Risk-based maintenance: an holistic application to the gas distribution industry

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Abstract

This dissertation aims to expose a risk-based methodology to manage maintenance for a critical piece of equipment in the gas distribution industry. With the methodology it is possible to find compelling trade-offs between risk and maintenance costs. The development was made in collaboration with a Portuguese company which faced excessive preventive maintenance spending, with little to no impact in asset performance. The creation of the tools necessary to increase the efficiency of the maintenance policies was the tangible goal of this project.

The approach consists of decomposing the equipment in its sub-equipment pieces and using reliability to model each piece's failure behavior. The translation of sub-equipment failure into equipment breakdowns and the study of failure modes is made using block diagram analysis. The consequences of each failure mode are then divided in categories. By weighting the categories, the total impact of a failure mode, for a piece of equipment, can be calculated. By combining the consequence and reliability analysis, risk can be assessed for each piece of equipment. Policy definition is approached with the use of a risk matrix in order to cluster the equipment pieces. Lastly, a simulation tool which facilitates the analysis of the risk-based policies was developed.

A case study demonstrating the implementation of the method is exposed. In this example we make use of expert elicitation to estimate failure data, so that the reliability analysis can be applied. Concepts particular to the case are presented and methods to deal with the estimation of consequences, for each criteria, are illustrated. A modification of the analytic hierarchy process is used to calculate the weight of each consequence category. The company's current policy is simulated and compared with risk-based ones, finding potential improvements in both the cost and risk perspectives.

A decrease of 8% in maintenance spending was found possible without any trade-off in risk. Decreases in risk are also possible without increasing maintenance spending, implying the current policy as inefficient. When trading-off risk, a cost reduction of 33% is possible within tolerable limits. Research opportunities are also found within the uniqueness of real-case scenarios and their particular modeling needs.

Resumo

Nesta dissertação é almejada a exposição de uma metodologia baseada no risco para gerir a manutenção de um equipamento crítico para uma distribuição de gás. A metodologia possibilita melhores *trade-offs* entre custos de manutenção e risco. A abordagem foi desenvolvida em colaboração com uma empresa Portuguesa que enfrentava exagerados gastos em manutenção preventiva, sem impacto significativo na performance dos seus ativos. Os objectivos tangíveis deste projeto consistem na criação das ferramentas necessárias para tornar as políticas de manutenção da empresa mais eficientes.

A abordagem consiste na decomposição de um equipamento num sistema dos seus sub-equipamentos. Teoria da fiabilidade é, seguidamente, utilizada na estimação dos tempos até avaria dos sub-equipamentos. A tradução de avarias dos sub-equipamentos em avarias do equipamento e o estudo dos modos de falha são feitos com recurso à análise por diagramas de blocos. Segue-se o estudo das consequências de cada modo de falha, analisadas por categorias. Pesando os valores das categorias, impacto de cada modo de falha de um equipamento é calculado. Com as análises de consequencias e fiabilidade, é possível determinar o risco para um equipamento. A definição de políticas é abordada com uma matriz de risco de modo a agregar os equipamentos e facilitar a definição de políticas de manutenção. Uma ferramenta de simulação para a análise de políticas foi desenvolvida.

A implementação do método deu lugar a um caso de estudo. Aqui, usou-se a elicitação de peritos de modo a estimar os dados de manutenção, de forma a tornar possível a aplicação da análise de fiabilidade. Conceitos particulares ao caso em estudo são apresentados, assim como métodos para lidar com a estimação de cosequências. O peso de cada categoria foi calculado usando uma modificação do processo analítico hierárquico. A política atual da companhia foi simulada e comparada com outras, baseadas no risco, encontrando melhorias potenciais em ambas as vertentes de custo e risco.

Um decréscimo de 8% nos custos de manutenção foi determinado sem qualquer contrapartida em termos de risco. Similarmente, verificou-se possível baixar o risco sem incrementar os gastos em manutenção, o que implica a ineficiencia da política atual. Quando alguma tolerância para aumentar o risco é negociada, uma redução de custos anuais em 33% é possível. Oportunidades de investigação foram encontradas nas particularidades de cada cenário real e nas potenciais diferenças na modelação.

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‘Ninguém gosta da manutenção.”

‘Nobody likes maintenance.”

Luís Guimarães

Contents

Acronyms

AHP	Analytic Hierarchy process
CBM	Condition-based Maintenance
RBM	Risk-based Maintenance
MMIS	Maintenance Management Information System
EDP	Energias de Portugal
PRM	Pressure Regulation and Measurement Station
FTO	Fail-to-open
FTC	Fail-to-close
MON	Monitor
MTBF	Mean Time Between Failures
MTTF	Mean Time to Failure
TTL	Time to Live
TTR	Time to Repair
VCE	Vapor Cloud Explosion
PE	Polyethylene
KPI	Key Performance Indicators

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Chapter 1

Introduction

Companies are facing an ever increasing pressure to perform and therefore, operational efficiency increasingly relevant (Schneider et al., 2006). Being technologically up-to-date and managing the societal impact of activities are criteria that come to mind when evaluating an organization's performance (Tsang, 2002). Consequently, asset management, which consists in the coordinated activity of an organization to realize value from assets (ISO, 2014), becomes a rather pertinent matter of research and practice.

Our goals are to define and implement a maintenance strategy adequate to an utility industry with high-impact failures. From a generic objective, we construct a particular risk-based approach, which is promising in improving risk and maintenance costs. Although the choice of a maintenance strategy requires knowledge of a organization's objectives and aims to be aligned with them, this perspective will not be prioritized. Alternatively, the maintenance management aspect of asset management will be greatly emphasized in this dissertation, as the objectives of this approach are to increase availability and reduce the impact of breakdowns, allowing the asset to be properly exploited.

This dissertation aims to instantiate the risk-based maintenance (RBM) methodology for a critical piece of equipment in the gas distribution industry, from the choice of the equipment to the definition of policies. Methods to deal with some of the hurdles that arise from the application of RBM are presented, applying techniques such as the analytic hierarchy process (AHP) and elicitation to deal with multiple criteria and lack of maintenance data are used in the consequence analysis, respectively. Additionally, techniques such as reliability engineering are used to overcome obstacles in the estimation of failure rates. As represented in Figure 1.1, with the approach scope in gray, the consequence and reliability analysis allow RBM to be applied. Having RBM as basis, a multiple-criteria resolution is proposed for the choice of the maintenance policies. This paper will focus on the risk-based maintenance part of a maintenance strategy which, in later stages, can be complemented with the adequate condition monitoring and maintenance other practices.

The case study underlying this dissertation is the result of a collaboration with EDP (Energias de Portugal) Gás Distribuição, the natural gas distributor for northern Portugal. In order to find a better balance between cost, risk and availability a RBM strategy was developed and tested. We developed a pilot case aimed to apply the methodology to the company's pressure regulation and measurement stations (PRM), as they are a critical piece of equipment. Simulation was used both to find efficient maintenance

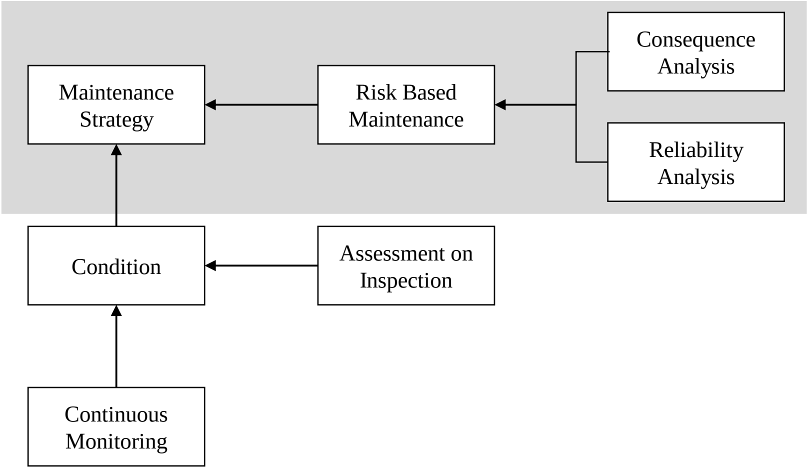

Figure 1.1: Summary of the approach.

policies and to test their performance against the current practices.

The methodology described in the paper starts with the choice of the equipment, followed by the application of the RBM methodology and elaboration of a risk matrix, and is concluded by the determination and simulation of maintenance policies. This is an holistic approach in the sense that, though it is not transversal to all equipment, it covers all the steps needed for the determination and testing of the policies. To assess the performance of the policies, maintenance costs and expected impacts of failures are estimated, for a set period of time.

In order to analyze the performance of a policy, impacts and maintenance costs can be reduced to the same unit and summed, or a weighted sum could be adopted, for example. This results in a single objective problem in which, traditionally, costs are minimized. On the other hand, the level of risk adopted could be made clear for the decision maker. We follow the latter approach and propose a multiple-criteria method. As impacts are discriminated by type and failure mode, weighting them represents of a source of subjectivity. To target this vulnerability, quantitative methods are proposed to deal with both the weighting of impacts and the problems which arise with multiple criteria.

With the application of our methodology, we estimated an 8% decrease in overall maintenance costs without any increase in risk. Within tolerable limits for the decision maker, a reduction in costs as sizable as 33% is possible. A broad interpretation of these new practices is considering that inspections were reallocated to where they were needed. Additionally, risk was quantified allowing the decision maker to trade it off with savings.

As contributions, this study adds a comprehensive instance of the application of the RBM methodology to the literature. We define and model failure modes for the PRM. Furthermore, it provides a multiple-objective approach to be used in settings similar to those described above. We also shed light in the effects of the variations in inspection periodicity, for this particular case, in addition to the various methods for accounting consequences and dealing with the lack of maintenance data provided.

This chapter will be followed by the literature review. A thorough explanation of the methodology, supplemented by practical examples, will succeed in Chapter 3. In Chapter 4, the application of the method to a real instance is presented. Finally, Chapter 5 will be dedicated to conclusions, remarks and prospects of future work.

Chapter 2

Literature review

In this chapter some we review maintenance management in a broad sense, its requirements, and prevalent objectives. Furthermore, we intend to express the current trade-offs and challenges faced. A review of maintenance strategies relevant for the approach follows. We first introduce condition-based maintenance, its advantages and disadvantages. Time and age-based maintenance strategies are then presented and compared with condition-based maintenance. Finally, we review risk-based maintenance, the approach most thoroughly covered in this dissertation, discussing its advantages and possible extensions to the methodology.

2.1 Maintenance Management

In most developed countries, the main players in equipment-intensive utility industries already have their operations fully established (Lahiri et al., 2008). As the financial effort to build the distribution network is already past, their value proposition and revenue sources change from getting the product to the customer to making it available at all times. On one hand, this brings more weight into maintenance, requiring the current infrastructure to be preserved, while still minimizing downtime. On the other hand, it is imperious for most of these companies to function in a profitable way, thus revealing the need for maintenance to be as efficient and effective as any other key activity, and it should not represent overwhelming costs (Goncharuk, 2008).

The correlation between maintenance spending and short term economic results is not direct. Additionally, this is a subject where many companies chose to delay investment and are now realizing the inefficiencies that can come from it (Murthy et al., 2002). The application of efficient maintenance practices represents therefore, a pertinent field for business opportunities. Nevertheless, maintenance 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). Separately, on the long term, asset performance and proper maintenance spending are usually correlated. To develop inspection and maintenance policies that are aligned with the companies' objectives various maintenance strategies must be compared, to find satisfying trade-offs between the costs and impacts.

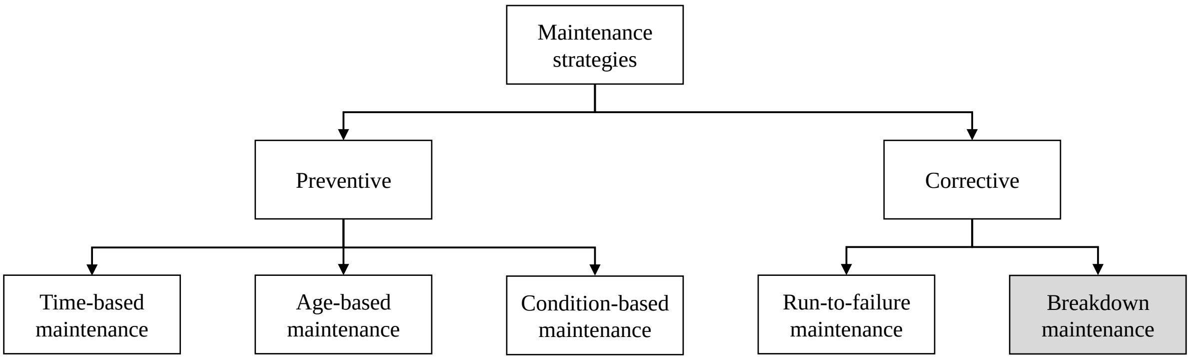

Figure 2.1: Basic maintenance strategies.

Figure 2.1 presents the main basic maintenance strategies. The unplanned breakdown maintenance strategy is highlighted in a gray box. It consists in repairing or substituting the equipment whenever it breaks down in an unplanned fashion. In white, we refer to the planned maintenance strategies. In time and age-based maintenance strategies maintenance is performed on a timely basis, or based on the age or use of the component, respectively. In condition-based maintenance (CBM), maintenance actions are triggered according to the condition of the equipment, which can be assessed through periodic or continuous monitoring. In the run-to-failure maintenance strategy, the equipment is deliberately let run until it fails, differing from breakdown maintenance only in planning. Basic preventive maintenance strategies will be reviewed in more detail, in order to contextualize the approach.

Crespo Marquez and Gupta (2006) and Crespo Márquez et al. (2009) define a framework to deal with maintenance management. In the latter, a set of tools which can aid the implementation of a maintenance strategy is added. Tsang (2002) takes on the theme from a strategic point of view, covering most decisions top management faces relative to maintenance. Murthy et al. (2002) also covers some of these decisions, adding recommendations for a proper strategy implementation. Bevilacqua and Braglia (2000) applies the Analytic Hierarchy Process to define the maintenance strategy of an oil refinery. An analysis of the Indian utility industry is elaborated by Lahiri et al. (2008), considering its maintenance practices. Labib (1998) demonstrates the use of computerized maintenance management systems in the development of maintenance policies, pondering conflicting objectives. Maintenance management literature is reviewed in Garg and Deshmukh (2006), Marketz et al. (2005) reviews maintenance strategies for distribution networks and overall models for maintenance management are reviewed in Sherwin (2000). Lee et al. (2006) covers the subject of e-maintenance.

2.2 Condition-based Maintenance

In the maintenance context, if the functioning conditions of an asset are known, there are usually two interesting prognostics to make. The time that the equipment will work as intended, and the likelihood that the equipment will work a certain time without failure. In addition to the diagnostic of the current condition, this information makes sure that maintenance is performed when needed, making CBM a most efficient method to deal with asset preservation (Ellis, 2008).

The inadequacies in CBM are evident when the implicating conditions for a failure need to be determined. Additional difficulties in defining which parameters should be measured may arise. Furthermore, there must be a distinction between parameters which a continuous control is more advantageous than periodic control, being the former generally more costly. Thirdly, change in the maintenance processes must be ensued in order to deal with the need for data. Finally, the boundaries for which the parameters translate a need for action must be assessed (Tsang, 2011). This makes it generally a costly, hard to implement methodology, as large investments are needed for build up the data collection requirements (Marketz et al., 2005).

