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Estimating Remaining Useful Life in Machines Using Artificial Intelligence: A Scoping Review

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Estimating Remaining Useful Life in Machines Using Artificial Intelligence: A Scoping Review

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Abstract

The remaining useful life (RUL) estimations become one of the most essential aspects of predictive maintenance (PdM) in the era of industry 4.0. Predictive maintenance aims to minimize the downtime of machines or process, decreases maintenance costs, and increases the productivity of industries. The primary objective of this bibliometric paper is to understand the scope of literature available related to RUL prediction. Scopus database is used to perform the analysis of 1673 extracted scientific literature from the year 1985 to 2020. Based on available published documents, analysis is done on the year-wise publication data, document types, language-wise distribution of documents, funding sponsors, authors contributions, affiliations, document wise citations, etc. to give an in-depth view of the research trends in the area of RUL prediction. The paper also focuses on the available maintenance methods, predictive maintenance models, RUL models, deep learning algorithms for RUL prediction challenges and future directions in the RUL prediction area.

Keywords: Artificial Intelligence; Bibliometric Analysis; Condition Monitoring; Industry 4.0; Industrial IoT; Predictive Maintenance; Remaining Useful Life (RUL).

1. Introduction

In manufacturing industries, machine maintenance is a crucial part of the overall cycle of production. Different maintenance strategies are applied in industries such as reactive, preventive, and predictive maintenance. In reactive maintenance, equipment or part is generally done once the equipment is down or starts malfunctioning. Reactive maintenance provides maximum utilization of that equipment or part, but at the same time, it leads to unplanned downtime of the machine due to sudden malfunctioning of the component. Malfunctioning of the component may potentially damage the machine or process, which also causes high maintenance cost. In the case of preventive maintenance, maintenance is done on an equal interval basis. The component is replaced after an equal interval of time to avoid further damage. Due to this preventive maintenance strategy, the overall malfunction of machines or equipment is reduced, but at the same time, it increases planned downtime of the machine. The component replacement at a regular interval increases the part cost and needs strong inventory management. In the case of predictive maintenance, analytics is used to predict the component or equipment failure. Better analytics options are available in this strategy with connected technology, which provides a holistic view of machine health. As it uses the sensors, data analytics, etc. the system becomes complicated and increases the infrastructure setup like sensors, data acquisition, and processing systems etc. Forecasting of the RUL of the machine or component by using a predictive maintenance approach is attracting most of the researchers and minimizing the prediction errors is one of the challenging areas for the research. Figure 1 shows the types of maintenance along with its benefits and challenges.

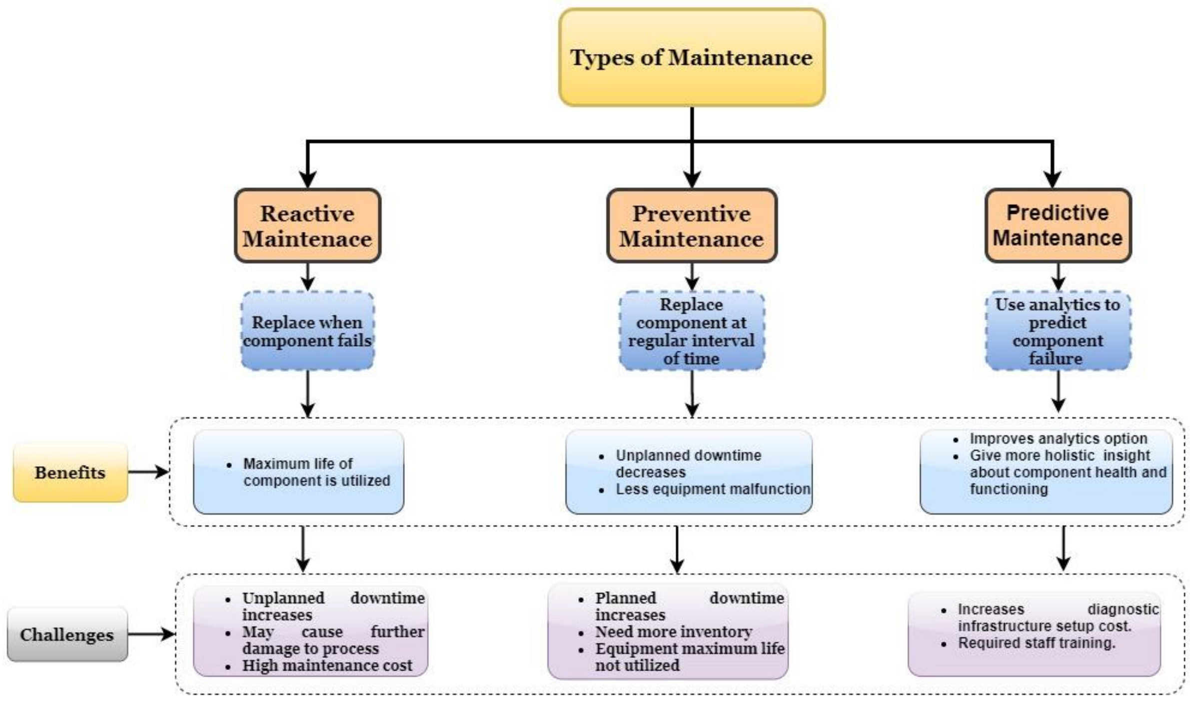

Figure 1: Types of maintenance strategies along with its benefits and challenges.

1.1 Predictive maintenance:

Predictive maintenance (PdM) plays a crucial role in prognosis and health maintenance (PHM) (Deutsch and He 2018; Kaur et al. 2018; Man and Zhou 2018; Jianwu Wang et al. 2018) of the machine in the era of industry 4.0. Predictive maintenance's ultimate objective is to forecast RUL of the product or equipment as it decreases the unplanned downtime of the process and takes cost-effective maintenance decisions. Figure 2 shows the principle, goals, and application areas of PdM in the context of smart manufacturing.

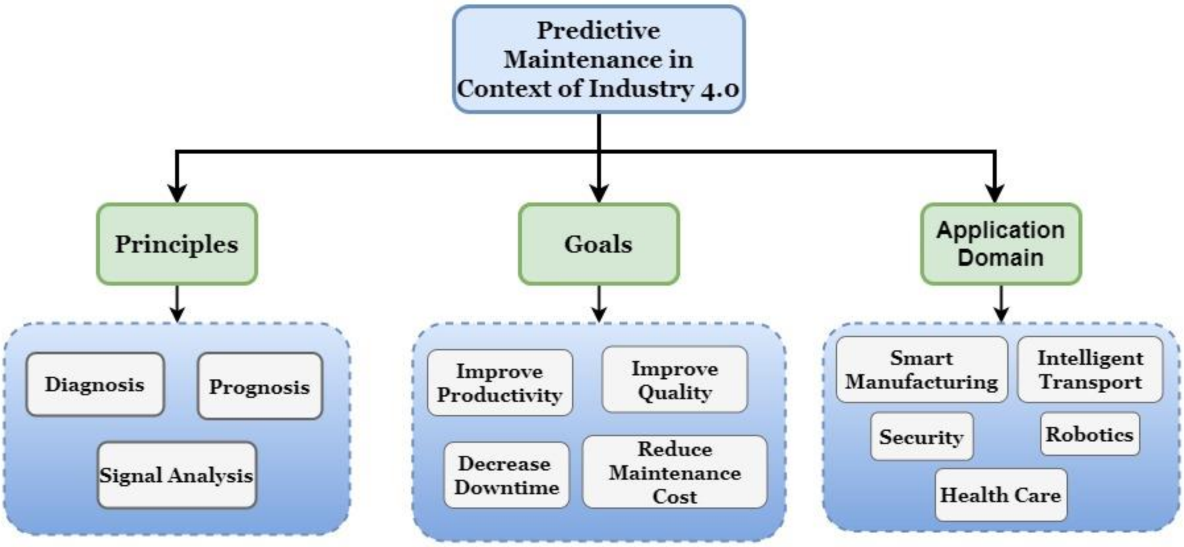

Figure 2: Principles, goals, and application domain of PdM in the context of industry 4.0

PdM methods are broadly divided into three types are as shown in figure 3, Knowledge-based method (experience-based), physical model-based method, and data-driven approach (Liao and Köttig 2014; Luo et al. 2020; Mobley 2002).

