Asset management optimization: a framework to reduce risk and cost for utilities

Luís Filipe da Silva Magalhães Dias

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Supervisor: Prof. Armando Leitão

Faculdade de Engenharia da Universidade do Porto
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Abstract

With the increasing age of assets related to operational functions, asset management has become increasingly more relevant. There is a need to extract the most value from the assets before they are retired from their functions, so maintenance policies are formulated to prolong the life of these assets. When establishing the maintenance policies, many companies prioritize the minimization of the probability of failure of the assets, compromising their financial efficiency.

In this dissertation, we consider an asset management problem in the electricity industry capable of being generalized to several kinds of assets in other industries. This problem takes into consideration the Power Transformer condition, the most critical equipment in the electricity distribution process. Based on a discrete set of states which evolve with the passage of time we model asset degradation. The goal is to determine the optimal degradation state in which preventive maintenance should be performed. The problem is formulated as a multi-objective search aiming at simultaneously optimizing two objectives of interest: risks and costs.

For a close approximation to reality, the model describing the evolution of the degrading system is based on the use of the Markov model and the Monte Carlo (MC) simulation. The transition probabilities are estimated from the data using a Hidden Markov Model- HMM algorithm (Baum-Welch algorithm). Maintenance policies are generated using a Genetic Algorithm (GA). The calculation of the risk objective function is based in several criteria that we must consider when analyzing an asset. These criteria coupled with the current asset state will be crucial to calculate the asset risk. The coupled (GA+MC) will be the key to establish the maintenance policies that are able to optimize costs and risks.

Resumo

Hoje em dia com o continuo aumento da idade dos ativos das empresas ligados às funções operacionais, leva a que a gestão de ativos comece a ter contornos mais relevantes nos dias que correm. Há uma necessidade de extrair o máximo de valor dos ativos antes que estes sejam aposentados das suas funções e por isso as políticas de manutenção são formuladas para prolongar a vida desses ativos. Por sua vez, ao estabelecer-se as políticas de manutenção, muitas empresas priorizam a minimização da probabilidade de falha dos ativos comprometendo assim a sua eficiência financeira.

Nesta dissertação considera-se um problema de gestão de ativos no setor da energia elétrica, capaz de ser generalizado para vários tipos de ativos em outras indústrias. Este problema tem em consideração a condição dos Transformadores de Potência, o equipamento mais crítico no processo de distribuição de eletricidade. A degradação destes equipamentos é modelada com base em um conjunto discreto de estados que evoluem com o passar do tempo. O objetivo é determinar o estado ótimo de degradação no qual a manutenção preventiva deve ser realizada. Este problema é formulado como uma busca multiobjectivo visando simultaneamente otimizar dois objetivos de interesse: riscos e custos.

Para uma aproximação à realidade, o modelo que descreve a evolução do sistema de degradação baseia-se na utilização dos modelos de Markov e da simulação de Monte Carlo (MC). As probabilidades de transição são estimadas a partir dos dados usando um algoritmo Hidden Markov Model – algoritmo HMM (algoritmo Baum-Welch). Já as políticas de manutenção são geradas usando um Algoritmo Genético (GA). O cálculo da função objetivo de risco é baseado em múltiplos critérios que devemos considerar ao analisar um ativo. Estes critérios combinados com o estado atual do ativo serão cruciais para calcular o risco do recurso. A combinação destas técnicas (GA + MC) será a chave para estabelecer as políticas de manutenção que são capazes de otimizar os custos e riscos.

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‘Another flaw in the human character is that everybody wants to build and nobody wants to do maintenance.”

Kurt Vonnegut

Contents

Glossary and acronyms

MCDM	Multi Criteria Decision Making
GA	Genetic Algorithm
NSGA	Non Sorting Genetic Algorithm
CBM	Condition-based Maintenance
RBM	Risk-based Maintenance
EDP	Energias de Portugal
EDPD	Energias de Portugal e Distribuição
PT	Power Transformer
HI	Health Index
MTBF	Mean Time Between Failures
HMM	Hidden Markov Models
MC	Monte Carlo
MO	Multi Objective
KPI	Key Performance Indicators
DGA	Dissolved Gas Analysis
DM	Decision Maker
TIEPI	Tempo de interrupção equivalente da potência instalada

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Chapter 1

Introduction

Asset management optimization is becoming topic of great relevance in recent years in the area of maintenance. Companies in the modern world face a constant pressure to improve every year, increasing the relevance of operational efficiency (Schneider et al., 2006). A good asset management strategy can prolong the life of assets and extract the most value out of them (ISO, 2014), creating a competitive advantage in the market where companies operate.

Our objectives are to define and implement a maintenance strategy that is able to optimize costs and risks in the utility industry. From a generic approach, we construct a condition/risk-based approach, which is promising in improving maintenance costs and risk. Although the formulation of a maintenance strategy requires knowledge of a organization's vision and mission, in order to be aligned with them, this perspective will not be studied in this dissertation. Instead, we will focus on the operational aspect of asset management, as the main objectives of this approach are to reduce the impact of failures and to increase availability in the assets, allowing the assets to be properly used in their operational functions.

This work aims to study the impact of the developed asset optimization methodology for a critical piece of equipment in the electricity distribution industry. There are some hurdles that arise from the application of this methodology, mostly related to the quality of the data provided by the company. Some techniques were used to overcome this hurdles, like AHP (Analytic Hierarchy Process) and HMM (Hidden Markov models), just to name a few.

The problem underlying this dissertation is the result of a project proposal launched by INESC TEC in partnership with a big Portuguese company - EDP. The company is focused primarily in the energy sector, serving a majority of the population in Portugal. This project in particularly was developed for EDPD (Energias de Portugal e Distribuição), which is the company responsible for distributing electricity. We developed a methodology aimed to the Power Transformers, as they are a critical equipment in the electricity distribution.

The methodology developed tries to conciliates two fronts. On one hand we have developed the methodology to be applied in the EDPD problem, on the other hand the methodology tries to be generic enough, therefore capable of being applied to other utilities. This methodology is essentially composed by three main phases. In the first phase we model the life degradation and improvement of the equipment. We define the health of the equipment in a set of discrete states and use the Markov models in order to model the life degradation of the equipment. To estimate the parameters of the Markov matrix we use the Baum-Welch algorithm. We also use the Monte Carlo simulation to study the life evolution of the equipment.

In the second phase of the proposed methodology we analyze the performance of the maintenance policy risks and costs. For the risk calculation we propose a multiple-criteria method. Quantitative methods are proposed to deal with both the weighting of impacts and the problems which arise with multiple criteria. The use of the risk matrix is crucial in the definition of the maintenance policies.

In the third and final phase of the methodology we run the optimization model that allows us to establish the ideal maintenance policies. The optimization algorithm that we use is a Multi Objective Genetic Algorithm because the problem of EDPD is framed as a multiobjective problem. The NSGA-II algorithm allows us to obtain the maintenance policies that minimize the costs and risks.

With the application of our methodology, we estimated an 10% decrease in maintenance costs without any increase in risk. We also prove possible to reduce the costs in 27% without increasing too much the risk. An assertive interpretation of these new policies is considering that maintenance is performed when needed. We quantify the risk in order to allow the decision maker to trade it off with savings.

As contributions, the studied problem adds a comprehensive instance of the application of the RBM and CBM methodology to the literature. We define and model the life of the Power Transformer in set of discrete states. Furthermore, it provides a multiple-objective approach to be used in similar settings. We also shed light in a new approach of the calculation of the risk.

In Chapter 2 we have an overview of the problem studied and the data handling required. In Chapter 3 we do a literature review. A thorough explanation of the methodology, supplemented by practical examples, will succeed in Chapter 4. In Chapter 5, the methodology is applied to the studied problem. Finally, Chapter 6 will be dedicated to conclusions, remarks and prospect of future work.

Chapter 2

Problem description

Power transformers are essential assets for the electric supplying industry. These equipment allows a company to ensure the transmission and transformation of electric energy. In this chapter, a description of the problem is presented as well as the procedures for the data gathering, specification and handling. As for the description, a summarized overview of the Power Transformers owned by EDPD is displayed, as motivation for the study of this problem. Then, a more detailed statement of the problem is presented, as well as a preview on the current procedures used by the company to face it. As for the data, the methods used for gathering and handling it are presented, as well as the main procedures that enable its transformation into valuable useful information.

2.1 Statement of the asset management optimization problem

EDPD currently relies on operational availability of their equipment in order to be able to satisfy an increasingly demanding market. Knowing when their equipment are likely to fail, which causes a downtime in service, is crucial in order to prevent the failures from occurring. Nevertheless, being able to reduce the maintenance costs and at the same time reduce the risk associated with the equipment is also very important, besides the availability.

Power Transformers are generally very reliable equipment with a life expectancy of 40 years. The truth is that there are Power Transformers that are capable to reach over 60 years of age. This endurance capacity in relation to the expected duration of the asset, is due in large part to the good maintenance practices applied in the transformer throughout its lifetime. Obviously, maintaining an equipment entails costs that are sometimes significant for a company. There is a need and concern to make a balance between the benefit for a given maintenance and the costs it entails, without calling into question the fact that maintenance is essential.

The main aim of this problem, is to know what is the ideal maintenance policy to be applied to a certain PT that can minimize the costs associated with the maintenance policy and the risk associated with the equipment failure. The maintenance policy used in this problem can either be time based or condition based. If the maintenance policy is time based, the interventions on the equipment will be performed in equals interval of times. In between this interval of times, if the equipment fails the PT is subjected to a repair intervention, either on the spot or in the factory where it was produced, otherwise only small interventions are performed. In case of the maintenance policy being condition based, the PT only will be subjected to interventions by the repair team if the state of the equipment is considered to be not acceptable, otherwise no action is performed. The condition of the PT is assessed through the HI (Health Index), which is the best KPI that indicates the current state of the equipment in a discrete set of states. This KPI is calculated through the analysis of different test applied in the PT, i.e. the oil that circulates in the equipment helps to assess the condition of the equipment.

Figure 2.1: Example of a Power Transformer

In this problem we have a restriction related to the amount of available repair teams to perform maintenance on the equipment in a given period. If the amount of assets to be subjected to maintenance interventions exceeds the amount of available repair teams, then the company will prioritize the repair actions in the higher risk equipment. Otherwise all the equipment are subjected to maintenance. In this problem, it is also considered that no PT will last more than 60 years of age. When the equipment reaches this threshold it is replaced by a new PT. For this work, we have currently 729 active PT distributed all over Portugal that will be the focus of the study.

2.2 Existing EDPD procedures

Currently, the asset management model of EDPD is based on preventing the PT from failing and to prolong the equipment expected lifetime. The maintenance policy that they currently use is a mix between condition based maintenance and time based maintenance. They perform periodic tests to the PT in order to get information that helps to access the equipment condition. All of this information is reported to the company manually which can lead to some errors in the data inputed in the database of the company. With the information gathered from the tests, they try to assess the equipment current condition. Whenever the condition of the equipment worsens considerably the equipment will be subjected to maintenance. Also, the PT that have a higher risk of failure are expected to be subjected to a bigger number of maintenances.

All of this analysis are done manually by the workers at EDPD, which often lead to unnecessary interventions in the equipment. In this work, we propose a methodology capable of optimizing both costs and risks associated with the maintenance policies performed in the equipment in a given period of time. In Chapter 4 we explain each of the steps of the proposed methodology.

2.3 Data specification and gathering

In order to better understand the potential of the developed methodology in this work, it was fundamental to carefully handle the data provided by EDPD. Data gathering and specification preceded the application of the solution methods. This step was fundamental since it involves the linkage of the methods to the data collection system used by the company, which is a system where the workers usually collect the data manually. The provided data will be the source used by the methodology proposed in chapter 4. Nevertheless, some specifications of the data are required, since it is important to have the information in the necessary format when retrieved from the company's system. The integrity of the data must also be assured for solutions with quality. This section describes the data requirements, as well as the processes used to gather the necessary information and develop it in order to become valuable data.

Oil quality (DGA)

As far as the oil quality of the PT is concerned, it is necessary to establish for each one: the starting date of the tests, the PT that was subjected to the test and the values of the analysis for each of the gases that are present in the oil.

A simple handling procedure, later described in Chapter 5, was applied to the supplied data since the data it was found not to be in a desirable format. It is important to have a good data integrity, since the results can be influenced by the quality of the information.

Power Transformers

As far as PT are concerned, the following data is needed: the location where the PT operates, the year that the equipment was made, the year that the PT started to operate and the date of failures that happened in the equipment.

The failures information are key to enable the calculation of the failure probability, since we use a data driven algorithm. However, we made a pre-processing of the data, since not all the failures were related to internal problems of the equipment.

Risk criteria informations

In Chapter 4, we propose a MCDM approach to calculate the risk in a given equipment. In order to be able to calculate this risk, we need information related to the criteria defined in this dissertation. The data requirements are related to: the People security, population area, number of priority clients for each equipment and total number of clients, repair times,electricity cost per minute, net results and the environment hazard of the equipment.

It is important to say, that this information was made available in a good format which allowed a direct use in the calculation of the risk.

Maintenance costs

Relatively to this information, it is important to know the total maintenance costs that each PT is subjected. Also, other crucial costs related to this subject are the preventive and corrective maintenance costs. This information allows us to compare in Chapter 5 the costs supported by the optimized maintenance policies with the ones currently used in EDPD.