Further costs should be accounted with the possibility of acquiring a maintenance management information system (MMIS), which is very recommendable to deal with such amounts of condition data, and translate them into maintenance information. Moreover these systems usually require a change in an organization's processes, necessary to take advantage of such a system. Another desirable requirement is the existence of historical data from the equipment condition, failures and its causes. This would enable the possibility of design of experiments and other research on the effect of relevant parameters on the assets' performance (Ahmad and Kamaruddin, 2012).

Overall the combination of CBM maintenance with a maintenance management information system is a powerful but expensive solution, recommendable for financially strong organizations with service as their main activity, and critical assets with considerable historical data as well as easy to define conditions for failure. High preventive maintenance costs due to overly conservative policies may also motivate the adoption of this maintenance strategy (Jardine et al., 2006). In addition to this, the high costs associated with condition monitoring represent a strong commitment that can tax operational and business flexibility, in exchange for further efficiency. Likewise, the transition into CBM requires strong change management and can be exceedingly challenging without proper knowledge of the assets.

Do et al. (2015) tackle condition based management in a two component system with dependencies. Grall et al. (2002) model and test the performance of a CBM policy in a stochastic deterioration process. Lu et al. (2007) present a methodology to model and forecast deterioration, allowing the probability of failure at a given time to be estimated. Fallible monitoring is dealt with in Sherwin (1990), where Markov models are used to assess the if it is advantageous to inspect other than monitor in particular situations. van der Weide et al. (2010) model degradation and renewal processes, and also state that condition-based strategy is likely to supersede the age-based replacement for minimizing the cost rate. Yam et al. (2001) propose the use of neural networks to assist condition-based fault detection. Wang et al. (2000) demonstrate the application of a CBM model to water pumps in a soft-drinks manufacturing plant. The subject has been reviewed by Ahmad and Kamaruddin (2012), in which a comparison with time based maintenance is also present. Ellis (2008) reflects on which situations fit condition based management the most. Tsang (2011), Jardine et al. (2006) and Peng et al. (2010) cover the subject of diagnostics and prognostics, defining how to obtain and analyze the data needed for this maintenance strategy.

2.3 Time-based and Age-based Maintenance

As a less costly method to define efficient maintenance policies, time-based periodic policies present themselves as a robust alternative, when there is no solid way to measure the condition of the equipment. Furthermore, if historical data is scarce, either because the equipment is unique or because failures have been cautiously avoided (thus majorly existing right-side truncated failure data), there are still ways to define the reliability curves of the equipment or components which allows this approach to fit in particularly well.

This maintenance strategy has the assumption that failures are statistically translatable into a model (Ahmad and Kamaruddin, 2012). Based on reliability curves and by knowing the costs of preventive and corrective maintenance actions, an optimal periodicity can be determined for the maintenance actions of each equipment. These reliability curves can be assessed both in a time or a use basis, depending on which would be the most relevant failure driver. Being purely time-based or considering the equipment's age or use is what differentiates the maintenance strategies in this section. As in a basic replacement policy, a component can be preemptively substituted after a fixed interval of time. When various components are substituted, this is called block replacement.

Though these solutions are usually less costly than CBM and do not include the troublesome steps of defining and calculating the equipment's condition, this same lack of exigency can lead to sub-optimal maintenance policies when real-world conditions are taken into account. Additionally, when there are various failure modes, their consequent effects can have different values for the decision maker, which should be considered.

The Weibull distribution is frequently used to define the statistical rules behind the breakdowns. Weibull (1951) defines this distribution and proposes a wide range of applications for it. Barlow and Hunter (1960) define optimum preventive maintenance policies for a simple equipment, considering as-good-as-new repair, and for complex equipment, considering minimal repair. Crow (1975) presents the maximum likelihood estimates and hypothesis tests for the Weibull distribution's parameters. Tango (1978) adds to block replacement the possibility of using new or used items, in accordance with the time interval in which the failure occurred. Nakagawa (1981) models periodic replacement with different types of renewal at failure. No repair until replacement, substitution by an used spare and replacement, substitution by a new spare and replacement, and substitution by a new spare or replacement are considered. Optimal policies, considering both age and use-based replacement are derived in Nakagawa (1984). Nakagawa (1986) covers the hypothesis of preventive maintenance being done at a set intervals, rather than periodically. Scarf et al. (2009) define an age-based inspection and replacement policy, considering a single component from an heterogeneous population. Minimal repair models are reviewed in Aven (2011), along with the definition of optimal policies or these models.

2.4 Risk-based Maintenance

RBM is a methodology capable of dealing with the different impacts of distinct types of failure. Risk, by definition, is calculated by multiplying the probability of an occurrence by the seriousness of its consequences. Therefore, it can be targeted by two angles: by reducing the number of failures of the equipment, and by diminishing the consequences of said failures (Vianello, 2012).

This methodology allows the discrimination of the equipment based on how grave is the impact of its failures. Time-between-inspections and preventive maintenance action can be specified for the each equipment piece based on this criteria. This manages a better allocation of the inspections, by basing the frequency of maintenance actions on risk. Additionally CBM techniques can be added such that more desirable compromises between risk and cost are achieved (Marketz et al., 2005).

If condition monitoring costs are kept low, RBM does not imply a massive financial commitment. Considering that it efficiently allocates maintenance resources, it can bring strong improvements in both the costs and safety fields, when compared to a simple time-based policy. Evaluating the consequences of a failure can be a bothersome task, with a strong need for making assumptions. This can represent a vulnerability but, if this task is properly elaborated, the deliverables of this methodology end up being sturdy maintenance policies, capable to deal with a variety of equipment and consequences at an affordable cost. From another perspective, if investments into condition-based monitoring are made to complement the strategy, RBM becomes a powerful tool to deal with the possibility high-impact occurrences.

Khan and Abbasi (1997) rate hazard in accidents in the chemical industry, considering multiple attributes. Khan (2001) proposes the use of maximum-credible accident scenarios in risk assessment. Khan and Haddara (2003) and Khan and Haddara (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. Selvik et al. (2011) add an uncertainty and sensitivity analysis to the methodology. Simchi-Levi et al. (2015) bring time-to-recover and time-to-survive models in the context of risk assessment in the automotive industry. Arunraj and Maiti (2007) review the extensive range of techniques which can be used in RBM. While Bertolini et al. (2009) develop this maintenance management's procedures for an oil refinery, Krishnasamy et al. (2005) use the approach in a power-generating plant. This methodology was applied to oil and gas pipelines multiple times (Shahriar et al., 2012; Singh and Markeset, 2009; Vianello, 2012; Vianello and Maschio, 2011).

2.5 Operations Research in Maintenance

Much of this theme is covered by the literature reviewed for the maintenance strategies, especially when modeling systems for the definition of time or age-based policies. Yet, as this dissertation also presents simulation techniques, this section will discuss the literature on the subject, particularly relevant for this aspect.

The applications of operations research in maintenance range from the optimization of time-based policies, to determining the proper conditioned preventive maintenance action moment. Additionally, the modeling of the events associated with maintenance, such as faults, repairs, breakdowns, is also covered by operations research.

The distance between the mathematical models developed in this context and its application is a frequent theme of discussion in the literature. Subsequently, the models and their respective maintenance optimization are often oversimplifying the possible scenarios, and are not flexible for the industry to properly implement them. Consequences, such as the preference for qualitative methods for maintenance management, can arise because of this gap. A tendency to use simulation-based optimization in this field has sprouted, though its integration with MMIS seems to lag behind.

Duffuaa et al. (2001) develop a conceptual model of the processes and events associated with maintenance and illustrates the procedure to simulate them. Nakagawa (1988) analyzes two imperfect preventive maintenance models, one where the hazard rate improves on repair, another where the age is reduced. Florian and Sørensen (2015) present a case study where the application of reliability theory and Monte Carlo generation is used to simulate off-shore wind turbine blades. Dekker (1995) appraises the role of operations research in maintenance, discussing difficulties and opportunities for research. In Dekker (1996) the need for software and hardware capable of materializing the advantages and facilitating the applicability of mathematical models is approached. An evaluation of the advantages of quantitative models over its qualitative counterparts is made in Dekker and Scarf (1998). Scarf (1997) discusses the implementation of models, MMIS and incentivizes the development of models in collaboration with the requiring industries. Sharma et al. (2011) review maintenance optimization and techniques, specifying gaps in the literature and identifying trends.

Literature summary and discussion

For a more structured analysis, the literature review is summarized in Table 2.1 and organized by this review's main subjects. The section *Based on a case study* applies when the main contribution is applying a method in a real instance and papers in which methods are reviewed are included in *Surveys and Reviews*. Additionally, the *Operations Research* subject includes articles which emphasize maintenance optimization and the application of mathematical models to maintenance.

The literature on maintenance has the persistent trait of either being too generic thus of difficult applicability, or being too specific and having an unreasonably restrict range of applications. Furthermore, when literature on a maintenance strategy matures, it tends for the development of complex mathematical models, which bring little value outside the academia. The dichotomy between complex analytic methods and simple empirical practices in the literature is striking, though not often is targeted. This dissertation aims to be didactic and provide an applicable methodology, whilst still keeping academic relevance. Additionally, literature was found scarce in the integration of simulation to similar approaches in maintenance.

The methodology in this dissertation was developed in a corporate context, as a consulting job, hence

Table 2.1: Summary of the literature review.

	Maintenance Management	Condition-based Maintenance	Time-based Maintenance	Risk-based Maintenance	Operations Research
Research	Crespo Márquez et al. (2009) Crespo Marquez and Gupta (2006) Murthy et al. (2002) Tsang (2002)	Do et al. (2015) Grall et al. (2002) Jones and Johnson (2007) Sherwin (1990) van der Weide et al. (2010) Yam et al. (2001)	Barlow and Hunter (1960) Crow (1975) Nakagawa (1981) Nakagawa (1984) Nakagawa (1986) Scarf et al. (2009) Tango (1978)	Khan and Abbasi (1997) Khan (2001) Khan and Haddara (2003) Kusiak and Larson (1994) Ma et al. (2013) Selvik et al. (2011) Simchi-Levi et al. (2015)	Duffuaa et al. (2001) Nakagawa (1988)
Based on a case study	Bevilacqua and Braglia (2000) Labib (1998) Lahiri et al. (2008)	Wang et al. (2000)		Bertolini et al. (2009) Khan and Haddara (2004) Krishnasamy et al. (2005) Shahriar et al. (2012) Singh and Markeset (2009) Vianello (2012) Vianello and Maschio (2011)	Florian and Sørensen (2015)
Surveys and Reviews	Garg and Deshmukh (2006) Lee et al. (2006) Marketz et al. (2005) Sherwin (2000) Wang (2002)	Ahmad and Kamaruddin (2012) Ellis (2008) Jardine et al. (2006) Peng et al. (2010) Tsang (2011)	Ahmad and Kamaruddin (2012) Nakagawa and Mizutani (2009) Aven (2011)	Arunraj and Maiti (2007)	Dekker (1995) Dekker (1996) Dekker and Scarf (1998) Scarf (1997) Sharma et al. (2011) Alrabghi and Tiwari (2015)

the dissertation conciliates to main fronts. On one hand, the pressure to satisfy the customer's requirements incentivizes straightforward implementability; on another, it can divert the approach from academically relevant subjects. Nevertheless, this case study is a multidisciplinary challenge, for which a solution is presented in the following chapters.

Chapter 3

A risk-based maintenance approach

The following methodology allows the decision maker to ponder between risk and maintenance spending. As Figure 3.1 shows, we start with the choice of the equipment. In this case we approach the PRM and succeed in studying what sub-equipment pieces compose it. The next steps are to study the failure modes and to elaborate the risk analysis. We determine probability of occurring a failure, and consequences for each piece of equipment. This allows risk to be calculated in the conventional way, by multiplying impacts of an event by its frequency. Having calculated the risk for each failure mode, pieces of equipment can now be aggregated and policies defined. These policies are to be tested by means of simulation and iterated upon according to the results.

Although some of the methodology can be adapted to other equipment, the solution we present can only be applied directly to pressure regulation and measurement stations. Each step will be covered in detail below. Auxiliary to the comprehension of this chapter, and the mathematical expressions used, notation Table 3.1 is provided.

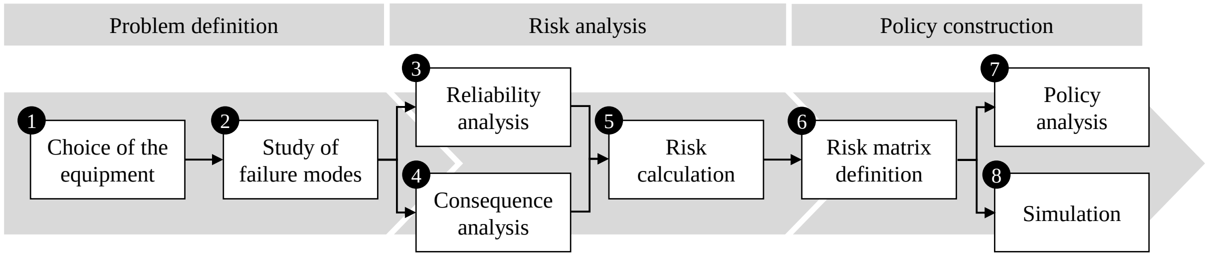

Figure 3.1: Description of the methodology.

Table 3.1: Notation table with variables and events, for this chapter.

Variables	
a^{mlq}	Age of sub-equipment q, in line l of equipment m.
A^{mlq}	Sub-equipment q's, in line l of equipment m, time-to-failure.
L^m	Number of lines in an equipment.
w_c	Weight for consequence category c.
θ^m_{cf}	Impacts in category c , caused by a failure of type f in equipment m.
Θ^m_f	Total impact caused by a failure of type f in equipment m.
R^m	Risk associated with equipment m.
u	Relative frequency of failures-to-activate for a shut-off spring.
r^s	Number of failures of sub-equipment pieces of type s.
k^s	Number of censorings for sub-equipment pieces of type s.
n^s	Number of failures and censorings for sub-equipment pieces of type s.
t^s_i	Time at which failure i occurred for sub-equipment pieces of type s.
T^s_j	Time at which censoring j occurred for sub-equipment pieces of type s.
C^s_j	Number of items censored at time j for sub-equipment pieces of type s.
H^{mlq}_t	Health of sub-equipment q, in line l of equipment m, at time interval t.
Φ	Random number between 0 and 1.
ϕ	Random number between 0.01 and 0.04.
δ^{mlq}	Delay-time.
γ	Inverse of the mean delay-time.
Δ^m	Time between inspections for equipment m.
β^s	Weibull's distribution shape parameter for sub-equipment of type s.
η^s	Weibull's distribution scale parameter for sub-equipment of type s.
Events	
Ω^m_f	Failure of type f, in equipment m in a given time-window.
ω^{mlq}	Failure in sub-equipment q, in line l of equipment m in a given time-window.
U^{ml}	Failure in the FTC regulator's shut-off spring, in line l of equipment m.
Decision Variables	
X^{mlq}	1 if sub-equipment piece q, is installed in line l of equipment m; 0 otherwise.

