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Asset Management, Reliability and Prognostics Modeling Techniques

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Abstract: In recent years, reliability engineering has seen significant growth in data-driven modeling, mainly due to the democratization of sensing technologies, big data processing, and computing capabilities. It has also seen a paradigm shift, with Engineering of Asset Management (EAM) becoming widely accepted as a high-level framework to support corporate policies and strategies. The rapid evolution of research leads to the development of multiple research communities, making it difficult for the uninitiated to navigate the literature. Indeed, system reliability encompasses several research subfields that focus on maximizing the life cycle of assets, including Reliability, Availability, Maintainability, and Safety (RAMS), Prognostics and Health Management (PHM), and Engineering of Asset Management. This article proposes a review of these concepts with the aim of identifying the different scientific communities, what differentiates them, and what connects them. It also addresses RAMS and PHM modeling techniques and highlights the significance of these disciplines in ensuring the functioning of complex systems. In summary, this article aims to clarify the interrelationship between the topics of reliability engineering, to simplify the search and selection for modeling methods.

Keywords: engineering of asset management; prognostic and health management; reliability; modeling

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Citation: Payette, M.; Abdul-Nour, G. Asset Management, Reliability and Prognostics Modeling Techniques. *Sustainability* **2023**, *15*, 7493. https://doi.org/10.3390/su15097493

Academic Editor: Abdelhakim Khatab

Received: 24 February 2023
Revised: 26 April 2023
Accepted: 28 April 2023
Published: 3 May 2023

1. Introduction

Reliability engineering is a relatively old research field. In fact, this scientific discipline has been in development since the 1950s. This area, based on the application of probabilities and statistics, is now omnipresent in sectors such as military, consumer, energy, etc. The success of the Japanese car manufacturers is a good example that reliability is one of the most important criteria for consumers. Over time, the field has evolved greatly and has influenced the emergence of complementary disciplines, including business management approaches. In addition, technological advances have also greatly contributed to the formation of new topics in reliability. As a result, there are now several domains and denominations, which makes research tedious. These include the domain of RAMS (reliability, availability, maintainability, and safety), PHM (prognostic and health management), AM (asset management), etc. There is little literature that defines the RAMS ecosystem in relation to PHM and asset management and the techniques inherent to these domains. The objective of this work is to review the concepts of reliability engineering and identify the different scientific communities related to the topic. It also highlights the importance of an integrated approach in the functioning of complex systems through the coordination of RAMS and PHM modeling techniques. By clarifying the interrelationships between these topics, the article seeks to simplify the search and selection of modeling methods for researchers and practitioners. The article is structured as follows: Section 2 presents the three different research topics and covers a model for the hierarchy of organizational decision-making, engineering of asset management, and defining the basics of maintenance and reliability. Section 3 defines different types of modeling methods, namely mathematical statistical and qualitative modeling. Sections 4 and 5 focus on the classical modeling methods used, respectively, in the field of RAMS and PHM. Section 6 illustrates the differences and complementarities in the modeling techniques and in the philosophy of the respective fields.

2. Research Topics in Reliability Engineering

2.1. Hierarchy of Organizational Decision-Making

Every enterprise must have a mission, objectives, and an action plan to achieve its goals. This section presents a hierarchical model of decision-making in an organization. In that respect, it is possible to put this model into perspective with asset management, RAMS and PHM. Figure 1, translated from [1], illustrates the hierarchy between mission and business strategies. According to their definition, the mission statement is a guide for formulating a company's strategies. It is intended to ensure that everyone in the company and at every level of management knows the purpose of the company. Business objectives are defined according to the mission and provide a clear direction for the organization. Organizational strategies are plans to achieve the company's objectives. They are global strategies that guide the entire organization. The functional strategies, which are related to the five functions of the company (finance, marketing, human resources, operations, and production) support the organizational strategies, the tactical strategies regroup the methods, and the action plans to achieve them [1].

Figure 1. Hierarchy of decisions.

The hierarchy of these strategies is related to the time frame in which they are deployed, in addition to their scope and level of detail. Indeed, the mission is established at a high hierarchical level and serves as a long-term guide for an organization. Its scope is very broad, but its level of detail is low. In contrast, tactical strategies have a very low hierarchical level and a short time frame, but the level of detail is high.

2.2. Engineering of Asset Management

It is important to define asset management, which represents a higher level of decision-making. By definition, an asset is an object or entity to which a value is assigned. An engineering asset has real value to an organization; it can be equipment, inventory, buildings, etc. [2,3]. Engineering of Asset Management (EAM) is the field that encompasses all organizational activities aimed at realizing the value of an asset. It is not to be confused with Financial Asset Management, which concerns investment and banking assets and not physical assets. The asset management system allows for the coordination of activities with the goal of achieving EAM objectives. The objectives of the EAM system must align with the strategic objectives of the company [4]. This involves balancing the costs, risks, opportunities, and benefits of performance [3]. The ISO standard also establishes the fundamental principles of asset management. A central concept in EAM is value and how the asset generates it. According to the ISO, this should be defined by the organization and its stakeholders, based on business objectives. Furthermore, value varies from one organization to another and is mainly driven by the business context and needs [3]. Therefore, the notion of alignment is important; the EAM must be aligned with the business objectives, based on this notion of value. The objectives must be translated into management policies and strategies [5]. The impact of asset management is not limited to the financial aspect. It plays a significant role in sustainable development; the long-term vision of AM life cycle optimization reduces waste by opting for a more robust and durable design. In addition, optimizing replacements reduces unnecessary maintenance and replacement of components that are still in good condition, reducing the carbon footprint of assets throughout their lifespan. In the perspective of the previous section, asset management engineering is established at an organizational strategy level, given that its scope extends to all business functions. Concrete examples are given in [6], where the author reviews the concepts of asset management applied to large power systems. He presents various application cases at different levels of enterprise management to highlight the benefits of an integrated approach to AM. In [7], he extends the concepts of asset management to the use of connectivity and big data. Furthermore, he discusses advances in monitoring, sensor technologies, and data science, and how they will be applied in support of asset management. Additionally, in [8], the author proposes a review of the concepts of Industry 4.0 in relation to asset management. The article focuses on applications for the electrical industry.

