree in mathematics from the University of Göttingen, with a thesis about percolation theory. During his dissertation, he worked as an Assistant at Berlin Technical University in teaching and research in the field of mathematical physics. He has worked at the Mathematics Department (Institute C), Graz' University of Technology and the Mathematical Institute, University of Jena, as a Postdoctor, and as a Guest Professor at the University of Colorado at Boulder (CU). From 2012 to 2015, he was a Lecturer in mathematics at the University of Denver (DU). In 2016, he joined the Software Competence Center Hagenberg. He is currently a Senior Researcher at the Data Science Laboratory, Software Competence Center Hagenberg focusing on Machine Learning for Fault Detection.



MARIO PICHLER received the master's and Doctoral degrees in computer science from Johannes Kepler University Linz, Austria, in 2001 and 2007, respectively, with a doctoral thesis on Ubiquitous Computing. Beyond that, he received the B.Sc. degree in geosciences and atmosphere sciences at the University of Innsbruck, in 2015. As a result of these research activities, he has published more than 40 scientific publications in the aforementioned areas. He has many years of project management experience in national and international projects. He is currently working with SCHH and coordinating the Interreg AT-CZ Project PredMAIn (AI-based Predictive Maintenance, ATCZ279) and the international project outreach in the H2020 Project TEAMING.AI (Grant nr. 957402). His current research interests include development of international collaborations and projects in the areas of green and digital (industrial) transformation and artificial intelligence with a personal interest in formal knowledge representation and reasoning.



BERNHARD A. MOSER studied mathematics in Salzburg and Linz. He received the Doctorate and Habilitation degrees from Johannes Kepler University Linz, Linz, Austria, in 1996 and 2017, respectively. He was with the Department of Computer Science, University of Salzburg, as a Research Assistant for two years, with a focus on fundamental research in the field of fuzzy similarity measures. Later, he joined the staff of the Fuzzy Logic Laboratory Linz–Hagenberg, Johannes Kepler University Linz, for four years, where he has participated in developing data and signal analysis systems. After this, he entered the Austrian research and technology organization SCCH, where he is currently a Research Director. His research interests include mathematical and geometric aspects of machine learning and neuromorphic computing. He is also coordinating the European H2020 Project Teaming.AI and the Austrian COMET Module S3AI. Since February, he is the President of the Austrian Society of Artificial Intelligence.



IVO BUKOVSKÝ (Senior Member, IEEE) graduated from Czech Technical University (CTU), Prague, where he received the Ph.D. degree in control and system engineering, in 2007. He was a Visiting Researcher at the University of Saskatchewan, Canada, in 2003, a short-term Visiting Researcher at the University of Manitoba, in 2010. He has been cooperating with Tohoku University, Japan, since 2009, where he was appointed as an Associate Professor at the Graduate School of Medicine during the last visit. He is currently in full with the Department of Computer Science, Faculty of Science, University of South Bohemia in České Budějovice. His research interests include novelty detection, multiscale-analysis approaches, dynamical systems data analysis, and novel informatic approaches via machine learning. He has served as the A/E for IEEE TNN, IEEE TNNLS, and IEEE TCyB, and as the PC for numerous IEEE conferences.

• • •