Review and Framework for Data-Driven Joint Predictive Maintenance and Inventory of Spare Parts

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Abstract

Predictive maintenance is one of the developments of maintenance activities to ensure the continuity of the production process, especially for companies with continuous production processes. However, predictive maintenance activities require support from other departments, one of which is the availability of spare parts. This study conducted an in-depth analysis of 11 previous studies regarding joint or integration in predictive maintenance. Based on the results of the research, it is known that only a few joint or integration models in predictive maintenance are included in the use of a data-based approach to utilize data collected in real-time. Furthermore, this study proposes a framework that can be used in developing a data-driven joint predictive maintenance and inventory model of spare parts in multi-components/ multi spare parts.

Keywords
Predictive Maintenance, Inventory Management, Spare Part, Data-driven

1. Introduction
Maintenance is one of the critical activities in the company, especially in companies with continuous production processes, to ensure production runs. The smooth production process for companies with continuous production processes is very important because unplanned termination of the production process can result in significant losses. Maintenance keeps the machine running to reduce the company's losses from downtime on the machine (Paul et al. 2022). Therefore, many studies focus on maintenance and how to improve the efficiency of the maintenance process.

The company's development towards Industry 4.0 also attracts the development of maintenance. One of the developments of Industry 4.0 is real-time performance measurement and production control Alarcón et al. (2021). The application of real-time performance measurement and production control in the company determines maintenance policies that can be done based on real-time measurements based on the sensors used. One of the developments of maintenance policy is predictive maintenance. Predictive maintenance uses predictive tools to determine the required maintenance actions. Predictive maintenance is famous because it can reduce maintenance activities related to maintenance costs and reduce downtime (Motaghare et al. 2018; Wen et al. 2022). Not only that, predictive maintenance can also increase productivity and increase efficiency in the use of finance and resources (Dalzochio et al. 2020). According to Montero Jimenez et al. (2020), predictive maintenance can reduce maintenance costs by up to 25-35%, reduce breakdowns by 70-75%, reduce downtime by 35-45%, and reduce production by 25-35%.

Maintenance policies, including predictive maintenance policies, of course, significantly affect the availability of spare parts. According to Driessen et al. (2014), the system's downtime can be divided into two, namely due to diagnosis & maintenance time and maintenance delays caused by the unavailability of the resources needed for diagnosis and maintenance. So, it can be seen that the resources required, in this case, spare parts, are closely related to maintenance, where a shortage of spare parts can cause downtime even though the maintenance policies applied are appropriate.

As mentioned earlier, maintenance performance is also related to the availability of spare parts. This dependence causes maintenance activities within the company to depend on activities supporting the availability of spare parts, such as storage activities or procurement of spare parts at the company. Not only related to storage and procurement activities of spare parts, but even production activities can also affect maintenance activities in the manufacturing industry (Rokhforoz and Fink 2021). On the other hand, policy determination of activities within the company is often done separately. For example, maintenance policies are only set by the company's maintenance department, inventory policies are only set by the warehousing department, and procurement policies are only set by the company's procurement department. Determining policies carried out separately causes the resulting policies to be not optimal for the integrated system.

This paper will begin by surveying all literature reviews on predictive maintenance, researching papers related to joint predictive maintenance of spare parts, and conducting a state-of-the-art analysis of joint predictive maintenance of spare parts. Based on an analysis of state of the art, this study will synthesize research challenges and propose a framework for joint predictive maintenance of spare parts.

2. Related Literature Review

Currently, several papers have done literature reviews regarding predictive maintenance. The focus of the literature review regarding predictive maintenance varies, ranging from predictive maintenance techniques and applications, industry applications, to the application of the latest technology in predictive maintenance. Literature reviews that focus on methods and the application of predictive maintenance were carried out by Hashemian and Bean (2011), Selcuk (2017), Bousdekis et al. (2019), Bousdekis et al. (2020), Dalzochio et al. (2020), Montero Jimenez et al. (2020) and Wen et al. (2022). An industry-focused literature review of predictive maintenance practices by Tinga et al. (2017) and Tiddens et al. (2022). A literature review discussing the latest developments in predictive maintenance based on technological developments was reviewed by Sang et al. (2020), Zonta et al. (2020), and van Dinter et al. (2022).

