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Decision Framework for Predictive Maintenance Method Selection

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Abstract: Many asset owners and maintainers have the ambition to better predict the future state of their equipment to make timely and better-informed maintenance decisions. Although many methods to support high-level maintenance policy selection are available, practitioners still often follow a costly trial-and-error process in selecting the most suitable predictive maintenance method. To address the lack of decision support in this process, this paper proposes a framework to support asset owners in selecting the optimal predictive maintenance method for their situation. The selection framework is developed using a design science process. After exploring common difficulties, a set of solutions is proposed for these identified problems, including a classification of the various maintenance methods, a guideline for defining the ambition level for the maintenance process, and a classification of the available data types. These elements are then integrated into a framework that assists practitioners in selecting the optimal maintenance approach. Finally, the proposed framework is successfully tested and demonstrated using four industrial case studies. It can be concluded that the proposed classifications of ambition levels, data types and types of predictive maintenance methods clarify and accelerate the complex selection process considerably.

Keywords: decision support; prognostics; predictive maintenance; condition-based maintenance

1. Introduction

In the last decades, maintenance has evolved from merely reacting to failures via preventive replacements at fixed intervals or based on visual inspections to automated methods that continuously inform about the asset's future state [1]. Many different maintenance policies are available now, ranging from traditional corrective maintenance to more advanced policies such as condition-based or predictive maintenance [2]. Moreover, many methods and techniques for monitoring and inspecting assets, analysing data or predicting remaining useful life have been developed [3]. Therefore, selecting the optimal approach for maintaining a specific asset has become quite a challenge for the asset owner.

The first step in this process is the maintenance *policy* selection, i.e., determining which maintenance policy is most suitable in a specific situation. This challenge has been addressed by many authors in the past. Well-known strategies are available to support asset owners in making decisions: reliability-centred maintenance (RCM) assists in selecting the proper maintenance policy, total productive maintenance (TPM) stimulates to improve the complete production process (including maintenance), and a more specific method such as the analytical hierarchy process (AHP) can be used to select the most appropriate policy (i.e., multi-criteria decision making). Moreover, Waeyenbergh and Pintelon [4] have proposed a decision tree for selecting the most suitable maintenance policy regarding both technical and economic implications. All of these concepts mainly advise either a reactive or a proactive (or preventive) maintenance policy, and depending on the method, make more detailed subdivisions in each branch (e.g., condition-based as a specific proactive

policy). As modern systems are, in most cases, critical to operations, proactive maintenance policies have become common practice.

The second step in selecting the most suitable approach is to determine how this policy must be executed. If, for example, a preventive maintenance *policy* has been selected, how can the optimal moment of replacement be determined? The methods and techniques that support the execution of a specific policy typically estimate the mean time between failures (MTBF), assess the system condition [5] or predict the remaining useful life (RUL). Since real-time logging of various parameters, sensors and microprocessors is feasible at present, this type of (big) data can assist in the execution of the selected maintenance policy [6]. However, the number of available methods and techniques is enormous (see, e.g., the recent review in [7]), while at the same time, limited support for this second-level decision is available in the scientific literature. About a decade ago, a study by Grubic and Redding [8] already showed that companies experience a gap between the potential and realised benefits of advanced maintenance methods and techniques. This is confirmed by more recent studies conducted by the authors [9,10], demonstrating that practitioners still find it difficult to select and effectively apply these techniques in practice.

The third and final step is to make detailed decisions on the implementation of the selected method. This concerns, for example, the selection of the sensors or the condition monitoring technique [11] to be used, determining the critical parts in the system [12], or the algorithm [13] and feature selection [14] in data-driven approaches. For all these detailed decisions directly related to the selected method, despite some remaining challenges on application in a real industrial setting (e.g., limited data) [15], quite some decision support methods are already available in the literature.

It can therefore be concluded that mainly the selection of a suitable maintenance method or technique (step 2) is not well-supported yet. These methods and techniques to operationalise the policy are denoted as *maintenance methods* (MMs) in this paper. For a reactive (corrective) policy, the operationalisation is rather trivial, as it just requires a repair or replacement as soon as a failure occurs. However, for a preventive policy, this challenge is acute, as an estimate or *prediction* of the component lifetime is required to properly set the maintenance interval. The latter implies that many of the available methods can be considered to be *predictive maintenance* methods. This work, therefore, focuses on selecting the most suitable predictive maintenance approach, although strictly speaking, some of the simpler methods would be denoted as (traditional) preventive MMs. Nevertheless, in some situations, these might still be the best choice for companies that initially aimed for a predictive maintenance approach.

The scientific contributions of this paper are primarily in the structuring and analysis underlying the proposed decision support framework: (*i*) detailed analysis and classification of the whole range of preventive and predictive maintenance approaches, assessing the strengths/weaknesses and requirements/limitations; (*ii*) definition of the various ambition levels in predictive maintenance and the available data types; (*iii*) linking the methods, ambition levels and data types into the decision support framework. This structured analysis provides valuable insights for researchers on how the large number of preventive and predictive maintenance methods that have been published differ but also relate to each other. This will enable them to develop new methods that can more easily be applied in practice.

For the development of the proposed framework, a design science [16] approach was followed, including three design stages: *problem exploration*, *solution design* and *solution evaluation*. Section 2 discusses the *problem exploration*. A previously reported multiple case study [9,10]—consisting of thirteen cases in various industries in the Netherlands—is used to (*i*) identify the difficulties that companies experience in maintenance decision making and (*ii*) the steps the academic literature describes to use methods and techniques for maintenance decisions. The *solution design* is discussed in Section 3, where solutions are proposed for the identified (sub-) problems. In Section 4, these elements are integrated into

the proposed framework. In Section 5, the framework is *evaluated* by applying it to four case studies. Finally, conclusions and general reflections are provided in Section 6.

2. Problem Exploration

As was discussed before, maintenance methods should support practitioners in maintenance decision making by providing information about the current and preferably also the future (predicted) performance of assets. However, from the performed case study [10], it appeared that practitioners experience several difficulties in the selection of a suitable maintenance method to apply. In this section, the three main difficulties that affect this selection and the application of the MM are introduced and discussed.

