

Derleme Makalesi -Review Article

Techniques for Apply Predictive Maintenance and Remaining Useful Life: A Systematic Mapping Study

Kestirimci Bakım ve Kalan Yararlı Ömür Uygulama için Teknikler: Sistemik Haritalama Çalışması

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ABSTRACT

With prognostic activities, it is possible to predict the remaining useful life (RUL) of industrial systems with high accuracy by following the current health status of devices. In this study, we have collected 199 articles on predictive maintenance and remaining useful life. The aim of our systematic mapping study is to determine which techniques and methods are used in the areas of predictive maintenance and remaining useful life. Another thing we aim is to give an idea about the main subject to the researchers who will work in this field. We created our article repository by searching databases such as IEEE and Science Direct with certain criteria and classified the articles we obtained. By applying the necessary inclusion and exclusion criteria in the article pool we collected, the most appropriate articles were determined and our study was carried out through these articles. When we focused on the results, it was learned that the SupportVector Machine algorithm is the most preferred predictive maintenance method. Most studies aimed at evaluating the performance and calculating the accuracy of the results used the Root Mean Square Error algorithm. In our study, every method and algorithm included in the articles are discussed. The articles were examined together with the goals and questions we determined, and results were obtained. The obtained results are explained and shown graphically in the article. According to the results, it is seen that the topics of predictive maintenance and remaining useful lifetime provide functionality and financial gain to the environment they are used in. Our study was concluded by light on many questions about the application of predictive maintenance.

Keywords- *Predictive Maintenance, Remaining Useful Life, Machine Learning, Deep Learning, Root Mean Square Error*

ÖZ

Prognostik faaliyetler ile endüstriyel sistemlerin kalan yararlıömürünü (RUL), mevcut sağlık durumlarının takip ederek yüksek doğrulukta tahmin edilmesi mümkündür. Bu çalışmadakestirimci bakım ve kalan faydalı ömür hakkında 199 makale topladık. Sistemik haritalamaçalışmamızın amacı, kestirimci bakım ve kalan faydalı ömür alanlarında hangi teknik ve yöntemlerin kullanıldığını belirlemektir. Amaçladığımız bir diğer konu da bu alanda çalışacak araştırmacılara ana konu hakkında fikir vermektir. IEEE ve Science Direct gibi veritabanları belirli kriterler ile aranarak makale havuzu oluşturuldu ve elde edilen makaleler sınıflandırıldı. Toplanılan makale havuzunda gerekli dahil etme ve hariç tutma kriterleri uygulanarak en uygun makaleler belirlendi ve çalışmamız

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bu makaleler üzerinden gerçekleştirildi. Sonuçlara odaklandığımızda Destek Vektör Makinesi algoritmasının en çok tercih edilen kestirimci bakım yöntemi olduğu öğrenildi. Performansı değerlendirmeyi ve sonuçların doğruluğunu hesaplamayı amaçlayan çoğu çalışmada Kök Ortalama Kare Hatası algoritması kullanılmıştır. Çalışmamızda makalelerde yer alan her yöntem ve algoritma tartışılmıştır. Makaleler, belirlediğimiz amaç ve sorularla birlikte incelenerek sonuçlar elde edilmiştir. Elde edilen sonuçlar makalede açıklanmış ve grafik olarak gösterilmiştir. Elde edilen sonuçlara göre, kestirimci bakım ve kalan faydalı ömür konularının, kullanıldıkları ortama işlevsellik ve finansal kazanç sağladığı görülmüştür. Çalışmamız, kestirimci bakım uygulaması ile ilgili birçok soruyu aydınlatarak sonuçlandırılmıştır.

Anahtar Kelimeler- *Kestirimci Bakım, Kalan Yararlı Ömür, Makine Öğrenmesi, Derin Öğrenme, Kök Ortalama Kare Hata*

I. INTRODUCTION

In recent years, the discipline of maintenance has started to change in the industrial field. When any failure is detected in the production area, it is common to shut down the machine as soon as possible to avoid vastating consequences, however performing such an action, which usually occurs at in appropriate times, typically causes considerable time and economic losses [1]. Therefore, factories have turned to a different maintenance strategy to prevent break down and minimize cost losses. Maintenance is generally divided into two main strategies; reactive and proactive. In a reactive strategy, there are a post-fault diagnostic status and cost losses, however, in the proactive maintenance strategy, the main goal is to reduce the cost and to keep the system operating at the highest level. For this reason, the maintenance strategy has changed from fail and fix practices (diagnostics) to predict and prevent methodology (prognostics) [2].

According to European standard EN 13306: 2010, maintenance is defined as a “Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function” [3]. There are two main types of maintenance; corrective and preventive as shown in Figure 1. Corrective maintenance aims to bring the system back to its proper function after a failure or obvious fault detection. Corrective maintenance is failure-based maintenance performed after failure. On the other hand, preventive maintenance is carried out at predetermined intervals that are in certain period and aim to reduce the break down in the operation of the system.

