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Steffen Jaap Bakker

Optimization models for the plugging and abandoning of offshore oil and gas fields

NTNU
Norwegian University of Science and Technology

Doctoral thesis

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Oil Wells That End Well

Adaption from
William Shakespeare

Abstract

This thesis applies operations research methods to planning problems related to the plugging and abandoning of offshore oil and gas wells. We consider two problem settings, for which we develop new models and solution approaches.

The first problem is on a tactical planning level and considers the optimal planning of a plugging campaign. The problem is defined as a variant of an uncapacitated vehicle routing problem with time-windows and is being treated in the first three papers in this thesis. We focus on different aspects, ranging from the application of different model formulations and solution methods, to obtaining more economically oriented insights. A main finding is that significant cost-savings can be made by using the developed methodology for planning plugging campaigns, as opposed to conventional methods. In addition, we contribute to the vehicle routing literature by developing a methodology that allows for incorporating a learning effect. That is, the time it takes to perform a particular operation reduces as similar operations have been performed before.

The second problem considers the strategic problem of developing a mature offshore oil field, and is treated in the fourth paper. We develop a multistage stochastic integer program and solve it using the stochastic dual dynamic integer programming algorithm (SDDiP). The problem can be considered to represent a portfolio of real options, incorporating both shutdown and expansion options. We show that the SDDiP algorithm is very suitable for solving complex real options problem. This enables us to perform an extensive analysis on factors affecting the abandonment decision. We show that traditional real options findings for single options might behave differently when considered in portfolios.

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Further, I would like to thank my colleagues in SINTEF with whom I collaborated on the ECOPA project. In particular, I would like to thank research managers Kjetil Midthun and Vibeke Stærkebye Nørstebø, who always provided a listening ear and kept the wheel going. I also would like to thank: Mats Mathisen Aarlott, for his discussions in the start of this PhD, especially when we both were not completely sure about which directions to take; Gerardo Perez-Valdes, for his support on more technically oriented programming issues; and Torbjørn Vrålstad, for a good cross-disciplinary collaboration, as well as teaching me the importance of identifying and targeting the right audience.

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Contents

Chapter 1

Introduction

In 2018, approximately 70% of the world's oil and gas production came from mature fields (O'Brien et al., 2016) and this share is most likely going to grow in the years to come. The low oil and gas prices of the recent years put pressure on the profitability of offshore fields. Especially in areas that have high operational expenditures, such as the North Sea. As a result, thousands of offshore wells are planned to be permanently plugged and abandoned in the upcoming decades. The total costs for performing these operations will be substantial (Myrseth et al., 2017; Oil & Gas UK, 2016). Operators now informally refer to this as the upcoming plugging wave.

This PhD thesis is part of the "Economic Analysis of Coordinated Plug and Abandonment Operations" (ECOPA) project[1]. The principal objective of the ECOPA project is to determine how the large costs of plug and abandonment can be reduced by better planning methods. Moreover, this thesis is written under the PhD program in Industrial Economics and Technology Management at the Norwegian University of Science and Technology. This is a multidisciplinary program that aims to bridge the gap between technology and industry on the one hand, and academic theory and methods on the other hand. In line with these objectives, this PhD thesis identifies planning problems connected to the plugging and abandoning of offshore wells, where methods from the field of Operations Research (OR) can be applied. We aim to develop knowledge, models and solutions methods that create value for both industry, society and academia.

The scope of this thesis is further restricted to the planning problems that are identified in Chapter 2.3. Moreover, the developed case studies, as well as certain elements in the problem formulations, are based upon the Norwegian Continental Shelf (NCS). Other production areas and/or regulatory regimes might possess different features. Nevertheless, the developed methods are constructed as general as possible and can easily be adopted to different settings.

The first three papers in this thesis consider the planning of an offshore plugging campaign and make use of vehicle routing methodology. The fourth paper targets the development of a mature offshore oil field and applies methods from multistage stochastic programming as well as real options.

The structure of this thesis is as follows. Chapter 2 puts the papers presented in this thesis into context. First, it provides a general background over relevant aspects of the oil and gas industry as well as the plug and abandonment process. Subsequently, we distinguish P&A planning problems on an operational, tactical and strategic planning level. We then discuss the methods and research topics that are used in the papers included in this thesis. This includes vehicle routing, real options and stochastic dual dynamic integer programming. We provide an overview of relevant literature, place the conducted research in this scientific landscape and elaborate on some of the methods. In Chapter 3 we provide a summary of each

[1]The ECOPA project is funded by the Research Council of Norway through the PETROSAM2 and PETROMAKS2 programs (p-nr 247589)

paper in this thesis. In addition, for each paper, we present the contributions to the research community and industry, and specify the individual contributions of each author. Finally, general conclusions based on the research are given in Chapter 4, as well as suggested further work. The papers presenting the actual research are included as appendices.

Chapter 2

Background and Literature

The purpose of this chapter is to put the papers presented in this thesis into context. We start by giving an overview of relevant aspects of the oil and gas industry and plug and abandonment process. Subsequently, we present planning problems related to the plug and abandonment process, where optimization methods can be of use. Finally, we discuss the different methods that we have used in solving these planning problems.

2.1 Oil and Gas Industry

The oil and gas value chain can be divided into three sectors: upstream, midstream and downstream. The *upstream sector* includes the exploration and production (E&P) of hydrocarbons, midstream includes transportation and processing, while downstream focuses on the filtering, sales and distribution. The work in this thesis can be related to the upstream sector, for which a detailed background is given in Jahn et al. (2008). It is common to define a life cycle for (offshore) oil and gas fields, consisting of five phases:

1. *Exploration.* Exploration is the process of locating potentially viable oil and natural gas sources. This is usually done through geological/seismic surveys.

2. *Appraisal.* Fields that are successfully identified during exploration are examined in more details in the appraisal phase. Initial infrastructure can be set up to access the sites and exploratory wells can be drilled to map the oil/gas reserves.

3. *Development.* During the development phase the company develops plans on how to produce the reserves. If the plan is approved by regulatory bodies, the required infrastructure and production facilities are developed. As a development concept, we distinguish between a platform-based or subsea-solution.

4. *Production.* The oil/gas reserves are being extracted during the production phase. Important activities during this phase include deciding on production levels, the drilling of new wells, maintaining old wells and injection of water/chemicals/gas.

5. *Decommissioning.* Finally, the field has to be decommissioned, which means that all wells have to be plugged and abandoned and pipelines, facilities and other structures have to be removed.

There are multiple actors involved in the life cycle of an oil and gas field. First, we have the state, which can be represented by national or local governments. They are responsible for regulations, managing legal and fiscal infrastructure, and collecting revenues through taxes. Within the oil and gas industry, the main actor is the E&P company that is responsible for production, known as the *operator*. The operator tends to operate on behalf of other E&P companies within a license/consortium. Finally, we mention *service companies*, whose main focus is to provide products and services associated with the oil and gas exploration and production process.

2.2 Plug and Abandonment (P&A)

Plug and abandonment (P&A) is part of the decommissioning phase of an offshore oil/gas field. In this section, we give a short introduction to the P&A process, and refer to Vrålstad et al. (2019) for a more detailed review.

Permanent P&A is the process of securing a well by installing required well barriers (plugs) such that it will not be used or re-entered again (Standards Norway, 2013, Chapter 9). P&A includes the setting of permanent *barriers* to isolate both the reservoir as well as other fluid-bearing formations. These barriers should prevent oil, gas and water to migrate to the surface or flow from one formation to another. A simplified illustration of a typical offshore production well before and after P&A is given in Figure 2.1.

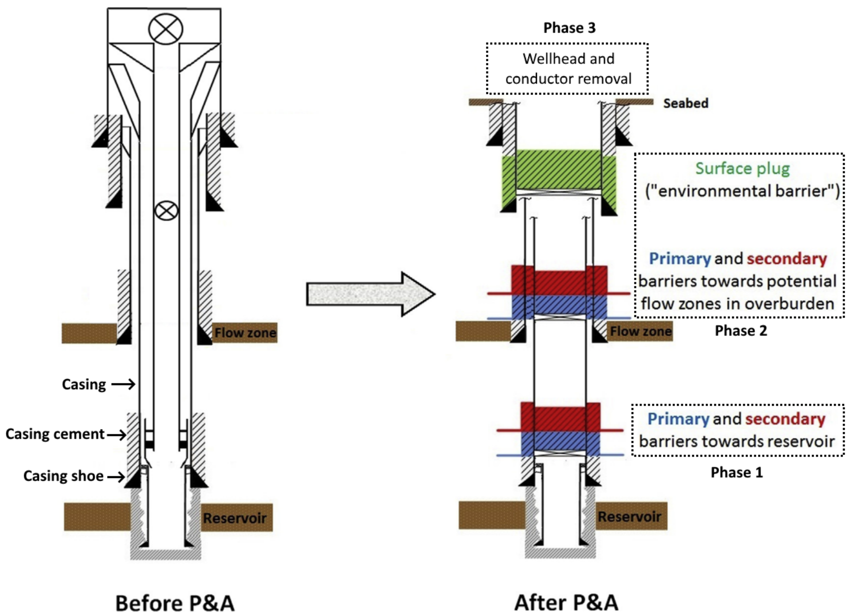

Figure 2.1: Simplified illustration of a typical offshore production well before and after P&A, adapted from Standards Norway (2013).

Barriers are usually constructed by the placement of cement plugs inside the wellbore, but other materials can be used as plugging material as well (Saasen et al., 2011; Khalifeh et al., 2014). Nevertheless, in many cases, placing a cement plug inside a cased wellbore is insufficient to prevent leakages. These leakages might for example occur due to poor annulus cement outside the casing. So, the barriers must cover the whole cross-section of the well, both vertically and horizontally. This implies that the barrier should stretch all the way to the formation surrounding the borehole, and should include all annuli as well as cement plugs. If one of these elements fails, potential leak paths might arise. To prevent such leak paths from forming, before setting the plugs, poor annulus barriers must be removed. Two of the conventional techniques that target this are section milling (Scanlon et al., 2011) and Perforate-Wash-Cement (Ferg et al., 2011; Delabroy et al., 2017). Section milling aims to create a cross-sectional barrier towards the formation. This is done by milling out, i.e. removing, sections of the wellbore where the annulus material is not suitable as a barrier. For this process, special milling blades and cutters are used. Perforate-Wash-Cement can be used when the annulus is filled with poor cement, or not cemented at all. In this case, the casing is perforated to gain access to the annulus. The annulus is then washed to get rid of any poor cement or debris and is subsequently filled with new cement. In some cases, a part of the casing string might have to be removed. Besides section milling, another method that can be used is to cut and pull the casing (Desai et al., 2013). However, a main downside here is that the casing can get stuck, which can lead to a huge delay in operations.

P&A operations can be classified based on three different *phases* (Oil & Gas UK, 2015). In addition, Moeinikia et al. (2014) proposed to include a Phase 0, *prepatory work*, which includes pre-P&A work such as killing the well, logging the tubing quality and establishing temporary barriers. We then have phase 1, *reservoir abandonment*, which comprises the installation of primary and secondary barriers towards the reservoir as given in Figure 2.1. For a typical well this includes the rigging of a blowout preventer (BOP), the pulling of tubing, installation of the primary barrier with its base at the reservoir and installation of the secondary barrier, such that the base of the barrier can withstand anticipated future pressures. Depending on the condition of the well and the bonding with the surrounding formation, some tubing and/or casing might have to be removed, which can be done by means of milling or cutting and pulling. These are very time-consuming operations, especially when several cutting and pulling trips have to be made into the well before the next phase can proceed. Phase 2, *intermediate abandonment*, includes the installation of potential barriers towards flow zones in the overburden as well as possible installation of a surface plug, depending on regulations. In addition, casing strings might have to be removed in this phase. Phase 3, *wellhead and conductor removal*, includes the cutting of casing strings and conductor below the seabed to prevent interference with marine activity. Moreover, casing strings and the conductor and wellhead are removed.

There is a huge difference in performing P&A operations on subsea wells compared to platform wells. The main difference being that subsea wells have the x-mas tree and all production equipment at the seabed. As a result, subsea wells require mobile offshore units (MOU) to perform P&A operations. The most expensive and versatile type of MOU are mobile offshore drilling units (MODU), also referred to as rigs. This category consists of drilling ships, jack-up rigs and semi-submersible rigs (SSR). These units are equipped with a derrick that can handle heavy loads and recover, for example, casing strings. Moreover, it is equipped with a marine riser system and internal BOP, making it possible to perform cement jobs by displacing and retrieving well fluids. In addition, riserless light well intervention vessels (RLWI) are vessels that are designed to do subsea well intervention activities using wireline or coiled tubing as opposed to a marine riser system. A downside is that RLWI vessels have limited capabilities in pulling casing strings. However, a RLWI has much lower operational costs compared to a MODU. Finally, light construction vessels (LCV) are even lighter and cheaper than RLWI vessels and can be used to perform very simple operations.

So, each of these MOUs has different characteristics in terms of compatibility with operations, durations, day rates, sailing times, and so on. Here, we highlight that MODUs can be used all year round, while lighter vessels have much lower operability due to weather conditions. With current available technology, a MODU is needed in the P&A process due to various reasons. It provides fluid handling capacity, rotation of drill string and pulling capacity and is required for complex operations such as section milling. compatibility. Nevertheless, significant cost-savings can be made when certain P&A operations are performed using lighter vessels, such as RLWI and LCV, that have much lower day rates (Sørheim et al., 2011; Varne et al., 2017). Additional costs might be saved when all phases of the P&A process can be performed from a vessel instead of a MODU. Øia et al. (2018) discusses how existing techniques can be used to perform full P&A of subsea wells using RLWI. They find that for more complex wells, a rig is still required to perform operations such as section milling and heavy lifting, and would be the least risky option. Moreover, a prerequisite for full subsea P&A from a vessel is that the production tubing has to be left in the well, which might lead to potential leak paths.

2.3 P&A Planning Problems

Planning problems can be divided according to different time horizons (Simchi-Levi, 2003). When focusing on petroleum production, different frameworks have been introduced (Schlumberger, 2005; Ulstein et al., 2007; Gunnerud et al., 2012). However, an overview over planning problems related to the P&A process has not been presented. In this section, we suggest different planning levels and identify related P&A planning problems that can benefit from optimization methods.

On a short time horizon such as days, *operational* planning focuses on generating detailed plans for the execution of P&A operations. Techniques and materials used, the number and length of the plugs set, or the deployment of workers are topics that can be considered.

Tactical planning takes place on a medium-term horizon, typically from a month up to a year. Related decisions involve the scheduling and planning of P&A operations for a number of wells that have to be shut down.

On a long-term horizon, typically from a couple of years in the future and up to the end of a license, *strategic* planning deals with decisions that have long-lasting effects. These decisions are based on, amongst others, production profiles, output prices and possibilities for extension of productive life (enhanced recovery). The main strategic decision for a license holder of a field is to determine when to cease production.

2.3.1 Operational level: configuration of a P&A plan

The operational level looks at the P&A process from a detailed, short term, single-well perspective. Operators on the NCS are obliged to hand in a plan for an abandonment program for each well that will be shut down. Such a plan includes, amongst others, techniques/technologies to use as well as locations, thicknesses and materials of the plugs. Plans are based on factors such as conditions of the well, locations of hydrocarbons, types of formations and well logs. These factors tend to be (partially) uncertain, due to the difficulty of obtaining information in the subsurface. Currently, plans are constructed manually by experts for each single well that has to be P&A'd, which might lead to non-optimal solutions. As many different combinations can be chosen, an optimization approach might prove to be very useful in deciding which technology/specifications to use. Even though the goal of plugging operations is to seal the wells with an eternal perspective (Standards Norway, 2013), there always is a risk of plug failure after abandonment (Mainguy et al., 2007). Optimization techniques allow for a risk-based approach, which is needed when evaluating different techniques to perform P&A. The main challenge in developing this problem setting is the availability of operational data due to confidentiality issues (Myrseth et al., 2017). We are not aware of any literature that applies mathematical programming methods to operational planning problems related to P&A. In the sequel we will focus on tactical and strategic planning problems. If detailed data on technical parts of the P&A process would be available, machine-learning techniques might prove a valuable tool in designing operational plugging plans.

2.3.2 Tactical level: offshore P&A campaign planning

On a tactical level, we have identified the planning of an offshore plugging campaign as the main problem. To plug a single well, a set of operations has to be executed. Depending on well-conditions, the time to plug such a well might range from a couple of days up to a couple of weeks. When plugging a set of wells, many operations have to be performed. As a result, planning for a large set of plugging operations quickly leads to a scheduling problem with a horizon of several months. Contrary to platform wells, subsea wells require MOUs to perform plugging operations. This adds an extra dimension to the planning of plugging operations: deciding on which MOUs are going to perform which operations. The problem of planning a *P&A campaign* aims to find the most cost-efficient routes and schedules for a set of MOUs to carry out P&A-operations on a given number of subsea-wells in a tactical planning horizon. Cost savings might result from decreased sailing time or usage of vessels with a low day-rate.

Related work has been performed by Moeinikia et al. (2015), who developed a simulation approach for obtaining cost and duration estimates of P&A campaigns. Nevertheless, we are not aware of any work that applies optimization methods to the planning of P&A campaigns.

The problem of planning a P&A campaign has been defined in Paper I (Bakker et al., 2017). The developed model is a variant of an uncapacited Vehicle Routing Problem and is improved in Paper II (Bakker et al., 2019) and Paper III (Bakker et al., 2020b). Moreover, Øia et al. (2018) use the model to evaluate the cost benefits of rigless techniques using RLWI vessels. Section 2.4.1 presents a literature review of vehicle routing problems and puts these three papers in perspective.

2.3.3 Strategic level: mature field development

The goal of a field's license holder on the Norwegian Continental Shelf is to extract as much hydrocarbons out of a field as possible, while this is economically feasible and environmentally responsible (Petroleumsloven, 1996, §4-1). To achieve this, the license holder has to consider his production strategy continuously. Inevitably, the question arises when a field should be shut down, which is alternatively referred to as abandonment or cessation of production.

The shutdown decision can be made on different levels of detail. We distinguish between a license, field, structure and well-level, where the structure level refers to a group of wells that are connected to a platform or subsea installation. As the shutdown decision is a complicated decision depending on many interacting factors, we define three factors influencing the shutdown decision:

1. *Economical*
   The main factor affecting the shutdown decision is based on the economics of the project. Clearly, low output prices can turn a profitable field into a loss incurring project, inducing premature shutdown. On the other hand, available projects that can increase production, might extend the lifetime of a field. The value of an asset is typically evaluated using the net present value criterion, and should be calculated using a method that takes into account the prevailing uncertainties. Although it might be profitable to invest in a project and continue production, resource restrictions can lead to premature shutdown. This can be due to restrictions on available capital, alternative projects that are more profitable or high utilization of scarce resources/equipment (e.g. rigs). This means that strategic decisions have to be evaluated based on a portfolio perspective.

2. *Natural*
   As hydrocarbons are produced, the reservoir pressure and hydrocarbon reserves drop. This phenomenon is known as depletion, and might make it impossible to continue production. A well that has run dry, has to be plugged at some point. Moreover, reservoir depletion can induce seabed subsidence, which can lead to sinking platforms. Other integrity problems can arise both on a well level (e.g. degrading wellbores) or a structure level (e.g. corrosion).

3. *Political/legal*
   An extraction license tends to give a company the rights to produce hydrocarbons for a limited amount of time. When the owner of the mineral rights (usually a government) decides not to extend a license, production has to stop. As an example, with the intended switch to sustainable energy sources, it might become a realistic scenario that fields with remaining reserves will not get a license extension.

The problem of shutting down an offshore oil field is a classical research question and has received attention from real options as well as mathematical programming. Section 2.4.2 and Section 2.4.3 give a literature review over these works respectively.

Paper IV (Bakker et al., 2020a) presents a multistage stochastic integer programming model that focuses on the development of a mature oil field. The value of the asset is affected by uncertain output prices, and can be influenced by shutting down or undertaking activities that increase production (such as drilling new wells). Moreover, increasing decommissioning costs due to integrity issues are considered. As such it incorporates important economical and natural factors, while the horizon of the problem is determined based on legal restrictions.

While the shutdown problem has received considerable attention, we are not aware of any other strategic P&A problems in the optimization literature. A possible research direction can be the construction of plug and abandonment portfolios. Taking the perspective of operators, when a field becomes economically unprofitable, it becomes a liability instead of an asset. As a result, operators are looking for the cheapest way to abandon the field. Organizing a decommissioning project can be a complicated and time consuming venture. So, selling/outsourcing (parts) of this project, can be an interesting alternative. A third party can specialize in such decommissioning projects. By bundling decommissioning projects in portfolios, resources can be utilized more efficiently, which might lead to potential cost-savings.

2.4 Methodology

The models developed in this thesis are based on methods from different fields within operations research. To put our research in perspective, we give a short background on these fields and methods. Paper I, II and III in this thesis (Bakker et al., 2017, 2019, 2020b) treat the problem of planning an offshore P&A campaign using a vehicle routing problem, while Paper IV Bakker et al. (2020a) draws from both the field of real options, as well as multistage stochastic optimization and in particular stochastic dual dynamic integer programming.

2.4.1 The Vehicle Routing Problem

The P&A Campaign Planning Problem (PACP) contains scheduling as well as routing aspects. That is, plugging operations on the different wells have to be scheduled to vessels, while at the same time optimal routes have to be constructed for each vessel. The Vehicle Routing Problem (VRP) methodology (Cordeau et al., 2007) allows for the modeling of these aspects.

A VRP tends to be defined on a graph. Customers that have to be visited, or operations that have to be performed, are represented by *nodes* (or vertices), while line segments connecting these nodes are referred to as *arcs*. These arcs can represent the physical time, distance or cost between nodes. Arcs can be directed and undirected, giving information about the direction of travel and possible precedence relationships. A *route* then specifies in which order nodes (or arcs) are being visited, whereas a *schedule* specifies when each node is visited.

The VRP literature is rich and there exist myriad variants of the VRP (Toth & Vigo, 2002). VRPs can be classified based on different characteristics, such as the number of available vehicles/vessels, capacity of the vehicles or timing restrictions such as synchronization (Drexl, 2012). At the basis of each VRP lies the traveling salesman problem (TSP). In the TSP, there is only one vehicle available, the nodes can be visited in any order and there are no capacity or scheduling restrictions. The multiple traveling salesman problem (mTSP) is obtained when allowing for multiple vehicles. A review of formulations and solution methods to the m-TSP is given in Bektas (2006). Real world VRPs gives rise to many constraints. This class of problems is known as rich VRPs. Lahyani et al. (2015) gives a taxonomy over all the different characteristics that rich VRPs can possess.

The PACP is formulated as an uncapacitated VRP with Time Windows and Precedence Constraints (uVRPTWPC) and can also be referred to as an mTSP with Time Windows and Precedence Constraints (mTSPTWPC) (Balas et al., 1995; Ascheuer et al., 2001). The PACP has a heterogeneous fleet, meaning that each vehicle/vessel can have different characteristics in terms of costs and operations. Another important characteristic is that The PACP does not consider capacity. Even though fluid returns are obtained when performing P&A operations, these returns can be stored in storage tanks and drained offshore by supply vessels of which the day rates are significantly lower than the vessels used to perform P&A operations. Finally, the PACP considers precedence between nodes and time-windows on when nodes can be visited.

Typically, VRPs involve binary decision variables and are formulated as mixed integer programs (MIP). Depending on the definition of the routing variables, the model formulation can be categorized as an *arc-flow* formulation or *path-flow* formulation (Toth & Vigo, 2002). An arc-flow formulation contains binary variables for traversing arcs in the graph, representing whether a vehicle travels between two distinct nodes. A path-flow formulation contains binary variables for routes/paths in the graph, representing whether a vehicle performs a certain route.