1.1.1 Knowledge-based model: In the knowledge method, generally, historical fault data is considered for prediction. It does not consider mathematical models for prediction (Li, Zhang, and Xu 2012). This method generally uses fuzzy logic, Weibull distribution, Bayesian approach, etc. for the fault prediction. It can be categorized in the fuzzy system and expert knowledge system. This method of prediction not so accurate and applicable for an only simple process or system.

1.1.2 Physics-based model:

In the physics based-model approach based on internal mechanism, a physical-mathematical model is developed, reflecting performance degradation of the system (Kwon et al. 2016; Liu et al. 2018; Ortiz and Carrasco 2016). This method is suitable for dynamic modelling and does not require collecting a lot of data, but it required expert knowledge. This model is further classified as a mathematical model, Hidden Markov model, Probability distribution model and filter models like Kalman and particle filter. It is challenging to construct a perfect model in a complex process or machine by considering all degradation mechanisms.

1.1.3 Data-driven model:

In the data-driven PdM method (Lee, Jin, and Bagheri 2017; Jianwu Wang et al. 2018; Wu et al. 2017; Xia et al. 2017), data is collected from the equipment or components for prediction of fault. It does not require a separate performance degradation process (Baptista et al. 2018). For the processing of collected data, different models such as ANN, SVM, Autoregressive, Gauss regression, etc. are used. For a collection of data, sensors should be installed at the appropriate place. The collected data features are extracted for processing, analysis, and degradation of information hidden in data. The proper algorithm needs to be selected based on corresponding parameters.

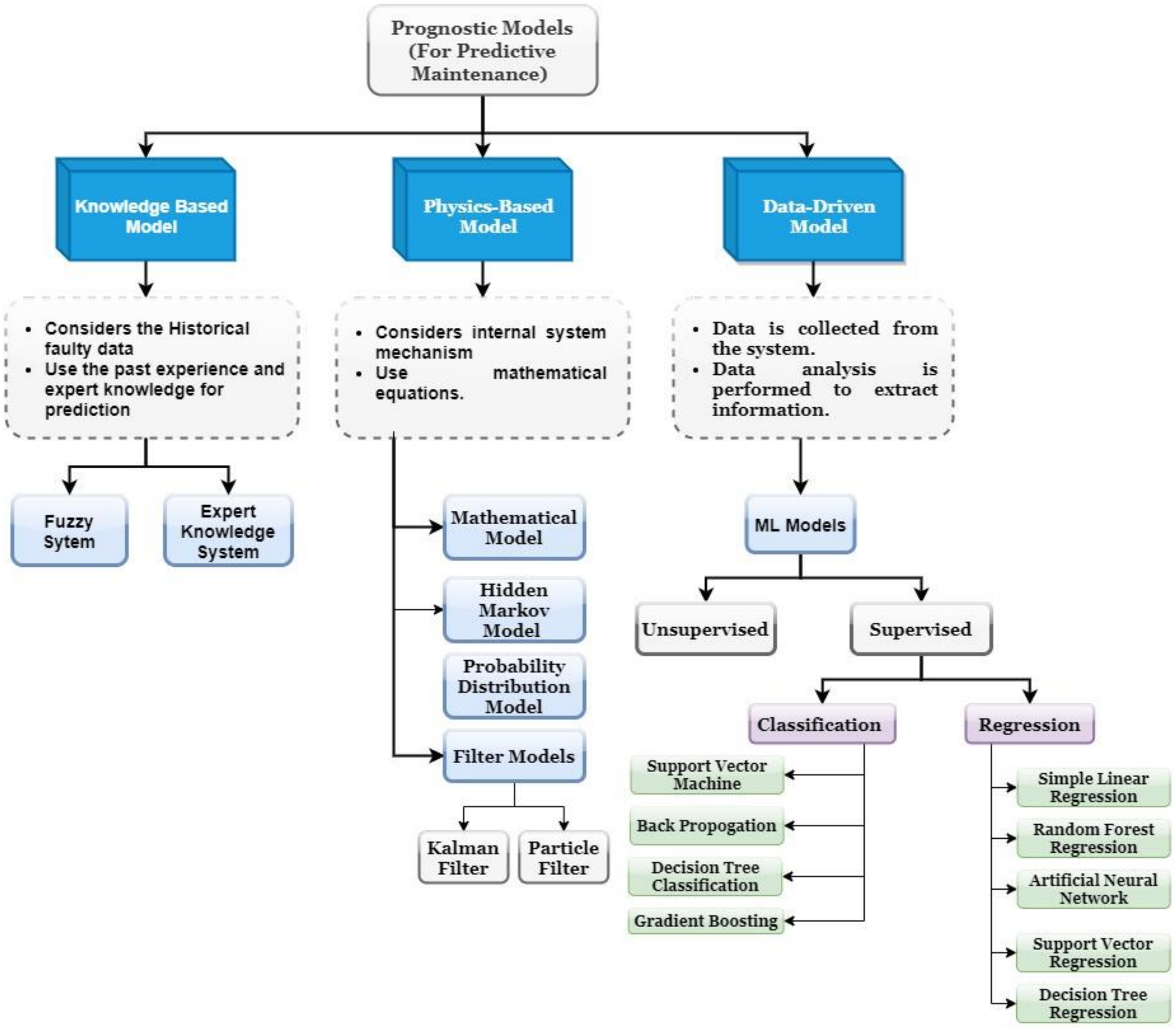

Figure 3: Prognostic model for Predictive Maintenance

This data-driven model further categorized in supervised, unsupervised, and semi-supervised models. Supervised models need the labelled dataset to train the model while unsupervised model uses the unlabeled data set to train the model. Supervised models are further classified as classification and regression models. Regression algorithms like simple linear regression, random forest regression, artificial neural network, support vector regression etc. are used where continuous values are needed to predict. Whereas classification algorithms like Support vector machine (SVM), backpropagation, decision tree classification, gradient boosting etc. are used to predict the discrete class label outputs.

1.2 Remaining Useful Life (RUL) Prediction:

One of the important aspects of predictive maintenance is the estimation of RUL (Amihai et al. 2018; Deutsch and He 2018; Man and Zhou 2018) of the equipment. The prognostic maintenance approach for RUL prediction gains more attention in the last few years. For efficient prognostic and health management of any machine or component prediction of RUL is a critical aspect. This RUL prediction technique helps to make decisions and optimization and this area has lots of research potential in complex machines and multi-component equipment or process (Van Horenbeek and Pintelon 2013). As prognosis deals with future behaviour forecasting, many uncertain factors and sources that affect the prediction results. So, a difficult task for any researcher to predict any machine's life accurately and precisely; still, researchers aim to minimize prediction error by developing different models for RUL predictions. Prognosis and RUL prediction is broadly divided into offline and online prognosis (Sankararaman and Goebel 2013). It is a complex and rigorous task to develop the offline prognostic model or method for the engineering components as they operate under different environmental and working conditions. While the online process is continuously monitoring the performance of the system throughout its operation.

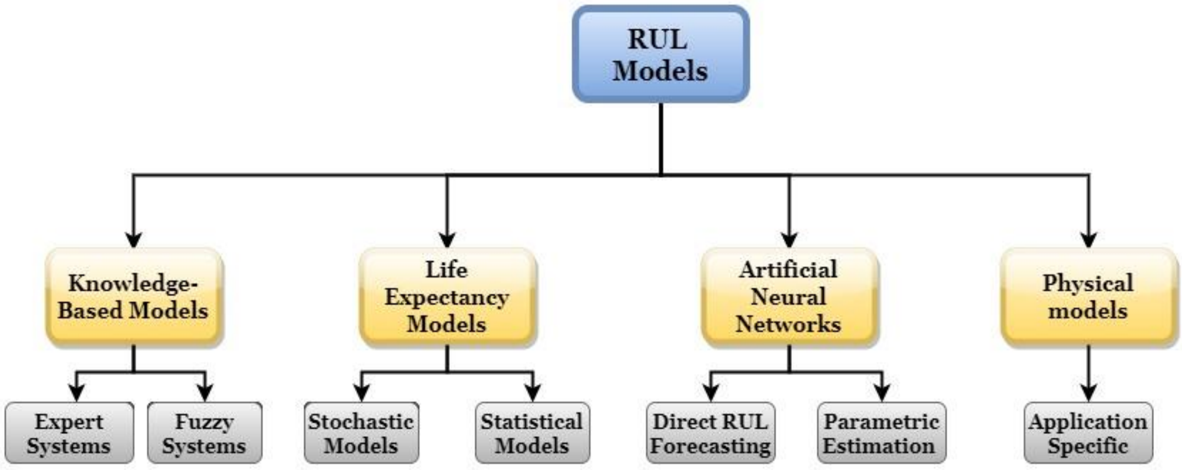

Figure 4: The RUL model classification

Different models are used to estimate the RUL of equipment or asset. RUL model is classified in four-part for making it suitable for selection as shown in figure 4 (Sikorska, Hodkiewicz, and Ma 2011).

