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INTRODUCING A DIMENSIONALITY REDUCTION APPROACH FOR DECOMMISSIONING OF OIL AND GAS INSTALLATIONS

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DISSERTAÇÃO SUBMETIDA AO CORPO DOCENTE DO INSTITUTO ALBERTO LUIZ COIMBRA DE PÓS-GRADUAÇÃO E PESQUISA DE ENGENHARIA (COPPE) DA UNIVERSIDADE FEDERAL DO RIO DE JANEIRO COMO PARTE DOS REQUISITOS NECESSÁRIOS PARA A OBTENÇÃO DO GRAU DE MESTRE EM CIÊNCIAS EM ENGENHARIA DE PRODUÇÃO.

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INTRODUZINDO UMA ABORDAGEM DE REDUÇÃO DA DIMENSÃO PARA DESCOMISSIONAMENTO DE INSTALAÇÕES DE ÓLEO E GÁS

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Programa: Engenharia de Produção

Problemas de descomissionamento na indústria de óleo e gás demandam, com frequência, processos de tomada de decisões robustos, que podem requisitar um grande número de critérios já que consideram os interesses, muitas vezes conflitantes, dos *stakeholders*. Além disso, cada critério deve ser avaliado com relação a cada equipamento para cada alternativa disponível de descomissionamento. Consequentemente, é provável que campos complexos de exploração de óleo e gás, compostos por um grande número de equipamentos, requeiram estudos de descomissionamento prolongados. Para contornar esse problema, este trabalho propôs a aplicação de métodos de aprendizado de máquinas de classificação para identificação de um número reduzido de critérios relevantes com respeito à escolha da alternativa de descomissionamento. O intuito foi desenvolver um método que, de posse das características dos equipamentos e de um número reduzido de avaliações de critérios, identifique a alternativa que emergiria de uma análise completa. Para validar a abordagem sugerida, um banco de dados foi composto baseado em dados reais de dutos submarinos através do método *bootstrap*. Dessa forma, basta avaliar os critérios mais relevantes para todos os equipamentos não pertencentes ao conjunto de treinamento, reduzindo assim tanto o custo quanto a duração do processo. Os resultados numéricos sugerem que o método proposto pode trazer benefícios significativos em ambos os aspectos.

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Decommissioning problems within the oil and gas industry often demand rather involved decision making processes, which may give rise to a large number of criteria since it considers the usually conflicting interests of multiple stakeholders. Moreover, each criterion must be evaluated in connection with each piece of equipment for each available decommissioning alternative. Hence, complex oil and gas fields comprised of a very large number of installations are likely to set up prolonged decommissioning studies. To circumvent this problem, this work proposed the application of feature selection and machine learning supervised techniques to simplify the process. The rationale is to make use of a training set to identify a reduced subset of criteria with significant impact on the selection of the decommissioning alternative. To validate the proposed approach, a dataset was composed based on real-world data from actual sub-sea pipelines through bootstrap techniques. By doing so, one only needs to assess the most significant criteria for all installations without the training set, thus reducing both cost and duration of the decommissioning study as a whole. Our numerical results suggest that the proposed method may induce significant savings in both aspects.

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Chapter 1

Introduction

Decommissioning, that is managing the end-of-life of a service or a installation, exists in several economical sectors, such as nuclear, mining, transportation and oil and gas (e.g., FOWLER *et al.*, 2014; NÓBREGA *et al.*, 2008; SMYTH *et al.*, 2015; SUH *et al.*, 2018). These are undoubtedly very complex problems, since they directly affect environmental and socio-economic issues and may impose risks for workers and the overall population. Even though decommissioning processes may differ depending upon the economic sector, there certainly exist similarities and cross-industry insights that can be exploited. For example, both the nuclear and the oil & gas sector need rigorous regulation, involve considerable amounts of financial resources and pose human and environmental risks (ARUP, 2015)

In particular, the end-of-life of oil & gas installation has become a worldwide concern. In fact, many countries that have a significant production have recently been discussing regulations and elaborating guidelines on the issue (DMIRS, 2017; MEI, 2018; OIL & GAS UK, 2015; ROUSE *et al.*, 2018). Other countries with a more recent oil & gas industry, such as Australia (BULL e LOVE, 2019) and Brazil, can take advantage of experiences already acquired. The sector presented some difficulties in the past that influence it to be more careful with regard to future decision-making. For example, one of the largest oil companies in the world experienced some problems with reference to the decommissioning of the Brent Spar platform, UK, in the mid-1990s (BULL e LOVE, 2019; RICE e OWEN, 1999).

Their fist decommissioning option was to sink the structure at the sea but they were stopped by the society, Greenpeace, and European governments over environmental concerns. Almost three years after this fist attempt, they finally found an acceptable decommissioning alternative that was to re-use the structure. One lesson to be learned from this experience is not to underestimate the importance of considering the opinion of the local community and of the whole set of stakeholders. Another lesson concerns the importance of keeping effective communication channels with the stakeholders. Overlooking such issues can reportedly result in severe consequences for the company's public image and finances.

Among the diversity of structures that are part of the offshore system, sub-sea installations demand a special attention due to both their sensitive nature and the logistic challenges associated to the decommissioning process. These installations comprise all pieces of equipment and facilities accommodated in the seabed that allow the control and operation of the production system, such as pipelines, flowlines, risers and manifold (PRADO, 2015). In addition, decommissioning is becoming more complex as time elapses due to the increased number of pieces of equipment operating in deep waters. Only in the North Sea there are more than 45,000 kilometres of pipelines, umbilicals and cables installed (OIL & GAS UK, 2013), all of which will require decommissioning at some point in the future (ARUP, 2015). Introduced in 1966 (OIL & GAS UK, 2013), sub-sea structures have different compositions and require distinct decommissioning activities and machinery. Initially, possible end-of-life measures include in-situ abandonment and total or partial removal. Furthermore, total or partial removal can be achieved by means of different alternatives, which depend on the available removal techniques. Given the distinct impacts and a possibly large number of criteria to consider, selecting a decommissioning alternative becomes a rather challenging problem.

To address such a problem, one must account for the great variety of technologies and materials available, as well as the distinct environmental and socio-economic conditions of each locality. Regarding environmental aspects, the hard substrate of a submerged jacket usually provides reef habitat for several flora and fauna species (BULL e LOVE, 2019). In addition, each of the available techniques used for removing installations may have different effects on marine animals, such as producing stress and loud sounds. Morevoer, considering socio-economic aspects, the decommissioning options might affect commercial and recreational fisheries, since offshore structures can provide a safe harbour for different species while also preventing access to some areas (KRUSE *et al.*, 2015). Furthermore, the analysis should consider safety issues, such as collisions and occupational hazards (BABALEYE e KURT, 2019). Each alternative should also consider technical feasibility, including possible crossings between pipelines and mobilisation of specialised vessels. Lastly, one should not forget to evaluate the costs associated with each of the actions required. Please observe that these are just some examples and the debates regarding all possible impacts can be extensive. All of the environmental, social, economical, safety and technical aspects interact with each other, often giving rise to complex trade-offs (FOWLER *et al.*, 2014). In order to evaluate the alternatives, a multidisciplinary approach is needed. Moreover, the possibly large number of stakeholders and their potentially conflicting interests can result in a very controversial process (e.g. FOWLER *et al.*, 2014; HENRION *et al.*, 2015).

The evaluations mentioned above can vary depending on the different environmental conditions where the oil structures are located, the wide range of ecosystems, distinct waterlines and distance from the coast. The physical condition of the structures themselves should also be accounted for. For example, pipelines can carry oil or water, can be inactivated for a long time or be trenched. Hence, it is unlikely that a single decommissioning alternative be the most adequate for all existing structures (FOWLER *et al.*, 2014).

1.1 Motivation and general problem approach

To the best of our knowledge, the majority of published oil and gas decommissioning reports so far have relied on a methodology called comparative assessment (DMIRS, 2017; MEI, 2018; OIL & GAS UK, 2015), often based on subjective judgements by stakeholders with respect to a number of pre-selected criteria and sub-criteria. Generally, the alternatives are ranked by means of a weighted sum of the evaluations with regard to the selected criteria (e.g., INEOS, 2018; REPSOL, 2017; SHELL, 2017a). The decision making process is commonly conducted individually for each piece of equipment, in a progression that can become rather cumbersome for large offshore systems. Given the possibly large extension of the sub-sea system, the application of multi-criteria methodology on a case-by-case basis often results in a very time-consuming process. Indeed, some reported studies have taken up to ten years to be finalised (SHELL, 2017b). In addition, the evaluation of sub-criteria for each alternative is often subjective, and based on the preference of either the decision maker or a group of stakeholders (DURO *et al.*, 2014). Hence, the process tends to become more complex, labour intensive and error prone as the number of criteria/sub-criteria increases (WAEGEMAN *et al.*, 2009).

Given the previously mentioned problems regarding an extensive evaluation of each equipment individually, the motivation of this work is to present a dimensionality reduction approach for decommissioning problems, making use of machine learning techniques. This work proposes a twofold approach to address such pitfalls. Firstly, it introduces a way to extract the necessary information while keeping criteria assessments to a minimum. Secondly, it seeks patterns in the decision making process to forecast the outcome of the decision-aid tool for each equipment without necessarily resourcing to the costly MCDA assessment phase.

1.2 Objectives

Based on the discussion previously exposed, the main objective of this study is to present a method for dimensionality reduction in decommissioning studies in the field of oil and gas, mainly focused on sub-sea systems. The proposed method should be devised in such a way that it can also ensure the selection of the most appropriate decommissioning alternatives. The rationale is to reduce not only the computational time required to reach a decision, but also the labour intensive process required to produce an appraisal of the performance of each piece of equipment with respect to each sub-criteria. It is expected that the decommissioning process can be further abbreviated if the decision maker elects to use the decommissioning alternatives predicted by the proposed algorithm for all installations outside the training set, instead of conducting an individual MCDA analysis for each of them individually.

To accomplish our aim, we will attempt to reach the following intermediate objectives:

- To introduce a dataset based on real-world data from actual sub-sea pipelines, in order to validate the proposed approach, which we believe can be used in the future for benchmarking purposes. It is worth emphasising that this training dataset should take into account evaluations of the impacts with respect to all criteria/sub-criteria and also physical properties of the equipment. Also, it should include a column containing the most appropriate decommissioning alternative for each piece of equipment, as identified by the application of a selected multi-criteria decision analysis (MCDA) tool;

- To compare the performance of selected supervised methods in order to obtain a model to classify the pieces of equipment, based on similarities in their characteristics and criteria/sub-criteria assessment;

- To employ a feature selection to identify the smallest subset of sub-criteria which are most relevant to reaching a decision, and whose application does not significantly alter the outcome of the MCDA tool when the remaining sub-criteria are left out of the analysis.

1.3 Outline

This work is organised in five Chapters as follows. The literature review is presented in Chapter 2, including a brief overview of decommissioning in several fields and a review of decision analysis methods, with emphasis on oil and gas applications. It also features an overall picture of the machine learning techniques considered in this present work. Subsequently, Chapter 3 describes problem setting for this study and explains the general method of analysis. The dataset of the numerical experiments is introduced in Chapter 4. This Chapter also introduces the experimental results, where the machine learning (ML) methods are compared and a variable relevance analysis is reported. Finally, Chapter 5 concludes the study and includes suggestions for future work.

Chapter 2

Literature Review

This chapter contains a bibliographical review of the main fields related to this study, namely decommissioning problems, decision analysis and machine learning. These topics are discussed in depth in the remainder of the chapter.

2.1 Decommissioning

Decommissioning refers to the adoption of measures, arrangements and procedures for the proper uninstalling of an enterprise after the end of its useful economic life cycle, taking into account environmental, safety, reliability and transparency requirements, among others (ANEEL, 2009; ANP, 2015).

As the term decommissioning is usually associated with a facility being withdrawn from service, it is often mistakenly treated as a synonym for removal or disposal (DMIRS, 2017). One can argue, however, that the latter are only two possible alternatives in a decommissioning decision-making process. Decision making is linked to several factors, such as regulation, cost, available technologies, safety, environmental and social impacts, among others. These factors may vary depending on the sector to which the decommissioning refers.

