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Review

A Scoping Review of Pipeline Maintenance Methodologies Based on Industry 4.0

Jose E. Naranjo [1,†], Gustavo Caiza [2,†], Rommel Velastegui [1,†], Maritza Castro [1,†], Andrea Alarcon-Ortiz [3,†] and Marcelo V. Garcia [1,4,*]

1 Faculty of Systems, Electronic, and Industrial Engineering, Universidad Tecnica de Ambato, UTA, Ambato 180103, Ecuador
2 Electronics and Automation Career, Universidad Politecnica Salesiana, UPS, Quito 170146, Ecuador
3 Instituto Superior Tecnológico Tungurahua, ISTT, Ambato 180108, Ecuador
4 Department of Systems Engineering and Automation, University of the Basque Country, EHU/UPV, 48013 Bilbao, Spain
* Correspondence: mv.garcia@uta.edu.ec; Tel.: +593-998-267-906
† These authors contributed equally to this work.

Abstract: The fourth industrial revolution was a milestone at the industrial level. It forced most industries to evolve technically and for their collaborators to prepare and advance together with technology; the oil industry was no exception. It develops its activities in dangerous and dynamic environments and needs to protect its human resources, equipment, and infrastructure. This article presents a scoping review, based on the PRISMA guidelines, of pipeline maintenance methodologies based on Industry 4.0. From the first collection of 123 articles from prestigious databases such as SpringerLink, MDPI, Scopus, IEEEXplore and ACM, a final sample of 31 articles was obtained. Here, technologies that enhance preventive and predictive maintenance systems are discussed. The results show that predictive maintenance compared to preventive maintenance has a percentage difference in upkeep time optimization of 38% in the last five years. This difference was corroborated with a Student's *t*-test for independent samples, with a significance of 0.023. Likewise, the most used technologies were analyzed, with artificial intelligence standing out with 45.16%.

Keywords: scoping review; oil industry; 4.0 maintenance; Industry 4.0; pipelines; digitization; digital technologies

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1. Introduction

The oil industry is a complex and resource-intensive sector. The human capital in this field must be highly trained and accompanied by technological tools to facilitate their work [1]. They are often obliged to work remotely, as hostile environments endanger their physical integrity. For these reasons, energy extraction and maintenance of equipment and facilities are becoming increasingly arduous and costly [2].

The area of industrial maintenance has been evolving in recent years, from a simplified view as a cost center to a profit center whose activities add value by avoiding the appearance of other costs linked to the malfunction of production equipment, as well as, of course, production losses due to unavailability [3].

Companies should optimize the maintenance function to achieve the highest levels of availability and reliability at the lowest possible cost by combining corrective, preventive, and predictive strategies.

Corrosion control and integrity management come at a critical cost to maintaining a pipeline. Maintaining the pipeline's asset and ensuring safe operation without breakdowns that could endanger public safety, result in product loss, or result in property and environmental harm is what motivates maintenance spending.

While integrity management focuses on condition evaluation, corrosion mitigation, life assessment, and risk modeling, general maintenance primarily involves monitoring and fixing issues. The entire corrosion operation and maintenance cost, according to [4,5], ranges from 2.42 billion to 4.84 billion dollars, with corrosion operation and maintenance costs ranging from 3100 to 6200 dollars per km. The National Association of Corrosion Engineers (NACE) estimates that the cost of repairing or replacing corroded pipes for oil and gas industries is more than 7 billion dollars a year.

As it can be appreciated, industrial maintenance is an investment that generates excellent benefits, among which we can list the following: (i) It prevents and avoids occupational accidents, thus increasing safety for the people involved in the production process, (ii) It avoids and reduces losses due to production stoppages, (iii) It allows for having documentation and follow-up of the necessary maintenance for each equipment, (iv) It prevents irreparable damage to industrial facilities, (v) It increases the useful life of equipment, (vi) It reduces costs (vii) It preserves capital goods in good condition, and (viii) It improves the quality of the industrial activity [6].

The top management of this industrial sector, realizing that their facilities, specifically the crude oil transportation pipelines, are the cornerstone for their business to be highly productive, have had to look for new ways to optimize their investments, reduce costs and minimize risks, relying on the technological solutions that today's world offers [7].

Industry 4.0 within the oil and gas field has been looking for innovative and efficient ways that allow companies to facilitate maintenance management, and several tools and methodologies have emerged in recent years. Thanks to the continuous monitoring of pipeline conditions and predictive analytics, appropriate maintenance can be scheduled without the need to incur significant losses of time and money. In addition, the cost–benefit analysis is favorable since it has demonstrated the reduction of unplanned downtime and a significant increase in productivity [8].

The real challenge of this industrial revolution is to discover ways to interconnect existing processes, i.e., using technology as a connector between machines, operations, equipment, and people. Through these 4.0 technologies, maintenance is more straightforward and easier to control and monitor operations.

The use of these technologies is not only changing business models but also the way they are managed and how they are produced. As they evolve towards Industry 4.0, production plants also have to adopt 4.0 maintenance systems that, although they involve more complexity due to using more technological resources, represent significant improvements [9].

The monitoring of machines implies, on the one hand, having specialized personnel to ensure their correct operation and, on the other, having the appropriate software to control all the assets. One of the advantages of industrial maintenance in Industry 4.0 is that, thanks to its digitalization, it allows two types of actions to be carried out to avoid paralyzing the factory's activity and ensure its resilience and adaptability [10].

In order to obtain reliability and availability of the equipment used in the production process, it is vital to implement a good maintenance and asset life cycle management strategy. In addition, it is necessary to integrate information transparency, decentralized decision-making, interoperability, total technical support, and the nine technological pillars of Industry 4.0 defined by the Boston Consulting Group to describe the characteristics of an intelligent company [11,12].

It has been observed that, from the literature reviewed, there are very few papers that refer to the implementation of 4.0 technologies in the pipeline maintenance process. This may be due to the fact that, as mentioned in previous paragraphs, senior managers are just realizing that the use of this type of tool is an investment and not an expense. As described in previous paragraphs, this article proposes a scoping review of crude oil pipeline maintenance methodologies based on Industry 4.0 to provide a new and validated source of information on issues related to the oil and gas industry. In addition, the objective is to establish the most efficient technological tools when structuring a maintenance plan that optimizes the productivity of such process.

This article is divided into five sections, including the Introduction. Section 2 presents the methodology followed in selecting the final sample of scientific articles. Section 3, on the other hand, shows the results of this research, where the literature review, the statistics of the most used articles, and types of maintenance during the last five years are presented. Section 4 answers and discusses the research questions posed in the methodology, and finally, Section 5 presents the conclusions.

2. Methodology

Like other literature reviews [13–19], this research has been carried out following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analysis) guidelines, whose objective is to help authors of systematic reviews, scoping reviews, among others, to generate a document free of bias.

Its first version was published in 2009. Due to advances in terminology and methodology, its latest version was released in 2020. This report reflects methodological advances in classifying, selecting, and summarizing different studies. The PRISMA guidelines were designed to evaluate studies and documents concerning the health area. However, its extraordinary versatility has allowed it to be applied in different fields such as education, engineering, and social sciences [20].

This guide is not intended to pigeonhole literature reviews into a single format or to force them to follow a hierarchy of established steps. Nevertheless, instead, it simply aims to ensure that all the information relevant to the topic under study is correctly summarized. Additionally, it is necessary to mention that this tool should not be used to evaluate the methodological quality of a systematic review, but it can serve as a guide to critically assess them [21].

With this background, this review has focused on extracting information from various prestigious databases to which the authors have access, such as SpringerLink, MDPI, Scopus WoS (Web of Science), ACM, and IEEEXplore. It is necessary to mention that, according to [22], Google Scholar, Scopus, and WoS are the most used tools academically. Nevertheless, the first one was not considered because it includes texts such as theses and reports that do not meet the selection criteria of this research. In addition, three steps were considered in order to carry it out. (i) Research questions, (ii) document search, and (iii) Paper selection.

2.1. Research Questions

A total of four research questions were formulated to understand the importance of using 4.0 technologies in pipeline maintenance in the oil industry. See Table 1.

Table 1. Research questions.