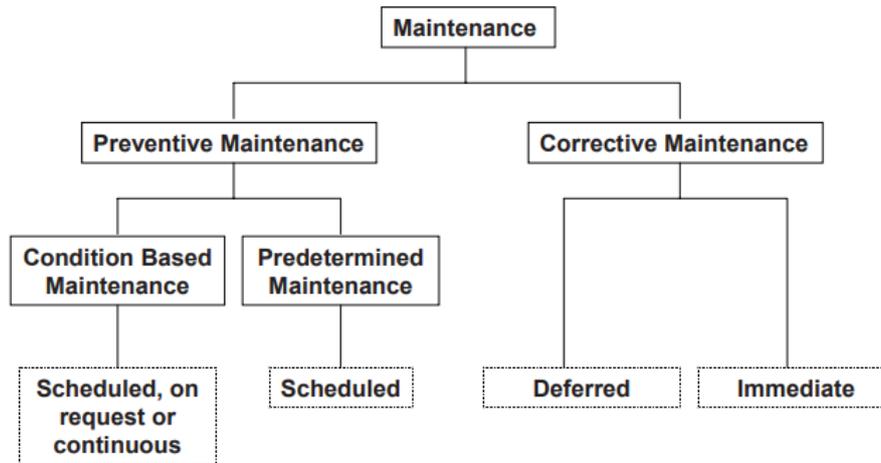


Figure 1. Maintenance Overview (EN-13306: 2010) [3]

According to European standard EN 13306: 2010, the definition of predictive maintenance is “A forecast derived from repeated analysis or known characteristic and evaluation of the significant parameters of the degradation of the item [3].” So predictive maintenance is future planned maintenance based on sensor measurement and analysis of its for mulas. The predictive maintenance integrate into the equipment or system condition monitoring, fault diagnosis, fault predicted maintenance decision support, and maintenance activities,

that is a new maintenance method and it can increase economic efficiency and equipment availability [4]. For this reason, predictive maintenance, which is a type of preventive maintenance, has recently been preferred in maintenance practices.

Prognostic technology includes many aspects such as giving advanced alerts about up coming faults and predicting remaining useful life, which ultimately results in increased availability, reliability, and reduced maintenance and logistics cost [5]. Factories aim to integrate the prognostic maintenance strategy into their factory environments to monitor and manage the production processes comfortably, to set maintenance times, to prevent costly losses, and to interfere in the system without causing system failure in case of any error. Prognostics have started to be applied to industrial environments to reduce cost and maximize working performance, and estimation of remaining useful life time, which is an area of prognosis and health management (PHM), has been more preferable. RUL estimation is a process that uses estimation methods to predict the future performance of the machines or equipment and obtain the remaining life time before the machine loses its ability to operate [2].

With Industry 4.0, factories can obtain information about the status of their equipment with the help of sensors and other tools. By processing this collected data and comparing it with other error conditions, they can predict future error situations and time or predict the remaining useful life of the device. They can make maintenance planning by transmitting information such as error cases that may occur and their remaining useful life estimates, to the relevant departments, change or fix them if the life time of any machine or equipment has expired, and prevent failures that may occur in the system. That's why, proactive maintenance benefits manufacturers by preventing failures in the production line, cost losses, and unnecessary maintenance costs.

II. SYSTEMATIC MAPPING PROCESS

Systematic mapping studies are like systematic review studies, however, they are intended to map out topics rather than synthesize study results and wide inclusion criteria are used [6]. A systematic literature review is a means of identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest [7]. The primary studies are used for the systematic review, however, the systematic review is itself a secondary study form. Systematic mapping study (also known as Scoping Studies) provides a wide overview of a research area [8] also focuses on primary studies in a specific topic area and aims to identify, classify, and map studies. A systematic mapping study ensures a categorical architecture for classifying researched reports which are published and their results [6]. The study presented here focuses on predictive maintenance and remaining useful life: conference papers and articles published between 2010 and 2020. Articles and conference papers published up to the 4th month in 2020 were checked.

The general steps of an SMS are shown in the following diagram (see Figure 2). The steps of our systematic mapping study are the determination of research questions, searching for relevant papers, screening of papers, the definition of the keyword of abstracts, and data extraction and mapping also every step has an outcome and the last step of the process is the systematic map [9].

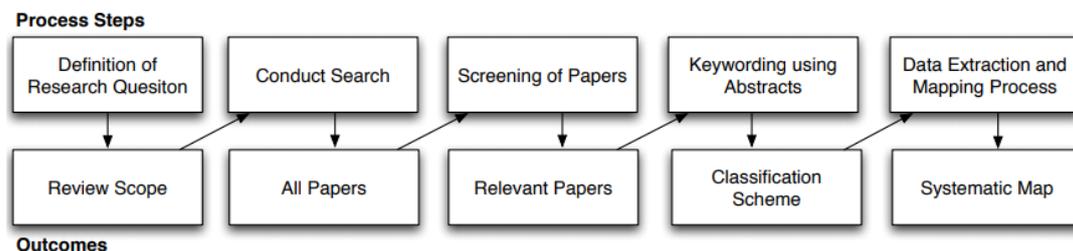


Figure 2. Systematic Mapping Process (Adapted from Petersen et al. [9])

This study was aimed to determine the methods used in predictive maintenance and remaining useful life, and to provide an overview of the topics by using articles and conference papers published between 2010- 2020. When searching the literature for related articles or conference papers, the usual rule is: be thorough, use various key words and data bases, and look at who has mentioned past relevant articles and book chapters [10].

A. Goals and Research Questions

In any study, research questions that are prepared and the study should have a purpose. The aims of this study have shown in the followings:

A1: To understand the content and purpose of articles that contain predictive maintenance and remaining useful life.

A2: To determine the techniques and algorithms used in predictive maintenance and classify articles.

A3: To identify in which area predictive maintenance activities are currently preferred and used.

A4: To learn the latest trends in predictive maintenance and to guide future research.

A5: To determine the most active researchers and the most influential articles in the area for predictive maintenance.

The aims lead to our research questions. Research questions need to determine the purpose and the goals of the study. In this study, we prepared a few research questions to classify studies. A1, A2 and A3 goals lead us to the first research questions set. Related research questions and their goals are shown below:

RQ1.1: What is the main motivation of the published article?