2.1. Problem 1—Difficulties in Identifying and Selecting Methods for Predictive Maintenance

Although many methods for maintenance policy selection are available in the literature, such as multi-criteria decision making (MCDM) [17], the analytical hierarchy process (AHP) [18], or reliability-centered maintenance (RCM) [19], methods to select the required MMs are non-existent. Moreover, the separation between policy selection and MM selection is not always completely clear. This is shown in Figure 1, providing an overview of the most common maintenance policies. At the highest level (A), a division is made between reactive, proactive and aggressive policies. The preventive maintenance branch is then subdivided into various policies at levels B and C, where they start to interact with the maintenance methods (e.g., condition monitoring and prognostic methods). The commonly used policy selection methods, such as RCM, support the selection at level A and, in most cases, also at level B. For the selection at level B, various methods are available in the literature that, for example, compare condition-based to time-based maintenance [20] or compare the performance of these methods in terms of life cycle costs [21]. However, the detailed selection at level C, where a specific MM, i.e., a specific monitoring technique or an algorithm to determine the expected failure time [22,23], must be selected, is not supported by these methods. Moreover, the evaluation system for setting up predictive maintenance programmes proposed by Carnero [24] and the process reference model for predictive maintenance proposed by Wagner and Hellingrath [25] do mention the aspects that need to be considered but lack specific guidance in making the decisions.
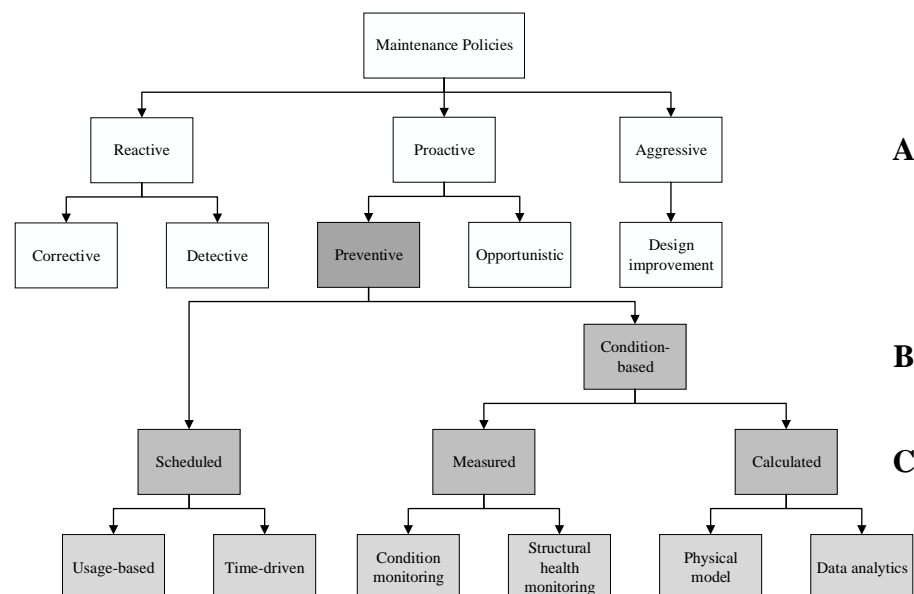

Figure 1. Overview of maintenance policies. At level A the main policy category is selected, level B (scheduled or dynamic) and level C (measured or calculated) distinguish the various preventive policies.

Therefore, available methods properly advise *what to do* but do not explain *how to do* it. This is also reflected in the survey conducted by Grubic and Redding [8], demonstrating about a decade ago that only 11–13 percent of UK-based manufacturers have adopted prognostics and decision-support techniques. The authors also more recently found that practitioners still often follow a costly trial-and-error process in developing more advanced approaches caused by a lack of guidance in the use of available MMs [10]. It is important that the selected combination of policy and MM suits the company's expertise, current situation and maintenance organisation. However, as research on this topic in the last decade yielded a vast amount of methods, companies typically find it difficult to identify the relevant methods and recognise the criteria to select one.

2.2. Problem 2—No Proper Fit between the Ambition Level and the Available Data

To manage their physical assets, practitioners traditionally use fixed maintenance intervals prescribed by the original equipment manufacturers (OEM). As these intervals are not company-specific and are mostly rather conservative, many practitioners feel the need to adapt their intervals to their specific situation and have the ambition to transition to a predictive maintenance approach. A first step would be to use past experiences and historical data as input for stochastic or statistical techniques of failure prediction [26–28]. Although these traditional methods are widely used, they are limited in effectively predicting the future reliability of individual systems, especially when the use of the system is variable. When the company has the ambition to incorporate these variable operational conditions in the maintenance approach, it is important that this requirement is defined explicitly to ensure the selection of a suitable MM [29]. This is confirmed by Carnero's framework [24], which explicitly includes the company (maintenance) *objectives,* as well as the predictive maintenance *necessity,* in the evaluation.

Moreover, such an ambition level sets requirements for the data to be used as input for the analyses, as the data completeness and quality significantly affect the outcomes [30]. The input data these models rely on can be imprecise or incomplete, especially when actual failure data are missing due to either bad registration or effective failure prevention. In the case studies, it was observed that the less mature companies struggled with scattered data (e.g., stored in multiple systems, local desktops), with data that are difficult to access (e.g., stored in legacy systems or in text format) or with incomplete data. Note that additionally, the knowledge level of the people involved can be considered part of the data quality, as experience and expert insight is often used in maintenance decision making. Carnero [24] specifies both data quality and maintenance employee quality as important aspects of predictive maintenance *capacity*.

The authors previously demonstrated [10] that the fit between data and the (strived-for) type of analysis seems to be leading for the success of the selected MM. However, this fit is not always checked properly beforehand, which often leads to the previously mentioned trial-and-error processes.

2.3. Problem 3—Financial Justification for a Specific Maintenance Approach Is Not Clear

The final problem identified in the case study is the financial justification for the implementation of the maintenance method. As *problem 2* shows, there is not always the right fit between the ambition level and the available data. To solve this, a company can either reduce its ambition level or collect the right data. The latter is often associated with substantial investment costs. Therefore, although it often seems to be difficult to (financially) justify these investment costs, a positive business case is important for the successful implementation of the selected maintenance method.

The benefit of MMs to asset performance can often (primarily) be found in reducing the number of unplanned failures while not conducting too many repairs or replacements. When, for example, a health monitoring system detects an anomaly, it will create a prognostic identification and estimate the remaining useful life (RUL), allowing the user to take preventive action before the system fails [31]. Such a maintenance technique creates timely

knowledge about failures and improves flexibility in managing the asset. The challenge is to express this benefit in financial terms, to enable a comparison to the required investment costs, or to find another (non-financial) way to weigh costs and benefits. It was observed that many companies do not make such an assessment before starting the development of an advanced maintenance approach.