Brief about RUL model classification (Sikorska et al. 2011):

1. The knowledge-based model uses the previously failure events to predict the life of the system. It uses an expert and fuzzy system for prognosis (Biagetti and Sciubba 2004; Guillaume 2001).
2. The life expectancy model is determined the life by considering deterioration under known operating conditions. This model can be divided into a statistic and stochastic models. Statistic model is again classified as Auto-regressive Moving Average (ARMA), Trend extrapolation and variants, and proportional hazards modelling (PHM). At the same time, the stochastic model is classified as conditional probability methods and aggregate reliability functions.
3. Artificial neural network (ANN) uses observed data for mathematical representation and estimates the component's RUL by the direct or indirect method. ANN model can be divided into a direct RUL forecasting model and a parametric estimation model.
4. The physical model considers the systems of physical degradation behaviour and represents an equivalent physical-mathematical model for the estimation of RUL.

1.3 Deep learning (DL) approach for RUL prediction:

For RUL prediction, use of artificial intelligence techniques is increasing in recent years. Growth of sensor technology, Internet of Things (IoT), big data processing techniques helps to attract the use of deep learning techniques. Use of DL techniques also helps to improve the prediction model accuracy. Few deep learning approaches are discussed below which can be preferred for the RUL prediction.

1.3.1 Auto-encoder (AE):

AE mainly contains the two phases, encoder and decoder which helps to reconstruct the input data. The encoder is used to compress the input into latent space representation (LSR) and decoder aims to reconstruct the input from the LSR by using decoding function. Practical application of AE is to denoise the raw data and perform the dimensionality reduction for proving more insights to raw data. AE models are generally used for the fault diagnostic. In RUL prediction for extraction of degradation features AE models generally use. Stacked sparse AE is used in the prediction of RUL of aircraft engine along with logistic regression (Ma et al. 2018). Combination of AE and deep neural network (DNN) is used to predict the RUL of bearing (Ren et al. 2018).

1.3.2 Convolutional Neural Network (CNN):

CNN is a feedforward multilayer artificial neural network. CNN shows better outcomes in machine fault diagnosis and surface integration nitration (Jinjiang Wang et al. 2018). The double-CNN framework is used for intelligent RUL prediction, shows a powerful feature extraction ability of CNN by extracting features from the vibration signals (Yang, Liu, and Zio 2019). New DL architecture in prognosis is developed for RUL estimation by using deep CNN (Li, Ding, and Sun 2018). CNN was used for the multi-scale feature extraction in the time-frequency domain for developing intelligent RUL prediction of bearing (Li, Zhang, and Ding 2019)

1.3.3 Recurrent Neural Network (RNN):

RNN is deep learning architecture to process the dynamic information from preceding layers by using feedback connection from hidden or output layers for the next layer (Malhi, Yan, and Gao 2011). Due to lack of trend identification of trained model, RNN is having limitations based on long term prediction of RUL. Long and short-term memory (LSTM) is used along with RNN to overcome this limitation. The RNN and LSTM network gains great attention nowadays in many applications related to RUL prediction. LST- RNN is used for the calculating RUL of lithium-ion batteries (Zhang et al. 2018). RNN based health indicator to enhance the bearing RUL prediction accuracy (Guo et al. 2017).

The objectives of this bibliometric review are:

- To understand the scope and trends of literature available related to RUL prediction.
- To observe the growth of the area based on the geographical location all over the world.
- To identify the different universities and research institute affiliated with the related research area.
- To perform the citation wise analysis of the publications in the related area.

2. Methodology

This bibliometric analysis is quantitative as well as a statistical method to examine the publishing trends and pattern of published scholarly work. This bibliometric paper explores the year wise publication data, document types, language-wise distribution of documents, funding sponsors, authors contributions, affiliations, document wise citations, source title, etc., which helps to understand the advancement trend particular research area. To perform this bibliometric analysis the Scopus database is used, as Scopus is having larger peered reviewed theoretical and reference databases in areas of Engineering and Technology, Science, etc. This bibliometric paper helps to analyze the documents from different sources such as journals, conferences, books, notes, etc. which helps understand the scope and trends of literature available related to RUL prediction.

2.1 Search Strategy

Scopus database is used for the selection of keywords string. Table 1 indicates the number of documents available on the Scopus database for key terms search during the keywords string selection. A total of five different strings are used before finalizing the keyword string. Search string number five is finalized for analysis as it gives more refine results.

Table 1: Number of documents available related to key terms searched
Source: https://www.scopus.com/ (accessed on October 13, 2020)

Search String No.	**Keywords**	**No. of documents (Scopus search results)**
1	(“Remaining useful life”)	3,654
2	(“Predictive maintenance”)	4916
3	(“remaining useful life”) AND (“artificial intelligence”) OR (“deep learning”) OR (“machine learning”) OR (“data driven model”) OR (“anomaly detection”) OR (“condition monitoring”) OR (“multi domain model”) OR (“industry 4.0”)	1549
4	(“predictive maintenance”) AND (“artificial intelligence”) OR (“deep learning”) OR (“machine learning”) OR (“data driven model”) OR (“anomaly detection”) OR (“condition monitoring”) OR (“multi domain model”) OR (“industry 4.0”)	1996
5	(“remaining useful life”) AND (“predictive maintenance”) OR (“artificial intelligence”) OR “deep learning”) OR (“machine learning”) OR (“data driven model”) OR (“anomaly detection”) OR (“condition monitoring”) OR (“multi domain model”) OR (“industry 4.0”)	1673

Based on the search string, the keywords are segregated into three groups as a master keyword, primary keyword using (AND) Boolean and secondary keywords using (OR) Boolean operator. The details of the keyword are given in Table 2.

Table 2 List of Master, Primary, and Secondary keywords
Source: https://www.scopus.com/ (accessed on October 13, 2020)

Master keyword	“Remaining Useful Life”
Primary keyword using (AND)	“Predictive Maintenance”

Secondary keywords Using (OR)	“Artificial Intelligence”, “Deep Learning”, “Machine Learning”, “Data-Driven Model”, “Anomaly Detection”, “Condition Monitoring”, “Multi-Domain Model”, “Industry 4.0”.

2.2 Analysis of year-wise publications trend:

Table 3 shows the year-wise publication trend of published documents in the field of RUL. For finding publications, the trend duration of years from 2000 to 2021 is considered. From the publications trend, it is found that the prediction of RUL is emerging and trending as publication count has increased significantly in the last five years.

Table 3: Year-wise publication trend
Source: https://www.scopus.com/ (accessed on October 13, 2020)

Year	No. of Publications	Year	No. of Publications
2021	7	2010	32
2020	269	2009	34
2019	323	2008	23
2018	181	2007	20
2017	164	2006	30
2016	126	2005	11
2015	108	2004	10
2014	72	2003	10
2013	84	2002	4
2012	68	2001	8
2011	65	2000	3

Figure 5 shows the graphical representation of table 3, showing the last ten years of publication trend in the field of RUL prediction. In the year 2019, the maximum number of around 323 documents were published in this field.