2.3. Failure, Maintenance, and Reliability

2.3.1. Failure

From the point of view of EAM, a failure means that an asset loses its functions temporarily or permanently and no longer generates value for its organization. Failure is an inevitable event for products and systems [9]. The failure of a system can be caused by internal factors such as wear, corrosion, etc., or by an external factor, for example, a tree falling on the power transmission line. Therefore, the study of degradation mechanisms and failure modes is essential to optimize the asset life cycle. Knowing when and why a system loses its functions allows managers to implement appropriate solutions. In order to maintain its assets, an organization might employ a different maintenance strategy, as described in the following section.

2.3.2. Maintenance

A failure is an event that prevents the system from performing its intended functions [10]. Maintenance is the combination of means used to ensure that the system can continue to perform these functions. It includes all the activities involved in planning, managing, and executing the maintenance of equipment in order to achieve these business objectives.

Preventive maintenance aims to keep the system in a functioning state, with maintenance performed before a failure occurs. If a failure occurs, corrective maintenance allows the system to be restored to operation. During an asset's life cycle, several factors deteriorate the condition of the components. These degradation mechanisms can be related to the use or to physical and environmental phenomena. When degradation is cyclic, systematic preventive maintenance will stop these degradation mechanisms before there is a failure. Systematic maintenance consists of performing maintenance at fixed intervals, and the periodicity can depend on the number of cycles (e.g., number of kilometers traveled) or the number of hours of service. In this case, the failure modes are known, predictable, and easy to plan. In some cases, component degradation is not cyclic, but signs of aging can be observed or measured during inspection. In this case, it is referred to as condition-based maintenance. This consists of repairing the system when an inspection or monitoring reveals signs of aging, indicating the presence of failure mechanisms. Generally, condition-based maintenance occurs when the failure modes are random. Predictive maintenance also occurs when signs of wear appear. In this case, the failure modes are known, and the occurrence can be modeled using historical data and real-time sensor data. Corrective maintenance corresponds to a repair when a failure occurs. Most of the time, it concerns events that are unwanted and problematic. However, in a reliability-centered maintenance (RCM) program, an organization can choose to opt for such a strategy for certain systems that are redundant or inexpensive to replace [11]. Figure 2, adapted from [11], shows the different types of maintenance and their characteristics, as described above.

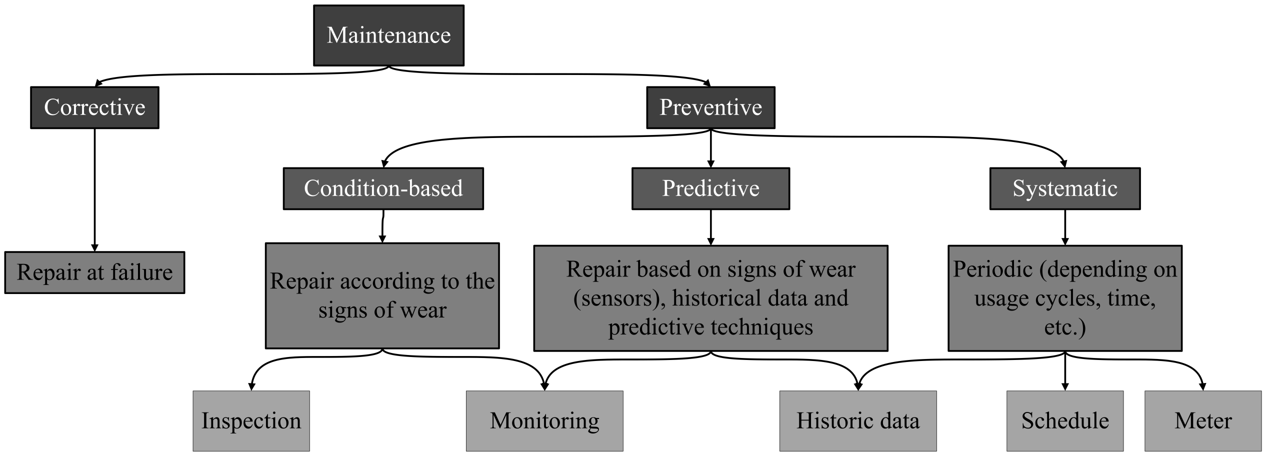

Figure 2. Maintenance classification (adapted from [11]).

2.3.3. Statistics of Failure

A failure is considered a random event. When it comes to maintenance, reliability is the ability of the asset to perform its intended actions within a given time interval. Thus, reliability can be expressed as the probability that the system operates correctly during that time interval and under predefined conditions [12,13]. The goal of the reliability study is to prevent and/or reduce the frequency of those failures by applying engineering and statistical techniques to identify and quantify the sources of faults. Reliability is often expressed as a mathematical model or as a statistical estimator, such as the mean time to failure (MTTF) or the mean time between failures (MTBF). There are two branches of engineering research that are interested in the study of system health management; reliability, availability, maintainability, and safety (RAMS) and prognostic and health management (PHM). In the literature, these disciplines are often hard to distinguish from each other. Both disciplines seek to optimize the value derived from assets throughout their life cycle. However, the models and tools used by each approach are very different. According to Pierre Dersin, RAMS focuses on the study of the general properties of a population, while PHM focuses on a single asset at a time [14].

3. Modeling

This section describes different modeling approaches used in EAM, RAMS, and PHM. First, the basics of mathematical modeling are presented. Then, the fundamental statistical modeling approaches are compared. Finally, qualitative modeling is discussed.

3.1. Basics of Mathematical Modeling

Modeling, in a very general way, is used to represent an object or situation, to simplify it, to understand it, and to analyze it. Mathematical modeling consists of representing a real-world situation by using mathematical equations. The mathematical modeling cycle is presented in Figure 3, and is adapted from [15].