The study of techniques and the application of predictive maintenance has evolved from general engineering studies conducted in predictive maintenance to the development of techniques and the application of predictive maintenance. Hashemian and Bean (2011) conducted a state-of-the-art search for techniques in predictive maintenance. The techniques referred to in this study are data collection techniques from existing sensors, data collection techniques from sensors installed on plant equipment, and injecting test signal techniques into the equipment. This study focuses more on the technical aspects of predictive maintenance. Selcuk (2017) developed a predictive maintenance analysis regarding implementation and the latest trends. This study discusses techniques for predictive maintenance ranging from vibration analysis to acoustic analysis. This study also examines the development of predictive maintenance, namely the application of a computerized maintenance management system (CMMS). This study also maps the application of each technology or technique of predictive maintenance. Bousdekis et al. (2019) conducted a study on decision-making in the application of predictive maintenance. Based on the study, there are five areas in predictive maintenance decision-making: maintenance planning and scheduling; reliability and degradation-based decision-making; joint optimization; multi-state and multi-component system optimization; and maintenance cost and risk estimation and optimization. Based on this research, it is known that several development directions can be carried out, namely the development of real-time decision-making and the development of feedback mechanisms.

Alexandros Bousdekis et al. (2020) conducted a study on the application of predictive maintenance from a business perspective. This study discusses the managerial and organizational implications of implementing predictive maintenance, which should be addressed more. Dalzochio et al. (2020) studied the challenges faced in using machine learning in predictive maintenance and the main contribution in the last five years of research. The study begins with mapping the machine learning used in the ontology of predictive maintenance. Montero Jimenez et al. (2020) studied the multi-model approach in predictive maintenance, which began by discussing the single-model approach. A multi-model approach is an approach that develops by combining models from a single model. This study examines the model used in the single model and the development of the model in the multi-model approach. Wen et al. (2022) studied the data-driven prognostic algorithm used in predictive maintenance. This study divides data-driven prognostic models into statistical-based models, conventional machine learning-based models, and deep learning-based models.

One study that discusses predictive maintenance in the industry is by Tinga et al. (2017). Tinga et al. (2017) deepened predictive maintenance application in the maritime system. This study discusses starting from the part selection step, developing predictive models for the selected part, to mentoring and data collection, which cannot be separated from the validation stage. Furthermore, Tiddens et al. (2022) developed by studying predictive maintenance applications in various industries. The research conducted by Tidden aims to find patterns of conditions as initial input for applying appropriate maintenance techniques. However, this research has yet to carry out a mapping of the application of maintenance in each industry. It has yet to provide suggestions for the application of maintenance in each industry and has yet to evaluate the application of maintenance in each industry.

Technological developments certainly bring developments to predictive maintenance. The development of predictive maintenance in Industry 4.0 was studied by Sang et al. (2020). Sang et al. (2020) conducted a literature review of predictive maintenance, starting from examples of predictive maintenance applications in the industry, the application of IDs and blockchain in predictive maintenance, to the framework of predictive maintenance. Zonta et al. (2020) conducted a development study of predictive maintenance due to the development of Industry 4.0. Zonta et al. (2020) also made a taxonomy of predictive maintenance research in the industry 4.0 era. One of the developments in predictive maintenance is the application of digital twins. Van Dinter et al. (2022) conducted a literature review on the application of predictive maintenance using digital twins. This study analyzes predictive maintenance research using digital twins, starting from the development goals, domains, digital twin platforms used, models developed, approaches used, to barriers to implementation.

There are quite a lot of literature reviews that have been done on predictive maintenance. However, these studies have not focused on predictive maintenance with specific objects. This research will conduct a literature study of predictive maintenance research focusing on spare parts. The previous literature review has yet to discuss the application of predictive maintenance integration with other sectors. Therefore, research will conduct a study on the integration of predictive maintenance with spare part objects that have never been done. Based on this investigation, this study proposed a framework for the integration of predictive maintenance of spare parts.

3. Methodology

The methodology used in this literature review is from Tranfield et al. (2003). The methodology begins with planning the review, conducting the review, and reporting and analyzing the report with details, as can be seen. The planning of the review is done by first determining the research questions and search strategy. The research question will be "What are the characteristics of studies related to the integration of predictive maintenance of spare parts?".

Search Strategy

In this part, we must define the strings we will use in databases. The databases that we will use are ScienceDirect, IEEE, and Scopus. The strings must accommodate other words or complementary words to the keywords used. Therefore, the word "integration" will also be supplemented with the word "joint" or "integrated". The strings used can be seen in Figure 1.

