# Reliability Analysis for Sustainable Asset Management Decision Support

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**Dissertação de Mestrado**

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# Abstract

The increasing relevance of renewable energy sources places strong demands on the reliability and availability of hydropower assets, which play a strategic role in ensuring both economic performance and sustainability objectives. Within this context, asset management decisions based solely on deterministic lifetime assumptions may lead to premature replacements or underestimated failure risks, with significant economic and environmental consequences.

This dissertation proposes a data-driven reliability analysis framework to support sustainable asset management decisions in hydropower generation. The study focuses on generator circuit breakers as a pilot asset class and applies survival analysis techniques capable of handling censored data and recurrent failures. The methodology follows the CRISP-DM framework and integrates semi-parametric and non-parametric models, namely the Cox Proportional Hazards Model and Random Survival Forests, to estimate failure probabilities based on historical operational and maintenance data.

Model performance is evaluated through stratified cross-validation using discrimination and calibration metrics, including the concordance index and time-dependent Brier Score. The estimated failure probabilities are subsequently integrated into a Monte Carlo–based economic risk simulation, enabling the quantification of expected costs and uncertainty at asset, plant, and portfolio levels.

The results demonstrate that both modeling approaches provide consistent and interpretable estimates of failure risk, with Random Survival Forests exhibiting superior predictive stability. The proposed framework supports the identification of critical assets and plants, translating technical reliability insights into economically meaningful indicators. Overall, this work contributes to more informed, risk-based, and sustainable asset management decisions in hydropower generation and establishes a methodological foundation that can be extended to other asset classes.

# Acknowledgments

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*"It always seems impossible until it's done."*

Nelson Mandela

# Contents

# Acronyms and Symbols

| | |
|---|---|
| CI | Confidence Interval |
| COX PHM | Proportional Hazard Model |
| CRISP-DM | Cross-Industry Standard Process for Data Mining |
| EDP | Energias de Portugal |
| HR | Hazard Ratio |
| IBS | Integrated Brier Score |
| IRR | Internal Rate of Return |
| ISO | International Organization for Standardization |
| KM | Kaplan-Meier |
| MC | Monte Carlo |
| MTBF | Mean Time Between Failure |
| MTTR | Mean Time To Repair |
| PWP | Prentice-Williams-Peterson |
| RUL | Remaining Useful Life |
| RSF | Random Survival Forest |
| SAP | System, Application and Products in Data Processing |
| TOTEX | Total Expenditure |

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# Chapter 1

# Introduction

## 1.1 Project context and Motivation

EDP has publicly reaffirmed its commitment to lead the energy transition and achieve ambitious sustainability targets. In its strategic plan for 2023–2026, the company outlined significant investments in renewable energy, with the objective of abandoning coal-fired generation by 2025, reaching 100% renewable electricity generation by 2030, and achieving net-zero carbon emissions by 2040. These strategic commitments place increased emphasis on the reliability and availability of renewable energy assets, which are critical to ensuring both environmental and economic sustainability (EDP, 2025).

Within this context, hydropower assets play a particularly strategic role. During the first half of 2025, approximately 28% of the total energy produced by EDP's assets was generated by hydropower plants. In the Iberian market alone, this corresponded to a production volume of 7.82 TWh (EDP – Energias de Portugal, 2025). Considering that the average electricity market price in first half of 2025 was approximately 64 €/MWh (REN – Redes Energéticas Nacionais, 2025), hydropower generation represented an estimated revenue of around 306 million euros over this period. These figures highlight the significant financial contribution of hydropower assets to EDP's overall performance.

Consequently, the unavailability of hydropower assets due to equipment failures or unplanned maintenance interventions has a direct and substantial impact on the company's revenues. Beyond the immediate economic losses for the company, such unavailability also compromises the supply of renewable energy, potentially requiring compensation through alternative generation sources with higher environmental impact. Therefore, failures in critical hydropower equipment simultaneously affect financial performance, operational reliability, and sustainability objectives.

At the same time, hydropower assets are characterized by long service life and high capital intensity. Maintenance and replacement decisions that are not adequately supported by an accurate assessment of failure risk may result in premature interventions, leading to unnecessary consumption of materials, increased logistics, and additional environmental impact associated with manufacturing and transportation. Conversely, insufficient or delayed interventions increase the likelihood of unplanned failures, amplifying both economic losses and renewable energy production shortfalls.

In this scenario, improving the accuracy of asset reliability assessment becomes a key enabler of sustainable asset management. By supporting maintenance and replacement decisions based on quantitative failure risk rather than deterministic lifetime assumptions, it is possible to strike a balance between avoiding unnecessary interventions and minimizing the risk of unplanned outages. This project, developed within EDP's Production division and in collaboration with the Reliability team, addresses this challenge by proposing a data-driven framework for reliability analysis and decision support, aligned with the company's economic objectives and long-term sustainability strategy.

## 1.2 Project and goals

This project was developed within EDP's Production division, in close collaboration with the Reliability department, which plays a central role in supporting asset management decisions across hydropower generation units. The responsibilities of this department extend beyond the evaluation of asset reliability for investment prioritization, encompassing the definition and promotion of best practices aimed at improving asset management performance at the production centers.

In particular, the Reliability department is responsible for assessing the condition and failure risk of critical assets, supporting decisions related to maintenance planning and equipment replacement. At the same time, it acts as a technical reference for local maintenance teams, proposing methodologies, analytical tools, and performance indicators that contribute to a more consistent and data-driven management of assets across the organization.

The initial ambition of the project was to develop an integrated asset management framework based on a total expenditure (TOTEX) perspective, combining acquisition costs, operational costs, and maintenance expenses. However, due to limitations in the consistency and completeness of available cost data, the scope of the study was refined to focus on reliability modeling and estimation of probability of failure. Accordingly, the main objectives of this project are to:

- Develop a quantitative and data-driven approach for assessing the reliability of critical hydropower assets;
- Estimate failure probabilities using historical operational and maintenance data, explicitly accounting for censored observations and recurrent failures;
- Support maintenance and replacement decisions that avoid unnecessary interventions while minimizing the risk of unplanned outages;
- Provide decision support tools that can be used by the Reliability department to guide production centers toward more sustainable asset management practices;
- Establish a methodological framework that can be extended to other asset classes and integrated into broader economic and sustainability-driven decision processes.

By reinforcing the role of reliability analysis as a decision-support instrument, this project contributes to improving consistency across the different asset management teams.

## 1.3 Methodology adopted in the project

The project was developed following the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology, ensuring a structured and iterative approach throughout the study. The main phases include business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

The work was carried out over a period of approximately four months, with the following key milestones:

- Analysis of the organizational context and definition of the problem;
- Exploration and assessment of the quality of the available data;
- Preparation and structuring of failure and censoring data;
- Development and validation of reliability models;
- Integration of the models into an economic risk simulation process.

This approach made it possible to iteratively adjust the objectives and methodology in response to data limitations, ensuring coherence between the results obtained and the organization's actual needs.

## 1.4 Document structure

This dissertation will be organized as follows:

- Chapter 2 reviews the main theoretical concepts related to asset management, reliability, and survival models;
- Chapter 3 describes the problem context, the case study, and the available data;
- Chapter 4 details the adopted methodology and the developed models;
- Chapter 5 presents the results obtained;
- Chapter 6 discusses the results and presents the final conclusions of the study.

# Chapter 2

# Literature Review

According to International Organization for Standardization (2014), an asset is defined as "an item, thing, or entity that has potential or actual value to an organization," including physical and non-physical elements whose value may evolve over the life cycle. This framework highlights that assets are not limited to equipment alone, but encompass any resource that contributes to the achievement of organizational objectives, and are therefore fundamental to an integrated life cycle management strategy.

This literature review places greater emphasis on physical assets, due to the specific context of the dissertation.

## 2.1 Asset Management

Campbell et al. (2011) show that the main objective of asset management is to optimize the balance between performance, risk, and cost. This asset management concept is also shared in International Organization for Standardization (2014).

An effective asset management allows organizations to improve financial performance, support investment decision-making, reduce environmental and operational risks, and increase reliability and service quality. These benefits demonstrate that asset management is not limited to maintenance activities or equipment operation, but constitutes a strategic system for value creation, particularly in organizations that depend on critical assets (International Organization for Standardization, 2014; Campbell et al., 2011; Hastings, 2010).

The ISO 55000 standard identifies a set of benefits associated with the implementation of an effective asset management system, emphasizing value creation through the balance between costs, risks, performance, and sustainability across the asset life cycle. Among the main benefits are improved financial performance through optimized investments and reduced operating costs, more informed decision-making supported by structured asset condition and risk data, and effective risk management that reduces financial losses, environmental impacts, and safety failures (International Organization for Standardization, 2014; Schuman and Brent, 2005).

Additional benefits highlighted in the literature include improved service levels and quality of delivery, enhanced regulatory compliance, demonstration of social responsibility, strengthened organizational reputation, long-term operational sustainability, and increased efficiency and effectiveness of internal processes (Hastings, 2010).

Asset management involves activities such as planning, acquisition, operation, maintenance, financial management, and continuous improvement, constituting a more holistic framework that integrates different organizational functions in order to extract maximum value from assets. Figure 2.1 illustrates this perspective through the total life cycle asset management model, in which the asset life cycle is managed from the design stage to the decommissioning of the asset (Campbell et al., 2011).

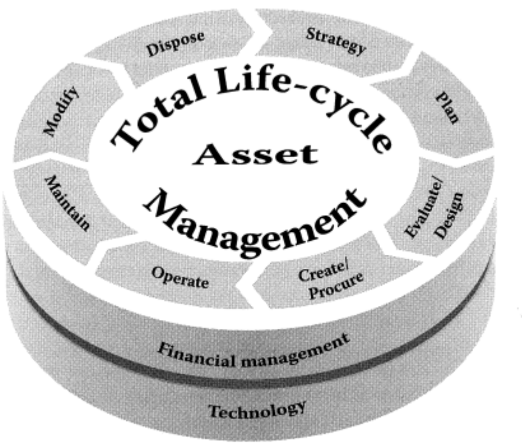


Figure 2.1: Total Life-cycle Asset Management, Source: Campbell et al. (2011)

Other authors, including Mitchell and Carlson (2001) and Wenzler (2005), also advocate for this framework. Similarly, the maintenance excellence pyramid shown in Figure 2.2 demonstrates that maturity in asset management depends not only on technical processes, but also on leadership, control, and organizational culture. Thus, maintenance is framed as an essential but not sufficient element within a broader strategic approach that supports investment, replacement, and reliability optimization decisions (Campbell et al., 2011).

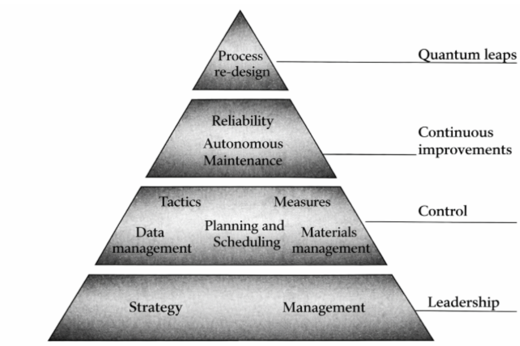


Figure 2.2: Maintenance Excellence Pyramid, Source: Campbell et al. (2011)

## 2.2 Maintenance

Maintenance plays a central role in asset management and constitutes one of the fundamental pillars of modern Asset Management. It is one of the key means of safeguarding asset value and ensuring that assets continue to perform their intended function in a reliable and efficient manner (Campbell et al., 2011).