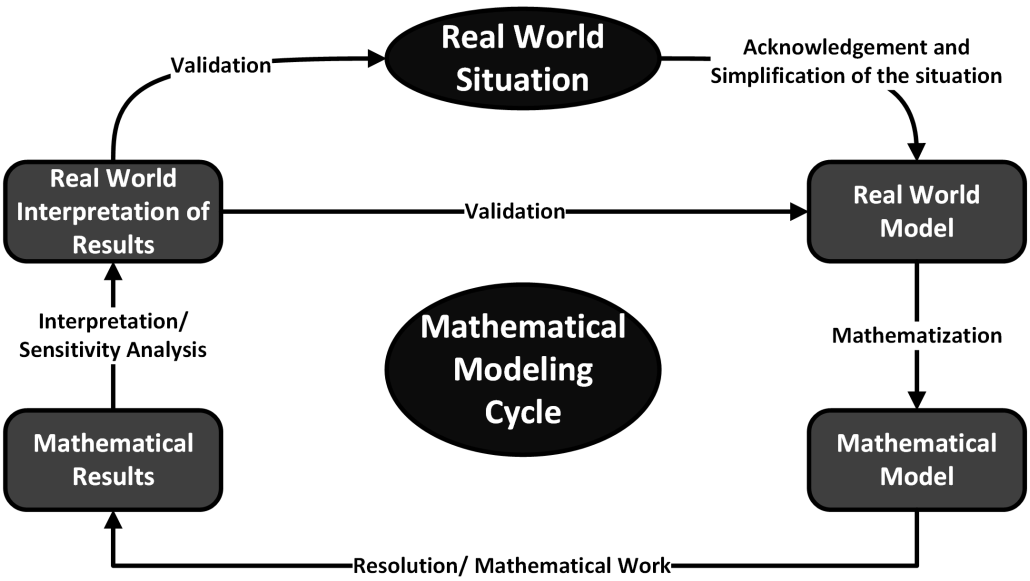

Figure 3. Modeling cycle (adapted from [15]).

This represents well the task of modeling, as well as the validation loop; the research hypotheses allow for simplifying a real situation and describing it using mathematics. The validation between the results of the model and the real situation allows for knowing if the model, although simplified, represents well the situation in question. This modeling process is repeated until the results produced are adequate [16].

3.2. Statistical Models

In statistical modeling, two types of approaches can be distinguished. Descriptive statistics aim to describe and summarize the observations of a sample using indicators, graphical construction, etc. [17]. Inferential statistics, on the other hand, aim to infer the characteristics of a population from a sample [18]. Figure 4 presents the most common approaches from both descriptive and inferential statistics. In inferential statistics, probability distributions are used to describe the random variables in a sample and to extract their characteristics. By knowing the type of random experiment, it is generally easy to associate the probability distribution to the sample, and to determine the parameters of this distribution from the sample. This process is often known as parametric analysis. In some cases, it is easy to define the distribution of the data, considering the operational and random context of the phenomena under study [19].

In contrast, descriptive analysis, also known as nonparametric analysis, is used to deduce the characteristics of a sample without the use of a statistical distribution. Measures of central tendency and dispersion are generally used to describe the parameters of a population under study. The construction of histograms, scatter plots, and box plots are widely used to study the behavior of systems in terms of reliability. Frequency tables can also be used to estimate the probability density function, without the need for a specific distribution law [19]. These statistical methods are used in many fields and are not limited to reliability. For example, Reference [20] presents a simulation of a manufacturing plant to test the implementation of Industry 4.0 technology. For this purpose, hypothesis testing and analysis of variance (ANOVA) are used for validation and parameter selection purposes, respectively. In [21], they use statistical metrics, particularly the confusion matrix, to evaluate the results of a text classification model. In [22], they used hypothesis testing (Pearson's Chi-square tests) to validate the choice and estimation of the parameters of a Weibull distribution. The study consists of a test bench to study the reliability of electronic components to determine the effect of gamma radiation on the breakdown voltage of gas-filled surge arresters.

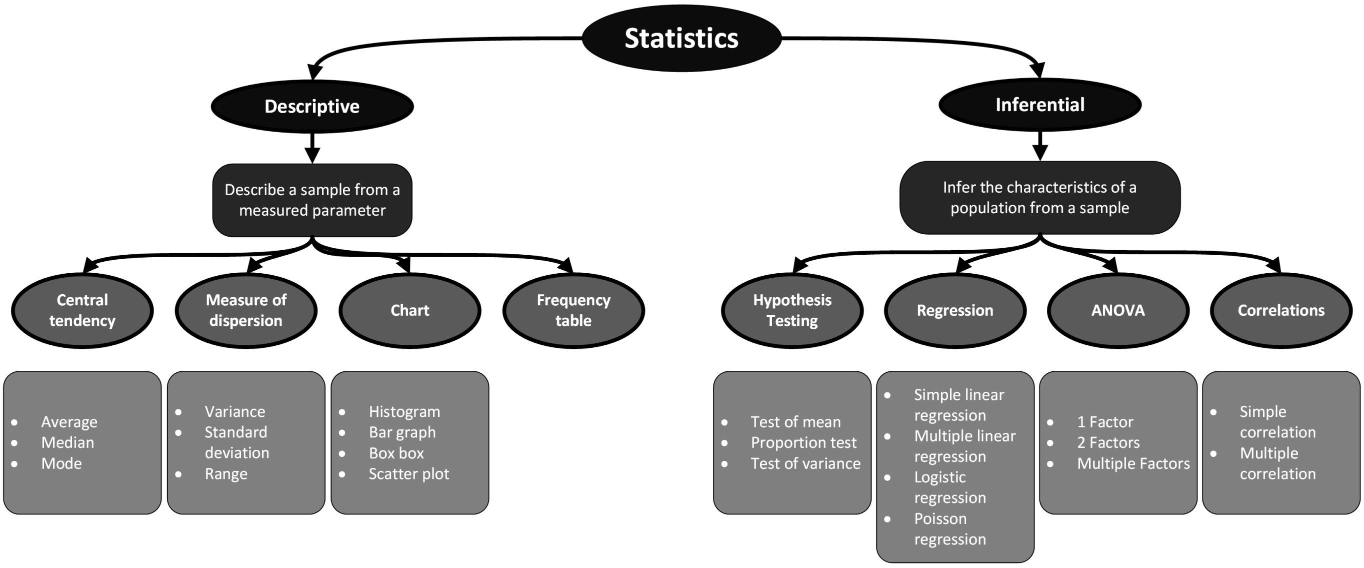

Figure 4. Common statistical modeling techniques.

3.3. Qualitative Modeling

The modeling methods presented previously are data-driven methods. However, in engineering, there are still several that are based on qualitative models. This brief section will serve to describe what a qualitative model is and what distinguishes them from data-driven models. Qualitative models aim to represent systems and reasoning in a symbolic way. The system and its constraints are represented in a discrete manner, rather than with data and mathematical equations. The objective is to infer as much behavior as possible from little information. Qualitative models are based on world experience and professional expertise. These experiences are used to decide what should be included depending on the situation, the important physical phenomena, and the simplifications that are relevant [23].