“predictive maintenance” AND “spare part” AND (joint OR integrated OR integration)

Figure 1. Search String

Article Selection

After searching the databases using the string indicated in Figure 1, the next step is to filter the results to ensure that they align with the target of the literature review. Several criteria filter the results, as shown in Table 1. The first criterion used is the time frame that is the focus. The time frame used is 15 years, from 2008 to 2023, considering that predictive maintenance is a development of maintenance policies due to technological advancements. Furthermore, a filter is applied to ensure that the results are from journals or conferences, and the language is English. To ensure that the results discuss the integration of predictive maintenance with spare parts as the object, a filter is applied by checking the keywords in the title, abstract, and keywords.

Table 1. Criteria of Article Selection

Section	Criteria
Criteria 1	Filter looking for the period for 15 years, 2008 to 2023
Criteria 2	Remove short surveys, letters, editorials, book
Criteria 3	Remove documents that are not in English

Criteria 4	Remove all publications that do not use the search term predictive maintenance and (joint, integrated, or integration) in the title, abstract, or keyword
Criteria 5	Remove all publications that do not discuss implementing predictive maintenance integration in spare part objects with other parts

This entire filtering process is carried out for each database used. The results of this filter are then entered into Mendeley for further checking. The results of the article selection with the criteria mentioned can be seen in Figure 2. After filtering the three databases, 13 selected papers were obtained, which will be reviewed in this study.

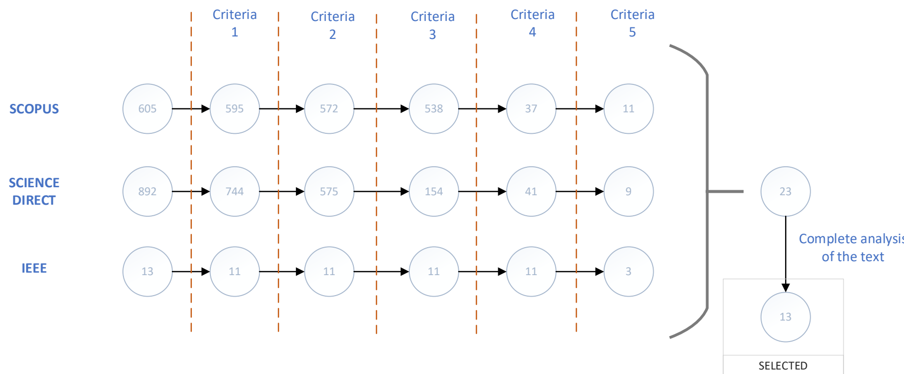

Figure 2. Screening of Research

4. Result & Discussion

The selected articles are listed in Table 2 and Table 3 with author, title, year, types of publications, publishers, and conference or journal names. It can be seen that around 60% of the selected papers are journals, while the rest are from conferences. The majority of the publishers of the selected papers are from Elsevier. Next, a more detailed discussion will be conducted for each paper chosen to search for research gaps in joint predictive maintenance of spare parts.

Table 2. Selected Articles

No	Author	Title	Year	Type	Publisher	Name
1	Liu et al.	A dynamic predictive maintenance model considering spare parts inventory based on hidden semi-Markov model	2013	Conference	SAGE	Proceedings of the Institution of Mechanical Engineers
2	van Horenbeek and Pintelon	A joint predictive maintenance and inventory policy	2015	Conference	Springer	Engineering Asset Management - Systems,Professional Practices and Certification, Lecture Notes in Mechanical Engineering
3	Peng and van Houtum	Joint optimization of condition-based maintenance and production lot-sizing	2016	Journal	Elsevier	European Journal of Operational Research
4	Nguyen et al.	Joint predictive maintenance and inventory strategy for multi-component systems using Birnbaum's structural importance	2017	Journal	Elsevier	Reliability Engineering and System Safety
5	Bousdekis et al.	A Proactive Event-driven Decision Model for Joint Equipment Predictive Maintenance and Spare Parts Inventory Optimization	2017	Conference	Elsevier	Procedia CIRP

Table 3. Selected Articles (continued)