Historically, maintenance practices have evolved from purely reactive approaches to increasingly preventive, predictive, and reliability-oriented methodologies. As discussed in (Mobley, 2004), the high cost of reactive strategies is evident, showing that post-failure interventions can cost up to three times more than planned interventions, while also contributing to unplanned downtime, low availability, and productivity losses. In many industrial sectors, between 15% and 60% of total operating costs are associated with maintenance, and approximately one third of this amount is wasted due to inadequate practices, unnecessary interventions, or a lack of data on the actual condition of the equipment.

### 2.2.1 Corrective Maintenance

According to Dhillon (2006) corrective maintenance refers to actions carried out after the occurrence of a failure, with the objective of restoring the asset to its operational condition. It is typically an unplanned intervention that must be urgently incorporated into scheduled work due to the immediate impact of equipment unavailability. Accordingly, this type of maintenance includes several actions, such as fail repair (repairing the item to restore its operational condition), overhaul (restoring the equipment to an “as-new” condition), salvage (recovering usable materials from non-repairable items), servicing (actions resulting from the repair), and rebuild (a near-total reconstruction to recover the original performance).

Although inevitable in any industrial system, corrective maintenance is associated with significantly higher operating costs when compared to planned strategies. Interventions carried out after failure tend to involve higher direct and indirect costs, including the urgent mobilization of resources, unplanned downtime, and productivity losses, and may amount to several times the cost of preventive or predictive interventions (Mobley, 2004; Hastings, 2010).

This type of maintenance may be appropriate for non-critical assets with low operational impact and that are quick and inexpensive to replace (Liu et al., 2024).

Thus, although it plays an essential role in restoring asset functionality, corrective maintenance is recognized as one of the least efficient approaches, thereby justifying the evolution toward more proactive strategies.

### 2.2.2 Preventive Maintenance

Preventive maintenance plays an important role in the historical evolution of industrial maintenance strategies. This type of maintenance constitutes one of the conceptual foundations for the development of condition-based maintenance. (Liu et al., 2024), clearly describes this trajectory, showing that industry transitioned from predominantly corrective practices (1930–1950) to structured preventive maintenance programs from the 1960s onward, in which interventions were carried out at fixed time or usage intervals, with the aim of reducing unexpected failures and improving equipment availability.

## 2.3 Reliability

Engineering systems are not perfect. A perfect system would be one capable of operating continuously, fully fulfilling its intended function, without experiencing any failure throughout its entire service life. However, this concept is idealistic, impractical, and economically unfeasible, since the costs associated with design, material selection, and testing required to ensure the complete absence of failures may far exceed the economic benefits obtained. As a result, practical and economic constraints needs the adoption of non-perfect systems, in which the occurrence of failures is inevitable. In this context, designers, manufacturers, and end users continuously seek to reduce both the probability and the consequences of failures through the systematic application of reliability principles and risk analysis (Modarres, 2016).

### 2.3.1 Reliability and Probability of Failure

The reliability of an item corresponds to the probability that it successfully performs its assigned mission under specified operating conditions over a given period of time (Carrión-García and Papić, 2015). Modarres (2016) gives a similar definition, defining reliability as the probability that a system or component performs its intended function without failure. The better it performs this function, the higher its reliability.

Reliability is represented by the equation 2.1.

$$R(t) = 1 - F(t) = 1 - P(T \leq t) = P(T \geq t) = \int_{t}^{\infty} f(t)\,dt \tag{2.1}$$

As can be observed in equation 2.1, reliability is the complement of the probability of failure. The probability of failure is the probability that an item or system will fail to perform its required function under specified operating conditions within a given period of time. It represents the likelihood of the occurrence of a failure event and is mathematically defined as the complement of the reliability function (Modarres, 2016; Carrión-García and Papić, 2015). This probability is expressed by Equation 2.2.

$$F(t) = P(T \leq t) = \int_{0}^{t} f(t)\,dt \tag{2.2}$$

Figure 2.3, taken from (Modarres, 2016), facilitates the interpretation of how reliability and unreliability operate.

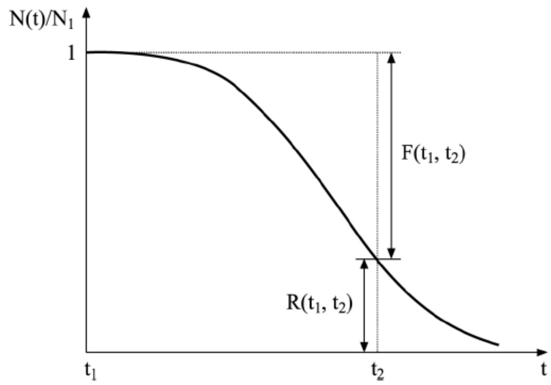


Figure 2.3: Reliability Function or Survival Function,
Source: (Carrión-García and Papić, 2015)

### 2.3.2 Other Reliability Concepts

An understanding of the following concepts is also important for the reading and interpretation of this dissertation.

**Failure:** "The event or inoperable state, in which any item or part of an item does not perform as previously specified." (Carrión-García and Papić, 2015)

**Degradation:** System degradation corresponds to a progressive and typically irreversible process of deterioration of its condition or performance, resulting from the accumulation of damage over time, which may lead to failure when a critical threshold is reached (Forouzandeh Shahraki et al., 2017)

**Soft Failure:** A soft failure occurs when system failure is caused by the gradual degradation of its performance, reaching a predefined critical threshold, without the occurrence of an abrupt or instantaneous event. When this type of failure occurs, restoring the equipment to an operable state requires a relatively low level of effort. (Forouzandeh Shahraki et al., 2017)

**Hard Failure:** A hard failure is characterized by a sudden and catastrophic failure, typically caused by shocks or excessive loads, occurring almost instantaneously and without directly depending on the accumulated level of degradation. In such failures, the equipment must be replaced or subjected to extensive repair (Forouzandeh Shahraki et al., 2017).

**Censoring:** Occurs when the exact time to an event, such as failure or end of life, is unknown. This may happen because the event has not yet occurred or because observation was interrupted before its occurrence. There are several types of censoring, including right-censoring, left-censoring, and interval-censoring. Among these, right-censoring is the most common and is examined in greater detail in the context of Survival Analysis (Maria Oliveira, 2019).

Figure 2.4 shows an example of right-censoring, where by the end of the study there are three units with recorded failures (Units 1, 2, and 4), while Unit 3 is censored, meaning that no failure event is observed for this unit by the end of the study.

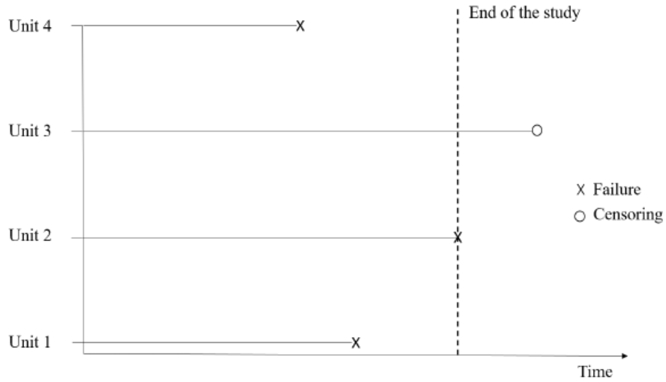


Figure 2.4: Units Failure and Censoring Times, Source: Maria Oliveira (2019)

**Mean Time Between Failures (MTBF):** "A basic measure of reliability for repairable items: The mean number of life elements during which all parts of the item perform within their specified limits, during a particular measurement interval under stated conditions." (Carrión-García and Papić, 2015).

**Mean Time To Repair (MTTR):** "A basic measure of maintainability: The sum of corrective maintenance times at any specific level of repair, divided by the total number of item failures during a particular interval under stated conditions." (Carrión-García and Papić, 2015).

**Remaining Useful Life (RUL):** Corresponds to the time interval during which a piece of equipment is expected to continue operating, from its current condition, until a failure occurs or a threshold requiring repair or replacement is reached (MathWorks, 2022).

### 2.3.3 Reliability Modeling

According to (Murthy et al., 2002), reliability modeling is associated with the development of models aimed at predicting, estimating, and optimizing the survival or performance of equipment over time. In this sense, reliability modeling involves the use of analytical methods to anticipate asset failure behavior, thereby supporting the definition of maintenance and management strategies throughout the life cycle. This perspective is consistent with the approach presented in (Modarres, 2016), which defines reliability modeling as the application of mathematical and statistical models to describe and analyze the failure behavior of engineering systems over time.

The estimation of RUL is one of the most widely used methods for reliability modeling (Maria Oliveira, 2019). For each type of data obtained, a specific modeling method is applied. In general, data can be classified into three main categories:

- Run-to-failure of similar equipment;
- Lifetime data of similar equipment;
- Equipment failure threshold for a certain condition indicator.

In turn, the models themselves can also be classified into three distinct groups, as illustrated in Figure 2.5, adapted from (MathWorks, 2022).

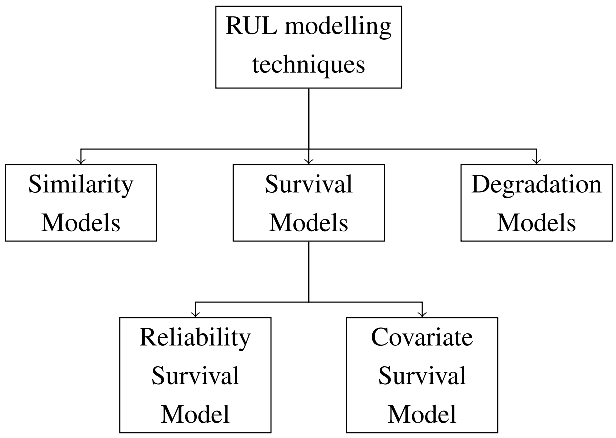


Figure 2.5: Classification of RUL modelling techniques

These modeling methods are explained below, with the exception of survival models, which are described in greater detail in the following section.

#### 2.3.3.1 Similarity Models

Similarity-based models estimate the RUL by comparing the current degradation profile of a piece of equipment with complete historical profiles of similar equipment that operated until failure. The estimation is based on identifying past degradation trajectories that exhibit behavior similar to that observed in the equipment under analysis, assuming that these assets will exhibit comparable future behavior. (Maria Oliveira, 2019)

This approach is particularly effective when run-to-failure data are available, that is, complete time series from the start of operation until failure. The RUL is estimated from the mean or distribution of the remaining lifetimes observed in the most similar equipment. Despite their flexibility and data-driven nature, these models require large and homogeneous datasets and are sensitive to the quality and representativeness of the available historical data.

In Figure 2.6, a graph illustrating this model can be observed, where historical condition data up to failure from similar equipment are shown together with the current condition of the equipment under analysis. Through a neighborhood-based approximation, the estimated RUL is determined.