The nuclear sector has a large number of infrastructures reaching their end of life (IAEA, 2017). SUH *et al.* (2018) have historically discussed the main parameters that influence the decommissioning decision making within the sector, highlighting the difficulties in the evaluation of possible strategies. They also argue that major accidents related to premature decommissioning reinforced the need to carry out prior and detailed planning. Perhaps because of its sensitive nature, it can be said that the nuclear sector has internationally more consolidated regulations than oil and gas, for example. Such regulations, however, are not prescriptive with respect to the strategic decisions to be taken. These, in turn, involve temporal (immediate or delayed dismantling) and spatial (storage location of radioactive material) issues.

Another interesting sector for decommissioning studies is that of hydroelectric plants' reservoirs. Many reasons can lead to the decommissioning of such a reservoir, not solely the end of its economic viability. Such motivations can be safety, non-compensatory exchanges between the beneficiaries of the dam, as well as the environmental impacts (USSD, 2015). As can be expected, there are also several decommissioning alternatives for this type of installation, such as complete or partial removal. Prior to selecting an alternative, the decision maker should analyse different variables, such as public safety, fish and aquatic life migration, river restoration, economic and social benefits, and potential environmental impacts. For more details, refer to (USSD, 2015).

Furthermore, decommissioning is a topic of interest in more recent energy sectors, such as wind and solar, which gained an increasing importance in recent years (SMYTH *et al.*, 2015). These require installations that may have a shorter service life - wind turbines, for example, can have a service life of only 20 years (SUN *et al.*, 2017). For this reason, future decommissioning processes within these sectors already raise discussions. According to SØNDERGAARD *et al.* (2014), different materials should be considered for the construction of solar panels, with a view at promoting increased efficiency, as well as to facilitate the search for suitable end-of-life alternatives. Under analogous motivations, SUN *et al.* (2017) propose a method to optimise the design of offshore wind turbines in order to reduce the decommissioning costs at the end of their operation.

It should be noted that decommissioning is not only an issue in the energy field. Instead, it is also relevant in several other economic sectors. For example, the mining sector demands several closure-related activities and requires careful evaluation of the environmental problems related to tailing damns (NÓBREGA *et al.*, 2008). Likewise, the transport sector seeks an adequate final destination for vehicles (SMYTH *et al.*, 2015) and submarines (ISM, 2011), among others.

In the oil and gas sector, the first decommissioning dates back to the 1970s (CHANDLER *et al.*, 2017). Currently, the subject has been the focus of many discussions, since only a small portion of platforms and sub-sea installations around the world has been decommissioned. There are, therefore, many decommissioning activities to be carried out in the future. In addition, many installations are in the final phase of their useful life (HAMZAH, 2003). Due to the still insipid specific legislation and the low availability of personnel with specialised qualification in the area, the decommissioning process can be long and bureaucratic (HAMZAH, 2003).

Other factor to be considered in connection to sub-sea decommissioning is the cost. Besides, it should be noted that the discussion regarding cost encompasses the financial responsibilities of the actors, as well as their impact on future projects (ALMEIDA *et al.*, 2017). There are also a series of debates that address different aspects, such as the proper disposal of materials, interference in the activities of other users of the sea, among others (e.g. CANTLE e BERNSTEIN, 2015; KRUSE *et al.*, 2015).

The need to adopt an efficient decision-making methodology is reinforced here, given the bureaucracy, the diversity of conflicting factors guiding the decision process and the need for a transparent decision-making that is also accepted by the stakeholders. Therefore, the forthcoming sections discuss decision analysis.

2.2 Decision analysis

Decision analysis aims to select the most suitable alternative in a process that generally includes trade-offs because it involves conflicting objectives and multiple options (HUANG *et al.*, 1995). Among the available analytic techniques, one finds Multiple

Criteria Decision Making (MCDM) methods and Decisions Trees (DT) (ROKACH e MAIMON, 2008), among others, as depicted in Figure 2.1. Notice that OMADM stands for other multiple attribute decision making methods (ZHOU *et al.*, 2006).

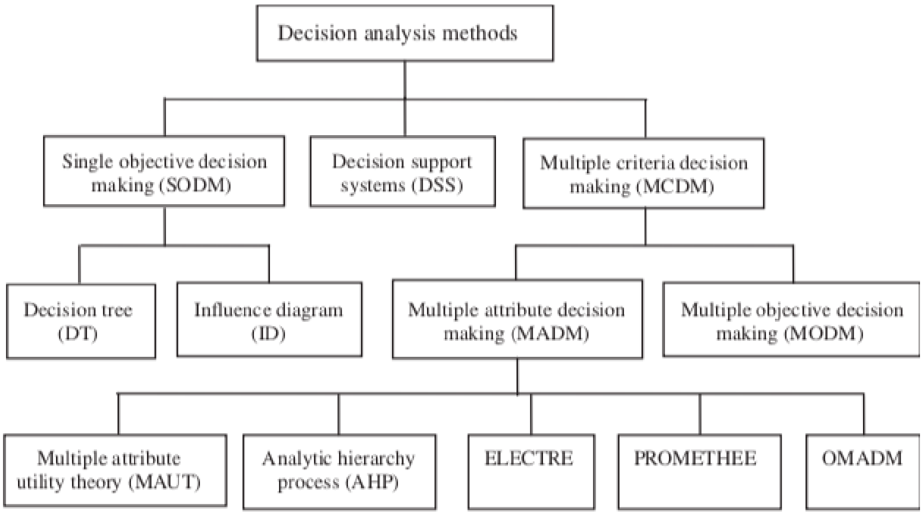

Figure 2.1: Most popular decision analysis methods.

Source: ZHOU *et al.* (2006)

Decommissioning is naturally a complex problem that involves multiple stakeholders with distinct goals, as well as multiple alternative courses of actions. Aiming to identify how this problem has been addressed in the literature, Section 2.2.1 briefly describes multiple criteria decision analysis. Also, Section 2.2.2 includes a survey of decision making techniques applied to decommissioning in the oil and gas sector.

2.2.1 Multi-criteria decision analysis (MCDA)

Multi-criteria decision analysis is a methodological framework that aims to support complex decisions, enabling the comparison of different alternatives according to established criteria, with the final goal of selecting one such alternative. MCDA methods can be roughly classified into single-criterion synthesis, outranking and iterative methods (ALMEIDA, 2000; GRECO *et al.*, 2005).

Unlike single-criterion synthesis methods, outranking approaches do not perform an aggregation step to reach a score for each alternative. Additionally, outranking allows for non-comparability according to the structure of preference prescribed by the decision maker. Hence, there may be alternatives that simply cannot be compared. Among the outranking methods, *Elimination and Choice Expressing the Reality* (ELECTRE) and *Preference Ranking Organisation Method* (PROMETHEE) families stand out as the most prevalent (ALMEIDA, 2000). The next session summarises the ELECTRE method, which was the method we applied in our numerical examples of Chapter 4.

ELECTRE

Regarding the ELECTRE family, the methods ELECTRE I and II were replaced by ELECTRE IS and III, respectively, and are currently only interesting from a pedagogical and/or historical standpoint (ROY, 1990). ELECTRE IS deals with the selection problem, i.e., that of finding the most appropriate alternative. On the other hand, ELECTRE III and IV tackle ranking problems, which aim to rank the alternatives in decreasing order of preference. Arguably, ranking problems are better suited to decommissioning because they provide the decision maker with a broader picture of the reality. ELECTRE IV is appropriate in applications with no specific information on the importance (weight) of each criterion in the aggregation process.

ELECTRE III (ROY, 1985) allows the ordering of alternatives based on outranking relationships and uses pseudo-criteria, introducing discrimination thresholds (preference and indifference), i.e., establishing ranges of values for accepting a preference relation (ROWLEY *et al.*, 2012). In order to establish an outranking relationship between alternatives a and b, it is necessary that a be at least as good as b. For each criterion j, $1 \leq j \leq n$, it is possible to associate an strict outranking relation S_j. Let A be the set of feasible alternatives and $g_j(a)$ represent the performance or the evaluation of the alternative $a \in A$ under criterion j. Furthermore, let $k_j \geq 0$ be the weight assigned for criterion j, and suppose that $\sum_{j=1}^{n} k_j = 1$.

Let $q_j \geq 0$ represents the indifference threshold, which delimits how much better $g_j(a)$ must be in relation to $g_j(b)$ for the preference relation to be established. Also let us define the preference threshold $p_j \geq 0$, which is a limit value above which the decision maker shows a clear strict preference for one alternative over other, under criterion j. Lastly, consider $v_j \geq 0$ as the veto threshold, a difference between alternatives a and b with respect to criterion j that prevents the decision maker from selecting alternative b, regardless of the outranking relationships under the remaining criteria. In that case, the decision maker considers that the performance of alternative b under criterion j is so poor that it cannot be selected, even if it performs well under the remaining criteria.

The preference relations are constructed according to the *concordance index* $C(a,b)$, which roughly assesses the degree to which a outranks b when the decision maker accounts for all criteria, and is computed by equation (2.1). The outranking relation between alternatives a and b with respect to an individual criterion j is given by $c_j(a,b)$, which is evaluated by means of equation (2.2).

$$C(a,b) = \sum_{j=1}^{n} k_j c_j(a,b) \tag{2.1}$$

$$c_j(a,b) = \begin{cases} 1, & \text{if } g_j(a) + q_j \geq g_j(b) \\ 0, & \text{if } g_j(a) + p_j \leq g_j(b) \\ \dfrac{p_j + g_j(a) - g_j(b)}{p_j - q_j}, & \text{otherwise.} \end{cases} \tag{2.2}$$

Furthermore, let us also define the *discordance index* $d_j(a,b)$ with respect to individual criteria j, given by (2.3), which roughly measures the level of disagreement with respect to a preference relation

$$d_j(a,b) = \begin{cases} 0, & \text{if } g_j(b) \leq p_j + g_j(a) \\ 1, & \text{if } g_j(b) > v_j + g_j(a) \\ \dfrac{g_j(b) - g_j(a) - p_j}{v_j - p_j}, & \text{otherwise.} \end{cases} \tag{2.3}$$

Based on the indexes shown above, the degree of outranking between alternatives is finally established by the *outranking relation* $S(a,b)$, which is defined in equation

(2.4) below

$$S(a,b) = \begin{cases} C(a,b) & \text{if } d_j(a,b) \leq C(a,b) \quad \forall j \epsilon J \\ C(a,b) \times \prod\limits_{j \epsilon J(a,b)} \dfrac{1 - d_j(a,b)}{1 - C(a,b)}, & \text{otherwise,} \end{cases} \tag{2.4}$$

where $J(a,b)$ is the set of criteria for which $d_j(a,b) > C(a,b)$. Note that the equation states that if the concordance index is greater than all discordance indices, the outranking relation is equal to the concordance index. Otherwise, when the concordance index is lower than at least one discordance index, the outranking relation is decreased accordingly.

2.2.2 Decision-making methods applied to decommissioning in the oil and gas sector

Multi-criteria decision analysis (MCDA) methods have been successfully applied in several sectors, such as agriculture (e.g. BLANQUART, 2009), healthcare (e.g. THOKALA *et al.*, 2016) and waste management (e.g. ANGELO *et al.*, 2017). They have also been utilised to aid decommissioning decisions in many distinct sectors, for instance, nuclear (e.g. KIM e SONG, 2009), vehicles dismantling (e.g. MERGIAS *et al.*, 2007) and mining (e.g. BANGIAN *et al.*, 2012). The decommissioning of oil and gas installations, in particular, has attracted considerable attention in the literature. Table 2.1 summarises the studies found in the literature, which include but are not limited to MCDA analysis.

Regarding MCDA methods, BERNSTEIN *et al.* (2010) and HENRION *et al.* (2015) report a decommissioning study involving oil and gas platforms in California. Both works make use of a tool based on *Multi-Attribute Utility Theory* (MAUT) with linear utility functions to evaluate the attributes (criteria). Weights were assigned by the swing weighting method (EDWARDS e BARRON, 1994), which assigns the weights in a comparative way. The users gives the highest weight to the criterion that they view as the most important one. Then, they order the other weights from the second most important down to the least one, always based on each criterion worst and best value. For more details refer to (EDWARDS e BARRON, 1994). After the weights were assigned, a sensitivity analysis was conducted to infer the effect of varying them. Finally, HENRION *et al.* (2015) highlight that the large number of available decommissioning alternatives may render the problem intractable, and suggest a preliminary screening based on economic, technical and political feasibility to tackle this issue.