3. Design of the Framework Elements

To overcome the problems identified above, this section introduces a number of elements that provide solutions to these problems. These elements are integrated into the final framework, as is proposed in Section 4, to help practitioners select the appropriate maintenance approach.

3.1. Element 1: Classification of the Available Predictive Maintenance Approaches

To be able to select a predictive maintenance approach, the various combinations of maintenance policies and MMs that are described in the literature have to be distinguished and classified first (problem 1). However, among reviewers within the diagnosis and prognostics field, little consensus exists as to which classification of methods is most appropriate [22]. In this paper, therefore, a broad classification is adopted to encompass the various views in this field and, at the same time, to be compatible with the different ambition levels (as will be presented later in the description of element 2). Thus note that the proposed classification is not claimed to be the best or only right structuring of the vast number of concepts and methods in this field, but merely the classification that fits the purpose of this paper best.

Further note that all maintenance methods that are included here are considered *predictive maintenance* methods. Strictly speaking, that might not be correct, although a generally accepted definition of predictive maintenance does not exist. However, to be able to optimise any preventive maintenance policy, an estimate or prediction of the time to failure is required. The methods considered here all provide such a prediction, albeit with different levels of accuracy. An expert giving an estimate of a component's lifetime based on many years of operational experience might not be considered to be part of predictive maintenance, but is in this work still included as a source of life 'prediction'. The case study demonstrated that this (least advanced) category is still the most used type of maintenance method in practice.

In the proposed categorisation, the model proposed by Coble and Hines [32], which has already been extended by Dibsdale [33] with an additional category (V-model-based), is adopted. This model has been further extended [10] with the experience-based approach by differentiating between methods that employ historical records (data) and those that only employ expert knowledge and the experience of people who use and maintain the equipment [19]. The framework is thus proposed to contain five types of predictive maintenance approaches:

I. **Experience-based predictions** of failure times are based on knowledge and previous experience outside (e.g., OEM) or within the company. Sometimes they are supported by limited or scattered data. Predictions are based on expert judgement (e.g., facilitated by failure mode, effect and criticality analysis (FMECA) techniques). These methods estimate the life of an average component operating under historically average conditions.

II. **Reliability Statistics prediction** techniques are based on historical (failure) records of comparable equipment without considering component-specific (usage) differences. This approach accurately describes population-wide failure probabilities. Examples are the reliability engineering or survival analysis [28] approaches and the analyses using fault trees, Markov chains or other stochastic processes [26,27]. These methods also estimate the life of an average component operating under historically average conditions.

III. **Stressor-based predictions** are based on historical records supplemented with stressor data, e.g., temperature, humidity or speed, to include environmental and operational variabilities and give results in terms of the expected lifetime of an average system in a specific environment. Examples of this type of method are the hazard or failure rate models from reliability handbooks that contain multiplication factors for certain covariates or stressors. Predictions are typically based on collected data from build-in tests or operating history under different conditions, but the effect of stressors can also be derived from expert knowledge or (simple) physical models [23].

IV. **Degradation-based predictions** are based on the extrapolation of a general path of a degradation measure to a predetermined failure threshold. By measuring symptoms of incipient failure, e.g., rises in temperature or vibration, the system can be diagnosed. The prognosis is inferred from sensor readings, i.e., is always based on *measurements*, e.g., from a condition monitoring or structural health monitoring system. The prediction starts from the current state of degradation and results in an expected remaining lifetime of a specific (individual) system in a specific environment.

V. **Model-based predictions** give the expected remaining lifetime of a specific (individual) system under specified conditions. Two types of model-based approaches can be followed:

  A. *Physical model-based*: The prognostic parameter is *calculated* using a physical model of the degradation mechanism based on direct sensing of the loads or usage that govern the critical failure mechanisms of individual components.

  B. *Data model-based*: The prognostic parameter is *calculated* or *inferred* using data analytics that uses sensed variations in loads, usage data, process data or condition/health monitoring data as input. The algorithms aim to derive patterns or relations in the data or try to detect anomalies by comparing them to historical data.

These five approaches all combine specific maintenance policies with certain methods and techniques. To clarify the link between policies and the proposed methods, Figure 2 schematically shows their relations. Note that in a bottom-up reasoning approach, a certain predictive maintenance method can only be combined with one specific policy: e.g., following the model-based method (V) automatically means that a condition-based policy is adopted. However, the other way around, selecting a condition-based maintenance policy (e.g., using some policy selection method) still leaves several options for the complete maintenance approach (III, IV and V). The present paper especially focuses on this final step.
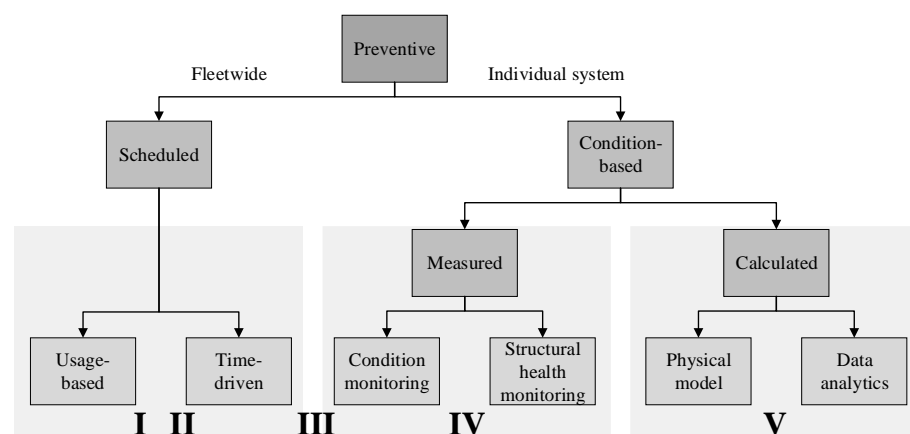

Figure 2. Relation between predictive maintenance policies and proposed types of MMs (and their clustering in approaches I to V).

An important aspect in differentiating the various approaches is how precisely the lifetime of a system can be predicted. The lower maturity methods of experience-based (I)

and reliability statistics (II) cannot predict the lifetime of an individual system or take into account a specific operating condition; they only provide fleetwide and long-time averages, e.g., an MTBF value. This branch is therefore referred to as 'fleetwide' in Figure 2. It could be argued whether these methods are true predictive maintenance methods, as they do not allow for failure predictions for individual systems. The more advanced approaches, III, IV and V, are based on condition-based policies, which differentiate between individual systems or operating contexts. However, a model-based approach (V) can also predict the lifetime for not previously encountered situations, while the degradation-based approach (IV) can only rely on extrapolating the current trend.