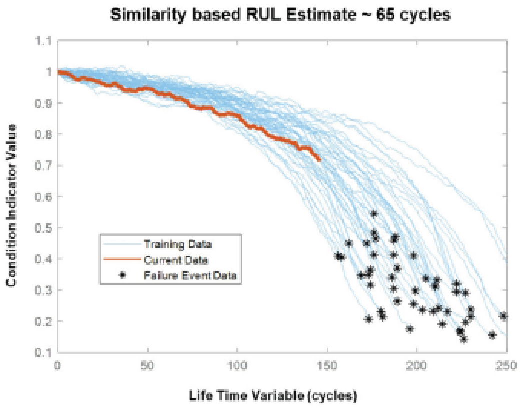


Figure 2.6: Similarity models capture degradation profiles based on run-to-failure data, Source: (MathWorks, 2022)

#### 2.3.3.2 Degradation Models

Degradation-based models estimate the RUL through explicit modeling of the evolution of condition indicators over time, such as vibration, temperature, wear, or other monitored parameters. In these models, degradation is represented as a continuous or stochastic process that evolves until a predefined failure threshold is reached. The RUL corresponds to the estimated remaining time until this threshold is reached (Maria Oliveira, 2019).

Degradation models may assume linear or nonlinear forms and can incorporate uncertainty associated with measurements and the future evolution of degradation. However, their application requires reliable sensors, a clear definition of failure thresholds, and sufficiently rich condition data.

Figure 2.7 shows an example of RUL estimation using a degradation-based model. In this figure, the failure threshold line, the degradation line shown in red, and the condition trajectory of the current machine can be observed. The degradation line is continuously updated as new condition data become available.

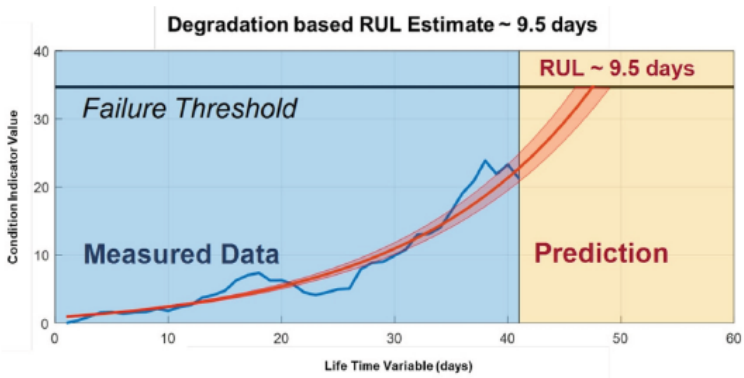


Figure 2.7: Degradation-Based Model,
Source: (MathWorks, 2022)

## 2.4 Survival Models

Survival analysis is a set of statistical methods developed to analyze the time until the occurrence of an event of interest, such as equipment failure, the occurrence of a defect, or the end of a system's life. One of its main objectives is to model and estimate the probability that a system remains operational over time, as well as to characterize the evolution of failure risk. For this purpose, fundamental functions are introduced, such as the survival function, which describes the probability that the event does not occur up to a given time instant, and the hazard function, which represents the instantaneous rate of event occurrence, conditioned on survival up to that moment. These functions allow for a complete probabilistic description of the system's temporal behavior (Kleinbaum and Klein, 2012).

Survival analysis is also distinguished by its ability to incorporate different types of incomplete data, namely right-censoring, enabling the use of partial information without introducing significant bias into the estimates. This characteristic makes survival analysis particularly relevant in applications where systems are observed over limited periods or subject to periodic inspections, as is often the case in reliability engineering and industrial asset management (Klein and Moeschberger, 2003).

Figure 2.5 shows that survival analysis can be divided into two different types: reliability survival analysis and covariate survival analysis. In reliability survival analysis, prediction is based on the occurrence or non-occurrence of the event and the lifetime variable, whereas in covariate survival analysis, external and internal covariates related to the equipment can also be incorporated. However, this classification is not unique. Alternatively, survival analysis methods can be categorized as parametric, semi-parametric, or non-parametric (Fan and Jiang, 2007).

### 2.4.1 Parametric Models

Parametric survival analysis models assume that the time to the occurrence of an event of interest, such as equipment failure, follows a known statistical distribution characterized by a finite set of parameters (Kalbfleisch and Prentice, 2002). This approach allows for an analytical description of the temporal behavior of reliability, enabling the explicit estimation of the survival function, the hazard function, and the mean lifetime of systems.

Among the most commonly used parametric distributions are the exponential, Weibull, and lognormal distributions, each suitable for different failure regimes and phases of the equipment life cycle. The choice of model depends on the observed behavior of the failure rate and the nature of the underlying degradation mechanisms. In this context, greater emphasis is placed on the Weibull model, as it is one of the most widely used in reliability engineering due to its high flexibility, allowing it to represent different failure rate behaviors over time. Depending on the value of the shape parameter, the Weibull model can describe early failures, random failures, or wear-out failures, thereby covering the different phases of the equipment life cycle (Carrión-García and Papić, 2015).

Failure Rate:

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{2.3}$$

Probability density function:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{2.4}$$

Cumulative Distribution function:

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{2.5}$$

$\beta$ is the shape parameter and $\eta$ is the scale parameter. Values of $\beta < 1$ indicate a decreasing failure rate, $\beta = 1$ corresponds to the exponential case, and $\beta > 1$ represents failures due to aging or wear. Figure 2.8 shows the variation of the Weibull distribution as a function of the value of the shape parameter $\beta$.

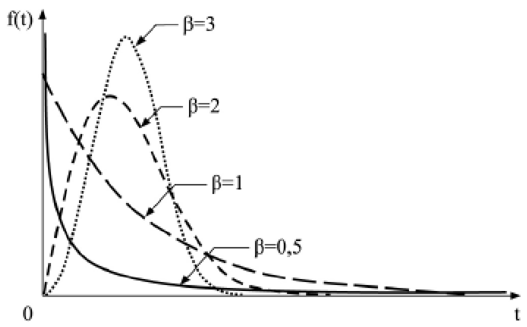


Figure 2.8: Weibull Distribution, Density function,
Source: (Carrión-García and Papić, 2015)

### 2.4.2 Semi-Parametric Models

Semi-parametric survival analysis models constitute an intermediate approach between parametric and non-parametric models. In these models, part of the structure is specified parametrically, while another part remains unspecified. This characteristic allows the effect of explanatory variables on the risk of event occurrence to be modeled without assuming a specific functional form for the distribution of time to failure (Kleinbaum and Klein, 2012).

In reliability engineering, semi-parametric models are particularly useful for analyzing the influence of operational, environmental, or usage conditions on equipment failure behavior, while maintaining a robust formulation in the presence of uncertainty regarding the baseline hazard (Kleinbaum and Klein, 2012).

### Cox PHM

The most widely used semi-parametric survival model is the Cox Proportional Hazards (PH) model, originally proposed by Cox (1972). This model is extensively applied in survival and reliability analysis due to its ability to incorporate covariates without requiring specification of the baseline hazard function. Unlike fully parametric models, the Cox model does not assume a specific distribution for the time-to-event variable, while still allowing the estimation of covariate effects on the hazard.

The hazard function for individual $i$ at time $t$ is defined as

$$h_i(t, X_i) = h_0(t) \exp\left(\beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}\right), \tag{2.6}$$

where $h_0(t)$ denotes the unspecified baseline hazard function, $X_i$ represents the vector of covariates associated with individual $i$, and $\beta = (\beta_1, \ldots, \beta_k)$ is the vector of regression coefficients to be estimated.

The main assumption of the model is the proportional hazards assumption, according to which the effect of the covariates on the hazard is multiplicative and constant over time. Consequently, the model enables the interpretation of $\exp(\beta_j)$ as the hazard ratio associated with a one-unit increase in covariate $x_j$, holding the remaining variables constant.

An additional advantage of the Cox PH model is its natural ability to accommodate right-censored observations through the use of partial likelihood estimation, allowing the incorporation of incomplete information without requiring full specification of the underlying survival distribution (Cox, 1972).

## 2.4.3 Non-Parametric Models

Non-parametric survival analysis models are characterized by not assuming any predefined functional form for the distribution of time to the event. Unlike parametric and semi-parametric models, these methods estimate the survival or hazard functions directly from the data, offering greater flexibility and reducing the risk of bias associated with incorrect assumptions about the underlying distribution. This class of models is particularly useful in exploratory contexts, in situations involving high complexity, or when the form of failure behavior is unknown (Modarres, 2016).

### Kaplan-Meier

The Kaplan–Meier method is a classical, non-parametric approach used in survival analysis to estimate the empirical survival function from censored data. This estimator constructs the survival function as a product of conditional probabilities associated with the observed failure times, naturally incorporating censored observations without the need to assume any statistical distribution for the time to failure (Kleinbaum and Klein, 2012). The Kaplan–Meier survival function is given by:

$$\hat{S}(t) = \prod_{i \in I} \frac{n_i - d_i}{n_i} \tag{2.7}$$

where $d_i$ is the number of failures in $t$ and $n_i$ is the number of assets at risk.

The Kaplan–Meier method presents important limitations, as it does not allow temporal extrapolation beyond the observed interval and does not directly incorporate covariates. Consequently, its use is generally restricted to exploratory analysis, comparisons between Equipment groups, or preliminary validation of failure behavior.

**Random Survival Forest (RSF)**

RSF constitute a non-parametric extension of random forest models for survival data. These models build an ensemble of decision trees adapted to censored data, using splitting criteria based on survival statistics, such as the log-rank test. The survival function is then estimated by aggregating the predictions of the individual trees (Ishwaran et al., 2008).

RSF models exhibit a strong ability to capture nonlinear relationships, complex interactions between covariates, and heterogeneity across assets, making them particularly attractive in predictive maintenance and RUL applications when large volumes of data and multiple operational indicators are available. However, like other non-parametric machine learning–based methods, RSFs trade interpretability for predictive performance and are therefore often used as complementary models alongside classical reliability methods (Ishwaran et al., 2008).

## 2.5 Evaluation of Survival Models

The evaluation of survival models is particularly challenging due to the presence of right-censored observations and the need to assess both discrimination and predictive accuracy over time. Consequently, no single metric is sufficient to fully characterize model performance. In this work, model evaluation is based on three complementary metrics: the Concordance Index (C-index), the Brier Score (BS), and the Integrated Brier Score (IBS).

### 2.5.1 Concordance Index (C-index)

The C-index is a discrimination metric that evaluates a model's ability to correctly rank individuals according to their risk. It is defined as the proportion of all comparable pairs for which the predicted ordering of risk is consistent with the observed ordering of event times. A pair is considered comparable if it is possible to determine which individual experienced the event first.

In the presence of censoring, a substantial fraction of pairs may be excluded from the computation, which can lead to optimistic estimates and increased variance in datasets with high censoring rates. Moreover, the C-index assesses only the relative ordering of individuals and does not capture the magnitude of the error in time-to-event predictions. As a result, models with similar C-index values may differ significantly in terms of temporal prediction accuracy (Qi et al., 2023).

### 2.5.2 Brier Score

The Brier Score is a proper scoring rule used to evaluate the accuracy of probabilistic predictions at a fixed time point. In survival analysis, the time-dependent Brier Score measures the squared error between the predicted survival probability and the observed survival status at time $t$.