	References	**Decision-making methods**	**Sub-sea assessment**	**Methods for selecting the criteria**
Articles	CRIPPS e AABEL (2002)	Impact Assessment		NR
	FOWLER *et al.* (2014)	SAW		Stakeholders' opinions
	HENRION *et al.* (2015)	MAUT		Literature and Stakeholders' opinions
	NA *et al.* (2017)	AHP		Literature and Stakeholders' opinions
Reports	XODUS (2017)	AHP	✓	BEIS (2018)
	REPSOL (2017)	AHP	✓	BEIS (2018)
	SHELL (2017a)	Comparative assessment	✓	BEIS (2018)
	INEOS (2018)	Comparative assessment	✓	BEIS (2018)
	MARATHON OIL (2017)	Comparative assessment	✓	BEIS (2018)
	ITHACA (2018)	Comparative assessment	✓	BEIS (2018)
	BG GROUP (2016)	Comparative assessment	✓	BEIS (2018)
	PERENCO & TULLOW (2014)	Comparative assessment	✓	BEIS (2018)
	CNRI (2013)	Comparative assessment	✓	BEIS (2018)
	SPIRIT ENERGY (2018)	Comparative assessment	✓	BEIS (2018)

NR - Not reported; AHP - Analytic Hierarchy Process; BEIS - Department for Business, Energy & Industrial Strategy; SAW - Simple Additive Weighting; MAUT - Multi-Attribute Utility Theory

Table 2.1: Summary of the decision-making methods applied to decommissioning in the oil and gas sector .

Another approach to the decommissioning problem of oil and gas installations is proposed by FOWLER *et al.* (2014). This approach is based on the ordering of the alternatives for each criterion by the stakeholders. Afterwards, the alternatives are classified as approved or disapproved based on a comparison with the average performance for each decommissioning criteria.

Arguably, the most prevalent MCDA method in the literature of oil and gas decommissioning is *Analytic Hierarchy Process* (AHP). It has been applied by NA *et al.* (2017), who made use of the Saaty scale (SAATY, 1990) to quantify expert evaluations. In contrast, an AHP-based method was applied in (REPSOL, 2017;

XODUS, 2017) which employs qualitative judgements based on quantitative data. Dubbed *Xodus's Multiple Criteria Decision Analysis*, this method differs from classical AHP in that it uses a purely qualitative scale.

In the context of real-world decommissioning processes in the field of oil and gas, some guidelines have been developed to standardise and aid company decisions. These guidelines are often referred to as *comparative assessment* (e.g., BEIS, 2018; BG GROUP, 2016; MEI, 2018) and make use of single-criterion synthesis, which essentially transforms the multi-criteria problem into a single-criterion problem whereby the single criterion is defined as a weighted average of the original criteria. Hence, the overall score of a given alternative becomes a weighted average of the scores of such an alternative with respect to all criteria. The Brunei guideline (MEI, 2018) proposes a qualitative approach based on a colour scale that associates each colour to a preference level. Considerably influential, the UK guide (BEIS, 2018) has already been used as a basis for several reports (BG GROUP, 2016; CNRI, 2013; INEOS, 2018; ITHACA, 2018; MARATHON OIL, 2017; SHELL, 2017a), as depicted in Table 2.1. The manual suggests the use of five criteria, namely safety, environmental, technical, social and economic, which were also proposed in (MEI, 2018).

It is also important to note that within the literature, only technical reports have addressed the decommissioning of sub-sea installations, generally with a focus on pipelines, as shown in Table 2.1. In addition, the guidelines suggest three possible methods for evaluating alternatives. The first is qualitative and based on a colour scale, the second and third allow to merge quantitative and qualitative analyses, and the third supports weight assignment.

The Windermere report (INEOS, 2018) developed a risk matrix to aid decommissioning decisions regarding umbilicals. The risk matrix contrasts the level of impact - ranging from negligent to catastrophic - with the probability of impact, which ranges from rare to very probable, for each criterion. A workshop was conducted to produce these qualitative evaluations. Finally, the global score of each alternative is computed as the weighted average of the scores for individual criteria. A similar approach was employed in (ITHACA, 2018). However, the latter also made use of quantitative evaluations that were later transformed into normalized scores.

The BG Group report (BG GROUP, 2016) also abides by the UK decommissioning guideline (OIL & GAS UK, 2015). Their method applies a colour scale in a preliminary screening designed to eliminate infeasible alternatives. They also make use of a weighted average of scores with respect to the criteria, whereby the weights are assigned through semantic pairwise comparisons. Finally, a comprehensive analysis was reported in (SHELL, 2017a) which includes both quantitative and qualitative evaluations, as well as the analysis of several weight assignment possibilities by means of a sensitivity analysis.

The decision methods previously described are applied individually for each piece of equipment. Additionally, the criteria are usually assessed by means of subjective evaluations by stakeholders, which render the process particularly laborious, time consuming and error prone. The last column of Table 2.1 conveys the methods that have been applied for criteria selection in oil & gas decommissioning decision-making. Most of the choices are based on the recommendations in (BEIS, 2018), literature findings and stakeholders' assessments. This means that in most cases there is no quantitative analysis of the impact of the subset of selected criteria on the final outcome of the decision analysis tool.

This study argues that machine learning (ML) methods are a natural way to mitigate the problems associated with the individual evaluation of pieces of equipment and abbreviate the duration of the decommissioning study. Indeed, ML can be applied to generate groups of similar pieces of equipment which can benefit from the same decommissioning alternative. Additionally, feature selection can be employed to simplify the analysis and hence reduce the total time devoted to the decommissioning study. As illustrated above, the use of dimensionality reduction in decommissioning problems is still incipient. Some works (e.g., AHMED *et al.*, 2016; ISM, 2011) advocated the use of expert judgement for criteria selection/elimination.

In contrast, an approach that is centred on information availability was introduced in (BERNSTEIN *et al.*, 2010).

The need for ML techniques in the context of decommissioning studies, which is reinforced in this study, has already been acknowledged in pioneering decommissioning studies (e.g., MEI, 2018; OIL & GAS UK, 2015), even though it was deferred to later work. Specifically, these references suggest clustering pieces of equipment based on similarities with respect to their characteristics, such as sub-sea status, diameter, installation data, proximity to other infrastructure, among others, and then conducting a unique combined comparative assessment. We argue that such a classification may be insufficient and should benefit from the assessment of a reduced number of criteria/sub-criteria that may act as proxies for the characteristics of the environment surrounding the installation, which certainly plays an important role in the selection of the decommissioning alternative. Classic MCDA methods are not designed to deal with big data and a desirable solution would be to find the most relevant subset of factors (CARLSSON e WALDEN, 2019). Therefore, there seems to be plenty of room for the introduction of formal machine learning techniques to address classification and variable selection in decommissioning problems, as suggested in DOUMPOS e GRIGOROUDIS (2013) and CARLSSON e WALDEN (2019). Accordingly, these methods are discussed in the next section.

2.3 Machine Learning

Machine learning (ML) can be understood as a set of techniques designed to extract models from vast quantities of data by finding structural patterns (WITTEN *et al.*, 2016). However, the same set of techniques can be employed in connection to small datasets, as long as some guidelines are followed in the process of producing large synthetic datasets based on real-world data. We defer the discussion of such guidelines to section 2.3.1.

An important application of ML is to reduce the dimension of large datasets. Some techniques applied to this end are principal component analysis (PCA), correlation matrix and clustering techniques (DEB e SAXENA, 2005; FAWZY *et al.*, 2018; MITRA *et al.*, 2002; PEREZ-GALLARDO *et al.*, 2018; ZHU *et al.*, 2015). A brief survey of dimensionality reduction methods and some of their applications will be presented in sections 2.3.2 and 2.3.3, respectively.

Furthermore, as mentioned previously in this work, classification analysis is suggested for dealing with the pitfalls related to decision making in oil and gas decommissioning. It can generate groups of pieces of equipment for which similar decisions are advisable, thus simplifying the analysis and contributing to the overall reduction of the total time devoted to the decommissioning study. In particular, supervised learning methods are the most adequate for decommissioning studies, given that training pairs of installations and decommissioning alternatives can be seamlessly produced by the MCDA analysis tool. Such methods are discussed in depth in section 2.3.4.

2.3.1 Reduced Datasets

Although *big data* is one of the hottest topics nowadays, the literature contains many reports of insufficient datasets in diverse fields, such as medicine and manufacturing. The lack of data is often connected to time consuming and/or uneconomical data collection (CHEN *et al.*, 2017; LATEH *et al.*, 2017). Machine learning algorithms are data-dependent and models based on small samples are often inefficient and unreliable (CHEN *et al.*, 2017).

Several approaches have been proposed by researchers to produce efficient studies when faced with small datasets. One such approach is adding synthetic data whilst making use of fuzzy theory results. HUANG e MORAGA (2004) suggest the application of fuzzy theory to derive distinct patterns in order to improve the accuracy of artificial neural networks subject to small data samples. Another alternative is the so-called synthetic minority over-sampling technique (SMOTE) (CHAWLA *et al.*, 2002), designed to deal with unbalanced data. This technique over-samples sparse classes and adjusts the feature vectors based on the $k-$nearest neighbours approach, with a view to producing a more balanced topology.

An additional possibility is to use the bootstrap technique (TIBSHIRANI e EFRON, 1993). CHAO *et al.* (2011) generated virtual samples to improve the accuracy metric in a dataset, initially composed of 36 samples, for predicting the outcome of radiotherapy in bladder cancer cells. The method was also implemented within the manufacturing field in order to predict future production after reducing the lead time based on pilot runs (TSAI e LI, 2008), for example. Furthermore, bootstrapping was applied for predicting workload with reduced availability of historical data (IVĂNESCU *et al.*, 2006).

This study applies a technique based on bootstrapping to generate a synthetic dataset for validation, which is further explained below.

Bootstrap

Bootstrap (TIBSHIRANI e EFRON, 1993) is a computationally intensive non-parametric statistical resampling technique which does not require large sample sizes. This approach is commonly used for statistical inference, where it is possible to construct a distribution of the variable of interest. This estimated distribution is used to make inferences and to obtain information about the parameter under study, that is, in possession of this bootstrap distribution it is possible to obtain information and even to test hypotheses. However, in this work we are interested in the possibility of generating virtual samples.

In this procedure, the original dataset is considered as a good estimate of the population density function. Operationally, this technique consists in performing sampling of the same size as the original sample with replacement of the same. In other words, n draws are performed with replacement from the original distribution, n being the number of observations available in the original sample, which originates a bootstrap sample. This procedure must be repeated B times to obtain B bootstrap samples. The new dataset is comprised of the original sample and the B additional bootstrap samples.

Bootstrap samples, however, are only comprised of elements that are part of the original sample. Hence, possible values that are not in the original sample are indiscriminately avoided. That would not be advisable in our procedure, since the intention is to generate a representative sample of parameters and evaluations. Hence, this study draws instead from a uniform distribution for each parameter. The minimum and maximum values of the distribution are defined to coincide with the minimum and maximum values of the original sample.

2.3.2 Dimensionality reduction

Dimensionality reduction, a method that has been continuously improved in recent years (XU *et al.*, 2019), is used for dealing with high-dimensional data, aiming to eliminate redundant and irrelevant information (SORZANO *et al.*, 2014). The method is highly used as a pre-processing tool and has been developed mainly as a tool for machine learning and statistics. It is comprised of feature selection, that analyses correlation coefficients and produces variable rankings, for instance (GUYON e ELISSEEFF, 2003), and feature extraction (KHALID *et al.*, 2014; XU *et al.*, 2019). While the former is concerned with selecting a meaningful subset of the original variables (e.g., GUYON e ELISSEEFF, 2003), the latter is devoted to synthesising a reduced subset of meaningful features from a high-dimensional space (JOLLIFFE, 2002; PEARSON, 1901). One of the most used feature extraction techniques is principal component analysis (PCA) (JOLLIFFE, 2002).

PCA (JOLLIFFE, 2002) is an orthogonal linear transformation, which conveys the data in new coordinate system, in such a way that the components are ranked in decreasing order of variance. It is usually applied to reduce the dimension of the dataset while also retaining essential information. Other uses include extracting the most important information from data and analysing the structure of the observations and variables.

The PCA components can be obtained through singular value decomposition (SVD). The SVD decomposition of a matrix is:

$$X = UDV' \tag{2.5}$$

where U is the matrix of left singular vectors; V is the matrix of right singular vectors and D is the diagonal matrix of singular values. Multiplying X by V gives the values of the projections of the observations on the principal components (ABDI e WILLIAMS, 2010).