3.2. Element 2A: Definition of the Ambition Level

The second identified problem was the commonly observed mismatch between the ambition level of the company and the initially available data and knowledge. Therefore, both a definition of the ambition levels (this subsection) and the data types (as defined as element 2B in the next subsection) are required. The ambition level is defined as the level of detail that is required in the maintenance decision making process. Therefore, it is important to consider the four aspects set out below:

1. Is it required to predict the lifetime of individual assets?

    -   If not, only a generic prediction can be made for a fleet or group of assets;
    -   If individual predictions are required, also monitoring of individual assets is required.

2. Should variations in the usage of the assets be included?

    -   If not included, maintenance will be based on calendar time;
    -   Typical variations to be included are operating hours, driven kilometres, start/stops;
    -   If variations are to be included, they must be monitored or registered during operation.

3. Should variations in environmental conditions be included?

    -   If not included, maintenance will be based on average conditions;
    -   Operation at other conditions may yield accelerated degradation;
    -   If variations are to be included, they must be monitored or registered during operation.

4. Do future conditions differ from current or historical conditions?

    -   If there is no difference, an extrapolation of a general trend can be made;
    -   Otherwise, these variabilities have to be included in the prediction using a model.

Based on these four aspects, five different ambition levels (AL) can be defined, as shown in Table 1. The decision scheme in Figure 3 then provides a guideline for selecting the appropriate ambition level.
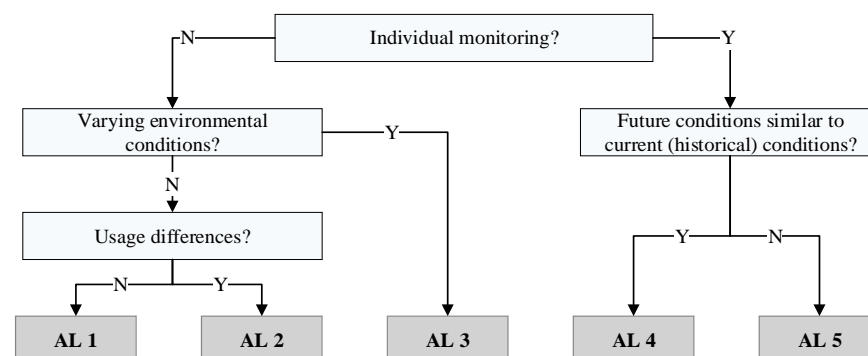

Figure 3. Guideline for the selection of the ambition level.

Table 1. Definition of different ambition levels.

Type	Level of Detail in Maintenance Decision Making
AL 1	Insight into future behaviour of the asset or fleet, considering static conditions
AL 2	Insight into future behaviour of the asset or fleet, considering differences in usage
AL 3	Insight into future behaviour of the asset or fleet, considering differences in usage and environmental conditions
AL 4	Insight into real-time deterioration of the individual asset and extrapolation to the future under constant conditions
AL 5	Insight into real-time deterioration of the individual asset and extrapolation to the future under largely varying conditions

3.3. Element 2B: Definition of the Data Types

The next step, which also follows from problem 2 (gap between ambition level and initially available data), is defining the various data types used in maintenance. Table 2 shows four types of data that are required for the five maintenance approaches as defined in Section 3.1.

Table 2. Description of data types.

Type of Data	Description
Historical data	These data can be gathered from technical knowledge, inspections and historical records of failures or costs. *Low-quality* historical data only contain the main parameters (e.g., time to failure). *High-quality* historical data also include information on historical usage, loads (including environmental stressors) or condition/health per group of systems (fraction of fleet, i.e., a specific unit or type). Historical data are collected by manual registration, e.g., logbooks or databases, instead of detailed monitoring.
Usage monitoring	The process of acquiring operational data, e.g., operating hours, mileage, or tons produced and/or process control data (e.g., supervisory control and data acquisition: SCADA). This preferably includes environmental data, e.g., measurements of temperature and moisture.
Load monitoring	The process of acquiring loading data, e.g., temperature, vibration, humidity, strain or electrical current [34].
Health or condition monitoring	The process of acquiring signs of degradation or imminent failure, e.g., vibrations, acoustics, temperatures, wear depths or data from oil analyses (all denoted *condition monitoring*) or data extracted from the measured (dynamic) system response to identify the presence and magnitude of damage in a system, denoted as *structural health monitoring*.

3.4. Element 2C: Mapping Data Inputs and Ambition Levels to the Five Maintenance Approaches

The final step in solving problem 2 is to map the various ambition levels to the required data types and link them to the predictive maintenance methods. This will reveal whether the chosen ambition level matches the available data. Selecting the appropriate predictive maintenance method is then proposed as a trade-off between the available input and the ambition level: the ambition level prescribes the methods that should be applied, while the available data limit what is applicable.

Figure 4 shows the relation between the ambition levels, the available predictive maintenance methods, and the required data types. The figure shows that with some maintenance methods, several types of ambition levels can be achieved (i.e., reliability statistics for AL 1 and AL 2). At the same time, the figure shows which data are required for each method. For example, required inputs for 'method V-A' are usage or load monitoring data (2 or 3) and condition- or health-monitoring data (4). Only when these high-level data sources are available an AL 4 or 5 prognosis is feasible. Note that the differences between