3.1 Problem definition

3.1.1 Definition of the subject equipment

The choice of PRM as the equipment to focus is based on how critical it is to the gas distribution network. They guarantee the safe distribution of natural gas by reducing the pressure from the primary transport network to the secondary distribution network. Additionally, when this reduction is not possible, PRM' shut-off valves should stop the flow of gas. Failures to perform these functions may result in impacts ranging from unsatisfied clients from lack of gas supply, to fatalities due to a vapor-cloud explosion. The variability and possibility of these dire scenarios make this equipment adequate for a risk-based approach.

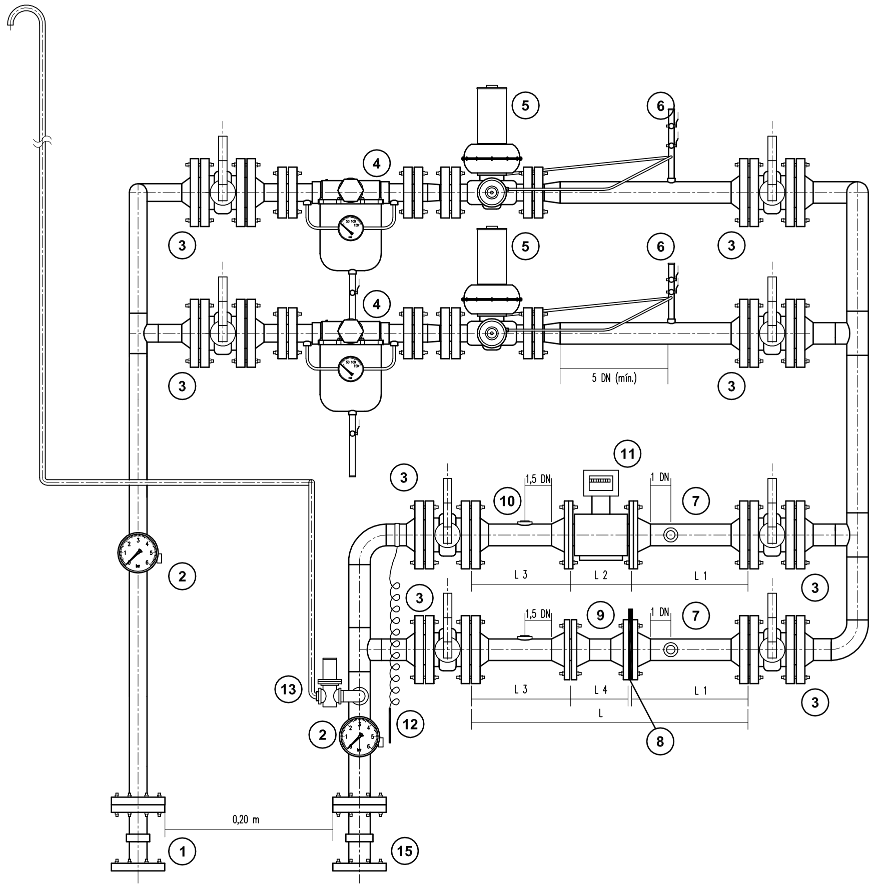

Figure 3.2: Technical drawing of the pressure regulator and measurement station.

In Figure 3.2 a possible configuration for a PRM with two lines is presented. The stream of gas flows from (1) to (15). For our analysis the only relevant pieces of sub-equipment are security valves (3), and regulators (5) which may have various configurations. Filters (4) may influence the failure rate, but a condition-based approach based on the differential pressure is more adequate for policy definition. Note that the representation shows the possible places to install shut-off valves (3), being common for PRM to only have one security valve downstream each regulator. The remaining valves are neither automatically activated or installed, with the exception of the valves upstream of the regulator. These are sometimes installed so that they activate with the pressure downstream the regulator.

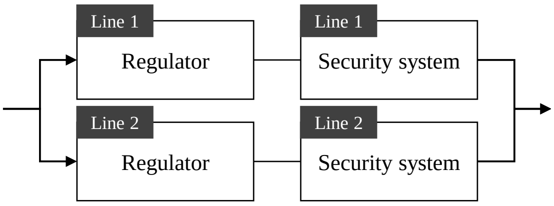

Figure 3.3: Block diagram of the equipment.

For the sake of the analysis, we reduce the PRM to a system of its main functional sub-equipment pieces. Accordingly, Figure 3.3 represents a block diagram of this system's usual configuration, which consists of two lines, each with a pressure regulator and a security system. This representation allows the study of failure modes and probabilities that will follow.

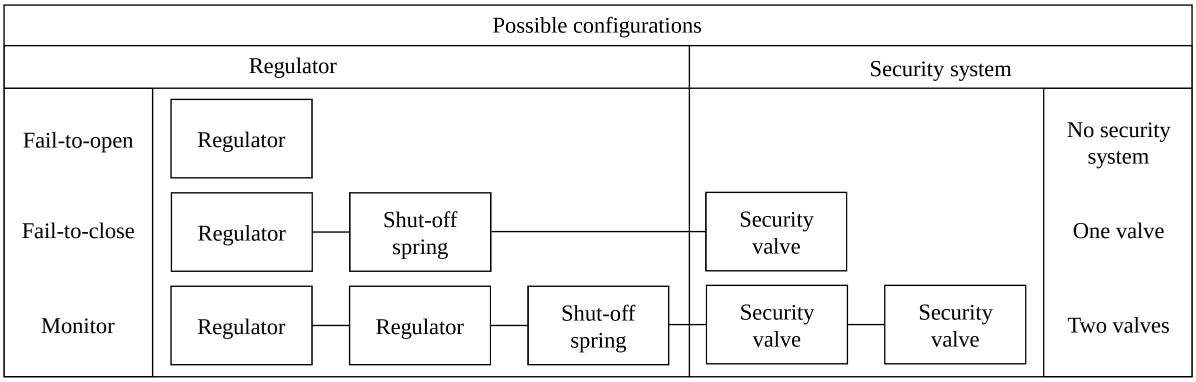

Figure 3.4: Possible regulator configurations.

While the security system can be composed of one or two security shut-off valves, the regulator module can have three main configurations, as Figure 3.4 describes. The fail-to-open (FTO) regulator which, on failure, will simply let the gas through without reducing the pressure to the required levels. The fail-to-close (FTC) one, which has a spring which shuts of the flow once the regulator fails. The monitor (MON) regulator works as a FTO followed by a FTC regulator. This makes MON the safest and most expensive configuration for this sub-equipment.

The equipment configuration possibilities can be translated in a two-dimensional vector. Adapted to our PRM analysis, $q = 1$ represents the FTO regulator, $q = 2$ represents the FTC, $q = 3$ and $q = 4$ represent security valves. The vector is composed of the decision variables X^{mlq} of value 1, if the sub-equipment is installed, and 0 otherwise. Table 3.2 exemplifies the configuration vector for an example with two lines.

Table 3.2: Configuration vector, for a given equipment *m*.

		Sub-equipment (q)			
		1	2	3	4
Line (l)	1	X^{m11}	X^{m12}	X^{m13}	X^{m14}
	2	X^{m21}	X^{m22}	X^{m23}	X^{m24}

An example of the most complex possible line is represented in Figure 3.5. It consists of a MON regulator with a security system of two shut-off valves . Its configuration vector would be represented as [1, 1, 1, 1], because every sub-component q is installed in this line. Gray represents failed sub-equipment. From the example we can determine that a supply failure occurred in this line, as the regulators fails to reduce the pressure, the spring fails to shut of the flow and, even though the first shut-off valve is out of service, the second one is functional. The next subsection will cover this aspect more thoroughly.

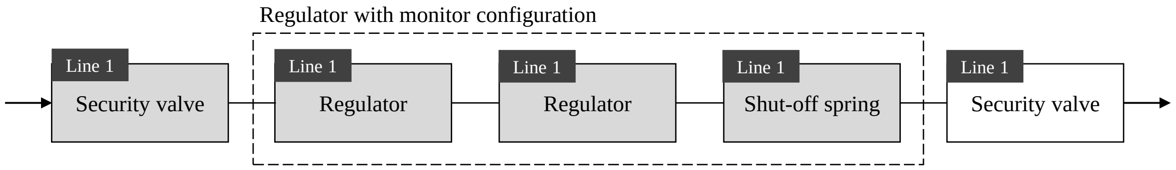

Figure 3.5: Example of line configuration.

3.1.2 Enumeration of the equipment's failure modes

For this study, two types of equipment functional failures are accounted for: (1) the PRM either fails to supply gas to the network (supply failure) or (2) leaks gas excess gas into the distribution network (stall failure), which is the result of failing to reduce the pressure from the transportation network. The supply failure mode is characterized by the breakdown of the regulators in both lines, while all the valves work as intended. This means the pressure would rise downstream to unsafe levels and the valve would shut off the supply. If, in a line, both the regulator and the valve fail to perform, high pressure gas is leaked into the distribution network, which describes the stall failure. As the pressure in the distribution network rises the failure becomes potentially more dangerous. The conditions for failure become explicit in Figure 3.6.

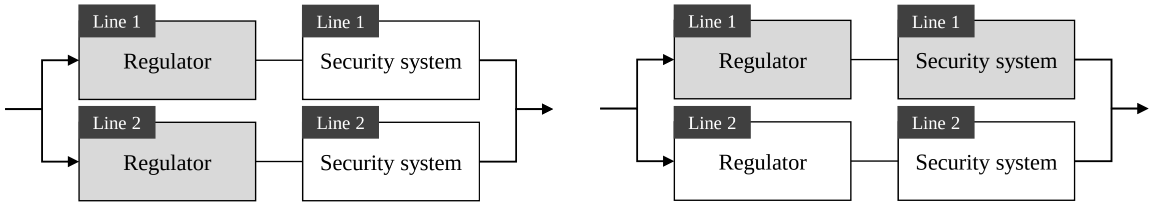

Figure 3.6: Supply failure mode (left) and stall failure mode (right).

It should be noted that MON and FTC regulators have a spring which can shut of the flow of gas. This means that, in order for the gas to be released downstream into the security system, this additional mechanism needs to fail. Furthermore if, in both lines, the regulator fails and the spring activates, a supply failure would occur without the gas reaching the security system.

3.2 Risk analysis

3.2.1 Calculation of failure probabilities for the equipment

In this section we apply reliability theory to handle the probabilities of failure for a piece of sub-equipment at a given time. Reliability theory states the probability of a given sub-equipment q, in line l of station m, to fail until time t is:

$$F^{mlq}(t) = \int_0^t f^{mlq}(t)dt \tag{3.1}$$

Additionally, the probability of a sub-equipment having survived until time t, or its reliability, is given by the equation:

$$R^{mlq}(t) = 1 - F^{mlq}(t) \tag{3.2}$$

Furthermore, the probability density of a sub-equipment failing, given that it survived until time t, or hazard, by definition, is calculated as:

$$h^{mlq}(t) = \frac{f^{mlq}(t)}{R^{mlq}(t)} \tag{3.3}$$

In order to apply reliability theory, we must adjust the times of failures t_i^s, associated with a given sub-equipment type s, to a distribution. We chose a two-parameter Weibull distribution to make this adjustment, as it is frequently used in maintenance and, given its flexibility, has a wide range of applications (Weibull, 1951). To that end make use of the censorings T_j^s for our estimates. Let r^s be the number of failures, k^s the number of censorings and C_j^s the number of tied items for censoring j, for sub-equipment type s. The maximum likelihood estimates used for the shape parameter β^s are given by (Crow, 1975):

$$\frac{\sum_{i=1}^{r^s} t_i^{s\beta^s} \log t_i^s + \sum_{j=1}^{k^s} C_j^s T_j^{s\beta^s} \log T_j^s}{\sum_{i=1}^{r^s} t_i^{s\beta^s} + \sum_{j=1}^{k^s} C_j^s T_j^{s\beta^s}} - \frac{1}{\beta^s} = \frac{1}{r^s} \sum_{i=1}^{r^s} \log t_i^s \tag{3.4}$$

The scale parameter η^s, for a given sub-equipment type s, can then be calculated as:

$$\eta^s = \left(\sum_{i=1}^{r^s} \frac{t_i^{s\beta^s}}{r^s} + \sum_{j=1}^{k^s} \frac{C_j^s T_j^{s\beta^s}}{r^s} \right)^{\frac{1}{\beta^s}} \tag{3.5}$$

Sets of distribution parameters are calculated for each sub-equipment type s as, in our case, every PRM can be composed by combining these elements. Shut-off springs are an exception for which no dataset could be arranged. The FTC regulator, disregarding the shut-off spring, was differentiated from FTO as its technology is more recent, and a higher mean-time-to-fail (MTTF) is to be expected. The probabilities for the MON regulators are equivalent to those of an FTO regulator installed in series with a FTC one, hence the its MTTF can be obtained from the estimates for these types of regulators. In the absence of data, the shut-off spring in the FTC and MON regulators, have their probability of failure estimated directly from the relative frequency.

Given β^s and η^s as the parameters for each sub-equipment type s, its correspondence with the sub-equipment q can be made with the aid of Table 3.3, leading to parameters β^q and η^q. With the exception

Table 3.3: Correspondence between q and s.

	Sub-equipment classification			
s	Fail-to-open	Fail-to-close	Shut-off valve	Shut-off valve
q	1	2	3	4

of the shut-off spring, which has a fix probability u of not activating with each request, the function of the probability density of failure at a given time for each equipment q, $f^{mlq}(t)$ can be expressed as:

$$f^{mlq}(t) = \begin{cases} \frac{\beta^q}{\eta^q}\left(\frac{t}{\eta^q}\right)^{\eta^q-1} & t \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{3.6}$$

Considering the probability distribution function and, taking into account the equipment configuration definition vector, the probability of failure for the sub-equipment q, in line l of equipment m in the given interval $t \in [a,b]$ is given by:

$$P(\omega^{mlq}) = 1 - X^{mlq}\left(1 - \int_a^b f^{mlq}(t)dt\right) \tag{3.7}$$

Having found a statistical rule for the sub-equipment failures, the probabilities of failure for an equipment piece can be calculated. With the use of block diagrams, the expressions are derived. Let ω^{mlp} be the event that a failure in sub-equipment q, in line l of equipment m occurs in a given time-window $t \in [a,b]$, and its complementary $\bar{\omega}^{mlp}$ be that the sub-equipment is functioning properly in that time-window. Likewise, let event U^{ml} be the failure in the FTC regulator's shut-off spring, in line l of equipment m, and its complementary $\bar{U}^{ml}$ that the shut-off spring functions properly. With Ω^m_{supply} denoting a supply failure for a given PRM m in the given time interval $t \in [a,b]$, the probability that it occurs, considering the possibility of two lines and possible line configurations analyzed in Section 3.1.1, is calculated as:

$$P(\Omega^m_{supply}) = P\{\left[(\omega^{m11} \cap \omega^{m12}) \cap (\bar{\omega}^{m13} \cup \bar{\omega}^{m14} \cup \bar{U}^{m1})\right] \cap \left[(\omega^{m21} \cap \omega^{m22}) \cap (\bar{\omega}^{m23} \cup \bar{\omega}^{m24} \cup \bar{U}^{m2})\right]\}$$

Repeating this process for Ω^m_{stall}, which denotes a stall failure in PRM m, its probability of occurrence can be obtained by the following expression:

$$P(\Omega^m_{stall}) = P\{\left[(\omega^{m11} \cap \omega^{m12}) \cap (\omega^{m13} \cap \omega^{m14} \cap U^{m1})\right] \cup \left[(\omega^{m21} \cap \omega^{m22}) \cap (\omega^{m23} \cap \omega^{m24} \cap U^{m2})\right]\}$$

From these expressions alone, we can conclude that an augment in the number of lines should increase the probability of stall failure and reduce the probability of a supply failure. Likewise, an increase in the number of shut-off valves and springs can lead to a higher probability of supply failure, yet it should make stall failures more improbable. Finally, an increase in the number of regulators would reduce the frequency of both supply and stall failure modes.