VRPs can be solved using an exact or a heuristic approach. The VRP is NP-hard and large instances are thus very difficult to solve. A large stream of literature focuses therefore on heuristic solution approaches (Toth & Vigo, 2002, Chapter 5). Nevertheless, the research in this thesis takes an exact approach. When the constructed MIP is solved exactly, the *branch-and-bound* technique lies usually at the basis. When an arc-flow formulation is used, valid inequalities tend to be added dynamically in a *branch-and-cut* framework. An application to a maritime routing problem can be found in Glomvik Rakke et al. (2012). For path-flow formulations, the large number of possible routes can be generated before the problem is solved or while the problem is solved. This is referred to as a priori and dynamic *column generation* respectively. The *branch-and-price* method is the main approach being used for the latter. An example of this method applied to a maritime routing problem is given by Stålhane et al. (2015).

The work in Paper I, II and III uses an arc-flow approach, as it more easily accounts for synchronization constraints between operations (nodes) and routes, compared to a path-flow approach. Paper I adapts a Miller, Tucker and Zemlin formulation, while Paper II switches to a commodity flow type formulation, leading to a tighter model formulation (Öncan et al., 2009). Finally, Paper III implemented a branch-and-cut approach that did not lead to any computational gains. This paper also introduces an approach to account for a learning effect in the setting of vehicle routing problems. A learning effect can occur when many similar operations are performed. That is, the time it takes to perform an operation reduces as similar operations have been performed before. Previous works have considered a learning effect in the context of a multi-day VRP, were the service time parameters are updated between model runs in an exogenous (Zhong et al., 2007; Kunkel & Schwind, 2012). The methods developed in Paper III allow for an endogenous learning effect, where the learning occurs within the time-horizon of the VRP.

2.4.2 Real Options

The term real options refers to the application of option pricing theory to valuating investments in *real* (non-financial) assets. Flexibility and the possibility to obtain information on the stochastic process over time are important factors contributing to the value of a real option. The oil and gas industry has been one of the main industries applying real options tools in practice (Smith & Mccardle, 1999). The option to shut down (or to abandon) an oil-field has been used as one of the main applications (Paddock et al., 1988; Ekern, 1988). Other typical real options include the option to expand, wait or switch. A real options problem then aims to exercise these options at the optimal time. Although there is agreement around the concept of real options, there exist many different approaches and underlying assumptions to implement such real options (Borison, 2005). Nevertheless, the main reference to the field of real options is Dixit & Pindyck (1994).

The foundation of traditional real options literature is financial option pricing. The main assumption is the existence of a replicating portfolio of financial instruments that can replicate the (uncertain) returns of the real option. This approach is used by Myers & Majd (1983); McDonald & Siegel (1985) to value an abandonment option using standard no-arbitrage arguments. It is typically assumed that the prevailing stochastic processes, such as the oil price or production rate, evolves according to a Geometric Brownian Motion (GBM). Based on these assumptions, analytical results can be calculated for single options. Examples include the optimal abandonment time (Olsen & Stensland, 1988; Clarke & Reed, 1990) or optimal switching time (Støre et al., 2018).

Real options problems are characterized by the possibility to take decisions in time, where information on an uncertain process is revealed during this time period. There are different methodologies that allow for these features, including decision analysis, dynamic programming and stochastic programming. Each of these methods allows for sequential decision making under uncertainty and therefore allows to value flexibility. However, there are also some key differences between these methods. For example, when considering restrictions on the stochastic process, dynamic programming bases itself on Markov properties, stochastic programming requires a finite scenario tree, while decision analysis needs full enumeration of the discrete process.

Traditional option pricing makes use of a replicating portfolio argument to value price uncertainty. Dynamic programming and stochastic programming use a different approach to value risk, in which a risk-free interest rate is used to discount future cash-flows.

Considering the real options problem to abandon a project with uncertain future revenues, Bonini (1977) formulated a discrete time dynamic programming model. Many recent applications take a similar approach (Lund, 2000; Fleten et al., 2011; Nadarajah et al., 2017).

An elegant way to integrate the option pricing approach and decision analytic approach is by Smith & Mccardle (1998, 1999). A distinction is made between market uncertainties (e.g. oil prices) and private uncertainties (e.g. production rates). The key difference being that market risks can be perfectly hedged by traded financial instruments, opposed to private risks.

Real options has been applied to many petroleum field development problems. For example, Lund (2000) describes a stochastic dynamic programming model for the development of a marginal offshore oil field under uncertainty through its entire life cycle. In addition, Dias (2004) presents an overview of real options occurring in petroleum exploration, development and production. In particular, the option to expand production is discussed.

Many real options problems are formulated as stochastic dynamic programs. In this case, the most common approach to value the options is by means of a Least Squares Monte Carlo Approach (LSM) (Longstaff & Schwartz, 2001), also known as the simulation-and-regression method. Applications of this approach in the oil and gas industry can be found in (Fleten et al., 2011; Jafarizadeh & Bratvold, 2012).

Even though in practice options tend to be available in portfolios, the approaches presented above have their limitations in allowing for multiple interacting options. A possible approach to resolve this challenge is by incorporating real options in a stochastic programming framework. This can in addition allow for the inclusion of more (technical) details. Nevertheless, this might come at a cost of an increase in computational complexity. A discussion on the differences and similarities between real options and stochastic programming has been given by Wallace (2010), while Wang & de Neufville (2004) proposes a method to incorporate real options in a stochastic programming framework. A more recent approach that allows for portfolios of real options is by (Maier et al., 2019, 2020). It is based on a stochastic dynamic program and extends the traditional LSM method. Paper IV (Bakker et al., 2020a) in this thesis takes a similar perspective, but uses the Stochastic Dual Dynamic Integer Programming (SDDiP) algorithm to solve the real options problem, as opposed to the LSM method. This appears to be a very promising approach to solve complex real options problems.

2.4.3 Multistage Stochastic Integer Programming

The model in Paper IV (Bakker et al., 2020a) is formulated as a multistage stochastic integer programming (MSIP) model and is solved using the Stochastic Dual Dynamic Integer Programming (SDDiP) algorithm. As such, the main focus of this section is to give an overview over the SDDiP algorithm, together with a course overview over MSIP.

Focusing on the mathematical programming literature, there are several works that develop MSIPs for planning problems in the oil and gas industry. To begin with, Jonsbråten (1998) presents a stochastic mixed integer program for the problem of optimally designing and operating an oil field under price uncertainty. A modified progressive hedging algorithm, that allows for integer variables, is used to solve the problem. In addition, Goel & Grossmann (2004); Tarhan et al. (2009); Gupta & Grossmann (2014) consider a MSIP for the planning of offshore oil or gas field infrastructure, making use of a Lagrangean Decomposition as well as a duality based branch-and-bound procedure. To be able to solve these problems, the size of the scenario set, as well as the number of stages, tends to be fairly limited.

SDDiP is another approach to solve MSIPs (Zou et al., 2019). SDDiP is an extension of the Stochastic Dual Dynamic Programming algorithm developed by

(Pereira & Pinto, 1991), that allows for (and requires) binary state variables. The algorithm is based on a dynamic programming formulation with a nested cost-to-go function and can be considered an adaptation of the nested benders decomposition (Birge, 1985). The SDDiP algorithm has been applied to problems in hydropower plant scheduling (Hjelmeland et al., 2019) and electric power infrastructure planning (Lara et al., 2019).

A conceptual description of the SDDiP algorithm is described below, while we refer to Zou et al. (2019) for a more detailed and formal treatment of the algorithm. The SDDiP algorithm is used to solve MSIPs and bases itself on a dynamic programming formulation that includes *expected cost-to-go functions* for each time stage. The problem is decomposed based on time stages, which prevents a combinatory explosion of the number of states/scenarios. We note that we consider a minimization problem and that the constraints need to be linear.

SDDiP explicitly distinguishes between two types of decision variables in each stage. That is, state variables linking successive stages, and local (or stage) variables. The SDDiP algorithm requires the state variables to be binary. This is not a big restriction for real options problems, as the decisions (to wait, abandon or expand) are of binary nature. Moreover, SDDiP puts several restrictions on the stochastic process. First, the stochastic process needs to be stage-wise independent. Second, the stochastic process needs to have a finite number of realizations. If this is not the case, such a process can be approximated using methods such as sample average approximation or other constructive methods (Pflug, 2001). The original (continuous) stochastic process, is sometimes referred to as the *true* distribution (Ding & Ahmed, 2019). Finally, the optimization problems in each stage need to be linear.

The cost-to-go functions are approximated in an iterative fashion using the solutions of the optimization problem in each stage, which can be interpreted as Benders cuts. Each iteration consists of a *forward pass* and a *backward pass*. In the forward pass a set of scenarios is sampled. The current *policy* (represented by the approximated cost-to-go function) is evaluated on each of these scenarios, leading to a set of policy values. Based on these realized policy values, a statistical upper bound on the objective function value can be constructed. This is an upper bound for the minimization problem, as the cost-to-go function is represented by an outer-approximation. The backward pass then generates cuts that outer approximate the expected cost-to-go function. The backward pass consists of solving relaxed subproblems from the last to the first stage, where the solutions of future stages are used to generate cuts and approximations to the cost-to-go function. The relaxed solution in the first time stage gives a lower bound to the problem, as only a subset of scenarios is considered. This procedure is repeated until a convergence criterion has been reached. The performance of the obtained policy can be tested on the (true) distribution by means of a simulation, which finally gives an expected policy value.

Chapter 3

Contributions

This chapter discusses the contributions of the research presented in this thesis. The thesis consists of four papers that are enclosed as appendices. For each paper, a summary is presented together with an overview of contributions to the research community and industry.

3.1 Papers

Paper I - Planning of an Offshore Well Plugging Campaign: A Vehicle Routing Approach

Authors: Steffen Bakker, Mats Mathisen Aarlott, Asgeir Tomasgard, Kjetil Midthun

Published in: Bektaş T., Coniglio S., Martinez-Sykora A., Voß S. (eds) Computational Logistics. ICCL 2017. Lecture Notes in Computer Science, Volume 10572, Pages 158-173. Springer, Cham.

Thousands of offshore wells are planned to be permanently plugged and abandoned in the upcoming decades, and the costs are to be substantial.

In this paper we present a new optimization problem targeting the planning of an offshore well plugging campaign. We propose a mixed integer linear programming model based on a variant of the uncapacitated vehicle routing problem including precedence and non-concurrence constraints. Subsea wells that have to be plugged are modeled using nodes representing plugging operations that have to be performed. A set of heterogeneous vessels is available to perform these operations. This is, to the best of our knowledge, the first paper that applies operations research techniques to a problem related to plug and abandonment. To account for multilateral wells, a new type of synchronization constraints referred to as non-concurrence constraints is defined. Further, we discuss and define different objective functions that can be used depending on various contract structures. Finally, a relatively small case study is constructed, consisting of three wells, that shows the value of the optimization approach for the planning of plugging campaigns. However, we are not able to solve cases with more than six wells to optimality.

The main contribution of this paper is the introduction of a new problem setting and corresponding model formulation for an increasingly relevant topic.

My contributions to this paper include the conceptualization of the problem, developing and formulating the model, performing the programming and performing the analyses. Together with my co-authors, I have analyzed and discussed the case study and results. Finally, I have been the main author of the manuscript.

Paper II - An optimization model for the planning of offshore plug and abandonment campaigns

Authors: Steffen Bakker, Torbjørn Vrålstad, Asgeir Tomasgard

Published in: Journal of Petroleum Science and Engineering, Volume 180, 2019, Pages 369-379.

Due to the nature of the project, the work in this thesis is multidisciplinary. The goal with this paper has been to target petroleum engineers and the oil and gas industry and show the value of an optimization model for the planning of plugging campaigns.

First, we give a detailed description of the P&A process and its connection with the planning of a plugging campaign. Second, the model is improved in different ways to be able to solve realistically sized instances of the problem. We adapt a commodity flow formulation instead of the Miller-Tucker-Zemlin formulation used in paper I. This leads to a tighter model formulation and allows us to solve larger instances. Moreover, we recognize that wells tend to be clustered on templates and use this feature to reduce the size of the model. In addition, the problem is made more realistic by allowing for restricted operability of light vessels during the winter-period. Then, a set of benchmark instances is constructed that span the sizes of realistic plugging campaigns, ranging from 8 to 44 wells, and these instances are solved to (near-)optimality. By comparing them with strategies that reflect current practice of operators, we show that there lies significant value in the use of an optimization approach.

The main contribution of the paper is that we demonstrate that the model can be used to solve large and realistic instances and that there lies significant value in using this approach opposed to conventional planning methods.

My contributions to this paper include the conceptualization of the problem, development of the model and case studies, programming, formal analysis, and writing of the manuscript. Torbjørn Vrålstad has given valuable input on the operational part of the P&A process, as well as reviewing and editing the final manuscript. Asgeir Tomasgard has contributed with general supervision.

Paper III - Vehicle Routing with Endogenous Learning: Application to Offshore Plug and Abandonment Campaign Planning

Authors: Steffen Bakker, Akang Wang, Chrysanthos Gounaris

A slightly revised version of this paper has been published in: European Journal of Operational Research, 2020, in Press.

The motivation for this paper originated from input from our industry partners. They made us aware about the fact that a significant learning effect is present when performing plugging operations. That is, when a particular operation is performed many times, the time it takes to perform this operations reduces as similar operations have been performed before. The vehicle routing literature has considered an exogenous learning effect for multi-period problems. In this approach VRP models are solved in a rolling horizon fashion and the service time parameters are updated in between the different periods.

However, in our problem setting the learning occurs within the same time period in an endogenous way. To be able to analyze the effect of learning, we had to develop an approach that can account for this effect.

The main contribution in this paper is that we present a general approach to account for an endogenous learning effect in the context of a vehicle routing problem. That is, service times at customers are dependent on the experience gained within the routing horizon. Here, the experience level is defined using flow variables that count the number of times a service has been performed before. We show that the non-linear effect of learning can be represented in an exact way using a piecewise-linear function, without introducing any new binary variables.

The planning of a plugging campaign is used as an application of a vehicle routing problem with endogenous learning and existing instances are extended with learning data. For this application, we develop a solution approach based on clustering, which allows us to improve on the computational results presented in Paper II.

Finally, computational results on the performance of the clustering approach are presented and the effect that learning can have on solutions is demonstrated. In general, significantly different plans are obtained when considering the learning effect. Optimal plans try to reap the benefits of learning by utilizing the vessels with most experience. Overall, we conclude that the implications of a learning effect on VRP solutions can be significant and that the should be explicitly incorporated in the decision-making process, whenever such effects are applicable.

I have conceptualized the problem, developed the clustering approach and written the manuscript. Chrysanthos Gounaris developed the main ideas for the learning effect methodology. Moreover, my co-authors contributed in the design of the analyses and review and editing part of the writing process.

Paper IV - Mature offshore oil field development: solving a real options problem using stochastic dual dynamic integer programming

Authors: Steffen Bakker, Andreas Kleiven, Stein-Erik Fleten, Asgeir Tomasgard

Submitted to an international, peer-reviewed journal.

Deciding when to shut down an oil or gas field has been a classical research question. However, after many discussions with industry partners and reading existing literature, we concluded that existing approaches do not capture all the important aspects related to this research question.

In this paper we acknowledge that the shutdown decision should be evaluated together with other activities that can enhance the life-time of a field, which might include the drilling of new wells. A real options problem is defined and formulated as a multistage stochastic integer program (MSIP). We identify the oil price as the main uncertain factor and include the short-term long-term of Schwartz & Smith (2000) to fully account for the dynamics in oil price fluctuations. Moreover, a linearization approach is developed to include this stochastic process in the MSIP and it is solved using the stochastic dual dynamic integer programming (SDDiP) algorithm. We then construct a case study based on realistic data and present computational results on the performance of the algorithm. We show that the value of stochastic solutions is considerable and evaluate the effect of different factors on the timing of the shutdown decision.

The main contribution of this paper is that we show that real options problems can be efficiently solved using the SDDiP algorithm. Utilizing the developed framework, we are able to analyze the interaction between different options in a portfolio. We find that an increase in uncertainty can decrease the expected shutdown time, which contrasts the traditional relationship that is found for single options.

My contributions to this paper include the conceptualization of the problem, development of the model and case study, programming and performing the analyses. I was the main author of the manuscript. My co-authors contributed in reviewing and editing the final manuscript, where Andreas Kleiven and Stein-Erik Fleten also contributed with valuable discussions on the methodology.

3.2 Additional Contributions

One of the initial research goals of the ECOPA project has been to develop an open-source plug and abandonment database. We have set up a prototype database that we filled with publicly available data. I have contributed in this study by mapping existing data sources and filling the database. Moreover, I have integrated the database with the decision-support models presented in this thesis. Due to several obstacles, we have unfortunately not been able to fulfill this ambitious project. Nevertheless, we have published our experiences in the following paper:

- Myrseth, V., Perez-Valdes, G. A., Bakker, S. J., Midthun, K. T., & Torsæter, M., 2017. Development of a Norwegian Open-Source Plug-and-Abandonment Database With Applications. SPE Economics & Management. 9, 27–31. `https://doi.org/10.2118/180027-PA`

The contributions of this paper lie outside the scope of mathematical programming, and as such we have decided not to include this paper in this thesis.

Chapter 4

Concluding Remarks and Future Research

The overarching goal of the works in this thesis has been to develop knowledge, models and solutions methods related to the plugging and abandoning of offshore oil wells, that can create value for both industry, society and academia.

The three first papers give a solid foundation for the development of a decision support tool for the problem of planning an offshore P&A campaign. While Paper I introduced this problem, Paper II and Paper III extended it with more realistic features and improved solution methods. Paper II showed that there are significant benefits in using the developed optimization approach for planning plugging campaigns, compared to conventional approaches. The results from this paper have been presented for a group of P&A managers from different operators on the Norwegian Continental Shelf. The general consensus was that there can be significant value in the use of a decision support system based on the developed model. Nevertheless, there are several practical challenges in applying the developed methodology. To begin with, decommissioning activities tend to be planned exclusively within a license or field. This makes it difficult to plan large plugging campaigns, that include wells from different fields. It might be necessary to change prevailing regulations to be able to obtain cooperation between different operators. Paper III treated the existence of a learning effect in the context of a vehicle routing problem. This feature leads to significantly different optimal plans compared to when neglecting this effect, but also increases the computational complexity of the problem. To be able to capture this effect, while still solving realistically sized instances, we developed a clustering-based solution approach. Paper III also investigated the effect of uncertainty around parameter estimates on optimal routes and plans, by means of a sensitivity analysis. An interesting extension would be to investigate the effect of uncertainty on this problem by means of an appropriate technique that deals with decision making under uncertainty, such as stochastic programming or robust optimization. As the deterministic versions of this problem are already difficult to solve, the use of heuristic approaches might have to be considered.

Paper IV focused on the development of a mature offshore oil field, and in particular the shutdown decision. We treated this as a real options problem and formulated it using a multistage stochastic integer program. To the extend of our knowledge, this is the first work that solves such a problem using the SDDiP algorithm. This framework allowed us to investigate the relationship between interrelated options that occur in portfolios. We found that, contrary to traditional findings for single options, an increase in long term price volatility can speed up the shutdown decision, when various (expand) options are available. The developed method easily accounts for different stochastic factors, such as price uncertainty. We show that the conventional planning methods of operators, based on expected values or high/low realizations of uncertain factors, can lead to sup-optimal plans.

Another interesting finding is related to the expected shutdown time. A common belief is that postponement of the shutdown decision is beneficial for operators, as the huge plugging costs are discounted away in the future. However, this effect can be counterbalanced by increasing decommissioning costs due to degrading well integrity, which can speed up the expected shutdown time. The research in this paper can be extended in many directions. The methodology can be applied to even more realistic case studies, or to other real options problems with different problem characteristics.

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Papers

I

Paper I

Planning of an Offshore Well Plugging Campaign: A Vehicle Routing Approach

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Planning of an Offshore Well Plugging Campaign: A Vehicle Routing Approach

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Abstract. When a petroleum well no longer serves its purpose, the operator is required to plug and abandon (P&A) the well to avoid contamination of reservoir fluids. An increasing number of offshore wells needs to be P&A'd in the near future, and the costs of these operations are substantial. Research on planning methods in order to allocate vessels that are required to perform these operations in a cost-efficient manner is therefore essential. We use an optimization approach and propose a mixed integer linear programming model based on a variant of the uncapacitated vehicle routing problem that includes precedence and non-concurrence constraints to plan a plugging campaign. P&A costs are minimized by creating optimal routes for a set of vessels, such that all operations that are needed to P&A a set of development wells are executed. In a case study, we show that our proposed optimization approach may lead to significant cost savings compared to traditional planning methods and is well suited for P&A planning purposes on a tactical level.

Keywords: Routing, Plug and Abandonment, Plugging Campaign

1 Introduction

An active petroleum well goes through different phases: exploration, production, and injection. After the well has served its purpose, and is no longer profitable, it must be plugged and abandoned. According to [13, Chapter 9], Plug and Abandonment (P&A) is the process of securing a well by installing required well barriers (plugs) such that the well will be permanently abandoned and cannot be used or re-entered again. We refer to P&A as the permanent abandonment of the well, as opposed to temporary P&A, where the well may be re-entered. Permanently plugged wells shall be abandoned with an eternal perspective taking into account the effects of any foreseeable chemical and geological processes. This definition holds for offshore and onshore wells, but in this paper we consider solely the former. Moreover, we only focus on development wells (consisting of production and injection wells), as exploration wells are P&A'd immediately after drilling.

To give an impression of the magnitude of future P&A work, [12] forecast a total of 1,800 development wells to be P&A'd the next decade on the United

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Kingdom and Norwegian Continental Shelf. The average P&A cost per well in the same period and regions is estimated to be around £$5-15$ million. Currently, approximately 50% of the costs of decommissioning, which also takes into account removal of installations, is related to P&A. On the United States Outer Continental Shelf, which most notably consists of the Gulf of Mexico, there are at present $5,082$ production wells and $3,220$ temporarily plugged wells, that are in need of permanent plugging [3].

The high costs related to these operations and opportunity costs of the vessels required to perform these operations (e.g. exploration or drilling activities), makes this topic highly relevant for research on efficient resource allocation and scheduling of P&A operations.

In this paper, we look at a tactical time horizon for the planning and scheduling of P&A operations for a number of subsea wells in which the production systems are located on the seabed. In this respect, a *P&A campaign* is an allocation of *vessels* (ships and rigs) to perform plugging operations on a set of wells.

As P&A costs derive mainly from renting vessels, cost savings can be achieved by, e.g., developing new or improving existing techniques such that the durations of the operations are reduced. When taking a system perspective, savings may also be obtained by optimizing routing of vessels and scheduling of operations. These cost savings might result from, for example, decreased sailing time or more use of vessels with a low day-rate. Here lies the basis for developing and demonstrating how an optimization approach based on vehicle routing theory may be used to reap these rewards.

In view of this, we propose an optimization model for the tactical planning problem concerned with P&A campaigns. We refer to this problem as the P&A Campaign Problem (PACP).

Even though optimization has been extensively applied to the petroleum industry (e.g. [10, 6]), literature on the use of optimization in P&A planning is, to the best of our knowledge, scarce. The only application of optimization to P&A that we are aware of is [1].