To account for right-censoring, the Brier Score is commonly computed using the Inverse Probability of Censoring Weighting (IPCW) approach. The time-dependent Brier Score at time $t$ is defined as (Qi et al., 2023):

$$\mathrm{BS}(t) = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\mathbb{I}(T_i \le t, \delta_i = 1)}{\hat{G}(T_i)}\left(0 - \hat{S}(t \mid \mathbf{x}_i)\right)^2 + \frac{\mathbb{I}(T_i > t)}{\hat{G}(t)}\left(1 - \hat{S}(t \mid \mathbf{x}_i)\right)^2\right], \tag{2.8}$$

where $T_i$ denotes the observed time (event or censoring), $\delta_i$ is the event indicator, $\hat{S}(t \mid \mathbf{x}_i)$ is the predicted survival probability, $\hat{G}(t)$ is the estimated censoring survival function, and $\mathbb{I}(\cdot)$ is the indicator function.

Lower values of the Brier Score indicate better predictive performance. The Brier Score is particularly suitable for evaluating predictions at specific time horizons, but its value depends on the choice of time $t$ and may be unstable at later times in highly censored datasets.

### 2.5.3 Integrated Brier Score

The Integrated Brier Score (IBS) extends the Brier Score by aggregating prediction errors over a continuous time interval, providing a global assessment of probabilistic accuracy across the entire survival curve. Instead of focusing on a single time point, the IBS computes the average Brier Score over a predefined evaluation horizon.

Formally, the Integrated Brier Score is defined as (Qi et al., 2023):

$$\mathrm{IBS} = \frac{1}{\tau}\int_0^{\tau} \mathrm{BS}(t)\,dt, \tag{2.9}$$

where $\tau$ represents the maximum evaluation time, typically chosen as the largest observed event time in the training or validation dataset.

The IBS is also a proper scoring rule under correct estimation of the censoring distribution and reflects both calibration and overall probabilistic accuracy. However, its interpretation is less intuitive than time-based error metrics, as it does not directly correspond to an error expressed in time units. Additionally, similar to the Brier Score, the IBS may be influenced by a small number of uncensored observations at later times in datasets with high censoring rates.

# Chapter 3

# Problem Description

Hydropower plants play a fundamental role in the production of renewable energy, assuming particular relevance within EDP Production. Although they account for approximately 25% of the total installed generation capacity, in 2024 they were responsible for around 31% of the total energy generated, worldwide, demonstrating their high availability and strategic importance for power generation(EDP – Energias de Portugal, S.A., 2025) .

In this context, the reliability of hydropower assets, such as circuit breakers, transformers, and other electrical and mechanical equipment, is a critical factor in ensuring plant availability, operational safety, and the achievement of the technical, economic and environmental objectives set by the managing entities.

## 3.1 Hydropower Generation Context

Currently, EDP operates a total of 49 hydropower plants in Portugal, each having one or more generation units. Hydropower plants distributed across three operational centers.

- Cávado-Lima: 15 hydropower plants corresponding to 29 generation units;
- Douro: 8 hydropower plants corresponding to 22 generation units;
- Tejo-Mondego: 26 hydropower plants corresponding to 59 generation units.

In total, these plants comprise 110 generation units. Each plant and each generation unit incorporate several items of equipment that are critical to their normal operation. Figure 3.1 shows a block diagram where some critical equipments are highlighted.

A failure in any critical equipment can cause unavailability of the unit and significant economic impact. Beyond economic and operational considerations, this also has a clear sustainability impact, since unplanned failures may result in the loss of renewable energy production. This loss may have to be compensated by alternative generation sources. This highlights the scale and complexity of the hydropower asset portfolio under analysis.

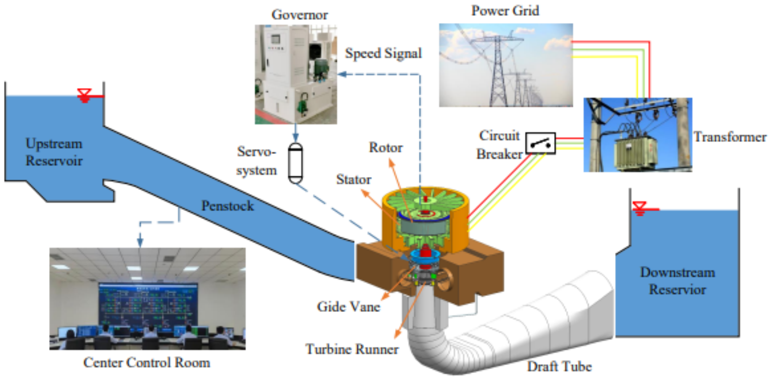


Figure 3.1: The block diagram of the system of hydropower plant,
Source: (Zhang et al., 2025)

## 3.2 Asset Management and Investment Decision Process at EDP

At EDP, a structured process is currently in place for the analysis of investment requests whenever these exceed a predefined financial threshold. This process begins at the hydropower production centers, where assets requiring replacement are identified and listed.

Subsequently, the reliability team is responsible for completing a technical assessment form, in which the relevant reliability parameters are documented. This information is then forwarded to the financial and risk analysis teams, with the objective of quantifying and prioritizing investments based on indicators such as the risk score and the Internal Rate of Return (IRR).

However, asset reliability assessments are often supported by a Weibull life time model, derived from manufacturer specifications or assumptions based on literature. Many assets currently in operation have already exceeded their nominal theoretical lifetime while continuing to operate with acceptable performance levels. This discrepancy between theoretical expectations and observed behavior introduces uncertainty into the decision-making process and may lead to premature replacement or to an underestimation of risk of failure.

From a sustainability perspective, these limitations are particularly relevant. On one hand, premature replacement of large-scale industrial equipment entails significant environmental impacts associated with manufacturing, transportation, installation, and end-of-life disposal. On the other hand, delayed or insufficient interventions increase the likelihood of unplanned failures, resulting in loss of renewable energy production and operational disruptions.

Within this context, EDP aims to evolve toward a more proactive and sustainable asset management approach, in which the reliability department is able to autonomously identify critical assets and propose maintenance or replacement actions based on quantitative, data-driven failure risk assessments, aligned with both economic efficiency and environmental responsibility.

## 3.3 Case Study - Generator Circuit Breakers

The comprehensive analysis of all critical equipment types would require a time frame exceeding the duration available for the present project, which is estimated at four months. Consequently, a pilot study approach was adopted.

The scope of this project was therefore restricted to generator circuit breakers, with the objective of developing a methodological framework that can later be generalized and applied to other asset classes within hydropower plants.

Generator circuit breakers are essential components for the safe and reliable operation of generation units (ABB Electrification U.S., nd). These devices ensure the switching operations required to connect and disconnect the generator from the electrical grid and act as the final actuating element of the protection systems, enabling the rapid isolation of the unit in the event of faults or abnormal operating conditions, thereby safeguarding equipment integrity and ensuring operational safety (F. Oliveira, personal communication, October, 2025).

The circuit breakers analyzed in this study are medium-voltage (4KV-17.5KV) circuit breakers, with physical dimensions and technical complexity that largely exceed those of low-voltage devices commonly found in residential environments. These are large-scale industrial assets, specifically designed to operate under demanding electrical and mechanical conditions typical of hydropower generation units. Figure 3.2 illustrates an example of a circuit breaker used for this purpose.

Figure 3.2: Medium Voltage Circuit Breaker

When a generator circuit breaker fails, the corresponding generation unit becomes unavailable until corrective actions are taken, leading to production losses and increased operational costs.

Additionally, generator circuit breakers constitute one of the assets with the most consistent set of technical, operational, and maintenance data available. The availability and quality of this information make generator circuit breakers a suitable pilot case for the development and validation of the proposed data-driven reliability framework.

## 3.4 Data Description

### 3.4.1 Available Data

For the purposes of this study, the following datasets were made available:

- A record of corrective and predictive maintenance activities, since 2014, for each item of equipment, including descriptions of the interventions performed and the corresponding associated costs;
- Technical specifications of the equipment, such as manufacturer, model, rated voltage, and nominal current;
- Operational data of the generation units, including hours of operation and number of operating cycles since 2002.
- Forecast energy generation for 2026, disaggregated by hydropower plant.

Figure 3.3 shows the Variables of each dataset.

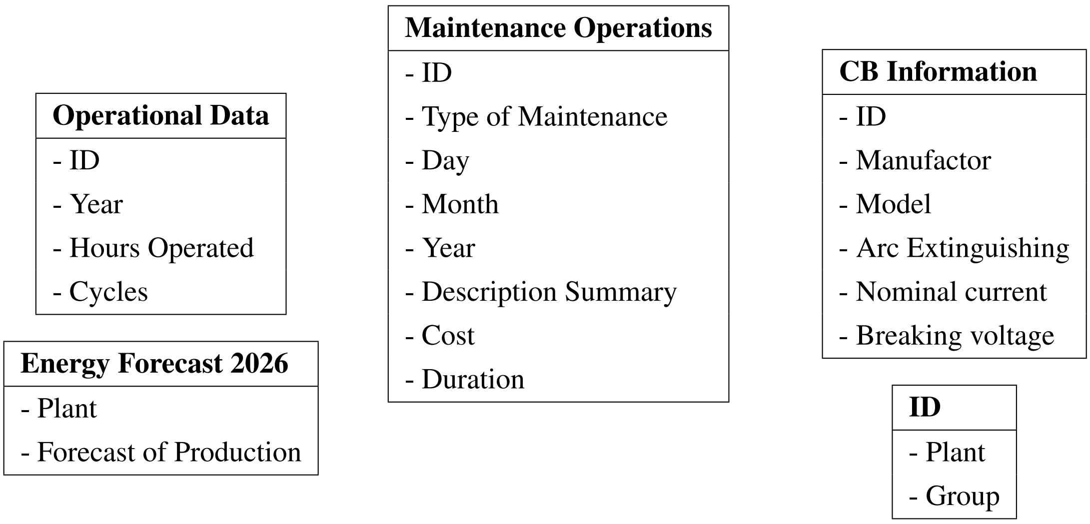


Figure 3.3: Available Data

### 3.4.2 Data-Quality and Pre-processing

The initial objective of this project was to develop an integrated asset management model that incorporates both capital expenditures and operational expenditures, including acquisition costs, operational costs, and maintenance-related costs, following a total expenditure (TOTEX) perspective.

However, during the initial exploration phase, several issues were identified, including incorrect data entries, missing information, and inconsistencies across different data sources. In particular, maintenance cost records presented significant variability and inconsistencies, which limited their direct applicability for quantitative economic analysis.

It should be noted that data quality issues are not exclusive to this project, but rather constitute a common challenge in the daily operations of many organizations, particularly in industrial and asset-intensive sectors. According to Gomstyn and Jonker (2025), problems such as incomplete, inconsistent, or inaccurate data are among the most frequent obstacles faced by companies when attempting to extract value from their data assets.

The limitations imposed by data quality also had a direct impact on the scope and objectives of this thesis. As a result, the initial objectives were reassessed and adjusted in order to ensure that the analyzes conducted remained feasible and aligned with the reliability and consistency of the available information. Thus, the analysis was focused on reliability modeling based exclusively on corrective maintenance records, which allowed the identification of failures.