With the assumption that failures in different sub-equipment pieces are independent it is possible to derive arithmetic expressions for these probabilities of failure. Substituting in the equations for the different failure modes, the probability of failure for each mode, at a given interval of time $t \in [a,b]$ is determined according to the following equations:

$$P(\Omega^m_{supply}) = \prod_{l}^{L^m} \left[\prod_{q=1}^{2} 1 - X^{mlq} \left(1 - \int_a^b f^{mlq}(t)dt \right) \right] \left[(1-u) \times X^{ml2} + \sum_{q=3}^{4} X^{mlq} \left(1 - \int_a^b f^{mlq}(t)dt \right) \right] \tag{3.8}$$

$$P(\Omega^m_{stall}) = \sum_{l}^{L^m} \left[[1 - X^{ml2}(1-u)] \times \prod_{q=1}^{4} 1 - X^{mlq} \left(1 - \int_a^b f^{mlq}(t)dt \right) \right] \tag{3.9}$$

With these expressions one can calculate the probability of failure for each equipment. Before risk can be assessed, the next section will cover consequence estimation for each failure mode.

3.2.2 Estimating the consequences for each failure mode

For each piece of equipment, the consequences of each failure are estimated. Given the sensible nature of some the possible impacts, a worst case scenario approach is used. The consequences were divided into five categories, as described in Figure 3.7.

Lost sales refer to the gas not provided to customers during a supply failure, and are assumed to be the variable cost of a supply failure. Affected clients is the number of clients which the supply failure affects, as it is a driver for the amount to be expended in compensations. There was a need to segregate from all clients those who were high-priority as the impacts can differ in nature. Material damages consist of the expected value of damages to the distribution network in the case of a stall failure. The last category amounts the expected number of fatalities, which should be relevant only for stall failures.

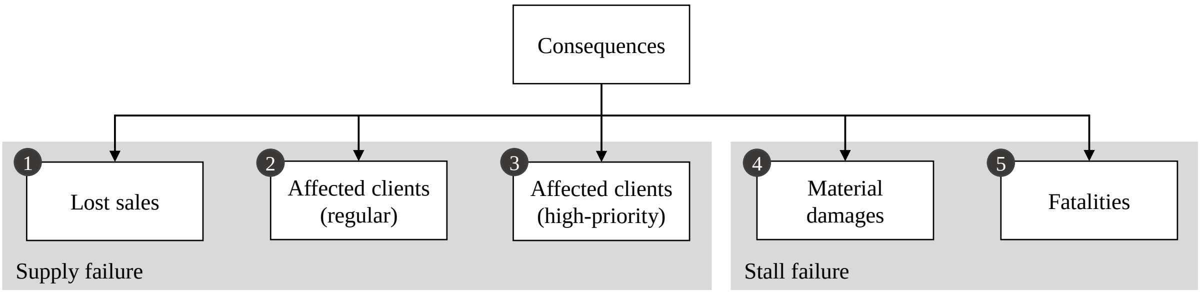

Figure 3.7: Consequence classification.

To deal with the fact that the results are obtained in a non-homogeneous fashion, one can reduce them to a single unit so that a value for the consequences can be calculated. Converting every field into monetary units is the most common approach. Alternatively, a weighted sum of the normalized values for each category could be a more adequate method.

The decision maker should be taken into account when pondering the relevance of each category, thus a method such as AHP can be used to determine the relative importance of the categories and establish weights. Only after both the method for assessing the weights and the weights themselves being determined, the calculation of consequences is possible. Let θ_{cf}^{m} be the impact of failure mode f of equipment m for category c and w_c the weight for category c, the impact total for a failure in a set equipment Θ_f^m is given by:

$$\Theta_f^m = \sum_c w_c \times \frac{\theta_{cf}^m - \theta_{cf}^{MIN}}{\theta_{cf}^{MAX} - \theta_{cf}^{MIN}} \tag{3.10}$$

3.2.3 Risk calculation

With both the frequency and consequences of an occurrence, for each piece of equipment, risk can now be calculated as in Equation 3.11. The failure modes must be discriminated in the calculation, as both the probabilities and impacts are specific to each mode. Because the consequences are already weighted, risk for each failure mode can be summed, resulting in a relative measure of risk for each piece of equipment. Let R^m be the risk for equipment m which, in this context, can be interpreted as an expected value of impacts. We can calculate it using the following expression:

$$R^m = \sum_f P(\Omega_f^m) \times \Theta_f^m \tag{3.11}$$

If we want a risk photography of our current network, given that we know the age of our pieces of sub-equipment, the probabilities of failure should be calculated, knowing that the equipment survived until now. For this calculation the hazard density functions should be used, instead of the failure probability density ones, in Equations 3.8 and 3.9.

3.3 Construction of maintenance policies

3.3.1 Risk matrix

From the previous step, every PRM should have a measure of risk and can now be compared with any other in this analysis. Though this is an useful feature, the final purpose of this analysis is the definition of maintenance policies. Hence, for practical purposes, it is more adequate to represent the results in a risk matrix. This way, PRM can be clustered by risk and time-between-inspections defined for each matrix division. There are various ways to divide a risk matrix (Vianello, 2012), in Figure 3.8 to the left the division is made in quarter-circles by risk. On the right side, the division is made in squares, based on the frequency and impact of failures.

While the division by risk is most fair for a quantitative approach, it does not distinguish high impact and low probability scenarios than those with high probability and low impact. On the other hand, the division by squares takes this into account, even though the boundaries dividing the quadrants are difficult to define. From a risk analysis perspective it is believed that the division by quarter-circles is more adequate, but when taking into account implementing the matrix in a real scenario the division in squares bring a flexibility, which is hard to disregard.

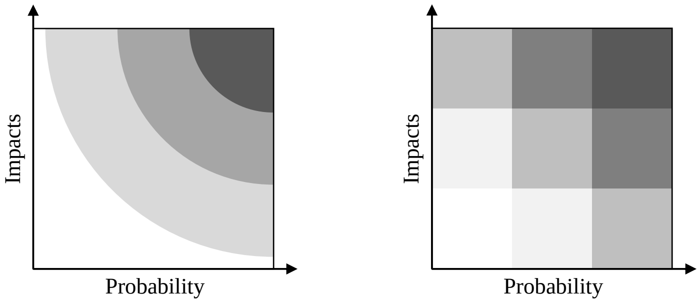

Figure 3.8: Matrix divisions by risk (left), and by impacts and probabilities (right).

The limit definition should also be up to the decision maker. The main recommendations associated with this process are: (1) to discriminate between the pieces of equipment, and (2) to take the objective of the analysis into account. In more detail, the first recommendation states that the limits of the matrix must be defined such that both the equipment and the differences within the equipment pieces 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. For the second recommendation, the purpose and scope 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 level of detail in the matrix is also strongly dependent of the level of the decisions it needs to support.

3.3.2 Analysis of maintenance policies

With the results of the risk analysis 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 equipment in another area of the matrix is adequate, and greatly reduces the number of solutions. When testing inspection periodicity, the total number of possibilities is then given by the sum of the number of times-between-inspections to test for each quadrant. Although this can have similarities with simulation-based optimization, a multiple-objective approach was taken, giving the decision maker power over risk.

Given the complexity of the an integrated model for the whole system, the use of simulator is recommended to obtain the necessary metrics to compare policies. Figure 3.9 demonstrates an analysis of the variation in consequences (full line) versus the variation in costs (dashed line), with the increase of the time-between-inspections. It should be noted that consequences and cost are not in the same unit, therefore the intersection should not represent a minimum. For policy definition, 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.

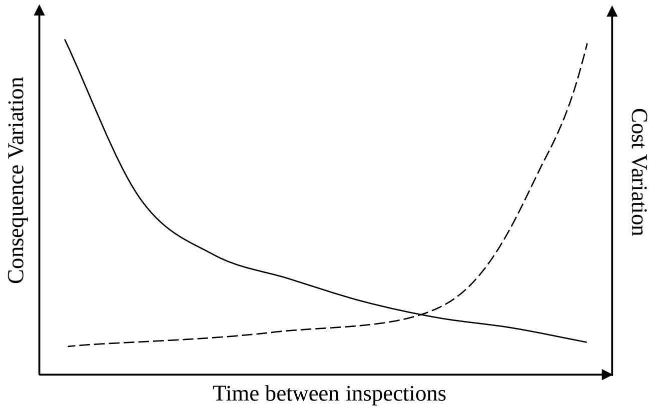

Figure 3.9: Consequence increase (full) versus cost variation (dashed), with periodicity.

3.3.3 Simulation

Analytically deriving the expressions needed to test policies and obtain indicators to compare them was found as impracticable. Therefore, a discrete-event simulator was found adequate to obtain the risk-cost curves and attain sensitivity about the effects of maintenance policies. The approach simulates the health of each sub-equipment piece for each PRM and, considering the conditions for equipment failure, determines supply and stall failures based on sub-equipment performance. By combining the consequence analysis with the simulation results, the expected value of consequences for a given interval can be obtained. Furthermore, if inspection, repair, and substitution costs are estimated, maintenance costs for that given period can also be calculated.

The sub-equipment involved consists of a mechanical system, and each piece can be interpreted as a stochastically degrading system with a statistically defined failure rate. Furthermore, before it fails it is believed that there is a period in which a repairable defect is detectable. This is a window of opportunity to improve the sub-equipment's condition and is defined as the concept of delay time (Baker and Wang, 1991) and it is assumed that its distribution is ascertainable.

Three concepts need to be distinguished, the *fault* which happens a delay-time before sub-equipment failure and is repairable; the *sub-equipment failure* which happens when the health of a sub-equipment reaches zero, thus losing its function; and the *equipment failure* which happens when a certain combination of sub-equipment fails in a PRM, leading to a stall or a supply failure, as defined in Section 3.1.2.

As Figure 3.11 describes, each equipment is inspected periodically. If, in an inspection a fault is found in a sub-equipment it is repaired and if a sub-equipment breaks down it is substituted. With each repair or substitution, a new MTTF and a new delay-time are generated. Each period t, each piece of sub-equipment is degraded knowing it will fail at a determined time. Overall its time-to-failure's distribution will be consistent with that calculated in Section 3.2.1. The degradation follows an exponential distribution which, experimentally, was found adequate for a mechanical system. When an equipment breakdown occurs, all the respective sub-equipment is inspected. Faults are corrected and broken sub-equipment is substituted. The dashed arrow maintains the flowchart's consistency, even though it will never be used.

This refers to the fact that equipment breakdowns cannot occur without any sub-equipment failing. The simulator moves on to the next period and the cycle continues until an end condition, such as a simulated time, is met. The number of failures, breakdowns, repairs, inspections and substitutions in the simulation can be used to calculate expected costs and consequences, being these the desired performance indicators for a maintenance policy.

Generating times-to-failure and delay-times

Times-to-failure t should follow the distributions referred to in Section 3.2.1. Delay-times are modeled after an exponential distribution, and modified so that there is the probability $1-p$ of undetectable defects (zero delay-time). Let δ be the delay-time, its distribution function should be given as:

$$F(\delta) = 1 - pe^{-\gamma\delta} \tag{3.12}$$

With γ being the inverse of the mean delay-time, and its maximum likelihood estimate given by the following equation (Scarf, 1997):

$$n - r = \frac{(n-r)\gamma\Delta}{e^{\gamma\Delta} - 1} + \frac{\sum_i \gamma t_i}{e^{\gamma t_i} - 1} \tag{3.13}$$

Where r is the number of failures and n is the number of failures and censorings observed, t_i is the time of failure i and Δ is the time between inspections.

Times-to-failure and delay-times were generated using the Monte Carlo method. A random number between 0 and 1 is generated which represents a cumulative probability that is used to obtain the value of a random variable, given that its distribution is known. Solving Equation 3.14 for A will generate a time-to-failure, which follows the desired distribution $f^{mlq}(t)$. The same logic applies to Equation 3.15, which generates a delay-time when solved for δ^{mlq}.

$$\Phi = \int_0^{A^{mlq}} f^{mlq}(t)dt \tag{3.14}$$

$$\Phi = 1 - pe^{-\gamma\delta^{mlq}} \tag{3.15}$$

Generating the degradation

In the simulation, a new sub-equipment starts with its health at 100%. The condition degrades in an exponential rate such that it hits zero when the sub-equipment reaches its time-to-failure. Given the sub-equipment MTTF A^{mlq}, and its age current a^{mlq} its health at a discrete period t is calculated by the following expression:

$$H_t^{mlq} = \begin{cases} H_{t-1}^{mlq} & \text{, if } H_{t-1}^{mlq} < 1 - \frac{e^{\phi a^{mlq}}-1}{e^{\phi A^{mlq}}-1} \\ 1 - \frac{e^{\phi a^{mlq}}-1}{e^{\phi A^{mlq}}-1} & \text{, otherwise} \end{cases} \tag{3.16}$$

Figure 3.10 depicts the health degradation. The equipment starts at top condition and is degraded throughout time, until in t_1 it loses its function. A delay-time h_1 is also generated. In this case, the first inspection occurred before the fault was detectable, hence no intervention was done. At t_1 an equipment failure occurred and the sub-equipment was substituted. Note that the sub-equipment failure lasts until the next inspection or equipment failure, for only then maintenance actions are executed. Regardless of finding a fault or not, in the second inspection the condition of the sub-equipment was too good for any repair to be done. This shows the concept of *repairable domain*, as maintenance interventions will only occur if sub-equipment health is below a certain level. In the third inspection repairs are executed. A fault is found and the sub-equipment health is low enough for intervention to be done. If not for this repair, the sub equipment would lose its function at t_2.

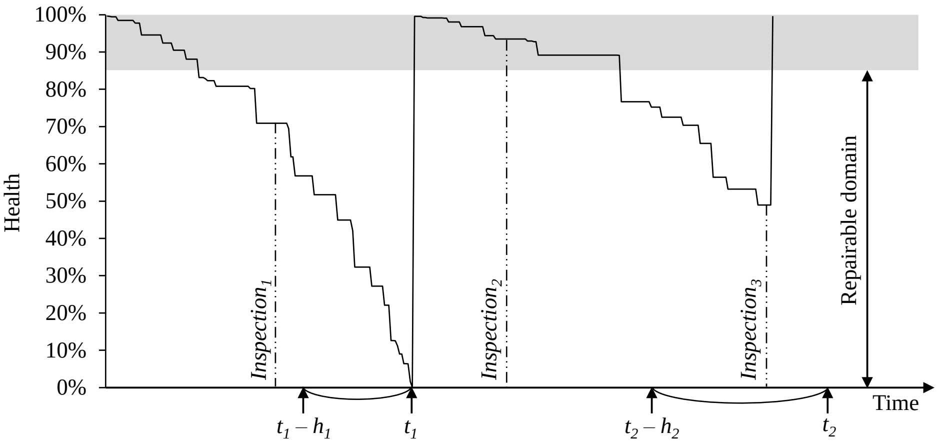

Figure 3.10: Example of a sub-equipment health curve.