Code	Research Question
RQ1	What are the most used 4.0 technologies in pipeline maintenance?
RQ2	What types of maintenance are most commonly used by the 4.0 industry?
RQ3	What are the benefits of applying 4.0 technologies in pipeline maintenance?
RQ4	What are the future challenges for 4.0 maintenance?

2.2. Document Search

A documentary search was conducted from 2017 to 2022. This time period has been chosen since information on the application of 4.0 technologies in pipeline maintenance is not yet so extensive. Although there is information from previous years (scarce), these documents do not have an important impact in the industrial field, let alone in academia.

Finally, it can be mentioned that, according to [23], for research in social sciences, it is recommended to use 10-year-old literature, while for faster paced fields such as engineering and the use of technology in general, it is recommended to use 5-year-old literature. In addition, documentation should be included, regardless of its age, as long as it provides relevant data to the research being conducted. This period has been approved as adequate in other literature reviews [16,17].

The search for documents in the different databases was carried out by entering the following combination of specific terms: (“oil pipes” AND (“maintenance” OR “servicing”

OR "upkeep")); ("oil and gas industry" AND ("maintenance techniques" OR "servicing techniques" OR "upkeep techniques")); ("oil and gas industry" AND ("4.0 maintenance" OR "4.0 servicing")); ("oil pipes" AND "digitization"), which had to appear in the context and summary of each document. These words relate to the research questions, considering that the search's central axis corresponded to 4.0 maintenance.

With sensors, IoT (internet of things), Big Data, Artificial Intelligence (AI), and other intelligent systems, it is possible to identify more quickly where failures occur. As a result, it is possible to discover which equipment is affected, the implications of these problems on the company's productivity and the best maintenance plan to minimize the recurrence of these failures. Therefore, companies need to optimize it as much as possible to reduce this type of risk and losses [24].

Generally, when it is necessary to collect data on the condition of machines, we resort to technicians specialized in this area. In Maintenance 4.0, with the development of new connected technologies, machines perform these tasks to maximize the useful life of machine components and avoid failures. With Maintenance 4.0 technologies, data seek out the human being, not the other way around. Maintenance processes have evolved from the preventive to the predictive model. Thus, the focus is no longer solely on prevention but forecasting.

2.3. Paper Selection

This section was divided into three phases: Identification, Screening, and Included. In the first phase, 123 articles were found. On the other hand, the first step of the second phase was to determine the eligibility criteria. See Table 2.

Table 2. Eligibility criteria.

Criteria	Description
Study design	All papers whose main objective was to improve the pipeline maintenance process by applying one or more of the Industry 4.0 technologies were selected. Literature reviews and duplicate studies were discarded.
Time range	Papers published from 2017 to 2022 were selected; articles that did not meet this criterion were discarded.
Language	Only articles written in English were selected.
Publication Status	Articles published in conference proceedings or indexed journals were considered, and it was also verified that they had DOI (Digital Object Identifier).

Next, the documents were sorted by relevance, title, abstract, and keywords. In this way, it was possible to analyze them hierarchically, obtaining, in the first place, the most recent technologies with the most significant benefit for pipeline maintenance. Then, we reviewed whether the information shown in the introduction, results, and conclusions provided the necessary data to answer the research questions in depth required by this document.

After this, a bias analysis was performed, i.e., it was verified that there is no tendency in the selection or preparation of the information. In order to carry out this phase, the Cochrane tool was adapted in 61 papers, which takes into account six domains: (i) Random sequence generation, (ii) Allocation concealment, (iii) Blinding of participants, personnel and outcome assessors, (iv) Incomplete outcome data, (v) Selective reporting, and (vi) Other sources of bias, which are evaluated as low risk, unknown risk, and high risk [25,26]. As a last step of the second phase, references were verified. The objective was to confirm if each of them is correctly located if it belongs to the information mentioned by the author and if it is aligned with the context of the topic developed. In addition, it is essential to point out that, in this last stage, it is also possible to locate factual data, obtain complete information and rule out any suspicion of plagiarism. The summary of the documents obtained at each stage is presented according to the PRISMA guidelines in Figure 1.

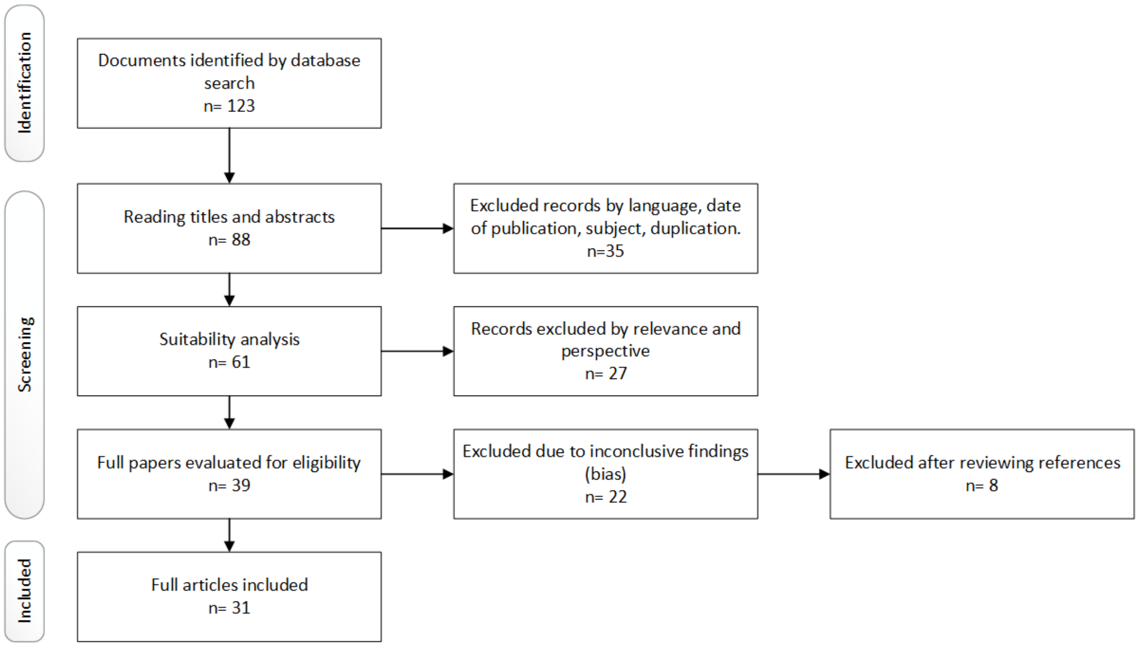

Figure 1. PRISMA flow diagram.The thirty-one final articles were reviewed again by the members of this research, corroborating that the selection was adequate.

Finally, in the third phase, the 31 selected articles were reviewed again by two members of this research, who have several years of experience in the oil industry, 4.0 technologies, and literature reviews. In Figure 2, an analysis of the co-occurrence of all keywords in each document was performed using VOSviewer to understand which terms identify them and which are the most relevant in each article. The main words are represented by the terms pipelines, intelligent systems, and maintenance. This network was constructed with a minimum of two occurrences per keyword.

The formation of a maximum pipelines light blue cluster can be seen, with 227 links and a total link strength of 509. The blue cluster corresponds to maintenance, which has 161 links and a total link strength of 277. It can also be seen that the yellow cluster, which belongs to intelligent systems, has 144 links and a total link strength of 307.

In addition, the formation of a purple cluster with Industry 4.0 technologies related to intelligent maintenance is correlated with the green cluster. In addition, a purple cluster with Industry 4.0 technologies related to intelligent maintenance, such as the use of intelligent robots, ultrasonic sensors, and industrial robotic designs, can be seen; this is correlated with the green cluster that associates with data management through artificial intelligence, data mining, and deep learning. This demonstrates the affinity of the paper portfolio to the research topic.

In addition, an analysis has been carried out, also in VOSviewer software, on the countries to which the most relevant authors of articles on pipeline maintenance 4.0 belong. The minimum number of papers per country has been set to two, while the minimum number of citations per country has been set to one. A green cluster can be seen, corresponding to China, which concentrates the largest number of nationalities of the authors in this scientific field. Here, there are five links and a total link strength of 5.