# Chapter 4

# Methodology

For the development of this dissertation, the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework was adopted as the methodological reference. This framework provided a structured and systematic approach for the estimation of asset reliability, namely the probability of failure of each circuit breaker, and for the subsequent assessment of the associated economic impact.

In particular, the estimated probabilities of failure were later integrated into a Monte Carlo–based economic risk simulation, enabling the forecasting of expected costs over the analysis horizon, both at portfolio level and disaggregated by power plant. This approach allows uncertainty to be explicitly incorporated into the decision-making process, transforming probabilistic model outputs into actionable risk indicators.

Originally published in 1999, CRISP-DM remains one of the most widely adopted methodologies for data mining and data analytics projects, due to its generic, iterative, and domain-independent nature (Data Science Process Alliance, 2024). The adoption of this framework enabled a clear and organized view of the entire analytical process, explicitly defining the procedures to be followed at each stage and guiding methodological decisions when addressing challenges such as data limitations, objective redefinition, or model selection.

The CRISP-DM methodology is divided into six main phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. Each of these phases is described in detail throughout this section, with specific adaptations to the context of reliability analysis and asset management.

Figure 4.1 presents the methodological framework adopted in this dissertation, based on the CRISP-DM model, illustrating the logical sequence of the different phases and the interactions between them.

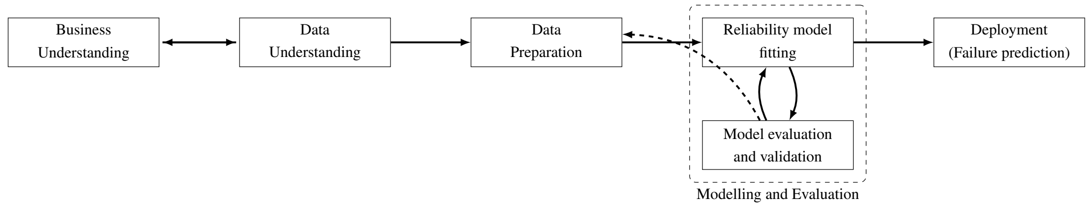


Figure 4.1: Methodology for failure prediction based on CRISP-DM

## 4.1 Business Understanding

The Business Understanding phase has as its main objective the comprehension of the business problem, the identification of project requirements, and the clear definition of the objectives to be achieved, ensuring that these are aligned with the organization's needs.

As shown in greater detail in Chapter 3, the problem is directly associated with the quantification of the reliability. This quantification influences the decision-making process, particularly with regard to maintenance management, investment planning, and cost control. Consequently, it became essential to understand the organizational context of the company, the role of the assets under study within the production system, and the maintenance processes currently in place. This analysis made it possible to identify the key information requirements and to define how the estimation of failure probability and associated costs could support more informed and risk-oriented decision-making.

In addition, during this phase, different methodological approaches, technologies, and analytical tools with potential applicability to the problem under study were analyzed and evaluated, and are presented in more detail in Chapter 2. In particular, survival analysis models were considered for the quantification of reliability.

## 4.2 Data Understanding

The Data Understanding phase constituted one of the most critical stages of the project, as it involved the exploratory analysis of the available data and the assessment of its suitability with respect to the objectives defined during the Business Understanding phase. The main tasks of this phase included collecting the initial data, describing their structure and content, exploring relevant patterns, and assessing data quality. The use of real operational and maintenance data proved to be particularly challenging, as this type of information frequently contains inconsistencies, incorrect records, and missing values. These issues are common in industrial contexts and are widely recognized in the literature as one of the main barriers to reliable reliability modeling (Gomstyn and Jonker, 2025).

The dataset initially made available for the development of the project, illustrated in Figure 4.2, consisted of historical records of corrective and preventive maintenance activities, including descriptions of the interventions performed and the costs associated with each work order. However, a preliminary exploratory analysis revealed unrealistic cost distributions, as well as extreme and inconsistent values, which compromised the direct use of this information for a reliable economic analysis.

| **Maintenance Data** |
| --- |
| - ID |
| - Type of Maintenance |
| - Day |
| - Month |
| - Year |
| - Description Summary |
| - Cost |
| - Duration |

Figure 4.2: Maintenance Data

In light of these limitations, several iterations were required to redefine the final objective of the study. As a result, the analysis strategy was refocused on an asset reliability–centred perspective, based exclusively on corrective maintenance work orders. This decision ensured greater consistency in the data used and improved coherence between the available information and the defined modeling objectives.

Furthermore, the assessment of data availability and completeness revealed that reliable maintenance records are only consistently available from 2014 onwards. Consequently, 2014 was defined as the beginning of the effective observation period. Despite the limitations identified in terms of data quality and historical coverage, the exploratory analysis and critical assessment of the available data led to the conclusion that the records provided were sufficient to support a reliability analysis over the period from 2014 to the end of the study horizon.

## 4.3 Data Preparation

The Data Preparation phase focused on the transformation, cleaning, and structuring of the data in order to make them suitable for the application of survival analysis techniques. At this stage, in addition to the datasets initially provided, the complete descriptions of corrective maintenance work orders were extracted from the SAP system, enabling a detailed identification and characterization of failure events.

With the support of generative artificial intelligence, each corrective maintenance intervention was analyzed and classified according to its nature, in order to determine whether it could be considered a relevant failure for the purposes of reliability modeling. In this classification process, technical failures, such as reclosing motor failures, and mechanical failures, including loosened springs and loosened coils, were considered. Failures associated with automation or control systems were excluded, as they were not directly representative of the intrinsic reliability of the circuit breakers under analysis.

Cycles between failures were represented using a gap time formulation, where each observation measures the elapsed time since the previous failure or, in the case of the first observation, since the asset entered into service. For this initial interval, it was assumed that no failures occurred between the commissioning date of the asset and the beginning of the observation period in 2014, due to the lack of available historical records prior to that year.

Censoring was handled during the data preparation phase through the definition of a binary failure indicator. For each observation, the event variable was defined as Failure = 1 when a failure occurred and Failure = 0 when the circuit breaker remained in operation until the end of the observation period. Observations with Failure = 0 were therefore treated as right-censored, allowing the dataset to incorporate incomplete failure information in a statistically consistent manner.

As a result of this process, a final dataset was constructed comprising multiple observations, in which each observation represents either an actual failure event or a censored observation. Since the assets under study are repairable systems, individual circuit breakers may experience more than one failure over the observation period, resulting in multiple records associated with the same asset. In order to explicitly account for recurrent events, the dataset includes the failure order for each circuit breaker, indicating the sequence number of each failure throughout its operational history.

Table 4.1 presents the variables resulting from the failure analysis process, as well as their respective roles in reliability modeling.

Table 4.1: Overview of dataset variables and their role in reliability modeling

| **Variable** | **Type** | **Role in analysis** |
|---|---|---|
| ID | Identifier | Asset tracking and grouping |
| Year of commissioning | Time-related | Asset age calculation |
| Year of last failure | Time-related | Start of survival interval |
| Year of next failure | Time-related | End of survival interval or censoring |
| Cycles between failures | Discrete | Possible life-time variable |
| Failure Order | Numeric | Order of failure |
| Manufacturer | Categorical | Explanatory covariate |
| Model | Categorical | Explanatory covariate |
| Breaking voltage | Categorical | Explanatory covariate |
| Nominal current | Categorical | Explanatory covariate |
| Arc Extinguishing | Categorical | Explanatory covariate |
| Failure | Boolean | Event |

During model implementation, a high number of distinct categories was observed in several technical variables, namely manufacturer, breaking voltage, and nominal current. This high level of granularity resulted in groups with a limited number of observations, thereby hindering the robust estimation of survival models and increasing the risk of overfitting. For this reason, these variables were aggregated into representative classes, with the aggregation criteria defined so as to achieve more balanced category frequencies. This approach reduced data sparsity while preserving the essential technical information required for reliability analysis.

With the data cleaned, structured, and transformed into a format consistent with survival analysis, including the treatment of recurrent failures, the handling of censored observations, and the aggregation of categorical variables to ensure robust estimation, the dataset was deemed suitable for the application of reliability modeling techniques. The following stage focuses on the selection, implementation, and evaluation of survival models aimed at quantifying the failure behavior of the assets and supporting decision-making based on estimated risk and uncertainty.

## 4.4 Modeling and Evaluation

The Modeling phase corresponds to the stage in which the most appropriate modeling techniques are selected, implemented, and calibrated in accordance with the objectives defined in the previous phases. In addition to model selection, this phase also includes the definition of the testing strategy, namely how the models are evaluated, compared, and validated based on the available data.

In this dissertation, the modeling phase focuses on the selection, implementation, and configuration of the analytical techniques used to quantify asset reliability. Building on the structured dataset obtained during the Data Preparation phase, this stage aims to model the failure behavior of repairable assets by explicitly accounting for recurrent events, censored observations, and relevant technical and operational covariates.

### 4.4.1 5-fold cross-validation

In order to ensure a robust and unbiased evaluation of the predictive performance of the survival models considered, a standard cross-validation strategy was adopted, enabling a direct comparison between models with different statistical assumptions.

A K-fold cross-validation scheme was used, with K=5. The dataset was initially divided into five mutually exclusive subsets (folds). In each iteration, four folds were used for training and one fold for testing.

Given the presence of censored observations and the limited number of observed failures, the cross-validation process was stratified based on the event indicator (failure versus censoring). This stratification ensured that each training–testing split exhibited a representative distribution of failures and censored observations, thereby avoiding situations in which the test set contained an insufficient number of events for a reliable evaluation.

In each cross-validation iteration, model-specific operations were performed exclusively on the training set, namely variable selection procedures (feature selection). The models were subsequently evaluated on the corresponding test set, using the variables selected in each fold and the performance metrics described in the following section. A detailed description of the variable selection procedures is provided in the sections dedicated to each model.

This cross-validation strategy provides an unbiased estimate of the models' generalization capability and establishes a consistent methodological framework to compare the performance of the Cox PHM and the RSF in the context of circuit breaker reliability modeling.

### 4.4.2 Cox PHM

As discussed in Chapter 2, the Cox PHM is a semi-parametric model widely used in survival analysis to assess the effect of covariates on the hazard rate, without imposing a specific functional form for the baseline hazard function. This model assumes proportional hazards and is particularly suitable for handling censored data.

In the context of repairable systems and recurrent events, a common extension of the Cox PHM is the Prentice–Williams–Peterson (PWP) model. The Cox PWP differs from the classical model by stratifying the analysis according to the order of failure, allowing the estimation of distinct reliability curves for each recurrent event (first failure, second failure, etc.). In this way, the PWP model makes it possible to capture potential changes in failure behavior as the asset undergoes successive interventions.

In light of the structure of the available data and the presence of recurrent failures, the "as good as new" assumption was adopted. Under this assumption, each circuit breaker is considered to return to a condition equivalent to its initial state after corrective maintenance. Consequently, the failure process is assumed to be reset after each repair, which is consistent with the use of a gap-time formulation, in which operating cycles and hours are restarted after each failure event.