Chapter 3

Literature review

In this chapter we make an overview of the theoretical framework that will serve as a foundation of the proposed asset management optimization methodology. We also want to give a brief summary of the literature available for the work developed in this dissertation. First, we start by reviewing the importance of maintenance and asset management. We then review risk based maintenance (RBM), the approach most thoroughly covered in this dissertation since it plays a role in the creation of the asset management model, discussing its advantages and possible extensions to the methodology. We also review and explain the importance of the Hidden Markov models since they are relevant for the life simulation model described in Chapter 4. Then we briefly explain what is the importance of the Multi criteria decision making (MCDM) methodology and what is the literature available. Finally, it is also presented a state of the art review of the Multi Objective Genetic Algorithms (MOGA) available.

3.1 Asset Management

Along the years, the relevance of asset management has grown considerably in companies, becoming one of the most important tasks to perform in order to reduce costs. Due to the widespread mechanization and automation of production processes in companies, it has reduced the number of production personnel and the capital employed in the production equipment have been increased. As a result, the amount of employees working in the area of asset management as well as the fraction of maintenance spending on the total operational costs has grown considerably over the years. In the energy industry, for instance, it is not out of ordinary that the operations and maintenance departments are the largest, each amounts to 30 percent of the total manpower (Garg et al., 2006). Yet, the key question faced by asset management is whether its output is produced more effectively, in terms of contribution to company profits or efficiently, in terms of manpower and materials employed (Dekker and Scarf, 1998).

In some companies, costs related to maintenance are usually divided into direct and indirect costs without taking into consideration maintenance savings and profits. Using this approach leads to falsely imply that maintenance is no more than a cost center. The economic benefits that could be gained by more efficient maintenance can be found as savings in the results of other working areas such as production, quality and capital tied up in equipment and spare part redundancies (Al-Najjar, 2004). Asset management is seen more broadly as a cost cutting field and not as an opportunity for sustainability, and is usually tackled as such when short term objectives come to mind (Bevilacqua and Braglia, 2000). However, on the long term, proper maintenance spending and asset performance are usually correlated.

In order to develop inspection and maintenance policies that should be aligned with the companies objectives, various maintenance strategies must be studied and compared in order to find satisfying trade-offs between the costs and impacts.

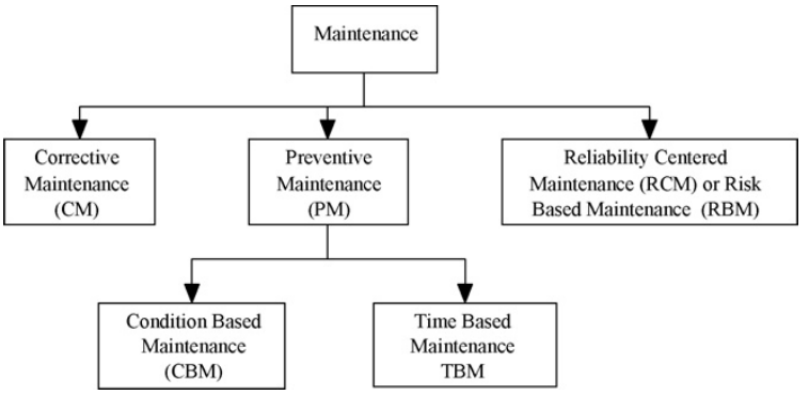

Figure 3.1: Types of maintenance activities.

Figure 3.1 represent the types of maintenance activities used more frequently in the industry. Corrective maintenance is designed to perform maintenance activity upon occurrence of failure in the assets. This type of maintenance is not widely spread due to the risk of a total loss of the asset. However this maintenance policy can prove to be effective in some cases when compared to preventive maintenance, since it minimizes the number of interventions performed on the assets. On the other hand, preventive maintenance is carried out at predetermined intervals or according to prescribed criteria, preventing the occurrence of failure and aiming to guarantee long lifetime of the asset. For TBM, this type of maintenance is based on examining and maintaining the assets according to a time schedule, i.e., performing the inspection and the maintenance activities at constant intervals. TBM is the current maintenance strategy for many industries and utilities. CBM is a type of maintenance policy that relies on performing maintenance when the monitoring system detects a problem in the asset. This problem will change to be a complete failure if not treated early by the workers, i.e., a suitable maintenance will be performed upon detection of a problem by the monitoring system. By using this type of policy, the risk of complete failure is greatly reduced in most cases. In short, CBM lets the operator know when to perform maintenance on the asset. Finally, RBM is a technique initially developed by the commercial airline industry. The fundamental goal of RBM is to preserve the function or operation of a system with a reasonable cost (Costa and Brandcio, 2004) and (Beehler, 1997). Risk-based maintenance is carried out by integrating analysis, measurement and periodic test activities to standard preventive maintenance. RBM can be defined as a mix of more than one maintenance strategy in an optimized manner in order to reduce the system risk. The RBM is used in this work as one of the main pillars of the proposed optimization framework intended to optimize costs and minimize risks.

A lot of literature is available from various resources in the field of maintenance and asset management. (Dekker and Scarf, 1998) have presented various classifications of maintenance optimization models by analyzing 112 papers. In the area of maintenance performance measurement an overview of various performance measurement systems (PMS), including indicators, reference numbers and surveys, has been discussed in detail (Pintelon and Puyvelde, 1997). Various approaches for measuring maintenance performance have also been reviewed in (Tsang et al., 1999). In another invited review, (Wang, 2002) has undertaken a survey of maintenance policies of deteriorating systems and has finally summarized, classified and compared various existing maintenance policies for both single and multi-unit systems with emphasis on single unit systems. (Crespo Marquez et al., 2006) and (Crespo Márquez et al., 2009) define a framework to deal with maintenance management. Maintenance management literature is reviewed in (Garg et al., 2006)

3.2 Risk-based Maintenance

One of the principal objectives of a good maintenance strategy is the minimization of risks, both to the environment and the humans, caused by the equipment unexpected failure. In addition, the strategy has to be cost effective (Khan et al., 2003). Using a risk-based approach ensures a strategy, which meets these objectives. Such an approach uses information obtained from the study of failure modes, the frequency of failures and their economic consequences. Risk analysis is a good technique for identifying, characterizing, quantifying, and evaluating the loss from a real world event. The risk analysis approach combines probability and consequence analysis at various stages of the analysis and at the same time attempts to answer the following questions:

- How likely is its occurrence?
- What can go wrong that could lead to a system failure?
- How can it go wrong?
- What would be the consequences if it happens?

Risk assessment can be quantitative or qualitative. The output of a quantitative risk assessment will typically be a number, such as casualties. The number could be used to prioritize a series of items that have been risk assessed. Quantitative risk assessment requires a great deal of data both for probabilities and consequences assessment. Fault tree or decision trees are often used to determine the probability that a certain sequence of events will result in a certain consequence. Qualitative risk assessment is less rigorous and the results are often shown in the form of a simple risk matrix where one axis of the matrix represents the probability and the other represents the consequences. There are various ways in the literature to divide a risk matrix (Vianello, 2012).

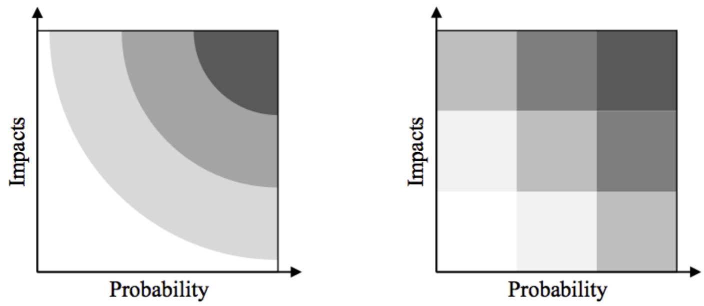

Figure 3.2: Two different configurations of a risk matrix

In Figure 3.2, on the left the division is made in quarter-circles by risk. This type of division is most fair for a quantitative approach, however it does not distinguish high impact and low probability scenarios than those with high probability and low impact. On the other hand, in the right side the division is made in squares based on the frequency and impact of failures. This type of division allows to have a better differentiation between the equipment in the analysis, even though the boundaries dividing the quadrants are difficult to define.

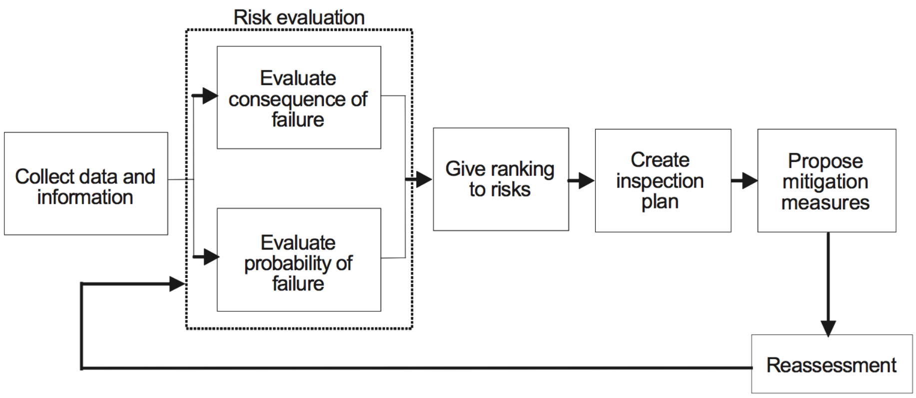

Figure 3.3: General approach of RBM methodology (Hudson and Brian, 2006)

If a value is given to each of the probability and a consequence, a relative value for risk can be calculated. It is important to recognize that the qualitative risk value is a relative number that has little meaning outside the framework of the matrix. Within the framework of the matrix, it provides a natural prioritization of the assets assessed using the matrix. However, as these risk values are subjective and ambiguous, prioritizations based on these values are always debatable.

Figure 3.3 shows the general procedures for RBM. In the first step, data and other needed information for evaluation are collected. With the collected data a risk evaluation is made for all instances. Risk is evaluated as defined in the literature: the product between consequence of failure and probability of failure. With the results of the risk evaluation, a decision is made related to the priority for inspections. After this step, a inspection plan is created based on the prioritization. As a result, a way to mitigate risk is indicated and proposed. In the final step, it is suggested a reassessment for the proposal by comparing the factors such as current regulations and laws. This operation is repeated from the beginning if problems are detected. In this work, the risk analysis coupled with the use of the risk matrix will be crucial to define the maintenance policies to be applied to the equipment.

Unexpected failures usually have adverse effects on the environment and may result in major accidents. Studies by (Kletz, 1994), (Khan and Abbasi, 1998), and (Kumar, 1998) show the close relationship between maintenance practices and the occurrence of major accidents. (Chen and Toyoda, 1990) proposed a strategy for maintenance scheduling based on equalizing incremental risk. (Khan et al., 2003) and (Khan et al., 2004) present a quantitative methodology for risk based management and instantiate it in the latter. (Kusiak and Larson, 1994) are more emphatic on reliability and block diagram analysis. (Ma et al., 2013) show the application of a risk based methodology to a natural gas pipeline. A risk-based approach has been applied successfully to the maintenance of oil pipelines. (Dey et al., 1998) discussed a simple risk based model for the maintenance of a cross-country pipeline.(Nessim and Stephens, 1998) proposed a quantitative risk analysis model, and recently (Dey, 2001) described a more general model for risk-based inspection and maintenance of cross-country pipelines.(Arunraj and Maiti, 2007) review the extensive range of techniques which can be used in RBM.

3.3 Hidden Markov models

Real-world events generally produce a set of signals (sequence of observations). This signals can either be discrete (characters from a finite alphabet, quantitative vectors or a codebook) or continuum (example of voices, temperature measures, music, etc.). Also, the signal source may be stationary (the statistical properties do not vary over time) or non-stationary (statistical properties vary over the time). In addition, the signals source can be pure (this means that the signal comes from a restricted source only) or not pure (the signal comes from noises or other sources of signals) (Rabiner, 1989).

This signals that are obtained from events can be modeled using statistical or deterministic models. The deterministic models usually exploit some of the signal properties, all that is required is to determine (estimate) the values of the signal (amplitude, frequency ...). On the other hand, the statistical models attempt to characterize only the statistical signals properties (Gauss, Poison, Markov, HMM among others). In this work we will only focus on one particular statistical model, more specifically the HMM, since it plays a major role on the methodology described in Chapter 4.

The HMM is a double Stochastic process with an invisible stochastic process, which is not observable (hence the name of Hidden), but that can be observed through another stochastic process that produces the sequence of observations (Rabiner, 1989). The hidden processes consist of a set of states connected by transitions with probabilities, while the observable processes (not Hidden) consist of a set of outputs or observations, each of which may be issued for each state according to some result obtained from the probability density function. Depending on your probability density function, several classes of HMM's can be distinguished as follows:

- Discrete: discreet observation by nature or discretized by a quantitative vector producing an alphabet or codebook.
- Continuous: continuous observation, with the probability density function usually approximated to a normal distribution.
- Semi-continuous: a hybrid between the continuous and the discrete.