The planning of a P&A Campaign can be considered to be a vehicle routing problem (VRP). In this context, "routing" can be defined as the assignment of sequences of operations to be performed by vessels. The term "scheduling" is then used when the timing aspect is brought into routing. Therefore, scheduling includes the timing of the various events along a vessel's route. [4] give a review of ship routing and scheduling problems within maritime transportation, categorized on the basis of strategic, tactical and operational planning levels. An optimization model for maintenance routing and scheduling for offshore wind farms, based on a VRP with pick-up and delivery, is proposed in [7]. This model has similar features as the PACP. However, just like most maritime transportation problems, it involves cargo or inventory considerations.

The PACP can be represented as an extension of the Uncapacitated Vehicle Routing Problem (u-VRP) or Multiple Traveling Salesman Problem (m-TSP) with precedence and non-concurrence constraints, a heterogeneous fleet of vessels and the possibility of multiple routes, see [14]. Related work is done in [5] and

[2]. The former paper considers an extension of the traveling salesman problem (TSP) with precedence constraints applied to ship scheduling and presents other related work on TSPs, whereas the latter contains a review of literature on the m-TSP and practical applications.

There are several ways in which the PACP problem can be formulated. We have investigated using a time-indexed mixed-integer programming formulation. However, as P&A campaigns are characterized by both a long time horizon (1-2 years) and a fine time resolution for individual operations (hours/days), this formulation leads to a large number of binary variables. As a result, the model quickly becomes intractable, even for toy-sized problems. Therefore, we formulate the model using an arc-flow formulation, treating time as continuous. This formulation requires significantly less binary variables and is capable of solving larger instances of the problem.

We extend current literature on vehicle routing problems by introducing a new practical application of an u-VRP, besides proposing 'non-concurrence' constraints, which are required when considering multilateral wells.

The remainder of this paper is structured as follows. We start by giving a problem description in Section 2 and provide a model formulation in Section 3. A case study consisting of three wells is then described in Section 4, of which the computational as well as economical results are presented in Section 5. The results are compared with other realistic routing alternatives. The paper concludes with Section 6, which summarizes the main findings from this work as well as suggesting the direction future research could take.

2 Problem Description

Offshore petroleum wells can be distinguished by being connected to either a subsea or platform installation, where the wells are usually clustered in *templates*. In order to P&A an offshore well, several operations have to be performed in a strictly ordered sequence. These operations consist of amongst others preparatory work, the setting of plugs and removal of the wellhead. Subsea wells need vessels to perform these operations. There are several classes of vessels that are able to carry out these operations. In general, Mobile Offshore Drilling Units (MODUs), also called rigs, can conduct all types of operations. This class of vessels includes jackup rigs, semi-submersible rigs (SSRs) and drillships. Another class consisting of lighter vessels such as light well intervention vessels (LWIVs) and light construction vessels (LCVs) can only perform a subset of operations, but have a cheaper day-rate compared to rigs.

A categorization of these different operations into phases is given by [11], which is also extensively used by the industry. Based on this categorization, we define four operation types, or phases, which will be used more explicitly in the case study in Section 4. Phase 0 consists of preparatory work, which can, in general, be executed by all vessels. Phase 1 comprises the cutting and pulling of casing and tubing and setting of primary and secondary barriers, which requires a rig. Phase 2 again requires a rig and includes the setting of a surface plug.

Finally, phase 3, removal of the conductor and well head, might be performed from some lighter vessels. An overview of compatibilities between phases and vessel classes is given in Table 1.

Note that this categorization is constructed for wells in the North Sea, and need not necessarily hold for wells under different regulatory regimes. Still, it is a good representation that is useful in showing the traits of the model.

Table 1. Compatibility of phases and vessel classes

Phase	SSR	LWIV	LCV
0	X	X	X
1	X	-	-
2	X	-	-
3	X	X	-

Besides traditional wells with a single wellbore, there also exist wells with multiple wellbores connected to a common wellhead. These wells are known as multilateral wells. To give an example, Figure 1 shows a multilateral well with three lateral wellbores and a mainbore. The nodes represent operations in the wellbores that have to be performed to P&A the well. Multilateral wells are designed to reduce construction costs and increase production from a reservoir. Operations in different lateral wellbores cannot be performed simultaneously, as these wellbores must be entered through the same mainbore.

P&A operations are in general not time-critical, which means that wells can be left temporarily or partially plugged, as long as the wells are continuously monitored. Nonetheless, there might be reasons to include time windows for the operations. This might be due to legal issues, such as the expiry of a lease contract, or plans made by the operators. Vessel-use can also be limited due to contractual issues, alternative usage such as exploration or drilling, or other conditions like harsh weather.

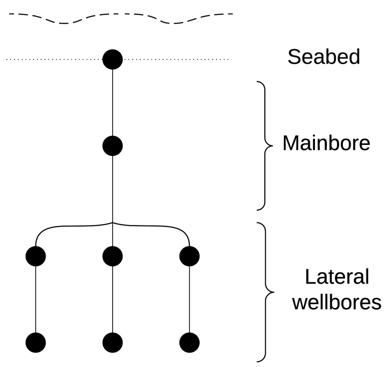


Fig. 1. Diagram of a multilateral well

Based on these different aspects of the P&A process we are able to formulate a general optimization model that minimizes the total costs related to a P&A campaign. The decision variables consist of binary variables determining the routes of the vessels and continuous variables specifying start times of operations. The constraints in the model are related to timing, precedence, non-concurrence and legal routes for vessels. The objective of the model is to minimize total rental costs, which is constructed based on time usage and day-rates of the different vessels.

3 Mathematical Formulation

In this section, we present the Mixed Integer Linear Programming (MILP) Model for the PACP. We explain the notation (sets, indices, parameters and variables) used in the model and we provide the mathematical formulation of the constraints and objective functions.

3.1 Sets and Indices

To P&A a well, a certain number of operations have to be executed. These operations might be represented by the previously defined phases, but can be more or less detailed. We therefore define the set $\mathcal{N} = \left\{1, ..., N^{OPS}\right\}$, which consists of all the operations required to be executed on all wells. The set $\mathcal{K} = \{k_1, ..., k_{N^{VES}}\}$ consists of N^{VES} heterogeneous vessel that are available to perform these P&A operations. For every vessel $k \in \mathcal{K}$, we define $\mathcal{N}_k \subseteq \mathcal{N}$ to be the set of operations that vessel k can perform. We define origin and destination vertices $o(k)$ and $d(k)$, which represent locations such as harbours, where the vessels are situated at the start and end of the planning period, respectively. We model routing options as arcs, and P&A operations as vertices. Let $\mathcal{A}_k = \{(i, j) : i, j \in \mathcal{V}_k\}$ represent the arc set corresponding to vessel $k \in \mathcal{K}$, where $\mathcal{V}_k = \mathcal{N}_k \cup \{o(k), d(k)\}$ is the vertex set of vessel k. The precedence set $\mathcal{P}$, consists of pairs (i, j) with $i, j \in \mathcal{N}$, for which operation i should precede operation j. This set is included to ensure correct sequencing of operations. Some operations are prevented, due to technical reasons, from being executed simultaneously. Therefore, we let $\mathcal{S}$ consist of pairs of operations (i, j) with $i, j \in \mathcal{N}$ that cannot be executed simultaneously.

Moreover, given vertex i, $\delta_k^+(i)$ is defined as the set of vertices j such that arc $(i, j) \in \mathcal{A}_k$. That is, the set of possible vertices j that vessel k can visit after visiting vertex i. Similarly, given vertex i, $\delta_k^-(i)$ is defined as the set of vertices j such that $(j, i) \in \mathcal{A}_k$, i.e. the set of possible vertices j that a vessel k may have visited before visiting vertex i. The term "visit" is used to include operations as well as leaving the origin or entering the destination.

The PACP is now defined on the directed graphs $G_k = (\mathcal{V}_k, \mathcal{A}_k)$ for all $k \in \mathcal{K}$.

3.2 Parameters

For each vessel $k \in \mathcal{K}$, non-negative durations T_{ijk}^S and T_{ik}^{EX} representing sailing and execution times, are associated with each arc $(i, j) \in \mathcal{A}_k$ and vertex $i \in \mathcal{V}_k$, respectively. Sailing times equal zero for arcs between operations in the same well and otherwise consist of (de-)mobilization time and actual sailing time between wells. For every vertex $i \in \bigcup_{k \in \mathcal{K}} \mathcal{V}_k$ we associate a time window $\left[\underline{T}_i, \overline{T}_i\right]$, where $\underline{T}_i$ and $\overline{T}_i$ represent earliest start time and latest completion time of the corresponding operation in vertex i, respectively.

Non-negative day-rates C_k are defined for each vessel $k \in \mathcal{K}$. When using an alternative objective function which depends on vessel usage, we make use of varying day-rates C_k^{EX}, C_k^S, C_k^{SB}, for execution, sailing, and stand-by time, respectively.

3.3 Variables

The aim of the PACP is to find a collection of feasible vessel routes that minimizes total cost. We present this problem using an arc-flow formulation. We define a binary flow variable x_{ijk} for each vessel $k \in \mathcal{K}$ and arc $(i,j) \in \mathcal{A}_k$; equaling 1 if vessel k traverses arc (i,j) in the optimal solution, and 0 otherwise. Moreover, we define the continuous time variables t_{ik}, for each $k \in \mathcal{K}, i \in \mathcal{V}_k$, specifying the start-time of operation i by vessel k. We also introduce auxiliary variables, y_{ij}, for all $(i,j) \in \mathcal{S}$, taking the value 1 if operation i is executed before operation j, to deal with non-concurrence in multilateral wells.

3.4 Constraints

The constraints defining the MILP are treated below.

Operations. To P&A all wells under consideration, all corresponding operations have to be executed. This is ensured by the following constraints:

$$\sum_{k \in \mathcal{K}} \sum_{j \in \delta_k^+(i)} x_{ijk} = 1, \quad i \in \mathcal{N}. \tag{1}$$

These constraints also restrict the assignment of each operation to exactly one vessel.

Routing. The following sets of constraints define the possible routes that the vessels are allowed to take. First, we make sure that a vessel's route starts at its origin, and performs only one route:

$$\sum_{j \in \delta_k^+(o(k))} x_{o(k)jk} = 1, \quad k \in \mathcal{K}. \tag{2}$$

The inclusion of an arc between the origin and destination with zero cost gives the option not to make use of a vessel. Then, we assure that each vessel ends its route in its destination:

$$\sum_{i \in \delta_k^-(d(k))} x_{id(k)k} = 1, \quad k \in \mathcal{K}. \tag{3}$$

Finally, we have flow balance constraints ensuring feasible routing, stating that if a vessel is used to perform a P&A operation, it must move to another operation (in the same or any other well), or to the destination:

$$\sum_{i \in \delta_k^-(j)} x_{ijk} - \sum_{i \in \delta_k^+(j)} x_{jik} = 0, \quad k \in \mathcal{K}, j \in \mathcal{N}_k. \tag{4}$$

Multiple Routes. The previous constraints force the number of times a vessel can be used to one, assuming that when a vessel has left its origin to perform P&A operations, it must perform all its planned operations on that one route. This is a reasonable assumption if vessels are committed to a project for a longer time and vessel rent has to be payed throughout this whole period, independent on whether it is executing an operation or remains idle. However, if a vessel is allowed to return to a harbour where rental costs are not incurred, the possibility of multiple trips should be taken into account. This can be done by redefining the set $\mathcal{K}$. We include copies of the vessels if multiple routes are allowed. Formally, this leads to the following. First, we define $\mathcal{R}_k := \left\{1,..,N_k^R\right\}, k \in \mathcal{K}$, where N_k^R equals the maximum allowed number of routes for vessel k. Now, let $\tilde{\mathcal{K}} = \left\{\tilde{k}_{kr} : k \in \mathcal{K}, r \in \mathcal{R}_k\right\}$. To make sure that the routes are then planned in correct order we define the following constraints:

$$t_{d(\tilde{k}_{kr})\tilde{k}_{kr}} \leq t_{o(\tilde{k}_{kr'})\tilde{k}_{kr'}}, \quad k \in \mathcal{K}, \quad r, r' \in \mathcal{R}_k \mid r' - r = 1. \tag{5}$$

That is, if we have two subsequent routes for a vessel, then the former route should be finished before the latter can start. The model now allows for multiple routes by replacing $\mathcal{K}$ with $\tilde{\mathcal{K}}$.

Timing. The time constraints ensure schedule feasibility with respect to start times of the operations. If a vessel performs an operation on a well (or enters its destination), it must have completed its previous operation (or left its origin) and travelled to the current location:

$$x_{ijk}\left(t_{ik} + T_{ik}^{EX} + T_{ijk}^{S} - t_{jk}\right) \leq 0, \quad k \in \mathcal{K}, (i,j) \in \mathcal{A}_k. \tag{6a}$$

This can be linearized as

$$t_{ik} + T_{ik}^{EX} + T_{ijk}^{S} - t_{jk} \leq M_{ijk}(1 - x_{ijk}) \quad k \in \mathcal{K}, (i,j) \in \mathcal{A}_k, \tag{6b}$$

where $M_{ijk} = \overline{T}_i + T_{ijk}^S - \underline{T}_j$.
Time windows for operations are defined by the following constraints:

$$\underline{T}_i \sum_{j \in \delta_k^+(i)} x_{ijk} \leq t_{ik} \leq (\overline{T}_i - T_{ik}^{EX}) \sum_{j \in \delta_k^+(i)} x_{ijk}, \quad k \in \mathcal{K}, i \in \mathcal{N}_k. \tag{7}$$

If a vessel does not perform a certain operation, then these constraints force the corresponding time variable to zero.

We also impose time windows for the origin and destination vertices, representing limitations in vessel use:

$$\underline{T}_i \leq t_{ik} \leq \overline{T}_i, \quad k \in \mathcal{K}, i \in \bigcup_{k \in \mathcal{K}} \{o(k), d(k)\}. \tag{8}$$

Precedence. As explained in Section 2, there exists a strict ordering in the sequence in which operations have to be performed within a well. This ordering is guaranteed to hold by the following precedence constraints:

$$\sum_{k\in\mathcal{K}} t_{ik} + \sum_{k\in\mathcal{K}} \sum_{l\in\delta_k^+(i)} T_{ik}^{EX} \cdot x_{ilk} - \sum_{k\in\mathcal{K}} t_{jk} \leq 0, \quad (i,j) \in \mathcal{P}. \tag{9}$$

Non-concurrence. The precedence constraints control the order in which operations in the same wellbore are being executed, but they cannot deal with the fact that operations from different lateral wellbores cannot be performed simultaneously. This phenomenon arises when considering multilateral wells. We refer to the constraints that arise in this situation as non-concurrence constraints. The following constraints enforce that for all non-concurrence pairs $(i,j) \in \mathcal{S}$ we have that either operation i is performed before operation j ($y_{ij} = 1$), or vice versa ($y_{ij} = 0$).:

$$\sum_{k\in\mathcal{K}} t_{ik} + \sum_{k\in\mathcal{K}} \sum_{l\in\delta_k^+(i)} T_{ik}^{EX} \cdot x_{ilk} - \sum_{k\in\mathcal{K}} t_{jk} \leq M_{ji}(1 - y_{ij}), \quad (i,j) \in \mathcal{S}, \tag{10a}$$

$$\sum_{k\in\mathcal{K}} t_{jk} + \sum_{k\in\mathcal{K}} \sum_{l\in\delta_k^+(j)} T_{jk}^{EX} \cdot x_{jlk} - \sum_{k\in\mathcal{K}} t_{ik} \quad \leq M_{ij} y_{ij}, \quad (i,j) \in \mathcal{S}, \tag{10b}$$

where $M_{ij} = \overline{T}_j - \underline{T}_i$.

Alternatively, one can represent multilateral wells in a more restricted way, such that constraints (10) are not necessary. We can obtain this by either bundling operations that have the same phase but are in different wellbores or imposing an order for the execution of operations in the different lateral wellbores. This approach leads to a reduction in the number of constraints and integer variables, but might lead to sub-optimality.

3.5 Objective Functions

Differences in the construction of P&A contracts leads to the need to model different types of objective functions. To illustrate this, we present two exemplifying objective functions. When service companies perform P&A operations for operators, contracts are usually written on a day rate or turnkey basis [8]. Day rates are made up of, amongst others, vessel rent and personnel and equipment costs. Specification of turnkey contracts needs a precise breakdown of P&A costs, which leads to an analysis of the same cost factors. Therefore, we formulate the objective function in its most basic form as the sum of individual day-rates multiplied by total time the vessels are used offshore:

$$\min \sum_{k\in\mathcal{K}} C_k(t_{d(k)k} - t_{o(k)k}). \tag{11}$$

Some contracts specify varying day rates, such as operating, sailing and stand-by rates (C_k^{EX}, C_k^S, C^{SB}, respectively), which can easily be taken into account by the following objective function:

$$\min \sum_{k \in \mathcal{K}} \left(C_k^{EX} t_k^{EX} + C_k^S t_k^S + C_k^{SB} t_k^{SB} \right), \tag{12}$$

with:

$$t_k^{EX} = \sum_{i \in \mathcal{N}_k} T_{ik}^{EX} \sum_{j \in \delta_k^+(i)} x_{ijk}, \qquad k \in \mathcal{K}, \tag{13}$$

$$t_k^S = \sum_{(i,j) \in \mathcal{A}_k} T_{ijk}^S x_{ijk}, \qquad k \in \mathcal{K}, \tag{14}$$

$$t_k^{SB} = t_{d(k)k} - t_{o(k)k} - t_k^S - t_k^{EX}, \qquad k \in \mathcal{K}, \tag{15}$$

where t_k^{EX}, t_k^S and t_k^{SB} denote the execution, sailing, and stand-by time, respectively.

In some cases, large operating companies perform the P&A operations themselves. They usually have entered into long-term contracts with ship companies to rent vessels, which are used for multiple purposes. In this situation, the objective function might reflect opportunity costs arising from alternative uses of the vessel, such as exploration or well development.

3.6 Variable Domains

The domains of the variables used in the aforementioned constraints and objective functions are declared below:

$$x_{ijk} \in \{0, 1\}, \quad k \in \mathcal{K}, (i,j) \in \mathcal{A}_k, \tag{16}$$

$$t_{ik} \in \mathbb{R}_0^+, \quad k \in \mathcal{K}, i \in \mathcal{N}_k, \tag{17}$$

$$y_{ij} \in \{0, 1\}, \quad (i,j) \in \mathcal{S}. \tag{18}$$

Thus, the PACP model used in the case study in this paper consist of constraints (1) - (10b), variables (16) - (18), and objective function (11).

4 Case Study

To test the functioning and show possible benefits of the model, we run the model under several scenarios. We then compare these results with the results resulting from the use of simple plugging strategies, reflecting different ways in which plugging campaigns currently are, or could be, executed. The scenarios consist of one base case scenario, and five alternative scenarios that are derived by changing some parameters of the base case scenario. In the base case, we consider three subsea wells (denoted by W1, W2 and W3) on which operations have to be performed such that all wells will be permanently P&A'd. We assume that the vessels under consideration are located at the same harbour at the beginning of the planning period, and that this harbour is also the destination. The wells have a single wellbore and are located on the same field, of which W2 and W3 are located on the same template. We assume that all wells are at a distance of 150 kilometers from the harbour and W1 is 5 kilometers apart from W2 and W3. The locations and distances between wells are taken from existing wells on the Alvheim field in the North Sea. We use the four phases as described in Section 2 as a categorization of the P&A operations for each well. We assume that two different vessels are available to carry out the operations: a Semi-Submersible Rig (SSR), that can perform operations in all phases, and a Light Well Intervention Vessel (LWIV), that can perform operations in phase 0 and 3. Both vessels have a fixed day-rate, independent of the activity (executing P&A operations, sailing, or stand-by). Input data to the model, retrieved from the P&A database as described in [9], is given in Table 2. Note that the execution

Table 2. Summary of input data for SSR and LWIV.

	Execution time (days)				Day Rate	Speed	(de-) Mobilization
Phase:	0	1	2	3	(k$)	(knots)	(days)
SSR	11.9	8.85	5.63	0.75	700	5	2.5
LWIV	11.9	-	-	0.75	450	15	0.2

times are the same for all wells, as we assume that all wells are similar. However, the model allows for unique values for execution times in the case where well specific duration estimates are available. Sailing times consist of actual sailing times (calculated based on distances between the wells and speeds of the different vessels), as well as mobilization and de-mobilization time. As opposed to LWIVs, some SSRs require anchor handling, which leads to a significant difference in (de-)mobilization time. We note that when a vessel moves between wells on the same template, no anchor handling is required.

4.1 Scenarios

We perform a sensitivity analysis in which we, ceteris parabus, change some of the parameters of the base case as defined above (*SCEN1*). As an LWIV is more sensitive to bad weather than a SSR, we look at the scenarios where we increase the execution times for the LWIV. To investigate this effect we multiply the duration of phase 0, when using a LWIV, by arbitrary factors 1.5 and 2 given in scenarios *SCEN2* and *SCEN3* respectively. In the fourth and fifth scenario (*SCEN4* and *SCEN5*), we multiply the duration of phase 3 by factors 1.5 and 2 as well, when executed by a LWIV.

Finally, in the sixth scenario (*SCEN6*) the execution time of phase 3 for both LWIV and SSR is multiplied by a factor of 2. This scenario is chosen to reflect a case where it is optimal to perform all possible operations using a LWIV in two separate trips.

4.2 Strategies

We now define five different strategies that might be employed to perform a plugging campaign. The first strategy is simply the optimal outcome suggested by the model (OPT), whereas the last four strategies are examples of how different P&A campaigns can be planned manually. Traditionally, P&A operations are performed by a single rig, which is characterised by *STRAT1*. The optimal solution in this case is to execute all operations in a well consecutively and find the optimal sequence of wells to visit for the rig. More recently, cheaper light vessels are being used to perform light P&A operations that do not require a drilling rig. This might be optimal from a well perspective, but not necessarily from a system perspective. Different variations of vessel use are given in *STRAT2*, *STRAT3* and *STRAT4*. We refer to these strategies as manual strategies, even though we solve restricted versions of the optimization model. The five strategies are now given by:

- OPT: In this case, we allow the model to find the optimal allocation of vessels to P&A operations. The SSR may perform all operations in all phases (but must perform all operations in phases 1 and 2. The LWIV may perform any operations in phases 0 and 3. Finally, the LWIV is allowed to perform two routes. That is, it can return to the harbour once, where it does not incur rental costs.
- *STRAT1:* We restrict the model only to make use of the SSR to perform all the P&A operations on the wells.
- *STRAT2:* We require that all phase 0 operations are performed by the LWIV, and that the remaining operations are done by the SSR. The LWIV is only allowed to perform one route.
- *STRAT3:* Same as *STRAT2*, but we also require that all operations in phase 3 are performed by the LWIV.
- *STRAT4:* Same as *STRAT3*, however this strategy allows the LWIV to perform two routes. This reflects the possibility to do all preparatory work with a light vessel (after which the vessel goes back to the harbour), then use a rig to perform the cutting and pulling operations in phase 1 and 2, and finally use the light vessel to perform phase 3.

5 Results

In this section, we present results from running the model for the different strategies and scenarios set out in Section 4. The model has been implemented in the Mosel programming language, and solved with FICO Xpress version 8.0.4. The analyses have been carried out on a HP dl165 G5 computer with an AMD Opteron 2431, 2,4 GHz processor, 24Gb RAM running Red Hat Linux v4.4.

Table 3. Cost increase (in percentage) for the different strategies compared to the optimal cost (in million dollars) and start- and end-times for the routes in the optimal strategy (second route in parenthesis).

