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INTELLIGENT PREDICTIVE MAINTENANCE: A BIBLIOMETRIC APPROACH THROUGH THE SCOPUS DATABASE

MANTENIMIENTO PREDICTIVO INTELIGENTE: UN ENFOQUE BIBLIOMÉTRICO A TRAVÉS DE LA BASE DE DATOS SCOPUS

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ABSTRACT

Intelligent predictive maintenance is an important technique to increase the efficiency and safety of the industry, since it allows detecting and preventing machine problems before they occur. **Objective:** This study aims to evaluate the scientific production and its evolution over time by means of a bibliometric analysis.

Methodology: The search was carried out in the Scopus and WoS databases. The R package Bibliometrix was used to determine the production, impact and collaboration indicators. Statistical software such as SPSS and UCINET were also used to analyze the main approaches. **Results:** 24 publications were found between 2011 and 2022, with authors Li. Z and Chiu. Y-C being the most relevant in the field. Topics identified as relevant but underdeveloped include "Deep Learning", "Artificial Intelligence", "Big Data Analytics", "Predictive Maintenance", "Industry 4.0" and "Intelligent Predictive Maintenance". **Conclusions:** As future perspectives in the research, the incorporation of additional techniques such as Bayesian networks, hidden Markov models, and Monte Carlo simulation have been identified. Also, the integration of historical machine operation and failure and maintenance data, along with condition monitoring data, into the data analysis has been proposed. **Value:** The findings of the study were presented with the intention of being useful to the scientific community.

KEYWORDS: Bibliometrics; Bibliometrix; intelligent predictive maintenance; artificial intelligence

RESUMEN

El mantenimiento predictivo inteligente es una técnica importante para aumentar la eficiencia y seguridad de la industria, ya que permite detectar y prevenir problemas en las máquinas antes de que sucedan. **Objetivo:** Este estudio pretende mediante un análisis bibliométrico evaluar la producción científica y su evolución en el tiempo. **Metodología:** La búsqueda se llevó a cabo en las bases de datos de Scopus y WoS. Se utilizó el paquete de R, Bibliometrix para determinar los indicadores de producción, impacto y colaboración. También los softwares estadísticos como SPSS y UCINET para analizar los principales enfoques. **Resultados**: Se encontraron 24 publicaciones entre 2011 y 2022, con los autores Li. Z y Chiu. Y-C siendo los más relevantes en el campo. Los temas identificados como relevantes, pero poco desarrollados incluyen "Deep Learning", "Artificial Intelligence", "Big Data Analytics", "Mantenimiento Predictivo", "Industry 4.0" e "Intelligent Predictive Maintenance". **Conclusiones:** Como perspectivas futuras en la investigación, se han identificado la incorporación de técnicas adicionales como las redes bayesianas, modelos ocultos de Markov, y la simulación de Monte Carlo. Asimismo, se ha propuesto la integración de datos históricos de funcionamiento y fallas de máquinas y de mantenimiento, junto con datos de monitoreo de condiciones, en el análisis de datos. **Valor**: Los hallazgos del estudio se presentaron con la intención de ser útiles para la comunidad científica.

PALABRAS CLAVE: Bibliometría; Bibliometrix; Mantenimiento predictivo inteligente; inteligencia artificial

INTRODUCTION

Intelligent predictive maintenance (IPdM) is a maintenance technique that uses data analytics, machine learning, and sensor technologies to predict the failure time of a piece of equipment or system before they occur (Wang et al., 2015). It is an approach in maintenance that uses Artificial Intelligence (AI) technology and data mining to monitor the condition of machines, equipment and production processes, which allows companies to plan maintenance, minimize downtime (Bakdi et al., 2022), automation and dynamics in decision making (Wang, 2014). This improves the efficiency and lifetime of equipment, reducing the costs associated with frequent equipment replacement (Lv et al., 2021). This is crucial for the industry, as unplanned downtime can have a significant impact on productivity, efficiency and costs (Shcherbakov & Sai, 2022), (Liu et al., 2022).

The importance of the topic has led the international scientific community to develop research. However, it is necessary to identify the most relevant contributions to understand the development and evolution of the technology, as well as to identify gaps and opportunities for future research that are useful for researchers and developers (Murillo-Gonzalez et al., 2023). In this context, state-of-the-art mapping and bibliometric analysis are fundamental tools to evaluate existing research and identify trends and critical areas in a specific field (Shi, 2021), (Cabeza-Ramirez et al., 2020).

According to Mesa-Bedoya et al. (2023) bibliometric tools serve to understand existing research and research trends. Many authors have devoted their efforts to the study of bibliometric indicators and the state of the art in the field of intelligent predictive maintenance, some of them are, Maktoubian et al. (2021), Lima et al. (2021), Mavhungu and Didam-Markus (2020), Achouch et al. (2022), Silvestri et al. (2020), Pech et al. (2021), Grubisic et al. (2020) and Keleko et al. (2022) these last three presenting more interest in bibliometric indicators.