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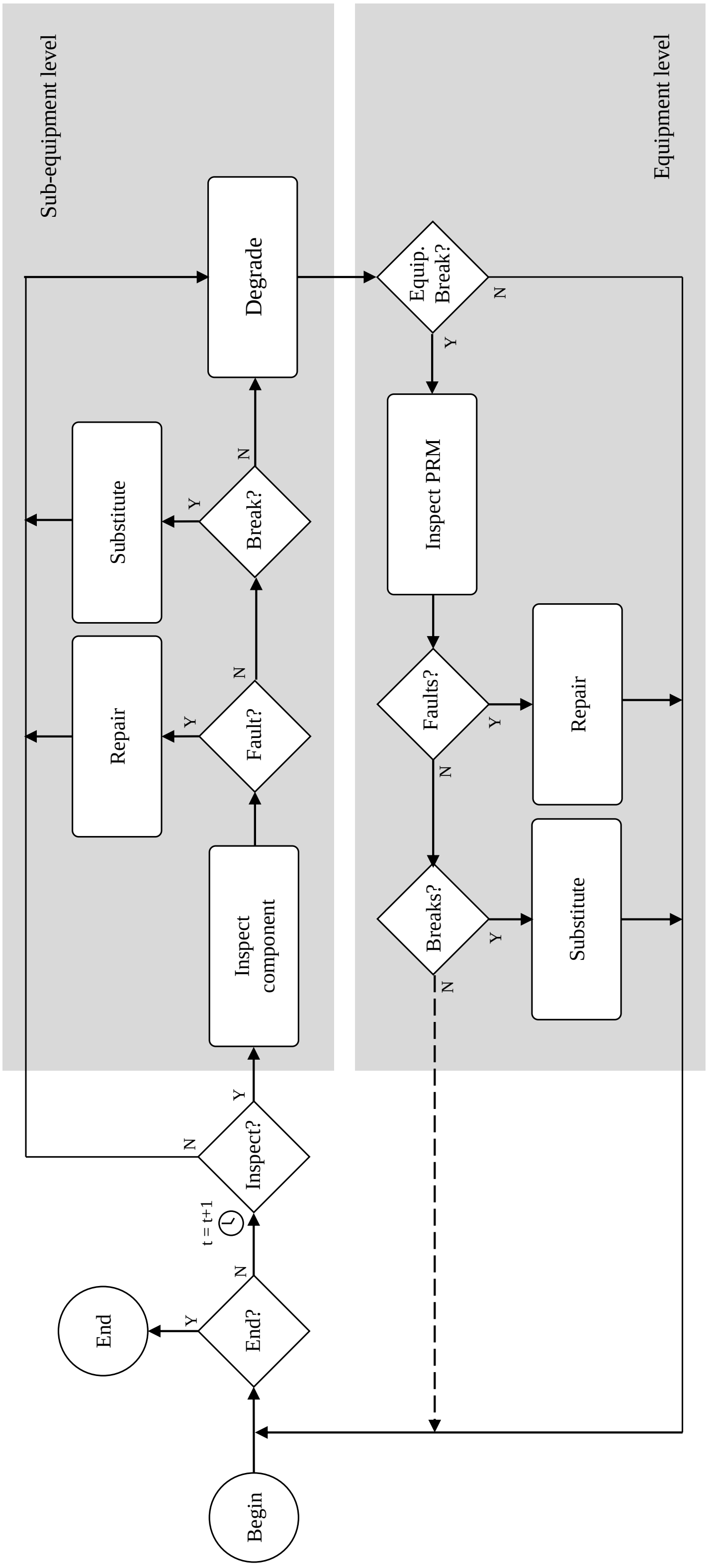


Figure 3.11: Simulation flowchart.

Chapter 4

Case study

This case study, demonstrating the application of the methodology analyzed in Chapter 3, is one of the fruits of our collaboration with EDP Gás Distribuição. Working under EDP group, the company is pressured to deliver growth and results, while avoiding incidents that can damage the brand. Gas distribution is a tightly regulated market, which limits customer base expansion, hence they must act on operations or customer relations to improve. These motives lead the company to procure a better compromise between service costs and safety. The developed risk-based approach is aligned with these objectives, thus befitting the company's needs. In this chapter we present our approach and results for this case-study, along with ways to deal with the absence of maintenance data and the quantification of subjective inputs.

For a better understanding of the expressions used in this case study the notation Table 4.1, 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.

4.1 Case description

In accordance to the companies objectives, PRM are the most critical equipment, as its failures' societal impact is high and volatile. The consequences of a failure can influence thousands of clients and even result in fatalities. Though the company intends to define maintenance policies conservatively, they work through a judgment-based method which has no quantitative confirmation whatsoever. Beyond improving the policies, the company aims to have justification for the improvement.

The analysis covers a network with 4 856 kilometers of extension, fed by 89 PRM which are distributed as displayed in Figure 4.1. The gas is transported at a pressure of 16 bar and, ideally, should enter the distribution network at a pressure of 3,7 bar to guarantee safe and proper flow. The PRM has the task of reducing the pressure to these levels. The company has bases of operations in Porto and Braga and is responsible for supplying gas to northern Portugal.

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

Variables	
δ^m	Travel-time to equipment m from the closest headquarters (with traffic).
δ_0^m	Travel-time to equipment m from the closest headquarters (without traffic).
$p^{mr}(t)$	Pressure in network r at time t, after a failure in equipment m.
m_0^r	Mass of gas in network r, given proper functioning.
v_0^r	Volume of gas in network r, given proper functioning.
$\rho_n g$	Volumetric mass density of natural gas.
$\dot{V}_{MAX}^{mr}$	Maximum flow which equipment m is able to supply to network r.
$\dot{V}^{mr}$	Flow supplied by equipment m to network r at its maximum demand.
$\dot{v}^r$	Minimum flow demanded by network r.
N_t^{mr}	Number of clients of type t, in network r, affected by a failure in equipment m.
N_t^r	Number of clients of type t, supplied by network r.
L^r	Total length of piping in network r.
D^{mr}	Setback distance for an explosion in network r given a stall failure in equipment m.
ϕ^r	Diameter of the weakest piping in network r.
w_c	Weight of category c.
w'_c	Ratio of category c.
r_{ce}	Category c's ranking, attributed by expert e.
K_{pipe}^r	Cost of substituting 100m of the weakest piping in network r.
K_{leak}	Cost of leak inspection per kilometer.
K_{man}	Labor costs for an inspection (implicit and explicit).
K_{veh}	Use costs of a vehicle per kilometer.
K_{sub}^s	Substitution cost for sub-equipment of type s.
K_{rep}^s	Repair cost for sub-equipment of type s.
K_{ins}^m	Total cost of inspecting equipment m, without intervention.
d^m	Distance to equipment m from the closest headquarters.
τ	Virtual time for each simulation.
S	Number of simulations.
Events	
ε^{mr}	Rupture in the weakest piping of network r, caused by a failure in equipment m.
Auxiliary	
m_i	Auxiliary constant, number i.

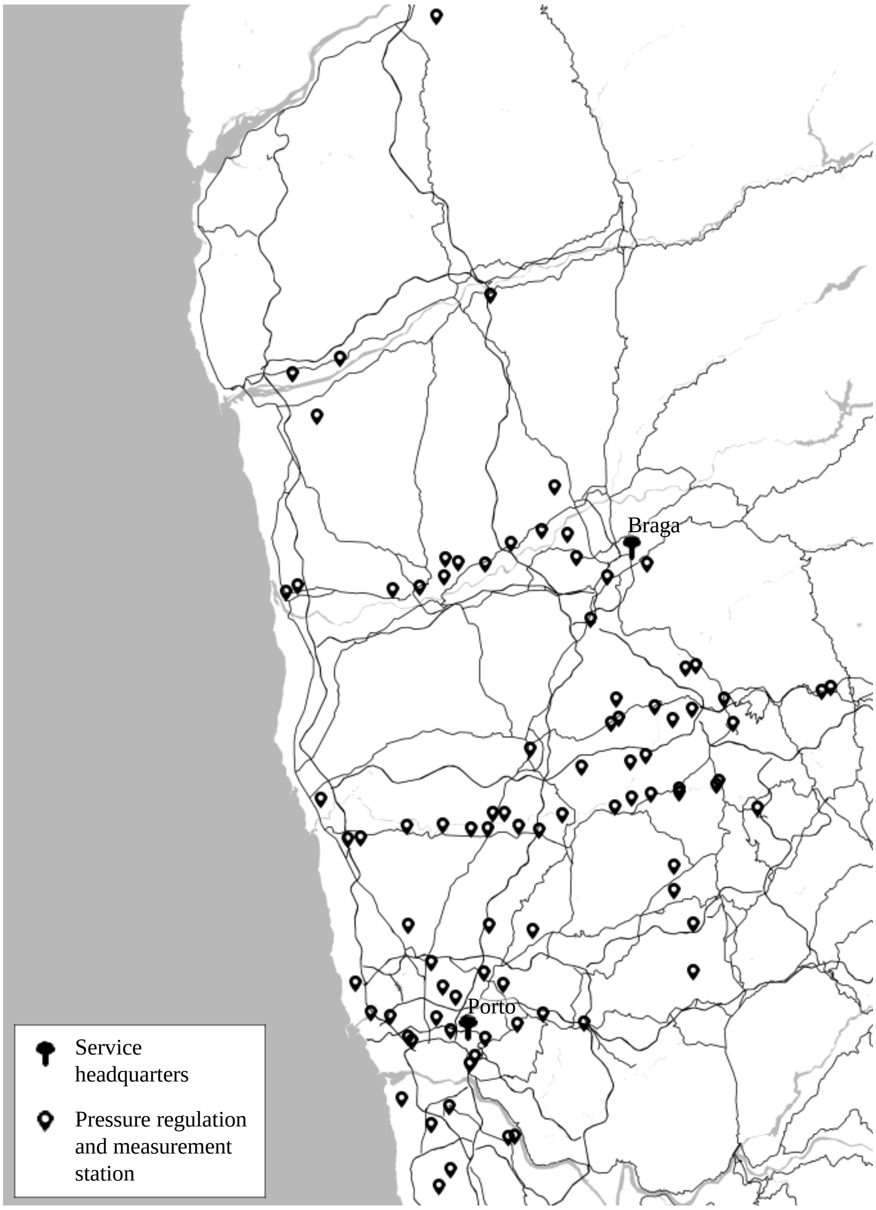


Figure 4.1: Equipment location, in northern Portugal.

PRM are currently inspected twice per year. This policy, which includes sub-equipment repairs and substitutions, has an estimated cost of 47 650€ per year. Furthermore, we estimate inspections to amount for 89% of this cost. It should be noted that the bulk of these inspections does not have any intervention. Therefore, they represent a cost which does not increase safety nor improve the equipment's performance. Additionally, the company's maintenance data is scarce and of poor quality. 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.

4.2 Risk analysis

Having chosen the PRM as the object of this methodology and already having studied its failure modes, we calculate the probabilities of failure for a given equipment. Ideally, for this step, maintenance data would be abundant, so that we would be able to fit a probability distribution to it. Adversely, we face the absence of registered maintenance data, and we must estimate the failure rates for sub-equipment pieces based only on expert knowledge.

4.2.1 Calculation of probabilities

Elicitation

To assess the probabilities of sub-equipment failure we resorted to elicitation as, with such scarce maintenance data, most relevant maintenance data for this problem was expert knowledge. We did a one-shot session where we applied the histogram technique (Van Noortwijk et al., 1992). A total of four experts from the company were present in the session, with positions ranging from management to maintenance technicians. While observing their own answers in an interactive histogram, the following questions were asked to the experts, for each sub-equipment type s:

From one hundred pieces of sub-equipment type s how many will fail given that no maintenance action is taken:

- in the following two years?
- between two and four years from now?
- between four and six years from now?
- between six and eight years from now?
- later than eight years from now?

The answers of other experts were not known to each one before the end of the session. When the procedure was finished, results were gathered and presented for everyone. Each answer was shown anonymously and was subject of an open discussion with the participation of every questioned individual. The objective for this discussion was the definition of weights for each expert.

From the expert elicitation process, we obtained the estimates for the frequency of failure for each component type s at a given time interval, by dividing the weighted average of the answers by the number of pieces of sub-equipment s in the question. So that we could apply the equations in Section 3.2.1 to the results and fit them to a two-parameter Weibull distribution, we used the midpoint from the histogram's intervals as a virtual failure time for the respective sub-equipment. Table 4.2 presents these results, with the midpoints in months. The scenario which the table presents states that at time $t_i^s = 36$ months of continuous use, ten out of one hundred fail-to-open regulators would have failed.

Table 4.2: Elicitation results.

	Frequency at:				
s	$t_i^s = 12$	$t_i^s = 36$	$t_i^s = 60$	$t_i^s = 84$	$T_j^s = 96$
Fail-to-open	2	10	13	24	50
Fail-to-close	2	7	10	15	67
Shut-off valve	1	2	4	10	83

Parameter estimation

With this adaptation, we can apply expressions 3.4 and 3.5 for each sub-equipment type s and obtain the correspondent maximum likelihood estimates for the Weibull parameters. By adjusting the discrete failure data obtained to a continuous distribution, we make possible the calculation of reliability statistics for any given time. Furthermore, we are able to extend the limits of our analysis to more than we have elicited. Figure 4.2 exemplifies the results for this procedure.

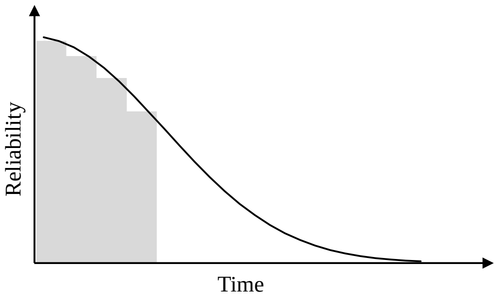


Figure 4.2: Elicitation results (gray bars) with Weibull (black line) fit, example.

By the maximum likelihood method, the resulting sets of parameters are presented in table 4.3. Note that η^s, the scale parameter is displayed in months.

The shape parameter β^s was tested for being significantly bigger than one, for all items in s. By finding which items meet this condition, we discover those with increasing hazard. Given that the costs

Table 4.3: Weibull parameters for different sub-equipment .

s	β^s	η^s
Fail-to-open	2,47	112,31
Fail-to-close	2,12	146,06
Shut-off valve	2,45	190,82

of corrective maintenance are higher than those of preventive action, we can now perceive which sub-equipment is adequate for the latter. The null hypothesis ($H_0 : \beta^s \leq 1$) was rejected for every s with $p < 0,5\%$, hence every sub-equipment is suitable for preventive maintenance strategies. This is to be expected, considering the mechanical nature of the sub-equipment pieces analyzed and its functions.