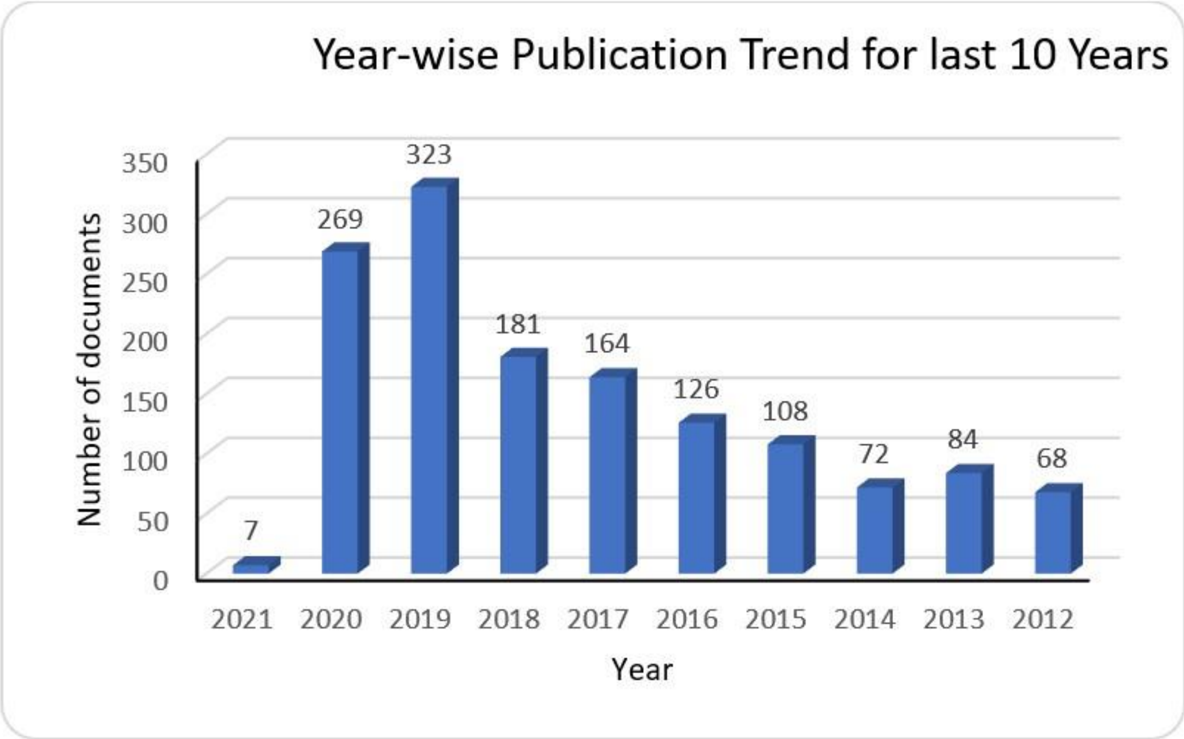

Figure 5: Year-wise publication trend for the last 10 Years.
Source: https://www.scopus.com/ (accessed on October 13, 2020)

2.3 Geographical/ country-wise trend analysis:

Table 4 shows the count of published documents in the field of RUL prediction (Scopus database). Figure 6 indicates the geographical region-wise location clusters in the world map created by using excel.

Table 4: Country-wise number of documents published
Source: https://www.scopus.com/ (accessed on October 13, 2020)

Name of Country	**No. of documents**	**Name of country**	**No. of documents**
United States	512	Singapore	34
China	506	Algeria	32
France	146	Sweden	30
United Kingdom	120	Brazil	27
Canada	83	Australia	21
Italy	71	United States	21
India	59	China	20
Germany	53	France	16
South Korea	45	United Kingdom	16
Spain	37	Canada	15

The maximum number of documents are published in the United States (512) followed by China (506), France (146), and the United Kingdom (120), etc. Figure 3 shows that most of the research is carried out in European countries except China.

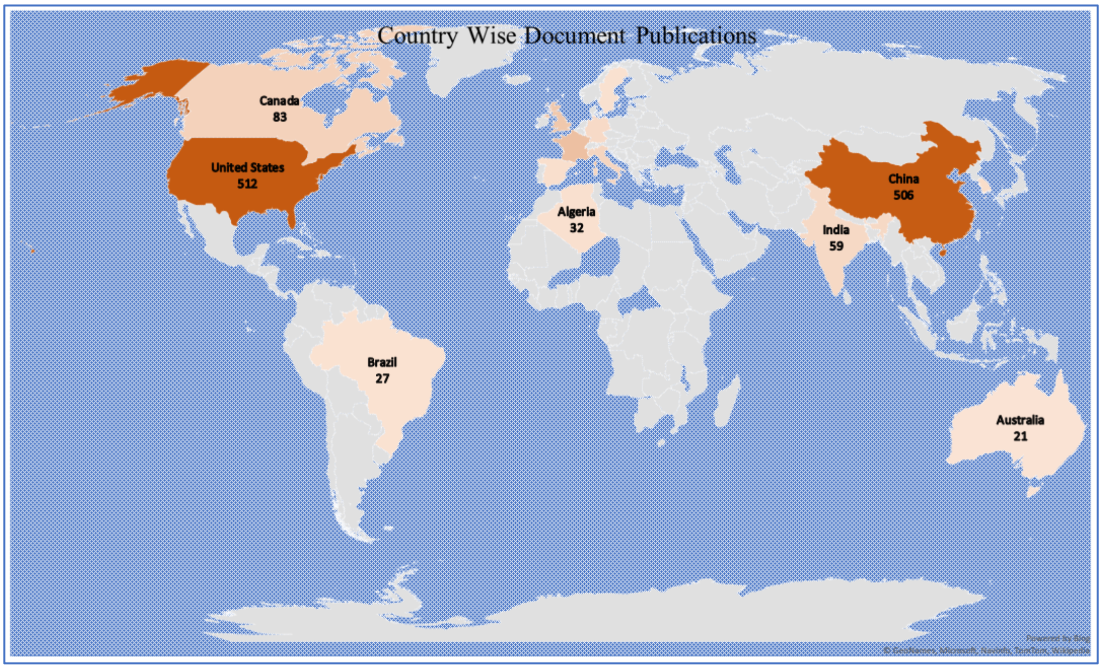

Figure 6: Geographic locations of research related to RUL Prediction
Source: https://www.scopus.com/ (accessed on October 13, 2020)

2.4 Subject Area wise Analysis

Figure 7 shows the top ten subject areas in the field of RUL predictions. Most of the research is carried out in the engineering field, followed by a computer science area.

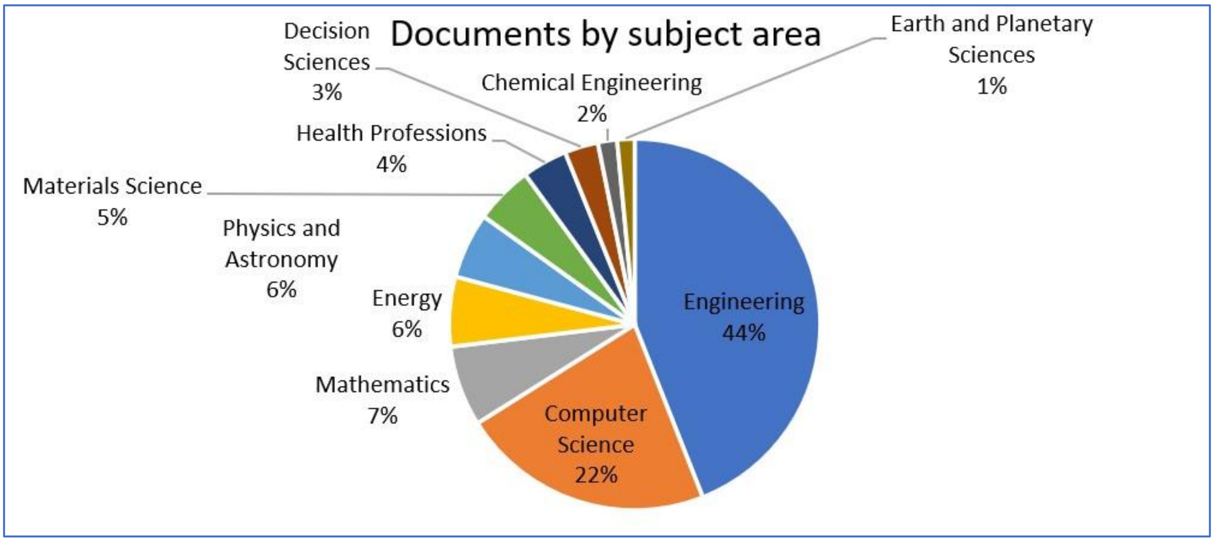

Figure 7: Top ten subject areas in RUL Prediction
Source: https://www.scopus.com/ (accessed on October 13, 2020)

Around 44% of research related to this field is done in Engineering, followed by 22% research in the Computer Science area, indicates that RUL prediction is having a crucial role in the field of Engineering. Another area, such as Mathematics (7%), Physics and Astronomy (6%), Material Science (5%), Chemical Engineering (2%) having less contribution of research in RUL prediction.