'V-A' and 'V-B' are the data requirements: a data model requires high-quality historical data to train the algorithm. If these data are not available, the only other option is to use a physical model.
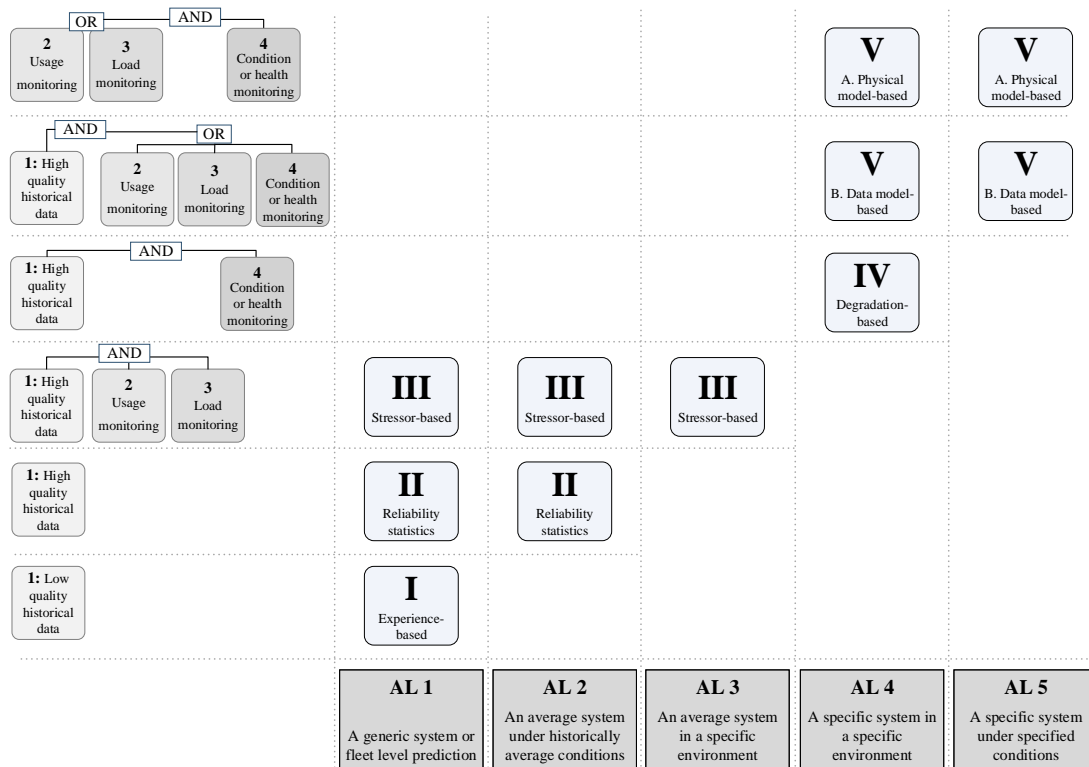

Figure 4. Mapping the preventive maintenance approaches to the ambition levels and data types.

Thus, the figure shows that there is no one-to-one relationship between the ambition levels and MMs. Reasoning from either the available data perspective or from the ambition level perspective (in most cases), several MMs are feasible. However, the combination of available data and the ambition level gives unambiguous and unique advice: the preferable MM.

3.5. Element 3: Business Case

The third identified problem is that it is difficult for the company to prove the added value of the implemented maintenance approach. However, it is well-established that developing a business case is key to project success [35]. Moreover, almost 30% of industrial equipment condition-based maintenance (CBM) does not provide any benefits [1]. Therefore, it is important to evaluate the investment in CBM in a structured way before the MM is actually selected.

For methods that are familiar to the company or proven within the field, a clear business case can often be defined, as reliable estimates of the costs and benefits can be made. However, when more innovative methods are developed, estimating the costs and benefits is difficult. Such a case often requires the costly collection of extra data for which sensors have to be acquired and installed. Moreover, the time before achieving the benefits is longer, and therefore the benefits are more uncertain.

In another work [36], the authors developed a hybrid method to construct the business case for condition-based maintenance. This method demonstrates that a justification should be composed of both a non-financial and a financial analysis. In the case of innovative techniques, with their highly uncertain costs and benefits, a business case should be composed of non-financial elements. When the costs and benefits can be reliably estimated, a financial evaluation should be added to this business case. In the present paper, this

existing method is adopted, and developing or enhancing the business case is outside the scope of this paper.

4. Framework for the Maintenance Method Selection

To offer decision support for practitioners, a predictive maintenance method selection framework is proposed in this section. This framework is constructed from the five elements that have been previously presented in Section 3. The proposed framework is shown in Figure 5 as a decision diagram. The choice for a specific maintenance method can be made via two starting points: (*i*) *decision pull*, based on the wish to achieve a certain ambition level (element 2A), or (*ii*) *technology push*, based on available and (possibly) useful data (element 2B).

Figure 5. Proposed preventive maintenance approach selection framework.

Ideally, the selection starts via the *decision pull* starting point. This gives the company the opportunity to select the optimal maintenance technique (i.e., a selection that is not directly limited by the available data). After the ambition level has been determined, the company checks whether there is a match with the available data, as follows from element 2B. When there is a match between the available data and the ambition level, the framework directly indicates the associated maintenance method, based on Figure 4 (element 2C). The only thing remaining then is that a business case should be made (element 3). When a positive business case can be made, the selected approach can be conducted.

However, in practice, there is quite often a mismatch between the ambition level and the available data. The framework then guides the user to a feasible combination. When the required data for the selected ambition level are not available, the first check is whether it is possible to start collecting these data. If so, the business case for the scenario associated with this ambition level should be checked to verify whether collecting this additional data (and the associated costs) is worth the effort. If not, the availability of other data is checked, starting from the lowest level (at the top of the diagram). Typically, other data appear to be available, but this mostly implies that the ambition level should be lowered.

When starting from the *technology push* point, the available data lead to the choice of the maintenance approach. Therefore, the first step after receiving advice for the associated maintenance approach is to examine the business case. If this check is negative, it should again be evaluated whether improvements can be made with a lower or different type of data. In that case, the associated ambition level will also be lower again.

Note that starting from a technology push, led by the available data, is a common approach in many companies. However, it is somewhat dangerous since the definition of the ambition level is neglected. This could lead to a positive business case for the selected data type and maintenance approach, but the company could discover at some stage that this approach does not perform as expected. Explicitly defining the ambition level beforehand and incorporating that in the selection process, as is performed in the framework, could prevent such a situation.

5. Evaluation of the Proposed Framework

To test and demonstrate the proposed predictive maintenance approach selection framework, four case studies were conducted. In these case studies, the logic proposed in Figure 5 was applied to the cases. Thus, the output of the case studies is the selection of the most suitable MM for that case. After introducing the case study method, each of the four cases is discussed.

5.1. Case Study Method

To be able to test all elements in the proposed framework, a specific case selection was applied based on the four criteria set out below. Such a structured approach to sampling is important in case study research [37]. The case study focussed on the typical industries where MMs are applied (aerospace, defence, marine, electronics, power, oil and gas, and energy [8]). Secondly, systems or assets were selected where MMs are applied most frequently. These have an average life cycle of more than ten years, are mechanical or electromechanical, highly complex or installed in large series [8]. Thirdly, both systems used in a static environment (i.e., nuclear reactor) and moving assets (i.e., vessel) were included. One of the challenges presented by these moving assets is that the maintenance needs of these assets can vary dramatically when operated under highly variable environmental conditions [34]. Finally, one case with a technology push starting point and three cases with a decision pull starting point was selected to illustrate both routes.