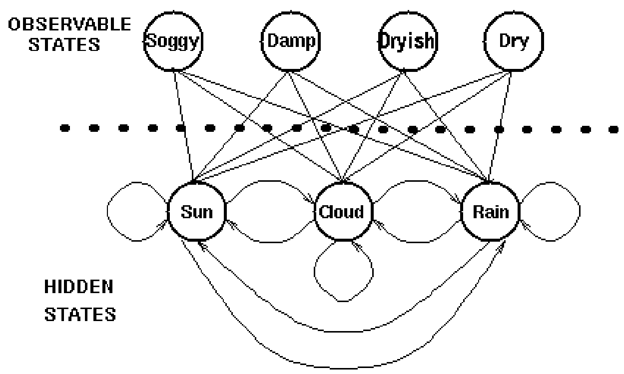

Figure 3.4: Example of a HMM situation

In recent years the HMM has become the predominant approach to the recognition of speech. These models have been shown particularly well adapted to characterize the variability involved in time-varying signals. The biggest advantage of HMM lies in its probabilistic nature, appropriate for information corrupted by noises such as speech or writing, and its theoretical foundation due to existence of powerful algorithms (i.e. Baum-Welch algorithm, Viterbi algorithm, etc.) to adjust the model parameters automatically through iterative procedures (Yacoubi et al., 1999). In this work we use the HMM models in order to model the degradation of the equipment. We believe that with the signals obtained from the equipment we are able to define the transition probabilities between the equipment state conditions.

HMM was first described in the late 60's and early 70's by (Baum and Petrie, 1966), (Baum and Eagon, 1967) and (Baum, 1972). The application of these models in word recognition began to be used in the mid 70's by (Baker, 1975). Over the last 15 years, the HMM has been widely applied in several areas including voice recognition (Lee et al., 1990) (Rabiner, 1989), modeling (Jelinek et al., 1992), recognition of handwritten words (Kundu et al., 1989) (Yacoubi, 1996) (Yacoubi et al., 1999), on-line signature verification (Yang et al., 1995), learning of human actions (Yang et al., 1997), detection off failures in dynamic systems (Smyth, 1994) and recognition of moving light displays (Fielding and Ruck, 1995).

3.4 Multi-Criteria Decision Making

In order to choose an alternative, from a set of possible alternatives in a classical optimization problem, there is an objective function that needs to be maximized or minimized, depending whether this function represents gains or losses, respectively. In a multicriteria problem, there is more than one objective to be addressed and in most cases this objectives conflict with each other. These objectives are associated with the possible consequences (or outcomes) that will result from choosing an alternative.

In many problems faced by companies nowadays, it is not uncommon to face a design challenge when there are several criteria or objectives to be met simultaneously. If these objectives are conflicting with each other, then the problem becomes one of searching the best possible solution that satisfy the competing objectives under different trade-off scenarios. With these multiple objectives and constraints taken into consideration, an optimization problem can then be formulated. This type of problems is known as multiobjective, multicriteria, or vector optimization problems (Zitzler and Thiele, 1999). Multiobjective optimization (MO) is a very "hot topic" because most real-world problems have not only a multiobjective nature, but also many open issues to be answered qualitatively and quantitatively. In fact, there is not even a universally accepted definition of "optimum" as in single-objective optimization (Hwang and Masud, 1979), because the solution to a MO problem (MOP) is generally more than a single point. It consists of a family of points in a feasible solution space, which describes the trade-off characters among contradicted objectives.

The MCDM methodology considers the preference structure of a decision maker (DM) and involves value judgment. The DM's preferences are incorporated in the decision model in order to support the choice of the alternative, and by doing so, the multiple criteria decision will be analyzed simultaneously. Using an MCDM method, the objectives are combined based on the DM's preferences. These preferences consist of the DM's subjective evaluation of the criteria. This subjectivity is an inherent part of the problem and cannot be avoided. Otherwise, it means that the model is related to any other problem, instead of the real problem faced by the DM. Thus, the methodological issues for dealing with this subjectivity have been one of the main purposes of research on MCDM. In this work we use the MCDM methodology for the risk calculation since we believe that we must take into account several criteria. We use more specifically the AHP to obtain the weights for each of the criteria selected.

A model for decision process in MCDM is given by (Simon, 1960), and consists of three stages. In the building models process the authors focus mainly on simplicity with a view to finding a degree of approximation that is good enough to make the model useful. (Bouyssou et al., 2006) point out that the use of formal models evokes the power of hermeneutics, associated with the facility with which a DM's preferences can be elicited. (Wallenius, 1975) states that normally, DMs do not trust models when they find them to be complex. With the continuing expansion of decision models, variants and their methods, it is relevant to have a good understanding of their related value. Each of the designed decision models uses numeric approaches to help DM's choose among a discrete set of alternative decisions.

In (Triantaphyllou, 2000) is possible to find some of the methods used in MCDM. (de Almeida et al., 2015) has done an extensive work about MCDM for a better comprehension of how it works and how should be applied. Most of the literature makes a distinction between the terms Multiobjective and Multicriteria (de Almeida et al., 2015). Therefore, one can say that a problem with multiple objectives can be approached by using either : MCDM or a multi-objective optimization approach. In this work we will be use a Multicriteria approach in order to estimate the risk associated to the assets and a Multiobjective approach to optimize the costs and risks. Multi-objective meta-heuristics are reviewed in (Jones et al., 2002).

3.5 Genetic Algorithms

In the area of genetic programming, more than three decades of research and applications have demonstrated that modeling the natural evolution for a search process can yield very robust and direct computer algorithms, although these models simplify the biological reality (Bäck and Schwefel, 1993). Evolutionary algorithms are based on the cumulative learning process through the generations within a population of individuals, each of which represents a search point in the space of potential solutions to a given problem. In the first generation, the population is randomly initialized, and through the generations tends to evolve toward better regions of the search space by means of randomized processes of selection (in some cases the algorithm uses deterministic rules) and recombination. The "environment" returns quality information (fitness value) about the search points, and the selection process often favors those individuals of higher fitness to reproduce more often than those of lower fitness. The recombination mechanism allows the mixing of parental information while passing it to their descendants (Bäck and Schwefel, 1993).

In the modern society, genetic algorithms are used to generate fast and high-quality solutions for optimization and search problems. This algorithms rely on biological inspired operators such as crossover, mutation and selection. In genetic programming, a population of possible solutions are always evolved toward better solutions. Each possible solution has a set of traits(its genotype or chromosomes) which can be altered and mutated. In most cases, the evolution process starts from a randomly generated population of individuals. This population evolves in an iterative process, with each iteration called a generation. In each generation, the fitness of every individual in the population is evaluated. Usually, the fitness is the value of the objective function in the optimization problem that is being solved. In general, the more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The more recent generation of possible solutions is then used in for the next iteration of the algorithm. In most cases, the algorithm halts the run when either a satisfactory fitness level has been reached for the population , or a maximum number of generations has been produced.

In this work we will use MOEAs, since the proposed asset maintenance methodology has two objectives that need to be optimized: the maintenance policies risks and costs. Methods and techniques can be found in four state-of-the-art MOEAs - MOGA, PAES, NSGA-II, and SPEA II - which are briefly reviewed in the following:

(a) **Multiobjective Genetic Algorithm (MOGA)**

In their MOGA, (Fonseca and Fleming, 1998) proposed a ranking system in which the rank of a certain individual equals the number of individuals in the current population by which it is dominated. Based on this system, all the nondominated individuals are assigned rank 1, while the dominated solutions are penalized according to the population density of the corresponding region. In order to prevent a premature population convergence, a niche-formation method to distribute the population over the Pareto front in the objective space is adopted.

(b) **Pareto Archive Evolutionary Strategy (PAES)**

As a local search algorithm that simulates a random mutation hill climbing strategy, PAES may represent the simplest possible, yet effective, nontrivial algorithm capable of generating diverse solutions in the Pareto optimal set (Knowles and Corne, 2000). In PAES, a pure mutation operation is adopted to fulfill a local search scheme. A reference archive of previously found nondominated solutions is updated at each generation in order to identify the dominance ranking of all the resulting solutions. This genetic algorithm is originated as the simplest version. PAES can also generate λ mutants by mutating one of the μ current solutions, which is called $(\mu + \lambda)$-PAES (Knowles and Corne, 2000). Since PAES does not perform a population-based search, only tournament selection can be applied to determine the survivors of the next generation.

(c) **Nondominated Sorting Genetic Algorithm II (NSGA-II)**

NSGA-II (Deb et al., 2000) was improved from its origin, NSGA (Srinivas and Deb, 1994). In NSGA-II algorithm, a nondominated sorting approach is used for each individual to create Pareto rank, and a crowding distance assignment method is applied to implement density estimation. In a fitness assignment between two individuals, NSGA-II prefers the point with a lower rank value, or the point located in a region with fewer number of points if both of the points belong to the same front. Therefore, by combining a fast nondominated sorting approach, an elitism scheme and a parameterless sharing method with the original NSGA, NSGA-II claims to produce a better spread of solutions in some testing problems (Deb et al., 2000).

(d) **Strength Pareto Evolutionary Algorithm II (SPEA II)**

Similar to NSGA-II, SPEA II (Zitzler et al., 2001) is an enhanced version of SPEA (Zitzler and Thiele, 1999). In SPEA II, instead of calculating standard Pareto rank, each individual in both main population and elitist archive is assigned a strength value, which incorporates both dominated and density information. On the basis of the strength value, the final rank value is determined by the summation of the strengths of the individuals that dominate the current one. Meanwhile, the nearest neighbor density estimation method is applied to obtain the density value of each individual. The final fitness value is the sum of rank and density values. In addition, a truncation method is used in elitists' archive in order to maintain the number of elitists to be constant. In the experimental results, SPEA II shows better performance than SPEA (Zitzler and Thiele, 1999) over all the test functions considered therein.

Literature review comments and discussion

The review of the available literature on the main topics of the theoretical framework, were very useful to understand what were the tools and methodology's that could be used in the creation of the proposed asset management optimization approach. We understood that in maintenance we either have complex mathematical models that are only applicable to certain cases or we have generic models that are difficult to implement. In this dissertation, we consider an asset management optimization problem that is generic enough to be applied to various types of assets, but at the same time is very easy to implement. It is to note that the literature associated with the proposed asset management optimization model is scarce, which gives some academic relevance.

The optimization model was developed with the main objective of being applied in companies, hence the dissertation conciliates two main fronts. On one hand, the objective of satisfying the customer's requirements leads to a more practical and more direct implementability; on another, it tries to keep a relevant academic approach. The solution of the presented case study in this dissertation will be discussed on the following chapters.

Chapter 4

An Optimization Methodology approach

The first priority when tackling the problem faced by a company is to obtain a cost efficient maintenance policy to be applied to their assets. Nevertheless, it is known that these plans, good for the short term, probably cease due to the risk of failure associated to the equipment. In this chapter we propose an optimization methodology capable of formulating a policy that allows to minimize the costs and risks for a group of equipment. As Figure 4.1 shows, the methodology proposed is composed by 3 main phases. We first start by describing the equipment life simulation model. This simulation model will allow to simulate how the life condition of the equipment will most likely evolve through time. After modeling the equipment behavior we start looking to the formulation of the maintenance policy. In this phase we define the risks and costs associated to the maintenance policy as well the risk matrix that allows us to define the maintenance policies. Finally, in the third and final phase we run the optimization algorithm that will allow to define various maintenance policies suited for the assets. Auxiliary to the comprehension of this chapter, and the mathematical expressions used, notation Table 4.1 is provided.

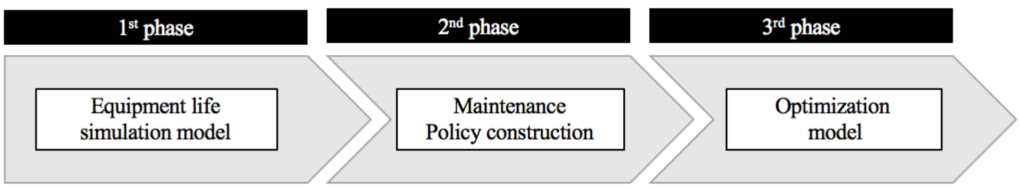

Figure 4.1: Description of the methodology

Table 4.1: Notation table with variables and events, for this chapter.

Variables	
t_m	Discretized time variable.
X_m	Level of degradation of the equipment.
$w(j\|k)$	Probability of an increase of j units of degradation starting from an initial degradation level of k units.
$P_n(k)$	Probability of being in degradation level n at time t_n of a certain m equipment.
k_m	Number of states for a given m equipment.
$f(k)$	Probability of component failure due to a random event which leads to the final degradation state x_{m+1}.
d_{ij}	Markov transition probabilities.
$Cost^m$	Total maintenance cost associated to a m equipment in a given period.
N_R^m	Number of preventive maintenances performed in an m equipment.
N_C^m	Number of corrective maintenances performed in an m equipment.
R^m	Risk associated with equipment m.
$f(m\|c)$	Probability of failure in equipment m given condition c.
$u_x(m)$	Utility function of criteria x in equipment m.
$\pi(m)$	Current condition in equipment m.
α_x^m	Weight of criteria x in equipment m.
C_p^m	Preventive maintenance cost of a m equipment.
C_f^m	Corrective maintenance cost of a m equipment.
α_{min}^x	Minimum relative weight of criteria x in the equipment.
α_{max}^x	Maximum relative weight of criteria x in the equipment.
$Availability$	It is the total time that the equipment is functioning without interruptions.

4.1 Equipment life simulation model

In this section, we describe a Markov approach for modeling the behavior of a deteriorating equipment subjected to maintenance. Although the resulting model accounts for the main issues concurring to the component degradation and improvement, it still has to resort on simplifying assumptions. To estimate the transition matrix we will use a HMM algorithm, more specifically the Baum-Welch algorithm. For a more realistic modeling of the system life we will use the MC simulation method. The details of the MC approach are also provided here.