2.5 Major document types on RUL literature:

Table 5 shows the analysis of the number of documents published in different types of documents. From the table, it is found that the maximum number of papers are published in conferences followed by article document type.

Table 5: Document type-wise number of publications
Source: https://www.scopus.com/ (accessed on October 13, 2020)

Document Type	Publications	Document Type	Publications
Conference Paper	823	Book	3
Article	765	Report	2
Conference Review	32	Data Paper	1
Book Chapter	25	Note	1
Review	21		

Figure 8 shows the percentage-wise graphical representation of the number of documents published in different types of documents. Conference paper and Articles contributes around 49% and 46% documents, respectively.

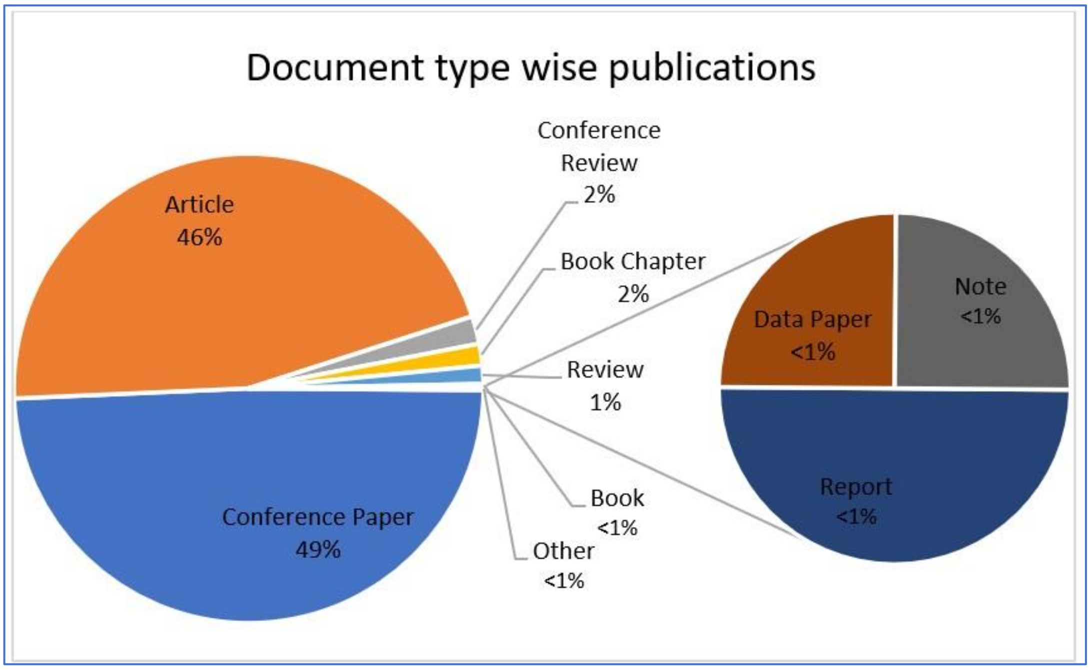

Figure 8: Document type-wise publications trend
Source: https://www.scopus.com/ (accessed on October 13, 2020)

2.6 Analysis Based on Authors:

Figure 9 shows the top 10 authors based on the number of publications. Noureddine Zerhouni (Zerhouni, N.) from France, has a maximum number (47 publications) of publications in this field. Other authors Zio, E., Goebel, K., Medjaher, K., Liu, D., Peng, Y. are having more than 20 publications in this research.

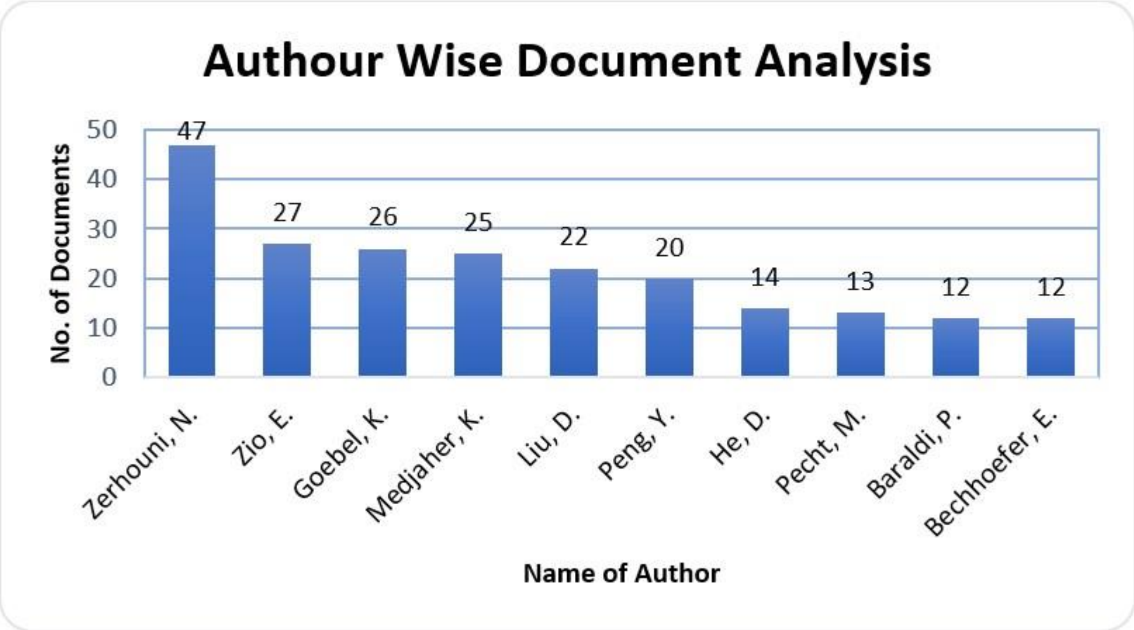

Figure 9: The author wise publications trend
Source: https://www.scopus.com/ (accessed on October 13, 2020)

2.7 Analysis Based on affiliation:

Figure 10 shows the top 10 affiliation institute/research centres/organizations in this area.

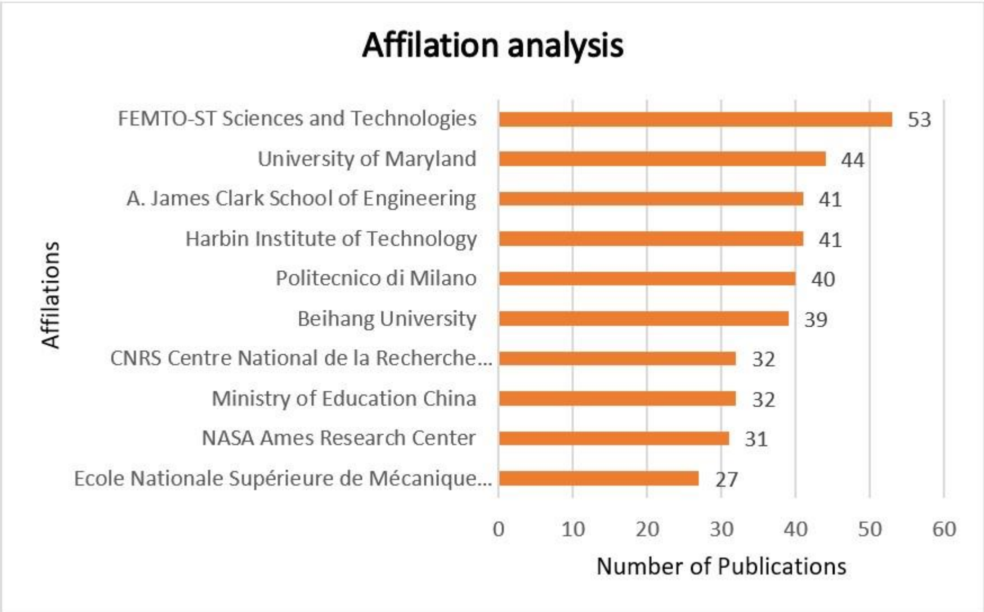

Figure 10: Top 10 Affiliation-wise institutes or research centres
Source: https://www.scopus.com/ (accessed on October 13, 2020)

FEMTO-ST Sciences and Technologies is having a maximum of 53 affiliations. The University of Maryland, A. James Clark School of Engineering, Harbin Institute of Technology, has more than 40 affiliations in this area.