- To identify the goal of the published article and to understand why predictive maintenance is needed.

RQ1.2: Which intelligent techniques are often applied for predictive maintenance and remaining useful life?

- To determine which intelligent techniques are used most in published studies and to classify which method works better.

RQ1.3: Which data set was used? What is the test/training ratio of the data set used?

- To determine whether the data sets were obtained from simulations, sensors, past studies, or public data repositories.

RQ1.4: Which estimation method is used for predictive maintenance?

- To classify in which area has been studied with which prediction method.

RQ1.5: How is feature extraction applied when performing predictive maintenance?

- To determine whether the feature extraction and selection step is applied

RQ1.6: In which venues have the works been published?

- To determine whether the studies have been published in conferences or journals and to identify their distribution in the period.

According to A4 and A5, we ask a few more questions to understand the latest trends, to determine in which area most popular for predictive maintenance, to classify articles, and to identify future aims in predictive maintenance. Aims are A4 and A5 lead us to our second research question set. The questions are shown in following:

RQ2.1: Which domains are the most preferred to apply predictive maintenance?

RQ2.2: Which methods have been used to determine the predictive maintenance performance achieved?

RQ2.3: What is the yearly article count?

B. Article Selection

Articles election is one of the most important steps for secondary studies. This is because the selected articles form the basis of the study. In this study, a three-stage process presented in previous systematic mapping articles [7, 9] has been adopted for the selection phase of the articles: first, the articles are determined using digital libraries and search engines, second, exclusion criteria are defined and the articles outside the scope of the study are

eliminated, finally, the inclusion criteria are defined and the sources that may have been missed include to the study.

- Step 1: Article Determination

First of all, we determinate key words to select the articles from the following digital libraries and search engines: IEEE Xplore and Science Direct. Also, we used Google Scholar to check citation count. The articles that include predictive emaintenance, remaining useful life, remaining useful life time, and machine learning key words and they are between 2010-2020 are selected. 199 articles are collected from the first step.

The query string created to search articles has shown below:

((("machinelearning")) AND "predictive maintenance") AND "remaining useful life")

- Step 2: Exclusion Criteria

In the second step, we identified the exclusion criteria: languages other than English, not relevant to the topic, book chapters, short communications, secondary studies, abstract only, and courses. When we applied these exclusion criteria's, the count of our result articles has been updated as 155 articles [47].

- Step 3: Inclusion Criteria

In the article determination step, we applied the inclusion criteria: primary work, relevant with the topic, the language in English, and using intelligent systems.

C. Data Extraction

In the data bases we have reviewed, we have identified 199 published studies on predictive maintenance and remaining useful life. Then, we applied the inclusion and exclusion criteria mentioned above to these articles. According to our results, 155 articles [47] in our article pool were found in accordance with the criteria we wanted. Finally, we examined each of the studies obtained according to the research questions we have identified and entered the answers we found in a file of .csv format.

III. RESULT OF SYSTEMATIC MAPPING

We evaluated all the studies we have obtained according to the research questions and goals we have created for our SMS. We also expressed some of our evaluation results graphically to make them more understandable. We are ready now to answer our original research questions from RQ1.1 to RQ1.6. Our first phase questions and their evaluations are below:

RQ1.1: What is the main motivation of the published article?

Figure 3 shows a pie chart arranging the answers to RQ1.1 for published works that are obtained. As shown in Figure 3, with 37%, most studies' subject is remaining useful life prediction. 29% examined detection of failure, and 13% directly investigated maintenance planning and its time. Usually, the useful life prediction in remaining useful life prediction studies reviewed was made to prevent unnecessary maintenance and to avoid costly losses. As an example, the approach in [11] emphasizes that it is necessary to analyze the history of a system to estimate RUL and calculates the remaining useful lifetime using historical data. The prognostic approach applied in references [12-15] has been made to plan maintenance requirements or time. A new cost-oriented predictive maintenance (CDPM) policy, which provides aircraft safety while minimizing maintenance costs, has been proposed with the prognostic method proposed in [16]. Nowadays, instant detection of failure and instant arrangements to be made without stopping the operation of the system have become important. In these requirements, it has shown up real-time and online failure detection applications. In [17], it is aimed to develop a real-time/online distortion detection application by using machine learning. Moreover, 7% studied condition-based monitoring, whereas %4 focused on modeling the degradation process. In [18-21] references, modeling, and analysis of degradation processes are prioritized. Meanwhile, 3% of works aimed to improve RUL accuracy, also %3 prognostics and health management system creation, %2 focused on feature selection modeling. For instance, [22] uses an adaptive-grade particle filter (AOPF) prognostic process to improve the long-term predictive accuracy of RUL with hybrid methods. [23] provides a hybrid feature selection scheme that provides useful and automated guidance in selecting the most representative features for machine health assessment without human intervention. In [2] proposed methodology includes procedures for identifying critical components, as well as tools for selecting the most appropriate algorithms for specific applications and to show how this methodology can help

in the design of an effective PHM system. Finally, the least studied topics with a ratio of 1% are the feature generation for RUL and classification of prognostic methods. Regarding the feature creation for RUL, the process of automatically generating features in accordance with the useful life estimation remaining in [24] has been carried out.