			Scenario					
			1	2	3	4	5	6
Cost ($M\$$)	Optimal		55.32	63.16	63.65	55.41	55.42	56.55
Cost increase (%)	Strategy	1	15.06	0.77	0.00	14.87	14.86	15.34
		2	0.17	0.44	12.30	0.00	0.00	0.77
		3	15.79	8.80	20.59	15.90	16.20	13.87
		4	0.39	0.64	12.49	1.14	2.06	0.00
Start- and end-times (days)	SSR	start	9.1	19.4	0	9.1	9.1	9.1
		end	63.5	73.2	90.9	64.3	64.3	62.0
	LWIV	start	0	0	-	0	0	0 (54.7)
		end	38.2	56.8	-	37.2	37.2	37.2 (60.7)

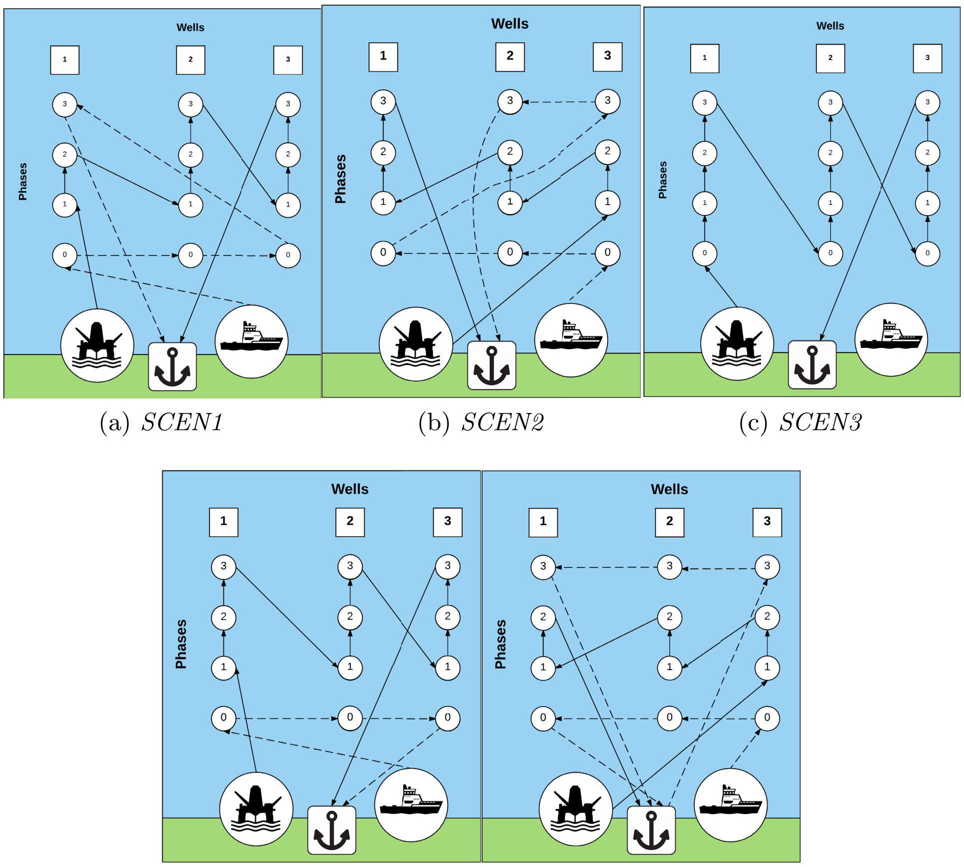
Table 3 shows numerical results for the different strategies and scenarios, whereas Figure 2 illustrates the optimal routes for each of the five scenarios.

There are several observations we can make based on these figures. To begin with, we see from Figure 2 that each scenario results in a different optimal routing (except for *SCEN4* and *SCEN5*), despite the differences between the scenarios being small. As the LWIV cannot perform operations in phases 1 and 2, the main differences between the optimal routing strategies become apparent in the choice of vessel to perform phased 0 and 3. Looking at Table 3, in the first two scenarios, none of the defined manual strategies is optimal (even though strategies 2 and 4 result in objective function values that are close to the optimal value). For each of the last four scenarios, one of the manually defined strategies is optimal, however none of these strategies performs well under all scenarios. Based upon the data input, the performance might even get arbitrarily bad. *STRAT3* performs worst under all scenarios. In this strategy we commit the LWIV to perform the operations in phases 0 and 4. But, since the LWIV cannot start operations in phase 4 before the SSR is done with phase 3, this strategy leads to an increase in costs due to idle time of the LWIV.

The dynamics in scenarios 1 to 3 are also worth mentioning. In the base case, the LWIV only performs phase 3 on one well. When it takes more time (factor 1.5, scenario 2) to perform phase 0, the LWIV no longer has to wait to perform an additional phase 3 operation. However, when the duration of phase 0 doubles (scenario 3), using the LWIV is no longer optimal at all.

The differences between scenario 4 and 5 are small as phase 3 has a relatively short duration

We conclude that the optimal routes depend heavily on differences in travel distance, execution times and day rates for the different vessels. Based on our inputs, assumptions, and choice of case study, we see that the optimal solution



(a) *SCEN1* (b) *SCEN2* (c) *SCEN3*

(d) *SCEN4* and *SCEN5* (e) *SCEN6*

Fig. 2. Optimal vessel routes for the six different scenarios. The solid and dashed routes correspond to the SSR and LWIV respectively.

might represent cost savings in the order of magnitude of US$ million compared to other and more conventional planning methods, represented by the manually defined strategies. This shows the strength of the application of an optimization model in planning of a P&A campaign.

Considering that the scenario in question consists of three wells, it is reasonable to assume that cost savings will be significant when including more wells.

The case study we considered consisted of three wells that needed to be P&A'd, which is a realistic sized problem. However, depending on the case, P&A campaigns on larger sets of wells can be planned, and might result in other system effects. We therefore perform a computational study, to investigate the scalability of the model. We take the previously defined case study with two vessels (SSR and LWIV) and three wells as base case. We then add wells that are located on the same field and are in need of P&A, and try to solve the model to optimality. The results are given in Table 4. The maximum run time is set to 24 hours, which is reached in the case with 7 wells. Since the addition of one extra well implies adding four different operations or vertices, we clearly see an exponential increase in the solution time. Moreover, we observe very slow convergence of the lower bound.

Non-concurrence in Multilateral Wells. In the following example we show the importance of including the non-concurrence constraints (10) as opposed to using a simplification. We consider a multilateral well that needs to be P&A'd. The well has one mainbore and three lateral wellbores, as represented in Figure 1. We assume that the well is located on the same field as in the case study, and we make use of the same vessels (i.e. a LWIV and SSR). Now assume that the LWIV is only available in the first month. Embracing the formulation with non-concurrence constraints, this leads to an optimal solution where the LWIV performs phase 0 operations in two lateral wellbores, after which the SSR performs the remaining operations. This results in an objective value of 47.806 million dollars. In a more restricted version of the model with an imposed order for the execution of operations in the different lateral wellbores, in the optimal solution, the SSR performs all operations and the LWIV is not being used. This leads to an objective function value of 53.116 million dollars. So, in this example, not including the non-concurrence constraints leads to an additional cost of approximately 5 million dollars. The simplified model consists of 61 binary variables and 124 constraints. Inclusion of non-concurrence constraints leads to an additional number of binary variables equal to the cardinality of the set $\mathcal{S}$ (denoted by $|\mathcal{S}|$) and $2 \cdot |\mathcal{S}|$ extra constraints. In the example above we have $|\mathcal{S}| = 12$, which does not lead to a significant increase in solution time.

6 Conclusions

The main contribution in this paper is a novel formulation of an optimization model for a P&A campaign. This is a field where, to the extent of our knowledge, optimization techniques so far have not been applied. In the case study, we show that there might be significant benefits from using this optimization model in monetary terms. Small changes in the data basis may lead to highly differing optimal routes. The manually defined planning strategies are therefore not robust to such changes in the data. Moreover, we show that the inclusion of non-concurrence constraints is preferred over a simplified representation of multilateral wells. As a result, the model may serve as

Table 4. Computational results

Wells	Time (sec)	MIP-Gap (%)
3	0.51	0
4	2.52	0
5	46.14	0
6	900.74	0
7	86401.50	0.48

decision support to decision makers. Nonetheless, we recommend to run more extensive case analyses, to evaluate alternative campaigns and discover general rules that can be used when planning P&A campaigns. The model can then also be used to run different scenario analyses to evaluate the effect of changes in parameters or definition of phases due to, for example, new technology.

The major challenge is related to scalability of the model. In order to solve more realistic cases, future research might therefor be conducted into several directions. To begin with, the literature suggests the implementation of decomposition techniques, such as column-generation, and inclusion of valid inequalities. Alternatively, when taking a non-exact approach, heuristics mights be developed for the problem, which however cannot guarantee that the obtained solution is optimal. Still, routes obtained from a heuristic approach might perform significantly better than existing planning approaches. Moreover, the case study in this paper did not define specific start and completion times for the individual operations and vessels. Inclusion of such time-windows might decrease computation time as well.

Another aspect worth looking at is the possible inclusion of a learning effect. Industry actors have observed that dedicated vessels performing operations during a P&A campaign have a significant reduction in execution times. The inclusion of such an effect is however challenging, and would lead to endogenous execution times.

Finally, there is a lot of uncertainty in the execution times of operations, due to unknown well conditions. Schedules and routes resulting from the deterministic model formulated in this paper might therefore be non-optimal when uncertainty is taken into account. Future work might therefore also focus on the application of stochastic programming to this problem.

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Paper II

An optimization model for the planning of offshore plug and abandonment campaigns

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II

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An optimization model for the planning of offshore plug and abandonment campaigns

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ABSTRACT

Plug and abandonment (P&A) operations can be time-consuming and thus very costly, especially for subsea fields. P&A of subsea wells require dedicated vessels such as high cost semi-submersible drilling rigs or lower cost Riserless Light Well Intervention vessels. This paper describes an optimization model that can be used to plan multi-well P&A campaigns by finding cost-efficient vessel routes and allocation of P&A operations to different rigs and vessels. The model's functionality is demonstrated on ten different synthetic cases, generated from realistic data. Results show that significant cost savings can be made by adapting the optimal solutions from this model compared to planning strategies that are currently used by operators, as well as by cooperating across fields and licenses in a large campaign.

1. Introduction

Thousands of offshore wells are planned to be permanently plugged and abandoned in the upcoming decades, and the total costs will be substantial (Myrseth et al., 2017; Oil & Gas UK, 2016). A significant portion of these wells are subsea wells, where the wells are located at one or more subsea templates across the entire field. In a mature area such as the North Sea for example, the Oil & Gas UK (2016) has estimated that the average P&A cost per well during the next decade is around £5–15 million. The main cost driver for plug and abandonment (P&A) operations is time consumption, and depending on well conditions, P&A operations can be very time-consuming (Ferg et al., 2011; Scanlon et al., 2011). Platform wells can be plugged and abandoned with the existing drilling rig at the platform or by coiled tubing and snubbing equipment, whereas subsea wells require dedicated vessels, conventionally semi-sub drilling rigs, with high spread rates. However, total rig rental time can be reduced if simpler parts of the P&A operation are performed by a riserless well intervention (RLWI) vessel (Saasen et al., 2013; Sørheim et al., 2011; Valdal, 2013).

Several authors have focused on duration- and cost-estimation of P&A operations. Kaiser and Dodson (2007) and Kaiser and Liu (2014) estimated the costs of different stages of the decommissioning operations in the Gulf of Mexico based on regression models. Moeinikia et al. (2014a,b, 2015a,b,c) developed a probabilistic method to estimate cost- and duration for P&A of subsea wells using a Monte-Carlo simulation approach. They showed that the implementation of rigless P&A technologies by moving operations from a rig to lighter vessels leads to significant cost and duration savings in subsea multiwell campaigns. Øia and Spieler (2015) and Aarlott (2016) presented statistics on the number of wells to be plugged and abandoned in Norway, and estimated total costs for P&A on the Norwegian Continental Shelf. They also conclude that there is potential for cost-savings when performing operations with a vessel instead of a rig.

Furthermore, since the rigs and/or RLWI vessels must physically move between the different subsea template locations, total time consumption can be reduced further by optimizing the allocation of the different types of mobile offshore units (MOU) during subsea P&A operations. As semi-sub rigs and light vessels can be used in many different combinations during multiwell campaigns, it may thus be challenging to manually find the most efficient allocation, sequence and routing of the required rigs and vessels. An optimization model can analyze all the different possibilities and suggest optimal solutions for MOU utilization for the entire campaign. This results in optimal plans that specify when particular operations on wells should be performed by which vessels or rigs, while complying to restrictions and constraints. Moreover, the optimization approach allows for scenario analyses, such that P&A engineers can evaluate how different strategies for vessel allocation, changed rental rates and effects of improved technology, affect decisions and the impact on total cost.

In this paper we describe an optimization model that can be used for

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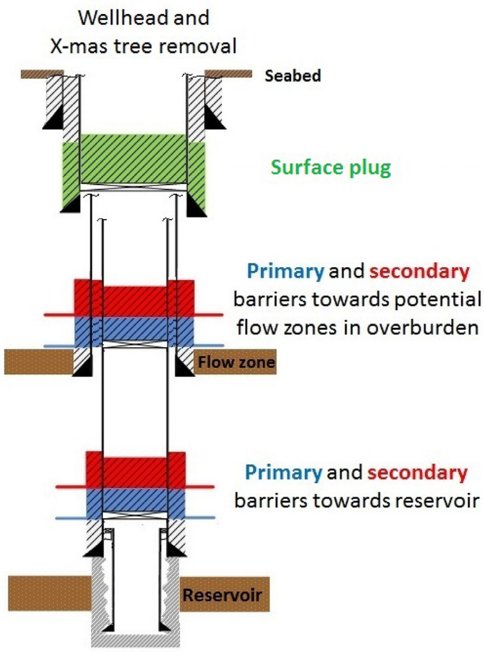


Fig. 1. Simplified illustration of a typical offshore production well after P&A. The color coding of primary barriers (blue), secondary barriers (red) and surface plug (green) are based on current Norwegian well barrier definitions (Standards Norway (2013)).

planning of P&A multiwell campaigns. Previously, Bakker et al. (2017) presented a simple version of the model used on relatively small cases, whereas in this paper we extend this model with more realistic features which enables us to solve realistically sized problems. We demonstrate the applicability of the model through different synthetic case studies based upon realistic data, and show that there is significant value in using an optimization model for planning P&A campaigns.

2. The plug and abandonment process

2.1. P&A operations

A review of P&A operations has been given by Vrålstad et al. (2019), but a brief summary is given below. Fig. 1 shows a schematic illustration of a plugged and abandoned well with the most important barriers and operations.

The purpose of P&A operations is to create several barriers in the well, where several plugs are placed inside the wellbore. Cement is normally used as plugging material, but other plugging materials can potentially be used as well (Saasen et al., 2011; Khalifeh et al., 2014; Vrålstad et al., 2019). P&A operations in a well-regulated area such as the Norwegian Continental Shelf require two independent barriers towards the reservoir (Standards Norway, 2013). Furthermore, any fluid-bearing formations in the overburden must also be isolated with two independent barriers. However, plug placement is only a small part of the full P&A operation. As the created barriers must cover the full cross-section of the well, poor annulus barriers must be removed. This can be achieved either by section milling (Scanlon et al., 2011) or the Perforate-Wash-Cement technique (Ferg et al., 2011; Delabroy et al., 2017). In addition, a surface plug is placed a few hundred meters below the seabed to prevent leakages of drilling mud from the well, and the wellhead and top of conductor are subsequently cut and removed. The total time spent on P&A operations can therefore be considerable.

To simplify P&A planning, the Oil & Gas UK (2015) has classified P&A operations into three distinct phases: Phase 1 “Reservoir abandonment” includes setting primary and secondary barriers towards the reservoir; Phase 2 “Intermediate abandonment” includes potential barriers in the overburden and the surface plug; and Phase 3 “Wellhead and conductor removal” includes shallow cuts of casings/conductor and wellhead retrieval. In addition to these three phases, Moeinikia et al. (2014a) suggested to include a Phase 0 “Preparatory work” as well, which includes pre-P&A work such as killing the well, logging the tubing quality and establishing temporary barriers. Table 1 lists these four phases and summarizes their contents, which are used in the remainder of this paper.

Subsea wells require mobile offshore units (MOU) to perform P&A operations. These MOUs comprise semi-submersible rigs (SSR), RLWI vessels and Light Construction Vessels (LCV). Each of these vessels might have different characteristics in terms of execution times, compatibility with operations, day rates, sailing times and (de-)mobilization times. We note that SSRs can be used all year round, whereas lighter vessels have a lower operability. On the Norwegian Continental Shelf, lighter vessels are not used in winter due to severe weather conditions (high waves). During these winter months they are either in the docks or operating in different countries/continents. To perform the plugging operations, the MOU must be able to maintain a position in line with the subsea wellhead. Depending on the water depth, an SSR has to be anchored, whereas an RLWI vessel always makes use of an integrated dynamic positioning system. Furthermore, rigs and vessels differ in the way they connect to a subsea well, what well control equipment they use and how fluid transport and intervention possibilities are organized. The main difference being that an SSR uses a workover or marine riser, whereas an RLWI vessel makes use of a riserless system. An illustration of these features is given in Fig. 2.

With current available technology, an SSR is required in the P&A process for various reasons. It provides amongst others fluid handling capacity, pulling capacity and rotation of drill string, and is needed to perform complex operations such as section milling. However, simpler elements of the P&A operation can be performed by lighter vessels to save rig time (Sørheim et al., 2011; Varne et al., 2017). An SSR can perform all P&A operations, whereas an RLWI vessel can perform Phase 0 and Phase 3 and an LCV can only perform Phase 3.

Table 1
Different phases of P&A operations for typical well with vertical Xmas tree (Vrålstad et al. (2019)).

Phase	Name	Contents
0	Preparatory work	Retrieve tubing hanger plugs, kill well, install deep set mechanical plug, punch/perforate tubing, circulate well clean
1	Reservoir abandonment	Rig up BOP, pull tubing hanger and tubing, install primary barrier with its base at top of influx zone (i.e. reservoir), install secondary barrier where the base of barrier can withstand future anticipated pressures
2	Intermediate abandonment	Remove casing strings (if necessary), install primary and secondary barriers towards potential flow zones in overburden, install surface plug
3	Wellhead and conductor removal	Cut conductor and casing strings below seabed to avoid interference with marine activity, retrieve casing strings, conductor and wellhead

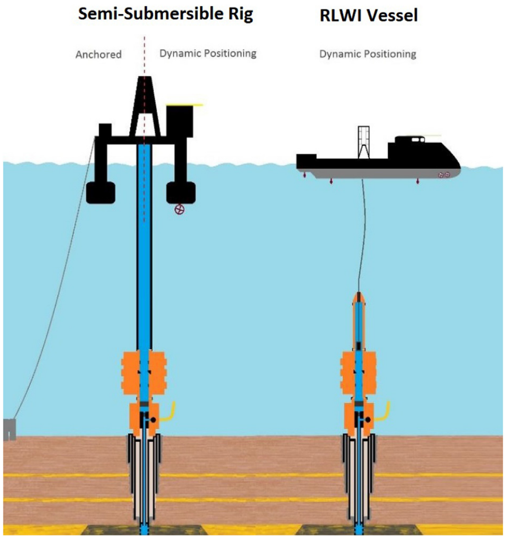


Fig. 2. Illustration of subsea P&A with an SSR with a workover riser (left) and an RLWI vessel with a riserless system (right), Øia et al. (2018).

2.2. P&A campaign planning

When several wells are plugged and abandoned together, making use of one or several MOUs, it can be called a “P&A campaign”. As subsea wells are located at different locations around the seabed, the MOUs must physically move from well to well to perform the plugging operations. The routing of MOUs is time-consuming and hence significant cost savings can be achieved by plugging subsea wells together in campaigns. Wells do not have to be plugged in one go, and different MOUs can be used to perform different phases. So, additional savings can be achieved by performing part of the campaign with light vessels, instead of the more expensive SSRs.

As an example, Sørheim et al. (2011) conducted an analysis where they showed that when at least two wellheads are removed in a plugging campaign, it is beneficial to use a dedicated light vessel to perform the Phase 3 operations, while using a rig for the other operations. Similarly, Varne et al. (2017) show in two case studies that the deployment of an RLWI vessel for Phase 0 (pre-P&A) operations can provide considerable cost savings, compared to only making use of a dedicated rig. Finally, Clyne & Jackson (2014) describes the planning and execution of Australia's largest subsea well abandonment campaign to date, which consisted of 19 wells, where they stress the importance of using light vessels to perform Phase 0 and Phase 3 operations. These findings have been quantitatively verified by Moeinikia et al. (2014a, b, 2015a, b, c). However, these studies do not describe a way to optimally plan plugging campaigns that take into account relevant constraints.

P&A decisions are taken on a field level by the responsible operator/license holders. When planning for a P&A campaign, in which several wells will be plugged with multiple MOUs, the scope is therefore restricted by the number of wells on the field under consideration. Subsea wells may be found individually (single satellite) or clustered on a template. Multi-well templates might consist of several wellheads and have the advantage that vessels don't have to be relocated when performing operations on the same template. In general, as long as the operator has well-control and there are no integrity issues, P&A operations are not time-critical. However, a well might have to be plugged and abandoned within a particular time-window, due to, for example, regulations.

We consider the situation where an operator has multiple subsea wells that have ceased production and have to be permanently plugged and abandoned within a time-horizon. On each well or template, several operations must be performed to permanently plug the well. We consider the previously defined phases as operations, however any other mutually exclusive and collectively exhaustive separation of operations can be used. The objective of planning a P&A campaign is therefore to find the most cost-efficient routes and schedules for a set of vessels to carry out P&A-operations on a given number of wells or templates in a tactical planning horizon, typically ranging up to 2 years, while satisfying a set of (time-)constraints.

3. Optimization

The problem of planning a P&A campaign can be addressed using the field of operations research (OR), also knowns as optimization. This problem contains elements of routing and scheduling and can be viewed as an uncapacitated Vehicle Routing Problem with Time-Windows (u-VRPTW), which has received a lot of attention from the OR community throughout the years. The problem is also known as the multiple Traveling Salesman Problem with Time Windows (m-TSPTW), see Toth and Vigo (2002). A review of formulations and applications to the m-TSPTW is given in Bektas (2006). In this context, Bakker et al. (2017) present a mixed-integer linear programming (MILP) model for planning relatively small plugging campaigns. But, we are not aware of any other research that combines the field of optimization with P&A. Nonetheless, there is a lot of research that applies OR to the (upstream) petroleum industry that can be related to our problem.

Notable examples of MILP models applied to upstream petroleum problems are the following. Iyer and Grossmann (1998); Goel and Grossmann (2004); Gupta and Grossmann (2014) developed MILP models for the planning and scheduling of investment and operation in offshore oilfield development. Another multi-period MILP model that focuses on investment planning for offshore fields is presented in Nygreen et al. (1998). This model has been extensively used by the Norwegian Petroleum Directorate, showing the practical relevance of using optimization models in the petroleum industry. A more recent contribution is from Rodrigues et al. (2016), in which a MILP is developed to minimize development costs by picking the optimal number and location of wells as well locations and capacities of production platforms. When focusing on the production phase, Ulstein et al. (2007) used optimization models for tactical planning of petroleum production in fields.

4. Model

In this section, we present the optimization model, which is a a Mixed Integer Linear Programming (MILP) Model, that is used for the problem of finding the most cost-effective plan to plug and abandon a given number of subsea wells within given time-horizons, using a set of heterogeneous MOUs.

A P&A plan consists of a collection of feasible routes and schedules for the different MOUs, such that all plugging operations are performed. A first model for this problem has been presented in Bakker et al. (2017), which formulates a m-TSPTW and adapts a Miller, Tucker and Zemlin formulation. We improve this model in several ways. To begin with, we switch to a commodity flow type formulation, which is known to lead to a tighter model formulation (Öncan et al. (2009)). This in turn allows for larger problems to be solved. Moreover, we change the way in which we allow MOUs to take multiple routes, which also reduces the size of the model. Finally, we take into account the restricted operability of lighter vessels during the winter season.