The above articles have as a common denominator that they all investigate intelligent predictive maintenance in industry, using various bibliometric tools to identify trends and gaps in the existing literature, as well as to analyze the productivity and citations of the papers. It also highlights the challenges and opportunities in this field, as well as the techniques and tools used for monitoring and predicting failures in industrial equipment. Table 1 presents the most outstanding articles in which the analyses carried out by the corresponding authors are compiled.

Table 1: Analysis of the aspects dealt with in the articles

	Articles	**Pech et al. (2021)**	**Grubisic et al. (2020)**	**Keleko et al. (2022)**
	Databases	Scopus y WoS	WoS	WoS
	Time frame	2010-2020	2010-2019	2000-2021
	Search equations	(“factory” OR “factories” OR “production” OR “manufacture*”) ; (“sensor” OR “sensors”); (“maintenance”) ; (“smart” OR “intelligent”).	Intelligent predictive maintenance and Design; Intelligent predictive maintenance and Industry 4.0; Maintainability and Intelligent predictive maintenance; Intelligent predictive maintenance; Intelligent predictive maintenance and Model; Industry 4.0 and maintenance; Industry 4.0 and maintainability; Intelligent predicting maintainability; Predictive Maintenance and Industry 4.0; Smart maintenance and Industry 4.0 y Emaintenance	(Fourth Industrial Revolution OR Industry 4.0 OR Mechanic* OR Real-Time) AND (Artificial Intelligence OR Machine Learning OR Deep Learning OR Artificial Neural Network) AND (Predictive maintenance OR Decision making OR Diagnostic OR Prognostic OR Monitoring)
	Number of articles analyzed	890	576	4065
	Productivity per year	X	X	X
Journals	**Citation**			X
Journals	**Productivity**			X
Author	**Citation**			X
Author	**Co-authorship**			X

	Collaboration			X
	Productivity			X
Countries	**Productivity**			X
	Collaboration			X
	keywords	X	X	X
Document	**Citation**		X	X
	Co-Citation		X	
Institutions	**Productivity**			X
	Collaboration	X		X
	Content analysis	X	X	X
	Gaps and future lines of research	X	X	X

In general, research has limitations in data collection, filtering and analysis. In particular, Keleko et al. (2022) used a limited keyword search and an open access journal database that did not cover all available publications. In addition, the study focused on English-language papers. On the other hand, Pech et al. (2021) acknowledges limitations in the search strategy, especially in relation to the synonymy of the term "factory". Also, highly cited medical-related publications were omitted from the burst analysis, and the results of burst detection were based on the occurrence of the terms in the titles of the publications, which does not necessarily reflect the quality of the research. Overall, both studies suggest that limitations in bibliometric research and keyword search strategy should be considered when analyzing the scientific literature. In addition, Grubisic et al. (2020) and Pech et al. (2021) also present limitations in terms of the number of indicators anal

The present research aims to map the scientific production of articles dealing with intelligent predictive maintenance. The novelty of the study lies not only in the timeliness of the time frame, but also in the identification of specific indicators. The search is made in the Scopus and WoS databases, avoiding the inclusion of non-relevant terms, which, although related to the topic, affect the results. Indicators such as productivity by years, productivity by authors, productivity by journals, productivity by countries are analyzed. In addition, citation indicators of authors, journals and articles are determined to identify the most relevant contributions to the subject and future research. Collaboration indicators, impact indexes of journals and authors are evaluated to assess their impact in the scientific field, and an analysis of keyword networks and thematic map is performed. The co-relation of the stages and AI methods used in the IPdM is calculated.

METHODOLOGY

The bibliometric method was used in the research. To obtain quality results in the mapping of scientific literature related to intelligent predictive maintenance, the scientific databases Scopus and WoS were used, as these are among the largest scientific databases of peer-reviewed articles (Andalia et al., 2010). The search results were then compared and duplicate results were eliminated. The literature search was conducted on

January 20, 2023. The search strategy consisted of filtering by title, abstract or keywords of research articles the following construct: "intelligent predictive maintenance" OR "smart predictive maintenance", the temporality was not restricted, in order to cover a larger number of articles.

Article references were downloaded in .ris and .csv format for further processing. These data were stored in the EndNote bibliographic manager. Using the R package, bibliometrix, the reference data contained in the .csv document were processed. With the implementation of this interface, bibliometric indicators of productivity by years, authors, journals and countries; citation of authors and documents, impact indexes of journals and authors and collaboration of authors, journals and countries were calculated. In this paper, global citations are used, which are measured by the number of citations received in the database in which the search was performed. In other words, global citation considers citations from a global perspective in terms of disciplines (Aria & Cuccurullo, 2017) and (Agbo et al., 2021).

To measure the impact factor between authors and journals, 3 different metrics are used, the "H", "G" and "M" indices. The H-index, also known as the Hirsch index, is a measure of an author's productivity and impact in his or her field. It is calculated by adding the number of publications of an author and the number of citations received by those publications, and is commonly used to identify leaders in a research field (Murillo-Gonzalez et al., 2023). The G-index is a measure of collaboration and interdisciplinarity in a research field. It is calculated by adding the number of co-authors in an author's publications and the number of disciplines represented by those co-authors (Cabeza-Ramirez et al., 2020). The M index is a measure of the centrality of an author in a network of coauthors. It is calculated using social network analysis techniques to identify the position of an author in relation to other authors in a research field.