4. Reliability, Availability, Maintainability, and Security

4.1. RAMS Basics

RAMS is the field of engineering that deals with the study of the reliability of a set of systems and/or equipment [14]. The objective is to determine the general behavior of a population to make decisions on maintenance policies, replacements, etc. For this, engineers use different statistical and qualitative modeling methods. The first step in establishing a maintenance policy for a system is to identify the risk associated with its operation [9]. To this end, the next section will present qualitative methods used to identify those risks, then, methods to quantify those risks will be presented.

4.2. Qualitative Modeling in RAMS

When analyzing the reliability of an asset, it is essential to identify the hazards associated with its operation. Section 4.2 is used to present two of the most popular qualitative methods to develop such models. These methods rely heavily on the elicitation of experts, typically those who have designed, operated, or maintained the system.

4.2.1. Failure Modes and Effect Analysis

The Failure Modes and Effect Analysis (FMEA) is an analysis method used to identify the failure modes of components. Failure mode is an observable cause of system malfunction. FMEA consists of the decomposition of the system into functionally independent subsystems. First, analysts must identify the different operating modes and the system's configurations of these operating modes. Then they compile this information into a table (by operating mode) and indicate the related failure modes and the effect they have on other entities in the system [9]. In addition, this simple method allows for the examination of potential system failures and the determination of preventive measures to avoid the identified problems [11]. As an example, the authors of [24] have developed a new method of multi-criteria analysis, in order to classify the failure modes according to the level of risk and the actions of mitigation and elimination of risks. The new method combines the Fuzzy Analytical Hierarchy Process (Fuzzy AHP) method and Fuzzy Multi-Attribute Ideal Real Comparative Analysis (FMAIRCA). Similarly, Reference [25] proposes a method based on Dempster–Schaffer theory to improve the traditional FMEA risk prioritization method. A case study is presented for the analysis of a liquefied natural gas terminal. FMEA is often used as a starting point for the construction of fault trees, which will be discussed in the next section, and for reliability-based maintenance programs [9].

4.2.2. Fault Tree Analysis

Sometimes, no data are collected to perform a statistical analysis of a system failure. In this case, it may be relevant to look at the underlying causes and the combination of events that may lead to a particular failure. One of the methods used is the Fault Tree Analysis (FTA), where Boolean logic is applied to link events by simple logical relationships (cause and effect links). The method starts by identifying a failure mode (one at a time) and determining all the elementary events that are related to it. As this qualitative method takes advantage of Boolean algebra, the tree can be described by a set of equations and random variables. Using the rules of Boolean algebra, it is possible to calculate the probabilities of failure of the system [9]. There are many other qualitative methods for modeling the failures of a system. Cause and effect (Ishikawa) diagram, check lists, Bayesian network, event tree analysis, hazard and operability analysis (HAZOP), and the hazard index method are example of commonly used methods in reliability [9,10].

4.3. Mathematical Modeling in RAMS

Reliability can be measured with the survivor function ($S(t)$ or $R(t)$), the probability density function, the failure rate $z(t)$, etc. [10]. These probabilistic functions are representations of statistical lifetime distribution [13]. $F(t)$ commonly refers to the cumulative distribution function, that is, the probability that the item will fail over a period of time. The probability density function (PDF or $f(t)$) is the derivative of the distribution function. The survivor/reliability function is the probability that an item does not experience a failure in a specified time interval. The equation is represented in Equation (1):

$$R(t) = S(t) = 1 - F(t) = Pr(T < t) \quad for\ t < 0 \tag{1}$$

On the other hand, the failure rate $z(t)$, often called the hazard rate $h(t)$, models the relationship of PDF with the survivor function [13]. The equation is represented in Equation (2):

$$z(t) = h(t) = \frac{f(t)}{R(t)} \tag{2}$$

The cumulative hazard function $H(t)$ is the integral of the hazard function and is used primarily for data generation in simulation [13]. With regard to reliability, there are two types of systems/components: repairable and non-repairable. A non-repairable system, as the name suggests, cannot be repaired and needs to be replaced when a failure occurs. In other words, it means that a failure leads to the end of the system's life. In contrast, a repairable system can be restored to a working state as a result of maintenance actions. The same functions apply to both types of system, but different distributions are used to model their behavior.

4.3.1. Non-Repairable System

In the case of non-repairable systems, the survival probability or the hazard rate are computed to determine the occurrence of failure events. The mean time to failure expresses the lifetime of the system involved [26]. The hazard rate is characterized by three states, decreasing at the beginning of the life, constant during the service life, and increasing at the end of the life. These behaviors are typically presented in the form of the bathtub curve as shown in Figure 5.

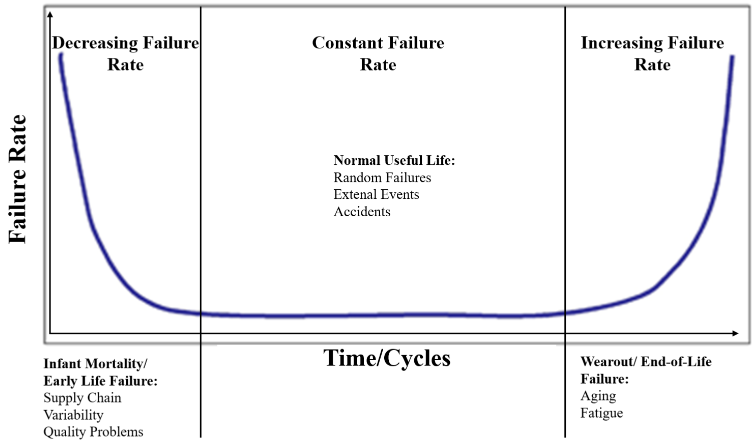

Figure 5. Bathtub curve (adapted from [27]).

Early life failures are often associated with defects due to production, assembly, etc. Various controls are used to prevent these products from reaching the customer. Regarding lifetime failures, they are often considered random failures, which means that an unusual level of stress on the system exceeds its capacity and causes the failure. Finally, when the number of failures is increasing (end-of-life), they are typically associated with aging and physical degradation of components [27]. By using the bathtub curves, it is easy for practitioners to know at what stage of the aging process the system is, and apply the maintenance program accordingly. As mentioned above, reliability is measured with probabilistic functions, which are derived from lifetime distributions. In inferential statistics, this is referred to as parametric analysis; first, the appropriate distributions are selected, and then the parameters are extracted from the data. The most commonly used distributions used in RAMS are the exponential distribution, the Weibull distribution, and the gamma distribution [13,19]. Table 1 shows the different representation function from these three lifetime distribution. These distributions all used three similar parameters: a scale parameter, a location parameter, and a shape parameter. The shape parameter (k or m) affects the shape of the probability distribution. The location indicates if the distribution is shifted to right or left on the time axis. Finally, the scale parameter (λ or θ) indicates whether the distribution is more compact or expanded along the time axis [13,19].