4.2.2 Estimation of consequences

In this section we expose our method of consequence calculation. For each failure, the values of each category are assessed, noting this is a worst case scenario approach. As network configuration has to be taken into account in these calculations, we introduce the two possible configurations. The 89 PRM are assigned to 54 networks, which can supply the customers in an antenna or a ring configuration. The former refers to the case that one PRM alone supplies a network of clients, the latter refers to the case in which there are many PRM for a network with the possibility of slack existing in capacity.

The redundancy present in the ring network configurations allows to mitigate the consequences from a supply failure in some networks, as the excess capacity may be able to supply the otherwise affected clients. Additionally, in big networks, where the consumption is so high that several PRM are required to satisfy it, the pressure rise from a stall failure may be attenuated by the network's strong gas pull. Additional to this case analysis, we note that there are five categories for consequences (being two of those related to the priority of the customer) that are accounted for 3.2.2. This section will cover the weighting of these categories. Transversal to all consequence estimation, the concepts of time-to-repair (TTR), and time-to-live (TTL) need to be clarified in this context. These metrics, along with the maximum pressure reached in a stall failure, are required for estimating the consequences.

Required metric: unavailability duration

To calculate TTR we account for the time it takes for the company to detect the failure and dispatch a team of technicians to repair it, which was estimated in 10 minutes. To this estimate we add the sum of the ideal travel time from the closest headquarters to the expected time lost in traffic. Finally, a repair time of five minutes, amounting for the time for the technician to change the functioning line, is added amounting to our whole TTR. Let δ_0^m be the ideal travel time, given by Google's Distance Matrix API and m_1 the auxiliary traffic multiplier. δ^m, the estimated total travel time is calculated by the following expression:

$$\delta^m = \delta_0^m \times \left(1 + \frac{\delta_0^{MAX} - \delta_0^m}{\delta_0^{MAX} - \delta_0^{MIN}} \times m_1\right) \tag{4.1}$$

It was found that, as headquarters are situated in city centers shorter trips have a bigger fraction of its travel-time spent in traffic. At rush hour, the estimates for the shorter and longest trips were $\delta^{MIN} = 2,38 \times \delta_0^{MIN}$ and $\delta^{MAX} = 1,07 \times \delta_0^{MAX}$. We then estimate $m_1 = 2,38 - 1,07$, completing the interpolation.

On the other hand, TTL amounts to the total time after a failure in which the network is still at proper functioning levels. The network is known to handle relative pressures between 1.3 and 6 bar. While the lower limit corresponds to the pressure below which supply is not guaranteed, the upper limit of 6 bar draws the line of where the flow of gas reaches unsafe levels, thus a stall failure may represent risk.

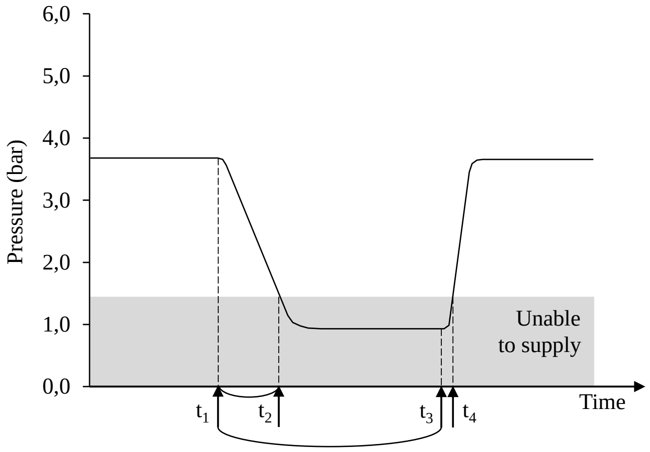


Figure 4.3: Supply failure pressure with time representation.

Figure 4.3 reflects these concepts. At t_1 a supply failure occurs, the pressure in the network starts lowering until in t_2 reaches reaches the critical value of 1.3 bar and the gas is failing to reach the customer. Although the failure was detectable from t_1, the detection, travel and repair time lasted until t_3. In t_3 the repair is finished and the pressure rises until in t_4 gas supply to the customer is reestablished.

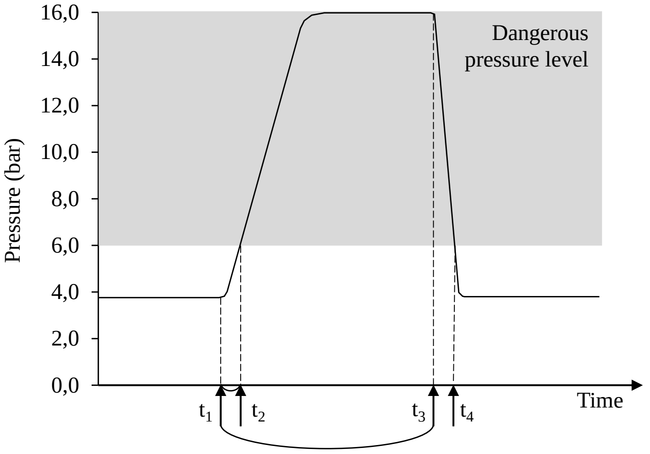


Figure 4.4: Stall failure pressure with time representation.

The same concepts are also represented in Figure 4.4. In this case pressure rises at t_1, and from t_2 on it is on unsafely high levels. Again, maintenance action to recover the equipment to a functional state endures until t_3 and pressure lowers until in t_4 it reaches tolerable levels.

For both these cases, the interval between t_1 and t_2, or the interval after the failure occurs and before it can represent an impact in the mentioned categories, is what we note as TTL. Similarly, TTR is the duration between t_1 and t_3, or the duration between the occurrence of the failure and the moment when the repairs are finished. For our impact calculation, we consider the interval between t_3 and t_4 as negligible. The duration of what, in the supply failure, would be an unavailability of the service can then be calculated by $t_3 - t_2$. This also represents the time at which the pressure is at dangerously high levels in a stall failure, yet we considered the maximum pressure reached in this period as the driver for consequences.

From this analysis we Figure that improving the detection, travel and repair time would be an efficient strategy, targeting both types of failures.

Required metric: maximum pressure calculation

Given the assumptions exposed in the previous section, for the the stall failure, we need to calculate at what moment the pressure hits 1.3 bar to calculate the TTL. Similarly, there is the need to know the maximum pressure reached in a stall failure. Let p_t be the absolute pressure at time t in Pa, m_0 is the initial mass of natural gas in the network in Kg, V_0 is the volume of the network in m^3 and ρ is the density of the gas in kg.m^{-3}, $\dot{V}$ is the volumetric flow rate which the clients expend in m^3.s^{-1}, R is the gas constant in J.(kg.K)$^{-1}$, T is the absolute temperature of the gas in K and Z is an adjustment coefficient based on the pressure and temperature. The pressure at a given time t, in seconds after the failure is given by:

$$p^r(t) = \frac{m_0^r - \frac{\dot{V}}{\rho}t}{V_0^r} RTZ \tag{4.2}$$

In the case of a supply failure, the equation is solved for t, at which $p(t) = 2.3$ bar of absolute pressure, or 1.3 bar of relative pressure. For the case of a stall failure, we calculate the pressure at t_3 to obtain the maximum pressure. The flow $\dot{V} = \dot{V}^{mr}$, in the case of a supply failure, being this the flow which the network r demands and the distribution network is unable to supply due to equipment m's failure. Similarly, in the case of a stall failure, $\dot{V} = \dot{v}^r - \dot{V}^{mr}_{MAX}$, with $\dot{V}^{mr}_{MAX}$ being the maximum flow that PRM m in network r can let through, and $\dot{v}^r$ is the minimum expected flow for network r. Note that a negative value of $\dot{V}$, means an inflow of gas and a subsequent increase in pressure.

Lost Sales

In the case of a failure that leads to the impossibility of supplying gas to the customers, the lost sales are calculated by multiplying the potential flow of gas with the time that the network is not being supplied. The flow of gas is estimated with the use of Synergee, a simulator capable of figuring which areas of the network would have pressure below the required minimum, and SYG, a simulator which can determine which clients are in that area and how much gas do they expend. For these simulations the maximum consumption of the previous year for the network was considered, adequate for a worst case scenario approach.

Synergee is also able to determine which PRM can fail and the supply still be compensated by the remaining stations in the network. For every network with ring configuration the scenarios of each supplying PRM failing was simulated. Three results can be classified in three cases: (1) the networks demand was fully compensated, (2) the network demand was partially compensated, (3) the network demand was fully unsatisfied.

The potential flow of gas not supplied on the first and third cases are of direct calculation. For the first, lost consumption is null. For the third one, all of the flow which that PRM was letting out is considered for lost sales. An additional simulation is required for the third case, for which SYG is used. From it we obtain the flow that would target the areas on which supply is cut, the individual consumption of each of those areas is then summed. This amounts for the flow of gas which will be accounted for in lost sales. We note that for the volume of unsold gas to be determined, this flow must be multiplied by the duration of the unavailability. Let $\dot{V}^{rm}$ be the flow which would not be supplied to network r because of equipment m failing, lost sales volume would be:

$$\theta^m_{1f} = (t_3 - t_2) \times \dot{V}^{rm} \tag{4.3}$$

Affected clients

If there is an unavailability, the clients it affects must be accounted for. As previously mentioned, with the combination of the company's simulators (Synergee and SYG), we can obtain which clients are affected. From these clients there was the need to make a distinction between regular clients, which are usually common households, and high-priority clients, which can be public services (schools, hospitals, police stations) or important production plants.

As the company's simulator is blind to this aspect, to determine from the clients affected which are high-priority, the data obtained from the simulator was crossed with the company's client records. Furthermore when, in ring network configurations, there were cases where the simulator could not determine which were the affected clients. An interpolation using the unavailable flow due to the breakdown of that PRM, and the total flow demanded by the network was used as an alternative. Let N^{mr}_t be the number of clients of type t in network r affected by a failure in equipment m, and N^r_t be the number of clients of type t in network r. The consequence in number of clients is given by:

$$\theta^m_{2f} = \begin{cases} N^{mr}_t & \text{, if data is available and } m \in r \\ N^r_t \times \frac{\dot{V}^{mr}}{\dot{V}^r} & \text{, if data is not available and } m \in r \\ 0 & \text{, otherwise.} \end{cases} \tag{4.4}$$

Material damages

In the case of pressure reaching critically high levels, given a stall failure, there is a risk that the pipes downstream the equipment will suffer from damages. We adjust the relation between probability of a pipe rupture and the maximum pressure reached due to the failure to a sigmoid curve. Let p^{mr}_{MAX} be the maximum pressure reached in network r due to a stall failure in equipment m, and P^{r}_{MAX} the maximum operating pressure for the network. Then, the probability that a rupture due to this failure $P(\varepsilon^{mr})$ is given by:

$$P(\varepsilon^{mr}) = \begin{cases} \{1+\exp[-m_2(p^{mr}_{MAX} - \frac{4P^{r}_{MAX}}{3})]\}^{-1} & \text{, if } m \in r \\ 0 & \text{, otherwise} \end{cases} \tag{4.5}$$

The model was validated with the company's maintenance experts and is based on two assumptions: (1) At the strongest pipe's maximum operating pressure, there is a chance of one in a thousand of occurring a rupture in it. (2) At four thirds of the maximum operating pressure, there is a fifty percent chance of damages to occur. The maximum operating pressure was calculated by an experimentally validated formula from GSP PE Pipe Systems for polyethylene (PE) piping, which relates it to the the ratio between the pipe's thickness and its diameter. Assumption (1) is used to calculate the auxiliary multiplier m_2.

It was then realized that pipes of larger diameter usually present a smaller thickness to diameter ratio. It is reasonable to assume that the rupture will occur wherever the piping is the weakest. Therefore, for a given network, the rupture will occur in the PE pipes with the largest nominal diameter. This conclusion brought to light that stall failure consequences can be mitigated with the use of an intentionally weaker piece of piping in a non-populated area.

The cost of a rupture is estimated by the cost of replacing 100m of the damaged piping. Moreover, if the pressure surpasses 6 bar, the cost of a leak search through the extension of the network is added to this value. Let K^{r}_{pipe} be the substitution cost per hundred meters of the weakest pipe in network r, K_{leak} the cost of leak search per kilometers, and d^{r} the total distance covered by network r, the consequences, in monetary units are given by:

$$\theta^{m}_{4f} = \begin{cases} P(\varepsilon^{mr}) \times K^{r}_{pipe} + d^{r} \times K_{leak} & \text{, if } p^{mr}_{MAX} > 6 \text{ bar} \\ P(\varepsilon^{mr}) \times K^{r}_{pipe} & \text{, if } p^{mr}_{MAX} \leq 6 \text{ bar} \end{cases} \tag{4.6}$$

Fatalities

Consistent with the worst case scenario approach, we consider that every time that there is a rupture in the pipes, a vapor-cloud explosion (VCE) can occur. This phenomenon occurs when, because of a fracture or hole in the piping, flammable gas is released into the atmosphere (methane, in this case) and the wind is unable to disperse it. A mixture of natural gas in air can be explosive when methane represents between 5% and 15% of the total volume of the mixture. Additionally, for other ranges of concentration, the methane is combustible.

If the vapor cloud is ignited, an explosion will affect a large area around it. Though the impact is not homogeneous throughout the whole range of the explosion, this analysis does not distinguish between severe burns and fatalities. Additionally, the radius is estimated based on an experimentally justified expression. The expression aims to calculate a conservative setback distance S^m, for each piece of equipment m based on thermal radiation levels, given the unpredictability of wind conditions and natural gas dispersion. The setback distance, from the center of the explosion, is related with the network's pressure and pipe diameter. We considered the auxiliary variable $m_3 = 4$, which means S^m is an estimate of at what radius the explosions thermal radiation would be equal to four times the solar irradiation. Let d^r be the diameter of the weakest piping in network r, and p^{mr}_{MAX} the maximum pressure in network r caused by a stall failure in equipment m, the setback distance S^m is given by (Rhodes, 2010):

$$S^m = \frac{17.71}{\sqrt[2]{m_3}} \times d^r \times (p^{mr}_{MAX})^{\frac{1}{4}} \tag{4.7}$$

To obtain the expected number of fatalities, the radius is then multiplied by the population density of the region concerned and by the probability of the rupture to occur. Pordata was the source for population density data. Let ρ^m_{pop} be the population density for the region where equipment m is installed, the expected number of fatalities is given by:

$$\theta^m_{5f} = P(\varepsilon^{mr}) \times S^m \times \rho^m_{pop} \tag{4.8}$$

Weighting

Having completed estimating the consequences, these must be weighted so that they can be compared. With this aim AHP, subject to some modifications, was applied to the results of a discussion with the company. 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:

Designation	(c)	r_{c1}	r_{c2}	r_{c3}	r_{c4}	r_{c5}	r_{c6}
Lost sales	(1)	5	3	5	5	5	4
Clients (regular)	(2)	4	2	4	4	4	3
Clients (high-priority)	(3)	3	4	2	2	3	2
Material damages	(4)	2	5	3	3	2	5
Fatalities	(5)	1	1	1	1	1	1

The priority matrix is then calculated. Let w'_c be the the non-normalized weight for category c. Given the way priorities were calculated, with any expert e', the normalized weights w_c would be the same, thus we can calculate the relative weights as:

$$w'_c = \frac{1}{\sum_e r_{ce}} \tag{4.9}$$

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

$$w_c = \frac{w'_c}{\sum_{i=1}^{C} w'_i} \tag{4.10}$$

With this method we obtained the set of weights $w_c = \{0.10, 0.13, 0.17, 0.14, 0.46\}$, for our categories. By applying the weights to the normalized values, and considering the material damages are presented in monetary units (u.m.), for analytical purposes, we can obtain the values of other categories relative to this unit. The results are that a cubic meter (m^3) of gas in lost sales corresponds to 7.16 u.m., taking into account that this value must reflect the variable cost of a supply failure. The fact that supply was ceased to a regular client alone is estimated at 1.13 u.m. This value rises to 1 096.74 u.m. when high-priority clients are the matter. Lastly an expected fatality is estimated at 4 186.84 u.m., being the clearly most valued criteria.