The United Kingdom and the United States of America are the next two countries with the most relevant research in intelligent maintenance in the oil industry. For the first one, there are seven links with a total link strength of 7, while for the second one, there are 3 links and a total link strength of 3. On the other hand, smaller clusters can be seen belonging to countries such as Australia, Hong Kong, Malaysia, India, Canada, Germany, and Italy. See Figure 3.

The information found has been divided into two groups to visualize the data better. Table 3 presents the articles that refer to preventive maintenance. They have been sorted by year of publication, the technology used, and the approximate percentage of downtime/productivity improvement. Similarly, in Table 4, the articles that use predictive maintenance have been placed, and the criteria of this table are similar to the previous one.

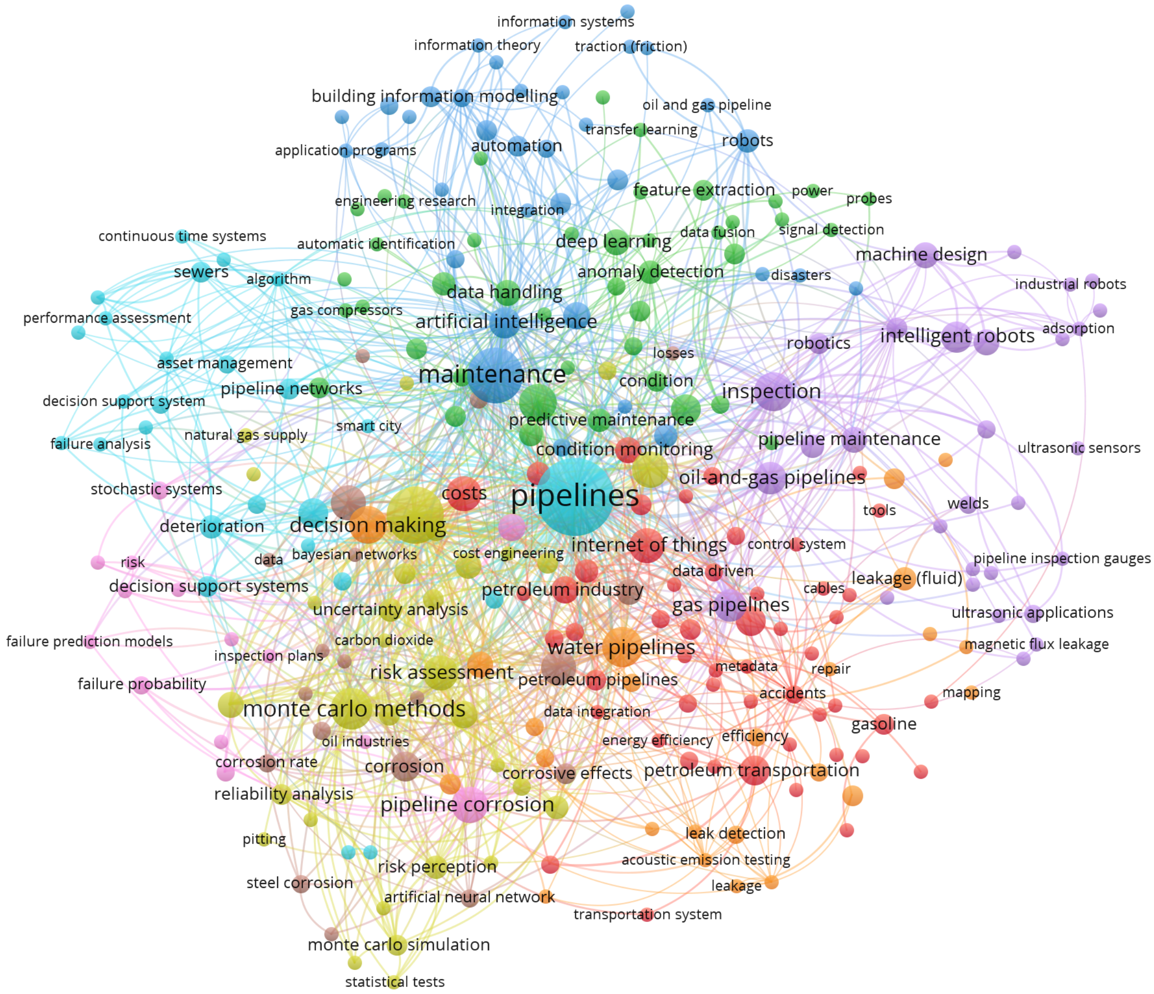

Figure 2. Co-occurrence of keywords.

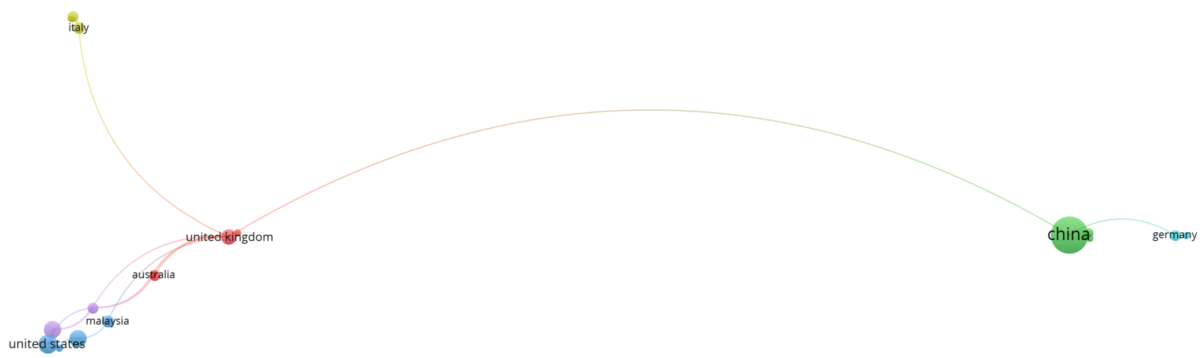

Figure 3. Affiliation countries.

Table 3. Preventive maintenance papers.

Code	Name	Year	Improvement	4.0 Tech
PVM1	Robust Visual Localization of a UAV Over a Pipe-Rack Based on the Lie Group SE(3)	2021	32%	Cobots
PVM2	Reliability-based preventive maintenance planning for corroded pipelines using a RBF surrogate model	2021	19%	AI
PVM3	Development of a Pipeline Inspection Robot for the Standard Oil Pipeline of China National Petroleum Corporation	2020	35%	Cobots
PVM4	Application of USCCD on Girth Weld Defect Detection of Oil Pipelines	2020	25%	Big Data
PVM5	A Zero Accident Strategy for Oil Pipelines: Enhancing HSE Performance	2020	17%	Big Data
PVM6	A Dynamic-Bayesian-Networks-Based Resilience Assessment Approach of Structure Systems: Subsea Oil and Gas Pipelines as A Case Study	2020	30%	AI
PVM7	Hierarchical Controller for Autonomous Tracking of Buried Oil and Gas Pipelines and Geotagging of Buried Pipeline Structure	2019	30%	Cobots
PVM8	Lightweight, High Performance Detection Method of Pipeline Defects Through Compact Off-Axis Magnetization and Sensing	2019	40%	Cobots
PVM9	Improved AHP–TOPSIS model for the comprehensive risk evaluation of oil and gas pipelines	2019	26%	Big Data
PVM10	Design of Informationized Operation and Maintenance System for Long-distance Oil and Gas Pipelines	2019	22%	Cobots
PVM11	Real time automatic object detection by using template matching for protecting pipelines	2018	18%	Cobots
PVM12	Integration of sUAS-enabled sensing for leak identification with oil and gas pipeline maintenance crews	2017	23%	Cobots

Table 4. Predictive maintenance papers.