No	Author	Title	Year	Type	Publisher	Name
6	Bousdekis and Mentzas	A Proactive Model for Joint Maintenance and Logistics Optimization in the Frame of Industrial Internet of Things	2019	Conference	Springer	Springer Proceedings in Business and Economics
7	Liu et al.	Single-machine-based joint optimization of predictive maintenance planning and production scheduling	2019	Journal	Elsevier	Robotics and Computer-Integrated Manufacturing
8	Foerster et al.	Integration of condition-based maintenance orders into the decision-making of autonomous control methods	2019	Conference	Elsevier	Procedia CIRP
9	Schreiber et al.	Integrated production and maintenance planning in cyber-physical production systems	2019	Conference	Elsevier	Procedia CIRP
10	Vu et al.	A predictive maintenance policy considering the market price volatility for deteriorating systems	2021	Journal	Elsevier	Computers & Industrial Engineering
11	Xue et al.	Joint Maintenance Decision Based on Remaining Useful Lifetime Prediction Using Accelerated Degradation Data	2022	Journal	IEEE	IEEE Access
12	Yu et al.	A two-stage Genetic Algorithm for joint coordination of spare parts inventory and planned maintenance under uncertain failures	2022	Journal	Elsevier	Applied Soft Computing
13	Liu et al.	Simultaneous predictive maintenance and inventory policy in a continuously monitoring system using simulation	2023	Journal	Elsevier	Computers & Operations Research

4.1 Joint Scheduling and Planning

As previously explained, this research will focus on predictive maintenance research that integrates with other parts. Based on the selected articles, as seen in Table 4, it can be observed that the integration of predictive maintenance can be divided into integration with inventory and production parts. Integration with inventory is carried out to anticipate spare part shortages when maintenance is to be carried out. Integration with inventory varies according to the model's decision variables; some studies focus on ordering policies in inventory problems, and some studies focus on integrating into setting storage policies in inventory problems. Unlike integration with procurement and inventory, integration with production parts relates to the production machine, which is the location of the spare parts object that becomes the focus of maintenance activities. This integration is carried out because the implementation of maintenance will cause the production machine to stop running, thereby causing production to be halted.

Of the 13 selected articles, 11 develop joint scheduling and planning models for predictive maintenance, while the rest focus on developing aspects of negotiation (Foerster et al., 2019) and procedures before integration is implemented (Schreiber et al., 2019). Foerster et al. (2019) developed a negotiation environment for integrating condition-based maintenance orders. Schreiber et al. (2019) developed a procedure for integrated production and maintenance planning. Next, the decision variables used in the joint predictive maintenance model will be discussed in more detail.

Table 4. Joint Predictive Maintenance

Integration/Joint	**References**
Predictive Maintenance & Inventory	van Horenbeek and Pintelon (2015) Liu et al. (2013) Nguyen et al. (2017) Bousdekis et al. (2017) Bousdekis and Mentzas (2019) Vu et al. (2021) Xue et al. (2022) Yu et al. (2022) Liu et al. (2023)
Predictive Maintenance & Production	Peng and van Houtum (2016) Liu et al. (2019) Foerster et al. (2019) Schreiber et al. (2019)

The decision variables of the joint predictive maintenance and inventory model are quite diverse, and this diversity is not only from the decision variables for the inventory or production problem, but even for the predictive maintenance problem. The summary of the decision variables used in each article can be seen in Table 5. In the decision variables summarized in Table 5, there are several combinations of decision variables based on the similarity of the definition of the decision variable described in the article.

Table 5. Decision Variable for Joint Predictive Maintenance

	Decision Variable								
	Predictive Maintenance			**Inventory**				**Production**	
References	**Maintenance Schedule**	**Inspection cycle**	**Degradation Threshold**	**Ordering Time**	**Ordering Threshold**	**Replacement Threshold**	**Inventory policy s, S**	**Production Quantity**	**Job Sequence**
Liu et al. (2013)	v			v					
van Horenbeek and Pintelon (2015)	v			v					
Peng and van Houtum (2016)			v					v	
Bousdekis et al. (2017)	v			v					
Nguyen et al. (2017)		v	v		v				
Bousdekis and Mentzas (2019)	v			v					
Liu et al. (2019)	v								v
Vu et al. (2021)		v	v			v			
Xue et al. (2022)	v			v					
Yu et al. (2022)		v					v		
Liu et al. (2023)			v				v		

The first combination is the combination of maintenance schedule (Bousdekis et al. 2017; Bousdekis and Mentzas 2019; Liu et al. 2013; Van Horenbeek and Pintelon 2015; Xue et al., 2022) and maintenance time (Liu et al. 2023) into maintenance schedule because both terms describe the time of maintenance execution. Another combination is the combination of the length of the review interval (Yu et al. 2022), inspection cycle (Vu et al. 2021), and inter-inspection interval (Nguyen et al. 2017) into inspection cycle because the definitions of the three terms discuss the period between inspections or reviews. The last combination is the Degradation Threshold as the limit of tolerance for damage as a limit in determining maintenance activities which comes from the threshold of maintenance scheduling (Nguyen et al. 2017), maintenance threshold (Vu et al. 2021), degradation level threshold (Liu et al. 2023), and control limit for scheduling maintenance (Peng and Van Houtum 2016).