We note that we do not consider capacity restrictions in our problem. The reason being that fluid returns are stored in storage tanks and can be drained offshore by supply vessels of which the day rates are significantly lower than the vessels used to perform P&A operations.

Moreover, when making use of rigs, anchor handling vessels are required to perform anchor handling operations such as transporting and deploying the anchors (Tjøm et al., 2010). Nevertheless, we have decided to keep these vessels out of the model. The aim of the model is to optimize the planning, routing and scheduling of the MOUs that perform the plugging operations. The model is not developed to obtain a cost-estimate of the whole plugging campaign. As anchor handling vessels are only required for a subset of wells, we consider the cost resulting from renting these vessels as a fixed cost, which we do not consider in the model. Nonetheless, these extra costs can be added to the total campaign costs if required.

We start by defining the notation and components being used in the model, after which the objective function and constraints that constitute the model are presented in a stepwise fashion.

4.1. Formulation

To find the optimal plan in a P&A campaign, we present a model that is a an extension of an m-TSPTW with precedence constraints, where we adapt an arc-flow formulation. An overview over all the sets, parameters and variables that are used in the model is given in Appendix B.

The set $\mathscr{N}$, indexed by i or j, consists of all the operations that have to be performed to plug all the wells that are considered in the P&A campaign. A single operation in this set is also referred to as a node. The MOUs that can perform these operations are collected in the set $\mathscr{K}$ and $\mathscr{N}_k$ consists of the subset of operations that unit $k \in \mathscr{K}$ can perform. Moreover, the cost of renting these MOUs is represented by the day rate for each vessel, C_k^{DAY}.

The time it takes for vessel k to perform operation i, also referred to as the execution time, is denoted by T_{ik}^{EX}. Each unit k starts and finishes in a location, referred to as its origin $o(k)$ and destination $d(k)$ respectively. These locations do not necessarily need to be equal. Moreover, the MOUs might have the opportunity to return to a harbor $h(k)$. This allows for MOUs to be used in separate campaigns and is alternatively referred to as multiple trips. The problem is defined on the directed graphs $G_k = (\mathscr{V}_k, \mathscr{A}_k)$, where the node set of unit k is given by $\mathscr{V}_k = \mathscr{N}_k \cup \{o(k), d(k), h(k)\}$ and the arc set $\mathscr{A}_k$ consists of feasible pairs (i, j) for which $i, j \in \mathscr{V}_k$, for all $k \in \mathscr{K}$.

In this context, we define binary routing variables x_{ijk} for all $(i, j) \in \mathscr{A}_k$ and $k \in \mathscr{K}$, equaling 1 if unit k performs operation j after operation i and zero otherwise. In addition, we will make use of the continuous variables t_{ik} and w_{ik}, for $i \in \mathscr{V}_k$ and $k \in \mathscr{K}$, representing the time when unit k arrives at node i and the time it waits there respectively. Finally, we let the continuous variables $\tilde{t}_{ijk}$ be defined as follows:

$$\tilde{t}_{ijk} = \begin{cases} t_{jk} & \text{if } x_{ijk} = 1, \\ 0 & \text{if } x_{ijk} = 0, \end{cases}$$

where $k \in \mathscr{K}$ and $(i, j) \in \mathscr{A}_k$. These variables are commodity flow variables, where the commodity can be considered to be the start time of the operations.

Lastly, we define sailing time parameters T_{ijk}^S for all $(i, j) \in \mathscr{A}_k$ and $k \in \mathscr{K}$. These sailing times equal zero when operation i and j are located on the same template or well and are otherwise equal to the sailing time between operation i and j for unit k, possibly increased with anchor handling time in the case of rigs. We note that this is the extra time the rig needs in the anchor handling process and does not reflect the need for anchor handling vessels.

4.1.1. Discussion on P&A operations

The operations in the set $\mathscr{N}$ can be defined in several ways and can have different levels of detail. To begin with, we work with a categorization of operations based on the four phases that where defined in Section 2.1. We consider the set of phases $\mathscr{P} = \{p0, p1 + p2, p3\}$, where phase 1 and phase 2 are merged, as it is assumed in this study that these phases only can be executed by a rig. When a rig performs a phase 1 operation, it is natural that it continues with phase 2 as well. Moreover, the operations can be defined on a well or template level. For single satellite wells, we are always on a well level. However, when several wells are clustered on a template, an MOU does not have to move when performing operations on these wells. In this situation, we assume that one would always use the same MOU to perform operations of the same phase. Operations can hence be defined on a template level, which reduces the complexity of the problem.

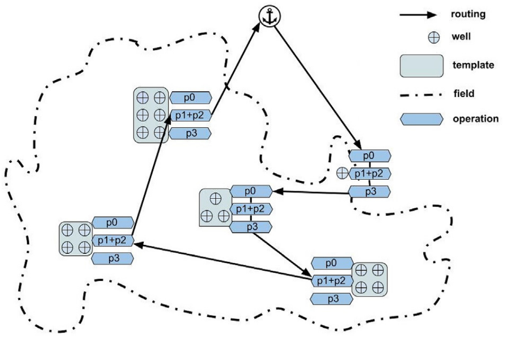


Fig. 3. Visualization of the operations that an SSR performs along its route.

As an example, Fig. 3 visualizes the operations an SSR performs along a particular route. It first visits a single satellite well, where it performs all operations, after which it moves to a template consisting of three wells, where it again performs all operations. On the last three templates it only performs operations in $p1 + p2$. For the campaign to be finished, another MOU must perform the remaining operations on the last three wells.

4.2. Constraints

4.2.1. Objective function

The aim of this work is to construct P&A campaigns that minimize total plugging costs, which mainly arises from renting MOUs. Operators that are planning P&A campaigns have to rent these rigs and vessels for the duration of the planned campaign. Although rig and vessel contracts might have different structures, typically, a day rate is specified. This day rate might be differentiated based on the type of activity, such as execution, sailing or waiting. Alternatively, operators might already have long-term contracts for some rigs and vessels that are being used for other purposes such as exploration and development/drilling activities. When using these MOUs in a plugging campaign, this leads to an opportunity cost, which can be represented by a specific day rate.

The objective of the problem is to minimize the sum of the rents for the MOUs, which is given by the product of the day rate of an MOU (C_k^{DAY}) and the duration it is being used. The duration a vessel is being used is given by the difference between the time the vessel enters the destination ($t_{d(k)}$) and leaves the origin ($t_{o(k)}$), subtracted with the time it possibly waits in the harbor ($w_{h(k)}$). The objective function is now given by:

$$\min \sum_{k \in \mathscr{K}} C_k^{DAY} (t_{d(k)} - t_{o(k)} - w_{h(k)}). \tag{1}$$

We note that various objective functions can be used. Bakker et al. (2017) shows that when considering different rates for distinctive activities this would still lead to an additive and linear objective function. However, as publicly available data on MOU rent typically is given using a single day-rate, we choose to present the objective function in this way.

Moreover, we assume that the MOUs do not incur any rental costs in the harbor, as we subtract the waiting time in the harbor from the total time usage.

4.2.2. Degree

The following constraints are known as degree constraints in the optimization literature. They contribute to the construction of feasible routes for each of the MOUs.

To begin with, we must ensure that all operations are being executed by exactly one MOU:

$$\sum_{k\in\mathcal{K}}\sum_{j\in\delta_k^+(i)} x_{ijk} = 1, \quad i \in \mathcal{N} \tag{2}$$

Here, $\delta_k^+(i)$ is defined as the set of operations j such that arc $(i, j) \in \mathcal{A}_k$. In other words, the set of operations j that unit k can perform after executing operation i. Similarly, given operation i, $\delta_k^-(i)$ is defined as the set of operations j such that $(j, i) \in \mathcal{A}_k$. Hence, Equation (2) ensures that for all operations $i \in \mathcal{N}$, there is exactly one MOU ($k \in \mathcal{K}$) that performs this operation and moves on to perform some other operation j.

Constraints (3) and (4) make sure that the routes of all MOUs start in their origins and finish in their destinations respectively:

$$\sum_{j\in\delta_k^+(o(k))} x_{o(k)jk} = 1, \quad k \in \mathcal{K} \tag{3}$$

$$\sum_{i\in\delta_k^-(d(k))} x_{id(k)k} = 1, \quad k \in \mathcal{K} \tag{4}$$

The inclusion of an arc between the origin and destination with zero travel time, allows for MOUs not to be used in the plan.

Finally, constraint (5) states that the flow into a node j ($\sum_{i\in\delta_k^-(j)} x_{ijk}$) should equal the flow out of a node j ($\sum_{i\in\delta_k^+(j)} x_{ijk}$) for each MOU:

$$\sum_{i\in\delta_k^-(j)} x_{ijk} = \sum_{i\in\delta_k^+(j)} x_{jik}, \quad j \in \mathcal{N}_k, k \in \mathcal{K} \tag{5}$$

So, if MOU k executes operation j, then the flow into and out of that node will both be equal to one.

4.2.3. Timing of operations

Constraint (6) ensures correct timing of all operations. It states that if unit k performs operation j after i, then, the start time of operation j should equal the start time of operation i increased with the execution time of operation i (T_{ik}^{EX}) and waiting time at i (w_{ik}) and the sailing time from i to j (T_{ijk}^{S}):

$$t_{ik} + \left(\sum_{j\in\delta_k^-(i)} x_{jik} T_{ik}^{EX}\right) + w_{ik} = \sum_{j\in\delta_k^+(i)} (\tilde{t}_{ijk} - x_{ijk} T_{ijk}^{S}), \quad i \in \mathcal{N}_k, k \in \mathcal{K} \tag{6}$$

Together with the degree constraints (2)–(5), this constraint eliminates subtours.

Moreover, we have to relate the start time variables t_{ik} with the commodity flow variables $\tilde{t}_{ijk}$. That is:

$$t_{ik} = \sum_{l\in\delta_k^-(i)} \tilde{t}_{lik}, \quad i \in \mathcal{N}_k \cup \{d(k)\}, k \in \mathcal{K} \tag{7}$$

$$t_{ik} = \sum_{j\in\delta_k^+(i)} (\tilde{t}_{ijk} - x_{ijk} T_{ijk}^{S}), \quad i = o(k), k \in \mathcal{K} \tag{8}$$

4.2.4. Precedence

Plugging operations on a single well or template have to be performed in a strictly ordered sequence, but not necessarily directly after each other. To control for this, we make use of the set $\mathcal{R}$, which consists of pairs (i, j) for $i, j \in \mathcal{N}$, for which operation i has to be performed before operation j. The precedence constraints read:

$$\sum_{k\in\mathcal{K}}\left(t_{ik} + \sum_{l\in\delta_k^-(l)} x_{lik} T_{ik}^{EX}\right) \le \sum_{k\in\mathcal{K}} t_{jk}, \quad (i, j) \in \mathcal{R} \tag{9}$$

That is, operation j should be started after operation i is finished.

The precedence relations that we use are based on the different phases that have to be performed. So, on an individual well or template, $p0$ has to be performed, before one can start executing $p1 + p2$.

4.2.5. Time-windows for operations

Operations can have time windows for when they must be performed. Examples of situations where time-windows might arise are the following. A well that is producing during part of the planning horizon cannot be plugged during that period and a well with integrity issues might need plugging operations within a short time-horizon and. Moreover, regulatory regimes might set time-windows for when a well has to be abandoned. For example, on the Norwegian Continental Shelf, a temporarily plugged and abandoned well that does not have access to a monitoring system must be permanently plugged and abandoned within three years (Standards Norway (2013)). To allow for these restrictions, we include the following constraint:

$$x_{ijk}\underline{T}_j \le \tilde{t}_{ijk} \le x_{ijk}\bar{T}_j, \quad (i, j) \in \mathcal{A}_k, k \in \mathcal{K} | j \in \mathcal{N}_k \tag{10}$$

However, we note that in this application the time-windows tend to be fairly loose.

Besides, satisfying time-windows, equation (10) forces $\tilde{t}_{ijk}$ to zero, when unit k does not move from node i to j.

4.2.6. MOUs

MOUs might have restrictions on when they can be used due to other planned activities or restricted rental periods. This leads to the following constraints:

$$\underline{T}_k^{MOU} \le t_{ik} \le \bar{T}_k^{MOU}, \quad i \in \{o(k), d(k)\}, k \in \mathcal{K} \tag{11}$$

In contrast to SSRs, RLWIs and LCVs cannot be used al year round due to rough weather conditions. During the winter months, these vessels therefore have to go back to the harbor. This is incorporated in the following way:

$$t_{h(k)k} \le \underline{T}_k^{WINTER}, \quad k \in \mathcal{K}^{WINTER} \tag{12}$$

$$t_{h(k)k} + w_{h(k)k} \ge \bar{T}_k^{WINTER}, \quad k \in \mathcal{K}^{WINTER} \tag{13}$$

So, vessel k has to arrive in the harbor before the start of the winter, where it has to wait until the end of the winter season.

4.2.7. Domains of the variables

Finally, the variables have the following domains:

$$x_{ijk} \in \{0,1\}, \tilde{t}_{ijk} \in \mathbb{R}_0^+, \quad (i, j) \in \mathcal{A}_k, k \in \mathcal{K} \tag{14}$$

$$t_{ik}, w_{ik} \in \mathbb{R}_0^+, \quad i \in \mathcal{N}_k, k \in \mathcal{K} \tag{15}$$

This means that all the variables are nonnegative and continuous, except for the routing variables which are binary.

5. Case study

A case study has been developed to demonstrate the potential of the optimization model. The case study consists of synthetically constructed subsea fields based upon realistic data and well locations, so that the field examples resemble typical Norwegian subsea fields.

5.1. Data

Input data on time durations for P&A operations have been obtained from Øia et al. (2018), who provide a thorough description of operational procedures for both SSRs and RLWI vessels, as well as presenting

Table 2
Durations (in days) of the different phases for different complexities when performed by SSRs or RLWI vessels. Based upon Øia et al. (2018).

	SSR			RLWI		
Phase	Low	Medium	High	Low	Medium	High
	5.29	4.71	4.58	3.33	4.81	8.33
	8.75	9.52	14.21	–	–	–
	1.38	1.38	0.88	1.38	0.96	1.38

duration estimates for three types of subsea wells (low, medium and high complex wells). These estimates are on a low level, and within each phase, multiple operations are defined. For use in our model, we aggregate the durations within each phase. An overview over the resulting data is given in Table 2.

Data on durations for LCVs are not presented in Øia et al. (2018), but since LCVs and RLWI vessels have similar capabilities, we assume that the durations of phase 3 are equal for these two vessel types. In the case study, each well is assigned a complexity, to account for the variations between wells.

As we want to test the performance of the model for different problem sizes, we have constructed 10 different cases. The optimization literature usually refers to a specific case of a problem as an instance. Nevertheless, we make use of the more general term 'case'. To generate these cases we have made use of an extensive publicly available dataset by Norwegian Petroleum Directorate (2019), that contains data on all the wellbores on the NCS. All cases are inspired by the topology, number of wells and templates on existing fields on the NCS. So, all the cases are based upon realistic data, but do not reflect any particular real life plugging campaigns. Descriptive statistics for the different cases are given in Table 3.

As one can see, the cases vary in size and differ in terms of the number of wells (ranging from 8 to 44), well complexities, templates, fields (and locations). As the size of a plugging campaign is in general bound from above by the maximum number of wells that can be plugged on a particular field, we had to add wells from neighboring fields to create the largest cases.

As an example, Fig. 3 shows a stylized visualization of case 3, which contains eighteen subsea wells spread out over four templates and one single satellite well. Of these 18 wells, 14 wells have medium complexity and 4 wells have a high complexity. Moreover, a possible route for an SSR is depicted, starting and finishing in the harbor.

The horizon of the cases is assumed to span two years and start in spring. We assume that the length of the winter season is four months (ranging from November to February), during which the lighter vessels must stay in the harbor. Moreover, since we know that we in general have loose time-windows, we have divided the wells into groups based on whether they have to be plugged during the first year, second year, or can be plugged at any time during the planning horizon.

Finally, in the analyses, we consider three MOUs (SSR, RLWI, LCV) that can be used during disjoint periods of time. The use of extra MOUs would be redundant, as it would never be optimal to make use of multiple MOUs of the same type in the problems that we consider.

The travel time between operations on two different templates comprises the physical moving time and possible demobilization and

Table 3
Count on the number of templates and wells (for each complexity) for the ten different cases.

Case		1	2	3	4	5	6	7	8	9	10
Number of Templates		4	5	5	8	8	11	11	14	14	16
Number of Wells		8	14	18	13	25	29	32	32	33	44
Complexity	Low	2	9	0	5	2	15	17	12	7	16
	Medium	6	5	14	6	19	6	5	10	20	22
	High	0	0	4	2	4	8	10	10	6	6

Table 4
Speed, day rate, (de)mobilization- and anchor handling-durations for the different vessel types.

Type	Speed (knots)	Day Rate (k$)	Harbor		Offshore	
			Mob	DeMob	Ancher	DeMob
			Durations (days)			
SSR	5	275	5	2	3	0.2
RLWI	11	230	3	2	0.1	0.1
LCV	11	200	2	2	0.1	0.1

mobilization times. The distances between all the wells are calculated using the coordinates of the wells in the different cases, taken from the Norwegian Petroleum Directorate (2019) database. Together with MOU speed, this gives us the physical travel time. Mobilization and demobilization times are defined when an MOU leaves or enters the harbor, as well as when it performs operations offshore. The offshore mobilization time of SSRs might be increased with the time required for anchor handling operations Tjøm et al. (2010), when the template is located at a water depth less than 190 m.

Day rates for MOUs are very volatile and depend on many factors such as type of unit, whether the unit has been in use recently (warm unit), whether it is a short or long contract, changes in oil and gas prices and/or demand for the units in general (Osmundsen et al. (2012)). We have chosen to work with the spread rate estimates from Øia et al. (2018). These spread rates include a daily rate and an approximation of the costs of the main equipment used. We note that changes in the spread/day rates give rise to different optimal solutions and plans, which makes this model a useful tool for engineers planning P&A operations.

An overview over MOU data that is used in the case study is given in Table 4.

5.2. Strategies

To demonstrate the usefulness of the model, we test the optimal solution found by the model, against several different *strategies*. The optimal solution is referred to as strategy 0, the base strategy. Inspired by the campaigns in Sørheim et al. (2011); Clyne and Jackson (2014); Varne et al. (2017), we define three additional strategies that operators might adopt. Using the first strategy, a campaign is planned where the operator only makes use of an SSR. This can be considered to be the traditional way of planning plugging operations. The second and third strategy, on the other hand, make use of an LCV to perform all Phase 3 operations, whereas the third strategy also uses makes use of an RLWI vessel to perform the Phase 0 operations. When solving the models using these strategies, we only fix the assignments of MOUs to operations. The routing and scheduling decisions are still chosen in an optimal way by the model. Hence, these strategies give lower bounds on the optimal values of the campaigns that would be constructed manually by engineers planning P&A operations. An overview over the different strategies is given in Table 5.

Table 5
Overview over the different planning strategies.

Strategy	Description
0	Optimal strategy, no restrictions
1	All rig
2	LCV for $p3$
3	RLWI for $p0$, LCV for $p3$

Table 6
A summary of the results for the different cases. We present the percentage increase of the objective functions for the different strategies compared to the cost of the best known solution that uses the optimal strategy ($s0$), besides the optimality gap for $s0$.

Case	Cost $s0$(mil$)	Optimality	Percentage cost increase		
			$s1$	$s2$	$s3$
1	36.88	opt.	7.12%	8.57%	1.71%
2	56.29	opt.	12.45%	12.33%	0.25%
3	83.42	opt.	6.91%	6.85%	3.41%
4	56.59	0.65%	8.49%	9.03%	3.24%
5	109.73	0.19%	9.14%	8.65%	2.60%
6	133.60	0.28%	9.05%	8.77%	4.20%
7	140.67	1.19%	8.60%	8.61%	6.21%
8	143.95	2.49%	6.37%	6.39%	4.88%
9	143.11	1.00%	9.31%	9.42%	3.02%
10	186.14	0.88%	infeas.	infeas.	3.33%

6. Results

6.1. Computational issues

The model has been implemented in Python 3.5.3, formulated using Pyomo 5.1.1 and is being solved with CPLEX version 12.7. The analyses have been carried out on a HP EliteDesk 800 G1 computer with an Intel Core i7-4790S CPU, 3.2 GHz processor, 16 Gb RAM, running Windows 10. All the cases are run with a time limit of 1 h. If a particular case has not been solved to optimality within this time limit, we present the relative optimality gap. The optimality gap is defined as the gap between the best known (integer) solution (BKS) and a lower bound on the optimal value. This is a measure of the amount by which the BKS possibly might increase. As we can see from Table 6, the BKSs are either optimal or close to optimal, with optimality gaps lower than 2.5%. This means that we can generate good solutions for all realistically sized cases within a reasonable amount of time, using an exact approach.

6.2. Value of the optimization model

To show the value of the optimization model, we compare the objective functions and plans for the best known solution ($s0$), with the ones resulting from the three different strategies. Fig. 4 shows the costs in million dollars for the different strategies and cases, while Table 6 shows the percentage increase in the objective function value, when embracing the 'manual' strategies instead of the plan suggested by the model without any restrictions ($s0$).

We note that the manual strategies all could be solved to optimality, except for strategy 1 and 2 in case 10. In this case, the problem turned out to be infeasible, since the time-horizon is too short.

We see that the costs for the optimal P&A campaigns ($s0$) range from 37 to 186 million dollars. The gains of using the optimal plan instead of the manual strategies are in the order of several million dollars for all the cases. Only for case 2 and when embracing strategy 3, we find that the objective function values are relatively close and differ by only 0.25%. Moreover, we observe that when embracing either strategy 1 (all rig) or 2 (inclusion of LCV) in an optimal way, this would lead to an increase in P&A costs ranging from 6% to 12% compared to the best known solution. In the case of strategy 3, the increase is between 0.25% and 6.2%.

To highlight the differences between the strategies, we take case three as an example. Fig. 5 shows the optimal plans for the four different strategies for case 3. We see that the savings between 3.41% and 6.91% are obtained by using a mixture of strategy 1 and strategy 3. That is, for the first three templates, an RLWI vessel and LCV are used for the $p0$ and $p3$ operations respectively, while on the last two templates the rig performs all operations.

6.3. Optimal plans

The optimal plans for the different cases all share similar features. To illustrate, Gantt charts representing the optimal plans for cases 2,4,8 and 8 are given in Fig. 6, while Gantt charts for the remaining cases are given in Figure C.7 in the Appendix. When studying these plans, we can make several observations. We know that the rig always performs $p1 + p2$, but we see that the plans differ in which MOU performs $p0$ and $p3$ operations.

To begin with, we observe that the RLWI vessel is being used in all cases to perform preparatory work on the majority of wells. After having done the $p0$ operations, the vessel might continue performing $p3$ operations on some of the wells, if it does not have to wait for it. This feature is displayed in the optimal plans for case 1,2,4 and 10.

In addition, we observe that, in general, the LCV is used in the campaigns to perform the majority of $p3$ operations. However, for smaller cases (that is 1,2 and 4), it is not beneficial to make use of such an MOU.

Finally, a vessel campaign might be split by the winter period, as can be seen in case 8 (for the RLWI vessel) and case 9 (for the LCV).