Code	Name	Year	Improvement	4.0 Tech
PDM1	A KPCA-BRANN based data-driven approach to model corrosion degradation of subsea oil pipelines	2022	35%	AI
PDM2	Approach to weld segmentation and defect classification in radiographic images of pipe welds	2022	63%	AI
PDM3	Application of artificial intelligence technologies in intelligent diagnosis of crude oil pipelines	2022	33%	AI
PDM4	A Case Study Showcasing the Use of Extreme Learning Machine Based on in-line Inspection Data	2022	37%	AI
PDM5	Optimal inspection and maintenance plans for corroded pipelines	2021	45%	AI
PDM6	An intelligent model to predict the life condition of crude oil pipelines using artificial neural networks	2021	51%	AI
PDM7	A data-driven corrosion prediction model to support digitization of subsea operations	2021	23%	AI
PDM8	A semi-empirical model for underground gas storage injection-production string time series remaining useful life analysis in process safety operation	2021	37%	AI
PDM9	An Implementation of Fuzzy Logic Technique to Predict Wax Deposition in Crude Oil Pipelines	2021	25%	AI
PDM10	Resilient IoT-based Monitoring System for Crude Oil Pipelines	2020	22%	IoT
PDM11	Doctor for Machines: A Failure Pattern Analysis Solution for Industry 4.0	2020	41%	AI
PDM12	Residual Stress in Oil and Gas Pipelines with Two Types of Dents during Different Lifecycle Stages	2020	19%	Big Data
PDM13	Investigating an assessment model of system oil leakage considering failure dependence	2020	42%	AI
PDM14	Integrity assessment of corroded pipelines using dynamic segmentation and clustering	2019	60%	Big data
PDM15	Integrated Cloud Cockpit: A viable approach to surveillance and detection of leaks in oil pipelines	2019	48%	Big data
PDM16	Study of the acoustic noise in pipelines carrying oil products in a refinery establishment	2019	35%	Cobots

Table 4. *Cont.*

Code	Name	Year	Improvement	4.0 Tech
PDM17	The Application Research of Internet of Things to Oil Pipeline Leak Detection	2018	15%	IoT
PDM18	An intelligent oil and gas well monitoring system based on Internet of Things	2017	25%	IoT
PDM19	Inspection and Maintenance Planning of Underground Pipelines Under the Combined Effect of Active Corrosion and Residual Stress	2017	36%	AI

3. Results

3.1. Literature Review

This section presents a summary of the selected papers.

A corrosion degradation model was built under a pressure failure criterion in this research work. The objective of this strategy focuses on identifying where and when to intervene in oil pipelines to avoid significant economic losses and excessive downtime. On the other hand, a cost analysis was also carried out, in which it was concluded that the investment in case of failure of a pipeline is 20 million more than the investment in predictive maintenance. Among the limitations found, it can be mentioned that pipeline integrity assessment is incomplete since a holistic assessment should include a space-dependent degradation process caused by external defects [27].

Ref. [28] proposes the design and implementation of a mobile robot for pipeline inspection. The implementation has been made possible thanks to the support of the China National Petroleum Corporation. In addition, the robot's current design is an improvement to the previous model used by Chinese oil companies. The robot can move on slopes with angles no more significant than 45° and adapt geometrically to a maximum of 10° to meet the requested requirements. The system has two operation modes, one manual and the other automatic. In the first one, the robot starts and ends the pipeline inspection through a command. On the other hand, in the automatic mode, the robot can move along the entire pipeline, finish the fault inspection, and return automatically. Furthermore, in contrast to the previous design, this prototype has a battery that can last more than 30 h in the pipeline, covering a distance of approximately 70 km. Finally, it is proposed to improve the robot using AI and sensors to enhance diagnostic efficiency.

Corrosion is one of the main reasons for the structural degradation of pipelines. This problem is aggravated when working in offshore stations, with irreparable economic and environmental consequences. For this reason, predicting the corrosion of these elements is essential. Ref. [29] proposes integrating KPCA (Kernel Principal Component Analysis) and BRANN (Based Artificial Neural Network) techniques to generate a more robust model to eliminate redundant information and reduce diagnostic time. The data were divided into two sets, a training set and a validation set. This model was compared with BRANN and KPCA-LMANN (Levenberg Marquart ANN), showing superiority in prediction with a mean square error of 0.46%.

Ref. [30] present to employ 4.0 technologies such as cloud computing with integrated platforms such as Google Cloud Platform and Microsoft Azure Cloud Platform, among others, to create a lightweight, fast, and efficient application to predict the most common pipeline failures. The images taken from the pipelines are transformed through Big Data processes, thus ensuring that the data are consistent. On the other hand, Machine Learning algorithms have also been used to identify patterns in the data obtained and thus develop more accurate forecasts. As a result, an accuracy of up to 0.98 was achieved with a minimum loss of 0.006. Furthermore, the use of this technology for pipeline maintenance was compared with standard leak detection methods, obtaining encouraging results.

Within non-destructive testing in oil pipelines, one of the main fields of research refers to the detection of welding defects. Due to this, several techniques have been developed to detect defects, segment the defective area, or classify such faults. However, although very useful, these techniques do not cover the necessary spectrum, having to be mixed with several additional techniques. To solve these drawbacks, Ref. [24] proposes the application of machine learning for the real-time processing of welding radiographs. The digital detector array method was employed. The most important contribution of this research was creating a web service based on neural networks that detect welds, segment them, and classify pipeline defects in real-time.

After applying UltraScan™ Circumferential Crack-Like Detection technology for oil pipeline inspection, Ref. [31] presents the results. In recent years, the integrity of circumferential welds has become more relevant. These failures generally occur during oil field construction and are subject to external loads due to earth movement. It is necessary to mention that, in newly constructed pipelines, these failures also exist. However, they are more challenging to detect due to their size. In addition, 102 flaws with an average width of 0.8 mm were considered for the probability of detection. These were classified concerning their relative position to the weld. Of the 36 defects present in the weld (first category), 35 were detected, corresponding to a detection rate of 97%. Finally, for the other category, the detection rate was 92%.

Several pipeline diagnostic, predictive, and information management technologies have emerged with the industrial revolution we currently find ourselves in. Thus, digital twins have become the cornerstone in oilfield equipment production, operation, and maintenance. Ref. [32] presents a case study on the Sino-Myanmar pipelines, where they use AI based on digital twins to predict oil demand. As a complement to this system, it is intended to optimize the operation of the pipelines in real-time and manage an intelligent diagnosis, in which the most common failures within this industry can be detected.

Ref. [33] proposes several options to prevent the number of pipeline adverse events caused by facility malfunctions, human errors, accidents, and external events. This research work aims to implement a visualization and prediction software based on Structured Query Language and Geographic Information Systems. This system processes crucial information such as the state of the pipeline infrastructure, transported volumes, land use, and areas affected by oil incidents. Among the alternatives presented in this document, two stand out: (i) databases and geo-reference visualization tools for risk management; and (ii) the implementation of SCADA systems to monitor and detect possible leaks.

The IoT has gained importance in recent years, and its application spectrum has grown in such a way that its functionality has been extended to industry, adapting and changing its name to the industrial internet of things (IIoT). However, both terms can be used interchangeably when the context is known. Ref. [34] focuses their research on detecting pipeline leaks via the (IoT). Pipeline pressure signals are stored and processed, and leaks are detected through the harmful pressure wave method. The case study uses a 100 m long pipeline with 50 oil leakage points. The authors concluded that, although the system has some room for improvement, it can effectively determine the existence of pipeline leaks.

In the United States, the Department of Energy and Transportation has made it a priority to contain pipeline leaks promptly. Although this aspect is important, economic and time losses are still incurred. Ref. [35] proposes the use of unmanned aerial systems or drones for the inspection of pipeline networks in order to detect leaks or failures on time. They use a combination of drones and human ground teams to reduce pipeline maintenance time. They have also used mixed integer programming methods to optimize routes and reduce the arrival time of the drones.

In Ref. [36], the authors state that pipelines worldwide are exposed to extreme environmental conditions. Because of this, the maintenance process is vital for this industry to operate efficiently. One of the most known techniques to perform routine maintenance is pigging; however, due to the complexity of this process, the times and costs are excessive. Because of this, Industry 4.0 plays an important role, meddling in this research with the application of an autonomous robotic inspection system, which detects the exact failure location through GPS coordinates.