Feature selection has the advantage of keeping important information regarding a specific feature. On the other hand, there is the risk of omitting a too much information, mainly when it is necessary to select a really small set of features. Feature extraction also has its advantages and pitfalls. None of the feature information is lost, but the feature interpretation becomes compromised because of the linear combination of the original features (KHALID *et al.*, 2014).

Feature selection methods can be classified as wrapper, filter or hybrid methods (XU *et al.*, 2019), as shown in Figure 2.2. The first type is based on current prediction information. Wrapper methods are able to obtain feature subsets that perform better than selection by filter methods. However, it has a higher computational cost since it evaluates the performance heuristically. On the other hand, filter methods use indirect measures, such as ranking and space search. also called ensemble methods, Hybrid methods are a combination of the others.

2.3.3 Dimensionality reduction methods applied to decision-making

One of the main steps for ranking alternatives by multicriteria methods is selecting a set of criteria to guide the decision. Table 2.1 illustrates that decision makers belonging to the oil and gas sector often select criteria according to the guidelines in (BEIS, 2018), or based on stakeholders' recommendations and literature review. Other sectors employ distinct approaches, as conveyed in Table 2.2.

There are few studies that apply dimensionality reduction techniques for criteria

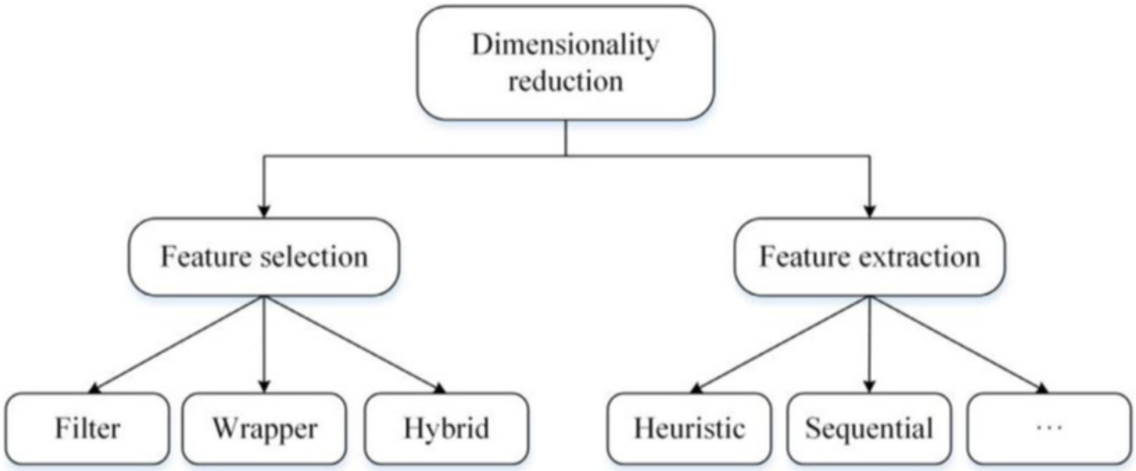

Figure 2.2: The specific methods of dimensionality reduction.

Source: XU *et al.* (2019)

References	**Applications**	**Decision-making methods**	**Criteria selection methods**
PEREZ-GALLARDO *et al.* (2018)	Ecodesign of photovoltaic grid-connected systems	TOPSIS	PCA
ZHU *et al.* (2015)	Reservoir flood control operation	TOPSIS and fuzzy methods	PCA
FAWZY *et al.* (2018)	Wind farm suitability design	AHP and Multi-Criteria evaluation	PCA
YURDAKUL e IC (2009)	Machine tool selection	TOPSIS	Correlation matrix - Spearman coefficient
LIMA-JUNIOR e CARPINETTI (2016)	Supplier selection	Fuzzy quality function deployment	Classification and decision makers opinion
AMIRSHENAVA e OSANLOO (2018)	Mine closure	PROMETHEE and TOPSIS	AHP weight attribution
AHMED *et al.* (2016)	Vehicle dismantling	AHP and fuzzy AHP	DEMATEL
ISM (2011)	Submarine dismantling	Comparative assessment	Stakeholders opinion

Table 2.2: Summary of methods used to criteria selection in decision-making.

selection in decision-making methods. The PCA technique explained before in Section 2.3.2 is usually applied to reduce problem dimension by identifying correlations between variables. For example, ZHU *et al.* (2015) used PCA to transform the original criteria into a system of independent synthetic criteria in order to eliminate the effect of the correlation between the original objectives. They tested the approach on a reservoir flood control operation problem. The MCDA results with and without PCA were compared in order to evaluate the consistency of the results. The same procedure was conducted for a wind farm suitability design problem (FAWZY *et al.*, 2018), transforming the correlated variables into a smaller number of uncorrelated counterparts, called principal components. Likewise, PEREZ-GALLARDO *et al.* (2018) applied PCA to reduce the number of criteria considered in the decision regarding an ecodesign of photovoltaic grid-connected systems.

Dimensionality reduction methods were further applied to machine tool selection (YURDAKUL e IC, 2009). The approach here is rather simple and involves the application of correlation tests for pairs of criteria in order to obtain a set of independent criteria whose cardinality is small enough to be manageable by the MCDA tool.

Oftentimes, however, the criteria are selected by simple ad-hoc methods that do not make use of orthogonal decomposition or statistical analysis (e.g., YURDAKUL e IC, 2009). One such method involves a systematic process based on the use of linguistic terms by a group of decision makers to judge the intensity of the relation between criteria (LIMA-JUNIOR e CARPINETTI, 2016). Such an assessment is then contrasted with the difficulty in collecting the data needed to evaluate each criterion, as well as the human resources and time required. The final selection is made through a classification process whose output is a set of four groups of criteria: priority, critical, complementary and costly. This last class is often avoided because it involves secondary criteria that demand a considerable data collection effort.

In certain cases, the set of criteria to be evaluated are obtained from subjective evaluations by key stakeholders (AHMED *et al.*, 2016; ISM, 2011). For instance, in the process of ranking vehicle dismantling possibilities, AHMED *et al.* (2016) incorporate stakeholders' opinions through the *Decision Making Trial and Evaluation Laboratory* (DEMATEL) method (GABUS e FONTELA, 1972), which is based on their evaluation of the direct influence between any pair of sub-criteria. In a related approach, criteria selection was the output of a workshop involving key stakeholders in (ISM, 2011), in the context of submarine dismantling.

Another group of methods that has been researched for evaluating which criteria should or should not be selected are the Hybrid Multi-Criteria Decision-Making (HMCDM) (ZAVADSKAS *et al.*, 2016), that combine MCDM methods with other methods used for identifying the importance (relative significance) of criteria. For instance, AHP can be used to identify the most relevant criteria by means of the pairwise evaluations which are characteristic of this method (AMIRSHENAVA e OSANLOO, 2018). In AMIRSHENAVA e OSANLOO (2018), the alternatives were later ranked using both PROMETHEE and TOPSIS methods, composing the HM-CDM method application. Moreover, there are several applications of AHP/ANP for evaluating the interdependent relationships among factors influencing the problem under consideration (ZAVADSKAS *et al.*, 2016). For example, RABBANI *et al.* (2014) applied ANP combined with COmplex PRoportional ASsessment (COPRAS) method in order to evaluate the performance of oil producing companies and AMIRI *et al.* (2009) applied AHP with TOPSIS for firms competence evaluation. Those applications could be easily extended for criteria selection.

2.3.4 Supervised methods

Supervised methods are generally used to aid in the decision making process in practical applications and encompass both classification and regression models, both of which aim to identify a relation between independent and dependent variables (KUHN e JOHNSON, 2013). The first one produce a continuous valued prediction, that is, it predicts categorical labels while the last one models continuous-valued functions. The models are developed based on the analysis of a training set where each observation has a related class label and it is used for predicting the classification of unlabelled objects. The focus here is on the classification methods.

Classification methods, in particular, have been successfully employed in a number of applications in the oil and gas industry. Some examples include the utilisation of Support Vector Machines (SVM), Decision Trees (DT) and Random Forests (RF) to predict corrosion in pipeline inspection (LIU *et al.*, 2019). Their goal was to automate the manual work of matching corroded areas with extracted features selected from in-line inspection. In a related work, EL-ABBASY *et al.* (2016) make use of regression analysis, artificial neural networks and DT to investigate the causes of pipeline failure. The main difference is that the latter is focused on unpiggable pipelines and use features not related to internal corrosion, such as diameter, crossing and age. Other applications were reported in (COPELAND *et al.*, 2009; SCHUETTER *et al.*, 2018). The former applies RF to forecast the development of oil and gas fields and estimate the impact on the decrease of animal species. The latter utilises classification models, such as SVM and GBM, to predict oil potential in unconventional shale reservoirs. Nonetheless, specific applications of machine learning to decommissioning problems have been found lacking. One of the innovations of this work is to fill this gap.

The following sections present a brief description of the four supervised methods applied in this work: decision trees, random forest, gradient boosting machines and support vector machine. Furthermore, we also present the metrics used for evaluating the outcomes of these methods.

Decision trees (DT)

Decision trees (ROKACH e MAIMON, 2008), illustrated in Figure 2.3, is one of the most popular classifiers. It is a supervised method that utilises a recursive partitioning algorithm to construct the tree and has the advantage of accepting both numerical and categorical variables. It is a top-down approach that models decisions and possible consequences, including growing and pruning stages. Basically, a decision tree comprises:

- Nodes - a test on a attribute;
- Root - the topmost node;
- Branch - an outcome of the test;
- Leaves - a class label.

The process consists in continuously splitting the training data into two or more descendant subsets, until a stopping criteria is reached or all classes are split. The splitting criterion is selected in order to identify the partition of the training set.

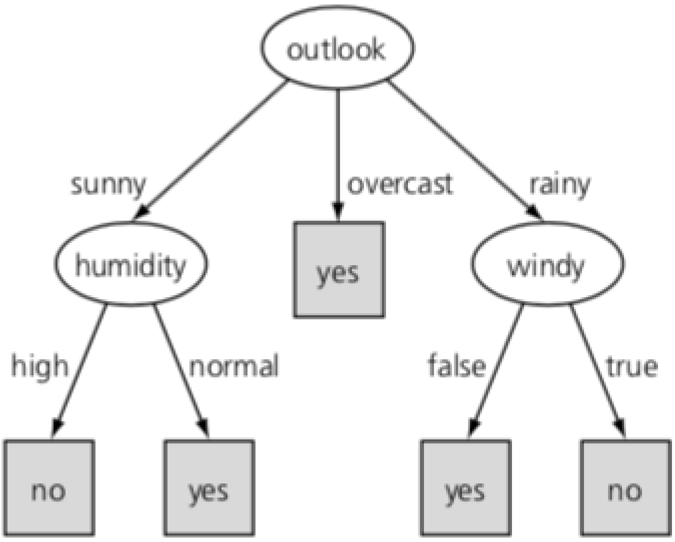

Figure 2.3: Decision tree example: weather condition for playing some unspecified game.

Source: WITTEN *et al.* (2016)

There are different criteria that can be used for this. Impurity-based criteria, information gain, Gini index and DKM criterion are some of the most common ones (MAIMON e ROKACH, 2005). In this work, we use Gini index, a measure of heterogeneity, as it is the default for the *rpart* package (THERNEAU *et al.*, 2019).

In order to avoid over-fitting, one can limit the growth of the tree or prune it. Pruning is often attained by recursively snipping off the least important splits, based on the complexity parameter (*cp*). On the one hand, because they depend on the observation values, decision trees are robust to outliers. They are also fairly easy to understand and interpret. On the other hand, they can be computationally expensive due to the need of identifying splits from multiple variables (HODEGHATTA e NAYAK, 2016).

Random forests (RF)

Random forests (BREIMAN, 2001) are a type of ensemble method, i.e., a method that combines the predictions of many models. The two most traditional ensemble algorithm types are bagging and boosting. Briefly, RF consists on first bootstrapping the dataset, and selecting random samples to construct the training sample of each tree, which defines it as a bagging method. After that, the method randomly selects the features of each tree and makes use of the Gini index to produce splits. Finally, the model utilises the samples that were not part of the training set, the so called *out-of-bag (OOB) data*, for testing purposes. The final response is based on a vote on the decisions generated by each of the constructed trees.