The study of the relationship between the keywords makes it possible to evaluate the intensity of the existing linkage between the most recurrent terms. The keywords play a fundamental role in the essence of the article and their analysis will make it possible to identify the trend, progress and orientation of the field of research (Shi, 2021).

A study of social networks of collaboration between authors and countries was carried out. For the analysis of the articles, SPSS and UCINET software were used to calculate the closeness of the main approaches and their relationship with the authors. Subsequently, the most relevant and novel articles were examined to identify gaps and future lines of research.

RESULTS AND/OR DISCUSSION

The Scopus search yielded 24 results, while WoS yielded only 19. A previous review of all the articles eliminated those that did not comply with the search strategy. Comparing the results showed that all the articles found in WoS appeared in the Scopus search results. Therefore, Scopus, using the search strategies employed, provides a broader coverage of articles in this field of research compared to WoS. Therefore, the Scopus CSV format was selected for processing in Bibliometrix.

The data from the general search information suggest that research is being conducted by a diverse group of authors and is evolving at a steady pace. The annual growth rate is 24.36% and the average age of the papers is 2.71 years. In addition, the papers have an average of 12.42 citations per paper, indicating a high level of impact and interest in the research topic. International authors predominate, with 29.17% of co-authorships. Most authors have more than one co-author per paper, with an average of 4.17 co-authors per paper.

Productivity per year in bibliometrics refers to the number of articles published in a given year. When analyzing Figure 1, a pattern of fluctuations in the production of articles related to the topic in question is observed. In the first years (2011 to 2015), the production of articles is low, with only one or two publications per year. However, in the years 2017 and 2019, there is an increase in production with two articles published in each year. Finally, in the years 2021 and 2022, there is a significant increase in production with 7 and 11 articles published respectively. In this case, it is concluded that there is an increase in the interest in the topic of IPdM in recent years, with a significant increase in the production of articles in 2021 and 2022 which demonstrates the evolution and interest in this topic due to its importance and applicability.

Figure 1. Productivity by year

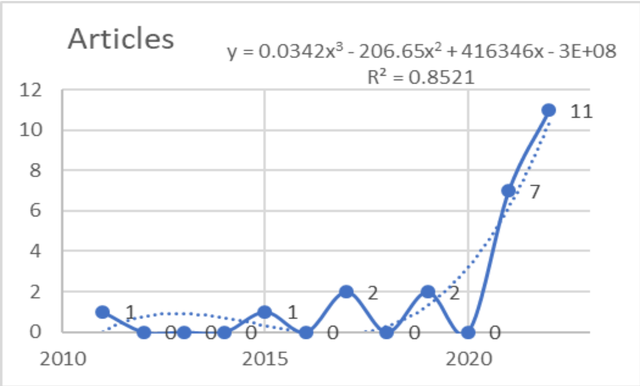
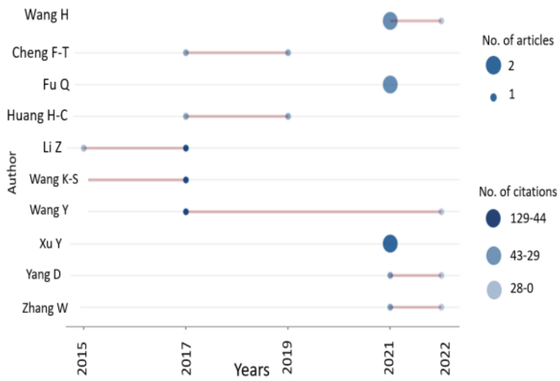


Figure 2. Author productivity and citations over time**.**



Analysis of the scientific productivity and citations of authors over time in the IPdM provides valuable information on research activity and developments in this area. From the data presented in Fig. 2, it is observed that there are a limited number of authors who have contributed to research in the IPdM, most of them having published one or two articles. Some authors have had higher productivity than others. For example, Li Z and Wang K-S published one article each in 2015 and two articles in 2017, while other authors such as Cheng F-T and Huang H-C published one article in 2017 and one article in 2019. The frequency of published articles per author and scientific productivity per year vary significantly among authors, suggesting differences in research intensity and quality. Authors, such as Li Z, Wang K-S, and Wang Y, have a high number of citations per article, an indicator suggesting that their contributions are valued and used by other researchers. Xu Y and Wang H have a moderate number of citations in 2021, but a significantly higher number in 2022, implying an increasing trend in the importance and relevance of their contributions.

Figure 3 shows the scientific productivity of journals in the field of the IPdM, measured by impact indicators and total citations. Significant differences are observed among the journals in terms of their impact indicators and total citations.