Table 1. Representation functions from lifetime distributions.

Distribution	Cumulative $F(t)$ or CDF	Probability Density $f(t)$ or PDF	Survival $S(t)$	Hazard $h(t) = z(t)$	Cumulative Hazard $H(t)$
Exponential	$1 - e^{(-\lambda t)}$	$\lambda e^{(-\lambda t)}$	$e^{(-\lambda t)}$	λ	λt
Weibull	$1 - e^{(-\lambda t)^k}$	$k\lambda^k t^{k-1} e^{(-\lambda t)^k}$	$e^{(-\lambda t)^k}$	$k\lambda^k t^{k-1}$	λt^k
Gamma	$I(k, \lambda t)$	$\frac{\lambda(\lambda t)^{k-1} e^{-\lambda t}}{\Gamma k}$	$1 - I(k, \lambda t)$	$\frac{\lambda(\lambda t)^{k-1} e^{-\lambda t}}{\Gamma k[1 - I(k,\lambda t)]}$	$-log(1 - I(k, \lambda t))$

4.3.2. Repairable System

In the case of a repairable system, it is characterized by the fact that when a failure event occurs, the system can be returned to its operating state. Reliability is then expressed as the rate of occurrence of failure (ROCOF or repair rate) or as the mean time between failures (MTBF). In contrast with the non-repairable system, the event of interest is recurrent, and the modeling techniques are chosen accordingly. In general, the stochastic process of recurrent failure events is represented by a counting process. Since an asset may experience several failures during its useful life, the frequency of occurrence may increase, decrease, or remain constant.

When the asset is repaired, three assumptions can be made about the quality of the intervention. Maintenance can be considered perfect, i.e., the device is considered as new after repair. In the case of minimal repair, the system is considered "as bad as old" after its repair, meaning that the system, rather than returning to the initial conditions, is returned to its pre-failure state [28]. Finally, imperfect maintenance lies between these two extremes. Figure 6, adapted from [10], presents the different approaches. For a repairable system, the failure rate is referred to as the intensity function, instead of the hazard function.

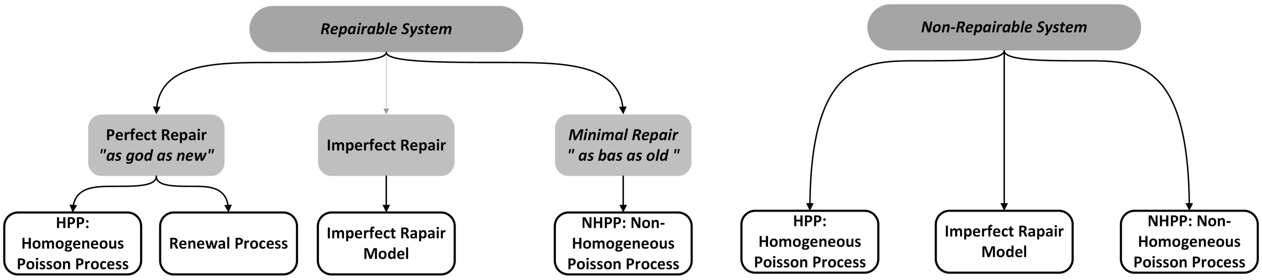

Figure 6. Types of system, stochastic point processes, and distributions [10].

Poisson's models are very common to the model counting process. The HPP model (Homogeneous Poisson Process) is a simple and popular form for probabilistic calculations of repairable systems. This model considers a constant time between failures, i.e., it follows an exponential distribution of λ and these events are independent and identically distributed [13]. Since the repair rate is constant, this model is most often used when the system is in its useful life period (see Figure 5). Furthermore, it implies that a repair returns the system to its original state of "as good as new" [29]. In contrast to the HPP, the NHPP model (Non-Homogeneous Poisson Process) does not consider perfect maintenance. The failure rate is not necessarily constant, it can evolve with the age of the asset and is referred to as a power law process. In other words, previous repairs will not affect future system performance [29]. Furthermore, the HPP model is a special case of the NHPP, when the shape parameters are equal to 1. The representation functions of both models are presented in Table 2. This model offers much flexibility because it can model increasing (system deterioration), decreasing (system regeneration), and constant failure rates. In addition, the intensity function of the power law has the same form as the hazard function of a Weibull distribution, presented in the following table. In the case of the NHPP, the system is considered "as old as new" after repair [13,29].

Table 2. Representation functions for repairable systems.

Distribution	Cumulative $F(t)$ or CDF	Probability Density $f(t)$ or PDF	Survival $S(t)$ or $R(t)$	Hazard $h(t)$ or $\lambda(t)$	Cumulative Hazard $H(t)$
HPP	$1 - e^{(-\lambda t)}$	$\lambda e^{(-\lambda t)}$	$e^{(-\lambda t)}$	λ	λt
NHPP	$1 - e^{(-\lambda t)^k}$	$k\lambda^k t^{k-1} e^{(-\lambda t)^k}$	$e^{(-\lambda t)^k}$	$k\lambda^k t^{k-1}$	λt^k

4.3.3. Survival Analysis

Parametric analyses are essential to estimate the failure rate of a group of assets. These analyses are very common in the field of reliability. However, they only consider failure events, without considering the influence of other factors on the system. In this regard, survival models allow determining a relationship between these failure events and some variables [28,30]. As with parametric analysis, there are specific techniques for repairable and non-repairable systems. The most well-known models, for dealing with non-repairable cases, are the proportional hazard model (Cox model), the additive Aalen model, and the accelerated life model. Several researchers have focused on developing extensions capable of handling the case of recurrent events. The most common variations of Cox models, known as proportional intensity models, are the Andersen–Gill, Wei-Lin and Weissfield, and Prentice–Williams–Peterson models [31,32]. As shown in Table 3, the intensity function of the survival model includes a β parameter, which is a coefficient vector, that is multiplied by X_i, a covariate matrix. In this way, the baseline hazard function $\lambda_0(t)$ is adjusted depending on the covariates, which is not the case with the NHPP. Thus, survival analysis can be used in reliability to obtain a more precise estimate of the failure rate, with respect to the parameters of a specific asset.