4.1.1 The degradation Markov model

We firmly believe that the equipment changes the state condition while it perform their operational functions. In this work, to better understand the degradation process, we build a Markov model for the life degradation. The probabilities from the Markov models allows us to describe the physics of the evolution of an equipment through its states of operation.

Let $t = (t_0, t_1, ..., T_M)$ represent the discretized time variable and $X = (x_0, x_1, ..., x_m, x_{m+1})$ be a discrete random variable denoting the level of degradation of the equipment. The process of degradation evolution is described through the first m states $(x_0, x_1, ..., x_m)$ while the state x_{m+1} refers to a condition where the equipment performance is greatly affected, reachable upon a possible random failure occurring while in any of the other operative states $x_i < x_{m+1}$. A possible realization of the time evolution of the equipment is shown in Figure 4.2.

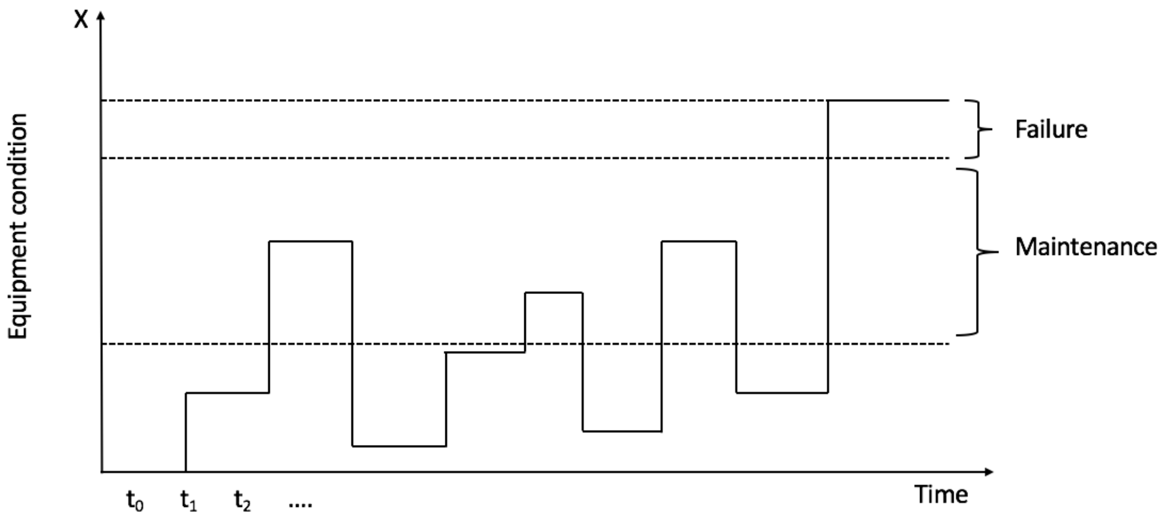

Figure 4.2: Time sketch of the degradation process of an equipment

On the basis of the previously variable definitions, we build a specific Markov model for the process of degradation of an equipment.

$$\begin{pmatrix} P_n(0) \\ P_n(1) \\ P_n(2) \\ P_n(3) \\ \vdots \\ P_n(m) \\ P_n(m+1) \end{pmatrix} = \begin{bmatrix} w_{00}(1-f(0)) & 0 & 0 & \cdots & 0 \\ w_{10}(1-f(0)) & w_{01}(1-f(1)) & 0 & \cdots & 0 \\ w_{20}(1-f(0)) & w_{11}(1-f(1)) & w_{02}(1-f(2)) & \cdots & 0 \\ w_{30}(1-f(0)) & w_{21}(1-f(1)) & w_{12}(1-f(2)) & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{m0}(1-f(0)) & w_{m-11}(1-f(1)) & w_{m-22}(1-f(2)) & \cdots & 0 \\ f(0) & f(1) & f(2) & \cdots & 1 \end{bmatrix} \begin{pmatrix} P_{n-1}(0) \\ P_{n-1}(1) \\ P_{n-1}(2) \\ P_{n-1}(3) \\ \vdots \\ P_n(m) \\ P_n(m+1) \end{pmatrix} \tag{4.1}$$

The system of equations 4.1 is intended to describe the behavior of a equipment which evolves through degradation. We associate to each level of degradation a probability of shock failure which, realistically, will increase as the component degradation increases. For modeling the effect of the failures we consider the absorbing state x_{m+1}, which can be reached upon equipment failure from states with degradation level $k \leq k_m$. From each operating state k, the component can either fail, i.e. transfer from state x_k to state x_{m+1}, with probability $f(k)$, or increase its degradation level of j units, with probability $w(j|k)(1-f(k))$, since the two events of failure and degradation are mutually exclusive.

This Markov model was formulated to be the most generic possible in order to be applicable to more than one type of equipment. The bigger the number of states utilized in this degradation model, the more realistic will be the simulation of the degradation process of the equipment.

4.1.2 The Baum-Welch algorithm

A hidden Markov model (HMM) is a numerical statement model which is based on the unobserved events of a Markov chain. Because the actual problem is more complex what the Markov chain describes, the observable events in HMM are not correspondence to each of its state, yet have a contact with each of state probability distribution. The difference between HMM and Markov model lies in that the state of Markov model can be directly observed, yet the state of HMM is hided in the observable value and is not directly observed. The HMM model must be expressed by two random processes, one is the state sequence, and another is the observable value sequence.

Due to the characteristics of most problems in the real world, we do not know the sequence of states of the equipment. However it is possible to have the sequence of observable values for each equipment. In this work we get this sequence through the oil condition that circulates in the equipment. In section 5 we explain how we calculate the oil condition of the PT with the DGA (Dissolved Gas Analysis) analysis.

In order to estimate the parameters of the transition matrix we first need to define the number of discrete states that define the condition of a equipment. In this work we considered that the equipment condition would range between 1 and 6, being $k = 1$ the best condition and $k = 5$ the worst condition. The last state always refers to the state of failure of the equipment. Only after defining the Markov matrix can we use the Baum-Welch algorithm. This HMM algorithm is used to train our dataset in order to estimate the values of the probabilities of the transition matrix.

$$T = \begin{bmatrix} 1-d12 & d12 & 0 & 0 & 0 & f(1) \\ 0 & 1-d23 & d23 & 0 & 0 & f(2) \\ 0 & 0 & 1-d34 & d34 & 0 & f(3) \\ 0 & 0 & 0 & 1-d45 & d45 & f(4) \\ 0 & 0 & 0 & 0 & d56 & f(5) \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.2}$$

$$d_{ij} = w_{ij} * (1 - f(i)) \tag{4.3}$$

This Markov matrix model is called a left-right model or a Bakis model as mentioned in (Bakis, 1976) and (Jelinek, 1976), because the underlying state sequence associated with the model has the property that as the time increases the state index increases(or stays the same),i.e., the states proceed from left to right. Due to the small number of states considered for the problem at hand, as shown in the system of equations 4.2, we assume that when the equipment is in a given state, no jumps of more than 1 state is allowed.

4.1.3 The improvement model

In most models revised in the literature, whenever a equipment is subjected to maintenance, most authors assume that the equipment returns to a "as good as new" state. They often assume this simple assumption in order to make the problems less complex. Nevertheless, in this work we will not consider this assumption because we want our simulation model to have a greater approximation to reality. What we assume in the problem studied in this work is that the improvement of states of the equipment will be dependent on the age of the equipment. The equipment will improve to a better state only if a maintenance related intervention is performed, otherwise the condition will continue to degrade overtime until eventually the equipment fails.

As already previously mentioned, for the studied problem we assumed that the equipment condition would be described in 6 different states. Given that we perform maintenance when the equipment is in a given state, we define for this problem how will the health of the equipment improves with time.

Table 4.2: Assumed improvement state given the age of the PT

Age(years)	State improvement
0-15	1
15-40	2
>40	3

As shown in the table above, we assume three different improvement levels that depend on the age of the PT. If the equipment age is smaller than 15, then we assume that when we perform maintenance the equipment improves to state 1, the best condition. If the age of the PT, falls in the interval between the age $[15;40]$, we assume that the equipment will improve to state 2. Finally, if the equipment is older than 40 years, we assume that the equipment will improve to state 3. The intention of this assumptions is to give a more precise approach to the MC simulation.

4.1.4 The Monte Carlo simulation model

The use of the MC approach in this work amounts to simulate a large number of system life histories to estimate the averages of the quantities of interest for the calculation of the objective functions defined in Section 4.2. Each of these simulated histories corresponds to a virtual experiment in which the equipment is followed in its life condition evolution throughout the mission time that we define. During the equipment life, the equipment undergoes stochastic transitions between the possible states, evolving through conditions of availability and unavailability due to maintenance or failure. During the simulation, knowing the simultaneous evolutions of all equipment and the failure configurations, we record, in appropriately devised counters, the observed realizations of the following random variables: the intervals of time during which the system remains in the down state; the number of times the system fails; the intervals of time during which each component is under maintenance. By performing multiple Monte Carlo histories, we obtain many independent realizations of these random variables whose combined averages estimate the equipment availability and the probability of the equipment being under maintenance. From these, we can then obtain an estimate of the two objective functions: the total maintenance costs T_C and the total equipment risks T_R achievable over the mission time.

For the modeling of the maintenance dynamics, the process is dependent on the availability of maintenance workers. If no worker is available, because all are currently working on other units, a needing equipment has to wait before its maintenance process can be started, i.e. in the Monte Carlo framework, the equipment is allowed to perform a stochastic transition towards an operative state only if the number of units simultaneously under maintenance is lower than the number of the available maintenance workers. As mentioned previously in Chapter 2, we always prioritize maintenance in the equipment that represent a higher risk.

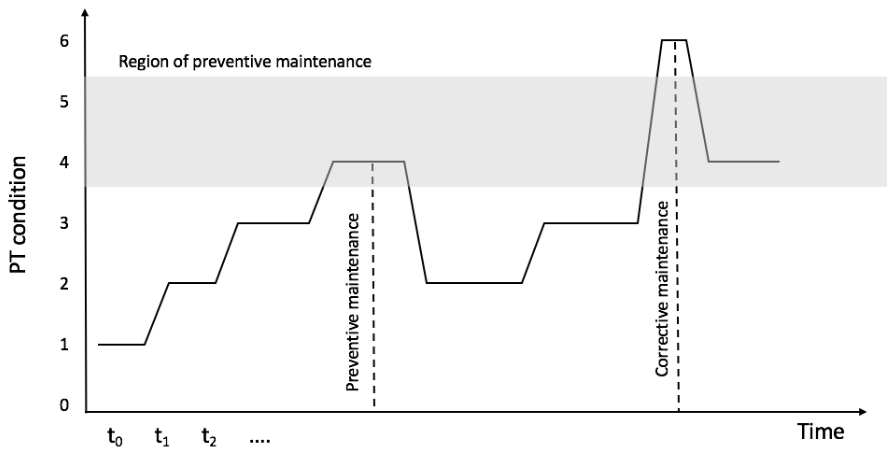

Figure 4.3: Example of a equipment life history

4.2 Maintenance Policy construction

In this section, we define our objective functions that allow to estimate the costs and risks associated to the maintenance policy to be implemented. We explain thoroughly how the risk of a given equipment is calculated and also how the cost is estimated. In the end of this section we explain how the decision maker should formulate the risk matrix that will allow us to categorize the equipment in this problem and help define the maintenance policy.

4.2.1 Risk and Cost Objective functions

Total cost objective function

First we start by defining the total cost objective function. The variables that influence the total costs of maintenance in a given equipment, is the number of times that we perform preventive maintenance N_R and the number of times that we perform corrective maintenance N_C. Due to lack of information in the data provided, the distance covered by each maintenance team to perform maintenance interventions on the equipment will not be considered separately. That cost will be absorbed in the variables of preventive maintenance C_p cost and corrective maintenance C_f cost.

$$Cost^m = N_R^m * C_p^m + N_C^m * Cf^m \tag{4.4}$$

By generalizing the equation 4.4 to all equipment, we obtain the total cost objective function shown in the following equation:

$$Min : T_c = \sum_m N_R^m * C_p^m + N_C^m * Cf^m \tag{4.5}$$

Risk objective function

Traditionally the risk of failure of a certain equipment is calculated by multiplying the probability of failure with the impact of the consequences of said failure. We believe that the calculation of the consequences impact can, in some cases, be very difficult to assess. With this in mind, for this work we decided that the risk of failure of certain equipment would be calculated using a multicriteria approach and the equipment condition.