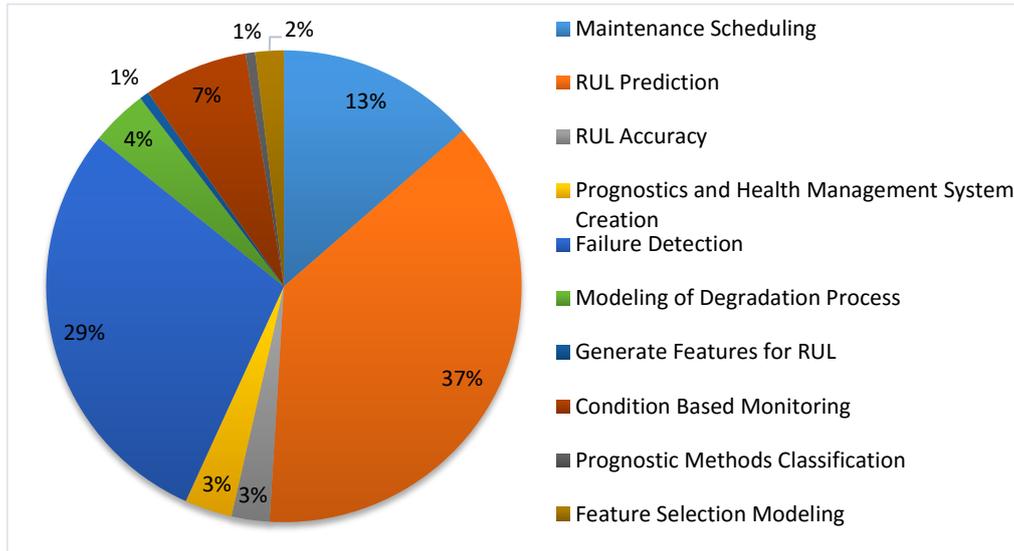


Figure 3. Main motivation of the selected publications

RQ1.2: Which intelligent techniques are often applied for predictive maintenance and remaining useful life?

In response to Question 2, Figure 4 shows the intelligent techniques used mostly in the articles we obtain. The algorithms used once or twice have not been included in the graph. Examples for only once or twice preferred algorithms; Probabilistic Neural Network, Multi-branch Hidden semi-Markov Model, Linear Fusion, Extreme Gradient Boosted Regression Tree, Deep belief network, Conditional Inference Tree, Deep Convolutional Neural Network, Deep long Short-Term Memory, Genetic Algorithm. Besides, in 23 of the articles we obtained, no method or explanation was made. For this reason, we could not include these articles in the graph for RQ1.2. When the graphic is examined, it is seen that the algorithm with the highest usage rate is the Support Vector Machine. Among other methods, other Machine Learning algorithms, Artificial Neural Network, Long Short-Term Memory, Decision Tree, Random Forest, Recurrent Neural Network, K-Means, and Bayesian Network algorithms were preferred more frequently than others. In recent years, the trend towards more Deep Learning algorithms has started. Generally, more than one intelligent technique is used in the articles we have examined. Some were used in data set training procedures and some were used to measure method accuracy, and the results were compared with other selected methods. Generally, it has been seen that the Support Vector Machine gives higher accuracy than other methods.

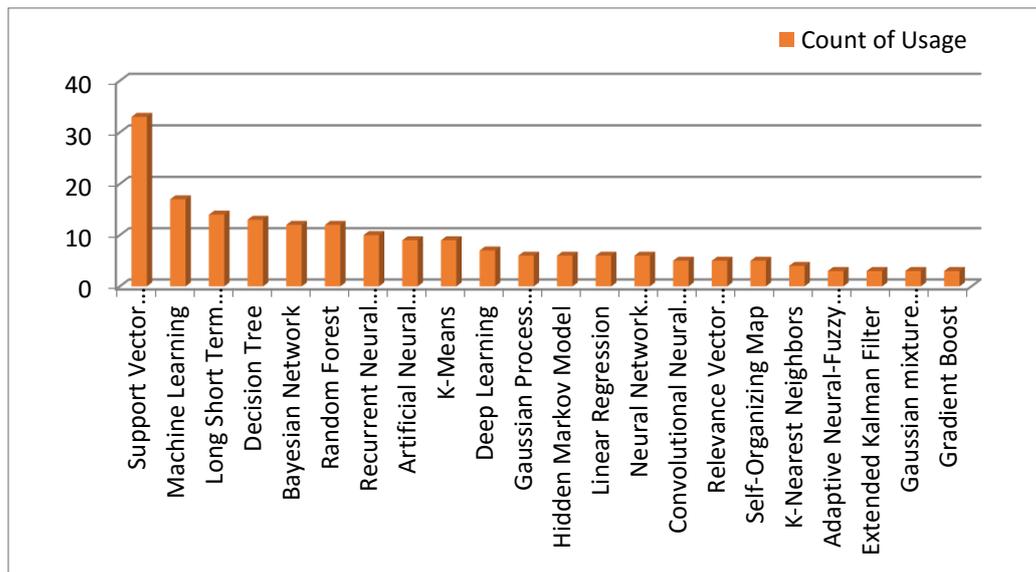


Figure 4. Distribution of the preferred intelligent techniques

RQ1.3: Which data set was used? What is the test / training ratio of the dataset used?

A general infographic about all datasets used in the articles we obtained in Figure 5 was created. As seen in the pie chart, the data used in the studies are generally collected from the machines in the working environments via sensors. Then, it is seen that the datasets that are taken from public data repositories at the rates of 9%, 6%, and 4% are preferred. These are the Turbofan Engine Degradation Simulation Dataset, Bearing Dataset of NASA Prognostics Data Repository, and PRONOSTIA System. Turbofan Engine Degradation Simulation Dataset has been preferred more than others. It is shown that on the graph 10% different data sets are used in the studies. Datasets such as Milling Data Set of NASA Prognostics Data Repository, Wind Turbine Dataset of Suzlon, Condition Monitoring of Hydraulic System Data, Battery Dataset of NASA Prognostics Data Repository and Aircraft Engine Simulation Dataset entered 10% slice. Another slice of 6% states that data sets produced by simulation are used. Because in some articles, if the desired working environment or arrangement cannot be provided, the data are produced in this way in a simulated environment and the studies continue. The least preferred data set was the integration of data from past studies into new articles. Generally, in the articles obtained, datasets are randomly divided into 70-80% training data and 20-30% test data. But this is completely related to your study. There is no rule about separating datasets. In some studies, other datasets are used for testing instead of dividing the dataset into training and testing parts.