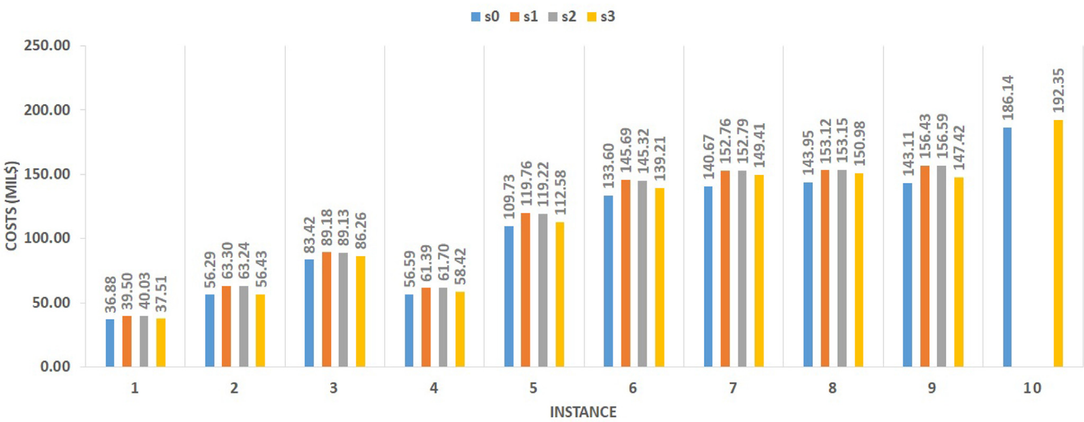
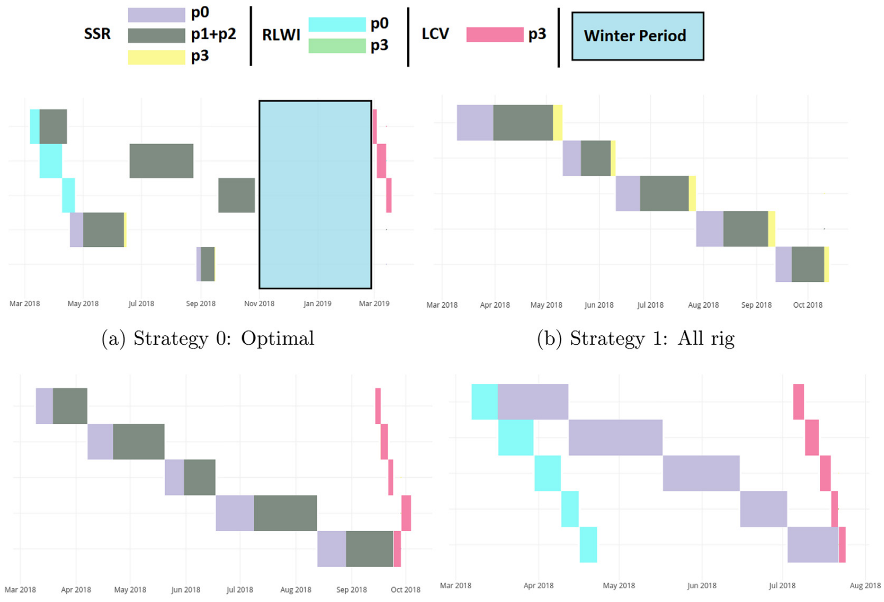


Fig. 4. Campaign costs (in million dollars) for the different cases and strategies.



(a) Strategy 0: Optimal (b) Strategy 1: All rig

(c) Strategy 2: LCV for $p3$ (d) Strategy 3: RLWI for $p0$, LCV for $p3$

Fig. 5. Gantt charts representing the different strategies for case 3.

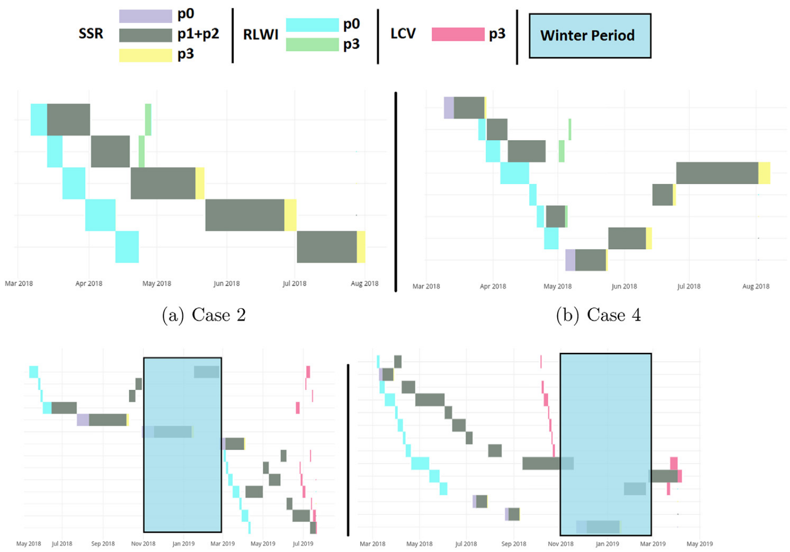
6.4. Value of cooperation

Each of the cases 5,7,9 and 10 is made up from wells belonging to two different fields. In practice, these fields will most likely be plugged in separate campaigns. When operators cooperate between licenses and fields and plan campaigns together, additional savings can be made. To quantify this effect, we present the costs for the separate campaigns in Table 7.

We present the objective function values of the optimal plans for the complete campaign or two separate campaigns. We see that planning for individual campaigns leads to relative cost increases between 3% and 5%, which equals somewhere between 4 and 6 million dollar for each case.

6.5. Sensitivity analysis

During the analyses we observed that the optimal solutions and plans are dependent on data input such as well complexity or spread



(a) Case 2 (b) Case 4

(c) Case 8 (d) Case 9

Fig. 6. Gantt charts representing the optimal plans for case 2,4,8,9 and 10.

Table 7
P&A Campaign Costs for the cases consisting of two fields when planned in one complete campaign, or for the two fields separate.

	P&A Campaign Costs (mil$)			Cost increase
Case	Complete	Field 1	Field 2	
6	109.73	31.47	83.42	4.70%
8	140.67	56.29	89.44	3.60%
10	143.11	83.42	64.05	3.05%
11	186.14	121.87	70.14	3.15%

rate. This means that the optimization model can be a useful tool for P&A campaign planners and/or rig/vessel contractors. With use of the model, they can quickly find out which campaign is optimal under different data inputs. To highlight this point, we investigate two scenarios.

While in a normal campaign one would expect to encounter wells of different complexities, we did not have data on this distribution. In the analyses performed so far, we worked with a random distribution of well complexities. The two extreme scenarios that we consider consist therefore of wells that all either have a low or high complexity.

For the high complex well scenario, we find that the optimal strategy is to only make use of an SSR in all the cases under consideration, whereas in the low complex well scenario the optimal plans change for each of the cases, while still having either one of the structures as described in Section 6.3.

7. Conclusions

In this article an optimization model has been developed for planning P&A campaigns. As planning such a campaign is a complex problem involving many constraints and combinatorics, this optimization model can be a useful tool for P&A planners. The methodology allows planners to find optimal solutions for many different cases and perform scenario analyses.

We developed ten different synthetic cases, generated from realistic data, to test the performance of the model. Even though the case study is based on data from the Norwegian Continental Shelf, the model can be applied to different countries and regulatory regimes. The results from the case study show the following. With our model formulation, we can solve realistically sized cases consisting of at least 44 wells. The optimal plans generated differ from strategies mimicking the behavior of actual planned campaigns. Depending on the case, the optimal plans make use of RLWI vessels and/or LCVs, to perform phase 0 and phase 3 operations. We find that for all 10 cases, savings can be made that are in the order of millions of dollars when adopting the optimal plans instead of the ‘manual’ strategies. On top of this, we show that there is significant value for operators from different fields to cooperate and combine their forces in one large plugging campaign.

Acknowledgments

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Appendices

A. Abbreviations

LCV	Light Construction Vessel
MOU	Mobile Offshore Unit
MILP	Mixed-Integer Linear Programming
NCS	Norwegian Continental Shelf
OR	Operations Research
P&A	Plug and Abandonment
RLWI	Riserless Light Well Intervention
SSR	Semi-Submersible Rig
u-VRPTW	uncapacitated Vehicle Routing Problem with Time Windows
m-TSPTW	multiple Traveling Salesman Problem with Time Windows

B. Nomenclature

B.1. Sets and Indices

$\mathscr{K}$	set of MOUs that are available to perform the plugging operations, indexed by k
$\mathscr{K}^{WINTER}$	set of MOUs that cannot be used during the winter months. This includes the RLWI vessels and LCVs
$\mathscr{N}$	set of operations that have to be executed to plug all the wells, indexed by i, j
$\mathscr{N}_k$	subset of operations that unit k can perform
o_k, d_k	origin and destination nodes for unit k, which represent the locations (harbours) where the MOUs are located at the start and end of the planning horizon respectively
h_k	harbor node for MOU k, where $k \in \mathscr{K}^H$
$\mathscr{V}_k$	node set for unit k, defined as $\mathscr{V}_k = \mathscr{N}_k \cup \{o(k), d(k)\}$
$\mathscr{A}_k$	set of feasible arcs for unit k, defined as $\mathscr{A}_k = \{(i, j): i, j \in \mathscr{V}_k$ and (i, j) feasible$\}$
$\delta_k^+(i)$	set consisting of nodes j, for which arc (i, j) is in the arc set $\mathscr{A}_k$
$\delta_k^-(i)$	set consisting of nodes j, for which arc (j, i) is in the arc set $\mathscr{A}_k$
$\mathscr{R}$	set of precedence pairs. Consists of pairs (i, j), for which operation i should precede operation j

B.2. Parameters

T_{ijk}^S	Sailing time of vessel k, when moving from node i to j

T_{ik}^{EX} Execution time of operation i, when performed by vessel k
C_k^{DAY} Day rate for vessel k
$\underline{T}_i$ $\bar{T}_i$ Time Window during which operation i has to be started
$\underline{T}_k^{MOU}$ $\bar{T}_k^{MOU}$ Time Window during which vessel k can be used
$\underline{T}_k^{WINTER}$ $\bar{T}_k^{WINTER}$ Time Window representing the period during which vessel k cannot be used

B.3. Variables

x_{ijk} Routing variable, equaling 1 if unit k moves from operation i to j
t_{ik} Start time of operation i for unit k
$\tilde{t}_{ijk}$ Commodity flow variable, equaling the start time t_{ik} when $x_{ijk} = 1 w_{ik}$ Waiting time for unit k in node i

C. Optimal Plans

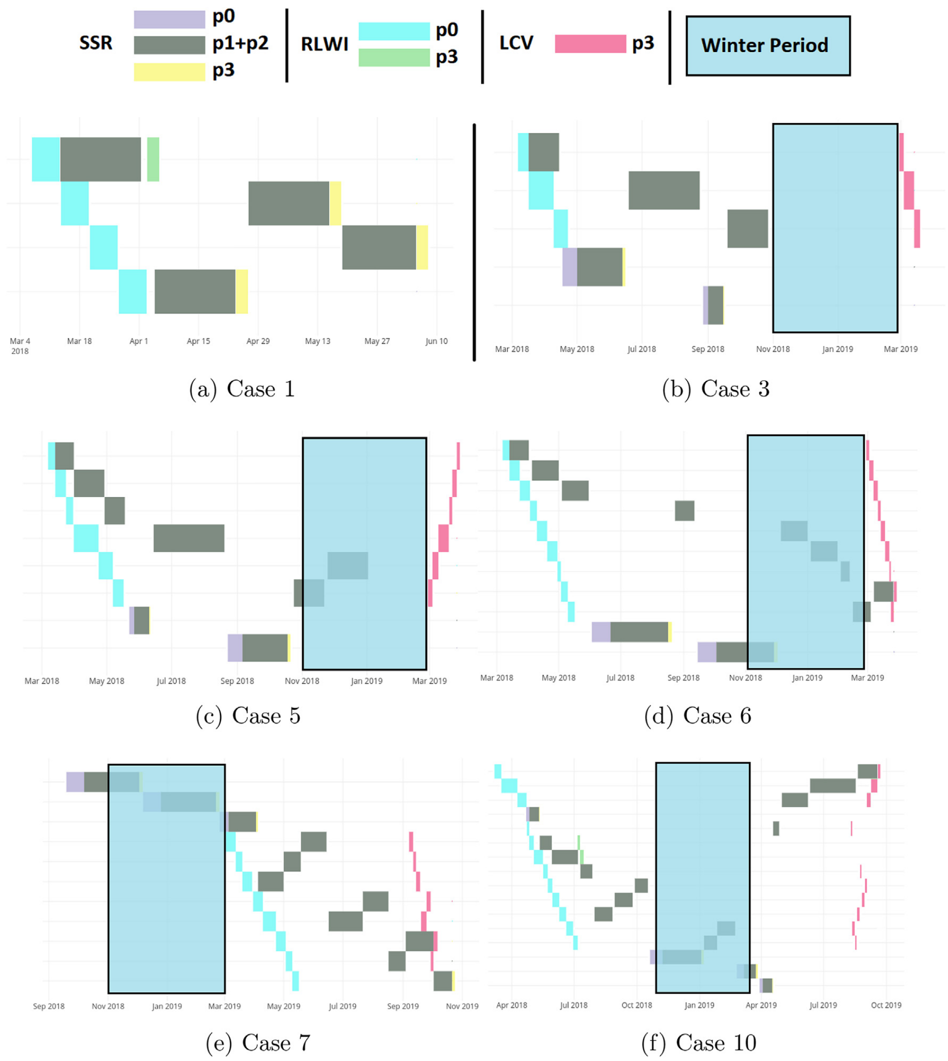

Fig. C.7. Gantt charts representing the optimal plans for case 1,3,5,6,7 and 10.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.petrol.2019.05.042.

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Paper III

Vehicle Routing with Endogenous Learning: Application to Offshore Plug and Abandonment Campaign Planning

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III

Vehicle Routing with Endogenous Learning: Application to Offshore Plug and Abandonment Campaign Planning

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Abstract

When a particular service is performed many times, the duration of the service might reduce due to the effect of learning from similar tasks that have been performed before. In this article, we present an approach to account for such learning effects that arise in the context of vehicle routing operations. Our approach enables the consideration of endogenous learning, where the service times are dependent on the experience that is to be gained in the same routing horizon. We apply our approach to the problem of planning an offshore plug and abandonment campaign, where different vessels are being used to perform plugging operations on offshore oil and gas wells. We extend existing instances for this problem with observed learning data and investigate the effects of learning and cooperation. Results show that the inclusion of an endogenous learning effect leads to different and significantly better solutions compared to those that are found when the learning effect is neglected.

Keywords: Routing, Endogenous Learning, Plug and Abandonment, Logistics, OR in Maritime Industry

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1. Introduction

The Vehicle Routing Problem (VRP) literature is rich and there exist myriad variants of the VRP (Toth & Vigo, 2002). Besides the routing part, most VRP variants also consider the performance of some service at the customer nodes. When this service entails a repetitive task, a learning effect might arise for the routed asset; for example, the duration of the service provided by a particular routed asset shall reduce when the latter performed similar tasks in the past. Since such a learning effect occurs within the routing horizon of the problem, it should be modeled in an endogenous way. In this article, we present a methodology to incorporate such a learning effect in VRP models, and we refer to this variant as the Vehicle Routing Problem with Endogenous Learning.

Our interest in this topic arises from our work on plug and abandonment (P&A) campaigns. When an oil or gas well reaches the end of its lifetime, it must be permanently plugged and abandoned (P&A'd) (Vrålstad et al., 2019). When several wells are P&A'd together, making use of one or several available specialized vessels, we call this a P&A campaign. Even though P&A operations have been conducted for a long time (Calvert & Smith, 1994), the focus on P&A has increased during recent years due to the large number of offshore wells that are approaching the end of their life-time in established areas such as the North Sea and the Gulf of Mexico (Khalifeh et al., 2013; Kaiser, 2017). As P&A operations can be very time-consuming and costly, it is of interest to optimize the P&A process as much as possible.

Bakker et al. (2019) developed an extension of an uncapacitated Vehicle Routing Problem with Time Windows (uVRPTW) model that can be used for the planning of P&A campaigns. However, this formulation does not allow for a learning effect. As recent experiences from operators show that a significant learning effect is present in the execution of P&A operations, it is important to be able to use models that are aware of this reality. Other variants of the VRP in which learning might occur due to the performance of repetitive services include the Technician Routing Problem (Chen et al., 2016), the Workover Rig Routing Problem (Aloise et al., 2006; Ribeiro et al., 2012), the Maintenance Routing and Scheduling Problem (Irawan et al., 2017), and the (multiple) Traveling Repairman Problem (Luo et al., 2014).

The main contributions of this article include: (i) the development of a method to incorporate an endogenous learning effect in a standard VRP setting by means of a linearization approach that does not introduce any additional binary variables, (ii) the compilation of a suite of realistic benchmark instances for the problem of planning a plug and abandonment campaign under learning, and (iii) the elucidation of the benefits from modeling such a learning effect as well as the quantification of the value of cooperation for operators.

The structure of this paper is as follows. Section 2 reviews relevant VRP literature as well as literature on learning effects. Section 3 presents the uVRPTW as the base model for our work and its extension to account for the learning effect. In Section 4, we introduce the problem of P&A campaign planning, which serves as an application of the VRP with endogenous learning. In addition, we develop a clustering-based solution approach that efficiently reduces the complexity introduced by the routing. Finally, Section 5 presents our computational studies, before we conclude in Section 6.

2. Literature Review

2.1. Related Vehicle Routing Problems

The problem studied in Bakker et al. (2019) arises from a real world problem and can be referred to as a rich VRP (Lahyani et al., 2015), which extends classical VRPs with issues arising in real world applications. At its base lies the Vehicle Routing Problem with Time Windows (VRPTW), which is one of the most important generalizations of the classical VRP (Cordeau et al., 2007).

We focus in particular on the uncapacitated VRP with Time Windows and Precedence Constraints (uVRPTWPC), which can also be referred to as the multiple Traveling Salesman Problem with Time Windows and Precedence Constraints (mTSPTWPC) (Balas et al., 1995; Ascheuer et al., 2001). An overview of formulations and solution procedures for these problems has been given by Bektas (2006).

2.2. The Learning Effect

The term *learning* has often been used in the literature to refer to the impact of experience on service or production times (Chen et al., 2016). This is motivated by the fact that, when engaged in repetitive tasks, workers tend to use less time to perform the later tasks due to their familiarity with the operation. Mathematical representations of this process are referred to as learning curves. There exists an extensive literature on the learning effect and corresponding learning curves. Detailed discussions of various learning curves and their applications are available in Anzanello & Fogliatto (2011).

The first quantification of a learning curve is given by Wright (1936). He observed that assembly costs of airplanes decreased as repetitions were performed. The Wright's model is now known as the Power, or Log-linear, model of learning. Many other learning models have since been proposed, in an effort to represent the learning effect more realistically in various contexts. Notable classes of learning models are, for example, the Stanford-B, DeJong, S-curve, plateau and the exponential model (Nembhard & Uzumeri, 2000).

In regards to the oil and gas industry, Brett & Millheim (1986) were the first to use a learning curve to assess drilling performance (in terms of completion time) for a series of similar wells that have to be drilled. They used an exponential model to specify the learning effect and their approach is still the standard when considering learning curves in offshore drilling operations. A visualization is given in Figure 1.

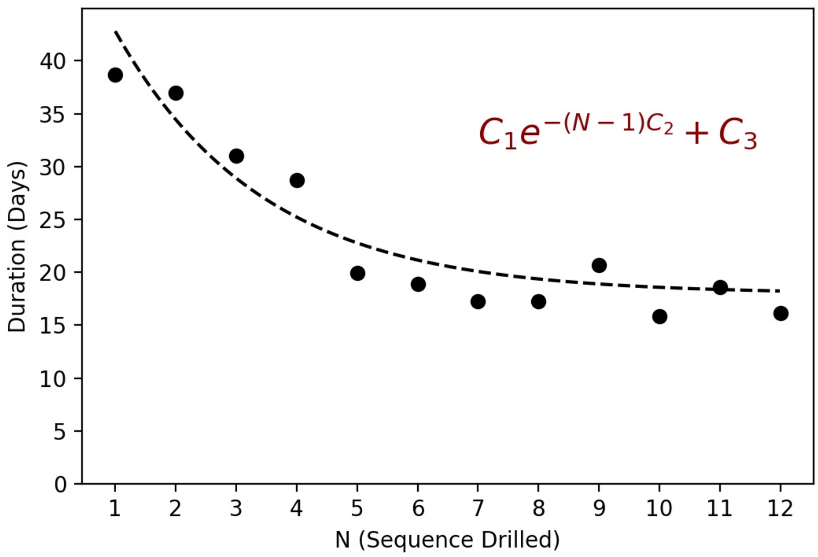


Figure 1: Visualization of a typical learning curve for the drilling of oil wells adapted from (Brett & Millheim, 1986).

More recently, Hellström (2010) studied learning curves in drilling and well operations for a Norwegian operator. He investigated amongst others the use of the model of Brett & Millheim (1986) applied to P&A operations. Moeinikia et al. (2014b) used the same learning curve model to evaluate cost efficiency of rigless P&A for subsea multiwell campaigns using Monte Carlo Simulations. In addition, data on observed learning effects in recent plugging campaigns has been presented by Straume (2018).

Whereas the learning effect has been extensively discussed in the context of manufacturing and machine/project/workforce scheduling (Biskup, 2008; Azzouz et al., 2018), it has received less attention in the VRP community. When learning is defined in the context of familiarity of vehicles with certain customers or areas, it is referred to as VRP with driver learning, driver familiarity or driver-specific travel time information. The first attempt to incorporate a learning effect targeting travel times is from Zhong et al. (2007). They consider a multi-day vehicle routing problem, where driver learning, or familiarity, results from visiting service areas repeatedly. With increased familiarity, driver performance increases due to ease of finding addresses and locations. The model is solved heuristically over a 30-day planning period simulation. The learning effect is then taken into account by updating the parameters between the model runs for each day. In a similar fashion, Kunkel & Schwind (2012) considers a multi-day VRP with Driver Learning, which again is solved heuristically. Contrary to the previous approaches, Schneider (2016) assumes that driver learning already has taken place in the past, leading to different familiarity levels. That problem can then be viewed as a variant of a heterogeneous fleet VRP. The authors note that the inclusion of a learning model that describes the reduction of travel and service times in dependence of the number of visits to each customer presents an interesting opportunity for future research.

The work of Chen et al. (2016) and Chen et al. (2017) focuses on a learning effect for service times, considering the Multi-Period Technician Routing Problem with Experienced-based Service Times. Their model is formulated based on a Markov decision process, and it is solved using a rolling-horizon procedure based on a heuristic. The service time parameters are then updated between the different periods, according to the attained increase in experience and defined learning effects.

The above presented VRP literature includes learning that tends to be on an operational level and is used for daily planning. The learning effect is treated in an *exogenous* way. That is, the learning effect is considered outside of the main model. These routing models are solved in a rolling horizon fashion, where the learning effect is taken into account by iteratively updating the parameters between the model runs. In contrast, in this work we consider a problem with a long time horizon at the strategic level. Learning occurs within the time horizon of the problem and directly depends on the decisions to be made. Hence, in the VRP with Endogenous Learning, we incorporate the learning effect directly into the model.

3. Mathematical Model

In this section, we present a commodity-flow formulation for the uVRPTW and show how to extend this with endogenous learning.We explain the notation (sets, indices, parameters and variables) used in the model and we provide the mathematical formulation of the constraints and objective function.