Results of the risk analysis

Continuing application of the method presented in the previous chapter, we calculate our relative measure of risk. Table 4.4 presents twenty pieces of equipment with the extreme values, in terms risk. As the age of the equipment was known and we aim to evaluate the company's current situation, probabilities were calculated as exemplified in the previous chapter, only using the hazard function instead of the probability density one.

An example for the application of the weighting and risk calculation can be made from these results. We can observe in the table that no fatalities nor material damages are expected from supply failures. Likewise, stall failures are not expected to affect the clients supplied nor their consumption.

As notable cases from the table, we have equipment $A04$, which has one outdated FTO regulator in each line. Moreover, the equipment supplies a major city, making it so that the consequences of a supply failure in this equipment are the highest of all the company's PRM. Another remarkable case is PRM $A06$, which is in a city center and has potentially high impact stall failures. Even so, the risk for this equipment is outstandingly low. This is due to the MON regulators that compose this equipment, which have an exceedingly low probability of failure. Moreover, analyzing the results for PRM $B4'$, we see that even though this PRM is the oldest with FTO technology it has the lowest risk. Though its probability of failure is high, failures in this piece of equipment have no impact. Although it is not evident within the results, the fact that this PRM is placed near the headquarters is the cause for the absence of consequences. Failures in this piece of equipment are dealt with before having an impact in any of the analyzed categories.

From our analysis of Table 4.4 we perceive the most relevant factors to risk. Impacts come in all categories, and are dependent of many factors and thus our measure of consequences must be considered. On the other hand, technology can be used as a proxy for failure frequency. From the reliability analysis we concluded that the probability of failure depends on the sub-equipment's age and technology. The former loses its relevance with repairs and substitutions, leaving technology as the most decisive factor.

Table 4.4: Risk calculation example.

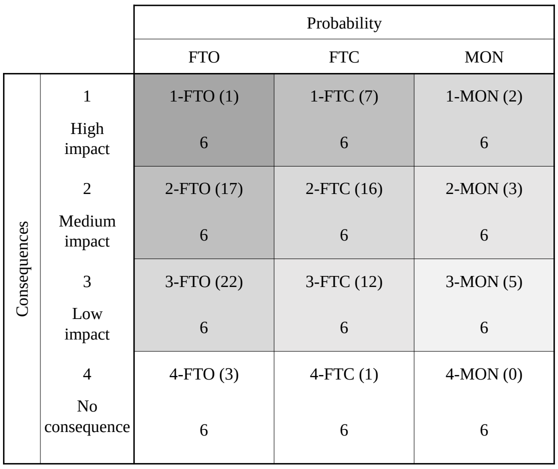
m	R^m	$P(\Omega^m_{supply})$	$P(\Omega^m_{supply})$	Θ^m_{supply}	Θ^m_{stall}	$\theta^m_{1supply}$ (m^3)	$\theta^m_{2supply}$	$\theta^m_{3supply}$	$\theta^m_{4supply}$ (€)	$\theta^m_{5supply}$	θ^m_{1stall} (m^3)	θ^m_{2stall}	θ^m_{3stall}	θ^m_{4stall} (€)	θ^m_{5stall}
A04	0,08	0,17	0,15	0,33	0,14	1916,67	21615,00	26,00	0,00	0,00	0,00	0,00	0,00	23890,35	3,10
B10	0,05	0,17	0,15	0,03	0,29	148,20	1698,00	2,00	0,00	0,00	0,00	0,00	0,00	7180,73	13,00
D08	0,04	0,15	0,13	0,06	0,20	1485,40	599,00	1,00	0,00	0,00	0,00	0,00	0,00	10075,15	8,27
D03	0,04	0,15	0,13	0,00	0,27	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	7838,59	11,97
D06	0,04	0,15	0,13	0,00	0,27	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	7838,59	11,97
E07	0,04	0,17	0,15	0,04	0,19	957,45	727,00	0,00	0,00	0,00	0,00	0,00	0,00	6455,11	8,27
E06	0,03	0,15	0,13	0,05	0,19	14,43	1924,00	8,00	0,00	0,00	0,00	0,00	0,00	6688,71	8,17
D12	0,03	0,15	0,13	0,05	0,19	890,70	830,00	2,00	0,00	0,00	0,00	0,00	0,00	6739,87	8,27
E12	0,03	0,15	0,13	0,03	0,19	227,94	751,00	4,00	0,00	0,00	0,00	0,00	0,00	6185,75	8,17
E10	0,03	0,17	0,15	0,00	0,19	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	6982,07	8,27
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
A06	0,00	0,00	0,00	0,00	0,48	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	6698,19	22,35
A03	0,00	0,00	0,00	0,02	0,31	354,17	17,00	1,00	0,00	0,00	0,00	0,00	0,00	5516,57	14,31
F04	0,00	0,00	0,00	0,00	0,07	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	18806,19	0,56
F05	0,00	0,00	0,00	0,00	0,27	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	5888,15	12,33
J02	0,00	0,00	0,00	0,00	0,06	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	7715,35	1,50
B06	0,00	0,00	0,00	0,00	0,15	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	40744,60	0,52
B03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
B05	0,00	0,01	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
B11	0,00	0,17	0,15	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
B4’	0,00	0,18	0,17	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

4.3 Construction of maintenance policies

4.3.1 Risk matrix

To establish the inspection policies, in a comprehensible and easily implementable way, the use of a risk matrix with division in squares was agreed upon with the company. For the columns, instead of probability, the weakest regulator technology in the station was taken into account. This translates that the MTTF expectation for FTO regulators is lower than FTC and MON ones. When maintenance is properly executed and the overall condition of the station is maintained, the technology of the regulator is the most relevant driver which can change the frequency of failures. The lines in the matrix, on the other hand reflect the consequence level. The interval between the lowest and highest expected normalized consequences was divided in three. To this we added the matrix divisions in which failures in the equipment pieces have no consequences. These make up the four lines of the matrix considered in the analysis.

Figure 4.5 is a representation of the matrix used. Inside the quadrant there is its designation, followed by the number of PRM which place there in terms of risk (between parenthesis). The number below this designation corresponds to the time between inspections for that quadrant, in months. The matrix, as is, reflects the company's current policy. Note that the highest risk quadrant is at the top left instead of the traditional top right. This change makes it the first quadrant to be instinctively read first, which we found more adequate given its importance.



		Probability		
		FTO	FTC	MON
Consequences	1 High impact	1-FTO (1) 6	1-FTC (7) 6	1-MON (2) 6
	2 Medium impact	2-FTO (17) 6	2-FTC (16) 6	2-MON (3) 6
	3 Low impact	3-FTO (22) 6	3-FTC (12) 6	3-MON (5) 6
	4 No consequence	4-FTO (3) 6	4-FTC (1) 6	4-MON (0) 6

Figure 4.5: Risk matrix with current policy.

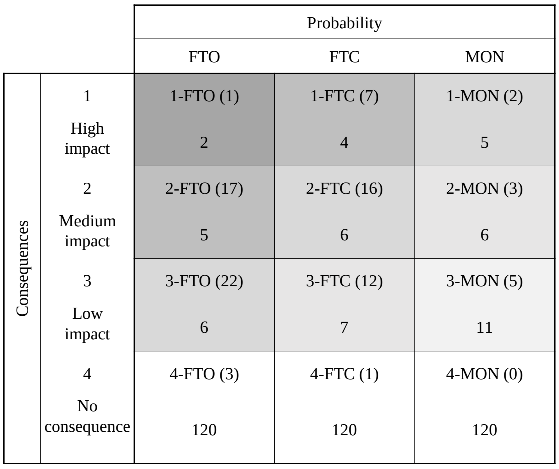
4.3.2 Policy elaboration

There were some constraints to policy elaboration, given this is a real case scenario. As a hard constraint, the maximum time between inspections is 120 months. As a soft constraint, the time between inspections was preferred as a multiple of 6, as it makes the policies less prone to disorder.

For the first policy tested, we aimed to reduce risk while maintaining costs. Hence as the number of planned inspections was maintained. We then proceeded to procure a policy which would minimize cost, while maintaining the expected consequences. Note that for these policies, our periodicity soft constraint was not considered. After we elaborated these policies, we started trading-off risk for cost reductions, by extensively testing the impact of changing the periodicity in each quadrant in both these criteria.

Maintaining cost

To obtain this policy, we aimed to maintain the number of planned inspections while minimizing the overall expected consequences. In this case we ignored the preference for periods multiple of 6, but fully considered that the period between inspections for an equipment must be under or equal to 120 months. This problem was solved and then adjusted so that the time between inspections Δ^m, for each equipment piece m, is an integer value. The matrix in Figure 4.6 presents the results. Overall, the inspections focused on the quadrants with the most risk per PRM. Likewise, the quadrants in which failures have no consequences, have the maximum time between inspections allowed.

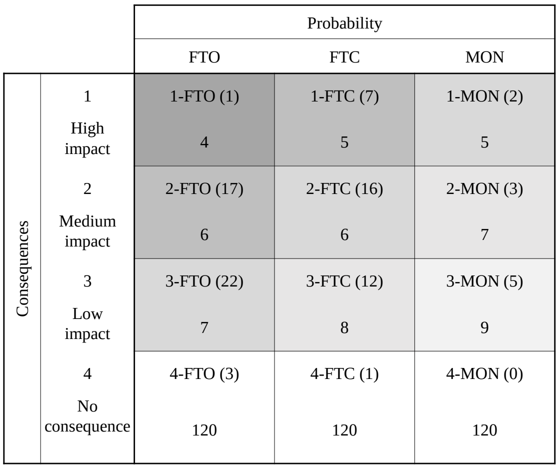


		Probability		
		FTO	FTC	MON
Consequences	1 High impact	1-FTO (1) 2	1-FTC (7) 4	1-MON (2) 5
	2 Medium impact	2-FTO (17) 5	2-FTC (16) 6	2-MON (3) 6
	3 Low impact	3-FTO (22) 6	3-FTC (12) 7	3-MON (5) 11
	4 No consequence	4-FTO (3) 120	4-FTC (1) 120	4-MON (0) 120

Figure 4.6: Risk matrix with policy which maintains cost.

Maintaining risk

For this policy, our aim was to maintain the overall expected consequences, while minimizing the number of inspections. The soft constraint referring to inspection periods multiple of 6 was also ignored, while the hard one, relative to the maximum time between inspections was considered. Similarly to the previous policy, this problem was solved and then adjusted so that Δ^m is an integer value. With the resulting policy (Figure 4.7), we managed to reduce the number of inspections in around 9% when compared to the initial one, while maintaining the expected consequences.

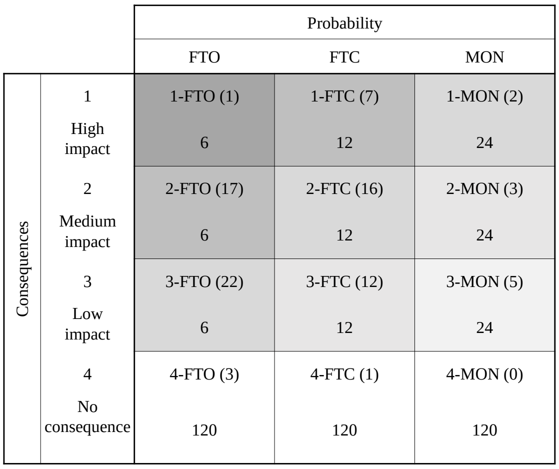


		Probability		
		FTO	FTC	MON
Consequences	1 High impact	1-FTO (1) 4	1-FTC (7) 5	1-MON (2) 5
	2 Medium impact	2-FTO (17) 6	2-FTC (16) 6	2-MON (3) 7
	3 Low impact	3-FTO (22) 7	3-FTC (12) 8	3-MON (5) 9
	4 No consequence	4-FTO (3) 120	4-FTC (1) 120	4-MON (0) 120

Figure 4.7: Risk matrix with policy which maintains risk.

Trading-off risk

In this case we used our multiple-criteria method to define the policy, by using the analysis present in Section 3.3.2. We defined a threshold in consequence increase, and choose the periodicity as the multiple of six just below it. This step was repeated for each quadrant, so that it would lead us to the policy presented in Figure 4.8. Although we reduce the number of planned inspections by around 32%, a considerable increase in risk is expected.



		Probability		
		FTO	FTC	MON
Consequences	1 High impact	1-FTO (1) 6	1-FTC (7) 12	1-MON (2) 24
	2 Medium impact	2-FTO (17) 6	2-FTC (16) 12	2-MON (3) 24
	3 Low impact	3-FTO (22) 6	3-FTC (12) 12	3-MON (5) 24
	4 No consequence	4-FTO (3) 120	4-FTC (1) 120	4-MON (0) 120

Figure 4.8: Risk matrix, with policy which trades off risk.

4.3.3 Simulation

The three policies considered for this case study were simulated for a span of τ years. To reduce dispersion in the results, each policy is simulated S times, with the results being the average of these S

simulations.

Input

This simulation has the assumptions that p fraction of the faults is undetectable. Additionally, in the beginning of each simulation, every component starts at is best condition, with 100% health. Furthermore, being the impact of time in the equipment uncertain, the as-good-as new assumption was taken for each sub-component, with no equipment deterioration. With the company's data we can obtain the mean delay-time $1/\gamma$ months. We considered an average cost of materials K^s per intervention for any given sub-equipment type s (substitution or repair of a sub-component) and the cost of an inspection calculated using K_{car} being the average cost per kilometer for the use of a commercial van, d^m the distance of a trip from the closest headquarters to the equipment m and back, and K_{man} is the cost of two men through five hours, thus the labor cost for an inspection. Table 4.5 summarizes the values used in our simulation.

Table 4.5: Input values for the simulator.

Input	Value	Unit
τ	240	months
S	500	
p	0,01	
$P(U)$	0,05	
K^s_{sub}	175	€
K^s_{rep}	175	€
$1/\gamma$	15,08	months
K_{veh}	0,41	€/km
K_{man}	225	€

The total cost of inspecting equipment m without any intervention, K^m_{ins} is given by:

$$K^m_{ins} = 2 \times K_{veh} \times d^m + K_{man} \tag{4.11}$$

Note that when an intervention is made, its cost (K^s_{rep} case it is a repair or K^s_{sub} case it is a substitution) is added to the cost of an inspection.