Figure 3. Source Impact

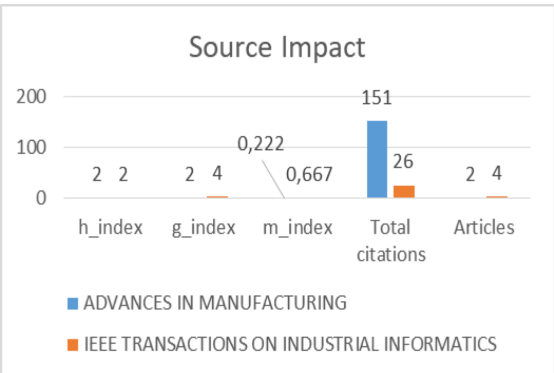
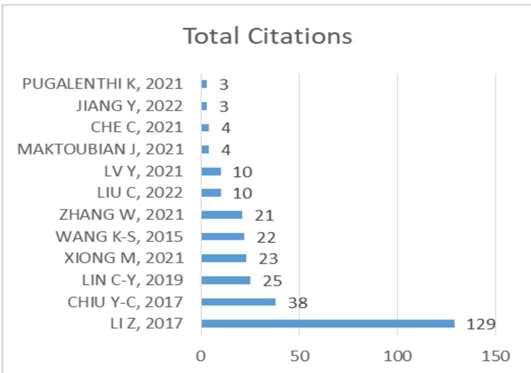


Figure 4. Total citations per article



In terms of h-index, IEEE Transactions on Industrial Informatics and Advances in Manufacturing have the highest value with 2 each. The rest of the journals have an h-index of 1. From the g-index approach, the IEEE Transactions on Industrial Informatics journal has the highest value with 4, followed by Advances in Manufacturing with 2. The rest of the journals have a g-index of 1. From the m-index approach, the IEEE Transactions on Industrial Informatics journal has the highest value with 0.667, followed by Advances in Manufacturing with 0.222. The rest of the journals have m-index values of less than 0.333. Advances in Manufacturing is the most cited journal with 151 citations, followed by IEEE Transactions on Industrial Informatics with 26 citations. Most journals have only one published article, only two journals (Advances in Manufacturing and IEEE Transactions on Industrial Informatics) have more than one published article. In conclusion, IEEE Transactions on Industrial Informatics and Advances in Manufacturing are the most productive journals and have the highest impact in the IPdM field. The production in the field is limited and most of the journals have a low number of citations and significantly lower impact and productivity.

After analyzing Fig. 4, total citations per document in the IPdM, the following trends and patterns are identified. There is a wide variety in the number of citations received per document, from 129 to 0. This indicates a variety in the relevance and impact of the documents. Papers with a high number of citations represent a significant proportion of the total citations. The two papers with the highest number of citations (Li. Z, 2017 and Chiu. Y-C, 2017) account for 43.4% of all citations. Most of the papers with a significant number of citations were published recently, from 2015 to 2022. This suggests a growing interest in this topic and further scientific production in this field.

Fig. 5 shows the results of the co-occurrence analysis of keywords related to the IPdM. The nodes show the individual keywords. The size of the nodes measures the number of times a keyword is an intermediate between two other keywords in a cluster. Thicker and closer curves indicate a strong relationship between terms (Shi, 2021). It is concluded that the main topic related to IPdM is "Predictive Maintenance" with high intermediate and closeness. In addition, it is observed that the topics related to "Industry 4.0" and "IPdM" also have a close relationship with "Predictive Maintenance". It also has that the topics related to "Machine Learning" and "Deep Learning" have a certain relationship with "Predictive Maintenance". Overall, the interpretation of the graph suggests that "Predictive Maintenance" is a central theme in the IPdM and is related to advanced technologies such as "Industry 4.0" and "Machine Learning". Although at a lower level it is also related to "Artificial Neural Networks", "Digital twin" and "Fuzzy Logic".

Figure 5. Keyword co-correlation network

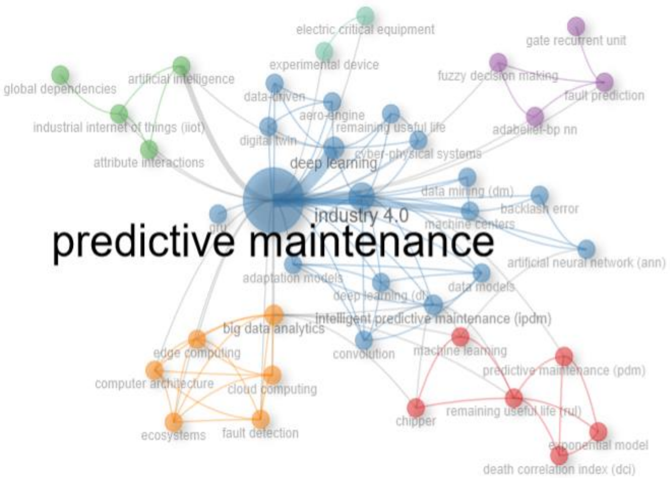
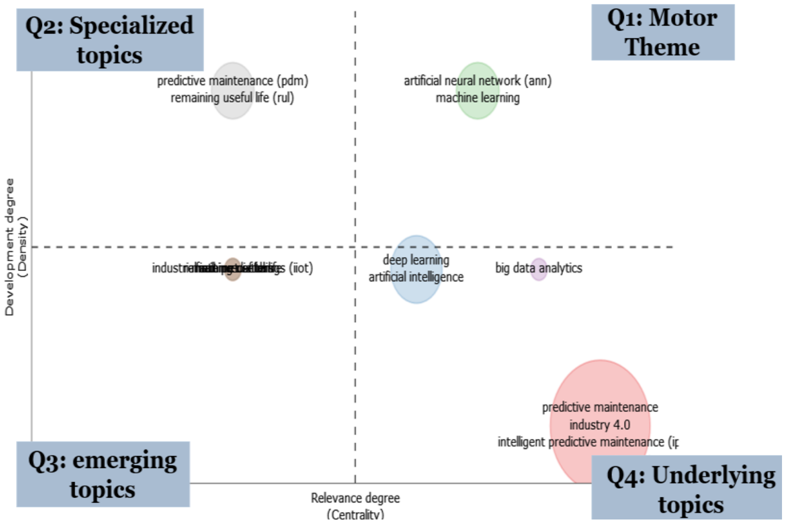