Making use of the technology that is currently available is essential to attack problems of leaks, ruptures, or fractures in oil pipelines. Under this concept, Ref. [37] discusses the proper maintenance method for corroded pipelines. Moreover, the probability of failure is calculated through a Monte Carlo simulation. Finally, a genetic algorithm has been used to optimize the inspection plan, i.e., to predict the possible failures that may occur in time.

Ref. [38] developed and implemented a program capable of analyzing photographs taken by an unmanned aerial vehicle to find pipeline faults. The inspection methodology previously used in this area has been changed, i.e., the human resource drove a vehicle along the pipeline, verifying that everything was in optimal conditions. The proposed system can accurately locate the pipeline failure and trigger an alarm. This way, maintenance personnel can make the right decision and take immediate action.

As seen in previous paragraphs, pipeline networks are the safest way to transport large volumes of oil, so they must be in optimal conditions. The goal of [39] is to use IoT, considering time, robustness, and scalability for detection and future mitigation of failures. The proposed model is cost-effective and efficient by considering trade-offs between density, detectability, and cost. The implementation is still in the simulation phase; however, encouraging results have been obtained, among which it can be mentioned that there is an accuracy of more than 95% in leak location. Finally, to complete the study, it is proposed to implement databases to filter the information, categorize it, and obtain trends to predict future failures.

Ref. [40] claims to be the first to design and implement an intelligent monitoring system for oil wells and pipelines based on the IoT, using intelligent devices to obtain detailed information such as pressure, temperature, and flow, among others. The proposed architecture detects adverse events such as leaks, valve strangulation, and fire incidents. On the other hand, automatic alarms have been created so that the personnel in charge of the maintenance process can act efficiently and optimally in any potentially dangerous condition.

Generally, preventive maintenance in pipelines is a costly and deficient process. Using 4.0 technologies optimizes the availability and durability of the facilities. Ref. [41] developed a system called Doctor for Machine, which employs different machine learning techniques. This framework has been applied to six data sets to create an optimal predictive model for pipeline anomalies. From a technical point of view, the usefulness of this system can be summarized as (i) standardizes the collected data; (ii) creates machine learning models; and (iii) drastically reduces the labor effort to generate predictive models.

The internal corrosion of oil pipelines is one of the most frequent problems within the oil and gas industry. Failing to take corrective action on this type of negligence can affect the integrity of human resources, generate unforeseen costs, and devastate the environment. Ref. [42] proposes a relatively new method using extreme machine learning to predict the internal corrosion of oil and gas pipelines based on historical data from previous online inspections. The case study focused on oil pipelines in Qinghai, China, which have a length of 170 kilometers and about 241 internal corrosion defects. This method has been compared with other machine learning techniques such as Back Propagation and Random Forest, significantly improving the accuracy and speed of calculation.

Ref. [43] establishes a lightweight, low-cost system for detecting defects in oil pipelines through compact off-axis magnetization and sensing. In this experiment, they avoided magnetic sensing saturation by placing the magnetic sensor under the edge of the magnet instead of placing it at its center. As a result, compared to conventional magnetic sensing methods, the sensitivity is improved by 2 to 12 times; and, in some cases, up to 20 times. Furthermore, this system is based on a probe, which is suitable for pipelines with unstable characteristics such as speed of movement. This system's accuracy percentage in the tests exceeded 97%.

The use of robots in the oil industry has gained strength in the last decade, to such an extent that they represent an emerging application for the maintenance process of facilities. Because of this, Ref. [44], in her research, proposed a pose tracking system based on a single camera sensor that allows, in conjunction with an unmanned aerial vehicle, to check for faults in the inspected pipeline. Several sets of numerical simulations were carried out to demonstrate the efficiency of the presented system.

Ref. [45] suggests a new way of assessing the resilience of pipelines once they have been exposed to natural disasters. They have developed an assessment approach based on the remaining lifetime of pipeline components within the oil and gas industry. Dynamic Bayesian networks have been applied and tested on subsea oil installations. The results show that the facilities' resilience is inversely proportional to the impact of natural disasters. Furthermore, it is established that pipelines with this type of defect can reach a total failure after 40 h. Therefore, they should be dealt with as soon as possible.

Ref. [46] developed an intelligent model that predicted lifetime conditions and detected metal loss failures in pipelines through ANN. The experiment was tested on various sections of pipelines, considering their length, width, depth, thickness, weld, and pressure. The results exceeded expectations. Life prediction accuracy reached 99.97%, while failure prediction achieved 90.18%.

The residual stress generated in pipelines is critical regarding their integrity and efficient operation. Ref. [47] proposed a three-dimensional finite element-based model to collect and organize data on residual stresses occurring at two stages of pipeline life: construction and operation. In addition, a nonlinear regression analysis was used to predict dents during the different stages of the life cycle. The most crucial conclusion they reached during pipeline operation is that the higher the pressure, the smaller the difference in residual stress between the different types of dents.

Ref. [48] establishes a holistic and objective evaluation model for oil and gas pipelines based on an improved analytical hierarchy process and an order preference technique by similarity to an optimal solution. The aspects taken into account for the creation of this model are: (i) corrosion, (ii) external interference, (iii) type of materials used, (iv) natural disasters, and (v) function and operation. In the results, pipelines of considerable lengths were used. In addition, it was shown that the failures determined by the proposed model are consistent with the current situation of each sample. Furthermore, the number of variables used makes the model robust and reliable compared to models using one or two variables.

An alternative approach based on preventive maintenance planning for oil and gas pipelines is presented by [49]. The objective of this methodology is to maintain pipeline condition reliability above a baseline level. In this research's state of the art, it is established that the equations used to calculate failure probabilities lead to economically unfeasible and very conservative results. On the other hand, finite element modeling is employed here, using radial basis functions. The results show that the proposed approach can lead to more realistic and economically optimal results.

A comprehensive model for inspecting corroded oil and gas pipelines, considering past inspection results, is developed by [50]. This research proposes the prediction of expected costs for performing an optimal inspection of different types of corrosion, with and without residual stresses. The results show that the developed model is consistent with the failures presented in oil installations. In addition, the maintenance time and cost have been reduced efficiently.

Corrosion is one of the major problems within the oil industry; in fact, a leak in a pipeline can lead to natural disasters of major proportions and affect the entire surrounding population. Ref. [51] suggests a methodology based on the probability of oil leakage. The results obtained in this work are comparable to other research, i.e., there is no significant improvement if failure dependence is not considered. Therefore, viewing this factor, this research is presented as an opportunity to improve the maintenance process in the oil industry.

The paper, developed by [52], presents an approach for the prediction of corrosion rate in offshore oil installations. The model is based on hybrid criteria such as (i) Principal Component Analysis, (ii) Artificial Bee Colony Algorithm, and (iii) Support Vector Regression. The case study has been applied to the crude oil pipeline in the South China Sea. The corrosion factors include (i) water content, (ii) temperature, (iii) PH, among others. The results show that the MAE and RMSE of the PCA-ABC-SVR model are 7.10% and 9.19%, respectively, while the coefficient of determination is 0.976.

Ref. [53] proposes a method to analyze the degradation state of oil and gas pipelines based on the remaining useful life of each one of them. A probabilistic semi-empirical digitization model has been used. Among the limitations of this research, it can be mentioned that the accuracy of the results depends on the number of simulated degradations. However, the amount of pipe thickness loss can be adequately predicted under normal conditions.

The research work of [54] analyzes the design of a maintenance system for oil and gas pipelines of considerable lengths, with characteristics of (i) Safety, (ii) Reliability, and (iii) Economy. For the development of this system, an unmanned aerial vehicle has been used, which is in charge of traveling through the pipelines and alerting, in real-time, the maintenance personnel about any failure such as possible leaks, external corrosion, damage to the infrastructure, among others. This information is stored in a database, which will be used in future work to predict the events above accurately.

Ref. [55] studies the characteristics of the noise generated in the pipeline network of an oil refinery known as Hellenic Petroleum S.A., located in Thessaloniki, Greece. Intelligent devices have been developed for leak detection in pipelines transporting oil products in boisterous environments. Noise characteristics have been extracted using time domain and frequency domain methods. In the results, it could be found that there are several man-made acoustic interferences in a low-frequency range up to 250 Hz. This part of the signal has been filtered, so that leakage signals can be obtained appropriately and classified through acoustic ranges to determine their size.