Output

From the simulation, as output, we know how many inspections, repairs, and substitutions were issued and on which equipment. By multiplying these indicators with the costs we have estimated we can obtain the economic indicators for our analysis. Additionally we can know how many failures, of which type occurred and on what piece of equipment they occurred. By multiplying the expected consequences, for each category, for each PRM, with the number of failures, by mode, in each PRM, we obtain the consequences for that simulated period. Finally, we can analyze the failure data obtained to grasp maintenance indicators, such as MTBF.

In a more thorough way, here are enumerated the economic indicators which we present after simulating a policy:

- Inspection spending;
- Repair costs;
- Preventive maintenance costs;
- Substitution costs, for each type of sub-equipment;
- Corrective maintenance costs;
- Total cost of maintenance.

As for the maintenance indicators, we found relevant to discriminate the following measures:

- Supply failures (total);
- Stall failures (total);
- Supply failures (with consequences);
- Stall failures (with consequences);
- Number of inspections;
- Number of substitutions;
- Number of repairs;
- Probability of occurring at least an equipment failure in 20 years.
- Mean-time-between-failures (everything).
- Mean-time-between-failures (with consequences).

Furthermore, for our consequence measures, we found adequate to present the following results:

- Supply interruption time;
- Lost Sales;
- Affected clients (regular);
- Affected clients (high-priority);
- Material damages;
- Fatalities;
- Relative consequence measure.

Finally, we were required by the company to calculate the following technical service indicators:

- Mean number of yearly interruptions;
- Mean interruption duration, per client, per year;
- Mean interruption duration.

Although these indicators can be useful, given the situation, any manager would reach the conclusion that they are in a excessive number. Taking this observation into account, we considered the choice of a few key performance indicators (KPI). We consider essential knowing the total cost of maintenance, in addition to what is spent in preventive and corrective maintenance. The MTBF, is an easy to interpret maintenance indicator and, specially when considering only failures which have consequences, it can transparently demonstrate the quality of the maintenance policy. Lastly, and to aid the comparison between policies, our relative measure of consequences as can be an exceedingly useful KPI.

Results of the simulation

In this section, we present the results of our policies, according to the simulator. We tested the three elaborated policies, versus the initial one. Figure 4.9 presents the maintenance costs for each policy. White refers to the preventive maintenance costs, and dark gray refers to the corrective maintenance costs. The change in total cost with each policy is also present in the graph. Figure 4.10 shows the mean-time between any failure (to the left) and the the mean-time between failures with consequences (to the right), for the considered policies. Figure 4.11 presents our relative measure of consequences, for each policy. Similarly, in Figure 4.9, the comparison with the initial policy was also calculated for the graph. Note that these values are totals for the network.

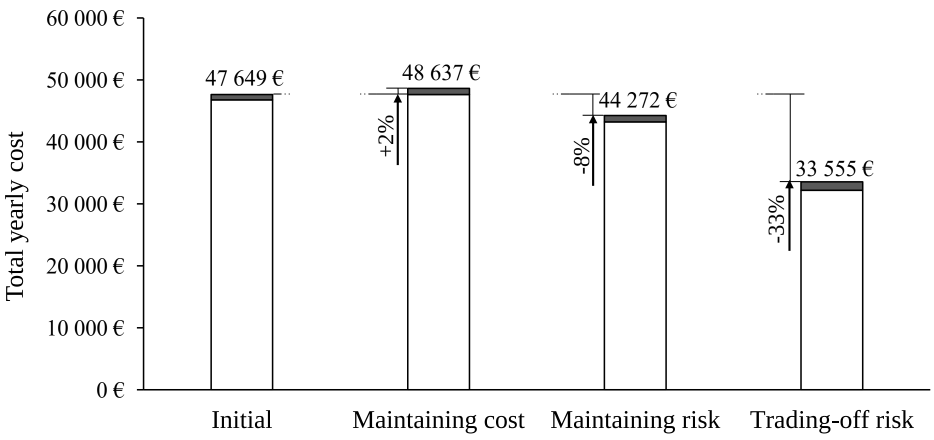


Figure 4.9: Economic performance indicators, for the tested policies.

In Figure 4.9 we can observe that corrective maintenance costs always represent a very small fraction of total costs. It must be noted that corrective maintenance costs only include the costs of the maintenance action, as the consequences are accounted for in the relative measure. There is a negligible increase in total costs for the policy in which costs are maintained, an 8% decrease in yearly costs for the policy maintaining risk and the last policy that trades-off risk for a 33% yearly cost reduction.

Table 4.6: Economic performance indicator values.

Economic Performance Indicators	Unit	Initial	Maintaining Cost	Maintaining Risk	Trading-off Risk
Inspection costs	€.year^{-1}	42 486	43 469	39 116	28 622
Repair costs	€.year^{-1}	4 288	4 191	4 111	3 562
Preventive maintenance costs	€.year^{-1}	46 774	47 660	43 228	32 183
Fail-to-open substitution costs	€.year^{-1}	356	385	419	529
Fail-to-close substitution costs	€.year^{-1}	224	267	275	394
Shut-off valve substitution costs	€.year^{-1}	295	324	350	448
Corrective maintenance costs	€.year^{-1}	875	976	1045	1372
Total maintenance costs	€.year^{-1}	47 649	48 637	44 272	33 555

For a more in-depth analysis Table 4.6 presents the economic indicators discriminated. The exaggerated representativity of the inspection is clear from the table. It can also be concluded that this is the item targeted for cost reductions in our policy elaboration, as the sum of the corrective maintenance costs with the repair costs exhibits little variation throughout the policies.

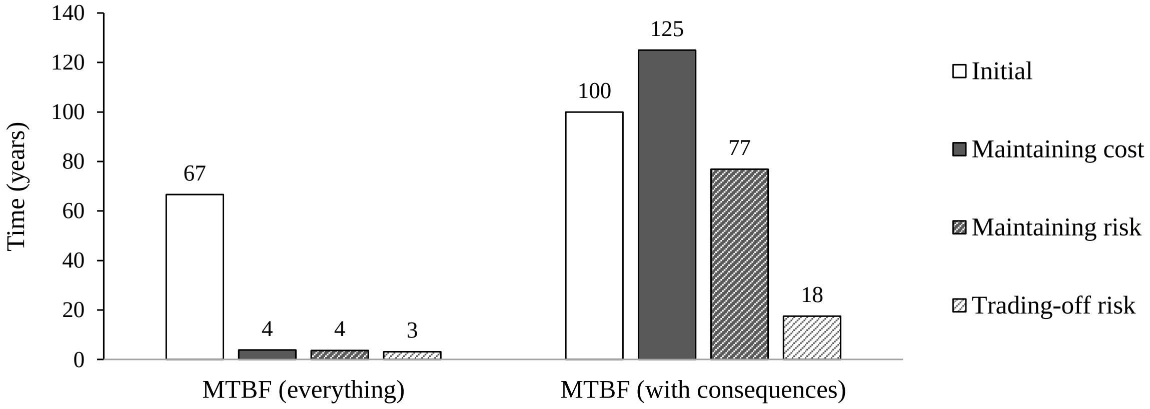


Figure 4.10: Maintenance performance indicators, for the tested policies.

From Figure 4.10 we ascertain that all of our policies do not focus resources on equipment for which failures have no consequences, hence the MTBF considering every failure assume such low values. Additionally we managed a 25% increase in MTBF for failures with consequences, without a significant increase in costs. This MTTF lowers when we develop a policy when maintaining risk, with further decrease in the policy on which we trade costs for risk. We have to note that although there is a large decrease in MTBF for this last policy, the value presented states that, on average, a relevant failure will occur every eighteen years.

Table 4.7: Maintenance performance indicator values.

Maintenance Performance Indicators	Unit	Initial	Maintaining Cost	Maintaining Risk	Trading-off Risk
Supply failures	year^{-1}	0,0	0,1	0,1	0,2
Stall failures	year^{-1}	0,0	0,1	0,1	0,1
Supply failures with consequences	year^{-1}	0,0	0,0	0,0	0,0
Stall failures with consequences	year^{-1}	0,0	0,0	0,0	0,0
Inspections	year^{-1}	4426	4522	4068	2965
Substitutions	year^{-1}	126	144	153	201
Repairs	year^{-1}	627	609	600	518
Probability of consequences in 20 years		18,2%	16,2%	20,0%	70,0%
MTBF	years	66,67	3,83	3,72	3,15
MTBF with consequences	years	100,00	125,00	76,92	17,54

Table 4.7 presents the maintenance performance indicators in detail. Beyond the contents of this table, the simulator allows to see in which equipment how many maintenance events occurred. The probability of a failure with consequences in 20 years was an indicator added to make these values more perceivable for maintenance technicians. We see that with the exception of when we trade-off risk, it is improbable that any failure with which has any impact will happen in the next 20 years. This brings to light the degree of maintenance over-sizing which is inherent to the initial policy. From the data on the table we can also conjecture that the cost reductions come from the decrease in the number of inspections.

Figure 4.11 shows our relative measure of consequences for the policies tested. It should be considered that, because of the low frequency of equipment failures which these policies allow, the indicator is considerably volatile. This being said, a 63% reduction in this indicator was possible while maintaining costs, a negligible difference is present when maintaining risk, and the expected consequences amount to more than trice the present value when the policy which trades of risk is applied.

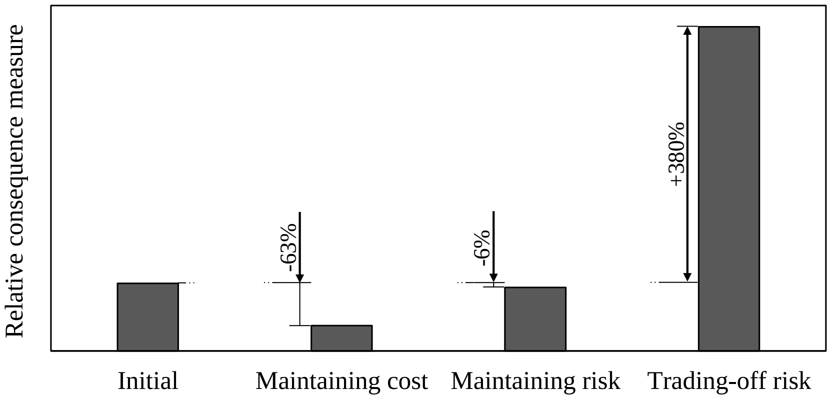


Figure 4.11: Consequence indicator, for the tested policies.

In Table 4.8 we present our indicators for all consequence categories, with the addition of the yearly service interruption time. By analyzing these values, we can conclude that the new policies manage to avoid supply failures which can affect a large number of clients. Likewise, stall failures with high numbers of fatalities are avoided, regardless of the material damages caused.

Table 4.8: Consequence indicator values.

Consequence Measures	Unit	Initial	Maintaining Cost	Maintaining Risk	Trading-off Risk
Service interruption time	min.year^{-1}	0,2	0,8	0,8	1,7
Lost sales	m^3.year^{-1}	9,7	0,7	0,2	17,6
Affected clients (regular)	year^{-1}	69,1	8,3	8,7	67,1
Affected clients (high-priority)	year^{-1}	0,1	0,0	0,0	0,1
Material damages	€.year^{-1}	26,8	36,7	87,0	423,3
Fatalities	year^{-1}	0,0	0,0	0,1	0,3
Consequences	year^{-1}	0,002	0,001	0,002	0,008

As resulted from the simulation, the technical service indicators required by the company are presented in Table 4.9. According to standards defined by the regulating entity the mean interruption duration must not exceed 300 minutes. The company fulfills these standards by a large margin. Although limits for the other indicators are not defined, the regulating entity recommends that these should be controlled.

Table 4.9: Technical service indicator values.

Technical Service Indicators	Unit	Initial	Maintaining Cost	Maintaining Risk	Trading-off Risk
Mean interruptions per client	(client.year)$^{-1}$	2,1E-09	1,7E-09	2,6E-09	1,2E-08
Mean interruption duration per client	min.client^{-1}	1,1E-05	3,3E-05	3,7E-05	5,3E-05
Mean interruption duration	min	3,75	10,73	12,04	17,40

Taking the indicators into account, we can perceive a reduction of 8% of the yearly costs, without any negative variation in the expected consequences. Furthermore, without any considerable increase in maintenance spending, we can see a fair improvement in the MTBF with consequences, and a strong decrease in the expected consequences. From these observations 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 previous policies are too much conservative. This way it can bring sizable savings, with an MTBF with consequences which seem acceptable.

Chapter 5

Conclusions and future work

Risk-based maintenance management is a broad technique which, to be applied in a quantitative way, must be subject to many adaptations. In this dissertation a methodology to facilitate the implementation of quantitative methods to this maintenance management strategy was exposed. Additionally, we expect that an adequate implementation of our method brings light to excessive preventive maintenance costs, and results in the necessary policies to effectively deal with this problem. Furthermore, we demonstrate procedures to deal with the steps of a risk analysis, with particular focus in the PRM.

By collaborating with of a Portuguese gas distributor, a solution was developed to justifiably reform maintenance into a safer and less costly practice. An extensive risk analysis and a simulator were developed for this end. Maintenance policies were developed and tested against the company's current practices. This showed that the current practices were inefficient, as it was possible to improve risk and cost levels, with little to no trade-off.

The developed approach fully covers an application of the risk-based maintenance to the PRM station. It must be noted that adaptations must be made such that it can be applied to different kinds of equipment. From our analysis we consider that, for the specific case of the regulator, although the strategy developed fitted in this situation, condition-monitoring would be an adequate complement. Although, no controllable parameter was found for this action, the possibility of measuring the ratio between the flow and how much the regulator is open, thus identifying the behavior which precedes stall failures, is to be tested.

Furthermore, the lack of data is an aspect that can influence the results of this dissertation. Actually, this is the most aggravated source of uncertainty in the whole analysis. Although it is expected for the elicitation process to have resulted in a conservative projection of sub-equipment durability, one of the initial objectives of this analysis was to take full use of this property. To further improve the case study results, the estimates must be fed with maintenance data, thus increasing the confidence in the obtained values. Van Noortwijk et al. (1992) exposes a possible method to add new data to the model. Specifically in this company's case, lack of trust in the information system and decentralized reports are problems to be tackled for the proper registry of maintenance data.

In additional developments, condition-monitoring is to be tackled along with information system redesign. Inspection represents an exaggerated portion of the maintenance costs, and these are the adequate tools to deal with this aspect. Additional hidden improvements can be materialized with an adequate information system for maintenance management, such as operational efficiency increases and better costing. Extending maintenance policy reformulation to other pieces of equipment is a possibility for which different maintenance strategies must be considered, depending on how they fit the equipment.

The unique nature of the failure modes, for the sub-equipment considered, can lead to particular and complex expressions. This aspect is commendable for further research, as different equipment should result in different expressions. Another underdeveloped element to consider is the estimation of consequences. The calculations can greatly vary, depending on the assumptions. Additionally the trade-off between applicability and correctness is ubiquitous to this element, which can lead to experimentally obtained expressions to be chosen over theoretically justified alternatives.

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