Figure 6 shows a thematic map of document keywords to assess the current status and future trends in a research field. The map is divided into four quadrants with different meanings according to the density and centrality of terms Agbo et al. (2021). Density measures the affinity between topics and centrality measures the correlation between terms. Quadrants Q1, Q2, Q3, and Q4 represent driving, specialized, emerging or disappearing, and underlying themes, respectively (Esfahani et al., 2019).

The analysis of the thematic map of keywords shows that "artificial neural network" and "Machine learning" are central and relevant topics (Quadrant 1), while "Predictive maintenance (PDM)" and "Remaining useful life" have high centrality, but low density (Quadrant 2). The terms "Deep learning", "artificial intelligence", "Big data analytics", "Predictive maintenance", "Industry 4.0" and "intelligent predictive maintenance" are important but not related to each other (Quadrant 4), and the terms in Quadrant 3 are emerging or developing, such as "Fault prediction", "Industrial internet of things (IIoT)", "Machine centers", "Predictive maintenance (PDM)" and "Remaining useful life". In general, the central theme is IPdM and the research focuses on the application of artificial intelligence and machine learning techniques to predict failures and improve efficiency and safety in industry.

Figure 6. Thematic map



The social network of users of a research topic provides a detailed view of the connections between authors, countries, or institutions working on that topic. According to Song et al. (2019), these relationships are represented by links in a network where nodes represent authors. The intensity of the collaboration is reflected in the size of the circle surrounding each author name. The larger the circle, the greater the breadth and depth of the collaborative network for that particular author. Figure 7 shows the social network of collaboration between authors on the research topic. In general, there are several authors with relatively high centrality and closeness, such as Wang H, Xu Y, Cheng F-T, Huang H-C, and Li Y. These authors are likely to be leaders in the field and have a strong influence on the collaborative network. In addition, there are several authors who are connected to each other, suggesting that they are important and have broad influence on research in the IPdM.

Figure 7. Collaboration network between authors

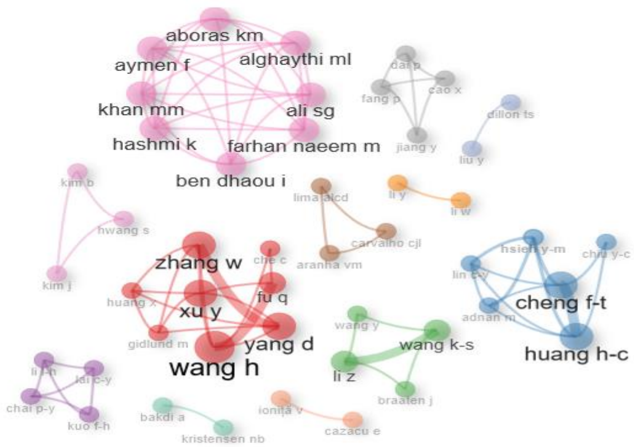
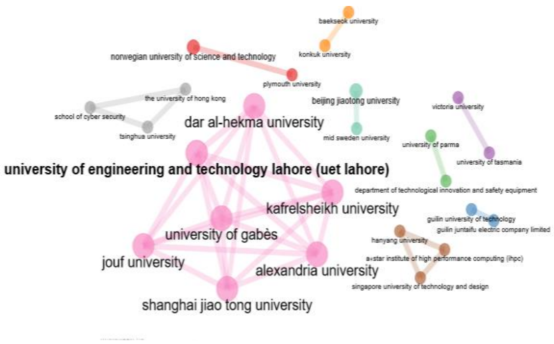


Figure 8 shows the collaboration between institutions, which forms 9 different clusters. The clusters indicate that the institutions have been grouped into different clusters or categories based on their similarities or relationships in the IPdM research. For example, the institutions in cluster 7 include the University of Engineering and Technology Lahore, Alexandria University, Dar Al-Hekma University, Jouf University, Kafrelsheikh University, Shanghai Jiao Tong University and University of Gabès. However, in the network all institutions have homogeneous proximity, meaning that they are all equally close to all other institutions. This suggests that the network is highly connected and that the institutions are working together collaboratively on IPdM research.