For the problem studied in this dissertation we used 5 different criteria:

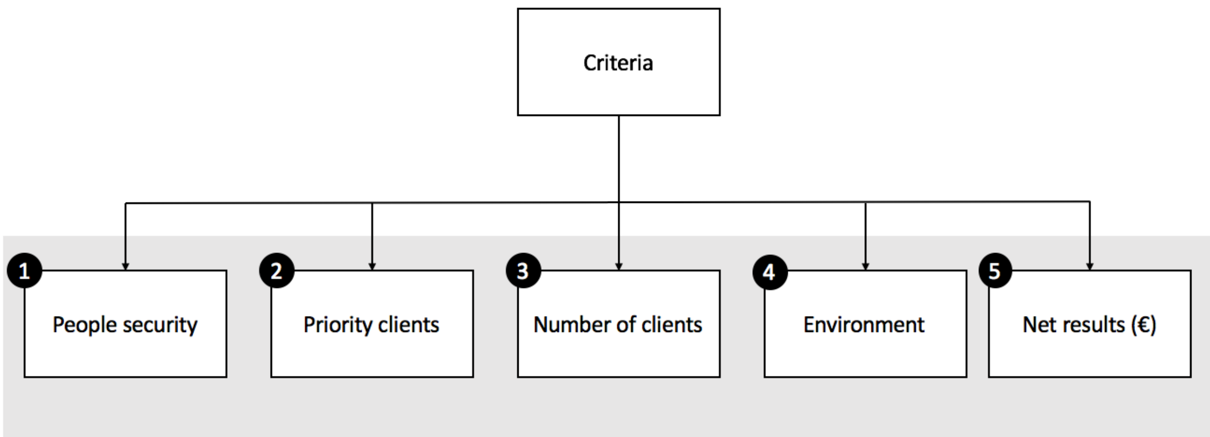

Figure 4.4: Criteria used to evaluate risk

Taking into consideration the criteria $u_x(m)$ that helps to measure the consequences, the current state of the equipment $\pi(m)$ and the probability of failure given a condition $f(m|c)$ we are able to formulate the equation that allows to calculate the risk of a given equipment:

$$Risk^m = \pi(m) * \int f(m|c) * \begin{pmatrix} k_a * u_a(m)da \\ +k_b * u_b(m)db \\ +k_c * u_c(m)dc \\ +k_d * u_d(m)dd \\ +k_e * u_e(m)de \end{pmatrix} \tag{4.6}$$

The decision maker should be taken into account when pondering the relevance of each category, thus a method such AHP (Analytic Hierarchy Process) can be used to determine the relative importance of the categories and establish weights k_x. For the utility function of the criteria all the values are normalized in order to fulfill the range of values necessary to evaluate the risk.

$$u_x(m) = \frac{\alpha_x^m - \alpha_{min}^x}{\alpha_{max}^x - \alpha_{min}^x} \tag{4.7}$$

The higher the value of equation 4.6, the bigger the risk. The values of the risk equation range from $[0;1]$. Generalizing the risk function to all equipment we obtain the total risk objective function:

$$Min : T_R = \sum_m Risk^m \tag{4.8}$$

4.2.2 Risk matrix

From the previously defined equation 4.6, every equipment can now be compared with any other. Though this is an useful feature, the final purpose of the equipment risk analysis is the definition of the maintenance policies. Hence, for practical purposes, it is more adequate to represent the results in a risk matrix. The risk matrix allows for a better differentiation between the studied equipment. As already mentioned in Chapter 3, there is two types of risk matrix: the division by quarter-circles and the division by squares. From a decision maker perspective it is believed that the division by quarter-circles is more adequate since it is the most fair for a quantitative approach, but when taking into account implementing the matrix in a real life problem, the divisions in squares bring a higher flexibility which is hard to disregard. Since this optimization methodology was developed to be applied to several utilities in real world problems, we firmly believe that the latter option is the one that best suits the needs of a DM. In the problem studied in this dissertation, the DM should be the one that defines the limits of the matrix.

The main considerations normally taken into account in this kind of process are: (1) to take the objective of the analysis into account, and (2) to discriminate between the equipment. For the first consideration, the scope and purpose of the analysis are questioned. The degree of similarity throughout the equipment in the analysis will be strongly related to the limits of the matrix. The second consideration recommends that the limits of the matrix must be defined such that difference between the equipment can be visualized. The effectiveness of the limits must be judged, as too much detail can make the matrix harder to interpret. This trades off implementability of the matrix and detail.

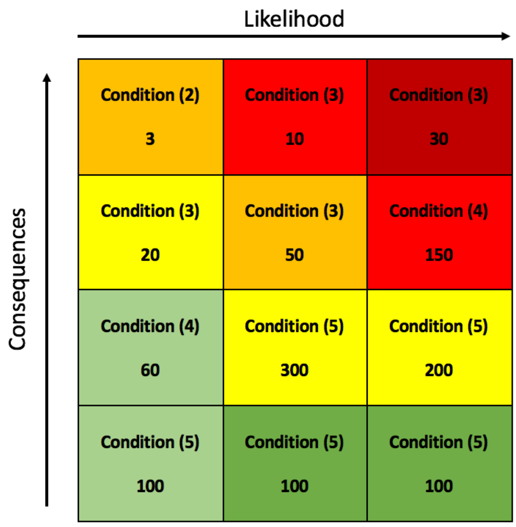

Figure 4.5: Example of the risk matrix with the maintenance policies

For this methodology we use the square-divided risk matrix since it brings a better differentiation between the different equipment. With the help of the risk matrix, for each of the quadrant we will define a condition-based maintenance policy that indicates what will be seemingly the most adequate state condition to perform preventive maintenance. Also, for each of the quadrant we will have the number of equipment subjected to that maintenance policy. In this phase we define the first guess of the maintenance policies to be applied, however the initial guess only enables us to obtain the possible solutions for the problem. In the following Section 4.3, we explain how the optimization model will allow to reach a numerous of solutions that allows us to have a good trade-off between the total risk and costs of the maintenance policies.

4.3 Optimization model

In order to optimize the initial established maintenance policies in the risk matrix we use genetic algorithm to reach an optimum solution. The search for the optimal thresholds of the equipment condition for maintenance intervention involves a choice among a large number of potential alternatives. In problems of this type, a crude search amounting to systematically running a full Monte Carlo simulation with accurate statistics for each alternative proves to be unfeasible. Instead, if we guide the search for an optimal solution with a genetic algorithm, a Monte Carlo iteration should ideally be run for each chromosomes population individual considered in the successive generations search: again, this proves to be impractical.

The possible solution to this problem kind of problems follows from the consideration that in the genetic algorithm approach, the best chromosomes appear a large number of times in the successive generations whereas the bad ones are readily eliminated (Joyce et al., 1998). Following this idea, for each proposed chromosome, we run a Monte Carlo simulation with a limited number of trials, e.g. 200, thus getting a rough estimate for each of the objective functions. During the genetic algorithm evolution, the archive of the best chromosome solutions obtained in previous MC runs, and the corresponding MC objective functions estimates, are updated: whenever a chromosome is re-proposed, the newly computed objective functions estimates can be accumulated with those stored in the archive and the large number of times a 'good' chromosome is proposed by natural selection allows accumulating over and over the results of the few registered runs, thus achieving at the end statistically significant results (Cantoni et al., 2000).

To further improve the statistical significance of the best solutions estimates, at the end of each generation the objective functions estimates of the (nondominated) solutions in the archive are reinforced by running 200 additional system life histories. We call this approach 'step-by-step' for its similarity to an iterative process(i.e. walking on the street). The main advantage of proceeding in this is to avoid wasting time on 'bad' solutions which will be simulated only a small number of times.

Due to the problem studied in this work being multi-objective we have to use a MOGA. The GA algorithm that we use to minimize the objective functions of the costs and risks is the NSGA-II since it is the one that has the best results in the benchmarking results across different problems proposed in the literature. The final result after applying the optimization model is the risk matrix, where in each of the quadrants we have the ideal state of the equipment where we have to perform maintenance.

Chapter 5

Numerical application and results

This Chapter, demonstrating the application results of the methodology analyzed in Chapter 4, is one of the results of our collaboration with EDPD. We start by first describing the information processing that had to be done in order to have a more robust dataset. Then we proceed to simplify the problem with the help of the risk matrix. This process allows us to obtain the results in a more efficient way. The calculations needed to solve the problem are explained in detail in this chapter. In the end, we compare the solutions obtained with the company current maintenance policy and give a better insight to the possible solutions to be applied in the company.

For a better understanding of the expressions used in this case study the notation Table 5.1, which complements the one in the previous chapter, follows. We introduce new variables, substitute old ones and add an auxiliary constant that aims to help with the use of experimentally obtained values.

5.1 Case description

Considering EDPD objectives, PT are the most critical piece of equipment, as its failures' can lead to a great loss of money for the company. The consequences of a failure can influence thousands of clients and in some cases they can affect the environment, i.e. starting a fire of great proportions. Though the company intends to define maintenance policies conservatively, they work through a judgment-based method which has a quantitative confirmation that heavily relies on conservative calculations. Beyond improving the current policies, the company aims to have justification for the improvement.

The analysis covers the entirety of Portugal, fed by 729 active PT. These equipment are intended to raise the electricity voltage produced in the power plants in order to be transported in high voltage to the areas of consumption or, once near the areas of consumption, lower the voltage level to enable

Table 5.1: Notation table with variables and events, for this chapter.

Variables	
θ_1^m	Consequence of an equipment m in the People security criteria.
θ_2^m	Consequence of an equipment m in the Priority clients criteria.
θ_3^m	Consequence of an equipment m in the Number of clients criteria.
θ_4^m	Consequence of an equipment m in the Environment criteria.
θ_5^m	Consequence of an equipment m in the Net results criteria.
S^m	People security classification for equipment m.
A^m	Population density in equipment m.
R^m	Reputation classification related to the priority clients in equipment m.
N_c^m	Number of clients served by equipment m.
T_R^m	Average repair time for equipment m.
T_R^{max}	Max repair time registered in all equipment.
$TIEPI^m$	Interruption time equivalent to the installed power in a given m PT.
EC^m	Electricity cost per minute of equipment m.
H^m	Environmental hazard classification of equipment m.
NI^m	Average net income of equipment m.
R_T^m	Time it takes to fully operationalize the m equipment.
L_S^m	Lost sales due to failure of equipment m.
k_c'	Non-normalized weight for criteria c.
k_c	Normalized weight for criteria c.
S_i	Score of gas i.
W_i	Weight of gas i.
t_n	Simulation period.
I_t	Number of iterations for each run.
C_p	Preventive maintenance cost.
C_f	Corrective maintenance cost.
S_t	Number of states in the simulation.
S_t	Risk multiplying factor.

the distribution in medium voltage. Generally these installations contain the gantry where they arrive and from where they leave the lines, the power transformers and the protective accessories. These installations are protected by a fence, with electrical danger signs inside that prohibit access to unauthorized persons. The company has multiple bases distributed in Portugal, that are responsible for surveying the electricity network condition.

PT are usually inspected once per year. This policy, which includes some minor repairs in the equipment, has an estimated cost of 1 065 312€ per year. It should be noted that every year EDPD changes some PT oil. Therefore, they represent a big portion of the maintenance costs. Additionally, the company's maintenance data is unstructured and sometimes lacks integrity. This is a result of a poor fit between the company's processes and the information system used. To these matters we add technician neglect in registering the data to the mentioned problems, which makes maintenance events nearly impossible to track.

5.2 Information processing

This brief section describes how certain types of data were transformed to a more accurate and functional format. Moreover, two major integrity flaws of the data retrieved from EDPD are presented, as well as the processing procedure enabling its use. This information is processing is key to give more robustness to the obtained solutions.

Lack of integrity in the data related to the DGA analysis

There was a major problem concerning the data provided from the company related to the DGA analysis. Some of the values related to the gases present in the oil test were declared as a Null value. This was considered to be a mistake since it seemed reasonable to assume that it is not possible not to have any kind of concentration in some DGA gases. This results probably happen due to interventions performed in the equipment oil before the tests. In order to solve this problem, we considered that the best estimate, when the value was considered to be 0 or null, was the last observed value in the last realized test. We believe that the best estimate for the next year is the previous registered results. In Figure 5.1 we have an example of the pre-processing method.

It is worth mentioning that we do not possess for this work, all the DGA tests performed in the 729 active transformers. We suspect that more recent transformers are not subjected to this type of tests since the equipment are considered to be in a good condition, however this was not confirmed by EDPD. Nevertheless, we still have available a good amount of data that allowed us to reach interesting findings in this work.

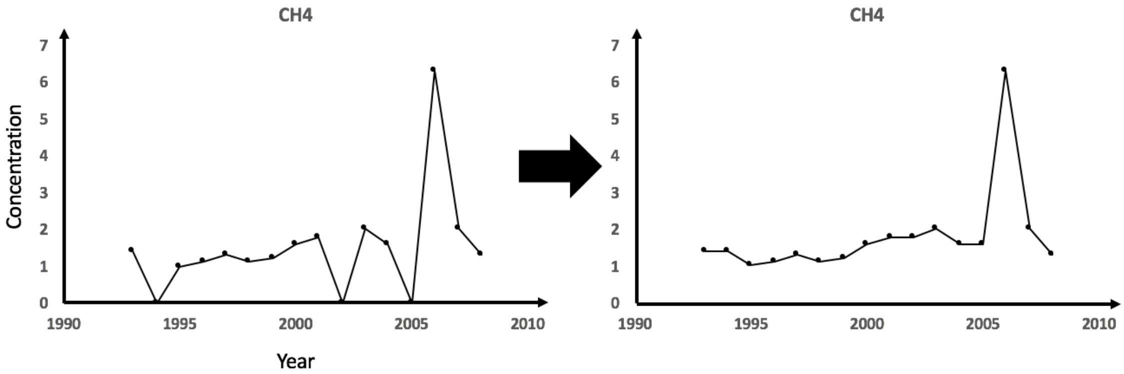

Figure 5.1: Example of a pre-processing in gas CH_4

Failures cleansing

Regarding the data related to the failures, not all the information provided was directly linked to the PT. Also, most of the data was found not be in an adequate format. In order to process all the information we did two filtering steps. In the first step we filter all the notifications related to the PT, and in the second step we separate the failures caused from external causes from the internal problems.