3.1. Model Formulation

In the uVRPTW, the objective is to find minimum-cost routes for a set of vehicles, $\mathcal{K}$, such that all customers, gathered in the node-set $\mathcal{N}$, are being served. We consider a heterogeneous fleet in which vehicles are not necessarily compatible with all customers. The vehicles start and finish at a depot, typically modeled as two locations, denoted by $o(k)$ and $d(k)$, respectively. The union of the depots and customers is denoted by the vertex set $\mathcal{V}$. Each vehicle $k \in \mathcal{K}$ has its own node- and vertex-set, denoted by $\mathcal{N}_k$ and $\mathcal{V}_k$ respectively. In addition, we associate arc sets $\mathcal{A}_k = \{(i,j) : i,j \in \mathcal{V}_k \wedge i \neq j\}$ with each vehicle k. Moreover, given vertex i, $\delta_k^+(i)$ is defined as the set of vertices j such that arc $(i,j) \in \mathcal{A}_k$. Similarly, given vertex i, $\delta_k^-(i)$ is defined as the set of vertices j such that $(j,i) \in \mathcal{A}_k$.

Each vehicle k has travel times T_{ijk}^{TR} for all $(i,j) \in \mathcal{A}_k$. Moreover, each customer i has a time window, $\left[\underline{T}_i, \overline{T}_i\right]$, when it may accept service. The service times at customers are given by the continuous variables τ_{ik}^{SE}. In addition, we define binary flow variables x_{ijk}, for each vehicle $k \in \mathcal{K}$ and arc $(i,j) \in \mathcal{A}_k$, such that x_{ijk} equals 1 if vehicle k uses arc (i,j) in the optimal solution, and 0 otherwise. The cost of traversing arc (i,j) for vehicle k is given by parameters c_{ijk}. We also define continuous variables t_{ik} and w_{ik}, for each $k \in \mathcal{K}, i \in \mathcal{V}_k$, representing the arrival time from and waiting time at customer i by vehicle k, respectively. When vehicle k does not visit customer i, these variables equal zero. The cost parameters corresponding to service times and waiting times are given by d_{ik} and e_{ik}, respectively. Note that we opt to model the waiting times explicitly because the cost of waiting might be different from the cost of serving customers, in general. In addition, let the continuous variables $\tilde{t}_{ijk}$ be defined as follows:

$$\tilde{t}_{ijk} = \begin{cases} t_{jk}, & \text{if } x_{ijk} = 1, \\ 0, & \text{if } x_{ijk} = 0, \end{cases}$$

where $k \in \mathcal{K}$ and $(i,j) \in \mathcal{A}_k$.

A commodity-flow formulation of the uVRPTW is given below:

$$
\begin{aligned}
\min \quad & \sum_{k\in\mathcal{K}} \left(\sum_{(i,j)\in\mathcal{A}_k} c_{ijk} x_{ijk} + \sum_{i\in\mathcal{V}_k} (d_{ik}\tau_{ik}^{SE} + e_{ik} w_{ik}) \right) && && (1)\\
\text{s.t.} \quad & \sum_{k\in\mathcal{K}} \sum_{j\in\delta_k^+(i)} x_{ijk} = 1 && i\in\mathcal{N} && (2)\\
& \sum_{j\in\delta_k^+(o(k))} x_{o(k)jk} = 1 && k\in\mathcal{K} && (3)\\
& \sum_{i\in\delta_k^-(j)} x_{ijk} - \sum_{i\in\delta_k^+(j)} x_{jik} = 0 && j\in\mathcal{N}_k, k\in\mathcal{K} && (4)\\
& t_{ik} + \tau_{ik}^{SE} + w_{ik} = \sum_{j\in\delta_k^+(i)} \left(\tilde{t}_{ijk} - T_{ijk}^{TR} x_{ijk}\right) && i\in\mathcal{N}_k, k\in\mathcal{K} && (5)\\
& t_{ik} = \sum_{l\in\delta_k^-(i)} \tilde{t}_{lik} && i\in\mathcal{N}_k \cup \{d(k)\}, k\in\mathcal{K} && (6)\\
& t_{ik} = \sum_{j\in\delta_k^+(i)} \left(\tilde{t}_{ijk} - T_{ijk}^{TR} x_{ijk}\right) && i = o(k), k\in\mathcal{K} && (7)\\
& \underline{T}_j x_{ijk} \le \tilde{t}_{ijk} \le \overline{T}_j x_{ijk} && (i,j)\in\mathcal{A}_k, k\in\mathcal{K} && (8)\\
& x_{ijk} \in \{0,1\}, \tilde{t}_{ijk} \in \mathbb{R}_+ && (i,j)\in\mathcal{A}_k, k\in\mathcal{K} && (9)\\
& t_{ik}, \tau_{ik}^{SE}, w_{ik} \in \mathbb{R}_+ && i\in\mathcal{N}_k, k\in\mathcal{K} && (10)
\end{aligned}
$$

The objective function (1) minimizes the routing costs and/or costs associated with time usage. Constraints (2)–(4) are the degree constraints. Constraints (2) require that all customers must be visited by exactly one vehicle, constraints (3) require that the routes start at the depot, and constraints (4) ensure that, when a vehicle arrives at a customer, it also leaves that customer. Constraints (5) are known as the commodity flow constraints. If a vehicle travels between two customers, then they ensure correct accounting of travel time and arrival time for each of the visits. Together with the degree constraints (2)–(4), the commodity flow constraints (5) are also responsible for eliminating subtours. Constraints (6) and (7) link the different departure time variables, while constraints (8) impose time windows on the times when the customers can be visited. Finally, the domains of the variables are defined in (9) and (10).

We observe that the service time variables τ_{ik}^{SE} only appear in constraints (5). When a learning effect is not considered, the following substitution can be made:

$$\tau_{ik}^{SE} = \sum_{j \in \delta_k^-(i)} T_{ik}^{SE} x_{jik}, \quad i \in \mathcal{N}_k, k \in \mathcal{K}. \tag{11}$$

Here, T_{ik}^{SE} are the deterministic service times. The uVRPTW now consists of constraints (1)–(11).

However, when there exist dependencies and/or restrictions between the start times of service at the different customers, then we can extend the formulation for the uVRPTW with generalized precedence constraints of the form

$$\sum_{k \in \mathcal{K}} (t_{ik} + \delta_{ijk}) \leq \sum_{k \in \mathcal{K}} t_{jk}, \quad (i, j) \in \Delta, \tag{12}$$

where the parameters δ_{ijk} specify the minimum difference in time between when customers i and j are being serviced, and the set Δ defines all customer pairs (i, j) for which a temporal dependency exists. This constraint captures all types of temporal dependencies between customers, such as, for example, synchronization, overlap or precedence. The resulting model is generally referred to as the VRPTW with Temporal Dependencies (Dohn et al., 2011).

3.2. Endogenous Learning

When services have to be performed at the customer nodes, a learning effect might arise; that is, the service times reduce as a function of the number of times this task has been performed before. Under this setting, the constraints (11) from the uVRPTW model would no longer be valid, as they assume a fixed service time for each customer. In the following, we describe a way to allow for an endogenous learning effect in the context of a commodity-flow uVRPTW model.

3.2.1. Experience Level

A learning effect arises when a particular task is being performed repeatedly. As different services might have to be done at different customers, we define the set $\mathcal{S}$ to contain the services for which a learning effect exists. To account for such an effect, we have to keep track of the *experience level* of the vehicles for these different services.

We define nonnegative continuous variables z_{isk}, $i \in \mathcal{N}_k, s \in \mathcal{S}_k$ and $k \in \mathcal{K}$, that measure the experience level. More specifically, if vehicle k performs service s at customer i, then z_{isk} will represent the number of times vehicle k will have performed a service s, after having visited customer i; it will equal zero otherwise. Moreover, we define nonnegative continuous variables $\tilde{z}_{ijsk}$ for $(i, j) \in \mathcal{A}_k, s \in \mathcal{S}_k$ and $k \in \mathcal{K}$. These variables are flow variables that keep track of the experience level. Finally, $\sigma(\cdot) : \mathcal{N} \rightarrow \mathcal{S}$ is a function that maps customers to the service they require.

The relationship between the experience variables is defined in the model in the following way:

$$z_{isk} = \sum_{j \in \delta_k^+(i)} \tilde{z}_{ijsk}, \quad i \in \mathcal{N}_k, s \in \mathcal{S}_k, k \in \mathcal{K}, \tag{13}$$

and

$$z_{jsk} = \sum_{i \in \delta_k^-(j)} \left(\tilde{z}_{ijsk} + \mathbb{1}_{\{\sigma(j)=s\}} x_{ijk} \right), \quad j \in \mathcal{N}_k, s \in \mathcal{S}_k, k \in \mathcal{K}, \tag{14}$$

where $\mathbb{1}_{\{\sigma(j)=s\}}$ is the indicator function, equaling one if the service required at customer j equals s, and equaling zero otherwise. Here, constraints (14) state that the flow of the experience level out of a certain node should equal the incoming flow, increased with the possible gain in experience level when executing that particular operation. In addition, the experience flow variables should only be allowed to be positive when their corresponding x-variables equal one, namely

$$\tilde{z}_{ijsk} \leq \tilde{M}_s x_{ijk}, \quad (i, j) \in \mathcal{A}_k, s \in \mathcal{S}_k, k \in \mathcal{K}, \tag{15}$$

where $\tilde{M}_s$ represents the maximum number of customers that require service s.

Finally, one might encounter a reduction in the experience level in a certain node. This can be the result of a change in the agent(s) performing these services. For a plugging campaign this means, for example, that the crew is being refreshed during a harbour visit. Let j' and k' represent the node and vehicle for which this is the case. We can then reset the experience level to zero, or to any other affine combination of the incoming experience level,

$$z_{j'sk'} = \alpha_{j'sk'} + \beta_{j'sk'} \left(\sum_{i \in \delta_{k'}^-(j')} \tilde{z}_{ij'sk'} \right), \quad s \in \mathcal{S}_{k'}. \tag{16}$$

3.2.2. Learning Effect Representation

Anzanello & Fogliatto (2011) present a wide range of learning curves based on different mathematical relationships. The most popular such relationships can be categorized as power models or exponential models. The typical learning curve in Figure 1 is an example of an exponential model. It is important to highlight that, even though these models of learning are non-linear, they are generally convex. It is also important to observe that we are interested in the values of the learning curve over a discrete range; that is, we are interested in the service time as a function of the number of times a similar task has been performed before. This implies that we can represent the (non-linear) learning curve in an exact manner (i.e., without any approximation error) using a single-variable continuous piecewise-linear function. Hence, moving forward, we can assume that the learning curves ($\tilde{f} : \mathbb{R} \to \mathbb{R}$) are of the following form:

$$\tilde{f}(z) := \max_{i \in \{1,\dots,N\}} f_i(z), \tag{17}$$

where z is the experience level (or sequence number), $f_i(z) := a_i z + b_i$, and the parameters a_i and b_i can be deduced from the original learning curve relationship. Figure 2 shows a typical learning curve, together with its linear representation.

We remark that, since our intentions in the VRP model are to minimize makespan/task durations, there will exist an incentive by the optimizer to maximize the experience level and minimize the service time. This implies that we only have to bound f from below. Consequently, in order to account for the learning effect, we need only define the following equations of the service time variables τ_{ik}^{SE}:

$$\tau_{ik}^{SE} + b_{ikl} \left(1 - \sum_{j \in \delta_k^-(i)} x_{jik} \right) \geq a_{ikl} z_{i\sigma(i)k} + b_{ikl}, \tag{18}$$

for $l \in \left\{1, ..., \tilde{M}_s\right\}, i \in \mathcal{N}_k, k \in \mathcal{K}$. Neglecting momentarily the second term on the left hand side, these equations impose that that the service times with learning should be larger than the piecewise linear functions evaluated at $z_{i\rho(i)k}$. This is represented in Figure 2. But as the service times are minimized, these functions will be bounding and the linear approximation will be exact. However, we should be careful not to apply such lower bounds when the vehicle k does not service customer i (i.e., when $z_{i\rho(i)k} = 0$). In this

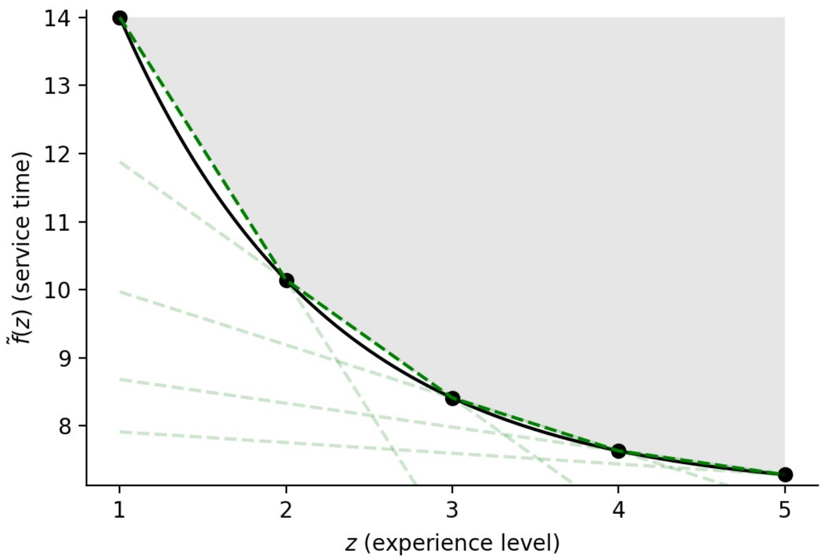


Figure 2: Visualization of a convex learning curve (solid line) and its representation using the epigraph of a piecewise linear function (dashed lines)

case, we must simply allow that $\tau_{ik}^{SE} \geq 0$. To that end, the second term of the left hand side of equation (18) adds b_{ikl} when vehicle k does not service customer i (i.e., when $\sum_{j \in \delta_k^-} x_{jik} = 0$) so as to appropriately relax these constraints. Finally, we can tighten the overall formulation by enforcing:

$$\tau_{ik}^{SE} \leq \bar{b}_{ik} z_{i\sigma(i)k}, \quad i \in \mathcal{N}_k, k \in \mathcal{K}, \tag{19}$$

where $\bar{b}_{ik} = \max_{l \in \{1,\ldots,\tilde{M}_s\}} b_{ikl}$.

4. P&A Campaign Planning

4.1. Problem Description

When an offshore oil or gas well has reached the end of its productive lifetime, it has to be plugged and abandoned to prevent leakages from or into the well. While platform wells can be plugged and abandoned with the existing drilling rig at the platform, subsea wells require dedicated vessels, referred to as mobile offshore units (MOU). When several subsea wells are plugged and abandoned together, making use of one or several MOUs, the process is referred to as a *P&A campaign* (Bakker et al., 2019). We use the problem of planning such a P&A campaign as an application of the Vehicle Routing Problem with Endogenous Learning.

When plugging a well permanently, several operations have to be performed. Based on the work by Oil & Gas UK (2015) and Moeinikia et al. (2014a), these operations can be divided into four phases. Phase 0 ("preparatory work") includes pre-P&A work such as stopping the flow from the well, logging the tubing quality and establishing temporary barriers. Phase 1 ("reservoir abandonment") and phase 2 ("intermediate abandonment") include the setting of barriers towards the reservoir, possible barriers in the overburden, and establishment of a surface plug. These two phases are typically performed consecutively, as a single service. Finally, phase 3 ("wellhead and conductor removal") includes the cutting of casing and conductor strings as well as retrieval of the wellhead (Vrålstad et al., 2019).

Conventionally, P&A operations are performed by semi-submersible rigs (SSR) with high spread rates. Current available technology still requires an SSR to perform phase 1 and 2 operations. Among other functions, the rig provides capacity to handle fluids returns as well as heavy lifting and cutting operations. However, more recently, lighter vessels are being used to perform simple P&A operations (Saasen et al., 2013; Sørheim et al., 2011; Valdal, 2013). This includes Riserless Light Well Intervention (RLWI) Vessels and Light Construction Vessels (LCVs).

P&A operations are in general not time critical. This means that when there are no integrity issues with the well and the operator maintains satisfactory control of the well, then the various phases can be executed at different times by different vessels. However, due to regulations or well conditions, wells might have to be plugged and abandoned within a certain time window.

Shut-down decisions are usually taken on a field level by the responsible operator/license holders. This implies that the scope of a plugging campaign usually is restricted to a single field. Nonetheless, plugging campaigns can be planned across multiple fields and licenses. As Bakker et al. (2019) shows, such large scale campaigns can lead to cost-savings. On a field, subsea wells can be found at different locations on the seabed. They may be located on their own as single satellites, or clustered on templates. As a result, the MOUs must move between the wells to perform the plugging operations. However, when performing operations on multi-well templates, a vessel does not have to be relocated.

The problem of planning a plugging campaign can now be defined as follows. A given number of subsea wells, possibly located on different fields, has to be plugged and abandoned within certain time windows. To plug a well, certain operations have to be performed in a strictly ordered sequence, but not directly after each other and different vessels can be used to perform these operations. The objective in a plugging campaign is then to find optimal routes and schedules for a fleet of MOUs, such that all plugging operations are performed.

Figure 3 visualizes the problem and a possible plan for the plugging of two offshore fields, making use of three vessels (SSR, RLWI and LCV). Each field contains three wells on which three operations have to be performed, related to the three different phases. In the first field, the RLWI vessel is used to perform all three phase 0 ($p0$) operations as well as the phase 3 ($p3$) operation on the first well, while in the second field, the LCV is used for the $p3$ operations. For all other operations, the SSR is being used.

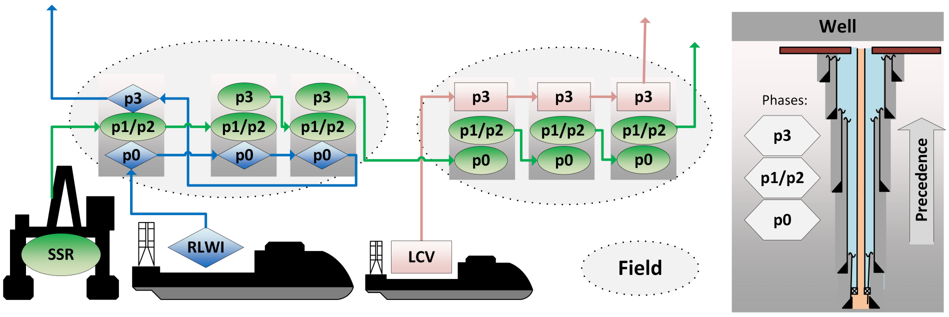


Figure 3: Visualization of a possible solution for the problem of planning a plugging campaign

4.2. Formulation

The problem of planning a P&A campaign can be formulated as a uVRPTW with Precedence Constraints. An extensive treatment is given in Bakker et al. (2019), but a short interpretation is provided here for completeness. Customer nodes represent operations, which have to be performed on wells to be plugged and abandoned. The vehicles now represent vessels that can perform these operations. On each well, three operations have to be performed. These operations are categorized into phase 0 ($p0$), phase 1 and 2 ($p1/p2$), and phase 3 ($p3$), which represent the three different services that can be performed.

We base our model on the formulation for the uVRPTW that was presented in Section 3. The objective (1) is to minimize total rental costs, which is a function of the durations the vessels are being used and their corresponding daily rates. This can be obtained by setting $c_{ijk} = T^{TR}_{ijk} C^{DAY}_k$ and $d_{ik} = e_{ik} = C^{DAY}_k$, where C^{DAY}_k represents a uniform day rate for vessel k. Constraints (2)–(11) can be interpreted in the standard way. In addition, we require precedence constraints that capture the fact that, on each well, the corresponding operations have to be performed in a strictly ordered sequence, starting with the $p0$ operation and finishing with the $p3$ operation. Constraints (12) capture this when setting $\delta_{ijk} := \tau^{SE}_{ik}$ and letting Δ consist of all pairs of operations (i, j) for which a precedence relationship exists. Besides time windows for the operations, we also impose restrictions on when the vessels can be used. This can be due to other planned activities or restricted operability during the winter months. For each vessel, we introduce an extra node to represent a harbour. This makes it possible for a vessel to return to the harbour during the winter months, where it does not incur any rental costs. We prescribe a learning effect for each of the different operation types. Consequently, we have that $\mathcal{S} = \{p0, p1/p2, p3\}$.

4.3. Learning Curve

We make use of the model developed by Brett & Millheim (1986) as a representation of the learning effect, since this model is being widely being used by the Oil & Gas Industry. However, we note that other specifications of the learning effect also may also be used as an alternative. A mathematical representation of the Brett and Millheim learning curve that was visualized in Figure 1 is given by:

$$t_n = C_1 e^{(1-n)C_2} + C_3, \tag{20}$$

where t_n is the time required to perform the n-th operation in a sequence, C_1 is a constant reflecting how much longer the initial operation takes to perform than the idealized operation, C_2 is referred to as the learning rate and reflects the speed with which the operator reaches the minimum execution time for an operation, and C_3 is a constant that reflects the idealized minimum execution time for an operation. We note that $C_2 \in \mathbb{R}^+$ and $\frac{\partial t_n}{\partial C_2} < 0$. This means that a high learning rate (C_2) leads to a shorter execution time compared to low learning rates.

4.4. Solution Approach

The computational study from Bakker et al. (2019) was based on ten realistically sized instances. In this study, only the three smaller instances could be solved to optimality within the given time limit, with the remaining seven larger instances having an integrality gap of up to 2.5% after one hour.

As the implementation of a general branch and cut framework proved not to be very effective, we need to investigate different solution approaches that target a certain problem characteristic.

More specifically, in the context of offshore logistics, locations tend to be clustered together. For example, oil and/or gas wells tend to be located relatively close to exist within the same field. In offshore windmill parks, wind turbines are positioned along narrow wind paths and the distances between them are relatively small. When servicing such clustered locations, the time it takes to travel between nodes within a cluster constitutes only a small fraction of the time required to travel across multiple clusters and to complete the whole route. Hence, when a cluster is serviced, the order in which the corresponding nodes are visited is insignificant for the evaluation of the total distance traveled or time consumed. This feature creates a certain kind of combinatorial hierarchy and makes the problems computationally difficult. In order to take into account the clustered nature of our datasets, we follow a solution approach as described below.

First, we define clusters of wells that meet the following two criteria:

1. the wells are located on the same field and are within a certain distance (application dependent) of each other, and
2. the wells have the same time windows.

Then, within a cluster, we define a fixed sequence in which the wells have to be plugged. This order can be chosen in different ways, such as based on the solution of a traveling salesman problem, or based on the complexity of servicing each specific well. The former would lead to shorter travel times within clusters, while the latter reaps the benefits from a learning effect. Specifically, when the wells have different complexities, one would start plugging the least complex wells first in order to accumulate experience for the more complex jobs scheduled for later. In this way, the learning gains can be more substantial. For reference, the solution visualized in Figure 3 abides to the proposed approach, where wells within certain fields are depicted such that they have to be plugged from left to right. The above defined rules can easily be enforced in the model by reducing the graph on which the problem is defined.

Finally, we remark that the above described clustering approach bears resemblance to the Generalized VRP (GVRP) (Baldacci et al., 2010; Pop et al., 2012) as well as the Clustered VRP (CluVRP) (Battarra et al., 2014). In both these problems, customers are grouped into clusters, each of which is being served by exactly one vehicle, while each cluster can only be visited once. The main difference between the two is that, whereas in the GVRP exactly one customer is visited in each cluster, in the CluVRP all customers have to be visited. So, our approach is related to the CluVRP, with the exception that we allow customers within a cluster to be serviced by multiple vehicles. We highlight that, even though we fix the order in which wells have to be visited in a cluster, we do not fix the assignment of vessels to operations.