Table 3. Intensity function comparison.

NHPP	$k\lambda^k t^{k-1}$
Anderson–Gill	$\lambda_0(t)e^{\beta X_i(t)}$

There are numerous applications of mathematical modeling for RAMS. As an example, the authors of [33] present a complete reliability analysis for different types of power transformers from an Australian electrical utility. They compare the results obtained by parametric analysis with Weibull to nonparametric analysis with Kaplan–Meier curves. In addition, a failure mode analysis is used to determine the prevalent causes of failure in relation to the age of the assets. In [34], the author proposes a methodology to quantify the uncertainty related to data quality in the application of statistical tools to estimate reliability. A case study on electrical utility assets in Canada is presented, and the HPP and NHPP methods are used to test the approach. In addition, a case study applied to the Dutch power system is presented by [35]. Reliability statistics are obtained with survival analysis, using Kaplan–Meier curves, and the parameters are estimated using a Weibull distribution. These results are then used in simulation scenarios to optimize maintenance and replacement policies.

5. Prognostic and Health Management

5.1. PHM Basics

As the name suggests, Prognostics and Health Management (PHM) is a discipline that focuses on system health management, prognostics, and enhanced diagnostic techniques [36], while RAMS focuses on studying the overall properties of a population, PHM proposes much more targeted approaches, by tracking individual assets. An important factor is that it implies that the assets must be continuously monitored in order to ensure the functions of the system. Thus, this discipline relies on data generated by sensors, which is different from RAMS, where historical data are generally used for modeling. The sensing system allows for real-time diagnostics as well as fault detection and isolation. The prognostic techniques allow for moving from a reactive to a preventive decision mode, especially in the execution of maintenance tasks. The general objective of this discipline is to optimally use an asset throughout its useful life. In other words, the prognostic goals align with those of asset management and RAMS. Estimation of the residual life of the system is the basis of the prognostic domain. To account for different failure modes, prognostics involves making multiple estimates of residual life. These estimates are made using historical data, projected scenarios, qualitative models (FMECA), manufacturing data, etc. In addition, prognostics aims at predicting the health of a system over time, to adapt maintenance actions and decision-making [37]. As PHM is about performing maintenance based on the predicted state obtained from monitoring, it is called condition-based maintenance, specifically, predictive maintenance.

Figure 7 shows that, before prognostics, decisions were taken based on data and diagnostics. With prognostics in the process, the decision-making is influenced by predictive modeling; with the estimation of the remaining useful life, the time to failure can be predicted, and the maintenance performed based on the actual system state. PHM methods are divided into physics-based approaches, data-driven approaches, and hybrid approaches [37]. Sometimes, some papers include reliability-based approaches in PHM modeling, but this section will describe the first three approaches, since reliability-based approaches have already been discussed.

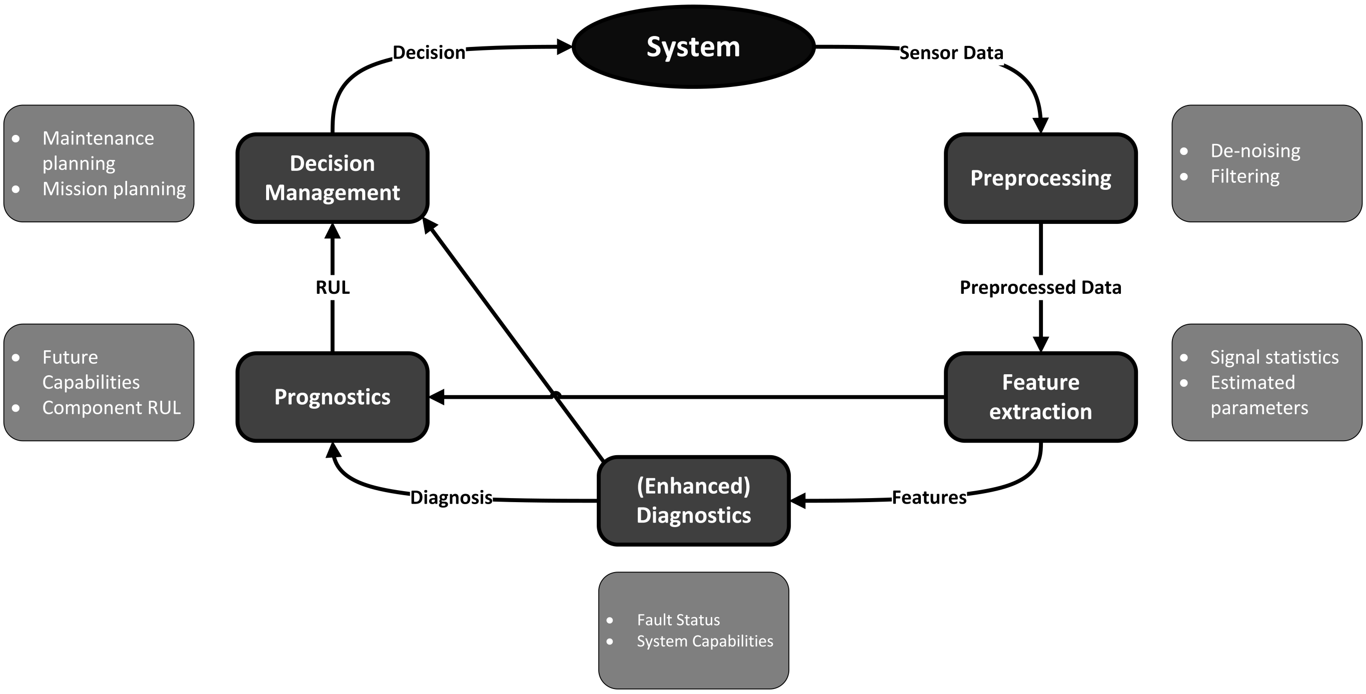

Figure 7. Prognostic in a health management process [38].

5.2. Qualitative Modeling in PHM

As with rams, PHM practitioners rely on qualitative models to establish a knowledge base on assets and their degradation. Indeed, it is common to use failure mode, effect, and criticality analysis (FMEA/FMECA), fault trees, and other methods to identify risks [38].