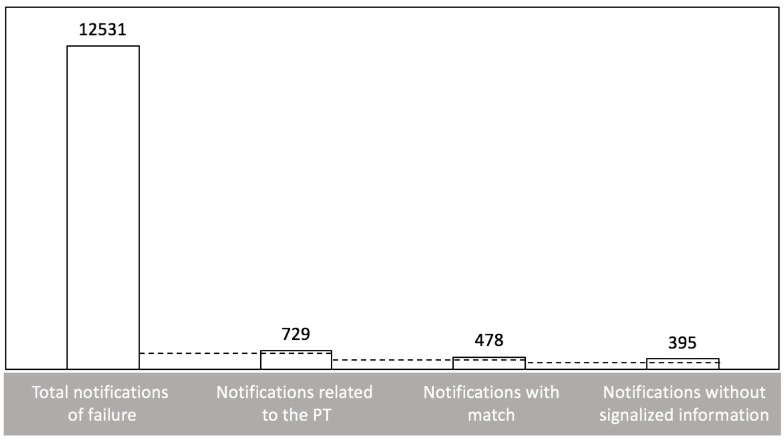

Figure 5.2: Initial filtering of the notifications of failures

In Figure 5.2 we have the results related to the first step of the filtering process. Initially we started with 12531 notifications of failures reported by EDPD, however only 729 were related to the PT. From those 729 notifications of failure, it was possible to directly match 478 failures to the PT. The rest of the failure notifications were not possible to associate to the equipment since we did not have the necessary information. Finally in the first step of the filtering process we ended up with 395 instances, because some failures were already notified by EDPD as information to be discarded.

With the provided information by the company workers, in the second step of the filtering process we had to remove all the failures that were not correlated with problems caused in the PT. In order to do that, we looked to all causes reported in the notifications only to conclude that 206 failures occurred due to internal problems in the equipment. The remaining informations was discarded since it was related to external causes that interrupted the normal function of the PT(i.e. a tree falls onto the PT). As a final result of our information processing we ended up with 158 failures. This happened due to the lack of information related to the DGA tests performed in the equipment, which coupled with this information is crucial to obtain the Markov matrix parameters.

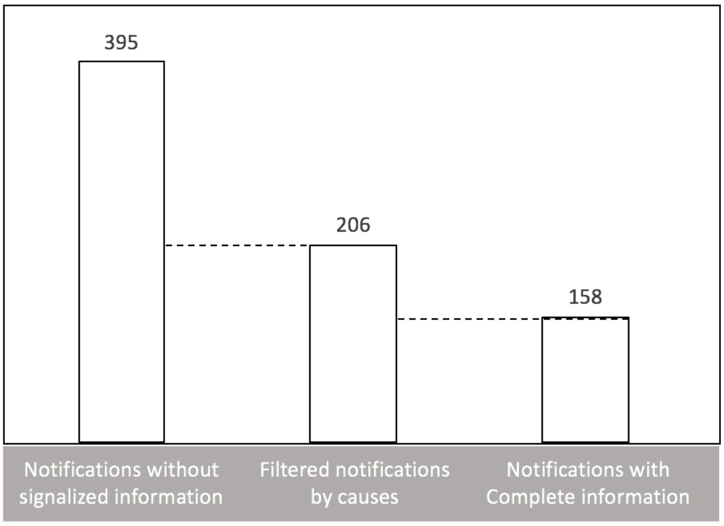

Figure 5.3: Second phase of the failures notifications filtering

5.3 Power Transformers clustering

In order to be able to optimize the costs and risks of the maintenance policies used in EDPD, we first needed to aggregate the different PT studied in this problem. In the problem studied in this dissertation, we have currently in the electricity network of EDPD, 729 Power Transformers that actively distribute electricity in Portugal. We decided that the best criteria to use to cluster the different PT was with the help of the risk matrix. Basically we aggregate the PT by the consequences that they represent for the company and by the likelihood of the consequences happening in the future. The clustering of the PT will be key to allow the estimation of the transition probabilities of the equipment life simulation model.

5.3.1 Consequences estimation

As previously showed in Figure 4.4, we defined 5 different criteria that represent the total consequences of a given equipment when it fails. In this section we explain how each of the criteria metrics are calculated and the respective results.

People security

In the case of the people security, it is important to know the distance that this equipment are to a certain populated area since when the equipment fails it can incinerate its proximities. Since EDPD categorizes the PT security in 4 different levels, we attribute different points to each of the the levels and then proceed to multiply the points attributed with the population area density where the equipment are installed. We believe that a PT in bigger population are can be more dangerous than in a more isolated are.

Table 5.2: Level of the PT people security

People Security	Classification
Power Transformer in buildings with normal presence of people	4
Houses adjacent to the Power Transformer (in Building or PEA)	3
Houses up to 10 meters away from the Power Transformer (PEA)	2
Power Transformer in abandoned installation	1

$$\theta_1^m = S^m * A^m \tag{5.1}$$

Priority clients

The estimation of the failure consequences related to the criteria "Priority clients" is similar to the previously defined calculation. Since EDPD categorizes the PT in 5 different levels of importance related to the priority clients, we used those categories in order to estimate the consequences. For each PT we attribute a classification between 1 and 4 related to the predefined categories by the company. Then we proceed to multiply the obtained classification by the average time that it takes to repair the failure (TTR) in a given *m* PT. It is also important to take into account the total number of clients that the equipment is responsible for. In Table 5.3 we have the classification attributed to each of the categories.

Table 5.3: Level of the PT Priority Clients

Reputation	Classification
Number of Priority Client Exits > 5	5
$4 \leq$ Number of Priority Client Exit ≤ 5	4
$2 \leq$ Number of Priority Client Exit ≤ 3	3
Number of Priority Client Exit $= 1$	2
Number of Priority Client Exit $= 0$	1

$$\theta_2^m = R^m * N_c^m * \frac{T_R^m}{T_R^{max}} \tag{5.2}$$

Number of clients

If there is an unavailability, the time that the clients are affected must be accounted for. With the provided information of EDPD, we can obtain in average, how much time a PT is unavailable when it fails to distribute electricity using a KPI provided by EDPD. We then proceed to estimate the consequence of the unavailability by multiplying the TIEPI KPI by the average cost of electricity per minute in a given PT.

$$\theta_3^m = TIEPI^m * EC^m \tag{5.3}$$

It is to note that this metric measures the consequence of a short-period unavailability. The previous criteria measured the consequences of a long-period unavailability of the equipment.

Environment

The only major hazard that the PT represent to the criteria "Environment" is the oil that circulates in the equipment. It is common knowledge that the when the oil is spilled on water, soil or other areas, it can negatively affect the environment. Some PT have protections related to leakage of the oil while others don't. Nevertheless, the estimation of the consequence related to the environment where the equipment is installed is rather important since it plays a major role in the estimation of the risk. In this problem, we defined 3 different levels of consequence related to the PT and we attributed different points to those levels.

Table 5.4: Level of the PT environmental hazard

Environment Security	Classification
Power Transformer without retention basin in high environmental risk zone	5
Power Transformer without retention basin in medium environmental risk zone	4
Power Transformer without retention basin in low environmental risk zone	3
Transformer with Oil Retention Basin	1

Due to a lack of data related to this matter, the environment consequence estimation in case of a failure will simply be the points attributed to the category.

$$\theta_4^m = H^m \tag{5.4}$$

Net Results

When a PT fails, we can have a complete destruction of the equipment. This loss represents a certain cost, that for this particular metric it isn't only associated with the replacement cost of the equipment, but also the amount of net income that a particular PT contributes to the company. For this particular criteria, the magnitude of the consequences of a total loss of the equipment will be associated with the income that the equipment generates, the lost sales that the failures causes and the time that we take to fully replace the equipment. In short, we multiply the net income NI^m generated by the PT by the time we take to replace R_T or repair the equipment, plus the amount of lost sales that we incur.

$$\theta_5^m = NI^m * R_T^m + L_S^m \tag{5.5}$$

Weighting

After we complete estimating the consequences, as previously addressed in Chapter 4, these must be weighted so that they can be compared. With this in aim we utilized AHP to determine which weights to attribute to each of the criteria. The mean ranking of the category, as defined by the experts, was used as input for the combined evaluation. The rankings are given as follows in Table 5.5.

Table 5.5: Expert category rankings

Designation	(c)	r_{c1}	r_{c2}	r_{c3}	r_{c4}	r_{c5}
People Security	(1)	1	1	1	1	1
Priority clients	(2)	2	4	2	2	3
Number of clients	(3)	4	5	5	4	2
Environment	(4)	5	3	4	5	5
Net Results	(5)	3	2	3	3	4

Following the ranking attribution by the experts to each of the criteria, we proceed to calculate the priority matrix. Let k'_c be the the non-normalized weight for criteria c. Given the way priorities were calculated, with any expert e', the normalized weights k_c would be the same, thus we can calculate the relative weights as:

$$k'_c = \frac{1}{\sum_e r_{ce}} \tag{5.6}$$

We then proceed to normalize the weights, which can be done using the following expression:

$$k_c = \frac{k'_c}{\sum_{i=1}^{C} k'_i} \tag{5.7}$$

By using the AHP method, we obtained the set of weights $k_c = \{0.456, 0.175, 0.114, 0.104, 0.152\}$, for our categories. This weights will be crucial to calculate the risk of a given equipment.

5.3.2 Probabilities calculation

Having chosen the PT as the object of this methodology and already having defined the health condition states in Chapter 4, we calculate the probabilities of failure for a given PT, when the equipment is in a given state. For this step, information related to the oil condition and registered failures was abundant. This amount of information will enable the estimation of probabilities of failures of the PT using the HMM algorithm (Baum-Welch).

DGA (Dissolved Gas Analysis)

By analyzing the dissolved gases in the insulating oil (DGA), it is possible to identify the gases that result from the degradation of the oil and the insulation paper. The DGA process not only analyzes the gases present in the oil, but also the atmospheric gases such as Oxygen (O_2) and Nitrogen

(N_2). Table 5.6 shows all the gases analyzed by the DGA as well as the type of defect associated with the formation of each gas.

Table 5.6: Gases analyzed by DGA and its associated defects

Gas	Designation	Fault
H_2	Hydrogen	Partial discharges in the insulating oil
CH_4	Methane	Partial discharges in the insulating oil
C_2H_6	Ethane	Local thermal defect
C_2H_4	Ethylene	Severe thermal defect in insulating oil
C_2H_2	Acetylene	Electric arches
CO	Carbon monoxide	Thermal Defect (paper degradation) Partial discharging on insulation paper
CO_2	Carbon dioxide	Thermal Defect (paper degradation)

It is important to note that the DGA process, besides being a powerful diagnostic technique, also has the advantage of being a non-intrusive process. This means that it is not necessary to go inside the PT to collect the sample needed for the process and, consequently, affect the performance of the equipment. There is numerous classic techniques that have been developed for DGA of PT in the past 30 years such as Rogers (Wang and Srivastava, 2002), Durenburg (IEEE, 1991), Duval Triangle (Duval, 2002). Most of these methods are based on the gas ratio, i.e. $\frac{CH_4}{H_2}$, $\frac{C_2H_4}{C_2H_6}$ and $\frac{C_2H_2}{C_2H_4}$.

In Table 5.7 we have the information related to the recommended alarm level of gases from different references. In most cases the numbers are similar, except the IEEE thresholds for carbon dioxide and acetylene.

Table 5.7: Gas limits recommendations [PPM]

Gas	Dorenburg	IEC	IEEE	Bureau of Reclamation
H_2	200	100	100	500
CH_4	50	75	120	125
C_2H_6	35	75	65	75
C_2H_4	80	75	50	175
C_2H_2	5	3	35	7
CO	500	700	350	750
$CO2$	6000	7000	2500	10000

In order to be able to have the information related to the observations of the condition of the oil, needed for the HMM algorithm, we consider a ranking method developed by (Naderian et al., 2008) for the estimation of the oil current condition in the PT. We firmly believe that with the information related to the oil condition, it will be possible to estimate the probability of failure of the equipment when it is in a given state and the transition probabilities between the hidden states.

The DGA factor is described in Equation 5.8, where S_i is the score of each gas based on Table 5.8 and W_i is the proper weighting factor. The rating code starts with A as the best condition to E, which represents the worst situation. We also introduce the letter F when we have a registry of an equipment failure. This type of coding is employed for the remaining factors presented in Table 5.9.

$$DGAF = \frac{\sum_{i=1}^{7} S_i * W_i}{\sum_{i=1}^{7} W_i} \tag{5.8}$$

Table 5.8: Scoring and weight factors for gas levels[PPM]

	Score(S_i)						W_i
Gas	1	2	3	4	5	6	
H_2	≤ 100	$100-200$	$200-300$	$300-500$	$500-700$	> 700	2
CH_4	≤ 75	$75-125$	$125-200$	$200-400$	$400-600$	> 600	3
C_2H_6	≤ 65	$65-80$	$80-100$	$100-120$	$120-150$	> 150	3
C_2H_4	≤ 50	$50-80$	$80-100$	$100-150$	$150-200$	> 200	3
C_2H_2	≤ 3	$3-7$	$7-35$	$35-50$	$50-80$	> 80	5
CO	≤ 350	$350-700$	$700-900$	$900-1100$	$1100-1400$	> 1400	1
CO_2	≤ 2500	$2500-3000$	$3000-4000$	$4000-5000$	$5000-7000$	> 7000	1

Table 5.9: Transformer rating based on DGA factor

Rating Code	Condition	Description
A	Good	DGAF< 1.2
B	Acceptable	$1.2 \leq$DGAF< 1.5
C	Need caution	$1.5 \leq$DGAF< 2
D	Poor	$2 \leq$DGAF< 3
E	Very poor	DGAF≥ 3

Failures probabilities results

Currently in Portugal we have 729 active PT, however in this problem we only had DGA data related to only 59% of the total available PT. Despite that, we still have a good amount of data related to the DGA analysis realized by EDPD. After processing the data we ended up with 7312 instances to feed our HMM algorithm(Baum-Welch). The periodicity of the sequence of the observations is approximately separated by one year. With all this information, we then proceeded to train our whole dataset in order to obtain the failure probabilities. By using the HMM algorithm (Baum-Welch), we obtained the set of failure probabilities $f(i) = \{0.008, 0.016, 0.029, 0.035, 0.046\}$ for the 5 health conditions previously defined in Chapter 4.