Next, a comparison is made of the objective function of each article to see the focus of each article. All articles use the objective function as the total cost of integration. However, the components of the total cost for each article are different. The cost components used in the joint predictive maintenance model can be seen in Table 6. Several components are combined from the maintenance cost and inventory cost components because of the similarity in the definition. The cost component connected to the maintenance cost is the downtime cost. There are several other terms used as references in defining downtime costs, namely failure costs (Liu et al. 2019), cost of failure (Bousdekis et al. 2017), shutdown costs (Nguyen et al. 2017), equipment downtime cost (Liu et al. 2013). However, they all define the same thing: the costs incurred due to the machine or component not working. Therefore, these definitions are combined into downtime costs in summary in Table 6. Another component resulting from the combination is the penalty cost in inventory cost. The terms used are shortage of spare parts, lost sales, and backorders. These terms describe different things, but both represent the costs incurred due to a spare parts or components shortage. Therefore, in Table 6, everything is combined into a penalty cost.

As seen in Table 6, the maintenance cost component used by all articles is corrective maintenance cost, specifically for the maintenance of the replacement type. Apart from corrective maintenance costs, other costs considered in most articles are preventive maintenance costs of the replacement type. Several articles consider repair-type corrective maintenance costs and only one includes a repair-type preventive maintenance cost component (Liu et al. 2023). In addition to these cost components, there are downtime costs that consider losses if damage occurs to the object, set-up costs related to preparation costs for carrying out maintenance, and there are also those that consider inspection costs for models that use input from inspection results.

The components of the inventory cost used are holding costs, purchasing costs, ordering costs, and penalty costs which describe the costs incurred if there is a shortage of inventory. Meanwhile, from a production cost standpoint, both articles use a purchasing cost component. However, the other cost components considered are different, namely the tardiness cost, which describes costs due to delays in the production process (Liu et al. 2019), and scrap costs which represent the costs of losses due to production when the machine is in a damaged position (Peng and Houtum 2016).

Table 6. Component Cost for Joint Predictive Maintenance

References	Maintenance Cost							Inventory Cost				Production Cost		
	Inspection Cost	Set-up cost	Downtime Cost	PM Cost		CM Cost		Penalty Cost	Ordering Cost	Purchasing Cost	Holding Cost	Processing Cost	Tardiness Cost	Scrapt Cost
				R	Rep	R	Rep							
Liu et al. (2013)		v	v			v	v	v	v		v			
van Horenbeek and Pintelon (2015)		v	v		v		v	v	v		v			
Peng and van Houtum (2016)	v	v	v		v	v	v	v			v	v		v
Bousdekis et al. (2017)			v				v	v		v	v			
Nguyen et al. (2017)	v	v	v		v		v		v		v			
Bousdekis and Mentzas (2019)			v			v	v					v	v	
Liu et al. (2019)			v		v		v							
Vu et al. (2021)					v		v	v			v			
Xue et al. (2022)					v		v	v	v	v	v			
Yu et al. (2022)		v	v	v	v	v	v	v	v	v	v			

PM Cost: Preventive Maintenance Cost; CM Cost: Corrective Maintenance Cost; R: Repair; Rep: Replacement

When viewed from the object of the developed model, the majority focuses on a single component/spare part. Some develop non-identical multi-components (Van Horenbeek and Pintelon 2015; Nguyen et al. 2017; Yu et al. 2022; Liu et al. 2023). Meanwhile, if seen from the parameters used as input from the model, they all use degradation parameters. However, this degradation parameter can be divided into two, namely degradation parameters taken from inspection (Van Horenbeek & Pintelon 2015; Nguyen et al. 2017; Vu et al. 2021; Yu et al. 2022) and parameters degradation taken from the sensor (Liu et al. 2013; Peng & Van Houtum 2016; Bousdekis et al. 2017; Liu et al. 2019; Xue et al. 2022; Liu et al. 2023). If we look at the approach the references used, the entire article uses a model-based approach and has yet to enter into a data-driven approach. Most approaches used in solving joint predictive maintenance problems produce exact solutions. However, two articles use heuristics (Liu et al. 2019; Yu et al. 2022).