Several measures were taken to ensure the reliability and validity of the data since that is the main concern of a case study [38]. To guarantee construct validity, multiple informants were interviewed (such as maintenance engineers and managers), multiple documents were studied, and when needed, informants were asked to provide additional information in follow-ups. These interviews were recorded, and the transcripts were analysed. The analysed patterns in the case study were matched with the expected dependent variables: type of data available, prognostic ambition level and the selected MM, to ensure internal validity. Finally, the reliability of the case study was ensured by using a semi-structured case study protocol during the interviews.

5.2. Case 1: Electrical Components of a Naval Vessel

Case description: This department maintains all electronic equipment aboard naval vessels. Due to the large differences between naval vessels, many one-of-a-kind systems are installed. Collecting accurate and representative failure data is, therefore, difficult. As the systems are critical for the operational effectiveness of the vessels, the maintainer aims to prevent unplanned downtime. Traditionally, maintenance plans are based on advice given by the OEM.

Challenge: The department recently executed a trial-and-error process in selecting the optimal maintenance method for their situation. In the (recent) past, the department relied on reliability statistics methods. These analyses, however, provided inaccurate results due to incomplete data, unreliable input and poorly filled recording systems. The department,

therefore, decided to fall back on using expert knowledge for making maintenance decisions. Since the department conducts maintenance for a large number of different systems, it is too difficult and time-consuming to develop more accurate physical or data models. Using the proposed framework, the analysis in Table 3 demonstrates that this trial-and-error process could have been accelerated considerably.

Table 3. Application of the decision framework to case 1.

Step in Framework	Result and Explanation
Starting point	**Decision pull**—ambition to optimise maintenance intervals
Ambition level	- Assets used in highly variable situations - Include environmental and operational variabilities (e.g., temperature, saline conditions) - Average degradation level of components can be estimated based on usage and environmental conditions (thus: no individual monitoring) →**Ambition level 3**

Types of data available	- Expert knowledge
	- Low-quality historical data:
	   ○ Amount of failure data limited (low failure frequency, small number of systems)
	   ○ Incomplete data, unreliable input and poorly filled recording systems

Match ambition level—data?	**No**—AL3 also requires data on the operational environment (stressors)
Can these data be collected?	**Possible**—Install sensors or collect more environmental data by hand
Positive business case?	**No**—Too costly and time-consuming due to variety of equipment types
Improve with a lower AL?	**Yes**—Experience-based techniques will also improve the current maintenance plans
Other data available?	**Yes**—Expert knowledge is available
Positive business case?	**Yes**—No major investments required (knowledge is available, organising FMECA studies for critical equipment is expected to improve maintenance)
MM selection	**Advice:** Apply an experience-based maintenance method. This method will not satisfy original ambition level, but with available data and expertise, it is expected to contribute to the maintenance program.

Conclusion: This structured way of comparing the ambition (decision pull, AL3) with the data availability, i.e., expert knowledge and low-quality historical data, reveals a clear mismatch. The framework explains why the attempt to use reliability statistics has failed: no sufficient *high-quality historical data* are available. Subsequently, the framework guides the user to alternative approaches. Firstly, it is checked whether the data required for the ambitioned type of approach can be collected. This appeared to be infeasible (no positive business case) at the moment. A suggested reduction in the ambition level to AL1, based on only expert knowledge, appeared to make the *experience-based* type of maintenance approach feasible. This is also the approach that is currently successfully applied. The trial-and-error process the company went through could thus have been accelerated considerably by using the proposed framework.

5.3. Case 2: Nuclear Reactor

Case description: This department conducts maintenance on the equipment of a nuclear facility. Due to the strict regulations within this sector, detailed analyses are conducted for critical equipment. Moreover, a high level of redundancy is present to guarantee safety in case of equipment or process failures. Due to the high amount of redundancy, little similar equipment is available. This reduces the applicability of reliability statistics approaches. A high level of knowledge and historical data on the usage and loading of the reactor is available. In process logs, every activity in the reactor is logged. However, since modifications on the reactor have taken place over the years, not all data are equally useful for maintenance analyses.

Challenge: The company wants to check whether the present predictive maintenance approach is appropriate. Table 4 shows the analysis using the prosed framework.

Table 4. Application of the decision framework to case 2.

Step in Framework	Result and Explanation
Starting point	**Decision Pull**—Ambition to understand deterioration of reactor core (also required by safety regulations)
Ambition level	- Monitor individual system - Include changes in future usage of reactor (e.g., different end products) →**Ambition level 5**
Types of data available	- Expert knowledge - High-quality historical data - Loading data and usage data - Condition and health data
Match ambition level—data?	**Yes**—AL 5 requires data on the usage or loads and data on the condition or health, which are available
Positive business case?	**Yes**—Possible impacts on safety create enough urgency for a maintenance approach giving insight into future conditions of the reactor
MM selection	**Advise:** Apply a model-based approach by using a physical model This approach satisfies the originally set ambition level

Conclusion: For this nuclear reactor case, there is a clear match between the ambition level and the data available. The framework correctly advises a model-based approach, which is also the approach currently followed by the company.

5.4. Case 3: Engine Condition Trend Monitoring for a Military Transport Aircraft

Case description: This department maintains military transport aircraft. For the engines, a fixed-interval preventive maintenance policy has been applied successfully in the past. Recently the engine condition trend monitoring (ECTM) technique has become available. ECTM is the process of using measured characteristics (i.e., compressor speeds, inter-turbine temperature and fuel flow) during specified flight conditions (i.e., altitude, airspeed, outside air temperatures) and comparing these to predicted values to provide confirmation of engine gas path efficiency and predict maintenance needs based on these data [39].

Challenge: To reduce maintenance costs, the department is investigating whether it is both economically and technically feasible to apply a condition-based maintenance approach using ECTM. Table 5 shows the analysis for this case using the prosed framework.

Table 5. Application of the decision framework to case 3.