Ref. [56] sets up an experiment to identify the effect of wax generation in oil pipelines during crude oil transportation. First, a mathematical model was created based on different parameters such as temperature, pressure, and molar flow. The values were determined through fuzzy logic in MATLAB software. The results showed that the mathematical model adequately predicts the wax deposition in oil pipelines, with a mean absolute percentage error of 0.09%.

3.2. Paper Data

Most selected papers use a single Industry 4.0 technology; however, some articles use two or more tools. It is due to their versatility and the fact that they are complementary, such as in the case of AI, whose functionality allows for predicting possible failures in pipelines. In addition to providing this valuable information, it is necessary to have a data backup and be able to access it whenever necessary, whether in real-time or not. Therefore, big data and cloud computing significantly facilitate information management and keep it safe from cyber attacks.

Figure 4 shows that, of the final sample of articles selected, 45.16% use AI, making it one of the critical technologies of the present and future of this industry. In second place is the use of collaborative robots or cobots and the IoT, whose use is advancing exponentially, representing 19.35% of the thirty-one articles. Finally, the use of big data occupies 16.13% of the total.

On the other hand, the selected articles were based on two points of reference: (i) Predictive maintenance and (ii) Preventive maintenance. Of the final sample selected (n = 31), 39% of the papers focus their methodology on preventive maintenance of oil facilities, specifically small and long-range pipelines. The rest of the documents developed systems that allow for predicting in advance the damage to some of their machinery and facilities, with critical thinking focused on the future, the optimization of economic and human resources, and the prevention of irreversible damage to the environment. This can be seen in Figure 5.

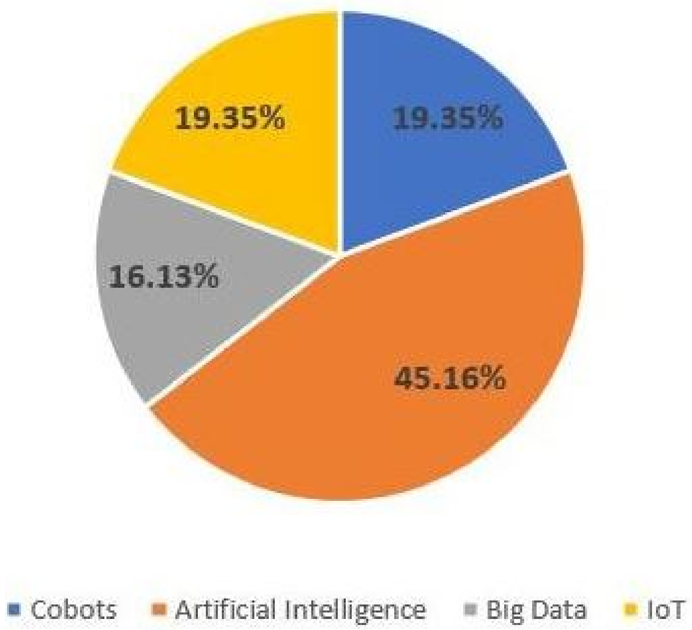

Figure 4. The most widely used technologies for the 4.0 maintenance of oil products. AI is the technological tool that has been extensively used in the last five years by the oil industry.

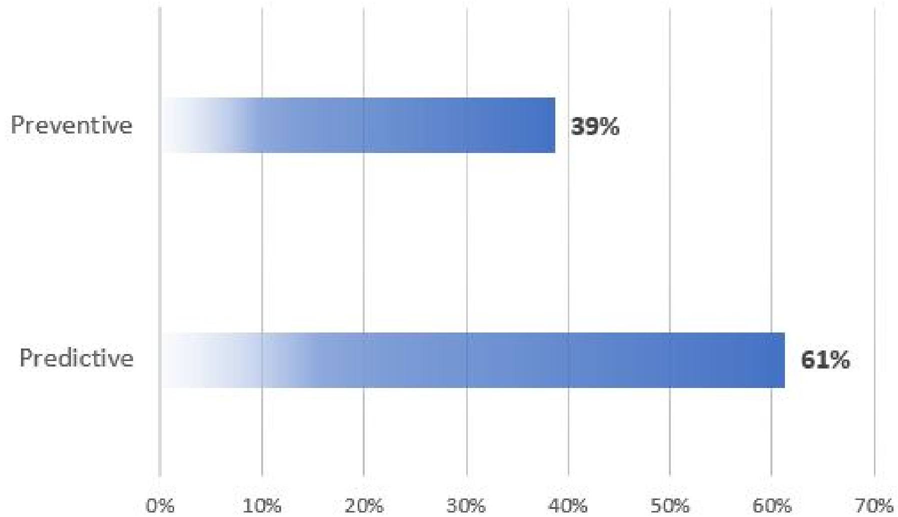

Figure 5. Types of maintenance. Preventive maintenance is a critical point to be considered in any oil company's facilities.

In order to determine the impact of preventive and predictive maintenance on downtime in the maintenance process, data have been collected for each element of the selected sample. This information directly or indirectly exemplifies the percentage of improvement compared to conventional methodologies. For example, of the 12 items of preventive maintenance, an average percentage of time optimization of 26% was obtained, while the average percentage of the 19 items that explain predictive maintenance was 36%. As can be seen, there is a difference between both types of maintenance. However, to statistically confirm which is more efficient in saving time in the maintenance process, performing a T-student test for independent samples is necessary.

A confidence level of α = 5% was selected, and two hypotheses have been established:

- H_0 There is no significant difference between the time optimization means of preventive maintenance and predictive maintenance.
- H_1 There is a significant difference between the time optimization means of preventive maintenance and predictive maintenance.

After this, it is necessary to determine the normality of the data; however, this test is sufficiently robust to be performed even if this criterion is not met. The Kolmogorov–Smirnov test is used for samples exceeding 30 elements, while for samples smaller than 30, as in this case, the Shapiro–Wilk test is used. The significance value for preventive maintenance was 0.778; see Figure 6. The significance value for predictive maintenance is 0.696, and it can be appreciated in Figure 7. As they are higher than alpha, normality is verified. On the other hand, Levene's test was performed to determine the equality of variances, obtaining a value of 0.100.

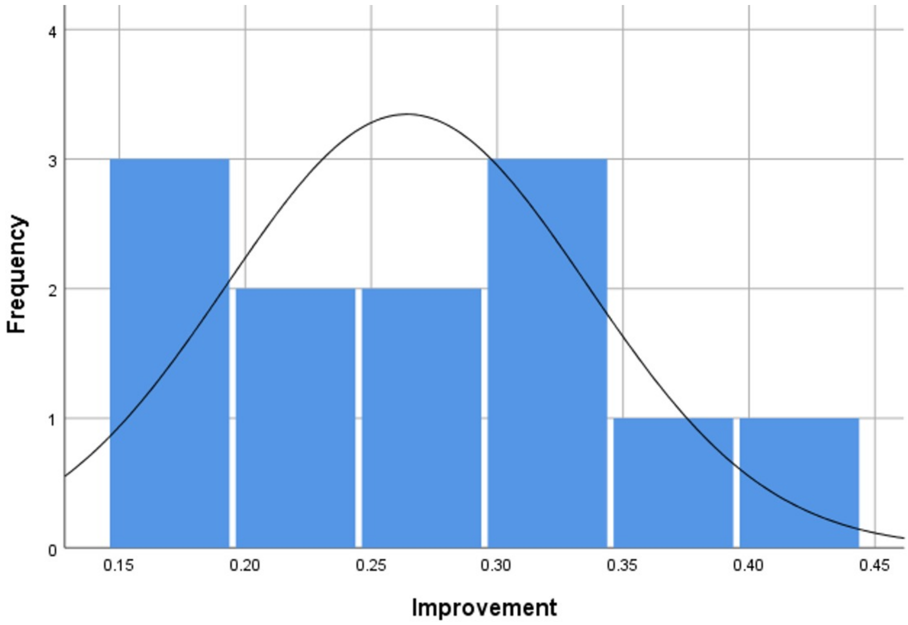

Figure 6. Histogram for preventive maintenance.