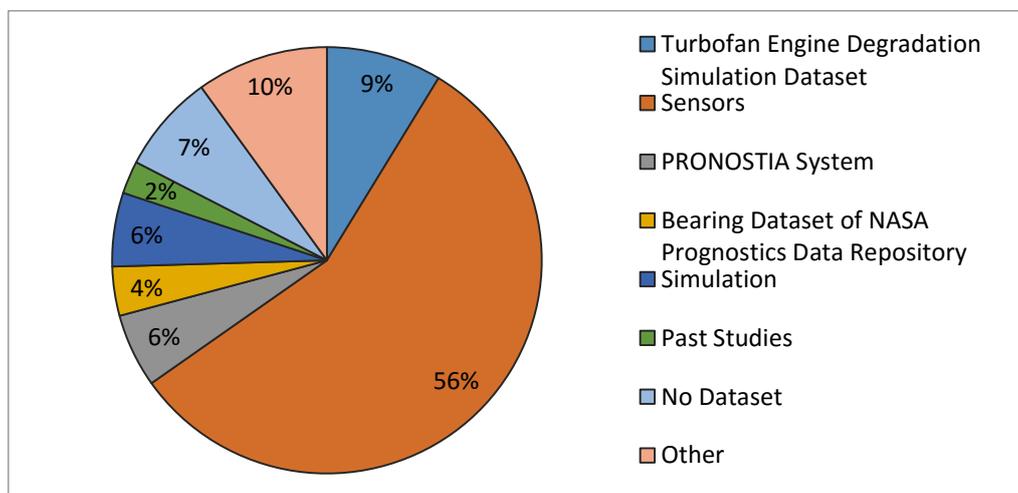


Figure 5. Distribution of the preferred dataset

RQ1.4: Which estimation method is used for predictive maintenance?

There are 3 methods for predictive maintenance to be applied to your problem. These are called data-driven methods, model-based methods, and hybrid methods. To summarize; if you have historical data of the problem and if you are going to perform predictive maintenance using this data, this will be the data-driven method, and if you have personal experience and knowledge, this will be the model-based method and finally, in the hybrid method, other two methods will be applied together. In Figure 6, information is given on which predictive maintenance method is used more frequently in which areas. When the graphic is examined, we see that the predictive maintenance method is most preferred in the industry-factory area. Also, the other most frequently used areas are aircraft components and bearings. The least preferred area is the heavy-tailed area. The articles we obtained are shown in the 'Others' section on the chart, which also includes different usage areas. It has been determined that there are 21 different usage areas in our studies. Examples of these areas of use are turbine blades, hydraulic systems, software reliability, power transformers, transportation systems, and medical devices.

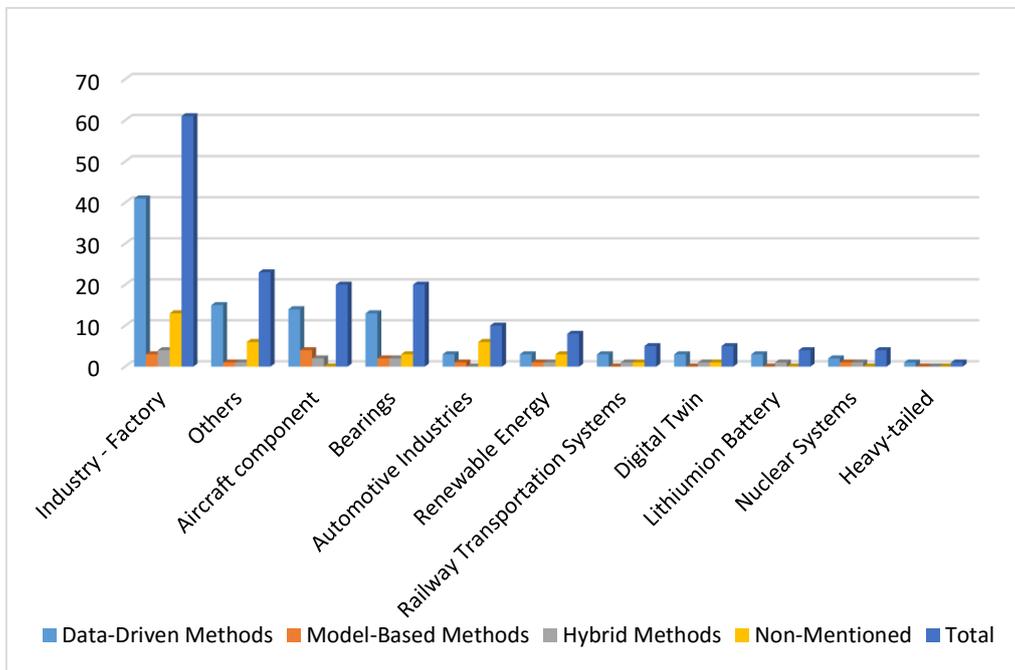


Figure 6. Distribution of the predictive maintenance methods applied to the preferred areas

RQ1.5: How is feature extraction applied when performing predictive maintenance?