Step in Framework	Result and Explanation
Starting point	**Decision Pull**—aim to reduce maintenance costs by applying CBM
Types of data available	- Expert knowledge is widely available within the department - Usage and load data (sensors on aircraft measure altitude, airspeed, outside air temperatures and inter-turbine temperature)
Ambition level	- Monitoring of individual engines - Operated in varying environmental conditions - Future conditions assumed to be similar (might be different, not included yet) →**Ambition level 4**
Match ambition level—data?	**Yes**—AL 4 requires condition monitoring data (available)Data required for physical model-based approach (AL5) are also available
Positive business case?	**Yes**—Financial justification conducted [36]: total lifecycle costs of ECTM lower than corrective or fixed-interval preventive maintenance
MM selection	**Advice:** Apply a degradation-based maintenance method Organisation will further develop ECTM, set ambition level is satisfied

Conclusion: For this aviation case, there is a match between the ambition level and the data available through the new technology (ECTM). The framework confirms that this degradation-based maintenance approach is the appropriate approach for this company.

5.5. Case 4: Predicting Rolling Stock Maintenance

Case description: This department conducts maintenance for rolling stock. Within their trains, many pre-installed sensors are available that provide data on parameters such as temperature and vibration. A large amount of expert knowledge is available within the department. This knowledge is used for the current experience-based maintenance program.

Challenge: The department is trying to use the available data to optimise its preventive maintenance and reduce system downtime and prevent safety incidents. Table 6 shows the analysis using the prosed framework.

Conclusion: Applying the framework from a technology push (a large amount of data available) perspective for this rolling stock case confirms that the available data allow for the increased ambition of the company. The company is now working on implementing this approach. Note that in this case, the company identified its ambition level and discovered that the approach selected from a technology-push perspective matched this ambition level. However, also other technology-push-oriented cases (not treated in detail here)were observed in this study, in which the company did not explicitly identify its ambition level, and by trial-and-error, discovered that the adopted approach did not yield the information at the (implicitly expected) ambition level.

Table 6. Application of the decision framework to case 4.

Step in Framework	Result and Explanation
Starting point	**Technology Push**—ambition to use available data to enable prognostics
Ambition level	- Detection of anomalies and prediction of future behaviour per individual train - Take into account actual usage - Future conditions similar to current/historical conditions →**Ambition level 4**
Types of data available	- Expert knowledge - High-quality historical data (inspection, costing and failure data) - Usage data of trains - Condition monitoring data
Match ambition level—data?	**Yes**—AL4 requires condition monitoring data (available) and high-quality historical data (available)
Positive business case?	**Yes**—Only minor investments required to check usability of data, high potential gain (expected extension of many maintenance intervals, reduced costs)
MM selection	**Advice:** Apply a degradation-based maintenance approach. This will satisfy the set ambition level

6. Conclusions

Although this is not recognised in large part of the academic literature, practitioners still experience difficulties in the selection and application of predictive maintenance approaches. This is especially true for selecting the more advanced approaches associated with condition-based maintenance policies. To aid practitioners in the selection of the appropriate predictive maintenance approach for their situation, a selection framework was proposed, which addresses the three main problems identified:

- Difficulty in distinguishing between the available maintenance methods;
- Mismatch between the ambition level and the required data;
- Difficulty in showing the added value of a certain maintenance approach.

Subsequently, five elements were developed that solve these three problems: (*i*) the various predictive maintenance approaches have been classified into five types, ranging from the traditional experience-based approach to an advanced model-based approach; (*ii*) five ambition levels were defined that specify the required performance of the maintenance approach; (*iii*) the various types of data for predictive maintenance were classified; (*iv*) the ambition levels and data types were mapped onto the maintenance methods; (*v*) a previously presented business case method for maintenance applications was discussed. The integration of these five elements provided a framework that uses the identified dependencies and ambition levels to steer the selection of the appropriate predictive maintenance approach.

Finally, four case studies have been used to test and demonstrate the proposed framework. The case studies demonstrated that the proposed selection framework helps to select the correct ambition level and the maintenance approach to achieve that. Furthermore, the framework provides insight into the required data. Thus, the proposed framework can help practitioners reduce the costly trial-and-error process in applying a predictive maintenance approach, while the individual elements developed can assist researchers in the field to better position new methods.