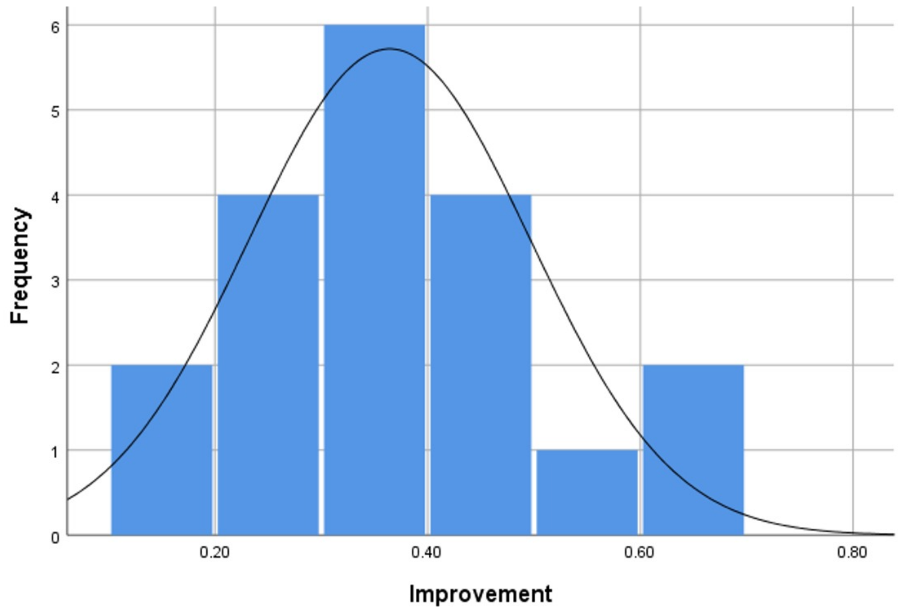

Figure 7. Histogram for predictive maintenance.

Finally, a significance value of 0.023 was calculated. Since this value is lower than the alpha significance level, the null hypothesis is rejected, and the alternative hypothesis is accepted; therefore, the numerical difference between both maintenance systems is statistically significant. With these results, it can be defined with certainty that, from the selected sample, predictive maintenance is more efficient in optimizing time in the value chain of the oil industry, resulting in lower costs and an efficient process.

Figure 8 shows that the percentage difference between the two types of maintenance is 38%. For preventive maintenance, 50% of the data are located between 21% and 31% approximately, while, for predictive maintenance, 50% of the data ranges between 25% and 43% approximately. In this case, there is a skewed asymmetry to the left, since the longest part of the box is below the median. In addition, the data are concentrated in the upper part of the distribution. Finally, it can be understood that there are outliers for neither of the two types of maintenance.

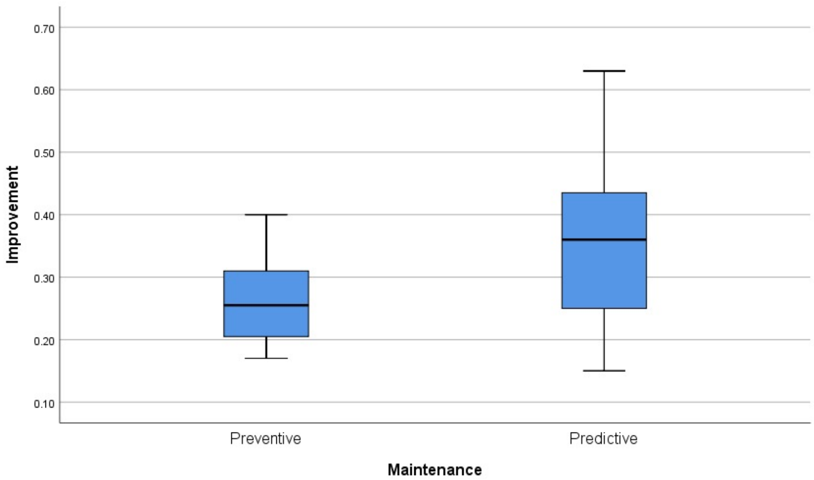

Figure 8. Comparative boxplot. Preventive maintenance has a higher means than predictive maintenance, showing that it is more efficient in optimizing resources in the oil industry.

4. Discussion

4.1. Research Questions

The 31 articles previously selected contain enough information to be able to issue a scientific criterion regarding maintenance using 4.0 technologies within the oil industry. Next, the questions posed in Section 2 are answered.

1. **RQ1**
   The technologies inherent to Industry 4.0 allow several changes with resource optimization, improving the productivity of companies and industries. Among the main characteristics, we can mention the following: (i) Production can be made more flexible to achieve efficient customization; (ii) Devices, machines, and facilities can be monitored remotely or in situ in real-time, thus facilitating the rapid detection of failures and problem-solving; (iii) In hazardous environments or environments that generate a risk for human beings, processes can be virtualized, safeguarding the integrity of human resources; (iv) By placing flexible technologies, these can be adapted to the company's needs, freeing up human personnel to perform other types of tasks; and (v) Intercommunication between devices and operators [57,58].
   Within the results shown in the previous section, it can be understood that AI and cobots, as core technologies, are the backbone of predictive maintenance and, in part, preventive maintenance. Through AI and its underlying technologies, real-time data can be collected from different sites and devices, which are the basis for generating intelligent algorithms to anticipate pipeline failures. The IoT supports them, a technology that allows the intercommunication of devices and the storage of the information generated. In general, the exemplified case studies are adapted to the following steps for implementing this new tool: (i) Data collection is necessary to generate relevant data, i.e., quality information, to build optimal models with small margins of error. Here, the equipment configuration is essential since external factors must also be considered to obtain clean information. (ii) Data cleaning—having

as much data as possible can be considered an advantage. However, it is always necessary to analyze the value of the data, filter, and classify them.
(iii) Interpret prediction needs, i.e., combine and complement data obtained from devices, machinery or facilities to generate robust and accurate models. What must be taken into account is the error history so that the algorithm includes normal and failure patterns, maintenance history, a critical factor to know where and when to work, operating conditions, to determine the environment in which it is working and verification if the life of each equipment is dynamic to those conditions. (iv) View the results critically to culminate the feedback process. This allows the maintenance personnel to correct any biases found. (v) Implementation, working with the models generated and data obtained in real-time [59,60].
On the other hand, the use of collaborative robots in hazardous environments has become popular in recent years. This is because they can work with humans to perform dynamic tasks, they are easy to program, and most have safety protocols that allow them to interact with processes and operators without putting human life at risk. Its purpose is to increase the accuracy of tasks and reduce both mental and physical fatigue of maintenance personnel.

2. **RQ2**
Maintenance is one of the most critical and undervalued processes in any industry. It guarantees the optimal operation of both machinery and facilities. Thanks to this process, it is possible to reduce costs, optimize quality, reduce time, and avoid occupational accidents. There are three types of industrial maintenance: (i) corrective maintenance, (ii) preventive maintenance, and (iii) predictive maintenance. In the past industrial revolution, corrective maintenance was predominant. However, with technological evolution and digitalization, this has become a thing of the past, giving way to preventive and predictive maintenance [61].
The information gathered showed that Industry 4.0 focuses more on predictive and preventive maintenance, specializing in the former. One of the reasons for not finding corrective maintenance within this field is the high cost generated once an installation or oil machinery fails. Furthermore, the unplanned stoppage of the tasks also entails mechanical collateral damage, loss of time, and non-compliance with the demand. In addition to these reasons, the environmental damage that a simple oil leak can generate must be taken into account, considering that most of these industries are located in priceless natural resources.
Predictive maintenance allows for taking care of the heart of modern industries and factories, i.e., machinery and facilities. Furthermore, combining the human factor with technologies such as the IoT, big data, cobots, and AI allows for communicating data efficiently and constantly, warning of any anomaly, thus optimizing the production cycle. In addition, it can be mentioned that, in the last five years, this maintenance has gained strength since the top management of industries has realized its value and the benefits it represents. In fact, at the general industry level, it is estimated that this maintenance represents forty percent savings in maintenance costs [62].