It presents some benefits compared to other machine learning methods, such as requiring only two parameters, namely the number of trees (*ntree*) to be generated and the number of variables selected for each tree (*mtry*). BREIMAN (2001) recommends that *mtry* be equal to the square root of the total number of variables. Other benefits include reducing over-fitting when compared to decision trees, since the response is the average of several trees. Additionally, the random selection of variables has the advantage of reducing the correlation between trees (FENG *et al.*, 2015). It may be argued that the technique is more robust by virtue of creating multiple decision trees and optimising the output to obtain a better-performing classifier (HODEGHATTA e NAYAK, 2016).

Gradient Boosting Machines (GBM)

Similarly to RF, Gradient Boosting Machines (GBM) (FRIEDMAN, 2001) are also a type of ensemble approach. The method relies on combining a large number of weak trees to obtain a stronger ensemble prediction. Unlike RF models, whose construction is based on a voting on the final decision of each tree, GBM is a type of boosting method (NATEKIN e KNOLL, 2013). And the boosting is iterative, consisting in adding new models to the ensemble sequentially, in such a way that each new weak learner is built to mitigate the error of the whole ensemble established so far. GBM consists in a gradient-descent based formulation of boosting methods. The error to be minimised refers to a loss function that can come from different distributions (e.g. binomial loss function, Gaussian L_2 loss function) according to the nature of the response variable (binary, continuous, categorical).

There are different approaches that can be introduced to GBM in order to avoid over-fitting, and therefore improve the model's generalisation capabilities (NATEKIN e KNOLL, 2013). One is sub-sampling and involves the selection of a random subset of the training set at each learning interaction, the length of which is defined by a parameter called *bag fraction*. This criterion is a positive value not greater than the ratio of the data to be used in each sub-sampling. This means implementing a stochastic gradient descent that steers the model away from local minima. Another approach is to properly adjust the learning rate (shirinkage) that controls how fast the gradient descent is, penalising the impact of each additional fitted base-learner. In spite of potentially providing better generalisation, reduced learning rates increase the computational cost. Hence, a compromise must be pursued. Besides, one can also optimise the number of trees in the ensemble. Furthermore, another aspect that can be controlled is the interaction depth, which can be defined as the number of nodes in each tree. Finally, the last parameter to be defined is the number of folds in the cross-validation process, that is further explained in section 2.3.4.

Support Vector Machines (SVM)

Support Vector Machines (BOSER *et al.*, 1992) are conceived to identify the hyperplane that maximises the distance between the two classes in a binary classification problem. The configuration of the hyperplane depends on the distance to the training samples at the edge of the class, dubbed *support vector points*, as illustrated in Figure 2.4. This example consists in a perfectly linearly separable two-class problem. SVM searches for the maximum marginal hyperplane because it increases the chances of getting higher accuracy in future data (WITTEN *et al.*, 2016).

The method was originally applicable only to linearly separable data, but can now be generalised by means of a transformation into a higher dimensional space (WITTEN *et al.*, 2016). Afterwards, the supervised method searches for a new hyperplane in the transformed space. This new multi-class problem can benefit from a "one-to-one" approach, which gives rise to multiple binary classifiers, each

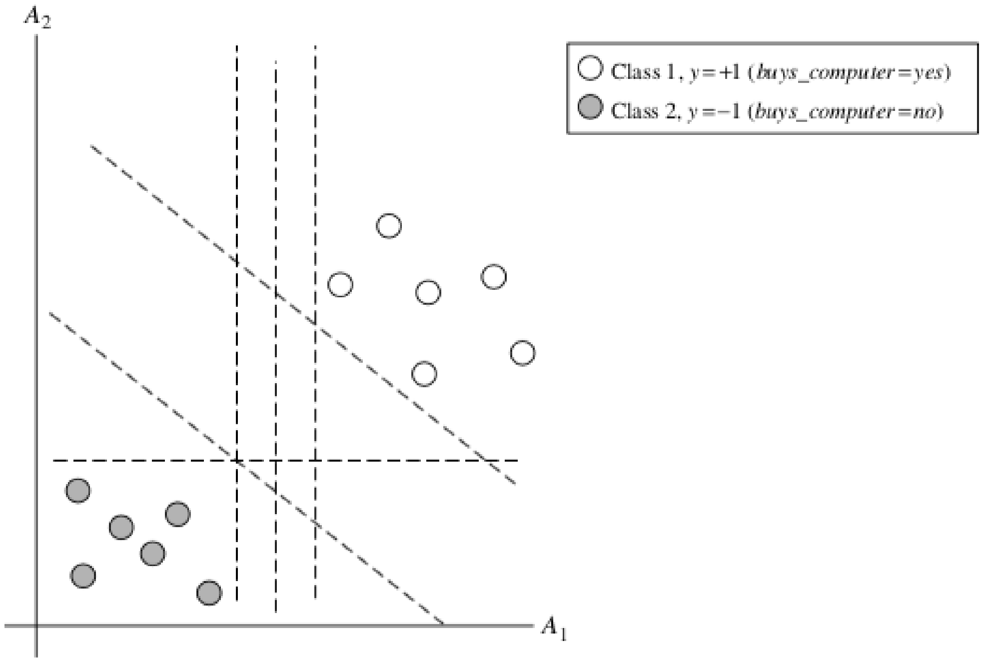

Figure 2.4: An example of a two-class problem where the classes are linearly separable. The dashed lines represent possible separating hyperplanes. SVM searches for the hyperplane with the largest margin.

Source: WITTEN *et al.* (2016)

separating the training samples of a pair of different classes (KIM *et al.*, 2003). The appropriate class is decided by a vote.

There are two parameters to be optimised, namely the cost of constraint violation (C) and sigma (σ), a parameter associated with the kernel function (GACQUER *et al.*, 2011). Compared with other supervised methods, SVM is effective in high dimensional spaces and memory efficient (BRAGA *et al.*, 2019; WITTEN *et al.*, 2016) since its complexity is associated with the number of support vectors rather than the dimensionality of the data.

Model evaluation and selection

Evaluation metrics are used for optimise each model parameter, compare the performance of competing models and understand their quality (MAIMON e ROKACH, 2005). Accuracy is a natural fit for defining the higher performance of a classifier. However, there are several other evaluation metrics that can be used for model assessment.

In this work, we consider both accuracy and a measure of agreement to be defined below. Firstly, we need to define the *confusion matrix* (RAZI *et al.*, 2019) $Q = [q_{ij}]$, $1 \leq i \leq m$, $1 \leq j \leq m$, where m is the total number of classes. Each element q_{ij} denotes the number of times that an element of class i was assigned to class j according to the classification method. Also, recall from Section 3 that the total number of pieces of equipment in the dataset is represented by r.

Accuracy is the percentage of correct predictions in a classifier when the classifier is applied to unseen data (HOSSIN e SULAIMAN, 2015; RAZI *et al.*, 2019). It is given by:

$$P(0) = \frac{1}{r}\sum_{i=1}^{m} q_{i,i} \times 100\%. \tag{2.6}$$

A measure that compares accuracy with the probability of agreement (COHEN, 1960; RAZI *et al.*, 2019) is given by κ, and is defined as:

$$\kappa = \frac{P(0) - P(E)}{1 - P(E)}, \tag{2.7}$$

where P(0) is the accuracy for classification models and P(E) is the chance of agreement, which is obtained as follows:

$$P(E) = \frac{\sum_{i=1}^{m}(q_{:,i}q_{i,:})}{r^2}. \tag{2.8}$$

In the expression above, $q_{:,i}$ and $q_{i,:}$ are, respectively, sum of i-th row and i-th column of the confusion matrix.

In order to obtain reliable estimates of classifier effectiveness, the model should be tested in a different data sample than the one used at the training stage. One method commonly used is called holdout, and consists in using a fraction of the dataset (for example $\frac{2}{3}$ of it) for training and the remaining fraction for testing. The drawback is that the training set may be considerably reduced (HAN *et al.*, 2011). Another option for small datasets is to re-sample the data and calculate an average evaluation metric for the model. k-fold cross-validation, for instance, consists in k training stages, each with k samples used for testing and the remaining ones for training (WITTEN *et al.*, 2016). By doing that, one makes sure that all samples are considered in the training phase on withheld portions of data.

Finally, statistical tests can be used for comparing machine learning methods with respect to a certain performance measures (HAN *et al.*, 2011; HOTHORN *et al.*, 2005). We compare the models based on the values of $P(0)$ and κ resulting from the $k-$fold cross validation. To determine whether a model is superior to another, we apply a t-test with Bonferroni correction (BLAND e ALTMAN, 1995) and use a 95% confidence level.

Chapter 3

Problem Description

This chapter aims to clarify the dimensionality reduction technique here proposed for decommissioning of oil and gas installations under an MCDA approach (Section 3.1) and provide details on the methodological procedure employed to reduce the dimension of the problem (Section 3.2).

3.1 Formulation

Decision making for decommissioning in oil and gas platforms is generally carried out from the analysis of each piece of equipment individually (e.g. BG GROUP, 2016; SHELL, 2017a; XODUS, 2017). Assume there is a set of decommissioning alternatives $A = \{a_1, a_2, \ldots, a_n\}$ for a given piece of equipment, and suppose the decision is to be reached based on a set of (sub)criteria $G = \{g_1, g_2, \ldots, g_m\}$. In a decommissioning study, generally the (sub)criteria are related to environmental, social, economic, safety and technical issues (MEI, 2018; OIL & GAS UK, 2015). The evaluation gives rise in an $N \times M$ matrix comprised of the evaluations of each alternative with respect to each (sub)criterion. As previously mentioned, the majority of published decommissioning studies so far have relied on a methodology called comparative assessment (e.g., MEI, 2018; OIL & GAS UK, 2015), which produces a performance index I_i for each alternative a_i as follows:

$$I_i = \sum_{j=1}^{m} k_j g_j(a_i), \tag{3.1}$$

where k_j is the weight attributed to (sub)criterion j, $1 \leq j \leq m$, and $g_j(a_i)$ is the evaluation of criterion j for alternative a_i, $1 \leq i \leq n$. The alternatives are then ranked in decreasing order of performance index. Other MCDA methods are also applied in different decommissioning studies, such as AHP (e.g. NA *et al.*, 2017; REPSOL, 2017; XODUS, 2017), ELECTRE (e.g. DIMITRIJEVIC *et al.*, 2014; SOLTANMOHAMMADI *et al.*, 2008) and PROMETHEE (e.g. KERKVLIET e POLATIDIS, 2016; MERGIAS *et al.*, 2007). The latter methods are somewhat more complex, but can also be employed to generate a ranking of the alternatives based on performance indices. A brief review of MCDA methods was presented in Section 2.2.1 and more details and analyses can be found in (GRECO *et al.*, 2005).

A common issue in oil and gas decommissioning studies, regardless of the MCDA approach employed, is that collecting information and producing each evaluation $g_j(a_i)$ for each piece of equipment often takes time. Furthermore, some criteria may be the product of multiple evaluations by different, possibly conflicting, stakeholders. On top of that, the abundance of pieces of equipment in the seabed leads to an increase in complexity, especially in deep waters. For example, the Brent infrastructure is shown in Figure 3.1. The evaluation of the most appropriate decommissioning alternatives for this field took almost ten years.