Figure 7 shows the pie chart of whether feature extraction or feature selection operations have been made according to the information from the studies. While 56% of the articles are applied the feature extraction step, 44% did not implement the feature extraction step or did not mention it in the article. In the 56% section that applies the feature extraction step, the extracted features, as in references from [25] to [32]; mean, skewness, kurtosis, peak, standard deviation, root mean square, minimum, maximum, etc. In some studies, more than one feature has been extracted according to the time-domain, frequency-domain, and time-frequency domain. For instance, in [33], 13-time domain features, 16 time-frequency domain features, and features based on trigonometric functions are extracted. In [34], a total of 28 features; 11 time-domain features, 9 frequency-domain features, and 8 time-frequency domain features, have been extracted. Moreover [35] and [36] Auto Encoder based, [2] Fast Fourier Transform (FFT) and [37] and [38] K-means based feature extraction method is used.

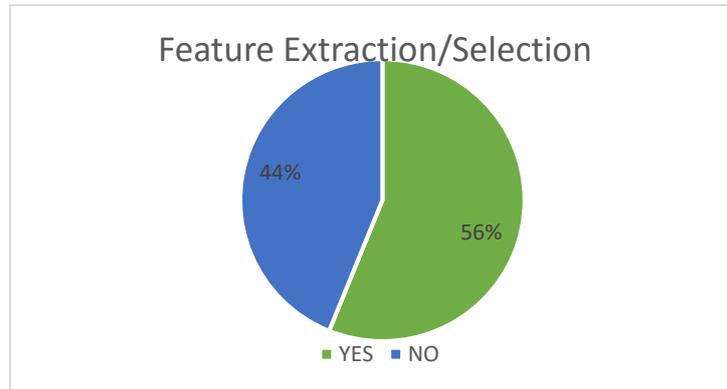


Figure 7. Feature extraction/selection of the selected publications

RQ1.6: *In which venues have the works been published?*

In response to RQ1.6, the publication types and publication frequency of the articles we have collected for our SMS study are shown in Figure 8. When the graphic is analyzed, we see that only the conference paper was published in 2010 and the only research paper was published in 2011. In this way, predictive maintenance and the remaining useful life have started to join the literature. Then, only conferences and research papers were published between 2012 and 2015. While no journal paper was published until 2016, all types of publications started to be published together in 2016, and it has been continued until today. When the general structure of the graph is analyzed, we see that generally the research studies have been published and the demand for research publications has increased since 2011. If we pay attention to 2019, we see the highest publishing rates in all types of the published papers. Since the conferences were canceled in 2020 due to the pandemic occurring worldwide, there was no conference paper among the articles we obtained until the period we examined.

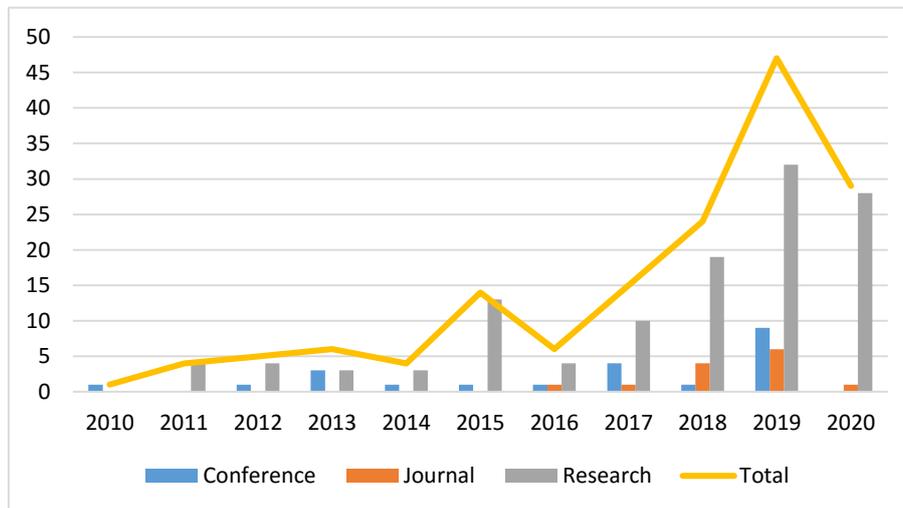


Figure 8. Yearly distribution of the selected publication types

After answering the questions in the first phase, we will answer the questions from RQ2.1 to RQ2.4 that we created in the second phase. You can find the second phase questions and their answers below:

RQ2.1: *Which domains are the most preferred to apply predictive maintenance?*

After classifying and examining the studies we have obtained according to the questions we have determined, we have seen that the predictive maintenance activities are preferred more in industrial works and factory environments. The reason for this is that the slightest error or breakdown that will occur in the production environment causes very high-cost losses. For this reason, with Industry 4.0, predictive maintenance activities have become more important in the development of a smart factory environment. In Figure 9, you can examine the graph consisting of the sectors where predictive maintenance is used the most. Also, aircraft component and

bearings are two of the most popular areas which are applied predictive maintenance. When the graphic is analyzed, the field 'Others' stands out. There are many different areas where predictive maintenance is applied and these areas have been considered in the 'Others' category since they are not among the most preferred areas. To give example to the 'Others' category; Hydraulic System, Railway Point Systems, Gas Turbine Exhaust System, Medical Devices and Software Reliability are just a few of them.