Figure 8. Collaboration network between institutions **Figure 9.** Collaboration network between countries



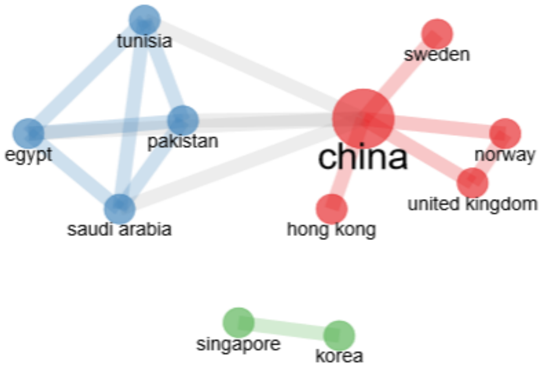


Fig. 9 shows the collaboration network between countries researching on the IPDM. The country with the largest intermediation is China. This means that it is an important node in the network, as it acts as an intermediary in communications and collaborations between other countries. In terms of closeness, all countries have similar distances. This indicator measures the closeness of a node to all other nodes in the network, so it appears to be highly interconnected, indicating effective collaboration between countries in the IPdM research.

An analysis was performed in UCINET software to see the correlation between the papers and the stages they use to implement the IPdM, which is shown in Fig. 10. It is observed that most of the authors have researched on sensor and data acquisition and data pre-processing, suggesting that these are critical stages in the IPdM. Several authors have researched on maintenance decision making, failure prediction, and optimization of maintenance scheduling and planning, suggesting that these are also important areas for research.

Figure 10. Network of the relationship between the stages and the documents**.**

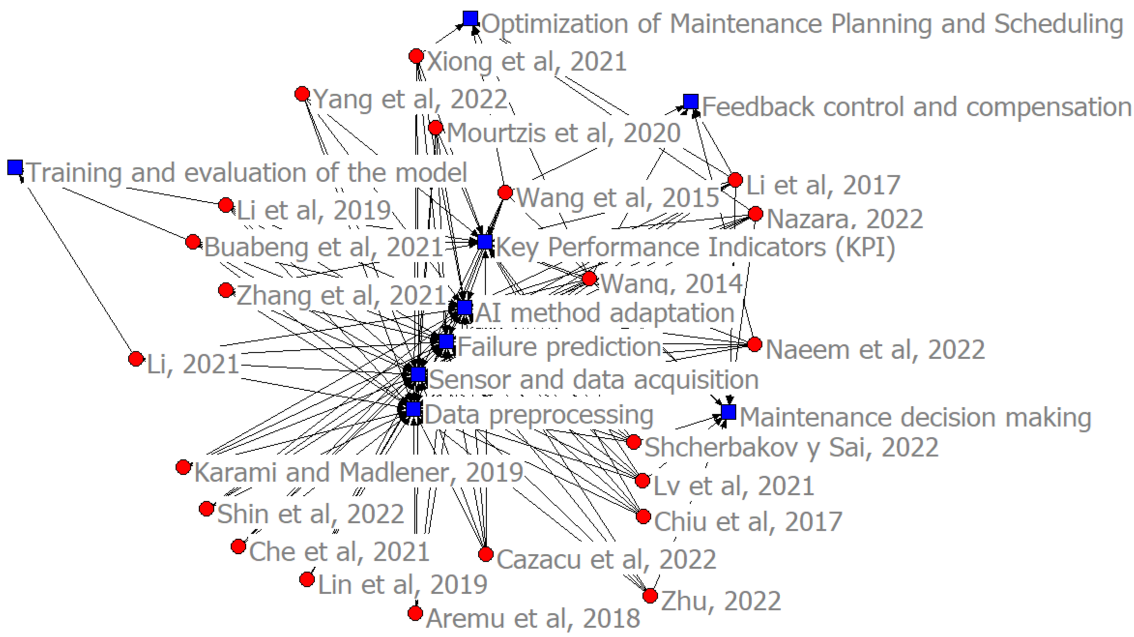


Figure 11. Network of co-occurrence of the IPdM stages.

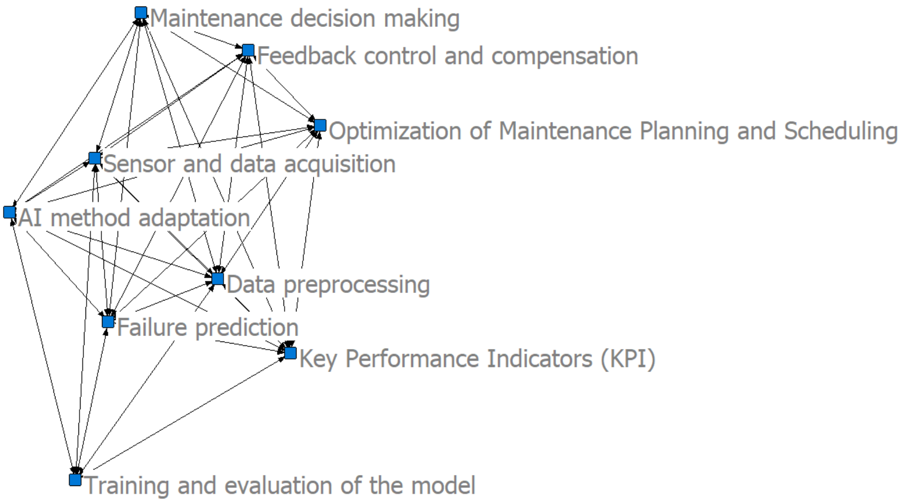


Figure 11 presents the co-occurrence network between the IPdM stages and shows the following results. It shows that sensor and data acquisition, data pre-processing and adaptation of artificial intelligence methods have a very high correlation with each other, suggesting a strong interdependence between these stages. On the other hand, maintenance decision making and KPIs also show a moderate correlation. However, maintenance scheduling and planning optimization and feedback and compensation control have a weaker correlation with the other stages. This points to the need to improve the integration of these stages into the overall IPdM process.