5.3. Mathematical Modeling in PHM

5.3.1. Physics-Based Model

In prognostics, physics-based modeling is one of the most accurate methodologies for the estimation of system parameters. To develop this type of model, it is necessary to have a thorough knowledge of the system, the interactions between the components and the environment, etc. In addition, it usually requires significant knowledge of mathematics and concepts of the physics of degradation. As shown in Figure 8, physical models can be developed using the finite element method, focusing on the physics of materials of a component, or even by simulation of the system and its stressors. They can also be established from the fundamental laws of physics using differential equations. In this approach, a physical model is developed for a system, a subsystem, or a component, describing the system based on mathematical equations. These equations represent the failure modes and degradation phenomena, based on the laws of physics that are applicable. Once the model is established, it allows for a diagnosis while monitoring the asset in operation. Given the state of the system, it is possible to predict future behavior. Physics-based models can be extremely accurate and very useful in prognostics. However, this implies that the model remains true to reality. As such, development can be difficult and require significant knowledge. Furthermore, the complexity of the models and the fidelity of the model can lead to computational difficulties [37,38].

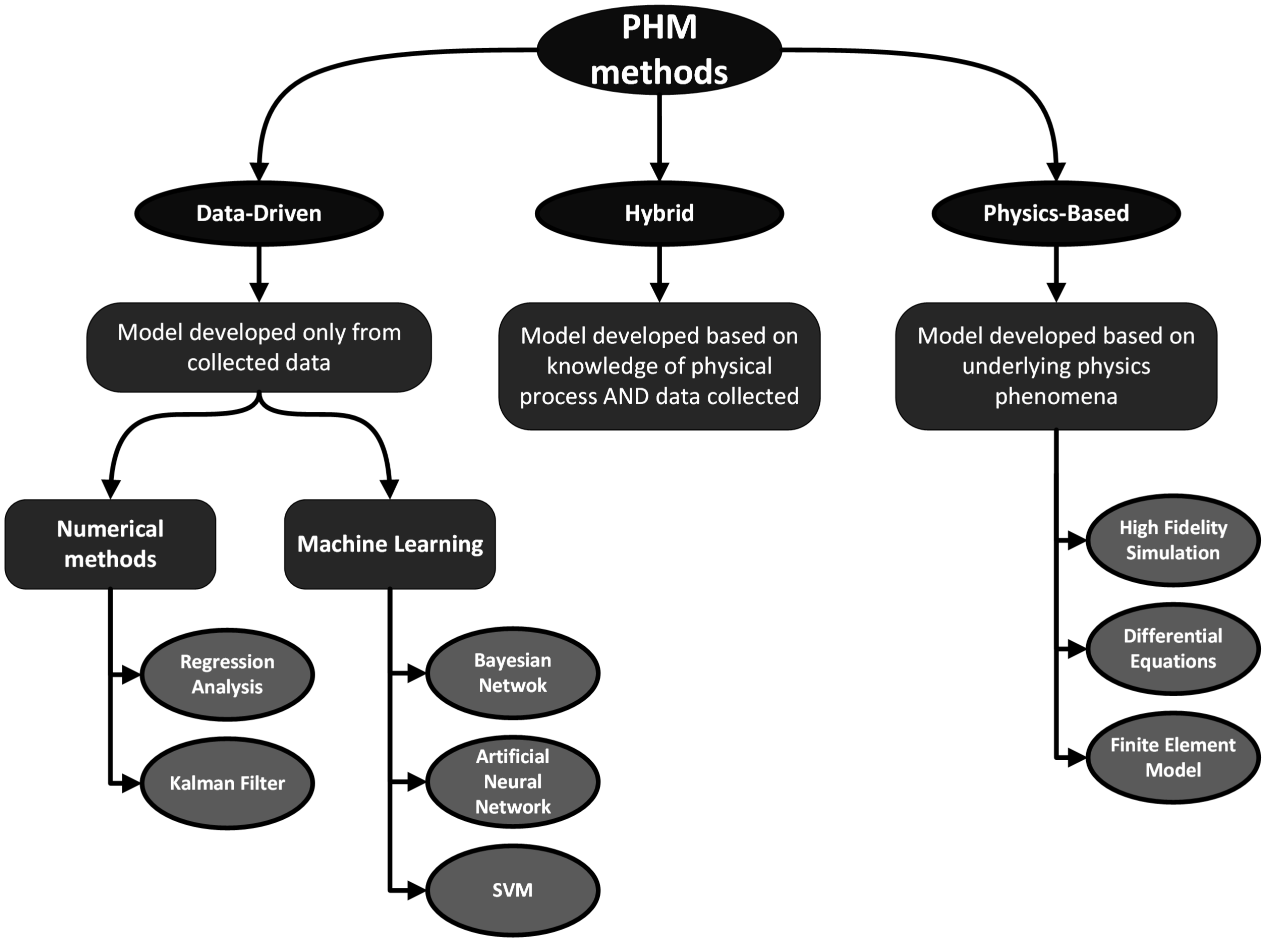

Figure 8. Prognostic methods (adapted from [37,38]).

5.3.2. Data-Driven Model

Data-driven modeling is, in theory, only based on data collected from the system [37]. Physics-based approaches are generally more accurate than data-based approaches [38]. However, data-based approaches generally require less knowledge of the system and the degradation phenomena, which makes them very attractive [37]. This is even more true when it is too difficult to model the system with physics-based approaches. Indeed, these allow a faster development and are therefore more widespread in the prognostic domain. In a simplified way, these methods consist of using historical or sensor data to determine system trends. When the system degrades, it is because the observed variables deviate from these trends and exceed a certain pre-established threshold. These models can then be used to estimate or predict the system's remaining useful life [37]. Data-driven techniques include statistical methods and machine learning (ML). The drawbacks of these techniques are the same as for data science projects; the models require a large amount of data to describe the phenomenon, which can be difficult when acquiring run-to-failure data. Moreover, choosing the right methods and avoiding overfitting and/or underfitting are also important challenges. Data-driven and machine learning applications are abundant in the literature. In [39], the authors present the development of a predictive maintenance model taking into account covariates and possible interactions, applied to a solar thermal power plant. The model developed combines survival analysis with artificial neural networks, with the aim of integrating it into a system for monitoring the state of the heat transfer pump and predicting failures according to the dynamic state of the system. Ref. [40] proposes a study for the selection of relevant variables to facilitate the deployment of a predictive maintenance and real-time monitoring program. From the same perspective, Ref. [41] proposes a framework and a methodology to decrease the dimensionality of asset life cycle data and minimize information loss.