2.8 Top funding organizations

Figure 11 shows the top ten funding sponsors in the RUL prediction. The majority and surprising funding are sponsored by the "National Natural Science Foundation of China" with 235 publications. Other funding supports "Fundamental Research Funds for the Central Universities" from China, "National Science Foundation" from the United States are in second and third place with 47 and 33 publications, respectively.

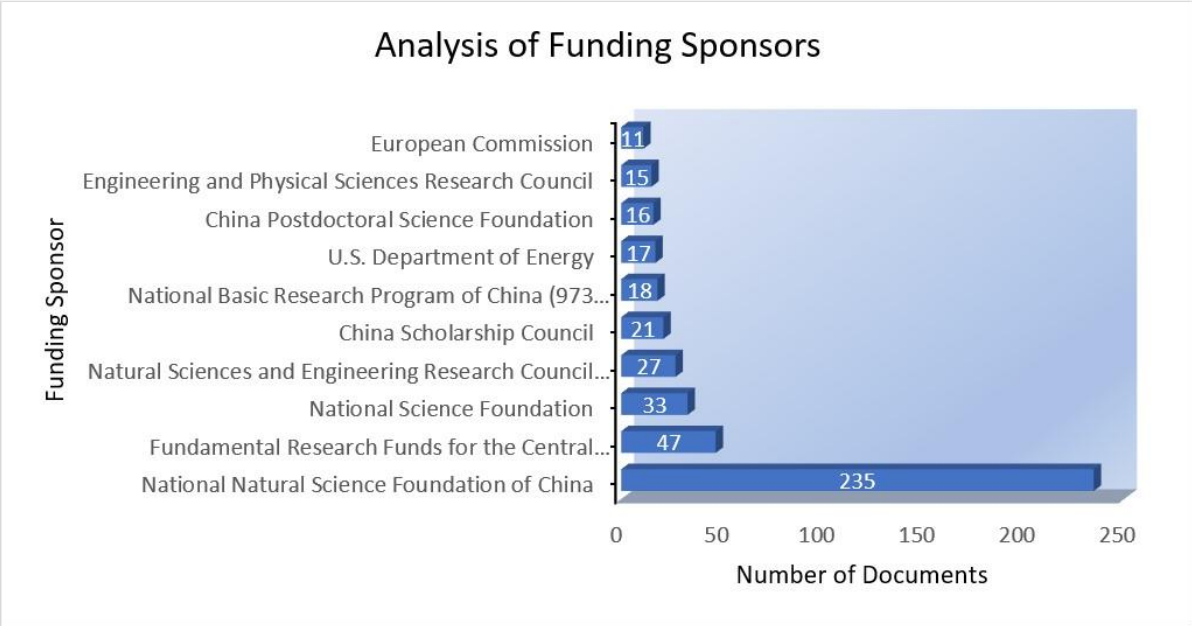

Figure 11: Top Ten funding organizations
Source: https://www.scopus.com/ (accessed on October 13, 2020)

2.9 Language-wise trend analysis

From language trend analysis is found that around 1630 documents are published in the English language. Very few papers are published in other languages, such as 39 documents in Chinese, 4 documents are in German, and one article in Italian and Spanish. Figure 12 shows the percentage contribution of languages in the available record. Most of the documents are restricted to the English language only.

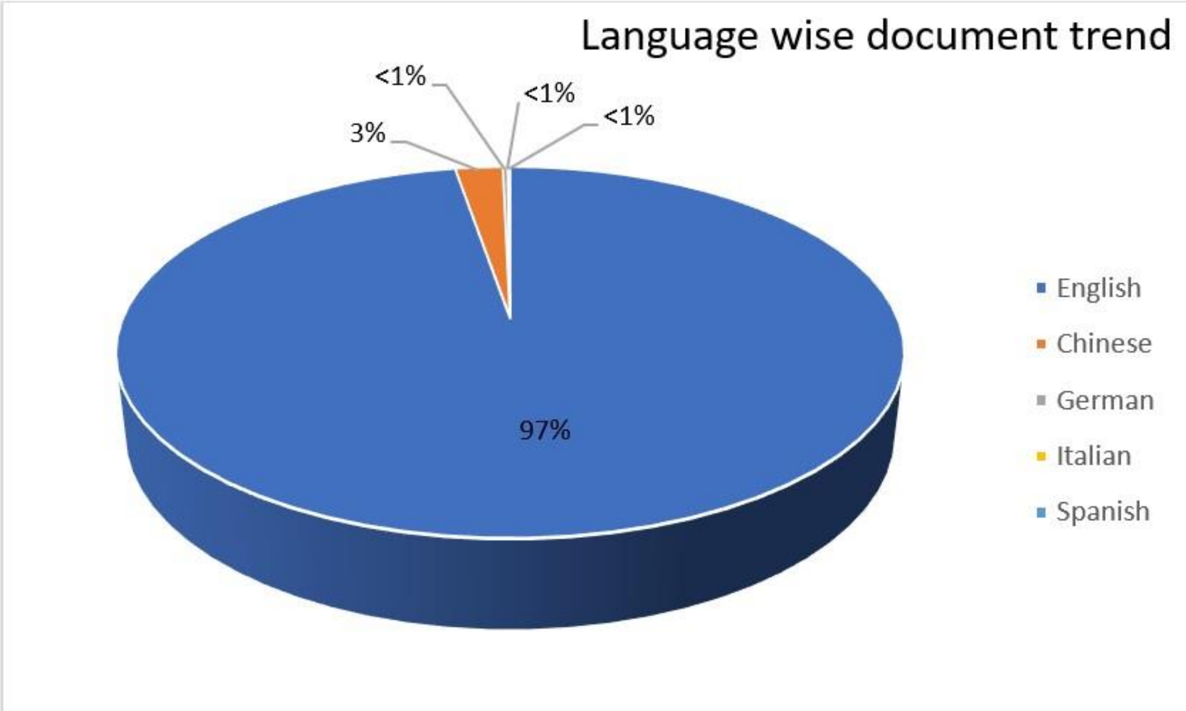

Figure 12: Language wise trend analysis
Source: https://www.scopus.com/ (accessed on October 13, 2020)

2.10 Source title wise trend analysis:

Figure 13 shows the top ten source title analysis; from the study, it is observed that Proceedings of "The Annual Conference of The Prognostics and Health Management Society PHM" having a maximum 45 number of documents. Another source title like IEEE Access, "Mechanical Systems and Signal Processing", "Reliability Engineering and System Safety", "IEEE Transactions on Reliability", etc. has more than 30 publications in this area.

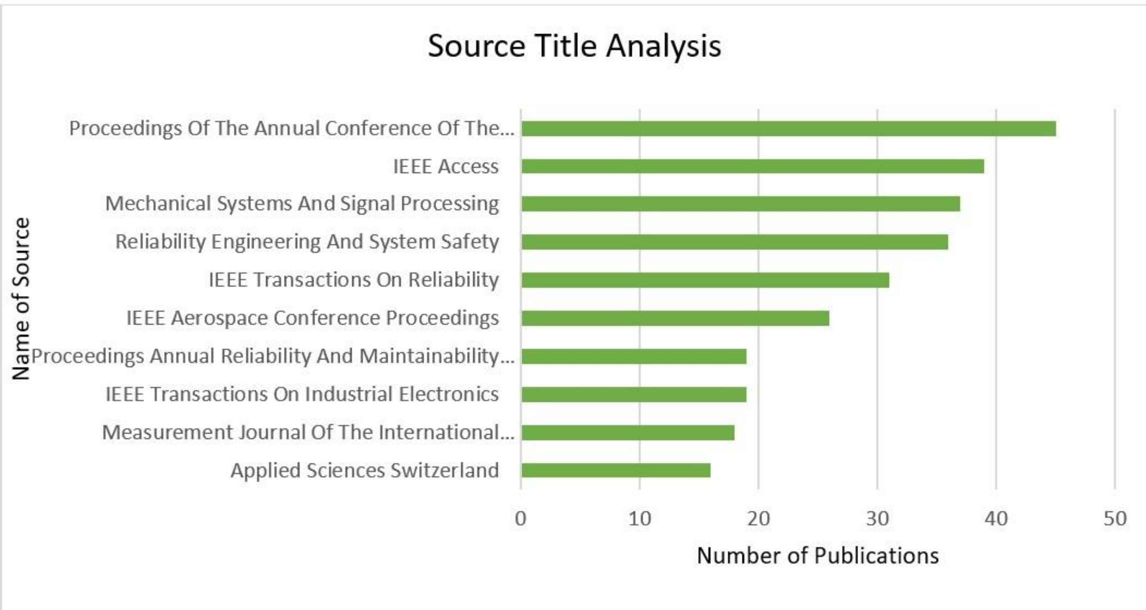

Figure 13: Analysis based on Source title.
Source: https://www.scopus.com/ (accessed on October 13, 2020)