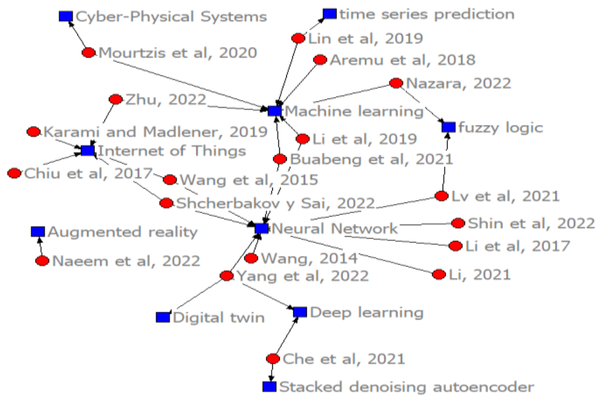
As for fault prediction, it has a moderate correlation with sensor and data acquisition, data pre-processing and adaptation of artificial intelligence methods, but a weaker correlation with the other stages. This is indicative of the need to improve the accuracy of fault prediction to achieve better overall system performance. Finally, model training and evaluation shows a very weak correlation with the other stages, pointing to the need to improve the integration of this process into the IPdM system.

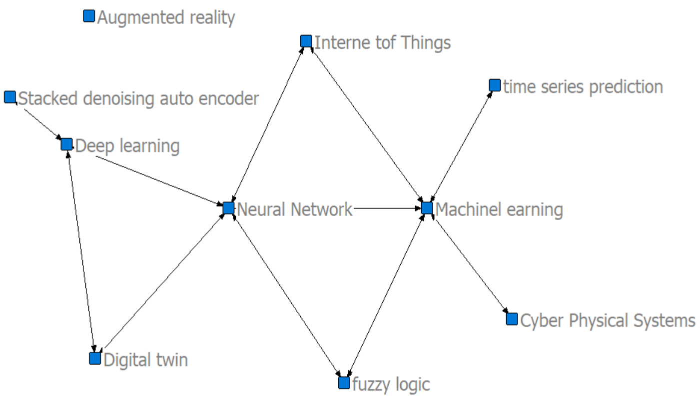
In the context of scientific research, these results are useful for improving and optimizing the IPdM implementation process and for identifying areas for further research. It also helps researchers to understand the relative importance of each stage and how they relate to each other. These results are useful for future research in this field and to guide the implementation of more efficient IPdM systems. It is important to remark that the maintenance decision making stage includes the integration of the AI method adaptation and failure diagnosis and prognosis stages, so the authors who used this stage already have these other two stages implicit.

Figure 12 represents the relationship between different artificial intelligence methods and their applications in the IPdM, according to the authors. From the network, the following can be concluded:

Figure 12. Network of the relationship between IA methods and documents

Figure 13. Correlation network between IA methods





The most commonly used methods in IPdM are Machine Learning, Neural Network and Deep Learning. Authors Buabeng et al, 2021 and Li et al, 2019 have used both Machine Learning and Neural Network in their research. Stacked Denoising Autoencoder technique has been used by Che et al, 2021 and Deep Learning has been used by Che et al, 2021 and Yang et al, 2022. Authors Chiu et al, 2017; Yu et al. (2022) Karami and Madlener, 2019 have investigated on IPdM in relation to Internet of Things. Time Series Prediction technique has been investigated by Lin et al, 2019. Fuzzy logic has been investigated by Lv et al, 2021, Farhan Naeem et al. (2022) and Nazara (2022). Mourtzis et al, 2020 and Zhu, 2022 have investigated on Cyber-Physical Systems and IPdM. Naeem et al, 2022 has researched on augmented reality and its relationship with IPdM. Shcherbakov and Sai, 2022, Wang, 2014 and Jiang et al. (2022) have researched on Neural Network. Some methods, such as machine learning, neural networks, and IoT, are widely used, while others, such as stacked autoencoders with noise, deep learning, fuzzy logic, and digital twin, are less common. This network reflects advances and trends in IPdM research. By knowing the most commonly used methods and the authors who have investigated them, it identifies opportunities for new research and collaborations in the field. It also identifies areas where there is a greater need for research and development.