Some authors also point out that a large number of criteria can render the decision making process more difficult and may generate confusion among the stakeholders (AMIRSHENAVA e OSANLOO, 2018). In order to address these issues, this paper builds upon a conjecture found in (MEI, 2018; OIL & GAS UK, 2015) that the similar features in distinct pieces of equipment may lead to similar choices of decommissioning alternatives. We argue, however, that similar features may not be enough, since the selection also depends upon other factors, such as the environment surrounding the piece of equipment. Fortunately, the evaluations of the alternatives

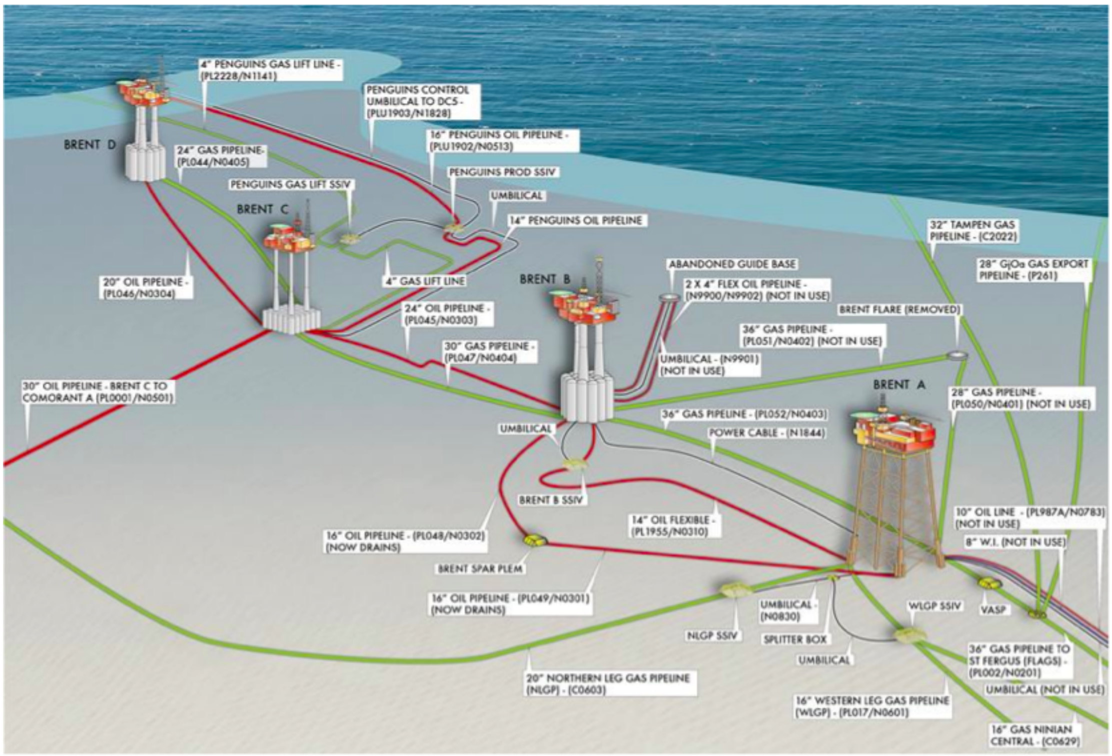

Figure 3.1: Brent field scheme, UK.

Source: SHELL (2017b).

for each equipment can serve as a proxy for these factors. In addition, it is possible that the evaluation of a reduced set of criteria may be enough to produce an accurate estimation of the course of action that would be selected if all criteria were accounted for.

Let $E = \{e_1, e_2, \ldots, e_r\}$, $1 \leq r \leq \infty$, be a small albeit representative subset of the pieces of equipment found in a given oil field pending decommission. Let $g_j^k(a_i)$, $1 \leq j \leq n$, $1 \leq i \leq m$, be the evaluation of the criterion j for alternative i relative to piece of equipment e_k, $1 \leq k \leq r$. The proposed procedure includes the three steps detailed in Algorithm 1 below:

Algorithm 1 (Classification Analysis of the Training Set)

1. *For each piece of equipment e_k, create a row vector p_k comprising all parameters and evaluations $g_j^k(a_i)$, $1 \leq j \leq n$, $1 \leq i \leq m$, as well as the action a_i^k assigned by the MCDA algorithm for this piece of equipment;*

2. *Use supervised classification to divide the population $P = p_k$, $k = 1, 2, \ldots, r$ in m*

groups, one for each decommissioning alternative;

3. *Find the characteristics and (sub)criteria that most impact in the action selection by the MCDA algorithm*

Observe that the decision maker can employ the output of Step 3 to simplify the assessment of the decommissioning alternatives for pieces of equipment outside of the training set. The assessment can now be performed as a function of the subset of most relevant characteristics and criteria. It is our belief that, in most cases, such a subset will have a rather reduced dimension when compared to the original set.

3.2 General method of analysis

As mentioned previously, this work proposes a twofold approach for mitigating errors and reducing the time span of a decommissioning study in the oil & gas industry. The suggested procedure includes finding the minimum possible number of criteria to be assessed and seeking patterns in the decision making process to forecast the outcome of the decision-aid tool for each installation without necessarily resourcing to the costly MCDA assessment phase. This approach falls under the umbrella of dimensionality reduction techniques, within the field of Machine Learning (ML). Subsequently, the general method of analysis will be explored in details.

The method in Algorithm 1 comprises two distinct tasks: dataset pre-processing and classification. Observe that Step 1 of Algorithm 1 generates a dataset where each piece of equipment is associated with both its characteristics and the scores for each alternative-(sub)criterion pair, as well as the decommissioning alternative recommended by the selected MCDA tool.

Observe in Figure 3.2 that some ML algorithms are applied to the dataset under a $k-$fold validation scheme (Steps 2-3 of Algorithm 1). As mentioned in Section 2.3.4, this technique consists in k training stages, each with k samples used for testing and the remaining ones for training (WITTEN *et al.*, 2016). Our case study,

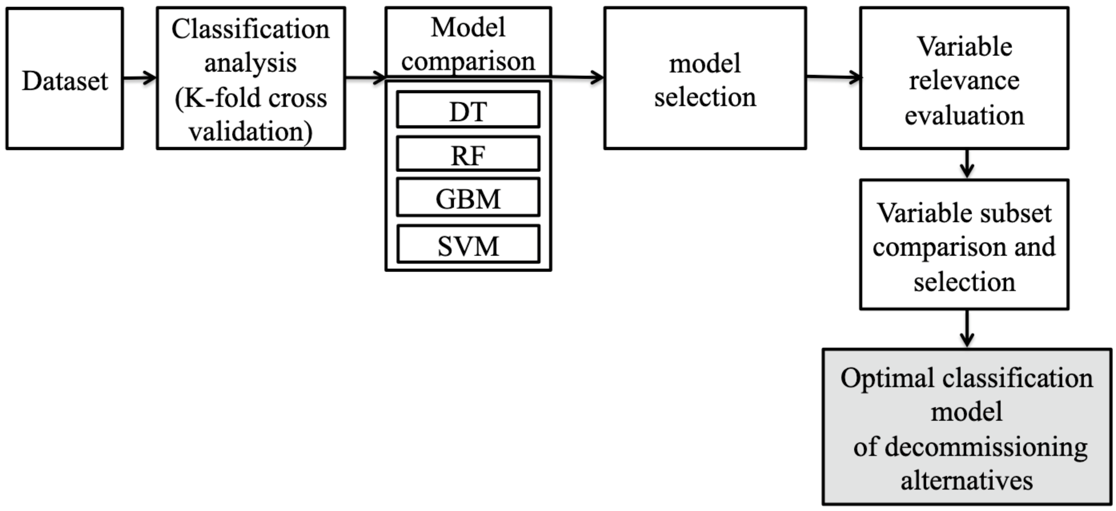

Figure 3.2: Methodology framework regarding steps 2-3 of Algorithm 1.

in particular, makes use of decision trees (DT), random forests (RF), gradient boosting machines (GBM) and support vector machines (SVM), explained previously in Section 2.3.4. Each method is calibrated individually considering the evaluation metrics accuracy and kappa (κ), as described in Section 2.3.4. The calibration is performed by means of the grid search tool *tunegrid* contained in the *carret package* (*R programming*).

In the model selection step, we compare the selected algorithms according to selected evaluation metrics and statistical analyses, previously explained in Section 2.3.4, and select a single model to be used in the remaining steps. A variable relevance analysis then follows for the selected model. After that, the decision maker chooses the smallest possible subset of the most relevant variables that maintains the accuracy of the model. Finally, this subset is then selected to comprise the reduced classification model in the last step.

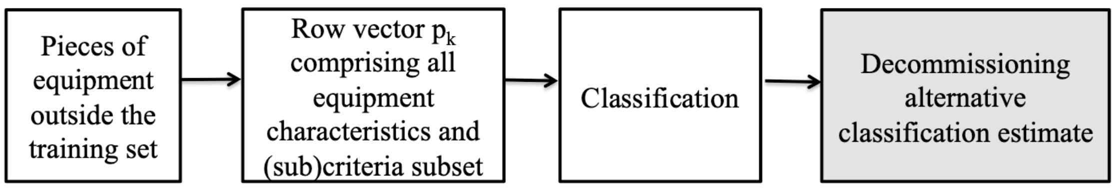

Figure 3.3: Classification model deployment for decommissioning.

The application of the framework in the context of a decommissioning study of an oil and gas field is depicted in Figure 3.3. Let E_s be the set of pieces of equipment left out of the training set, with $s >> r$. It is this set that is fed to the first step in Figure 3.3. For each piece of equipment $e_k \in E_s$, a vector p_k is formed with the evaluation of all relevant sub-criteria selected in Step 3 of Algorithm 1. Then, the reduced model is applied to forecast the selected decommissioning alternative (classification step), which is the output of the last step in Figure 3.3.

Chapter 4

Numerical experiments

For the sake of validation, we applied the framework proposed in Chapter 3, to pipeline data from the Brent field (SHELL, 2017a). The decommissioning alternatives are presented in Table 4.1. A single alternative is to be selected considering the set of twelve sub-criteria described in Table 4.2.

Alternatives	**Description**
A1	Leave in situ with no further remediation required
A2	Leave tied-in at platform; remote and trenched
A3	Leave tied-in at platform; remote and rock-dumped
A4	Trench and backfill whole length
A5	Rock-dump whole length
A6	Recover whole length by cut and lift
A7	Recover whole length by reverse S-lay

Source: Adapted from SHELL (2017a).

Table 4.1: Pipeline decommissioning alternatives.

An important part of the proposed framework is the MCDA analysis for each piece of equipment in the sample, refer to Step 1 of Algorithm 1 for details. However, the approach is designed to work with any MCDA technique available to the decision maker. At this point, it is worth emphasising that a discussion about the choice of the MCDA approach to be employed is besides the scope of this study. It suffices to say that we utilised the classical ELECTRE III (ROY, 1985) method, which makes use of outranking to select an available course of action (ROWLEY *et al.*, 2012).

Moreover, all machine learning experimental results were generated with 10-fold

Criteria	Label	Weight	Sub-criterion
Safety	C1	$\frac{0.2}{3}$	Safety risk to offshore project personnel
	C2	$\frac{0.2}{3}$	Safety risk to other users of the sea
	C3	$\frac{0.2}{3}$	Safety risk to onshore project personnel
Environmental	C4	$\frac{0.2}{4}$	Operational environmental impacts
	C5	$\frac{0.2}{4}$	Legacy environmental impacts
	C6	$\frac{0.2}{4}$	Energy use
	C7	$\frac{0.2}{4}$	Emissions
Technical	C8	0.2	Technical feasibility
Social	C9	$\frac{0.2}{3}$	Effects on commercial fisheries
	C10	$\frac{0.2}{3}$	Employment
	C11	$\frac{0.2}{3}$	Communities
Economic	C12	0.2	Cost

Source: Adapted from SHELL (2017a).

Table 4.2: Sub-criteria for the decommissioning of the Brent field.

cross validation in order to obtain reliable estimates of the classifier effectiveness, testing in a different data sample than the one used at the training stage. The computational experiments were performed in R and made use of some public machine learning libraries, namely *rpart, caret, kernlab* and *gbm*.

The following Section describes the data pre-processing and Section 4.2 features an overview of the results.

4.1 Dataset

To validate our approach, the original intent was to use real-world data from decommissioning reports. In that sense, we found a dataset of sub-sea ducts in the context of a classical report (SHELL, 2017a,c). It is composed by rigid and flexible pipelines, umbilicals and cables, involving a total of 28 pipelines to be decommissioned.

According to SHELL (2017c), the decisions were considered for each pipeline individually through a comparative assessment of the feasible alternatives. This evaluation could be qualitative, quantitative or semi-quantitative and their methodology was based on the guidance notes in (DECC, 2011). They considered that some pipelines would be evaluated only qualitatively, while others should be assessed quantitatively. To assign pipelines to either of these two groups, they made use of the decision tree depicted in Figure 4.1.