3. **RQ3**
By using the digital world in which the industry currently finds itself, it is possible to obtain great benefits, which can be summarized in a single sentence: optimize the fidelity and availability of machinery and facilities at the lowest cost. However, it is necessary to establish in detail the utility that this type of technology can add to the maintenance of oil pipelines: (i) Automatic planning of maintenance, having previous or historical information of maintenance, allows algorithms to determine how often the pipelines should be checked for faults and predict the useful life of its components. (ii) Optimization of overall productivity, by not having unscheduled stops or unnecessary downtime; the value chain of the oil industry improves its times and overall profitability.
(iii) Increased profitability of machinery when preventive maintenance is applied, the useful life of machinery and equipment is extended, making them more reliable and

increasing their availability exponentially. (iv) Decrease in the loss of product and raw material. Not considering an oil pipeline leak or suffering any breakdown can cause the crude oil to be wasted and useless. (v) Reduction of labor accidents, the fact of having machinery working at its optimum level, is synonymous with efficiency and reliability. Therefore, the flaws that may occur, if they do, are not a threat to the integrity of people. (vi) Reduction of environmental damage. Preventive maintenance focused on the oil industry is based on two essential axes, the prevention of spills in the unloading process and the integrity of assets. With these characteristics, the probability of failure and contamination is very low, allowing pipelines and their environment to coexist [63].

Finally, it is necessary to understand that implementing predictive maintenance in the oil industry is a qualitative advantage. This can be achieved as long as the necessary human resources are available to implement systems according to the industry and technological equipment that allows this process to be carried out satisfactorily [64]. Likewise, there must be leaders and senior managers who are interested and deeply involved in the activities of the oil industry so that they understand the cost–benefit of implementing these new technologies.

4. **RQ4**

   Although significant progress has been made in using 4.0 technologies, there are still things to be corrected and polished. Therefore, one of the significant challenges is to balance human resources work with the integrated intelligent devices so that the coordination between the two is accurate and reduces time even more. Understanding the fundamental role of this evolution for top management is also a challenge, as most see technology as an expense rather than an investment. Changing the mindset of these people can be a much more significant challenge than implementing any system [65].

   Maintaining current technologies and keeping pace with technological advancement are critical when discussing the automated maintenance process. However, having installed or purchased a predictive system and obtaining encouraging results is not all. It is only the beginning of the technological transformation. For this reason, the oil industry must have highly trained and young personnel who know how to adapt to changes and maintain the maintenance system, i.e., constantly feed it with data and investigate other low-cost technologies that can complement and improve its current architecture.

   However, this does not mean that older or physically/mentally challenged workers should be left out. It is a difficult and critical decision to be made by the human resources department, who are in charge of ensuring that each work team is diversified and inclusive [66]. For example, the experience of older workers can be used to teach and train new employees about the petroleum industry, supporting and guiding them so that their adaptation to these demanding environments is not exhausting. Finally, people with mild autism, whose visual and spatial skills can be essential in handling large volumes of data, recognizing patterns and anomalies quickly and accurately in the facility, can be hired.

4.2. Paper Selection Analysis

As seen in the previously studied sections, most articles point to the use of predictive maintenance, leaving preventive maintenance behind and discarding corrective maintenance. Equipment, machines, systems, and installations have evolved, becoming increasingly sophisticated, demanding continuous improvement in maintenance processes and more rigorous work by the maintenance manager.

Corrective maintenance, characterized by maintenance actions after a breakdown, is ideal for low-priority equipment, without which the company's operations can continue to function normally. The same applies to low-value equipment, as the work required to maintain or constantly monitor it can be more expensive than repair or replacement in case of a breakdown.

Since not much programming is required for this approach, its implementation cost is very low compared to the alternatives. However, efforts are being made worldwide to avoid using this type of action, since the problem comes when relying on corrective maintenance for medium or high-priority assets. Once no preventive actions are performed in a corrective maintenance strategy, the lifetime of the equipment will end up being shorter than with one of the alternative strategies. Applying to high-priority or high-value equipment will lead to unexpected downtime and probably high repair costs [67].

On the other hand, preventive maintenance occurs on a cyclical and scheduled basis, independent of the asset's condition and to avoid breakdowns and minimize the consequences of equipment breakdowns. The maintenance manager defines the frequency based on an assessment of the useful life of the equipment and the manufacturer's recommendations. Examples of preventive maintenance actions include periodic reviews, inspections, cleaning, and lubrication of parts.

This type of maintenance is essential for the equipment that is essential to the company's normal operation. Moreover, the greater the risk associated with a given failure, the greater the need for preventive maintenance to increase the asset's useful life and reduce unplanned downtime. Once they are not based on the actual condition of the equipment, preventive maintenance plans can sometimes be inefficient and result in unnecessary maintenance actions (including parts replacement) that cost time and money [37].

The effect is compounded when a preventive approach is applied to low-priority or low-cost assets that could generate lower costs if only repaired reactively. Because of this, this type of maintenance is still employed, but it must be properly matched to the variables of each of the oil industry's machinery and infrastructure.

Finally, predictive upkeep is the one that requires more investment at a technological level. Its objective is to foresee when a breakdown is about to occur. When certain undesirable conditions are detected, a repair is scheduled before the equipment breaks down, thus eliminating the need for costly corrective maintenance or unnecessary preventive maintenance. It is based on the physical and operational condition of equipment through regular monitoring and testing of equipment condition and performance.

This approach is based on assets' physical or operational condition at upkeep time rather than on pre-defined statistics and schedules. It attempts to detect the failure in its still hidden phase, before any visible sign, and in its potential phase. Thus, the maintenance will be more informed, necessary, and timely since the equipment will only undergo upkeep when a failure is foreseen. This will lower the costs and labor time invested in maintenance [68,69].

The need to invest in specific monitoring equipment, as well as in training personnel to use it correctly and interpret the data collected, makes the implementation of this strategy very expensive. For this reason, it is not cost-effective for assets that are not essential to properly functioning their operations. Each company must decide and act according to its reality, considering upkeep as a short, medium, and long-term investment.

5. Conclusions and Future Research Avenues

In recent years, there have been many changes in the way the oil industry manages its maintenance process, realizing that this is an investment rather than an expense. In this sense, it is necessary to understand the Industry 4.0 technologies that allow for optimizing this process and therefore generating significant economic savings/revenue.

Thus, this article has presented a scoping literature review summarizing the most relevant information of the last five years regarding pipeline maintenance methodologies based on Industry 4.0. Sophisticated systems and architectures have been analyzed, concluding that implementing preventive maintenance plans, in conjunction with innovative technologies, such as AI, IoT, and cobots, considerably reduces costs in the value chain, optimizes maintenance process times, and preserves the integrity of human resources.

It was statistically proven that predictive maintenance makes a significant difference when it comes to optimizing productivity or downtime. In addition, it was found that AI is the most used technology when performing predictive maintenance; however, it should be clarified that, to use this technology, industries must have large amounts of information that has been previously debugged and treated so that the results are accurate.

Industry 4.0 was the beginning of the technological transformation, where there was the necessary time to know its benefits and applications. However, the oil industry must keep up with this evolution, always flexible and open to the rapid changes that the expert environment demands.

The infrastructure and projects in the oil sector comprise an extensive network of equipment, resources, and human resources. Scheduled maintenance shutdowns imply that a plan is made months in advance and that the activity is known throughout the value chain. For this reason, this industry must rely on current technologies to optimize time and costs.

Implementing a predictive maintenance plan is essential for the reliability and availability of equipment and resources to be high. However, it is impossible to reach 100% effectiveness. This is because technological development depends on human beings, and there is a large amount of data that, if we do not know how to deal with it, instead of being a support, can harm the correct development of the processes.

For future work, it is proposed to conduct a systematic literature review to complement this research with information on money and time invested in the process of both preventive and predictive maintenance. This will be helpful for industries in this sector that have not yet migrated to new technologies, to have support and put together an efficient maintenance plan according to their economic possibilities.

In addition, it is intended to consider within this economic analysis the human resource and how the disruption of 4.0 technology can affect their jobs. Finally, possible solutions will be given so that technology does not replace workers completely but so that both can coexist in a balanced manner.

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