2.11 Analysis of citations:

Citation wise analysis trend is shown in figure 14. In the last six years, the citation count is increased significantly. The graph shows the increasing trend continues in the previous few years. In the year 2020 maximum of 5231 times, area-related documents are cited.

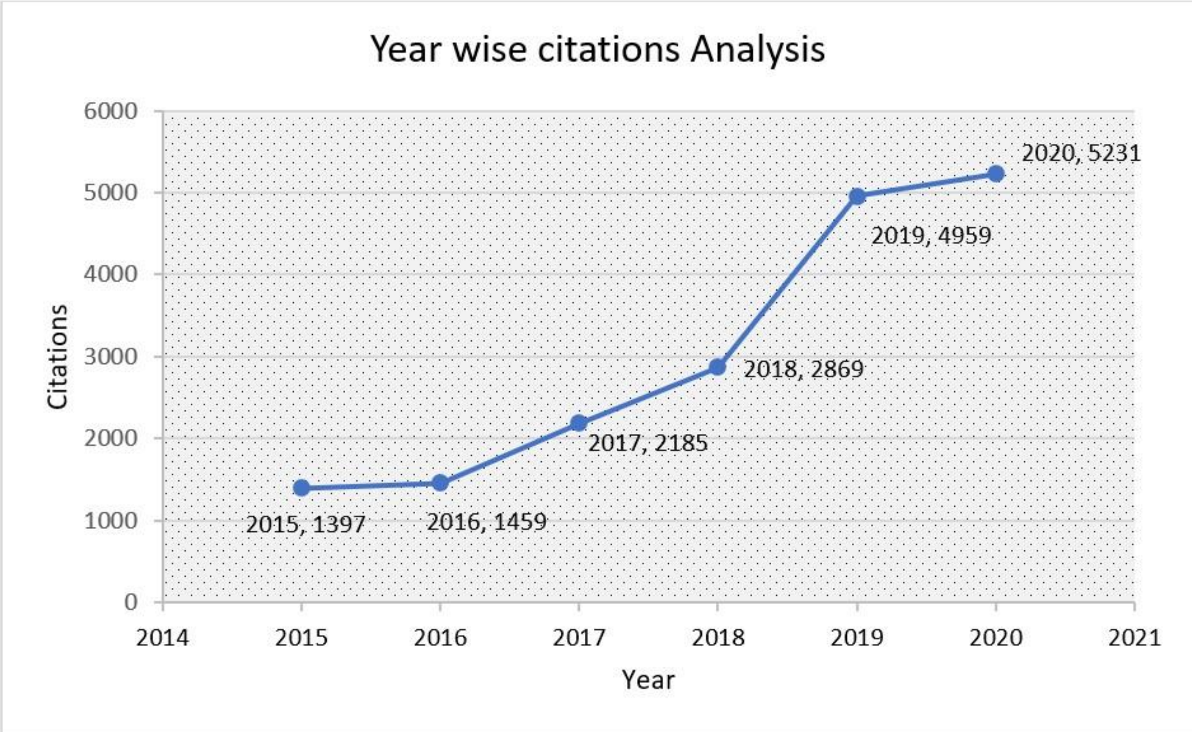

Figure 14: Last six years of citations.
Source: https://www.scopus.com/ (accessed on October 13, 2020)

Table 6 shows the top ten documents in the field of RUL predictions based on the Scopus database. Publications having the title “Remaining useful life estimation - A review on the statistical data-driven approaches” having the maximum number of 844 citations from the year 2015 to 2020

Table 6: An analysis of top ten publication based on citations
Source: https://www.scopus.com/ (accessed on October 13, 2020)

Sr. No.	**Document Title**	**Authors**	**Journal Title**	**Citations received by the Publications yearly**						
				2015	2016	2017	2018	2019	2020	Total
1	"Remaining useful life estimation - A review on the statistical data-driven approaches"	Si X.-S. et al.	European Journal of Operational Research	118	96	156	145	185	144	844
2	"Prognostics methods for battery health monitoring using a Bayesian framework"	Saha B. et al.	IEEE Transactions on Instrumentation and Measurement	73	45	65	44	54	29	310
3	"Prognostics in battery health management"	Goebel K. et al.	IEEE Instrumentation and Measurement Magazine	34	23	28	32	42	17	176
4	"A segmental hidden semi-Markov model (HSMM)-based diagnostics and prognostics framework and methodology"	Dong M. et al.	Mechanical Systems and Signal Processing	29	17	27	18	20	22	133
5	"A prognostics and health management roadmap for	Pecht M. et al.	Microelectronics Reliability	22	23	30	19	30	16	140

	information and electronics-rich systems”									
6	“Remaining useful life estimation in prognostics using deep convolution neural networks”	Li X. et al.	Reliability Engineering and System Safety	0	0	0	13	99	104	216
7	“Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods”	Nuhic A. et al.	Journal of Power Sources	24	22	27	34	60	37	204
8	"Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network”	Yang B. et al.	Mechanical Systems and Signal Processing	4	19	32	36	62	50	203
9	“Recurrent neural networks for remaining useful life estimation”	Al-Dulaimi A. et al.	2008 International Conference on Prognostics and Health Management, PHM 2008	13	13	12	21	58	42	159

10	"HMMs for diagnostics and prognostics in machining processes"	Wang B. et al.	International Journal of Production Research	18	12	14	8	17	15	84

2.12 Network analysis:

Network analysis is a graph-based representation of showing the relationship between various attributes. Different software platforms are available to perform network analysis. In this paper, Gephi and VOSviewer are used to perform the network analysis on available Scopus data.

2.12.1 Network analysis of keywords

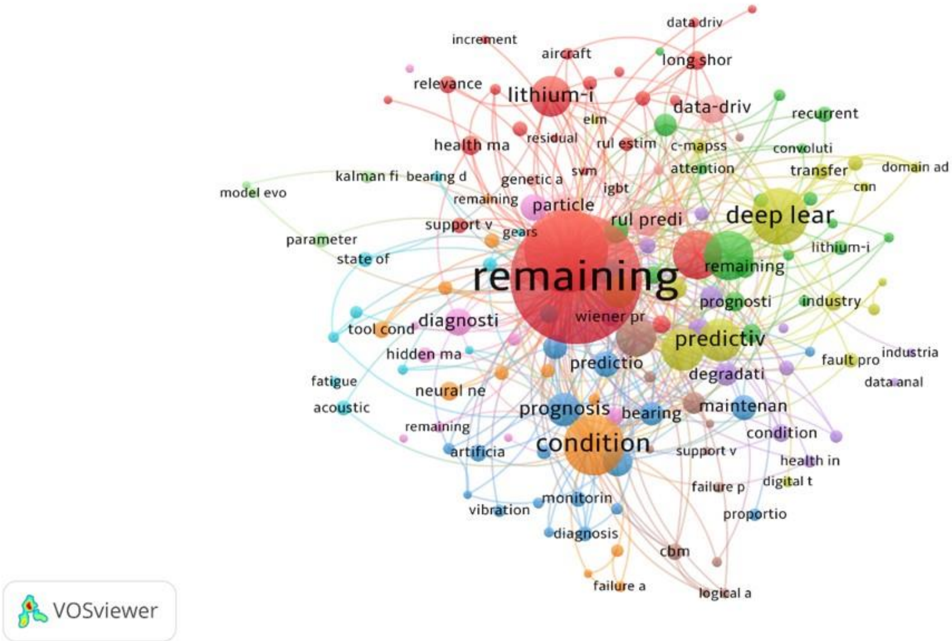

Figure 15: Network visualization diagram based on keywords
(Source: https://www.scopus.com/ and https://www.vosviewer.com)

Figure 15 shows the visualization network between keywords. The size of the circle indicates the level of incidence of that keyword. If the distance between the keywords' network is small, it shows the strong correlation between the keywords and vice versa. Network shows that, from extracted documents, the “remaining useful life” keyword having a strong influence with other keywords like “condition monitoring”, deep learning”, “predictive maintenance, “etc. The keywords with the same colours show that the formation of clusters by those keywords, a total of 11 different clusters, is formed from the network visualization diagram. From all the extracted documents, the author selects the threshold value for a minimum number of a keyword number is limited to 6. By selecting threshold value, 147 keywords are chosen for network analysis to draw the relation between source title and keywords.