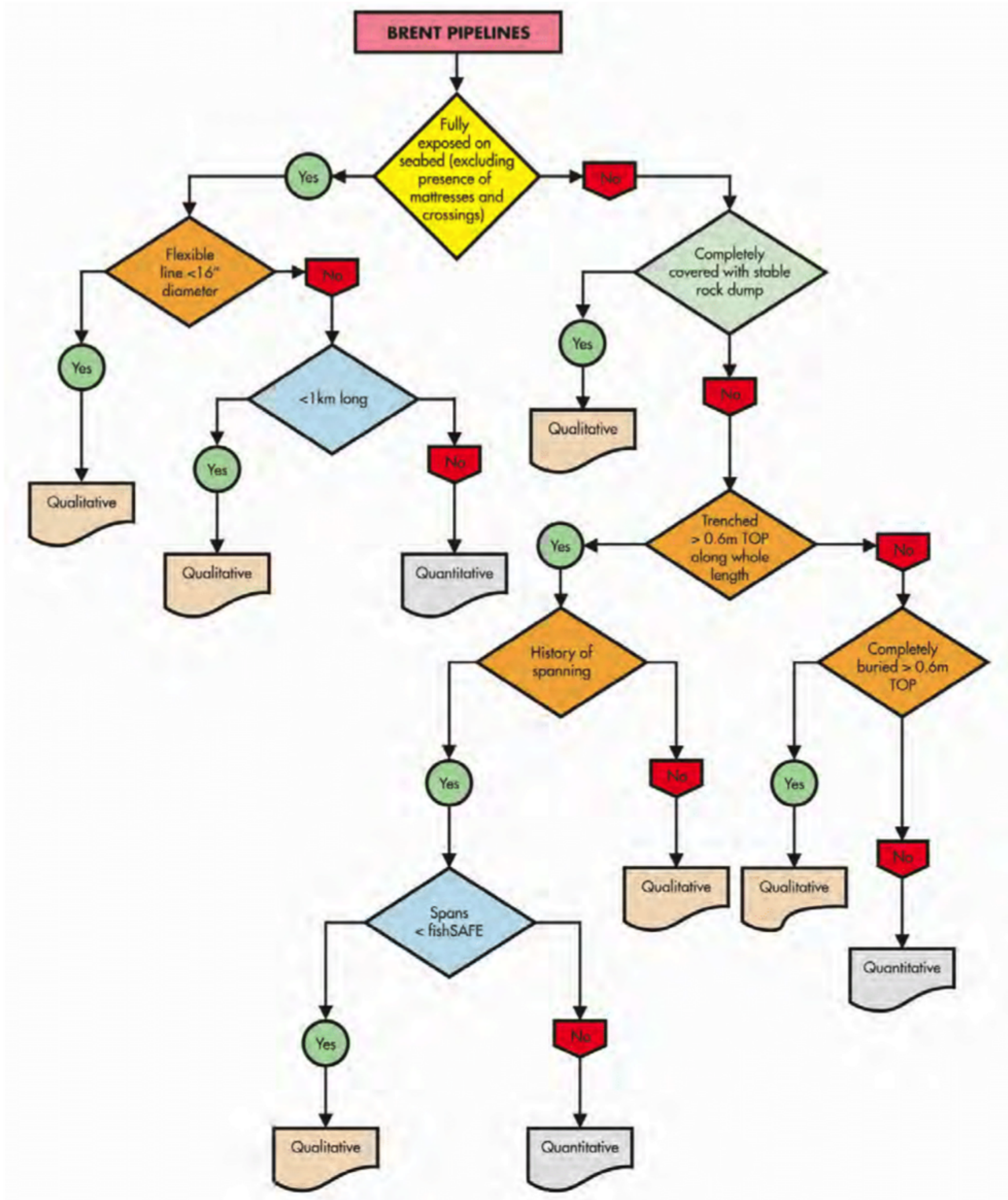

Figure 4.1: Brent decision tree to assign pipelines to qualitative or quantitative assessment.

Source: SHELL (2017c).

Unfortunately, the final dataset of pipelines subject to quantitative evaluation is comprised of only 14 samples, which is insufficient for our purposes (CHANG *et al.*, 2014; CHEN *et al.*, 2017). In this study, we apply a variation of bootstrapping to generate a synthetic dataset for validation. We observed that the dataset could be clustered in four different groups according to their possible alternatives. The groups are represented by different colours (green, blue, yellow and orange) in Table 4.3. The process described on Section 2.3.1 was applied to each group individually. The bootstrap resample were produced by randomly drawing from a uniform distribution for each variable of the dataset. The minimum and maximum values of the uniform distribution coincided with those of the corresponding variable in the original dataset.

Pipeline	Fluid	Cleaning[1]	On bottom status	Crossing	Installation date	Weight (kg)	Diameter (")	Length (km)	Concrete (%)	Steel (%)
N0501	oil	Brent	Partially trenched	7	1978	25529	30	35.9	0.469	0.502
N0201	gas	degassing and flushing	Surfaced	0	1976	1246	36	1.3	0.482	0.505
N0601	gas	degassing and flushing	Surfaced	2	1979	121	16	0.4	0.562	0.405
N0405	gas	Brent	Surfaced	0	1976	2025	24	4.2	0.489	0.483
N0303	oil	Brent	Surfaced	5	1976	2218	24	4.6	0.489	0.483
N0304	oil	Brent	Surfaced	0	1978	1407	20	4	0.468	0.5
N0404	gas	Brent	Surfaced	1	1979	3110	30	4.4	0.471	0.505
N0302	oil	Brent	Surfaced	0	1976	600	16	2.3	0.493	0.473
N0301	oil	Brent	Surfaced	5	1976	730	16	2.8	0.44	0.526
N0401	no	Brent	Surfaced	0	1977	2267	28	3	0.474	0.499
N0402	no	Brent	Surfaced	0	1976	2483	36	2.6	0.472	0.507
N0403	gas	Brent	Surfaced	3	1977	2164	36	2.3	0.477	0.515
N9903A	oil	no	Surfaced	0	1976	820	24	1.7	0.489	0.483
N9903B	oil	no	Surfaced	0	1976	1398	24	2.9	0.489	0.483

[1] "Brent" cleaning type correspond to default cleaning operation conduct for pipelines in Brent field, including pigging operations, chemical and seawater flushing.

Source: Adapted from SHELL (2017c).

Table 4.3: Parameters of the 14 original samples of sub-sea pipelines from the Brent field.

Observe that there is a high discrepancy between the costs of the alternatives. That is one of the reasons that influences the decision making methods to often select the less invasive, and hence less costly, alternatives. Because of that, some costs were artificially changed in the synthetic database generated from the bootstrap technique previously described, in order to increase the variability of alternatives selected. The resulting synthetic dataset with 1313 pipelines was made public for benchmarking purposes (MARTINS *et al.*, 2019), containing the evaluation of each sub-criteria for each alternative and the physical features considered. The resulting probability of selecting each of the seven available alternatives is depicted in Figure 4.2.

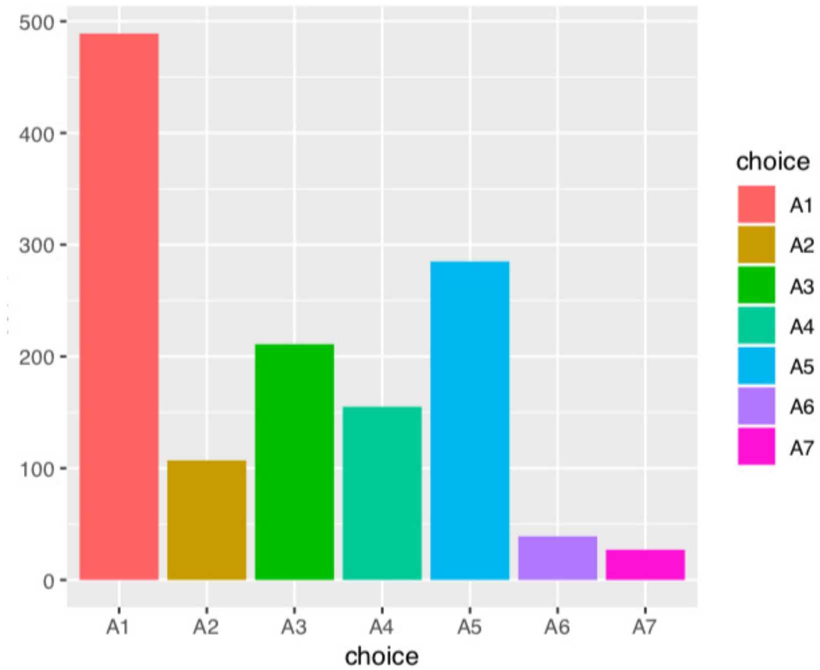

Figure 4.2: Data distribution.

The decommissioning guidelines in (MEI, 2018; OIL & GAS UK, 2015) gave rise to the conjecture that the following variables could be used for classifying pipelines: type (e.g. rigid, flexible); fluid (e.g oil, gas, water); size; length; coated/uncoated; installation date; on bottom status (e.g. fully exposed, rock dumped), proximity to other infrastructure; residues likely/ability to clean; condition (e.g. good and recoverable, damaged). Bearing that in mind, and in possession of the dataset in SHELL (2017c), we selected the following parameters of sub-sea ducts: diameter; length; concrete, steel and coat composition; weight; fluid; proximity to other in-

	Comparative Assessment	**Brent Recommendation**	**ELECTRE III**
N0201	A5	A4	A3
N0601	A5	A6	A2
N0405	A5	A4	A1
N0303	A1	A4	A1
N0304	A5	A4	A1
N0404	A1	A4	A1
N0302	A5	A4	A3
N0301	A5	A4	A3
N0401	A5	A4	A1
N0402	A5	A4	A1
N0403	A5	A4	A1
N0501	A4	A4	A1
N9903A	A5	A4	A5
N9903B	A5	A4	A4

Table 4.4: Decommissioning alternatives recommended by comparative assessment, Brent report and ELECTRE III.

frastructure (number of crossings); installation date; cleaning type and on bottom status.

The initial dataset in (SHELL, 2017a,c) contained all of the eleven parameters mentioned above for each piece of equipment. In addition, it also included the evaluation of each of the seven alternatives with respect to each of the twelve sub-criteria described in Table 4.2. For each piece of equipment, we applied the ELECTRE III tool, with the same set of weights used in the original decommissioning report - which appears in Table 4.2, to produce the recommended decommissioning alternative. The values of indifference, preference, and veto thresholds were set to zero.

The decommissioning alternatives recommended by the comparative assessment method, Brent report final choice and ELECTRE III are presented in Table 4.4 for the fourteen pipelines from the original dataset. Observe that Brent final recommendations were equal to the comparative assessment results in only one of the fourteen samples.

The recommended decommissioning alternative acts as the independent variable in the supervised training routine in Step 2 of Algorithm 1. In that routine, each equipment $e_k = (x_k, y_k)$ is an entry in the dataset, where x_k is a vector containing all the parameters and sub-criteria assessments and y_k is the independent variable, i.e., the decommissioning action the MCDA tool recommended for the respective installation.

4.2 Experimental results

This section is divided into two subsections. In the following subsection, we report the results of each selected machine learning technique in the supervised classification problem of Step 2 in Algorithm 1. Then, Section 4.2.1 illustrates the results of Step 3 of Algorithm 1, that was performed only for the GBM model, which outperformed the competing methods in Step 2.

4.2.1 Model comparison

The aim of this section is to compare the performance of selected machine learning techniques, namely DT, RF, SVM and GBM, for predicting decommissioning decisions based on the input variables described in Section 4. We implemented Grid search (BERGSTRA e BENGIO, 2012), a method to perform hyper-parameter optimisation, was implemented in order to optimise accuracy of each techniques evaluated. The parameters are briefly discussed below:

- DT: The only specification to be optimised for decision trees is the complexity parameter and it was set as 0.047.
- RF: The number of trees was set as 1000. We tried each value in the set $\{8, 9, \ldots, 13\}$ for the parameter *mtry*, i.e. the optimal number of variables selected for each tree. The optimal value obtained was 13.
- SVM: We used the radial basis function kernel and the parameter search was for σ in the set $\{0.01, 0.02, 0.025, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.25, 0.5\}$

and $C \in \{1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5\}$. The selected values were $\sigma = 0.04$ and $C = 5$.

- GBM: All combinations involving interaction depth in the set $\{6, 7, 8\}$, number of trees in the set $\{130, 131, \ldots, 140\}$ and shrinkage in the set $\{0.1, 0.15, 0.2, 0.3\}$ were evaluated. Also, the multinomial distribution was assumed. The best results were obtained with 140 trees, interaction depth equal to 7 and shrinkage equal to 0.1. The bag fraction was set to 0.8.