References

1. Hashemian, H.M.; Bean, W.C. State-of-the-art predictive maintenance techniques. *IEEE Trans. Instrum. Meas.* **2011**, *60*, 3480–3492. [CrossRef]
2. Scott, M.J.; Verhagen, W.J.C.; Bieber, M.T.; Marzocca, P. A Systematic Literature Review of Predictive Maintenance for Defence Fixed-Wing Aircraft Sustainment and Operations. *Sensors* **2022**, *22*, 7070. [CrossRef] [PubMed]
3. Ton, B.; Basten, R.; Bolte, J.; Braaksma, J.; Di Bucchianico, A.; Van De Calseyde, P.; Grooteman, F.; Heskes, T.; Jansen, N.; Teeuw, W.; et al. PrimaVera—Synergising Predictive Maintenance. *Appl. Sci.* **2020**, *10*, 8348. [CrossRef]
4. Waeyenbergh, G.; Pintelon, L. A framework for maintenance concept development. *Int. J. Prod. Econ.* **2002**, *77*, 299–313. [CrossRef]
5. Tiboni, M.; Remino, C.; Bussola, R.; Amici, C. A Review on Vibration-Based Condition Monitoring of Rotating Machinery. *Appl. Sci.* **2022**, *12*, 972. [CrossRef]
6. Lee, J.; Bagheri, B.; Kao, H.-A. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manuf. Lett.* **2015**, *3*, 18–23. [CrossRef]
7. Achouch, M.; Dimitrova, M.; Ziane, K.; Sattarpanah Karganroudi, S.; Dhouib, R.; Ibrahim, H.; Adda, M. On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. *Appl. Sci.* **2022**, *12*, 8081.
8. Grubic, T.; Redding, L.; Baines, T.; Julien, D. The adoption and use of diagnostic and prognostic technology within UK-based manufacturers. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2011**, *225*, 1457–1470. [CrossRef]
9. Tiddens, W.; Braaksma, A.; Tinga, T. The Adoption of Prognostic Technologies in Maintenance Decision Making: A Multiple Case Study. *Procedia CIRP* **2015**, *38*, 171–176. [CrossRef]
10. Tiddens, W.; Braaksma, J.; Tinga, T. Exploring predictive maintenance applications in industry. *J. Qual. Maint. Eng.* **2022**, *28*, 68–85. [CrossRef]
11. Carnero, M.C. Selection of diagnostic techniques and instrumentation in a predictive maintenance program. A case study. *Decis. Support Syst.* **2005**, *38*, 539–555. [CrossRef]
12. Tiddens, W.W.; Braaksma, A.J.J.; Tinga, T. Selecting Suitable Candidates for Predictive Maintenance. *Int. J. Progn. Health Manag.* **2018**, *9*, 1–14. [CrossRef]
13. Arena, S.; Florian, E.; Zennaro, I.; Orrù, P.; Sgarbossa, F. A novel decision support system for managing predictive maintenance strategies based on machine learning approaches. *Saf. Sci.* **2022**, *146*, 105529. [CrossRef]
14. Aremu, O.O.; Cody, R.A.; Hyland-Wood, D.; McAree, P.R. A relative entropy based feature selection framework for asset data in predictive maintenance. *Comput. Ind. Eng.* **2020**, *145*, 106536. [CrossRef]
15. Calabrese, F.; Regattieri, A.; Bortolini, M.; Galizia, F.G. Data-Driven Fault Detection and Diagnosis: Challenges and Opportunities in Real-World Scenarios. *Appl. Sci.* **2022**, *12*, 9212. [CrossRef]
16. Holmström, J.; Ketokivi, M.; Hameri, A.-P. Bridging practice and theory: A design science approach. *Decis. Sci.* **2009**, *40*, 65–87. [CrossRef]
17. Shafiee, M. Maintenance strategy selection problem: An MCDM overview. *J. Qual. Maint. Eng.* **2015**, *21*, 378–402. [CrossRef]
18. Goossens, A.J.; Basten, R.J. Exploring maintenance policy selection using the Analytic Hierarchy Process: An application for naval ships. *Reliab. Eng. Syst. Saf.* **2015**, *142*, 31–41. [CrossRef]
19. Moubray, J. *RCM II, Reliability-Centred Maintenance*; Industrial Press Inc.: New York, NY, USA, 1997; Volume 440.
20. de Jonge, B.; Teunter, R.; Tinga, T. The influence of practical factors on the benefits of condition-based maintenance over time-based maintenance. *Reliab. Eng. Syst. Saf.* **2017**, *158*, 21–30. [CrossRef]
21. Kim, J.; Ahn, Y.; Yeo, H. A comparative study of time-based maintenance and condition-based maintenance for optimal choice of maintenance policy. *Struct. Infrastruct. Eng.* **2016**, *12*, 1525–1536. [CrossRef]

22. Sikorska, J.; Hodkiewicz, M.; Ma, L. Prognostic modelling options for remaining useful life estimation by industry. *Mech. Syst. Signal Process.* **2011**, *25*, 1803–1836. [CrossRef]

23. Tinga, T.; Wubben, F.; Tiddens, W.; Wortmann, J.; Gaalman, G. Dynamic Maintenance based on Functional Usage Profiles. *J. Qual. Maint. Eng.* **2021**, *27*, 21–42. [CrossRef]

24. Carnero, M.C. An evaluation system of the setting up of predictive maintenance programmes. *Reliab. Eng. Syst. Saf.* **2006**, *91*, 945–963. [CrossRef]

25. Wagner, C.; Hellingrath, B. Supporting the implementation of predictive maintenance—A process reference model. *Int. J. Progn. Health Manag.* **2021**, *12*, 1–17.

26. Van Noortwijk, J. A survey of the application of gamma processes in maintenance. *Reliab. Eng. Syst. Saf.* **2009**, *94*, 2–21. [CrossRef]

27. Zio, E.; Broggi, M.; Golea, L.R.; Pedroni, N. Failure and reliability predictions by infinite impulse response locally recurrent neural networks. *Chem. Eng. Trans.* **2012**, *26*, 1–6.

28. Singpurwalla, N.D. Survival in dynamic environments. *Stat. Sci.* **1995**, *10*, 86–103. [CrossRef]

29. Nguyen, K.T.; Fouladirad, M.; Grall, A. Model selection for degradation modeling and prognosis with health monitoring data. *Reliab. Eng. Syst. Saf.* **2018**, *169*, 105–116. [CrossRef]

30. Sandborn, P.A.; Wilkinson, C. A maintenance planning and business case development model for the application of prognostics and health management (PHM) to electronic systems. *Microelectron. Reliab.* **2007**, *47*, 1889–1901. [CrossRef]

31. Haddad, G.; Sandborn, P.A.; Pecht, M. Using maintenance options to maximize the benefits of prognostics for wind farms. *Wind. Energy* **2014**, *17*, 775–791. [CrossRef]

32. Coble, J.B.; Hines, J.W. Prognostic Algorithm Categorization with PHM Challenge Application. In Proceedings of the International Conference on Prognostics and Health Management, Denver, CO, USA, 6–9 October 2008.

33. Dibsdale, C. Holistic Prognostics. In *Through-Life Engineering Services*; Rajkumar, R., Redding, L., Eds.; Springer: New York, NY, USA, 2015; pp. 71–82.

34. Tinga, T. Application of physical failure models to enable usage and load based maintenance. *Reliab. Eng. Syst. Saf.* **2010**, *95*, 1061–1075. [CrossRef]

35. Fortune, J.; White, D. Framing of project critical success factors by a systems model. *Int. J. Proj. Manag.* **2006**, *24*, 53–65. [CrossRef]

36. Tiddens, W.W.; Tinga, T.; Braaksma, A.J.J.; Brouwer, O. *The Business Case for Condition-Based Maintenance: A Hybrid (Non-) Financial Approach in Safety and Reliability—Theory and Applications*; Cepin, M., Bris, R., Eds.; Taylor & Francis Group, London: Portoroz, Slovenia, 2017; pp. 821–829.

37. Eisenhardt, K.M.; Graebner, M.E. Theory building from cases: Opportunities and challenges. *Acad. Manag. J.* **2007**, *50*, 25–32. [CrossRef]

38. Yin, R.K. *Case Study Research: Design And Methods*, 4th ed.; Applied Social Research Methods Series; Sage Publications, Inc.: New York, NY, USA, 2009.

39. de Mesquita Guimarães, D.M.Q.R. Implementation of an Engine Condition Trend Monitoring (ECTM) Program in a Part M Organization: Pratt & Whitney PT6A-67D Engine. Ph.D. Thesis, University of Beira Interior, Covilhã, Portugal, 2015.