After obtaining the failures probabilities for each of the states we needed to match these results with our data set. However, one of the problems that we face in this work is the fact that we do not know the sequence of states of the health condition of the PT. Since we do not know the current state of the equipment we can not associate directly the failure probabilities to the PT. In order to solve this problem we use an assumption already defined in the previous Chapter. With the information in Table 4.2 we assume that the equipment current condition, using age as input, will be equal to the state condition after we perform maintenance interventions on the equipment.

Results of the clustering and risk analysis

Continuing the application of the methodology, we calculate our relative risk measures and consequent cluster where the PT belongs. Table 5.10 presents the 10 more riskiest PT and the 10 lowest risk PT results obtained from the available data. For the problem studied, we considered 12 quadrant to be used in the risk matrix. An example for the application of the risk calculation and weighting can be made from these results. We can observe in the table the classification of the quadrant where the PT will be in. The probability of failure is rated between $[1;3]$ while the consequences are rated between $[1;4]$. With the combination of this ratings we can obtain the area where the equipment will be. The bigger the rating, the higher the values of the consequences and failure probabilities. In Figure 5.4 we have the number of PT distributed in each of the areas in the risk matrix.

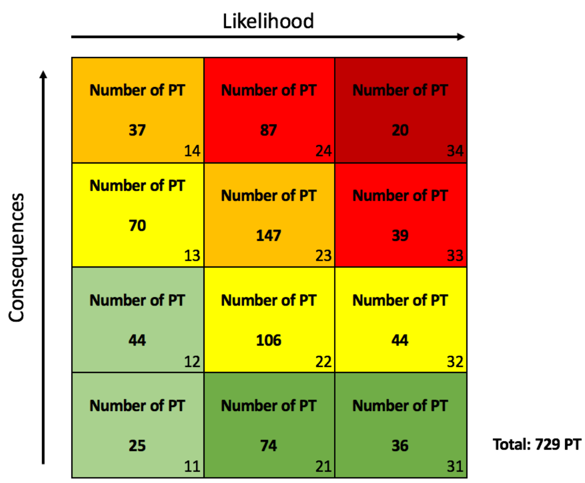

Figure 5.4: Results of the clustering by risk

Table 5.10: Results of the 10 best and worst risk PT

ID	Age	θ_1^m	θ_2^m	θ_3^m	θ_4^m	θ_5^m	$f(i)$	Consequences	Failure rank	Consequence rank	Quadrant
13069 C	41	1	0,75	0,593	0,018	1	0,046	0,791	3	4	34
13047 C	42	0,5	0,75	0,614	0,064	0,75	0,046	0,534	3	4	34
6278 S	52	1	1	0,252	0,032	0,5	0,046	0,683	3	4	34
7318 S	50	1	1	0,204	0,054	0,25	0,046	0,639	3	4	34
7674 S	48	1	0,75	0,107	0,037	0,5	0,046	0,632	3	4	34
7684 S	47	1	1	0,284	0,034	0,5	0,046	0,689	3	4	34
10407 S	45	0,5	0,75	0,488	0,022	0,75	0,046	0,507	3	4	34
LEL 2656	50	0,5	1	0,402	0,014	0,75	0,046	0,517	3	4	34
B 604652	53	0,5	1	0,536	0,032	0,75	0,046	0,543	3	4	34
10444 S	43	0,5	1	0,671	0,057	0,75	0,046	0,569	3	4	34
C-0035A	12	0	0	0,222	0,011	0,5	0,035	0,116	1	1	11
C-0038A	12	0	1	0,092	0,034	0,25	0,035	0,161	1	1	11
C-0173A	9	0	1	0,000	0,012	0	0,035	0,105	1	1	11
LEL 86278	14	0	0	0,293	0,017	0,5	0,035	0,129	1	1	11
1LIT754605.01	3	0	0	0,360	0,038	0,5	0,035	0,143	1	1	11
LEL 93063	12	0	0	0,207	0,024	0,25	0,035	0,077	1	1	11
LEL 92253	12	0	1	0,000	0,000	0	0,035	0,104	1	1	11
C-0039A	12	0	1	0,002	0,015	0	0,035	0,106	1	1	11
C-0080A	11	0	1	0,005	0,021	0	0,035	0,107	1	1	11
LEL 97207	11	0	0	0,284	0,013	0,5	0,035	0,127	1	1	11

5.4 Maintenance policies construction and optimization

In this section we explain how we used the results obtained from the risk analysis to enable the estimation of the respective parameters of the Markov matrix. We also demonstrate the results obtained from the simulation of the current maintenance policy of EDPD and compare it with the solutions obtained. In the end of this section we study the obtained solutions and propose three different approaches to the company.

5.4.1 Parameters estimation

With the results of the clustering we reduced the computational complexity of the problem studied. To establish the inspection policies in a comprehensible and easily implementable way, we use a risk matrix with division in squares that will be integrated in the life simulation and optimization model. In the columns of the risk matrix, we took into account the probability of failure of the PT. This means that equipment with higher probability of failing will represent a higher risk for the company. The lines in the matrix, on the other hand represent the severity of the consequences. The higher we go in the matrix, and the further we go to the right, the higher the risk will be.

Figure 5.5 is a representation of the matrix used. Inside of each quadrants we have the number of PT represented by the number bellow. The above designation represents the most often condition when the company should perform maintenance on the PT. The matrix represented in the figure below represents the company's current policy.

		Probability		
		1 Low probability	2 Medium probability	3 High probability
Consequences	4 High impact	Condition (3) 37	Condition (3) 87	Condition (3) 20
	3 Medium impact	Condition (3) 70	Condition (3) 147	Condition (3) 39
	2 Low impact	Condition (3) 44	Condition (3) 106	Condition (3) 44
	1 No impact	Condition (3) 25	Condition (3) 74	Condition (3) 36

Figure 5.5: Risk matrix with current policy

With the results of the aggregation of the equipment by risk, we now are able to use the Baum-Welch algorithm. It is assumed that the PT that are in the same quadrant of the risk matrix, will behave similarly in terms of degradation. In short, we estimate only one Markov matrix for each of the quadrant, meaning that we will have 12 different types of degradation with different parameters. As already mentioned in the previous chapter, we use the observations related to the oil quality for each PT to estimate the parameters of the matrix.

In this phase of the study results, we notice that not every estimated matrix for each of the quadrants had the same level of precision, since we did not possess all the PT DGA tests. We notice that the HMM algorithm had a better performance when we trained the algorithm in a bigger dataset. Nevertheless, the Baum-Welch algorithm was always able to estimate the parameters of the Markov matrix. However, to evaluate the precision of the parameters estimated in the Markov matrix, we came up with a precision KPI.

$$Precision = \frac{Available\ PT\ data}{Total\ active\ PT} \tag{5.9}$$

In Equation 5.9 we divide the available number of PT that we have information about the DGA test, by the total number of PT. This calculation was done for each of the areas of the risk matrix in order to assess the precision of the Markov matrix parameters. Since we are generalizing a single Markov matrix for all PT in a given quadrant, we believe that the estimated parameters will be more precise when we train our HMM algorithm in all of the active transformers in the same quadrant.

Table 5.11: Precision of the Markov matrix for each risk quadrant

Quadrant	Number of active transformers	Number of transformers with DGA tests	Precision
11	55	8	15%
12	64	16	25%
13	41	9	22%
14	16	13	81%
21	128	114	89%
22	167	138	83%
23	76	66	87%
24	43	36	84%
31	58	39	67%
32	40	27	68%
33	26	14	54%
34	15	9	60%
Total	729	489	

The results shown in Table 5.11 serve to ascertain how good will be the results obtained from the MC simulation. The higher the precision of the Markov matrix, the more confidence we have in the maintenance policy to be applied in a given quadrant of the risk matrix.

5.4.2 Maintenance policies analysis

With the results obtained previously and after defining the risk matrix, we procure efficient maintenance policies for each matrix division. The assumption that a policy does not affect the performance of any of the PT in another quadrant of the matrix seems to be more than adequate. This assumption also allows us to reduce the number of solutions possible. In the problem of EDPD we have a number of decision variables that it is equal to the number of areas present in the risk matrix. In total, we have $5^{12} = 244.140.625$ possible solutions for our problem.

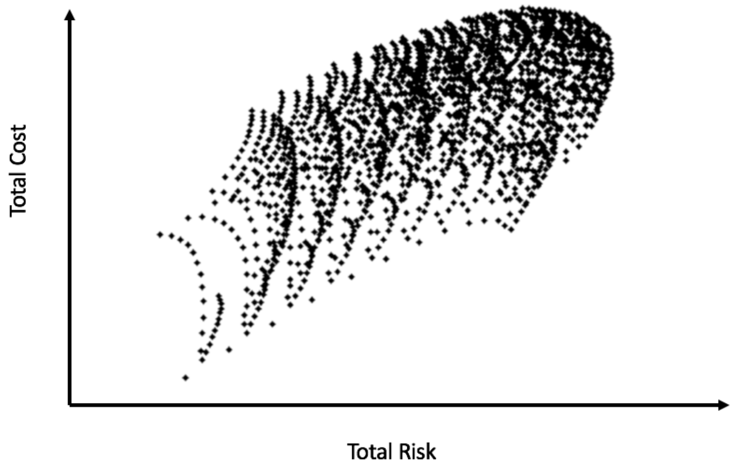

Figure 5.6: Solution search space

Given the complexity of the problem, we believe that the use of the MC simulation coupled with the MOGA will allow us to reach a numerous of solutions that optimize the costs and risks of the maintenance policies to be applied. Figure 5.7, demonstrates a good analysis of the variation in costs (blue line) versus the variation in risks (red line), with the increase of the preventive maintenance threshold condition. It should be noted that consequences and costs are not in the same unit, therefore the intersection does not represent a minimum. While defining the maintenance policies, one should look for trade offs in this information, and look for how much risk is the decision maker willing to take for a given cost. Increasing risk means increasing the expected value of consequences and is represented by a positive consequence variation.

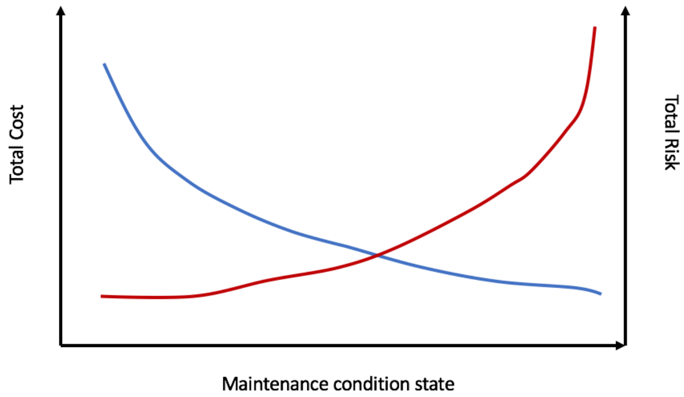

Figure 5.7: Costs increase versus risk variation with condition

Inputs of the optimization model

In the MC simulation we assume that in the beginning of each iteration the equipment starts at his best condition. We run the simulation for each of the quadrants of the risk matrix, computing the transitions with the respective Markov matrix. The time gap between each consecutive transition is approximately one year, since the parameters were obtained from the one year periodic DGA tests. We assume in the simulation that in the same year we only perform 3 actions: Preventive maintenance, Corrective maintenance or "no action" is performed. Preventive maintenance are accounted when the equipment improves from a non failure state while the "no action" intervention is related to the continuous degradation of the PT. Corrective maintenance is always performed when the PT reaches the failure state. In this work we considered a simulation for a time period of $t = 20$ years. We believe that this period is the one that best suits this problem since it allows to have more accurate results. The costs inputed in the model were obtained with the help of EDPD. Table 5.12 summarizes the values used in the MC simulation.

Table 5.12: Input values for the model

Input	Value	Unit
t_n	20	years
I_t	100	
C_p	2.000	€
C_f	50.000	€
S_t	6	
R_p	20.000	

The MC simulation is incorporated with NSGA-II algorithm. This combination is what allows us to obtain in a efficient way the maintenance policies that minimize the costs and risks. In Table 5.13 we have the values used in the NSGA-II algorithm.

Table 5.13: NSGA-II parameters and rules

Input	Value
Number of chromosomes (population size)	100
Number of generations (termination criterion)	200.000
Selection type	Binary tournament selection
Crossover type	Arithmetic
Crossover fraction	0.8
Mutation type	Gaussian
Mutation fraction	0.3

Results of the optimization model

When we computed the optimization model we obtained more than one possible solution, due to the characteristics of a multiobjective problem. In total, we obtained 79 possible solutions that minimize the costs and risks of the current problem. In Figure 5.8 we have the results obtained with the optimization model (GA+MC) in 48 min of CPU time, using an Intel (R) Core (TM) i7-4790 CPU @ 3.60GHZ processor. The numerical values of the objective functions and of the corresponding variables are reported in Table 5.14.