Table 4.5 and Figure 4.3 summarise the evaluations of accuracy ($P(0)$) and κ for the optimised models. Also, Table 4.6 shows the p-values of pairwise t-test results. The significance threshold was $\alpha = 0.05$. Each element in Table 4.6 is the $p-$value of the null hypothesis, according to which the algorithms in the corresponding line and column, respectively, are indifferent with respect to the performance measures. One can see from the referred table that this hypothesis is rejected in all pairwise comparisons.

Accuracy

	Min	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max**
GBM	0.78	0.80	0.82	0.82	0.83	0.88
RF	0.74	0.77	0.79	0.79	0.81	0.84
SVM	0.67	0.70	0.70	0.71	0.74	0.75
DT	0.59	0.61	0.62	0.62	0.63	0.64

Kappa

	Min	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max**
GBM	0.71	0.73	0.76	0.76	0.78	0.84
RF	0.64	0.69	0.71	0.72	0.74	0.78
SVM	0.55	0.60	0.60	0.61	0.65	0.66
DT	0.43	0.45	0.47	0.47	0.48	0.49

Table 4.5: Model comparison through accuracy and kappa evaluation metrics.

An inspection in the preceding results yields that the GBM model presents the best overall performance considering all features. It boasts a mean accuracy of 82% and $\kappa = 72\%$. At the other end, the worst performance is attained by DT, with significantly lower accuracy and κ. Bearing that in mind, the GBM algorithm was selected for feature selection in Step 3 of Algorithm 1.

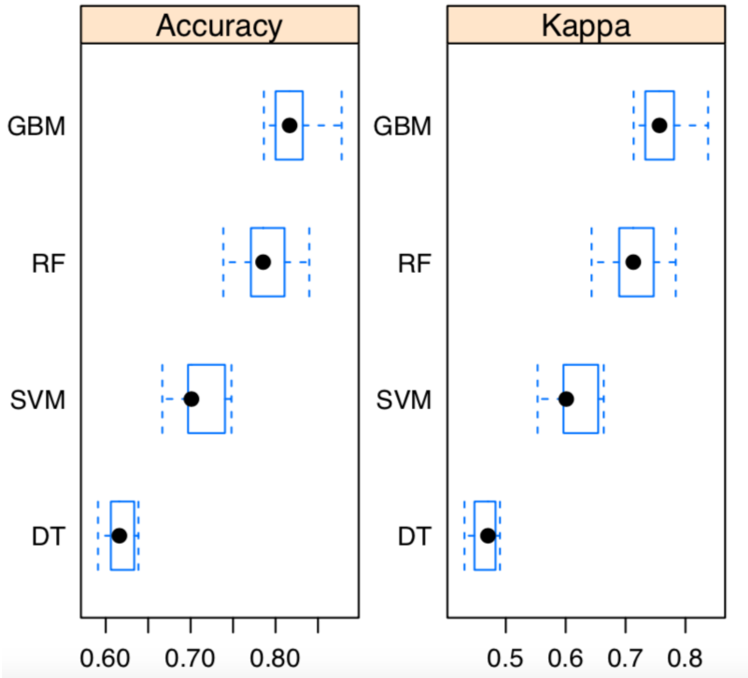

Figure 4.3: Model comparison.

Accuracy

	RF	SVM	DT
GBM	0.026	2.71e-05	1.758e-08
RF		2.5e-04	1.26e-07
SVM			3.58e-06

Kappa

	RF	SVM	DT
GBM	0.019	3.18e-05	5.56e-09
RF		3.6e-04	3.56e-08
SVM			1.06e-06

Table 4.6: The p-values corresponding to pairwise comparison of different classification models.

Feature selection

GBM's feature selection tool is hybrid and combines learning and feature selection (LISO, 2016). The measure of relative importance is due to FRIEDMAN (2001) and is a function of the number of times that a variable is selected for splitting nodes, modulated by the model improvement as a result of each split. For the sake of comparison, the measures of importance are standardised.

As previously stated, GBM was the chosen method for variable selection because it performed best in the classification step. The goal here is to eliminate irrelevant features, i.e., installation parameters or sub-criteria assessments with very limited impact on the output of the MCDA method. By doing so, one can build a lower dimensional model with comparable performance and decreased computational cost (GUYON e ELISSEEFF, 2003). From a practical standpoint, this means that we can find an alternative model that requires a reduced number of sub-criteria assessments and data collection. This, in turn, implies in an accelerated decision making process, with potentially considerable reductions in both costs and times for data acquisition and sub-criteria evaluation.

In our case study, we opted to maintain all eleven features associated with the installation parameters, which were enumerated in Section 4. This is because this information is very easy to obtain, and hence the omission would not bring any relevant benefit. Figure 4.4 conveys the relative importance of each sub-criteria that appears in Table 4.2. It stands out that the sub-criteria C12 (Cost) was the most important. In addition, we found that C12 (Cost), C6 (Energy Use), C11 (Communities), C1 (Safety risk to offshore project personnel), C7 (Emissions), C4 (Operational environmental impacts), C2 (Safety risk to other users of the sea) and C9 (Effects on commercial fisheries), are responsible for about 91.85% of the total importance. Furthermore, it is also striking that the sub-criteria C8 (Technical feasibility) presents a very limited relevance, representing only 0.24% of relative influence.

To test the effect of removing the less significant variables from the model, we tested the GBM model with the subset of most relevant sub-criteria that account for 92%, 83%, 68% and 56% of relative importance, respectively. Obviously, the objective is to come up with the smallest possible subset of sub-criteria that produces no significant decrease in accuracy.

Table 4.7 summarises accuracy and kappa evaluation metrics for each subset considered. The p-values produced by each $t-$test with respect to a pair of models are unveiled in Table 4.8. One can easily see from the latter table that the models with 92% and 83% of the total importance are indistinguishable from the original

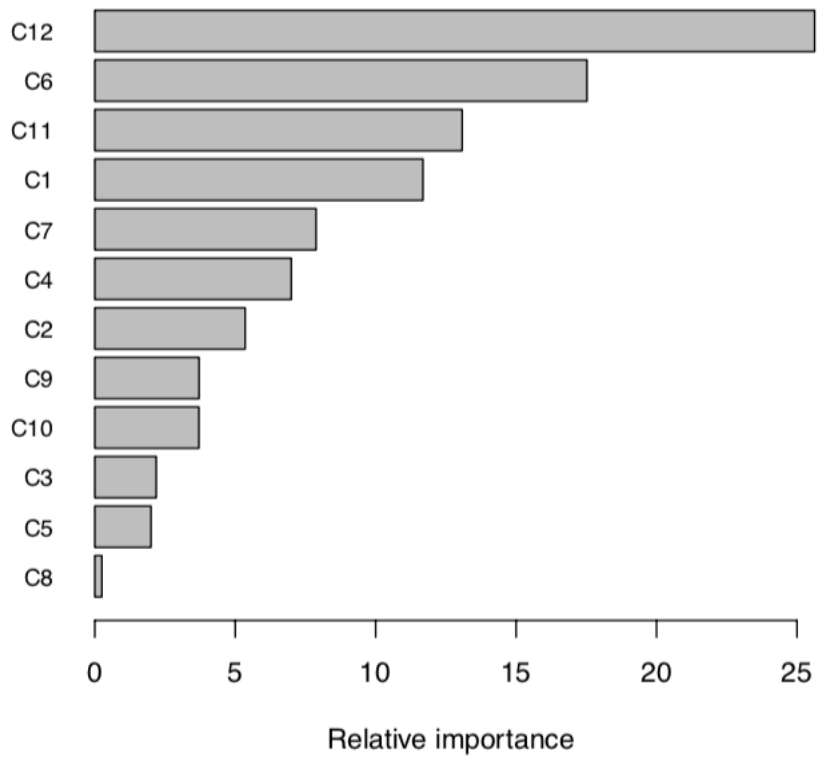

Figure 4.4: Criteria variables relative importance.

Accuracy

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
GBM (100%)	0.79	0.80	0.82	0.82	0.83	0.88
GBM (92%)	0.78	0.79	0.80	0.81	0.83	0.88
GBM (83%)	0.76	0.80	0.81	0.81	0.83	0.86
GBM (68%)	0.76	0.78	0.80	0.80	0.81	0.83
GBM (56%)	0.75	0.76	0.78	0.78	0.80	0.82

Kappa

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
GBM (100%)	0.71	0.73	0.76	0.76	0.78	0.84
GBM (92%)	0.71	0.73	0.74	0.75	0.77	0.84
GBM (83%)	0.68	0.74	0.75	0.75	0.77	0.81
GBM (68%)	0.67	0.71	0.74	0.73	0.75	0.78
GBM (56%)	0.67	0.68	0.71	0.71	0.74	0.76

Table 4.7: Performance comparison of GBM considering different subsets of variables through accuracy and kappa evaluation metrics.

model. This means that we can keep only half of the sub-criteria assessments, namely sub-criteria C12, C6, C11, C1, C7 and C4, with virtually no impact on the performance of the classification method.

The results seem very promising, and suggest that the decommissioning study

Accuracy

	GBM (92%)	**GBM (83%)**	**GBM (68%)**	**GBM (56%)**
GBM (100%)	1	1	0.18	0.054
GBM (92%)		1	1	0.259
GBM (83%)			0.563	0.029
GBM (68%)				0.28

Kappa

	GBM (92%)	**GBM (83%)**	**GBM (68%)**	**GBM (56%)**
GBM (100%)	1	1	0.20	0.064
GBM (92%)		1	1	0.279
GBM (83%)			0.560	0.030
GBM (68%)				0.31

Table 4.8: p-values corresponding to pairwise comparison of GBM models considering different subsets of variables, according to the percentage of relative importance of the criteria given by the method of FRIEDMAN (2001).

of an oil field can be considerably simplified with the application of the proposed method. Indeed, eliminating half of the sub-criteria assessments with no significant loss in performance would be a very welcome development in a long, complex process. Arguably, one can expect considerable reduction in the number of sub-criteria since, in a complex process such as that which sets up the sub-criteria, it is possible that many criteria and sub-criteria assessments be highly correlated. Such a correlation can be captured my machine learning techniques in the process of generating a simplified analysis tool with comparable results.

Another potential gain of the proposed approach is that one does not need to deploy the MCDA tool for all installations. Instead, it is only utilised in the training set. For all installations outside this set, the decision maker can simply make use of the predictions provided by the machine learning classification tool.

Chapter 5

Conclusions

This study developed a framework based on supervised algorithms and dimensionality reduction techniques aiming to reduce the time and effort of sub-criteria evaluations in a decommissioning study. The framework makes use of a reduced dataset comprised of installations' characteristics and sub-criteria evaluations. A number of machine learning algorithms is then applied to the dataset and that with the best overall performance is singled out for variable selection. This latter step then produces a reduced subset of relevant sub-criteria that should be measured for the pieces of equipment left out of the training dataset. The reduced model can be used to predict the decommissioning alternative for these pieces of equipment, thus circumventing the need for a case by case MCDA analysis.

The framework was validated through numerical analyses for a synthetic dataset based on real data for pipelines in the Brent field (SHELL, 2017c). The synthetic dataset generated through bootstrap contains 1313 samples and played a fundamental role in the validation of the proposed approach. The variables included eleven characteristics, such as diameter and fluid type, and the evaluation of twelve sub-criteria for each of the seven decommissioning alternatives. We used ELECTRE III to generate the recommended alternatives for each installation in the dataset.

Another proposed objective was to compare the performance of different supervised methods to classify the oil & gas installations according to the selected decommissioning alternative, considering accuracy and kappa as evaluation metrics.

In the numerical experiments, GBM was the best classification tool, outperforming DT, RF and SVM. The variable selection stage for GBM yielded very promising results, fulfilling the last specific objective proposed in this study. This procedure showed that half of the sub-criteria could be left out of the analysis with virtually no effect on the performance, keeping Cost, Energy use, Communities, Safety risk to offshore project personnel, Emissions and Operational environmental impacts.

One significant contribution is the suggestion that the decision maker can accurately predict the recommended decommissioning alternatives with a reduced number of sub-criteria evaluations. In addition, the use of machine learning precludes the need for a case by case MCDA analysis, since the recommended alternatives for the installations outside the training set can be accurately forecast by the classification method.

The current work can be extended in future studies. For instance, different supervised methods could be considered and compared with the ones already applied. In addition, this study considered the same set of weights used in the original decommissioning report. Future studies could evaluate the effects of varying weights on the final decommissioning alternative recommended.

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