5.3.3. Hybrid Model

It is evident that, in practice, modeling still requires basic knowledge of the system and, in this case, of the failure modes and data that are available (sensors or history), even for data-driven techniques. Most applications in PHM are developed from both the data and the physics of the system [38]. For example, as for any data science project, prior knowledge of the system and its functioning is required to select appropriate methods (regression, classification, clustering, etc.), relevant variables, and performance metrics. This is where hybrid models come in. Hybrid techniques combine data-driven and physics of failure approaches for modeling. In this way, physics-based techniques are applied when possible, and if not, data are used to overcome the lack of knowledge. The worst-case scenario is where modeling by physics is impossible and there is not enough data. This is one of the main problems that can occur with this method. As it has advantages from the two types of techniques, it can also have disadvantages from both [37,38].

6. Discussion

As demonstrated, the two research areas are complementary, although they differ in some respects. RAMS focuses on the health of a group of systems, whereas PHM studies a single system in a closer manner. A parallel can be drawn with the field of medicine, where public health focuses on studying health issues on a national, provincial, or regional scale, while physicians treat patients individually, based on their history, current problems, and data collected during medical examinations. In the perspective of the hierarchical model of decision-making, the RAMS strategies are mainly at the tactical level. Indeed, the models allow for medium-term decisions over the life of the assets, and the level of detail provided is moderate. As for the PHM, it is generally operational strategies; the relationship with the asset is direct, and the level of detail of the information is very high and allows for short-term decisions, or even real-time decisions. Nevertheless, the two fields generally have influence at several levels of the company, up to the choice of system design. Four types of modeling approaches were presented: qualitative, physics-based, data-based, and hybrid. Qualitative approaches are used to establish basic knowledge about the system, its design, components' interactions, and associated failure risks. Qualitative approaches are used for both RAMS and PHM, and the most commonly referred to approaches in the literature are failure mode, effects and criticality analysis, and fault tree analysis. The techniques based on the physics of failures are more associated with the PHM domain. Data-driven approaches are applicable to both domains, and some techniques are similar. RAMS is an older field, and the mathematical methods generally derive from inferential statistics and regression analysis. PHM is a more recent research domain that tends to use sensor and connectivity technologies, and modeling is often performed with machine learning techniques. Reliability techniques, such as exponential models (Weibull, Gamma, etc.), are sometimes used in PHM, but these techniques require much failure data, which can be difficult to obtain when studying a single system. The time to accumulate sufficient failure data would be prohibitive. Instead, PHM relies on sensor data to develop predictive maintenance and anomaly detection models. When models are built from data, the procedure is similar to that used in data science, whether it is for RAMS, PHM, or any other application. In addition, the Engineering of Asset Management aims to coordinate efforts to optimize the life cycle of assets. Its application is of crucial importance for asset-intensive organizations, such as the energy, aeronautics, or aerospace sectors. The EAM framework provides long-, medium-, and short-term strategies in the management of activities. Thus, it integrates RAMS and PHM in the planning and optimization of the life cycle, the RAMS having a general aim on the long and medium terms, and the PHM on a medium- and short-term horizon of decision-making. It is also important to acknowledge the impact of asset management, not only from an economical perspective, but also from a social and environmental point of view. Asset management objectives actively contribute to sustainable development. Indeed, the optimization of the asset life cycle aims to reduce waste through a long-term vision, from a more durable design, through optimal maintenance, to the disposal of the system. It has been shown by numerous applications, asset management and maintenance strategies are largely employed in the public and energy sector, where resources must be carefully allocated. In summary, this work helps researchers in the field to correctly identify the different theoretical approaches to reliability engineering, while giving some concrete examples of applications. Moreover, this text allows distinguishing the different modeling methods related to each discipline and to identify the similarities and limitations of these disciplines. However, this work is limited to asset management in the perspective of reliability engineering. As stated before, EAM is an integrated framework, therefore it goes beyond the scope of maintenance activity. Furthermore, the article covers the basic mathematical modeling methods of RAMS and PHM. It is intended to be a starting point for research rather than an in-depth review of all available methods.

7. Conclusions

The field of reliability engineering, like many other fields, is evolving rapidly thanks to the democratization of data acquisition and processing technologies. In this paper, we have tried to provide a unified perspective of the different research fields, namely RAMS, PHM, and Engineering of Asset Management. This review also addressed RAMS and PHM modeling techniques and highlighted the importance of these disciplines in ensuring the reliability, availability, maintainability, and security of complex systems. It also presented how they are defined in a management and decision-making model by including the hierarchy of organizational decision-making in management. The first sections have defined the basic concepts of maintenance, failure, and aging, in addition to defining the different modeling concepts. The importance of understanding the basics of mathematical modeling and statistical models was also emphasized. Furthermore, the most common analysis methods were associated with their respective fields, from qualitative modeling to data-driven techniques. This review highlighted the different modeling approaches used in RAMS, including qualitative modeling techniques such as failure modes, effect analysis, and fault tree analysis, and statistical modeling techniques for repairable systems and non-repairable systems. In PHM, the review explored qualitative modeling and different mathematical modeling techniques, including physics-based models, data-driven models, and hybrid models. From this, the distinction between the different subjects has been clarified, in accordance with their analysis objective. In conclusion, this review of the literature provides a comprehensive overview of the different aspects of RAMS and PHM modeling techniques, emphasizing their importance and complementarities in an asset management program. This allows new researchers to become familiar with the field of reliability and bridge the gap between traditional analytical techniques and the latest developments. Indeed, artificial intelligence techniques, although of increasing interest, are still not widely applied in practical contexts with operational data. This reflects an opportunity to link reliability and machine learning for industrial applications.

Author Contributions: Conceptualization, M.P. and G.A.-N.; methodology, M.P. and G.A.-N.; validation, G.A.-N.; writing—original draft preparation, M.P.; writing—review and editing, M.P. and G.A.-N.; supervision, G.A.-N.; project administration, G.A.-N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data sharing is not applicable.

Acknowledgments: This research was supported by Hydro-Québec, the Natural Sciences and Engineering Research Council of Canada (NSERC), and the Université du Québec à Trois-Rivières through the Hydro-Québec Asset Management Research Chair.

Conflicts of Interest: The authors declare no conflicts of interest.

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