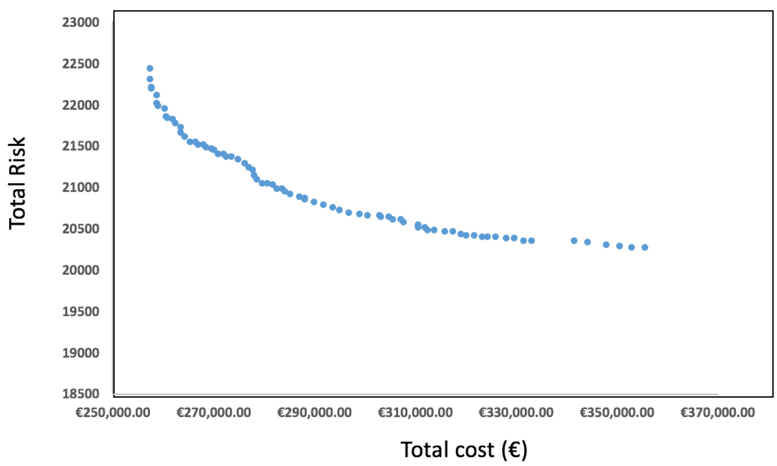

Figure 5.8: Multiobjective optimization results

Table 5.14: Multiobjective search results

Q_{11}	Q_{12}	Q_{13}	Q_{14}	Q_{21}	Q_{22}	Q_{23}	Q_{24}	Q_{31}	Q_{32}	Q_{33}	Q_{34}	Total costs	Total risks
6	6	6	2	5	4	5	6	4	4	5	2	257 402€	22439
6	6	6	2	5	4	5	6	4	4	4	2	257 414€	22315
6	6	6	2	5	3	5	6	4	4	4	2	257 476€	22221
6	6	6	2	5	3	5	5	4	4	4	2	257 682€	22192
6	6	6	2	5	4	4	6	4	4	4	2	258 596€	22115
6	6	6	2	5	3	4	6	4	4	4	2	258 658€	22020
6	6	6	2	5	3	4	5	4	4	4	2	258 864€	21992
6	6	6	2	5	3	4	4	4	4	4	2	260 340€	21959
6	6	6	2	5	3	3	6	4	4	4	2	260 404€	21867
6	6	6	2	5	3	3	5	4	4	4	2	260 610€	21838
5	6	6	2	5	3	4	6	4	4	4	2	261 722€	21819
4	6	6	2	5	3	4	6	4	4	4	2	262 452€	21772
3	6	6	2	5	3	4	6	4	4	4	2	263 346€	21735
5	6	6	2	5	3	3	6	4	4	4	2	263 468€	21665
4	6	6	2	5	3	3	6	4	4	4	2	264 198€	21619
3	6	6	2	5	3	3	5	4	4	4	2	265 298€	21552
3	6	6	2	5	3	3	5	4	4	3	1	266 420€	21544
3	6	6	2	5	3	3	4	4	4	4	2	266 774€	21520
3	6	6	2	5	3	3	4	4	4	3	1	267 896€	21512
2	6	6	2	5	3	3	5	4	4	4	1	268 300€	21485
2	6	6	2	5	3	3	5	4	4	3	1	269 422€	21477
4	6	5	2	5	3	3	5	4	4	4	2	269 956€	21449
3	6	5	2	5	3	3	5	4	4	4	2	270 850€	21412
3	6	5	2	5	3	3	5	4	4	3	2	271 972€	21404
3	6	5	2	5	3	3	4	4	4	4	2	272 326€	21379
3	6	5	2	5	3	3	4	4	4	3	1	273 448€	21371
6	6	6	1	5	3	3	3	4	4	4	1	274 804€	21342
5	6	6	1	5	3	4	3	4	4	4	1	276 122€	21295
4	6	6	2	5	3	4	3	4	4	4	1	276 852€	21248
3	6	6	2	5	3	4	3	4	4	4	1	277 746€	21210
5	6	6	1	5	3	3	3	4	4	4	1	277 868€	21141
4	6	6	2	5	3	3	3	4	4	4	1	278 598€	21094
3	6	6	2	5	3	3	3	4	4	4	2	279 492€	21056
3	6	6	2	5	3	3	3	4	4	3	2	280 614€	21048
3	6	6	2	5	3	3	2	4	4	3	2	281 716€	21039
2	6	6	2	5	3	3	3	4	4	4	2	282 494€	20989
2	6	6	2	5	3	3	2	4	4	4	2	283 596€	20979
4	6	5	2	5	3	3	3	4	4	4	1	284 150€	20953
3	6	5	2	5	3	3	3	4	4	4	2	285 044€	20916
3	6	4	2	5	3	3	3	4	4	4	2	286 904€	20885
3	6	4	2	5	3	3	2	4	4	4	2	288 006€	20875
2	6	5	2	5	3	3	3	4	4	4	2	288 046€	20848
2	6	4	2	5	3	3	3	4	4	4	2	289 906€	20817
3	5	5	2	5	3	3	3	4	4	4	2	291 790€	20787
3	5	4	2	5	3	3	3	4	4	4	2	293 650€	20756
2	5	5	2	5	3	3	3	4	4	4	2	294 792€	20720
2	5	4	2	5	3	3	3	4	4	4	2	296 652€	20688
1	5	4	2	5	3	3	1	4	4	3	1	298 876€	20671
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	2	1	3	3	2	2	3	4	3	4	355 420€	20269

5.4.3 Results discussion and analysis

It was possible to verify that the optimization methodology approach leads to better results when considering the risks and costs. We also confirm that the maintenance policy risks and costs are directly correlated as shown in Figure 5.8. Due to the EDPD problem being framed as multiobjective, we have more than one possible solution for the problem. However, out of the 79 possible solutions we believe that only 3 solutions must be considered when analyzing the DM risk profile. In this work, we assume that the DM can either be risk averse or a risk taker. Having this in mind we analyze three types of solution:

- Problem solution with the lowest cost - the DM is a risk taker.
- Problem solution that maintains the current risk - the DM is risk averse.
- Problem solution with the lowest risk - the DM is risk averse.

In Table 5.15, we have the comparison between the current maintenance policy of the company and the three possible solutions when considering the DM risk profile.

Table 5.15: Transformer rating based on DGA factor

Maintenance policy	Costs(€)	Risks	Cost indicator	Risk indicator
Company policy	350 712€	20447	0%	0%
Maintaining risk	315 812€	20462	-10%	0%
Lowest cost	257 402€	22439	-27%	10%
Lowest risk	355 420€	20269	2%	-1%

First we start by analyzing the solution where we maintain the current maintenance policy risk. The optimization methodology proves that it is possible to reduce the current costs in 10% without trading off risk. This solution is indicative of the current maintenance inefficiency, meaning that the company performs unnecessary maintenance interventions. In Figure 5.9 we have that confirmation since the optimization methodology only performs on average per year 83 maintenance interventions (35 less than the current maintenance policy).

The optimization methodology also confirms that it is not possible to have the lowest maintenance cost possible without trading off some risk. In this solution we are able to reduce the maintenance costs in 27%, however we increase the total risk in 10%. This reduction in costs is directly related to the optimized number of interventions (only 52 maintenance interventions are performed per year). On the other hand, the increase of the total risk is related to the PT failure probability. The less maintenance interventions we perform, the higher the probability of a PT failing, as shown in Figure

5.10. However, we believe that this is the best solution to apply considering that the current company maintenance policy is too conservative.

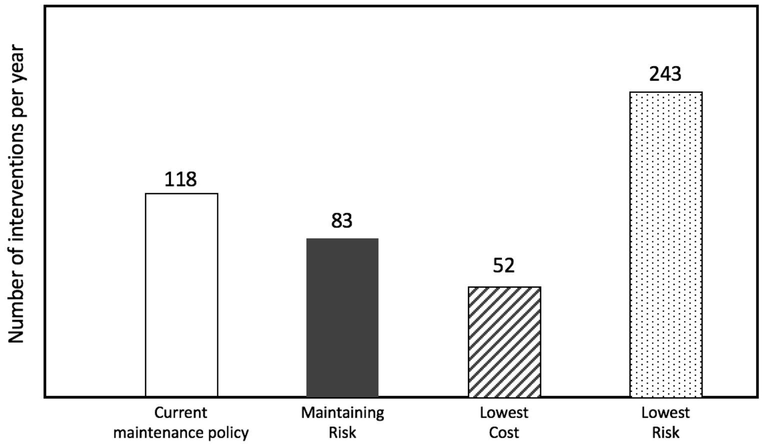

Figure 5.9: Number of maintenance interventions performed in the PT per year on average

Finally, we analyze the solution where we have the lowest possible total risk. In this solution we are able to reduce the risk only in 1% with a 2% increase in costs. This solution confirms that currently the company is using a conservative maintenance policy. In this case the company clearly has an excessive amount of maintenance interventions in the equipment. Though, a higher number of interventions decreases the total risk it does not justify the current company maintenance costs. We only suggest this solution if the company is currently trying to reduce the current risk, otherwise we strongly advise the previous solutions.

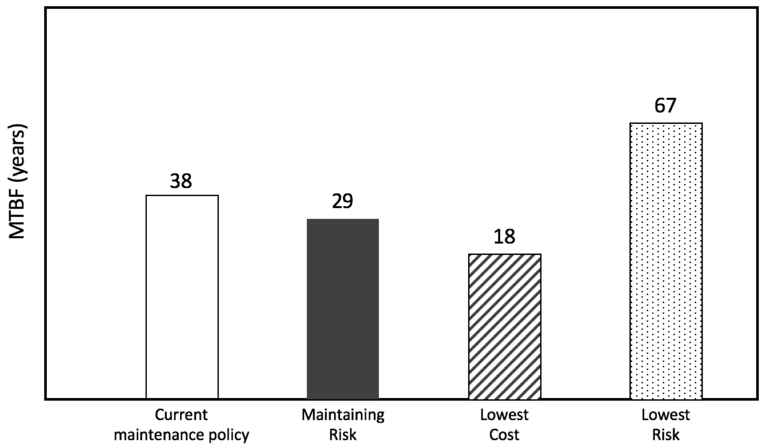

Figure 5.10: Maintenance performance indicators for the tested policies

From these solution we can see that even though we clustered the equipment in a matrix for policy definition, solid improvements are possible. The case of the policy which trades off risk tackles the hypothesis that the current maintenance policy are too much conservative. The optimization methodology proves that can bring sizable savings, with maintenance indicators which seem acceptable for the DM. We also proved that is possible to reduce the current maintenance costs without trading off risk.

Chapter 6

Conclusions and future work

In this dissertation we presented a methodology with a main goal of optimizing the costs and risks in maintenance. This approach was developed with two intentions: solving the problem faced by the Portuguese company EDPD and extend the methodology to other types of utilities. The identification of adequate maintenance policies for the equipment in a company is of great importance, both from the financial and safety perspective. In this work, we proved that when we perform maintenance in an adequate health state of the equipment we can have a reduction in unnecessary maintenance, thus reducing the costs. The idea of performing maintenance only when a equipment reach a certain condition was thoroughly explored in this work. The life simulation model is created with the aim of studying the behavior of the equipment. By acquiring a better understanding of the health evolution of an equipment we were able to assess which was the best condition to perform maintenance, while trying to match our goals. However, the relevant phenomena behind degradation processes can be very complicated to model.

Risk played a major factor in the definition of the maintenance policies, since there were consequences inherent to the failures that had to be taken into account. In this dissertation we developed an approach for the calculation of the risk that takes into account the different consequences and the current condition of the equipment. We needed to quantify our risk, since our problem is framed as multiobjective. The results obtained showed that it was possible to obtain a solution where it was possible to reduce the costs in 27% without increasing too much the current risk. We also demonstrated that is possible to have a reduction in the current costs of 10% without trading off risk. Although is possible to have further reduction in risks, that meant that we had to increase the total costs.

The created methodology fully covers an application of a Condition and Risk based maintenance. It must be noted that some adaptations were made in order to be suitable for the problem. From the results obtained, we can conclude that the condition monitoring complements very well the risk analysis performed in the equipment. The coupled (GA+MC) proved to be crucial on getting quick and good solutions for the problem. The combination of this types of techniques enabled the development of a new type of approach in the area of asset management optimization.

However, the lack of integrity of the data is an aspect that can influence the results of this dissertation. In reality, this is the most aggravated source of uncertainty in the whole analysis. The simplifying assumptions that we took in order to give more integrity to the data may prove to be damaging for the algorithms used in this dissertation. To further improve the obtained results, the estimates must be fed with more complete and accurate data, thus increasing the level of confidence in the results. In the case of this company, the lack of a better collection of data related to the tests and adequate reports of failures are problems to be solved for the proper registry of maintenance data.

In future works, different methods should be explored in the estimation of the Markov matrix transition probabilities. Due to the limitation of the HMM algorithms, we believe that other techniques may reach more accurate results. Also, in further studies the effects of maintenance in the equipment health should be studied for a more robust health simulation. Alternatives to the MC simulation should be also explored for quicker results. To verify the accuracy of the results a good health index should be calculated for the equipment.

For future developments in this area, this methodology should be applied to other utilities in other industries. Although this approach by itself led to significant improvements in the current maintenance policies, this extensions should be studied thoroughly in order to explore the potential of this approach.

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