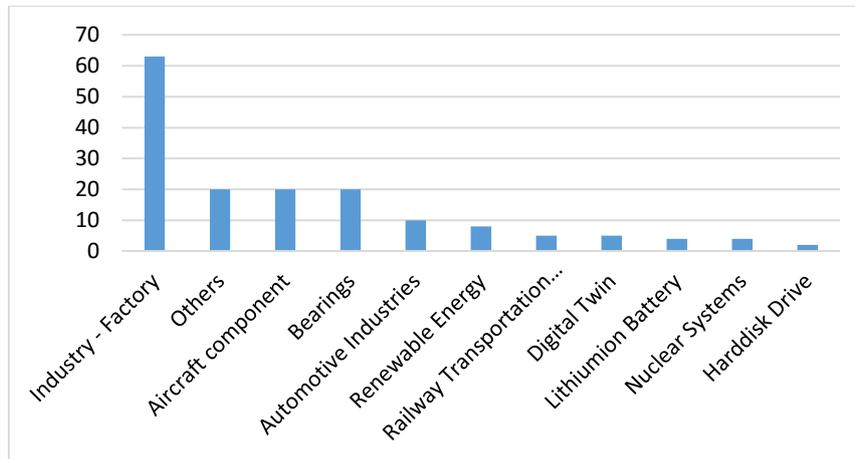


Figure 9. Distribution of the preferred predictive maintenance areas

RQ2.2: Which methods have been used to determine the predictive maintenance performance achieved?

In response to question RQ2.2, Figure 10 shows the performance metrics applied to all the studies we have. As can be seen from the bar graph, the most preferred performance measurement method was 'Root Mean Square Error'. The next 'Experimental Study' shows us that the performance measurements of the studies are performed in a simulated or experimental environment. Another preferred method 'Comparison of Intelligent Methods' means measuring the accuracy of the results obtained by comparing them with other methods. As in the studies [17, 34, 39, 40], the results of predictive maintenance are compared with other selected methods or methods. As a result, the most optimum solution is found by comparing methods from given the best results. The area that appears on the graph as 'Other' contains performance metrics such as Model Correlation Coefficient [35], Software Product Quality Metrics (ISO / IEC 9126, 25041, 25051) [41], α - λ Metric [42] and Opinion of a Machining Expert [43]. To evaluate the performance of clustering algorithms, metrics that not sufficiently reliable are used such as homogeneity score, integrity score, V measurement, corrected Rand index, corrected mutual information, silhouette coefficient. In this case, as in [43], the results can be evaluated in the opinion of a machining expert. Another outstanding performance measurement criterion is the 'Compared Actual RUL and Estimated RUL' option. As in [44-46], estimated remaining useful lifetime (RUL) were compared with the real value and the performance was measured.

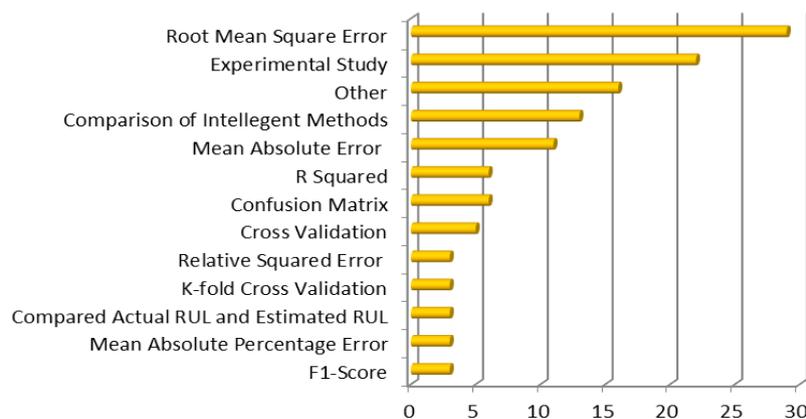


Figure 10. Distribution of the performance metrics

RQ2.3: *What is the yearly articles count?*

Figure 11 provides information on the years of publication of the articles we have obtained on predictive maintenance and remaining useful life. As can be seen from the column chart, the predictive maintenance topics more and more became popular between 2010 and 2014, and after 2015, further studies were carried out. Among the studies we have collected, the studies published in 2019 show an increase compared to other years. For this reason, as seen in the graph, 2019 appears to be the year in which most studies were published on predictive maintenance and remaining useful life. Articles we obtained were collected from the period until the middle of 2020, so the published article result could be different for the end of 2020.

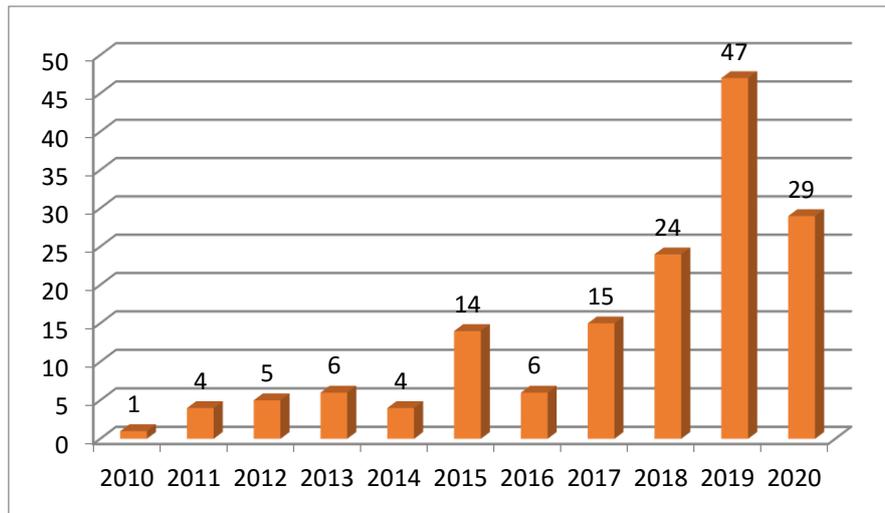


Figure 11. Distribution of the selected publications per year

We have shown the results graphically by answering all the questions we have created according to the goals we have determined. The answer to all these questions will guide people who will work with predictive maintenance and remaining useful life. The questions we answered responded to a lot of information such as why predictive maintenance is necessary, which areas it is applied to, where datasets are obtained, what techniques are used, and what kind of studies are published in which period.