Accordingly, the classical Cox PHM was selected as one of the main models for estimating the reliability behavior of the circuit breakers. As a survival model, the cox PHM requires the definition of both an event variable and a duration variable. In this study, the event variable corresponds to the occurrence of a failure (Failure = 1) or a censored observation (Failure = 0), while the duration variable is defined as the number of operating cycles between failures, measured using a gap-time approach.

The explanatory variables considered included aggregated technical characteristics of the circuit breakers, encoded using dummy variables, as well as the failure order, which initially allowed the influence of recurrent events on the risk of failure to be assessed.

Variable selection was performed using a backward stepwise procedure, applied exclusively to the training data in each iteration of the cross-fold validation. The procedure started with the full set of candidate variables and iteratively removed the covariate with the highest p-value, provided that it exceeded a pre-defined threshold $\alpha = 0{,}05$.

After completion of the cross-validation, the variables selected in each fold were aggregated and analyzed in terms of their selection frequency. Covariates that appeared in at least 50% of the folds were retained as final variables, ensuring that only consistent and stable effects were included in the final model.

The final Cox PHM was then refitted using the entire available dataset, relying exclusively on the selected variables, in order to maximize the information used in the final estimation and to prepare the model for subsequent analysis and prediction.

The soundness of the proportional hazards assumption was assessed in the final model using the Schoenfeld residuals test, which makes it possible to verify whether the effects of the covariates remain constant over time. The absence of statistically significant p-values indicated that the proportionality assumption is acceptable for the set of variables considered.

In addition, the overall significance of the model was evaluated using a Likelihood Ratio Test, comparing the final model with a null model without covariates.

### 4.4.3 RSF

Similarly to the Cox PHM, RSF was implemented under the “as good as new” assumption and using a gap-time formulation, according to which each corrective intervention resets the failure process. The event variable was defined as the occurrence of a failure (Failure = 1) or a censored observation (Failure = 0), while the duration variable corresponds to the number of cycles between failures.

The initial explanatory variables considered in the RSF model consisted of technical characteristics of the circuit breakers. Variable selection within the RSF framework was performed based on permutation importance, evaluated on the test set of each fold of the cross-validation procedure. This metric quantifies the variation in model performance—measured through the C-index, resulting from the permutation of each variable’s values, reflecting its effective contribution to predictive capacity.

In each fold, the RSF was fitted exclusively using the training data and evaluated on the corresponding test set, employing the same performance metrics applied to the Cox PHM, namely the C-index, the time-dependent Brier Score, and the Integrated Brier Score (IBS). Only variables with positive importance were retained for model refitting. After completion of cross-validation, the importance measures were aggregated across folds, and variables exhibiting positive mean importance were selected as final covariates, ensuring stability and consistency in the selection process.

The final RSF model was then fitted using the entire available dataset and only the selected variables, maximizing the information used in the final estimation and enabling its application in prospective analyzes and failure risk prediction.

By relaxing parametric assumptions and allowing the modeling of complex patterns, the RSF constitutes a complementary approach to the Cox PHM. While the Cox PHM offers greater interpretability and support for statistical inference, the RSF stands out for its flexibility and predictive robustness, being particularly suitable for reliability contexts characterized by heterogeneous data and complex failure structures.

## 4.5 Deployment

The final phase of CRISP-DM corresponds to Deployment and aims to ensure that the results obtained throughout the modeling and evaluation phases provide useful insights for the organization (Sharma, 2025). Accordingly, this phase focuses on the practical application of the developed models.

Within the context of this dissertation, deployment consists of the structured use of the final models to generate forecasts, quantify risk, and support decision-making in the field of asset management. Following the modeling and evaluation phases, two final reliability models were obtained: the Cox PHM and the RSF.

These models form the core of the deployment phase, enabling the estimation of survival functions, conditional failure probabilities, and the quantification of risk at the asset level. However, their practical application requires the definition of future operational conditions, namely the expected operating cycles of the equipment. Furthermore, for risk assessment purposes, it is also necessary to quantify the cost of failure at each power plant.

### 4.5.1 Failure Prediction

Estimating the probability of failure over a future horizon also requires the definition of operational conditions over the same period, namely the number of operating cycles. This analysis can be performed using different approaches, including multiple linear regression models that incorporate variables such as historical generated power, the power plants, and the corresponding years. However, to estimate the number of cycles in the t+1 interval, a weighted moving average approach was adopted, as explained below.

#### Future cycles calculation

Given that the operational context is subject to variations over time, such as changes in operating regimes, hydrological conditions, or dispatch strategies, it was decided to forecast the number of cycles using a weighted moving average. This approach makes it possible to assign greater importance to more recent years, while simultaneously reducing the influence of older observations that may reflect outdated operational regimes.

Considering a time window of $W = 5$ years, let $C_{s,y}$ denote the number of cycles observed at plant $s$ in year $y$. The weighted moving average of cycles is defined in Equation 4.1.

$$\widehat{C}_s = \frac{\sum_{k=0}^{W-1} w_k C_{s,Y_{\max}-k}}{\sum_{k=0}^{W-1} w_k} \tag{4.1}$$

where:

- $C_{s,y}$ represents the number of cycles observed at plant $s$ in year $y$;
- $Y_{\max}$ corresponds to the most recent year available in the historical data;
- $W$ is the size of the time window considered (in this case, $W = 5$);

- $w_k$ are the weights assigned to each annual observation, giving greater importance to more recent years.

In this work, a linearly decreasing weight structure was adopted, as defined in Equation 4.2.

$$w_k = W - k, \quad k = 0, 1, \ldots, W - 1 \tag{4.2}$$

After estimating the average number of cycles for each plant, a uniform distribution of the operational load among the existing units was assumed. With the equation 4.3 possible to obtain the average number of cycles per circuit breaker, which was used in the subsequent stages of the reliability analysis.

$$\widehat{C}_{s,i} = \frac{\widehat{C}_s}{G_s} \tag{4.3}$$

where:

- $\widehat{C}_s$ represents the predicted average number of cycles for plant $s$;
- $G_s$ corresponds to the number of units (or circuit breakers) at plant $s$;
- $\widehat{C}_{s,i}$ represents the average number of cycles assigned to circuit breaker $i$ at plant $s$.

**Probability calculation**

Probability of failure was predicted by assuming that each circuit breaker is subject to a failure process described by a random variable $T$, representing the time to failure measured in operating cycles. Since only assets that remain operational at the end of the observation period are relevant for prospective analysis, the prediction was conducted conditionally on survival up to the current time.

For each circuit breaker $i$, the following time instants were defined:

- $t_{0,i}$: cumulative number of cycles up to the end of the observation period;
- $\widehat{C}_{s,i}$: predicted average number of additional cycles up to the considered horizon;
- $t_{1,i} = t_{0,i} + \widehat{C}_{s,i}$: future time instant corresponding to the forecasting horizon;
- $\mathbf{x}_i$: covariates associated with circuit breaker $i$.

Let $S(t \mid \mathbf{x}_i)$ denote the survival function conditional on covariates $\mathbf{x}_i$. The conditional probability of failure of circuit breaker $i$ over the future interval $[t_{0,i}, t_{1,i}]$ is given in Equation 4.4.

$$P_{f,i} = \mathbb{P}(t_{0,i} < T \leq t_{1,i} \mid T > t_{0,i}, \mathbf{x}_i) = 1 - \frac{S(t_{1,i} \mid \mathbf{x}_i)}{S(t_{0,i} \mid \mathbf{x}_i)} \tag{4.4}$$

This expression allows the direct quantification of failure risk over a defined horizon, conditioning the analysis on the fact that the equipment has remained operational up to the current time.

In the case of the *Cox Proportional Hazards Model*, the conditional survival function is expressed in Equation 4.5.

$$S(t \mid \mathbf{x}) = S_0(t)^{\exp(\beta^\top \mathbf{x})} \tag{4.5}$$

where $S_0(t)$ represents the baseline survival function and $\beta$ denotes the vector of estimated coefficients.

In the case of the RSF, the survival function is estimated non-parametrically by aggregating the survival functions obtained from the individual trees that compose the ensemble.

Both models allow the estimation of an individualized survival function for each circuit breaker, reflecting its technical characteristics and observed failure history.

### 4.5.2 Economic risk simulation

After estimating the individual failure probabilities, an Economic Risk Simulation based on Monte Carlo methods was developed in order to quantify the economic impact associated with failure occurrences over the considered analysis horizon. This approach explicitly incorporates the uncertainty associated with the failure process and the economic consequences of service interruptions, providing a probabilistic assessment of risk at the asset, plant, and portfolio levels.

This simulation represents the final stage of the Deployment process, translating the failure probabilities estimated by the reliability models into distributions of economic losses that can be directly used to support decision-making in asset management.

#### Stochastic modeling of failure

Each circuit breaker $i$ was modeled as a Bernoulli random variable, representing the occurrence or non-occurrence of a failure within the analysis horizon:

$$X_i \sim \text{Bernoulli}(P_{f,i})$$

where $P_{f,i}$ corresponds to the estimated probability of failure for circuit breaker $i$. In this context, $X_i^{(m)} = 1$ indicates the occurrence of at least one failure of circuit breaker $i$ within the considered horizon, whereas $X_i^{(m)} = 0$ indicates the absence of failure during this period.

Conditional independence between circuit breakers is assumed, given the vector of probabilities $\{P_{f,i}\}$.

In each Monte Carlo iteration $m$, with $m = 1, \ldots, M$ and $M = 10\,000$, one realization $X_i^{(m)}$ was generated for each circuit breaker.

The total number of failures in each iteration was calculated by Equation 4.6.

$$N_{\text{failures}}^{(m)} = \sum_{i=1}^{N} X_i^{(m)} \tag{4.6}$$

**Economic impact modeling**

Each circuit breaker $i$ was assigned a failure cost $c_i$, representing the total economic impact of the unavailability associated with a failure. This cost simultaneously incorporates the cost of unproduced energy and the operational intervention costs, and is defined by the Equation 4.7.

$$c_i = h_i \left(P_i \cdot \bar{p}_e + C_{\text{labor}} \cdot n_i\right) \tag{4.7}$$

where:

- $h_i$ represents the number of hours of unavailability;
- $P_i$ represents the unit rated power;
- $\bar{p}_e$ represents the average electricity price;
- $C_{\text{labor}}$ represents the hourly labor cost per person;
- $n_i$ represents the number of personnel involved in the intervention.

**Economic risk simulation**

In each Monte Carlo iteration $m$, the total economic cost was computed using Equation 4.8

$$C_{\text{total}}^{(m)} = \sum_{i=1}^{N} X_i^{(m)} \cdot c_i \tag{4.8}$$

Repeating the process over $M$ simulations made it possible to obtain the empirical distribution of the total cost, from which relevant statistics were estimated, such as:

- the expected economic cost;
- cost variability;
- percentile-based scenarios (e.g., P10, P50 and P90).

**Risk aggregation at plant level**

In addition to the overall portfolio assessment, the simulation results were aggregated at the plant level. Let $\mathscr{I}(s)$ denote the set of circuit breakers belonging to plant $s$. In each Monte Carlo simulation $m$, the economic cost per plant was calculated using the Equation 4.9.

$$C_s^{(m)} = \sum_{i \in \mathscr{I}(s)} X_i^{(m)} \cdot c_i \tag{4.9}$$

This aggregation makes it possible to compare the economic risk profile across plants and to identify critical units.