2.12.2 Network analysis of co-authors and authors based on co-appearance

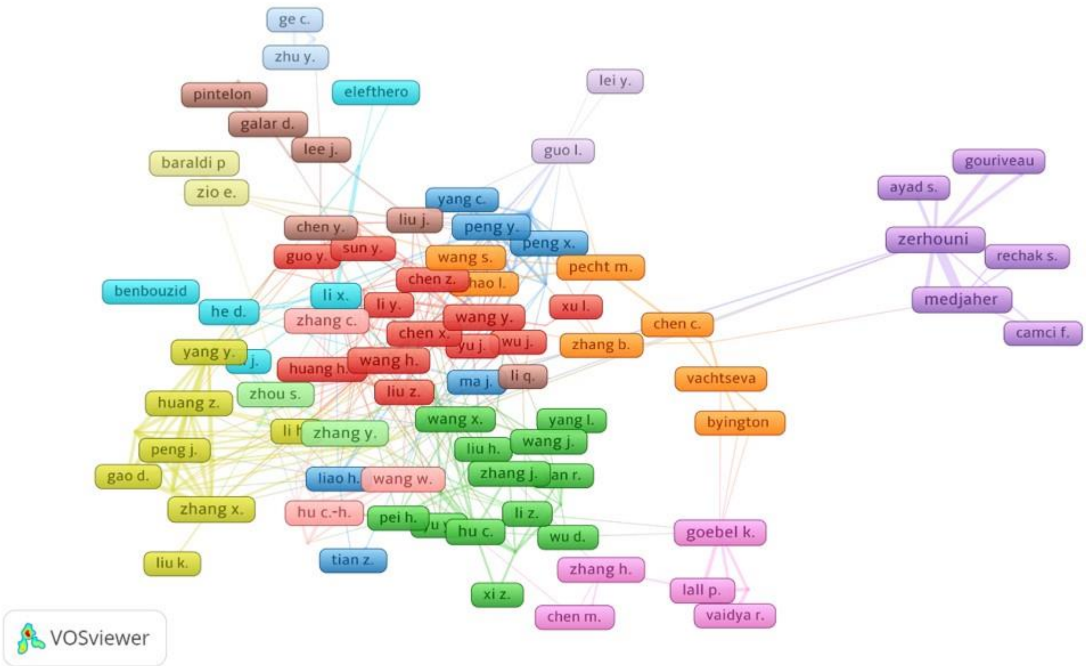

Figure 16: Network analysis diagram of co-authors and authors based on co-appearance. (Source: https://www.scopus.com/ andhttps://www.vosviewer.com)

Authors and co-authors, co-appearance in the same papers is shown in figure 16. This network helps to analyse the collaborative works amongst the authors. The links represent the joint work of authors on published documents. The authors who have a minimum of five numbers (threshold value) of publications are considered for the network analysis. The number of authors reduced to 131 by finalizing six as a threshold value for network analysis. A total of 14 different clusters are formed with strong authors and co-authors, co-appearance, and it is indicated by using 468 links in the network analysis.

2.12.3 Network analysis of publication title and the citation clusters:

Figure 17 shows the network analysis based on document titles and citations received by publications. Network map draws using Gephi software by using the Fruchterman-Reingold layout. The network shows 3477 nodes as the publication title is the collaborative work of different authors and having 2816 edges. In degree, the property is set for the edges, which shows the arrows coming towards the node, which is cited. Network shows the eight different clusters and having dark dots which indicates the publications titles having higher citations.

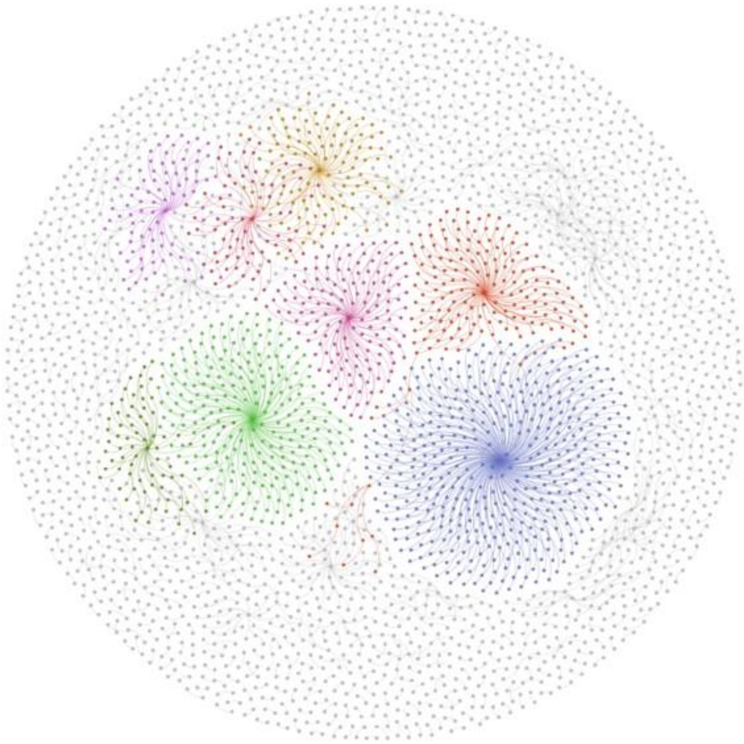

Figure 17: Network map of publication title and the citation clusters
(Source: https://www.scopus.com/ and https://gephi.org/)

Limitations of the study

This paper analysis is limited to the Scopus database, one can go for multiple databases like Web of Science, ScienceDirect, Google Scholar etc. for exploring more in this research area.

Challenges in this area

Most of the researchers focused on the diagnostic approach rather than prognostic approach. It is challenging to apply real-time predictive maintenance in different application areas. As prognosis deals with future behaviour forecasting, many uncertain factors and sources affect the prediction results. So, it's a difficult and challenging task for any researcher to predict any machines or equipment life accurately and precisely.

Future scope

This approach can be used for detection of anomalies at the early stage during the process on a real-time basis to avoid further damage to equipment or process. As an individual prediction model having certain disadvantages as mentioned in this paper, subject to uncertainties, causes prediction errors. Development of hybrid model i.e. combination of data-driven, physics-based, and simulation-based models' approach can be used to minimize the disadvantages of the individual models and reduces the errors and uncertainties in predictions.

Conclusion

Paper represents the bibliometric analysis of the remaining useful life (RUL) prediction based on published documents extracted from the Scopus database. The study shows that RUL prediction is an emerging area and attracts researchers' attention. Countries like United States, China, France, and the United Kingdom are leading nations and have published maximum documents in the relevant research area. Most of the research is carried out in the engineering and computer science domain. Zerhouni, N., Zio, E., Goebel, K., Medjaher, K. are some of the predominant authors. Leading two funding sponsors are the “National Natural Science Foundation of China” and “Fundamental Research Funds for the Central Universities” are from China. This area plays a pivotal role in the era of industry 4.0. The paper focuses on the available maintenance methods, predictive maintenance models, RUL models and challenges in the area of RUL prediction. Paper also discussed some important deep learning algorithms for RUL prediction. RUL estimation by using a hybrid predictive maintenance approach has a lot of scope for further research.

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