IV. DISCUSSIONS

We evaluated the articles we have collected according to certain criteria according to the questions we have formed in terms of different aspects and functioning of the application areas of predictive maintenance and remaining useful life. By explaining the general results, it has been provided that the results are shown graphically for each question created about the topic discussed in the article. Below, the main results of the systematic mapping study questions we discussed are briefly mentioned.

According to our research results, the most common purpose of using predictive maintenance is the remaining useful life estimation with a ratio of 37%. Next is the detection of the failure with 29% and maintenance planning with 13%. These three methods, whose rates are given in any production area, will prevent time losses by providing financial gain. The most common algorithm used in predictive maintenance is the Support Vector Machine algorithm. Machine Learning algorithms, Long Short-Term Memory, Decision Tree, Random Forest, Recurrent Neural Network, K-Means, and Bayesian Network algorithms come after the Support Vector Machine. Besides, the use of Deep Learning techniques has increased in recent years. Generally, more than one algorithm is used at the same time in the articles we have discussed. Some are used to get results; others are used to evaluate the result and provide a comparison. 56% of the data to be used in the methods discussed are collected through the sensor from the application area. The data and amount of data have varied for each problem. Other data acquisition methods are to take data from public data repositories. If we look at the areas where predictive maintenance is mostly applied; we can see that there are industry and factory environments or aircraft components. Generally, the data-driven method is preferred because the data are taken from the sensors in the application area. To make our

results smoother and more useful, operations, such as extracting the features in the data and selecting the features are performed. In the articles, we collect 56% feature extraction and selection steps have been applied.

If we explain the progress of the studies on predictive maintenance and remaining useful life until today; with the publication of all kinds of studies such as conference, research, and journal after 2016, the topics of predictive maintenance and remaining useful life continued to be included in literature with each type of studies. After 2016, we see that the rate of publishing research articles has increased every year and in 2019, the most research articles were published compared to all years.

The SMS study's findings may have been affected by the determined search criteria and keywords, the selected databases, the period (years) chosen, and the terms preferred. The potential threats to the validity of our SMS have been discussed below and it explained how we take precaution for threats:

Internal validity: Internal validity supports that the results of a causal study should be reliable. To collect the articles used in our SMS study, a search was made according to the queries determined in various databases. Afterward, exclusion criteria were applied as mentioned in the Article Selection section, and the studies that remained outside the subject were removed. All the goals of our SMS study and all questions created to achieve the determined goals are directly related and all of them are designed properly to apply the topic of predictive maintenance and remaining useful life.

External Validity: External validity supports the generalizability of a study's findings. SMS research findings shed light not only on predictive maintenance and remaining useful life but also on artificial intelligence methods and areas of use. On the other hand, there may be a potential use of an artificial intelligence method that has not been used in the field of predictive maintenance yet, but it is not mentioned in the SMS study because it has not been published yet.

Conclusion Validity: By visually presenting the findings of the questions determined for the targeted aims is significant for our SMS study. By visually arranging all the results obtained in our SMS study, subjective interpretation of the collected results was prevented and the follow-up of the results by the researchers was made easier. The findings obtained for each target and each question created for the targeted objectives were supported by using various graphics or figures.

V. CONCLUSIONS

In this research, we have conducted an SMS study surveying the publications of 2010 and 2020. Studies are obtained about predictive maintenance and remaining useful life. Predictive maintenance activities started to enter our lives with Industry 4.0 to provide smart factory environments. However, maintenance is costly and maintenance times are difficult to set up. Failure of any equipment can cause the system to stop or other parts to malfunction. Continuous unnecessary maintenance and problems that cause the system to breakdown cause cost losses. With predictive maintenance, enterprises can take the information about which equipment will fail and the remaining useful lifetime and they will arrange maintenance planning, equipment replacement. Therefore, the importance of predictive maintenance in businesses is increasing day by day. By using electronic databases, such as IEEE Xplore, Science Direct, and Google Scholar, 199 studies were obtained that meet the criteria we want. Then the exclusion and inclusion criteria we determined were applied to the studies obtained and evaluated. A total of 155 studies were found to be interrelated and they are included in the SMS study. According to our results, the purpose of lots of the studies is related to the remaining useful lifetime prediction. While the general target is the calculation of the remaining useful lifetime, the second purpose is determined as failure detection. Also, the general goal of these studies is the remaining useful life estimation after failure detection. When the studies were examined, it was seen that the studies on predictive maintenance and the remaining useful life have provided functionality and financial gain to the environments in which they are applied.

According to our research results, predictive maintenance studies increase after 2016. Generally, the dataset used is obtained from the sensors. Whichever machine learning is being applied to predictive maintenance, healthier results can be obtained by collecting data from that machine or equipment. If there is no environment to collect data, studies can be continued by applying the intelligence techniques by obtaining data from public data repositories. In the studies we collected, predictive maintenance applications were mostly applied to industrial and factory environments. Considering the results of the studies, most of them preferred the Support Vector Machine algorithm and used Root Mean Square Error for performance evaluation. In future studies, predictive maintenance studies can be used to obtain information about the general condition of the system, not just equipment, and the overall maintenance schedule can be adjusted automatically.

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