# Chapter 5

# Results

## 5.1 Dataset characterization

The study covers generator circuit breakers installed across multiple hydropower plants operated by EDP. This portfolio includes plants such as Alqueva 1 and 2, Aguieira, Belver, Salamonde, Bouçã, Torrão, Crestuma, Régua, Castelo de Bode, Pocinho, Cabril, Fratel, Varosa, Carrapatelo, Frades 1 and 2, among others. In total, there were 27 plants.

The final dataset comprises observations collected between 2014 and 2024, corresponding to generator circuit breakers operating in the hydropower plants under analysis. Over this observation period, a total of 57 failure events were identified, while 65 observations correspond to right-censored assets, for which no failure occurred within the study horizon. As illustrated in Figure 5.1, censored observations represent approximately 53% of the dataset, while failures account for the remaining 47%.

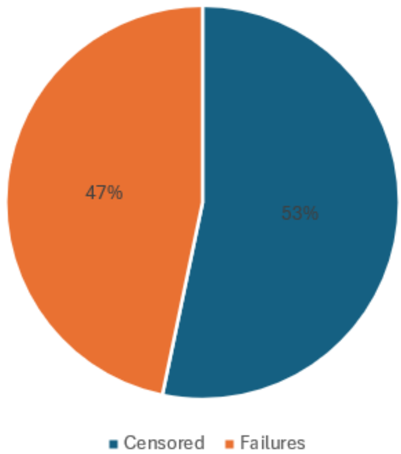


Figure 5.1: Censored and Failure Observations

The temporal distribution of failures over the analysis horizon is shown in Figure 5.2. Failure events are observed throughout the entire period, with variability in the number of failures recorded each year. Lower failure counts are observed in the early years of the dataset, followed by higher failure occurrence in later years.

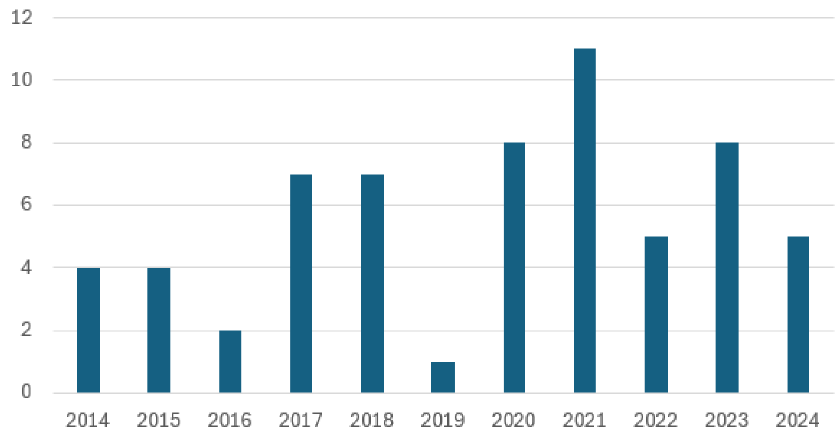


Figure 5.2: Failures per year

Figure 5.3 presents the distribution of failures and censored observations according to the arc extinguishing medium of the circuit breakers, including air, SF6, and vacuum.

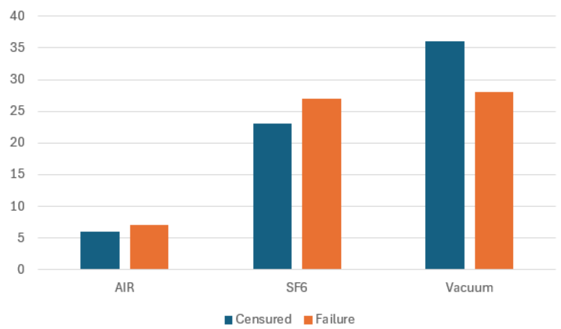


Figure 5.3: Censored and Failures by Arc Extinguishing Medium

The distribution of observations by nominal current rating is shown in Figure 5.4, with assets grouped into four rating classes: low ($\leq$ 2000 A), mid (2000 $-$ 4000 A), high (4000 $-$6300 A), and very high ($\geq$6300 A). Most observations are concentrated in the mid and high current categories.

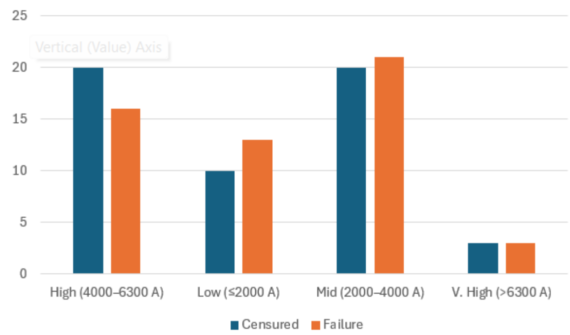


Figure 5.4: Censored and Failures by CB Rating

Figure 5.5 illustrates the distribution of failures and censored observations by rated voltage class, grouped into low ($\leq$ 10 kV), mid (10-17 kV), and high ($\geq$ 17 kV). High-voltage circuit breakers constitute the largest share of the dataset, while mid- and low-voltage assets present a more balanced distribution.

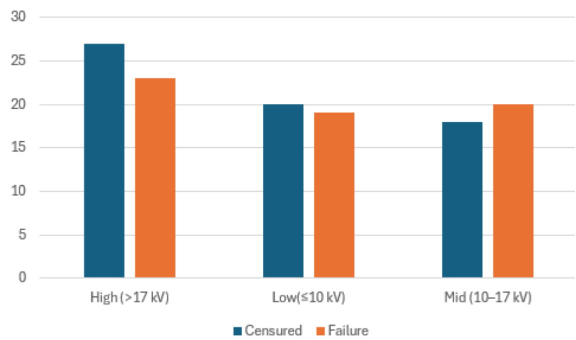


Figure 5.5: Censored and Failures by Voltage

Finally, Figure 5.6 presents the distribution by manufacturer. For confidentiality reasons, manufacturers are codified. The dataset is dominated by a small number of manufacturer categories, with several others grouped under a residual category.

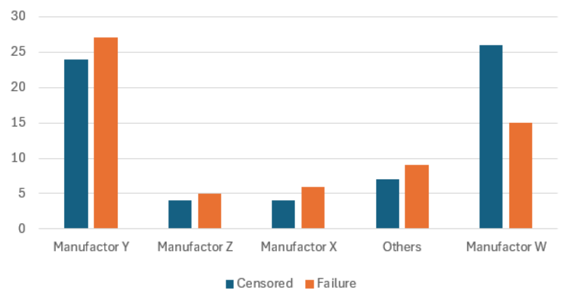


Figure 5.6: Censored and Failures by Manufacturer

## 5.2 Reliability Model Performance and Validation

### 5.2.1 Cox PHM

The Cox PHM was evaluated using a stratified 5-fold cross-validation (CV) procedure, ensuring a representative distribution of failure events and censored observations in both training and test sets. Prior to model fitting, multicolinearity among candidate covariates was assessed, and no pairs of variables with absolute correlation above 0.90 were identified.

Model performance was primarily assessed using the concordance index (C-index), complemented by the time-dependent Brier Score and the Integrated Brier Score (IBS). Table 5.1 summarizes the CV results obtained across the five folds.

Table 5.1: Cox PHM cross-validation performance metrics

| Fold | C-index | Brier Score | IBS |
|---|---|---|---|
| 1 | 0.545 | 0.197 | 0.199 |
| 2 | 0.564 | 0.168 | 0.169 |
| 3 | 0.566 | 0.154 | 0.156 |
| 4 | 0.429 | 0.180 | 0.180 |
| 5 | 0.728 | 0.141 | 0.142 |
| Mean ± Std | $0.566 \pm 0.095$ | $0.168 \pm 0.022$ | $0.169 \pm 0.022$ |

Across the folds for which time-dependent metrics could be reliably computed, the Cox PHM achieved a mean Brier Score of $0.168 \pm 0.025$ and a mean IBS of $0.169 \pm 0.025$, indicating acceptable probabilistic calibration.

Table 5.2: Frequency of variable selection across CV folds

| Covariate | Selection frequency |
|---|---|
| Manufacturer (X) | 5 |
| Arc extinguishing medium (Vacuum) | 4 |
| Voltage class (10–17 kV) | 1 |

Based on a stability criterion requiring selection in at least 50% of the folds, two covariates were retained for the final model: the aggregated manufacturer category *X* and the arc extinguishing medium *Vacuum*.

Table 5.3: Final Cox PHM parameter estimates

| Covariate | Coef. | HR | 95% CI (HR) | $p$-value |
|---|---|---|---|---|
| Manufacturer (X) | 1.04 | 2.83 | [1.20, 6.69] | 0.02 |
| Arc extinguishing medium (Vacuum) | 0.66 | 1.93 | [1.14, 3.25] | 0.01 |

Both covariates exhibit a statistically significant effect on the hazard rate. CBs manufactured by X present a hazard ratio (HR) of 2.83, while units using vacuum as the arc extinguishing medium exhibit an HR of 1.93, indicating an increased risk of failure relative to their respective reference categories.

Table 5.4: Schoenfeld residuals test for proportional hazards (PH) assumption

| Covariate | $p$-value |
|---|---|
| Arc extinguishing medium (Vacuum) | 0.765 |
| Manufacturer (X) | 0.940 |

No statistically significant violations of the PH assumption were detected, supporting the adequacy of the Cox PHM for the selected covariates.

The overall significance of the final model was assessed using a likelihood ratio test. The model achieved a likelihood ratio statistic of $\chi^2 = 11.08$ with 2 degrees of freedom ($p = 0.0039$), indicating that the inclusion of covariates significantly improves model fit relative to the null model.

Using the fitted Cox PHM, conditional failure probabilities were estimated for the forecasting horizon corresponding to the year 2026. The expected number of failures across the asset population was estimated at 7.52 events.

Table 5.5: Highest expected failures by plant and generation unit (2026)

| Plant | Unit | Expected failures |
|---|---|---|
| SD | 3 | 0.48 |
| AV | 1 | 0.45 |
| BC | 2 | 0.38 |
| AQ | 1 | 0.38 |
| AQ | 2 | 0.37 |

### 5.2.2 RSF

The RSF model was evaluated using the same stratified 5-fold CV strategy adopted for the Cox PHM, ensuring consistency in model comparison. Predictive performance was assessed using the C-index, the time-dependent Brier Score, and the IBS.

Table 5.6: RSF cross-validation performance metrics

| Fold | C-index | Brier Score | IBS |
|---|---|---|---|
| 1 | 0.598 | 0.197 | 0.199 |
| 2 | 0.642 | 0.156 | 0.158 |
| 3 | 0.626 | 0.158 | 0.160 |
| 4 | 0.598 | 0.171 | 0.173 |
| 5 | 0.671 | 0.164 | 0.165 |
| Mean $\pm$ Std | $0.627 \pm 0.031$ | $0.169 \pm 0.017$ | $0.171 \pm 0.017$ |

The RSF model exhibited stable predictive performance across the five CV folds. The mean C-index achieved was $0.627 \pm 0.031$, indicating moderate discriminatory ability and lower variability across folds when compared to the Cox PHM.