5. Computational Studies

5.1. Data

We apply the learning effect methodology to the problem of planning a P&A campaign. To test this effect, we make use of the instances that were defined in Bakker et al. (2019). These consist of synthetically constructed subsea fields based upon realistic data and well locations resembling typical Norwegian subsea fields. Each of these instances contains data on the number of wells, well complexities, templates, and operations. An overview of the dataset is given in Table 1. Moreover, Bakker et al. (2019) present information about the different vessels that are available for these campaigns. This includes traveling speeds, day rates, operability restrictions and (de-)mobilization times.

Table 1: Overview of the data instances

Instance	1	2	3	4	5	6	7	8	9	10
Number of Operations	12	15	15	24	24	33	33	42	42	48
Number of Templates	4	5	5	8	8	11	11	14	14	16
Number of Wells	8	14	18	13	25	29	32	32	33	44
Complexity										
Low	2	9	0	5	2	15	17	12	7	16
Medium	6	5	14	6	19	6	5	10	20	22
High	0	0	4	2	4	8	10	10	6	6

We extend these instances to include a learning effect in the model. For this, we calibrate the learning curve from Equation (20) using data about the learning rates (C_2), minimum execution times for operations (C_3) and maximum execution times ($C_1 + C_3$). Brett & Millheim (1986) categorizes the values of C_2 in four groups, namely excellent, good, average and poor performers. Operators are assumed to work with a learning rate value corresponding to an average performer. This implies a value of C_2 between 0.25 and 0.45. In our analyses, we fixed $C_2 = 0.35$, which has been found to be the industry average for the drilling of wells. To obtain values for C_1 and C_3, we make use of the data presented in Øia et al. (2018). They provide a thorough description of operational procedures for both SSR and RLWI vessels, as well as they present duration estimates for three types of subsea wells (low, medium and high complexity wells). These duration estimates are provided as minimal, expected and maximal values. On our end, we aggregated the data from Øia et al. (2018) at a phase level. That is, we determined the duration of a phase by summing up the durations of all the operations that are included in this phase. Finally, as we lack data on durations of performing services using LCVs, and since LCV and RLWI vessels have similar capabilities, we assumed that the durations of phase 3 operations are equal for these two vessel types. A summary of the resulting data is presented in Table 2.

Table 2: Durations (in days) of the different phases when performed by SSR or RLWI vessels, for wells of different complexities, and categorized by minimum, expected and maximum value (data based on Øia et al. (2018)).

Complexity	Low			Medium			High		
	Min	Exp.	Max	Min	Exp.	Max	Min	Exp.	Max
SSR									
p0	3.75	5.29	6.88	3.65	4.71	6.19	3.58	4.58	5.79
p1/p2	6.04	8.75	12.50	7.94	9.52	12.71	11.33	14.21	18.17
p3	1.08	1.38	1.75	1.08	1.38	1.75	0.58	0.88	1.17
RLWI									
p0	2.58	3.33	4.50	4.06	4.81	6.08	6.58	8.33	10.92
p3	1.08	1.38	1.75	0.69	0.96	1.38	1.08	1.38	1.75

5.2. Results

In this section, computational results are presented and discussed for the ten different instances defined above. We focus on the inclusion of a learning effect as well as the performance of the clustering approach. The model was implemented in Python 3.5.3, formulated using Pyomo 5.1.1 and is solved with CPLEX version 12.7. The analyses have been carried out on an HP EliteBook 820 G2 computer with an Intel Core i5-5200U CPU, 2.2 GHz processor, 16Gb RAM, running Windows 10 and using up to eight threads.

5.2.1. Clustering Approach Validation

We shall first focus on quantifying the performance of the clustering based solution approach. We start by comparing the results from the original approach as presented in Bakker et al. (2019) with the results obtained using clustering. As we do not yet consider a learning effect, we fix the sequences within the different clusters using the shortest route. The instances are run with a time limit of one hour. Table 3 presents objective function values, optimality gaps and CPU times as well as a summary of the plans for each of the two approaches. In addition, we show the percentage change in objective function value between the original and clustering approach.

Table 3: Performance of the clustering approach as compared to the original approach from Bakker et al. (2019), including the best known solution (BKS) in million dollars ($MM), MIP gap, and CPU time (in seconds) for each instance. The last six columns show the number of times a particular vessel is used to perform a certain phase*.

Inst.	Original		Cluster			Orig.	Clust.	Original			Cluster		
	BKS ($MM)	MIP gap(%)	BKS ($MM)	MIP gap(%)	ΔBKS (%)	CPU time (s)		RLWI		LCV	RLWI		LCV
								p0	p3	p3	p0	p3	p3
1	36.88	(opt.)	36.88	(opt.)	0.01	14.2	0.2	4	1	0	4	1	0
2	56.29	(opt.)	56.31	(opt.)	0.02	316.7	0.2	5	2	0	5	2	0
3	83.42	(opt.)	83.42	(opt.)	0.01	21.0	0.2	5	3	0	3	0	3
4	56.59	(0.65)	56.67	(opt.)	0.15	3,600	0.4	6	3	0	6	1	0
5	109.73	(0.19)	109.75	(opt.)	0.02	3,600	1.0	6	0	6	6	0	6
6	133.60	(0.28)	133.61	(opt.)	0.01	3,600	0.4	9	0	9	9	0	9
7	140.67	(1.19)	140.51	(opt.)	-0.11	3,600	8.6	8	0	7	8	0	8
8	143.95	(2.49)	143.54	(opt.)	-0.28	3,600	1.1	11*	0	11	11*	0	8
9	143.11	(1.00)	142.55	(opt.)	-0.39	3,600	205.9	10	0	10*	10	4	6
10	186.14	(0.88)	186.21	(0.50)	0.04	3,600	3,600	12	2	10	12	2	10

* Since a rig always performs $p1/p2$ operations, a plan is characterized merely by the allocation of vessels to $p0$ and $p3$ operations.

Firstly, we observe that the objective function values for the most of the instances are nearly identical. The worst deviation arises in the fourth instance, where we observe a 0.15% upwards change in objective value as compared to the full (non-clustering based) search. In fact, for instances seven through nine, we manage to get a small improvement in the objective function value due to the original approach not having converged to zero gap. This empirical evidence suggests that clusters constructed in this way make sense for the real problem setting and lead to solutions that do not significantly sacrifice optimality.

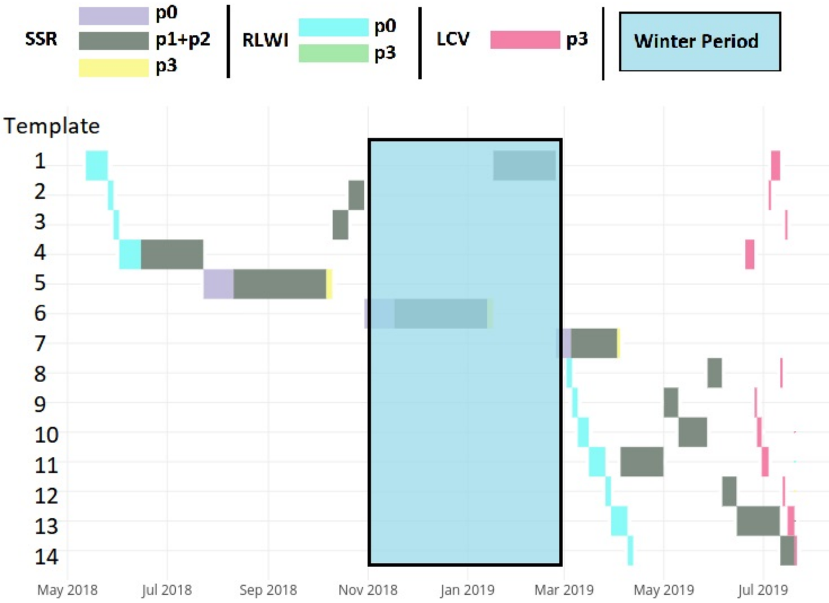
From a computational tractability perspective, we observe that the solution times drastically decrease in the clustering approach, which can be attributed to the reduction of the combinatorial feasible region compared to the original model. In fact, for nine out of ten instances, we can solve the reduced problems to zero optimality gap in mere seconds. In contrast, the majority of the problems solved with the original model timed out after an hour with a residual–albeit small–optimality gap.

Focusing on the generated plans, we can make several observations. In particular, there is a trade-off between using the different vessels. In every optimal plan, we need an SSR to perform $p1/p2$ operations, while the other operations also can be performed by the lighter vessels. Hence, a plan is mainly characterized by the usage of these lighter vessels and assignment to $p0$ and $p3$ operations at the different wells. As an example, Figure 4 shows Gantt charts representing the plans for the representative instance 8 resulting from the original and the clustering approach. We note that, on eleven out of the fourteen templates, an RLWI vessel is being used to perform the $p0$ operations. Moreover, we see that the RLWI performs two disjoint campaigns, separated by the winter period. The main difference between the two plans lies in the fact that in the original approach the LCV performs eleven $p3$ operations, while it only performs eight $p3$ operations in the clustering approach. Finally, as can be seen from the last six columns of Table 3, in all instances the clustering approach provides solutions with similar structure as those provided by the original approach, as the assignment of vessels to operations tends to be nearly identical.

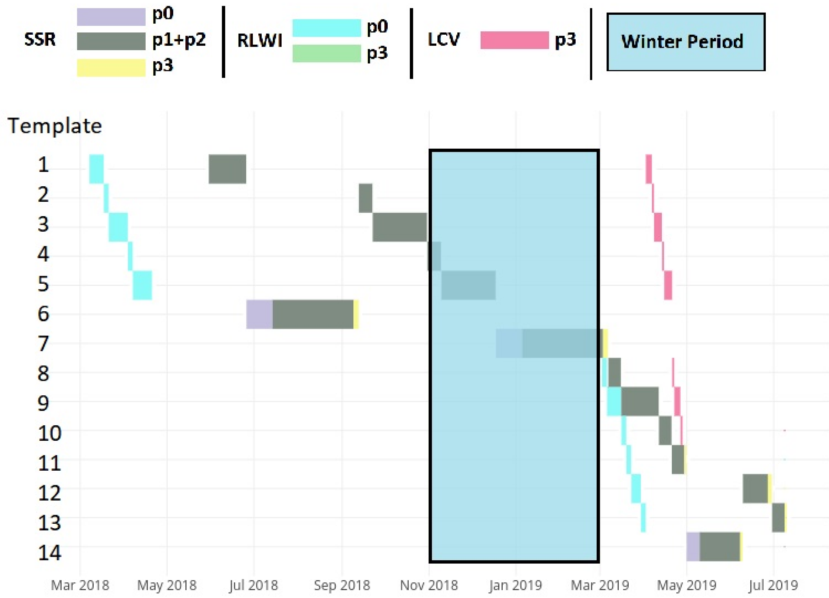
5.2.2. Learning Effect

In order to judge the impact of the inclusion of an endogenous learning effect, we take the model including learning and solve it in two different ways. First, we take the best known plan that results from the model using the expected execution times. We then solve the learning model with the obtained routing variables fixed. This gives us a measure of how the plan that does not consider learning would perform in the real setting. Second, we solve the learning model without any restrictions, resulting in the optimal plan for that case.

Table 4 presents a summary of this comparison for all instances. Firstly, we note that the *no learning* plan is not feasible in the learning model for instance 6. In addition, we observe that the plans that do not consider learning perform significantly worse than the plans that do. More specifically, we can achieve reductions in the objective function values between 3% and 20%, which results from significant changes in the plans. For example, we see in the last six columns that the distribution of which vessels perform the $p0$ and $p3$ operations changes significantly. More specifically, when not taking into account learning, both the RLWI vessel and LCV are being used to perform $p3$ operations. However, in this way, the benefits from learning are not optimally utilized. When we consider learning, we see that, in the



(a) Original Approach (adapted from Bakker et al. (2019))



(b) Clustering Approach

Figure 4: Gantt charts representing the solution for the original (a) and the clustering (b) approach for representative instance 8.

optimal plans, the solution utilizes the RLWI solely for $p0$ operations and the LCV for $p3$ operations. Therefore, in general, we can argue that the inclusion of learning leads to the use of fewer vessels to perform certain operations.

Table 4: Comparison of the plans resulting from the *no learning* (*NL*) and *learning* (*L*) model, evaluated in a learning setting. We present the best-known solution and the distribution of vessels to operations. The CPU time for the learning model is also provided.

Instance	*NL* BKS ($MM)	*L* BKS ($MM)	Change	CPU time (s)	*NL* RLWI p0	*NL* RLWI p3	*NL* LCV p3	*L* RLWI p0	*L* RLWI p3	*L* LCV p3
1	58.04	52.32	-10 %	0.2	4	1	0	0	0	0
2	73.53	71.46	-3 %	0.2	5	2	0	3	0	5
3	118.95	105.63	-11 %	0.2	4	0	4	0	0	5
4	76.11	64.08	-16 %	0.7	6	2	0	0	0	8
5	168.26	134.11	-20 %	0.8	7	0	7	0	0	8
6	-	130.59	-	1.6	-	-	-	8	0	11
7	146.73	135.98	-7 %	75.5	8	0	8	9	0	12
8	152.24	145.00	-5 %	655.4	11*	0	11	7	0	14
9	178.50	153.65	-14 %	289.4	11	4	7	0	0	14*
10	217.91	197.62	-9 %	3,600.0	13	2	10	6	0	12

*Operations performed over two disjoint periods, separated by the winter period.

5.2.3. Benefits of learning in large campaigns

In previous work, Bakker et al. (2019) have quantified potential benefits in running large plugging campaigns in lieu instead of several small ones. They refer to this as the *value of cooperation*. The presence of learning effects should make these benefits even more pronounced. To test this hypothesis, we focus on instances 5, 7, 8 and 10, for which the wells could be located on fields belonging to two different operators. Note that the results that we have obtained so far assume that these operators cooperated in one big campaign. We now consider the execution of two separate campaigns for the different operators. Table 5 compares the total costs of these two campaigns with the cumulative cost of the single cooperative campaign. Overall, we observe that cooperation in the planning of these campaigns leads to cost savings in the $11 - 13\%$ range, approximately. This is significantly more than the $3-4\%$ cost savings that Bakker et al. (2019) calculated when not considering a learning effect. Finally, Figure 5 depicts the cost savings when operators cooperate instead of planning separately for different values of the learning rate, C_2. We observe that the benefits of cooperation peak somewhere at a

Table 5: Total P&A campaign costs (in million dollars) for the two operators ("Oper. 1" and "Oper. 2"). The last column provides the percentage cost savings when cooperating ("Coop.") instead of running separate campaigns.

	P&A Campaign Costs ($MM)				
	Separate campaigns			Coop.	Cost Savings
Inst.	Oper. 1	Oper. 2	Total	Total	
5	45.59	105.63	151.22	134.11	11.3 %
7	71.46	84.07	155.53	135.98	12.6 %
9	105.63	71.48	177.11	153.65	13.2 %
10	143.98	77.51	221.49	197.62	10.8 %

learning rate between 0.2 and 0.4, resulting in gains between 11% and 20%. After these peaks, the gains slowly decrease to a steady value of around $7-12\%$. Interestingly, these results suggest that there are significant gains for relatively slow learning rates.

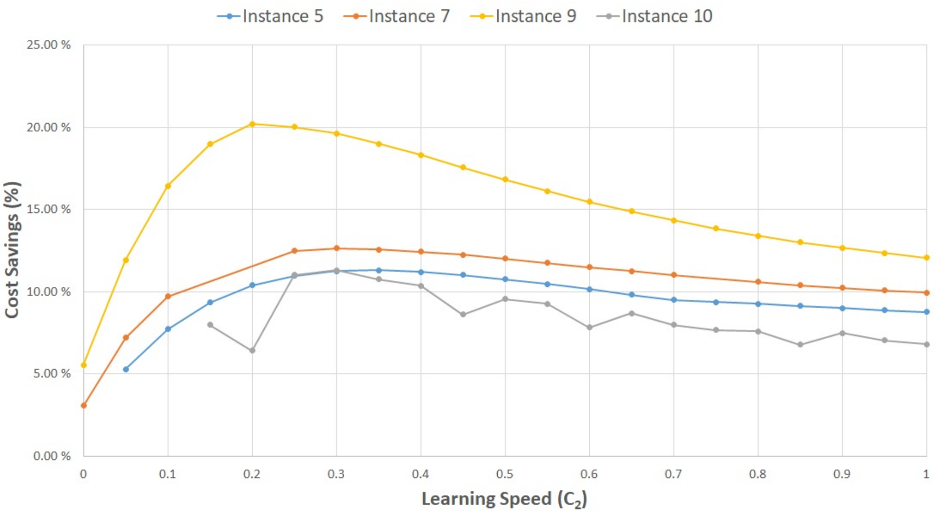


Figure 5: P&A cost savings when operators cooperate instead of planning separately, as a function of learning rate.

5.2.4. Sensitivity Analysis

The parameters of the learning curves have to be estimated based on the results of previous plugging campaigns. However, the properties of a new campaign are likely to be somewhat different, and as a result, we might observe a different learning effect than the one postulated. We are therefore interested in the *robustness* of the optimal solutions of the different instances against changes in the learning effect. The minimum and maximum times it takes to perform an operation are represented by C_3 and $C_1 + C_3$, respectively. These parameters are mainly determined by technical restrictions, and can therefore be reasonably well estimated. In contrast, the learning rate parameter C_2 might vary significantly between different campaigns and is more difficult to estimate. To this end, we will focus here on evaluating the effect of having misspecified parameter C_2, noting that similar analyses can be performed around the other parameters as well, if desired.

More specifically, we first determine the optimal plan using the nominal value of $C_2 = 0.35$ (average performer), and we fix the obtained routing variables. We then consider six different possibilities for the realized learning rate that span the learning rate categorization of Brett & Millheim (1986), namely the values $C_2 = 0.05$ and $C_2 = 0.20$ (poor performers), $C_2 = 0.50$ and $C_2 = 0.65$ (good performers) and $C_2 = 0.80$ and $C_2 = 0.95$ (excellent performers), and we solve the partially fixed model to determine actual timings and costs in each case. Table 6 presents the percentage cost differences in objective function values compared to the optimal solution for the postulated value of $C_2 = 0.35$, which provides an indication of the robustness of this solution to changes in the learning rate parameter.

Table 6: Performance of the optimal plan corresponding to the nominal learning rate value ($C_2 = 0.35$), under different realizations of the actual learning rate.

Inst.	Change in realized cost using nominal solution as reference					
	$C_2 = 0.05$	$C_2 = 0.20$	$C_2 = 0.50$	$C_2 = 0.65$	$C_2 = 0.80$	$C_2 = 0.95$
1	13.1 %	5.5 %	-4.0 %	-6.9 %	-9.1 %	-10.7 %
2	infeas.	6.6 %	-4.5 %	-7.6 %	-9.9 %	-11.5 %
3	21.5 %	8.2 %	-5.2 %	-8.6 %	-10.9 %	-12.5 %
4	infeas.	8.6 %	-4.2 %	-6.4 %	-7.7 %	-8.5 %
5	26.4 %	8.3 %	-4.2 %	-6.5 %	-7.9 %	-8.8 %
6	26.2 %	7.7 %	-3.7 %	-5.8 %	-7.1 %	-8.0 %
7	infeas.	infeas.	-4.0 %	-6.2 %	-7.6 %	-8.5 %
8	infeas.	8.4 %	-4.3 %	-6.7 %	-8.2 %	-9.1 %
9	infeas.	6.7 %	-2.4 %	-3.4 %	-4.0 %	-4.3 %
10	infeas.	7.0 %	-2.9 %	-4.3 %	-5.2 %	-5.7 %

We observe that the realized learning rate strongly affects the feasibility and costs of a plugging campaign. In fact, when the realized learning rate is lower than the anticipated (nominal) rate, the overall duration of the campaign increases. This causes the planned routes to become infeasible in many instances, while even when this is not the case, the campaign costs increase between 5.5% and 26.2%. On the other hand, for a realized learning rate that is higher than the nominal rate, the campaigns turn out to be between 2.4% and 12.5% cheaper than anticipated.

Despite the sensitivity of the total costs on the learning rate, we highlight that advance knowledge of the exact learning rate does not necessarily help. To showcase this, we conduct an alternative analysis where we judge the quality of the obtained plan under the nominal learning rate. Again, we fix the routing variables obtained from the nominal case, and resolve the model for the cases with different learning rates. Subsequently, we solve the model without any restrictions for the different learning rates, to obtain the optimal plans in each case. Table 7 now presents the percentage cost increase of the objective function value of the nominal plan compared to the optimal plan, as the latter is evaluated under the different realizations of the learning rate. This can be considered to be a measure of the *v*alue of perfect information.

Table 7: Comparison of the plan obtained from the nominal learning rate ($C_2 = 0.35$) and the optimal plan obtained under different realizations of this parameter.

Inst.	Difference in optimal costs using nominal solution as reference					
	$C_2 = 0.05$	$C_2 = 0.20$	$C_2 = 0.50$	$C_2 = 0.65$	$C_2 = 0.80$	$C_2 = 0.95$
1	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
2	infeas.	0.0 %	0.0 %	0.1 %	0.1 %	0.1 %
3	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
4	infeas.	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
5	0.0 %	0.0 %	0.0 %	0.0 %	0.4 %	0.8 %
6	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
7	infeas.	infeas.	0.0 %	0.0 %	0.0 %	0.0 %
8	infeas.	0.7 %	0.0 %	0.0 %	0.0 %	0.0 %
9	infeas.	0.0 %	0.1 %	0.1 %	0.1 %	0.1 %
10	infeas.	0.0 %	0.2 %	0.5 %	0.2 %	0.5 %

We observe that, as long as the plan corresponding to the nominal learning rate remains feasible, then this plan tends to be (nearly) optimal. This means that the value of perfect information is relatively low. In other words, knowing the realization of C_2 a priori would not affect the plan that would be generated from solving the optimization model. This finding follows from the fact that the optimal plans that are generated when considering learning tend to have a structure as described in Section 5.2.2. Moreover, these structures tend to be similar for different realizations of the learning rate.

6. Conclusions

In this article, we presented an approach that allows for the inclusion of an endogenous learning effect in the setting of the uncapacitated Vehicle Routing Problem with Time Windows. This approach consisted of the definition of continuous experience variables as well as the formulation of (possibly non-linear) learning curves using piecewise-linear functions. To evaluate the effects of the endogenous learning effect, we applied the methodology to the problem of planning a Plugging and Abandonment campaign in the context of the offshore oil and gas industry. For this application, we developed a solution approach based on clustering that manages to solve the majority of real-life instances in seconds. Moreover, we extended existing instances for this problem with additional data on the learning effect. We observe that the inclusion of a learning effect leads to significantly different optimal plans than when neglecting the learning part. In general, we see that the optimal plans try to reap the benefits of learning by utilizing the vessels with most experience. The consideration of learning in the planning of plugging operations might lead to savings in the order of $3-20\%$. In addition, we showed that there exists significant value in cooperation between operators in terms of planning campaigns together, as a result of learning effects. This effect occurs even for very slow learning rates. We also tested the robustness of the obtained solutions for possible deviations in the learning curves, and we showed that deviations in the realized learning rate strongly affect the feasibility and costs of the campaign. However, we found that the value of perfect information is very low, and hence the nominal plan would perform equally well under different realizations of the learning rate. Only when the learning effect is much smaller than anticipated, the original plan might become infeasible, due to an increase in time usage. A possible direction for future work can be to investigate this challenge by means of an appropriate technique that deals with decision making under uncertainty. Overall, we conclude that the implications of a learning effect on VRP solutions can be significant and should therefore be explicitly incorporated in the decision-making process, whenever such effects are applicable.

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Paper IV

Mature offshore oil field development: solving a real options problem using stochastic dual dynamic integer programming

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