4.2 Discussion Research Challenges

Based on the results of subchapter 4.1, it can be seen that joint predictive maintenance has developed from inventory and production, with the majority of articles in joint predictive maintenance and inventory. The decision variables used in joint optimization on predictive maintenance problems are divided into a degradation threshold policy to determine maintenance policies up to the maintenance schedule. The inputs in developing problems range from the degradation parameters measured in each inspection to the degradation parameters obtained from the sensors in real time. The development of input collection shows that research has developed into technological developments where degradation parameters have begun to be collected automatically through sensors. However, the data from these sensors is then applied to static batch data and fed into the modeling. This can also be seen from using a model-based approach in all research that uses a mathematical system to produce heuristic and exact solutions. The application of sensors in measuring degradation can become the basis for model development towards a data-driven approach so that the prediction process as the basis for policymaking can be more precise. Model development is also expected to be increasingly moving towards multi-components/spare parts to pay more attention to the dependencies of components/spare parts on real systems, especially for maintenance systems where the interrelation of spare parts can affect the performance of the machine and for inventory systems where procurement can provide lower costs when ordering in large quantities.

5. Framework for Joint Predictive Maintenance and Inventory of Spare Part

Based on the research challenges described, a synthesis is carried out to produce a framework for joint predictive maintenance of spare parts with a joint between predictive maintenance and inventory. The development carried out is in the approach used, which is data-driven using data from sensors collected in real-time. The different approaches will cause the methods used to differ where machine learning will be used in this research. The framework of the model can be seen in Figure 3.

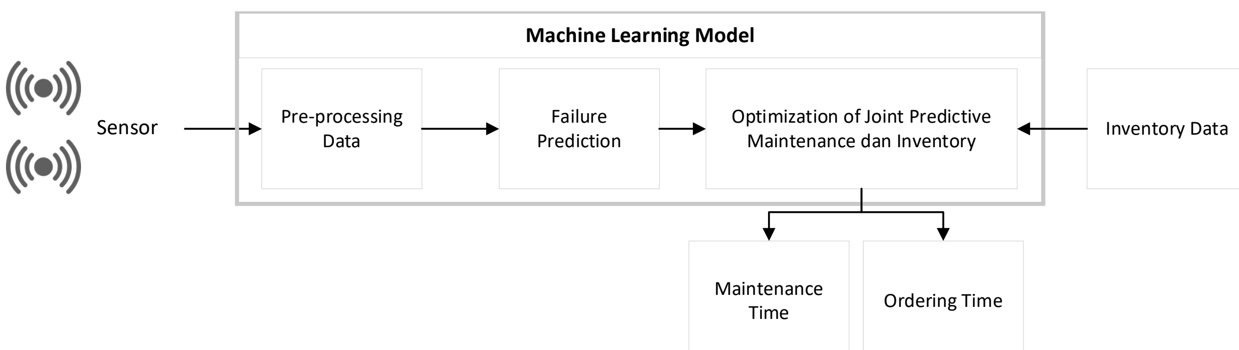

Figure 3. Framework of Joint Predictive Maintenance and Inventory Model

Based on the framework, machine learning will be used in the early stages, starting from failure prediction to optimizing the predictive maintenance and inventory policies that are carried out. The model will also consider multi-components/spare parts so that it will affect the maintenance time policy and order time policy. Multi-component maintenance time policies will affect maintenance time, where maintenance carried out simultaneously will reduce the maintenance cost. Meanwhile, the ordering time policy will also try to combine procurement times to reduce procurement time. The model to be developed will then be tested for the energy industry.

6. Conclusions

This research studies eleven articles that developed an integrated maintenance model, specifically predictive maintenance. The discussion on the predictive maintenance integration model is seen in the integrated parts, decision variables, cost components, objects, and models used. Based on the discussion, it was identified that little goes into multi-component objects or spare parts by using a data-driven approach to produce more optimal results, especially for joint predictive maintenance and inventory problems. The identification results were then developed into a framework to create joint predictive maintenance and inventory of spare part model.

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Acknowledgments

We gratefully acknowledge the funding from the ITB research grant under PPMI (Research, Community Service, and Innovation) 2022 Program.

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