Probabilistic calibration metrics also showed consistent results, with a mean Brier Score of $0.169 \pm 0.017$ and a mean IBS of $0.171 \pm 0.017$. Overall, both models show moderate discrimination and acceptable calibration, with RSF providing more stable results across folds.

Table 5.7: Covariates retained in RSF across CV folds

| Fold | Retained covariates |
|---|---|
| 1 | Manufacturer, Arc extinguishing medium, Voltage, Current |
| 2 | Arc extinguishing medium, Voltage, Current |
| 3 | Manufacturer, Arc extinguishing medium, Current |
| 4 | Voltage, Current |
| 5 | Manufacturer, Arc extinguishing medium, Voltage, Current |

Table 5.8: Mean permutation importance ($\Delta$C-index) of covariates in RSF

| Covariate | Mean $\Delta$C-index |
|---|---|
| Arc extinguishing medium | 0.080 |
| Nominal current | 0.031 |
| Voltage class | 0.028 |
| Manufacturer | 0.014 |

The set of retained covariates varied across folds, reflecting the ability of the RSF to adapt to different data partitions and capture heterogeneous effects without relying on a fixed parametric structure.

Table 5.9: Top assets with highest predicted failure probability for 2026 (RSF)

| Plant | Unit | $P_{fail,2026}$ |
|---|---|---|
| AV | 1 | 0.520 |
| AV | 2 | 0.399 |
| AQ | 1 | 0.364 |
| AQ | 2 | 0.344 |

Based on the aggregation of individual failure probabilities, the expected number of failures for the year 2026 was estimated at 6.98 events using the RSF model.

## 5.3 Economic Risk Analysis and MC Simulation

Following the estimation of failure probabilities at the asset level, an economic risk analysis was performed using an MC simulation approach. The objective of this analysis is to translate technical failure risk into economically meaningful metrics that can support maintenance and investment decision-making.

For both modeling approaches, failure occurrence for each asset was represented as a Bernoulli random variable parameterized by the corresponding estimated failure probability. The economic impact of each failure was quantified using a cost model that incorporates production losses and intervention-related costs, as described in Chapter 4.

MC simulation enables the estimation not only of expected economic impact, but also of the variability and distribution of potential outcomes, thereby providing insight into downside risk and extreme scenarios. This analysis was applied consistently to both the Cox PHM and the RSF models in order to enable a direct comparison of results.

### 5.3.1 Cox PHM

The MC simulation based on failure probabilities estimated using the Cox PHM was applied to a subset of 65 CBs considered at risk during the forecasting horizon.

The analytical estimate of the expected number of failures, computed as the sum of individual failure probabilities, resulted in 7.33 expected failures. The MC simulation yielded a mean of 7.30 failures, indicating strong agreement between analytical and simulated results and confirming the internal consistency of the simulation framework.

The expected economic cost associated with failures was estimated analytically at approximately 153,111 euros, while the MC simulation produced a very similar mean total cost of 152,179 euros. The standard deviation of the simulated total cost was estimated at 63,311 euros, reflecting significant variability in the economic impact of failures.

Percentile-based scenarios extracted from the empirical cost distribution indicate a total cost of approximately 75,424 euros at the 10th percentile (P10), 146,430 euros at the median (P50), and 238,049 euros at the 90th percentile (P90).

When aggregating simulation results at the hydropower plant level, the plants with the highest average simulated economic cost were identified as Salamonde, Alqueva 1, Alqueva 2, Frades 1 and Aguieira. These plants therefore represent the highest contributors to the overall economic risk under the Cox PHM.

### 5.3.2 RSF

An equivalent MC simulation was performed using failure probabilities estimated by the RSF model, applied to the same subset of 65 CBs in order to ensure comparability between modeling approaches.

The analytical estimate of the expected number of failures resulted in 6.86 expected events, which matches the MC mean of 6.86 failures. This agreement confirms the consistency of the simulation framework when applied to RSF-derived probabilities.

The expected economic cost associated with failures under the RSF model was estimated analytically at approximately 139,501 euros. The MC simulation yielded a mean total cost of 139,582 euros, with a standard deviation of 61,468 euros.

The distribution of simulated costs exhibits a total cost of approximately 66,789 euros at the 10th percentile (P10), 131,657 euros at the median (P50), and 224,704 euros at the 90th percentile (P90), illustrating the presence of low-probability, high-impact outcomes.

Aggregation of results at the hydropower plant level indicates that the plants with the highest average simulated economic cost under the RSF model are Alqueva 1, Frades 1, Alqueva 2, Aguieira and Varosa.

# Chapter 6

# Discussion and Conclusion

In this dissertation, a quantitative and data-driven framework to support sustainable asset management decisions in hydropower generation was developed, addressing the limitations of traditional deterministic lifetime-based approaches. The main objective was to estimate failure probabilities of critical assets under uncertainty and translate these reliability insights into economically meaningful indicators that can support maintenance and replacement decisions.

The results obtained demonstrate that the proposed objectives were successfully achieved. Both survival modeling approaches implemented, the Cox PHM and the RSF, proved capable of modeling the failure behavior of generator circuit breakers while explicitly accounting for censored observations and recurrent failures. The cross-validation results show that both models achieved acceptable levels of discrimination and calibration, confirming their suitability for prospective reliability assessment. The Cox PHM offered valuable interpretability, allowing the identification and quantification of the impact of specific technical characteristics on failure risk, while the RSF exhibited superior predictive stability and robustness across validation folds, particularly in the presence of heterogeneous and nonlinear effects.

The integration of failure probability estimates into a Monte Carlo–based economic risk simulation further reinforces the practical relevance of the proposed framework. The close agreement between analytical expectations and simulation results confirms the internal consistency of the approach. By providing not only expected costs but also uncertainty ranges and percentile-based scenarios, the framework supports a risk-based perspective that goes beyond point estimates and enables more informed and robust decision-making. In this sense, the study demonstrates how reliability modeling can be effectively translated into decision-support tools aligned with both economic efficiency and sustainability objectives.

Although the proposed framework does not prescribe specific maintenance or replacement actions, it directly supports the adoption of a risk-based maintenance (RBM) approach by providing quantitative failure probabilities and economic risk indicators. These outputs are intended to support decision-making rather than to act as fixed decision rules. Asset ranking based on predicted failure probability and expected economic impact enables the prioritization of maintenance actions, detailed inspections, or replacement analyses according to risk exposure, instead of predefined time- or cycle-based intervals. This represents a shift from traditional preventive maintenance strategies toward a risk-based maintenance paradigm, in which resources are allocated to the assets that contribute most significantly to operational and economic risk.

In addition, the interpretability of the Cox Proportional Hazards Model provides actionable insights beyond asset prioritization. The identification of technical characteristics associated with higher failure risk, namely the manufacturer category X and the use of vacuum as the arc extinguishing medium, both exhibiting hazard ratios greater than one,offers objective evidence to support upstream decision-making. These results can inform supplier evaluation, definition of technical specifications, and equipment selection in future investment and renewal decisions, thereby linking reliability analysis with strategic procurement and asset renewal processes.

Despite these positive outcomes, several aspects can be improved in future developments. Data-related limitations remain a central challenge and should be explicitly addressed in future work. A fundamental improvement lies in the development and adoption of a maintenance data platform that is fully transparent, standardized, and easily accessible, not only to the production centers responsible for managing the assets, but also to the Reliability department. Such a platform would enable centralized access to consistent maintenance and operational data, significantly reducing the effort currently required in the data understanding and data preparation phases and allowing analytical resources to be focused on modeling, validation, and decision support rather than on data cleaning and reconciliation.

While this structural data issue is being progressively addressed, the methodology adopted in the data understanding and data preparation phases of this dissertation remains valid and can continue to be applied. To further increase the efficiency of this methodology, it would be highly beneficial to extract maintenance description fields available in maintenance work order in the main dataset. With the support of Copilot the identification and classification of relevant failure events could be performed more rapidly and consistently, reducing manual effort and improving scalability.

In addition, it is essential that the datasets associated with the assets analyzed are continuously updated and that the same methodological framework is reapplied over time. This continuous update process would allow the models to progressively incorporate new failure information and improve their predictive accuracy. In particular, as more second- and third-order failures are observed, it will become possible to reassess the relevance of recurrent failure structure and to retest the Cox PWP model. Under these conditions, the statistical significance of failure order and its impact on asset survival can be re-evaluated, potentially leading to a more refined representation of the failure process in repairable assets.

One relevant extension concerns the temporal resolution of predictions. In this study, failure probabilities were estimated over an annual horizon, which is appropriate given the available data. However, failures in hydropower equipment may have different impacts depending on the time of year, due to seasonal variations in hydrology, electricity prices, and system dispatch. Achieving a monthly or seasonal prediction level would significantly enhance the operational value of the model, enabling better alignment between reliability risk and production planning.

Another important improvement area relates to the definition of the lifetime variable. Although operating cycles constitute a meaningful proxy for asset usage, the accuracy of lifetime estimation could be enhanced by incorporating additional usage and condition indicators, such as operating hours, load profiles, or condition-monitoring data. This would allow a more precise representation of degradation processes and potentially improve the accuracy of failure probability estimates.

Finally, although this dissertation focused on generator circuit breakers as a pilot case study, the adopted methodology is not asset-specific. The structured CRISP-DM-based approach, combined with survival analysis and economic risk simulation, is fully transferable to other asset classes within hydropower plants and to different industrial contexts. As long as failure events, censoring information, and relevant covariates are available, the framework can be readily adapted to analyze other critical assets and support broader asset management decisions.

Table 6.1 provides a structured summary of the main future work directions identified in this study, highlighting the proposed improvements and their expected impact on reliability analysis and asset management decision support.

Table 6.1: Summary of future work directions

| **Topic** | **Proposed improvement** | **Expected impact** |
|---|---|---|
| Maintenance data and accessibility | Development of a transparent and centralized maintenance data platform, accessible to both production centers and the Reliability department | Reduction of effort in Data Understanding and Data Preparation phases, improved data consistency, and faster analytical cycles |
| Maintenance data processing | Structured extraction of maintenance description fields and automated failure classification using Copilot | Faster and more consistent identification of failure events, increased scalability of the methodology |
| Temporal resolution of predictions | Transition from annual to monthly or seasonal failure probability estimation | Better alignment between reliability risk, hydrological seasonality, and production planning |
| Lifetime variable definition | Incorporation of additional usage and condition indicators such as operating hours, load profiles, and condition-monitoring data | More accurate representation of degradation processes and improved failure probability estimates |
| Recurrent failure modeling | Reassessment of the Cox PWP model as more second- and third-order failures become available | Improved modeling of repairable asset behavior and validation of the relevance of failure order |
| Methodology extension | Application of the CRISP-DM-based framework to other asset classes | Generalization of the methodology and broader support for risk-based asset management |

In conclusion, this work demonstrates that survival analysis, combined with probabilistic economic risk assessment, provides a solid and flexible foundation for risk-based and sustainable asset management. The proposed framework contributes to more informed decision-making under uncertainty and establishes a methodological basis that can be extended and refined as data availability and quality continue to improve.

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