Figure 13 shows the correlation between the different AI methods used in the IPdM. It is observed that the highest correlation is found between the columns "Deep Learning" and "Stacked denoising autoencoder". "Machine learning" and "Neural Network" have a moderate correlation. On the other hand, "Interne of Things", "time series prediction", "fuzzy logic" and "Cyber Physical Systems" have a low correlation with the other AI methods. This analysis is useful for understanding which AI methods are most appropriate to use in different situations and for determining which combinations of methods may be most effective in the IPdM. It also provides valuable information on the strengths and weaknesses of each method and help researchers decide which areas to focus more research on. The findings suggest that a combination of artificial intelligence methods is needed to achieve optimal effectiveness in IPdM. In addition, these results are useful for future research in the area, where new combinations of artificial intelligence methods can be explored to improve effectiveness in IPdM. It is important to note that the network shows correlations, but not necessarily causality between variables. Therefore, further research is required to determine the effectiveness and role of each AI method in the IPdM.

Gaps and future research lines

After the analysis of the most relevant and novel articles, a series of gaps have been identified that may represent future lines of research for the development of the field in question. In the research of Li et al. (2017) it is stated that, there are still challenges in the application of data mining for fault diagnosis and prognosis. Although neural networks have the advantage of fault tolerance, generalization and adaptability, their limitation is the lack of an explanation function. The genetic algorithm is a robust search, but it can take a long time to converge to the optimal solution. Fuzzy logic can be applied if mathematical models are not available, but requires empirical knowledge of the problem. Most of the research is based on current conditions or natural attrition, so further research and development of a data mining based fault diagnosis and prognostics system for machine centers is still needed.

Aremu et al. (2018) raises the need for additional research that is more aligned with fault identification, in order to determine whether methods such as entropy, which measure information within a variable, can be used to differentiate between fault types. Then, it can be assumed that the same methods can be used to measure the retention of fault implications during asset data dimensionality reduction. For their part, Buabeng et al. (2021) recommends future research to improve the feature extraction technique and deal with extremely large data sets. The use of filters capable of dealing with signals with similar mutations and dominant frequencies should be explored, as well as the application of deep learning. This will improve the optimization of pre-processed signals for different fault classification tasks in the field of predictive maintenance.

Cazacu et al. (2022) proposes further research to improve the process of calculating operational energy parameters for electric motors, consideration of other essential power quality parameters that define machine functionality in other states, such as unbalanced or distorted states often found in low-voltage installations. And develop a better determination of machine circuit parameters. This could be achieved by adopting an advanced machine model that also requires machine construction and material data. In the case of Shcherbakov and Sai (2022) plan in future work, to apply the hybrid deep learning based predictive model of Convolutional Neural Network and Long Short-Term Memory to predictive maintenance tasks and further optimize the models to improve their performance.Shin et al. (2022) expose the need to develop graphical user interfaces to visualize the IPdM results.

Xiong et al. (2021) identify the need to investigate effective learning methods based on semi-supervised and unsupervised Long-Cut Recurrent Memory Recurrent Neural Networks for failure diagnosis and remaining service life prediction to incorporate them into the decision diagram model and provide better intelligent predictive maintenance of civil aircraft operation safety. The authors Yang et al. (2022) remark that in the utilization of convolutional neural networks and Kalman filter, there are areas that require improvement and refinement, such as long-term monitoring of transformer condition and collecting more data on transformer condition to improve the database and its analysis in the future. In addition, implementation of intelligent predictive maintenance algorithms at the local end is required to achieve effective fault warning.

Zhang et al. (2021) propose for future work, to improve the generalization capability of AI-driven DeepHealth-based IPdM models and to investigate the combination of IPdM models to ensure efficient operation of industrial systems.

It is highlighted that no models using Bayesian networks, hidden Markov chains or Monte Carlo simulations as the basis of frameworks for IPdM implementation were found in the analyzed research. These are methods widely connected with machine failure diagnosis and prognosis and maintenance decision making, presenting very good results and great application. It would be interesting to see the results of their integration in this field and the combinations that could be made with the methods already employed. Explore new combinations of artificial intelligence methods to improve efficiency in IPdM. More research is needed to determine the effectiveness and role of each AI method in IPdM.

CONCLUSIONS

The study of the IPdM has experienced a significant increase in article production in recent years, reflecting a growing interest in the field. Authors Li Z and Wang K-S have shown increased productivity and appreciation for their contributions, while Xu Y and Wang H have experienced an increase in the number of citations in 2022, suggesting an increasing trend in the importance and relevance of their research. The most productive journals with the highest impact are IEEE Transactions on Industrial Informatics and Advances in Manufacturing. IPdM is a highly collaborative and multidisciplinary field, involving a wide range of institutions and universities. Predictive maintenance is a key topic in IPdM and is related to advanced technologies such as Industry 4.0 and Machine Learning. Authors Wang H, Xu Y, Cheng F-T, Huang H-C and Li Y are leaders in the field and have a strong influence on the research. Different methods are used to predict problems and improve efficiency, including machine learning and neural networks, as well as stacked autoencoders with noise, deep learning, fuzzy logic and digital twin.

Research has focused on the stages of data acquisition, data processing, maintenance decision making, fault prediction and maintenance optimization. The integration of other methods such as Bayesian networks, hidden Markov models and Monte Carlo simulation are proposed as future lines of research. Further research is also needed in areas such as key performance indicators, feedback control and compensation, adaptation of artificial intelligence methods, model training and evaluation. The study has limitations, such as the lack of search in other databases and the limited number of articles found. It is recommended that these limitations be considered for future research.

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